Spatial Modeling of Deforestation and Land Suitability Assessment in the Tam Dao National Park Region, Vietnam

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Abstract

Deforestation is the conversion of forest to non-forest land. This process may be the result of the removal of forest cover for agricultural expansion or timber harvesting. It may lead to several environmental consequences that include changes in ecological, hydrological and climatic processes at both the local and global scales. It is occurring at an alarming rate in many parts of the world, especially in developing countries. Vietnam's deforestation rate recognized to be the highest level of low-income countries in the last decades, and this trend continued until recent years. An understanding of deforestation process is crucial for sustainable land use management in protected area (PA) setting. This study aims to analyze land use/cover changes (LUCC) and driving factors of deforestation in the Tam Dao National Park (TDNP) region and forecast areas vulnerable to future forest conversions. In addition, land suitability assessment in combination with ecosystem service valuation was employed for the promotion of sustainable land uses as well as the prevention of further deforestation of the region. The multispectral and temporal remote sensing imagery were employed to produce land use/cover maps for the years 1993, 2000 and 2007. Then, a cross-tabulation technique was used to measure changes in land use/cover over the years. The predictive empirical model of region's deforestation was developed using multi-layer perceptron neural network-Markov chain (MLPNN-M) approach. The model was validated to forecast areas vulnerable future forest conversions in the region. A multi-criteria evaluation (MCE) based land suitability assessment was then employed as a decision-guiding tool for preventing further deforestation and improving ecosystem service supply in the region.

The region's LUCC analysis showed that forest conversions were major LUCC in the study area. Of the total study area, primary forest declined from 27.06% in 1993 to 18.03 % in 2007. Physical and accessibility factors were determined to constitute a considerable share of the factors driving forest conversions. They include elevation, slope, the proximity to water, the proximity to roads, the proximity to cropland, the proximity to primary forest, the proximity to secondary forest and the proximity to settlements. Each forest conversion was driven by a unique set of factors. It was found that the proximity to primary forest was the most important factor affecting to the conversion from primary to secondary forest, followed by the proximity to roads, elevation, slope, the proximity to water and the proximity to settlements. For the conversion from primary forest to cropland and the conversion from secondary forest to cropland, the role of driving factors was found to be quite similar. The proximity to primary or secondary forests played the most influential role, followed by the proximity to cropland, the proximity to water, slope, elevation, the proximity to roads and the proximity to settlements.

The deforestation prediction results indicated that primary forest may decline from 18.03% in 2007 to 12.66% in 2021, and secondary forest may decline slightly as well. As a result, non-forest area can increase from 50.81% in 2007 to 57.16 % in 2021. The forest conversion resulted in a change in ecosystem service supply. It was found that the land use map of 1993 had the greatest value of ecosystem services, followed by the land use/cover maps of 2000, 2007, 2014 and 2021, respectively. Obviously, a decline in primary forest area caused a reduction in ecosystem service provision. To prevent further deforestation, the spatial patterns of sustainable land use are proposed to better match land use management with their suitability. A land use scenario for the region was delineated based on the land suitability map. The scenario proposed an increase in primary forest, secondary forest and agro-forestry area to improve the supply of region's ecosystem services. Direct payments from government's budget and ecosystem service market-based mechanism need to be combined to promote the adoption of sustainable land use practices in the area.

The most significant contribution of the study is the development of the empirical deforestation model for forecasting the temporal-spatial process of deforestation in rapidly changing protected area setting of Vietnam. In addition, the study combines the use of the MLPNN-M and the MCE in serving to improve the quality of sustainable land use decision-making for the PA setting. The entire approach can be applied to the sustainable management of other PAs across Vietnam.

Keywords: deforestation, neural network, Markov chain, land suitability analysis, multi-criteria evaluation, fuzzy set, analytical hierarchy process.

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List of Abbreviations

ADB	Asian Development Bank
AHP	Analytic Hierarchy Process
UNCBD	United Nations Convention on Biological Diversity
ES	Ecosystem Service
ESP	Ecosystem Service Provision
FAO	Food and Agriculture Organization of the United Nations
FMF	Fuzzy Membership Function
IUCN	International Union for the Conservation of Nature
ICEM	International Center for Environmental Management, Australia
GHG	Greenhouse Gas Emissions
GIS	Geographical Information System
GPS	Global Positioning System
LSA	Land Suitability Assessment
LCM	Land Change Modeler
LUCC	Land Use/Cover Change
MARD	Ministry of Agriculture and Rural Development, Vietnam
MA	Millennium Ecosystem Assessment
MCE	Multi-Criteria Evaluation
MLPNN-M	Multi-Layer Perceptron Neural Network and Markov Chain Model
MOLA	Multi-Objective Land Allocation Algorithm
PA	Protected Area
TDNP	Tam Dao National Park Region
REDD	Reduction of Emissions from Deforestation and Forest Degradation
TDMP	Tam Dao National Park and Buffer Zone Management Project
UNFCCC	United Nations Framework Convention on Climate Change
WCPA	World Commission on Protected Areas

Chapter 1
Introduction

1.1 Problem statement

Land use/cover change (LUCC), one of the main driving forces of global environmental changes, is considered as a central issue to sustainable development debate (Lambin *et al.,* 2000) because it plays as an agent of change that influences and is affected by climate change, the loss of biodiversity and the sustainability of human-environment interactions. Changes in land use/cover are directly linked to the issues of the sustainability of social-economic system because they influence essential parts of human natural capitals, *i.e.,* climate, soils, vegetation, water and biodiversity (Mather and Sdasyuk, 1991). LUCC has been continuously transforming the essential functions of the Earth's terrestrial systems (Lambin *et al.,* 2000; Singh *et al*., 2001) and affecting to the structuring and functioning of ecosystems (Vitousek *et al.,* 1997). Evidences on the impacts of LUCC on ecosystem services are increasingly accumulated at both the local and global scales. In particular, the LUCC directly influence the loss of biological diversity worldwide (Sala *et al.,* 2000), create significant effects on biogeochemical cycling and soil erosion (Douglas, 1999) and contribute to local and global climate change (Houghton, 1994; Chase *et al.,* 1999). Deforestation is widely known to be the major component of LUCC. The clearing of forests in the tropic and subtropical regions has been occurring at unprecedented rate (FAO, 2006). These regions are well known to comprise most of biological species in the world (Myers *et al.,* 2000).

The impact of LUCC on the loss of biodiversity is one of major environmental concerns because biodiversity is of fundamental component to the functioning of all natural and human ecosystems. Living organisms play central roles in the cycles of major elements, *i.e.,* nitrogen, carbon and water in the environment. Biological diversity is also especially important in providing multiple ecosystem services to human. To protect world's biological diversity under the changing of terrestrial ecosystem for the benefits of current and future generations, United Nations convention on biological diversity (UNCBD) was voted to adopt at the United Nations conference on environment and development (earth summit) held in Rio de Janeiro in 1992. The establishment of protected areas (PA) within representative ecosystems of the world is one of key tools to implement the UNCBD. A PA is defined as "an area of land and/or sea especially dedicated to the protection of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means" (IUCN, 1994). PA's primary objective is to protect the range of genes, species, populations, habitats and ecosystems in an area of interest (IUCN, 1994). Through signing the UNCBD, most of the countries have committed themselves to preserving biodiversity within their national boundaries.

The PAs have become a universally adopted means of conserving biodiversity for a wide range of human values because they are known as the most promising and effective response strategy to fight against biodiversity loss worldwide. A number of the PAs have sharply risen in the recent decades around the world. Globally, 11.2% of the total forest area has been designated for the conservation of biological diversity (FAO, 2006). In Vietnam, protected areas including nature conservation areas, national parks and historical-cultural-environmental sites were established in most of the representative ecological zones. The country's protected areas now account for 14.7% of the total forest area (FAO, 2006). The PAs are major locations for biodiversity conservation; however, they are increasingly in danger due to conflicts between biodiversity conservation goals and local livelihood strategies. In Vietnam, the PAs are often surrounded by buffer zones with rapidly growing human populations. LCCC is an important threat to biological diversity and the associated ecosystem services that need to be preserved in the PAs of Vietnam. In the larger context, LUCC has widely occurred in Vietnam. For example, the primary forest of Vietnam declined from 40.7% in 1943 to 27.7% in 1993 (Do Dinh Sam, 1994). Recently, the primary forest per the total forest area of the country remains at only 0.7% in 2005 (FAO, 2006).

LUCC can be locally documented through ground-based measurements; however, a large-scale LUCC investigation requires remote observations. Ground-based traditional surveys are very restricted for LUCC studies because they are often unable to analyze the spatial patterns of LUCC in a given time period or several times. Advancement in remote sensing (RS) and geographical information system (GIS) techniques allows one to make it easier to monitor and predict LUCC processes. RS involves measuring and acquiring information about land surface features using sensors typically found onboard aircraft and satellites. RS is an essential tool of LUCC studies because it facilitates remote observations across larger extent of the Earth surface than ground based observations. In particular, it is essential for measuring forest cover change in the areas that are inaccessible and impracticable of using ground-based methods (Tucker and Townshend, 2000) and provides an accurate measure of forest cover change (Turner *et al.*, 2003). Recently, remotely sensed images from airborne and satellite sensors provide a large amount of cost-effective, multi-spectral and multi-temporal data for monitoring LUCC. Observations of LUCC can be derived from remotely sensed data by a variety of land use/cover classification procedures, including statistical methods and human interpretation. Based on observed LUCC, driving forces behind LUCC can be examined and understood. An understanding of LUCC's drivers is very important because it is required for the development of LUCC forecasting models. These models can be developed by the integration of GIS and RS techniques. The models are extremely effective tools for protected area managers and policy makers because they can offer the forecasts of future LUCC across a wide range of spatial and temporal scales. In particular, the models can guide land managers and decision makers towards sustainable land-use management decisions.

The TDNP region is one of the most important PAs of Vietnam. It is endowed with rich biodiversity and is known to host a number of rare and endemic animal species (Khang *at al.*, 1997). Yet, the park has been experiencing considerable forest changes (TDMP, 2005; Khoi and Murayama, 2010a). Sustainable land use management is a central challenge in the sustainable management of the region (Khang *et al.*, 1997; TDMP, 2005; Khoi and Murayama, 2010a). Management policies and practices providing incentives to change the activities causing land use conversions are likely to be a useful means for the protection of the park. The sustainable management practices should be proposed based on an understanding of past and future LUCC in combination with a comprehensive land evaluation of the region. An understanding of LUCC is crucial for both sustainable agriculture and forest management decisions. Modeling is an important tool for gaining such understanding because of its ability to incorporate observations of change and the associated driving forces (Lambin *et al.*, 1991). A comprehensive land evaluation offers the basic for the development of land use policies in support of sustainable development pattern scenario. A lack of an integrated study for the region motivates this study. Therefore, an integrated framework of deforestation modeling and land suitability assessment is proposed to investigate forest changes and develop the scenario of sustainable land use patterns for the region (Figure 1-1).

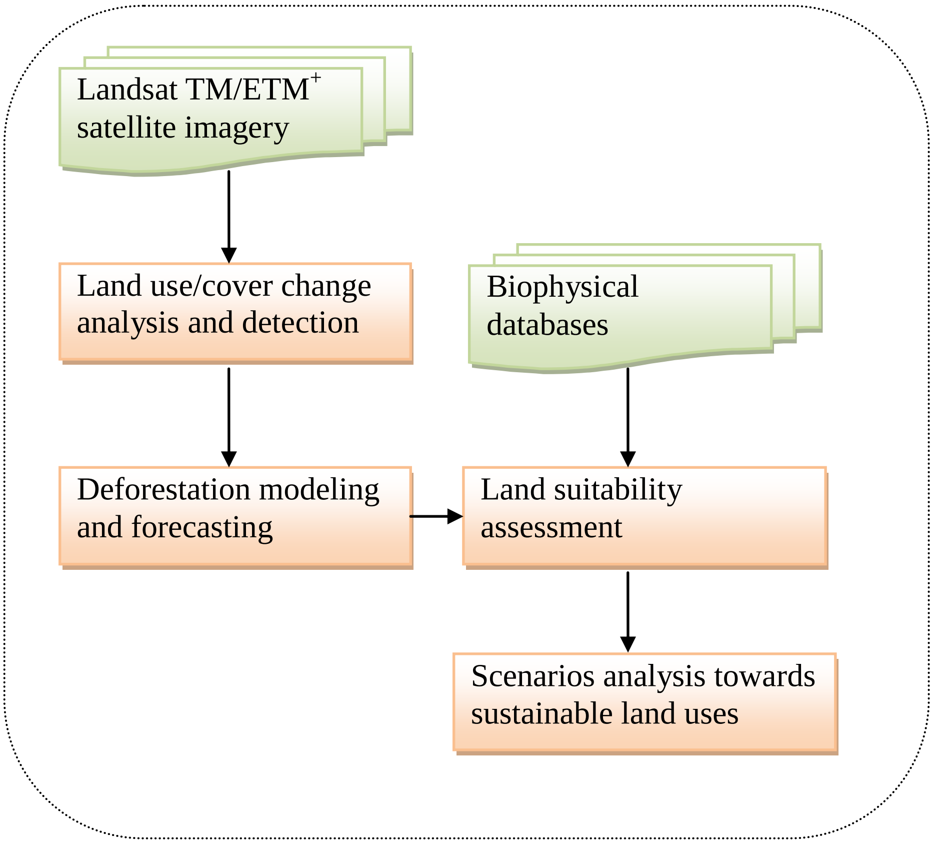


Figure 1-1: Research framework

The dissertation is structured as follows. A summary of key research contents, inputs, methods and outputs are briefly summarized in Table 1-1. Chapter 1 presents problem statement, the objectives of the study and a brief survey of relevant studies. Chapter 2 analyzes LUCC and the factors driving forest changes in the TDNP region. This chapter outlines the characteristics of study area, measurement of LUCC and driving factors in the region. Chapter 3 is to model and predict forest conversions using MLPNN-M approach. Modeling and prediction include the calibration of the MLPNN-M, model validation and the simulation of forest conversions in the future. LUCC analysis and prediction in Chapters 2 and 3 are essential steps to understand forest changes and other changes in the past and future and therefore offers basic inputs for estimating the effects of LUCC on the production of ecosystem services. Chapter 4 deals with land suitability assessment using MCE approach. The assessment emphasizes on cropland because the enlargement of cropland into forested lands may influence the sustainability of the region. A land suitability map provides critical information for developing the scenario of land use patterns that aims to improve the protection of forested lands, and therefore the provision of ecosystem services is enhanced as well. Chapter 5 proposes a guiding tool for the development and adoption of land use practices towards sustainable development goals. This chapter also discusses an integration of Chapters 3 and 4’s results for the spatial decision-making process towards sustainable land uses based on the ecosystem services provision. Finally, Chapter 6 presents conclusions and recommendations.

Table 1-1: A summary of key research contents, inputs, methods and outputs

Research content		Input	Method	Output
Measurement of land use/cover changes	Satellite images: importing and geo-referencing	Raw satellite images in the .tiff files and ancillary data	Nearest neighbor algorithm	Geo-referenced images
	Land use/cover classification	Geo-referenced images, reference land use maps (1993 and 2000), prior knowledge of the author on the study area	Maximum likelihood classifier	Land use/cover maps of 1993, 2000 and 2007
	Accuracy assessment of LUCC maps	Ground control points, GPS based interviews, reference land use maps (1993 and 2000)	Randomly stratified sampling, Kappa statistics	Validated LUCC maps of 1993, 2000 and 2007
Identification of spatial variables of forest changes	Creation of spatial variables	Biophysical and socio-economic data	GIS techniques	Thematic maps of spatial variables
	Measuring the relationship between forest changes and spatial variables	Observed forest changes and the thematic maps of spatial variables	Cramer's coefficient approach	The knowledge of the relationship between forest changes and spatial variables
Forecasting of forest conversions	Modeling forest conversion potentials	Forest cover maps of 1993, 2000, 2007 and the thematic maps of spatial variables	Multi-layer neural network model	Forest conversion potential maps
	Estimation of forest transition probabilities	Forest cover maps of 1993, 2000 and 2007	Markov chain model	Forest transition matrices for 1993-2000 and 2000-2007
	Model validation and forecasting	Forest conversion potentials and transition probabilities for 1993-2000 and 2000-2007	Combined MLPNN-M	Predicted forest cover maps of 2007, 2014 and 2021

Table 1-1: A summary of key research contents, inputs, methods and outputs (continued)

Research content		Input	Method	Output
Land suitability assessment	Generation of single evaluation factors	Biophysical factor data	GIS procedures	The maps of evaluation factors
	Standardization of factors	The maps of single evaluation factors	Fuzzy membership function	Standardized factor maps
	Estimation of factor weights	The knowledge of TDNP's experts and references	Pairwise comparison method, AHP	Relative weights of factors
	Deriving suitability map	Relative weights of factors and relative weights of factors	Weighted linear combination	Overall suitability map
Sustainable Land use analysis	Review of development goals	Documents, discussion with decision makers and other stakeholders	Group discussion	Defined goals for sustainable land uses
	Development of the land use scenario	Defined goals for sustainable land uses and land suitability map	GIS technique	The scenario of sustainable land uses
	Examination of ESP outcome	Land use maps of 1993, 2000, 2007, 2014, 2021 and the scenario of sustainable land uses	Constanza *et al.*1997's method	Change in ESP of land use/cover maps

1.2 The objectives of the study

The main objectives of the study are (1) to analyze land use/cover changes and determine factors driving forest changes in the TDNP region, (2) to forecast the spatial patterns of future forest and identify areas vulnerable to forest conversions in the future and (3) to assess land suitability and ecosystem services provision for the promotion of sustainable land uses as well as the prevention of further deforestation of the region.

In order to achieve sustainable development goals for the TDNP region, land use/cover change study is essential. It is critical for assessing and predicting past, current and future trends. This study attempts to analyze and simulate forest changes in a typical protected area of the tropical rainforest of Vietnam. The TDNP region is an interesting example because it represents the interacting effects of biophysical and socio-economic driving forces on forest changes. The past land use/cover changes were measured using the satellite images for the years 1993, 2000 and 2007. The nature and strength of the relationship between observed forest changes and spatial driving factors were then explored using the Cramer's coefficient approach. Then, MLPNN-M approach was parameterized and validated to simulate the future patterns of forest until 2014 and 2021. Finally, MCE approach was used to produce a land suitability map for the delineation of suitable areas for cropland development and other sustainable land uses in the region. The results and proposed methods of the study is useful means for the improvement of the sustainability of the TDNP region. Equally important, it expects that the proposed framework can apply to other PAs or scale up anywhere in Vietnam.

To better forecast the dynamics of forest cover changes and offer a sound decision platform towards sustainable land uses for the TDNP region, key research questions focused as follows:

(1) What are factors driving the rates and patterns of forest cover in the region?

(2) Can MLPNN-M model forecast forest conversions in the study area?

(3) What are biophysical factors and their relative importance that determine cropland suitability in the study area?

(4) What land-use management scenario should be adopted to prevent further deforestation and improve the provision of multiple ecosystem services in the region?

1.3 Review of relevant studies

The study focuses on the integrative framework of deforestation modeling and land suitability assessment for promoting the sustainable management of the TDNP region. The review presents theoretical domains of deforestation modeling and land suitability assessment. The valuation of forests is a starting point of the review, followed by deforestation, drivers of deforestation, remote sensing of deforestation, approaches to deforestation modeling and land suitability analysis.

1.3.1 Valuation of forests

The importance of forests in our planet's functioning has been documented in multilateral environmental agreements, *i.e.*, the United Nations framework convention on climate change (UNCCC) and the UNCBD (Mayaux *et al.*, 2005). Forests playing a wide variety of functions known as ecosystem services (ES) are critical to the functioning of the Earth's life support system (Costanza *et al.*, 1997). The ES represents the benefits that human derive from them directly or indirectly. A wide range of the ESs has been recognized and quantified (Daily, 1997; Costanza *et al.*, 1997) because of the intrinsic importance of ESs for human well-being and environmental concerns. They have increasingly valued (Peters *et al.*, 1989; Guo *et al.*, 2001; Pearce and Moran, 1994; Costanza *et al.*, 1997) at varying scales to offer an important tool to ensure social recognition of the public management of ecosystems (Costanza *et al.*, 1997; Daily, 1997). Regrettably, ESs are recently not captured in commercial markets and not adequately quantified as compared with the other economic services and manufactured goods; therefore, they are often given little weight in policy decisions (Costanza *et al.*, 1997).

Fundamentally, the ESs are classified into provisioning services, regulating services, cultural services and supporting services (MA, 2003; Hein *et al.*, 2006). The provisioning services are mainly described as food, fresh water, wood and genetic resources. These services are crucial for recent and future human survival. The regulating services are mainly referred to climate regulation, pest and disease regulation, control of soil erosion and water quality control. The cultural services include spiritual, recreational, aesthetic and educational functions. The supporting services consist of wildlife habitat, soil formation, nutrient cycling and primary production (Hein *et al.*, 2006). The most important role of forests is the function of biological diversity preservation. Biodiversity can be a central component because it directly associates to the production of all other ecosystem services. Among the world's forests, tropical forests, which cover less than 10% of the land area, play greatest roles as the repositories of biological diversity and the regulators of global biogeochemical and hydrological cycles (Cairns *et al.*, 2000; Myers *et al.*, 2000). More than 50% of plant species has been recorded in the tropical forests (Mayaux *et al.*, 2005). Furthermore, forest plays a critical role in the global carbon cycle, which regulates global warming because it is known as a sink and source of the dioxide carbon. Deforestation may hamper this function seriously. For example, tropical deforestation released dioxide carbon amount of about 20-29% of the global anthropogenic greenhouse gas (GHG) emissions (Watson *et al.*, 2000). Therefore, the reduction of emissions from deforestation and forest degradation

(REED) is universally recognized as one of promising strategies for reducing atmospheric GHG emissions (Naughton-Treves, 2003). The implementation of REDD in the tropics is a cost-effective way of reducing global GHG emissions (Stern, 2007). The REDD is one of the United Nations international agreements that aim to lessen the impacts of global warming (Gibbs *et al.,* 2007).

1.3.2 Deforestation process

LUCC can be defined as the human modification or conversion of the terrestrial surface of the Earth (also see concepts in the Appendix I-B), mainly for agricultural expansion and timber harvesting. The current rates and extent of LUCC are causing unprecedented changes in ecosystems and environmental processes at the local to global scales. These changes may lead to the greatest environmental consequences of human populations, *i.e.,* climate change, biodiversity loss, the pollution of soils, water and air (Meyer and Turner, 1992; Vitousek, 1994; Turner, 2007). The LUCC research program, a joint initiative of the international geosphere-biosphere program (IGBP) and the international human dimensions program (IHDP) can consider as the greatest efforts of scientific community to understand LUCC process and its impacts at the global level. The programs aimed to understand the relationship between LUCC, biogeochemistry and climate change because global climate system is directly affected by LUCC through biogeochemical processes. For example, greenhouse gases can uptake or release by the land cover of terrestrial biosphere to atmosphere. Therefore, LUCC studies provide critical inputs for modeling greenhouse gas emissions, carbon balance and ecosystems.

Deforestation is one of the most important LUCC processes. Until the early 19th century, many developed countries, including template Europe and United States, experienced massive deforestation because of industrialization and agricultural expansion. However, much of deforestation in the second half of the 20th century occurred in the tropical, subtropical and boreal regions (Mayaux *et al.,* 1998). About 50% of tropical closed canopy forest removed and the land converted into other uses (Wright, 2005). Despite increased awareness of the extent and unsustainable nature of forest clearing, the loss of tropical forests still occurred at the highest rate for the 1980s and 1990s (Ramankutty and Foley, 1999). In this period, the annual deforestation of the humid tropics was 5.8 million ha, while the annual deforestation of the sub-humid and dry tropics were 2.2 and 0.7 million ha, respectively. Southeast Asia had the highest pressure with an annual change rate of from - 0.8 to - 0.9%. Latin America and Africa was from - 0.4 to - 0.5% (Mayaux *et al.,* 2005). This trend continued to increase for the period from 1990-2005. Globally, deforestation experienced at the alarming rate of 13 million hectares per year (FAO, 2006).

A central concern of deforestation studies is the adverse impacts of forest clearing. The use of the land by human over the past five decades changed forest ecosystems more rapidly than in any comparable periods in history (Watson and Zakri, 2003) and resulted in rapid alternations in structure and functions of ecosystems (Vitousek *et al.,* 1997). The deforestation leads to both environmental and socio-economic impacts, and the former may receive more attention than the latter. It should be noted that the environmental and the socio-economic impacts are closely interrelated. The former causes the latter which then feedback to the former again, potentially causing successive rounds of the change.

The impacts of deforestation are recognized and quantified, and they mainly include changes in ecological, hydrological and climatic processes at the local and global scales (Walker, 2004). The transformation of forest cover has been the major drivers of the loss of biodiversity and ecosystem services (Hansen *et al.,* 2000; Haines-Young, 2009). In particular, large-scale deforestation occurring in the tropical forests that contain most of the species in the world (Mayer *et al.*, 2000) may lead to habitat loss, habitat fragmentation and adverse changes in local species richness and biodiversity. The effects of forest cover change on biodiversity may be greater than climate change, nitrogen deposition, biotic exchange and elevated carbon dioxide concentration at global scale (Sala *et al.,* 2000). The hydrological impacts consist of loss of infiltration capacity and acceleration of surface runoff flows. These impacts aggravate problems from water pollution and sedimentation, and may alter the balance and volumes of ground water and surface water flows regimes available to sustain agricultural ecosystems. Soil loss may occur as the result of active surface erosion and the loss of soil organic matter accumulation. The climate impact of deforestation is mainly reduction in carbon sink due to the buildup of atmospheric carbon dioxide (Hogan, 2010). A significant portion of terrestrial carbon is retained in forest biomass, which contributes to regulation of climate change. Tropical forests are capable of storing a biomass amount of more than 200 tons ha^{-1}, while temperate and boreal forest can store an average biomass amount of 90 tons ha^{-1} (Houghton, 2005). The burning and clearing of large-scale forest contribute to the release of dioxide carbon in the atmosphere, which is one of major global greenhouse gases. The biomass contained in forested lands is significantly reduced by deforestation and forest degradation (Houghton, 2005).

1.3.3 Drivers of deforestation

The descriptive study of LUCC can refer as a first attempt to identify factors driving changes in land use/cover. Such study measures changes from one type of land use to another over a given time period and within a given spatial entity. The study of description is not enough to provide the basis to guide policy and decision making towards effective ways to cope with the adverse implications of such changes. Explanatory analyses attempt to fill this gap. Explanation study is to address the question of why these changes have occurred and uncovers the factors that bring about these changes directly or indirectly in the short or the longer period.

The in-depth analysis of LUCC mainly concerns with the two central questions is that what drives/causes LUCC and what are the adverse impacts of LUCC. This part explains the first question. LUCC is usually explained by a variety of forces, and they vary according to different spatial and temporal settings. The causes can be categorized into biophysical and socio-economic factors. The biophysical factors represent the variability of biophysical factors, *i.e.*, climatic conditions, terrain, soils and water availability (Verburg *et al.*, 2004). The socioeconomic factors represent economic, technological, demographic, institutional, factors (Briassoulis, 2000) and globalization factors. The biophysical factors are often considered as the critical conditions for human decision-making processes that lead land use change.

The drivers of deforestation are quite similar to the key drivers of LUCC. The literature is rich in local case studies investigating the causes and processes of deforestation in specific localities. Fundamentally, the drivers can be classified into proximate causes, underlying driving forces and predisposing factors (Geist and Lambin, 2002). Proximate causes are human activities at the local level, while underlying driving forces are social processes that underpin the proximate causes and operate at such scale. The links between proximate causes and underlying driving forces have conceptualized (Meyer and Turner, 1992; Tuner *at el.*, 1993; Ojima *et al.*, 1994). Land use activities reflect human goals, which constitute underlying driving forces. Population growth creates a variety of demands, linked to land use activities (Semwal *et al.*, 2004). High rates of deforestation often link to population growth and poverty (Mather and Needle, 2000). In particular, the intensity of human demands influences land use decision-making (Narumalani *et al.*, 2004; Tang *et al.*, 2005) and thus affects to regional land use patterns. The main land-use conversion activities include infrastructure expansion, agricultural expansion and wood extraction. Biophysical factors, *i.e.*, soil quality, terrain and accessibility, are mainly considered as the predisposing factors of deforestation. Among the proximate causes, agricultural expansion is the leading cause of deforestation. Agricultural expansion consists of various forms such as permanent cropping, cattle ranching and shifting cultivation. Permanent cultivation was widely occurred in Asia, Africa and South America. Shifting cultivation in uplands was more widespread in Asia than elsewhere. Pasture creation for cattle ranching was a striking cause of deforestation in South America. Commercial wood extraction was frequent in Asia, while the harvesting of fuel wood frequently occurred in Africa. Road construction is the most important in infrastructure expansion forms (Helmut and Lambin, 2002).

It is difficult to establish a clear link between deforestation and the underlying drivers, but they are only recognized to be the fundamental forces that underpin land use conversion activities. Underlying driving forces consist of economic and technological factors, *i.e.*, market growth and economic structures; policy and institutional factors, *i.e.*, properties rights and credits; demographic factors, *i.e.*, population density and migration; and cultural factors. Among the forces, economic factors are dominant factors, followed by institutional factors, technological factors, cultural or sociopolitical factors and demographic factors (Helmut and Lambin, 2002). The economic factors and policies influence land use decisions by adjusting prices, taxes, subsidies on land use inputs and outputs and changing investment flow, credit access, trade and technologies. Political institutions directly affect forest conversion because access to land and other capitals are structured by local and national policies and institutions. Cultural factors, *i.e.*, motivations, attitudes, values, beliefs and individual perceptions of land users influencing land-use decisions and the consequences of land use decision depend on the knowledge and management skills of land users.

Identifying the drivers of deforestation is particularly an essential step to develop an empirical deforestation model for forecasting the dynamics of deforestation patterns in the future. Remotely sensed data, *i.e.*, Landsat images and spatially referenced biophysical and socio-economic data are required to understand the location of deforestation and driving factors. It should be noted that socio-economic factors are arguably non-spatial; however, they clearly exert their influence over a certain geographical extent or diverse geographical scales.

1.3.4 Remote sensing of deforestation

Traditional global forest inventory was initiated by the food and agriculture organization of United Nations (FAO) in 1945 (Holmgren and Persson, 2002). Few regional and global forest cover assessments were conducted in the 1970s, such as Person (1974) and Sommer (1976). The assessments of tropical forest distribution and evolution at the global scale only received the attention of the scientific community since the early 1990s. Before 1990, the assessments at the global scale often derived from statistical reports from individual countries. The accuracy of such assessments is the matter of controversy and discussion because the assessments lack reliable data. In order to improve the quality of forest cover maps and deforestation rate, remote sensing imagery is more useful than other data sources.

Remote sensing is broadly defined as the science of measuring and acquiring information about land surface features using onboard and satellite sensors without direct physical contact with the features. Earth observation from airborne platforms has a history of one hundred and fifty years, but the majority of technical innovation and development has taken place in the last three decades. The earth observation using a balloon in the 1860s referred as a starting point in the history of remote sensing (Lillesand *et al.*, 2008). The launch of first remote sensing satellite of the United States in 1972 paved the way for applications of remote sensing in Earth's resources management including the management of forests. New generations of platforms and scanning sensor systems, *i.e.*, RADAR, LIDAR and SONAR systems are rapidly emerging in the recent decade. Optical remote sensing (*i.e.*, Landsat) provides digital images of the amount of electromagnetic energy emitted from the surface of Earth at various wavelengths, while active remote sensing of long-wavelengths microwaves (RADAR), short wavelength laser light (LIDAR) and sound waves (SONAR) gathers the amount of backscatter from electromagnetic energy emitted from sensor itself.

The 1980s witnessed a sharply increasing applications of remote sensing for natural resources, especially tropical deforestation monitoring. Multispectral data acquired by onboard sensors provide the increasing availability of earth observation high-resolution satellite data, which has the great potential for identifying and monitoring land use change and deforestation at desirable spatiotemporal scales. Remote sensing data is a powerful means for monitoring tropical forest change (Jensen *at al.*, 1993; Hansen *et al.*, 2000) and increasingly used for the determination of tropical deforestation because of the inaccessibility of remote areas and the impracticality of aircraft based survey. In particular, it is used to measure changes in land use/cover and reveal aspects of biodiversity (Turner *et al.*, 2003). Satellite imagery offers a typical ability to visualize large areas at a given time. It is the best sources of information for up to date and consistent estimates of deforestation with a cost effective manner. The number of improvements in earth resources observing sensors over the past two decades has fundamentally altered capacity to observe and monitor LUCC. Global data allows global assessments of changes in net primary productivity, flora, source and sink of carbon and biodiversity.

Although many airborne and satellite sensors are currently available for land use change studies, the majority of LUCC data have been provided by Landat, high-resolution satellite sensors with 30-meter resolution. Landsat is a series of the United States satellites launched between 1972 and 1999. The satellite's sensors are the multispectral scanner (MSS) carried by Landats 1-5, the thematic mapper (TM) carried by Landats 4-5 and the enhanced thematic mapper plus (ETM^+) carried by Landsat 7. The combined use of the three sensors of MSS, TM and ETM^+ allow one to monitor LUCC and forest change at high spatial resolution. Landsats used to perform detailed assessments of deforestation rates worldwide (Foody, 2003), humid tropical forests (Archard *et al.*, 2002), Amazonian regions (Skole and Tucker, 1993; Steininger *et al.*, 2001). In particular, NASA's (National Aeronautics and Space Administration) Landsat pathfinder project on deforestation in the humid tropics (Kalluri *et al.*, 2001) and the TREES (tropical ecosystem environment observations by Satellite) project (Stibig and Achard, 2003) were most notable projects on deforestation monitoring by remote sensing technology. Concerns about the losses of habitats and tropical forests biodiversity have promoted applications of Landsat for monitoring forest cover in protected areas (Sanchez-Azofeifa *et al.,* 1999; Kinnaird *et al.,* 2003; Linkie *et al.,* 2004; Curran *at al.,* 2004). The monitoring of protected areas based on Landsat data is practical because of low conservation budgets for complex terrain regions. Field based monitoring is a nonviable solution for most protected areas.

Though satellite technology rapidly advances, the production of land-cover maps remains the issues regarding accuracy and consistency. For example, estimated deforestation varies according to different land cover classification projects. The TREES project estimated that net annual deforestation area of humid tropical forest for the period from 1990-1997 in Latin America, Africa, South Asia and Pan-tropical were 2.2±1.2, 0.7±0.3, 2.0±0.8, 4.9±1.3 million ha, respectively. However, the forest resource assessment by FAO for the period from 1990-2000 reported that net annual deforestation area of humid tropical forest in Latin America, Africa, South Asia, Pan-tropical were 4.2±1.1, 2.1±0.4, 2.3±0.6 and 8.6±1.3 million ha, respectively (Mayaux *et al.,* 2005). These differences may be caused by the use of different classification algorithms and lack of reliable training data. A combination of the use of high-resolution satellite data, appropriate statistical methods, human interpretation and the extensive involvement of local experts may help to improve the better quality of land use/cover map products.

1.3.5 Approaches to deforestation modeling

The most important purpose for conducting LUCC studies is to predict the patterns of future changes because predictions offer essential information for land-use management interventions. The development of theories and mathematical models of land cover changes offers essential tools for such prediction and simulation studies. Predictions provide information about the future dynamics of land use/cover patterns in an area of interest within a given time and space scale. The prediction of land cover change is a starting point for assessing adverse ecological and environmental impacts, such as land degradation, loss of biodiversity habitat, soil erosion, release of carbon into atmosphere and other ecosystem services.

Theories in land cover change studies just emerged in the first half of the 20th century. The theories were independently developed by scientists from different fields of study, such as urban and regional economics, urban and rural sociology, geography and planning as well as natural sciences. Quantitative revolution in geography, economics, sociology and planning in the 1950s and 1960s facilitated the development of the models and theories of land cover change. In addition, advancement and progress in computer and data processing technology reinforced the quantitative studies, particularly the development of remote sensing and GIS technology.

Interdisciplinary approach of LUCC studies appeared after the 1970s. Thematic studies of land cover change from forestry, agronomy, biology, ecology, urban and regional economics are attempting towards interdisciplinary approach.

The early land cover models can tract back to *econometric models* that are based on the economic principle of land asset. Every parcel of land has a fixed location with its associated unique attributes such as soil quality, slope, elevation and accessibility (Koomen and Stillwell, 2007). Ricardo and Von Thünen are the early land use/cover economic theorists. Ricardo (Koomen and Stillwell, 2007) explained land price according to soil fertility or land quality. Von Thünen (Koomen and Stillwell, 2007) explained land use patterns based on distance and transportation cost variables. Under this vein, a range of econometric models was developed, *i.e.*, area base model (Hardie and Parks 1997), univariate spatial model (Mertens and Lambin 1997), econometric model (multinomial logit) (Chomitz and Gray 1996), Markov model (Wood *et al*., 1997), simple log weights (Wear *et al.,* 1998) and logit model (Wear *et al.*, 1999). Econometric land use models have the particular strength that explains the primary driving forces of land use changes, but they have limitations in applications because these models cover mainly economic aspects of LUCC. The environmental factors affecting to LUCC are often ignored in the analysis.

The *statistical models* offer another approach for land-cover change modeling studies. These empirical models are developed by the use of multi-regression analysis techniques to describe the distribution of LUCC in the past in a particular area and then use this model to predict land cover change in that area. In regard with the statistical models, a change in land use/cover plays as a dependent variable, while driving factors play as independent variables. This approach provides an exploratory mechanism to identify key driving variables behind LUCC process (Turner *et al.,* 1993). Such models have the advantage of being relatively easy to construct; however, they miss a theoretical foundation as no attempt is made to understand and simulate the progresses that actually drive LUCC (Koomen and Stillwell, 2007). Another limitation is that the drivers of LUCC vary from region by region, countries and localities across a country. Statistical models developed for a particular area of interest cannot apply for other areas.

The *cellular automata (CA)* can be a useful means of land cover change modeling studies (Clarke *et al.,* 1998, Kirtland et al., 2000). The CA can be used for simulating complex spatial processes based on simple decision rules (Wolfram, 1984). Every pixel has a certain state that is affected by its surrounding pixels and the characteristics of the pixels itself. The degree and direction of interaction between pixels is determined by transition rules. A range of CA models have been applied in geographical modeling (Toler, 1979), urban land use simulation (Batty, 1997; Clarke *et al.,* 1997; Clarke and Gaydos, 1998), land use planning (Wu, 1998; Li and Yeh, 2000; White and Engelen, 2000). The CA models have a limited theoretical relationship with decision-making process that drives LUCC process. Recent CA applications are trying to incorporate these dimensions into LUCC simulation studies (Koomen and Stillwell, 2007).

An alternative approach for the spatial modeling of LUCC is the use of *spatially explicit models*. This approach is known as most promising trend because geospatial technologies can support the integration of environmental, social, economic and institutional dimensions of LUCC process. California urban and biodiversity analysis model (CURBA) (Landis *et al.*, 1998) and California urban future (CUF) (Landis 1995, Landis and Zhang 1998) are good examples in this category. CUBA model based on the logit model is an effective tool to help urban planners to evaluate the possible effects of alternative urban growth patterns and policies on biodiversity and natural habitat quality. The CUF model also focuses on the simulation of urbanization growth. The land change modeler (LCM) of IDRISI Taiga (Eastman, 2009) is another choice of LUCC modeling studies. This model has proved to be more powerful than CUBA and CUF models because LCM can be used for change prediction with a variety of land cover types, including urbanization growth simulation studies. Notably, implication analysis and planning algorithms are included in the LCM model for a variety of applications. Artificial neural network (ANN) and Markov chain are fully integrated within the LCM. The ANN is an efficient learning algorithm to model the complex nonlinear relationships between input and output variables (Bishop, 1995), whereas multi-regression linear models often give low performance when the relationships between variables are nonlinear (Lek *et al.*, 1996).

Integrated models appear to be the future trend of LUCC modeling studies. The integrated models attempt to portray social, economic, environmental and institutional dimensions in modeling the changing process of land use (Rotmans and van Asselt, 2001). In addition, the integrated models are recently the research agenda among land-use change scientists. Many land use change models focus on specific processes affected by a defined set of variables, but they are changing to system approach. However, one difficulty of the integrated approach is the cooperation between social and natural scientific communities. The social scientists tend to add complexity on the social side while generalizing components on the biophysical side, whereas the natural scientists do the opposite (Argawal *at al.*, 2001). Following this vein, several integrated models were developed in the last decade. Some of these promising models are general ecosystem model (GEM) (Fitz *et al.*, 1996), conversion of land use and its effects (CLUE) (Veldkamp and Fresco, 1996a), Patuxent landscape model (PLM) (Voinov *et al.*, 1999), natural environment research council (NERC) and economic and social research council (ESRC): NERC/ESRC land use program (NELUP) (O'Callaghan, 1995), spatial dynamic model (Gilruth *et al.*, 1995), land use change analysis system (LUCAS) (Berry *et al.*, 1996), dynamic model (Swallow *et al.*, 1997) and forest and agriculture sector optimization model (FASOM)

(Adams *et al.,* 1996).

A large number of land-cover change models have been developed in recent years, but many challenges remain in this modeling area. They may regard to the issues of theory, spatial-temporal and decision-making complexity and model validation. In particular, the complexity of temporal-spatial and human decision-making dimensions is considered as the most challenging issue in LUCC modeling studies (Argawal *at al.,* 2001).

The issue of theory is one of the most important aspects in LUCC model development. A theory is important not only for model development, but also for interpretations of modeling results. The use of an appropriate theory is indispensable, but integrated economic-environmental modelers recognize the lack of a theory that assists them in making important choices and model specifications (Verbug *et al.,* 2004). Land cover change models often justify spatial, temporal and functional specifications based on certain theoretical statements and assumptions. Some models are solely based on economic theory; however, economic theory is not adequate for providing a comprehensive theoretical basic for land cover change modeling because land cover change is influenced by both environmental and human factors. Theoretical foundations and assumptions have strong influence on the output of the models; however, they are not often examined (Verbug *et al.,* 2004). Interpretations in the results of the models in term of assumptions and other limitations make the modelers to improve the weakness of the models (Briassoulis, 2000).

The second challenging issue concerns the complexity of temporal, spatial and human decision-making. The *temporal scale* is described as a length of time that is the smallest unit of analysis for change. The temporal complexity varies from few time-steps (short duration) to a large number of time-steps (long duration). Analyses over long periods of time attempt to reveal the macro-forces that induce land cover changes such as social, cultural and technological change. On the contrary, short-term analyses seek for more immediate factors affecting human behavior that leads to land cover change although the influence of the larger macro-forces can be taken into account as conditioning the shorter-term phenomena. The *spatial scale* represents the smallest geographical unit of analysis for the model that represents as pixel-size (resolution) in raster maps. The spatial complexity represented by a range of resolutions. For example, common spatial scales used in deforestation models include individual household, farm, region, country and the world. Macro-analyses necessarily refer to global changes and take into account global explanatory factors or determinants of land use change. As analysis moves towards lower spatial levels, explanation moves deeper into the social and psychological dynamics that underlie human behavior and consequently land use change. The spatial scale is received much more attention than the other scales because it closely relates to the selection of the model variables. Different spatial scales, different variables can be considered to structure deforestation models. The household or farm scale often depends on the agents' decisions. The watershed level or small area scale models emphasizes on local variables such as climate, topography, soil fertility, vegetation, access to road and market, land ownership and population. The regional models cover both biophysical and socioeconomic variables of deforestation. The national and global scale models often emphasize on population growth, policies, macroeconomic trends, prices, institutions and technologies (Kaimowitz and Angelsen, 1998). The *human decision making scale* is currently not described clearly as temporal and spatial scales. The human decision making complexity represented by number of social factors are integrated into the model. The mismatch between human decision-making scale, temporal and spatial scale is a central challenge in integrating social dimensions in land-cover change modeling studies. The complexity of land-cover change models can be described by an index that measures its level of complexity in temporal-spatial and human dimensions (Argawal *at al.*, 2001).

The last challenge regards to the issue of model validation. For the application of a model, model validation for any area of interest is needed. Model validation is the process of making a measure of agreement between a simulated map and a reference map that is assumed to be true. Validation answers two important questions. How well do a pair of maps agree in term of the quantity of pixels in each category, and how well do a pair of maps agree in term of the location of pixels in each category (Eastman, 2009). The model validation is an important component in model development and application because it is essential to know a model's prediction accuracy. Currently, model validation is the weakest part of land-cover change modeling community because there is no universally accepted criterion to evaluate a land cover model versus another land cover model or compare one run versus other runs of a same model (Pontius, 2004).

1.3.6 Land suitability analysis

The theoretical framework for land evaluation and land use allocation decision-making is based on the decision theory that concern with the logic by which one arrive at a choice among alternatives. One of the most commonly used decision theories in field of land suitability analysis is multi-criteria evaluation (MCE) framework (Eastman, 1993). The MCE is one of recently developed approaches that facilitate the decision analysis process. The MCE methodology emerged in the early 1970s as a response to the criticism of traditional neoclassical environmental economics (Voogd, 1982). The weakness of traditional views of decision-making is the ignorance of environmental effects of land use activities. Multi-dimensional decision making and evaluation frameworks provide tools for analyzing the complex tradeoffs among choice alternatives with different environmental and economic effects (Carver, 1991). The mathematical framework employed to depict multiple dimensional decision-making is multi-objective optimization theory (Eastman *et al.*, 1993). A major advantage of a multi-criteria analysis framework in land evaluation and allocation problem is its capacity to take account of a number of differing, yet relevant factors. The MCE is a set of systematic procedures for analyzing complex decision problems. The basic strategy is to divide an evaluation problem into small parts, analyze each part, and integrate the parts in a logical manner to produce meaningful solution (Malczewski, 1999b). In any evaluation, steps may include problem identification, criteria selection, alternatives generation, criterion weighting, ranking alternatives by decision rules, sensitivity analysis and recommendation (Malcewski, 1999).

Making decisions about how land should be used is one of the most important activities of land resources managers (FAO, 1976). The MCE model provides a useful means for such decisions. The purpose of MCE is to investigate a number of choice possibilities in light of multiple criteria and multiple objectives (Carver, 1991). In doing so, it is possible to generate various alternatives and rankings of alternatives according to its attractiveness. A decision is a choice among alternatives based on a set of criteria (Eastman *at al.*, 1995). An alternative can be understood as a pixel in GIS raster map or a parcel of land, a point, a polygon in GIS vector map. The two types of distinguished data for generating criteria are factor and constraint data. Factor data is the one that can enhance or detract from the suitability of a specific alternative for an activity under consideration. Another is constraint data that serve to limit the alternatives available for consideration (Eastman *at al.*, 1995).

The procedure by which the factors and constraints are combined to arrive at a particular evaluation is known as a decision rule. Specifically, data and decision maker's preferences are integrated into an overall assessment of the alternatives. A decision rule allows one to order alternatives. It dictates how best to order alternatives or to decide which alternative is preferred to another. There are numerous decision rules that can be used for ordering alternatives. Eastman *et al.* (1995) distinguished the two types of decision rules, which are the choice function and choice heuristic. The choice function is a mathematical means for comparing alternatives. It may involve some form of optimization. On the other hand, the choice heuristic specifies a procedure to be followed rather than a function to be evaluated. In most situations, the choice heuristic provides a solution that is approximate to the choice function result. In particular, this heuristic method is easy to understand and implement (Diamond and Wright, 1989; Eastman *et al.*, 1995). However, Malczewski (1999a) classified the decision rules into the five types, including additive decision rules, value/utility function rules, analytical hierarchy process rules, ideal point methods, concordance methods and fuzzy aggregation operations. The additive decision rules (ADR), *i.e.*, weighted linear combination, are the best known and most widely used methods in GIS based decision making. The ADR is based on the concept of a weighted average. The decision makers assign directly weights of relative importance to each criterion. A total score is then obtained for each alternative. It should be noted that there are two assumptions in the use of the ADR methods: the linearity and additivity of criteria (Bodily, 1985). The linearity means that the deriability of additional unit of criterion is constant for any level of that criterion. The additivity means that there is no interaction effect between criteria.

The major element of the MCE is the development of the evaluation procedure (Carver, 1991). Given the variety of scales on which criteria can be measured, the decision rule requires that values contained in the various criteria be transformed to comparable units. A number of techniques can be used to make criterion maps comparable. Linear scale transformation can be used to transform input data into commensurate criteria maps. Another way of developing comparable criteria maps is to use value/utility function approaches. Fuzzy set membership function provides a promising tool for the development of commensurate factor maps (Malczewski, 1999a).

The evaluation of land suitability based on only objective factors often do not provide an appropriate understanding of the suitability because the factors have usually the varying levels of importance. Therefore, it is necessary to include criteria weight in order to examine the effects of criteria while resolving the objective. The procedure for weighting the factors can be approached using different methodologies. Saaty (1977) suggested the use of comparison matrices for deriving weights from expert opinions. Other approaches, *i.e.*, ranking and rating methods, requires verbal response and non-parametric statistics (Malczewski, 1999a). Such approaches rely on some level of group decision-making (Eastman *et al.*, 1993). Saaty's method has been well documented and become very popular among researchers.

In the recent years, the development of spatial decision support systems based on the MCE (MCE-SDSS) has been recently one of research focuses in the SDSS field because this approach is particularly useful in cases in which decision makers are difficult to define clearly their semi-structured problem and their objectives. The rapid growth of these systems has occurred in the past decade; however, this field is far from maturity (James *et al.*, 2007). The MCE-SDSS offers a flexible, problem solving environment in which decision problem can be explored, understood, and redefined; trade-off between multiple and conflicting objectives are investigated; and priority action set is evaluated and analyzed (Carver *et al.*, 1996). It also provides a control mechanism for decision makers and allow them introduce qualitative and subjective information during evaluation and solution process (James *et al.*, 2007).

Many MCE based SDSS have been developed and applied in land use management, *i.e.*, integrated wetland ecosystem management (Janssen, 2005), land suitability analysis (Banai, 1993; Jankowski and Richard, 1994; Bojorquez-Tapia *et al.*, 1999; Bojorquez-Tapia *et al.*, 2001; Joerin *et al.*, 2001; Malcewski, 2006), land use planning (Mardonald and Faber, 1999; Mohamed *et al.*, 2000; Dai *et al.*, 2001), location analysis (Hill *at al.*, 2005), water resource management, natural resources conservation and habitat (Genneletti, 2004 and 2007; Palma, 2007), watershed management (Macleod *et al.,* 2007). Ochola and Kerkides (2004) developed a spatial decision support system for land quality assessment in Kenya. This system was designed to support land use scientists, agricultural extension officers and farmers to classify and characterize land quality, assess the sustainable land management and identify potential land use solutions at farm level. Rudner *et al.* (2007) developed a system for evaluating the ecological and economic impacts of various management scenarios for dry grasslands in Germany. Van Delden *et al.* (2007) developed the policy support system for land degradation and desertification, sustainable farming and water resources for Mediterranean watershed. Rivington *et al.* (2007) developed a land-allocation decision support system (LADSS). This system supports the possible adjustments of land management and is suitable for land use analysis at farm level. Dorner *et al.* (2007) used the Bayesian network based multi-objective modeling approach for testing the effects of land management scenarios. A MULINO decision support system was introduced by Giupponi (2007). This system aims at holistic analysis in change in management of land and water resources, which is mandated by the implementation of the EU water framework directive. The driving force-pressures-states-impacts-response framework in combination with multi-criteria evaluation was used in land-use decision process for structuring problem, discussing decision and communicating proposed solution. Schuter and Ruger (2007) presented a decision making model coupling a multi-objective water allocation model and landscape dynamics and habitat suitability assessment. It is applied in river basin management in Amudarya River Delta.

Chapter 2
Land Use/Cover Changes
in the Tam Dao National Park Region

2.1 Importance of land use/cover changes

On a global level, increased carbon dioxide in the atmosphere, alterations in the biochemistry of the global nitrogen cycle and LUCC are well known as critical changes in the environment (Vitousek, 1994). Changes in land use/cover have important implications for the future changes in Earth's climate. LUCC causes the release of greenhouse gases, the loss of biodiversity and the sedimentation of lakes and streams (Walker, 2004). In particular, it is recognized as the major driver of the loss of biodiversity and ecosystem services (Sala *et al.*, 2000).

Deforestation is known as one of the most important elements in LUCC processes. Large-scale deforestation is occurring in the tropical forests, which contain most of the species in the world (Myers *et al.*, 2000). Globally, deforestation has been occurring at an alarming rate of 13 million hectares per year (FAO, 2006). In Vietnam, two-thirds of the territory was primary forest until the mid-twentieth century (Poffenberger and Nguyen, 1998). Though forest cover in the country as a whole was 40.7% in 1943, it declined to 27.7% by 1993 (Do Dinh Sam, 1994). Primary forest was deforested to its lowest levels in the late 1980s and early 1990s (Meyfroidt and Lambin, 2008). Vietnam's deforestation rate was the highest among low-income countries over the period from 1965 to 1989 (World Bank, 2002). This trend 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 (FAO, 2006). However, from the mid-1990s until now, there has been an increase in reforestation across the country (Meyfroidt and Lambin, 2008).

Deforestation not only reduces forest area but also alters landscape configuration. Therefore, protected areas need to 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 (FAO, 2006). 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 (FAO, 2006). Many protected areas in the country are experiencing forest changes (ICEM, 2003). 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 (TDMP, 2005). 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 to map forest change patterns. Satellite remote sensing plays a key role in mapping and predicting forest changes (Linkie *et al.,* 2004; Giriraj *et al.,* 2008). Satellite imagery provides an accurate measure of forest cover and deforestation (Turner *et al.,* 2003).

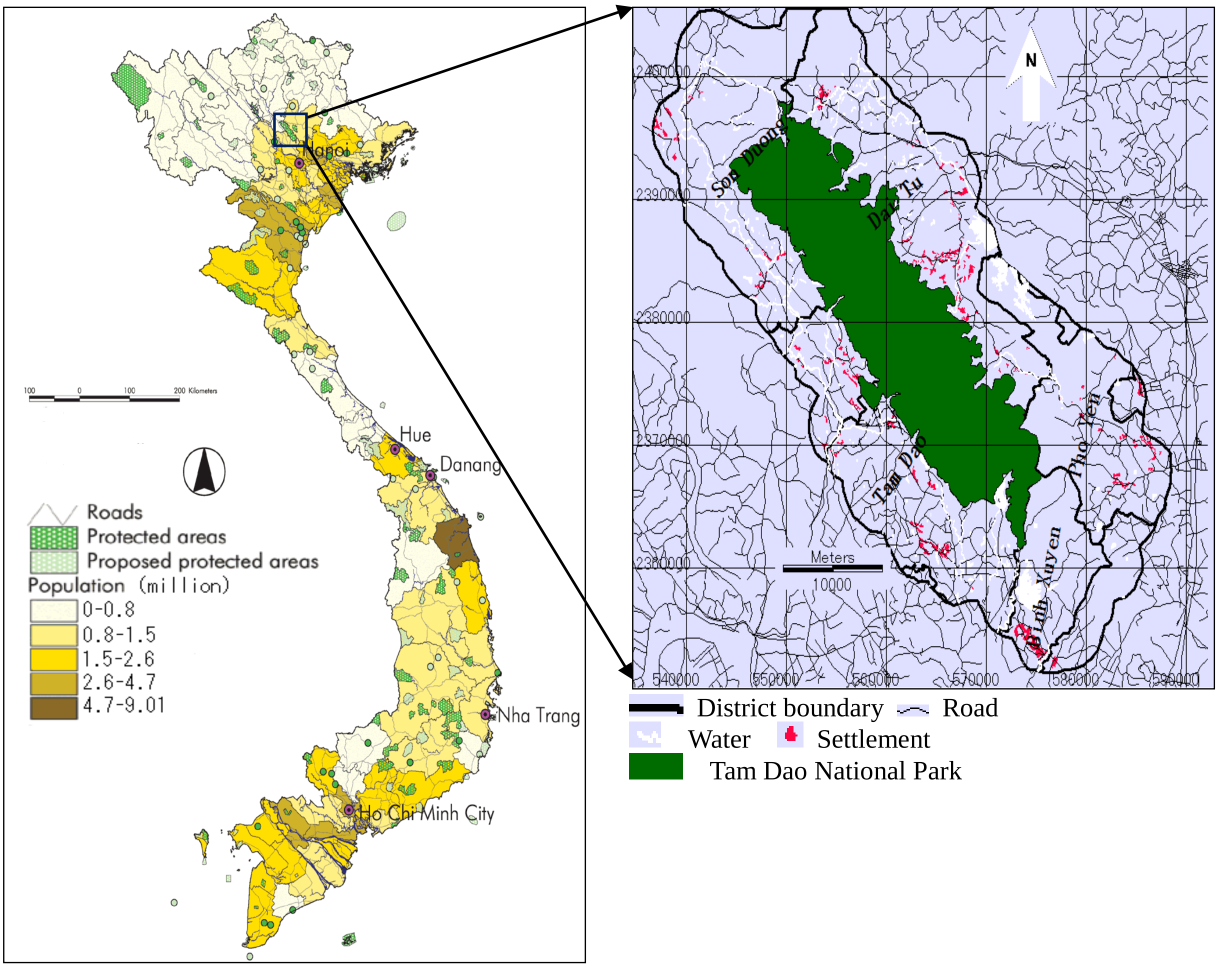
The TDNP region is one of the most important protected areas in Vietnam. It contains the last remaining primary forest. It is endowed with rich biodiversity and is known to host a number of rare and endemic animal species. Yet, the park has been experiencing considerable forest changes due to overpopulation 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 (Khang *et al.,* 2007). 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 (TDMP, 2005).

In the context of protected areas, the monitoring and analysis of LUCC are critical because LUCC has several impacts in the provision of ecosystem services. Few LUCC studies have conducted in Vietnam (*i.e.,* Do Dinh Sam, 1994; Lang, 2001), and these descriptive studies were interpretations of the roles of causes of LUCC. These interpretations did not often attempt in empirically verifying changes with their driving factors due to a lack of spatial databases; therefore, such studies provided only limited insights into the spatial and temporal dynamics of land use/cover changes. This chapter is to analyze the process of land use/cover change in the region using Landsat imageries and spatially referenced ancillary data. A hybrid unsupervised and supervised approach was used to produce land use/cover maps for the years 1993, 2000 and 2007. A post-classification comparison technique was employed to measure changes in land use/cover, especially forest changes. Then, the temporal and spatial dynamic of forest conversions for the period 1993-2007 and their driving factors were examined. This analysis serves as a basic for developing an empirical prediction model of forest cover changes in the future and ultimately supports decision making towards sustainable uses.

2.2 Study area description

2.2.1 Location of the study area

The study area covers a region of 141,238 ha that includes the TDNP (about 35,000 ha) and the buffer zone. The area is situated within the five districts of the 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 mountainous part of Vietnam (Figure 2-1). The TDNP region is considered one of the best and largest examples of the tropical rainforest habitats of Vietnam. It is known to host a variety of insects, butterflies, birds, medical plants and rare animal species (Ghazoul, 1994). Furthermore, the TDNP region supports some of the highest levels of recorded insect diversity in Vietnam. A recent biological survey has identified 1,436 plant species and 1,141 animal species in the park (Khang *et al.*, 2007).



Map of Vietnam (ICEM, 2003)

Figure 2-1: Location of the Tam Dao National Park region

2.2.2 Physical characteristics

The study area consists of the mountain range with the elevation of the park between 100 to 1,580 m above mean sea level (Figure 2-2). The topography is very complex, and the range of mountains is dissected by many narrow valleys. It stretches over a length of roughly 80 km and a width of around 15 km. The mountains with very steep slope create a variety of fast streams, rivers and waterfalls into the valleys. In general, the area can be separated by the upper part, which is the strictly protected core area and the lower part, which is the agricultural and residential lowland areas.

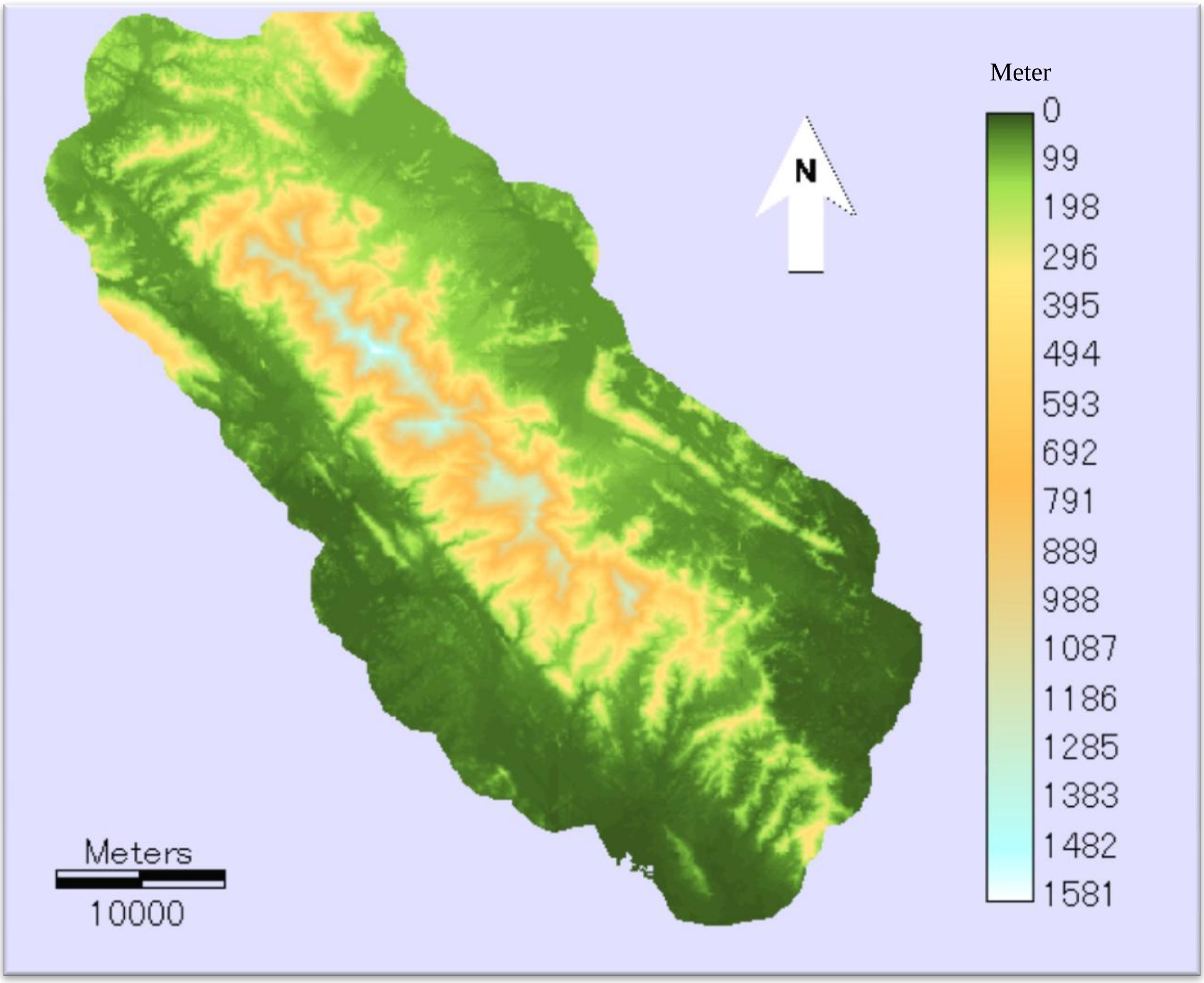


Figure 2-2: Variation in elevation in the study area

According to the Vietnam soil map with a scale of 1:100,000 published by National Institute of Agricultural Planning, Ministry of Agriculture and Rural Development of Vietnam, the TDNP region consists of 20 soil types belonging to four soil groupings: Ferralsol, Fluvisol, Regosol and Acrisol. The *Ferralsol* is a red and yellow weathered soil and its color results from an accumulation of metal oxides, particularly iron and alum. Geologically, it is formed on old parent materials in humid tropical climates with rainforest vegetation growing in natural state. The *Fluvisol* is the result of process of river sedimentation. It is technically defined by a weak or nonexistent surface horizon and by parent material derived from river, lake sediments that have been deposited at regular intervals or in the recent past. The *Regosol* is characterized by shallow, medium to fine textured and unconsolidated parent material that may be of alluvial origin and by the lack of a significant soil layer formation. The *Acrisol* is formed on undulating topography and hence strongly weathered acid soils with low base saturation. Typical topographical characteristics significantly influence soil formation in the region. For example, the land surface runoff and orientation of slope affects microclimate condition, which in turn affects vegetation regime and soil quality. Major soil textural classes include sandy clay loam, sandy loam, silt loam and loam. In general, soils in the region have a depth of from 40 to 150 cm, only a small percentage of area is rocky maintains with a thin topsoil layer. The region is characterized by a tropical monsoon climate with two distinct seasons, a wet and dry season. The dry season from October to April is characterized by a low temperature and a little rainfall. The wet season has a more rainfall (Figure 2-3) and a higher temperature (Figure 2-4).

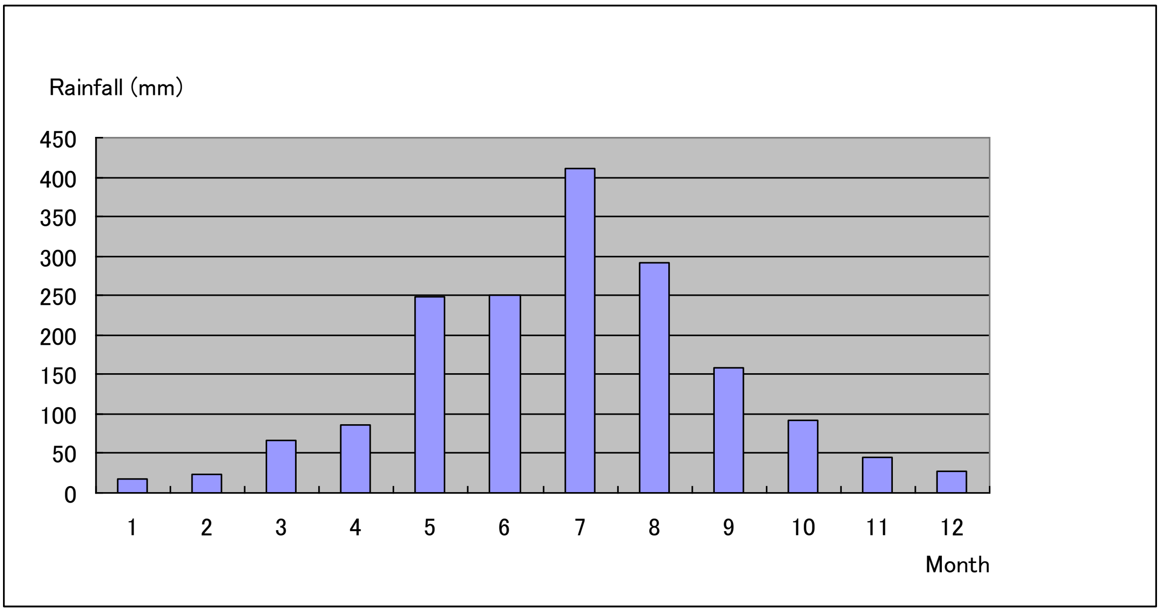


Figure 2-3: Monthly average rainfall in the TDNP region for 1997-2006

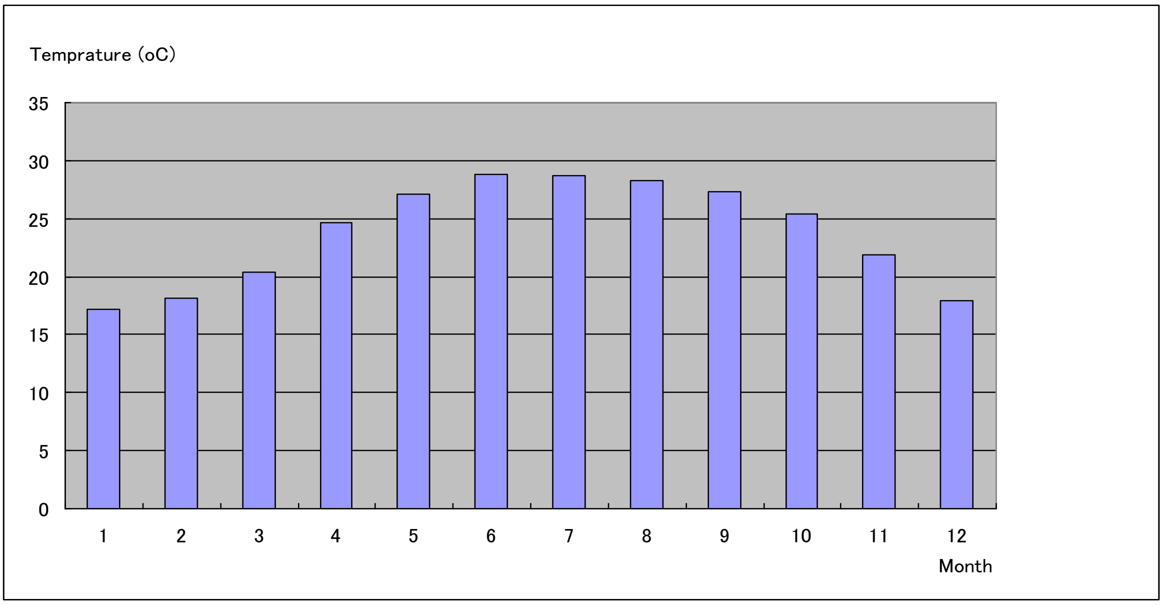


Figure 2-4: Monthly average temperature in the TDNP region for 1997-2006

2.2.3 Social-economic characteristics

History of the TDNP region: French colonial administration established the Tam Dao town at the beginning of the 20th century as a tranquil resort in the northern Vietnam. In the early 1960s, the population density in the area was relatively low; therefore, primary forest was dominant over the entire region. At that time, the Tam Dao refers as a large area of lower evergreen forest with lowland evergreen forest at lower areas and dense forest on the highest peaks of Tam Dao mountain range. In the 1970s, primary forest was gradually deforested by slash and burn farming (or known as shifting cultivation). Shifting cultivation involves clearing a small patch of forest, releasing nutrients to topsoil layer by burning logged trees and then growing annual crops in clearing areas for a short period of two to three years. The fundamental soil nutrients for crop growth, *i.e.*, nitrogen, phosphorus, potassium and organic matter, is substantially reduced from two to three years because of soil erosion, and the process is repeated elsewhere. Where population density is low, this approach works well. Small and abandoned clearing fields are well re-colonized and recovered before cultivators are needed again for next cultivation.

In 1977, the government of Vietnam established a 19,000 ha nature reserve or *so-called* Tam Dao reserve because the area has a biological diversity representing the northern part of Vietnam. Before 1985, forest logging activity took place at low level, but in the early 1990s, the intensity of logging activity increased in response to an increased demand for timber (Khang *et al.*, 2007). In 1993, an investment plan for the Tam Dao was proposed to upgrade the nature reserve to national park status. 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 activity 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 due to the high level of firewood extraction and agricultural encroachment.

Population growth: Over four decades, the region has experienced increasing population growth because of new settlement policy introduced by the government of Vietnam. Recently, the study area has a total population of 192,697 persons. The number of households was 41,951 in 2007 and the natural growth rate of the population still remained at a high rate of 1.66% per year. Population density varies from 100 to 300 inhabitants per km^2 and the average is 204 inhabitants per km^2. About 11.3% household have their income lower than the poverty threshold of Vietnam. Kinh people (74.7%) and ethnic minority groups (25.3 %) are major groups in the region (Khang *at al.,* 2007). The ethnic groups' education is generally lower than that of the Kinh's group. The low education level of ethnic peoples is one of main challenges in improving their awareness of conserving biodiversity and natural resources.

Economic activities: High population density in combination with dependence on agriculture has increased pressure on available natural resources, such as forest and agricultural land for semi-subsistence farming. The major economic activity in the area is semi-agriculture with major food crops such as paddy rice, maize, tea and vegetables. The non-agricultural households account for only 5.6%. Many households require more lands for their farming in order to safeguard their food production revenues. About 23.7% of the households are in this situation, and thus forests may be highly converted into croplands in the area (TDMP, 2005). Aside from agricultural production and forest products exploitation, there are few economic development opportunities there.

Transportation infrastructure: roads network is one of the most important infrastructures that significantly shape the rate of deforestation. Roads building investment has traditionally been one of the most important tools for rural development and regional economic development; however, they also contribute to the acceleration of deforestation process. In particular, roads are well known as a key driver of forest loss because they open forest areas to logging and agricultural expansion. New roads offer market access for timber and agricultural products. Roads also lower the cost of migration, land accessibility and land clearing for subsistence farmers. In the TDNP region, the two major highways influence the transportation of timber and agricultural products from the region to the surrounding cities. The first highway connects the TDNP region with Vinh Yen city of Vinh Phuc province and then links to Ha Noi city (the capital of Vietnam) and Hai Phong city (seaport for goods export). The second highway connecting Tuyen Quang province's city with Thai Nguyen province's city crosses at the Dai Tu district of the TDNP region. These cross-province highways favor forest clearing for commercial crops, *i.e.*, tea plantation and timber extraction, while commune and district roads stimulate the spread of shifting cultivation.

2.3 Landsat satellite images and ancillary data

Multi-temporal Landsat images acquired in the years 1993, 2000, and 2007 were processed for deriving land use/cover patterns and quantifying temporal changes in land use/cover. The images were obtained from the Global Land Cover Facility, the University of Maryland (http://www.landcover.org). They were downloaded in the .tiff files format, and then were together imported into GIS IDRISI Taiga software. Each set of Lansat 5 Thematic Mapper (TM) images and Landsat Enhanced Thematic Mapper Plus (ETM^+) images for a year includes the seven bands of three visible, one near infrared (NIR), two short-wavelength infrared (SWIR) and one thermal band. The thermal bands (band 6) have a coarser spatial resolution; therefore, they were excluded from the classification procedure of land use/cover. The study used only the six bands with a same spatial resolution of 28.5m x 28.5 m as follows (Table 2-1).

Table 2-1: Landsat satellite images used for land use/cover classification

Satellite	Path/ Row	Spectral range (µm)	Pixel resolution	Acquisition date	Remark
Landsat TM	127/045	B1: 0.44-0.52 B2: 0.52-0.60 B3: 0.63-0.69 B4: 0.76-0.90 B5: 1.55-1.75 B7: 2.08-2.35	28.5m x 28.5m	December 27, 1993	Dry season
Landsat ETM^+	127/045	B1: 0.45-0.52 B2: 0.53-0.61 B3: 0.63-0.69 B4: 0.78-0.90 B5: 1.55-1.75 B7: 2.09-2.35	28.5m x28.5m	October 04, 2000	Dry season
Landsat ETM^+	127/045	B1: 0.45-0.52 B2: 0.53-0.61 B3: 0.63-0.69 B4: 0.78-0.90 B5: 1.55-1.75 B7: 2.09-2.35	28.5m x 28.5m	November 11, 2007	Dry season

Note: B1-5 and 7 are bands 1-5 and 7

The study area clipped from the scenes to increase the contrast in the images helps to identify and recognize features more transparently and easier. Then, enhancement techniques such as stretch technique were used to uncover the spectral patterns and distribution of land use/cover patterns in the region. In order to classify the images into land use/cover patterns, ancillary data are also needed to carry out a supervised classification procedure. In particular, ancillary data serves for the delineation of training areas for the classification. This data consist of 1:50,000-scale contour line map produced in 1972, stream and river network map, road map, general land-use map published by the Tam Dao National Park office and GPS based intensive interviews with local people and experts. In addition, report and documents relating to land-use in the study area were collected. All kinds of ancillary data were provided by TDNP office and TDNP and buffer zone management project.

2.4 Land use/cover classification procedures

The Landsat satellite images contain only the information in digital numbers; therefore, a classification procedure is required to transform those digital numbers into understandable land use/cover patterns. An image processing procedure can be defined as a process of extracting distinct land use/cover classes or categories from satellite imagery data based on supervised or unsupervised classification methods. The unsupervised method is the division of the whole image into different categories based on the similarity of spectral signatures, and each category is leveled by a certain name. In contrast, supervised classification method uses existing knowledge (such as existing land use maps, ground based observations and airplane photos) for classifying the images into land use/cover patterns. In this study, both supervised and unsupervised classification methods were used. The classification procedure was carried out by the following major steps: pre-processing, delineation of training areas, signatures development, classification and accuracy assessment.

Pre-processing: Pre-processing mainly relates to the geographical registration of the images, decision about resolution and visualization tasks with an aim to improve the quality of classification products in the later stage. Accurate registration of satellite imageries is essential for analyzing the LUCC of a particular area. Each image was georefereced to a common UTM based 1:50,000 scale topographic map of the study area. All images were then resampled using the nearest neighbor algorithm. In IDRISI Taiga software, this was implemented by Resample module. The root mean square error of the images was found to be less than one pixel. The administration boundary map was used to mask out and extracted the study area for processing and classification. All images were then adjusted a resolution from 28.5 m x 28.5 m to 30 m x 30 m. This was implemented by using Project module.

The visualization of spatial patterns of digital numbers in the images is very important for understanding major features or patterns dominant within the entire region. Individual bands were carefully visualized to improve the interpretability of the image. Band visualization provides an understanding of the spectral patterns of the image. The band 1 provides information about penetration of water bodies and thus is able to differentiate soil and rock from vegetation and to detect cultural features. The band 2 is sensible to water turbidity differences. This band can separate vegetation types, *i.e.,* forest and cropland from soil. In this band, settlement and infrastructures have brighter tone, but vegetation has dark tone. The band 3 is a strong chlorophyll absorption spectral region; therefore, this band can distinguish vegetation and soil. The band 3 is particularly useful in the study area. It is capable of separating primary forest, secondary forest and cropland areas (see the a, b and c images of the Appendix III). However, this band fails to differentiate forest and water in the area. Forest and water body appear to have similar spectral values. This band is capable of separating cropland and forest. The band 4 can distinguish vegetation and its conditions; therefore, it is able to separate primary forest and secondary forest (degraded forest) in the area. Water bodies are a strong absorber of near infrared energy; therefore, this band clearly delineates water bodies and separate dry and moist soils. The band 5 is capable of separating forest, cropland and water bodies. Forest has darker tone than cropland. Water bodies have darker tone than forest and cropland. The band 7 shows the capacity of separating secondary forest from primary forest areas. Aside from visualization of individual bands, composite images were also employed to enhance the interpretability of features of the images. In the region, composite images were mainly valuable to visualize water bodies and agricultural areas. Water bodies were recognized by the composite images of bands 7, 4 and 2 (see the d, e and f images of the Appendix III).

Delineation of training areas: The training areas (TA) are known areas of a land use/cover category determined by ground observations or inspection of airplane photos and the reference land use/cover maps that are assumed to be true information. In GIS system, a TA area is represented as a set of pixels for the known area of that land use/cover class. The delineation of TA is most effective when an image interpreter has full knowledge of the study area and a good reference land use/cover map. In this study, a TA was delineated by the combined use of ground observations and the reference maps. They include reference land use maps of 1993 and 2000, the visualization of individual bands, the band combinations (the composite images) and the author’s knowledge on the relative locations of land-use types in the study area gained through ground observations.

TAs for land use/cover classification for the years 1993, 2000 and 2007 were identified as follows. Primary forest was identified based on the legend of the reference land use maps. This class is also easy to recognize by visualizing band 3 and the composite image of bands 7, 4 and 2 (also see d, e, f images in the Appendix III). Secondary forest class was identified by the reference land use maps, the visualization of band 7, GPS based intensive interviews with local land managers and the author's knowledge on the relative locations of secondary forest gained through field observations in the study area. Rain-fed agriculture class was delineated by existing land use maps and band 3. Paddy rice class occupies the areas with the slope of less than three degree. This was verified by field observations. Water bodies were identified by the composite image of bands 7, 4 and 2. Settlement was recognized using the existing land use maps. After all TAs were identified, they were individually digitized by the on-screen method based on IDRISI software.

Signature development: A spectral signature (signature) is a set of pixels that statistically defines a training site set for a specific land-use type. Spectral signature files were generated from six adopted bands. Each signature is defined by statistical parameters, including the number of bands, the minimum, maximum, and the mean value of training areas, the covariance matrix of training areas and the number of pixels in training areas. After the development of the training areas for each land use/cover, the Makesig module in IDRISI Taiga was used to create the signature files that use for the classification. The Makesig creates signatures from information contained in input images using training site data.

Supervised classification with maximum likelihood algorithm: The effective classification of remote sensing data depends on separating land use/cover types into a set of spectral classes (signatures) that represent the data in a form suitable to particular classifier algorithm. Supervised classification process involves the initial selection of training areas on the image, which represent specific land use/cover classes to be mapped. Several mathematical algorithms can be used as supervised classification procedures. In this study, maximum livelihood algorithm was employed to the separation of land use/cover classes for the region. This method is adopted because it requires a minimum training area data, but it can achieve a high accuracy. The maximum livelihood classifier is a probability density function that associates with a particular training area signature. The classifier evaluates the probability that a given pixel belongs to a category and classifies a pixel to the category with the highest probability. The image interpreter trains the software to recognize spectral values associated with the training areas. After the signatures for each land use/cover are defined, the software then uses those signatures to classify the remaining pixels.

Post-classification processing and accuracy assessment: Post-classification processing is very important to remove the mismatch locations of classified land use/cover. The slope and elevation data were used to examine the correctness of all land use/cover classes. For example, the pixels of paddy field with a very high slope were considered as the mismatch locations.

These locations was re-assigned into rain-fed agriculture or secondary forest class. The next step is accuracy assessment that is a critical step in the process of evaluating the quality of land use/cover map product. Accuracy assessment is to compare a classification map to the reference map that is assumed to be true (Lillesand *et al.,* 2008). The most common way to express classification accuracy is the preparation of *so-called* error matrix. It is also known as confusion matrix or contingency matrix. Such matrix shows the cross-tabulation of the classified land use/cover and the actual land use/cover according to the results of sample site observations. The matrix lists the values for known land use/cover type of the reference data in the columns and classified land use/cover data in the rows. The main diagonal of the matrix shows the correctly classified pixels. The producer's accuracy, user's accuracy, overall accuracy and kappa statistic were calculated for the evaluation of land use/cover classification performance.

The overall accuracy knows as the percentage of correctly classified samples. It was calculated by dividing the correctly classified pixels, the sum of the values in the main diagonal, by total number of pixels checked by reference maps/air-photos or observed in the field. It is given as follows

$$\frac{D}{N} x100\%, \tag{2-1}$$

where: D is total number of correct pixels summed along the major diagonal, and

N is total number of pixels (site observations) in the error matrix.

Aside from the overall accuracy, classification accuracy of individual classes can be calculated in a similar way. The producer's accuracy and user's accuracy are possible. The producer's accuracy is the measure of omission errors that correspond to those pixels belong to the class of interest that the classifier has failed to recognize. It was derived by dividing the number of correct pixels in one class by the total number of pixels as derived from the corresponding reference data class (the column total).

$$\frac{X_{ii}}{X_{+i}} x100\%, \tag{2-2}$$

where: X_{ii} is total number of correct cells in a land use/cover class, and

X_{+i} is sum of cell values in the column.

In a similar way, if the correct classified pixels in a class are divided by the total number of pixels that are classified in that class, this measure is called user's accuracy. The user’s accuracy is the measure of commission errors (Richards and Jia, 1999) or simply the measure of the reliability of the map. It informs users how well the map represents what is really on the ground. This measure is calculated as follows

$$\frac{X_{ij}}{X_{+j}} x100\%, \tag{2-3}$$

where: X_{jj} is total number of correct cells in a land use/cover class, and

X_{+j} is sum of cell values in the row.

The Kappa coefficient is a measure of the overall agreement of a matrix. In contrast to the overall accuracy, the ratio of the sum of diagonal values to total number of cell counts in the matrix, the Kappa coefficient also takes into account non-diagonal values. The Kappa coefficient has become a standard component of most every accuracy assessment (Congalton, 1991; Hudson and Ramm, 1987). It is given as follows

$$\widehat{\mathrm{K}} = \frac{\mathrm{N}\sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{X_{ii}} - \sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{X_{i+}} \mathrm{X_{+i}}}{\mathrm{N}^2 - \sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{X_{i+}} \mathrm{X_{+i}}}, \tag{2-4}$$

where:

r = number of rows and columns in error matrix,

N = total number of observations (pixels),

X_{ii} = observation in row i and column i,

X_{i+} = marginal total of row i, and

X_{+i} = marginal total of column i.

The accuracy of the classifications was assessed using the same reference sample. Using a stratified sampling method, a set of reference pixels per class were randomly selected for the accuracy assessments. Randomly selected reference pixels lessen or eliminate the possibility of bias (Congalton, 1991). The sample size for each land use is based on its spatial extent. A total of 270 sites (pixels) were collected by ground observations in March and April 2009. A geographical position system (GPS) and a digital camera were used to collect the site data and record the views of the sites for analysis. The three error matrices for the three classifications were generated by visually and carefully interpreting each sample pixel.

2.5 Results and discussion

2.5.1 Land use/cover classification

The land use/cover patterns for the years 1993, 2000 and 2007 (Figures 2-5, 2-6 and 2-7) were derived using maximum livelihood supervised classification algorithm. The remote sensing images were classified into six land use/cover classes: primary forest, secondary forest, rain-fed agriculture, paddy rice, settlement and water (Table 2-2). Primary forest includes the dense vegetation area, which is almost free from human disturbance (also see Appendix IV). It can be described as a forest ecosystem that has the typical characteristics and key elements of native ecosystems such as complexity, structure, diversity and abundance of mature trees. Secondary forest can be described as the mosaic of forest plantation, shrub and bare land. Bare lands have been disturbed by human activities in a number of ways such as forest logging and slash and burn farming practice. Rain-fed agriculture includes the mixture of multiple crops such as tea plantation, pasture, cassava, maize, peanut and vegetables. This land-use type was extended when irrigated agriculture was fully extended in the lowland area of the region. Paddy field is for rice production system. Settlement includes rural residential and other public infrastructures. Water body consists of streams, rivers, lakes and ponds.

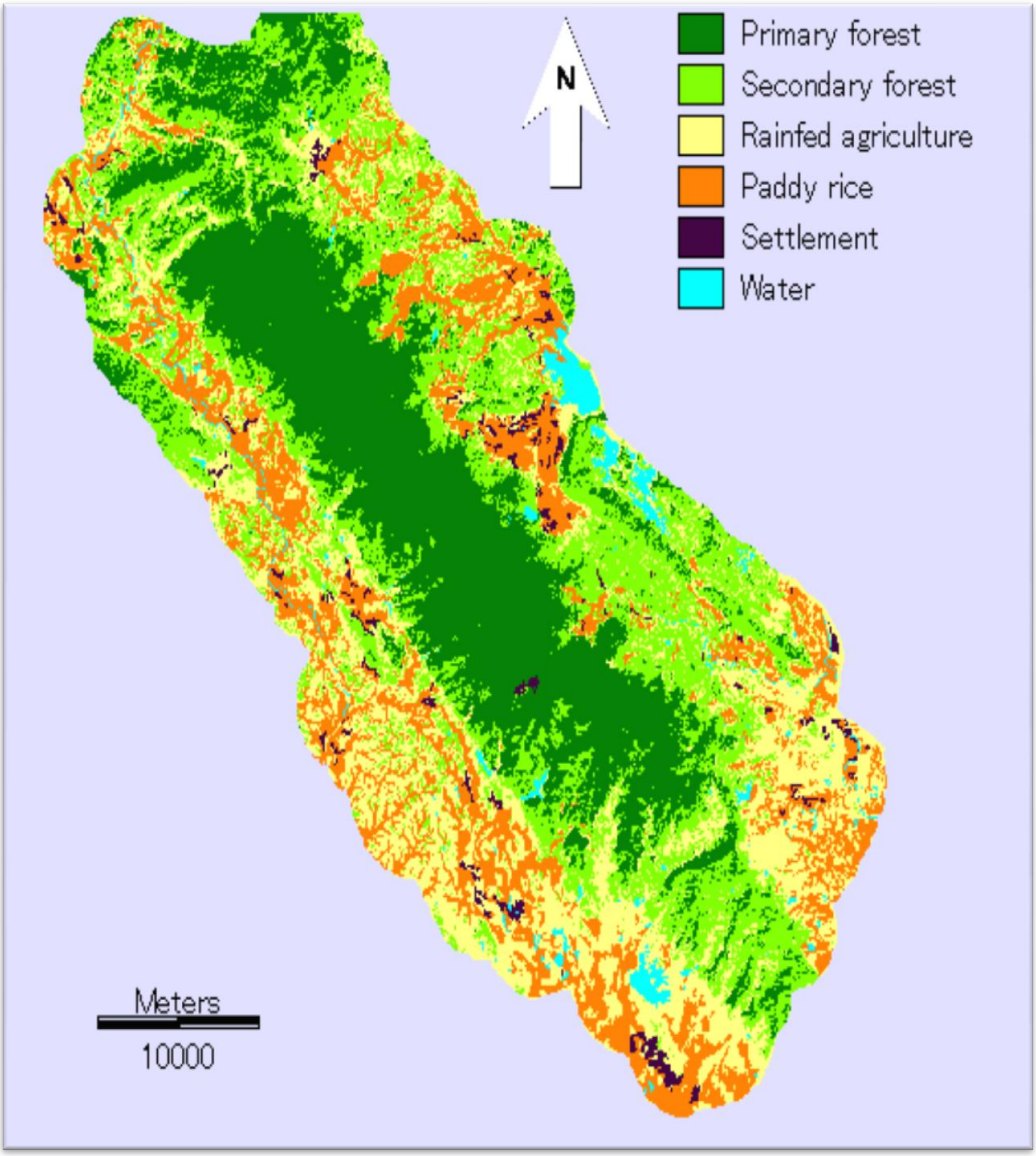


Figure 2-5: Land use/cover map derived from Landsat in 1993

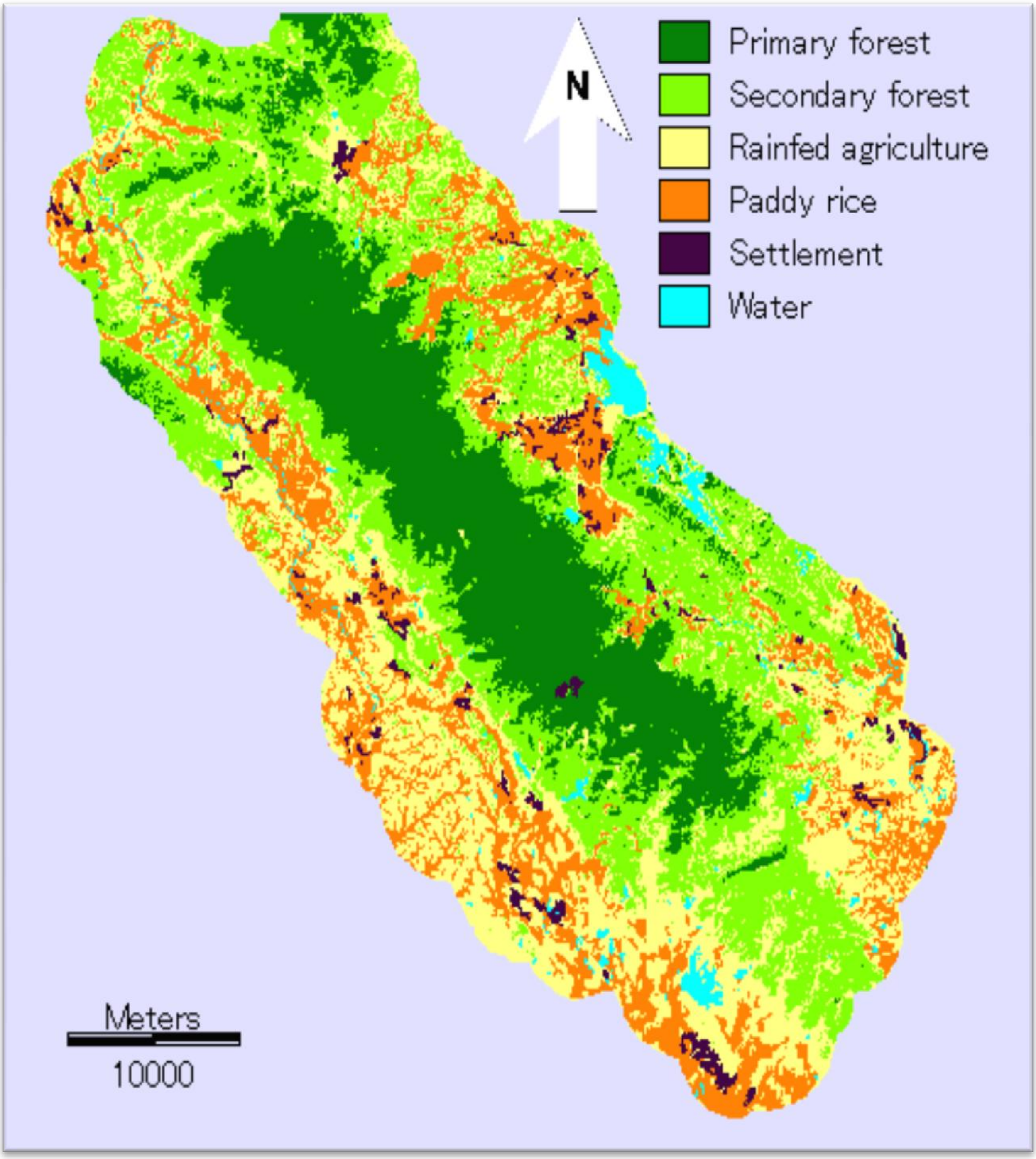


Figure 2-6: Land use/cover map derived from Landsat in 2000

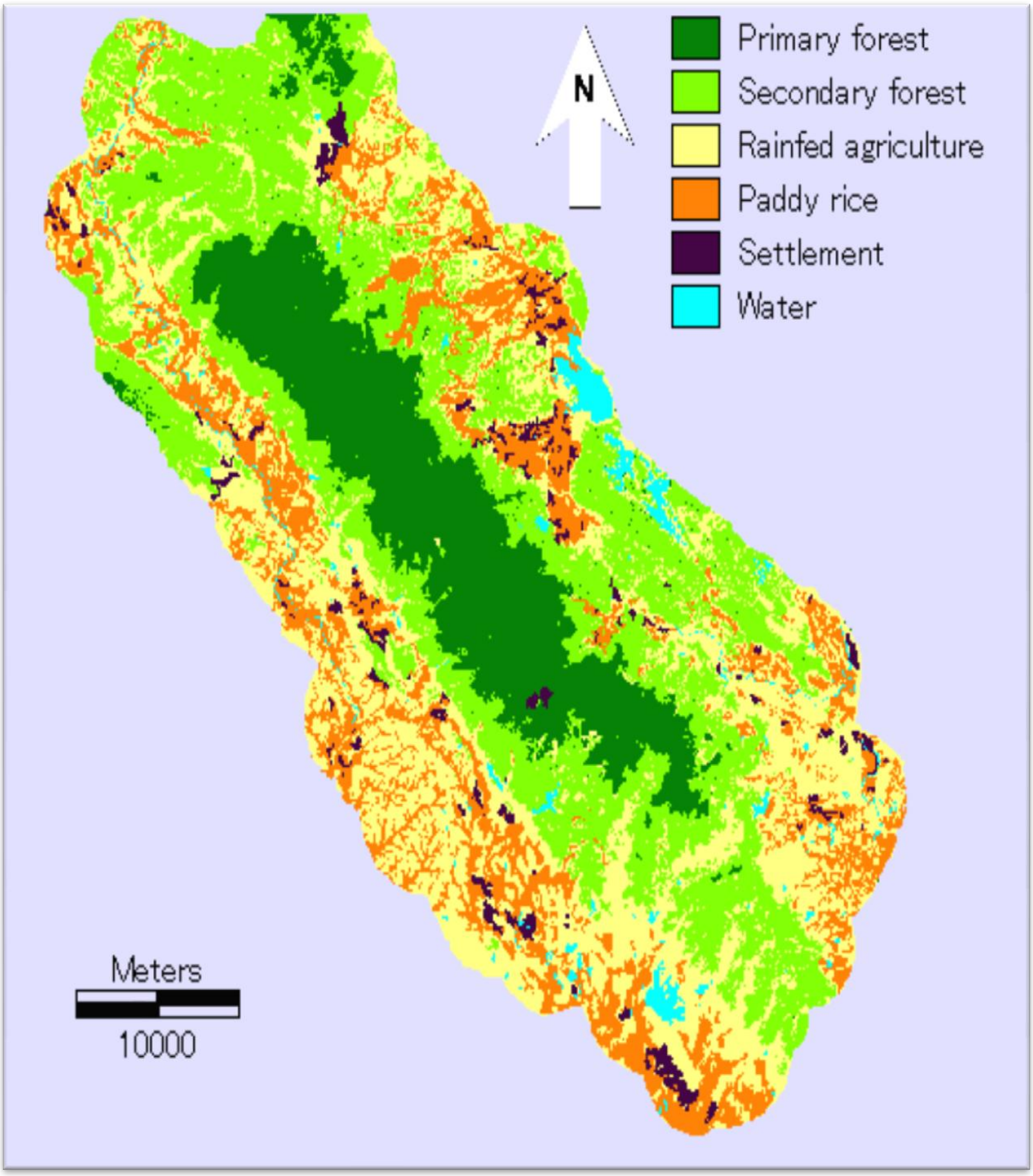


Figure 2-7: Land use/cover map derived from Landsat in 2007

Table 2-2: The extent of land use/cover in the region for 1993-2007

Land use/cover	1993		2000		2007	
	ha	%	ha	%	ha	%
Primary forest (PF)	38,218	27.06	30,352	21.49	25,459	18.03
Secondary forest (SF)	39,842	28.21	43,633	30.89	44,018	31.17
Rain-fed agriculture (RA)	34,560	24.47	38,045	26.94	42,018	29.75
Paddy rice (PR)	23,525	16.66	23,725	16.80	23,925	16.94
Settlement (S)	2,224	1.57	2,514	1.78	2,919	2.07
Water (W)	2,868	2.03	2,968	2.10	2,898	2.05
Total	141,237	100	141,237	100	141,237	100.00

2.5.2 Accuracy assessment

An error matrix was prepared for each thematic map of land use/cover. The matrix provided the correspondence between the classified and the reference data to examine the agreement between the two. The reference sample sizes were determined according to spatial extents of the classes. The producer's, user's, overall accuracy and Kappa statistic examined the accurateness of the thematic maps. The overall accuracy of the land use/cover maps for the years 1993, 2000 and 2007 were 86.67%, 89.26% and 90.01%, respectively (Tables 2-3, 2-4 and 2-5). The overall accuracy of land use map of 2000 was close to the overall accuracy of the land use map of 2007.

Looking into individual class, primary forest and water had higher producer's and user`s accuracies than the paddy field, secondary forest and rain-fed agriculture. On the other hand, settlement category had the lowest accuracy. The mixture of land surface features in the rural settlement, *i.e.*, house, garden and backyards scored the user's and producer's accuracies poorly in the settlement class. Similarly, the user and producer's accuracies of the rain-fed agriculture class were lower than the others because of the mosaic of different cropping systems within a same area. Finally, Kappa indices were estimated to be 0.83, 0.86 and 0.87, respectively.

Table 2-3: The error matrix for the assessment of land use/cover classification in 1993

Classified data	Reference data							
	PF	SF	RA	PR	S	W	Total	U.Acc
PF	72	4	2	2	2	0	82	87.80
SF	2	45	5	0	3	0	55	81.82
RA	1	4	47	0	2	0	54	87.04
PR	0	0	2	36	2	1	41	87.80
S	0	0	0	2	18	0	20	90.00
W	2	0	0	0	0	16	18	88.89
Total	77	53	56	40	27	17	**270**	
P.Acc	93.51	84.91	83.93	90.00	66.67	94.12		
Overall accuracy	**86.67**							
Kappa index	**0.83**							

Notes:
U.Acc is user's accuracy.
P.Acc is producer's accuracy.
Other abbreviations see Table 2-2.

Table 2-4: The error matrix for the assessment of land use/cover classification in 2000

Classified data	Reference data							
	PF	SF	RA	PR	S	W	Total	U.Acc
PF	65	5	2	1	0	0	73	89.04
SF	2	63	3	0	1	0	69	91.30
RA	1	3	47	0	2	0	53	88.68
PR	0	0	2	38	2	1	43	88.37
S	0	0	0	2	14	0	16	87.50
P.Acc	1	0	0	1	0	14	16	87.50
Total	69	71	54	42	19	15	**270**	
P.Acc	94.20	88.73	87.04	90.48	73.68	93.33		
Overall accuracy	**89.26**							
Kappa index	**0.86**							

Table 2-5: The error matrix for the assessment of land use/cover classification in 2007

Classified data	Reference data							
	PF	SF	RA	PR	S	W	Total	U.Acc
PF	66	3	2	1	0	0	72	91.67
SF	2	63	3	0	1	0	69	91.30
RA	1	3	48	0	2	0	54	88.89
PR	0	0	2	38	2	1	43	88.37
S	0	0	0	2	14	0	16	87.50
W	1	0	0	1	0	14	16	87.50
Total	70	69	55	42	19	15	**270**	
P.Acc	94.29	91.30	87.27	90.48	73.68	93.33		
Overall accuracy	**90.01**							
Kappa index	**0.87**							

2.5.3 Changes in forest cover

In this study, the forecasting of forest conversions was the main focus; therefore, these classified land use/cover maps were aggregated into primary forest, secondary forest and non-forest areas (Figures 2-8, 2-9 and 2-10). Figures 2-8 and 2-9 show the spatial patterns of forest changes for the periods from 1993-2000 and 2000-2007. The total primary forest loss for the period from 1993-2000 was 7,870 ha, equivalent to 20.59% of the primary forest area in 1993. For the period 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. Because 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.

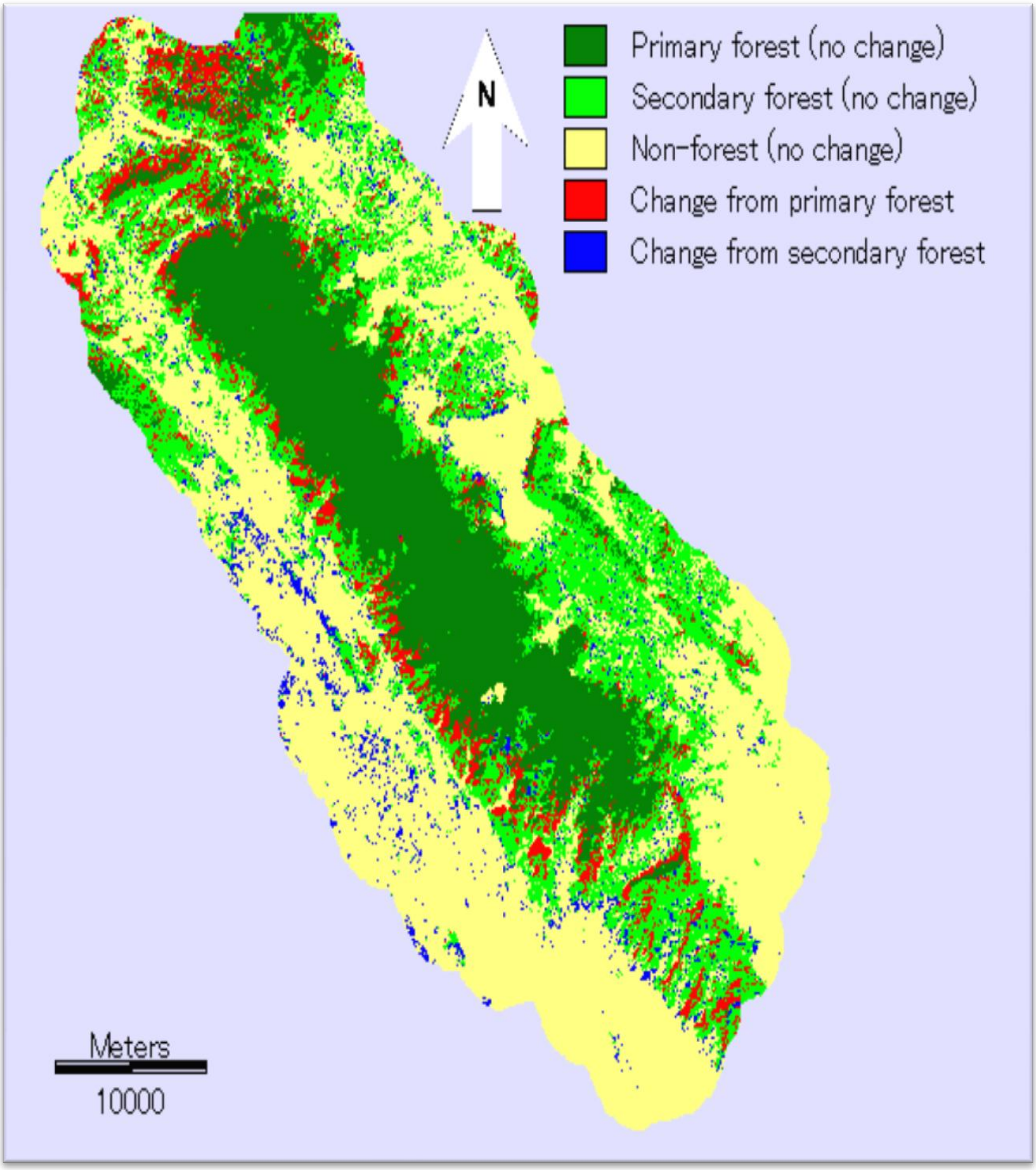


Figure 2-8: Forest persistence and change for 1993-2000

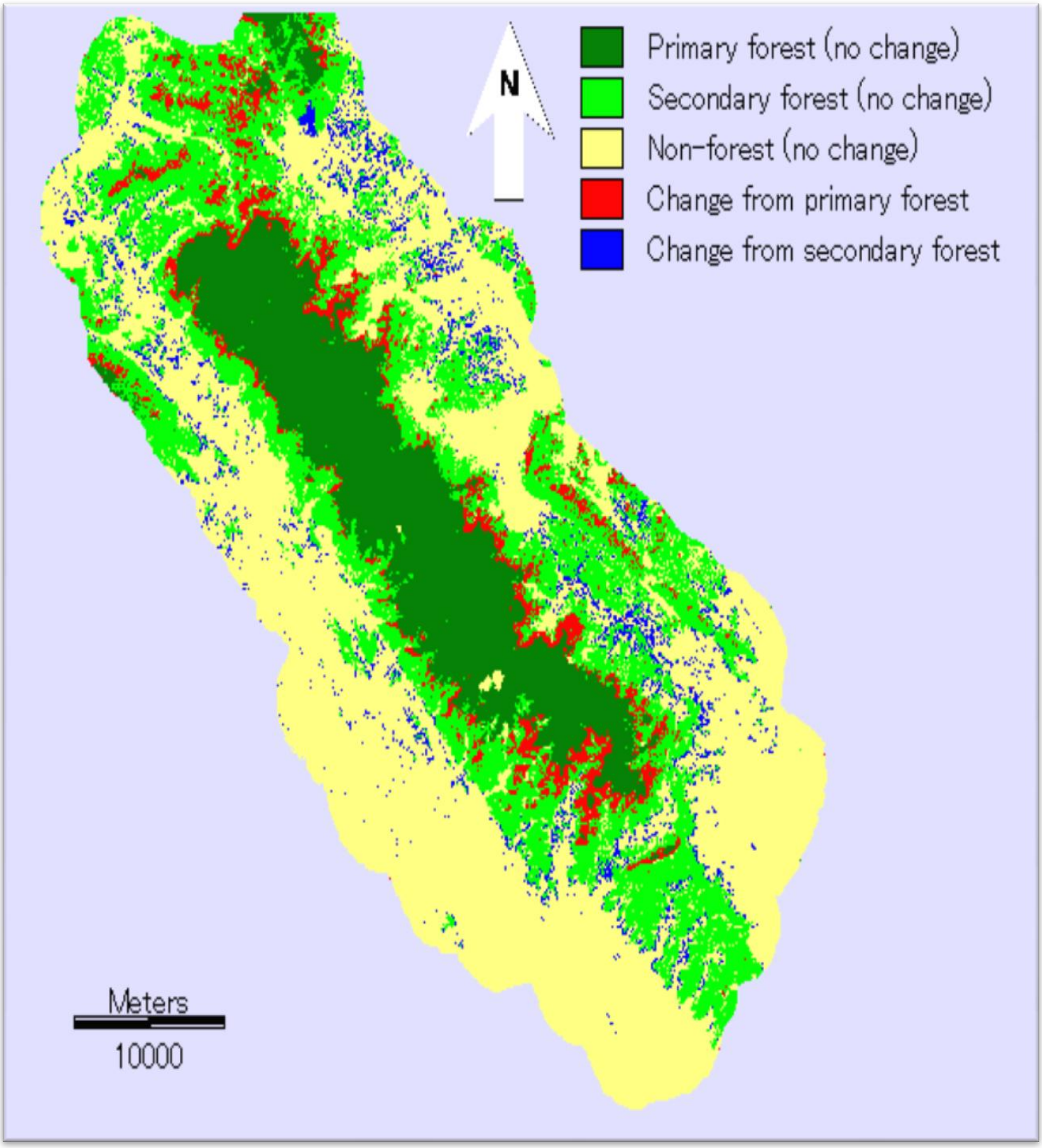


Figure 2-9: Forest persistence and change for 2000-2007

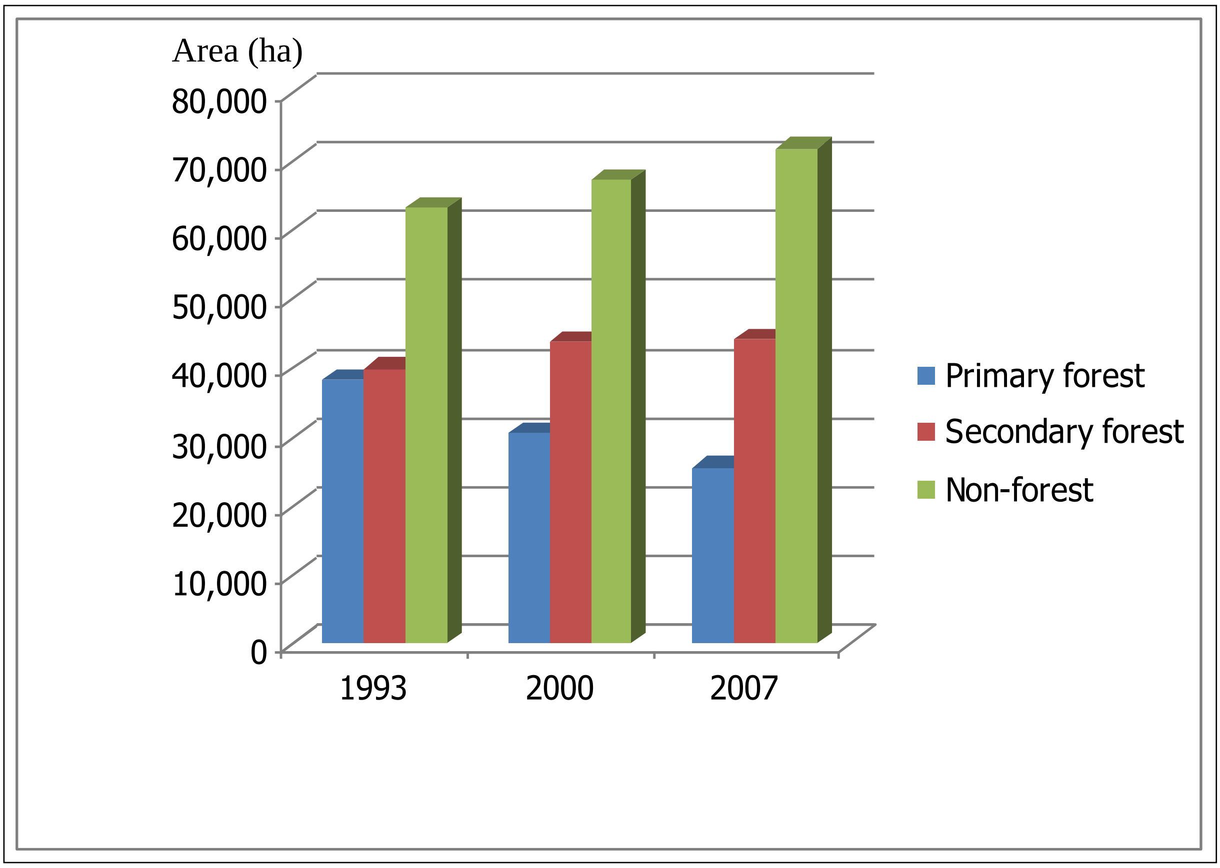


Figure 2-10: Areas of primary forest, secondary forest and non-forest

2.5.4 Factors driving forest conversions

An understanding of the forest conversions and their associated driving factors in the TDNP region is critical for developing an empirical forest change model for future scenarios prediction. In the study area, the conversion from primary forest to secondary forest (PSC), the conversion from primary forest to cropland (PCC) and the conversion from secondary forest to cropland (SCC) were identified to be the major conversions over the period from 1993-2007. The link between the driving factors and deforestation is described in Figure 2-11.

First, PSC was the dominant trend over the study periods. This conversion was occurred for mainly the purpose of commercial forest logging over 1993-2007. If this trend continues in the future, the loss of wildlife habitat is become a serious threat. The major agents for this conversion were the state forest enterprises. In addition, ethnic groups also contributed to the removal of the primary forest via illegal logging activity. In some cases, local people logged forest for fuel and house building needs. The PSC also observed in many mountainous parts of Vietnam. State enterprises and local people were well known as the major agents of the conversion. The state forest enterprises extracted and logged forest over a long period. Millions of hectares of natural forest were logged in Vietnam in the last half century. This timber wealth was gone into the government treasury and private entrepreneurs (William and Huynh Thu Ba, 2005). In the 1990s, with rapid decline of forest, government imposed a series of forest logging and export bans (Lang, 2001). Because of this response, the commercial logging activity in 300 out of 400 state forest enterprises were suspended, and these agencies shifted their missions from production and harvesting to forest protection (ICEM, 2003). The annual reports from the state forest enterprises indicated that the timber productivity reduced from 3.5 million cubic meters (World Bank, 2002) to 0.3 million cubic meters in 1998 (MARD, 2001). For local people, their increasing demands (ADB, 2000; De Koninck, 1999) were forced them to do illegal forest logging for timber and non-timber forest products (NTFP). The illegal logging timber was from 0.5 to 2.0 million cubic meters (World Bank, 2002). NTFP is important to the livelihoods of millions of people in the uplands of Vietnam. These products are sold for cash income or traded for buying basic foods. The poorest of the poor normally live in the uplands. It is difficult to have accurate statistics of illegal logging activities, but it is actually serious and contributes considerably to forest loss in Vietnam. The extent and intensity of illegal forest logging activity across the country has documented in many studies (Social Forest Development Project in Vietnam, 1994; ADB, 2001; Rambo *et al.*, 1998; Cao Thi Ly, 2001; Huynh Thu Ba, 1998; Dao Trong Hung, 1998; Sowerwine *et al.*, 1998).

The PCC is different from commercial forest logging activity. The major agents of this conversion were shifting cultivators. In term of land degradation, this conversion type leads to most serious consequence than the others because high risk of soil erosion often occurs in slopping lands if land cover is removed. Soil erosion removes or redistributes the fertile topsoil layer and fundamental soil nutrients that is essential for crops. This imposed the issue of sustainability of food productivity systems and socio-economic development in the area. The PAC also observed across Vietnam. This situation has reported in many studies. For example, Le Quoc Doanh and Ha Dinh Tuan (2004) reported that between 1960s and 1980s, most farmers extended their slash and burn agriculture over the mountains of Vietnam. Up to 2000, about 9 million people were still engaged in slash and burn cultivation for their livelihoods, and particularly three million people mainly earned their income from this practice (Do Dinh Sam, 1994). The upland rice, corn and cassava were the major crops grown by this practice (Le Trong Cuc, 1997). The crop yield in the uplands was much lower than river delta fertile areas as the result of widespread soil erosion and resources degradation. For example, the yield of upland rice reached a rather low level of 0.4-0.6 ton per ha while lowland rice had a higher yield of 6-7 ton per ha. Driven by population growth, upland farmers shortened the fallow period, which caused the accelerated rate of soil erosion; therefore, crop yield was decreased significantly over time (Jenieson *et al.*, 1998).

The SCC often occurs after commercial forest logging or selective logging. State forest enterprises or local people logged primary forest, and these areas were then used for agricultural production. Recently, forest logging for commercial purpose is strictly banned, but illegal forest logging activity is still happening for the increasing timber demand of the local people and surrounding areas.

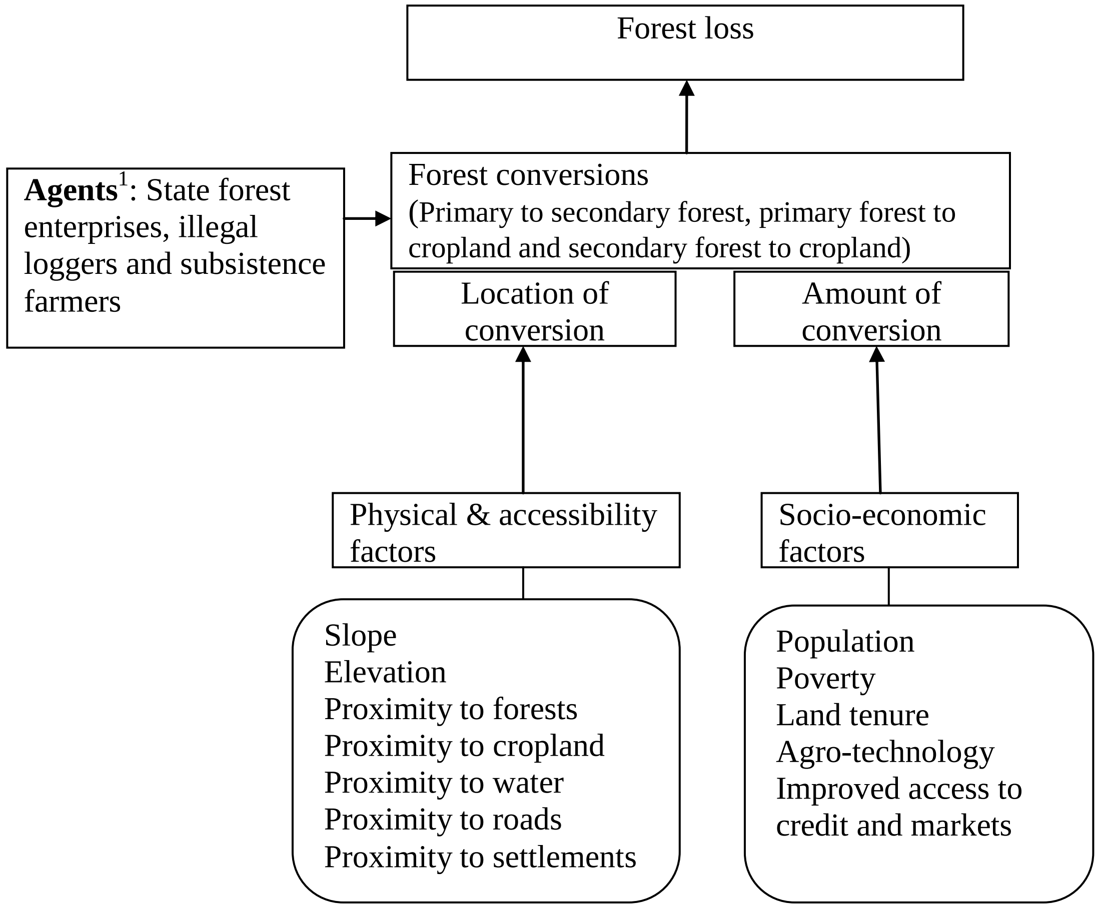


Figure 2-11: The link between the causes and deforestation in the TDNP region

Note: [1]State forest enterprise agents involving forest logging stopped since 1996. Currently, illegal loggers and subsistence farmers play key roles in forest

In general, LUCC in general and deforestation in particular is driven by a complex combination of biophysical and socio-economic factors. The specific combinations of factors vary from region by region, country by country and even locality by locality in one country. Socioeconomic factors determine land demands, while biophysical factors influence essential conditions or capacity for the decision-making of land use. There is not a universal set of driving forces of deforestation, a range of driving factors have been investigated in several case studies. The expansion of cropped land and pasture, *i.e.,* permanent cultivation, cattle ranching and shifting cultivation, is the most frequently reported proximate causes of tropical deforestation (de Koninck, 1999; Hemmut and Lambin, 2002; Briassoulis, 2000; Verburg *et al.,* 2004).

Economic, technological, demographic, institutional and cultural factors were determined to be the key underlying drivers of the forest conversions in the study area (ICEM, 2003; TDMP, 2005; Khang *et al.,* 2007; Khoi and Murayama, 2010a). These factors influenced forest changes in the other mountainous parts of Vietnam (Do Dinh Sam, 1994; Jenieson *et al.,* 1998; Rambo *et al.,* 1998; Huynh Thu Ba, 1998; de Koninck, 1999; Lang, 2001). A clear link between forest conversion and mentioned individual socio-economic factors is still a key research question needs to be examined. Forest change is often driven by a full interplay of all underlying forces. At the broad aggregate level, these factors have been recognized as fundamental forces that regulate the amount of forest change, as shown in Figure 2-11. The interplay of socio-economic factors can be explained through the linkage between land use activities and the behavior of state and private agents. In the 1960s, small famers played a key role in deforestation and much of forests was also destructed by wars. In the 1970s-1980s, number of deforestation agents increased, state forest enterprises, new settlers and local farmers (known as shifting cultivators) were together involved in forest logging. State forest enterprises played the most important role in deforestation for the 1970s-1980s because they operated commercial timber logging activity at a large scale. At this period, markets for timber became more globalized, and this event seemed to be closely linked to forest cover loss in Vietnam as well as developing countries. The second important agent was the new settlers who moved to forested lands under new settlement programs of the government. In the 1970s, the government of Vietnam established a new settlement program aiming to redistribute lowland people to mountainous regions at national scale. Under this program, about 4 million people were forced to settle in the mountainous northern and central parts of Vietnam (Lang, 2001). The new settlers promoted agricultural expansion into forests (Lang, 2001; Do Dinh Sam, 1994). The TDNP region was not an isolated region; therefore, it was affected by such kind of policy. Together with this policy, the investments of government were allocated to construct roads to make lands accessible to new settlement areas. As roads were constructed, timber products were easily transported for selling;

therefore, road building contributed to the motivation of forest logging activities. Although new settlers destroyed forests, they still received subsidies from the state in term of houses and subsidized credits. Until the early 1990s, commercial logging was banned because of increased awareness of environmental consequences; however, illegal loggers (*i.e.*, local farmers) continued. As of the 1990s, state forest enterprises transformed their mission from forest logging to forest protection. Recently, subsistence farmers play a key role in the conversion of forests into agricultural lands.

Biophysical factors *i.e.*, soils, terrain and accessibility, directly associate to forest conversion because they influence favorable conditions for land use activities. For example, forest on fertile soil located in the flat ground has been reported to undergo rapid agricultural expansion (TDNP, 2005; Khang *et al.*, 2007). Therefore, this study only focused on the biophysical and accessibility factors that expect to comprise a considerable share of the factors driving the conversion of forests. In the region, slope, elevation, the proximity to primary forest, the proximity to secondary forest, the proximity to cropland, the proximity to water, the proximity to road, the proximity to settlement were empirically identified to be the major driving factors of forest conversions. The nature and strength of relationship between each conversion and the driving factors are presented in Chapter 3.

The empirical findings of the forest changes and associated driving factors indicated that deforestation was a multiform process, represented by the three forest conversion types. This implies that deforestation forecasting model for the area should be developed according to multiple conversions driven by multiple driving factors.

Chapter 3
Forecasting Deforestation Using Multi-Layer Perceptron Neural Network-Markov Chain Model

3.1 Significance of deforestation forecasting

Deforestation is a serious threat to ecological sustainability and socio-economic development in the long-term. In order to center on the intervention of protected area managers and planners, measurement of the past rates and impacts of deforestation are required, and the dynamics of future forest cover need to be anticipated. Theses monitoring and prediction are needed because forest cover changes are directly linked to the supply of different ecosystem services vital to the sustainable livelihoods and well-being of the people. In particular, timely and accurate information about the outcome of ecosystem service supply provides as an essential input for sustainable land use decision-making.

The spatial models of deforestation can provide an important instrument for forecasting the dynamics of forest cover patterns in the future of the region. Deforestation 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 (Lambin, 1994). Deforestation is often associated with multiple factors. The relationships between a change and its driving factors can be very complex and are often non-linear (Mas *et al.,* 2004), requiring an appropriate modeling approach that accounts for such complex non-linear relationships.

Deforestation can be predicted using empirical models and simulation models (Lambin, 1997). MLPNN-M is a recently developed approach for spatiotemporal dynamic modeling of forest change (Eastman, 2009). 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 (Lek *et al.,* 1996). Many studies have reported that the MLPNN models can perform better than other land change modeling approaches (Mas *et al.,* 2004; Lek *et al.,* 1996; Zhou and Civco, 1996). In a recent study, the MLPNN was found to be better than logistic regression and other empirical modeling approaches, such as empirical probabilities and empirical likelihoods, in land change modeling area (Eastman, 2009).

To forecast deforestation, it is necessary to first develop an empirical model of main driving factors of deforestation. The identification of factors driving deforestation in an appropriate space and time scale allows a reliable prediction of the future pattern of deforestation. There is no a universal model that can be applied for the prediction of deforestation anywhere because deforestation is a diverse phenomenon. One difficulty in the development of an empirical model is that driving factors are diverse, and they vary in time and space. Therefore, the development of spatial models of deforestation requires an understanding of current deforestation process and physical, socio-economic and accessibility factors representing the vulnerability (propensity) to deforestation. The purpose of this chapter is to develop an empirical spatial model of deforestation for the TDNP region.

3.2 Methods for deforestation forecasting

3.2.1 Model development flowchart

Overall, the land change modeler (LCM) available in IDRISI Taiga GIS and Image Processing software (Eastman, 2009) was used to develop empirical models to predict primary and secondary forest conversions in the TDNP region. Specifically, the modeling of deforestation within the LCM is a process of developing empirical forest conversion models and then uses them for the prediction of forest conversions in some points in the future. The empirical modeling method for this study is the use of MPLNN approach using the areas of known forest conversion (observed forest change) from land use/cover maps along with explanatory variables that express the driving forces to experience a specific conversion. The result is a conversion potential map for each modeled land cover conversion, which is an expression of the propensity of land to undergo to a specific conversion in the next time step. These conversion potential maps serve as primary inputs for the prediction process, along with predicted quantities of change derived from Markov chain analysis. Specific allocation of change is then achieved by a means of a multi-objective land competition (MOLA) process and associated conversion potential maps.

Specifically, the two forest cover maps derived from satellite imagery from the 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 3-1). Firstly, observed forest changes were employed as the dependent variables and spatial driving variables were used as the independent variables (Table 3-1) 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 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 (Eastman, 2009). Detailed descriptions of the multi-objective land allocation algorithm can be found in (Eastman *et al.*, 1995).

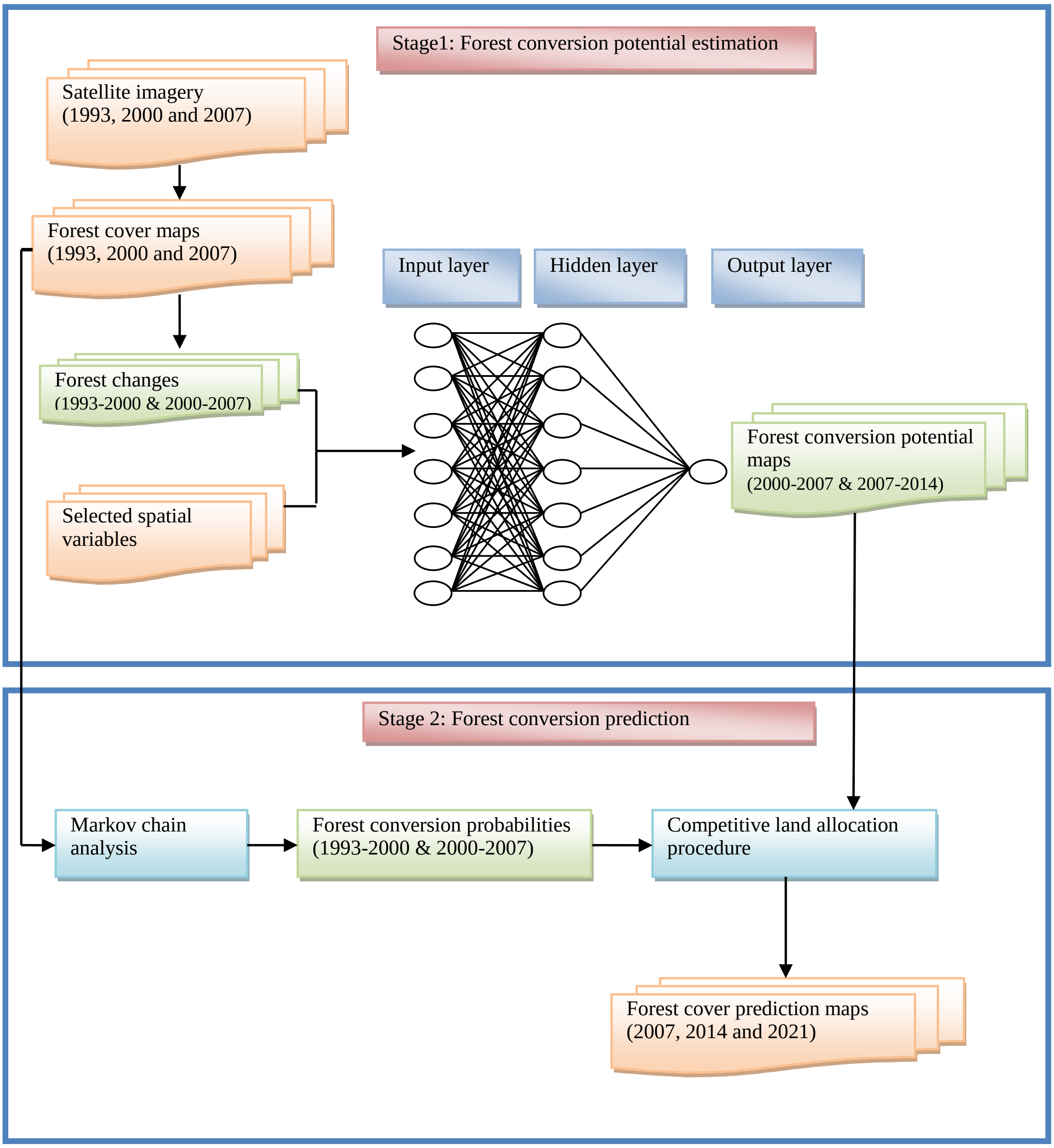


Figure 3-1: Flowchart of the MLPNN-M for modeling forest conversions

3.2.2 Creation of dependent and independent variables

As mentioned above, the modeling procedure based on the MLPNN-M approach was performed using the dependent and independent variables. The dependent variable was defined as the presence or absence of the observed forest changes for the periods of the two observation years (1993-2000 and 2000-2007). The independent variables were defined to be explanatory variables (or spatial driving variables) of the forest changes. The relationship between the spatial changes of forest and independent variables/explanatory variables was tested by the Cramer`s coefficient approach.

In order to identify the forest changes, the first step was to obtain the maps of forest cover for the years 1993, 2000 and 2007. The land cover maps with the six land cover categories of primary forest, secondary forest, rain-fed agriculture, settlement and water were re-classed into the maps of the three categories of primary forest, secondary forest and non-forest area. The changes in forest cover were quantified for the two consecutive periods 1993-2000 and 2000-2007, and they were used as the dependent variables for the prediction of forest cover of 2007, 2014 and 2014, respectively (also see the section 2.5.3 of Chapter 2).

The explanatory 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 3-1 and Figure 3-2. Such variables have highlighted in many studies, such as in (Pijanowski *et al.*, 2002), and land-use change models, such as in (Li and Yeh, 2002; Dendoncker, 2007).

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 emphasized in predicting the location of deforestation in many areas, such as the Basho Valley, Northern Pakistan (Ali *et al.,* 2005), Northern Thailand (Cropper *et al.,* 2001) and the Congo Basin (Wilkie *et al.,* 2000). 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.* (1990) 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, I included the proximity to cropland, which was measured as the shortest distance from each location to the nearest cropland. Some studies have found a strong relationship between deforestation and the expansion of cultivation in the mountains of northern Vietnam (Meyfroidt and Lambin, 2008; de Koninck, 1999).

Topography often influences the spread and extent of forest conversion. For example, a case study in Costa Rica (Sader and Joyce, 1998) 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 (Li and Yeh, 2002). In this study, the nature of the association between observed forest changes and spatial variables was examined using Cramer’s V coefficient (Eastman, 2009). The quantitative variables were binned into 256 categories to conduct the test (Eastman, 2009) (Table 3-2). A Cramer’s coefficient 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 (Eastman, 2009).

Table 3-1: Statistical summary of spatial variables

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

Notes: S.D is standard deviation of a spatial variable. Min. is minimum value of a spatial variable. Max. is maximum value of a spatial variable.

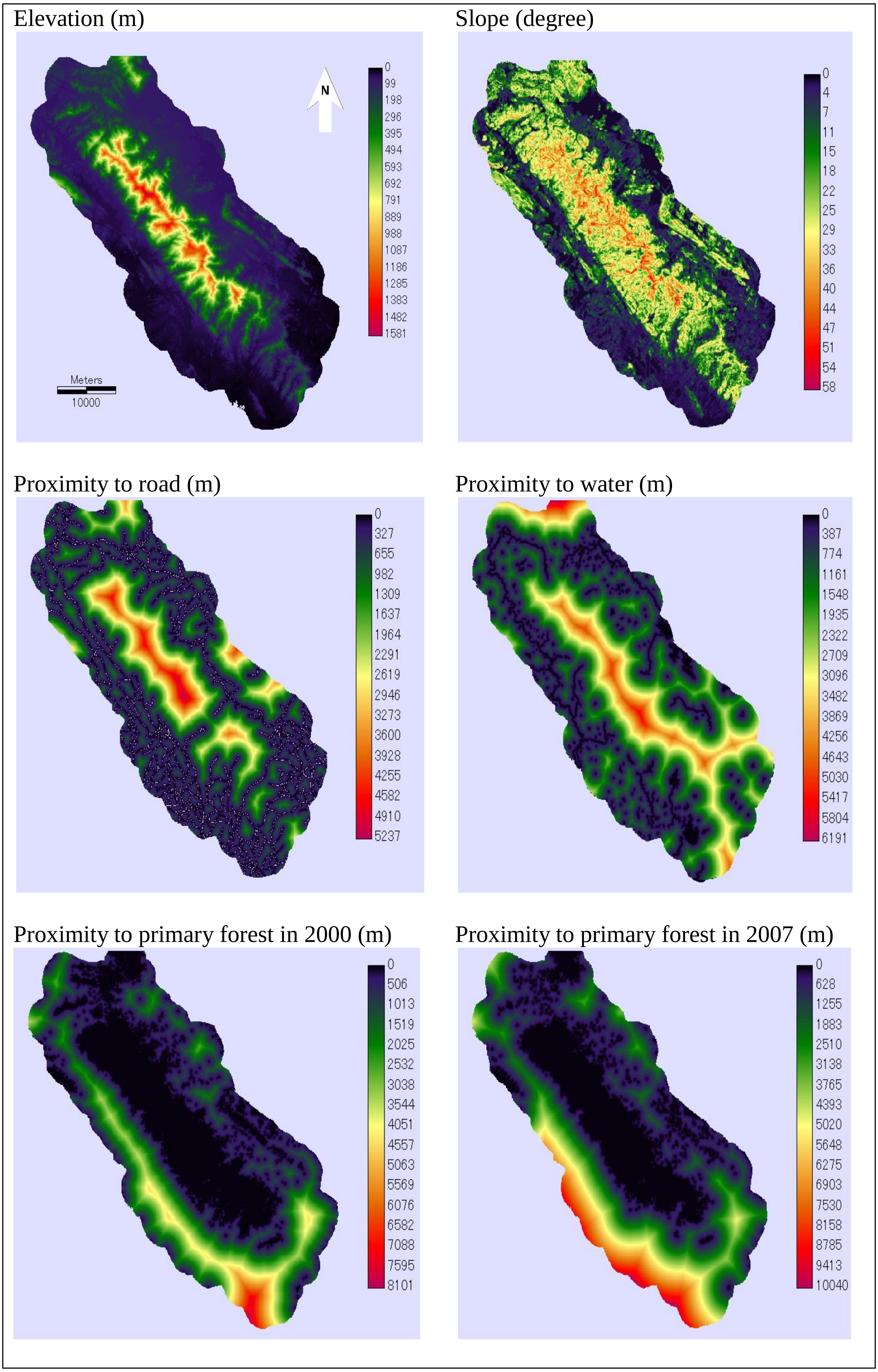


Figure 3-2: Spatial variables

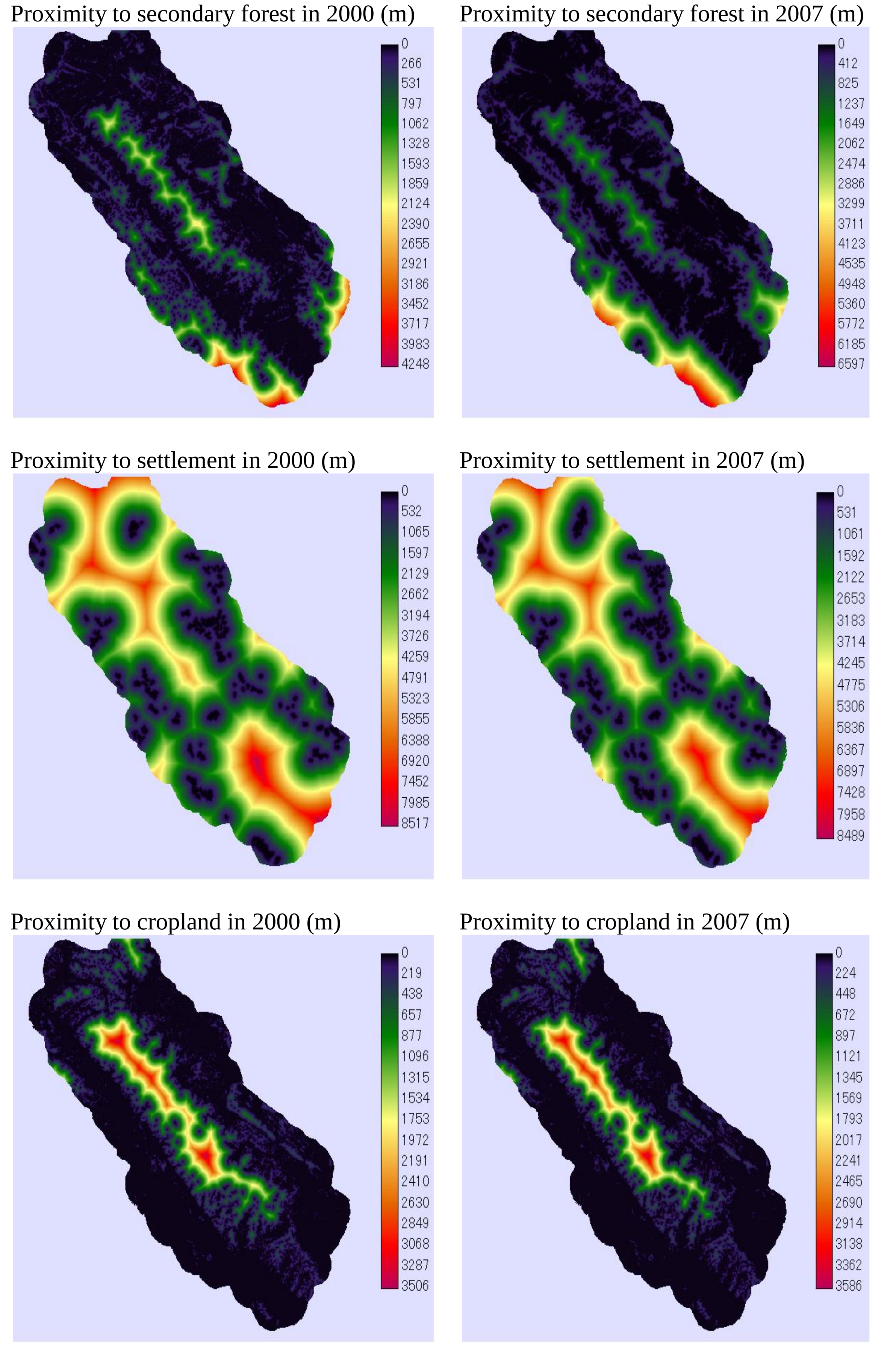


Figure 3-2: Spatial variables (cont.)

Cramer's V (V) is a statistic measuring the strength of association between two categorical variables in a contingency table. A contingency table contains the count of occurrences of category X_i in X and Y_j in Y. These two categorical variables are observational data. In this case, they are a map of forest change and a driving variable. Firstly, chi-square is calculated and then V is estimated according to Equation 3-1.

$$V = \sqrt[2]{\frac{X^2}{N(K-1)}}, \tag{3-1}$$

where:
X^2 is square root of chi-square,
N is number of cases in table, and
K is the lesser of number of rows and columns.

The V ranges from 0 to 1. The closer V is to 0, the smaller the association between the two categorical variables. V being close to 1 is an indication of a strong association between the two variables.

3.2.3 Modeling forest conversion potentials

A neural network, employed for modeling forest conversion potentials, can be thought as a diagram that illustrates how computations are implemented (Figure 3-1). The diagram includes *circles* called neurons and arrows called *connections*. The entire diagram represents a single composite mathematical function. The neurons represent some sort of computation known as their *activation*. Connections represent the activation of a neuron (computation result), which is passed along to another neuron. Each connection has a weight associated with it. Activation from one neuron to the next is sent via a connection, the activation is multiplied by this weight. The receiving neuron gathers all incoming scaled activations and sums them. The final activation of the neuron is determined by applying an activation function (*i.e.*, sigmoidal function) to this sum. The neural network used in the study is MLPNN known as feedforward neural networks. Feedforward means that as the neurons activate and send their activations to other neurons. Signals of those neurons only goes forwards through the network and never loops back. In this study, the network consists of the three types of neurons: input, hidden and output (Figure 3-1). The input neurons appear at the left side of the diagram and represent the drivers of forest conversion (spatial variables). The output neurons appear at the right side of diagram and represent the potential (probability) for forest conversion. The output neuron receives incoming activations from the earlier neurons in the network. The hidden neurons simply pull in the arriving activations, perform the sum, apply their activation function and send new activation to the output neuron.

Specifically, the MLPNN was trained as a network with the three layers: an input layer with the number of neurons equal to the number of spatial variables; a hidden layer with the same number of neurons; and an output layer with one neuron representing a forest conversion potential map (Figure 3-1). 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. In principle, an empirical model is developed by fitting the data to determine appropriate parameters of a model. The training of the network here is to serve the determination of a single mathematical function with appropriate connection weight values (Equations 3-2). 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 (Kanellopoulos and Wilkinson, 1997).

During the training process, the computations in the layers of the neural networks are implemented from the hidden to output layers. It does not implement in the input layer. The computation in the hidden layer neurons can be expressed as Equation 3-2.

$$net_j = \sum_i w_{ji} o_i, \tag{3-2}$$

where:

net_j is weighted sum,

w_{ji} represents connection weights from neuron i (input variables) to neuron j (hidden layer), and

o_i is input variable value from neuron i.

The sigmoidal function, mostly used nonlinear transfer functions, is used in the computation in hidden neurons before releasing to the output layer neuron. The calculation can be expressed as Equation 3-3.

$$0_j = \frac{1}{1 + e^{-net_j}} \tag{3-3}$$

The connection weights are updated during training process according to the generalized delta rule (Rumelhart *et al.*, 1986), given as Equation 3-4.

$$\Delta W_{ji(n+1)} = \eta(\delta_j o_i + \alpha \Delta w_{ji(n)}, \quad (3\text{-}4)$$

where:

$\Delta w_{ji(n+1)}$ is a change of a weight from neuron i to neuron j at the (n+1) iteration,

η is learning rate,

δ_j is an index of the rate of change of the error with respect to output from neuron j, and

α is momentum term.

In the study area, selective logging directly converted primary forest into secondary forest. Another pathway was the conversion of primary forest into cropland by shifting cultivation. The third way was 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 for the years 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 3-2). 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. The MLPNN was trained in form of automatic dynamic mode where all training parameters were automatically changed to better model the data. A detailed of the MPL training procedure can be found in (Eastman, 2009).

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, the training of the network was stopped after 5,000 iterations with a minimum loss of accuracy. According to Eastman (2009), the accuracy rate of training should be achieved at approximately 80%. Therefore, the training of the network was terminated when the accuracy rate exceeded the minimum level. Once the network was trained, new data could be run through it.

3.2.4 Simulating the spatial patterns of forest conversion

The prediction procedure used by the IDRISI's LCM is based on a competitive land allocation procedure similar to the MOLA (Eastman, 2009). 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 the MLPNN model. In dealing with how forest change process evolves over time, a Markov chain analysis was employed to identify the quantities of conversion area or the amount of change that may occur to some point in the future. It means that if the initial condition (a starting point) is known, many possibilities (conversion probabilities) can be quantified.

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 (Eastman, 2009). Markov chain has several assumptions, this study assumed forest cover changes as a finite-first order Markov chain with stationary transition probabilities. Different land use/cover changes also assumed to be the states of a Markov chain (Weng, 2002). A Markov chain is defined as a stochastic process having the property that the value of the process at time t, X_t depends on only its value at time t-1, X_{t-1}, and not on the sequence of X_{t-2}, X_{t-3}…, X_0 that the process passes through in arriving at X_{t-1}(Wu *et al.*, 2006). Based on such assumptions, a Markov process is formally described by transition probability function $P(t|X,t_0)$ representing the conditional probability that the state of the system will be at time *t*, given that at time t_0 ($< t$). Thus, a transition probability matrix describes the specific character of the system where the elements of the matrix are the individual transition probabilities of one state moving to another state after one time increment. The transition matrix is as follows:

$$P = \begin{bmatrix} P_{1.1} & \cdots & P_{1.m} \\ \vdots & \ddots & \vdots \\ P_{m.1} & \cdots & P_{m.m} \end{bmatrix}$$

Subject to $\sum_{j=1}^{m} P_{ij}$ where: P_{ij} is transition probability and i = 1, 2…m.

The conversion probability (P_{ij}) between a pair of states is easily calculated by dividing the cells (n_{ij}) of the transition matrix by its row marginal frequency ($n_{i.}$). It expresses as follows (Pettit *et al.*, 2001).

$$P_{ij} = \frac{n_{ij}}{n_{i.}}, \tag{3-5}$$

where: $n_{i.} = \sum_{j=1}^{q} n_{ij}$.

This means that conversion probabilities (P_{ij}) are calculated based on the frequency of the observations. Given on land cover classes, a frequency table is constructed where a count is the number of pixels of a conversion from one state to another over a specified period. In the frequency table, each row is summed ($n_{i.}$) and the values in each matrix element (n_{ij}) are divided by the row sums to compute conversion probability values (P_{ij}). In each row, the probability values sum to 1.0. The diagonal of the matrix represent the self-replacement probabilities, whereas the off diagonal values indicate the probability of change occurring from one state to another state or class.

During the MOLA process, IDRISI's Markov module was employed to produce the 1993-2000 forest conversion probability matrix based on the forest-cover maps of 1993 and 2000. 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 3-5). 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.

3.2.5 Model validation

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.

There is recently not a universally accepted criterion to assess the goodness of fit of validation for land cover change models (Rykiel, 1996). According to Pontius *et al.* (2004), land cover modelers should use criteria that are likely to produce information useful to improve the prediction model. Therefore, it is helpful to use a validation technique that budgets the sources of errors and compares a predicted model with a null model. In this study, the Pontius's validation technique was applied for the validation of the forest cover prediction.

This technique considers the agreement between the two pairs of maps, which are a predicted land use map and an actual land use map, according to percent correct criterion. The percent correct tells about the level of similarity between the two. A higher percent correct between the two indicates sound predictive ability of a land use/cover change model. 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.

3.3 Results and discussion

3.3.1 Spatial patterns of forest change

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.

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 (TDMP, 2005). Similarly, a considerable primary forest loss was observed across the country during the period from 1990 to 2005. This conversion is a common trend in tropical forests (Brown and Lugo, 1990; Wright, 2005). 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 (ICEM, 2003) and mountainous areas of Vietnam (de Koninck, 1999), and they have occurred in many other countries, particularly in developing countries. For example, (Bawa and Dayanandan, 1997) found that deforestation was strongly correlated with the extension of cropland area in Asia and Latin America.

3.3.2 Strength of the relationship between forest change and spatial variables

The strength of the relationship between forest conversion and individual variable was measured by the Cramer's V coefficient approach. V value of more than 0.4 with p value of 0.0 indicates a good association. If a variable with the Cramer's V coefficient of more than 0.15 is useful and it can be included in the model (Eastman, 2009). Tables 3-2, 3-3 and 3-4 show the strength of association between spatial variables and each forest conversion.

Of the entire study area, the frequency of pixels classified as forest conversion (each conversion) and the different independent variables of the conversion model. For the conversion from primary to secondary forest, the conversion seemed to have the highest association with the proximity to primary forest, followed by the proximity to road, elevation, slope, the proximity to water and settlement. For both the periods, these variables showed similar trends (Table 3-2). The proximity to existing primary forest was strongly related to the observed forest change. A higher occurrence of forest change was near the forest edges. The relationship with the proximity to cropland showed that higher frequency of forest change was located in the nearest edge of the cropland. The frequency of forest change sharply declined when moving from the nearest cropland. The relationship with the proximity to water indicated that frequency of forest change declined gradually as moving from nearest water. For the proximity to settlement, this variable had poorer relationship with observed forest change. The forest change fluctuated among various distances. This can be partly explained that commercial forest logging had occurred in the area. This activity was conducted by the outsiders such as state forest enterprises; therefore, the pattern of deforestation may not be strongly associated with the distribution of settlements.

Table 3-2: Conversion from primary to secondary forest and spatial variables

1993-2000	Cramer's V	2000-2007	Cramer's V
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

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.

Table 3-3: Conversion from primary forest to non-forest and spatial variables

1993-2000	Cramer's V	2000-2007	Cramer's V
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

Table 3-4: Conversion from secondary forest to non-forest and spatial variables

1993-2000	Cramer's V	2000-2007	Cramer's V
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

For the conversion from primary forest to cropland and from secondary forest to cropland, similar trends have been explored. The proximity to secondary forest acted as a largest influential role on these conversions, followed by the proximity to cropland, the proximity to water, slope, elevation, the proximity to road and the proximity to rural settlement (Tables 3-3 and 3-4).

There may be many driving factors of forest conversion, and they may vary from place to place. In this 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 found to be important in other areas. For example, (Merten and Lambin, 1997) identified proximity to road, town and forest/non-forest edge as the important drivers of forest change in southern Cameroon. Elevation and proximity to road were highlighted as the important factors of forest change in the lowlands of Sumatra, Indonesia (Linkie et al., 2004). Elevation, slope, proximity to road, settlement and proximity to forest/non-forest edge were the key factors of forest change in southeast Mexico (Mas *et al.*, 2004). Aside from these biophysical factors, socio-economic factors are often known as underlying driving forces of forest cover changes (Bawa and Dayanandan, 1997; Geist and Lambin, 1997) 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, empirical analysis in the present study was based solely on the site factors of forest conversions.

3.3.3 Model validation

Figure 3-3 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 3-6). Figure 3-4 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.

For the agreement components, both the two models had 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 (Pontius *et al.*, 2004), 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 (Figures 3-5a, b and c). 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 category others.

Table 3-5: Agreement and disagreement of the null and predicted models at 30-meter resolution (percent of the entire region)

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 the contents of nitrogen, phosphorus, potassium, soil fertility may improve the forest conversion potential maps because forest is mainly converted into agricultural land in the region. However, these 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 variable others. These variables were also found to be important drivers of forest conversion in other areas (Linkie *at al.*, 2004; Merten and Lambin, 1997). 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 3-6: 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

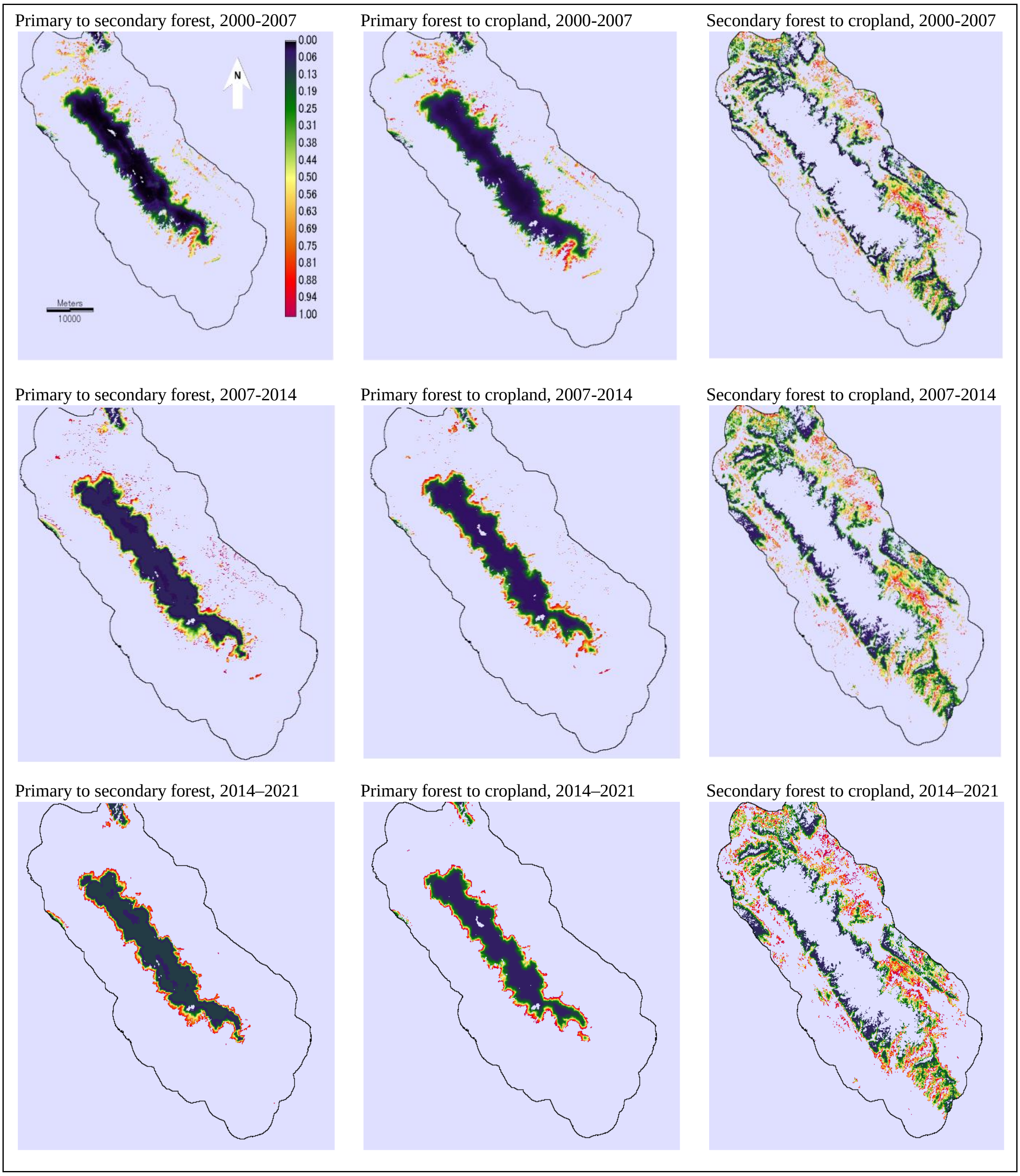


Figure 3-3: Forest conversion potential maps

Notes: The legend is the same in all conversion potential maps. It shows pixels with continuous scores varying from 0 to 1. A pixel with a higher value indicates a higher potential level for forest conversion.

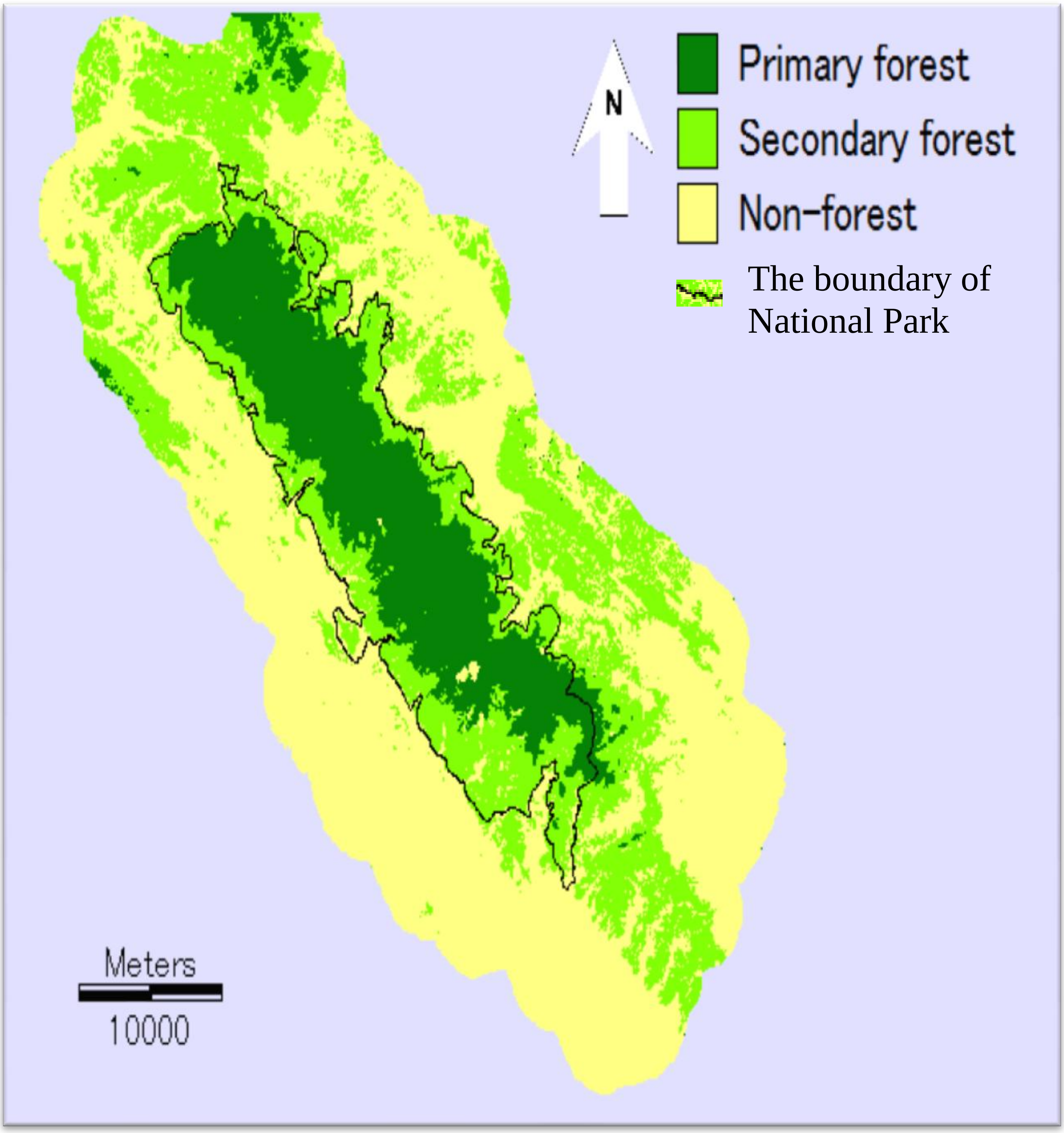


Figure 3-4a: Predicted forest cover map of 2007

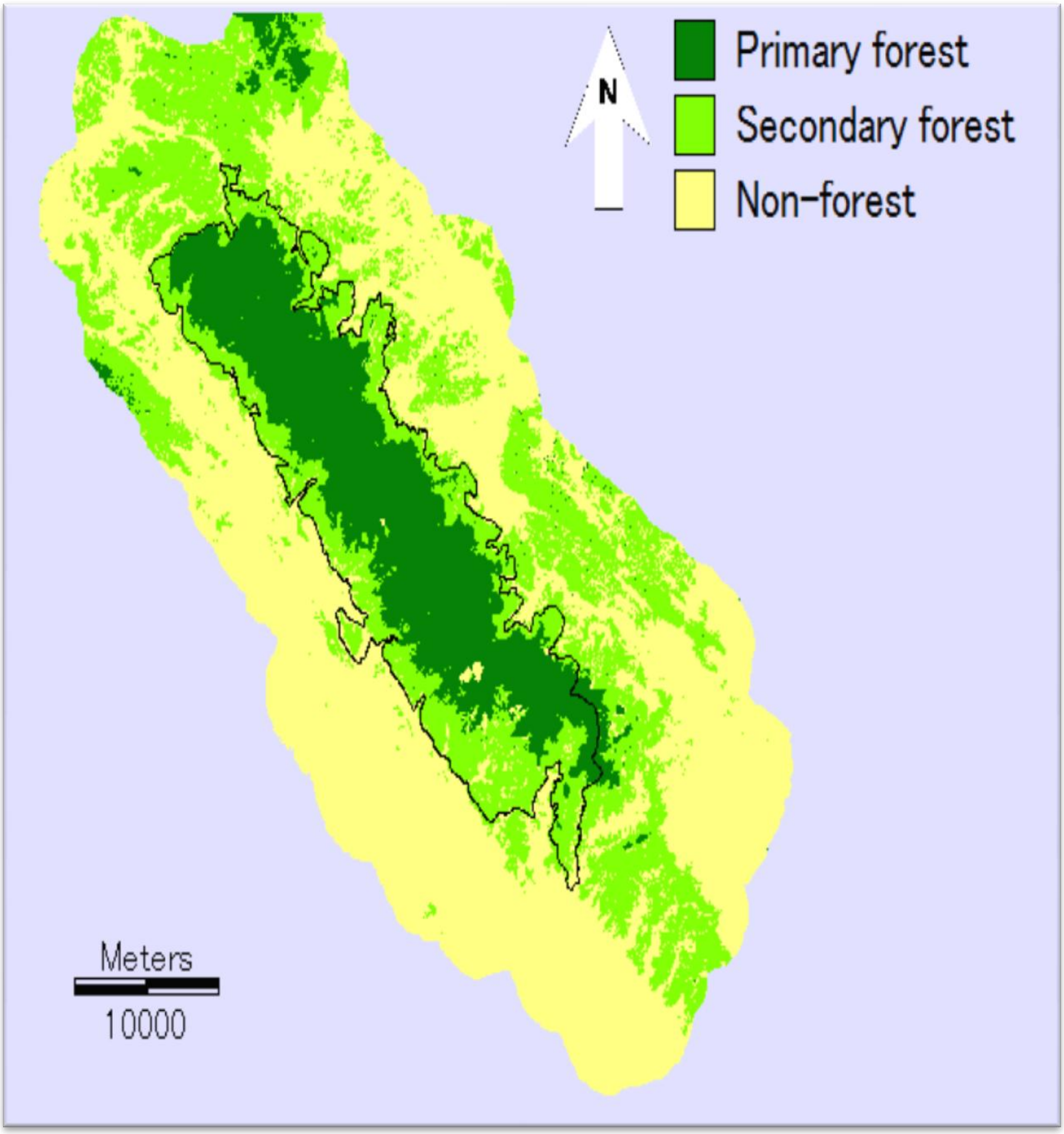


Figure 3-4b: Actual forest cover map of 2007

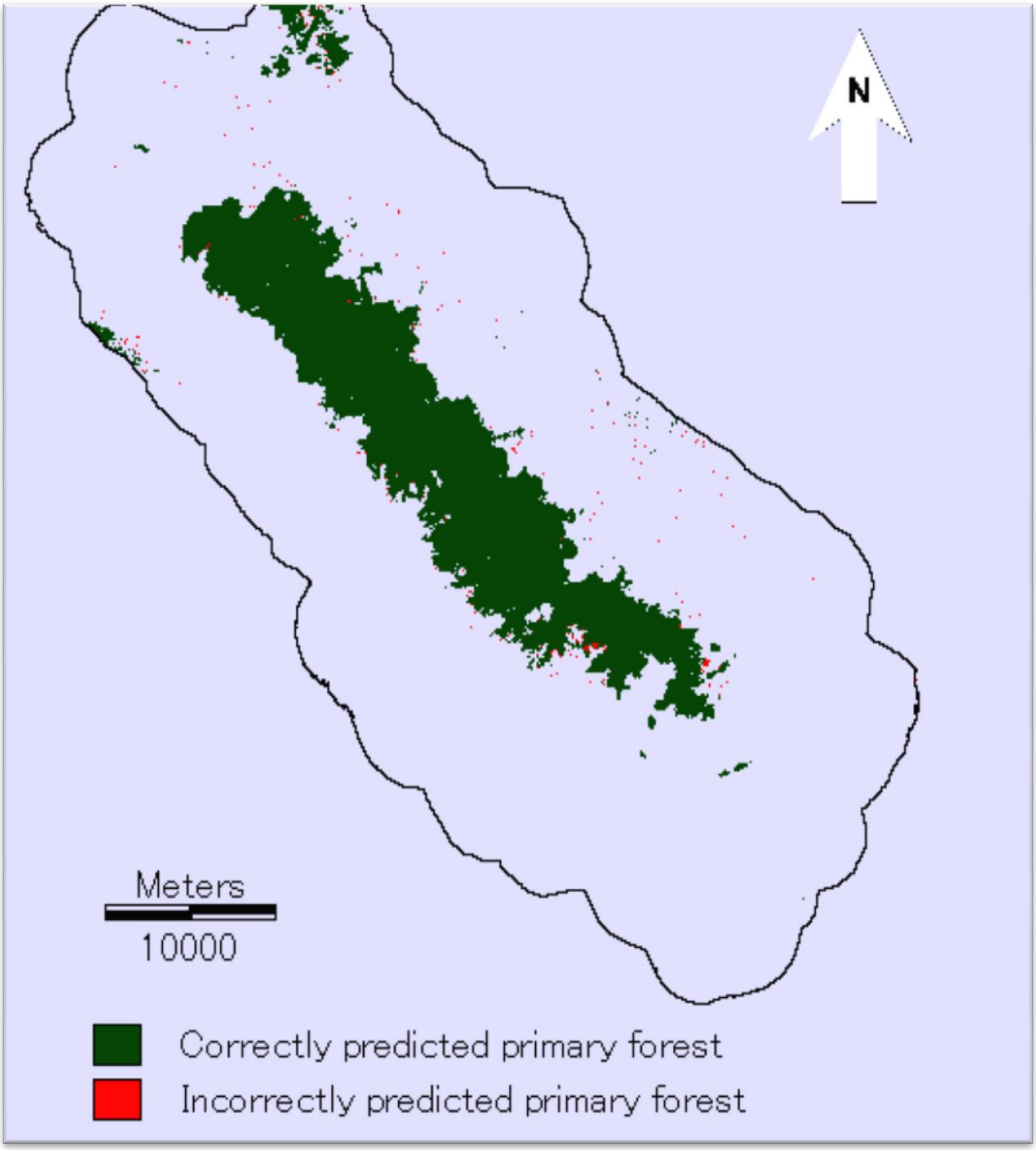


Figure 3-5a: Correctly and incorrectly predicted areas of the primary forest of 2007

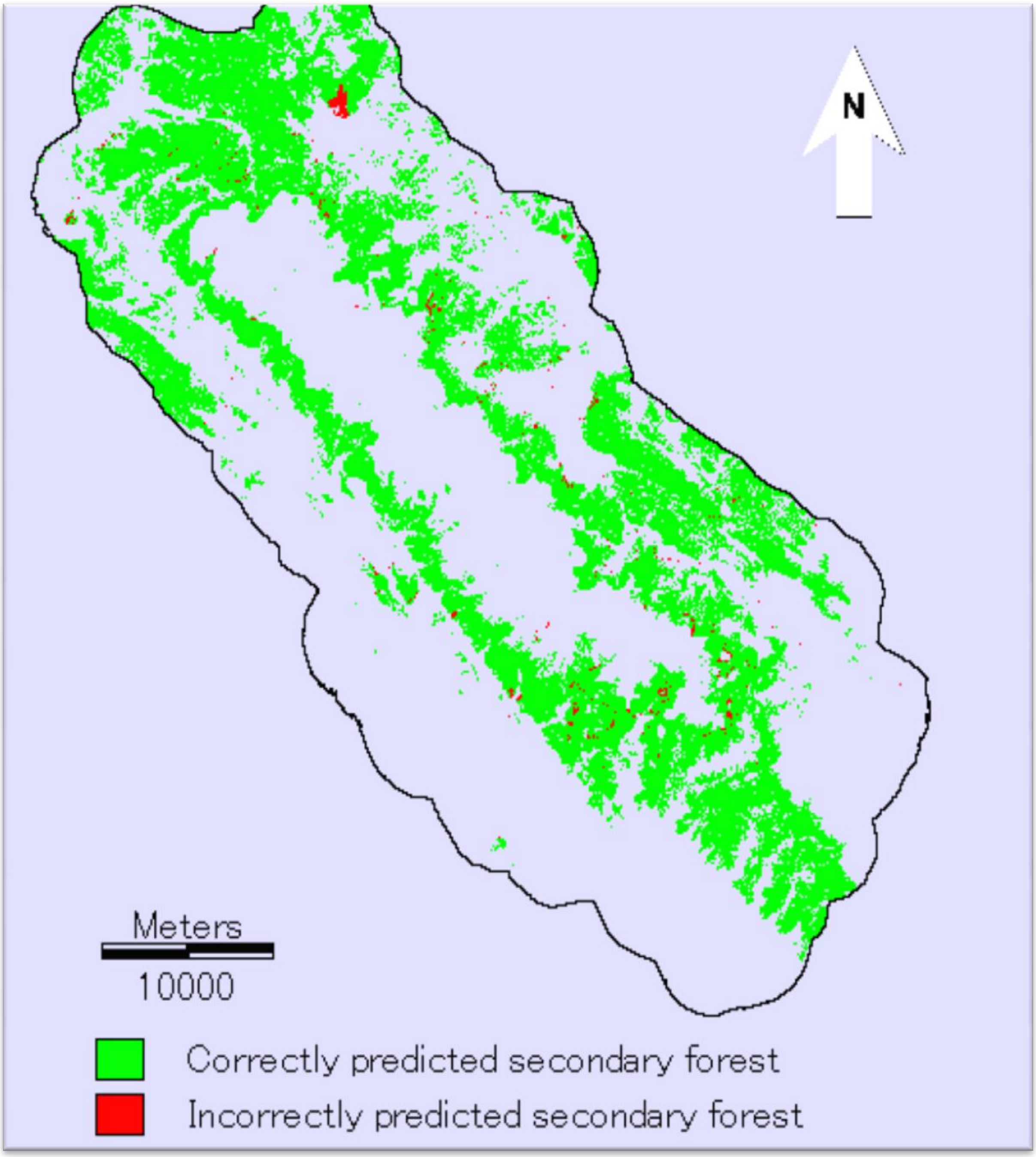


Figure 3-5b: Correctly and incorrectly predicted areas of the secondary forest of 2007

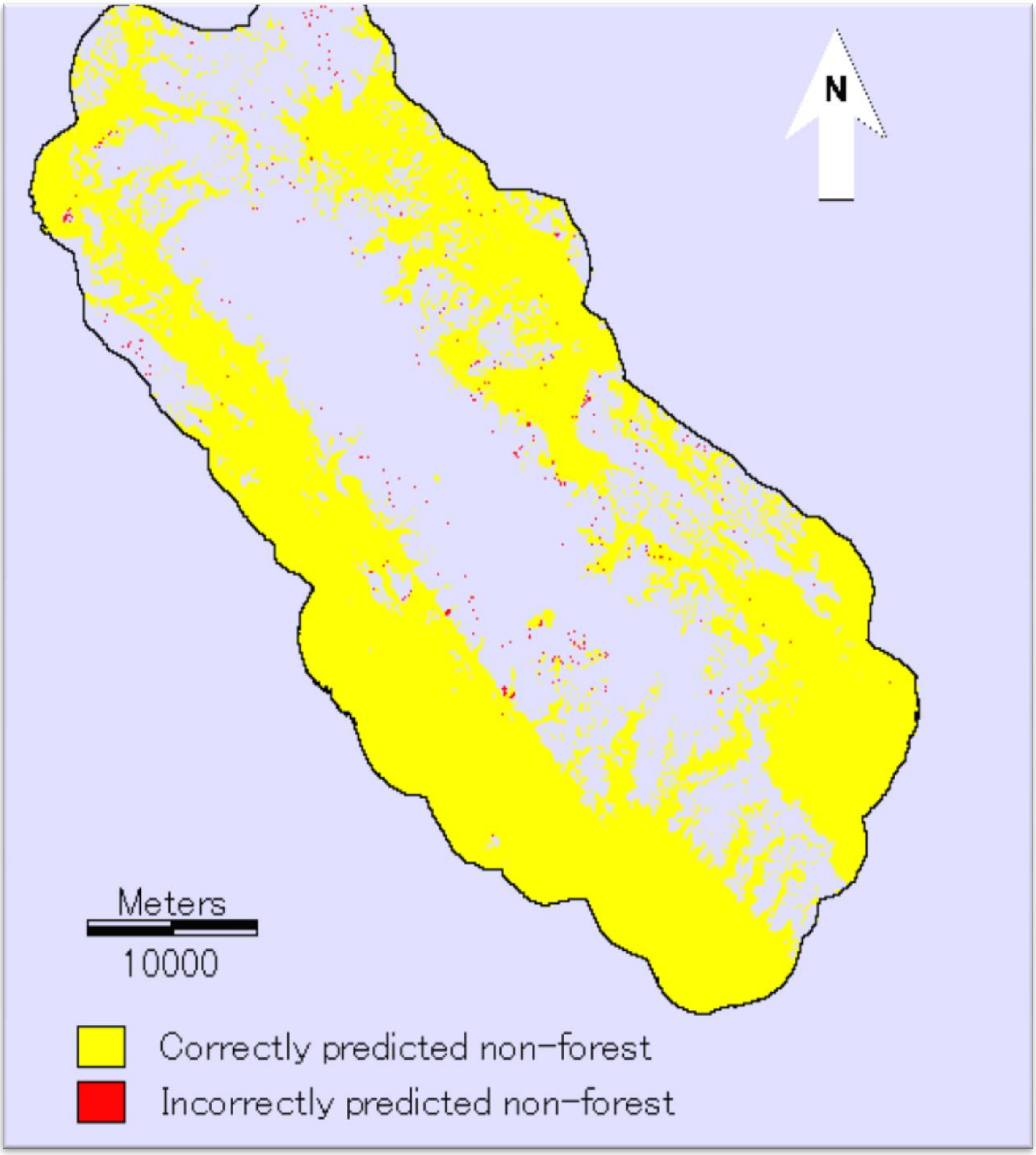


Figure 3-5c: Correctly and incorrectly predicted areas of the non-forest of 2007

3.3.4 Future forest patterns and areas vulnerable to forest conversion

The forest conversion potential maps for the years 2014 and 2021 are presented in Figure 3-3. Table 3-7 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 (Figures 3-6 and 3-7). Within the study area, the MLPNN-M model predicts that the remaining primary forest may decrease from 18.03% in 2007 to 15.10% in 2014 and 12.66% in 2021. The secondary forest areas may 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 because of the conversion of both primary and secondary forest into these areas (Table 3-8).

Table 3-7: Forest conversion probability matrix for 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

Table 3-8: Forest cover for 1993-2007 and predicted forest cover in 2014 and 2021 (%)

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

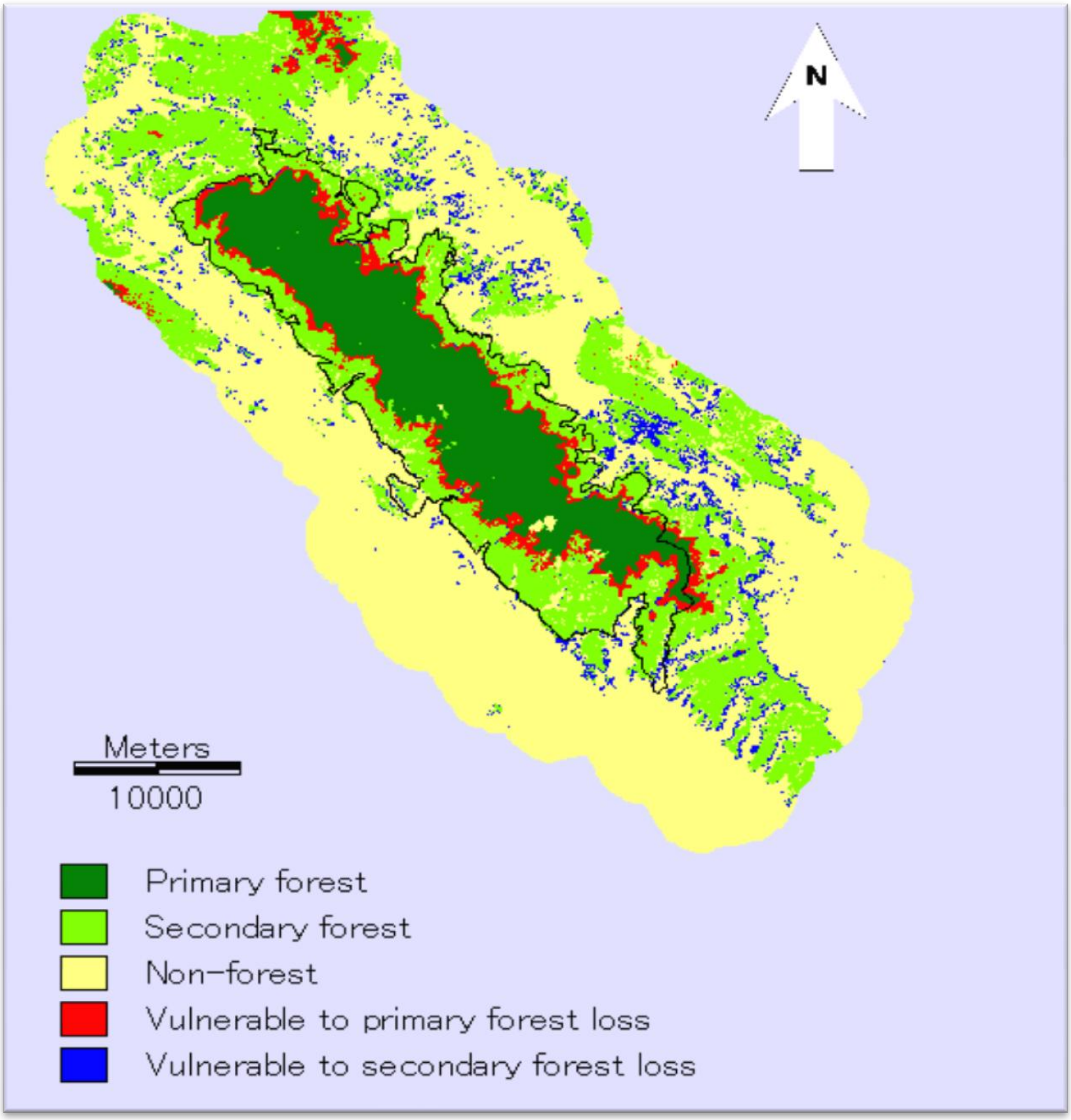


Figure 3-6: Forest map predicted for 2014 and areas vulnerable to forest changes

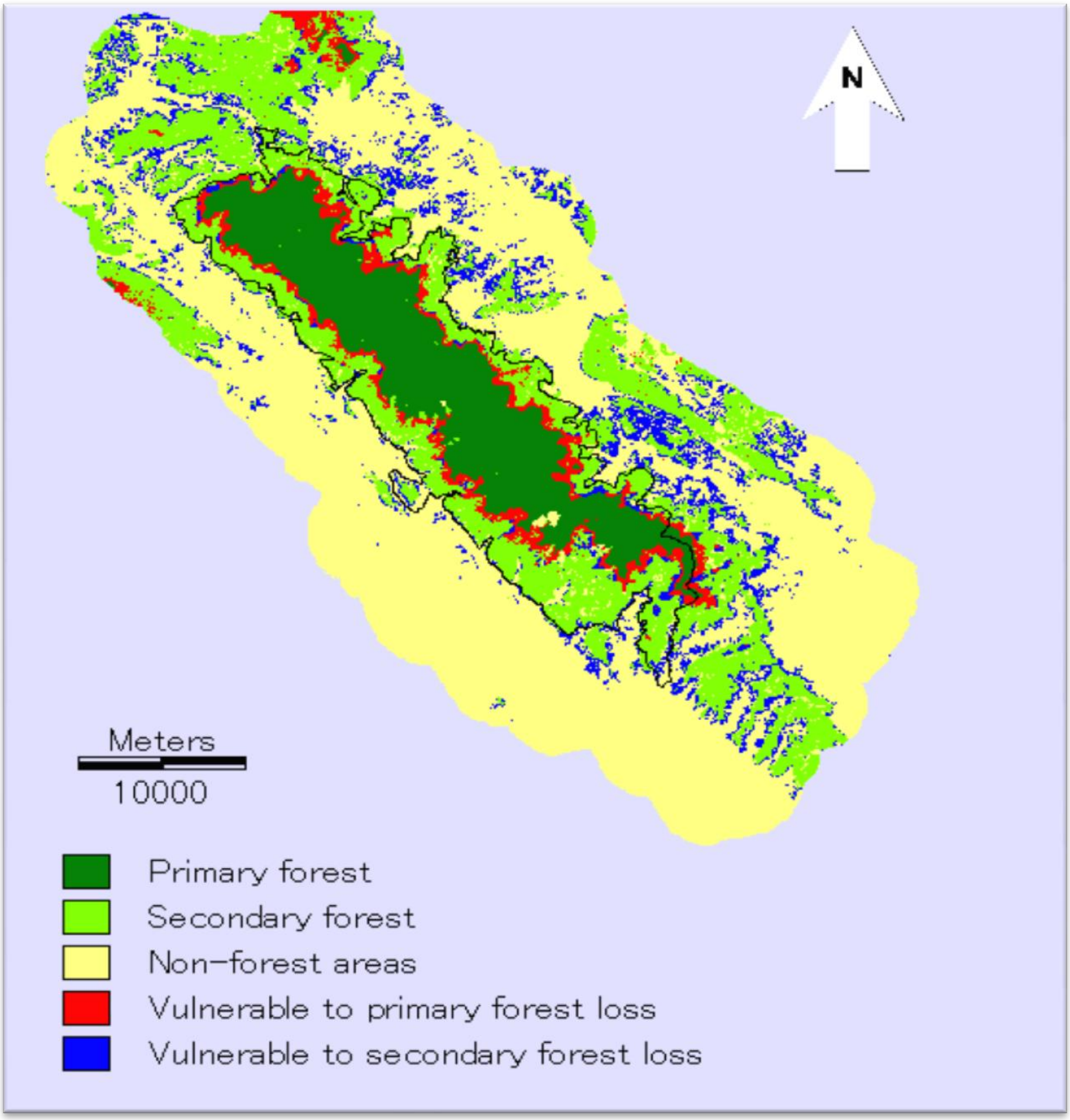


Figure 3-7: Forest map predicted for 2021and areas vulnerable to forest changes

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 Figures 3-6 and 3-7. 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.

It should be noted that the predicted forest changes are based on the assumption that forest changes may follow the 2000-2007 Markovian dynamics. In this area, the trends used in the predictions were largely driven by population pressure, and might be conservative. Increasing population, the high incidence of poverty, and the poor awareness of conservation among local residents contributed to the loss of the primary forest and the conversion of secondary forest into cropland (TDMP, 2005). Forest conversion tended to occur in land suitable for agriculture. Shifting cultivation and commercial tea plantations were the 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 had the most structurally complex and richest in plant species composition, particularly in the areas from 350 to 800 meters above mean sea level (Kuznetsov, 2005). According to the predictions in the present study, forest loss is likely to occur within this range of elevation. The loss of the remaining primary forest may threaten the survival of many species in the region. In particular, cultivation within primary forest areas drastically altered the composition and abundance of plant species (Ghazoul, 1994). 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.

More importantly, the prediction maps of forest change patterns can help protected area managers identify areas of interest for conservation and forest management efforts with the aim of improving the production of ecosystem services. 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.

Chapter 4

Land Suitability Assessment for Cropland Using Multi-Criteria Evaluation

4.1 Land suitability assessment as a tool for deforestation control

Given on Chapters 2 and 3, the occurrence of TDNP region's land use/cover changes was observed in the past (1993-2007). In particular, forest changes are forecasted to continue in the future (until 2014 and 2021). Forest changes are serious because they hamper the ecosystem services supply that affects to benefits of the current and future generations. For example, Zheng *et al.* (2005) found that, after seven years of deforestation, the occurrence of soil erosion resulted in a substantial decline in soil organic matter, nitrogen and phosphorus in the Loess plateau of China. Another important example of deforestation impacts is the reduction of carbon sequestration and storage capacity or increases the release of dioxide carbon into the atmosphere. One hectare of tropical forest can sink a total of roughly 263 metric ton ha^{-1} of aboveground biomass, which is equivalent to a carbon stock of 130 metric ton ha^{-1} (Fearnside *at al.*, 1999). According to the forest changes observed, the loss of primary forest for the period 1993-2007 in the TDNP region was about 12,700 hectare. Assuming that the recent price of carbon is US$ 30 per metric ton of carbon (Nordhaus, 2007), the loss of economic return for such period can be estimated to be about 49.5 US$ million.

In the TDNP region, farmers are looking for more land to satisfy farming needs (Figure 4-1). In order to control agricultural expansion into the PA and ensure sustainable uses of the land in the region, there is a great need to allocate land for agricultural production activities in priority areas to avoid the above-mentioned ecological consequences. Allocating an appropriate location or a parcel of land for an activity (land use) is apparently an issue of decision making according to multiple factors (Khoi and Murayama, 2010b). Such allocation should be carried out based on a comprehensive land suitability assessment (LSA). A LSA is a preliminary stage while assessing whether land is likely to be practical and successful for sustainable development of intended goals. In many cases, cropland has been promoted in areas, which are unsuitable in term of soil conditions. Due to increasing population pressure, agricultural expansion has been increasing in the TDNP region without consideration of the site suitability. Land use allocation is a most important step in land use planning process. The LSA is the mandatory component of the local land use planning. A key output of the assessment is a land suitability map that shows vacant and utilized lands that match the expected patterns for development in a certain region of interest. Therefore, this map is a prerequisite of the foundation for planning land use patterns in the future (Van Ranst *et al.,* 1996; Collin *at al.,* 2001) and the development of land use policies.

Figure 4-1: The removal of forest for agricultural expansion in the TDNP region (photo by author, 2009).

The LSA is the process of determining the fitness of a given parcel of land for a defined use (Stainer, 1991). A LSA involves the selection of biophysical factors and/or and socio-economic factors of an area and the combination of the selected factors with decision maker's preferences to obtain a composite suitability index (Sui, 1993). Therefore, it can be conceptualized as a multiple criteria decision-making problem (Pereira and Duckstein, 1993). Several methods can be used for the LSA. Boolean overlay and modeling approaches, *i.e.,* neural networks and evolutionary algorithms, are recently developed methods for the LSA in the GIS environment. However, these approaches lack a well-defined mechanism for incorporating decision maker's preferences into the GIS procedures (Malcewski, 2006). This disadvantage can be solved by integrating GIS and multi-criteria evaluation (MCE) methods. The MCE is an effective tool for multiple criteria decision-making issues (Malcewski, 2006). The purpose of the MCE is to investigate a number of choice possibilities in light of multiple criteria and multiple objectives (Cover, 1991). The integration of the MCE and GIS (GIS-MCE) may help land use planners and managers to improve decision-making processes (Malcewski, 1999). GIS enables computation of assessment factors, while a MCE aggregates them into a land suitability index.

The purpose of this chapter is to develop a GIS and MCE based land evaluation methodology for the TDNP region. The land suitability assessment was to guide the allocation of the land for agricultural activity and the other land uses according to varying suitability levels. It expects that the methodology can be applied in other protected areas in Vietnam.

4.2 Input data gathering and processing

Input databases used for the assessment was based on selected evaluation factors discussed in the next part. They include topographical map, soil map, water resource map, road network map and park boundary map (Table 4-1). These data were used for delineating suitable areas for cropland (Khoi and Murayama, 2010b). Landsat satellite images were used to derive the current land use map to analyze spatial matching between the current land-uses and suitable patterns.

Table 4-1: List of databases used in the assessment

Data types	Year	Scale/ resolution	Sources
Topographical map	1972	1:50,000	TDNP Management Office
Soil map	2005	1:100,000	National Institute for Agricultural Planning, Ministry of Agriculture and Rural Development and TDNP Management Office
Road network	2007	-	TDNP Management Office
Water body	2007	-	TDNP Management Office
Park boundary	2007	-	TDNP Management Office
Landsat images	2007	28.5 meters	University of Maryland
Field survey	2009.3		TDNP region

Once the databases were collected, thematic maps were developed for each factor. A digital elevation model (DEM) was constructed using a contour map with a scale of 1:50,000 and interval of 20 meters. The slope factor was derived from this DEM. Soil texture, soil depth, soil organic matter and soil pH factor maps were extracted from the digitized soil map with a scale of 1:100,000. The distance to water, distance to road and distance to the park boundary were generated from the water, road network and park boundary maps. Resolution of all raster factor maps was set at 30m x 30 m. The Landsat satellite images acquired in 2007 were used to derive the recent land-use map. The procedure for the interpretation of land use map is presented in Chapter 2.

4.3 GIS and MCE based assessment procedure

The land suitability assessment defines as the process of assessment of land performance when the land is used for specified purposes (FAO, 1985), or as all methods to predict the use potential of land (van Diepen *et al.*, 1991). The land suitability is known as the fitness of a given land-mapping unit for a land utilization type, or the degree to which it satisfies the land user. It is expressed on a continuous fitness scale or more generally, as a set of discrete classes is numbered from completely unsuited to completely suited class (Rossiter, 1996). In context of agriculture, land suitability evaluation for crop production involves the interpretation of data of soils, vegetation, topography, climate to match land characteristics with crop requirements (Wang *et al.*, 1990).

In general, land suitability evaluation types are classified into qualitative approach, parametric approach and process-based models (Van Lanen, 1991). The qualitative approach is the use of the knowledge of expert judgment for land evaluation. The parametric approach is the assessment of land suitability based on scientific survey data and multiplicative or additive index. A series of FAO methods (*i.e.*, guidelines for land evaluation in dryland agriculture (FAO, 1983), forestry (FAO, 1984), irrigated agriculture (FAO, 1985), extensive grazing (FAO, 1991), and steeplands (Siderius, 1986)) can be referred as parametric approaches. The FAO methodologies have used to support land use planning in many countries around the world (FAO, 1993). However, these methods lack a transparent and concrete mechanism for expressing participant's preferences and objectives to generate a compromise solution. Process modeling based approach is the assessment of land performance based on modeling techniques representing specific processes such as crop yield, soil erosion or water movement. This approach allows one to simulate various outcomes and negative consequences under different land use management scenarios based on biophysical processes. Nevertheless, this approach requires huge and detailed data that are currently not available, particularly in developing countries setting.

A successful land suitability assessment depends on how the activities and interactions of the relevant stakeholders are engaged in assessment process (Malczewski *et al.,* 1997) and how decision rules are constructed in a way that all of the stakeholders' land utilization factors are satisfied (Eastman *et al.*, 1992). It should be noted that a decision is understood to be a choice between alternatives (Eastman *et al.*, 1995). An alternative refers to a pixel in GIS raster data layer or point, line and polygon in GIS vector data layer. The MCE is adopted for the land suitability assessment in the present study because it has sound theoretical foundations and offers a transparent mechanism for the integration of various stakeholders' participation in evaluation process. The approach is widely applied in a wide variety of issues and domains, *i.e.,* land suitability, site selection, resources allocation, environmental impact assessment (Malczewski, 2006). The MCE provides a rich collection of techniques and procedures for structuring decision problems, designing, evaluating and prioritizing alternative decisions (Malczewski, 2006). The integration of MCE techniques within the GIS offers more functionality to land evaluators and improve decision-making capacity (Carver, 1991). The GIS-MCE can be understood as a process that transforms and combines spatial data and decision maker's preferences to obtain information for decision-making (Malczewski, 2006).

In this study, the GIS-MCE procedure for the cropland suitability assessment in the TDNP region included several stages framed in Figure 4-2. The determination of the relevant factors is the starting step in the assessment, followed standardizing the factors, weighting the factors, combining the factors with their weights and finally spatial matching between suitability map and current land-use map. The procedures and algorithms available in IDRISI Taiga (Eastman, 2009) were employed to implement the assessment.

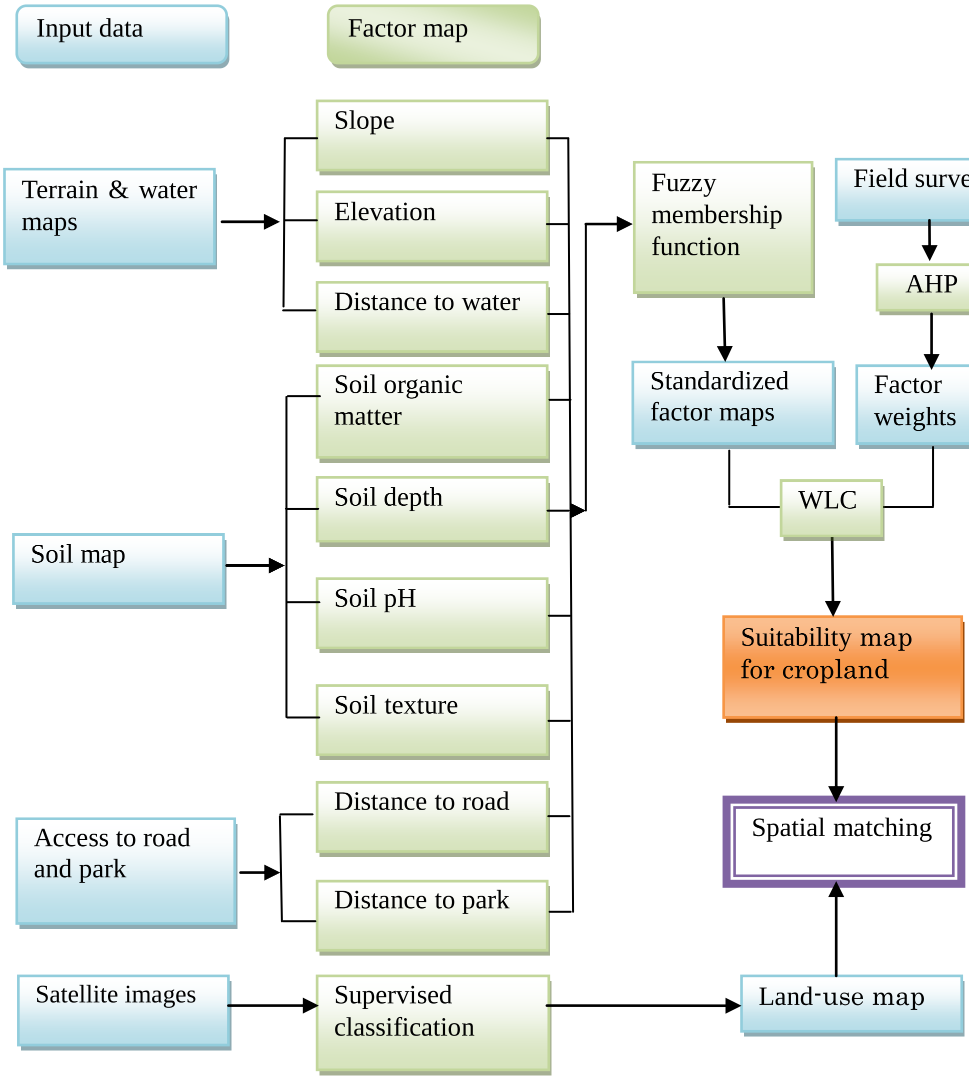


Figure 4-2: The flowchart of land suitability assessment for cropland

Notes: AHP is Analytical Hierarchy Process.

WLC is Weighted Linear Combination.

4.3.1 Selecting the factors

The factors are the variables that affect the performance (*i.e.*, crop yield, benefit and cost) of a land utilization type on a land unit, and they serve as the basis for classifying the suitability of land for a given use. The most important factors need to be assessed and aggregated into land suitability classes (FAO, 1985). Factors identification is often a difficult task in land evaluation process. Initially, a systematic analysis of any factors potentially influencing suitability for cropland should be undertaken to select those most relevant and important for a specified use. The factors are then checked against available data and spatial resolution. In particular, the selection of factors should consult local experts who have best knowledge about a certain area;

therefore, they can choose the factors that are most relevant and important.

In this study, the factors were selected according to their most relevance to suitability for cropland and the availability of databases. The selection of factors is a technical process that is based on expert knowledge or empirical research. In particular, expert knowledge or indigenous knowledge is vital to land evaluation and planning (FAO, 1993; Steiner, 1998; Ryder, 2003). Scientific surveys and local knowledge are often combined simultaneously in land evaluation and planning (Messing & Fagersrom, 2001). We selected 12 experts to be involved in the assessment, who were between 30 and 50 years of age. They participated in selecting the factors, identifying the suitable ranges of the factors, and evaluating the weights of the factors. They include five agronomy experts, five soil experts and two forestry experts. Eleven of the experts have bachelor's degrees, and one expert has a master's degree. These experts have worked at least five years at the office of the TDNP and have ever worked for the district department of agriculture and rural development in the region. Note that some factors were chosen by all the experts, others were only significant for some certain experts. Discussion continued until the list of the factors satisfied all experts.

After discussion with the experts during the field survey period, nine factors (slope, elevation, distance to water, soil organic matter, soil depth, soil pH, soil texture, distance to roads, and distance to the TDNP boundary) were identified to be most relevant for the suitability assessment of crop growing areas in the region. The elevation, slope (terrain) and the distance to water are important determinants of cropland suitability because the terrain often has a relationship with soil fertility as well as with the vulnerability of soil to degradation. The slope relates to the retention and movement of soil particles and the rates of runoff and soil erosion; therefore, it closely regulates the soil quality condition. The soil characteristics (soil organic matter, soil depth, soil pH and soil texture) represent soil nutrients and water availability for crop growth. The distance to roads is important for crop production because it relates to the transportation cost of input and output items. The distance to the park is defined as the suitability that is monotonically reduced in areas closer to the park boundary. This variable is included in the land suitability assessment because cultivation areas closer to the park may alter more seriously the environmental quality of the protected area.

4.3.2 Standardizing the factors

Data used for generating land evaluation factors are often collected from different sources, which have different measurement units. For example, elevation is measured in meter, but soil organic matter is measured in percentage. These factors need to be converted into a common comparable unit for MCE based aggregation. In this case, the factor maps were measured in different original scales; therefore, these maps were standardized to a uniform suitability rating scale. The standardization transforms the disparate measurement units of the factor maps into comparable suitability values (Eastman, 2009). The fuzzy membership function (FMF) approach was applied to standardize the factors. In recent years, a noticeable mark is made in the increasing use of fuzzy set in land evaluation because traditional methods, *i.e.,* Boolean methods, fail to incorporate the inexact or fuzzy nature of resource data. By the use of fuzzy set method, the Boolean logic of suitability determined suitable or non-suitable is replaced by fuzzy membership functions or membership values.

The FMF method provides a useful means of dealing with uncertainty that result from the imprecise boundaries between suitability classes (Mcbratney and Odeh, 1997; Ahamed *et al.,* 2000). An FMF can be characterized by a fuzzy membership grade that ranges from 0 (non-membership) to 1 (complete membership) (Eastman, 2009). It means that the maximum suitability level of a factor that accurately matches the clearly defined suitable level is assigned to a membership value of 1. The other suitability levels of a factor are given a membership grade between 0 and 1. The membership function of a fuzzy set defines how the grade of membership of factor suitability in different land units (pixel) is determined.

Several FMFs can be used to standardize the factors. A critical issue in the use of fuzzy set methodology is the selection of appropriate FMF types. The adoption of FMF type may depend on the nature of factors, which need to be expressed. This is not a straightforward task because decisions have to be made on membership values according to the varying levels of suitability. In this study, the sigmoidal fuzzy membership function was selected for the factors standardization. Such kind of the function is one of the most widely used fuzzy membership functions in land evaluation (Eastman, 2009). A sigmoidal fuzzy membership function is given as the following:

$$\mu = \cos^2 \propto, \tag{4-1}$$

where: μ is degree of membership and α is score of factors.

In case of sigmoidal monotonically increasing fuzzy membership function (SMIFM), α is given as

$$\propto = \frac{(x-c)}{(d-c)}\frac{pi}{2}, \tag{4-2}$$

where: $x < c$, then $\mu = 1$.

In case of sigmoidal monotonically decreasing fuzzy membership function (SMDFM), α is determined as

$$\propto = \left[\frac{1-(x-a)}{b-a}\right]\frac{pi}{2}, \tag{4-3}$$

where: x >b and then μ=1. The points a, b, c and d are illustrated as the following (Figures 4-3a and b).

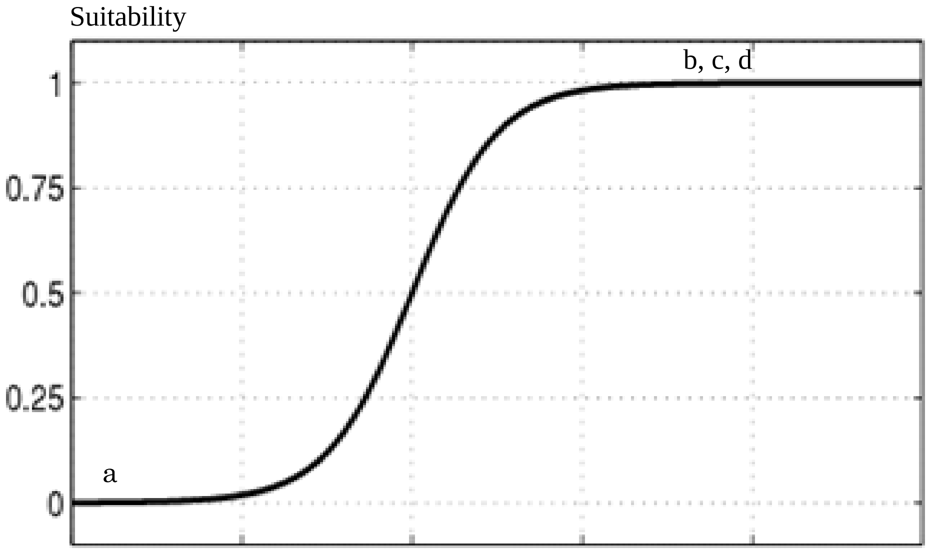


Figure 4-3a: The shape of the SMIFM function

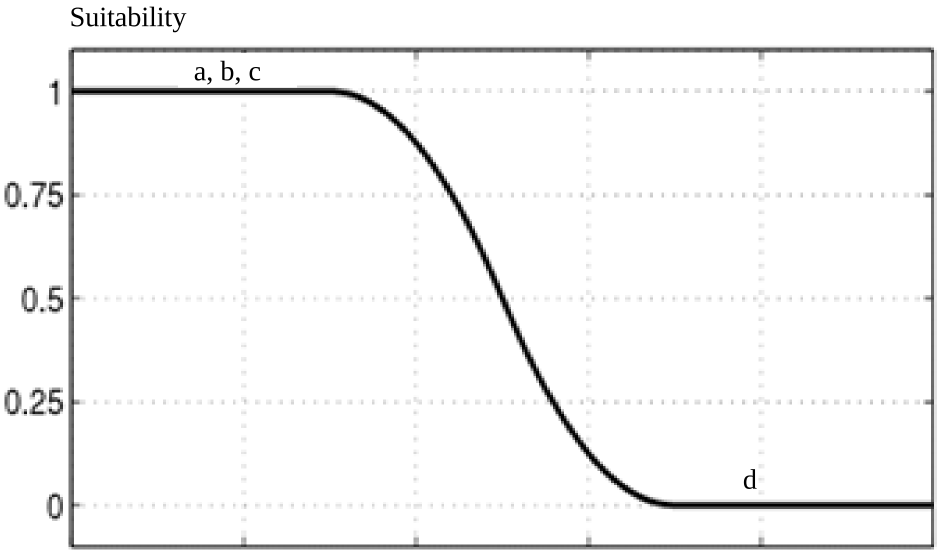


Figure 4-3b: The shape of the SMDFM function

Table 4-2: Suitable ranges used for fuzzy membership function

Factor	Non-membership (unsuitable)	Membership grade (suitable range)	References
Slope (degree)	>15	1-15	TDNP agronomy experts Slope from 1 to 25^{o} (Liu *et al.*, 2006), 1 to 15^{o} (Quan *et al.*, 2007; Wang *et al.*, 2007)
Elevation (m)	>400	1-400	TDNP agronomy experts Elevation from 1 to 500 m (Quan *et al.*, 2007)
Distance to water (m)	>2,000	100-2,000	TDNP agronomy experts
Soil organic matter (%)	<0.5	0.5-2.3	TDNP agronomy experts Less than 1% to 3% (Quan *et al.*, 2007)
Soil depth (cm)	<20	20-150	TDNP agronomy experts Soil depth range from 10 cm to 60 cm (Quan *et al.*, 2007), 15 cm to more than 30 cm (Wang *et al.*, 2007)
Soil pH	<4.5 and >7.5	4.5-6.9	TDNP agronomy experts pH range from 5 to 8 (Quan *et al.*, 2007)
Soil texture (class)	-	Sandy clay loam, sandy loam, silt loam, loam	TDNP agronomy experts Medium loam is most suitable, light and heavy loam is moderately suitable, sandy loam and medium clay is marginally suitable (Quan *et al.*, 2007; Wang *et al.*, 2007)
Distance to roads (m)	>4,000	100-4,000	TDNP agronomy experts
Distance to the park boundary (m)	<500	500-11,277	TDNP agronomy experts

In the use of FMF for the standardization of the factors, each factor was defined that the least suitable level is 0, and the most suitable level is 1, which may call a suitable range. Within this range, the fuzzy membership degrees of a factor gradually increase or decrease on this defined range. The suitable ranges were determined based on the experts, and somewhat similar studies had been successfully conducted for cropland suitability assessment (Liu *et al.,* 2006; Quan *et al.,* 2007; Wang *at al.,* 2007) (Table 4-2). These ranges were also verified by field visits.

Then, the two forms of fuzzy sigmoidal function, the SMDFM and SMIFM, employed to standardize the factors. Higher values in elevation, slope, distance to water and distance to road would indicate continuously decreasing suitability; therefore, the SMDFM was used to standardize these factors. On the other hand, higher values in soil organic matter, soil depth, soil pH and distance to park boundary factors would show continuously increasing suitability, so the SMIFM was used to standardize these factors. Suitable values for soil texture were assigned according to each textural class. Specifically, the slope factor was standardized using SMDFM with a suitability range of 0-15 degree (Liu *et al.,* 2006; Quan *et al.,* 2007; Wang *et al.,* 2007). A slope of less than 1 degree was assigned a membership of 1, and a slope of 15 degree was assigned a membership of 0. Between less than 1 and 15 degree, the fuzzy membership grades of the slope gradually decrease on the scale from 1 to 0. The elevation at more than 400 meters above mean sea level is not suitable for cultivation because the areas beyond 400 meters are defined to be the national park boundary. In a similar way, the SMDFM was used to rescale the elevation between 1 and 400 meters above mean sea level into a continuous suitability factor map. The distance to water was rescaled to a range of suitability. The shortest distance (within 100 meters) has the highest suitability score, and the greatest distance (2,000 meters) has the lowest suitability. Areas in excess of 2,000 meters were identified to be unsuitable for cultivation. Again, this factor was standardized using the SMDFM.

The soil organic matter, soil depth and soil pH were standardized using the SMIFM with the ranges of suitability as shown in Table 4-2. For soil texture factor, this categorical factor needs assigning a rating to each soil texture class. The soil textural classes of the region include sandy clay loam, sandy loam, silt loam and loam. Sandy clay loam, sandy loam, silt loam and loam were assigned to be 1.0, 0.8, 0.5 and 0.3, respectively. The factor of distance to road, TDNP agricultural experts identified the areas within 4 km of road as suitable. In determining a range of suitability for this factor, they identified areas within 100 meters of road as the most suitable and areas further than 100 meters as having a continuously decreasing suitability. Again, this factor was standardized using the SMDFM. The distance to the park boundary, suitability defined to be very low within 500 meters of the boundary. More than 500 meters, TDNP experts agreed that suitability progressively increase with distance. Therefore, this factor was standardized using the SMIFM.

4.3.3 Weighting the factors

The evaluation of suitability involves many factors that have varying importance levels to decision makers; therefore, each should be weighed according to its relative importance for the growth conditions of crops. This can be obtained by assigning a weight to each factor. A weight can be defined as a value assigned to an assessment factor that indicates its importance relative to other factors under consideration. The weight of a factor is larger means it is more important.

Several methods can be used for estimating the weight of factor. Pairwise comparison, ranking, rating and tradeoff analysis methods are commonly used in the estimation (Malczewski, 1999). The ranking and rating methods should be applied if the easiness of use and saving of time and cost are the matter of concerns. However, these methods lack sound theoretical foundation, and the accuracy is the matter of controversy. On the other hand, pairwise comparison and tradeoff analysis methods are the ones that have sound theoretical foundation and better accuracy levels (Malczewski, 1999). The empirical applications proved that the pairwise comparison method is one of the most effective techniques in spatial decision-making (Eastman et al., 1993).

Therefore, in this study, the weight of each factor was estimated by the use of the pairwise comparison method (PWC) developed by Saaty (1980 and 1990). The PCM developed in the context of a decision-making process known as the analytical hierarchy process is the most commonly used method (Eastman *et al.,* 1995). Specifically, the factor weight was derived from a pairwise comparison matrix (PWCM) according to the PCM. In the PWCM, a pairwise comparison is a rating of the relative importance of the two factors regarding the suitability of the cropland. The PWCM method uses a scale with values from 9 to 1/9 to rate the relative importance of the two factors (Table 4-3a and b). A rating of 9 indicates that in relation to the column factor, the row factor is more important. On the other hand, a rating of 1/9 indicates that relative to the column factor, the row factor is less important. In cases where the column and row factors are equally important, they have a rating value of 1 or the two factors contribute equally to the suitability of cropland.

Table 4-3: (a) Rating scale for the relative importance of two factors

1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2	3	4	5	6	7	8	9
Extremely		Very strongly		Strongly		Moderately		Equally	Moderately		Strongly		Very strongly		Extremely	
Less important									More important							

(b) The description of relative importance

Intensity of importance	The description of relative importance (Saaty, 1980)
1	Two factors of I and J are of equal importance
2	Equal to moderate importance of I compared to factor J
3	Moderate importance of I compared to factor J
4	Moderate to strong importance of I compared to factor J
5	Strong importance of I compared to factor J
6	Strong to very strong importance of I compared to factor J
7	Very strong importance of I compared to factor J
8	Very to extremely strong importance of I compared to factor J
9	Extreme importance of I compared to factor J

Notes: The row factor (I) compares to the column factor (J). The pairwise comparisons are based on experience and adjustment from experts.

In determining the ratings, 12 experts as previously described in the factor selection section, worked as a group to determine the ratings of the factors. To reach agreement among evaluation experts in rating the relative importance of the factors, a majority rule was applied. This means that each rating in the pairwise comparison matrix was carefully compared and decided based on the agreement of the majority of experts. In the context of the workshop for determining the relative importance of the factors, a description of the evaluation purpose, an identification of the set of relevant factors, and an explanation of a PWCM and completion procedure were carried out. After discussion and careful examination of the set of factors, the group made all the pairwise comparisons for the set of factors. The PWCMs developed are shown in the next result section. The weights of the factors were then calculated from such PWCMs. Tables 4-4 and 4-5 demonstrate an example of spreadsheet calculations for consistency ratio of overall site suitability factors for cropland. The points (a) and (b) show the calculation of the factor weights. The parts (c), (d) and (e) show the calculation of the CR. Note that the matrices for the estimation of factor weights were individually constructed for the three factor groups: terrain and water, soil and access to road and park. Then, one matrix was constructed to estimate the factor group weights of overall site suitability for cropland

Table 4-4: Example of spreadsheet calculations for consistency ratio of site suitability for cropland in the TDNP region

	Values			Decimal			Normalization			Weight	λ	CI	RI	CR
	TW	S	RP	TW	S	RP	TW	S	RP					
TW	1	1/2	3	1.00	0.50	3.00	0.30	0.27	0.43	0.3338				
S	2	1	3	2.00	1.00	3.00	0.60	0.55	0.43	0.5247	3.0538	0.0269	0.58	0.0464
RP	1/3	1/3	1	0.33	0.33	1.00	0.10	0.18	0.14	0.1415				
Sum				3.33	1.83	7.00				1.0000				

Notes:
TW is terrain and water.
S is soil.
RP is access to road and park.

(a) Sum the numbers in each column of the values matrix; divide each number in the decimal matrix by the column sum; the resulting matrix is the normalization matrix.
(b) Average the numbers in each row of the normalization matrix; the average value is the weight.
(c) Compute lambda (λ) as follows (Malcewski, 1999). The first step is to determine the weighted sum vector by multiplying the weight of the TW, the weight of the S, and the weight of the RP times the first column, the second column, and the third column of the values matrix, respectively, and finally, sum these values over the rows. Then second step is to determine the consistency vector by dividing the weighted sum vector by the factor weights as per the following.

Table 4-5: Computation of lambda

Step 1	Step 2
(1)(0.3338) + (0.5)(0.5247) +(3)(0.1415) = 1.0208	1.0208/0.3338 = 3.05837
(2)(0.3338) + (1)(0.5247) + (3)(0.1415) = 1.6169	1.6169/0.5247 = 3.08168
(0.3333)(0.3338) + (0.3333)(0.5247) +(1)(0.1415) = 0.4277	0.4277/0.1416 = 3.02140

Then, λ = (3.05837+3.08168+3.02140)/3 = 3.0538

(d) The Consistency Index (CI) is (λ − n)/(n − 1), (3.0538 − 3)/2 = 0.0269

(e) The Consistency Ratio (CR) is CI/RI, where RI is the Random Consistency Index. For n = 3, RI = 0.58. CR = 0.0269/0.58 = 0.0464.

4.3.4 Weighted linear combination

The procedure by which factors are combined to derive at a particular evaluation is well known as a weighted linear combination (WLC) (Eastman *et al.*, 1995). After the standardized factor maps and the weights of the factors were constructed and generated, the WLC was used to combine the standardized factors and their corresponding weights to obtain an overall suitability map for the cropland. All of the factors were combined as

$$\mathrm{Grid}_{\mathrm{result}} = \sum \mathrm{Grid}_{\mathrm{i}} \text{ x } \mathrm{Weight}_{\mathrm{i}},$$

where: Grid_i is the factor i, and

Weight_i is the relative weight of factor i.

Specifically, the three factors of terrain and water, the four factors of soil quality, and the two factors of access to roads and the park were calculated by Equations (4-4), (4-5) and (4-6), and then they were all overlaid to produce the overall cropland suitability map according to Equation (4-7). Finally, the recent land-use map and the suitability map were overlaid to analyze the spatial matching. A simple overlay technique was used between the land-use map and the suitability map, and then the statistics of the suitability classes for each land use were calculated.

$\text{Terrain and water grid} = \text{Grid}_{\text{slope}} \times 0.2856 + \text{Grid}_{\text{elevation}} \times 0.2856 + \text{Grid}_{\text{distance to water}} \times 0.4288$	(4-4)
$\text{Soil quality grid} = \text{Grid}_{\text{soil organic matter}} \times 0.4073 + \text{Grid}_{\text{soil depth}} \times 0.2384 + \text{Grid}_{\text{soil pH}} \times 0.1444 + \text{Grid}_{\text{soil texture}} \times 0.2099$	(4-5)
$\text{Access to road and park grid} = \text{Grid}_{\text{distance to road}} \times 0.6 + \text{Grid}_{\text{distance to park}} \times 0.4$	(4-6)
$\text{Overall suitability grid} = \text{Grid}_{\text{terrain and water}} \times 0.3338 + \text{Grid}_{\text{soil quality}} \times 0.5247 + \text{Grid}_{\text{access to road and park}} \times 0.1415$	(4-7)

4.4 Results and discussion

As indicated in the methodology, the land suitability analysis was carried out in the two consecutive stages. The first stage is to delineate the TDNP region into different suitability classes using MCE and AHP. The standardized factor maps and the weights of factors are the results of the first stage. After that, in the second stage, the land use map of 2007 derived from satellite image was overlaid with the final land suitability map to examine the extent of each land suitability class per land use category.

4.4.1 Standardized factor maps

The outcome of the expert consultation and discussion resulted in nine assessment factors of elevation, slope, distance to water, soil organic matter, soil depth, soil pH, soil texture, distance to road and distance to the park boundary. Figure 4-4 shows the spatial patterns of factors. By the use of fuzzy membership function, these factors were standardized into a common comparable scale from 0 to 1, representing the varying levels of suitability from the least to most suitable. For the easier representation, the levels of factor suitability was grouped into 4 classes (least suitable: 0-0.25, marginally suitable: 0.25-0.50, moderately suitable: 0.50-0.75 and most suitable: 0.75-1.0). The distribution of suitability levels for each factor in term of area and its proportion is summarized in Table 4-6.

The distance to the park boundary, soil pH, soil organic matter, slope and distance to water have greater proportions of area than the others in term of the least and marginally suitable level. The sums of least and marginally suitable classes of these factors vary from 50.67 % to 82.67%. On the other hand, the combined proportions of least and marginally suitable classes in the remaining factors (distance to road, elevation, soil texture, and soil depth) vary from 17.69 % to 41.08 %.

Specifically, in term of the elevation, 72.55 % of the total area of 141,237 ha was found to be suitable for cultivation, and the other percentage of 27.45% may not fit the cultivation of crop. For the slope factor, 55.1% of the territory was estimated to be suitable for farming, but 44.9% of the area had least suitability level for cultivation requirement. The distribution of suitability levels of the distance to water was somewhat similar to slope. For the soil organic matter factor, there was 36.97% of the entire area favorable to farming; however, the remaining area of 63.03% was determined to be only least and marginally suitable for cropping. The unsuitable and suitable areas of soil depth factor were 41.08 % and 58.92%, respectively. The soil pH factor appears to be a constraint for cultivation because 67.94 % of the area that have pH values in the least and marginally suitable levels. However, the factors of soil texture and distance to road, the areas that have higher moderately to most suitable area percentages are 74.37% and 82.31% respectively. Finally, in term of the distance to the park boundary, 82.67 % of the territory was classified to be least and marginally suitable. It should be noted that suitable ranges were based on the opinions of the experts and references. Such values can be updated if new data or surveys are available.

Table 4-6: The distribution of suitability levels of individual factor in the study area

Factor	Least suitable		Marginally suitable		Moderately suitable		Most suitable	
	ha	%	ha	%	ha	%	ha	%
Elevation	29,862	21.14	8,914	6.31	13,534	9.58	88,927	62.96
Slope	71,509	50.63	6,306	4.46	12,680	8.98	50,742	35.93
Distance to water	56,804	40.22	14,760	10.45	18,863	13.36	50,810	35.97
Soil organic matter	38,164	27.02	50,852	36.00	12,403	8.78	39,818	28.19
Soil depth	38,211	27.05	19,816	14.03	37,953	26.87	45,257	32.04
Soil pH	89,016	63.03	6,946	4.92	16,709	11.83	28,566	20.23
Soil texture	-	0.00	3,621	25.63	20,764	14.70	84,270	59.67
Distance to road	15,635	11.07	9,356	6.62	13,355	9.46	102,891	72.85
Distance to park boundary	76,359	54.06	40,398	28.60	19,069	13.50	5,411	3.83

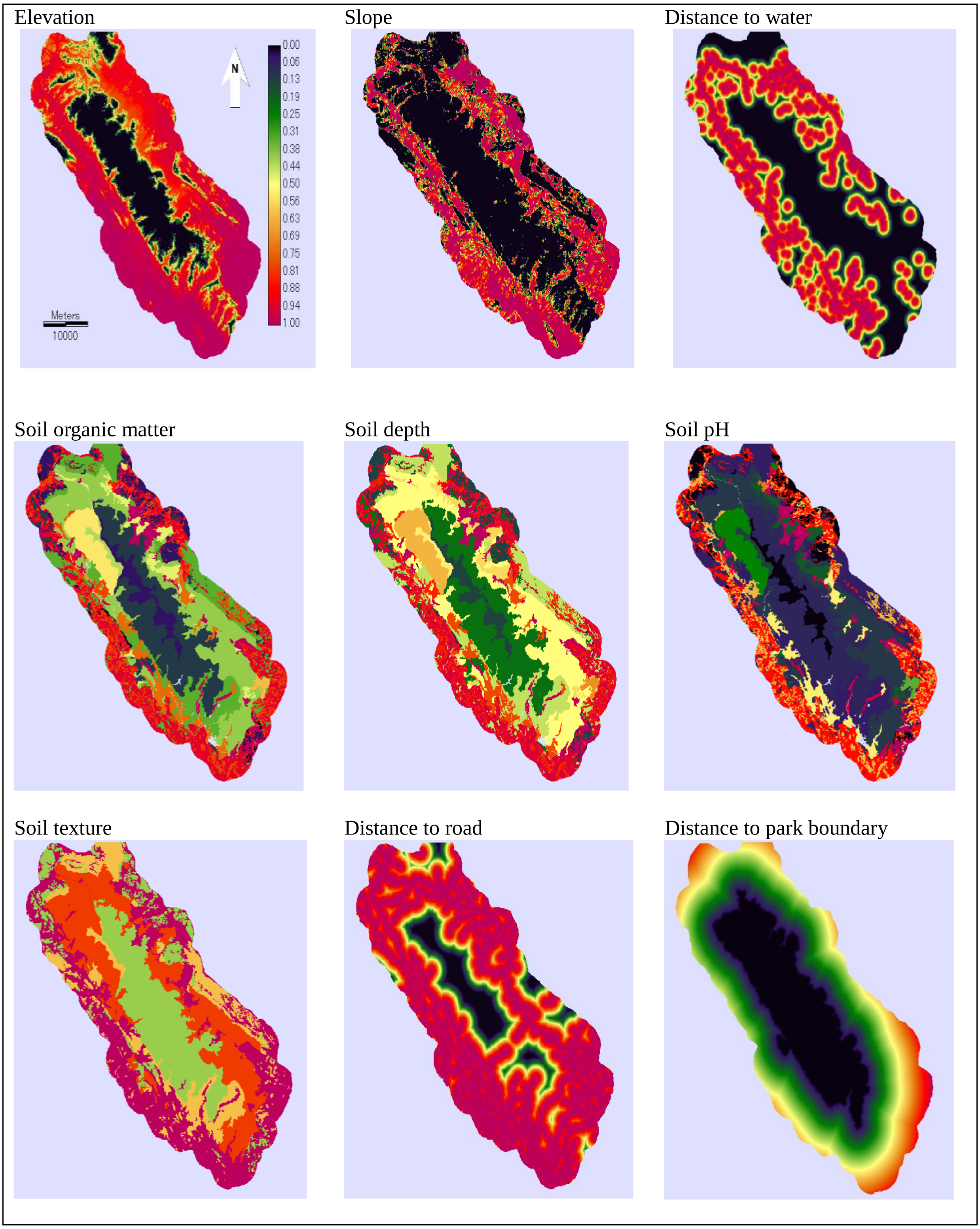


Figure 4-4: Standardized factor maps

Notes: The legend is same as elevation map to all factor maps. A pixel with a higher value in the range indicates the level of more suitable.

4.4.2 Relative weights of the factors

The weights of the factors were then calculated from the PWCMs (Table 4-7a, b, c and d). The consistency ratios (CRs) of 0.000 to 0.087 for the matrices were within the acceptable level (Saaty, 1980 and 1990). According to Saaty (1980 and 1990), the calculated CR must be less than 0.1, which is the acceptability cut-off. This means that if the computed CR is less than 0.1, the calculated weights of the factors are consistent. If the calculated CR is more than 0.1, the pairwise comparison matrix needs to be re-evaluated, and the weights of the factors also need to be re-calculated accordingly.

Table 4-7: The pairwise comparison matrix for evaluating the relative importance of the factor for each land use requirement

	Slope	Elevation	Distance to water	Weight
(a) Terrain and water				
Slope	1	1	2/3	0.2856
Elevation	1	1	2/3	0.2856
Distance to water	3/2	3/2	1	0.4288
Consistency ratio (CR) =0.000				

Note: The number in the cell indicates the rating of the row factor relative to the column factor.

	Soil organic matter	Soil depth	Soil pH	Soil texture	Weight
(b) Soil quality					
Soil organic matter	1	3	2	3/2	0.4073
Soil depth	1/3	1	3/2	2	0.2384
Soil pH	1/2	2/3	1	1/2	0.1444
Soil texture	2/3	1/2	2	1	0.2099
CR =0.087					

	Distance to road	Distance to park	Weight
(c) Access to road and park			
Distance to road	1	3/2	0.6000
Distance to park	2/3	1	0.4000
CR =0.000			

	Terrain and water	Soil quality	Access to road and park	Weight
(d) Land use requirement for assessment of site suitability for cropland				
Terrain and water	1	1/2	3	0.3338
Soil quality	2	1	3	0.5247
Access to road and park	1/3	1/3	1	0.1416
CR=0.046				

Different factors played different importance levels for the site suitability of cropland. The result of evaluating the relative importance of factors indicated that the soil quality (soil organic matter, soil depth, soil pH and soil texture) was the most important, followed by the terrain and water (slope, elevation and distance to water) and access to roads and the park (distance to roads and distance to the park boundary). The soil quality with a weight of 0.5247 was determined to have a major impact on the overall suitability. The soil quality plays a key role because it regulates the storage of soil nutrients and the water-holding capacity, which are necessary biophysical conditions for crop growth. The terrain and water factor, with a weight of 0.3338, was the second contributor. The slope affects the retention and movement of water and soil particles, the rate of runoff and accelerated soil erosion. These effects are closely linked to the soil quality conditions. Elevation relates to increased water-pumping costs for agricultural production. Water availability is very important for crop growing in the area. Natural lakes, ponds, streams and rivers are major water providers for agricultural production in the area. Water resources in the region mostly depend on sources from the TDNP forest ecosystems. Therefore, there is a strong link between the conservation of native forest ecosystems and agricultural development in the region. The access to roads and the park played a weaker role compared to the others. Road networks are significant for local communities by enhancing commercial agricultural activities and transportation. The distance to the park boundary affects the biodiversity conservation activity of the TDNP; therefore, it relates to the site suitability of cropland.

4.4.3 Overall cropland suitability map

Figure 4-5 shows the suitability map for the cropland in the TDNP region. The map contains pixels with varying degrees of suitability from 0 to 1. A higher pixel score shows a higher suitability level. The map was re-classified, for easier representation, into four classes based on the structure of the FAO suitability classification (FAO, 1976): the most suitable (0.75-0.96), the moderately suitable (0.5-0.75), the marginally suitable (0.25-0.5), and the least suitable (0-0.25). The most suitable is the land with minor limitations that do not significantly affect crop farming. The moderately suitable is the land with limitations that, in aggregate, are moderately limiting to crop farming. The marginally suitable is the land that has limitations, which, in aggregate, are severely damaging to crop farming. The least suitable is the land with limitations that, in aggregate, are very severely damaging to crop farming.

The extent of each class is summarized in Table 4-8. It indicated that 28.10% of the total study area was found to be the most suitable class. These most suitable areas are mainly characterized by flatness, a nearness to water and deep soil depth. The moderately suitable class was found to be 23.96% of the territory. Both the most and moderately suitable classes were 52.06% of the total area, whereas the existing cropland area was 46.5%. This result highlights that the most and the moderately suitable areas have been used for the cropland in the region. The least suitable and marginally suitable classes were 19.17% and 28.77%, respectively. These areas are often located in areas with steepness, low soil depth and less water access. If the farmers are forced to reclaim land for agriculture due to population pressures, the marginally suitable areas that are highly vulnerable to soil erosion may be the target areas of the future.

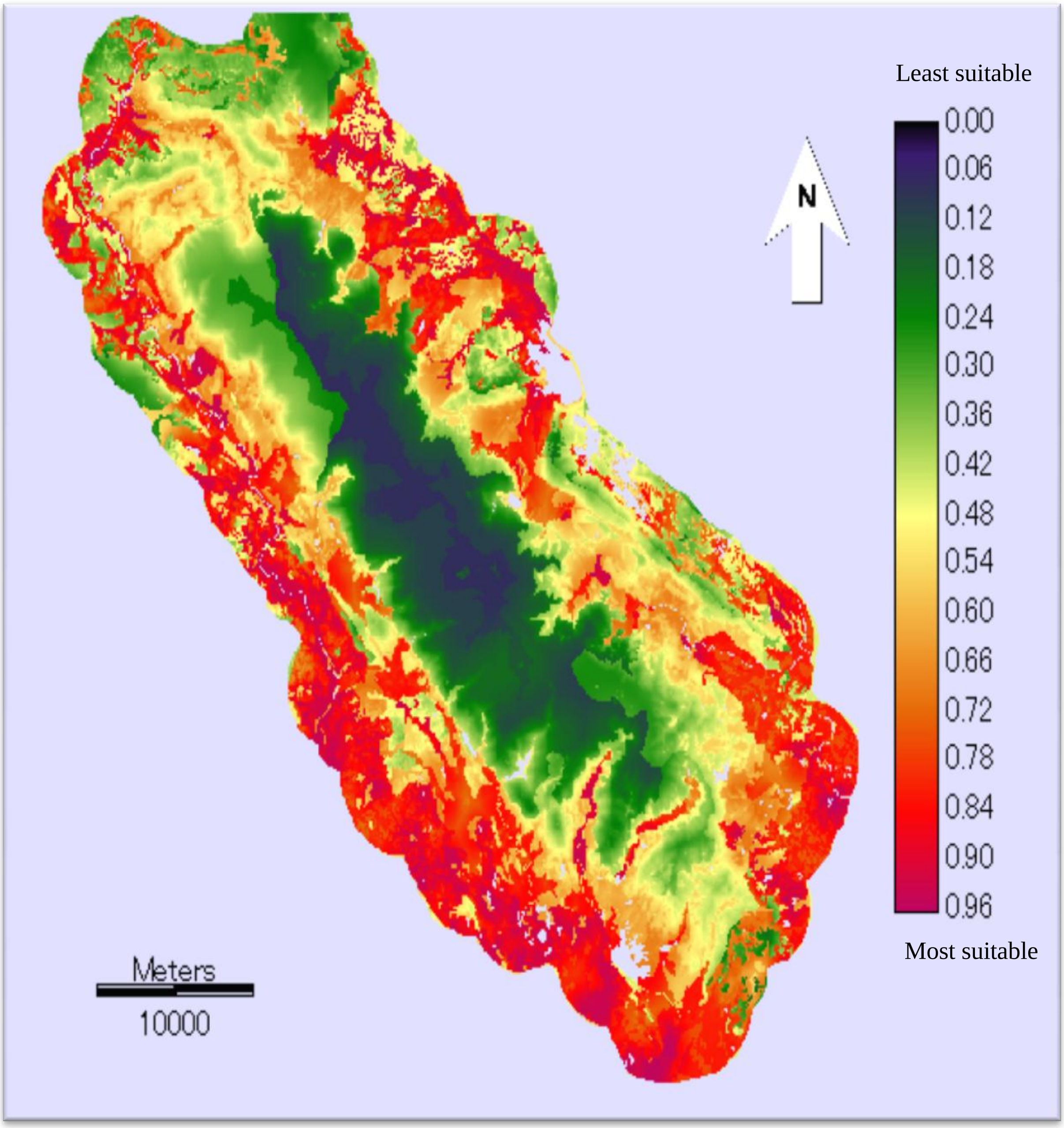


Figure 4-5: Land suitability map for cropland in the region

Note: A pixel with a higher value in the range indicates a higher suitable level.

Table 4-8: Area of the cropland suitability classes

Suitability class	Area (ha)	Proportion (%)
Least suitable	27,069	19.17
Marginally suitable	40,639	28.77
Moderately suitable	33,846	23.96
Most suitable	39,683	28.10
Total	141,237	100.00

4.4.4 Matching between land use map of 2007 and suitability patterns

The spatial matching offered valuable information to identify whether the land was optimally utilized in the region. The result of overlaying the suitability map (Figure 4-6) with the land-use map of 2007 (see Chapter 2) is presented in Table 4-9.

Table 4-9: The matching between the suitability map and the land use map of 2007

Land-use type	Level of suitability								
	Most suitable		Moderately suitable		Marginally suitable		Least suitable		Total land-use
	ha	%	ha	%	ha	%	ha	%	ha
Primary forest	8	0.02	42	0.12	6,072	14.94	19,337	71.44	25,459
Secondary forest	1,339	3.37	11,359	33.56	29,006	71.37	2,314	8.55	44,018
Rain-fed agriculture	19,039	47.98	16,738	49.45	5,099	12.55	241	0.89	41,117
Paddy rice	18,748	47.24	5,394	15.94	251	0.62	174	0.64	24,567
Settlement	549	1.38	313	0.92	212	0.52	2,056	7.60	3,130
Water	-	-	-	-	-	-	2,947	10.89	2,946
Total suitable class	39,683	100.00	33,846	100.00	40,640	100.00	27,069	100.00	141,237

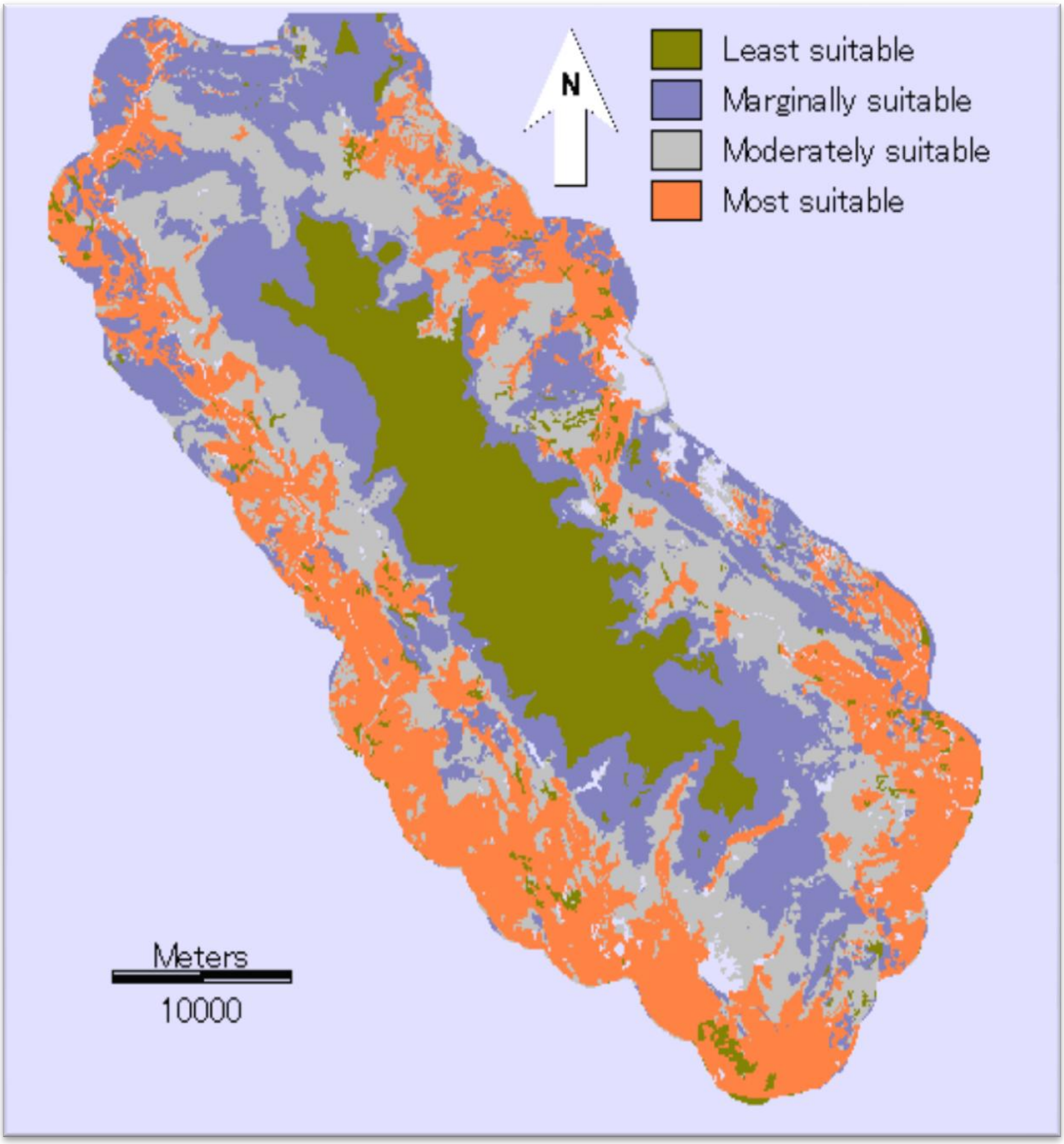


Figure 4-6: Map of the suitability zones

As expected, the most suitable and moderately suitable areas were found in the existing rain-fed agriculture and paddy fields. The result indicates that 95.22% of the most suitable class was distributed over the rain-fed agriculture and the paddy rice, while only 3.37% of the class was located in the secondary forest. With respect to the moderately suitable class, 83.01% of the class was found in the rain-fed agriculture and the secondary forest, whereas only 15.94% of the class was located in the paddy rice. For the marginally suitable class, 71.37% of the class was found in the secondary forest. This class was also found in the primary forest (14.94%) and the rain-fed agriculture (12.55%). Finally, the least suitable class was mainly stretched over the primary forest. The most and moderately suitable areas have already been utilized for paddy rice and rain-fed agricultural crops. Although some of the rain-fed agricultural areas may cause land degradation due to soil erosion, these utilized lands may not be easily changed towards more sustainable uses, such as agro-forest farming or fruit trees, in the future because of the growing population in the area.

It is important to note that the farmers are not aware of formal land suitability assessment methods, but they trust their own experience regarding land suitability. The farmers have a profound knowledge of their lands and classify the suitability of the land according to crop yield. Crop yield often correlates with biophysical factors of the soil, such as terrain, fertility and water availability. In the study, the factors selected based on the opinions of the experts cover the farmers' perception; therefore, the assessment spatially matches with the majority of existing cropland.

Though GIS-MCE approach provides an effective framework for land evaluation, the selection of assessment factors and the identification of suitable range for each factor have direct influence on the results. In this study, the factors were selected based on the local experts; therefore, they represented a considerable share of the factors relevant to the suitability of growing areas in the region. Moreover, the FMF approach was used to standardize the factors. The FMF approach is useful because it is good at dealing land use suitability classes that do not have clearly defined boundaries (Groenemans *at al.,* 1997). Therefore, the suitability map represented more accurate result. In particular, integration of spatial databases and expert knowledge significantly enhanced decision-making capacity while undertaking land suitability evaluation. Moreover, the approach highlights on participatory decision-making process (Eastman *et al.,* 1992). Therefore, it can minimize and solve conflicts among competing interests in the area of protected area and buffer zone land use management.

The GIS-MCE approach has been widely applied in land suitability analysis (Malcewski, 2006); however, the application of the method in protected area-buffer zone management is relatively new in Vietnam. GIS-MCE has shown the capacity as a tool for decision support in making choices among land use alternatives. MCE of soil, topography and accessibility factors exemplified to be useful to delineate suitable areas for cropland in the TDNP region. In particular, the involvement of local experts was vital to obtain consistent results. The experts played key roles in the selection of the evaluation factors and the determination of the factor weights. Remote sensing data offered land use information that was crucial to examine the spatial matching between the potential suitability areas and the current land use patterns. This information helped to identify whether the land has been used optimally, and future land uses can be recommended for the region. The application of the methodology can be useful for managers and planners to manage protected area-buffer zone resources.

Chapter 5
Towards Sustainable Land Uses for Ecosystem Service Provision

5.1 Decision platform for sustainable land uses

A healthy ecosystem plays long-term roles in the sustainable provision of human wellbeing, economic development and poverty alleviation across the world (Turner and Daily, 2008). The TDNP region ecosystem, if appropriately managed, produces a variety of ecosystem services that are vital to the people, including the production of goods (*i.e.*, foods, timber), life support processes (*i.e.*, water supply, soil retention), life fulfilling conditions (*i.e.*, recreation opportunities) and the conservation of nature (*i.e.*, genetic resources, medicine). Many types of ecosystem services (ES) are traditionally undervalued to be free benefits to society; therefore, their valuable contributions are often ignored in public, enterprises and individual decision-making processes.

The potential to provide such ESs depends on the spatial arrangement of land use/cover types within a certain landscape, particularly tradeoffs among land uses. In general, land uses often relate to the two major functions of provision of foods and other ecosystem services. The use of the land for food production usually competes with the use for the other ES supply (Nelson *et al.*, 2009). It means that if farmer decisions are solely based on the production of foods, they tend to generate land use/cover patterns with the lower provision of ESs and biodiversity conservation. The tradeoff between the provision of foods and the other ESs can be modified by policy interventions. Alternatively, if markets for ESs are developed, farmers may choose land use/cover patterns favoring conservation goals.

Though the values of ESs are widely recognized, they are poorly monitored and managed in the TDNP region. As a result, they have been seriously degrading and depleting in the region. In particular, the massive forest conversion in the region profoundly declined the provision of ESs. This situation highlighted an urgent need to develop strategies to safeguard them. At the entire region level, the main challenge is recently to decide about the optimal land use allocation that both protect biodiversity and improve human livelihoods of the region. The allocation of land uses within the entire region that provides the greatest ESs can be a new platform for decision-making process. This new approach should be considered because sound management practices may influence a positive change in the provision of ecosystem services in the future.

This chapter proposes an ecosystem service supply based methodology to analyze land use options towards sustainable land use (SLU) for the region. The future scenario of land use patterns for the TDNP region was envisioned and developed. The ecosystem service provision based approach is useful to facilitate land use decision-making process because the overall outcome of land-use pattern scenario can be easily quantified to guide decision alternatives.

5.2 Land use option analysis framework

The TDNP managers have been confronting with tradeoffs of the allocation of the land to competing uses. In general, the economic benefits of land use often dominate ecological and cultural values; therefore, a strategic land use option should be analyzed and evaluated on the provision of multiple benefits to guide an appropriate strategy. The ecosystem service provision (ESP) based approach proved an effective tool for SLU decision-making, especially a useful means for the resolution of conflicts arising from land use options (Vihervaaha *et al.*, 2009). This approach has received wide acceptance and has been incorporated in research activities and policy interventions at local to global levels (Larigauderie and Mooney, 2010).

The ES can be defined as the conditions and processes through which natural ecosystems and species that comprise them, sustain and fulfill human life (Daily, 1997) or they represent the benefits that people derives from ecosystems, both directly and indirectly (Costanza *et al.*, 1997). Each land use/cover can be defined as an ecosystem; therefore, land use types are *so-called* ESs providers. The ESs can be grouped into provisioning services, *i.e.*, agricultural commodities; supporting services, *i.e.*, nutrient cycling; regulating services, *i.e.*, maintenance of biodiversity; and cultural services, *i.e.*, artistic and recreational benefits (MA, 2005). The livelihood of the people definitely depends on agricultural commodities and other ESs. It is apparent that LUCC influence the quality and quantity of the provision of the ESs. Therefore, an understanding of changes in ESs under different land-use options offers basic information for the decision-making of the land use patterns towards sustainable development.

In this chapter, land use option analysis process towards sustainable development for the TDNP region is proposed based on the ESP approach. Specifically, the review of goals or visions from the stakeholders is the first step in the process, followed by mapping the scenario of future land uses, evaluating the ESP outcome of different land use options, and finally decision making and policy interventions (Figure 5-1). The interests and concerns of policy makers, communities and protected area managers need to be reviewed to define the goals of the scenario. These goals were reviewed from the TDNP documents, reports and expert consultations during the land suitability assessment process. The map of land suitability provides the basic for mapping the scenario of future land uses because land use activities should be allocated on the site suitability of biophysical factors. The land suitability map was used to delineate the patterns of future land use scenario according to the defined goal of the scenario. The land suitability assessment was carried out using multi-criteria evaluation approach as shown in Chapter 4.

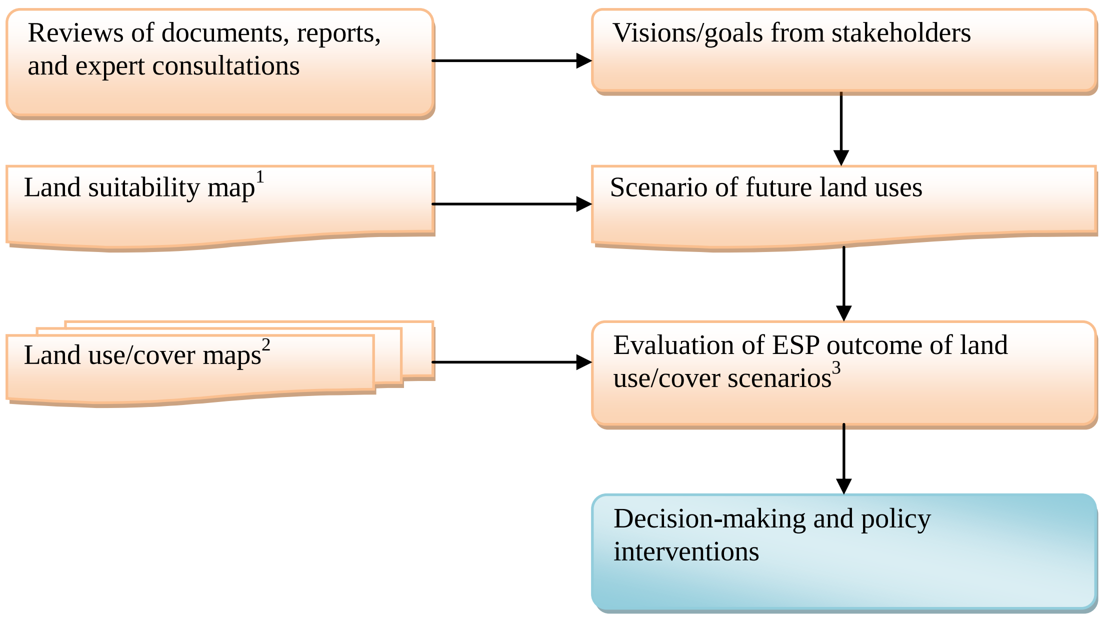


Figure 5-1: Land use options analysis framework

Notes:

[1]Land suitability map was produced in Chapter 4.

[2]Land use/cover maps of 1993, 2000 and 2007 were produced in Chapter 2 and land use/cover maps of 2014 and 2021 were predicted in Chapter 3.

[3]ESP was estimated by the method developed by Constanza *et al.* (1997).

Following the development of the scenario, the outcome of different land use scenarios in term of the ESP was quantified and evaluated. The purpose of the evaluation is to compare the amount of the ESP value of different land use scenarios. The evaluation of the ESP for each scenario offers most important information for guiding sustainable land use decision-making in the future. In particular, the outcome of past different land use/cover scenarios should be learnt to improve better ESP outcome in the future. In this study, the status of past land use/cover of the region were assumed as the representations of the land use/cover scenarios; therefore, the outcome of each scenario in term of the provision of the ESs were examined. Specifically, the land use/cover maps for the years 1993, 2000 and 2007 were used as the past scenarios. The land use maps of 2014, 2021 and the land-use planning scenario were referred as the future scenarios. The land use maps of 2014 and 2021 are the maps forecasted in Chapter 3. The planning scenario is the map of future land uses delineated by the use of the land suitability map predicted in Chapter 4.

5.3 Scenario of the future land use patterns for the region

The allocation of lands to different human activities often involves a zero sum game (Daily, 2000). Clearly, a decline in forest leads to an increase in agriculture or urban. Tradeoffs among land uses are becoming increasingly difficult to resolve. As demand for a specific ES increases, people often act in response by modifying land use/cover to increase its provision capacity. The transformation of a land use/cover often enhances the production of some services at the expense of the others (Jackson *et al.*, 2001). For example, an increase in foods and timber services results in a decline in most of the other ESs (MA, 2003). To ensure the continued delivery of bundle of goods and services, the management of land-use with a long-term view is very essential. Such management requires difficult decisions about tradeoffs among land uses with uncertainties. One way of coping with the high levels of uncertainties about the future is to evaluate the scenarios of land uses to adopt an appropriate strategy (Peterson *at al.*, 2003).

It argues that the increased ESP may enhance incomes for the region's farmers if the development of markets or other direct payment mechanisms for the ESs are developed. Before the scenario development, the places that have a considerable decline in the ESP over the last years were visualized. The purpose of the visualization is to examine the spatial matching between deforested areas and land suitability patterns. Understanding this relationship is to identify the places for restoring the ESP in the future by the planning scenario. The maps of observed and predicted forest conversion were overlaid with the land suitability map to examine the areas vulnerable to forest conversion in the past (Figures 5-2 and 5-3) and in the future (Figure 5-4). The statistics of overlaying areas between forest conversion and suitability patterns were extracted to understand the nature of the relationship (Table 5-1).

Table 5-1: Matching between forest conversions and suitability patterns

Suitability class	Accumulative forest conversion area over the periods					
	1993-2007[1]		1993-2014[2]		1993-2021[3]	
	ha	%	ha	%	ha	%
Least suitable	1,793	8.65	4,453	15.27	5,774	15.67
Marginally suitable	4,072	19.64	6,394	21.93	8,840	23.98
Moderately suitable	12,980	62.60	16,372	56.16	19,199	52.09
Most suitable	1,891	9.12	1,935	6.64	3,046	8.26
Total	20,736	100	29,154	100	36,859	100

Notes:

[1]Accumulative area of forest conversion for 1993-2007 is the summed area of the three forest conversions (primary to secondary forest, primary forest to cropland and secondary forest to cropland) observed for 1993-2000 and 2000-2007.

[2]Accumulative area of forest conversion for 1993-2014 includes accumulative forest conversion area for 1993-2007 plus forest conversion area predicted for 2007-2014.

[3]Accumulative area of forest conversion for 1993-2021 includes accumulative forest conversion area for 1993-2014 plus forest conversion area predicted for 2014-2021.

The area of forest conversions for the periods 1993-2000, 1993-2014 and 1993-2021 were accumulatively summed to be 20,736 ha, 29,154 ha and 36,859 ha, respectively. Table 5-1 indicated that forest conversions were occurred in the areas with varying suitability levels. Notably, the majority of forest conversion area was found in the moderately suitable class. It is true that conversion from forest to cropland often occurs if the land is highly suitable to agricultural production. This could explain why the majority of forest conversion occurred in the moderately suitable. However, the occurrence of forest conversion was also located in the areas that have the least or marginally suitable levels. Driven by population pressure, local famers conducted illegal timber logging as well as the extraction of non-timber products for generating their income. For harvesting such timber, forest logging activity can happen in any places that have varying suitability levels. This may explain why forest conversion occurs in both least and marginally suitable classes.

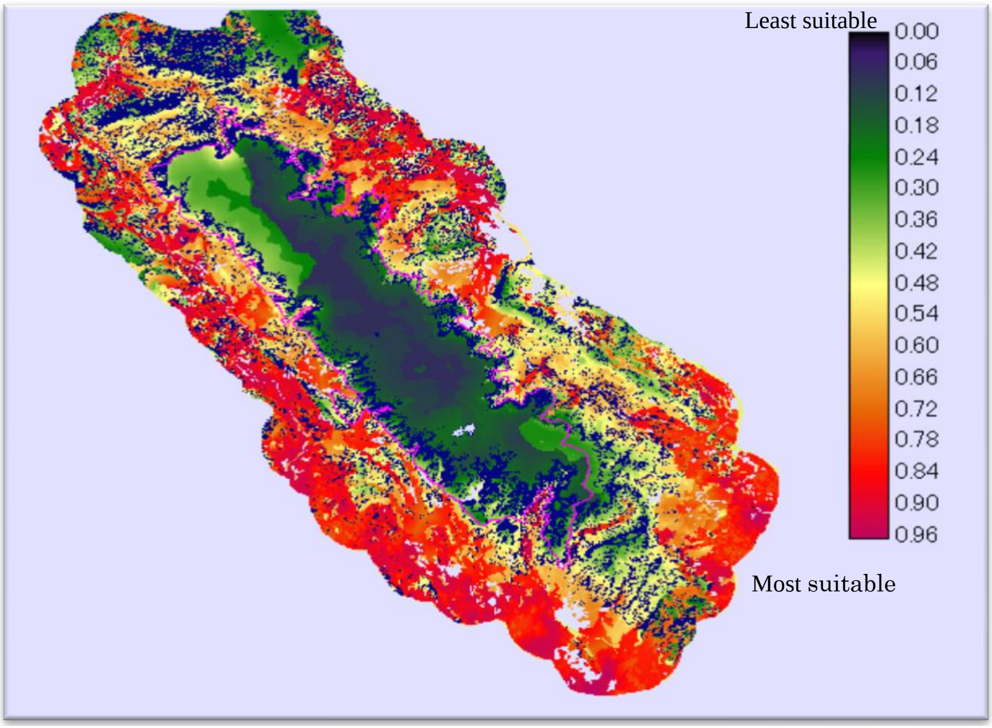


Figure 5-2: Spatial matching between 1993-2007 forest conversion and cropland suitability pattern

Notes: A pixel with a higher value indicates a more suitable.

Blue pixels indicate deforestation area (forest conversion).

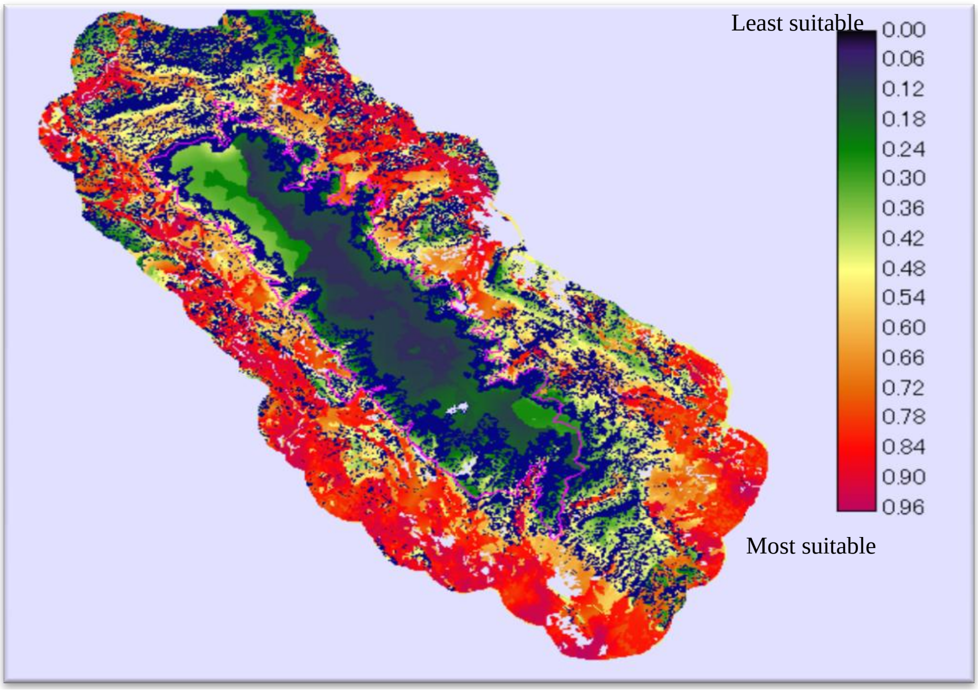


Figure 5-3: Spatial matching between 1993-2014 forest conversion and cropland suitability pattern

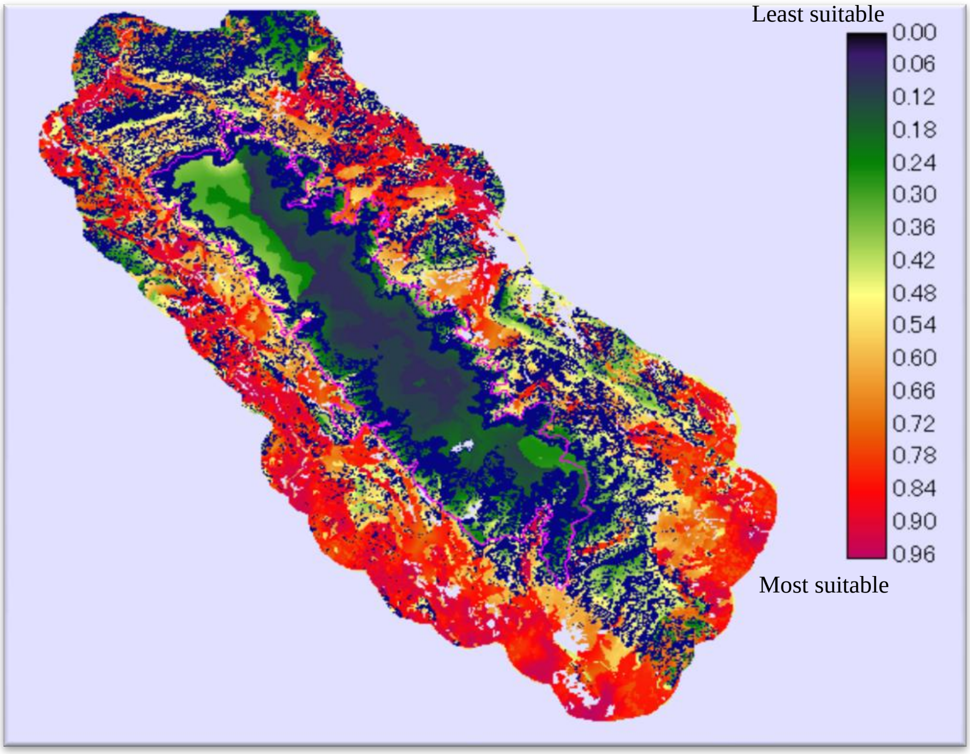


Figure 5-4: Spatial matching between 1993-2021 forest conversion and cropland suitability pattern

After examining the spatial matching, TDNP and its buffer zone management documents were reviewed to develop the scenario. The TDNP-buffer zone management has emphasized on the integrity of the buffer zone and the TDNP, particularly sustainable land uses in the buffer zone (Khang *et al.*, 2007; TDMP, 2005; Khoi and Murayama 2010b). Buffer zone land use management affects to the protected area because environmental quality of buffer zone is critical to maintain ecological functions for the protected area (Bridle *at al.*, 2004). In the TDNP region, land is an important resource to the enhancement of the living standard of local people nearby PA. Land use management of the buffer zone is facing an issue of balancing agricultural development and forest conservation. Then, the land suitability map was used to delineate the scenario of future land use patterns for the region. It is assumed that different land use strategies should be practiced according to the varying degrees of suitability; therefore, the land use strategy based on the levels of land suitability was recommended. The patterns of land uses for the region in the future include protection (primary forest), reforestation (secondary forest), agro-forestry, agro-intensification, settlement and water (Figures 5-5, 5-6 and Table 5-2).

Table 5-2: The extent of land use categories of the planning scenario until 2021

Land use category	The planning scenario	
	Area (ha)	Proportion (%)
Protection	35,000	24.78
Reforestation	28,636	20.28
Agro-forestry	32,050	22.69
Agro-intensification	38,648	27.36
Settlement	3,837	2.72
Water	3,066	2.17
Total	141,237	100,00

The delineation of primary forest for biodiversity protection was based on information about the land suitability levels and the boundary of the park. According to the estimated land suitability map, the area within the boundary of the park was the least and marginally suitable class; therefore, such areas should be strictly restricted to agricultural activities. The total area within the boundary of the park was delineated as the primary forest in the future. It should be noted that much of area within the boundary of the park has been deforested (Figure 5-6); therefore, forest plantation is needed to recover the native state in the long-term. The remaining area of the marginally suitable was assigned to reforestation class (secondary forest). For the moderately suitable areas, the majority of the zone has been the rain-fed agriculture. The development of agro-forestry system (AFS) should be a strategic option for such areas. In particular, the existing least productive rain-fed agriculture should be converted into the AFS. The AFS, combined use of crop and trees on the same area of land, plays ecological, social and economic roles (Jianbo, 2006). For example, the AFS can reduce soil erosion, the loss of soil nutrients, improve landscape diversity (Palma *et al.*, 2007) and generate income for farmers. Furthermore, the AFS can increase land coverage and thus can be a more sustainable land use type. For the most suitable class, most of this class has been paddy field. This class is distributed over the lowland around the region. Every household can improve their income if the productivity of crops is improved from this class. Therefore, the intensification of crops such as paddy rice and maize should be focused to enhance agricultural productivity in this zone, and thus production pressure on the marginally suitable zone can be reduced. This strategy has been arguably explained to be one of main causes leading to an increase in reforestation across Vietnam (Meyfroidt and Lambin, 2008).

Land use patterns in the context of protected areas should be focused on the conservation of biodiversity. Generally, developing countries have been adopted the North America approach for management of the PAs. This approach emphasizes on only nature conservation (Colchester, 1997), but the livelihoods of local population in nearby PAs have often been ignored (Pinbert and Pretty, 1997). Recognition of the PAs is parts of a broader socio-economic system (McNeely, 1993) leads to the consideration of the protected area-buffer zone land use management integrity. Biodiversity conservation management cannot be achieved in isolation because it influences the livelihoods of the local population. Conservation affairs can only be effective if protected area-buffer zone management is perceived as a holistic way and managed as one entity. It is argued that the improved maintenance of primary forest, reforestation forest, agro-forestry and agro-intensification practices are the key activities that enhance the provision of the ESs. The primary forest provides the greatest benefit in term of the ESP; therefore, intensified measure is needed to prevent further deforestation within the boundary of the park. In particular, reforestation should be prioritized in the deforested areas. Figure 5-6 shows that the hotspots of deforestation that may occur in the future. Intervention policies need to be focused to protect the areas vulnerable to primary forest conversion. The development of AFS in the existing rain-fed agriculture also contributes to increase the provision of multiple services. The policies that discuss in the next section are needed to achieve these patterns. Crop intensification systems in the irrigated land aims to minimize the expansion of new cultivation area into the forest because they expect to increase agricultural productivity in the lowland area. Every household can improve their income if the productivity of crops is improved from this intensive farming system. Therefore, a greater intensification of crops, such as paddy rice and maize, should be encouraged to enhance agricultural productivity in this zone, and thus, the production pressure on the marginally suitable zone can be reduced.

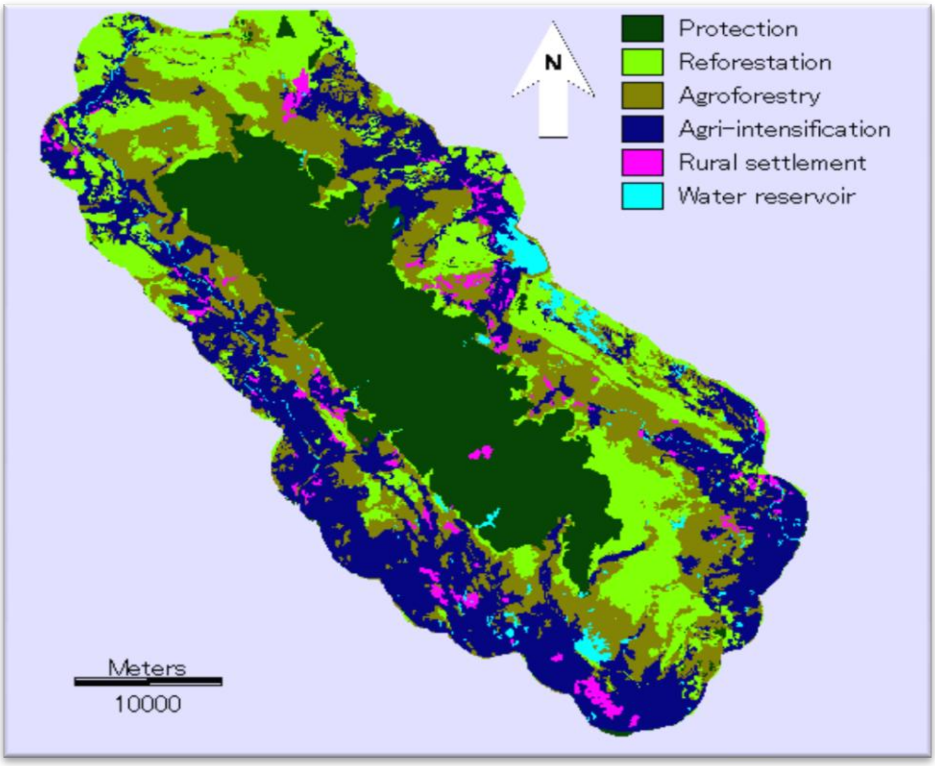


Figure 5-5: Sustainable land use option for the region

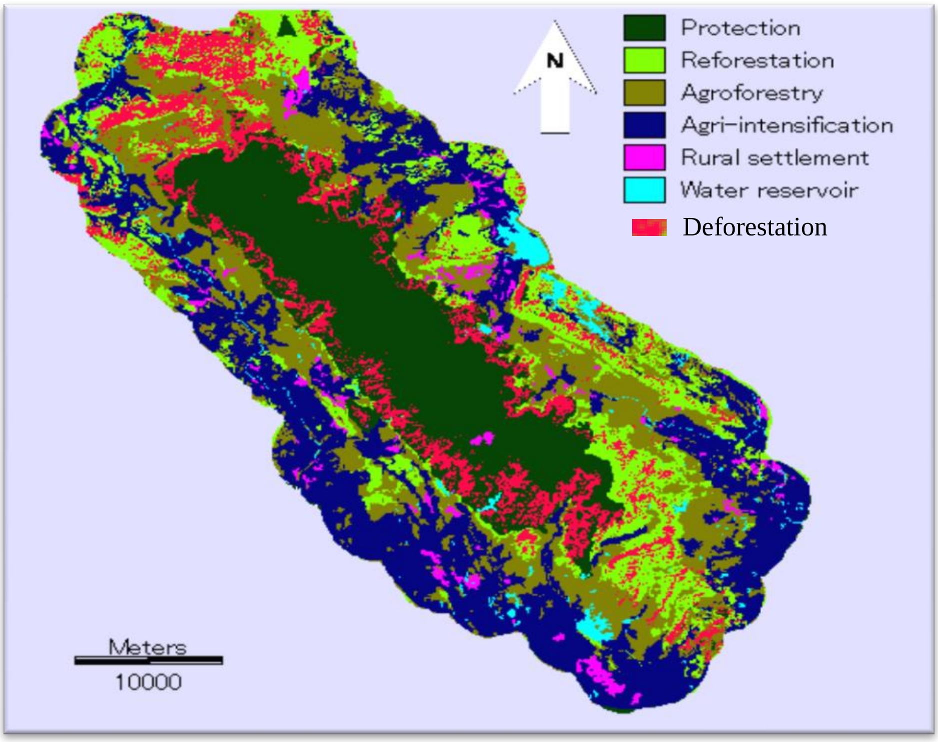


Figure 5-6: Sustainable land use option with deforestation

Note: Deforestation until 2021 predicted in Chapter 3.

5.4 Ecosystem service provision outcome of the land use scenarios

The planning scenario may support land use management decisions towards a more sustainable PA system. The scenario indicates that the land use activities are divided into different areas according to the varying levels of suitability: the most suitable, the moderately suitable, the marginally suitable and the least suitable zones. The outcome of the planning scenario's ESP was compared with the past and future land use scenarios to facilitate decision-making process towards sustainable development patterns. The purpose of the scenarios analysis is to examine changes in the ESP under different scenarios because the distribution of the ESs depends on the location and amount of the land use/cover types within the area.

5.4.1 Past land use/cover scenarios

In order to estimate the outcome of the past scenarios in term of the total value of the ESs, the methodology developed by Constanza *et al.* (1997) was applied. This method is a useful means for quantifying the spatial-temporal dynamics of ecosystem services provision and translating them into a common monetary unit. Briefly, the methodology estimates ecosystem service value (ESV) in term of monetary unit for different land use categories using published studies. According to the method, the global biosphere classified into 16 types of *so-called* biomes (land use/cover), and the ecosystem services of the biomes are divided into 17 types (Table 5-3). It should be noted that the biomes were used as the proxies for land use/cover categories, but they may be not perfect matches in every cases because of different climate conditions causing spatial variation. Constanza *et al.*'s estimated coefficients were used in the study. In this case, primary forest and water category's ESV coefficients were used as the proxies for the tropical forest and lakes/rivers, respectively. Secondary forest's ESV coefficients were assumed equal to 50% of the primary forest. The ESV coefficients for rain-fed agriculture, paddy rice modified according to the local crop yield, and settlement assigned no ESV, as shown in Table 5-4. The total ESV for the land use maps of 1993, 2000 and 2007 were estimated as follows.

$$\mathrm{ESV} = \Sigma \mathrm{A_i VC_i}, \tag{5-1}$$

where: ESV is the estimated ecosystem service,

A_i is the area (ha) of land use/cover i, and

VC is the value coefficient for land use/cover i ($ ha^{-1} $year^{-1}$).

Using data on the areas of land cover categories in the land use/cover maps of 1993, 2000, 2007 and the value coefficients presented in Table 5-4, the ESV of each land cover can be simply obtained by multiplying the area of land use category and the value coefficients. Finally, the total ESV for the entire area can be derived from the summed ESV of land use/cover in the area. The results of estimating ESV for each land use type for the years 1993, 2000 and 2007 are presented in Table 5-5. It was found that there was firmly a substantial decline in the ESV over the years 1993, 2000 and 2007. The total ESV for the entire region was estimated to be 247.8 $US million in 1993, 240.6 $US million in 2000 and 235 $US million in 2007. During the period of 1993-2000, within the entire study area of 141,237 ha, there was a reduction of 7.21 $US million, a decline of 5.64 $ US million for the period of 2000-2007 and the total loss of 12.85 $US million for the entire period of 1993-2007. The rate of the decline in the value of the ESs for the period of 1993-2000 was greater than that in the period of 2000-2007.

Table 5-3: The coefficients of ecosystem services (US$ $ha^{-1}year^{-1}$)

#	Ecosystem service	Forest	Cropland	Lakes/rivers
1	Gas regulation	-	-	-
2	Climate regulation	223	-	-
3	Disturbance regulation	5	-	-
4	Water regulation	6	-	5,445
5	Water supply	8	-	2,117
6	Erosion control and sediment retention	245	-	-
7	Soil formation	10	-	-
8	Nutrient cycling	922	-	-
9	Waste treatment	87	-	665
10	Pollination	-	14	-
11	Biological control	-	24	-
12	Refugia	-	-	-
13	Food production	32	54	41
14	Raw materials	315	-	-
15	Genetic resources	41	-	-
16	Recreation	112	-	230
17	Cultural value	2	-	-
Total ecosystem services value		2,007	92	8,498

Source: Costanza *et al.* (1997)

Table 5-4: Land use/cover and the value coefficients for the TDNP region

Land use type	Biome equivalents	ESV ($ ha^{-1}year^{-1})
Primary forest	Tropical forest	2,007.0
Secondary forest	Tropical forest	1,003.5
Rain-fed agriculture	Cropland	945.0
Paddy rice	Cropland	3,150.0
Settlement	Urban	-
Water	Lakes/rivers	8,498.0

The estimated ESV shows a very interesting implication. Clearly, agricultural productivity increased over the period of 1993-2007, but the total ESV decreased significantly. These empirical findings are very helpful to guide land use management decisions for improving the provision of the ESs. Land use/cover changes significantly declined the provision of the ESs. In particular, a considerable portion of primary forest loss (also see Chapter 2) resulted in a massive loss in the total value of the ESs in the area. This implies that if reforestation and other sustainable land uses are recommended, the total ESV may be substantially enhanced in the future. This evaluation has the potential to inform policy decision makers by highlighting the benefits of sustainable land use management. It should be noted that the value coefficients used in the estimation may overestimate or underestimate the actual value of the total ESV provided by forests; however, a considerable decline in such services undoubtedly results in serious ecological consequences in the future. The approximation of the ESV coefficients is due to complex, dynamic, nonlinear ecosystems (Limburg *et al.*, 2002; Turner *et al.*, 2003) and ecosystem (land use) heterogeneity. In addition, Costanza *et al.'s* value coefficients were also criticized for theoretical and empirical foundation (Konarska *et al.*, 2002).

Table 5-5: The total ESV (in US$ million year^{-1}) estimated for each land cover using Costanza *et al.*'s coefficients and land use/cover maps of 1993, 2000 and 2007

Land use type	ESV in US$ million year^{-1}			1993-2000		2000-2007		1993-2007	
	1993	2000	2007	$ x 10^6	%	$ x 10^6	%	$ x 10^6	%
Primary forest	76.7	60.9	51.1	-15.79	-20.58	-9.82	-16.12	-25.61	-33.38
Secondary forest	40.0	43.8	44.2	3.80	9.52	0.39	0.88	4.19	10.48
Rain-fed agriculture	32.7	36.0	39.7	3.29	10.08	3.75	10.44	7.05	21.58
Paddy rice	74.1	74.7	75.4	0.63	0.85	0.63	0.84	1.26	1.70
Settlement	0.0	0.0	0.0	0.00	0.00	0.00	0.00	0.00	0.00
Water	24.4	25.2	24.6	0.85	3.49	-0.59	-2.36	0.25	1.05
Total	247.82	240.61	234.97	-7.21		-5.64		-12.85	

5.4.2 Future land use/cover scenarios

The estimation of the ESP outcome of the past scenarios indicated that different land-use/cover maps produced the varying levels of the ESV. Clearly, changes in land use/cover caused change in the ESP. To explore the future scenarios, the business as usual and planning scenarios were further examined. The business as usual scenario consists of the land use/cover maps predicted in 2014 and 2021. The planning scenario is the map of future land use/cover delineated by the land suitability map produced in land suitability assessment.

In estimating the ESV of the future scenario, reforestation forest's ESV was used as surrogate for the secondary forest. The rain-fed agriculture's ESV can generate 945 \$ ha^{-1}year^{-1} equivalent to 47% of the primary forest (see Table 5-4). Therefore, agro-forestry's ESV was assumed to be appropriately 30% of the primary forest's ESV. Agro-intensification's ESV was used as a proxy for the paddy rice because the majority of this category is the existing paddy rice. The results of estimating the total ESV for the two scenarios are presented in Table 5-6.

Table 5-6: The ESV for the future scenarios (in US$ million year^{-1})

Business as usual scenario for 2014 and 2021			The planning scenario until 2021	
Land use/cover	ESV in 2014	ESV in 2021	Land use/cover	ESV in 2021
Primary forest	42.81	35.87	Protection	70.25
Secondary forest	43.77	42.77	Reforestation	28.74
Rain-fed agriculture	42.52	46.34	Agro-forestry	19.30
Paddy rice	77.88	78.10	Agro-intensification	121.74
Settlement	00.00	00.00	Settlement	00.00
Water	26.07	26.05	Water	26.05
Total	233.05	229.14	Total	266.07

By comparing the ESP outcome of land use/cover maps in 1993, 2000 and 2007 as the past scenarios (Table 5-5) and the future scenarios (Table 5-6), the results indicates that the planning scenario may have the greatest ESV outcome, followed by the land use/cover maps of 1993, 2000, 2007, 2014 and 2021, respectively. Clearly, the decline of primary forest area from 38,218 ha in 1993 to 17,874 ha in 2021, causes a considerable loss of the ESV over the years. The estimated ESV of primary forest is reduced from 76.7 $ US million per year in 1993 to 35.87 $ US million per year in 2021. On the other hand, the estimated ESV of secondary forest, rain-fed agriculture and paddy rice categories increase over the years.

5.5 Policy instruments for the promotion of sustainable land use

Biodiversity conservation approaches are usually based on scientific and ethnic intrinsic value arguments; therefore, any state and private agents must be responsible for the maintenance of primary forests. These arguments prove to be insufficient because they do not capture the dependence of human well-being on natural capitals (Turner and Daily, 2008). Therefore, land use and development policies must strive to achieve the patterns of future land uses for the region. The policy instruments are mainly to protect the primary forest and restore the secondary forest and the development of the AFS across the region. A variety of policy tools can be employed to promote the implementation of the planning scenario. These tools may include regulations, ecosystem service market based mechanism, voluntary approaches and education and information (Cock *et al.*, 2007). These approaches are not mutually exclusive, but all depend on some extent of education and information provision. The education and information tool is important because it fosters continuous improvement of awareness and actions among farmers. It should be noted that this tool is a slow process for achieving the SLU. Building the awareness of the services provided by ecosystems is important to gather public support for conservation at protected area or larger scale. The use of the approaches is changing from regulation tools to economic instruments (Jenkins *et al.,* 2004). Policy instruments should be applied flexibly. Economic tools should be prioritized for short-term conservation objectives, while the development of ecosystem service markets can be a useful means for long-term conservation goals for the region as well as other PAs of Vietnam.

Short-term management instruments

In order to support the restoration and conservation of TDNP region ecosystem, a variety of instruments should be combined in the short-term. These instruments aim to influence the behavior of small landholders in the implementation of the planning scenario. The prioritized tools should be direct payments, education and information and regulations based approaches. Direct payments can help farmers to increase their income when applying sustainable management practices. In case farmers may not stop their practices and adopt sustainable practice when receiving direct payment; therefore, education and information tool is needed. The education program should aim at capacity building strategy, *i.e.*, technical training courses, provision of small grants or microfinance credits. In addition, regulations based approach or the enforcement of law should be included to protect existing primary forest area.

Economic incentive approach is likely to be more successful than regulatory approach. This approach uses financial incentives, *i.e.*, direct payment to modify the behavior of land users towards sustainable development goals. Direct payments for local farmers are a useful means for the working landscapes that have a mix of human use and conservation activity. Such payments are often implemented via conservation subsidy programs. The farmers are paid to change or maintain some practices on their lands that are thought to improve the conservation values. Such payments are done by government's subsidy programs. The use of the direct payments to change the behavior of landowners allows PA managers to meet conservation management goals and thus stop or minimize the destruction of habitat (Ferraro and Kiss, 2002). The payments narrow the gap between the private and public benefits provided through land-use management practices. In particular, direct payments are widely employed in developed countries. For example, the United States spent about $1.8 billion per year for conservation subsidies (Goldman and Tallis, 2009). This approach can be effectively applied to the sustainable management of the primary forest, the secondary forest and the agro-forestry systems for the region. However, developing countries often lack financial resources for the implementation of the direct payment for famers because the majority of the population works in agricultural sector (Pearce, 2007).

The lack of knowledge and information may hinder progress in implementing sustainable land management practices; therefore, education and information approach fostering land users' continuous improvement leads to more informed practices and stimulates awareness and action. State agricultural extension agencies can play important roles in providing information services. In Vietnam, the training and advisory services provided by state agricultural extension agencies are free of charge to farmers. These training activities should be implemented by field demonstration approach because the level of education of small farmers is often limited. The purpose of demonstration is to help local farmers to acquire knowledge of how to carry out sustainable land use practices, *i.e.*, agro-forestry farming practice. In addition, when promoting better land use practices, it is also important to motivate farmer innovations because farmers always actively experiment their management practices. This can improve the sharing of knowledge and extension among communities. A major advantage of innovations by famers is that they are site-specific and readily acceptable to neighboring farmers. The incorporation of farmer innovation within the extension agencies' activity may significantly improve the quality of information services for land users.

Regulations based or limited access management approach often refers as the earliest regulatory approach for the protection of native forest ecosystems. However, this approach should be employed as the last choice because it often fails in many cases. This approach is the copy of the Yellow Stone National Park model, established in United States in 1872. Today, the model has been developed through the world for the purpose of conservation, wildlife preservation and scenic beauty (Goldman and Tallis, 2009). It proves to be efficient and successful in the conservation of biodiversity in many countries (Bruner *et al.*, 2001). However, they should be not seen as the only means for future biodiversity conservation (Goldman and Tallis, 2009). This approach was applied for the management of the primary forest for the TDNP; however, it produced a low expected result. For instance, deforestation has been occurring in the area. Furthermore, the approach appeared to have a low efficacy for the management of the secondary forest and the agro-forestry systems surrounded by the national park. In general, for the management of protected areas in developing countries, this approach often hampered by weak management, high transition costs and information regarding the design of effective utilization rules, monitoring and enforcement at the local level (Baland and Platteau, 1996). The poor communities around protected areas heavily depend on forests and other bio-resources for their livelihoods; therefore, restrictions on the use of forest resources can lead to economic crisis and may trigger social conflicts. Although limited outcome results from this approach, it continues to play an important role for the management of forest resources in the region. This approach should be combined with the use of environmental and resource tax tool. The taxes, which are charges on environmentally damaging activities, are also critical instrument for managing natural resources. Such taxes impose the cost of ESs protection on farmers rather than the users of ESs. This approach should apply for the TDNP region because farmers may receive direct payment for sustainable land use practices, alternatively they should be responsible for their environmentally damaging production activities.

Long-term management instruments

The development of ecosystem service markets should consider as a useful means for the long-term conservation of PA forest ecosystems. This mechanism may ease the financial burden of conservation costs in developing countries. By enlarging the focus from the conservation of biodiversity alone to the conservation of biodiversity and ESs, such approach may increase the support and resources for conservation efforts (Armsworth *et al.*, 2007). It is true that a PA is designed for the protection of biodiversity, but it also provides a variety of ESs coincidentally (Benayas *et al.*, 2009). Therefore, the development of ecosystem service markets can be used to generate money for conservation and development success. The inclusion of the ESs and their anthropocentric values in conservation planning can help improve the relevance and ease the implementation of conservation programs (Naidoo and Ricketts, 2006). The development of ecosystem service markets can improve conservation and development goals by the use of the benefits of the ESs. A full set of ESs can be covered, but most of the cases emphasized on carbon sequestration, water supply, flood control, biodiversity conservation and enhancement of scenic beauty (Turner and Daily, 2008). This trend proves a shift in the focus of conservation organizations toward a more inclusive, integrated and effective set of strategies (Daily and Ellison, 2002). For example, a number of projects regarding the development of ecosystem service markets have been designed and implemented by conservation organizations, such as the Nature Conservancy and the World Wildlife Fund (Tallis *et al.*, 2009).

In developing ecosystem service markets (known as payment for ecosystem service (PES) mechanism), the PES schemes are defined as transactions in which an ES is bought by a buyer from a seller (provider) only if the provider secures service provision. The PES can be used to pay for the landowners based on the value of the ESs. The PES is rapidly proliferating worldwide in the conservation of biodiversity (Goldman and Tallis, 2009). By this mechanism, farmers or rural communities are ES providers/sellers, while private enterprises, state agencies or individual citizens play as potential buyers. Private consultancies can play as verifiers or regulators for the quantification of the ES. The public sector sets up legal, financial and institutional means for market development (Corbera and Brown, 2008).

By implementing sustainable land uses, farmers produce public benefits, but costs are private; therefore, the PES mechanism should be considered to apply in the TDNP region. This mechanism is recommended because there is the potential for the small landholders to get benefits from sustainable use of the land. Surely, a shift in land use towards sustainable uses is possible if the benefits are made clear. The PES mechanism can mobilize the support from various stakeholders (*i.e.*, government, private companies and international donors/agencies) to subsidize the SLU practices, *i.e.*, agro-forestry systems in the region. Based on the conservation of primary forest, the restoration of secondary forest and the development of AFS, some ESs can be easily identified for the payments for the service providers (Table 5-7). Such ESs are recommended for the implementation of the PES mechanism because they are public goods and their provisioning ability can be sustained in the long-term if the planning scenario is practiced in the region.

First, genetic resources or biodiversity service is the most important ES needs to be prioritized for the implementation of PES mechanism because it is closely linked to the delivery of the other ESs. This service offers long-term benefits for the public, but it appears to be difficult to encourage potential buyers. National conservation fund should be established to subsidize the preservation of this service. This service is safeguarded if habitats for species are protected. Habitats can be defined as the resources and conditions in the area that produce occupancy by a given organism (Hall *at el.*, 1997). Land use changes affects to the ability of the habitats to provide conditions and resources available for the survival and reproduction of species. Habitat quality depends on habitat’s proximity to intensified land uses. Habitat quality is often seriously degraded as nearby land uses is enlarged and intensified (McKinney, 2002).

Second, the carbon sequestration and storage service is considered because local landowners can obtain incentive payments through international donors or ESs markets or both. If all protected areas across the globe are strictly protected, and they may contribute to the storage of dioxide carbon. The forest ecosystems collectively store carbon in wood, soil and other biomass; and they keep dioxide carbon out of the atmosphere. On the other hand, deforestation releases large amount of dioxide carbon to the atmosphere. The carbon sequestration is perhaps the most widely recognized ecosystem service in the marketplace. The market for forest carbon, such as the Chicago Climate Exchange and the European Climate Exchange, is increasingly developing, and expects that it may contribute to the efficiency of conservation of biodiversity in protected areas around the world, especially in developing countries.

Table 5-7: Ecosystem services and potential buyers

Ecosystem service[1]	Roles [2]	Potential buyers[3]
Genetic resources	Medicine and genes for agricultural uses	State agencies, universities, research institutes, pharmaceutical companies and commercial farms
Climate regulation	Forest carbon sequestration and storage	State agencies, industrial cooperates, and international agencies
Water regulation	Provision of water for agriculture	State agencies
Erosion control	Maintenance of soil loss within watershed	State agencies
Nutrient cycling	Storage and cycling of soil nutrients	State agencies
Recreational and cultural values	Ecotourism, scientific values and scenic beauty	Ecotourism companies, universities, research institutes, individuals and state agencies

Notes:

[1]Ecosystem services are provided by primary forest, secondary forest and agro-forestry systems in the TDNP region. These services are enhanced if the planning scenario is practiced.

[2]Roles are defined according to Costanza *et al.* (1997).

[3]Potential buyers are possible stakeholders who involve in PES mechanism.

Third, fresh water supply provided by forests is also a vital ES that contributes to the welfare of society in the region, mainly including the provision of water supply for agriculture. Land use/cover change can alter hydrological cycles and affect the distributions of evapotranspiration, infiltration, water retention (Ennaanay, 2006) and surface water yield. Therefore, sustainable land use can improve the ability of water supply. *Fourth*, soil erosion control is particularly an important service in the protection of the removal of top soil layer in the sloping lands. Excessive erosion can reduce agricultural productivity, increase the removal of soil nutrients and cause pollutants. Vegetation holds soil in place and capture sediment moving overland. Changes in land use may alter sediment retention capacity. Once vegetation holding sediment in place no longer exists, and a top soil layer can be carried downstream by overland runoff. In particular, deforestation leads to this occurrence of the process. *Finally*, recreational and cultural services are included because the payment can be obtained from various private companies, individual, and public agencies. These services yield many activities, such as ecotourism, education, scientific research and other outdoor recreational activities.

Many types of the ESs generate the benefits at local scale. The value of such ESs may not be easily traded through well-functioning markets. The markets for such services are currently absent; therefore, there is little incentive to farmers to safeguard such services. Therefore, government, as the users of the services, should play as key buyers in the initial development of the ES markets to provide incentives to farmers in exchange for the conservation of ESs, especially in the stage of implementation of the planning scenario. Such incentives may offer a more attractive conservation option for the farmers. If the planning scenario is practiced and sustainable land uses (*i.e.,* the restoration of secondary forest, the development of agro-forestry systems) are developed and improved considerably, the other stakeholders (*i.e.,* ecotourism companies, universities, research institutes and pharmaceutical companies) should be forced to be buyers for ESs from the region because they obtain the greatest benefits of conserving such ESs.

The development of the ESs markets is somewhat new in Vietnam. Every market requires institutions in order to operate and function. Therefore, institutional mechanisms should be developed to strategically channel financial payments to rural communities nearby protected areas. Policy makers and public agencies play a decisive role in creating such mechanisms. Major rules, which should be focused, may be the rights of ESs and regulations regarding the enforcement of contrasts and the settlement of ESs ownership disputes. It should be noted that multiple actor market for the ESs of protected areas should also be understood as the obligations of stakeholders within an institutional framework. Mobilizing and organizing buyers for ESs may be most important task. The willingness to pay for ES strategy should be organized at local and national scales. In particular, private companies should be responsibly engaged in such strategy.

Another challenge for the development and implementation of markets for ESs may be the valuing of ESs in term of monetary unit. For example, the price of carbon can be valued in different prices according to different points of view. The carbon price can be estimated on the marginal damage associated with the release of additional metric ton of carbon into the atmosphere or it can be valued on at least cost level for storing a metric ton of carbon by utility plants. According to the first point of view, recent estimates recommend that the price of carbon vary from US$ 30 per metric ton of carbon (Nordhaus, 2007) to US$ 310 per metric ton of carbon (Stern, 2007). Given the latter point of view, the minimum cost for storing a metric ton of carbon has estimated to be about US$ 100 (Socolow, 2005; Socolow and Pacala, 2007).

Chapter 6
Conclusions

The TDNP region represents a rapidly changing protected area of Vietnam. Though the area was designed for the conservation of biodiversity, the region was driven by increasing population over the last decades. As a result, primary forest area was considerably cleared for agricultural expansion. The predominantly native vegetation landscape was gradually modified by shifting cultivation and timber harvesting in the 1960s and 1980s. This process was accelerated from the 1990s in response to increasing timber demands. The process appeared to have a slow-down signal in the 2000s due to increased public awareness and government conservation policies.

The results of LUCC analysis and detection based on satellite imagery revealed that forest changes are one of the major land use/cover changes in the TDNP region for the period of 1993-2007. Deforestation process in the study area was determined to be a multiple-conversion process consisting of the conversion from primary forest to secondary forest, the conversion from primary forest to cropland and the conversion from secondary forest to cropland. Primary forest per the entire study area reduced from 27.06% in 1993 to 18.03% in 2007. As a result, secondary forest increased from 28.21% in 1993 to 31.17 % in 2007. Rain-fed agriculture covered 24.39% in 1993 and increased to 29.11% in 2007. An increase in rain-fed agriculture mainly resulted from the transformation of secondary forest and partly primary forest. Only 1.5% of the area was covered by the settlements in 1993, and it slightly increased to 2.22% in 2007. Similarly, a small proportion of the water (2.03%) was observed in the area. Streams, river, lakes and ponds are major water resources in the area.

Changes in forest cover were driven by several variables in the region. Among the driving factors of the forest conversions in the study area, physical and accessibility factors were identified to comprise a considerable share of the factors driving forest conversions. These variables include elevation, slope, the proximity to water, the proximity to roads, the proximity to cropland, the proximity to primary forest, the proximity to secondary forest and the proximity to settlements. By the use of the Cramer’s coefficient test, the strength of association between observed forest changes and the variables were measured. The strength of association between the two depends on each forest conversion and seemed to change slightly over time. For the conversion from primary forest to secondary forest, it was found that the proximity to primary forest was the most important factor affecting to this conversion. The proximity to roads and terrain (elevation and slope) were the second and third most influential factors, respectively. The proximity to water was found to be the fourth most important contributor to the conversion. The proximity to settlement played a smaller role in influencing the conversion than others. For the conversion from primary forest to cropland and from secondary forest to cropland, similar trends have been identified. The proximity to secondary forest played the most influential role on these two conversions, followed by the proximity to cropland, the proximity to water, slope, elevation, the proximity to roads and the proximity to settlements.

Based on the measurements of the rates of forest changes and the identification of the driving factors of forest changes, the MLPNN-M model was validated to forest conversions in the future (2014 and 2021). The results of the model validation showed that the model simulated deforestation pattern quite reasonably in the study area. The model was accurate at predicting the location and quantity of forest cover of 2007 as compared with the actual forest cover map of 2007. Based on the 2007 model validation scenario, the forest cover in 2014 and 2021 was simulated to identify areas vulnerable to the conversion from primary and secondary forest. According to the predictions, a considerable portion of primary forest within the park is threatened by forest clearance. Secondary forest in the steep areas in the buffer zone of the park is likely to be converted into agricultural land. Of the total study area, primary forest is predicted to continue a considerable decline from 18.03% in 2007 to 12.66% in 2021, but secondary forest area may decline slightly. As a result, non-forest area may increase from 50.81% in 2007 to 57.16 % in 2021.

These prediction maps of forest changes provide essential inputs for quantifying the effects of forest changes on ecosystem services provision as an overall outcome. This can help protected area managers in adjusting mismanagement practices. LUCC, especially forest changes, considerably influence the provision of ecosystem services. Change in ecosystem service value was quantified for the land use/cover maps of 1993, 2000, 2007, 2014 and 2021. It was found that the land use map of 1993 had the greatest value of ecosystem services, followed by the land use/cover maps of 2000, 2007, 2014 and 2021, respectively. Evidently, a decline in primary forest caused a considerable loss of the ecosystem services value over the years. The ESP based methodology can be a vital tool for monitoring the remaining primary and secondary forest in the region.

To prevent further deforestation, the land suitability assessment was conducted for allocating the land to cropland and other sustainable land uses. GIS-MCE based land suitability assessment can be employed as a tool for deforestation control. Nice factors (slope, elevation, distance to water, soil organic matter, soil depth, soil texture, distance to roads and distance to the park) were identified to be most relevant to the suitability of cropland in the region. The resultant map of the cropland suitability indicated that the most suitable and moderately suitable areas were found in existing rain-fed agriculture and paddy field. Most of the suitable class (95.22%) was distributed over rain-fed agriculture and paddy rice. The majority of the moderately suitable class (83.01%) was found in rain-fed agriculture and secondary forest, whereas only 15.94% of the class was located in paddy rice. For the marginally suitable class, 71.37% of the class was found in secondary forest. The majority of primary forest has the least suitable level for cropping. In particular, the overlay between forest change and the suitability map indicates that farming area may extend into primary forest and secondary forest. The suitability map offered valuable information for the TDNP managers.

Towards sustainable land uses, priority areas for farming and other land uses need to be addressed to enhance the ESP. The TDNP region ecosystem, if properly managed, yields a variety of ecosystem services. The potential to provide such services depends on the spatial patterns of land uses within the area. The land use multi-objective decision-making for the region should consider the ESP as an overall outcome. According to the ESP based decision framework, sustainable land use patterns is proposed to better match land use management with their suitability. The scenario recommends an increase in primary forest, secondary forest and agro-forestry systems enhance ESP for region because forests provide greater ESP than the others. To ensure the implementation of the recommended scenario, policy instruments are needed for the protection of primary forest and the restoration of secondary forest and the development of agro-forestry systems across the region. The ecosystem service market based mechanism is highly recommended as the most important instrument for TDNP region. This mechanism can ease the financial burden of conservation costs for the management of protected areas because there is the potential for the small landholders to get benefits from the protection of existing forests and the development of agro-forestry systems. In particular, if mechanisms for ES markets are nationally institutionalized, financial resources can be strategically channeled to rural communities nearby PAs. In addition, government agencies should play as key buyers for the above mentioned ESs in the stage of the development or the restoration of forests and agro-forestry systems. As agro-forestry systems are widely established, other stakeholders should be forced to be buyers for ESs in the region.

The most significant contribution of the study is the development of spatially integrated framework of deforestation modeling, land suitability assessment and ecosystem services valuation for the sustainable management of TDNP region ecosystem. In particular, the study developed an MLPNN-M based empirical deforestation model and validated the model's predictive capacity for forecasting the temporal and spatial process of deforestation in the tropical rainforest of Vietnam. The modeling approach in the study is particularly significant because it helps protected area managers and other stakeholders to improve the understanding of forest changes and associated driving factors in their localities. In addition, the study demonstrates that the combined use of MLPNN-M and MCE can serve to enhance the quality of sustainable land use decision-making for PA setting. The MLPNN-M provides a robust methodological foundation for the simulations of forest cover dynamics, while MCE offers an operational platform for real land use decision-making. This entire approach can be applied to the sustainable management of other PAs across Vietnam was well as developing countries. The empirical findings of the rate and location of past and future deforestation and land suitability map serve to improve the sustainable land use management of the TDNP region. In a broader context, the empirical findings of forest conversion processes and associated driving factors explored in this case study enrich the knowledge of tropical deforestation process in less developed countries.

Although the impacts of LUCC on the provision of ecosystem services have quantified, the present study only evaluated the impacts of LUCC on the ESP as an overall outcome. Detailed evaluations need to be further investigated individually because they may provide critical information for PA managers and policy makers in the development and implementation of ecosystem services based PA management mechanism. In particular, the impacts of LUCC on carbon sequestration and storage, water supply, wildlife habitat quality and soil erosion should be the prioritized research themes for the region in the future.

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Appendices

Appendix I: Defining the terms

Because of the multidisciplinary nature, a number of disciplines are touched on this study. Each of disciplines comes with a unique set of concepts and terms; therefore, these concepts and terms are defined for clarity and consistency. The list of the terms is grouped according to the contents of the dissertation for easier search.

I-A Protected area

Protected area (PA) is defined as an area of land and/or sea especially dedicated to the protection of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means (IUCN, 1994). Under the IUCN guidelines for protected area management, six types can be defined from category I to VI. Category I include protected areas managed mainly for science or wilderness protection (I-a strict nature reserve and I-b wilderness areas). Category II consists of protected areas managed mainly for ecosystem protection and recreation (national park). Category III are protected areas managed mainly for conservation of specific natural features (natural monument). Category IV are protected area managed mainly for conservation through management intervention. Category V are protected areas managed mainly for landscape/seascape conservation and recreation (protected landscape/seascape). Category VI are protected areas managed mainly for the sustainable use of natural ecosystems (resource protected areas).

In Vietnam, protected areas reported until 2003 is 122 (2,390,135 ha), including 25 national parks (851,361 ha), 60 nature conservation areas (1,351,106 ha) and 37 cultural, historical and environmental sites (187,668 ha) (ICEM, 2003).

I-B Land use/cover change analysis and modeling

Land

A delineable area of the earth's terrestrial surface encompasses all attributes of the biosphere immediately above or below this surface. It includes those of the near-surface climate, the soil and terrain forms, the surface hydrology, the near-surface sedimentary layers and associated groundwater reserve, the plant and animal populations, the human settlement pattern and physical results of past and present human activity (FAO, 1995). The term land is used in a comprehensive and integrating sense to denote space and refer to a wide array of natural resource attributes in a profile from the atmosphere above the surface down to some meters below the land surface.

Land cover

A physical state of the land, such as croplands and forests, embraces the quantity and type of surface vegetation, water and earth materials. The term "land cover" originally refers to the type and state of vegetation, *i.e.*, forest cover; however, the term has been broadened to include human structures such as building, pavement and other aspects of the environment (Mayer, 1995).

Land use

Arrangements, activities and inputs people undertake on a certain land cover type to produce, change or maintain it (FAO, 2000). This definition establishes a direct link between land cover and the activities of people in their environment. Land use involves both the manner in which the biophysical attributes of the land are manipulated and the purpose for which the land is used. Land use itself is the human employment of a land cover type. The description of land use has a certain meaning at a given spatial level and for a given area. At macro-scale, a land use often specifies a mix of land use types or the particular pattern of these land use types.

The terms "**land cover**" and "**land use**" are closely associated, and they can be used interchangeably. However, it notes that a single land use may correspond fairly well to a single land cover. On the other hand, a single class of cover may support multiple uses. The importance and the necessity of distinguishing between land use and land cover may be most evident in analyses of the environmental impacts of land cover changes. The distinction between land use and land cover is not straightforward in practice as available data do not make this distinction clearly all the time.

Land cover change

The alteration of the physical and biotic nature of a location is defined as land cover change (LCC) while land use change involves the alteration of the way humans use land (Meyer and Turner, 1992). LCC is described as a quantitative change in the area of a given cover type. It is the conversion or modification from one cover type to another (Lamptey *et al.*, 2005). It is important to note that the detection and measurement of change depends on spatial scale. The higher the spatial level of detail, the larger the changes in the extent of land use and land cover which can be detected and recorded. The literature distinguishes between the two types of change: conversion and modification. Land cover conversion involves a change from one cover type to another. Land cover modification involves the alterations of structure or function without a wholesale change from one type to another. It involves changes in productivity and biomass. Most of the land cover changes of the present and the recent past are due to human actions. LCC is well known as one of three global changes. Other changes are increasing concentrations of carbon dioxide in the atmosphere and alternations in the biochemistry of the global nitrogen cycle (Vitousek, 1994). Therefore, LCC study has recently emerged as a central component of global environmental and sustainability researches (Turner, 2007).

Deforestation

Deforestation is the direct human-induced conversion of forested land to another land use or the long-term reduction of tree canopy cover below the minimum 10% threshold (FAO, 2000). Deforestation is widely recognized as the most important component of land use/cover changes at the local and global scales. In Vietnam, the major types of deforestation include forest clearing for the expansion of crops, commercial logging and selective timber harvesting, the burning of forests for subsistence farming (known as shifting cultivation), livestock grazing, natural events, *i.e.*, forest fires and wars. The war against the colonial administration of French (1930-1954) and United States (1954-1975) contributed to the vast destruction of primary forest area in the central highlands and the northern mountainous parts of Vietnam. In the 1970s and 1980s, the clearing of forests for agricultural expansion occurred rapidly for serving the shortage of foods across the country. In addition, a large number of timber volumes were also harvested for such periods for both domestic uses and timber export.

Land use change

A process may involve either conversion from one type of use to another or modification of a certain type of land use. Modification of a particular land use may involve changes in the intensity of this use as well as alterations of its characteristic qualities/attributes. The linkage between land use and land cover change is emphasized because they may has the different levels of environmental impacts to global change. The specification of the spatial and temporal levels of detail is of crucial importance for the analysis of both changes. It guides the selection of the types of land use and land cover that may analyze, it determines the drivers and processes of change that can be detected, and it affects to the identification and explanation of the linkages between land use and land cover within particular spatial-temporal frames.

Land degradation

A natural process or a human activity causes land no longer being able to sustain properly its economic functions or original ecological functions (FAO, 1998). In mountain ecosystems, land degradation leads to many environmental impacts such as accelerated soil erosion, soil acidification, the destruction of soil structure and the loss of organic matter.

Drivers of land use/cover changes

Drivers of land use/cover change can be divided into proximate and underlying causes. The proximate causes explain why land use/cover is modified by humans, while the underlying causes explain fundamental forces underpinning these actions. In general, the proximate cause operates at the local level, but the underlying causes originate from regional (*i.e.,* district, province or country or even global scale). The underlying causes are often exogenous to local communities and are thus uncontrollable by these communities.

Land Change Modeler

LUCC is a complex process and driven by a large number of driving factors. This requires predictive modeling approach for understanding this process. The LUCC models address the allocation of land to specific land use types. They are used to understand the dynamics of land use change and particularly project the future development of land use patterns.

Land Change Modeler (LCM) is a software solution designed to deal with the pressing problem of land use/cover change (Eastman, 2009). The LCM is integrated within IDRISI GIS software and available as an extension to ESRI's ArcGIS. The LCM can be organized into the five analysis components: analyzing past land-cover change, modeling the potential for change, predicting change in the future, assessing implications for biodiversity and evaluating planning interventions for maintaining ecological sustainability.

The change analysis tools offer the rapid assessment of change in term of gains and losses, net change, persistence and specific conversions. Change potential modeling tools allow one to group transitions into sub-models to explore the potential power of explanatory variables. Once model variables are selected, each transition is modeled using either logistic regression or multi-layer perceptron neural network. The result is a transition potential map for each transition. Change prediction tools provide controls for a dynamic land cover change prediction process. The two basic models of change provided are a hard prediction model and a soft prediction model. The hard prediction model is based on a multi-objective land competition model. The soft prediction yields a map of vulnerability to change for the selected set of transitions. The hard prediction yields only a single realization while the soft prediction is a comprehensive assessment of change potential.

Furthermore, a wide range of tools are provided for assessing the impacts of change for ecological sustainability such as species habitat assessment, changes in habitat, species distribution modeling. The LCM also allows the planning interventions that may alter the course of development such as roads development and biological corridors.

Land-use/cover change model validation

The validation of a LUCC model is the comparison of a predicted land use/cover map with a reference map assumed a truth map or observed map. If a predicted map is similar to a reference map, a LUCC model performs well in a particular area. Kappa statistics and its variants are commonly used for the validation of a LUCC model (Pontius, 2004).

I-C Land suitability analysis

Land suitability assessment

An assessment of land performance when used for a specified use, involving the execution and interpretation of surveys and studies of land forms, soils, vegetation, climate and other aspects of land in order to identify and make a comparison of promising kinds of land use in terms applicable to the objectives of evaluation (FAO, 1998).

Land suitability

A given type of land is given to a specific kind of land use (FAO, 1998). It can express as the fitness of a parcel of land for a defined use. The land suitability has different meanings in different applications. Habitat suitability, agricultural land suitability, geological favorability and suitability for public facilities are some examples (Malczewski, 2004).

Decision

A decision is a choice between alternatives. The alternatives may represent the different kinds of land use activities. In GIS, a pixel or a point/a polygon/a line correspond to an alternative. Therefore, land suitability analysis is the ranking of alternatives that offers the basic for land use decision-making.

Criterion (factor)

Evaluation criterion is some basic for a decision that can be measured and evaluated (Eastman *et al.*, 1995). A factor/criterion map is a unique geographical attribute of alternative decisions that can be used to evaluate the performance of alternatives (Malczewski, 1999). A criterion map represents the spatial distribution of an attribute that measures the degree to which its objective is achieved. Evaluation criterion maps are referred to as attribute maps or thematic maps or data layer in GIS terminology.

Criterion weight

A criterion weight is decision maker’s preference with respect to evaluation criteria. Preference is typically expressed in terms of the weights of relative importance assigned to the evaluation criteria under consideration. The purpose of criterion weights is to express the importance of each criterion relative to other criteria (Malczewski, 1999).

Fuzzy set

A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging from zero and one (Zadeh, 1965).

Multi-criteria evaluation (also known as decision rule)

A procedure by which criteria are selected and combined to arrive to a particular evaluation, and by which evaluations are compared and acted upon, is known as a multi-criteria evaluation or decision rule. Several criteria need to be evaluated; therefore, such a procedure is called a multi-criteria evaluation (MCE) (Eastman *et al.*, 1995). The MCE can be achieved by one of the two major procedures of Boolean overlay and weighted linear combination. The MCE often operates according to a particular evaluation objective. For example, the MCE procedure for the land evaluation of irrigated agriculture is different from that of rain-fed agriculture.

Land evaluator

A land evaluator is a person who carries out land evaluation. The evaluators need to understand the concepts and methodologies of the evaluation and able to use analytical techniques and computerized tools. A land evaluator must have a good knowledge of natural resources and land uses.

Land use expert

A land use expert is person who has information about land use and associated natural resources. Soil scientists, agronomists, economists, and rural agents and farmers can be experts.

Stakeholders

Stakeholders are all parties who are affected by land use planning decisions taken on the basic of land evaluation. This is usually the total rural population of a certain planning area.

I-D Ecosystem services

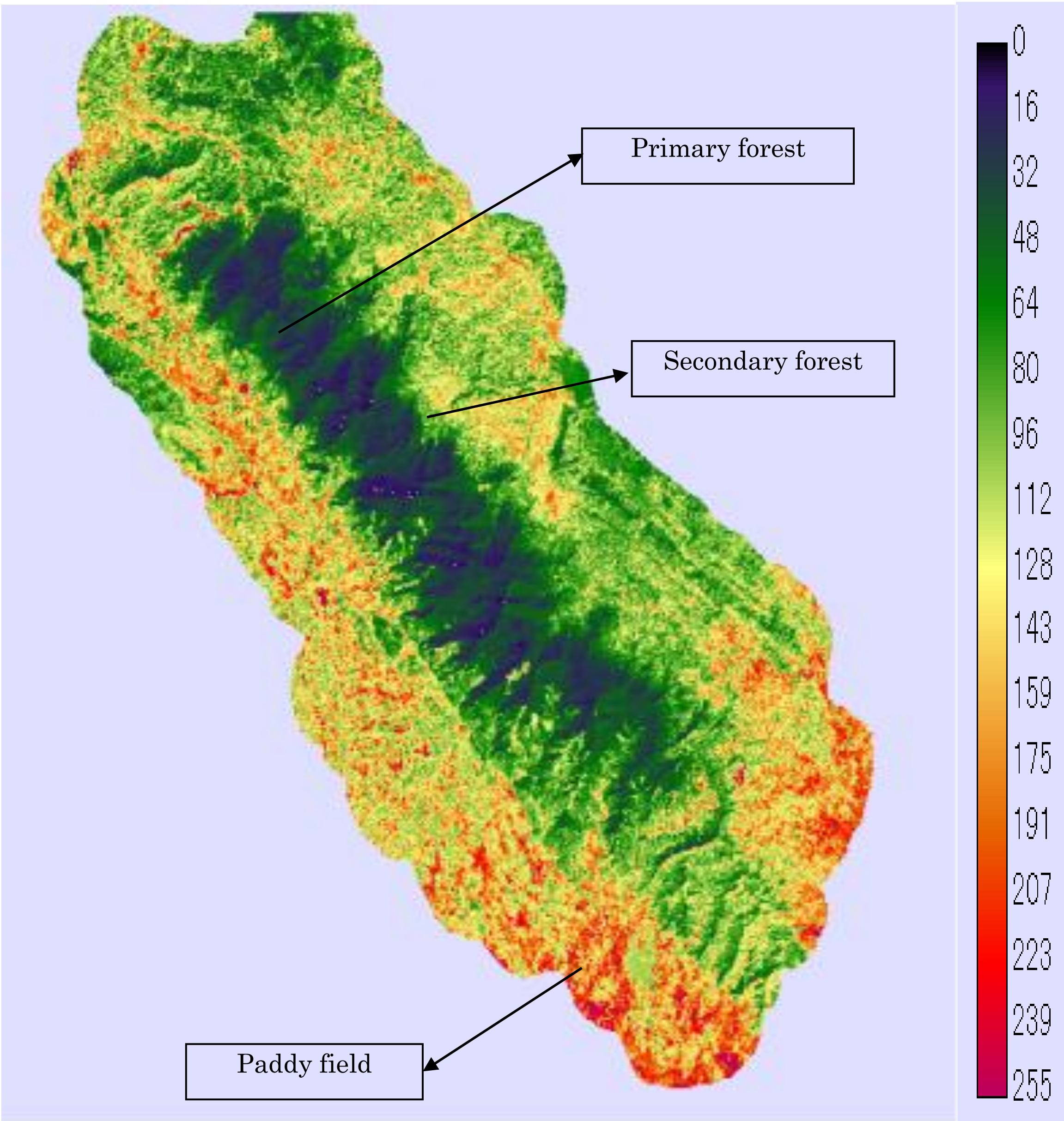
Ecosystem services (or environmental services or nature's services) are the goods and services that are provided by ecosystems to humans. These goods and services constitute a large share of social and economic welfare. It is necessary to developing ecosystem service valuation to support landscape conservation and land management plans. The provisioning services, regulating services, supporting services and cultural services have clarified in the Millennium Ecosystem Assessment (MA, 2003) as follows. *Provisioning services* provide goods such as food, freshwater, timber and fiber for direct human use and these are a familiar part of the economy. *Regulating services* maintain a world in which it is biophysically possible for people to live, providing such benefits as water purification, pollination of crops, flood control and climate stabilization. S*upporting services* create the backdrop for the conditions and processes on which society depends more directly. C*ultural services* make the world a place in which people want to live, and they include recreation as well as esthetic, intellectual and spiritual inspiration. All of these services are provided by complex chemical, physical and biological cycles powered by the sun and operate at scales ranging from smaller than the period at the end of this sentence to as large as the entire biosphere.

Appendix II: Major land use types in Vietnam

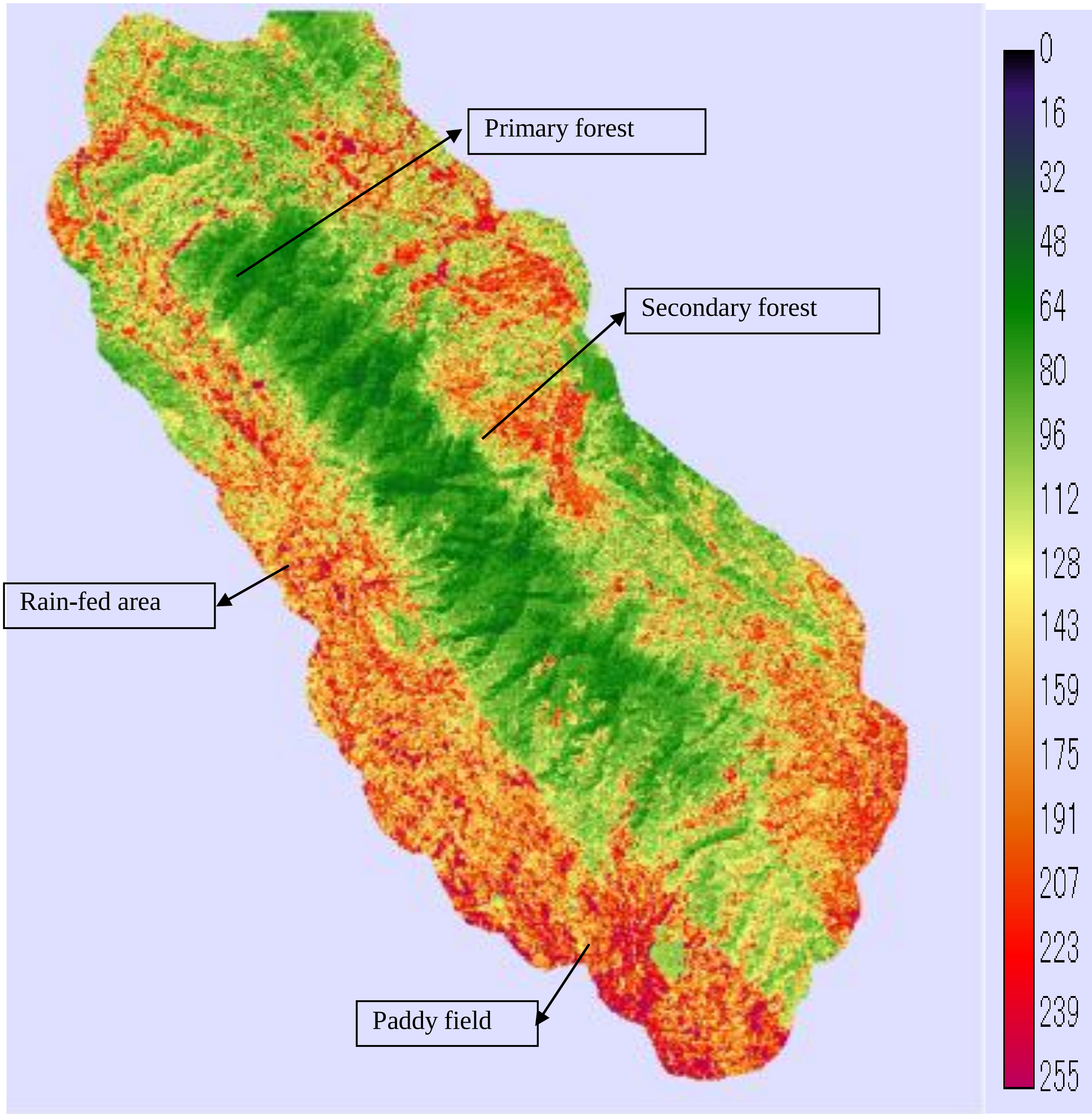
According to 2003 land law of Vietnam, land use system is classified into the following types according the purpose of land utilization:

- **Annual arable lands**: these lands consist of paddy field, grassland and other annual crops. They are legally used and managed by individual agricultural households. The conversion of annual arable lands to other land uses are strictly restricted by the law.
- **Perennial arable lands**: these lands are legally used for crops, which have a life cycle of more than one year, *i.e.*, fruit trees, coffee tree and tea plantation. They are managed by the state enterprises in the past decades. Currently, they are used and managed by individual agricultural households.
- **Production forestlands**: these lands are legally used for forest enterprises or households investing on forest plantation for commercial purpose.
- **Forests for environmental protection**: these forests are protected for controlling natural hazards, *i.e.*, flooding, landslide, water supply and protection of watershed.
- **Special forests** (also *so-called* protected areas): these spatial forests include national parks, nature conservation areas and cultural-historical-environmental sites.
- **Aquaculture lands**: they include streams, rivers, lake, ponds, sea surface and are legally used for aquaculture production or water resource supply. They are managed by both the state and individual agricultural households.
- **Built-up lands**: these lands consist of urban, rural settlement and public infrastructure and other facilities. These lands are managed by the state agency.
- **Vacant lands**: these lands are used for public and managed by the state.

Appendix III: Identification of training areas for land use/cover classification in the region

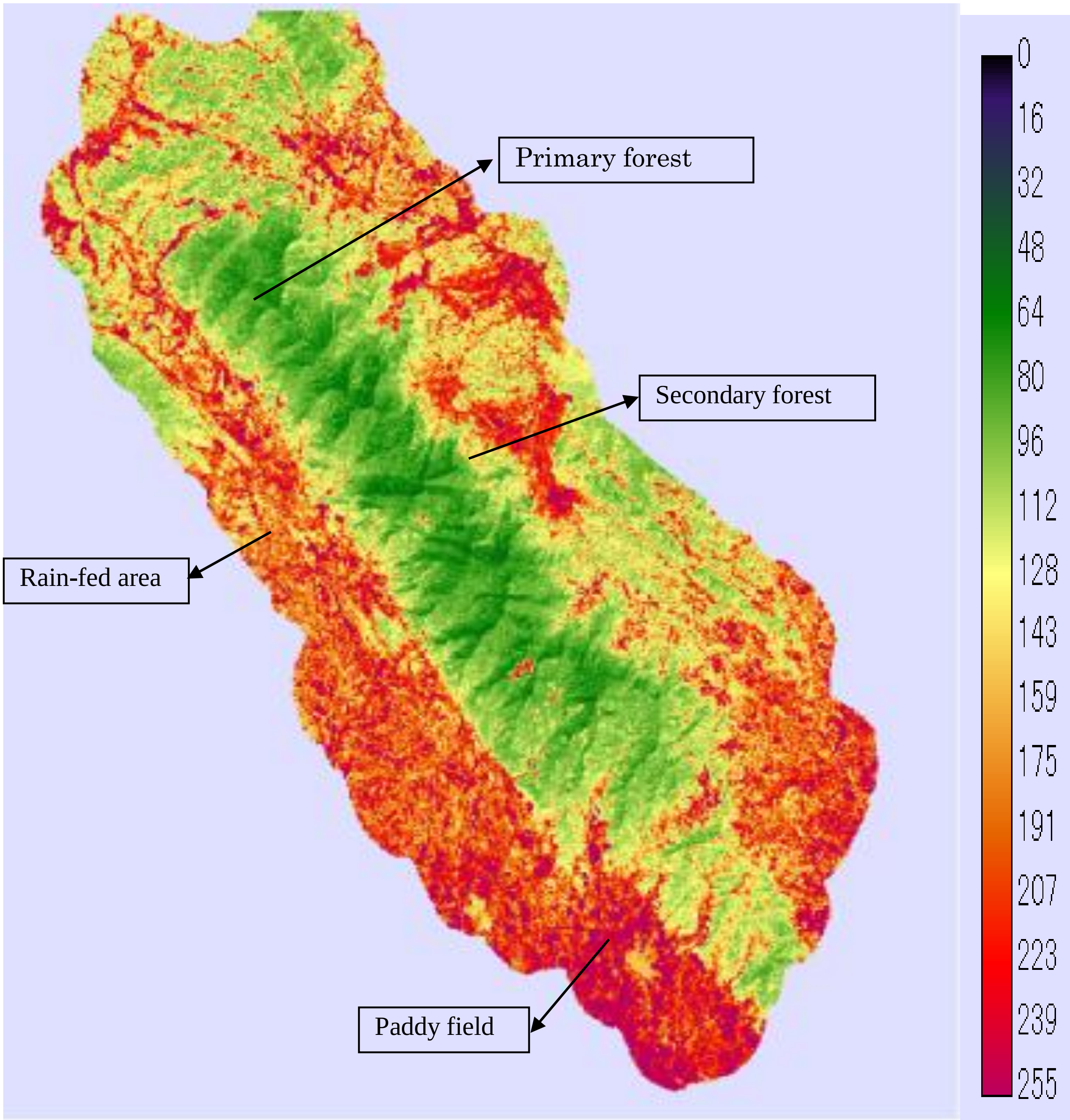


(a) Band 3 for the year 1993
Notes: The band 3 is able to separate primary and secondary forest and cropland in the area.



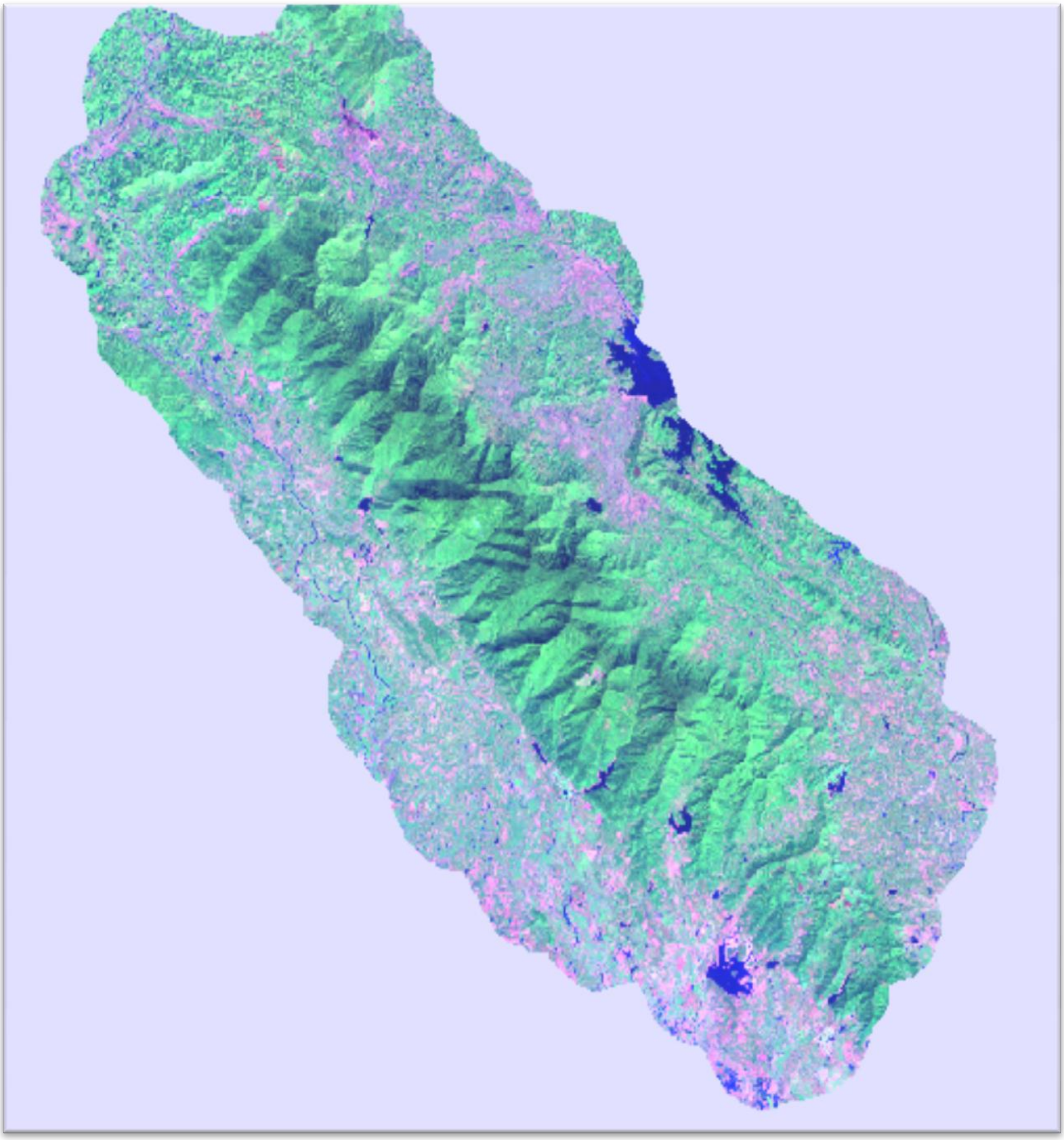
(b) Band 3 for the year 2000

Notes: In the year 2000, band 3 is capable of separating primary forest, secondary forest, rain-fed agriculture and paddy field.



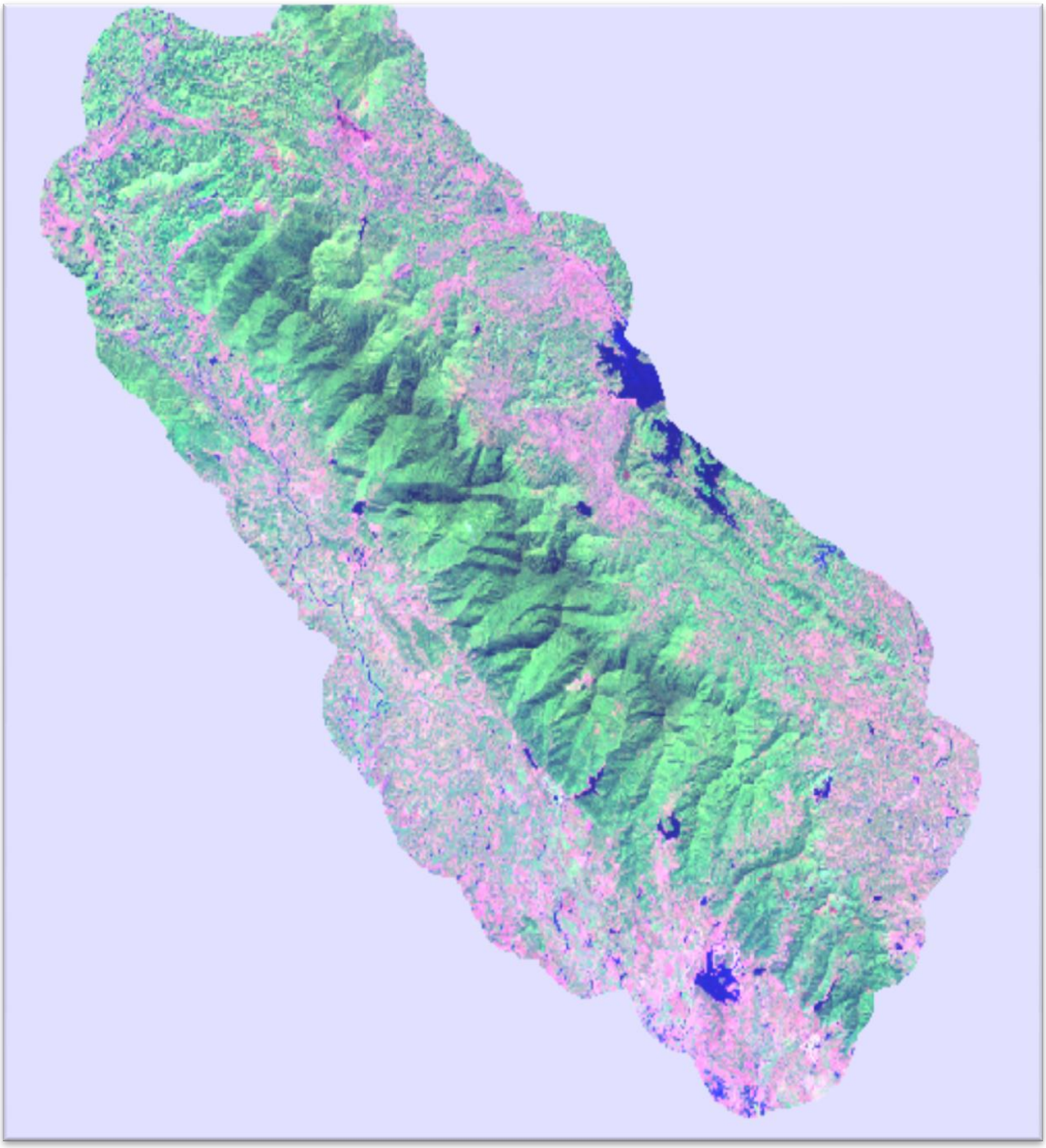
(c) Band 3 for the year 2007

Notes: In the year 2007, band 3 is also capable of separating primary forest, secondary forest, rain-fed agriculture and paddy field.

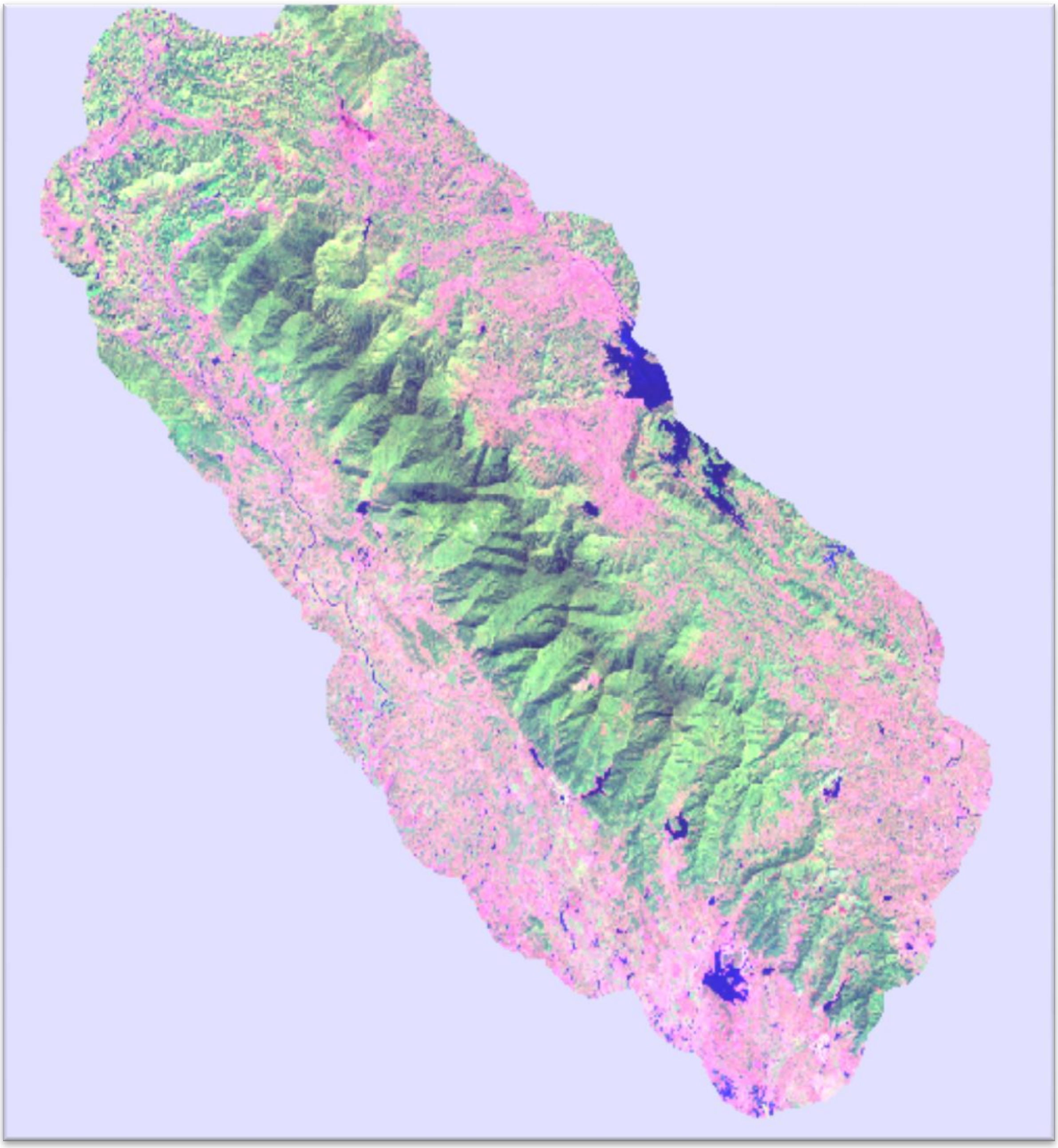


(d) The composite image of bands 7, 4 and 2 for the year 1993

Notes: The composite image created from the bands acquired in 1993. The image was used to visualize the spectral patterns of water bodies and primary forest. In the image, primary forest, natural lakes, streams and rivers can be recognized. This information was used for delineating training areas for water class.



(e) The composite image of bands 7, 4 and 2 for the year 2000



(f) The composite image of bands 7, 4 and 2 for the year 2007

Appendix IV: The photos of land use/cover types in the study area (Author, 2009)

Primary forest: this forest is located within the boundary of the TDNP.


Secondary forest: eucalyptus forest are commonly observed as secondary forest in the region.




Clearing of forest for agriculture: forests were cleared for annunal crops in sloping lands in the buffer zone of the TDNP, and then these lands were seriously degraded due to soil eosion.

Rain-fed agriculture: this land use includes annual crops such as maize, peanut, sweet potatos and vegetables in the bufer zone of the TDNP.

Paddy field: paddy rice in the irrigated lands of the buffer zone of the TDNP.

Settlement: small houses with surrounding gardens are commonly observed in rural settlement area in the region.