Spatial Dynamic Modeling of Tropical Forest Change

by

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Abstract

Traditional Land Use and Cover Change (LUCC) studies have focused on the change in attribute data (e.g., forest area, forest change rates, forest types, etc.) with few cases considering spatial data embedded in the dynamic process. However, LUCC varies with spatial and temporal dimensions in the real world, and these spatial dynamic features are considered to be indispensable in LUCC modeling. With the development of Geographical Information System (GIS) techniques and the increasing accessibility of Remote Sensing images, today we have the opportunity to study spatial dynamic modeling of LUCC and the related issues of spatiotemporal analyses. In this context, the goals of this dissertation are to undertake a retrospective analysis of tropical forest change (both forest loss and gain) in the Guanacaste region, Costa Rica; to explore its spatiotemporal features; to detect geographical factors which potentially act on forest loss/gain in the past 36 years (1979-2015); and then to reproduce and forecast tropical forest change from 1979-2100 in the Guanacaste region. As such, chapter 2 describes the spatiotemporal characteristics of tropical forest change in the Guanacaste region, and explores the spatiotemporal interactions of tropical forest change in two time periods (1979-1997 and 1997-2015) by using historical forest cover data. Chapter 3 aims to detect those geographical factors acting on tropical forest loss/gain from political, natural and biophysical aspects, and assesses the magnitude of each geographical factor affecting forest loss/gain by using geographical detector. Meanwhile, all the assessments and analyses of driving forces in this chapter considered spatial autocorrelations that may exist among each geographical unit of a given factor. Chapter 4 reproduces and simulates tropical forest change of the Guanacaste region in the past 36 years by using a combined model of cellular automata model (CA model) and agent based model (AB model). Pilot model was validated by the historical scenarios of forest change. Afterward, this model was used to forecast

future simulations with different assumptions: current trend scenarios, economy-development-driven scenarios, and ecology-protection-driven scenarios. This research contributes to filling important knowledge gaps on contemporary research which is aimed to understand tropical forest dynamic processes.

Preface

This thesis is an original work completed by Jing Chen. No part of this thesis has been previously published.

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List of Abbreviations

AB models	Agent-Based models
ANNs	Artificial Neural Networks
ANOVA	Analysis of Variance
CA models	Cellular Automata models
CA-AB models	Cellular Automata-Agent Based models
CLUE models	Conversion of Land Use and Its Effects models
CPI	Contagion Pattern Index
DEM	Digital Elevation model
FONAFIFO	National Forestry Financing Fund (Fondo Nacional de Financiamiento Forestal, Costa Rica)
GDP	Gross Domestic Product
GIS	Geographic Information System
GMM	Generalized Method of Moments
IDB	Inter-American Development Bank
IMF	International Monetary Fund
INEC	National Institute of Statistics and Censuses
IQR	Inter Quartile Range
IUCN	International Union for the Conservation of Nature
LISA	Local Indicators of Spatial Association
LUCC	Land Use/Cover Change
MAUP	Modifiable Areal Unit Problem
ML	Maximum Likelihood
MINAE	Ministry of Environment and Energy (Ministerio del Ambiente y Energia, Costa Rica)

MPA	Mean Patch Area
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
PES	Payments for Environmental Services
RS	Remote Sensing
SEM	Spatial Error models
SINAC	National System of Conservation Areas (Sistema Nacional de Áreas de Conservación, Costa Rica)
SLM	Spatial Lag models
SVM	Support Vector Machine
USDA	United States Department of Agriculture

Chapter 1: Introduction

1.1 Introduction

Land Use and Cover Change (LUCC) is a global environmental change research field that has gain significant interest over the past 30 years. It aims to understand complex spatial interactions among human, natural, and land driving factors (Schaldach and Priess, 2008), and the imprints of those factors in the landscape. LUCC research also strives to understand the links between anthropogenic and natural activities at different spatial and temporal scales (Mackiewicz et al., 1979; Marfai, 2011; Wang et al., 2012).

As of today, there are a growing number of studies addressing dynamic process of LUCC and its related issues (Foley et al., 2005). Current LUCC models are based on the hypothesis that humans respond to their natural and social environments to improve their economic and social-cultural well-being (Verburg et al., 2004). Thus, LUCC models are always regarded as selection functions with respect to economic and biophysical variables, which are called as "driving forces" or "driving factors" (Turner et al., 1993). Consequently, driving forces are basic determinants of LUCC models. In some cases, driving forces are assumed to be exogenous variables, and this assumption has influenced the LUCC system (Verburg et al., 2004). For example, Pahari and Marai (1999) demonstrated that population is an important factor towards modeling of global deforestation. However, Pfaff (1997) pointed out that population varies with local policy, and they share collinearity (a process in which one predictor variable on a multiple regression can be linearly predicted from the others with substantial degree of accuracy). In the first case of Pahari and Marai (1999), if the population growth and policy are taken into account in the regression function, the estimation of LUCC is biased. In the second case of Pfaff (1997), the estimation would be unbiased, but the transformation of variables, which is done in order to remove collinearity, leads the models that are inefficient and can potentially provide false interpretations. Other examples of exogenous factors in LUCC modeling are given by Chomitz and Gray (1996), Mertens and Lambin (1997) and Irwin and Geoghegan (2001). As such, the relationship between driving factors and LUCC is not statistically correlated or uncorrelated; it is necessary to consider spatial/geographical and qualitative data in the analysis according to spatial and temporal heterogeneity.

Lamb et al. (2015) indicates that one of the most important land use/cover change events of the past century was the unexpectedly rapid decline in the extent of tropical forests. Tropical forest is extensive in the forest system, making up around 45% of global forests (Grainger, 2008; Keenan et al., 2015; FAO, 2016). As an important ecosystem in the world, tropical forests sequestrate carbon dioxide from the air, improve the conditions of global climate change, prevent land desertification, and provide many direct and indirect ecosystem services (Houghton et al., 2012). As of today, tropical forests have become one of the most threatened ecosystems worldwide due to uncontrolled anthropogenic disturbances and climate change (Hoekstra et al., 2005). Human activities (e.g., excessive logging, ranching, and migration, etc.) and climate change (e.g., global warming and drought) have made tropical forests suffer unprecedented damage (Mathews, 1989; Siegert et al., 2001; Wright, 2005). According to Achard et al. (2014), tropical forest area was estimated to be 1,635 million ha by 1990 at the global level. As of 2010, it had been reduced to 1,514 million ha. The gross loss of tropical forest extent was 8.0 million $ha \cdot yr^{-1}$ during the 1990s, and 7.6 million $ha \cdot yr^{-1}$ during the 2000s. At the regional level, the loss over the two decades was 56.9, 30.9, and 32.9 million ha in South and Central America and the Caribbean, sub-Saharan Africa, and South and Southeast Asia, respectively.

Despite the fact that most tropical forests are in a threatened situation around the world, there are still some places in the world where the deforestation process has been reversed. The Guanacaste region is an example of deforestation reversal. The forests total area in the Guanacaste region, Costa Rica, was up to 54.1% (of land area) by the year 2010, whereas it was 26.5% (of land area) in 1979. Costa Rica is a country of significant reversal of tropical forests deforestation that is not observed in other countries of Central and South America (Miles et al., 2006). As such, the experience of forest regrowth in that region is regarded as a successful case of tropical forest restoration and warrants detailed studies (Arroyo-Mora et al., 2005a; 2005b; Calvo-Alvarado et al., 2009; Cao and Sánchez-Azofeifa, 2017).

In the past few decades, much of the work on tropical forest change in Costa Rica has been conducted in Costa Rica. Sader and Joyce (1988) reported deforestation rates and trends in Costa Rica from 1940 to 1983. Sánchez-Azofeifa et al. (2001) analyzed deforestation in Costa Rica by a quantitative analysis based on remote sensing imagery. More recently, Stan and Sánchez-Azofeifa (2019) reported deforestation and secondary growth trajectories in Costa Rica. From the dynamics of forest change perspective, Sánchez-Azofeifa et al. (2002) analyzed the dynamics of tropical deforestation around the national parks of Costa Rica by using remote sensing. Sánchez-Azofeifa et al. (2003) studied the integrity and isolation of Costa Rica's national parks and biological reserves to examine the dynamics of forest change. Meanwhile, there are also some studies focusing on the policies of Costa Rican forest change, which are beneficial to forest restoration. Sánchez-Azofeifa (2007) discussed the intention, implementation, and impact of an important Costa Rican policy: Payment for Environmental Services (PES) program. PES is a formal, country-wide program of payments for environmental services (they are mainly funded from a national tax on fuel consumption, private companies, and international sponsorship) and has been credited for helping the country to achieve negative net deforestation rate in the early 2000s. Van Laake and Sánchez-Azofeifa (2004) focused on deforestation in the Limón province and zoomed in on hot spots in highly fragmented ecosystems in this area. Schelhas and Sánchez-Azofeifa (2006) detected post-frontier forest change adjacent to Braulio Carrillo National Park, Costa Rica. Algeet-Abarquero et al. (2015) analyzed the land cover dynamics in southern Costa Rica, and reported that secondary forest there to stay.

Although a large number of studies on tropical forest change have been done in Costa Rica, there are still some gaps that remain. For example, few studies focus on the interaction effects of space and time, and most of the related studies do not take spatiotemporal features into account when analyzing a dynamic process of forest change. On the other hand, almost all issues related to tropical forest change address driving forces, in some way or another. Driving forces of tropical forest change always include quantitative factors and descriptive factors (Lambin et al., 2001). Descriptive factors are the main constituents of driving factors, which were largely ignored by the previous research. Moreover, the problems that arise from relationships between spatial dynamic model and driving forces are yet to be resolved. Both of the non-linear relations between tropical forest change and potential drivers, and the contradictions among the fitting accuracy of model, the number of drivers, and the explanation of dynamic system need to be further explored. Therefore, understanding the dynamic processes of tropical forest change, exploring the existing spatiotemporal features and detecting the sensitive driving factors, and creating the effective solution have become a particularly important part in LUCC studies and modeling.

1.2 Thesis overview

The main objective of this dissertation is to understand and analyze the spatial and temporal features of LUCC in the context of tropical forest change, and how given political, natural, and biophysical factors can drive its spatial and temporal features. By using a suite of GIS, RS, spatial analysis techniques, and spatial dynamic tools, this thesis contributes to filling important knowledge gaps on contemporary research which is aimed to understand tropical forest dynamics. As such, this dissertation is divided into the following chapters:

Chapter 2: *Spatiotemporal Features of Tropical Forest Change in the Guanacaste Region, Costa Rica.* This chapter aims to analyze the spatiotemporal features of tropical forest change in the Guanacaste region and determine the spatial characteristics and spatiotemporal interactions of tropical forest change over different time periods. In this chapter, spatially explicit methods, cross-sectional data, and geo-referenced data were used to analyze changes in tropical forest over the past 36 years (1979-1997, 1997-2015), and explore the spatial characteristics and the spatiotemporal interactions of tropical forest change in the Guanacaste region.

Chapter 3: *Geographical Detector-Based Factors Detection of Tropical Forest Change in the Guanacaste Region, Costa Rica.* The aim of this chapter is to detect the impacts of geographical driving forces on tropical forest change in the Guanacaste region, Costa Rica. The detection of driving forces was based on the descriptive attributes in each geographical division without quantification. Meanwhile, it also assessed and considered spatial autocorrelations that may exist among geographical divisions. In this chapter, spatial pattern analysis and geographical detectors were used to detect the impact of geographical factors on forest change over the past 36 years, between two time periods of 1979-1997 and 1997-2015, and to explore the effects of spatiotemporal autocorrelation among geographical divisions that acts on forest change (both loss and gain) and the magnitude of a given geographical factor on tropical forest loss/gain.

Chapter 4: *Simulations of Tropical Forest Change in the Guanacaste Region, Costa Rica.* The main purpose of this chapter is to simulate tropical forest change in the Guanacaste region and to forecast scenarios of its change in the future. In this chapter, historical data of 1979, 1997, and 2015 was used to train the transition regulations of tropical forest change and the decision behaviour of individual agents. Then, a model that combines CA model, AB model, and geographical constraint information was developed to simulate the evolution of tropical forest change during the past 36 years and the future scenarios of tropical forest change based on the assumptions of current trend scenarios, economy-development-driven scenarios, and ecology-protection-driven scenarios.

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Chapter 2: Spatiotemporal Features of Tropical Forest Change in the Guanacaste Region, Costa Rica

2.1 Introduction

Land Use and Cover Change (LUCC) research aims to understand complex spatial interactions between human, natural, and land driving factors (Schaldach and Priess, 2008) and the imprints of those factors in the landscape. LUCC research is also oriented to understand how anthropogenic and natural activities link themselves at different spatial and temporal scales (Mackiewicz et al., 1979; Marfai, 2011; Wang et al., 2012).

Over the past several decades, an increasing number of scientists have been interested in forest change (Hansen et al., 2013), with the common denominator being studied on time series of forest change by using attribute data (Sudhira et al., 2004). In fact, few studies focused on the interaction effects of space and time. Much work of forest change has been focused on the magnitude of change but not on the location of change. Meanwhile, most of the related studies do not take spatiotemporal features into account when analyzing a dynamic process of forest change. Since the 1940s, Moran (1948) realized the presence of spatial autocorrelation, and proposed a statistic to measure this phenomenon: the Global Moran's I. This measurement is reflected in the proposition of Tobler 1970's First Law of Geography (Tobler, 1970), which states that everything is related to everything else, but near things are more related than distant things. In the 1980s, Goodchild (1986) pointed out that it is impossible for a geographer to imagine a world that could be absent from spatial autocorrelation. He argued that the methods of classical statistics are not suitable for spatial analysis, because of the spatial characteristics, especially the presence of spatial autocorrelation (Gould, 1970). In the following decade, there was a growing interest in local measures of spatial autocorrelation. Much related work was inspired by the thoughts of local spatial autocorrelation. For examples, Stone (1988) investigated excess environmental risks. Cuzick and Edwards (1990) studied the spatial clustering of the inhomogeneous population. Cressie (1992) smoothed regional maps by using empirical Bayes predictors (Ord and Getis, 1995). Meanwhile, a variety of local indicators were put forward and applied, such as Local indicators of spatial association (LISA) (Anselin, 1995), Getis-Ord G^* & G_i^* (Getis and Ord, 1992; Ord and Getis, 1995), and Kulldorf Space Scan (Kulldorff, 1997). All the statistics mentioned above were calculated by considering spatial information, which is called spatial relation matrix. That is the most crucial difference between classic statistics and spatial statistics that has been the core of many LUCC studies.

As of today, much of the work on tropical forest change in Central America has been conducted in Costa Rica. At the national level, Sader and Joyce (1988) reported deforestation rates and trends in Costa Rica from 1940 to 1983. Sánchez-Azofeifa et al. (2001) analyzed deforestation in Costa Rica by a quantitative analysis based on remote sensing imagery. More recently, Stan and Sánchez-Azofeifa (2019) reported deforestation and secondary growth in Costa Rica along the path of development. From the dynamics of forest change perspective, Sánchez-Azofeifa et al. (2002) analyzed the dynamics of tropical deforestation around the national parks of Costa Rica by using remote sensing. Sánchez-Azofeifa et al. (2003) studied on the integrity and isolation of Costa Rica's national parks and biological reserves to examine the dynamics of forest change. Meanwhile, there are also some studies focusing on the policies of Costa Rican forest change, which are beneficial to forest restoration. Sánchez-Azofeifa (2007) discussed the intention, implementation, and impact of an important Costa Rican policy: Payment for Environmental Services (PES) program. PES is a formal, country-wide program of payments for environmental services (they are mainly funded from a national tax on fuel consumption, private companies, and international sponsorship) and has been credited for helping the country to achieve negative net deforestation rate in the early 2000s (Pagiola, 2008).

At the regional level, Sánchez-Azofeifa et al. (2002) studied the dynamics of tropical deforestation in the Osa Peninsula using remote sensing. Van Laake and Sánchez-Azofeifa (2004) focused on deforestation in Limón province and zoomed in on hot spots in highly fragmented ecosystems in this area. Schelhas and Sánchez-Azofeifa (2006) detected post-frontier forest change adjacent to Braulio Carrillo National Park, Costa Rica. Algeet-Abarquero et al. (2015) analyzed the land cover dynamics in southern Costa Rica and reported secondary forest there. The Guanacaste region is an example of deforestation reversal at the regional level. The total area of forest in the Guanacaste region, Costa Rica, was up to 54.1% (of land area) by the year 2010, whereas it was 26.5% (of land area) in 1979. Costa Rica is a country of significant reversal of tropical forests deforestation observed in other countries of Central and South American (Miles et al., 2006). As such, the experience of forest regrowth in that region is worth to be studied (Arroyo-Mora et al., 2005a; 2005b; Calvo-Alvarado et al., 2009; Cao et al., 2017). The research on the causes of forest restoration and the recovery of tropical forests by interactions between anthropogenic and natural activities provides significant benefits to the countries that are suffering from tropical deforestation.

In this context, the main goals of this study are to analyze the spatiotemporal features of tropical forest change in the Guanacaste region, and to determine the spatial characteristics and spatiotemporal interactions of tropical forest change over different time periods. In this chapter, spatially explicit methods as well as cross-sectional and geo-referenced data are used to analyze changes in tropical forest over the past 36 years (1979-1997, 1997-2015) and to explore the following two questions: (1) What are the spatial characteristics of tropical forest change? and (2) What are the spatiotemporal interactions of tropical forest change?

2.2 Methodology

2.2.1 Study area

This study was conducted in the Guanacaste region, Northwest Costa Rica. This region covers an area of 11,337 km^2, and it is divided into 12 counties and 64 districts (Figure 2. 1). The Guanacaste region experiences light rain and consistently high temperatures from November to April (dry season: average accumulated precipitation is 308 mm, and average monthly temperature is 25.9 degrees Celsius). From May to October, the climate in the Guanacaste region is considerably warm and rains daily (wet season: average accumulated precipitation is 1,616 mm, and average monthly temperature is 25.9 degrees Celsius). The study area has three conservation areas embedded in the Costa Rica National Conservation System: the Guanacaste Conservation Area, the Tempisque Conservation Area, and the Arenal Huetar Norte Conservation Area. These three conservation areas, account for 1,879 km^2 (16.6%) of Costa Rica. The conservation areas include 10 national parks, 3 biological reserves, 23 wildlife refuges, 4 wetlands, 6 protective zones, 1 forest reserve, 2 natural reserves, and 2 other reserves (Frankie et al., 2004, Protected Planet, 2019) (Figure 2. 1). According to the geographical features (terrain and soil), the study area is mainly divided into two geographical zones: the Tempisque Basin and the Nicoya Peninsula (Figure 2. 1). The Tempisque Basin is a flat and alluvial lowland area which is mainly covered by fertile soils, whereas the Nicoya Peninsula is characterized by steep terrain and infertile soil (Arroyo-Mora et al., 2005a; 2005b).

Historically, the main income source for a household in the Guanacaste region came from cattle ranching, especially from the beef industry (Kaimowitz, 1995). As such, much of the original extent of tropical forests in this region was converted into pasture. In the early 16th century, the first Spanish colonists arrived in Guanacaste (Hall, 1984), and by the 1800s, they began to establish large-scale farms (Edelman, 1985). In the mid-1800s, the demands for land increased drastically (Gleick, 2000) due to the increasing population. From the 1930s and onwards, Costa Rica's landless people were forced by survival pressure to migrate from central Costa Rica to surrounding areas, especially to the Guanacaste region (Hamilton and Chinchilla, 1991; Cruz et al., 1992). The expansion of road networks aggravated this process, as well as colonization policies promoted by the central Government and the World Bank (Calvo-Alvarado et al., 2009).

From the 1950s to 1970s, the global consumption of beef increased (Kaimowitz, 1995; Steinfeld et al., 2006), and with that Costa Rica became the main beef exporter due to its own agro-economic structure (Sánchez-Azofeia, 2009). By the early 1960s, almost 40% of all cattle in Costa Rica were fed in the Guanacaste region (Janzen, 2018), with cattle population reaching a peak (2.3 million head in Costa Rica) in the early 1970s (Calvo-Alvarado et al., 2009). By then, the beef industry was not only the primary source of income but also the main factor leading to deforestation. However, deforestation in the Guanacaste region took a favorable turn in the middle of the 1980s (Calvo-Alvarado et al., 2009; Sánchez-Azofeifa et al., 2007) as the global beef consumption per capita fell. This drop on price prompted most Costa Ricans to abandon cattle ranching and changed the way of land use/land cover for more economic benefits. In addition, the government made a series of policies to restrict timber extraction and land clearing and encouraged protection and restoration forests (Sánchez-Azofeifa et al., 2007).

2.2.2 Materials and Methods

Our study focuses on studying the dynamic processes of tropical forest change in the Guanacaste region, Costa Rica. Thus, all the methods introduced here were applied for two periods of land use cover change: 1979-1997 and 1997-2015. The 1979-1997 time period covers the period of forest restoration via the national park system establishment and the economic transition. The 1997-2015 time period covers the period which Payments for Environmental Services (PES) are established (Sánchez-Azofeifa et al., 2007). The year of 1997 is an important and epochal year in the history of tropical forest restoration in Costa Rica, since it is when the PES started (Sánchez-Azofeifa et al., 2007).

The data used in this study not only considered the spatial information associated with forest change, but it also took temporal information into account. In this specific case, data features are composed by the initial state, the final state, and the trajectories in each period. Combining with the spatially explicit information, the forest change in this study was considered in two change types, forest loss and forest gain.

2.2.2.1 Land cover classification

The foundation of all approaches was implemented on three different Landsat images: 1979, 1997 and 2015 (Table 2. 1). The land cover classification applied to these images consists of the following classes: forest (dry, moist, and wet tropical forests), grass/pasture, agriculture, mangrove, urban, and water. For the purposes of our study, forests are defined as more than 80% canopy cover, and both of natural primary forest and secondary forest (e.g., forest regrowth and forest plantation) are included (Sánchez-Azofeifa et al., 2001). In particular, images taken in January were selected to account for the end of the wet season and the beginning of the dry season. At this time of year, the deciduous tropical forest still has full leaf cover and images are relatively clear with fewer clouds.

The land cover maps of 1979, 1997, and 2015 were processed from Landsat images (Figure 2. 1). The categories of land cover include forest (green), grass/pasture (brown), agriculture (yellow), mangrove (pink), urban (red), and water (blue). The blank areas (white) are the areas with the presence of clouds.

The land cover maps were produced by using Support Vector Machine (SVM) classification. The SVM is a supervised classification method used on pattern recognition of non-linearly separable and high-dimensional training data with small samples (Vapnik, 2013). By comparing the classification results with the google earth data (1979 and 1997) and ground truth data (2015), the overall accuracies of land cover classification in 1979, 1997, and 2015 are assessed as 87.6%, 86.5%, and 90.9% (Table 2. 2), respectively by using confusion matrix. Considering the different spatial resolutions, we redefined the spatial resolutions of 1997 and 2015 as 60m.

2.2.2.2 Quantification of spatial characteristics of forest change

The Moran's I and LISA spatial statistics were used to explore and detect the spatial autocorrelations and the spatial patterns over two different time periods. Comparing Moran's I with other widely used statistics, which are applied to the continuous data as well, such as Geary's

C, and Getis-Ord G^* & G_i^*, Moran's I is the most well-known statistic for geographers (Getis and Ord, 1992). To the lesser extent, Geary's C is in second place. A common feature of Moran's I, Geary's C, and Getis-Ord G^* is that they are applied in the whole study area. But the expressions of Moran's I and Geary's C are opposite; they are inversely related to each other. In general, Moran's I is more sensitive and effective at detecting spatial autocorrelation than Geary's C, especially when stationarity is violated (Fortin and Legendre, 2012). Spatial stationarity is an assumption of spatial statistics that states the mean (i.e., the first order stationarity) and/or the variance (i.e., the second order stationarity) of the system property is constant over space (Ord, 2001). Cliff and Ord (1982) also pointed out that Moran's I is more preferable in many applications because it is less affected by the deviations from the normal and Gaussian distribution than Geary's C. For Getis-Ord G^*, it differs in the pattern of spatial weights and the expressions with Moran's I (Getis and Ord, 1992).

Spatial autocorrelation analysis

The spatial autocorrelation of tropical forest loss/gain in the Guanacaste region was analyzed by using the Global Moran's I (referred to as Moran's I) and the Local Indicator of Spatial Autocorrelation (LISA) (Moran, 1948; Anselin, 1995). Moran's I is a tool used to measure spatial autocorrelation based on both of feature locations and feature values simultaneously, and it was popularized through the classic work on spatial autocorrelation by Cliff and Ord (1973). Moran (1948) calculates spatial autocorrelation of spatially explicit features, using:

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{1}$$

where N is the number of units; w_{ij} is the matrix of spatial weights which represents the spatial structure of tropical forest loss/gain and quantifies the spatial relationships existing among the spatial units in our research (ArcGIS Pro, 2018a); W is the sum of all w_{ij}; i, j is spatial units index; $\bar{y}$ is the average of y. In our case, y indicates the tropical forest loss/gain (the forest loss/gain rates). The spatial weights, which are used to model the spatial relationships, were polygon contiguity (first order, Bartels and Hordijk, 1977) and Queen's contiguity (Anselin and Griffith, 1988). This method is used for polygon feature classes and is suitable for modeling contagious process or dealing with continuous data represented as polygons (ArcGIS Pro, 2018b).

For statistical hypothesis testing, Moran's I values can always be normally transformed to Z-scores with (Cliff and Ord, 1982):

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{2}$$

where:

$$E(I) = -\frac{1}{N-1} \tag{3}$$

$$Var(I) = \frac{NS_4 - S_3S_5}{(N-1)(N-2)(N-3)W^2} - (E(I))^2 \tag{4}$$

$$S_1 = \frac{1}{2}\sum_i \sum_j \left(w_{ij} + w_{ji}\right)^2 \tag{5}$$

$$S_2 = \sum_i \left(\sum_j w_{ij} + \sum_j w_{ji}\right)^2 \tag{6}$$

$$S_3 = \frac{N^{-1}\sum_i (x_i - \bar{x})^4}{\left(N^{-1}\sum_i (x_i - \bar{x})^2\right)^2} \tag{7}$$

$$S_4 = (N^2 - 3N + 3)S_1 - NS_2 + 3W^2 \tag{8}$$

$$S_5 = (N^2 - N)S_1 - 2NS_2 + 6W^2 \tag{9}$$

where $E(I)$ is the expectation with the null hypothesis of no spatial autocorrelation among spatial units. The range of I value is usually from -1 to +1, indicating that the spatial autocorrelation is from negative to positive, and there is no spatial autocorrelation when Z-score is 0. Thus, Moran's I shows the general spatial autocorrelations across a region: positive autocorrelation, none autocorrelation, and negative autocorrelation.

In our case, the reference distribution of Moran's I is constructed by a 999 random permutation. Thus, 0.001 is regarded as a typical value of the smallest pseudo p-value, and establishes a 99.9% confidence level, although it is not necessary (Anselin, 2018). Therefore, when p-values are smaller than 0.001, we trust the forest loss/gain is significantly autocorrelated in space.

Local spatial pattern analysis

LISA, as a local indicator, was improved by Anselin (1995) on the basis of Moran's I, and it measures spatially local heterogeneity (Wang et al., 2016), which can be regarded as local spatial patterns. LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation. Comparing with Moran's I, it satisfies the sum of LISAs for all observations is proportional to I value (Anselin, 1995):

$$LISA_i = \frac{y_i - \bar{y}}{S} * \frac{\sum_j w_{ij}(y_j - \bar{y})}{S} \quad (10)$$

where S is the standard deviation of y_j ; w_{ij}, i, j, $\bar{y}$, y represent the same variables with Moran's I. Differing with Moran's I, LISA indicates where the spatial autocorrelations are (local spatial patterns).

LISA is an indicator which shows the comparisons between focal observation and surrounding observations by using the Moran scatterplots (Figure 2. 3). As it was first proposed by Anselin (1996), the scatter plot is comprised by the original variable (from focal observations) on the x-axis and the spatially lagged variable (from surrounding observations) on the y-axis. The term "spatial-lag" of the dependent variable assumes that the dependencies exist among the dependent variables based on their locations. This term describes that the observation at one location is affected by observations from surrounding regions (LeSage and Pace, 2009). The advantage of the Moran scatterplot is distinguishing high-value clusters or low-value clusters, both of which are regarded as positive autocorrelation in Moran's I (Anselin, 2018). In practice, scatter plots classify the spatial autocorrelations into four quadrants and make the connection between global and local spatial measurements. The linear slope of scatterplots depicts the value of Moran's I. In the case of this study, each point represents a district with its original forest loss/gain on the x-axis and the spatially lagged forest loss/gain on the y-axis. Then, the point clouds of four quadrants delineate different local spatial patterns of forest loss/gain. The points which are in quadrant Ⅰ and Ⅲ represent high-high pattern (red points, high-value clusters) and low-low pattern (blue points, low-value clusters) respectively. They are typically referred to as spatial clusters, which mean that high values or low values of forest loss/gain rate are more similar to its neighbors. The points in quadrant Ⅱ and Ⅳ, which show the negative autocorrelation, are termed by Anselin (1995) as spatial outliers. Quadrant Ⅱ represents low-high pattern (purple points) and quadrant Ⅳ represents high-low pattern (pink points). While outliers are single locations according to the definition, they are not the cases for clusters.

The permutations of LISA are similar to Moran's I, except that it is carried out for each observation in turn (Anselin, 2017). Since the default settings are 999 permutations, the significance map starts with $p < 0.001$. The different p-values are able to be regarded as the degree of spatial clustering.

2.2.2.3 Spatiotemporal interactions

Contagion and association analyses are the methods used in the fields of spatial analysis and data mining (McGarigal and Marks, 1995; Banerjee et al., 2014). In this study, all the forest change data was processed as spatial and temporal information. Thus, contagion and association analyses in this paper are tested to understand spatial and temporal interactions of forest loss/gain in the Guanacaste region.

Spatiotemporal contagion analysis

Contagion refers to the manners of forest change at the patch level in terms of loss or gain. In this study, contagion was measured by using the Contagion Pattern Index (CPI), which calculates the ratio between a common boundary (a boundary between a forest loss/gain patch and the adjacent persisting forest patch) and the perimeter of a given forest loss/gain patch (Xu et al., 2007):

$$CPI = \frac{L_{ij}}{P_{ijk}} \tag{11}$$

where i is the i^{th} patch of persisting forest; j is the j^{th} patch of forest loss/gain; k is forest loss or gain; L_{ij} is the common boundary between patch i and patch j; P_{ijk} is the perimeter of patch j.

In the context of this study, contagion implies and explains the mechanisms which are driving forest loss/gain in the Guanacaste region. Generally, contagion can be classified into three patterns (Xu et al., 2007; Liu et al., 2010; Nong et al., 2014; Weerakoon, 2017): 1) *Infill pattern*. This is considered as the most compact contagion pattern, and it is recognized when $0.5 \leq \text{CPI} \leq 1$. From a physical point of view, it is that forest loss/gain patches are encompassed by persisting forest patches and it usually happens in the inside or the edge of persisting forest. 2) *Edge pattern*. This is a less compact contagion pattern than infill one, but forest loss/gain patches and persisting forest patches are still adjacent. It is collected when $0 < \text{CPI} < 0.5$. This pattern is generally observed in the boundaries between forest and other land covers. 3) *Spontaneous pattern*. This pattern is that forest loss/gain patches are in random places, which away from persisting forest patches (no common boundaries). That is when $\text{CPI} = 0$. It is the most disordered and low-density contagion pattern (Figure 2. 4) (Yue et al., 2010).

Spatiotemporal association analysis

The analysis of spatiotemporal association was used in this study to reveal spatially associated relationships among land covers in time series, then to extract and simplify spatiotemporal association regulations. Spatiotemporal association regulations are defined as the consistencies between the occurrence of focal observation and the occurrence of surrounding observations (Li et al., 2015). Moreover, the spatiotemporal association analysis is also used for extracting association information and collecting spatiotemporal rules from land cover change processes in the study area. For our study, the consistencies of spatiotemporal association are expressed as a series of probabilities that describe the change potential between land covers over the past 36 years (two time periods), as well as the transition rules of spatiotemporal processes between focal pixels and surrounding pixels. In this study, the pixel-based land cover change produced tens of millions of records. For the purpose of simplifying and extracting the spatiotemporal association regulations; 16,563 focal pixels and 16,563×8 surrounding pixels were chosen randomly for each period in our analysis. The accuracy of this sampling satisfies a margin of error in 1% at the 99% confidence level (Rea and Parker, 2014). The determinants of spatiotemporal association used in this study are: 1) the transformation status of focal pixel, 2) the lattice geometry (spatial relationships), and 3) the transformation status of neighbourhood pixels.

2.3 Results

2.3.1 What are the spatiotemporal characteristics of tropical forest change?

2.3.1.1 Forest cover change

Forest cover change maps (Figure 2. 5(a)) of the Guanacaste region were produced from the land cover maps. They present the results of forest cover change over two time periods. The maps include the spatial distributions of forest loss/gain as well as persisting forest and persisting non-forest.

Results (Figure 2. 5(b)) indicate the forest loss/gain rates of total area. The forest gain rate (19.6% of total area, 1,994 km^2) is significantly higher than the forest loss rate (6.7% of total area, 684.6 km^2) in the first period. Thus, in the first period, the gross forest change rate increases by 12.9% of total area and the gross area growth of forest is up by 1,309.1 km^2. Although forest loss is significant in the second period, the total forest area becomes nearly stable because the forest loss rate (9.8% of total area, 1,000.6 km^2) is similar to the forest gain rate (9.6% of total area, 978.5 km^2).

From Figure 2. 5(a), although the gross forest area presents an increasing trend in the first period, there is a sizeable area in the middle of the Guanacaste region experiencing forest loss. In the second period, the rates of forest loss and gain are very similar, but the forest loss/gain has a strong spatial differential. In this period, the areas of forest gain are mainly in the northwest of Guanacaste. Meanwhile, the areas of forest loss appear mostly in the surrounding areas, especially in the northeast mountain region and the coastal area in west Guanacaste.

The areas of persisting forest and forest loss/gain are presented on Table 2. 3. The persisting forest is the most dominant category of forest change during two time periods, accounting for 61.1% and 72.3% of total forest area. For forest loss/gain, the most common transformations are taking place between "grass/pasture and forest", especially forest gaining from grass/pasture in the first period, reaching to 1511.7 km^2, 22.1% of total forest area. The other manners of forest loss/gain from high to low follow as "forest to/from agriculture", "forest to/from mangrove", and "forest to/from urban".

2.3.1.2 Spatiotemporal variabilities and disparities

Figure 2. 5(a) and Figure 2. 5(b) present an immense uneven distribution of forest loss/gain over space and time, which is hardly able to be derived from the attribute values directly. Considering these differentials, we explored the spatial and temporal variabilities and disparities of forest loss/gain. Meanwhile, we revealed the significance of spatiotemporal variabilities of forest loss/gain and the locations of spatiotemporal disparities of forest loss/gain.

Figure 2. 6 presents the spatiotemporal variabilities of forest loss/gain rates of districts. For forest loss rates, the second period (Median=9.8%) are generally higher than the first (Median=6.4%). Also, the variability of the second period (IQR=9.2%) is larger than the first (IQR=4.8%). In contrast, for forest gain, the rate of the second period (Median=8.1%) is visibly lower than the first (Median=19.2%), and the variability (IQR=7.4%) is much smaller than the first period (IQR=14.0%). The rates of forest loss are dramatically higher than forest gain in 1979-1997, whereas the rates of forest loss and gain exhibit a similar trend in 1997-2015.

The maps in Figure 2. 7 present the distribution of forest loss/gain rates at the district level, and they indicate the spatial tendencies and visual information of forest loss/gain in two periods. The extreme forest loss takes place in the district of Santa Rosa with the loss rate of 35.5% (25.1 km^2) in 1997-2015. For forest gain, the districts with high rates are Arenal (42.0%, 21.9 km^2) and Puntarenas (53.2%, 4.3 km^2) in 1979-1997. From Figure 2. 7, the forest gain districts and forest loss districts are not completely coupled in space. At the same time, the relationships between forest loss and gain vary with both space and time. In this first period, central districts exhibit high rates (>20%) of forest loss and their surrounding districts exhibit low rates (<10%). This trend is inversely correlated with forest gain, as the central districts and their surrounding districts exhibit forest gain rates of 5-10% and 20-50%, respectively. In the second period, there is no clear relationship between forest loss and forest gain (Figure 2. 7(c) and Figure 2. 7(d)).

2.3.1.3 Spatial autocorrelation analysis

Table 2. 4 presents the Moran’s I values, Z-scores, and p-values of forest loss/gain rates over 1979-1997 and 1997-2015. According to the positive and high values of Moran’s I, we can see positive spatial autocorrelations over two time periods for both forest loss and gain. Meanwhile, when the Z-scores>1.96 and p-values<0.05, the clustered structure of forest loss/gain exhibits statistical significance. All p-values are smaller than 0.001, and they suggest extremely strong clustered distributions for forest loss/gain in two periods. Furthermore, in the second period, both forest loss and gain have stronger clustered distributions than the first period. Even though the forest loss in 1979-1997 has the weakest clustered distribution in Table 2. 4, the cluster is still strong with a Z-score of 4.0.

The Moran scatterplots (Figure 2. 8) show each observation by setting the original forest loss/gain on the x-axis and the spatially lagged forest loss/gain on the y-axis at the district level. The linear slopes represent the Moran's Is, and the values are exhibited at the top of each figure. They are collected by the linear regressions from the points of each observation. From the figures of Moran scatterplots, four categories of the nature of spatiotemporal autocorrelation are classified. Generally, forest loss/gain of more than 75% districts exhibit the signs of positive spatial autocorrelation (clustered distribution, the points distributing in quadrant Ⅰ and Ⅲ) and less than 25% districts show the signs of negative spatial autocorrelation (dispersed distribution, the points distributing in quadrant Ⅱ and Ⅳ), which are also regarded as outliers.

2.3.1.4 Local spatial pattern analysis

From Figure 2. 8, it shows that different local spatial patterns exist simultaneously in our study. It also indicates the presence of strong local characteristics, which can be considered as local patterns in this study. Thus, further explorations of LISA were made at the district level. Figure 2. 9 not only spatialized the local patterns of forest loss/gain but also passed the significance test for each observation.

Differing from the analysis of global spatial autocorrelation, LISA focuses on the efforts of exhibiting local spatial patterns of clustering and dispersion. Throughout the whole time span, the clusters of high forest loss rates are in the center in the first period, then they are relocated to the eastern of Guanacaste in the second period. The clusters of low loss rates move from the northern of Guanacaste to the southern within two periods (Figure 2. 9(a) and Figure 2. 9(c)). Regarding forest gain, the clusters of low gain rates move from the center to the east and the west over time. Meanwhile, the clusters of high gain rates, especially the clusters in south Guanacaste, extend from one district to the whole Nicoya Peninsula (Figure 2. 9(b) and Figure 2. 9(d)). In our study, only few districts of low-high pattern (Trnadora in 1979-1997 and Aanta Cecilia in 1997-2015) have passed the significance test and no district of high-low patterns has passed the significance test. Although there is no significant spatial coupling between forest loss and forest gain in the Nicoya Peninsula in the second period (Figure 2. 7(c) and Figure 2. 7(d)), a certain local pattern was detected in this area. It shows that the clusters of low loss rates is completely spatial coupled with the clusters of high gain rates in the Nicoya Peninsula (Figure 2. 9(c) and Figure 2. 9(d)).

2.3.2 What are the spatiotemporal interactions of tropical forest change?

2.3.2.1 Spatiotemporal contagion

The spatiotemporal interactions were calculated and analyzed at the patch level and pixel level. Thus, they reflect and explore micro details of forest loss/gain in the Guanacaste region.

The contagion Pattern Index (CPI) is a statistic which has the advantages of simple computation, efficient analysis, and explanatory results. By conducting the calculations of CPI over two time periods, the contagion patterns of forest loss/gain were determined. As Table 2. 5 presents, the infill pattern is the dominant pattern (>50% of total area) for both forest loss and gain through the whole time span, edge pattern is in second place (27%-44% of total area), and spontaneous pattern is last (<6% of total area). Generally, the area proportions of contagion pattern decrease from a compact pattern to a disordered pattern. Table 2. 5 also illustrates the Mean Patch Area (MPA) for three contagion patterns of forest loss/gain. The largest MPA is observed in edge pattern for both forest loss and gain. By contrast, MPA of infill pattern is relatively small. The smallest MPA is observed in spontaneous pattern. From a time-series perspective, the areas of infill pattern in the first period are smaller than the second period, for both forest loss and gain. Meanwhile, MPA of forest gain observed in the first period is larger than it in the second period.

2.3.2.2 Spatiotemporal association

The spatiotemporal association was studied at the pixel level. The main results of this part are used to detect and describe the relations between the forest loss/gain pixels (treated as focal pixels) and the surrounding pixels, and then to figure out the spatiotemporal association rules and the evolutional ways of forest loss/gain in the Guanacaste region.

Figure 2. 10(a)(b)(c) and Figure 2. 10(d)(e)(f) present the top five probabilities of spatiotemporal association rules for persisting forest (rules *Ps*), forest loss (rules *Ls*), and forest gain (rules *Gs*) in two time periods. The spatiotemporal association rules were extracted from 16,563 samples, including 16,563 focal pixels and 16,563×8 surrounding pixels.

For persisting forest, the cumulative probabilities (rules of *P1-P5*) account for 76.5% and 77.8% of the whole spatiotemporal association rules in 1979-1997 and 1997-2015, respectively. From Figure 2. 10(a) and Figure 2. 10(d), the rules of *P1-P5* for staying as forest in the next time step are due to the surrounding pixels or most of the surrounding pixels staying as forest. For forest loss/gain, the rules (*L1-L5*/*G1-G5*) are more complicated. The cumulative probabilities (rules of *L1-L5,* rules of *G1-G5*) are 28.0% and 38.2% of the whole spatiotemporal association rules for forest loss in two periods, and 43.5% and 34.6% for forest gain. Although the expressions of spatiotemporal association rules of forest loss/gain are less correlated than persisting forest, some hints are still able to be extracted. From Figure 2. 10(b)(c) and Figure 2. 10(e)(f), all rules (rules of *L1-L5* and rules of *G1-G5*) depict the transformations of "forest to/from grass/pasture" and "forest to/from agriculture". The transformations of "forest to/from grass/pasture" are the most likely to occur, and these regulations work for both forest loss and gain. Being similar to persisting forest, the rules for losing forest or gaining (rules of *L1-L5,* rules of *G1-G5*) forest are in the next time step are due to the surrounding pixels or most of the surrounding pixels losing or gaining forest.

2.4. Discussion

2.4.1 The disparities of tropical forest change

All the measurements and analyses of the tropical forest change were applied on both loss and gain in our study. Overall, the distribution, autocorrelation, local pattern, contagion, and association of tropical forest loss/gain vary over time and space. One of the main reasons that is responsible for these spatiotemporal disparities can be attributed to the spatiotemporal disparities of LUCC driving forces. The drivers contributing to forest loss and gain in economic and biophysical contexts have been demonstrated in several studies (Rudel et al., 2009; Hosonuma et al., 2012), and the potential causes are also included (Sulieman, 2018). Many causes drive deforestation. According to WWF reports, half of all trees illegally harvested from the forest are used as fuel (Bradford, 2018). Some other common drivers are housing and urbanization, commercial uses (paper, furniture, and other commercial goods from timbers), and cattle ranching (Agrawal et al., 2013). For forest gain, the restoration of forest mainly comes from two aspects: natural and anthropogenic factors (Sakho et al., 2011). Generally, forests are able to naturally recover from deforestation in some certain areas, such as in some inaccessible areas or low accessible areas (Nagendra et al., 2003). Most of forest cover is driven by the anthropogenic disturbance. The establishments of national parks and conservation areas, the improvement of environmental awareness among people, and the economic benefits from plantation have been proven to be important for forest gain (Thacher et al., 1996). However, some of the causes are from the intersections of natural and anthropogenic effects. For examples, the site selections of the national park and protected area highly rely on the natural conditions; the anthropogenic disturbance is also affected by geographic elements, such as terrain, soil, etc. (Pfaff, 1997).

In our case, the spatial characteristics of tropical forest loss/gain differ among the two time periods. In 1979-1997, the change of forest cover is dominated by forest gain, whereas in 1997-2015, rates of forest loss and gain are similar. Looking back to the land use history in the Guanacaste region, we are able to discover some clues regarding the temporal disparities. Since the 1950s, the beef industry was prevalent in Costa Rica, especially in the Guanacaste region which accounted for 40% of all beef export in the whole country. Worldwide high beef price drove people to convert forest and other agricultural covers to pasture (Janzen, 2018; Ibrahim et al., 2000). The beef price increased from 2.46 USD/kg in 1960 to 3.59 USD/kg in 1970, then fell to 2.65 USD/kg in 1980, and subsequently to 2.15 USD/kg in 1985 (de Camino Velozo, 2000). In addition, official records showed that a steady supply of mahogany was exported to the United States from 1908 to 1966 (Lamb, 1966). Most of this timber product was from the Guanacaste region (Bolaños and Navarro, 1999; Calvo-Alvarado et al., 2000). Therefore, by the year of 1979, deforestation in the Guanacaste region reached its peak. At that time, forest only covered 26.5% of land area. The upward trend of deforestation leveled off in the middle of 1980s when the beef industry collapsed in Costa Rica. Most of private landowners urgently sought alternative ways of land use to make up for the economic loss caused by the less favorable beef and dairy products.

The Costa Rican government established a national p

ark system by the first forest law (No. 4465) in 1969 (de Camino Velozo, 2000; Campbell, 2002). It explicitly declares that the tax collected by the General Directorate of Forestry should be used for forest restoration and this tax was previously collected by the Public Treasury Ministry (Sittenfeld et al., 1999; de Camino Velozo, 2000). The political support for tropical forest restoration in 1979-1997 was mainly derived from this forest law and the national park system. It was used to restore the tropical forest until 1997. In the year of 1997, a sustainable environmental program which was called the Payments for Environmental Services (PES) started to run. It is formed and completed by three laws in Costa Rica; they are Environmental Law No. 7554 (1995), Forestry Law No. 7575 (1996), and Biodiversity Law No. 7788 (1997) (Sánchez-Azofeifa et al., 2003; 2007; Pagiola, 2008). This program is administrated by the National Forestry Financing Fund (FONAFIFO) (Malavasi and Kellenberg, 2002), an organization for managing and operating the national forestry financing fund in Costa Rica. Several other countries in the region have been watching the results of this program closely, and some are attempting to develop similar programs.

Although the forest policies were applied to two periods, the impacts of them on reforestation were not exactly the same. Comparing the political supports in two periods, the related forest laws in Costa Rica have moved from a “command-and-control” forest strategy in the first period to deregulation of harvests and delegation of responsibility for forest management and conservation to private owners in the second period (de Camino Velozo, 2000). Even though this shift may cause the weakening of government enforcement on reforestation, it witnessed the evolution of centralized administration to regional forestry institutions (such as FONAFIFO). The law 7575 helped more small and medium-sized forest landowners in the rural area during the second period. More than that, this evolution not only made them benefit from forestry incentives but also provided them advance forest technologies, and improved their awareness for sustainable forest development. Unlike the second period, some international agencies, such as the World Bank, the International Monetary Fund (IMF) and the Inter-American Development Bank (IDB), provided funding to reforestation in the early of first period, but they tended to emphasize international trade instead of considering the environmental impacts (de Camino Velozo, 2000).

The spatial disparities of tropical forest loss/gain exist in our study. According to terrain and soil of the Guanacaste region, our study area can be split into two main geographical zones: the Nicoya Peninsula and the Tempisque Basin (Figure 2. 1) (Calvo-Alvarado et al., 2009). The Nicoya Peninsula is covered by a large proportion of steep terrain and thin or infertile soils that are mostly identified as unsuitable or non-arable for agriculture. In contrast, the Tempisque Basin is a much flatter region and is predominantly covered by more fertile soils than the Nicoya Peninsula (Arroyo-Mora et al., 2005a; 2005b). From our results, the frequent forest loss in the first period is concentrated in the central area that belongs to the flat and arable Tempisque Basin. Therefore, such distribution of forest loss is to some extent explained by the terrain and soils over space in 1979-1997. Most of forest gain is detected in the northeastern and southwestern regions, particularly in the Nicoya Peninsula. It is inseparable from the establishment of the protected area (Figure 2. 1). Moreover, the inaccessible and cliff areas provide a natural fence to protect the tropical forest from forest clearing (Pfaff et al., 2014).

Besides the fact that plains and arable soils are much more suitable for agricultural activities, the rapid growth of population is another important reason. According to national statistics (INEC Costa Rica, 2017), the population in the Guanacaste region grew from 191,912 in 1979 to 277,768 in 1997, and then jumped to 396,705 by 2015. The increasing rates are 44.7% and 42.8% in 1979-1997 and 1997-2015, respectively. Nevertheless, from our results (), the surge in population had no significant impacts on urban expansion, and only 16.4 km^2 and 4.7 km^2 of forest were changed to urban area in two time periods. Dramatic transformations of forest areas have occurred in "forest to/from agriculture", and "forest to/from grass/pasture". Therefore, the rapid clearing of forest is more likely to meet the larger demands of agricultural activities that are caused by the growth of population. In addition, the growth of population is not homogeneous over space, such as that the population growth in large cities is supposed to be much faster than small cities or ecological conservation areas. Consequently, the demands for land vary with the sizes of population growth, so the population growth also becomes one of the main reasons for causing the spatial disparities for forest loss/gain. Being similar to population, the uneven spatial distributions of climate, hydrology, economy, and protected areas affect directly or indirectly on the forest loss and gain as well.

The positive spatial autocorrelation of forest loss/gain is present during two time periods. According to the implications of spatial autocorrelation indices, our results indicate that the forest loss/gain has strong clustering, dependency, and similarity with its surrounding districts. Moreover, these clustered distributions exhibit local features across our study area. This spatial feature is largely derived from the nature of driving forces that suggest features near one another are more related than features that are distant. Due to this spatial disparity of forest loss/gain, it is impossible to take advantage of an undifferentiated policy for the whole area. The studies on spatiotemporal pattern of forest loss/gain contribute to the policies of the corresponding forest protection and the strategic forest harvest. In addition, forests provide habitat for a vast array of plants and animals (Stirton, 2018). Thus, the continuous and large-extent of forest loss/gain will have a significant impact on the determination of biodiversity loss/gain. Due to these reasons, the internal mechanisms or potential driving forces that cause a specific spatiotemporal pattern of forest loss/gain are worth to be considered by the government. In our study, a notable spatial pattern in Nicoya Peninsula in 1997-2015 is present. This pattern is explained by a low-low spatial pattern of forest loss and a high-high spatial pattern of forest gain (Figure 2. 9). Combining with the conditions of terrain and soils in Nicoya Peninsula that are not suitable for reforestation (low forest loss and high forest gain), human intervention (e.g., the national park, protected area and PES program) becomes the dominant factor and achieves the success of reforestation in this area.

2.4.2 The spatiotemporal interactions of tropical forest change

The spatiotemporal interactions were analyzed at both patch level and pixel level by using the techniques of spatiotemporal contagion and spatiotemporal association. Spatiotemporal contagion, as a manner of explaining spatiotemporal interaction of forest loss/gain at the patch level, it explores how forest loss/gain patches change over space and time in our study area. Our results indicate that the compact contagion patterns (e.g., infill pattern and edge pattern) are much more than the disordered contagion pattern (spontaneous pattern), no matter for forest loss or gain (Table 2. 5). These results tend to suggest that most patches of forest are changed in an organized way. This is usually observed in the inside or the edge of the forest. This is relatively straightforward to understand in forest loss because forest loss must be losing from persisting forest that is most likely in the edge or the inside of forest. For forest gain, human intervention and natural mechanisms would be discussed in our study. From a human intervention perspective, the growing condition (e.g., soil condition, mean temperature, and precipitation) is one of the effective factors considered for reducing mortality of trees (Günter et al., 2009). Generally, the inside or the edge of persisting forest has more suitable growing conditions than a random location. In addition, the extension of forest is effective in reducing the impacts from edge effects of patches and in conserving biodiversity (Klooster and Masera, 2000). Therefore, in the context of human control, human intervention of forest restoration prefers the edges or the inside of forest rather than random places.

The ways of forest gain subsequent to human intervention can be related to natural mechanisms, such as wind or vertebrate dependent seed dispersal mechanisms (Castillo-Núñez et al., 2011). Comparing with human intervention, natural mechanisms of forest are obviously characterized by the spatial contagion such as their proximity to seed sources or remnant forest, and dispersal locations (Janzen, 1988; Guariguata and Ostertag, 2001; Chazdon et al., 2007). When wind or vertebrate acts as the dominant dispersion mechanism, the forest gain tends to be closer to their seed source (Dosch et al., 2007) and exhibits a higher density in comparison to other forest patches (Muller-Landau et al., 2008). The forest gain patches of vertebrate-borne seed distribution, by comparison, tend to be located further than the patches of wind-borne seed distribution. However, the wind-borne seed distribution is more easily located in the preferred post-feeding territory of the dispersers (Murray, 1988) and most patches show the morphological characteristics of strips.

Additionally, the edge of forest has more potential to gain forest than the internal because the MPA of edge pattern is larger than infill pattern in our study. Meanwhile, the edge is also more prone to lose forest than the inside. From the time perspective, the forest strategies from "command-and-control" in the first period to private management in the second period (de Camino Velozo, 2000) promote that the MPA of forest gain in the second period is smaller than the first period to some extent. Combining with the area difference of infill pattern of forest gain between two periods (the first period is less than the second), it illustrates that the patches of forest gain in the second period are more fragmental than the first period, but the contagion pattern is more compact.

The results of association explain spatiotemporal interactions at the pixel level. From the pixel perspective, the trends of forest change (both loss and gain) observed in the two time periods are similar. The highest probability of forest change is staying as forest in the next time step. The transformations occurred in "forest to/from grass/pasture", and "forest to/from agriculture" take the second and third place. Our results indicate that the transformation of focal pixel highly relies on the transformation of surrounding pixels. On the other hand, it reflects that forest loss/gain of spontaneous pattern accounts for the lowest probability and most of forest is changed in a regular and compact way. Being in line with contagion, the result of spatiotemporal association illustrates that the edge areas between forest and other land covers, especially grass/pasture and agricultural areas, are more easily converted. This result helps to explain the findings by Janzen (2018) and Ewel (1999) who demonstrated that topography, adequate climatic conditions, and accessibility allowed for an easy transformation of forest to pasture and agricultural land.

Understanding the specific ways of forest loss/gain in the Guanacaste region is indispensable to help the government and decision-maker establish and implement related policies in the future. In our case, the patch or pixel features of spatiotemporal contagion and spatiotemporal association can be used to represent the ways of forest loss/gain distribution to some extent. It has been demonstrated that more than 90% forest gain patches appear in the inside or the edge of forests, especially in the second period. Although there is no evidence to exclude the human interventions completely, the influence of natural extension cannot be denied in the internal forest. The fewest contagion pattern is spontaneous pattern, and the role of human intervention in this contagion pattern cannot be ignored as well. Correspondingly, the boundaries between human and nature effects are not very clear in the real world; the most common ways of forest loss/gain are the combinations of natural extension and human plantation.

2.5 Conclusions

This study only considered spatiotemporal features at levels of district, patch, and pixel. However, the connections and variations among different scales were not disclosed in this section. This study provided a method to explore the spatiotemporal features of tropical forest change in the Guanacaste region which also can be used in different LUCC research in the future. In this chapter, it discussed the possible reasons that caused forest loss/gain according to terrain, policy, society, economy, etc. However, what drove the tropical forest change? How much did the drivers affect the tropical forest change? These questions are still needed to be addressed. There is no doubt that the drivers are a series of complex, interactive and hierarchical factors. A more integrated approach to explore the driving factors of forest loss/gain in the Guanacaste region is necessary. Relying on the spatiotemporal features in this study, we can use them for detecting the driving forces in future research, for maintaining the forest system and protecting the forest from the possible threat of deforestation. The results of spatiotemporal features of forest loss/gain, e.g., the spatiotemporal characteristics and the spatiotemporal interactions, also build a foundation for learning land use and land cover from the spatiotemporal evolution and establish a theoretical framework for spatiotemporal modeling in future research. Although considering the spatiotemporal data and the interaction between space and time increases the difficulty of modeling, it will simulate the land cover change much closer to reality.

2.6 References

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2.7 Tables and Figures

Table 2. 1 Acquisition dates, instruments, resolutions, and number of path/row of the data source used for land cover classification.

Acquisition date	Instrument	Resolution	Path/Row	Source
1979-01-06	Landsat 2 MSS	60m	017/052, 017/053, 016/53	https://earthexplorer.usgs.gov/
1997-01-10	Landsat 5 TM	30m	017/052, 017/053	https://earthexplorer.usgs.gov/
2015-01-02	Landsat 8 OLI	30m	017/052, 017/053	https://earthexplorer.usgs.gov/

Table 2. 2 The summary of asscuracies (%) of land cover classification in the years of 1979, 1997, and 2015. The accuracies are assessed by confusion matrix. The land cover categories are as follow: forest, grass/pasture, agriculture, mangrove, urban, and water.

Category	1979 Accuracy (%)		1997 Accuracy (%)		2015 Accuracy (%)	
	Producer's	User's	Producer's	User's	Producer's	User's
Forest	90.2	92.1	86.2	85.9	92.5	93.1
Grass/Pasture	86.3	82.5	84.3	88.2	89.4	82.5
Agriculture	85.2	89.3	82.1	90.1	88.3	89.3
Mangrove	89.0	87.6	88.4	86.7	87.2	88.6
Urban	91.4	86.5	87.1	88.0	89.0	85.2
Water	100.0	100.0	100.0	100.0	100.0	100.0
Overall accuracy	87.6		86.5		90.9	

Table 2. 3 The area of persisting forest and forest loss/gain for the periods of 1979-1997 and 1997-2015. Persisting forest represents forest without any land cover change during a given period. Forest loss/gain is explained by the transformations of "forest to/from other land covers (grass/pasture, agriculture, mangrove, and urban)". The percent of each change type of forest is listed.

Change types	Before	After	1979-1997		1997-2015	
			Area (km^2)	Percent (%)	Area (km^2)	Percent (%)
Persisting forest	Forest	Forest	4,176.9	61.1	5,170.0	72.3
Forest loss	Forest	Grass/Pasture	362.0	5.3	631.1	8.8
		Agriculture	262.6	3.8	336.9	4.7
		Mangrove	30.6	0.5	26.3	0.4
		Urban	16.4	0.2	4.7	0.1
Forest gain	Grass/Pasture	Forest	1,511.7	22.1	654.2	9.2
	Agriculture		360.9	5.3	301.7	4.2
	Mangrove		108.6	1.6	6.3	0.1
	Urban		1.6	0.0	16.2	0.2

1. The percents in table 2. 3 represent the ratios of forest area of each change type and total forest area.

Table 2. 4 The Moran's Is, Z-scores, and p-values in 1979-1997 and 1997-2015 at the district level. The Moran's Is represents the spatiotemporal autocorrelations of forest loss/gain. Z-scores and p-values are returned by a statistical test. The spatiotemporal structure exhibits a statistically significant clustered distribution, when Z>1.96 and p<0.05.

Periods	Change types	Moran's I	Z-score	p-value
1979-1997	Forest loss	0.3	4.0	0.000
	Forest gain	0.4	4.9	0.000
1997-2015	Forest loss	0.5	6.5	0.000
	Forest gain	0.5	5.9	0.000

Table 2. 5 The area proportions and Mean Patch Area (MPA) of three contagion patterns for forest loss/gain in 1979-1997 and 1997-2015 at the patch level. Contagion patterns were calculated by using the Contagion Pattern Index (CPI). Contagion patterns include three categories: infill pattern, edge pattern, and spontaneous pattern; the expressions are from compact to disordered. Mean Patch Area (MPA) is listed in the unit of hectare.

Periods	Change types	Contagion patterns					
		Infill		Edge		Spontaneous	
		Area (%)	MPA (ha)	Area (%)	MPA (ha)	Area (%)	MPA (ha)
1979-1997	Forest loss	50.0	1.1	43.3	3.9	6.7	1.3
	Forest gain	54.1	3.9	42.8	5.7	3.2	0.8
1997-2015	Forest loss	69.6	1.9	27.7	2.3	2.7	0.6
	Forest gain	61.1	1.7	34.8	2.7	4.2	0.8

1. Infill pattern: the most compact contagion pattern ($0.5 \leqslant CPI \leqslant 1$). This pattern is that forest loss/gain patches are encompassed by persisting forest patches and it usually happens in the inside or the edge of persisting forest;
2. Edge pattern: a less compact contagion pattern than infill pattern ($0 < CPI < 0.5$). This pattern is generally observed in the boundaries between forest and other land covers;
3. Spontaneous pattern: the most disordered and low-density contagion pattern ($CPI = 0$). This pattern is that forest loss/gain patches are in random places, which are away from persisting forest patches (no common boundaries).

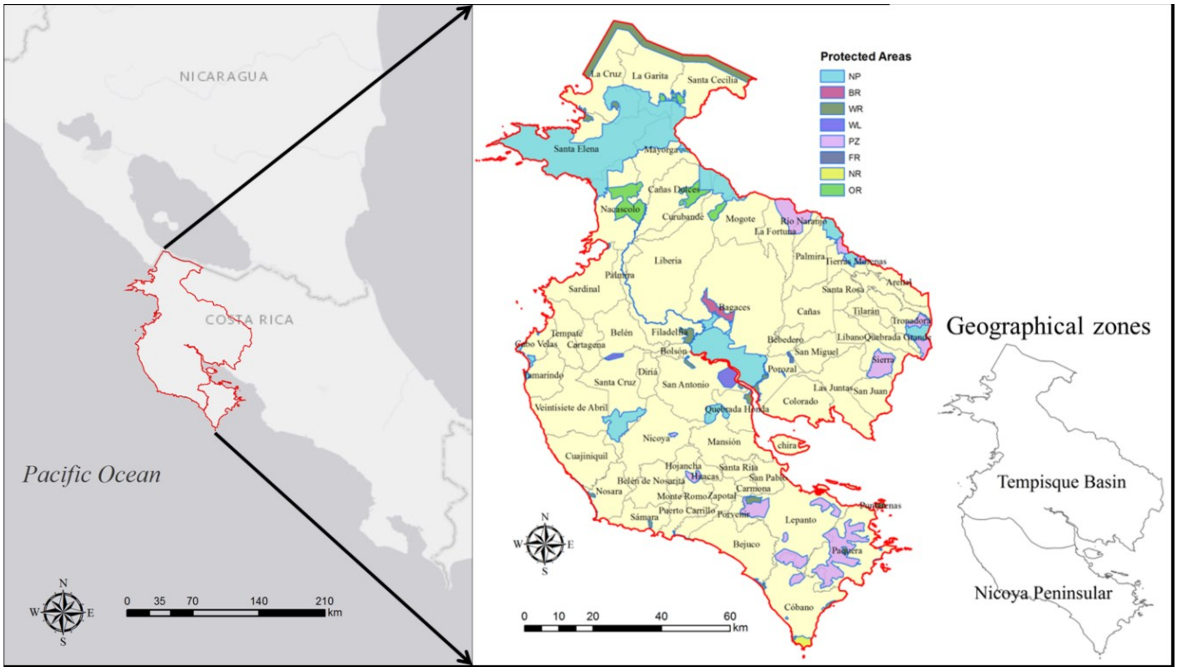

Figure 2. 1 Map of the Guanacaste region, Costa Rica, Central America. This region is located in the northwest of Costa Rica and covers an area of 11,337 km^2. The divisions of districts and geographical zones are shown in the figure.

1. Protected areas: NP = National Parks; BR = Biological Reserves; WR = Wildlife Refuges; WL = Wet Lands; PZ = Protective Zones; FR = Forest Reserves; NR = Nature Reserves; OR = Other Reserves.

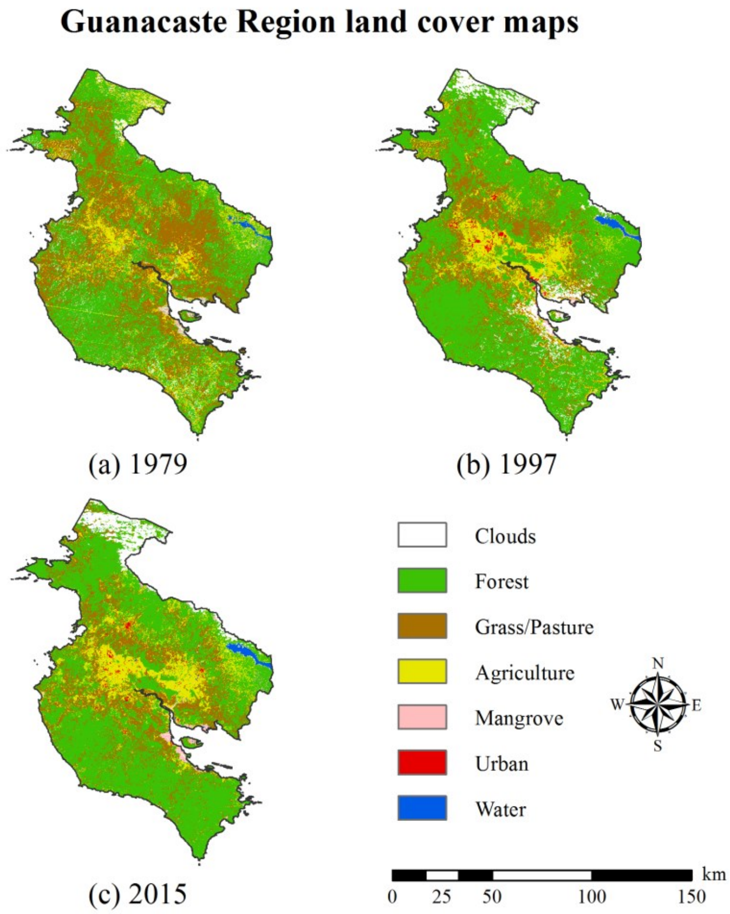

Figure 2. 2 Land cover maps of the Guanacaste region, Costa Rica (1979, 1997, and 2015). The classes of land cover include forest, grass/pasture, agriculture, mangrove, urban, water, and clouds.

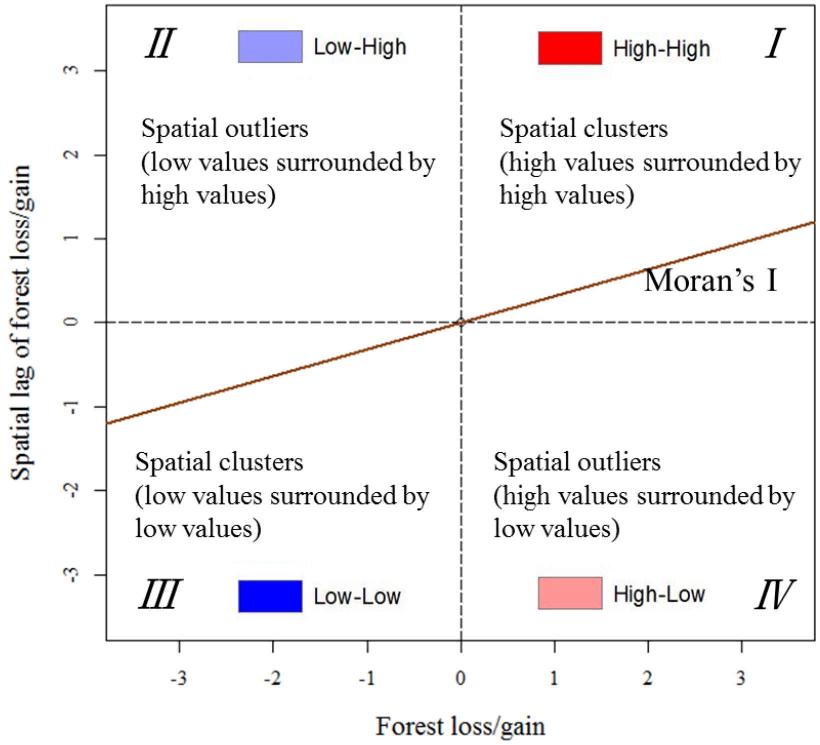

Figure 2. 3 Conceptual figure of Moran scatterplots. X axis represents the forest loss/gain of focal observations; y axis represents the forest loss/gain from surrounding observations. Four local spatial patterns are classified in this figure. Points in quadrant Ⅰ represent high-high pattern (high-value clusters), marked by red; points in quadrant Ⅱ represent low-high pattern, marked by purple; points in quadrant Ⅲ represent low-low pattern (low-value clusters), marked by blue; points in quadrant Ⅳ represent high-low pattern, marked by pink. The linear slope indicates the value of global Moran's I.

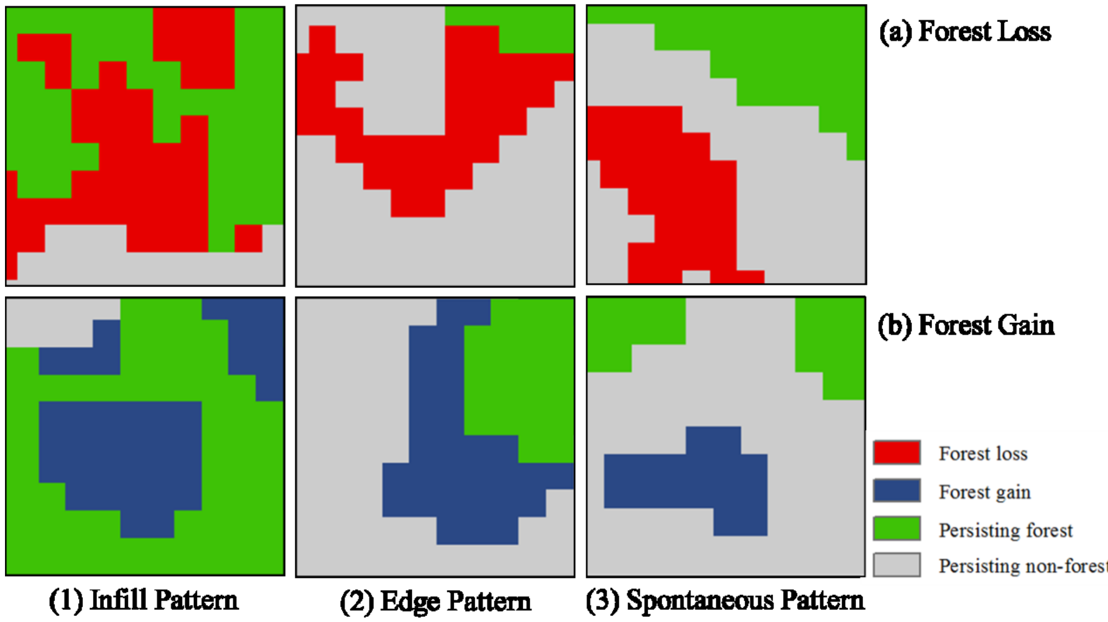

Figure 2. 4 The contagion patterns of tropical forest loss/gain in the Guanacaste region. There are three contagion patterns: (1) infill pattern ($\mathbf{0.5 \leq CPI \leq 1}$), (2) edge pattern ($\mathbf{0 < CPI < 0.5}$), and (3) spontaneous pattern ($\mathbf{CPI = 0}$). (a) represents the contagion patterns of forest loss; (b) represents the contagion pattern of forest gain.

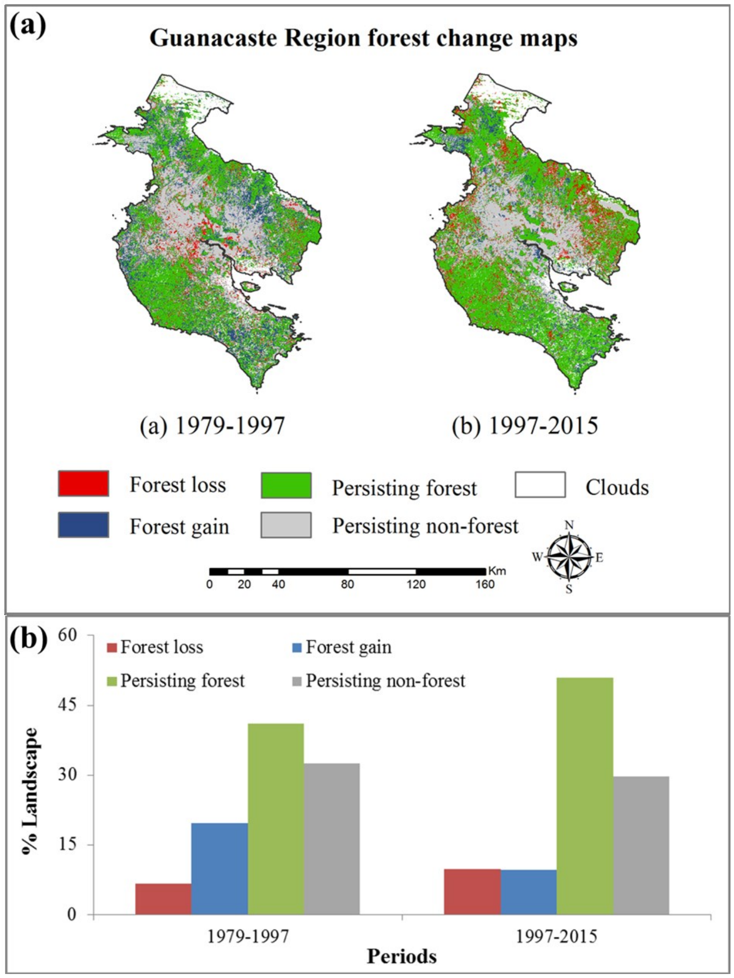

Figure 2. 5 Forest cover change in the Guanacaste region, Costa Rica, during two time periods: 1979-1997 and 1997-2015. (a) Forest change maps: grey areas correspond to persisting non-forest during the research period; red areas correspond to forest loss; blue areas correspond to forest gain, and green areas correspond to persisting forest. (b) Forest cover change percent of total area.

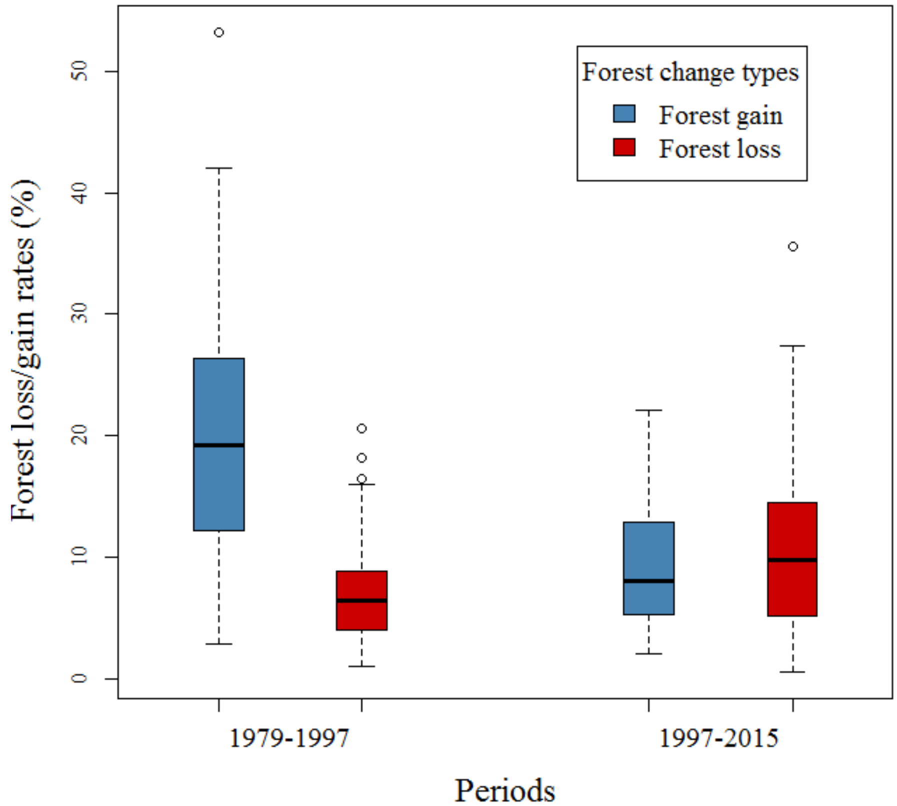

Figure 2. 6 The boxplot of forest loss/gain rates of districts in the time periods of 1979-1997 and 1997-2015. The red ones represent forest loss rates and the blue ones represent forest gain rates. The hollow dots outside of the box plot represent the suspected outliers. The solid lines inside of the box represent the median; the shaded area represents the 1st and 3rd quartiles.

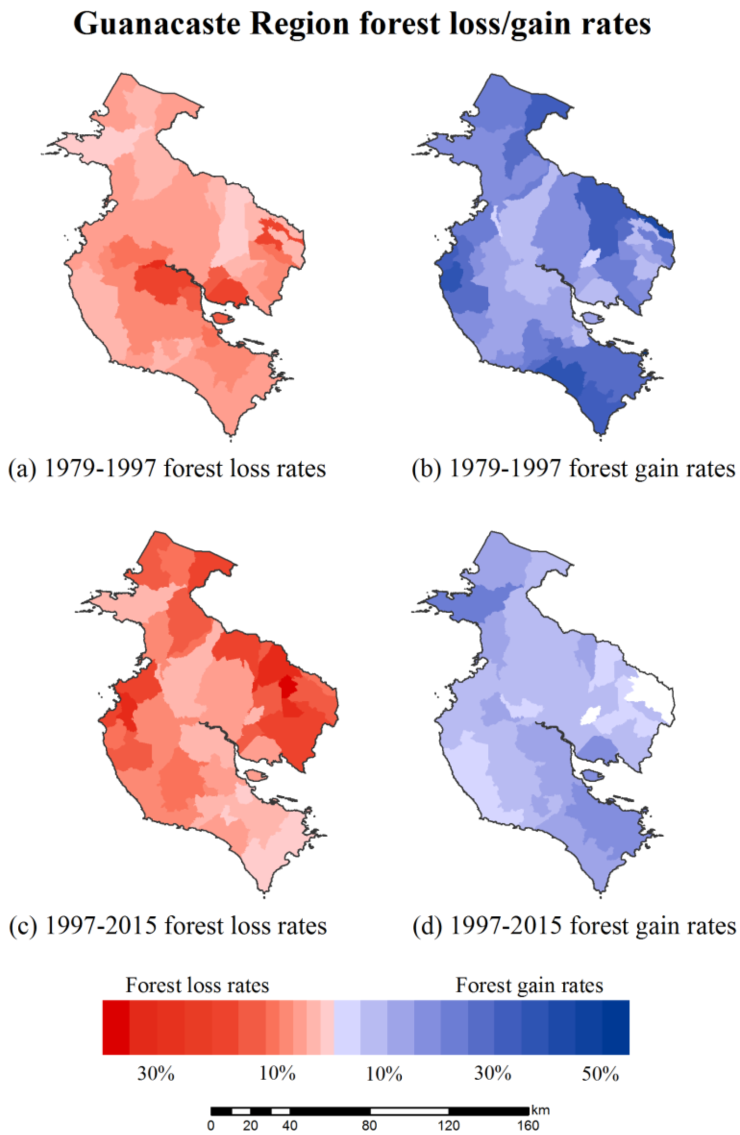

Figure 2. 7 The spatial distributions of forest loss/gain rates in the periods of 1979-1997 and 1997-2015 at the district level. The red figures, (a) and (c), represent the forest loss distribution by districts, and the blue figures, (b) and (d), represent the forest gain distribution.

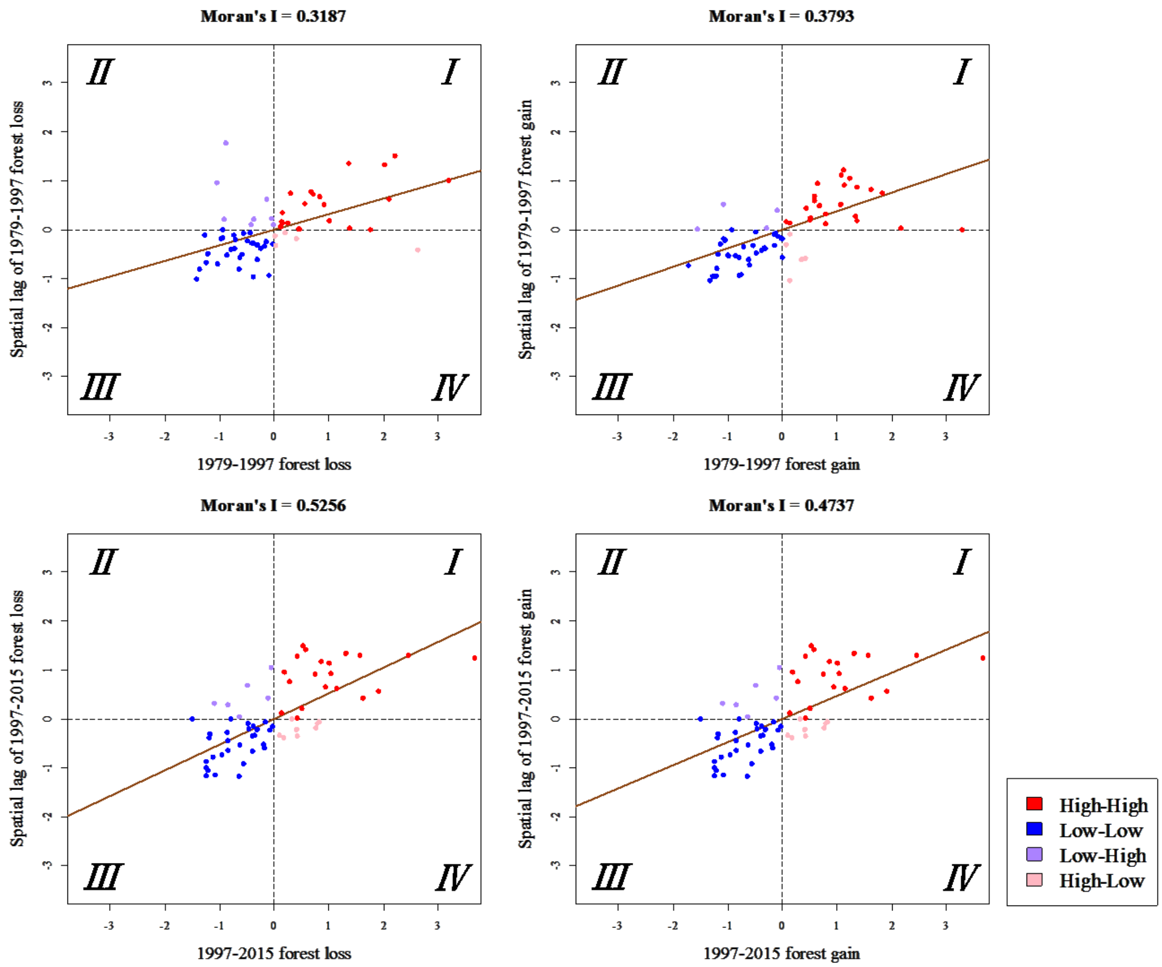

Figure 2. 8 Moran scatterplots for forest loss/gain in two time periods of 1979-1997 and 1997-2015 at the district level. Quadrant Ⅰ and Ⅲ represent the positive autocorrelation, and quadrant Ⅱ and Ⅳ represent the negative autocorrelation. Red points in quadrant Ⅰ are the clusters of high forest loss/gain rates. Blue points in quadrant Ⅲ are the clusters of low forest loss/gain rates. The purple and pink points in quadrant Ⅱ and Ⅳ are low-high pattern and high-low pattern, which also belong to outliers. The solid lines are the linear regression results of points and represent the Moran's Is.

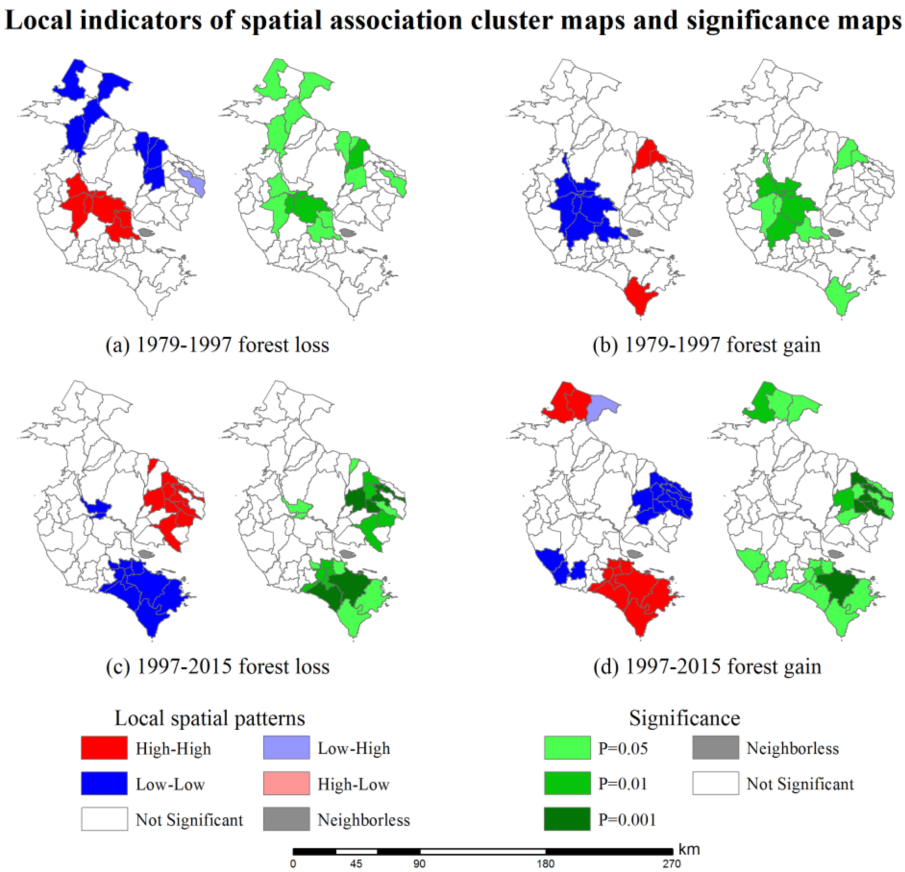

Figure 2. 9 Local indicators of spatial association (LISA) cluster maps and significance maps in time periods of 1979-1997 and 1997-2015 at the district level. The forest loss/gain rates of each district in two time periods are the observations of LISA. The left figures of (a), (b), (c), and (d) represent the districts of local spatial patterns which have passed the significant test. Four significantly local patterns are being detected: high-high pattern, low-low pattern, low-high pattern, and high-low pattern. The right figures show the degree of spatial clustering (three significance levels, p=0.05, p=0.01, and p=0.001).

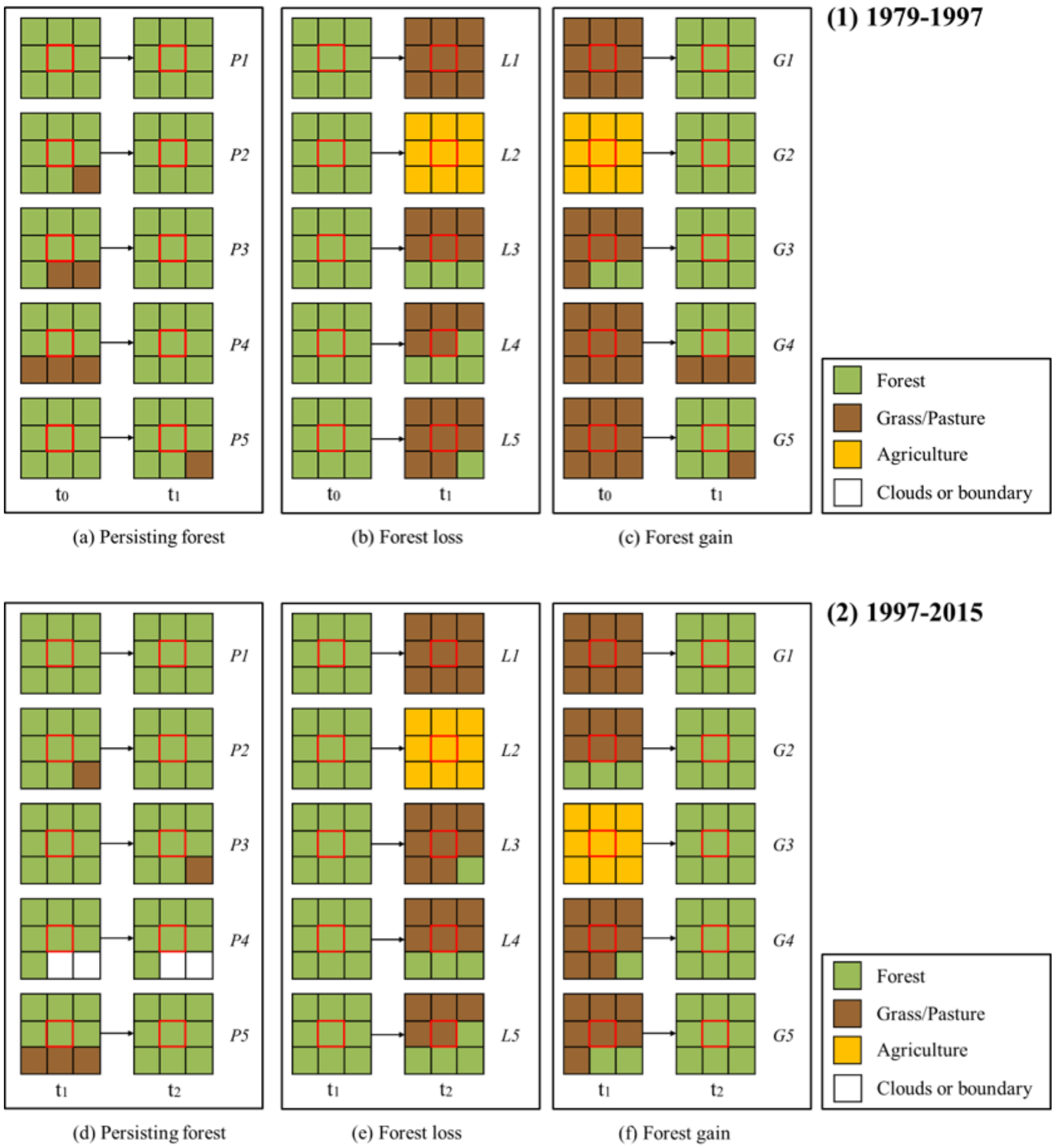

Figure 2. 10 The spatiotemporal association rules of persisting forest and forest loss/gain in 1979-1997 and 1997-2015 at the pixel level. This figure shows five rules with the largest probabilities for each change type. (a)(d) represents persisting forest (rules *Ps*) in two periods; (b)(e) represents forest loss (rules *Ls*), and (c)(f) represents forest gain (rules *Gs*). The pixels with red boundaries are focal pixels. t_0 is the land cover status of pixels in 1979; t_1 represents land cover status in the next time step, 1997; t_2 represents land cover status in 2015.

(a)(b)(c) show five highest probabilities of all spatiotemporal association rules in 1979-1997:

(a) *P1*=66.3%, *P2*=3.0%, *P3*=2.9%, *P4*=2.2%, *P5*=2.1%;

(b) *L1*=10.4%, *L2*=7.7%, *L3*=4.0%, *L4*=3.5%, *L5*=2.5%;

(c) *G1*=26.3%, *G2*=5.2%, *G3*=4.0%, *G4*=4.0%, *G5*=3.9%.

(d)(e)(f) show five highest probabilities of all spatiotemporal association rules in 1997-2015:

(d) *P1*=70.0%, *P2*=2.7%, *P3*=2.2%, *P4*=1.4%, *P5*=1.4%;

(e) *L1*=17.3%, *L2*=6.8%, *L3*=5.4%, *L4*=5.1%, *L5*=3.7%;

(f) G1=16.7%, G2=5.4%, G3=4.6%, G4=4.3%, G5=3.6%.

Chapter 3: Geographical Detector-Based Factors Detection of Tropical Forest Change in the Guanacaste Region, Costa Rica

3.1 Introduction

The influences of forests on our planet have long been postulated. As early as the beginning of the 16th century, from the onset of European settlement in North America, it was believed that the cultivation of forests, wood products, and human settlement had altered the earth's climate (Thompson, 1980). Early in the 18th century, von Carlowitz (1713) firstly put forward the notion of "sustainable forestry". During the late 19th and early 20th centuries, British India, the United States, and Europe started to establish forest preservation (Grove, 1987). As of the 21st century, forestry studies have developed a series of methods for planting, protecting, thinning, controlled burning, felling, extracting, and processing of timber for the purpose of reforestation (Verma, 2015).

Tropical forest is extensive in the forest system, making up around 45% of global forests (Grainger, 2008; Keenan et al., 2015; FAO, 2016). It supports biodiversity of plant and animal species, maintains a balance of carbon dioxide in the air, improves conditions for global climate change, prevents land desertification, and provides many direct and indirect ecosystem services (Houghton et al., 2012). Despite the fact that tropical forests only cover less than 10% of the total landscape, it represents the most abundant ecosystem and the largest terrestrial reservoir of biological diversity, from the genomic to the habitat level (Mayaux et al., 2005). Mayaux et al. (2005) suggested that more than 50% of all known plant species grow in tropical forest ecosystems. However, being such an important ecosystem for the planet, tropical forests are suffering from rapid land use/land cover change (LUCC) (Achard et al., 2002). Agricultural expansion, ranching, fuelwood harvest, commercial harvest, plantation development, shifting cultivation, mining, industry, urbanization, and road building are the factors causing deforestation in tropical regions (Lambin et al., 2001; Elias and May-Tobin, 2011). In recent decades, the situation of clearing tropical forest has shown improvement (Foley et al., 2005), due to the increasing awareness of the importance of tropical forest change (Mittermeier, 1988; Bonan, 2008).

From the related literature, tropical forest change is typically understood as a result of complex interactions between human and environmental driving factors (Schaldach and Priess, 2008). The impact of human activities is becoming more and more dominant in the whole LUCC system. Song et al. (2018) indicated that 60% of all the LUCC processes are associated with direct human activities and 40% with indirect drivers, such as climate change. There is no exception for tropical forest change. The research on tropical forest change has already been one of the most important topics in both human and natural activities (Marfai, 2011; Wang et al., 2012). The key problems in tropical forest change projects are to understand the intrinsic mechanisms of tropical forest change, and then to simulate the dynamic process of tropical forest change. Thus, the research on the rules or the simulations of tropical forest change is always regarded as the research on human and natural variables which are called "driving forces" or "driving factors" (Turner et al., 1993).

Almost all issues related to tropical forest change address driving forces, in some way or another. Generally, driving forces of tropical forest change can be divided into three categories: political drivers, natural drivers, and biophysical drivers (Lambin et al., 2001). Unlike natural drivers, biophysical drivers do not affect tropical forest change directly. In contrast, they can influence tropical forest change and reforestation by the allocation decisions (e.g., through soil quality and landform) (Chowdhury, 2006). The drivers of tropical forest change also highly rely on spatial scales (Geist and Lambin, 2002). In regard to the issues of spatial scales, each scale of tropical forest change system has its own dominant drivers. For local scale, local policy by local policy-makers and small ecological valuable areas might be the important factors (Gibbs and Jonas, 2000). For the regional scale, the degree of connectivity between residential areas and some suitable infrastructures play a significant role (Hodgson et al., 2009). For the national scale, the rules of macro-economy and society should be the main determinants of tropical forest change (Ostrom, 1998).

As of today, there are a growing number of studies addressing the issues of dynamic processes and driving forces of tropical forest change (Foley et al., 2005). However, there are still several problems with future research that must be resolved. Firstly, tropical forest change is caused by a series of complex determinants (Wang et al., 2010). Moreover, non-linear relations between tropical forest change and potential drivers increase the complexity of drivers' analyses (Verburg et al., 2004). Secondly, driving forces of tropical forest change always include quantitative factors and descriptive factors. Descriptive factors are the main constituents of driving factors, which were largely ignored by the previous research. For descriptive data, although it can explain the state of land use pattern exactly, it is not efficient for calculations that are used in land use change model (Lambin et al., 2001). In the space, descriptive drivers can generally be characterized by geographical divisions with distinctly descriptive information. The commonly used technique for considering descriptive data into a LUCC model is quantification. Generally, three different techniques can be distinguished: 1) Statistical theories and physical laws-based methods, all the relations are used on the LUCC processes directly (Ruben et al., 1998; Fischer and Sun, 2001). However, these methods are difficult to use for the quantification of social-economic factors due to lacking priori or empirical data. Because of this, they are hardly used in integrated landscape. 2) Empirical methods, the main steps of them are using past data as empirical drivers to construct transformed functions for the processes of LUCC and then estimating LUCC in the future (Bockstael, 1996; Chomitz and Gray et al., 1996; Geoghegan et al., 1997; Pfaff, 1997). The disadvantages of these methods are low explanation and the uncertainty of forecasting, which is caused by the inconsistency between past data and future data (Hoshino, 1996; Veldkamp and Fresco, 1996). 3) The methods of experts' ratings, which highly rely on the experiences of experts. The results would be too arbitrary and have individual differences (Lau and Redlawsk, 2001). Thirdly, the spatial patterns of tropical forest change are supposed to be considered as variables in spatial structure analysis algorithms (Mackiewicz et al., 1979). However, few studies have taken this into account. Diniz-Filho et al. (2003) determined that spatial autocorrelation in ecological data can inflate Type I errors in statistical analyses. In the current studies, the Spatially Lagged Regression Model can contribute to eliminating the spatial autocorrelations while conducting spatial analyses (Anselin, 1988a).

The aim of this study is to detect the impacts of geographical drivers on tropical forest change in the Guanacaste region, Costa Rica. The driver's detection is based on each geographical division without quantification. Meanwhile, it also considers spatial autocorrelations that may exist among each geographical division of a given driver. In this section, spatial pattern analysis and geographical detector are used to detect the impact of geographical factors on forest change over the past 36 years, between two time periods of 1979-1997 and 1997-2015, and to explore the following three questions in the Guanacaste region: (1) Does spatiotemporal autocorrelation affect forest change (both loss and gain) among different geographical divisions? (2) How does a given geographical factor act on tropical forest loss/gain? and (3) Which geographical factor is responsible for such a loss/gain? How much does a given geographical factor affect forest loss/gain?

3.2 Methodology

Our study aims to analyze the geographical factors of tropical forest loss/gain based on dynamic processes. It takes two time periods into account, which are 1979-1997 and 1997-2015. The year 1997 was chosen as an interval year because this year was an important political era in Costa Rica. The protected policies were changed from the National Park Systems to Payments for Environmental Service (PES) program contracts since 1997. In the previous research, some findings reported that quantitative drives affected tropical forest change in the Guanacaste region. For example, Calvo-Alvarado et al. (2009) discussed a series of socioeconomic data which might affect tropical forests change. This study involved population, percentage of population (classified as urban and semi-urban), percentage of workers (employed in agriculture), percentage of households (using electric lighting), percentage of households (using wood or coal for cooking), national tourist visitation and spending, hotel numbers, PES contracts in the Guanacaste region, cattle farmers, national beef price and exports. In our study, we paid more attention to descriptive data (also regarded as geographical data) by using a method, which is called geographical detector, to explore the geographical drivers without quantification. At the same time, it also takes spatial characteristics into account when conducting geographical detectors. It not only maintains the objectivity of analysis but also avoids the uncertainties caused by quantification.

3.2.1 Study area

The Guanacaste region is located in the northwest of Costa Rica (coordinates: 10°37'N, 85°26'W) and includes the Guanacaste province and the Nicoya peninsula (belongs to Puntarenas province) (Figure 3. 1). It is bordered by Nicaragua to the north, faces the Pacific Ocean to the west, and has a long coastline in the south. The Guanacaste region is a seasonally tropical area. The annual average temperature in this region is 25.8 ℃, and it is derived from the meteorological data of 33 years (1981-2013). Our study area experiences seasonal rainfall. The average annual precipitation is 1919.5 mm, and more than 85% of the total precipitation occurs mainly between May and October, which is known as the wet season. The rest of the year is called dry season (from November to April), but the precipitation in November is relatively high compared with other months during the dry season, because it is a transition month between dry and wet seasons.

3.2.2 Materials and Methods

3.2.2.1 Geographical factors

In this study, the Guanacaste region is able to be divided into different geographical divisions (geographical units) based on the different descriptive information of a given driving factor. According to previous research (Veldkamp and Fresco, 1996; Letcher and Chazdon, 2009) and the current situation of our study area, geographical factors from three aspects were collected: political factors, natural factors, and biophysical factors. The landform data was derived from Digital Elevation Model (DEM) data by following the Hammond's macro landform classification procedure (Hammond, 1954; 1964; Morgan and Lesh, 2005). The DEM data was from the National Forestry Financing Fund (Fondo Nacional De Financiamiento Forestal, FONAFIFO) (FONAFIFO, 2019). The others were acquired from ATLAS Costa Rica 2014 (Ortiz-Malavasi, 2014) and the Ministry of Environment and Energy official website (Ministerio del Ambiente y Energia, MINAE) (MINAE, 2019).

Political factors are policy-based geographical units which reflect how policies vary over space. These factors include conservation divisions, protected areas, and PES-priority areas. 1) Conservation divisions. They are administrative divisions which have autonomy on forest management, and are managed by the National System of Conservation Area (Sistema Nacional de Áreas de Conservación, SINAC) directly. 2) Protected areas. They are divided by the different forest laws and regulations. According to the classification from the International Union for the Conservation of Nature (IUCN) (Dudley, 2008), protected areas are divided into geographical units which have different protection levels. 3) PES-priority areas. The areas are divided into geographical units by whether PES program preferentially funds or not.

Natural factors consist of 1) ecoregion, which presents the geographical divisions that assemble different natural communities and species; 2) watershed, which divides geographical units by different drainage basins, and 3) life zone, which depends on the classification of Holdridge life zone system and includes the information of annual precipitation, bio-temperature, potential evapotranspiration ratio, etc. (Holdridge, 1967).

Biophysical factors are composed of 1) landform, which, according to the Hammond's procedure, is made up of the characteristics of slope, relief, and profile; 2) relief; and 3) soil order, which is a general soil taxonomy that is used to describe soil nature and properties (USDA, 2019).

The divisions for each geographical factor are shown in Figure 3. 2. The detailed attributes for each geographical division are listed below Figure 3. 2.

3.2.2.2 Spatial relationships

Spatial relationships were considered as spatial autocorrelation and local spatial patterns in this study. They were detected using the techniques of Global Moral's I (referred to as Moran's I) and Local Indicator of Spatial Autocorrelation (LISA) (Moran, 1948; Anselin, 1995) for each geographical factor. Moran's I is used to measure spatial autocorrelation based on both feature locations and feature values simultaneously (Moran, 1948). LISA was improved by Anselin (1995) based on Moran's I, and it measures spatially local heterogeneity (Wang et al., 2016), which can be regarded as local spatial patterns.

In this study, spatial autocorrelation is used to explain the relationship of cluster, dispersion, or random of forest loss/gain among divisions for a given geographical factor in a map. Meanwhile, LISA is used to indicate the specific geographical units of clustered and dispersive distribution of forest loss/gain. At the same time, the local clustered distributions (clustered patterns) are categorized as high-high pattern (the focal division with high forest loss/gain rate surrounded by the divisions with high forest loss/gain rate) and low-low pattern (the focal division with low forest loss/gain rate surrounded by the divisions with low forest loss/gain rate), and the local dispersive distributions (dispersive patterns) are categorized as low-high pattern (the focal division with low forest loss/gain rate surrounded by the divisions with high forest loss/gain rate) and high-low pattern (the focal division with high forest loss/gain rate surrounded by the divisions with low forest loss/gain rate) (Anselin, 1995).

3.2.2.3 Spatial lag inverse operators

According to the potential presence of spatial autocorrelation and local spatial patterns of forest loss/gain, the exhibitions of forest loss/gain are affected not only by driving forces but also by spatial relationships. To eliminate the effects caused by spatial relationships, we used a model known as the Spatial Linear Regression Model (Anselin, 1988a). It is based on Tobler's First Law of Geography (Tobler, 1970), and it states that everything is related to everything else, but near things are more related than distant things. The general expression of Spatial Linear Regression Model was proposed by Anselin (1988b):

$$\boldsymbol{y} = \rho \boldsymbol{W_1} \boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1}$$

$$\boldsymbol{\varepsilon} = \boldsymbol{\lambda} \boldsymbol{W_2} \boldsymbol{\varepsilon} + \boldsymbol{\mu}, \boldsymbol{\mu} \sim N(\boldsymbol{0}, \boldsymbol{\Omega}), \Omega_{ii} = h_i(za), h_i > 0 \tag{2}$$

where $\mathbf{y}$ is a $n \times 1$ vector and is the dependent variable in the equation; $\mathbf{X}$ is a $n \times k$ dependent matrix; $\mathbf{W_1}$ and $\mathbf{W_2}$ are $n \times n$ standardized or unstandardized spatial weight matrices and represent spatial autoregressive processes of dependent variables and residuals. ρ is the coefficient of spatially lagged variable $\mathbf{W_1 y}$; $\boldsymbol{\beta}$ is a $k \times 1$ parameter vector of dependent matrix $\mathbf{X}$; $\boldsymbol{\varepsilon}$ represents a vector of random error. The disturbance p is taken to be normally distributed with a general diagonal covariance matrix $\mathbf{\Omega}$. Ω_{ii} represents the diagonal elements of the error covariance matrix. The diagonal elements allow an exogenous variables z and a constant term a. h_i is a function relationship.

When $\rho = \lambda = a = 0$, the equation (1) is a general regression model without reflecting spatial relationships among geographical units. Based on equation (1), two commonly used models are built, Spatial Lag Model (SLM) and Spatial Error Model (SEM) (Anselin, 1988a). SLM model considers spatial autocorrelation, which is from the independent variable. That is the feature in one location is not only affected by dependent variables in this location, also affected by features in the surroundings (Fischer and Wang, 2011). When $\rho \neq 0, \lambda = 0$, the equation (1) is transformed as SLM (Anselin, 1988b). SEM considers spatial autocorrelation, which is from the residuals. When $\rho = 0, \lambda \neq 0$, the equation (1) is transformed as SEM. Generally, Maximum Likelihood (ML) and Generalized Method of Moments (GMM) can be used to estimate SLM and SEM instead of Ordinary Least Squares (OLS) (Fischer and Wang, 2011).

Considering the fact that geographical factors were analyzed in our study, the quantification of dependent variables would cause the uncertainties in the system. Therefore, we chose SLM to avoid the risk of quantification in this case. When $\lambda = 0$, the expression of SLM is:

$$\boldsymbol{y} = \rho \boldsymbol{W_1} \boldsymbol{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{3}$$

Therefore, according to SLM, forest loss/gain can be explained by the idea that forest loss/gain in a focal division is not only affected by independent variables (geographical factors) but is also influenced by forest loss/gain in surrounding divisions.

According to the study of Anselin (1988a), he considered ρ as a global parameter in models, and ρ is derived from global spatial autocorrelation. However, the spatial relationships are characterized by local spatial patterns in reality. Thus, for adjusting the local spatial heterogeneity of forest loss/gain, we adopted a local parameter of spatial patterns, $\boldsymbol{P}$, instead of global parameter ρ in our study. The expression of local SLM is transformed into:

$$\boldsymbol{y_t} = \boldsymbol{PW}\boldsymbol{y_t} + \boldsymbol{X\beta} + \boldsymbol{\mu} \tag{4}$$

where $\boldsymbol{y_t}$ is a $n \times 1$ vector and represents forest loss/gain rates of the t^{th} geographical factor in each unit; n means the unit number of the t^{th} geographical factor; $\boldsymbol{P}$ is a $n \times n$ diagonal matrix, and reflects significantly local spatial patterns; $\boldsymbol{W}, \boldsymbol{X}, \boldsymbol{\beta}$ represent the same variables with equation (1).

Equation (4) provides the relationship between forest loss/gain rates and geographical factors under the condition of the presence of local spatial patterns. Then, a method which is called spatial lag inverse operator is adopted to filter out the effects of spatial lag based on equation (4). In our study, spatial lag is marked by local spatial patterns. The term, spatial lag, is not the same as the concept of time lag in time series analysis, but instead, it can be understood as a concept of distributed lag. Being different from the time lag operator, spatial lag inverse operator is an algorithm to resolve spatial autocorrelation by considering a weighted sum of all values belongings to a given class (Chen et al., 2015). At the same time, spatial lag inverse operator helps us to filter out this spatial relationship (Anselin, 1988b). The operator is expressed as:

$$\boldsymbol{y'_t} = (\boldsymbol{I} - \boldsymbol{PW}) * \boldsymbol{y_t} \tag{5}$$

$$\boldsymbol{P} = diag(\rho_1, \rho_2, \rho_3, \cdots, \rho_n) \tag{6}$$

where $\boldsymbol{I}$ is a n by n identity matrix; $\boldsymbol{P}$ is a diagonal matrix of significant LISAs; $\boldsymbol{W}$ is the spatial weights matrix; n is the unit number of the t^{th} geographical factor. $\boldsymbol{y'_t}$ is a n by 1 vector of forests change rates after filter out the local spatial autocorrelation. Considering the Modifiable Areal Unit Problem (MAUP) may be caused by the area differentials among geographical units in our study, all the filtering out calculations are conducted on the rates of forests loss/gain.

3.2.2.4 Geographical detector

Geographical factors are mainly detected by the technique of "geographical detector" in this study. The geographical detector is based on spatial variation analysis of a given geographical strata in order to assess the effect of geographical factors on tropical forest change (Wang et al., 2010), and it assumes that tropical forest change is distributed homogenously in each geographical division. This method is able to be used to detect the locations of forest loss/gain accurately, to determine the geographical factor that is responsible for this loss/gain, to calculate the magnitude of the effect, and to examine how a given geographical factor acts on tropical forest loss/gain. The expressions of geographical detector are:

$$P_x = 1 - \frac{\sum n_{x_i} Var_{x_i}}{nVar} \tag{7}$$

$$\sum n_{x_i} = n \tag{8}$$

where x is factor X; n_{x_i} is the i^{th} unit of factor X; n is the total area; $Var_{x_i}$is the variance of forest loss/gain in the X_i unit; Var is the total variance of forest change of a given geographical factor. Values of P_x are the explanation degrees of factors and usually range from 0 to 1. When P_x is 0, that means factor X can explain 0% on forest loss/gain, and when P_x is 1, that means factor X can explain 100% on forest loss/gain.

The geographical detector takes advantage of the comparisons of variances within units, variances between units, and total variance to analyze the descriptive and geographical data. In other words, this technique can be understood as an ANOVA implemented in space. Considering a descriptive or geographical factor as a block, it not only explains how a factor impacts forest loss/gain spatially, but it also avoids the uncertainties from quantifying descriptive information.

3.3 Results

3.3.1 Spatial autocorrelation

Spatial autocorrelations were calculated among different divisions for all geographical factors, and comparisons were made for both forest loss and gain in two time periods (Table 3. 1). For political factors, both forest loss and gain are positively spatially autocorrelated ($\mathrm{I} = 0.17, \mathrm{p} < 0.001$ and $\mathrm{I} = 0.14, \mathrm{p} < 0.001$) among the geographical unis of PES-priority areas in the first period. In the second period, the spatial autocorrelation of forest gain is statistically significant ($\mathrm{I} = 0.11, \mathrm{p} < 0.05$), whereas forest loss is not spatially autocorrelated. Also, there is no significantly spatial autocorrelation among the geographical units of conservation and protected areas, regardless of forest loss or gain.

For natural factors, there is no significant spatial autocorrelation among the geographical divisions of watershed. Among the geographical divisions of ecoregion, Forest loss in the second period is positively spatially autocorrelated ($\mathrm{I} = 0.03, \mathrm{p} < 0.05$). Additionally, forest loss and gain in the second period among the geographical divisions of life zone are positively spatially autocorrelated as well ($\mathrm{I} = 0.19, \mathrm{p} < 0.05$ and $\mathrm{I} = 0.27, \mathrm{p} < 0.01$).

For biophysical factors, spatial autocorrelations among the geographical divisions are more significant than the geographical divisions of political factors and natural factors. All forest loss and gain in the geographical divisions of biophysical factors exhibit significant positive spatial autocorrelation except for forest gain in the geographical divisions of soil order in the second period. The Moran's Is of forest loss in the first period and forest gain in the second period in the geographical divisions of landform reach up to 0.53 ($p < 0.001$) and 0.47 ($p < 0.001$), respectively.

3.3.2 Factor detection of forest change

The detection of geographical factors on forest loss/gain in two periods was shown in Figure 3. 4. Our result indicates the relative importance of each geographical factor, and it demonstrates how much geographical factors can explain forest loss/gain. It varies with forest change type (forest loss and gain) and the time period in our study.

For the first period (Figure 3. 4(a)), the importance of conservation, PES-priority area, ecoregion, and watershed is relatively low, and these geographical factors can explain less than 5% of forest loss/gain according to our results. Although the factor of protected area has a low explanation as well, it explains 11.5% of forest loss in the first period, which is much higher than forest gain (3.8%) in the same period. In this period, the factor of life zone has the highest importance, and it explains 27.3% of forest loss and 27.7% of forest gain, respectively. Additionally, the biophysical factors, such as landform, relief, and, soil order, have relatively high importance on forest loss/gain. Generally, the effects of biophysical factors acting on forest loss play a slightly more important role than forest gain.

For the second period (Figure 3. 4(b)), the importance of conservation, PES-priority area, and ecoregion is still relatively low. However, watershed becomes the most important factor in this period, regardless of forest loss or gain (39.6% and 43.8%). The explanations of relief and soil order on forest loss/gain maintain between 20%-30%. Generally, the explanations of conservation, PES-priority area, ecoregion, watershed, landform, relief, and soil order have no remarkable differences between forest loss and gain. However, it is worth mentioning two factors: protected area and life zone. From Figure 3. 4(b), it shows that the effect of protected area explains 18.6% of forest loss, which is significantly higher than forest gain (10.2%). In contrast, the life zone factor is more important to forest gain in the second period, and it explains 8.0% of forest loss, whereas it explains 17.9% of forest gain.

Comparing with two periods, we demonstrate that the factor of life zone is the most important in the first period, whereas, in the second period, it turns out to be the factor of watershed.

Additionally, there are obvious differences of watershed between two periods. Watershed explains 5.1% of forest loss in the first period, which increases to 39.6% in the second period, and it explains 4.2% of forest gain in the first period, which increases to 43.8% in the second period. In contrast, the explanations of life zone decrease dramatically, regardless of forest loss or gain. The importance of landform on forest loss/gain also decreases in the second period, from about 13% to about 10%. Our results indicate that the importance of PES-priority area steadily rises from 5.3% on forest loss and 5.4% of forest gain to 8.8% on forest loss and 6.9% on forest gain. Generally, forest gain in the first period is obviously stronger than the second period. The impacts of political factors on forest loss/gain are the lowest among the geographical factors in three categories.

3.3.3 Forest change detection in each geographical unit

Analysis of geographical factors detected the differences of importance and explanations on forest loss/gain for each geographical factor during two periods. However, figures in this section explain how a given geographical factor acts on forest change loss/gain and what differences exist among the geographical units of each geographical factor (Figure 3. 5, Figure 3. 6, and Figure 3. 7).

3.3.3.1 Political factors

For conservation, our results indicate that it has a relatively stronger effect on forest gain in the first period than the second period (Figure 3. 5(a)(b)). In the second period, the forest gain rate in the Guanacaste Conservation Area (ACG, 12.7%) is higher than that of other conservations (Figure 3. 5(b)). Also, the impact of protected area on forest gain in the first period is stronger than the second (Figure 3. 5(c)(d)). In the first period, forest gain rates in all divisions of protected area are higher than 15%, except wetlands (WL, the forest gain rate is 1.7%) and biological reserves (BR, the forest gain rate is 12.7%). Additionally, forest loss in wetlands is higher than forest gain in the first period (Figure 3. 5(c)). However, forest gain in wetlands (the forest gain rate is 22.6%) and national parks (NP, the forest gain rate is 21.1%) are higher than in other units of protected area in the second period (Figure 3. 5(d)). From Figure 3. 5(e)(f), it can be seen that forest gain rate in the units of PES-priority area is higher than in the unit of none PES-priority area, for both two periods.

3.3.3.2 Natural factors

Regarding the natural factors, Figure 3. 6 presents the different impacts of natural divisions on forest loss/gain. For the factor of ecoregion, the impacts on forest loss/gain have a significant difference between two time periods (Figure 3. 6(a)(b)). The rates of forest gain are between 20%-30% in the first period, whereas the rates are under 10% in the second period, especially for forest gain in the unit of Santa Clara plain (SCP, the gain rate is 29.3% in the first period, and it drops down to 2.4% in the second period). The units of Tilaran cordillera (TC) and Lomas Buenavista cordillera (LBC) have relatively high forest loss rates, and they are 17.1% and 13.7%, respectively. As presented in Figure 3. 6(c), the impacts on forest gain have no remarkable difference among the geographical units of watershed in the first period, except for Papagayo gulf island (PGI) with a low gain rate of 0.1%. However, the rates of forest loss in Santa Elena bay island (SEBI, the loss rate is 21.7%) and Nicoya gulf island (NGI, the loss rate is 14.0%) draw our attention in the same period. A significant difference of forest gain can be seen in the second period (Figure 3. 6(d)). Our results indicate that the forest gain rates in Papagayo Gulf watershed (PG) and Nicaragua lake watershed (NL) are relatively high with 21.5% and 18.4%, respectively. The gain rates in Nicoya Gulf watershed (NG, 12.5%), Nicoya gulf island (NGI, 15.7%), and Papagayo gulf island (PGI, 14.2%) are moderate. The rates in the rest of the units of watershed are comparatively low (under 10%). The most drastic difference is observed in the factor of life zone (Figure 3. 6(e)(f)). There are three geographical units with extremely high forest gain rates in the first period. They are the divisions of premontane into basal moist forest (bh-p6, 44.5%), tropical dry forest (bs-T, 43.3%), and tropical dry into moist forest (bs-T2, 47.4%). Moreover, there are two units with distinctly low forest gain rates, lower montane wet forest (bmh-MB) with 6.2% and tropical wet forest (bmh-T) with 0.1% (Figure 3. 6(e)). Although forest loss in the first period is less than the second period, the loss rate of premontane into basal moist forest (bh-p6) is fairly high (20.5%) in the first period. In the second period, the difference of forest gain is larger than forest loss (Figure 3. 6(f)). Most rates for forest gain tend to be similar in this period, except for premontane into basal moist forest (bh-p6, the gain rate is 42.5%). The high forest loss rates are observed in premontane moist forest (bh-P, 28.7%), premontane into basal moist forest (bh-P6, 33.4%), tropical moist forest into premontane (bh-T12, 23.3%), lower montane wet forest (bmh-MB, 24.7%), tropical wet forest (bmh-T, 27.6%), and tropical dry into moist forest (bs-T2, 20.2%). Then, the forest loss rates in other divisions are below 15%.

3.3.3.3 Biophysical factors

From a biophysical factor perspective, forest gain in each unit of landform is obviously more than forest loss in the same unit during the first period (Figure 3. 7(a)). The sequence of forest gain rates from high to low is in the hill (26.3%), mountain (21.8%), and plain (18.1%) in the first period. In the second period, forest loss is slightly more than forest gain for the landform factor, except the unit of plain. The rates of forest loss (10.5%) and gain (12.3%) are very similar in the plain in the second period. The differences among the divisions of relief are much more significant than landform. From Figure 3. 7(c), we can see that the units of flat, moderately wavy, and softly wavy have a powerful impact on forest gain (the gain rates are 43.0%, 29.3%, and 24.9%) in the first period, which are much higher than the units of strongly wavy and extremely wavy (the gain rates are 8.8% and 13.0%) in the same period. However, it is worth mentioning that the units of strongly wavy and extremely wavy not only have low forest gain rates but also have relatively high forest loss rates (12.8% and 15.3%) in the first period. Meanwhile, the forest loss rate of flat subdivision (11.9%) is second only to the subdivisions of strongly wavy and extremely wavy. In the second period (Figure 3. 7(d)), the rates of forest gain in all subdivisions are very similar (between 13%-18%), but there is no forest gain occurring in the subdivision of strongly wavy. The rates of forest loss in the subdivisions of moderately wavy and flat are considerably high (18.7% and 15.2%). For soil order, forest gain in the first period is obviously more than the second (Figure 3. 7(e)(f)). Meanwhile, forest loss is opposite to forest gain, especially in the units of andisols (An, the loss rate is 38.6%) and ultisols (U, the loss rate is 27.2%).

3.4 Discussion

3.4.1 The influence of spatial autocorrelation

With the development of Geographical Information System techniques and the increasing accessibility of Remote Sensing images, today about 60% of all information is geospatially referenced (Hahmann and Burghardt, 2013). Therefore, it is imperative to introduce spatial information into classic statistical analyses. Generally, statistical analyses assume independence among observations (Kruskal, 1988). However, Legendre (1993) indicated that when data represents the measurements with spatial information, the assumption of independence is not always met because of spatial autocorrelation. Meanwhile, Mets et al. (2017) summarized the defects of spatial models without considering the assumption of independence. They mainly affect statistical inference in the following ways. (1) Cliff and Ord (1972) demonstrated that spatial autocorrelation emerges as a non-random geographic association of residual errors in regression analyses. (2) Legendre (1993) claimed spatial autocorrelation might strongly inflate the risk of Type I errors when testing the statistical hypothesis by using a standard method (e.g., ANOVA, regression, and correlation). (3) Telford and Birks (2005) reported that non-spatial models used for spatial data would internally transform spatial autocorrelation into the goodness of fit for the model, and it undermines the comparisons of model performance. (4) Lennon (2000) explained non-spatial models would enlarge the effects of more autocorrelated variables if the variables exhibit different degrees of autocorrelation.

All of our results were analyzed based on considerations of spatial autocorrelation in this study. Also, our results indicate that the spatial autocorrelations of forest loss/gain exist for most geographical factors (Table 3. 2). The spatial autocorrelations of forest loss/gain among the units of biophysical factors were revealed to be more significant than political factors and natural factors. It also indicates that forest loss/gain in each unit of biophysical factors is dependent from forest loss/gain in the surrounding units. Considering forest loss/gain is partly caused by spatial autocorrelation, we can explore the dependence and the continuity among the units of geographical factors to explain, to some extent, the spatial autocorrelation in forest loss/gain. From the political factors perspectives, the divisions are considerably decided by policy-makers and existing administrative boundaries in our study area. For example, conservation was used to integrate development and conservation around its extensive protected areas (Jones, 1992). Similar to conservation, the system of protected areas has been developed for many years, and it was legislated to be established, monitored, and managed by the National System of Conservation Area (SINAC) (SINAC, 2019). The protected areas are defined as follows: delimited geographical space, and officially declared and designated to a management category by virtue of its natural, cultural, and/or economic importance (Weisleder-Weisleder, 1998). The classifications of protected areas not only follow the IUCN protected area categories (Dudley, 2008) but also added some nuances that are more representative of the reality of Costa Rica (SINAC, 2019). Thus, the units of protected areas largely reflect integrated artificial planning. According to the program of PES that began to run since 1997 in Costa Rica, the high spatial autocorrelation of forest loss/gain among the units of PES-priority areas in the first period is not impossibly affected by the PES-priority planning. However, it still requires further research to determine whether the spatial pattern in the first period has an impact on the decision and allocation of PES-priority area in the second. The PES-priority areas are artificial divisions, which are aimed at reforestation and forest protection. They are considered to be artificial planning geographical divisions as well. Thus, we deduce that for the geographical factors with more intense human intervention, forest loss/gain is less spatially autocorrelated among the units. The artificial planning would intervene and prevent the spatial patterns of forest loss/gain from occurring to some extent.

For natural factors, our results indicate that there is no significant spatial autocorrelation of forest loss/gain among the geographical units, except for the units of life zone factor in the second period. Unlike political factors, the natural factors-based units are almost always continuous and dependent with surrounding geographical units in space (Rahbek and Graves, 2001; van Rensburg et al., 2002), such as ecoregion and life zone. According to the study by Diniz-Filho et al. (2003), he explained the relations between spatial autocorrelation and red herrings in geographical ecology, and asserted that the similar environmental factors among adjacent cells caused the spatial autocorrelation of species richness at small scales. However, the similarities of natural factors among adjacent divisions have no significant impacts on the spatial autocorrelation of forest loss/gain in our study. The potential causes can be explained as the scale effects and the complexity of integrated factor in our case. When the scale of geographical divisions is much larger than the characteristic scales of spatial pattern of forest loss/gain, it may cause no significant spatial autocorrelation exhibited among the geographical units (Delcourt et al., 1982; Wu, 2004). As the descriptions of natural factors, ecoregion and life zone are comprehensive concepts. The ecoregion is a conceptual ecosystem associated with characteristic combinations of soil and landform that characterize the region (Omernik, 2004; Brunckhorst, 2013). Life zone is classified by the combination of annual precipitation, biotemperature, potential evapotranspiration ratio, latitudinal regions, and altitudinal belts (Holdridge, 1967). In fact, these two geographical factors imply more than one variable when we are conducting the analyses of ANOVA or regression. Thus, in some cases, the integrated or comprehensive factors would spuriously internalize spatial pattern into the overfitting of different attributes (Mets et al., 2017). This also suggests that the integrated or comprehensive variables are supposed to be selected and processed carefully when modeling for a spatial dynamic process. Alternatively, the low influence of a given geographical factor on forest loss/gain is another explanation of no significant spatial pattern in our study. However, further comparisons need to be discussed with the impacts in each unit of geographical factors.

Significant spatial autocorrelations were observed in forest loss/gain divided by biophysical factors. Being similar to natural factors, the geographical units of biophysical factors are characterized by the continuous and dependent features with adjacent units. However, forest loss/gain is significantly spatially autocorrelated among the geographical units of biophysical factors. Although the scale effects still exist in these factors, the monotonous attribute of biophysical factor may be the main reason for the presence of highly spatial autocorrelation of forest loss/gain. Each of landform, relief, and soil order represents monotonous variables or similar attributes. Also, the importance of a given biophysical factor on forest loss/gain in each unit is another potential feature in our study.

3.4.2 The interpretations of geographical factors

The causes behind forest loss/gain are complicated (Barbier et al., 2010), and they have not yet been systematically studied until Calvo-Alvarado et al. (2009) discussed a series of socioeconomic data which might affect tropical forest change in the Guanacaste Region (Castro-Salazar and Arias-Murillo, 1998). However, there is summative evidence for lack of research in descriptive factors of forest change (Lambin et al., 2001). Thus, techniques that can detect the factors of forest loss/gain, especially for the descriptive factors, are needed. Nine geographical factors were detected in this paper as a response to our objective.

Wang (2010) reported the health risk assessment of neural tube defects in the Heshun region, China, by using geographical detectors. He firstly proposed this technique to detect the impact of geographical factors on the health risk assessment over space. Additionally, he claimed the presence of global spatial autocorrelation in his study. However, local spatially autocorrelated indicators were considered in our study instead of global spatial autocorrelation when eliminating the effects derived from spatial relationships. Local indicators tend to be more sensible and accurate than global indicators due to the presence of local spatial patterns of geographical data (Bivand et al., 2009). According to the different local spatial patterns, forest loss/gain in each geographical unit was supposed to be adjusted by the corresponding autocorrelated coefficients in this study.

Our results indicate that forest gain in the first period is stronger than that of the second period. Comparing the backgrounds of two time periods in our study, we found that the beef industry, which was regarded as the primary income in the Guanacaste region in the early 1970s (Calvo-Alvarado et al., 2009), got a tremendous beating in the middle of the 1980s (Sánchez-Azofeifa et al., 2007). The drop on global beef price (from 3.59 USD/kg in 1970 to 2.15 USD/kg in 1985) (de Camino Velozo, 2000) prompted most Costa Ricans to abandon cattle ranching and changed the way of land use/land cover for more economic benefits, and it directly caused reforestation in our study area. Additionally, the government took a series of policies to restore and protect forests, such as the National Park System in the first period and PES program in the second period (Sánchez-Azofeifa et al., 2007). However, the crisis of the beef industry and the urgent demand of increasing income are still the main reasons of reforestation. Thus, forest gain in the first period is more dominant than the second period.

In our study, the impacts of political factors on forest loss/gain are the lowest among the factors in three categories, especially the factor of conservation (Figure 3. 4). Therefore, the situation of forest loss/gain in each unit of conservation is found to be similar. The factor of protected area is the most important factor among political factors, and it influences forest loss greater than forest gain, regardless of the time period. The rates of forest loss in the unit of biological reserve (BR) are extremely low in two periods (Figure 3. 5(a)(b)). This can be attributed to the fact that the Biological reserve is a strict nature reserve and has the highest level of protection according to IUCN categories (Dudley, 2008). There are three biological reserves in our study area (Islas Negritos (1973), Isla Guayabo (1973), and Lomas Barbudal (1986)) (SINAC, 2019). These areas are strictly protected from all human disturbance, except for scientific research, environmental monitoring, and education (Jeffries, 2006; Lausche and Burhenne-Guilmin, 2011). Long-Term protection and strict restriction create an ideal eco-environmental region in biological reserves. Meanwhile, the non-protected area has an obvious higher forest loss than the protected areas in the second period. From our results, the system of protected area plays an important role in forest restoration, especially in stopping forest loss in the second period. The factor of PES-priority area contributes to forest gain in the second period, since the PES program began to run in 1997. In general, the related forest policies are beneficial to reforestation and forest protection, but they are not the dominant factors.

The impacts of natural factors exhibit a large difference based on our results. The factor of ecoregion contributes little to forest loss/gain in both time periods. Our findings indicate that the factor of life zone strongly controls forest loss/gain occurrence in the first period, whereas watershed is the most important factor of forest loss/gain in the second period. Watershed provides a hydrologic condition for forests, especially in the dry season, and forests also protect watershed health (Master et al., 1998). One of the most notable weather patterns, El Niño, reduces the rainfall and increases the drought of forests in our study area. The more frequent and more severe El Niño in the second period (Table 3. 2), released by National Oceanic and Atmospheric Administration, NOAA) (Jan Null, 2019) is partially responsible for the large difference of forest loss/gain among the units of watershed in this period. According to the ways of life zone classification, this factor mainly conveys the integrated information about forest growing (annual precipitation, biotemperature, potential evapotranspiration ratio, etc.) (Holdridge, 1967). It is the most important factor in the first period, and also Figure 3. 6(e) shows premontane into basal moist forest (bh-p6), tropical dry forest (bs-T), and tropical dry into moist forest (bs-T2) are highly responsible for forest gain in the first period. Combining with the figure of Holdridge life zone (Figure 3. 8), we demonstrate that sub-humid area in premontane or lower montane belts strongly controls forest gain occurrence in our study area. Apart from human intervention, the natural conditions cannot be ignored. The results illustrate that the area with the conditions of 1000-2000 mm annual precipitation, >18 ℃ biotemperature, and potential evapotranspiration ratio between 0.5 and 2, helps reforestation and plantation in the first period. Additionally, a similar situation of forest gain happens in the second period (Figure 3. 8). Meanwhile, forest loss is mainly distributed among humid and per-humid areas with the conditions of 1000-8000 mm annual precipitation, >12 ℃ biotemperature, and 0.25-1 potential evapotranspiration ratio.

Biophysical factors were determined to be more important than political factors and natural factors in controlling forest loss/gain. Landform has a relatively moderate impact on forest loss/gain in both two time periods. In the first period, the plain area has the lowest forest gain rate and the highest forest loss rate. Thus, even under the situation of the prevalence of forest gain in the first period, the plain area is still a geographical unit experiencing the rapid shifts from forest to non-forest (Figure 3. 7(a)). This could be partially attributed to the plain area being suitable for both plantation and agricultural activities. Also, it could be explained by the expansions of agriculture and urbanization. The inaccessibility or low accessibility of strongly wavy and extremely wavy areas determines the low forest gain rate in two time periods, which are mainly reforested by nature or compulsory intervention. From the attributes of soil, our results demonstrate that andisols and ultisols highly contribute to forest loss in our study area. In United States Department of Agriculture (USDA) soil taxonomy, it is known that andisols is formed in volcanic ash or other volcanic ejecta (USDA, 2019). It contains a high proportion of glass and amorphous colloidal materials, and is typically fertile (Shoji et al., 1994). This soil generally supports intensive croppings in the world, such as rice, fruit, tea, coffee, or tobacco (Baligar et al., 2004). Thus, this is also a reason that the forest is transformed into agricultural area in the unit of andisols, which is expressed as forest loss in this study. Considering the other soil order with high forest loss, ultisols, it is also known as red clay soil and characterized by acidic soil with relatively low fertility (Schoenholtz et al., 2000). Grainger (2013) proposed that ultisols' lack of plant nutrition is a driving factor behind tropical deforestation.

3.5 Conclusions

Generally, the geographical factors with more human intervention or highly comprehensive attributes would cause the reduction or elimination of spatial autocorrelation in our study. Alternatively, forest loss/gain exhibits highly spatially autocorrelated patterns among the geographical units with natural, continuous, dependent, and monotonous attributes. For reforestation and forest protection, human intervention is as important as natural factors, because human intervention is able to effectively eliminate the side effects of spatial autocorrelation on forest loss/gain. For example, appropriate policies can reverse the situations of forest loss clusters which are caused by natural, continuous, dependent, and monotonous factors.

From our results, the impacts of political factors are very limited to forest loss/gain among the geographical factors. The most important factors are still biophysical factors, especially the factor of soil order. The characteristics of soil strongly control forest change in our study, and it is also an important determinant of land use planning. Relief is another important factor in controlling forest change. Thus, the accessibility is still a problem to be considered in future planning of land use. The impacts of watershed and life zone on forest change vary with time; this means forest change depends on the conditions which are related to climate change, such as the changes of annual precipitation, average temperature, etc.

Our study is only conducted on geographical factors. There is no discussion about the factors from the aspects of society, economy, population, etc. Thus, we could not isolate all the potential factors which drive forest loss/gain. Additionally, forest loss/gain cannot be partially explained by one or a series of factors. Actually, it is always a comprehensive consequence of the interaction of multiple factors (Wang et al., 2010). Thus, more combined and comprehensive driving factors of forest change should be addressed in future research. This study detected impacts on forest loss/gain not only from natural or biophysical aspect but also from human intervention. These findings provide valuable information for future planning, which is supposed to rely on natural and biophysical conditions. They also contribute to the simulation of LUCC process through laying out the restricted information for each geographical unit.

3.6 References

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3.7 Tables and Figures

Table 3. 1 The global spatially autocorrelated coefficients (Moran's I) of forest loss/gain among the units of geographical factors in two time periods (1979-1997 and 1997-2015). Three categories, nine geographical factors, were considered.

		Moran's I			
		1979-1997		**1997-2015**	
		Forest loss	**Forest gain**	**Forest loss**	**Forest gain**
Political factors	Conservation	-0.27	-0.22	-0.60	0.12
	Protected area	0.05	0.09	0.08	0.04
	PES-priority area	0.17^{***}	0.14^{***}	0.11^{*}	0.07
Natural factors	Ecoregion	0.19	-0.18	0.03^{*}	0.20
	Watershed	-0.32	0.02	-0.17	0.32
	Life zone	0.11	0.02	0.19^{*}	0.27^{**}
Biophysical factors	Landform	0.53^{***}	0.29^{*}	0.24^{*}	0.47^{***}
	Relief	0.27^{***}	0.30^{***}	0.36^{***}	0.13^{**}
	Soil order	0.22^{***}	0.25^{***}	0.18^{**}	0.06

1. *** Denotes the spatial autocorrelation is statistically extremely significant ($p < 0.001$);
2. ** Denotes the spatial autocorrelation is statistically highly significant ($p < 0.01$);
3. * Denotes the spatial autocorrelation is statistically significant ($p < 0.05$);
4. Numbers without a symbol reflect no statistically significant spatial autocorrelation;
5. According to the values of autocorrelated coefficients for some geographical factors are very small, the Moran's Is were kept two decimals.

Table 3. 2 The years and magnitudes of El Niño. The magnitudes were classified into four categories released by the National Oceanic and Atmospheric Administration (NOAA): week, moderate, strong, and very strong. The dashed line splits the El Niño years in the first and the second periods.

El Niño years and magnitudes			
Weak	Moderate	Strong	Very strong
1979-1980	1986-1987	1987-1988	1982-1983
2004-2005	1994-1995	1991-1992	1997-1998
2006-2007	2002-2003		2015-2016
2014-2015	2009-2010		

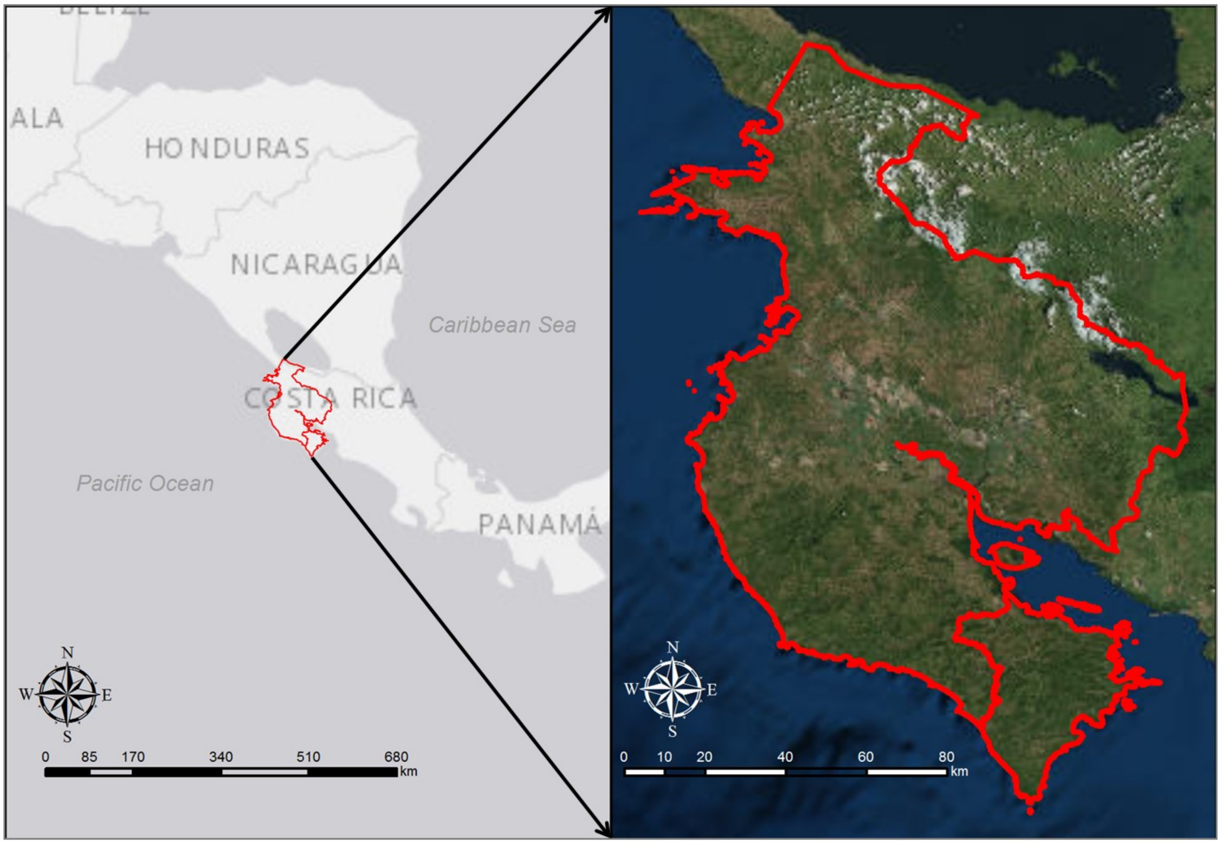

Figure 3. 1 Map of the Guanacaste region, Costa Rica, Central America (coordinates: 10°37'N, 85°26'W). This region includes the Guanacaste province in the north and the Nicoya peninsula in the south.

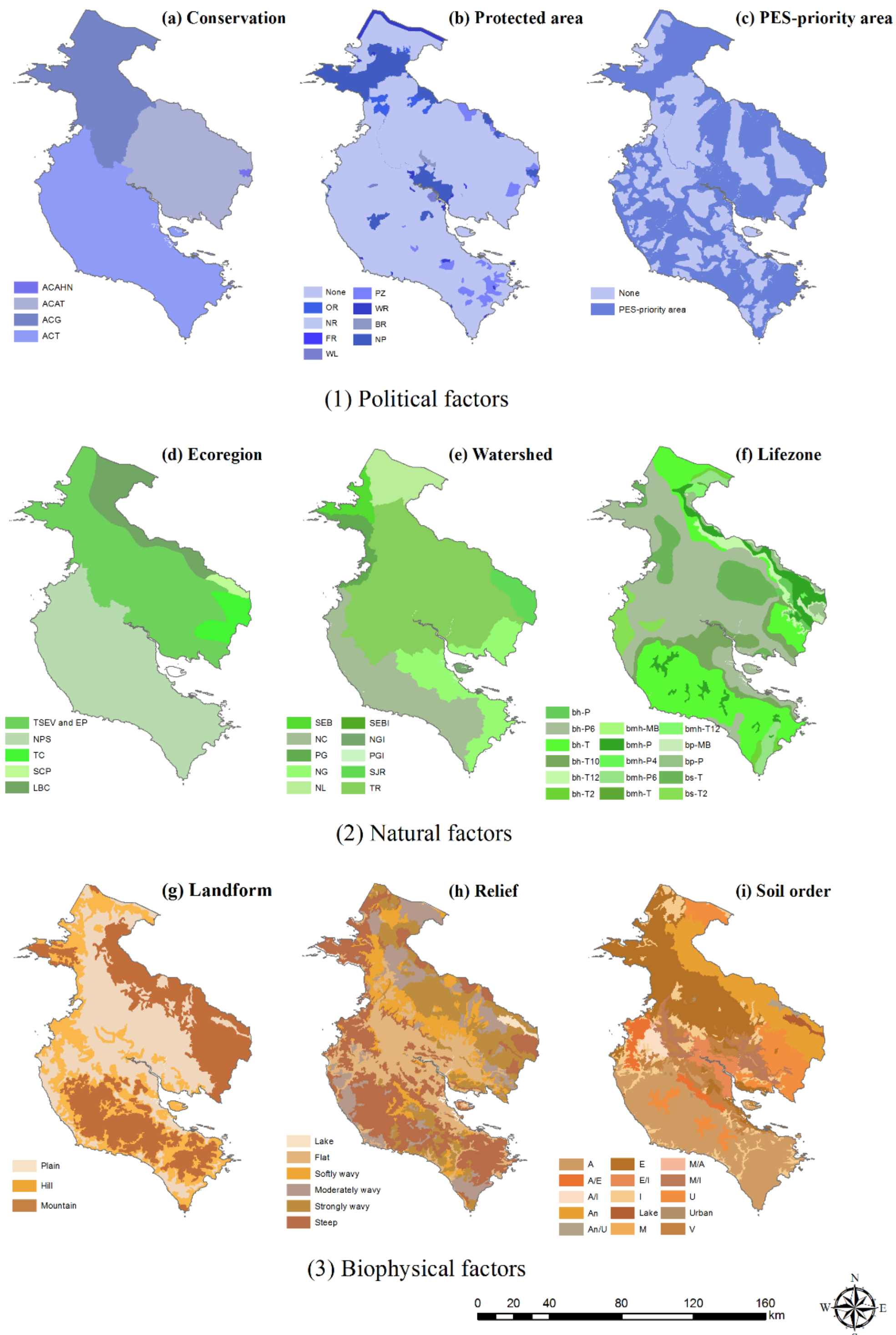

Figure 3. 2 Divisions for each geographical factor. The geographical factors were collected from three aspects: political factors, natural factors, and biological factors. The attribute for each geographical division was listed below.

1. Political factors:
   (a) Conservation: ACAHN = Arenal Huetar Norte Conservation Area, ACG = Guanacaste Conservation Area, ACAT =Arenal Tempisque Conservation Area, ACT = Tempisque Conservation Area;
   (b) Protected area: None = Non-protected area, OR = Other Reserves, NR = Nature Reserves, FR = Forest Reserves, WL = Wet Lands, PZ = Protective Zones, WR = Wildlife Refuges, BR = Biological Reserves, NP = National Parks;
   (c) PES-priority area: None = Not being funded by PES, PES-priority area = Priority being funded by PES;
2. Natural factors:
   (d) Ecoregion: TSEV = Tempisque-Punta Santa Elena Valley and Esparza-oro Plain, NPS = Nicoya Peninsula Sierra, TC = Tilaran Cordillera, SCP = Santa Clara Plain, LBC = Lomas Buenavista Cordillera;
   (e) Watershed: SEB = Santa Elena Bay watershed, NC = Nicoya Costal watershed, PG = Papagayo Gulf watershed, NG = Nicoya Gulf watershed, NL = Nicaragua Lake watershed, SEBI = Santa Elena Bay Island, NGI = Nicoya Gulf Island, PGI = Papagayo Gulf Island, SJR = San Juan River, TR = Tempisque River;
   (f) Lifezone: bh-P = Premontane moist forest, bh-P6 = Premontane into basal moist forest, bh-T = Tropical moist forest, bh-T10 = Tropical moist into dry forest, bh-T12 = Tropical moist forest into premontane, bh-T2 = Tropical moist into wet forest, bmh-MB = Lower montane wet forest, bmh-P = Premontane wet forest, bmh-P4 = Premontane wet into rain forest, bmh-P6 = Premontane into basal wet forest, bmh-T = Tropical wet forest, bmh-T12 = Tropical wet forest into premontane, bp-MB = Lower montane rain forest, bp-P = Premontane rain forest, bs-T = Tropical dry forest, bs-T2 = Tropical dry into moist forest;
3. Biophysical factors:
   (g) Landform
   (h) Relief: Flat = Slope area 0-2%, Softly wavy = Slope area 2-15%, Moderately wavy = Slope area 15-30%, Strongly wavy = Slope area 30-60%, Extremely wavy = Slope area >60%;
   (i) Soil order: A = Alfisols, A/E = Alfisols/Entisols, A/I = Alfisols/Inceptisols, An = Andisols, An/U = Andisols/Ultisols, E = Entisols, E/I = Entisols/Inceptisols, I = Inceptisols, M = Mollisols, M/A = Mollisols/Alfisols, M/I = Mollisols/Inceptisols, U = Ultisols, V = Vertisols.

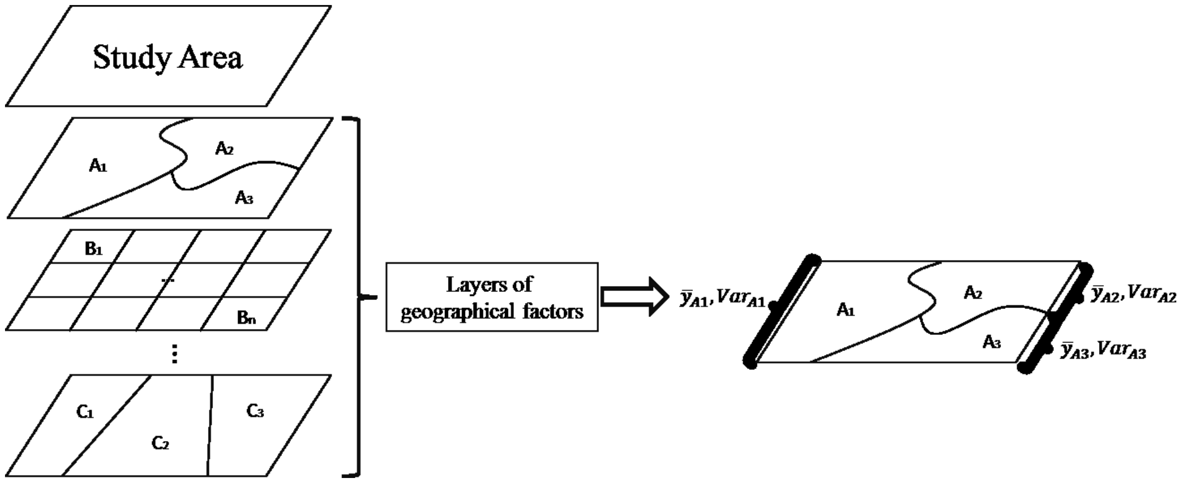

Figure 3. 3 Principle of the geographical detector. The study area can be divided into different divisions by layers of geographical factors. Such as by factor A, it is divided into $\boldsymbol{A} = \{\boldsymbol{A_i};\ \boldsymbol{i} = \mathbf{1, 2, 3}\}$, then by factor B, factor C, … The geographical detector compares variances within units, variances between units, and total variance to analyze the descriptive and geographical data. In other words, this technique can be understood as an ANOVA implemented in space (Wang et al., 2010)

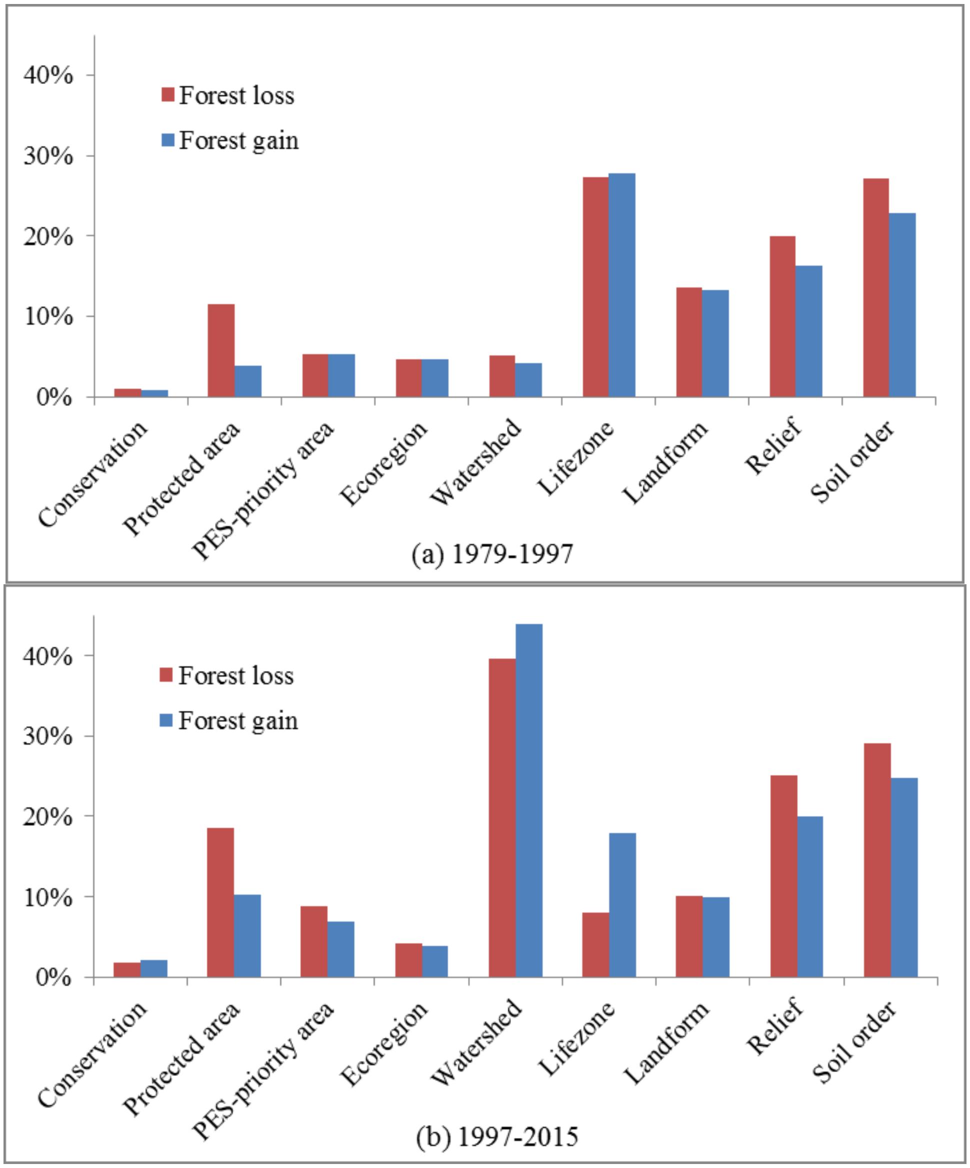

Figure 3. 4 The explanation degrees of geographical factors on forest loss/gain in two periods (1979-1997 and 1997-2015). X-axes represent geographical factors; y-axes represent the explanation degree of each geographical factor. When $\boldsymbol{P_x}$ is 0, that means factor X can explain 0% on forest loss/gain, and when $\boldsymbol{P_x}$ is 1, that means factor X can explain 100% on forest loss/gain.

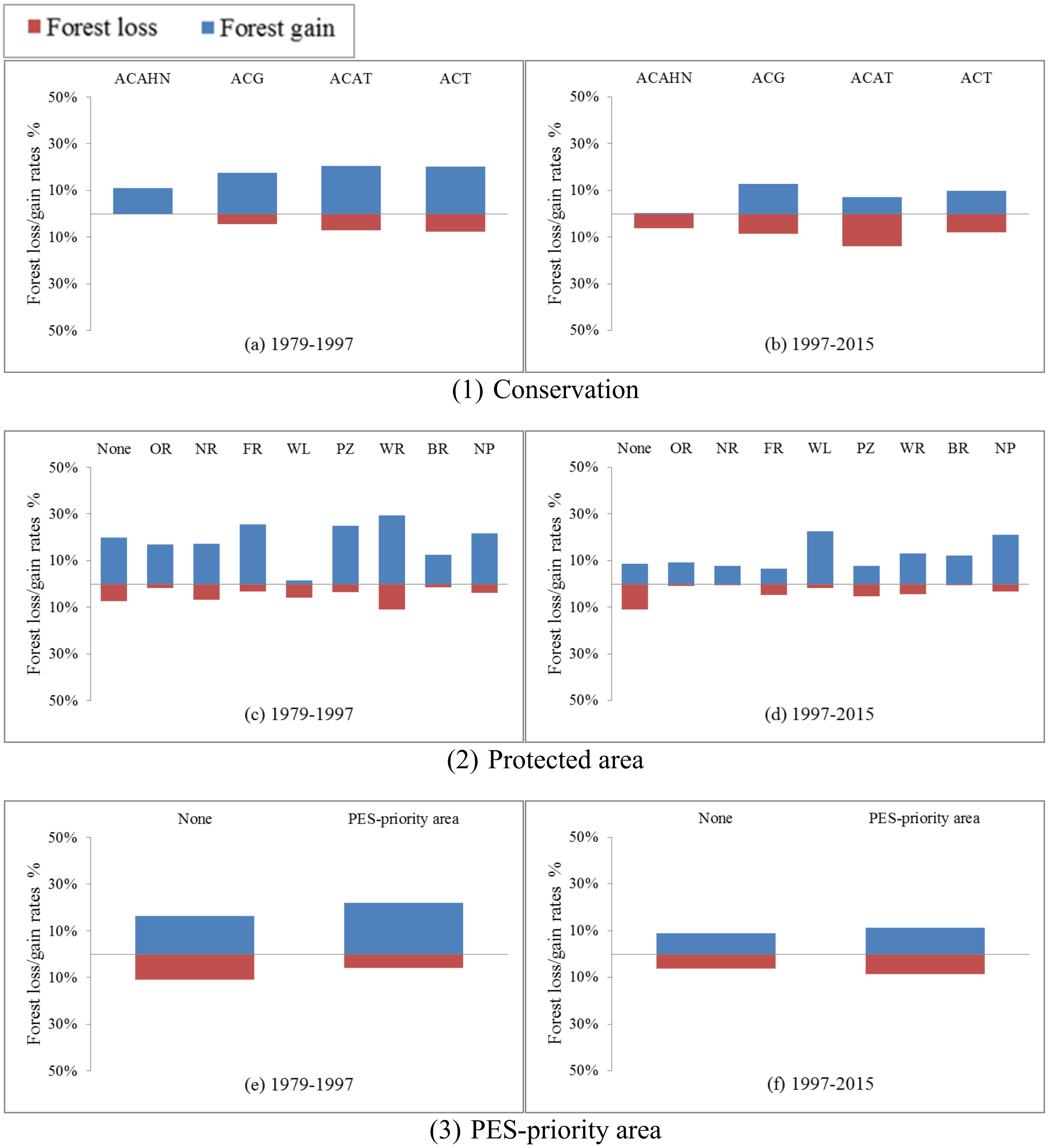

Figure 3. 5 The forest loss/gain rates in the units of political factors in two time period (1979-1997 and 1997-2015). X-axes represent the units of each political factor; y-axes represent forest loss/gain rates of each geographical unit. The positive y-axes correspond to forest gain rates; the negative y-axes correspond to forest loss rates.

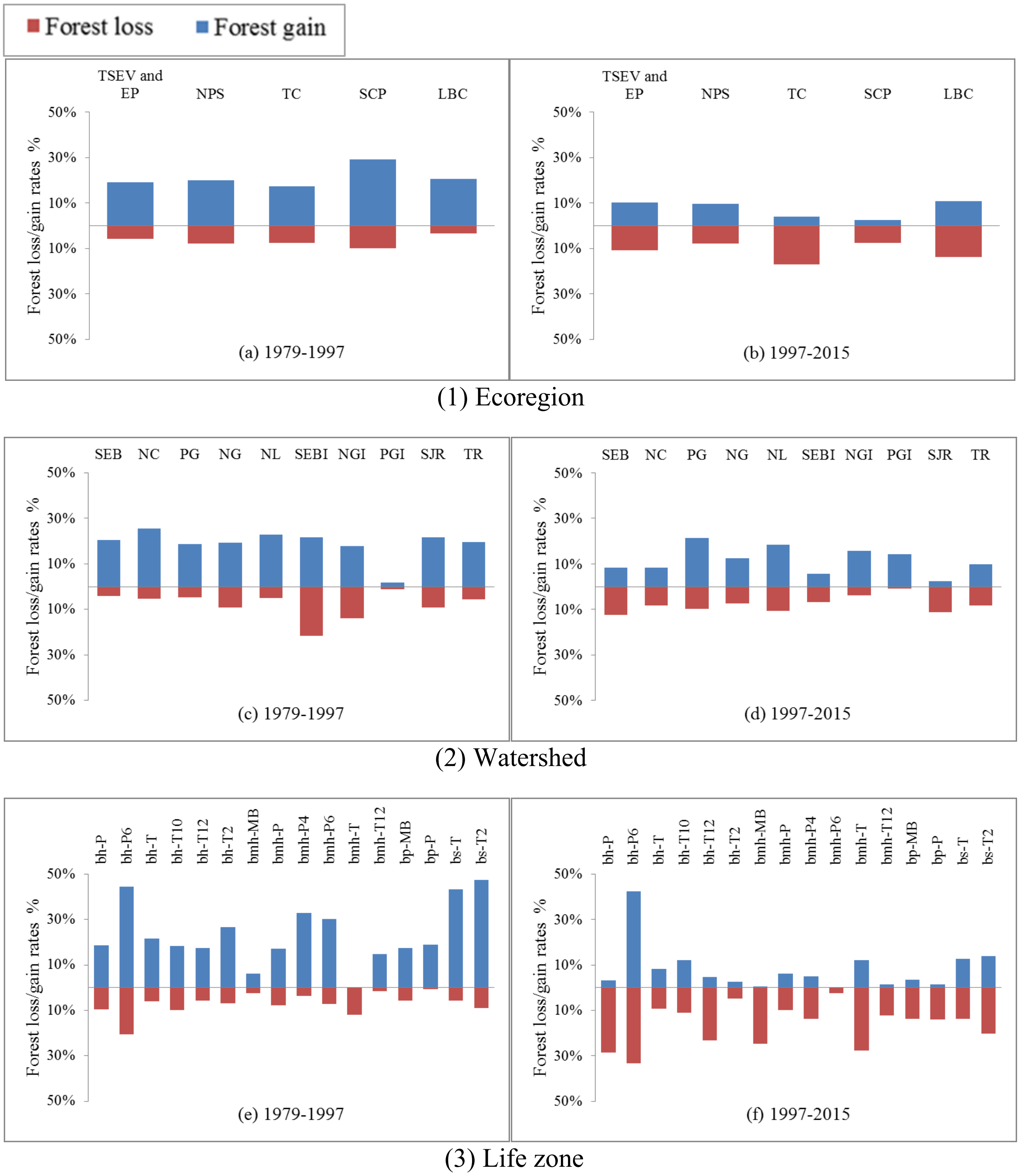

Figure 3. 6 The forest loss/gain rates in the units of natural factors in two time period (1979-1997 and 1997-2015). X-axes represent the units of each natural factor; y-axes represent forest loss/gain rates of each geographical unit. The positive y-axes correspond to forest gain rates; the negative y-axes correspond to forest loss rates.

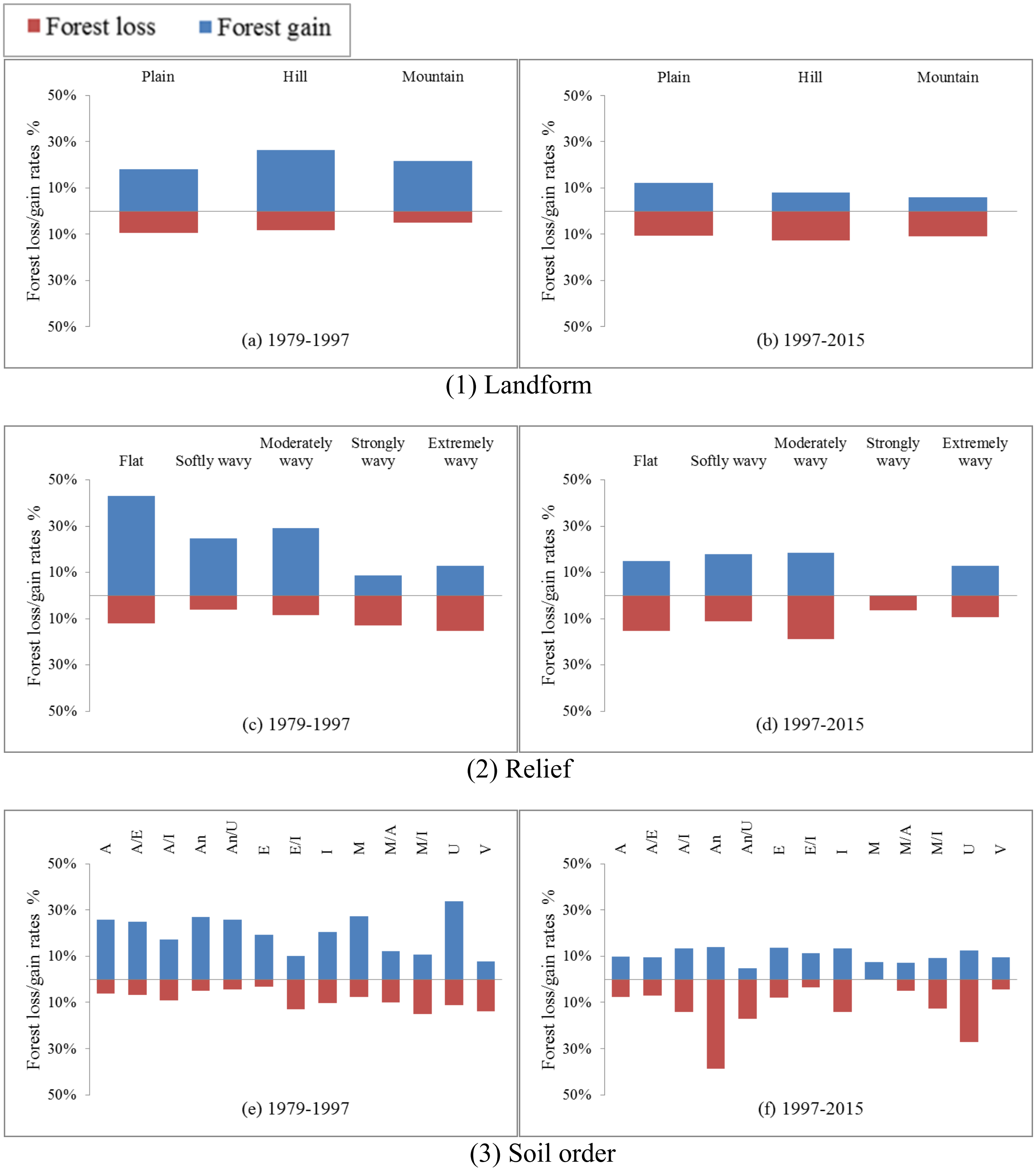

Figure 3. 7 The forest loss/gain rates in the units of biophysical factors in two time period (1979-1997 and 1997-2015). X-axes represent the units of each biophysical factor; y-axes represent forest loss/gain rates of each geographical unit. The positive y-axes correspond to forest gain rates; the negative y-axes correspond to forest loss rates.

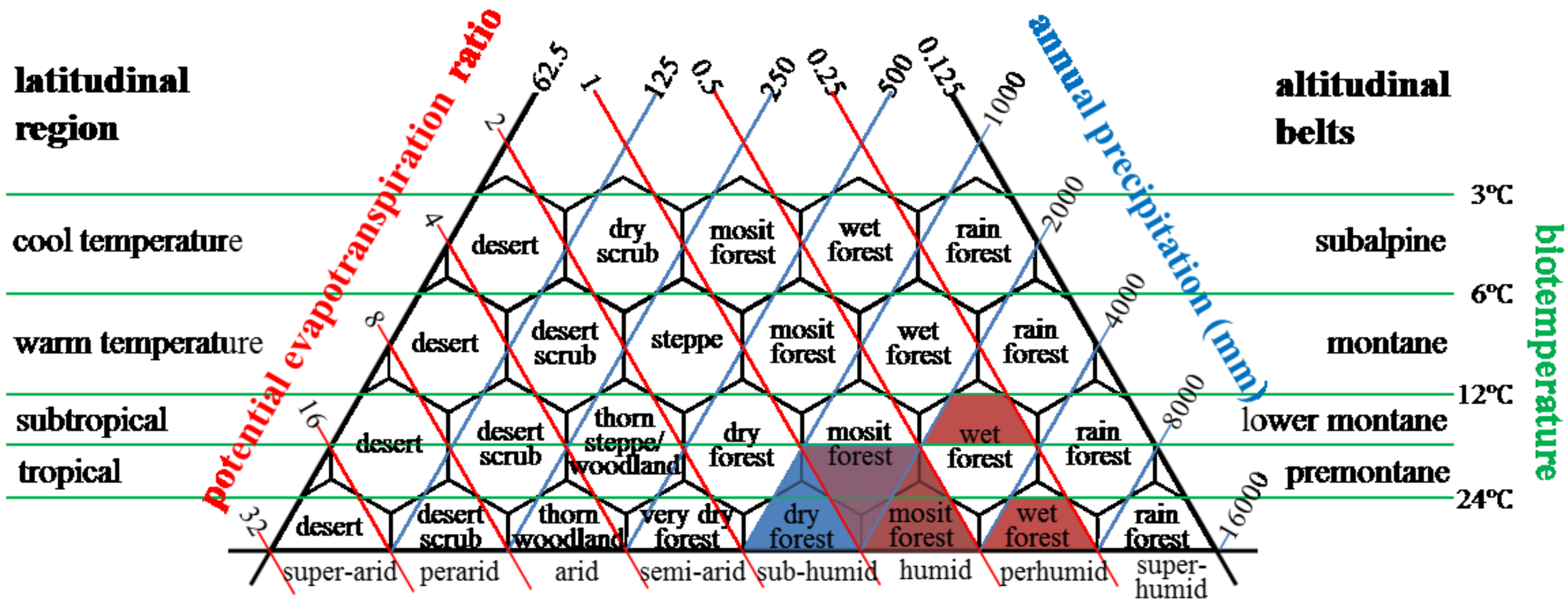

Figure 3. 8 The referenced figure of Holdridge life zone (Holdridge, 1967). Life zone plays an important role in forest loss/gain in the first period in our study. This figure indicates the areas with high forest loss/gain rates in the first period. Also, the relationships of annual precipitation, biotemperature, and potential evapotranspiration ratio were shown in this figure. The blue areas correspond to high forest gain rates in the first period; the red areas correspond to high forest loss rates in the first period.

Chapter 4: Simulations of Tropical Forest Change in the Guanacaste Region, Costa Rica

4.1 Introduction

In the past few decades, research on land use/cover change (LUCC) modeling has received significant interest from global researchers, ranging from environmentalists to ecologists (Foley et al., 2005). With the considerably increasing amount of data from Remote Sensing (RS) and the widely used techniques of Geographic Information System (GIS) (Mesev, 1997), analyzing LUCC can now be feasible and effective.

Numerous LUCC models have been developed in the past few decades (Verburg et al., 2004). From a functional point of view, these models can be divided into two groups: 1) descriptive models that aim to simulate the functioning of LUCC system and predict future LUCC patterns; and 2) prescriptive models that aim to calculate and optimize LUCC (Verburg et al., 2004). Some commonly-used models are: 1) Agent-based models (AB models) that simulate decision-making with individual agents of LUCC, explicitly expressing interactions among individuals. In this context, an agent is a real or abstract entity which can act on itself and on its environment, and its decision behaviors come from the result of its observations, knowledge, and interactions with other agents (Sanders et al., 1997). 2) Conversion of Land Use and Its Effects Models (CLUE Models), they are dynamic simulation models using empirically derived relations between LUCC and driving forces from cross-sectional analysis at multiple scales (Veldkamp and Fresco, 1996). 3) Cellular Automata Models (CA Models) are the spatially and temporally discrete mathematical systems (Ilachinski, 2001). These models are based on Tobler's First Law of Geography that states that everything is related to everything else, but near things are more related than distant things (Tobler, 1970). 4) Artificial Neural Networks (ANNs) that use a machine learning technique to quantify and model the complex behaviors and processes of LUCC (Skapura, 1996; Atkinson and Tatnall, 1997; Dzieszko, 2014).

In the existing research associated with LUCC modeling, numerous models have been developed for simulations and forecasts (Haase and Schwarz, 2009). Tobler (1970) firstly used cellular automata model in simulating urban growth of Detroit region between 1960s and 1970s. Henceforth, the applications of CA model were extended from biology and physics to geography

(Tobler, 1979). Torrens (2003) prompted a new wave of urban system simulations by using cellular automata and multi-agent models. Britz et al. (2011) modeled the land cover and agricultural change in Europe mainly based on CLUE model. Deng et al. (2015) confirmed the ANN-CA model is capable of simulating the processes of LUCC for multiple classes. These studies have typically involved two fundamental steps: detections of specific changes in the landscape, and descriptions of those changes as functions of some human and natural factors (Dzieszko, 2014). From the view of system dynamics, there is an additional step, because of the feedback that exists between LUCC systems and the driving factors. According to the fundamental steps of LUCC modeling, several problems are supposed to be resolved with future research. One is the contradictions between the accuracy of LUCC system and the number of driving forces. In LUCC models and approaches, many factors have been identified to be responsible for changes in LUCC systems. These factors include biophysical, economic, social, cultural, political, institutional aspects, etc. (Turner et al., 1995). It is clear that for a given LUCC study, it is impossible to use all of these approaches at the same time or to take each driver into account. Generally, more complex and interdisciplinary models result in stronger and more powerful outputs. However, taking a large number of factors into account has its own disadvantages, since more factors tend to blur the direct casual effects of these factors (Verburg, 2006). Although the fitting accuracy of simulating and forecasting models should be enhanced with an increasing number of drivers in a certain range, it must be reduced when the number of drivers exceeds a reasonable threshold (Serneels and Lambin, 2001; Wegener, 2004). Therefore, a scientific selection of factors is one of the bases of a successful model. The other problem is related to scaling. With respect to scaling, the largest issue is the disparity between spatial and temporal scales and their interactions as the changes that have occurred over the past decades. The most common theories of scaling are associated to "scaling" from cross-scale and from neighboring-scale (Gibson et al., 2000). The distinction between these two theories is whether the scales included in the process of deducing and interpreting is neighboring or not. From the point of view of a given interpretation, scaling can be divided into up-scaling and down-scaling (Zhang, 2007). Up-scaling refers to interpreting information from fine scales to large scales, which is a process of aggregation. On the contrary, down-scaling is a process of dis-aggregation, which means deducing and interpreting information from large scales to fine scales (Becker and Braun, 1999). Although some recent publications have demonstrated that it is possible to deal with scaling transformation successfully (Briassoulis, 2000), LUCC systems are complex mechanisms which show distinct characteristics of spatial and temporal scales in both different levels and different cycle periods (Quillet et al., 2010).

One of the most important LUCC events of the past century was the unexpectedly rapid decline in the extent of tropical forests (Lamb et al., 2005). Tropical forests, as important ecosystems in the world, became one of the most threatened ecosystems worldwide due to uncontrolled anthropogenic disturbance and climate change (Hoekstra et al., 2005). Human activities (e.g., excessive logging, ranching, and migrating, etc.) and climate change (e.g., global warming and drought) have made tropical forests suffer from unprecedented damage. Therefore, understanding the dynamic processes of tropical forest change and discovering preventive solutions have become a particularly important part in LUCC studies and modeling.

In this study, the combination of CA-model and AB-model was considered as a solution to simulate and forecast tropical forests change in the Guanacaste region, Costa Rica. CA-model has a powerful and complex computing ability derived from its discrete spatial structure, but it contradicts with the real LUCC and the definition of transition rules (White and Engelen, 2000). To complement the CA-model, AB-model can simulate decision behaviors of agents, but it has no spatial expression (Sanders et al., 1997). In this context, tropical forests change could be regarded as the results of a series of transition rules from focal and surrounding pixels and behaviors from specific agents. Thus, the simulation of tropical forests change in the Guanacaste region would be derived from the transition rules and the properties of agents.

The main purposes of this study are to simulate tropical forest change in the Guanacaste region and to forecast scenarios of tropical forest change in the future. In this paper, historical data of 1979, 1997, and 2015 was used to train the transition regulations of forest change and the decision behaviors of agents. Then, a model that combines CA model, AB model, and geographical constraint information was developed to seek the following answers in the Guanacaste region: (1) Is a combination of CA-model and AB-model capable of reproducing the process of tropical forest change? (2) How did tropical forest evolve during the past 36 years? And (3) What are the scenarios of tropical forest change in the future under different conditions?

4.2 Methodology

4.2.1 Study area

The Guanacaste region is located in the northwest of Costa Rica (coordinates: 10°37'N, 85°26'W) and includes the Guanacaste province and the Nicoya peninsula (belongs to Puntarenas province) (Figure 4. 1). This region covers an area of 11,337 km^2. In the past 36 years (1979-2015), the area of persisting forest is 4176.9 km^2 (36.8% of total landscape), the area of forest loss is 1,670.6 km^2 (14.7% of total landscape), and the area of forest gain is 2,961.2 km^2 (26.1% of total landscape). The land use changes between "forest and grass/pasture" dominate the first place in all land use changes. The area of forest loss to grass/pasture is 993.1 km^2, and the area of forest gain from grass/pasture is 2,165.9 km^2. Another significant land use change during the 36 years has occurred between "forest and agriculture area". An area of 599.5 km^2 has been changed "from forest to agriculture area", and an area of 662.6 km^2 has been changed "from agriculture area to forest". Data of land cover change in two time periods (1979-1997 and 1997-2001) was used to learn the regulations of forest change and to validate CA-AB model.

4.2.2 Materials and Methods

4.2.2.1 Materials

Forest cover data, location data, socioeconomic data, and geographical data of 1979, 1997, and 2015 were included in this study. They were collected from different sources (Table 4. 1). Land cover data was derived from Landsat images (1979, 1997, and 2015), and the classification applied to these images consists of the following classes: forest (dry, moist, and wet tropical forests), non-forest, and water. The forest cover maps were produced by using the classification technique of Support Vector Machine (SVM). Location data is made up by distance to road networks, and distance to towns, and they were processed from the data of road network and towns in ATLAS Costa Rica 2014 (Ortiz-Malavasi, 2014). Socioeconomic data was mainly collected from the National Institute of Statistics and Census (INEC) and the Ministry of Agriculture. It includes population, percentage of population, national beef price, household income, and gross domestic product (GDP). Geographical data includes conservation, protected areas, PES-priority areas, ecoregion, watershed, life zone, landform, relief, and soil order. They were from National Forestry Financing Fund (Fondo Nacional De Financiamiento Forestal, FONAFIFO) (FONAFIFO, 2019), ATLAS Costa Rica 2014, and the Ministry of Environment and Energy official website (Ministerio del Ambiente y Energia, MINAE) (MINAE, 2019).

4.2.2.2 CA-AB model

Our spatial dynamic model is formed by three layers (Figure 4. 2). The top layer is CA layer, the middle layer is AB-model layer, and the bottom layer is constraint layer.

Cellular Automata model (CA layer)

Cellular Automata models (CA models) are originally used in the simulations of biological and physical processes (White and Engelen, 1993). After Tobler realized that the potential applications of CA models in the field of geography in 1979 (Tobler, 1979), much work has been focused on this model to analyze spatial interactions in the following few decades (Veldkamp and Lambin, 2001; Overmar et al., 2003). Most recently, this model has been widely used in land use change research, such as simulations of urban expansion (Li and Yeh., 2000), zoning agricultural protection (Li and Yeh, 2001), and predicting forest fire (Karafyllidis and Thanailakis, 1997; Encinas et al., 2007). As of today, there are also many applications implemented in land use models that are able to simulate multiple land use types (White and Engelen, 2000).

Cellular automata (CA), as a mathematical idealization of physical system, expresses discreteness over space and time, and also expresses physical quantities by taking on a finite set of discrete values (Wolfram, 1983). CA calculates the state of a pixel based on its initial state, and the conditions in the surrounding pixels using a set of transition rules (Figure 4. 3). Although the rules are very simple, they can generate a very rich behavior (Wolfram, 1986; White and Engelen, 2000). Classic CA model is combined with some additional rules of spatial interaction (Couclelis, 1997; Moghadam et al., 2018). Some researchers proposed that CA models as a bottom-up method are not suitable for land use change modeling, because some land use changes are caused by natural constraints and human demands rather than transition rules (Jenerette and Wu, 2001; Mao et al., 2013). Fortunately, constrained CA model has been improved based on classical models that achieve more expanded information about spatial and temporal autocorrelation than classic model (Li and Yeh, 2000; Ward et al., 2000). Compared with classical model, constrained CA model can effectively transform human demands to constraint conditions, which are allocated into each pixel. Then, feedback to the regional level is incorporated from the cell level through the next iteration (Engelen et al., 1995). CA model or constrained CA model has its own strengths: it allows each pixel to act independently according to rules and uses fine-scale data for detailed analysis. On the contrary, some weaknesses still exist: it does not unpack human decisions that lead to the spread of built areas and does not include biological factors.

The CA layer in our study is a pixel-based layer on the basis of CA model. It is used to simulate tropical forest change and transmit change over time by iterative operations. The transition rules and spatial association regulations were trained from historical land cover data of 1979, 1997, and, 2015 (chapter 2). The spatial resolutions of 1997 and 2015 were uniformed as 60m. For the purpose of simplifying and extracting the spatial association regulations and transition rules, 16,563 focal pixels and 16,563×8 surrounding pixels (Moore neighborhood) were chosen randomly for each period in our analysis. The accuracy of this sampling satisfies a margin of error of 1% at the 99% confidence level (Rea and Parker, 2014).

In this study, CA pixels were evolved from original pixels ($BasicPixel$) by $TransitionRules$ (Figure 4. 4, CA layer). The original pixel of CA model with the following properties:

$$BasicPixel = \{F_p, S_p, L\} \tag{1}$$

where F_p is the status of focal pixel and $F_p \in$ {*forest, non-forest*}; S_c represents the number of forest pixels surrounded focal pixel; L represents the location of focal pixel.

The transition rules derived from sample pixels are decided by the information of surrounding pixels, constraint magnitude, and suitability:

$$TransitionRules = \{P_l, P_g, Ct, St, Rd\} \tag{2}$$

where P_l is the probability of forest loss based on the statues of surrounding pixels, and P_l is applied on forest pixels; P_g is the probability of forest gain based on the statues of surrounding pixels, and P_g is applied on non-forest pixels; Ct is the natural and biophysical constraint information; St is the suitability of forest change and it is based on whether the pixel is water or not; Rd is a random variable and represents uncertainty in the simulation.

Agent-based model (AB layer)

Agent-based model (AB model, also known as multi-agent model) has shown tremendous growth in the past decade (Farmer and Foley, 2009; Heppenstall et al., 2011). It is used to simulate decision-making behaviors of individual agents in land use change and to explicitly express interactions among individuals (Benenson, 1998). In the early 1990s, mathematical and computational capacity limited the operation of AB models (MacLennan, 2004). A few years later, AB models had been developed with an improvement in mathematical and computational capacity. Much work was done on AB model to simulate changes not only in the area of land use change but also in many other purposes. Ligtenberg et al. (2001) proposed a spatial planning model to resolve the issues of interactions between decision behaviors and agents. Loibl and Toetzer (2003) modeled growth and densification process in suburban regions by using spatial agents. Miller et al. (2004) developed an integrated model of land use and transportation by analyzing the travel behaviors of individuals. Guzy et al. (2008) assessed the political impacts on urban extension into farmland and forests in the future by agent-based modeling. In most recent studies, an increasing number of comprehensive models have been built, which took into account more interacting agents and factors (Kanaroglou and Scott, 2002; Taillandier et al., 2015; Ponta et al., 2018).

The core concept of agent is "a real or abstract entity which can act on itself and on its environment. Agents can communicate with each other in a multi-agent case, and the behavior of an agent comes from the result of its observations, knowledge and interactions with other agents" (Sanders et al., 1997). The principle of AB-model links the agents of decision making to land use changes, which means relations between 'people and pixels' (National Research Council, 1998; Rindfuss et al., 2004). As a complex system, the development of AB model is based on micro-behaviors of individual agents and interactions with other agents, which causes a lack of spatial expression. At the same time, CA model exactly complements this disadvantage of AB-model.

According to the situation of our study area, three agents were considered in this study. They are: central government, local governments, and residents. The agents are driven by their motivations or purposes to narrow the gap between current land use and expected land use in the future (Ligtenberg et al., 2001) (Table 4. 2). For the central government, its main functions are macro-regulation, control, and forest laws legislation. For local governments, such as MINAE, SINAC, and FONAFIFO, the main behaviors of them are setting up a fund, increasing farmers' income, spreading the importance of ecology, and enforcing laws. For the residents, they have two understandable decision behaviors: increasing the household income and protecting individual rights to achieve a good life.

In our study, the factors which potentially cause agents' behaviors were considered from the aspects of location and socioeconomy (Table 4. 1). Then, the agents' behaviors are also restricted by the related policies which can be calculated from political constraint factors.

According to the different purposes, the spatial criterions of agents can be expressed as follows:

(1) Central government:

$$P_{CG}(i,j) = \frac{S_{Ecology}(i,j)}{S_{Economy}(i,j)+S_{Ecology}(i,j)} \quad (3)$$

The central government maintains stability between economy and ecology primarily through assessing the suitability of economy or ecology by equation (3). $S_{Ecology}(i,j)$ is the suitability for changing land use to ecological purpose (it is changing to forest in this study) in location (i,j); $S_{Economy}(i,j)$ is the suitability for changing land use to economic purpose (changing to non-forest). Both of $S_{Ecology}(i,j)$ and $S_{Economy}(i,j)$ depend on whether the area is protected, the magnitude of protection, and whether it is planned for plantation.

(2) Local governments:

$$P_{LG}(i,j) = P_{CG}(i,j) + P_{Funding}(i,j) + g \cdot P_{Re}(i,j) + h \cdot \Delta P_1 \quad (4)$$

The purpose of local governments is to balance the central government goals and residents' rights. The spatial criterion is expressed as equation (4). $P_{CG}(i,j)$ is the suitability of economy or ecology, which local governments accept from central government. $P_{Funding}(i,j)$ is amount of funding by each autonomous conservation (assessed by the PES contract number and funding situation in previous years). $P_{Re}(i,j)$ is the land use decision from residents. If land use in location (i,j) has been changed, the probability of land use change in surrounding locations would become higher than land use in location (i,j) has not been changed. ΔP_1 is designed for this difference in our model.

(3) Residents:

$$P_{Re}(i,j) = a \cdot E_{Income}(i,j) + b \cdot E_{Environment}(i,j) + c \cdot E_{Convenience}(i,j) + d \cdot E_{Ecology}(i,j) + \varepsilon_{kij}(i,j) \quad (5)$$

Residents in our study area were assumed to agree or disagree with the land use plans made by central or local governments for protecting their rights. Agreement or disagreement relies on the conditions of household income ($E_{Income}(i,j)$), living environment ($E_{Environment}(i,j)$), convenience ($E_{Convenience}(i,j)$), and ecology awareness ($E_{Ecology}(i,j)$). $\varepsilon_{kij}(i,j)$ is a random variable.

Constraint layer (Ct layer)

The descriptive factors which affect forest change were taken into account in the constraint layer. In this study, the Guanacaste region is able to be divided into different geographical divisions (geographical units) based on the different descriptive information of a given driving factor. According to previous research (Veldkamp and Fresco, 1996; Letcher and Chazdon, 2009) and the current situation of our study area, nine geographical factors were collected: political factors, natural factors, and biophysical factors. Political factors are conservation divisions, protected areas, and PES-priority areas. Natural factors consist of ecoregion, watershed, and life zone. Biophysical factors are composed of landform, relief, and soil order. The data sources were listed in Table 1.

According to the historical forest loss/gain data in the Guanacaste region, the magnitudes of effect of given geographical factors which act on tropical forest loss/gain were detected by the technique of geographical detector in Chapter 3. In this study, the natural and biophysical factors affect forest change by changing the evolutions of CA layer, whereas the political factors constrain forest change by changing agents' decision behaviors (Figure 4). The parameters of constraint factors in CA model were estimated by binary logistic regression.

4.2.2.3 Pilot application and model validation

The pilot model has been developed for the Guanacaste region by training sample data of forest loss/gain and simulating decision-making behaviors of individual agents. The workflow of CA-AB model is shown as Figure 4.

Pilot application was conducted on the historical forest cover data (1979 and 1997) to simulate the historical scenarios of 1979-1997 and 1997-2015. Firstly, forest changes in two time periods were simulated by CA model. Then, the interactions among individual agents were assembled as a planning agent based on the political constraint factors. Afterward, a logical judgement was applied between planning agent and CA pixels. If land use from CA model and AB model are consistent, logical judgement would be true, and subsequently output this land use in simulation pixels. If they are not consistent, logical judgement would be false. A final decision would be made for conflicts between CA model and AB model based on constraint information, and then land use would be reassigned and output the new land cover as final simulation results. Parameters in the model were adjusted and the models were validated by comparing the land use derived from CA simulations and CA-AB simulations with the land use of 1997 and 2015. The simulation pixels would be as new land use assignment back to model in the next simulation.

4.2.2.4 Scenario simulations

Forecasting future scenarios of tropical forests change is an important part of this study. It can be regarded as an application of CA-AB model that performs training and validation by simulating historical land cover data. All the forecast models have their own assumption, characteristics, and emphasis in past research. This is difficult to avoid. Considering the possible future developments and the potential requirements of government, three scenarios were simulated by adjusting the parameters and changing constraint factors: 1) Current trend scenarios, they are based on the trends of current forests change, the current decision behavior of agents, and current geographical factors; 2) Economy-development-driven scenarios, they regard economic development as the dominant factor; and calibrates the decision behavior of agents; and 3) Ecology-protection-driven scenarios, they assume ecology protection as the dominant factor; and calibrates the decision behavior of agents.

4.3 Results

4.3.1 Tropical forest evolutions in the past 36 years

4.3.1.1 Simulations of tropical forest change

Table 4. 3 lists the correlated coefficients between constraint factors and forest loss/gain that are derived from training data during two time periods after conducting binary logistic regression. On account of the potential presence of multi-collinearity among constraint factors, some constraint factors have no significant correlated relations with forest loss/gain in two time periods, such as watershed and life zone with respect to forest loss, landform and relief with respect to forest gain in the first period, and soil order with respect to forest loss and watershed, life zone and landform with respect to forest gain in the second period.

Table 4. 4 lists the adjusted correlated coefficients and constants after removing the constraint factors which do not significantly act on forest loss/gain during the two periods. By verifying the regression equations， R-squares are: $R^2 = 0.664$ for forest loss regression and $R^2 = 0.518$ for forest gain regression in the first period, $R^2 = 0.618$ for forest loss regression and $R^2 = 0.535$ for forest gain regression in the second period. On the basis of R-squares in our case, the goodness of fit for four regressions can be accepted.

Comparing with the results of chapter 3 (Figure 3.4), the drivers with high correlated coefficients are different with the high explanation drivers. The potential reason is that the results of Table 4. 3 and Table 4. 4 are derived from multivariate regression, whereas the chapter 3 is a univariate analysis. The nature of multivariate analysis may cause the weakness or elimination of explanation degree of some variables, which is from multi-collinearity.

Figure 4. 5 exhibits the comparisons of real forest covers, forest covers simulated by CA model, and forest covers simulated by CA-AB model in the periods of 1979-1997 and 1997-2015. From Figure 4. 5(a)(b), it is indicated that the gross forest area presents an increasing trend in the first period, but there is a sizeable area in the middle of the Guanacaste region experiencing forest loss. Comparing simulations with actual forest cover in 1997, it is demonstrated that forest of CA simulation is over covered in the middle area (Figure 4. 5(b)(c)). By contrast, the simulation of CA-AB model effectively corrects the false simulation in the same area by individual agents' behaviors (Figure 4. 5(b)(d)). For the area south of the Guanacaste region, the forest of CA simulation is obviously less covered than forest in reality (Figure 4. 5(b)(c)), whereas forest cover simulated by CA-AB model is much closer to the real forest cover in 1997 (Figure 4. 5(b)(d)). The same situation is also observed in the Santa Rosa National Park (in the northwest of study area) and in the northeast mountain region (Figure 4. 5(a)(b)(c)(d)). Although the CA-AB simulation is more similar to the real forest cover than CA simulation, there are still some spatial differences between CA-AB simulation and the real cover, such as in the districts of Cañas, Nicoya, and Hojancha. Highly dense population in these three districts causes CA-AB model to improperly clear forest cover in excess when CA-AB model is simulating forest change in the first period. The population densities of Cañas, Nicoya, and Hojancha are 93.7 people/km^2, 65.1 people/km^2, and 45.8 people/km^2 in 1997, and they rank 2nd, 4th, and 11th among 64 districts at that time.

Figure 4. 5(e)(f) demonstrates the real forest change in the second period, and Figure 4. 5(e)(f) are the results of CA simulation and CA-AB simulation of forest cover in 2015. From these figures, it can be seen that the spatial differences between CA simulation and CA-AB simulation are less obvious than the previous period. Similar to that of the first period, forest cover of CA simulation in the middle area is more than the real forest cover in the same places (Figure 4. 5(f)(g)). Meanwhile, compared to CA simulation, CA-AB simulation is much improved in this area (Figure 4. 5(f)(h)). It is worth mentioning that the real forest cover is more greatly restored in the Santa Rosa National Park in 2015. Although the forest cover of CA-AB simulation in the Santa Rosa National Park is more than CA simulation, it is still less than the real forest cover (Figure 4. 5(f)(g)(h)).

Generally, Figure 4. 5 indicates that forest covers simulated by CA-AB model are more closely matched with the real forest covers than forest covers simulated by CA model, especially in the middle area of the Guanacaste region and the Santa Rosa National Park. The application accuracies of CA model and CA-AB model in the second period are slightly higher than the first period.

4.3.1.2 Model validation and accuracies

Figure 4. 5 provides the information of locational and visual differences between the simulated results and the real forest covers from the perspective of space. In addition, Table 4. 5 indicates the accuracies of simulations of CA model and CA-AB model in 1997 and 2015.

In Table 4. 5, the overall accuracies of the combined model of CA and AB models are significantly higher than CA model. The overall accuracies of CA-AB simulations are 83.2% and 84.0% in two time periods, whereas the overall accuracies of CA simulations are 78.4% and 81.2%. Meanwhile, Table 4. 5 confirms that the accuracies of simulations in the second period are higher than the first period, regardless of CA model or CA-AB model. In addition, there is an obvious feature in the accuracy table which shows that accuracies of forest cover simulations are higher than non-forest cover simulations, regardless of the time period or model. The accuracy of forest cover of CA-AB simulation is as high as 87.4% in the second period.

4.3.2 Future scenarios of tropical forest change

Future scenarios of forest change in the Guanacaste region were simulated CA-AB model, and the results are presented in Figure 4. 6. In our study, the future scenarios in the years of 2040, 2075, and, 2100 were imitated based on three assumptions: current trend scenarios, economy-development-driven scenarios, and ecology-protection-driven scenarios. Figure 4. 7 presents the area of forest and the trends of forest change in past 36 years and in the next century (2015-2100) under different conditions.

4.3.2.1 Current trend scenarios

In regard to the simulations that are based on current trend, the forecasted area of forest is nearly stable during the next century (Figure 4. 7). The forest cover in 2040 and 2075 (6,780.4 km^2 and 6,796.2 km^2) increases slightly and then forest area decreases to a slight extent in 2100 (6,584.7 km^2), due to a surge in population in the study area. However, how does the simulated forest cover change spatially with the condition that forecasted forest area is almost constant during the next century? Figure 4. 6(a)(b)(c) indicates the spatial differences of forest simulations in the next century. From the figures, they indicate that forest cover experiences a good recovery in the protected areas, especially in Santa Rosa National Park and the protective zones in the south of the Guanacaste region. In contrast, forest cover in the middle of the Guanacaste region is largely cleared. The forest cover tends to concentrate in the surrounding areas of the Guanacaste region instead of middle areas. This feature presented in 2100 is particularly significant (Figure 4. 6(c)).

4.3.2.2 Economy-development-driven scenarios

Unlike the forest area simulated by current trend scenarios, the forest area simulated by economy-development-driven scenarios decreases over time during the next century (forest areas are 6,533.2 km^2 in 2015, 6,169.8 km^2 in 2040, 6,046.7 km^2 in 2075, and 5,742.4 km^2 in 2100) (Figure 4. 7). With the assumption that economic development is the dominant factor in these scenarios, a large amount of forest are lost and transformed for economic usages (such as for industrial, agricultural usages, and urban extensions), not only in the middle of study area but also in some parts of protected areas, which do not include the absolutely protected areas (e.g., national parks, biological reserves, and national wildlife refuges are defined as absolutely protected areas) (Figure 4. 6(d)(e)(f)).

Compared to the simulations of current trend scenarios, the simulations of economy-development-driven scenarios have a wider extent of forest in the middle area that will have been cleared during the next one hundred years. Not only that, forest area also decreases in the Nicoya Peninsula, where forest loss is seldom observed in forest cover of current trend scenarios, especially in the urban areas with dense population.

4.3.2.3 Ecology-protection-driven scenarios

The forest areas forecasted by ecology-protection-driven scenarios show an increasing trend during the following century. The simulated areas of forest are 7295.2 km^2 in 2040, 7499.2 km^2 in 2075, and 7361.6 km^2 in 2100 respectively. Although the total trend of forest area increases in the next century, the area presents a slight drop in 2100 (Figure 4. 7), because of the limitation of land resources, the surge in population, and other potential causes.

A similar feature with two previous simulations is that forest is lost gradually in the middle area over time. Although the magnitude of forest loss of ecology-protection-driven scenarios is much smaller than the other two scenarios, the extent of forest loss is significantly larger than 2015 in this area (Figure 4. 6(g)(h)(i)). Meanwhile, forest of ecology-protection-driven scenarios in the protected areas is the best protected and recovered in the three assumed scenarios.

4.4 Discussion

4.4.1 Simulations of CA model and CA-AB model

In our study, natural and biophysical geographical factors were considered as constraint information in the simulations of CA model. Compared to traditional CA model, which adopts the same transition rules for the whole study area, the CA simulations in our case are improved by the geographical constraints. Based on the original simple transition rules, more flexible rules were generated by adding constrains of geographical units. The new rules not only take into account more factors related to forest change, but also they tend to be closer to real scenarios. Regarding the selections of geographical factors in this section, we removed the geographical factors which are not statistically significant to forest loss/gain. In addition, the removed factors vary with periods because of the temporal disparity of forest change. However, it does not indicate that the removed factors have no significant relations with forest loss/gain. One of the main reasons is that the multicollinearity exists among geographical factors due to the similarities of attributes of factors, such as landform and relief. Removing collinear variables is a simple and effective method in regression analysis (Farrar and Glauber, 1967; Chong and Jun, 2005). More solutions on multicollinearity in this model deserve to be discussed in future research.

Some previous studies show the important role of CA model in land use/cover change with highly anthropogenic disturbance (García-Frapolli et al., 2007). Some studies simulate the anthropogenic disturbance by using the transition rules instead of agents' decision behaviors (Manson and Evans, 2007). Although these simulations of land cover change have achieved some improvements, they cannot completely replace the position of agents' behaviors in the model. In our study, the disadvantages of CA model simulations are observed not only in the middle area of the Guanacaste region but also in the protected area, such as the Santa Rosa National Park (Figure 4. 5). Combining with the features of landform and relief, the middle area of the Guanacaste region belongs to the flat and arable Tempisque Basin. Chapter 2 demonstrates that the plains and arable soils are much more suitable for agricultural activities, and the rapid population growth is another important reason for deforestation. In our study, the population in the Guanacaste region grew from 191,912 in 1979 to 277,768 in 1997, and then jumped to 396,705 by 2015 (INEC Costa Rica, 2017). The actions of agricultural activities and urban extension, which cause deforestation, more rely on the choices of “people” (individual agents) rather than three basic components of CA model (initial state of focal pixel, the conditions in the surrounding pixels, and transition rules). By contrast, forest in the Santa Rosa National Park is another choice of individual agents. The related forest laws (First Forest Law No. 4465 (1969), Environmental Law No. 7554, Forestry Law No. 7575 (1996), and Biodiversity Law No. 7788 (1997)) expressly prohibit the actions of timber extraction in the national parks and other absolutely protected areas (Sittenfeld et al., 1999; de Camino Velozo, 2000; Campbell, 2002; Sánchez-Azofeifa et al., 2003; 2007; Pagiola, 2008). Therefore, land use has been changed under the decision behaviors of individual agents, either changing from forest to non-forest (e.g., the central area) or changing from non-forest to forest (e.g., Santa Rosa National Park). The forest change, which highly depends on decision behavior, also explains that CA-AB simulations are more accurate than CA simulations in our case. Only using CA model to simulate the moving entities, such as relocated residents and location-selecting governments, is powerless.

Moreover, the presence of spatial and temporal disparities of forest loss/gain is verified and the spatiotemporal characteristics are tested in chapter 2. Those disparities of spatiotemporal and the spatiotemporal patterns of forest change explain why the CA-AB simulations are closer to real forest cover than CA simulations. Although the presence of constraint factors corrects the disadvantage of adopting the same set of transition rules of CA simulations to some extent, the transition rules within each geographical unit are still the same. However, the spatiotemporal disparities and characteristics of forest change exist within the geographical unit. Thus, the nature of CA model dictates that it is impossible to describe and simulate the disparities of spatiotemporal and the spatiotemporal characteristics of forest change adequately.

In addition, chapter 2 in our study indicates that tropical forest area in the Guanacaste region had a considerable increase in the period of 1979-1997 (from 4,848.5 km^2 to 6,159.7 km^2), whereas forest area in the periods of 1997-2015 is nearly stable (from 6,159.7 km^2 to 6,148.4 km^2). Comparing the accuracies of CA-AB simulations in two time periods, the accuracy of the second period is higher than the first period, regardless of the accuracies of forest and non-forest simulations or the overall accuracies. One of the possible reasons is that the area of forest change (both forest loss and gain) in the first period is larger than the second. It increases the potential probability of forest change in random locations. The results of the spatiotemporal contagion pattern in chapter 2 also support this view. The forest change belonging to the spontaneous pattern in the first period is 108.4 km^2, whereas it is 68.1 km^2 in the second period. The spontaneous pattern indicates that forest loss/gain patches are in random places (Xu et al., 2007; Liu et al., 2010; Nong et al., 2014; Weerakoon, 2017). Furthermore, the forest change of spontaneous pattern is largely caused by uncertain causes. Therefore, the increase of the effect of random factors in the model would decrease the accuracies of CA-AB simulations to some extent in our study.

From our results, the overall accuracies of CA-AB model of reproducing forest change are more than 83% in the time periods of 1979-1997 and 1997-2015, and the overall accuracies of CA model are 78.4% and 81.2% in those two periods (Table 4. 5). Therefore, CA-AB model, in this case, is capable of simulating forest change in past scenarios. Meanwhile, this chapter indicates that the simulations of CA-AB model is closer to reality than the simulations of CA model when the spatiotemporal disparities of land use change are widespread in the study area, especially when the disparities are mainly caused by agents' decision behaviors.

4.4.2 Future scenarios of tropical forest change

Our results indicate that the sequence of simulated forest areas of three scenarios from high to low is ecology-protection-driven scenarios, current trend scenarios, and economy-development-driven scenarios. These results are in line with general situations. In our study, the forecasted populations are 640,000 in 2040, 940,000 in 2075, and 1,270,000 in 2100. The population was forecasted as a surge increase in the next century. The demands of agriculture and urban extension would increase in accordance with the population. Consequently, we can find that a great amount of forest in the middle of the Guanacaste region would be cleared in our future scenarios, regardless of assumptions (Figure 4. 6). The deforestation in this area mainly owes to the limitation of land resources, the shortage of other resources, and the surge in population.

For the simulations of economy-development-driven scenarios, the main purposes of local and central governments are to focus on economic development. Therefore, under the assumption to pursue economic benefits, governments and residents are encouraged by these policies to transform forest to land covers of economic purposes, such as industries, cropland areas, pastures, and urban areas (Bann, 1997). This assumption affects the individual agents' decision behaviors directly, and it may cause a wide range of forest degradation, especially in the surrounding areas around the large cities where the population is forecasted to increase explosively in the following century, such as Liberia, Nicoya, Santa Cruz, and Cañas.

By contrast, if the forest cover is highly protected by laws and regulations, the recovery of forest would be greatly improved by protected actions of the governments. However, these scenarios are at the expense of slowing economic development. Although the PES program, plantation, and the prosperous tourism caused by the improvement of ecology are able to subsidize the rural and urban residents, in some way or another, the economic benefits of this assumption are still unable to fully meet the demands of population growth (Omer, 2008). Thus, compared to economy-development-driven scenarios and current trend scenarios, not only does the national economy and household income become limited, but the living area per capita is also significantly reduced under this assumption.

For the current trend scenarios, all the variables in this assumption are based on the current trend, and all the agents' decision behaviors are built on the current policies and living conditions. The ecology-protection-driven scenarios and economy-development-driven scenarios that we discussed in this study are based on two relatively extreme assumptions. One only considers ecology protection, whereas the other entirely considers economic development. However, the simulations of those two extreme assumptions in this study suggest the possible range of forest change rather than the actual forest cover in the future. We consider that forest cover in the future tends to be more similar to the current trend scenarios or the scenarios that are in between those two extreme scenarios. This result provides the valuable information to the governments for balancing the ecology protection and economic development, and for achieving the goal of sustainable development in the future.

In our study, all assumptions were established under the condition that the absolutely protected areas, such as national parks, biological reserves, and national wildlife refuges, strictly restrict timber extractions, even in the simulations of the economy-development-driven scenarios. Meanwhile, this condition is guaranteed by the existing laws and regulations, and it also can be regarded as one of the reasons for the success of forest restoration in Costa Rica (Zbinden and Lee, 2005).

4.5 Conclusions

This study was trying to consider as many as possible variables related to tropical forest change, and these variables not only include quantitative variables but also descriptive variables. However, the contradictions between the explanation degree of CA-AB model and the number of driving forces, and the related discussions are still to be resolved in future research. Normally, the high explanation of model accompanies with great number of driving forces. Moreover, we removed the constraint factors which do not significantly act on forest loss/gain when conducting the regression analyses in modeling. Although removing variables is a basic and effective method of eliminating the multicollinearity in regression analyses, a better resolution is expected to be developed to deal with the multicollinearity, especially on keeping the constraint variables which were shown to be highly correlated with forest loss/gain in chapter 3. In addition, another problem in this chapter which is worth to be addressed in the future is studying the indirect variables of forest change, e.g., education and technology. The improvement of environmental awareness among people would profit from education. It would be an important factor which highly affects the residents' behaviors in the future. For the technology, it would help not only to increase the agricultural integration and intensification but also to solve the contradictions of the shortage of resources and the surge in population (Lele, 1991; Cutter, Mitchell, & Scott, 2000). At last, although we can add a random variable in the model, the randomized behaviors and the randomized land cover change are still difficult to be simulated. This would be an important source of model errors.

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4.7 Tables and Figures

Table 4. 1 The variables in the cellular automata-agent based model (CA-AB model) of simulating tropical forest change in the Guanacaste region, Costa Rica. The variables include forest cover data, location data, socioeconomic data, and geographical data.

Data	Description	Units	Data sources
Forest cover in 1979	Defined as more than 80% canopy cover.	Spatial resolution is 60m	USGS https://earthexplorer.usgs.gov/
Forest cover in 1997		Spatial resolution is 60m	USGS https://earthexplorer.usgs.gov/
Forest cover in 2015		Spatial resolution is 60m	USGS https://earthexplorer.usgs.gov/
Distance to road network	Distance to the nearest roads or towns.	m	ATLAS Costa Rica 2014
Distance to towns		m	ATLAS Costa Rica 2014
Population	Population by districts.	people	INEC http://www.inec.go.cr/
Percent of population	Classified as urban and semi-urban.	%	INEC http://www.inec.go.cr/
National beef price	The average beef price in the whole country.	USD/kg	Ministry of Agriculture https://www.mag.go.cr/
Household income	Gross income of all people occupying the same housing unit.	USD/household	INEC http://www.inec.go.cr/
GDP	Gross domestic product for the whole country.	USD	INEC http://www.inec.go.cr/

Data	Description	Units	Data sources
Conservation	Divided by administrative boundaries.	Geographical units	MINAE https://minae.go.cr/
Protected areas	Divided by forest laws and regulations.		MINAE https://minae.go.cr/
PES-priority areas	Divided by PES program preferentially funds or not.		MINAE https://minae.go.cr/
Ecoregion	Divided by natural communities and species.		ATLAS Costa Rica 2014
Watershed	Divided by drainage basins.		ATLAS Costa Rica 2014
Life zone	Divided by Holdridge life zone classification system.		ATLAS Costa Rica 2014
Landform	Derived from DEM data and divided by plain, hill, and mountain.		FONAFIFO https://www.fonafifo.go.cr/
Relief	Divided by the percent of wavy area.		ATLAS Costa Rica 2014
Soil order	Divided by general soil taxonomy from USDA.		ATLAS Costa Rica 2014

Table 4. 2 The main purposes and decision behaviors of individual agents. The spatial criterions of individual agents, which cause land use change in cellular automata-agent based model (CA-AB model), are decided by their main purposes.

	Central government	**Local governments (MINAE/SINAC/FONAFIFO)**	**Residents**
Main purposes	**1.** Maintain social stability; **2.** Boost the economic development; **3.** Preserve the ecology and environment; **4.** Maintain a sustainable development.	**1.** Achieve ecology protection goals; **2.** Protect farmers' rights.	**1.** Achieve a good life.
Decision behaviors	**1.** Macro-regulation and control; **2.** Establish forest laws.	**1.** Set up a fund; **2.** Increase farmers' income; **3.** Spread the importance of ecology; **4.** Enforce the laws.	**1.** Increase the household income; **2.** Protect individual rights.

Table 4. 3 The correlated coefficients between natural/biophysical constraint factors and forest loss/gain in the periods of 1979-1997 and 1997-2015. The correlated coefficients were calculated by binary logistic regressions. The significant levels of constraint factors are also listed.

Constraint factors	1979-1997		1997-2015	
	Forest loss	Forest gain	Forest loss	Forest gain
Ecoregion	101.2***	-16.7***	-38.4***	16.0***
Watershed	-3.4	-6.7***	-76.0***	-1.2
Life zone	-11.4***	-1.1***	-5.3***	0.3
Landform	0.9	-1.1	57.7***	1.6
Relief	11.4***	-0.3	1.6*	-1.5***
Soil order	17.1***	-1.6**	-0.1	19.8***

1. *** Denotes the correlation between constraint factor and forest loss/gain is statistically extremely significant ($\mathbf{p < 0.001}$);
2. ** Denotes the correlation between constraint factor and forest loss/gain is statistically highly significant ($\mathbf{p < 0.01}$);
3. * Denotes the correlation between constraint factor and forest loss/gain is statistically significant ($\mathbf{p < 0.05}$);
4. Numbers without a symbol reflect no statistically significant correlation.

Table 4. 4 The adjusted correlated coefficients between natural/biophysical constraint factors and forest loss/gain in the periods of 1979-1997 and 1997-2015 after removing the constraint factors which not significantly act on forest loss/gain during two periods. The constants in the binary logistic regressions are listed below.

Constraint factors	**1979-1997**		**1997-2015**	
	Forest loss	**Forest gain**	**Forest loss**	**Forest gain**
Ecoregion	99.4	-17.1	-38.3	15.7
Watershed	-	-6.8	-76.0	-
Life zone	-11.0	-1.1	-5.3	-
Landform	-	-	57.6	-
Relief	11.1	-	-1.6	-1.3
Soil order	17.3	-1.4	-	19.8
Constant	-10.1	4.8	4.1	-5.4

Table 4. 5 The overall accuracies of cellular automata model (CA model) simulations and cellular automata-agent based model (CA-AB model) simulations in 1997 and 2015. The overall accuracies were assessed by comparing the simulated forest covers and real forest covers and comparing the simulated non-forest covers and real non-forest covers.

Year 1997		**CA simulations**		**Accuracy (%)**	**CA-AB simulations**		**Accuracy (%)**
		Forest	**Non-forest**		**Forest**	**Non-forest**	
Observations	**Forest**	1514449	312763	82.9	1589800	237412	87.0
	Non-forest	310773	750411	70.1	247897	813287	76.6
Overall accuracy (%)				78.4			83.2
Year 2015		**CA simulations**		**Accuracy (%)**	**CA-AB simulations**		**Accuracy (%)**
		Forest	**Non-forest**		**Forest**	**Non-forest**	
Observations	**Forest**	1542663	272101	85.0	1586674	228090	87.4
	Non-forest	271027	802605	74.8	234719	838913	78.1
Overall accuracy (%)				81.2			84.0

1. The number (not includes accuracies) in this table indicates the number of pixels of land covers.

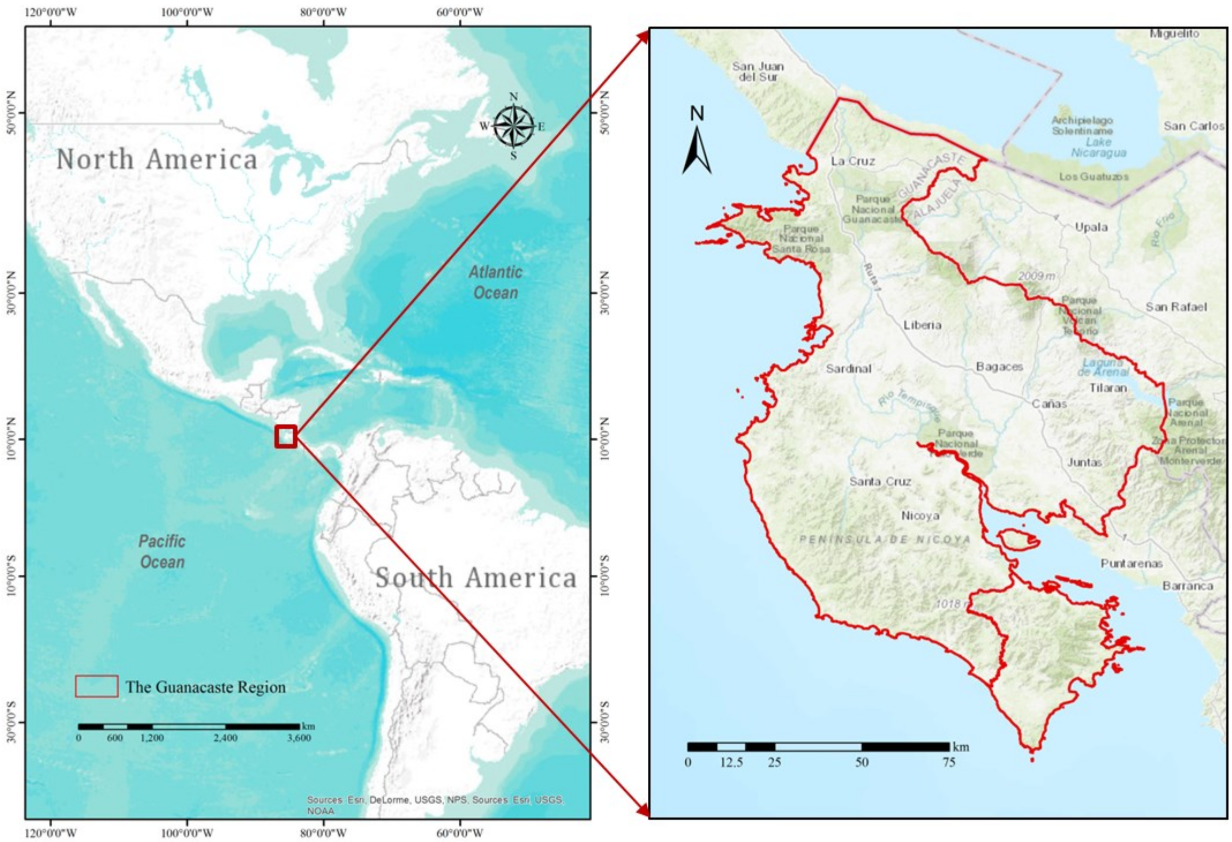

Figure 4. 1 Map of the Guanacaste region, Costa Rica, Central America. This region is located in the northwest of Costa Rica (coordinates: 10°37'N, 85°26'W) and covers an area of 11,337 km^2. In the past 36 years (1979-2015), the area of persisting forest is 36.8% of total landscape, the area of forest loss is 14.7% of total landscape, and the area of forest gain is 26.1% of total landscape.

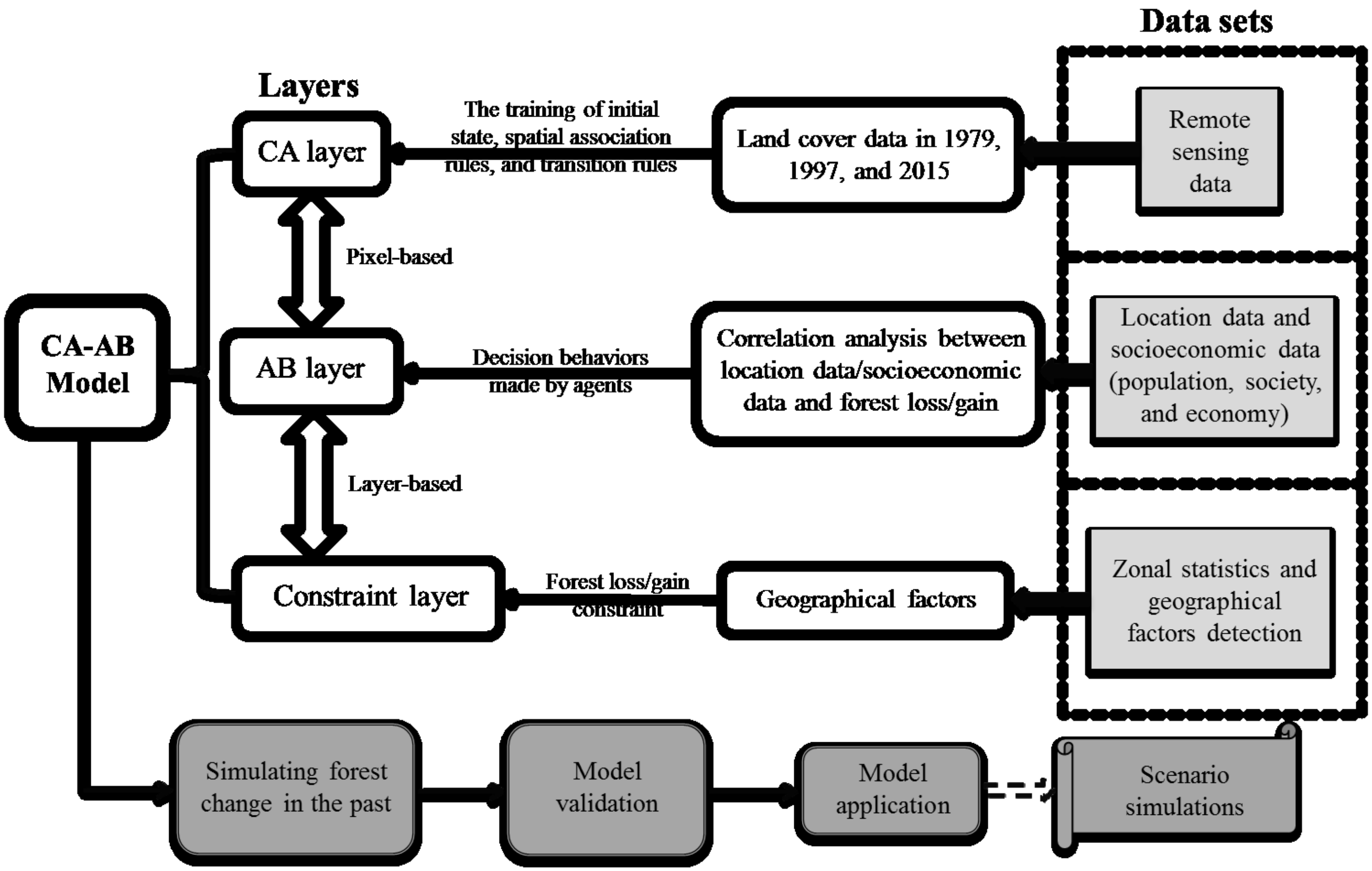

Figure 4. 2 Structure of cellular automata-agent based model (CA-AB model). The top layer is CA layer, and it simulates land cover change based on the initial state, spatial association rules, and transition rules. The middle layer is AB layer, and it simulates land cover change by individual agents' decision behaviors. The bottom layer is constraint layer, and it constrains land cover change by acting on the environmental conditions in CA layer and affecting agents' decision behaviors. The pilot model was used in simulating forest change in past 36 years and then model validation was conducted. The model can be used for the simulations in future scenarios.

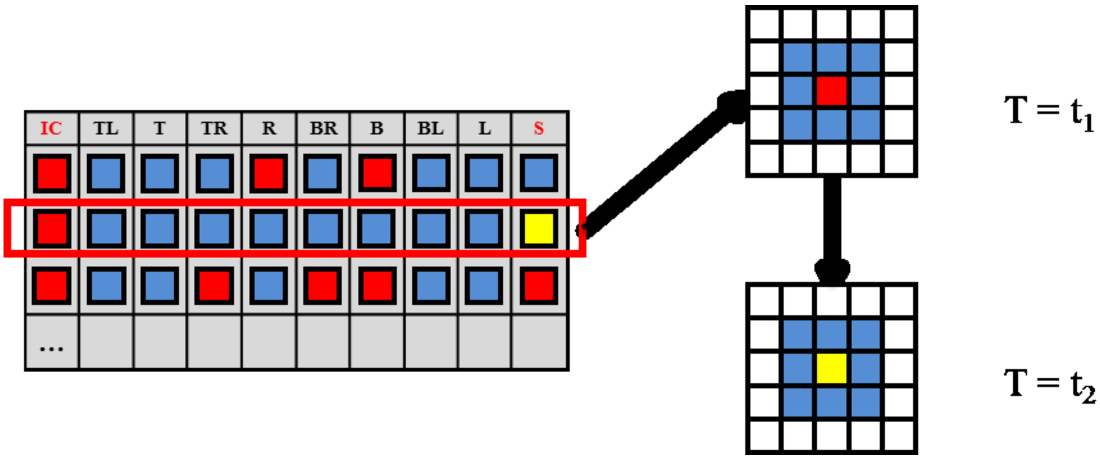

Figure 4. 3 The principle figure of cellular automata model (CA model). The state of focal pixel at t2 (the figure in bottom right corner) is decided by the initial state (the figure in top right corner) at t1, the conditions in the surrounding pixels (TL, T, TR, R, BR, B, BL, L) using a set of transition rules (left figure).

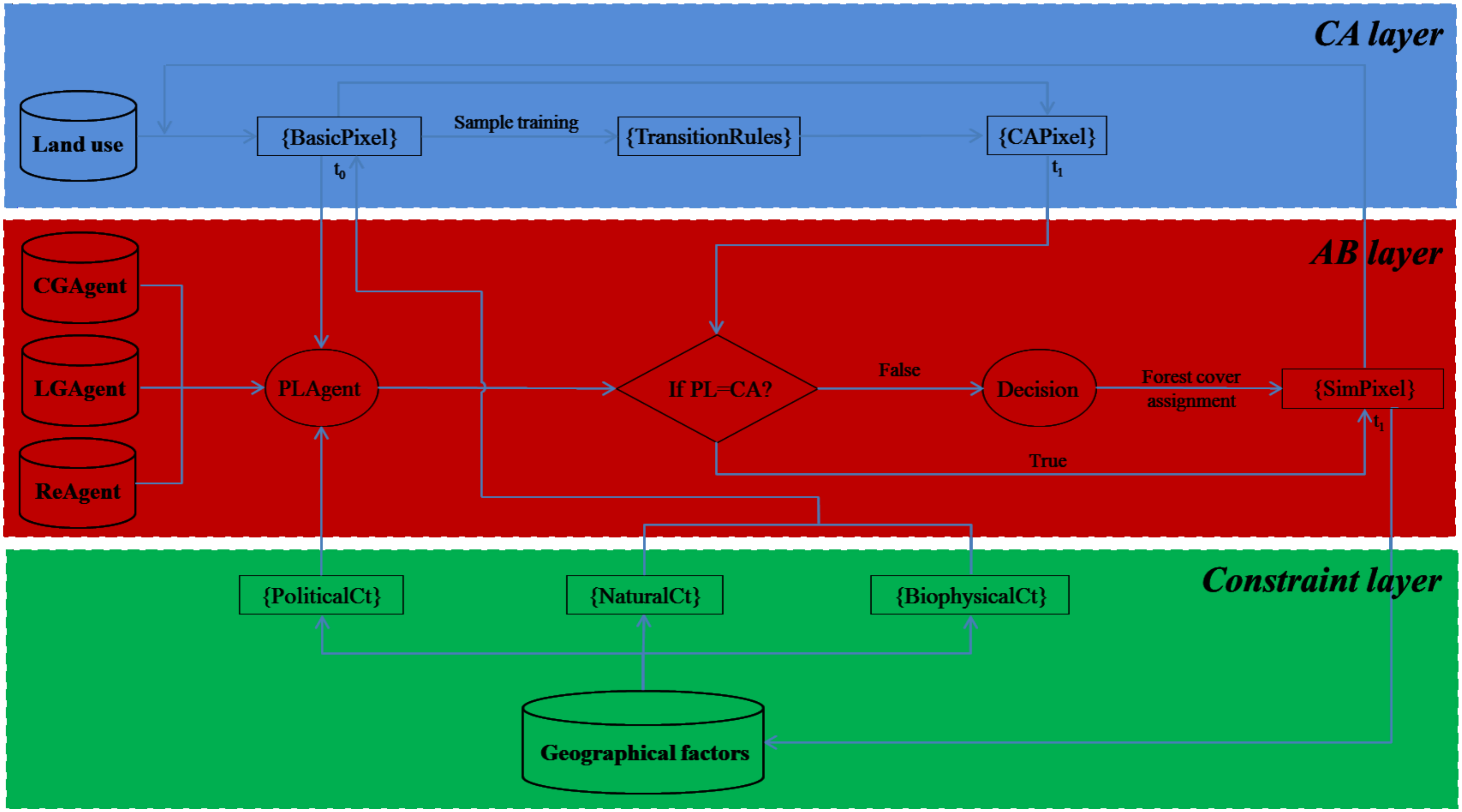

Figure 4. 4 The workflow of cellular automata-agent based model (CA-AB model). Land use data was simulated by cellular automata model (CA model) with taking natural and biophysical constraint factors into account. Then the interactions among individual agents were assembled as a planning agent based on the political constraint factors. A final decision would be made for conflicts between CA model and AB model based on constraint information, and then land use would be reassigned and output the new land cover as final simulation results.

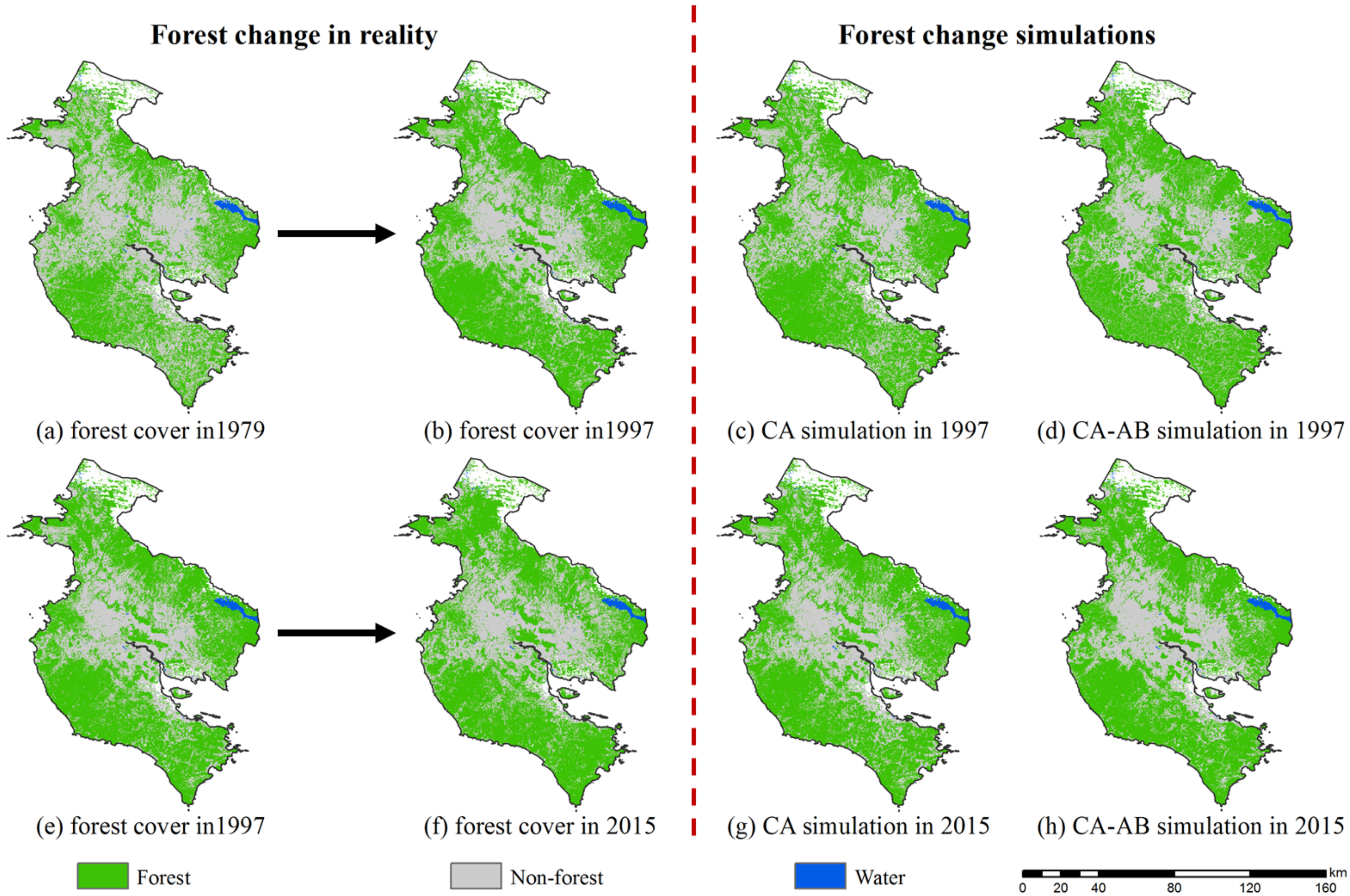

Figure 4. 5 The comparisons of actual forest covers, cellular automata simulations (CA simulations), and cellular automata-agent based simulations (CA-AB simulations). Figure 5(a)(b) and Figure 5(e)(f) present the real forest change in the periods of 1979-1997 and 1997-2015 respectively. Figure 5(c)(d) present CA simulation and CA-AB simulation in 1997; Figure 5(g)(h) present CA simulation and CA-AB simulation in 2015.

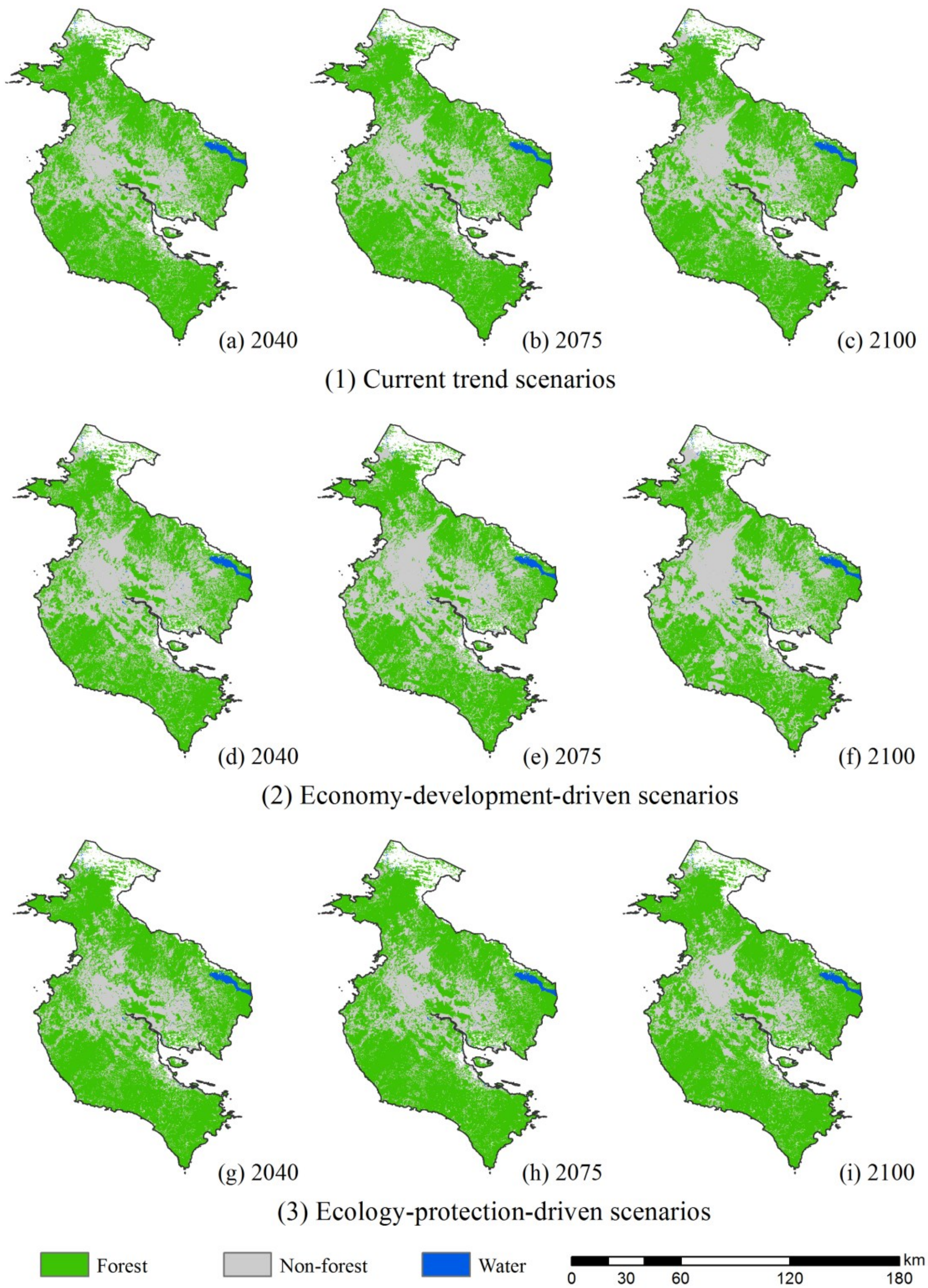

Figure 4. 6 Forest cover simulations in future scenarios. Forest covers in 2040, 2075, and 2100 were simulated by cellular automata-agent based model (CA-AB model). Figure 6(a)(b)(c) represent forest simulations based on current trend scenarios; Figure 6(d)(e)(f) represent forest simulations based on economy-development-driven scenarios; Figure 6(g)(h)(i) represent forest simulations based on ecology-development-driven scenarios.

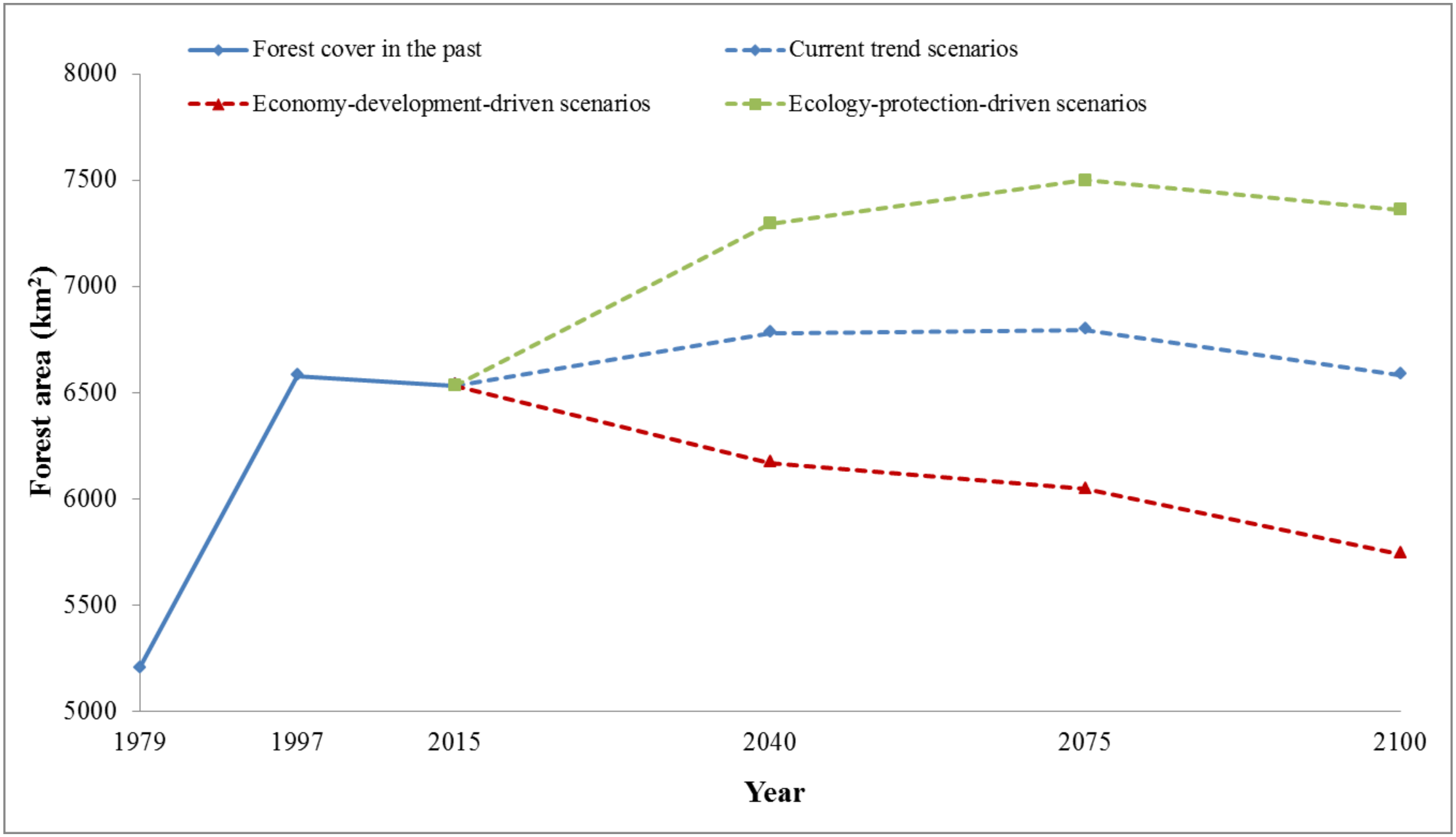

Figure 4. 7 Figure of the areas of forest and the trends of forest change in past 36 years and in the following one hundred years (1979-2100). The solid line represents forest areas in the past (1979-2015); the dash lines represent forest areas in future scenarios (2015-2100). Three assumptions of future scenarios were considered in this figure: current trend scenarios, economy-development-driven scenarios, and ecology-development-driven scenarios. Forest areas are in unit of square kilometer.

Chapter 5: Synthesis

5.1 Conclusions and significant contributions

The objectives of the dissertation are to i) analyze, describe, and quantify the spatial and temporal features of land use/cover change in the context of tropical forest change; ii) to explore how given political, natural, and biophysical factors can drive the forest change and its spatial and temporal features; and iii) to understand the dynamic processes of tropical forest change in the Guanacaste region, Costa Rica. This research helps us to reproduce, simulate, and forecast dynamic scenarios of tropical forests change of my study area not only in the past 36 years but also in the next century (1979-2100). Regarding the historical data of forest cover, two time periods were considered in my study (1979-1997 and 1997-2015). The 1979-1997 time period covers the period of forest restoration via the establishment of the National Conservation Area system and the presence of a process of economic transition from 1960 to 1985 (de Camino Velozo, 2000; Campbell, 2002). The 1997-2015 time period covers the period which Payments for Environmental Services (PES) are scheduled (Sánchez-Azofeifa et al., 2007). The year of 1997 is an important and epochal year in the history of tropical forest restoration in Costa Rica since it is when the PES started (Sánchez-Azofeifa et al., 2003; 2007). The studies in this dissertation devote to filling important knowledge gaps in contemporary research, which is aimed to understand tropical forest dynamic processes.

In chapter 2, I undertook a retrospective analysis of tropical forest change (both forest loss and gain) in the Guanacaste region, Costa Rica and explored its spatiotemporal features, including spatiotemporal disparities, autocorrelation, local pattern, contagion and association of forest loss/gain in the past 36 years (1979-2015). Data of forest loss/gain was derived from satellite images. In addition, I explored the change rules of tropical forest loss/gain based on the results of spatiotemporal contagion and association. My study finds that the forest loss/gain in the Guanacaste region shows a strong spatiotemporal disparity and exhibits a powerfully positive spatial autocorrelation in two periods (1979-1997 and 1997-2015). Regarding the spatiotemporal contagion patterns (Xu et al., 2007; Liu et al., 2010), the infill pattern is the dominant pattern (>50% of all patterns) for both forest loss and gain through the whole time span, edge pattern is in second place (27%-44% of all patterns), and spontaneous pattern is last (<6% of all patterns). Generally, the proportion under contagion pattern decreases from a compact pattern to a disordered pattern.

The most frequent forest change process appears in the central plain of the study area and is mainly affected by human intervention, such as policies, economic development, and population growth, but is still restricted by the natural factors; such as terrain and soil. The transformations of "forest and forest (persisting forest)", "forest to/from grass/pasture" and "forest to/from agriculture" are the most likely to occur.

The findings of chapter 2 have important implications regarding the uses of spatial characteristics and spatiotemporal interactions when modeling forest change. In addition, this chapter explored the spatiotemporal features of tropical forest change in the Guanacaste region, which also can be used in different Land Use Cover Change (LUCC) research in the future. This chapter demonstrated the specific ways of forest loss/gain in the Guanacaste region from the spatial and temporal perspectives, and it is indispensable to help the government and decision-maker establish and implement related policies in the future. Moreover, the possible reasons that caused forest loss/gain according to terrain, policy, society, economy, etc. have been discussed. Relying on the spatiotemporal features in this chapter, I can use them for detecting the driving forces in future research, for maintaining the forest system and protecting the forest from the possible threat of deforestation. The results of spatiotemporal features of forest loss/gain, e.g., the spatiotemporal characteristics and the spatiotemporal interactions, also build a foundation for learning land use and land cover from the spatiotemporal evolution, and establish a theoretical framework for spatiotemporal modeling in future research. Although considering the spatiotemporal data and the interaction between space and time increases the difficulty of modeling, it will simulate the land cover change much closer to reality.

In chapter 3, different method from the previous studies was used to detect the descriptive driving forces which potentially act on tropical forest change. They are geographical factors in this chapter and collected from three aspects: *political factors* (conservation divisions, protected areas, and PES-priority areas), *natural factors* (ecoregion, watershed, and life zone), and *biophysical factors* (landform, relief, and soil order). Then I estimated magnitude of each geographical factor on forest loss/gain with taking the presence of spatial autocorrelations into account. The spatial autocorrelation strongly inflates the risk of Type I errors in this chapter, which was also demonstrated by Legendre (1993). In this chapter, the geographical factors with more human intervention or highly comprehensive attributes would cause the reduction or elimination of spatial autocorrelation, such as the factor of PES-priority area and the factors of ecoregion and life zone.

Alternatively, forest loss/gain exhibits highly spatially autocorrelated patterns among the geographical units with natural, continuous, dependent, and monotonous attributes (e.g., biophysical factors). After by using a spatial lag inverse operator to eliminate the effects caused by spatial autocorrelation, the assessments of geographical factors were as the following: the impacts of political factors are very limited to forest loss/gain among the geographical factors. The most important factors are biophysical factors, especially the factor of soil order. The characteristics of soil strongly control forest change in my study, and it is also an important determinant of land use planning. Relief is another important factor in controlling forest change. Thus, the accessibility is still a problem to be considered in future planning of land use. The impacts of watershed and life zone on forest change vary with time; this means forest change depends on the conditions which are related to climate change, such as the changes of annual precipitation, average temperature, etc.

Those assessments in chapter 3 contribute to providing valuable information for future planning, which is supposed to rely on natural and biophysical conditions. They also contribute to the simulation of LUCC process through laying out the restricted information for each geographical unit. In this chapter, I analyzed the descriptive factors by using a method of geographical detector instead of quantifying those factors. This method is verified to be more objective than other existing methods which are based on quantification, such as statistical theories and physical laws-based methods (Ruben et al., 1998; Fischer and Sun, 2001), empirical methods (Bockstael, 1996; Chomitz et al., 1996; Geoghegan et al., 1997; Pfaff, 1997), and methods of experts' ratings (Lau and Redlawsk, 2001). Also, the spatial autocorrelations of factors among the geographical units were taken into account. It eliminates the impacts of spatial pattern which act on forest loss/gain in my study area and decreases the risk of Type I errors when using geographical detector to assess the magnitude of geographical factors to a large extent (Anselin, 1988; Diniz-Filho et al., 2003). My results indicate that the accessibility is still a problem to be considered in future planning of land use.

Finally, I explored the spatial dynamic processes of tropical forest change in the Guanacaste region in the past 36 years (including two time periods: 1979-1997 and 1997-2015) by using cellular automata model (CA model), and a combined model of cellular automata model (CA model) and agent based model (AB model). By comparing the results of CA simulations and CA-AB simulations of past forest cover with the real forest cover, I demonstrated that the simulations of CA-AB model are closer to the real forest cover in 1997 and 2015 than the simulations of CA model in my case. The main reason is caused by the presence of spatial and temporal disparities, especially the disparities are mainly caused by agents' decision behaviors. Meanwhile, the simulation in the second period is better than the first period, and the potential reason is that the area of forest change (both forest loss and gain) in the first period is larger than the second. It increases the potential probability of forest change in random locations. The results of the spatiotemporal contagion pattern in chapter 2 also support this finding. For the future scenarios, the simulations were based on three assumptions: current trend scenarios, economy-development-driven scenarios, and ecology-protection-driven scenarios. From my results, the simulated forest areas of ecology-protection-driven scenarios are larger than the other two assumptions; the forest areas of current trend scenarios go the second place; the last one is economy-development-driven scenarios. The common features of three scenarios are that the forest cover tends to concentrate in the surrounding areas of the Guanacaste region, and the forest cover in the middle area is largely cleared over time because of the limitation of land resources, the surge of population, and other potential causes.

One of the contributions in chapter 4 is that it considered the constraint factors in the CA simulations. Comparing with the traditional CA model, which adopts the same transition rules for the whole study area, the CA simulations in my case are improved by the geographical constraints. My results demonstrated that CA-AB model is capable of simulating forest change in the past and future scenarios. Meanwhile, this chapter verified that the simulations of CA-AB model are closer to reality than the simulations of CA model. In this study, I took both of quantitative variables and descriptive variables into account and simulated the past scenarios and future scenarios. The selection of those variables also contributes to the overall accuracies. For future scenarios, this study used three potential assumptions: ecology-protection-driven scenarios, current trend scenarios, and economy-development-driven scenarios. Two relatively extreme assumptions (ecology-protection-driven scenarios and economy-development-driven scenarios) suggested the possible range of forest change in the following century. In addition, I considered that forest cover in the future tends to be more similar to the current trend scenarios or the scenarios that are in the middle of those two extreme scenarios. This result provides the valuable information to the governments for balancing the ecology protection and economic development, and for achieving the goal of sustainable development in the future.

5.2 Future research

Chapter 2 analyzed the spatiotemporal characteristics and spatiotemporal interactions at the pixel level, patch level, and district level. However, the connections and variations among different scales were not disclosed in this section. Thus, the issues related to scales are still the tricky problems to be resolved in the future (Mackiewicz et al., 1979; Marfai, 2011; Wang et al., 2012). There is no doubt that the drivers are a series of complex, interactive, and hierarchical factors. Based on the framework of chapter 2, a more integrated approach to explore the driving factors of forest loss/gain in the Guanacaste region is necessary. Relying on the spatiotemporal features in this study, I can use them for detecting the driving forces in future research, for maintaining the forest system and protecting the forest from the possible threat of deforestation. Although considering the spatiotemporal data and the interaction between space and time increases the difficulty of modeling, it will simulate the land cover change much closer to reality.

My findings of chapter 3 was only derived from geographical factors. There is no discussion about the factors from the aspects of society, economy, population, etc. In fact, I could not isolate all the factors which potentially drive forest loss/gain in a study of driving forces. Fortunately, chapter 3 provided a new thought of exploring the descriptive drivers of forest loss/gain without quantification. However, the models which can combine the geographical detectors and regression analyses to collaborate on the descriptive factors and numerical variables are to be explored in future research. Additionally, forest loss/gain cannot be partially explained by one or a series of factors. Actually, it is always a comprehensive consequence of the interaction of multiple factors (Wang et al., 2010). Thus, more combined and comprehensive driving factors of forest change should be addressed in future research. Also, increasing the explanation of driving forces is another problem to be resolved.

In chapter 4, the contradictions between the explanation of CA-AB model and the number of driving forces and the related discussions are still to be resolved in future research. Moreover, I removed the constraint factors which do not significantly act on forest loss/gain after conducting the regression analyses. Although removing variables is a basic and effective method of eliminating the multicollinearity in regression analyses, a better resolution is expected to be developed to deal with the multicollinearity, especially on keeping the constraint variables which were authenticated that highly control forest loss/gain in chapter 3. In addition, another problem in this chapter is studying the indirect variables of forest change, e.g., education and technology.

Education is a considerable source of the improvement of environmental awareness among people. It would be an important factor which highly affects the residents' behavior in the future. For the technology, it would help not only to increase the agricultural integration and intensification but also to solve the contradictions of the shortage of resources and the surge of population (Lele, 1991; Cutter et al., 2000), and it indirectly protects the forest. Thus, the ways of assessing the relationship between forest change and indirect variables are supposed to be considered. Another limitation of chapter 4 in this study is the accumulative error. The simulations of CA model and CA-AB model are based on the results of classification, but the errors (Table 4. 5) are only from the simulations. The accuracies of land cover classification were not taken into account in this chapter. For the future research, the errors both from classification and simulation are supposed to be assessed simultaneously. At last, although I added a random variable in the model, the randomized behaviors and the randomized land cover change are still difficult to be simulated.

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