

**CHARACTERIZING AND MODELING AGRICULTURAL AND FOREST  
TRAJECTORIES IN THE NORTHERN ECUADORIAN AMAZON: SPATIAL  
HETEROGENEITY, SOCIOECONOMIC DRIVERS, AND SPATIAL  
SIMULATIONS**

**Carlos F. Mena**

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Geography

Chapel Hill  
2007

Approved by:

Dr. Stephen J. Walsh

Dr. Richard R. Bilborrow

Dr. Flora Lu

Dr. Conghe Song

Dr. Thomas M. Whitmore

© 2007  
Carlos F. Mena  
ALL RIGHTS RESERVED

## **ABSTRACT**

**CARLOS F. MENA: Characterization and Modeling Agricultural and Forest Trajectories in the Northern Ecuadorian Amazon: Spatial Heterogeneity, Socioeconomic Drivers and Spatial Simulations**  
(Under the Direction of Stephen J. Walsh)

This research shows that agricultural frontier regions are heterogeneous and complex entities. This dissertation links four interconnected questions that seek to generate new insights into the processes of land use and land cover change in the Northern Ecuadorian Amazon (NEA). The research uses household survey data collected in the study area in 1990 and 1999 and a set of classified Landsat images for 1973, 1986, 1999, 1996, and 2002. This study, first, analyzes the composition and spatial configuration of the Land Use and Land Cover (LULC) trajectories in the NEA. Land trajectories are built using image algebra and stratified by deforestation stage and census sector. The analysis of LULC trajectories has suggested a core and periphery pattern of transitions in the NEA and shows the complexity of land changes in the region. Second, this research characterizes secondary forest succession, its extent and the socioeconomic, demographic, and biophysical factors that control forest generation. The analysis, using logistic regression, shows how improvements in accessibility and off-farm employment contribute positively to forest regeneration. Third, this research analyzes the spatial heterogeneity and spatial dependence of the relationships between socioeconomic, demographic, and biophysical drivers and LULC. The intent of this question is to find the spatial non-stationarity of the relationships between factors and LULC change using Geographically Weighted Regression and Spatial Lag Models. There is also an

emphasis on new spatial representations of the parameters resulting from the regression analysis. This research component determined that the intensity of the drivers of LULC change is heterogeneous across space. Four, this research develops a cellular automata model that simulates LULC trajectories using pixels, neighborhoods, and spatial regimes that interact to produce broad LULC patterns. LULC patterns emerge from rules that control interactions among cells, cell neighborhoods and other spatial regimes created using GWR models. The aim of this research is to clarify the spatial and temporal nature of the relationship between population and land change and to predict positive and negative feedbacks between social, geographical, and biophysical factors that have implications for environmental management and policy.

## ACKNOWLEDGMENTS

There are a number of people that have supported my work. Thanks to my advisor, mentor, and friend, Steve Walsh, for his constant encouragement, advice, and opportunity. Thanks to Dick Bilsborrow, who persuaded me to come to UNC and for his constant support and friendship. Thanks to Flora Lu, for the ideas, energy, and motivation to continue. Tom Whitmore and Conghe Song always connected to the research and were open to discuss ideas and provide good counsel. Thanks also to my friends of the Ecuador Project, including Chris Erlien, Clark Grey, Alisson Barbieri, Bill Pan, Brian Frizzelle, Jason Bremner, Ashley Carse, Paul Delamater and Joseph Messina. Thanks to my friend of the Salab, including Yang Shao, Dan Weiss, Greg Taff, Amy McCleary, Julie Tuttle, Patricia Polo, Kriengsak Rojnkuressatien, and Laura Brewington. Thanks to my classmates: Christian Cellar, Jonnel Allen, Dilys Bowman, Angela Cacciarru, Timothy Baird, Joseph Palis, Linda Quiquivix, David Havlick, and Tina Mangieri. Special thanks to Jan Hendrickson-Smith for her constant support from the CPC Training Program. Also thanks to Barbara Entwisle, Tom Heath, Ron Rindfuss and the staff at the Carolina Population Center. Thanks to Barbara Taylor and Nell Phillips for always being there to help, and to my family, Carlos Mena, Mariana Mena, Mauricio Mena, Daniel Mena, and Carolina Mena. Most important, thanks to Lucía, who has supported me all this time, never doubted and always inspired me.

Institutions that also have supported my work are: The UNC Department of Geography, Carolina Population Center, National and Aeronautics Space Administration,

Fogarty International Center, National Science Foundation, UNC Institute of Latin American Studies, EcoCiencia, Ministry of Environment of Ecuador, Searth, the Association of American Geographers, Clirsen, Mellon Foundation, and Cepar.

This research was possible thanks to the small farmers of the Amazon who with generosity answered our questions and explained part of their lives.

## **DEDICATION**

This work is dedicated to my wife Lucía.

To my daughters Alejandra and Paula.

To my parents Mariana and Carlos.

To my grandmother Julia.

And to the people of the Amazon.

## TABLE OF CONTENTS

LIST OF TABLES.....xi

LIST OF FIGURES.....xiii

### Chapter

1.	LAND USE AND LAND COVER TRAJECTORIES IN THE NORTHERN ECUADORIAN AMAZON.....	1
1.1.	INTRODUCTION .....	1
1.2.	THE NORTHERN ECUADORIAN AMAZON.....	3
1.3.	ORGANIZATION AND CENTRAL QUESTIONS IN THIS RESEARCH .....	6
1.4.	IMPORTANCE OF THIS STUDY .....	10
1.5.	THEORETICAL CONSTRUCT AND THE ADAPTIVE SYSTEM .....	10
1.6.	RETHINKING LAND USE TRAJECTORIES .....	31
1.7.	CONCLUSIONS.....	34
2.	LAND USE/LAND COVER TRAJECTORIES IN THE ECUADORIAN AMAZON .....	36
2.1.	INTRODUCTION .....	36
2.2.	THE STUDY AREA: THE NORTHERN ECUADORIAN AMAZON .....	40
2.3.	LANDSCAPE CHANGE: THEORETICAL IMPLICATIONS .....	42
2.4.	METHODOLOGY .....	47
2.5.	RESULTS .....	56

2.6.	CONCLUSION AND DISCUSSION .....	95
3.	SECONDARY FOREST SUCCESSION IN THE NORTHERN ECUADORIAN AMAZON: SPATIAL PATTERNS AND DRIVERS .....	99
3.1.	INTRODUCTION .....	99
3.2.	THE NORTHERN ECUADORIAN AMAZON (NEA) .....	101
3.3.	CONCEPTUAL MODEL AND THEORETICAL FRAMEWORK.....	104
3.4.	METHODOLOGY .....	109
3.5.	STATISTICAL ANALYSIS .....	113
3.6.	RESULTS .....	119
3.7.	CONCLUSIONS.....	126
4.	CHARACTERIZING THE SPATIAL DEPENDENCE AND SPATIAL HETEROGENEITY OF THE DRIVERS OF LAND CHANGE IN THE NORTHERN ECUADORIAN AMAZON .....	128
4.1.	INTRODUCTION .....	128
4.2.	THE NORTHERN ECUADORIAN AMAZON (NEA) .....	131
4.3.	THEORETICAL CONSIDERATIONS .....	133
4.4.	METHODOLOGY .....	141
4.5.	RESULTS .....	149
4.6.	CONCLUSIONS.....	176
5.	SIMULATING LAND COVER TRAJECTORIES, SPATIAL HETEROGENEITY, AND LOCAL VARIATION THROUGH CELLULAR AUTOMATA MODELING IN THE NORTHERN ECUADORIAN AMAZON .....	179
5.1.	INTRODUCTION .....	179
5.2.	THE STUDY AREA: THE NORTHERN ECUADORIAN AMAZON .....	185
5.3.	CELLULAR AUTOMATA MODELS IN THE ECUADORIAN AMAZON.....	187
5.4.	THE SIMULATION PROCESS.....	189

5.5.	RESULTS .....	195
6.	CONCLUSION .....	204
6.1.	REVISITING RESEARCH QUESTIONS .....	204
6.2.	MAIN FINDINGS, APPLICATIONS, AND CONTRIBUTIONS .....	206
6.3.	MAIN CHALLENGES .....	210
6.4.	RETHINKING AGRICULTURAL FRONTIERS .....	213
6.5.	CONNECTIONS TO FUTURE RESEARCH .....	213
6.6.	SUMMATION.....	217
	REFERENCES .....	218

## LIST OF TABLES

### Table

1.1. Property regimes in the Ecuadorian Amazon. ....	21
1.2. Effects of higher scale institution in local institutions.....	22
2.1. Central and grouped classification schemes. ....	48
2.2. Variables used in the logistic regression model.....	55
2.3. Top 10 LULC transitions in the nea and its proportion in the landscape. ....	57
2.4. Main agricultural transitions by period of deforestation in the NISA. ....	62
2.5. Top LULC trajectories within six clusters of the NEA. ....	62
2.6. Descriptive statistics of independent variables and expected relationship. ....	94
2.7. Logistic regression coefficient for the logistic regression. ....	94
2.8. Classification of cases and odds ratio. ....	95
3.1. Types of secondary forest succession in the Ecuadorian Amazon. ....	105
3.2. Independent variables at the farm-level for 1990 and 1999. ....	115
3.3. Secondary forest for the nea obtained from satellite imagery. ....	120
3.4. Land in secondary forest reported by farmers in 1990. ....	120
3.5. Land in succession reported by surveyed farmers in 1999. ....	121
3.6. Logistic regression model for secondary forest in 1990.....	125
3.7. Logistic regression model for secondary forest in 1999.....	125
4.1. Selected independent variables used in the regression models.....	143
4.2. Central and grouped classification schemes. ....	144
4.3. OLS regression results -- land change (1986-1996). ....	144
4.4. OLS regression results -- land change (1996-2002). ....	145
4.5. Spatial lag model results -- land change (1986-1996). ....	152
4.6. Spatial lag model results -- land change (1996-2002). ....	152

4.7. Results of Monte Carlo test for the spatial variability of parameters in land change models (1986-1996). .....	154
4.8. Results of Monte Carlo test for the spatial variability of parameters in land change models (1986-1996). .....	154
5.1. Set of independent variables from 1990 used to parameterize the GWR model. ....	192
5.2. Layers used to characterize the suitability for flux class change or urban change.....	193
5.3. Comparison of the total land class areas and percentage of the landscape obtained using landsat classification and simulations for the year 2002. ....	200
5.4. Comparison of relevant spatial pattern indices obtained from landsat classification and simulations for the year 2002. ....	201

## LIST OF FIGURES

### Figure

1.1. The Northern Ecuadorian Amazon.....	5
1.2. Household life cycle and land use.....	15
1.4. Property in relation to rights, benefits and duties.....	20
2.1. Different land use transitions at different stages of settlement. ....	37
2.2. LULC trajectory composition. ....	39
2.3. The study area: Ecuador and the Northern Ecuadorian Amazon. ....	42
2.4. Pixel history to trajectory name.....	51
2.5. Census sectors in the Northern Ecuadorian Amazon. ....	53
2.6. Visual representation of selected LULC trajectories. ....	60
2.7. Location of lulc trajectories according to the deforestation period.....	61
2.8. Spatial distribution of six LULC transitions clusters. ....	89
2.9. Distribution of landscape metrics calculated using census sector as unit. ....	91
2.10. Landscape metrics and their relationship to accessibility. ....	92
2.11. Probability of transitioning in the Northern Ecuadorian Amazon ....	95
3.1. The Northern Ecuadorian Amazon.....	102
3.2. Land cover change detection in sample farms. ....	111
3.3. Land use change from parcel history and gps survey. ....	112
4.1. The northern ecuadorian amazon. ....	133
4.2. Two adaptive moving weighting kernel.....	149
4.3. Moran's I index for selected variables for 1990. ....	146
4.4. Moran's I index for selected variables for 1999. ....	147
4.5. Local indicators of spatial autocorrelation for the variable <i>deforestation</i> in the period 1986-1996. ....	148

4.6. Local indicator of spatial autocorrelation for the variable <i>walk</i> (walking distance to the main road) in 1990. ....	149
4.7. GWR results for selected significant variables in the deforestation (1986-1996) model. ....	156
4.8. GWR results for selected significant variables in the deforestation (1996-2002) model. ....	157
4.9. GWR results for selected significant variables in the pasture (1986-1996) model. ....	158
4.10. GWR results for selected significant variables in the pasture (1996-2002) model. ....	159
4.11. GWR results for selected significant variables in the small scale agriculture (1986-1996) model. ....	160
4.12. GWR results for selected significant variables in the small scale agriculture (1996-2002) model. ....	161
4.13. Residuals of the large scale agriculture model (1996-2002).....	175
4.14. 3-d representation of the effect of the variable <i>male</i> on the proportion of deforestation for the period 1986-1996.....	175
4.15. 3-d representation using contour lines of the effect of the variable <i>child</i> on pasture for the period (1986-1996): the colors represent t-test values in the GWR model.....	176
5.1. The north intensive study area (NISA) within the colonization area of the Northern Ecuadorian Amazon.....	187
5.2. Main components in the process of land change using the CA model.....	194
5.3. Simulation results: (a) the initial land cover in 1986, and (b) the simulated land cover in 2010. ....	196
5.4. Results of 100 runs of the model for the year 2010 for different land classes. ....	197
5.5. Areas of land cover generated by the model between 1986 and 2010. ....	199

## CHAPTER 1

### Land Use and Land Cover Trajectories in the Northern Ecuadorian Amazon

The soul of geography lies in its origins as a discipline involved with both the natural world and the created second world within the world of nature and their mutual interaction (Glacken, 1967 c.f. Brookfield, 2004(c.f. ))

#### 1.1. Introduction

Land Use/Land Cover (LULC) change is an anthropogenic activity as old as civilization, as people in need of land systematically clear natural vegetation for different uses. The impacts of land change have several dimensions. Agricultural expansion, for example, has been basic for the survival of civilization since the domestication of wild plants 12,000 years ago. Today the conversion of natural areas into agriculture is one of the core problems of global environmental change. It is estimated that by 2050 nearly  $10^9$  hectares of natural ecosystems will be converted to agriculture. This change will produce a 2.5-fold increase in nitrogen- and phosphorus- driven eutrophication of terrestrial, freshwater, and marine ecosystems, and a comparable increase in pesticide use (Tilman et al. 2001). The impacts of LULC change are more evident in agricultural frontiers, where several processes, including deforestation of native vegetation and demographic and socioeconomic change, occur on vast geographical scales and accelerated rates.

The Northern Ecuadorian Amazon (NEA) is not an exception. In the last four decades, almost 40 percent of the forested landscape in the region has been transformed into

agricultural fields, pasture, secondary succession, and urban areas. This transformation has contributed to the accelerated destruction of the Ecuadorian rainforest and the associated ecological services.

Although there have been unprecedented advances in the study of the driving exogenous and endogenous forces of land change<sup>1</sup>, several challenges remain, including: (a) the study of the processes behind the spatial patterns, (b) extrapolation of results in space and time, (c) linkage of data of varying quality, and (d) the study of culture as a driver of landscape change (Bürgi et al. 2005). This research deals with these challenges in different ways, through the use and linkage of household socioeconomic and demographic data and remotely sensed data to identify agricultural expansion, spatial pattern and processes, and future land use change scenarios<sup>2</sup>. The aim of this research is to characterize, model, and spatially simulate the relationships between LULC trajectories of change (both composition and spatial structure) in response to socioeconomic, geographic, demographic, and biophysical processes acting across different temporal and spatial scales linked through remote sensing data, household survey, geographic information systems, and spatially explicit models.

The objectives of this introductory chapter are twofold: first, to define the scope of the research, research questions to be addressed, and hypothesis of land use/land cover change, and second, to describe the theoretical and methodological linkages between data

---

<sup>1</sup>A number of studies have reviewed and synthesized theoretical and methodological approaches and case studies, mainly focused on tropical regions (Geist and Lambin 2001; Geist and Lambin 2002; Kaimowitz and Angelsen 1998; Lambin et al. 2001; Rudel and Roper 1997; Southgate 1990).

<sup>2</sup> A notable exception is the relationship of culture (or cultural change) and land use that is indirectly addressed. Although the dataset used here does not contain direct measures of culture, the study assumes that culture is heterogeneous across households and communities within the Northern Ecuadorian Amazon.

sets and research questions. This chapter reviews the characteristics of the study area and data collected beginning in 1990. The research questions, hypothesis, and importance of the study are then described, followed by a discussion of the relevant bodies of literature related to land change science and links to the theoretical structures that guide the four research questions. Finally, the main methodological approaches are described and linked to support the aims of this research.

## **1.2. The Northern Ecuadorian Amazon**

The study area is located in the northeast portion of the Ecuadorian Amazon. The region covers an approximate area of 34,000 km<sup>2</sup> (Figure 1.1), which is comparable to the area of the State of Maryland, USA. The Northern Ecuadorian Amazon (NEA) has a variety of natural vegetation types represented: evergreen forest of lowlands and foothills, evergreen forest flooded by white water, evergreen forest flooded by black water, cloud forest, palm forest, and humid brush (Palacios et al. 1999). The Ecuadorian rainforest is among the most biologically diverse and unique environments in the world and has been considered one of the world's ecological hotspots, i.e., areas with high biodiversity under intense human pressure (Myers 1988; Myers 1990; Orme et al. 2005), and an area with the highest alpha biodiversity (Pitman et al. 2003). The NEA has seven national protected areas within its region, but despite this status, the pressures of agricultural expansion and petroleum activity continue to increase through time. Ethnic diversity is also high in the region, as the Ecuadorian Amazon is home to approximately 30,000 indigenous people from seven ethnic groups (i.e., Quichua, Shuar, Ashuar, Huaorani, Cofan, Siona, Secoya, and Saparo) who have adapted to the Amazonian environment over hundreds of years.

The discovery of petroleum marked the division between two periods in the history of

the NEA. Prior to the exploitation of petroleum, the natural landscape was essentially intact and populated by indigenous peoples and very few colonists who were devoted to subsistence agriculture. The petroleum era began after 1967 when Texaco drilled its first oil well in the Ecuadorian Amazon. Roads were opened, oil pipelines laid, and colonists began to populate the rainforest. Between 1964 and 1992, 322,176 km<sup>2</sup> within the NEA were colonized by 41,737 farmers, but only 133,448 km<sup>2</sup> have been legalized through land titles (Barsky 1984; Ruiz 2000). Between 1974 and 1982 when the pace of colonization was at its highest, annual population growth rates were 8 %/yr compared to 6 %/yr for 1982 to 1990, 5%/yr between 1990 and 2001, in each period double the national average (Bilsborrow 2003). Migration from the Highlands and Coastal regions of Ecuador is the main factor contributing to population growth and agricultural expansion in the NEA. Lately, unofficial reports have shown evidence of high international migration: refugees from neighboring Colombia, escaping the violence from the civil war. Today the Northern Ecuadorian Amazon has one of the highest population densities in the Amazon Basin (ECORAE 1996).

As indicated, colonization is strongly associated with oil exploitation in the Ecuadorian Amazon. The petroleum industry built new roads to lay pipelines for oil exploration and settlers concentrated along the roads. Two small planned colonization projects were developed in the study area in the early 1970s and reflected government concerns about national security and desire to expand the agricultural frontier (Uquillas 1984), but virtually all the colonization has been spontaneous. Petroleum from the region is crucial to the Ecuadorian economy, and attracts labor and services to the region. Petroleum provides nearly one-half of Ecuador's export revenues, almost all coming from the provinces of Napo, Sucumbios, and Orellana in the study region (Kratsas and Parnell 2001). More oil

infrastructure development is expected due to the large petroleum reserves located in the region. Ecuador is ranked third for oil reserves in South America (Energy Information Administration 2003). New deforestation fronts are expected, if not already being created, near protected areas and indigenous territories in the NEA. Assessment of these land transformation patterns is among the central aims of this research.

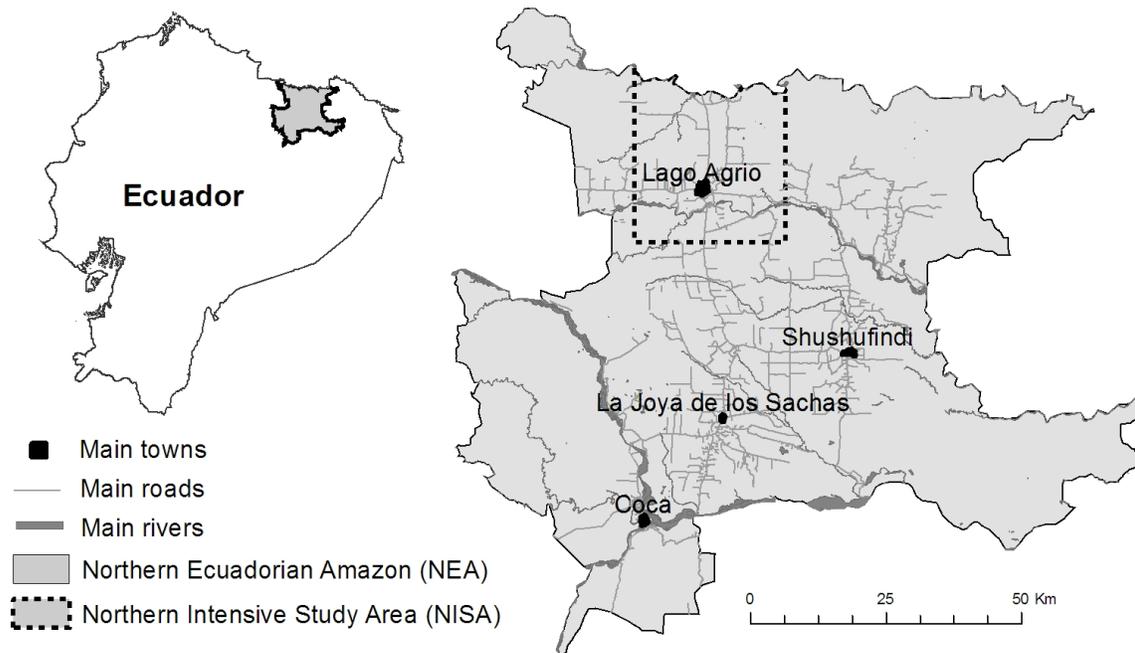


Figure 1.1. The Northern Ecuadorian Amazon.

Land cover change, primarily deforestation, in the region has been estimated by Sierra (2000). He estimates deforestation rates for the Napo region, including portions of Colombia, Ecuador, and Peru, at 0.6%/yr and for the NEA at 3.2%/yr. Ecuadorian official reports have pointed to colonization and agricultural expansion, timber extraction, monocultivation plantations, oil and mining, weak land titling programs, and poverty as the main overall causes of forest cover change in Ecuador (Food and Agriculture Organization 2000). More detailed, small-scale studies show patterns in which larger cleared areas emerge

among households with greater farm labor resources (i.e., male workers per household) (Marquette 1998), duration of settlement, soil quality, road access, education (Pichón 1997; Pichón et al. 2002), and household demographic characteristics (Pan et al. 2004). Migrant women in the Ecuadorian Amazon who have greater numbers of children are more likely to be involved in agriculture and engaged in clearing more forest for pasture and cattle ranching (Keshari et al. 1996). Southgate et al. (1991), in a statistical analysis of deforestation, supports the argument that the settlement of forested lands is driven by the prospect of collecting agricultural rents. Deforestation in the Ecuadorian Amazon is thus framed by a set of scale-dependent socioeconomic conditions and biophysical settings. Land cover change on fincas in the NEA appears related to the development of local agricultural markets, road accessibility, demographic pressures, and cultural practices, while at regional scales, land cover change responds to national and global oil prices and markets, internal migration, and infrastructure extension. This brief review of case studies suggests that different socioeconomic and demographic factors interact with different agents and drivers that operate at different spatial and temporal scales to produce agricultural extensification through deforestation. As such, the need for an integrated approach capable of capturing the forces and factors of land dynamics in the NEA, and within a spatially explicit context is a critical need.

### **1.3. Organization and Central Questions in this Research**

This research will map, statistically model, and spatially simulate LULC trajectories in the Northern Ecuadorian Amazon related to different socioeconomic, demographic, and geographical processes at work across different social or political units. The work will inform policy and environmental management concerns in the region. The dissertation research

revolves around four interconnected research questions, each developed and expressed in the form of a journal article that deals with land change in the following domains: (a) a regional assessment of the temporal and spatial dimension of land change trajectories in the colonization area; (b) an analysis of the emergence of secondary forests in the study area and the socioeconomic and demographic factors that promote the emergence of secondary forests. This section constitutes the next step following previous studies related to the deforestation in the Ecuadorian Amazon (Mena et al. 2006a; Mena et al. 2006b); (c) an analysis of the spatial non-stationarity of the relationships between the drivers of land use and land cover change in the Ecuadorian Amazon; and (d) the spatially explicit simulation of land cover change using cellular automata models that link the socioeconomic, demographic and biophysical drivers of change at the regional level with transition probabilities derived from an assembled satellite time series.

### **1.3.1 Research Questions and Hypotheses**

*Research Question 1:* What is the compositional and spatial configuration of the land use and land cover transitions in the NEA between 1986 and 2002?

Such questions include: is there any regular cycle in the composition of LULC trajectories: from forest to perennial crops, annual, semi-annual, and pasture, etc? Are there spatial differences in the trajectories of land use change between the core and periphery regions in the colonization area? Do new colonization areas tend to have a higher rate of LULC and different trajectories of change? Are there distinct clusters of unique sets of LULC trajectories?

*Hypothesis 1:* It is hypothesized that the land use/land cover transitions in the Northern Ecuadorian Amazon have spatial and temporal patterns that emerge according to

the lines (or *lineas*) of colonization and the influence of urban centers.

Research Question 2: What is the extent of secondary forest succession and what are the socioeconomic, demographic, and biophysical factors contributing to the generation of secondary forests in the Northern Ecuadorian Amazon between 1986-1996 and 1996-2002?

This question addresses the main drivers of secondary forest generation or forest transition in two periods (1986-1996 and 1996-2002) with a special emphasis on the influence of socioeconomic and demographic factors. The two study periods are defined through the dates of the longitudinal household surveys (1990 and 1999) and the assembled remote sensing time series. Sub-questions include: is LULC change dependent upon demographic factors at both time periods? Are forest transitions controlled by accessibility to agricultural markets? The intention of this question is to clarify the temporal nature of the relationship between population and secondary forests and to infer future positive and negative feedbacks between socioeconomic, demographic, and biophysical considerations of reforestation as suggested in the sequence of changes captured in the LULC trajectories?

Hypothesis 2: At the farm level, forest transitions respond to several socioeconomic, demographic, and biophysical factors. Forest transition, the production of secondary forest, is less intense in the early stages of the settlement when farmers had more incentive to keep agricultural lands active (e.g., higher soil fertility, higher agricultural rents), however in a later period, farmers face decrease in soil fertility and there are more off-farm employment opportunities, push farmers to seek other livelihoods, which have spatially-explicit land use responses, such as an increase in secondary forest.

Research Question 3: What is the spatial heterogeneity of the relationships between socioeconomic, demographic, and biophysical drivers of LULC in 1990 and 1999?

The intent of this question is to examine the spatial non-stationarity of the relationships between factors of LULC change created when a stimulus provokes different responses in different parts of the study area. As has been observed in pre-dissertation fieldwork, the region has intrinsic differences in the farmer's adaptation to the different environments and a different natural resource base, therefore, exogenous and endogenous factors might affect land use in different ways the rates and patterns of LULC dynamics depending on location or place.

*Hypothesis 3:* There is spatial heterogeneity in the relationships between land use and land cover change and their socioeconomic, demographic, and biophysical drivers.

*Research Question 4:* Can LULC patterns be modeled using complex systems as a theoretical framework? If so, is it possible to model and spatially simulate LULC trajectories as a complex adaptive system using Cellular Automata (CA) approaches that account for feedbacks, self organization, and spatial interaction of individuals and communities?

Might decisions made by farmers about the use of the land, particularly LULC change trajectories, indicate emergent behavior expressed at some higher order of spatial organization or scale (i.e., the pixel). Can land use plots function as independent units, where aggregation creates complex LULC change patterns?

*Hypothesis 4:* It is possible to model LULC change produced by farmers on agricultural lands, which is influenced by socioeconomic, geographic, biophysical, and demographic factors. A CA spatially-explicit model will be developed that can capture the changing environment and model the feedbacks between actors and the surroundings in which uncertainties play an important role.

#### **1.4. Importance of the Study**

The modeling and simulation of LULC change have strong local to global implications. Linked to global environmental change, modeling and spatially-explicit simulations of LULC transitions greatly enhance our ability to predict biodiversity loss, the impact of future climate scenarios, and carbon budget estimates. In the Amazon Basin, at the local scale, the study of the drivers of LULC change is of special interest, because the generally poor local populations (i.e., indigenous communities, colonist farmers, and urban residents) are vulnerable to drastic and pronounced environmental changes that can undermine food security, socioeconomic conditions, and human health. The efficacy by which governments and local populations cope with these drastic LULC changes depends on their ability to predict the likely consequences of various actions. Specifically, the spatially-explicit simulations can be used by Ecuadorian organizations such as ECORAE (the Ecuadorian governmental agency for the Eco-development of the Amazon), the Ministry of Environment, EcoCiencia (a leading Ecuadorian non-governmental organization for ecological studies) to create response scenarios to new policies (i.e., new Forestry Law), projected development efforts (i.e., new roads), and changes in cultural and demographic characteristics of the population.

#### **1.5. Theoretical Construct and the Adaptive System**

This section reviews the linkages among the main theoretical approaches that guide the research questions. In this research, population and environment is intended to be seen as a dynamic and adaptive coupled human-natural system. Population encompasses demographic, socioeconomic, and institutional changes, while environment includes the natural resource base, the biophysical template and LULC dynamics.

### **1.5.1 Socioeconomic and Demographic Drivers of Land Use and Land Cover Change**

Although the effects of population growth and its potential negative effects were reported at several points in human history, just in the early 1970s theoretical and empirical models were used to explain the effects of uncontrolled population growth on the environment at global scales (Meadows et al. 1972; Pestel 1989). The connection between population growth and environmental degradation, however, was studied earlier two centuries ago by Malthus (1803), who pointed out that human populations could collapse due to their size increasing at geometric rates since the food supply would increase at an arithmetic rate. In terms of LULC change, neo-Malthusian theories are built on the assumption that land productivity is fixed and returns to capital investments tend to bring diminished returns (United Nations Organization 2001). Consequently, it is necessary to expand agricultural lands to feed the growing populations. Some cross-national and regional studies in frontier settings have shown that population growth results in higher rates of deforestation (Ehrhardt-Martinez 1998; Parayil and Tong 1998). Among the observations made by Malthus is that the most productive land is generally used first, and consequently, newer agricultural lands tend not to be as productive. In the NEA land occupied in the later stages of colonization have disadvantages related to their natural resource base, geographic accessibility, and access to technology that renders these lands less suitable for highly productive agriculture. In frontier environments, such as the NEA, population pressure affects LULC dynamics. As migration to the Amazon increased, coupled with the high human fertility, growing populations of farmers and urban centers expanded, creating needs for new agricultural products and agricultural land for production. The assumption that land productivity is fixed is also taken into consideration by classical agricultural economics. The

Law of Diminished Returns (Ricardo 1887) argues that when land is fixed, increased applications of labor inputs generate a decrease in the productivity of the mean output per worker (Bilsborrow and Carr 2000).

Opposed to the Malthusian view, Boserup (1965; 1981) challenges the Ricardian and Malthusian assumption of fixed land productivity. She argues that more people create technological changes that intensify land use so higher populations per unit area can be supported without overall resource decline. Boserupian theory is important in that it enhances the possible role of population pressure on natural resources as a catalytic component in the process of land use intensification. According to Boserup, the increase of labor inputs per unit of land through time creates the following stages of intensification that ranges from low to high intensity: (a) forest fallow with long fallows with 20-25 years between crops; (b) bush fallow with 6-10 years between crops; (c) short fallows with 1-2 years between crops; (d) annual cropping; and (e) multiple cropping, within a year. Modern conceptualizations of land use intensification are associated to increases in input variables, e.g. chemical fertilizers, pesticides, and output intensification, that measure the increases in production against constant units of land area and time, e.g. calories/hectare/year (Lambin 2000). Critics of the Boserupian view argue that the endogenous character of the intensification process applies only to particular settings, relatively rich soil areas where investments in new technologies are possible and in areas where population density is *relatively* low with a capacity to change tenure regimes (Lee et al. 2000).

Beyond Boserup, the theory of induced innovation argues that technological change and innovation, an endogenous product, is associated with basic institutional changes and market demands (Lambin 2000). In the Northern Ecuadorian Amazon, two different types of

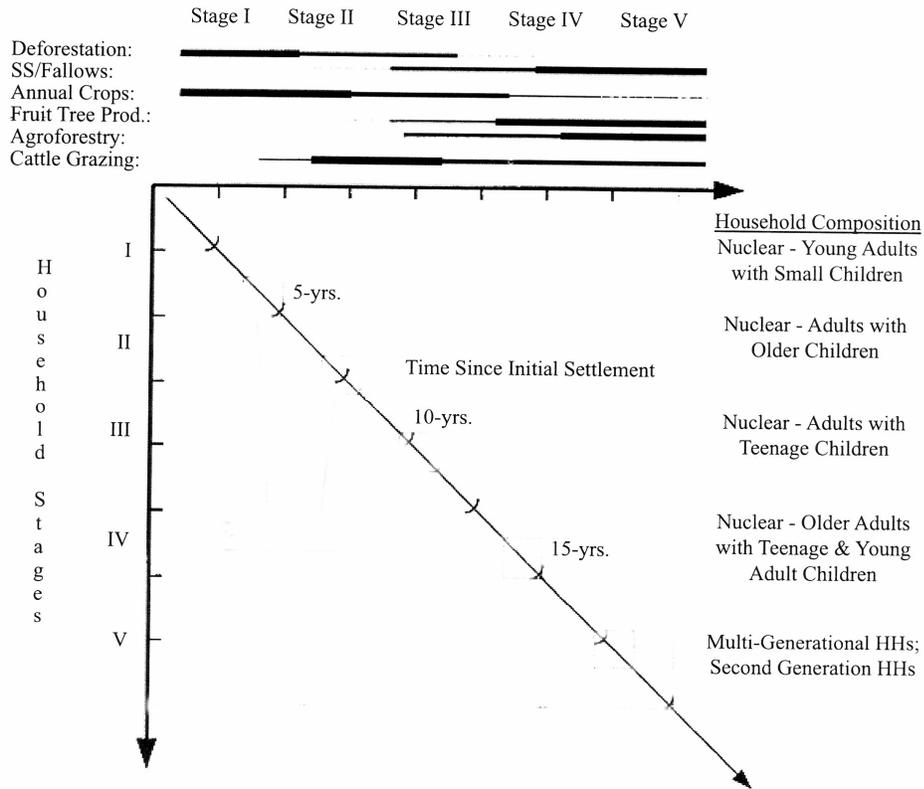
intensification scenarios are present. First, in colonist environments, where the population pressure on natural resources emerges in the form of farm subdivisions, the rapid decrease in soil nutrients in small areas coupled with expensive cost of technology (e.g., fertilizers), makes the process of intensification unsustainable for long periods of time, ending with the decline of the natural resource base. Second, in indigenous territories, where exogenous forces (e.g., reduction of ancestral territory due colonization) and endogenous factors (e.g., high fertility rate) emerge to create growing population pressures on the natural resource base, intensification occurs through decreasing the fallow periods of *chacras* (i.e., vegetable gardens) across the different ethnic groups.

Other relevant theoretical approaches, such as multiphasic response and the household life cycle theory will be also used to interpret outcomes and guide modeling. Multiphasic response (Davis 1963) explains how possible demographic responses (i.e., postponing marriage, reducing fertility, and out-migration) are followed to avoid a decline in living standards produced by increases in population density. In this context, Bilborrow (1987) and Bilborrow and Okoth-Ogendo (1992) extend multiphasic response to include economic and other economic-demographic changes. Accordingly, human responses to population pressure on natural resources can emerge in four ways. First, an increase in food production can occur by either intensifying or extensifying land use to keep pace with population growth. If these two forms of adaptation fail, another strategy is possible, i.e., temporary migration of individuals to urban centers or other rural destinations to overcome insufficient available land. The fourth strategy engages household members in permanent migration to areas with more available land. Finally, the fifth strategy invokes the decline of human fertility only if the strategies presented above fail. The interpretation of LULC

transitions can be seen as responses and adaptations to the changing environment (e.g., improvements in accessibility, soil fertility decrease, and fall of market prices).

To include the relationship between "time since settlement" and LULC transitions, the household life cycle theory is used and adapted to the reality of the NEA. This theoretical approach argues that the changes in the extent/intensity of agricultural activities are dependent upon the household life cycle. Chayanov (Cancian 1989; Chayanov 1966) explored the size and age structure of households and their affect on the proportion of land cultivated. He observed, in the early 20<sup>th</sup> century on isolated farms in Russia, that older households with a greater number of adults meant a higher local labor force, and the necessity and means for generating increases in cultivated land. In later years, some studies tried to extend and adapt Chayanov's findings to the Brazilian Amazon. For instance, McCracken et al. (1999), Perz and Walker (2002), and Walker and Homma (1996) identified five stages of a household life cycle of small farmers in the Brazilian Amazon (Figure 3). They describe the life cycle as (1) young parents who recently arrived in the area (i.e., duration of settlement <5 years) who initiate forest clearings for annual crops for subsistence, (2) parents with growing children (i.e., duration of settlement ~5 years old) become engaged in the cultivation of perennials and pasture, in addition to the cultivation of annual crops, (3) older parents with teenage children (i.e., duration of settlement ~10 years) produce a decrease in the cultivation of annuals and an increase in cattle raising and secondary vegetation, (4) pasture and perennial crops dominate with increasing proportions of secondary forest as parents age and children research young adulthood (i.e., duration of settlement ~15 years), and (5) children begin to leave the farm (i.e., duration of settlement > 15 years), and the presence of perennials remains a large portion of farm land use, as secondary forest

succession increases.



Source: McCracken et al. (1999)

Figure 1.2. Household life cycle and land use.

In terms of the household life cycle, there is a basic difference between the scenario in the Brazilian Amazon and the one in the Ecuadorian Amazon. In the NEA, the space for future agricultural expansion is extremely limited as the total area is relatively small and the geographic accessibility to the region remains a constraining factor to settlement and development. Land scarcity has produced little farm abandonment and instead a process of farm subdivision is on-going. When young adults marry, they claim a portion of the farm for their own agricultural activities and new households are created that begin using portions of the existing farm plot. Although, these young adults might leave to work temporarily outside the farm, the subdivision remains with relatively active agricultural production, which has

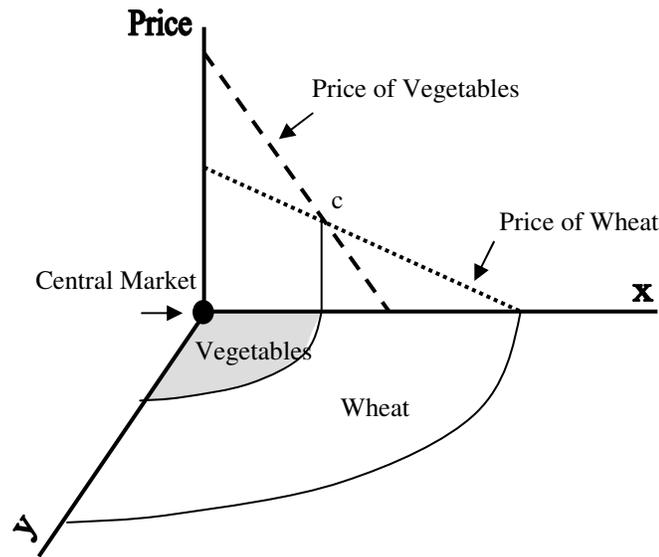
implications for land use. For example, the regeneration of secondary forest in the NEA does not increase with advances in household life cycle, rather, it is generated through the abandonment of cultivation plots within working farms. This is, in part, caused by the opportunity for off-farm employment, poor and inconsistent crop prices, the effects of globalization on the supply and demand of the primary commercial crops within the region (i.e., coffee, cacao, and pasture for cattle), relatively infertile soils, increases in the cost of transportation, general political instability in the country and region, and the continued difficulties associated with the 1999 “dollarization” of the Ecuadorian economy.

### **1.5.2 Economic Approaches to Land Use and Land Cover Change**

Land and agricultural economics are sub-disciplines of Economics that traditionally have dictated governmental policies for rural areas. Although theories and models of land use change have been widely studied, the foundations include the Theories of Malthusi, Boserup, and Chayonov. In this section, two relevant additional views are presented: von Thünnen land use models and economic models of agricultural households.

Early advances of the relationship between transportation and accessibility were produced by German Geographer, Johann von Thünnen, who in 1826 develop a model that illustrated the connection between land use, location, and transportation costs and, thereby, generated the first serious treatment of spatial economics (Nelson 2002). Nelson explains the von Thünnen model as follows (Figure 1.3.): "...suppose a plain, featureless, landscape with a central market and two crops, wheat and vegetables. All locations have identical production characteristics, including profit maximizing operators, but transport costs to the central market, with exogenously determinate prices. The prices of vegetables in the central market (a) is higher than the price of wheat (b), but vegetables are more expensive to transport.

Hence price of vegetables falls faster than the price of wheat as distance from market increases. Beyond point *c* the price of wheat is higher than vegetables. The result is a series of concentric rings of land use around the central market."



Source: Nelson (2002)

Figure 1.3. Von Thünen model of land use.

The von Thünen model is an oversimplification of the relationship between transportation costs and land use. When land productivity, input costs, and labor markets are introduced, the model becomes more complex, but the basic features remain the same. In this research, the implications of the von Thünen model are more practical than theoretical, because prices of agricultural products can be a determinant of land use, and as such, it can be coupled with GIS functions to indicate the possible suitability for different crops depending upon transportation cost and distances.

There is a wide range of economic theories and models that explore relationships between human activities and agriculture at different levels of organization (e.g., households, firms). Microeconomic models, most of the time, see households as a singular type of firm,

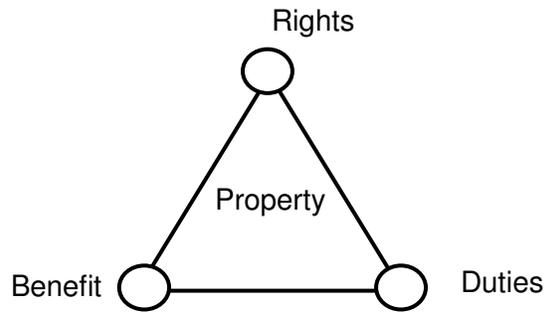
where relationships with markets and inputs are simplified in different degrees, almost always, following a profit maximizing assumption. Small open economy models of land use in rural areas assume that (1) all relevant prices are exogenous, which indicates that the actions and behavior of agents of land use change (i.e., farmers and households) do not have an affect on prices, and (2) markets fully determine how farmers value their resources and inputs (Kaimowitz and Angelsen 1998).

### **1.5.3 Development, Institutions, and LULC Change**

Detractors of the pure population and economic approaches argue that they ignore the historical and political-economic factors underlying rural poverty, deprivation, and environmental degradation (Parayil and Tong 1998). Studies of environmental change in the developing world should pay attention to the localized social and economic dynamics involving population and social change, rather than solely focusing on population and economic growth (Taylor and Garcia-Barrios 1995). One of the most applied paradigms of development to explain how the different paths of development affect LULC change is Modernization theory (also called Dual Society Models in Economics). In this approach, there are two clear sectors: a core, which is the urban, modern, production center, and the periphery, which is mainly a rural subsistence sector. Core and periphery are linked by mechanisms of polarization (i.e., the core growths) and spread (i.e., periphery growths) (Brown 1991). The modernization approach argues that environmental degradation (e.g., deforestation) is a function of the level and rate of development within a given country (Ehrhardt-Martinez 1998). Development can be explained as the increasing use of technology to achieve development, including economic growth, infrastructure, technology, urbanization, education, and extractive practices or improvements.

The role of poverty in rural areas is important in explaining small-holding LULC change, but this relationship is complex and likely not linear. It can be viewed from two different contrasting perspectives. First, rural populations are often impoverished by a declining resource base, and as a consequence, they are forced by their circumstances to further degrade the environment creating a cycle difficult to break. In addition, short-term attention to current needs takes precedence over long-term stewardship of resources (de Sherbinin 2000). Second, small farmers with increasing amounts of cultivated land tend to have the capital, access to technology, education, and subsidies necessary to succeed (Marquette 1998; Pichón 1997). The political and economic inequalities in the larger society, where urban systems are incapable of assimilating demographic growth, compel poor, dispossessed peasants to seek a livelihood on the margins of society, in the rain forest (Rudel and Horowitz 1993). At the same time, inequality creates the need to understand the role of institutional and household level factors in influencing the observed variation in the strategies of forest clearing (Pichón 1997). One clear critique to the studies based on household surveys that explore the agency of the agricultural household is that they ignore the larger structural setting within the regional and national economy (Chowdhury and Turner 2006). Theories, such as modernization, try to understand LULC change at cross-national scales, but do not work properly when applied to regional and sub-regional settings (Runge 1992). The complexity of the relationship between LULC change and development depends on a range of macro- and micro-economic variables, that drive LULC change with different degrees of intensity at different levels of social organization. A theoretical approach that deals with the institutional relationships between state, local communities, individuals, and natural resources is the study of regimes of property rights. A regime of property rights is the

structure of rights to natural resources and rules under those rights are exercised (Hanna et al. 1996). The study of property rights is important, because the change of property rights is the preferred alternative by governments and international organizations to improve ecosystems management. Bromley (1992) defines property as the social relationship that defines the property holder with a benefit stream (i.e. natural resource). Property is, in consequence, the claim that some higher body (the State) will protect property through the assignment and enforcement of duties, as rights have no meaning without duties (Figure 1.4).



Source: Bromley (1992)

Figure 1.4. Property in relation to rights, benefits and duties.

Open access (i.e., non-owner) resources have been strongly linked to environmental degradation. Individuals tend to exploit natural resources on open access lands without concern for the cost to society, according to what is called the “Tragedy of the Commons” (Hardin 1968). It holds that as long as incentives exist to privatize open access resources, there will be a tendency, at the societal level, to over-exploit available resources. Hardin assumes that an individual in his or her self-interest will try to maximize gains despite the negative effects on society. Unfortunately, open access resources have been confused by planners and national governments with common property regimes and have privatized communal lands. Common properties are different from open-access lands in the fact that

open-access lands have no rules regulating individual use rights, whereas common right property involve tacit cooperation by individual users according to a complex set of rules that regulate the rights of joint use (Runge 1992). Table 1.1 modified from Hanna et al. (1996), describes the several property regimes that currently exist within the NEA.

Table 1.1. Property Regimes in the Ecuadorian Amazon.

<b>Property-rights regimes</b>	<b>Owner</b>	<b>Owner Rights</b>	<b>Owner Duties</b>	<b>In the NEA</b>
Private	Individual	Acceptable social uses and control of access	Avoid un-acceptable uses	Farms
Common-Property	Collective	Exclusion of non-owners	Maintenance and sustainability	Indigenous communities and colonist communities
State owned	Citizens	Creation of duties	Maintain social objectives	National parks / sub-soil
Open Access	None	Capture	none	Rivers

Central questions in property rights research include: How are incentives shaped by systems of property rights? How do those incentives lead to particular patterns of environmental use (Hanna et al. 1996). Young (2002) points out that the land use patterns and sustainability of human-environment relationships are associated with and determined by the interplay of sub-national (i.e., modern, formal) institutions and local (i.e., informal) land tenure regimes. Within this context much of the LULC patterns are dependent on the interplay between institutions across-scales. Cross-scale institutions deal with horizontal (i.e., across space) and vertical linkages (i.e., across levels of social organization). Much of the natural resources needed to be managed across several scales are not isolated from one another, but occur simultaneously (Berkes 2002). National arrangements offer greater opportunities to include management practices in large ecosystems however these regimes

tend to include consumptive/extractive practices managed by elites. Local systems are adapted to small-scale users, less tied to markets, and maintain ecosystems for longer time. The pattern of local LULC is affected by the cross-scale integration operating at different levels of social organizations. Berkes (2002) lists the effects of higher institutions in local institutions as both positive and negative (Table 1.2).

Table 1.2. Effects of higher scale institution in local institutions.

Negative	Positive
Centralization of decision-making	State legitimizing of local institutions
Shifts in systems of knowledge	Enabling legislation
Colonization	Cultural and political revitalization
Nationalization of resources	Capacity building
Increased participation of markets	Institution building
Development of policies	

In the Ecuadorian Amazon, the process of agricultural colonization shows the evolution of the perceptions about property rights regimes among colonist, indigenous, and the state. In the early stages of colonization, the NEA was seen by local authorities, international development agencies, and poor colonist as an open access regimen, and, therefore, played a central role in the agrarian reform or *reforma agraria* and larger development schemes (Barsky 1984). When farmers settle on new lands, the colonization processes favor forest clearing to access property rights, specifically, privatization of lands that induces a cycle of excessive land clearing and inadequate soil conservation (Southgate 1990). Only 40 percent of the proportion of lands in the NEA have legal title over the land (Ruiz 2000), however, despite the absence of land titles, farmer hold an informal private regimen or effective possession that consists of the physical delimitation of the property and recognition from neighbors. Rudel (1995) has found that the lack of title does not contribute to deforestation in the central Ecuadorian Amazon. It is also important to note that in the

Ecuadorian Amazon, the legal title or *escritura* is central to the access of agricultural or non-agricultural credits. State and private banks grant loans to support agricultural activities (e.g., cattle raising and coffee production) and other non-agricultural activities (e.g., acquisition of small trucks to be used as taxis).

#### **1.5.4 Landscape Ecology: Scale, Pattern, Process, and Hierarchy**

Conceptualizations of landscapes and landscape ecology have evolved at a remarkable pace in the last few decades. Different definitions offer disciplinary and regional biases. The landscape definition used in this research is based on one proposed by Burdel and Baudry (2003), as a level of organization of ecological systems that is higher than the ecosystem level, characterized essentially by its spatial and temporal heterogeneity and its dynamics, and partly governed by human activities. It exists independently of perceptions.

Three fundamental landscape characteristics associated with the study of landscape ecology are structure, function, and change (Turner 1989; Turner et al. 1989). *Structure* refers to the spatial relationships between distinctive ecosystems, that is, the distribution of energy, materials, and species in relation to the sizes, shapes, numbers, kinds, and configurations of components. *Dynamic* (i.e., function) refers to the interactions between spatial elements, including the flow of energy, materials, and organisms among the component ecosystems. *Change* (i.e., transformation) refers to alterations in the structure and function of the ecological mosaic through time.

Landscape Ecology is based on the premise that there are strong links between ecological (spatial) pattern and ecological process evident at different spatial and temporal scales (Gustafson 1998). Previous ecological studies of the landscapes and regions have centered on the description of the processes that create certain biotic patterns, while

landscape ecology emphasizes the effects of spatial patterning on ecosystems.<sup>3</sup> Specifically, landscape ecology considers (a) the development and dynamics of spatial heterogeneity, (b) interactions and exchanges across heterogeneous landscapes, (c) the influences of spatial heterogeneity on biotic and abiotic processes, and (d) the management of spatial heterogeneity (Turner 1989).

Spatial pattern has been used extensively in the landscape ecological literature, primarily to describe both the composition and structure of landscapes. The terms spatial heterogeneity and spatial pattern are used synonymously to refer comprehensively to its main parts: composition, configuration, and temporal aspects of heterogeneity. Pattern is generated by process at various space-time scales (Urban et al. 1987).

The dynamics of landscapes depends on the relationships between societies, different levels of social organization (from households to states), and their environment (from small ecosystems to plateaus). Scale creates structures that change in space and time. Spatio-temporal heterogeneity controls the landscape dynamics (Burel and Baudry 2003). Because landscapes are spatial entities, their structure, function, and change are scale dependent. There is no single natural scale at which ecological phenomena should be studied; systems generally show characteristic variability on a range of spatial, temporal, and organizational scales (Levin 1992).

The problem with scale, as a concept, lies in the fact that scale has a variety of meanings according to the research focus or discipline involved. Cao and Lam (1997) categorize geographical scale in four dimensions: (1) cartographic and map scale refers to the

---

<sup>3</sup> For example heterogeneity mapped versus heterogeneity ecologically relevant.

ratio of a distance on a map to the corresponding distance on the ground, (2) the geographic or observational scale refers to the size or spatial extent of the study, (3) the operational scale refers to the scale at which certain processes operate across the environment: the operational scale is dependent on the geographical phenomenon being studied, and (4) measurement scale is intrinsically linked to the concepts of grain and extent. Grain refers to the smallest unit that can be distinguished, while extent refers to the size of the study area.

An important consideration related to scale is that geographical and ecological phenomena are scale dependence, where the pattern under observation varies with scale (Walsh et al. 1999; Walsh et al. 1997). The failure to account for scale-dependent changes in pattern and process relationships have confused and confounded the synthesis of ecological data and the extrapolation of ecosystems effects from sample plots to landscape scales (Wiens et al. 1993). The ability to detect changes in patterns and make predictions at more than one level of scale resolution requires identifying the physical and biological processes of interest, estimating the variables and parameters that affect these processes at several scales, and developing rules to translate the information across scales (Gardner 1998).

It has been shown that pattern is generated by processes at various scales. A system can be divided or decomposed into components operating at different scales. There is no continuum in scale, but a set of levels. Hierarchy theory (Allen and Starr 1982) defines a system that can be divided or decomposed into several components. The level 0 is bounded and controlled by a higher level. Level 0 can be divided into its interacting components at level -1, with which phenomena at level 0 can be explained. Hierarchy implies that to understand a phenomenon, it is necessary to understand processes at its lower and higher levels (de Koning 1999). Lower level "events" are small and occur rapidly, while higher

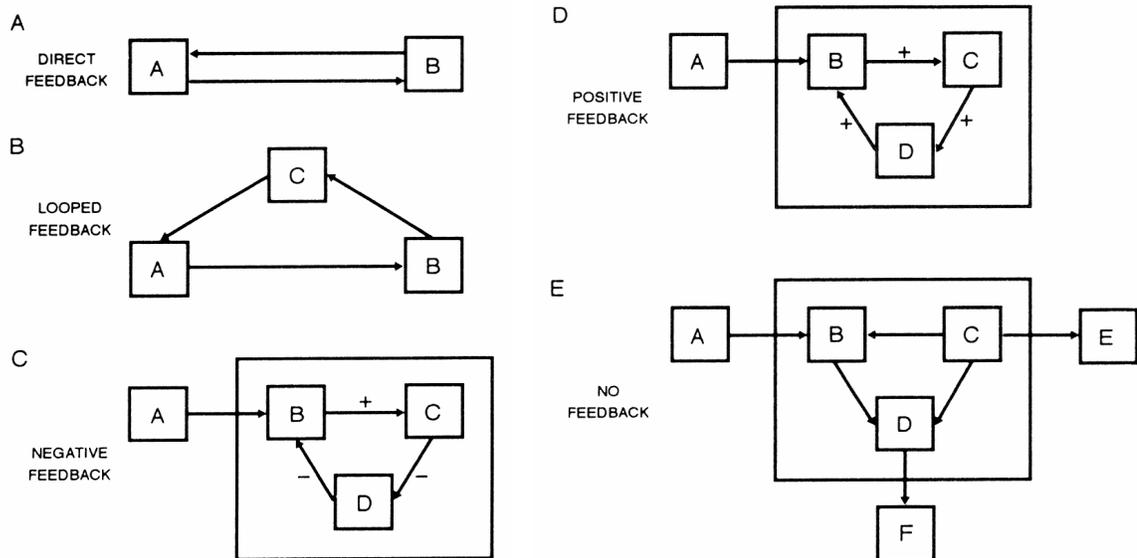
level "events" are larger and occur slowly. Levels in the hierarchy also have interactions. Rate aggregated or rate-structured components of one level interact more frequently with similar components (i.e., due similar rate in what is called horizontal structure). Here, vertical structure is the structure of spatially nested systems (Urban et al. 1987). Another proposition of Hierarchy theory is that spatial and temporal scales tend to covary, processes that operate over long temporal scales also operate over large spatial scales (Goodchild and Quattrochi 1997). Critics to the Hierarchy theory emphasize that the theory does not validate, a-priori, established theoretical concepts, therefore the theory itself seems arbitrary or heuristic. The theory does not provide methods for extracting levels from observed data.

### **1.5.5 Complexity and Complex Adaptive Systems**

In science, social processes are usually regarded as complex outcomes of interactions between social structure and human agency, while natural processes are usually regarded as determined by laws of nature (Blackman 2000). Currently, there is a certain degree of convergence in the study of social and natural systems supported by developments in the fields of systems theory, chaos, and emergence. Beyond some terrible legacies of environmental determinism, complexity research tries to find coincident points in morphology of patterns and processes in both social and natural processes.

The definition of complexity theory and complex systems is difficult, in the sense that there is no identifiable complexity theory. Different disciplines and theories concerned with complex systems are gathered under the banner of complexity research (Manson 2000). To understand how complexity and complex systems contribute to this research, it is necessary to review some concepts related to the foundation of complexity science. The origin of systems theory in social (Von Bertalanffy 1950) and natural (Patten 1959; Watt 1966)

sciences are the basis for the development of several concepts related to complex systems, among them feedback mechanisms. Chorley and Kennedy (1971) define feedbacks (Figure 1.5a, 1.5b, 1.5e) as the property of systems that when changes are introduced via one of the system variables, transmission through the structure leads the effect of the change back to the initial variable, to give a circularity of action. With a negative feedback (Figure 1.5c), the system is maintained in a steady state by self-regulation processes termed morphostatic. With a positive feedback (Figure 1.5d), the system is characterized as morphogenetic, changing its characteristics as the effect of B on C leads to further changes in B, via D.



Source: Chorley and Kennedy (1971)

Figure 1.5. Feedback mechanisms in systems theory.

Blackman (2000) explains Complexity theory as a type of Systems theory that approaches explanation in terms of causes and effects, but is not deterministic. According to Blackman (2000), the basic principles of complexity can be summarized as: (1) system-

environment interactions that allows feedbacks, (2) systems of social and environmental characteristics that have multiple and interacting causes with non-linear trajectories of change occurring within a phase space (i.e., neither totally ordered nor totally chaotic) of possible attractors, (3) certain parameters that govern the general properties of a system and its trajectory in phase-state, and (4) system states that are not predictable in the long-term, but the generic class to which they belong can be described, investigated, and perhaps anticipated.

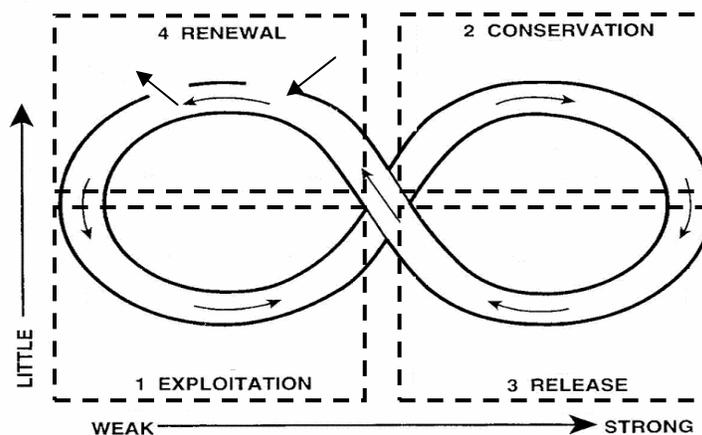
A Complexity theory analysis of LULC change aims at understanding the dynamics of LULC change patterns in terms of a state-space within which the system functions. Characteristics of complexity in this state-space include thresholds that cause rates of change to vary, bifurcations that cause systems to diverge from similar states, folds that lead to jumps of state, and various stability conditions. All of these characteristics can be thought of as constraints on LULC dynamics and future trajectories. A relevant topic within Complexity is the concept of self-organizing systems: spatially extended, dynamic systems can self-organize to generate order. Complexity conceives a system as either reproducing its current state (i.e., stable state) via negative feedbacks with the environment or moving along trajectories from one state to another (i.e., state cycle) as a result of positive feedbacks (Blackman 2000). State cycle is known in complexity theory as a system phase, and embodies all the possible states for a system in a possible environment. In this research, the system phase is the possible LULC trajectories. Environmental change (e.g., the construction of a road or the implementation of a new policy) can cause perturbation to the system that can "soften" its development by a negative feedback or develop into a chaotic behavior with a positive feedback that generates change along a trajectory within the system's state-space.

Complexity theory can be applied to the analysis of LULC transitions, because landscape frontiers (i.e., the NEA) are emergent phenomena resulting from human-environment interaction at local scales. Specifically, complexity provides a framework for two important features in the NEA agricultural system: feedbacks and uncertainty. Positive and negative feedbacks need to be accounted for in the spatially-explicit and dynamic models; important positive and negative feedbacks include the creation/improvement of accessibility, a decrease in the natural resource base, and subdivision and immigration to the area. In terms of uncertainty, peasant farmers might not be fully capable of outlining a clear maximizing strategy when planting food crops as "small farmers can strive, but they cannot maximize, because they lack the information that would allow them to do so" (Ortiz 1973). Complex approaches, such as agent based models, can account for a degree of "communication" and can account for local uncertainty and random behavior to create regional homogeneous patterns.

In social systems, the existence of institutions and networks that learn and store knowledge and experience, create flexibility in problem-solving, and balance power among interest groups play an important role in adaptive capacity (Berkes 2002). Social organizations can act as an adaptive system that behaves in a complex way, that is, with higher degrees of freedom and with numerous components. The adaptive cycle (Gunderson and Hollings 2002; Hollings and Sanderson 1996) alternates between long periods of aggregation and transformation of resources and shorter periods that create opportunities for innovation. The adaptive cycle is proposed as a fundamental approach to understand complex systems that extend from cells to ecosystems and to societies. In the adaptive cycle, four distinct stages have been identified (Figure 1.6): (1) growth or exploitation, (2) conservation,

(3) collapse or release, and (4) reorganization.

The adaptive cycle has been used to guide adaptive ecosystem management, which identifies uncertainties, and then establishes methodologies to test hypotheses concerning those uncertainties. It uses management as a tool not only to change the system, but as a tool to learn about the system (Gunderson & Hollings, 2002). There are several processes, both scientific and social, that are vital components of adaptive management: (1) management is linked to appropriate temporal and spatial scales, (2) management retains a focus on statistical power and controls, (3) use of computer models to build synthesis and an embodied ecological consensus, (4) use embodied ecological consensus to evaluate strategic alternatives, and (5) communicate alternatives to political arenas for negotiation of a selection (Gunderson & Hollings, 2002). The relevance of the adaptive cycle for this research is that it provides a framework to test different future scenarios of LULC change, in the spatially-explicit modeling phase, concerning to decision-making strategies. When adaptive local cycles are embedded in higher order cycles, they can mimic the relationships between lower and higher level forms of social and natural organization that operate under great levels of uncertainty.



Source: Gunderson & Hollings (2002)

Figure 1.6. The adaptive cycle in complex systems.

## **1.6. Rethinking Land Use Trajectories**

Despite the numerous theoretical approaches that explain environmental degradation in the tropics as a response of single socio-economic or demographic factors, such as population, technology, or economic dependency, a number of cases studies suggest that single-factor determinants of LULC change do not exist. Land cover is a result of contextual factors or different combinations of various proximate causes and underlying driving forces that are associated with different social, geographical, biophysical, and historical circumstances (Geist and Lambin 2001; Lambin et al. 2001). It is also evident, from the empirical perspective, that statistical "global" models that have supported traditional theoretical explanations do not fully capture the complexities of LULC change. For example, household LULC statistical models rarely explain the majority of the variation produced. Within a region, the subtle heterogeneity or inhabitants inequalities produce different responses that are masked by equations that generalize the relationships across temporal and spatial scales.

In this research, a single theoretical framework will not be used. Instead an articulation of different theoretical frameworks based on linkages of drivers operating at different time-space scales will be developed. The assembly of hypotheses, observations, analyses, interpretations, and discussions will be used as pivotal frameworks: household life (i.e., at the farm scale), and landscape ecology (i.e., regional scale), and complexity theory (i.e., linking between scales). The coupling of rigorous statistical methods with complex approaches (e.g., Cellular Automata) offers a tool to explore LULC trajectories in more pragmatic ways, because quantifies the localized parameters of relationships and also captures the uncertainty inherent in peasant agricultural farming.

The methods to be used to address the research questions in this research are structured in a form that they link research questions. When possible outcomes in one questions are used to inform other questions. Figure 1.7 shows the configuration of the different phases of the methodology.

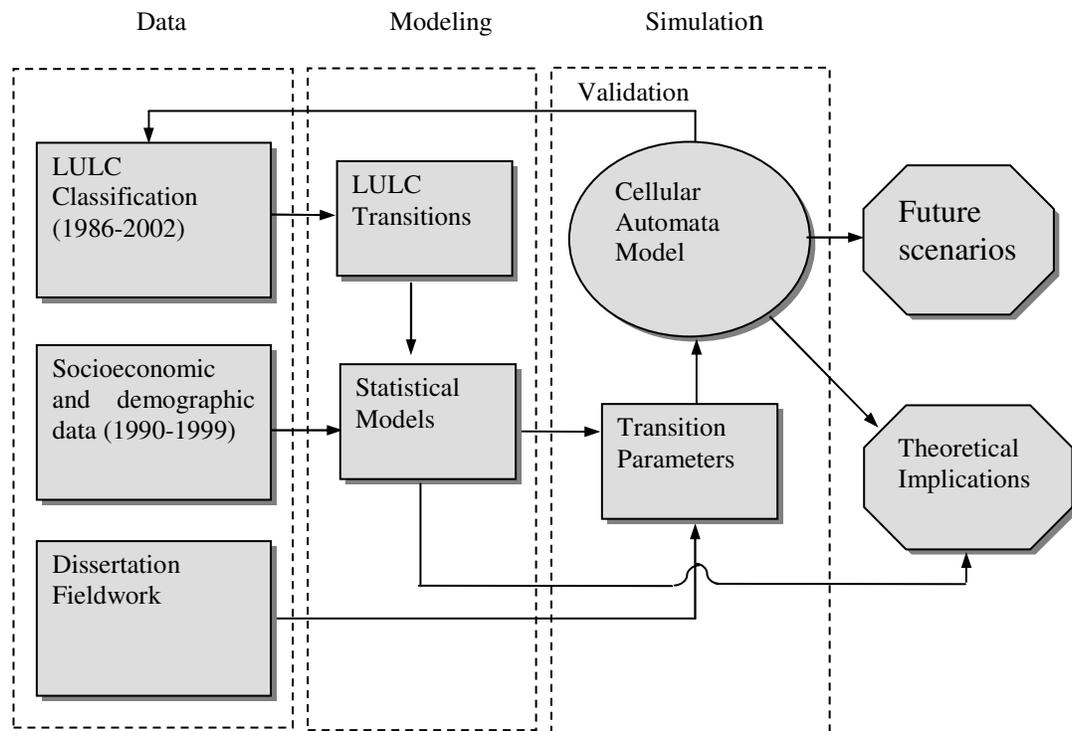


Figure 1.7. Diagram of the methodological approach.

Chapter 2 deals with the assessment of land cover transitions, which is based on satellite imagery classifications analysis, statistical methods, and landscape ecology approaches. A time-series of Landsat TM images (path 60 row 9) for 1986, 1989, 1996, 1999, and 2002 were classified by the Ecuador Project using a hybrid approach. These classifications are based on a central LULC scheme that includes 16 land cover that can be grouped depending upon the trajectory to be analyzed.

Chapter 3 is devoted to deriving the magnitude and direction of relationships among secondary vegetation, and demographic, socioeconomic, and biophysical variables. The

temporal nature of these relationships will be assessed for the Ecuador-NASA surveys conducted in 1990 and 1999, based on a representative probability household sample (5.9% of the rural populations) and selected in 1990 to implement the first household survey (Pichón 1997). The household surveys encompass aspects related to demographic, economic, and agricultural characteristics of the households, but also include institutional characteristics (i.e., land tenancy) and health. The follow-up survey was made in 1999 on the same farms visited in 1990. The unit of analysis is the farm or plot and the sample consist of 450 plots. Farms were chosen as the unit, because spatially-explicit information (GPS data) were available only at the farm level. Using the GPS data, it is possible to link farms to the LULC trajectories.

Chapter 4 explores the spatial heterogeneity of the relationships between factors of change and trajectories of LULC. This analysis is performed using the same independent variables used in Research Question 2. Two separated cross-sectional models will be created for 1990 and 1999. The dependent variable is continuous and represents the proportion within the farm  $i$  of certain LULC class as in 1990 and 1999. Geographically Weighed Regressions (GWR) are used. GWR is a local statistical technique to analyze the spatial variation in *relationships*. Through the use of GWR, this research examines the spatial non-stationarity in the relationships between LULC change and demographic and socioeconomic factors that are produced when the same stimulus produces different responses in different locations of the study area. The output from GWR is a set of location-specific parameters estimate  $\beta'$  that can be mapped and analyzed to provide information on relationships (Fotheringham et al., 2002).

Chapter 5 is devoted to the Cellular Automata (CA) spatially-explicit modeling. The

process of conceptualization, formalization, and parameterization of the model will be informed on statistical analysis performed in earlier components of this research. The outputs from logistic models, geographically-weighted regression models will be used to parameterize or set the transition functions in the spatially-explicit simulations using the Cellular Automata (CA) model approach.

CA models are examples of mathematical systems constructed from many simple identical components that together are capable of representing complex behavior. From their analysis, CA can, first, develop specific models for particular systems, and second, hope to abstract general principles applicable to a wide variety of complex systems (Wolfram 1984). The geographically-weighted model will create "regions" of relationships within the NEA. The 1990 classified image is used to create the initial conditions in the landscape and the later images are used for verification, analysis, and validation. Chapter 6, the final and concluding chapter, synthesizes main findings, charts subsequent research directions, and places in context the approaches, questions, data, methods, and results.

## **1.7. Conclusions**

This research presents an interconnected set of analyses that explore the trajectories of land change in the Northern Ecuadorian Amazon. An assessment of the trajectories at the landscape-level analyzes regional trends beginning in 1986 to draw policy and environmental management implications. An analysis of the extent and drivers of the secondary forest regeneration is conducted at the farm level to better understand the patterns of succession that complement other studies related to deforestation in the NEA. Also, at the farm-level, but with regional implications, geographically weighted regression analysis is used to understand the spatial non-stationarity or heterogeneity in the relationships between drivers and land use.

Finally, the results of the previous research questions are linked to generate a spatially-explicit model that, based on systems and complexity theory, generates future scenarios of land change.

## CHAPTER 2

### Land Use/Land Cover Trajectories in the Ecuadorian Amazon

#### 2.1. Introduction

Land use and land cover (LULC) change is recognized as a core concern of global environmental change. Nearly one-quarter of the tropical rainforest biome have been fragmented or removed by humans (Wade et al. 2003) and converted to agricultural fields, urban areas, and other anthropogenic land uses. Despite an increasing awareness of the consequences of land change in tropical areas, global carbon cycle (Cramer et al. 2004; Levy et al. 2004), climate (Laurance 2004; Mayle et al. 2004), biodiversity (Gaston et al. 2003; Sala et al. 2000) and to local health (Patz et al. 2004), culture and economy (Godoy et al. 2005a), the need reminds to address complex interplay of population, land use, and environment and to examine the causal relationships between drivers of change and the contextual factors (Entwisle and Stern 2005).

Land use and land cover trajectories are the temporal sequence of LULC classes at the pixel level described through classified image assembled in a satellite time-series. They can be used as an assessment tool that helps to sketch policy or environmental management implications linked to the consequences of land use. At global scales, there has been a general trajectory of different land-use regimes associated with frontier development: from pre-settlement natural vegetation to frontier clearing, then to subsistence agriculture and

small-scale farms, and intensive agriculture, urban areas, and protected recreational lands (Figure 2.1.) (Foley et al. 2005).

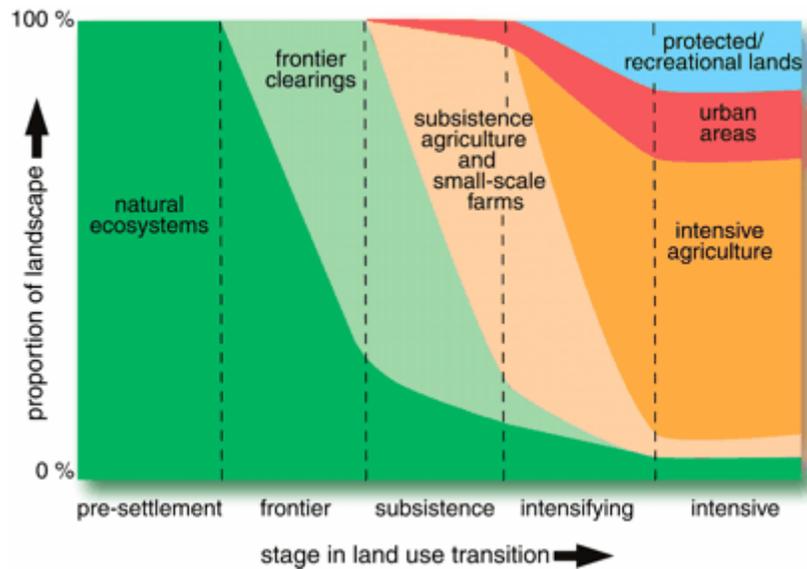


Figure 2.1. Different land use transitions at different stages of settlement.

From the methodological point of view, different disciplinary approaches, practical applications, and technical restrictions have created different ways to quantify LULC change. These procedures can be classified based on its degree of methodological complexity: (1) simple measures of change, such as the proportion of change, (2) annual rates of change, (3) changes in the spatial arrangement or structure of LULC, (4) and spatially-explicit representation of change at the pixel level using a panel approach and the concept of pixel histories. The first category, widely used, is the simple difference of areas or proportions of certain class or classes, sometimes divided by time to obtain the rates of change within a certain area and land class between two points in time without being spatial explicit (Fearnside 1993; Godoy and Contreras 2001; Sierra 2000; Wood and Skole 1998). The second category involves the calculation of the annual rate of change assuming linear or non-linear changes between end-members periods. For example, annual deforestation rates using

formulas that originate in the Compound Interest Law are capable to capture the annual exponential discount within the forest class between two time points (Food and Agriculture Organization 2000; Food and Agriculture Organization 2001; Mena et al. 2006b; Ochoa-Gaona and Gonzales-Espinosa 2000; Puyravaud 2003). The third approach, based on the principles of Landscape Ecology quantify the changes in the spatial configuration and composition of LULC at multiple dates and between dates of change (Pan et al. 2004; Walsh et al. 2002; Walsh et al. 2003). Another type of multitemporal analysis, the spatially-explicit representation of change refers to the maps or raster objects that locate change of one or more land use categories per area (e.g., pixels) between two points in time in only one surface. In general, most of these analyses come from the use of aerial photography and/or satellite imagery change-detection (Castro et al. 2003; Foody and Curran 1994; Lu et al.). In general, traditional land change measurements to quantify LULC change are performed using pairwise comparisons that emphasize composition or configuration changes between dates. LULC trajectory is the representation of the temporal sequence of land use dynamics that refers to the succession of land cover types for a given sampling unit over *more* than two observation years (Crews-Meyer 2002; Crews-Meyer 2004; Mertens and Lambin 2000). This study characterizes LULC trajectories over space and though time by focusing on: composition, configuration, and probability of change across the time-series of classified images.

The examination of the composition of the LULC trajectories explores the landscape temporal dynamics by describing patterns of change (e.g., cycles) represented within the satellite image time-series. LULC trajectory composition is used to define land use types assigned to certain unit of analysis (e.g., pixels, patches, parishes). The LULC composition

characterizes the static or dynamic nature of a place (i, j) for a series of (k + n) snapshots in time (Figure 2.2). The LULC compositional trajectory depends on a number of factors, including the classification scheme, scale of observation and spatial resolution, and temporal considerations.

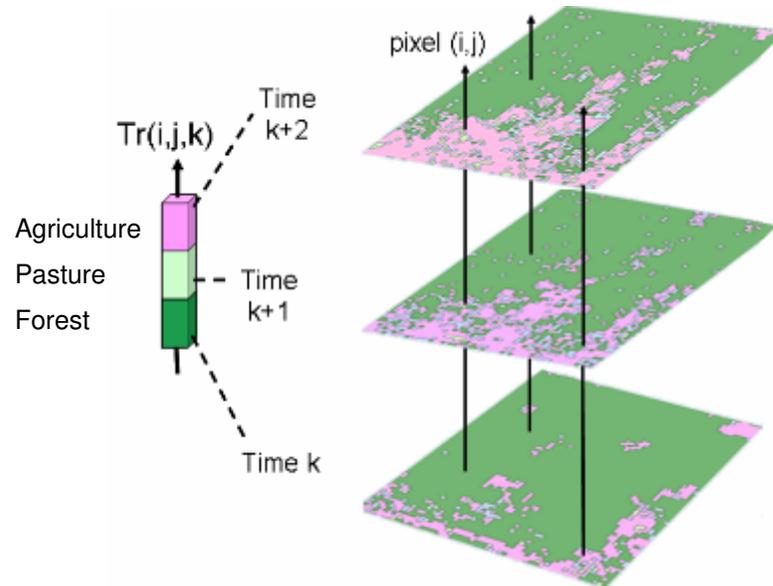


Figure 2.2. LULC trajectory composition.

The spatial configuration of land use change is based on the paradigms of landscape ecology, which emphasize the strong links between landscape spatial patterns and ecological functions and processes (Gustafson 1998). Configuration of a LULC trajectory refers to the changing spatial arrangement created by different land uses and land cover across the classification time-series and at different levels of organization: patch, class, and landscape.

Although, the prospects of a landscape or a region to change have been explored extensively in social and natural sciences, the probabilities of a landscape to change from a spatial-explicitly perspective is less studied. The spatial-explicit probability of a land use unit (e.g., pixel) to change is captured by (a) the use of geographic relationships (e.g., proximity)

of different drivers of change (Geoghegan et al. 2001; Turner 1989; Waggoner and Stephens 1970) and (b) the representation of these probabilities in space (Chomitz and Gray 1996; de Koning 1999; Florax and Van der Vlist 2003). The probability of a land use unit to maintain its stability across time or transition to other land uses will depend also on the types of geographical relationships and how these relationships are represented.

In this research, a regional approach is taken to address the problems of LULC change in an evolving agricultural frontier. The objectives of this paper are: (a) to explore the composition of the main LULC trajectories across time, (b) to examine the spatial configuration of the LULC trajectories and (c) find the probabilities of LULC transitions in the NEA. This research uses a set of classified Landsat images time-series that ranges from 1974 to 2002. Additional data includes a set of spatial socioeconomic, demographic, and accessibility data assembled in a geographic information system. The methodological aspects of this research are divided in three phases: (1) description of the LULC trajectories in the Northern Intensive Study Area (NISA), an area where a deeper image time-series exist; (2) analysis at the regional-level (i.e., the Northern Ecuadorian Amazon) using LULC trajectories by census sectors using a cluster analysis and landscape pattern metrics; (3) generation of a spatially explicit model of the stability versus dynamics of the trajectories using variables that represent geographic accessibility, biophysical variability and demographic and socioeconomic characteristics.

## **2.2. The Study Area: The Northern Ecuadorian Amazon**

This study focuses on land change in the Northern Ecuadorian Amazon (NEA) (Figure 2.3). Ecuador had the highest deforestation rate in South America during the 1980s and 1990s (Food and Agriculture Organization 2005), which has had significant impact on

loss of biodiversity. About 282 plant species are qualified as critically endangered (Pitman et al. 2002). The NEA, the second deforestation front within Ecuador (Sierra 2000), is a region where LULC change is a spatially-explicit response to several processes occurring at different levels of social organization. In the NEA, landscape dynamics can be explained by two contrasting processes: (a) the agricultural frontier expansion and its intrinsic components: population change, land tenure regime change, extensification and intensification of agriculture, increase in geographic accessibility, and market integration (Rindfuss et al. In Press) and (b) the changing characteristics of indigenous populations that adapt to the new conditions of the frontier development (Godoy and Contreras 2001; Godoy et al. 2005a; Holt et al. 2004). The NEA, a frontier environment, is a good example of a coupled human-natural, where humans and the environment interact in complex ways within a unique set of ecosystems that for centuries has been a social and economic space under different types of management. The dynamics of coupled human-natural system have implications for ecosystem sustainability, resilience, and trajectories of change.

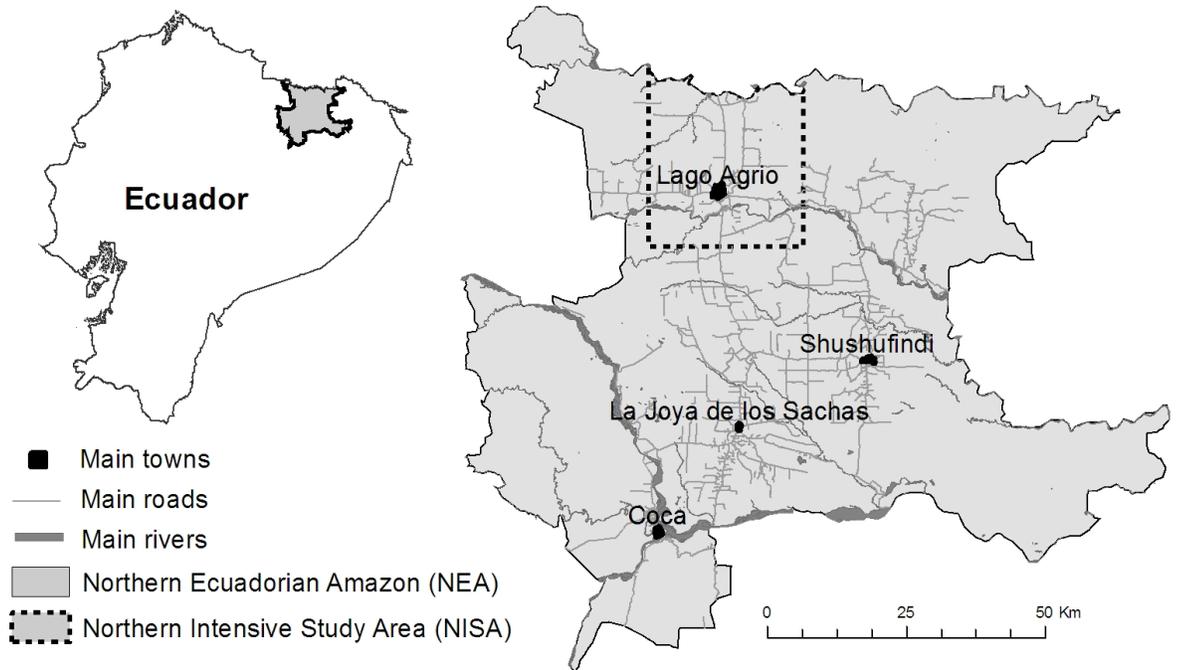


Figure 2.3. The study area: Ecuador and the Northern Ecuadorian Amazon.

### 2.3. Landscape Change: Theoretical Implications

The emphasis of the analysis in this section is theoretical implications related to land use change at the regional or landscape level. At this level of spatial aggregation, and specifically in tropical areas, the separation of human and natural systems is a challenge. Natural scientists often see human activities on the landscape as disturbances in the ecosystems (e.g., Barbero 1990). On the other hand, social scientists often treat the environment as the "background" context where economic, social, and cultural processes develop. Often, too, applied science related to environmental conservation or economic and social development assumes that complex problems are driven by a number of critical factors and processes whose assumptions derive from disciplinary theoretical and methodological approaches, which generates contrasting and competing objectives and strategies that make difficult to achieve sustainability (Hollings and Sanderson 1996). The NEA, a frontier

environment, is a good example of a coupled human-natural, where humans and the environment interact in complex ways within a unique set of ecosystems that for centuries has been a social and economic space under different types of management. The dynamics of coupled human-natural system have implications for ecosystem sustainability, resilience, and trajectories of change.

Conceptualizations of landscapes have evolved at a very fast pace in the last few decades. Different definitions have disciplinary and regional biases. The landscape definition used in this research is based on one proposed by Burdel and Baudry (2003); i.e., landscape is a level of organization of ecological systems that is higher than the ecosystem level, and it is characterized essentially by its spatial and temporal heterogeneity and its dynamics, partly governed by human activities. Landscape exists independently of perceptions. There are three fundamental landscape characteristics: structure, function, and change (Turner 1989; Turner et al. 1989). Structure refers to the spatial relationships between distinctive ecosystems, that is, the distribution of energy, materials, and species in relation to the sizes, shapes, numbers, kinds, and configurations of landscape components. Function refers to the interactions between spatial elements, including the flow of energy, materials, and organisms among the component ecosystems. Change refers to alterations in the structure and function of the ecological mosaic through time. In landscape ecology, anthropogenic activities are seen as a set of disturbances that affect the physical and biotic templates of the landscape. Studies of the landscapes and regions have centered on the description of the processes that create biotic patterns, with an emphasis on the effects of spatial patterning on ecosystems function.

Spatial pattern and scale are two important conceptualizations in landscape ecology.

Spatial pattern has been used extensively in the landscape ecology literature, primarily to describe both the composition and structure of landscapes. Spatial heterogeneity and spatial pattern are used synonymously to refer comprehensively to its central elements: composition, configuration, and temporal aspects of heterogeneity. Patterns are generated by processes at various scales (Urban et al. 1987). But scale is just an artifice that creates structures helpful to analyze change in space and time. Regional dynamics depends on the relationships between societies, different levels of social organization (e.g., households to districts), and their environment (e.g., slope units to watersheds). Because landscapes are spatial hierarchical entities, their structure, function, and change are scale dependent.

There is no single natural scale at which ecological phenomena should be studied; systems generally show characteristic variability on a range of spatial, temporal, and organizational scales (Levin 1992). The problem with scale, as a concept, lies in the fact that scale has a variety of meanings according to the research focus or discipline involved. Cao and Lam (1997) categorize geographical scale in four dimensions: (1) cartographic and map scale that refers to the proportion of distance on a map to the corresponding distance on the ground, (2) the geographic or observational scale refers to the size or spatial extent of the study, (3) the operational scale refers to the scale at which certain processes as operate in the environment: operational scale then is dependent on the geographical phenomenon studied, and (4) measurement scale that is intrinsically linked to the concepts of grain and extent. Grain refers to the smallest unit that can be distinguished, while extent refers to the size of the study area. An important consideration related to scale is that geographical and ecological patterns under observation vary with scale (Walsh et al. 1999; Walsh et al. 1997). The failure to account for scale-dependent changes in patterns and processes can confuse and confound

the synthesis of ecological data and the extrapolation of ecosystem's effects that range from sample plots to landscape scales (Wiens et al. 1993). The ability to detect changes in spatial pattern and make predictions at more than one level of spatial resolution requires identifying the physical and biological processes of interest, estimating the variables and parameters that affect these processes at several scales, and developing rules to translate the information across scales (Gardner 1998).

In theory, a system can be divided or decomposed into components operating at different scales. Hierarchy theory defines a system that can be divided or decomposed into several components (Allen and Starr 1982) . As such, level 0 is bounded and controlled by a higher level. Level 0 can be divided into its interacting components at level -1, with which phenomena at level 0 can be explained. Hierarchical implies that to understand a phenomenon, it is necessary to understand processes at its lower and higher levels (de Koning 1999). Lower level "events" are smaller and occur faster, while higher level "events" are larger and occur slower. Levels in the hierarchy also have interactions. Rate-aggregated or rate-structured components of one level interact more frequently with similar components (Urban et al. 1987). Another proposition of Hierarchy theory is that spatial and temporal scales tend to co-vary, processes that operates over long temporal scales also operate over large spatial scales (Goodchild and Quattrochi 1997).

One of the most applied paradigms of development that is used to explain how the different paths of development on LULC change is Modernization theory (also called Dual Society Models). In this approach, there are two clear sectors: a core (i.e., the urban, modern, productive center) and the periphery (i.e., a rural subsistence sector). Core and periphery are linked by mechanisms of polarization (the core growths) and spread (periphery growths)

(Brown 1991). The modernization approach argues that environmental degradation (e.g., deforestation) is a function of the level and rate of development within a given country (Ehrhardt-Martinez 1998). Development can be explained as the increasing use of technology to achieve development, including economic growth, infrastructure, technology, urbanization, education, and extractive practices or improvements.

The role of economic development in rural areas is important to explain small-holding LULC change, but this relationship is complex. Economic development can be viewed from two different contrasting perspectives: first, rural populations are often impoverished by a declining resource base, and as a consequence, they are forced by their circumstances to further degrade their environment creating a cycle difficult to break. In addition, short-term attention to current needs takes precedence over long-term stewardship of resources (de Sherbinin 2000). The second perspective shows that small farmers with increasing amounts of cultivated land tend to have the capital, access to technology, education, and subsidies necessary to succeed (Marquette 1998; Pichón 1997). The political and economic inequalities in the larger society, where urban systems are incapable of assimilating demographic growth compel poor, dispossessed peasants to seek a livelihood on the margins of the society in the rain forest (Rudel and Horowitz 1993). At the same time, it creates the need to understand the role of institutional and household level factors in influencing the observed variation in forest clearing strategies (Pichón 1997). Theories, such as modernization, try to understand LULC change at cross-national scales, but such theories do not work properly when applied to regional and sub-regional settings (Runge 1992). The complexity of the relationship between LULC change and development depends on a range of macro or micro-economic variables that drive LULC change with different degrees of

intensity at different levels of social organization.

## **2.4. Methodology**

The methodology in this research lies heavily in spatial analysis, geographic information systems, and satellite image processing. In addition to data pre-processing, satellite imagery classifications, and geographic information database construction, the methods used are divided in two main components: (a) analysis of LULC trajectories at the pixel-level for the Northern Intensive Study Area (NISA) and (b) analysis of LULC trajectories at the *censal* sector-level, which include examination of LULC compositional patterns, and probability of change analyses.

### **2.4.1 Data**

***Land Use Land Cover Data:*** A time-series of Landsat TM images, path 60/row 9, for 1973<sup>4</sup>, 1986, 1996, 1999, and 2002 were classified by the Ecuador Project<sup>5</sup> using a hybrid approach. Pre-processing steps included atmospheric correction, geometric correction, and extensive fieldwork for geodetic control and land use validation. For geometric correction, the 1996 image was selected as the original, or master, image and was rectified using a set of geodetic control points (GCP) collected using global positioning system (GPS) receivers and topographic maps. The remaining images were rectified using the master image as the reference (i.e., relative registration) (Frizzelle 2004). A hybrid classification approach uses a combination of unsupervised and supervised approaches applied to defined spectral features,

---

<sup>4</sup> The 1973 is a Landsat MSS

<sup>5</sup> The Ecuador Project is an interdisciplinary project at the Carolina Population Center, Departments of Geography and Biostatistics ([www.cpc.unc.edu/projects/Ecuador](http://www.cpc.unc.edu/projects/Ecuador)).

such as an extended set of layers that includes Landsat spectral bands, principal components, and fractional cover and vegetation indices (Messina and Walsh 2001; Walsh et al. 2003) to extract the land use/land cover classes. The resulting classifications are based on a central LULC scheme that includes 16 land use/land cover types that were grouped to represent, for instance relative categories of economic activity and deforestation (Table 2.1).

Table 2.1. Central and Grouped Classification Schemes.

CENTRAL SCHEME	GROUPED SCHEME 1
Primary Forest	Forest
Swamp	
Secondary Forest	Succession
Rastrojo	
Pasture No Trees	Pasture
Pasture Few Trees	
Pasture Many Trees	
Coffee	Mostly Cash Crops or small scale agriculture
Cacao	
Banana	
Corn	
Palmito	Alternative crops and industrialized agriculture or large scale agriculture
African Palm	
Barren	Barren/Urban
Urban	
Water	Water
Unclassified	Unclassified

***Geographic and Demographic Data:*** A set of spatially-explicit variables were generated and assembled in a Geographic Information System: (1) Ecuador 2001 National Census Data at the census sector-level boundaries (i.e., a sub-parish level). Parish is the minimal political unit within Ecuador; (2) Population counts at the census sector-level for 2001; (3) location of main cities (i.e., Lago Agrio, Coca, Shushufindi, and Coca); (4) location of main communities (64 communities) surveyed in 1999 using Global Position Systems (GPS); (5) a road network obtained from topographic base maps at a scale of 1:50,000 and updated through fieldwork conducted in 2000 and 2001 using GPS measurements; (6)

elevation data obtained from the Shuttle Radar Topographic Mission (SRTM); and (7) official boundaries of the Ecuadorian System of Protected Areas.

#### **2.4.2 Methods**

The characterization of the LULC trajectories was restricted by the availability of cloud-free satellite imagery. This limitation necessitated the separation of the analysis into two segments: (a) the analysis of the trajectories of LULC in the NISA, using satellite images for 1973, 1986, 1996, 1999, and 2002, and (b) the analysis of the LULC trajectories in the larger colonization area (NEA) that covers an area of approximately 775,000 ha using satellite imagery for 1986, 1996, and 2002. The first analysis, in the NISA, is an exploratory examination of the compositional arrangement of the LULC trajectories by settlement stage, a pattern that shows the advance of a deforestation front across the region. The second phase, at the regional level, which constitutes the core of the study, characterizes the trajectories by LULC composition, spatial configuration, and factors contributing to the stability or dynamics of the LULC transitions, with implications for environmental management.

*(a) LULC Trajectories in the NISA:* A categorical map that contains the pixel history, or the LULC trajectory, at the pixel-level were created using map algebra. Land classes are converted to a number, multiplied by a factor distinctive for each year, then summed to obtain a sequence for every pixel transition, and then a name is assigned to the respective combination. The LULC classes used in this analysis are indicated in the Grouped Scheme 1 (Table 1). Classes for each year are: forest (F), succession (S), pasture (P), small scale agriculture (Sa), large scale agriculture (La), barren/urban (U), water, and unclassified. For 1973, the classification represented only forest and non-forest classes due the quality of the Landsat MSS (Multi Spectral Scanner) data. Figure 2.4 illustrates the map algebra

procedure. Later, unnecessary pixels (i.e., water bodies, clouds, and shadows) were excluded from the analysis and finally, pixel histories that were inconsistent (e.g., a transition from forest to urban to forest in a short time period) were excluded from subsequent analysis as they were judged to be artifact of classification error. The Classification Scheme 1 is highly simplified, because more detailed classification scheme (i.e., 16 LULC classes) have increased uncertainty related to its accuracy due the lack of ground control points to assess the classification.

The quantification of error in classifications at the pixel level (Foody 2002) and in multi-temporal analysis (Lunetta 1999) is challenging for different reasons including: (1) the lack of temporal coherence of the measures for validating images assembled within a time-series, (2) demands of field sampling in remote and inaccessible environments, and (3) linkage between the documentation of error and uncertainty through an error matrix and standard reporting protocols and the improvement of the classification to reduce ambiguity. The problem of the uncertainty related to the accuracy of the classifications is exacerbated in frontier areas, most of the time considered marginal lands, where ground data or other types of complementary remote sensing information (e.g., aerial photography) for past years do not exist and Landsat Images are the best information available. The approach taken here is that acknowledging that there must be error and misclassification related to the classifications, these errors will be detected and eliminated using the trajectories themselves. Only logical trajectories, where land use changes are consistent with anecdotal information will be used to find general LULC patterns or trends.

Grouped Scheme 1 captures socioeconomic characteristics of land use (e.g., degrees of extensification), but also the spectral characteristics. For example, small agriculture (Sa),

in Grouped Scheme 1 includes coffee, cacao, banana, and corn, and likely fruit trees (i.e., orange, lemon, etc.). These agricultural crops are small, mostly subsistence agriculture that have similar spectral characteristics, particularly related to cash crops (i.e., coffee and cacao).

The analysis conducted within the NISA performs an exploratory description of the LULC trajectories by age of deforestation<sup>6</sup>. To carry out this task an additional map was created: a *stage of deforestation map*. It was produced for data of actual forest clearing, i.e., the image date where LULC change was initially observed Landsat images from 1973, 1986, 1996, 1999, and 2002 to illustrate the areas that were deforested within the periods between images (prior-1973, 1973-86, 1986-96, 1996-2002). It is important to note that the aim of this complementary map is not to provide a chronological account of the colonization process, but a meaningful strategy to separate the LULC trajectories. Trajectories were mapped and ranked based on the proportion of LULC changes at the landscape-level and stratified by periods of deforestation.

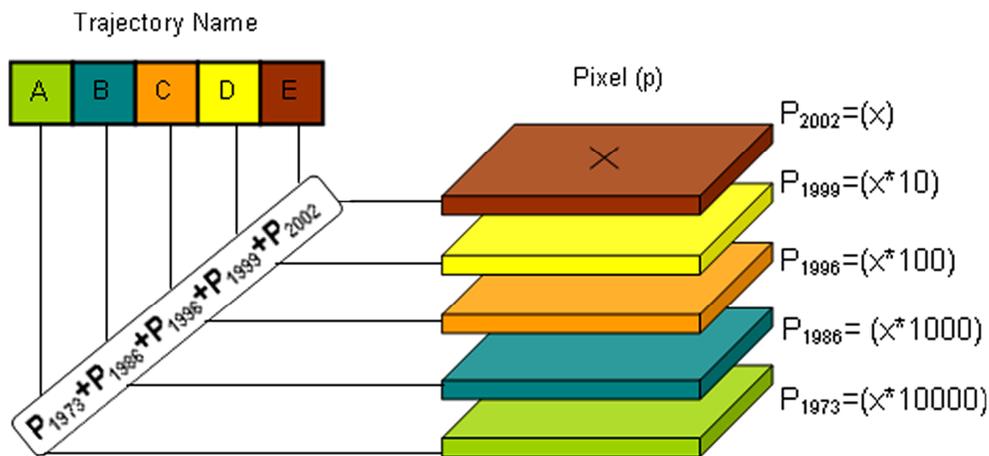


Figure 2.4. Pixel history to trajectory name.

<sup>6</sup> *Deforestation Age* is the actual clear of the forest within a certain period.

*Composition and Configuration of LULC Trajectories in the NEA:* This section describes the analysis of LULC trajectories at the sector-level to explore the spatial and temporal patterns of trajectories within the region. The methodology follows the same logic used in the above section (a): first, a categorical map is developed containing the pixel trajectories in for 1986, 1996, and 2002; second, unnecessary pixels were excluded and third, pixel histories that were inconsistent were also excluded from subsequent analysis.

Due the extensiveness and diversity of LULC trajectories (i.e., 665 trajectories after exclusion of non-relevant trajectories), the trajectories were stratified by *sector censal* or census sector, which is in the hierarchy of the Ecuadorian political division after province, canton, and parroquia. The original census sector maps from INEC (Instituto Ecuatoriano de Estadísticas y Censos) were digitized by the Spatial Analysis Unit at the Carolina Population Center. They contained 233 census sectors that were distributed across the land colonization area (Figure 2.5). In each of the census sectors, the proportion of area covered by each of the transitions was calculated and used in the cluster analysis.

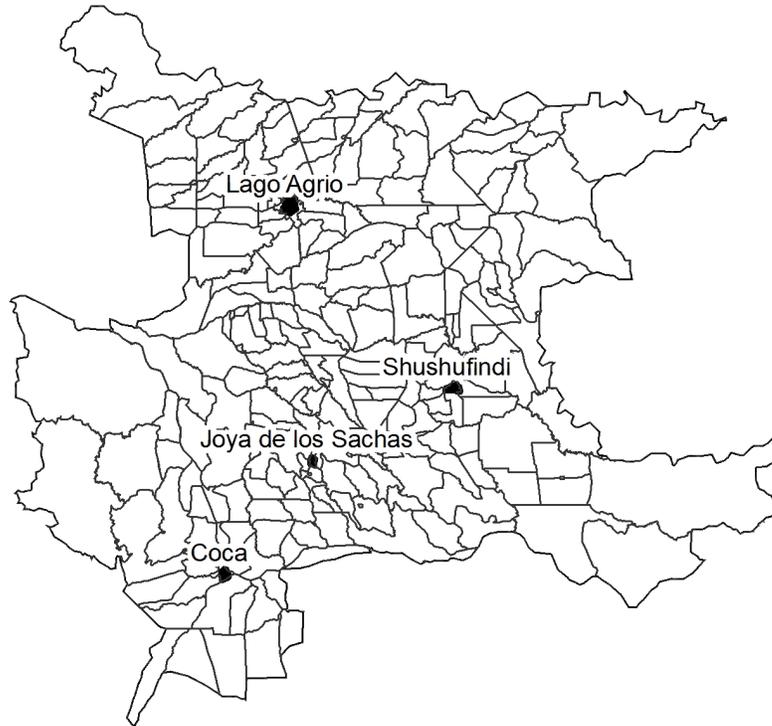


Figure 2.5. Census sectors in the Northern Ecuadorian Amazon.

A hierarchical-divisive clustering algorithm is used to identify the main trends and associations of trajectories. The hierarchical algorithm divides groups that produce a hierarchical structure, displaying the order in which groups are merged or divided (Kaufman and Rousseeuw 1990; MathSoft 1999). The method is divisive, because it starts with all the observations in a single group and proceeds until each observation is in a separate group. The data set for clustering is a matrix ( $n \times p$ ) with the following structure:

$$\begin{bmatrix} X_{11} & \dots & X_{1p} \\ \vdots & \ddots & \vdots \\ X_{n1} & \dots & X_{np} \end{bmatrix}$$

where rows represent objects (i.e., sectors) and columns represent variables (i.e., proportion of LULC transitions). The algorithm creates a dissimilarity matrix ( $n \times n$ ) that indicates the distance or dissimilarity between two different objects (i and j). Dissimilarity between two

objects is computed using Euclidean distance:

$$d(i, j) = \sqrt{\sum_{f=1}^p (X_{if} - X_{jf})^2}$$

where,  $d(i,j)$  is the Euclidean distance which measure the difference or dissimilarity between the objects  $i$  and  $j$  and  $p$  is the number of columns.

The divisive cluster algorithm finds the object with the highest average dissimilarity, which initiates the first object of a different cluster. The rest of the objects, based on their dissimilarity, are divided between the two clusters. The cluster with the largest dissimilarity follows a similar process until the number of desired clusters is achieved.

**Landscape Pattern Indices:** For each of the 233 census sectors, a set of landscape pattern indices are calculated for 1986, 1996, and 2002 at the landscape level (assuming that each census sector is a landscape) and for each LULC class. The spatial pattern indices used are: (1) Patch Density (PD) that measures the number of land cover patches per 100 hectares; patch density is an indicator of the degree of fragmentation of a landscape; (2) Perimeter Area Fractal Dimension (PAFRA) is a index that indicates the complexity of the shape of the landscape or class; the range of PAFRA is between 1 and 2 (no units). For a 2-dimensional landscape, a fractal dimension greater than 1 indicates a departure from a Euclidean geometry (i.e., an increase in patch shape complexity) (McGarigal et al. 2002); (3) contagion index that refers to the tendency of patch types to be spatially aggregated. It ranges from 0 to 100, where 0 is totally disaggregated and interdispersed patches, while 100 is a single patch (McGarigal et al. 2002); and (4) the division index that measure the diversity of LULC types in the landscape. It is 0 when the landscape consists of single patch, and one when the landscape is maximally subdivided (McGarigal et al. 2002).

**Probability of Transitioning:** The objective of this analysis is to create a spatially

explicit model of the probability of LULC transition (versus stability) in the region based on accessibility, biophysical, and demographic factors. Stability is represented by trajectories or "pixel histories" that are constant through time (e.g., f-f-f or p-p-p), and change is represented by pixels with different or dynamic trajectories across the time-series. The model is created using a spatially-explicit logistic regression approach, where the dependent variable is a binary *image* that contains constant trajectories (value 0) versus pixels with dynamic trajectories (value 1). The independent variables are a set of accessibility, biophysical, and demographic factors (Table 2.2):

Table 2.2. Variables used in the Logistic Regression model.

VARIABLE	TYPE	SOURCE/DERIVED FROM
Distance to main city	Interval: 1 Km categories	1:50,000 topographic map updated to 2001
Distance to community	Interval: 1 Km categories	1:50,000 topographic map updated to 2001
Distance to oil camp	Interval: 1 Km categories	Ministry of Environment of Ecuador
Distance to protected area	Interval: 1 Km categories	Ministry of Environment of Ecuador
Distance to main road	Interval: 1 Km categories	1:50,000 topographic map updated to 2001
Elevation	Continuous (resolution 90 m)	Shuttle Radar Topographic Mission
Slope	Continuous (resolution 90 m)	Shuttle Radar Topographic Mission
Soil	Categorical (Good soil=reference)	Ministry of Agriculture of Ecuador
Population Density	Number of people/1000 hectares	2001 National Ecuadorian Census

Although the objective of this portion of the research is not to test statistically test the significance of the main drivers of landscape transition, because of the limited number of variables available for the model, it is hypothesized that accessibility characteristic of the landscape, such as distance to roads, to promotes different types of conversion of the land. In other words, distance to roads will be negatively related to flux or transitions. For example,

cheaper transportation costs will provide the opportunity to effectuate different types of investments on the land and to induce LULC change accordingly. Nearness to cities and communities will provide access to different markets (e.g., labor, agricultural outputs, and inputs), therefore, increasing the transitions among land use classes and generating negative relationships to flux of transitions. Protected areas, low quality soil, and steep slopes are hypothesized to promote stability of the landscape. Finally, population density should be positively related to flux and transitions, because people provide the labor that induces the transitions.

The logistic regression module can be estimated using the formula:

$$P(y = 1 | X) = \frac{\exp(\sum BX)}{1 + \exp(\sum BX)}$$

where:

P is the probability of the dependent variable being 1

X is the set of independent variables

V is the estimated parameters

The model is fitted using a Maximum Likelihood Estimator (MLE) procedure to find the best fitting set of parameters (coefficients). A 10 percent pixels of the landscape was sampled for the regression analysis (819,134 observations) using a stratified random sample to decrease spatial autocorrelation. Parameters of the regression are extrapolated to a surface of probabilities of transitioning.

## **2.5. Results**

### **2.5.1 LULC Trajectories in the NISA**

In the NISA, in general, the trajectories are dominated (i.e., in terms of area) by recent transitions that contain forested classes (i.e., primary forest or succession), as well as the consistent representation of pasture through time. Table 2.3 presents the top 10 LULC

"all" pixel trajectories in the NISA (column a) and the top 10 *agricultural* transitions (column b) in the NISA. This table sorts the transitions in terms of area and shows the dominance of pasture and succession in the "all" trajectories (i.e., column a). There is a dominance of pasture and small and large scale agriculture (i.e., column b). Small-scale agriculture is produced in major amounts of area in the later stages of the trajectory.

Table 2.3. Top 10 LULC transitions in the NEA and its proportion in the landscape.

(a) All trajectories		(b) Agricultural trajectories <sup>7</sup>	
Trajectory	% <sup>8</sup>	Trajectory	%
F-F-F-F-F	30.83	F-F-F-F-P	2.15
F-F-F-F-S	2.67	F-F-F-F-La	1.29
F-F-F-F-P	2.15	F-F-F-F-Sa	1.10
F-F-S-F-F	1.56	F-F-P-P-P	0.84
F-F-F-S-F	1.37	F-F-F-P-P	0.63
F-F-F-F-La	1.29	F-P-P-P-P	0.49
F-F-F-F-Sa	1.10	F-F-P-P-Sa	0.34
F-F-P-P-P	0.84	F-F-F-P-Sa	0.33
F-F-F-P-F	0.79	F-F-F-La-La	0.24
F-F-P-F-F	0.68	F-F-F-Sa-P	0.22

Figure 2.6 is a visual representation of selected LULC transitions in the NEA<sup>9</sup> that illustrate different views at varying scales and areas. While it is very difficult to make a visual interpretation of the LULC patterns, because of the diversity and mix of transitions,

---

<sup>7</sup> Agricultural trajectories exclude forest succession and urban/barren classes, to emphasize change between pasture, small, and large agriculture.

<sup>8</sup> One percent of the landscape in the NISA is 802 hectares about 1,000 soccer fields.

<sup>9</sup> Figure 3 contains trajectories that started in 1973 as Forest. For visual purposes trajectories that in 1973 were non-forest class and water, clouds, and shadows were excluded.

being represented, it is possible to identify a number of very interesting patterns. For example, trajectories illustrated in "green" illustrate stability of forest through time; grey indicates recent changes (i.e., appearing in 2002); light purple indicates changes that began earlier (since 1999) that transitioned from forest to other land uses; dark purple indicates relatively old transitions (since 1996) that started with large agriculture and transitioned to other land uses; blue represent changes (since 1996) that started with succession or secondary forest<sup>10</sup> and transitioned to other land uses in later years; and green, yellow and brown represent older transitions (from 1986) that started to change from large scale agriculture to pasture and successional vegetation.

The results of the LULC transitions in the NISA, stratified by period of deforestation are shown in Table 2.4 and Figure 2.7. Table 2.4 shows the top agricultural transitions by area and confirms the presence of pasture (P) as a dominant class across all the periods, of deforestation. In all the deforestation periods the presence and permanence of pasture is clear. The second detectable trend across all the deforestation periods is the irregular cycle between pasture and large scale agriculture (La) and small agriculture (Sa). With a couple of exceptions, pasture (P) is always interdigitated in the agricultural transitions. The trajectories produced in the oldest deforestation period (i.e., before 1974) are the most stable. Changes to the urban class are produced within this set of transitions. Large-scale agriculture is dominant during the two following periods (i.e., 1974-86) and (i.e., 1986-96). Table 2.4 ranks the transitions based on area so the dominance of large scale agriculture is expected. Small agriculture is also important in earlier periods of deforestation. In terms of overall area, later

---

<sup>10</sup> Succession here can indicate a selective degradation of forest (e.g., selective logging or a combination of pasture and tress), which can be characterized as a secondary forest.

and less diverse transitions are more extensive.

### **2.5.2 Composition and Configuration of LULC Trajectories in the NEA**

This section of the research contains the results of the analysis of the LULC composition and spatial configuration of LULC trajectories for the entire region (NEA). The objective of this section is to identify census sectors that can be grouped according to the proportion of trajectories that they contain. A data set containing the proportion of each trajectory per census sector was created and the hierarchical-divisive clustering algorithm applied. The clustering algorithm was used to create 3, 6, 9, and 12 cluster groupings of similar LULC trajectories across census sectors. The different number of clusters, in general, followed the same pattern: clusters forming rings that buffered the main cities or followed a core-periphery patterns. Table 2.5 describes the results of the clustering technique using six clusters and the area characterized of the main transitions. The results are mapped and the trajectories of each cluster described.

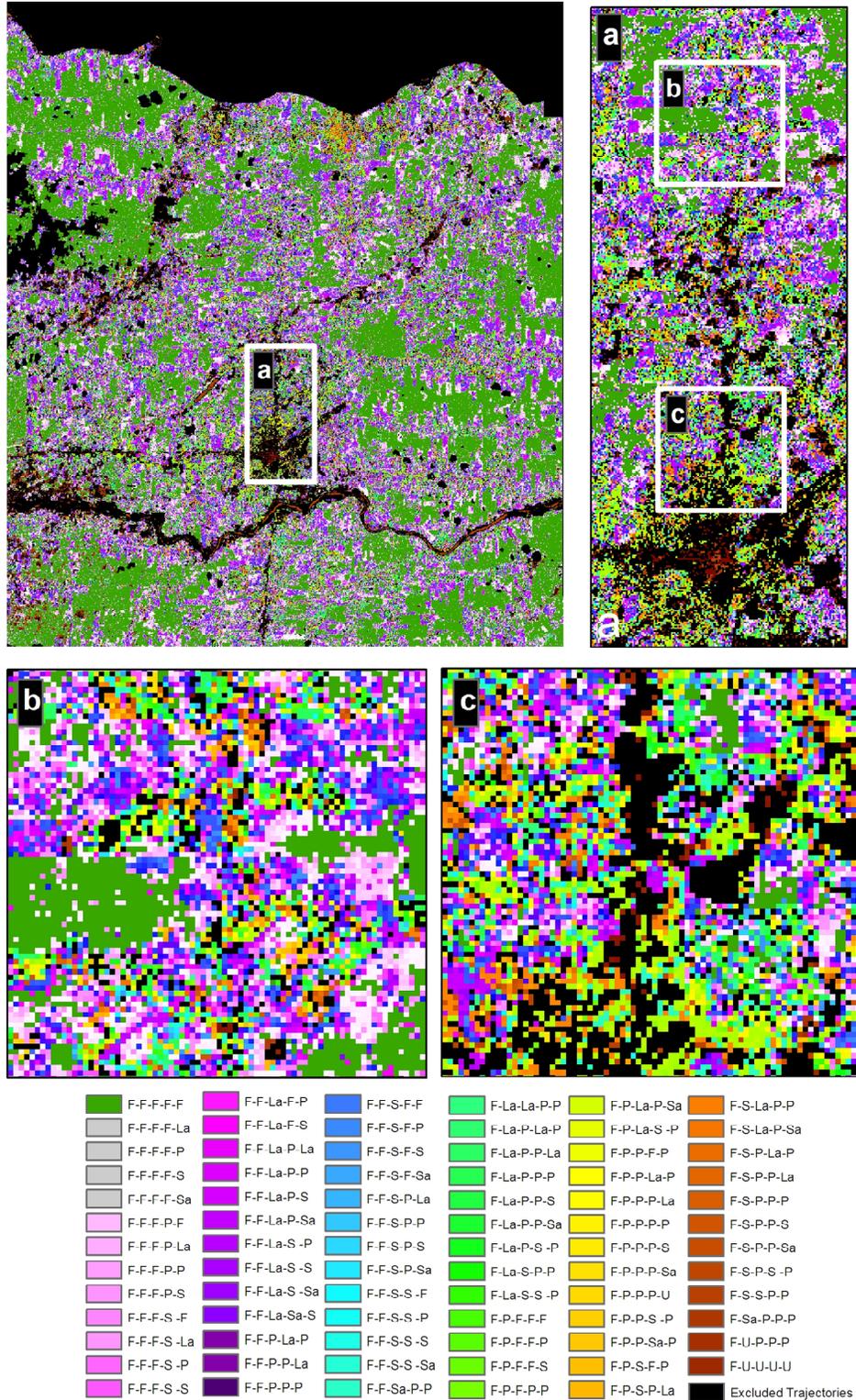


Figure 2.6. Visual representation of selected LULC trajectories.

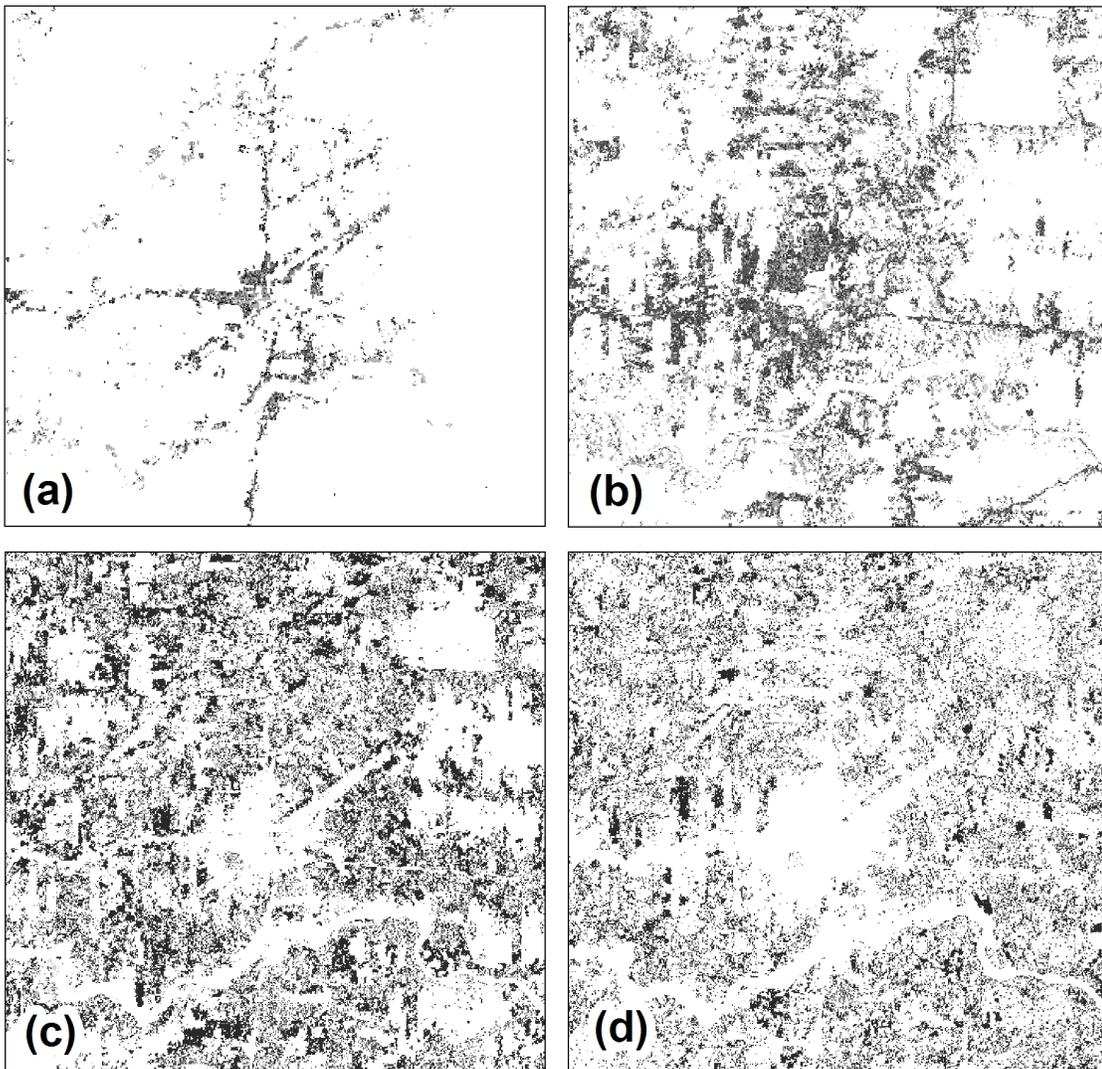


Figure 2.7. Location of LULC trajectories according to the deforestation period.

(a) before 1974, (b) between 1974-1986, (c) between 1986-1996, and (d) 1999-2002. Grey areas represent agricultural trajectories and black areas represent succession. Stable forested areas are excluded.

Table 2.4. Main Agricultural Transitions by period of deforestation in the NISA.

Deforestation before 1974			Deforestation 1974-1986			Deforestation 1986-1996			Deforestation 1996-1999			Deforestation 1999-2002		
Trajectory	Ha	%	Trajectory	Ha	%	Trajectory	Ha	%	Trajectory	Ha	%	Trajectory	Ha	%
Nf-P-P-P-P	63.00	1.49	F-P-P-P-P	392	2.62	F-F-P-P-P	674.01	3.20	F-F-F-P-P	506.16	5.63	F-F-F-F-P	1729.53	11.79
Nf-U-U-U-U	29.34	0.69	F-La-P-P-P	212	1.42	F-F-La-P-P	443.97	2.11	F-F-F-P-La	348.93	3.88	F-F-F-F-La	1033.38	7.04
Nf-La-P-P-P	28.17	0.67	F-P-La-P-P	154	1.03	F-F-La-P-La	318.96	1.52	F-F-F-P-Sa	262.35	2.92	F-F-F-F-Sa	882.09	6.01
Nf-La-La-La-La	25.92	0.61	F-P-P-P-La	106	0.71	F-F-P-P-La	296.46	1.41	F-F-F-La-La	193.68	2.15			
Nf-La-La-P-La	24.12	0.57	F-La-La-P-P	104	0.69	F-F-La-P-Sa	227.43	1.08	F-F-F-Sa-P	178.92	1.99			
Nf-P-La-P-P	16.56	0.39	F-P-P-P-Sa	97.4	0.65	F-F-La-La-La	196.20	0.93	F-F-F-La-P	167.04	1.86			
Nf-La-P-P-La	16.11	0.38	F-La-La-P-La	83.1	0.56	F-F-Sa-P-P	167.49	0.80	F-F-F-Sa-La	143.10	1.59			
Nf-P-P-P-U	15.93	0.38	F-La-P-P-La	82.6	0.55	F-F-P-La-P	166.23	0.79	F-F-F-La-Sa	100.80	1.12			
Nf-La-La-P-P	15.30	0.36	F-P-La-P-La	72	0.48	F-F-La-La-P	154.35	0.73	F-F-F-Sa-Sa	96.48	1.07			
Nf-P-U-U-U	14.9	0.4	F-P-P-La-P	70	0.47	F-F-P-La-La	135.00	0.64	F-F-F-P-U	13.95	0.16			

Table 2.5. Top LULC trajectories within six clusters of the NEA.

Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 6	
Traj	%										
F-F-F	10.14	F-F-F	26.79	F-F-F	47.57	F-F-F	66.84	La-F-La	11.56	F-F-F	82.82
F-F-P	4.30	F-F-P	4.73	F-F-S	4.09	F-S-F	3.38	F-F-F	10.38	F-F-S	2.23
F-F-La	3.68	F-F-S	4.52	F-F-P	3.87	F-F-S	3.33	F-F-La	8.56	F-S-F	1.95
F-P-P	3.54	F-F-La	3.83	F-S-F	3.27	F-F-P	2.27	F-La-La	7.63	F-F-P	1.47
F-F-S	3.48	F-S-F	3.02	F-F-La	2.61	F-F-La	1.98	La-La-La	7.14	F-P-F	0.95
F-La-P	3.18	F-F-Sa	2.62	F-F-Sa	2.13	F-P-F	1.96	F-P-La	6.16	F-F-La	0.94
F-La-La	3.09	F-La-La	2.50	F-P-F	1.96	F-La-F	1.30	La-S-La	5.23	F-F-Sa	0.77
F-S-P	2.78	F-P-P	2.48	F-P-P	1.88	F-F-Sa	1.21	F-S-La	3.95	F-La-F	0.70
F-P-La	2.52	F-La-P	2.38	F-S-P	1.60	F-Sa-F	0.60	La-P-La	3.43	F-Sa-F	0.34
F-F-Sa	2.27	F-S-P	2.35	F-La-F	1.59	F-S-P	0.57	F-La-P	1.84	F-S-P	0.29

The clusters are characterized based on the composition of the dominant trajectories. Although the definition of the clusters is relative and depend on the number of clusters identified, the clusters can be categorized by the trajectories they contain. In this case for example, the six clusters classified can be labeled:

Cluster 1: very low forest stability, new pasture and large scale agriculture, transitions between pasture, large scale agriculture, and succession.

Cluster 2: low forest stability, new pasture and large scale agriculture, transition to succession.

Cluster 3: medium forest stability, transition to succession, transitions between pasture, large scale agriculture, and small scale agriculture.

Cluster 4: High stability of forest, transitions to succession, new pasture, and large scale agriculture.

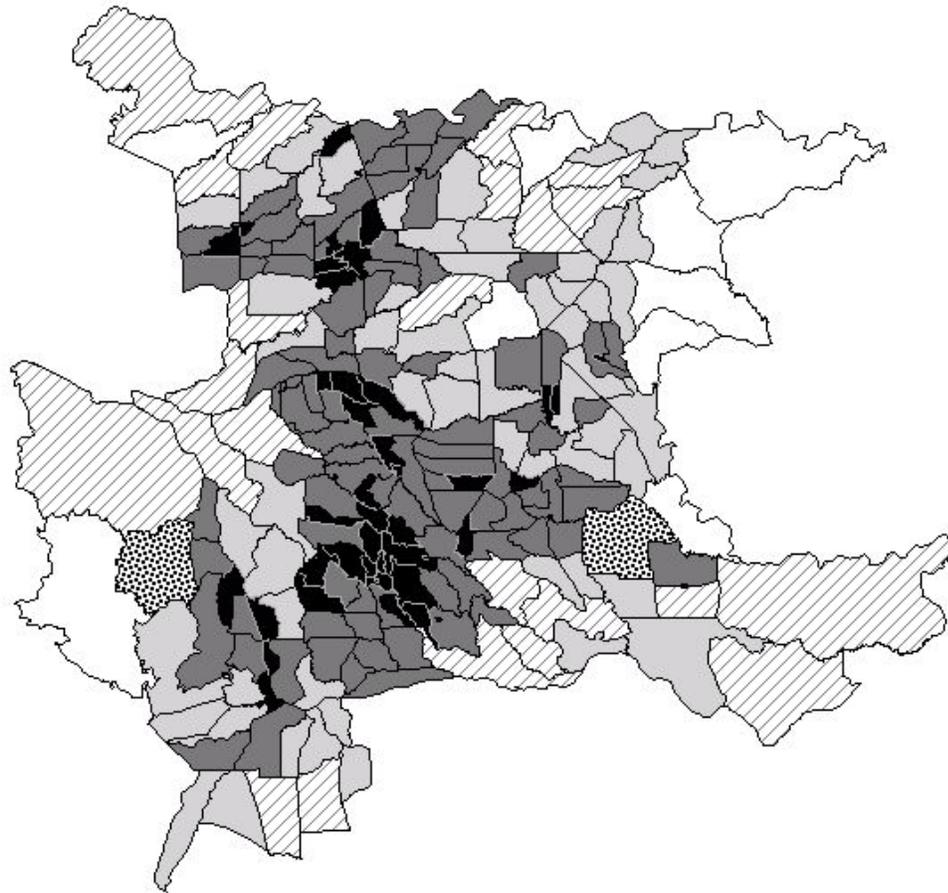
Cluster 5: Dominance of large scale agriculture.

Cluster 6: Very high stability of forest, dominance of succession, new pasture, small agriculture, and large agriculture.

Figure 2.8 is a map of the six clusters in the NEA that shows the spatial arrangement of the clusters is in the form a *core-periphery*<sup>11</sup>. The core is located in the proximity of main towns of (Lago Agrio, El Eno, Coca, and Joya de los Sachas). The periphery is located in areas close to the national parks, where indigenous communities and less connected colonist populations are distributed.

---

<sup>11</sup> This core and periphery clustering pattern was also found when 3, 9, and 12 clusters were generated using the clustering algorithm.



- Very low F stability, new P and La, transitions between P-La-S.
- Low F stability, new P and La, transition to S
- Medium F stability, transition to S, transitions between P- La-Sa
- High stability of F, transitions to S, new P and La
- Very high stability of F, dominance of S, new P, Sa, La
- Dominance of large scale agriculture

Clusters have different temporal compositions of Forest (F), Pasture (P), Large-Scale Agriculture (La), Small-Scale Agriculture (Sa), and Succession (S).

Figure 2.8. Spatial distribution of six LULC transitions clusters.

Landscape Pattern: A set of landscape pattern metrics are calculated for the NEA using census sectors as the unit of analysis. Figure 2.9 shows the results for three years: 1986, 1996, and 2002. Figure 2.9 (a) shows frequencies of the contagion index for the census sectors across the NEA. The graph indicates that for 1986 the number of census sectors with a high connectivity between patches was dominant. With time the landscape became more fragmented, although 1996 and 2002 had similar; 2002 shows census sectors with patches. Figures 2.9 (b) and (c) shows similar results for the landscape index and patch density respectively. In 1986, the number with patches across the landscape was relatively low and consistent. In 1996 and 2002 the density of patches increased, suggesting an intense fragmentation of the landscape.

Figure 2.10 illustrates the relationship between patch density across census sectors and distance to road (a) and the perimeter/area fractal dimension with distance to city (b). These graphs indicate that patch density decreases with distance to roads and cities. The same pattern is found using fractal dimension. In all the cases, the difference between 1986 and 1996 is larger than the difference between 1996 and 2002 suggesting that the process of fragmentation of the landscape occurred at a higher rate in earlier periods.

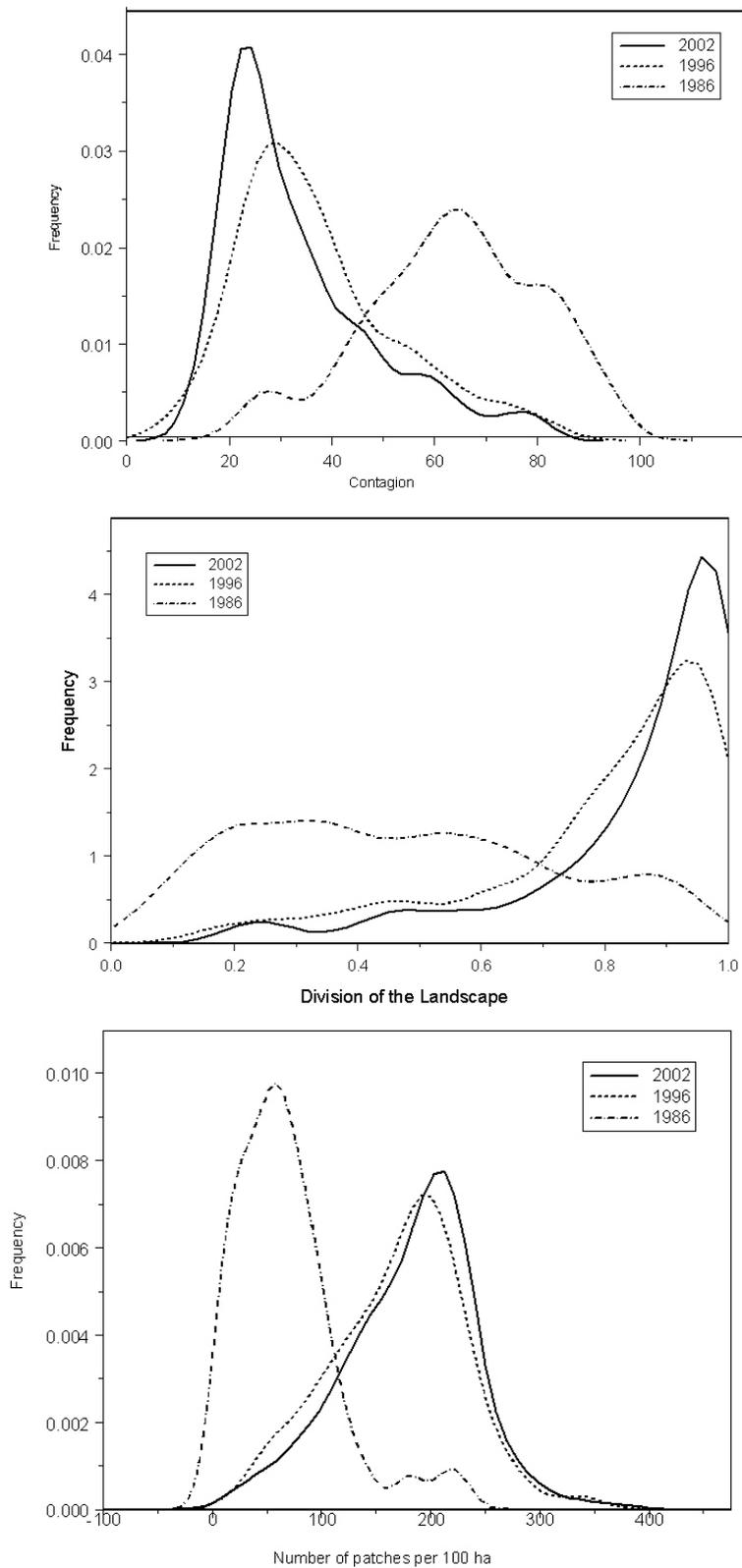


Figure 2.9. Distribution of landscape metrics calculated using census sector as unit.

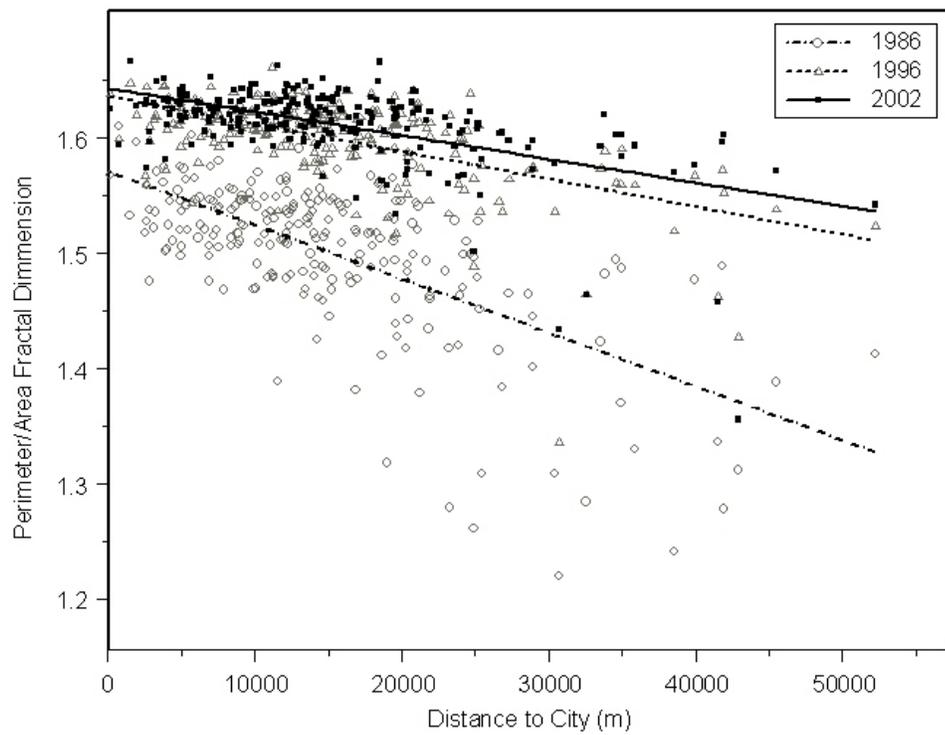
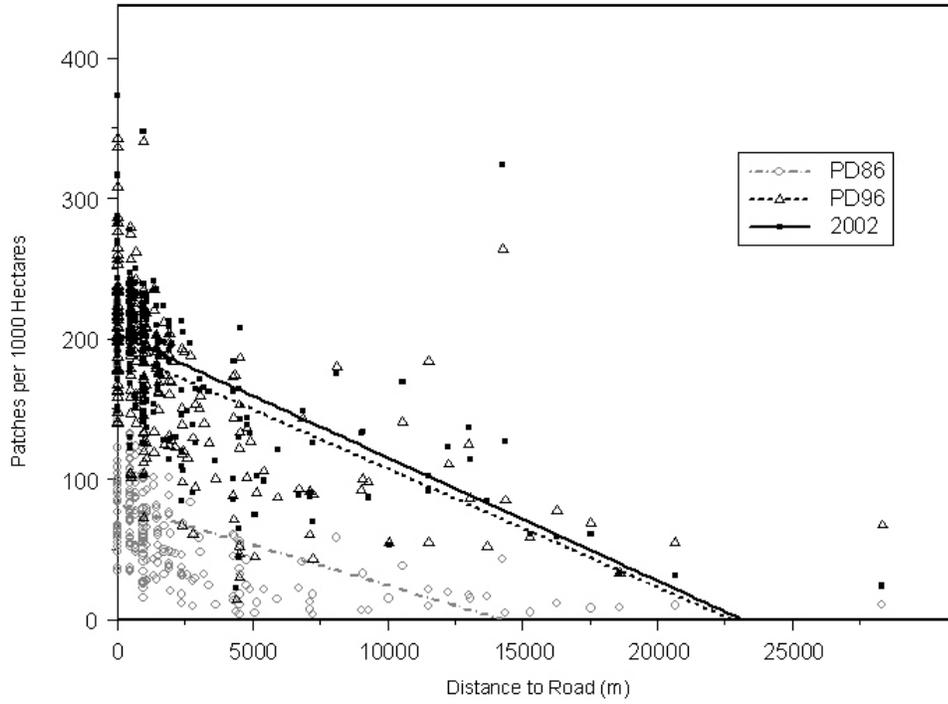


Figure 2.10. Landscape metrics and their relationship to accessibility.

Statistical Analysis: This section of the research presents the results of the statistical model. The aim of the logistic regression analysis is to create a spatially-explicit model of the flux (versus the stability) of the transitions based on geographic, demographic, and biophysical characteristics within the NEA. This model is graphically presented in Figure 2.11. The number of sampled observations used in the model is 820,132 defined using a stratified random sample. The percentage of sampled pixels with stable transitions (i.e., LULC constant across time) is 58.08% (Value=0), and percentage of sampled landscape with dynamic transitions is 41.91% (Value=1). Table 2.6 shows a set of descriptive statistics for the independent variables.

Table 2.7 indicates the coefficients obtained for each of the explanatory variables. The direction of the relationships between the dependent and independent variables is as expected. The exception is the distance to the two main cities (i.e., distance to Lago Agrio and Coca), which is positively related in the model is positive. Distance to communities is negatively related however, community includes all the small and medium towns, which probably captures better the effect of urban areas.

In terms of how well the model performs, ROC (Relative Operating Characteristic) measures the goodness of fit of the logistic regression, and compares Boolean maps of “reality” versus a “suitability” map (Idrisi 2006). ROC for this model is 0.7532 that indicates a relative regular fit<sup>12</sup>. Also, Pseudo R\_square = 0.13 that indicates an average goodness of fit<sup>13</sup>. Another method of assessing the overall fit of a model is to consider its prediction

---

<sup>12</sup> ROC=1 indicates a perfect fit; and ROC=0.5 indicates a random fit.

<sup>13</sup> Pseudo R\_square > 0.2 is considered a relatively good fit (Clark and Hosking 1986)

success. Table 2.8 contrasts the observed versus the predicted observations. The higher probabilities of transitioning are found in the core of the NEA, close to the towns of Coca and Joya de los Sachas, and relatively low probabilities are found in the periphery, close to protected areas.

Table 2.6. Descriptive statistics of independent variables and expected relationship.

Independent Variables	Mean	Std. Deviation	Expected relationship
Distance to city (km)	22.596	12.622	(-)
Distance to community (km)	9.075	6.648	(-)
Distance to oil wells (km)	6.928	4.972	(-)
Distance to protected area (km)	19.403	11.403	(+)
Distance to main roads (km)	5.687	6.456	(-)
Elevation (m)	255.816	646.485	(-/ +)
Slope (degrees)	-37.072	626.609	(-/ +)
Population Density (persons/ha)	-19.279	439.703	(+)
Soil (good soil=reference)	0.468	0.499	(-)

Table 2.7. Logistic regression coefficient for the logistic regression.

Variables	Coefficient
Intercept	2.170786
Distance to city	0.000061
Distance to community	-0.028418
Distance to oil well	0.008013
Distance to protected area	0.028398
Distance to main road	-0.086366
Elevation	-0.007524
Slope	0.007948
Population Density	0.000017
Soil	-0.584315
-2logL0	1115411.6
-2log(likelihood)	967999.8
ChiSquare( 9)	147411.8

Table 2.8. Classification of cases and odds ratio.

Observed	Fitted 0	Fitted 1	% Correct
0	352334	124031.	73.96
1	124031	219736	63.92

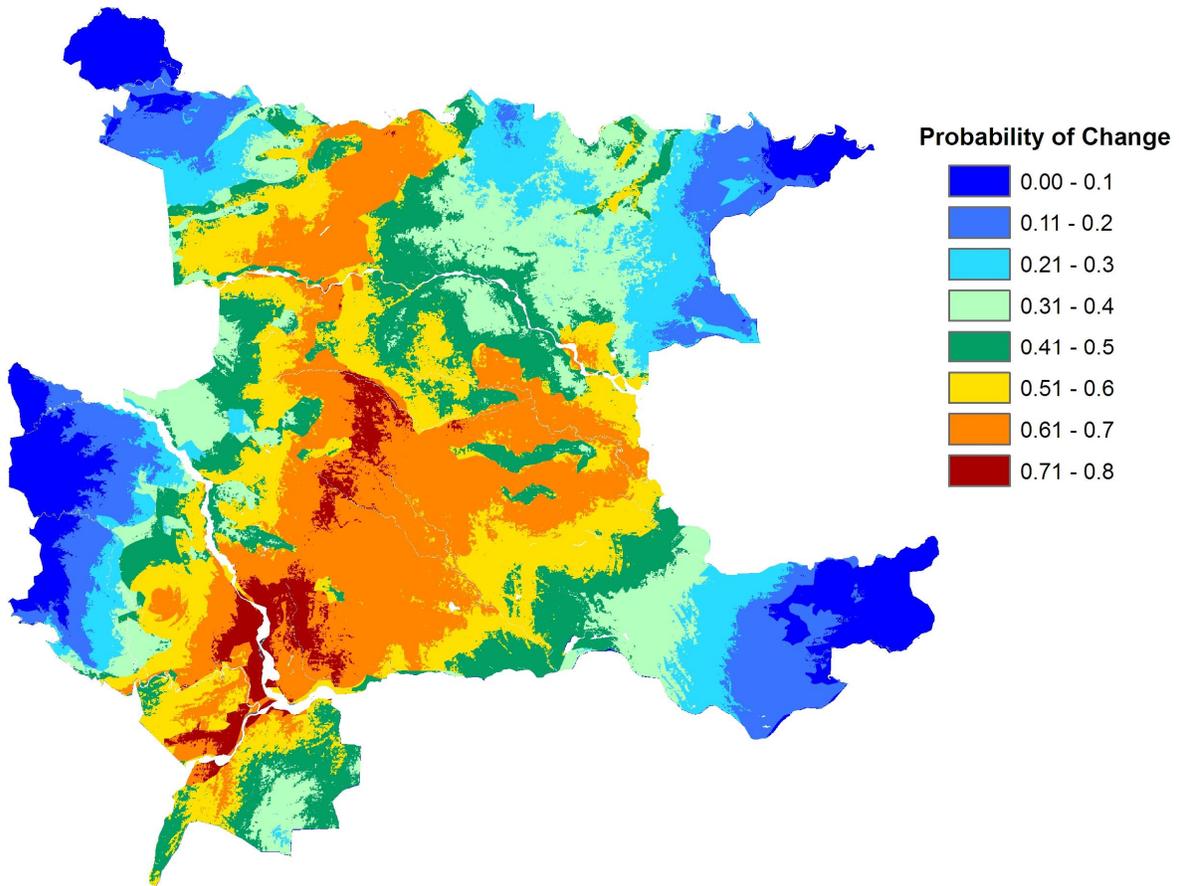


Figure 2.11. Probability of transitioning in the Northern Ecuadorian Amazon

## 2.6. Conclusion and Discussion

This work provides an exploratory assessment of LULC change patterns in the Northern Ecuadorian Amazon. It shows a complex and diverse sets of LULC trajectories in the study area. There are, however, patterns that can be observed and discriminated using

statistical analysis. From the methodological point of view, there are implications related to the accuracy of the classification and the use of pixel-based trajectories and ranks based on proportions. Lastly, there are connotations for future research related to theory and spatially-explicit complex modeling.

The exploration of trajectories at the "pixel" level has many drawbacks that make its analysis complicated. For instance, through the analysis of the LULC transitions in the Northern Intensive Study Area (NISA), it was found that the quantity and diversity of LULC transitions makes it impractical to generate comprehensive assessments of the status and change patterns without the use of some type of generalization and segregation of the trajectories. A commonly encountered concern in the multi-temporal analysis of frontier environments is the lack of multi-temporal control data that prevent the quantification of the error produced within the land use classification for earlier periods. The lack of data and methods to capture systematic errors of the classification creates a high level of uncertainty for the LULC transitions. In the case of this research, the objective was to find the main patterns of spatial and temporal organization of the trajectories. As such, they were aggregated or stratified by different spatial units. It was crucial to eliminate trajectories that were clearly not consistent or occupied a small proportion of the landscape. In other words, the methods employed transitions that were most important, in terms of area, to ameliorate the uncertainty produced by the lack of control data and the amount of information produced by the diversity of trajectories.

The analysis of LULC transitions has suggested a "core and periphery" pattern of transitions in the NEA. It is well accepted that land use change within farms in the Ecuadorian Amazon is, in great part, a spatially-explicit response to different demographic

and socioeconomic processes at the household- (e.g., farm subdivision) and community-levels (e.g., urbanization, territory reduction). Von Thünen in 1826 already described the generation of concentric circles around market towns that are composed of different land use types and demonstrated the connection between land use, location of the property, and transportation costs to markets (Nelson 2002). Processes at higher levels of social, political, and spatial organization are, in turn, dependent on economic development policies and, in the Amazonian case, also on conservation policies. The agricultural and forest trajectories occurring in urban or semi-urban places and marginal lands are sufficiently different to produce diverse and explicitly explicit responses. In the case of the NEA, where regional planning is restricted to the timing and territorialization of natural resources exploitation and agricultural growth is mostly spontaneous, LULC patterns are good indicators of the link between agricultural development and environmental change (i.e., forest change). Future studies on the NEA should benefit from core and periphery models of the economic change that have been extensively studied through Dual Society-Models, Modernization, and New Economy Geography (e.g., Brown 1991; e.g., Gradus and Lithwick 1996; Krugman 1991). The key question to address is whether greater level of aggregation or concentration of land investments in the core areas, without the regulatory presence of the governments (i.e., land protection) by itself will imply forest retention in periphery areas.

The LULC transitions also have implications for the condition of ecosystems and landscapes. The NEA is a frontier environment flanked by a set of *relatively* healthy and protected ecosystems: the Cayambe-Coca, Llanganates, and Gran Sumaco protected areas to the west and the Cuyabeno and Yasuni to the east. It is well know that connectivity among protected areas is vital to achieve real and effective protection of sensitive environments. The

designs of corridors will be an effective approach to ecosystem conservation, particularly, if the relative stability of current land use transitions is taken into consideration. For example, in the case of the NEA, clusters with forest stability or areas with low probability of transitioning to other land uses should be taken into consideration to form parts of corridors for restoration efforts.

## CHAPTER 3

### **Secondary Forest Succession in the Northern Ecuadorian Amazon: Spatial Patterns and Drivers**

#### **3.1. Introduction**

It is estimated that one-third of the world's tropical forest area is now covered by secondary forests (Center for International Forest Research 2002). In the tropics, secondary forests offer an alternative to accelerated environmental degradation by restoring deforested and disturbed habitats to a transitional land use/land cover (LULC) type and often providing income to the inhabitants of tropical forests. The analysis of secondary forests in tropical regions has recently received renewed attention, because of its importance in the calculation of carbon budgets, as an option for the sustainable management of forests, and for biodiversity conservation. As a carbon sink, the growth of biomass is in fact more rapid in young forests. Forest regrowth produces an accumulation of carbon at rates that range from  $1.5 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  in forests with biomass  $< 100 \text{ Mg C ha}^{-1}$  to  $5.5 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  in forests with biomass  $> 190 \text{ Mg C ha}^{-1}$  (Houghton et al. 2000). Also, secondary forests serve as connectors between primary forest remnants, decrease edge effects on primary habitats, affect biodiversity conservation by serving as critical habitat for key species, and protect soils and watersheds. Little is known, however, about secondary forest management as an effective conservation strategy that has both biotic and economic relevance (Center for International Forest Research 2002).

An accurate understanding of the extent of secondary forests and their formation is key to recognizing their potential for conservation and development. Recent advances have addressed (a) secondary forests in different parts of the Amazon: in Brazil (Perz and Skole 2003a; Perz and Skole 2003b; Perz and Walker 2002; Smith et al. 2003), Peru (Coomes et al. 2000; De Jong et al. 2001), and Ecuador (Rudel et al. 2002), (b) ecology of secondary forests (Brown and Lugo 1990; Chokkalingam and De Jong 2001; De Jong et al. 2001; Fearnside 1996), (c) remote sensing of successional vegetation (e.g., Castro et al. 2003; Foody and Curran 1994; Kimes et al. 1999; Kimes et al. 1998; Rignot et al. 1997; Tokola et al. 1999; e.g., Vieira et al. 2003), (d) socio-economic drivers of secondary forests (e.g., Perz and Skole 2003a; Perz and Skole 2003b; Perz and Walker 2002; Rudel et al. 2002; Smith et al. 2003), and (e) secondary forest management (e.g., Chokkalingam et al. 2001; e.g., Kammesheidt 2002). This study will examine secondary (or successional) forest and rastrojo (or early successional vegetation) that are formed following agricultural extensification and years of land use in the Northern Ecuadorian Amazon (NEA).

The definition and classification of secondary forests varies from one context to another, but invariably it depends on the age, use, and composition of the forest. Secondary forests are those formed as a consequence of the human impact on forested lands (Brown and Lugo 1990). For this study, secondary forest excludes extensive mono-species plantations as well as secondary forests formed by natural disturbances (e.g., fire or wind blow-down). Within this context, in the NEA successional vegetation occurs as a result of: (a) traditional or deliberate land use practices employed by colonists and indigenous groups as a mechanism to restore soil nutrients through recharge, and (b) abandonment of farms or agricultural plots on active farms. In the NEA, where household decision-making is the

primary proximate cause of land transformation (e.g., Bromley 1989; Pichón and Bilsborrow 1999; Rudel and Horowitz 1993; Southgate and Whitaker 1994) this research hypothesizes that the emergence of secondary forests in the NEA depends upon factors such as local biophysical and terrain conditions, antecedent and contemporary land use practices, market demands and labor availability, geographic accessibility, socioeconomic and demographic characteristics of households, and the links between households and local communities.

The specific objectives of this research component are to: (a) quantify the extent of secondary forest and fallow at the regional level between 1986 and 2002 in the NEA; and (b) analyze the socioeconomic, demographic, and biophysical factors that contribute to the generation of secondary successional vegetation at the farm-level in the NEA for 1990 and in 1999.

The results of this research contribute to (a) the understanding of the patterns and processes of secondary forest generation in the NEA, (b) the improvement of the measurement of the area in secondary forest through remote sensing, and (c) the use of longitudinal household socioeconomic survey data to build statistical models that examine the influence of socioeconomic, demographic, biophysical, and geographical factors on succession of forests.

### **3.2. The Northern Ecuadorian Amazon (NEA)**

The study area is located in the colonization area of the northeastern portion of the Ecuadorian Amazon (Figure 3.1). The region covers an area approximately 7,096 km<sup>2</sup> and comprises 19 *parroquias* or parishes located in the provinces of Sucumbios, Orellana, and Napo. The NEA exhibits a variety of natural vegetation types: evergreen forest of the lowlands and foothills, evergreen forest flooded by white waters, evergreen forest flooded by

black waters, palm forest, and humid brush (Palacios et al. 1999). The Ecuadorian rainforest is among the most biologically diverse and unique environments in the world. It has been considered one of the world's ecological hotspots, an area with extraordinary levels of biodiversity, and at the same time, at risk from high human demand for land conversion and development (Myers 1988; Myers 1990; Orme et al. 2005). This region has experienced considerable LULC change primarily through deforestation and agricultural extensification on household farms located on or near petroleum roads. Deforestation rates have been approximately 2.5 percent/year for the 1986-1996 and 1.8 percent/year for 1996-2002 (Mena et al. 2006b).

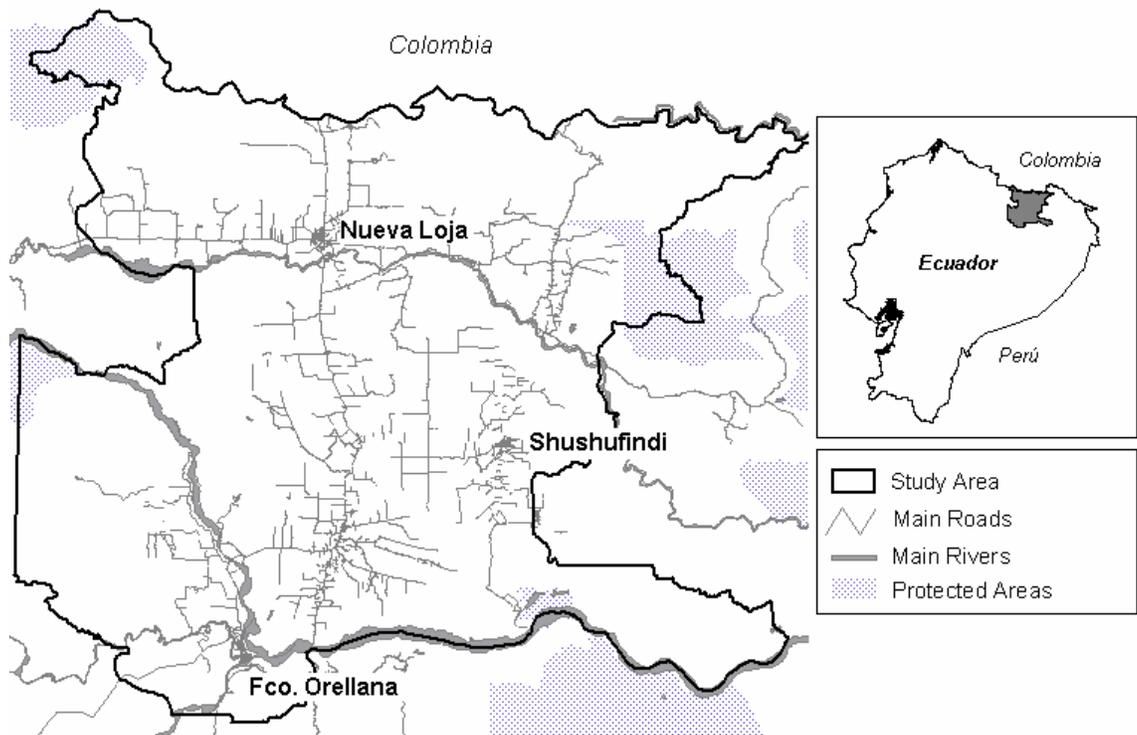


Figure 3.1. The Northern Ecuadorian Amazon.

Demographic change has been dramatic in the last 30 years. Population growth was 8 percent/year in the period 1974-1982, 6 percent/year for 1982-1990, 4 percent/year between 1990 and 2001, more than double the national average (Bilsborrow 2003). Migration from the *Sierra* and *Costa* regions of Ecuador is among the main factors contributing population growth and agricultural expansion in the NEA (Uquillas 1984). More recently, refugees from neighboring Colombia are arriving in the region to escape the violence. As a result, the NEA has one of the highest population densities in the Amazon Basin. Household farms extend up to 8-*lineas* (i.e., development lines) or 14-km from the nearest primary road, that links farms to market towns and population centers. Farm formation in areas of limited accessibility farther from primary roads reflects growing population density in the region, that is also manifest in increasing subdivisions of plots, community creation and expansion, and the direct and indirect effects of continuing expansion of oil extraction.

Prior studies in the NEA have found land use change on farms linked to farm labor (i.e., more male workers per household) (Marquette 1998); duration of settlement, soil quality, education (Pichón 1997; Pichón et al. 2002); household socioeconomic and demographic characteristics (Pan and Bilsborrow 2001; Pan et al. 2004); and urbanization, subdivision of property, road expansion and resulting improved geographic accessibility and access to growing agricultural markets (Barbieri et al. 2005; Barbieri and Carr 2005; Pan and Bilsborrow 2005; Pan et al. 2004). Land use in the NEA is thus framed by socio-economic conditions and biophysical settings that give context to this study, and includes secondary forests as an important landscape element that reflects ecological transition and dynamism caused by social, biophysical, and geographical drivers of LULC change.

### **3.3. Conceptual Model and Theoretical Framework**

In the NEA, nearly 40 percent<sup>14</sup> of the forest cover has been transformed to agriculture between 1974 and 2002. Deforestation is a process of land change that cycles between a forest-dominated landscape, an agriculture/pasture-dominated landscape, and a fragmented landscape of multiple land uses and land covers. Secondary forest is often a transitional LULC type that mediates the landscape matrix and links change and no-change patterns across the NEA.

Based on work by Chokkaliangam and de Jong (2001), secondary forests in the NEA have been classified into several classes depending on their use and age (Table 3.1). The perceptions and uses of secondary forest among indigenous and colonist populations may be different, which has implications for conservation and sustainable development. Indigenous groups use secondary forest plots (i.e., agricultural gardens that are partially abandoned or inactive) mostly for fruit collection and as hunting magnets for animals. Thus an ethnographic study carried out in eight indigenous communities in the Ecuadorian Amazon by Holt et al. (2004) reports that inactive gardens are used in different ways after cultivation by the ethnic groups in the NEA. Gardens are used for about three years and then left fallow for one to 18-years. Post-cultivation use in the fallow period is diverse but mostly to collect fruit and less frequently for hunting. Colonists, on the other hand, sometimes allow secondary forests to regenerate to recharge soil nutrients and prevent erosion, and often renew cultivation after a relatively short period of time. Alternative, they abandon farms or agricultural parcels on active farms as a consequence of declining soil fertility.

---

<sup>14</sup> Characterizations made using Landsat MSS and Landsat TM images.

Table 3.1. Types of secondary forest succession in the Ecuadorian Amazon.

Use	Definition	Observation (Age)
Swidden (slash and mulch)	Forest regenerating for the purposes of restoring the land for cultivation.	<ul style="list-style-type: none"> <li>▪ Low <i>Rastrojo</i> or resting (&lt; 2 years)</li> <li>▪ High <i>Rastrojo</i> or <i>barbecho</i> (2-7 years)</li> <li>▪ Secondary forest (&gt; 7 years)</li> </ul>
Secondary forest gardens	Less-intensively-managed smallholder plantations or home gardens, mainly in indigenous territories, where regeneration is tolerated.	<ul style="list-style-type: none"> <li>▪ Semi-abandoned <i>chacras</i> (&lt; 7 years)</li> </ul>
Post-extraction & agriculture secondary forests	Forest regenerating after significant reduction in the original forest through tree extraction or agriculture at a single point in time or over an extended period.	<ul style="list-style-type: none"> <li>▪ Abandoned agricultural plots (&gt; 7 years of abandonment)</li> <li>▪ Selective logging</li> </ul>

The general approach in this study is to view the formation of secondary forests and fallow as linked to socioeconomic, demographic, biophysical, and geographical characteristics at the farm-level. It is expected that secondary forest succession and fallow are positively linked to land security, that is, tenancy over the farm through a land title. During the early stages of colonization, farmers deforested a proportion of their land to help establish a claim to the land and gain title (Uquillas 1984). Once the farmer secures tenancy over property and the responsibility of deforestation is met, cleared areas that were not directly involved in the cultivation process were left to fallow. However, land tenancy and deforestation in the Ecuadorian Amazon are only weakly coupled, because of informal mechanisms of land tenancy and transfer (Bilsborrow et al. 2004; Rudel 1995). The general recognition of “land possession” through a *certificado de posesión* as a valid form of tenancy has reduced the perceived need for a formal land title or *escritura*. As a result, informal land security has afforded farmers the opportunity to consider long-term investments in the land,

such as the regeneration of forests for selective logging and the security that “un-worked” land is still a secure part of the landholding.

Another important factor affecting deforestation, agricultural extensification, and secondary forest succession is off-farm employment, which is often at oil related installations, in nearby cities or market towns, or associated with agricultural activities away from the household farm. Members of farm households increasingly migrate, permanently or temporarily, to local towns. Off-farm employment is hypothesized to have a positive effect on the regeneration of forests. Fewer workers on the farm implies less labor dedicated to agricultural activities, and therefore, the possibility of an increase in successional vegetation. On the other hand, hiring temporary labor for agricultural activities on the farm is hypothesized to retard the regeneration of secondary forests by keeping land in active agricultural use.

Forest transition theory suggests that forests follow an inverse U-shaped curve (Mather 2000) in which initially rapid deforestation is followed by regeneration in the later stages of economic development, in broad terms (Klooster 2003). Forest transition theory has been used to explain forest succession at higher scales of spatial and social aggregation in temporal environments, its applicability in tropical environments have its limitation (Perz 2007). In the NEA, economic development in the form of expanding urban centers and the perceived availability of jobs in the oil industry attract farmers and adult members of their households seeking off-farm employment to increase and diversify farm household income. However, because rural economic activities in the NEA are centered on natural resources extractive practices, factors such as household assets, education, access to electricity, loans, and technical assistance are expected to be negatively associated with secondary forest

generation, since they are positively related to agricultural land use. In the NEA, development, in the context of forest transition theory, defined broadly, is in its very early phases and will probably positively influence further deforestation and agricultural extensification rather than support forest regeneration.

In isolated areas with weak agricultural and labor markets, population pressure declines on the farm (due to out-migration of children reaching adulthood), thereby promoting forest succession. Chayanov (c.f. Cancian 1989) explored the effects of the size and age structure of households and their effects on the proportion of land cultivated. In the early 20<sup>th</sup> century, older households with a greater number of adults present on isolated farms in Russia had both the necessity and means for cultivating more land. More recently, Walker and Homma (1996) McCracken et al., (1999) and Perz and Walker (2002) identified the relationship of the household life cycle and land use change on frontier environments as composed of five stages: (1) young parents recently arrived in the area (duration of settlement <5 years) and initiate forest clearings for annual crops for subsistence; (2) parents with young children (duration of settlement ~5 years) become engaged in the cultivation of perennials and pasture, in addition to annual crops; (3) older parents with teenage children (duration of settlement ~10 years) decrease the cultivation of annuals and increase cattle raising and secondary vegetation; (4) pasture and perennial crops dominate, with increasing proportions of secondary forest as parents age and children reach young adulthood (duration of settlement ~15 years); and (5) children often leave the farm (duration of settlement > 15 years), family labor supply declines, and perennials remain a large portion of farm land use, as secondary forest succession further increases.

In terms of the household life cycle, there is a basic difference between the scenario

in the Brazilian Amazon and that in the NEA. Unlike Brazil, in the NEA, space for agricultural expansion is extremely limited as the total area is relatively small and large areas of forest have also been set aside in national parks or titled to indigenous communities. Land scarcity has led to little farm abandonment in the region and instead a process of farm subdivision is on-going. In later stages of the household life cycle, when young adults marry, they often claim a portion of their parent's farm for their own agricultural activities rather than create a new farm. Although, these young adults might work temporarily outside the farm in off-farm employment, the subdivision remains. The regeneration of secondary forests in the NEA is generated through the abandonment of cultivation of certain plots on working farms, rather than the abandonment of farms as in Brazil (Barbier and Burgess 2001). This is in turn partly caused by growing opportunities for off-farm employment, declining crop prices (i.e., coffee, cacao, and beef), and declining soil fertility due to previous use.

Other relevant factors that contribute to change in population-environment relations include accessibility, which has been found to be increasingly important to explain rural to rural, rural to urban mobility, urbanization, and deforestation in the region (Barbieri and Carr 2005; Pan et al. 2004; Pichón 1997). Higher levels of deforestation occur in areas close to main roads and with vehicle access. It is expected that the generation of secondary forests will follow a similar pattern, that is, succession will be more common in deforested areas that initially had relatively high degree of accessibility. Also, farm subdivision in the NEA is a process that drives LULC change (Bilborrow et al. 2004) and might also affect secondary forest succession. It is expected that the process of subdivision will be affected by neighborhood conditions that are not easily captured at the household level. For example, these neighborhood effects can be explained by the emergence of small towns linked to

industries or services which may generate diffuse *parcelization* processes. Here we examine whether the number of subdivisions within 3 km, 5 km, and 10 km of sample farms has a negative effect on secondary forest generation.

Biophysical factors, such as declining soil fertility, play an important role in forest succession. Moran et al. (2000) found that inter-regional differences of forest succession in the Brazilian Amazon are explained by differences in soil fertility. In the NEA, the typical soils are dystropepts (oxic or typic) and typic dystrandeps. The dystropepts may be either red or grey in color and are generally low in fertility. Dystrandeps have much higher fertility and are dark in color due to their composition (volcanic ash). In both the 1990 and 1999 household surveys, farmers were asked about the color of the main soil and its soil quality in the farm. In addition, farmers were asked about farm topography. Although optimal environmental conditions would favor forest regeneration, here soil fertility is hypothesized to be negatively associated with secondary forest generation, because lands with less fertile soil or steep topography are more likely to be abandoned to natural vegetation succession.

### **3.4. Methodology**

#### **3.4.1 Remote Sensing of Secondary Forest**

The proportions of secondary forest and fallow land at the landscape level were obtained using remotely sensed data. The limitations and uncertainties of remote sensing characterizations of secondary are well documented (e.g., Castro et al. 2003; e.g., Foody and Curran 1994; Kimes et al. 1999; Kimes et al. 1998; Rignot et al. 1997; Song and Woodcock 2003; Song et al. 2002; Tokola et al. 1999). Besides the errors related to geometric rectification and classification *per se*, uncertainties also exist related to the temporal synchronization of satellite and field data, correlation of plant greenness and spectral

response (particularly, of older secondary forests), ambiguity in the trajectory of secondary forest succession between image dates of the time-series, atmospheric issues and cloud concealment (and their shadows) of landscape features, and topographic effects related to moisture patterns and spectral biases. Specific to the NEA, older coffee, cacao plantations, and secondary forests have similar spectral response patterns. Coffee and cacao, the primary cash crops cultivated during the period studied, are often inter-cropped, further confusing their spectral separation through the concept of the integrated pixel. Finally, the small area of older *chacras* or successional gardens in indigenous communities (often < 1 ha in size) are difficult to categorize as they appear similar to surrounding primary forest, particularly when characterized at the 30-m pixel of Landsat TM. However, our use of fairly broad LULC classes in the analysis tends to alleviate some of the within and between class uncertainties implied in this discussion.

Figure 3.2 shows eight sample farms and their individual land parcels mapped through a digital classification of Landsat Thematic Mapper (TM) data for 1986, 1996, and 2002. Note the type and spatial pattern of LULC on these sample farms and the nature of change across the image time-series. Figure 3.3. shows a farm that also has been characterized at the individual parcel level through field surveys conducted in 2001. GPS technology was used to spatially locate the main corner points of each land parcel for each sample farm, averaging 50 hectares, with the assistance of the farmer. Farm owners also were interviewed and a land use questionnaire was administered to identify land use practices in 2001. Retrospective questions were also asked about parcel-specific land use practices on the farm in 1996, and prospective questions about parcel-specific land use practices anticipated in 2003. A GIS database was developed to track the changes in LULC types and parcel

location, shape, and orientation for each farm, with emphasis on deforestation and secondary forest succession. These datasets were used for training of the classification and validation purposes, but they also suggest that in the NEA farms are characterized by LULC dynamism, which has implications for mapping and modeling secondary forest succession and fallow.

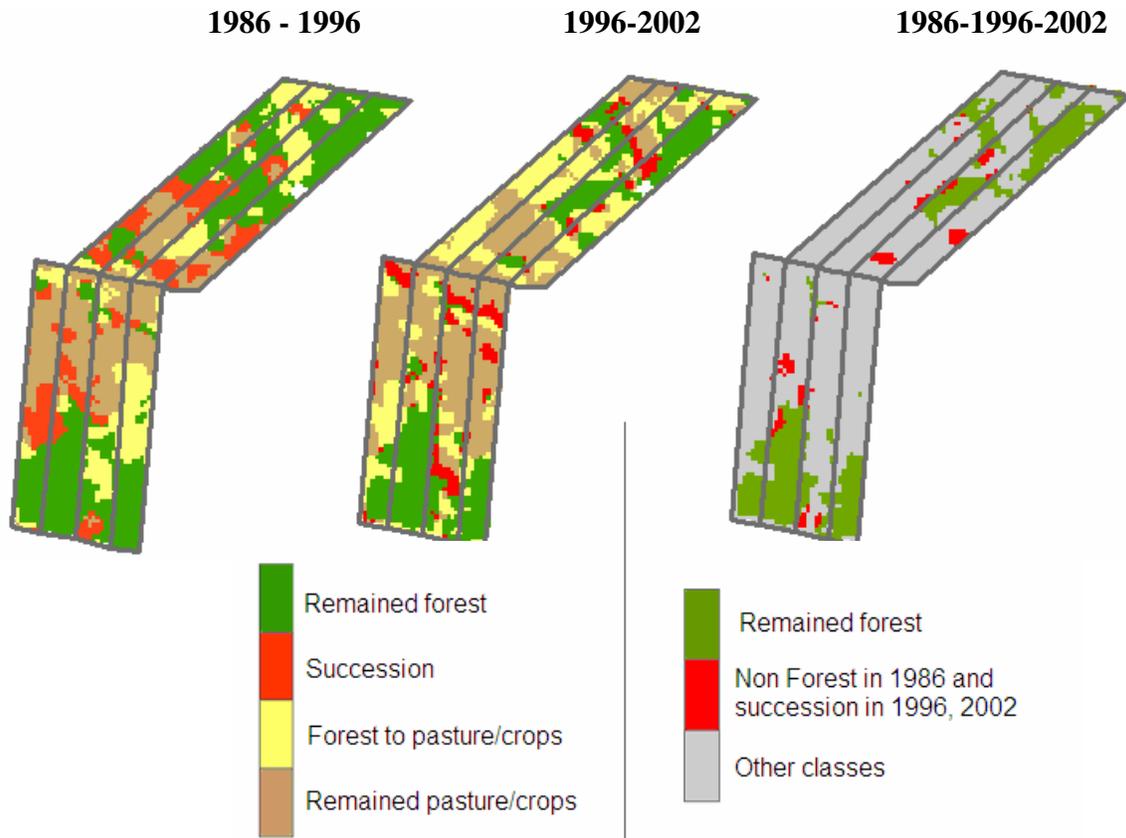


Figure 3.2. Land cover change detection in sample farms.

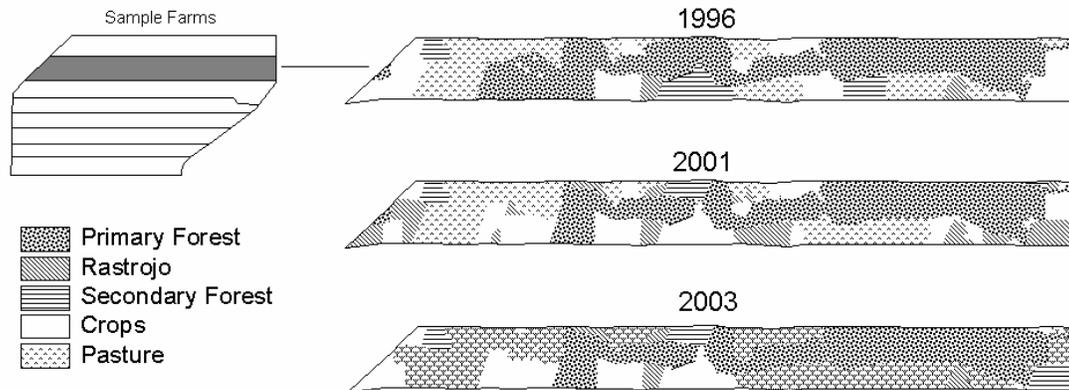


Figure 3.3: Land use change from parcel history and GPS survey.

The proportions of secondary forest and fallow land at the landscape level were obtained using remotely sensed data. This analysis uses a hybrid supervised-unsupervised classification of Landsat TM images for 1986, 1996, and 2002. As described by Walsh et al. (2002), the approach was designed to be repeatable across images in the assembled time-series; uses image characteristics assessed through statistical measures for characterizing class types; and limits the use of alternative field and/or air photo data in the classification process for consistency across the images. The hybrid approach begins with a supervised classification using the ISODATA classifier to define approximately 500 “naturally” occurring spectral classes. Using output statistics such as the transformed divergence and divergence statistics, the 500 spectral classes are reduced by approximately 50 percent. Then a supervised classification is applied using a maximum likelihood classifier to relate unclassified pixels to the 250 classes (i.e., the training data) defined through the unsupervised classification approach (Messina and Walsh 2001). This approach relies upon a hierarchical classification scheme to characterize the LULC types in the study area. Classes were then grouped into 5 broad categories: primary forest, secondary forest, rastrojo, other vegetation classes (including all crops and pasture), and other anthropogenic features (including towns

and roads). Secondary forest and *rastrojo* were used to calculate respective proportions for 1986, 1996 and 2002.

### **3.5. Statistical Analysis**

This analysis was performed on 125 *finca madres*, which are farms colonized by initial settlers of approximately 50 ha in size. This set of farms is a sub-sample of about 30% of all farms surveyed in 1990 (i.e., 405 farms and 418 households) and 1999 (i.e., 405 farms and 767 households). The selected farms are those located in intensive study areas (ISAs) where cloud-free Landsat images and classifications were available at the time of this research, which allows further comparison between remotely sensed data and survey data. The original sample of farms, collected in 1990, was derived from a two-stage probability sample design and a 6 percent probability sample of all sectors in the development region. The first stage was the selection of sectors or “pre-cooperatives” or groups of individual farms. A list of official settlement sectors was compiled from maps of IERAC (Ecuadorian Institute for Agrarian Reform and Colonization). A random sample of 64 sectors was drawn from this list. The second stage of sampling was the selection of individual farms: 5-10 contiguous farms were randomly selected from each sector using a probability proportional to the size of the sector (Pichón 1997).

The data collected in the 1990 and 1999 household surveys cover many topics, including land use and agriculture, socio-economic and demographic aspects, and technical assistance. The dependent variable in the cross sectional models represents the presence or absence of secondary successional vegetation on the farm at the moment of interview, which includes *rastrojo* and secondary forest. The independent variables represents a set of socioeconomic, technological, biophysical, geographical (accessibility),

and intensification variables operating at the local farm-level, which are used to examine the probability of secondary forest at the farm-level. Table 3.2 shows the independent variables used in this study, their definitions, and means and standard deviations.

Table 3.2. Independent variables at the farm-level for 1990 and 1999.

Domain	Variable	Definition	Expected Effect	1990Mean		1999	
				Std.Dev	Mean	Std.Dev	
Economic & Technology	LABORH	Person-months of hired labor on the farm	(-)	7.68	16.54	5.16	6.94
	OFE	Person-months of off-farm employment on the farm	(+)	4.72	9.14	3.44	9.19
	INCOME	Total annual income of the household	(- / +)	65.87*	110.29	1729.97*	461.27
	ASSETS	Average assets within the farm	(- / +)	7.89	2.32	6.65	2.13
	LOAN	Loans received (0/1)	(- / +)	0.25	0.43	0.88	1.67
	TITLE	Percentage of the farm under title	(+)	0.67	0.46	0.62	0.45
	TECH	Percentage of the farm received technical assistance	(- / +)	0.39	0.48	0.37	0.48
	EDUC	Education of head of household	(- / +)	1.46	0.71	2.66	0.98
	POWER	Electricity in the farm	(- / +)	0.2	0.4	0.66	0.48
Demographic	NHH	Number of households on the farm	(-)	1.15	0.44	2.15	1.54
	POPF	Number of adult females living on the farm	(-)	2.36	1.68	3.45	2.66
	POPM	Number of adult males living on the farm	(-)	3.05	1.83	4.72	3.59
	AGE	Age of the head of household	(+)	46.89	12.73	46.21	10.12
	YRSET	Years since settlement	(+)	9.96	4.57	19.84	5.10
	SUBDIV	Number of farm subdivisions	(-)	1.15	0.44	2.63	2.04
Biophysical	FLAT	Proportion of flat land on the farm	(-)	0.57	0.49	0.68	0.43
	BLACK	Proportion of the farms with black soils	(-)	0.79	0.41	0.59	0.46
	NCROPS	Number of crops grown	(+)	3.2	1.61	3.81	2.06
	GOOD	Proportion of good soil on the farm	(-)	0.4	0.48	0.38	0.43
	MEANSLP	Mean slope of the farm	(-)	1.21	1.53	1.21	1.52
	PROPF86	Proportion of primary forest in 1986 <sup>a</sup>	(-)				
PROPF96	Proportion of primary forest in 1996 <sup>b</sup>	(-)					
Accessibility	WALK	Walking distance to main road	(+)	2.00	2.86	0.58	0.95
	ROAD	Distance traveled by road to reference town	(+)	16.97	11.78	14.09	9.26
	TOWATER	Euclidean distance to rivers	(+)	397.54	296.94	390.48	299
	TOREFCOM	Euclidean distance to reference community	(-)	9.99	7.29	10.32	7.57
	ACCESS	Vehicle access to the farm	(-)	0.65	0.48	0.85	0.36
Densification	NSUB_3K	Number of subdivisions within 3-km	(-)	7.58	2.93	18.36	10.34
	NSUB_5K	Number of subdivisions within 5-km	(-)	8.92	3.49	20.9	11.22
	NSUB_10K	Number of subdivisions within 10-km	(-)	26.57	12.65	67.76	45.7

<sup>a</sup> In 1986: mean = 0.801 and std.dev = 0.239; <sup>b</sup> In 1996: mean = 0.480 and std.dev=0.160; \*In Sucre, not corrected for inflation

Statistical methods are used to examine the probability, direction, and significance of the relationships between secondary forest and a variety of socio-economic, demographic, and geographical variables. Methods included descriptive statistics and logistic regression models. The logistic regression model for  $\pi(x) = P(Y=1=\text{secondary forest})$  at values  $X=(x_1, x_2, \dots, x_p)$  of  $p$  predictors is:

$$\text{logit}(\pi(x)) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p$$

Where the parameter  $\beta_i$  refer to the effect of  $x_i$  on the logs odds that  $Y=1$ , controlling for the other  $x_j$  ( $j \neq i$ ). Two cross-sectional logistic regression models were created for 1990 and 1999 based on the longitudinal household survey performed in the study area during these years.

## **3.6. Results**

### **3.6.1 Measurement of Secondary Forest**

This study is concerned with secondary forest succession in a young frontier environment, where, as noted above, new agricultural land is scarce and little farm abandonment occurs. Remotely sensed information shows the extent and proportion of secondary forest and rastrojo (Table 3.3) for the entire NEA. These numbers, although showing the expected pattern of low levels of succession during the early years and higher levels in the middle of the 1990s, also provide an incomplete picture of the forest regeneration processes. Land in fallow and secondary forest can be conceptualized as land use categories that are in continuous flux. Between the years when Landsat images are available (i.e., 1986, 1996, and 2002), there may have been several cycles of deforestation and regrowth as new forests grow at a fast rate and farmers clear land.

Table 3.3. Secondary forest for the NEA obtained from satellite imagery.

	1986		1996		2002	
	Ha	(%)	Ha	(%)	Ha	(%)
Primary Forest	599,532.21	(84.61)	467,828.01	(66.02)	426,785.76	(60.30)
Secondary Forest	17,683	(2.50)	67,114	(9.47)	47,706	(6.74)
Rastrojo	6,188	(0.87)	5,457	(0.77)	16,796	(2.37)

The proportion of secondary forest and fallow suggests three distinct periods in the NEA. Up to the mid-1980s, when spontaneous colonization was at its maximum rate, about 15-percent of primary forest had been converted to other uses, and the amount of secondary forest was still very small (less than 1-percent of the landscape). Between 1986 and 1996 the period with the highest annual rate of deforestation (about 2.45 percent/year) - 130 thousand hectares of primary forest were transformed to other uses, and the proportion of secondary forest increased to 49,000 ha (9.5 percent of the NEA). By 2002, the proportion of primary forest was the lowest as result of further continued deforestation and the proportion of secondary forest was lower than in 1996, decreasing by 19,000 ha. This is consistent with the data showing a fall in the percent secondary forest reported in our longitudinal survey by farmers in 1990 (mean = 5.17%) and in 1999 (mean= 3.64%) (Tables 3.4 and 3.5, respectively).

Table 3.4. Land in secondary forest reported by farmers in 1990.

Statistic 1990	Secondary Forest (%)
Min.	0.00
Mean	5.17
Max.	66.00
Std. Dev.	10.30

Table 3.5. Land in succession reported by surveyed farmers in 1999.

	Young Fallow (%) < 2 years old	Old fallow (%.) 2-7 years old	Secondary Forest (%) < 7 years old	All Succession (%)
Min.	0.00	0.00	0.00	0.00
Mean	1.71	5.85	3.64	11.20
Max.	21.53	37.50	78.75	80.00
Std. Dev.	3.22	8.70	12.04	14.86

### 3.6.2 Logistic Regression Results

The results of the logistic regression models of the determinants of the presence of secondary forest in the farms for 1990 and 1999 are shown in Table 6 and Table 7, respectively. A number of additional independent variables were examined in earlier models, but are not shown here, since they did not have significant effects on dependent variable, or they varied in collinear ways with other variables and have been omitted from the analysis. Nevertheless, variables with a strong theoretical base were retained. In general, the results of the logistic regressions indicate that various demographic, accessibility, biophysical, and socioeconomic factors are important in explaining the presence of secondary forest succession on farms. Densification, measured by the number of subdivisions within a certain prescribed Euclidean radial distances of the farm, has less effect than anticipated once other factors are controlled, including population.

Table 3.6 shows three models for 1990. Model 1 comprises variables that capture the main socioeconomic, geographical, and biophysical characteristics of the farm and that are not collinear with other independent variables. Consistent with expectations, the variable AGE, representing the household life cycle, is statistically significant and has a positive sign, which indicates higher odds of having secondary forest on an older farm. Thus, farms with

older heads of household have a higher probability of having secondary forest in 1990. The findings in the 1990 regression support this household life cycle. The proportion of good soils (GOOD) on the farm and walking distance to the nearest main road (WALK) also show strong relationships with secondary forest; their negative sign indicates a decrease in the odds of having secondary forest. Although soils characterized as good would facilitate a rapid regeneration of forest, the relationship can exist in either direction. Good soils facilitate maintaining agricultural uses and encourage more deforestation. Contrary to what was expected, accessibility, represented by WALK, indicates that a higher walking distance to the road in 1990 decreases the odds of secondary forest. In other words, there is a higher probability of secondary forest regeneration on farms located close to roads. This can be explained by the fact that more deforestation, an obvious requirement for forest regeneration, occurred on farms close to roads. Farms with more deforestation produce greater opportunities for land to cycle into fallow or secondary forest. Legal title over the farm (TITLE) increases the odds of secondary forest in the farm. As hypothesized, title might give a transient security that allows the abandonment of cultivated plots without the concern of having a productive farm thereby that justifying colonization.

Model 2 in Table 3.6 comprises the statistically significant variables from Model 1. The variable TITLE shows a reduction of statistical significance which might indicate a degree of interaction with another independent variable in Model 1. Nevertheless, title is potentially important variable that represents how institutional factors affect secondary forest succession. In Model 3, the demographic variable, male population in the farm (POPM), was included. Contrary to what was expected, POPM is positively linked to secondary forest. A higher number of male adults in the household increases the odds of the existence of

secondary forest. POPM is also correlated with other demographic variables not included in the regressions (i.e., number of households, number of females, number of males, and subdivisions in the farm). It was hypothesized that increases in population pressure over the land would produce a decrease of secondary forest. However, regression results show that demographic variables have only an indirect relationship with succession. Indicators of pressure on the land (e.g., number of households, number of males) have a direct causal relation to the original deforestation, so being deforested is the requirement for secondary succession. Thus, demographic factors should be positively related to land in secondary forest.

Table 3.7 shows the results of the logistic regression for 1999. Model 1 and Model 2 show that the variables: education of the head of household (EDUC), proportion of forest in 1986 (PROPF86), and years since settlement (YRSRT) have statistically significant negative relationships with secondary forest succession, while off-farm employment (OFE) and walking distance to the main road (WALK) have statistical significant positive relationship. As expected more education (EDUC) decreases the odds of having secondary forest in the farm. More educated farmers are more successful in optimizing the use of deforested lands. That is, in intensifying land use to support the families. Increases in education, besides supporting access to new agricultural techniques and financial opportunities, can bring changes in expectations about land and production. The lagged proportion of primary forest in 1986 (PROPF86) is also a strong predictor of secondary forest succession in 1999. As expected, it indicates that higher proportion of primary forest in 1986 is linked to lower odds of secondary forests in 1999. Although not statistical significantly for 1990 the negative sign of this relationship confirms the relationship between deforestation and secondary forest.

Years since settlement (YRSET) has a statistically significant negative relationship with secondary forest. The direction of this relationship in 1999 is consistent with the overall decline of secondary forest in the NEA between mid-1990s and 2001.

As hypothesized before, more off-farm employment increases the odds of secondary forest succession within the farm. As oil related and service jobs increased between 1990 and 1999, off-farm employment is increasingly important to explain land use changes in the farm. Walking distance to the main road (WALK) is another variable that is statistically significant in 1999, as it was in 1990. However, in 1999 as opposed to 1990, WALK has a positive relationship with secondary forest. Farms located farther from main roads have a higher probability of having secondary forest. The difference in the sign in the relationship between WALK and the probability of secondary forest may indicate a non-linear relationship, but also might be explained by changes in accessibility. While in 1990 the mean walking distance was 2 km, in 1999 it was only 0.56 km, therefore, less likely to be important. In 1990 when main roads were scarce, succession happened in areas where earlier deforestation happened -- close to roads. By 1999, when the majority of farms were close to roads, and deforestation was common across the landscape, succession occurred in areas more likely to be abandoned, those further away. As in 1990, finally, Model 3 of Table 3.7 indicates, the final model showing a positive significant relationship between the number of households and the presence of secondary forest in 1999.

Table 3.6. Logistic Regression Model for Secondary Forest in 1990.

Variables	Model 1		Model 2		Model 3	
	$\beta$	s.e.	$\beta$	s.e.	$\beta$	s.e.
(Intercept)	-0.429	(1.554)	-2.016	(1.196)	-2.513	(1.261)
POPM					0.223	(0.123) <sup>+</sup>
YRSET	0.039	(0.050)	0.035	(0.047)	0.025	(0.049)
AGE	0.029	(0.018) *	0.027	(0.017) <sup>+</sup>	0.027	(0.018)
EDUC	-0.258	(0.328)	-0.191	(0.304)	-0.123	(0.309)
GOOD	-0.991	(0.473)	-1.089	(0.449) *	-1.228	(0.470) *
SLOPE	0.036	(0.169)				
WALK	-0.160	(0.091) <sup>+</sup>	-0.114	(0.081) *	-0.135	(0.083) *
ROAD	-0.018	(0.019)				
ASSETS	-0.203	(0.131)				
POWER	-0.092	(0.676)				
LABORH	-0.005	(0.019)				
OFE	0.007	(0.023)	0.008	(0.022)	-0.006	(0.023)
TITLE	1.162	(0.571) *	0.727	(0.493)	0.690	(0.503)

\*\* Significant at 1%; \* significant at 5%; <sup>+</sup> significant at 10%

Table 3.7. Logistic Regression Model for Secondary Forest in 1999

Variables	Model 1		Model 2		Model 3	
	$\beta$	s.e.	$\beta$	s.e.	$\beta$	s.e.
(Intercept)	10.018	(2.985)	7.511	(2.186)	3.171	(1.160)
POPM					0.106	(0.086) *
GOOD	-0.417	(0.540)	-0.285	(0.513)	-0.366	(0.506)
ROAD	-0.005	(0.025)				
POWER	0.338	(0.528)				
AGE	-0.039	(0.025)				
YRSET	-0.079	(0.048)	-0.083	(0.045)	-0.082	(0.043) <sup>+</sup>
EDUC	-0.942	(0.314) *	-0.743	(0.253) *	-0.532	(0.251) <sup>+</sup>
MEANSLP	0.013	(0.159)				
PROPF86	-5.048	(2.142) **	-4.373	(1.865) **		
TITLE	0.248	(0.546)				
OFE	0.010	(0.005) *	0.010	(0.005) *	0.009	(0.005) *
WALK	0.666	(0.350) *	0.615	(0.318) *	0.457	(0.297) <sup>+</sup>

\*\* Significant at 1%; \* significant at 5%; <sup>+</sup> significant at 10%

### **3.7. Conclusions**

The succession of vegetation in the NEA is still an incipient process. At the farm-level, farmers reported that the proportion of successional vegetation within farms was 5.17% in 1990 and 11.20% in 1999. These differences in the proportion of secondary vegetation are small in relation to other changes in LULC on the same farms (Walsh et al 2003, Bilsborrow et al 2004). For the entire NEA, remotely-sensed data indicate that the area of secondary forest increased between 1986 and 1996 (49,400 ha), but decreased by 19,400 ha between 1996 and 2002. Conversely, the area in rastrojo maintained relatively constant values between 1986 and 1996, but increased from 5,457 ha in 1996 to 16,796 ha in 2002. Although the information provided by farmers through the longitudinal survey, and that obtained through remotely sensed methods, are not directly comparable, both sources show that in the late 1990s and early years of the present decade, there has been a decrease in the relative proportion of secondary forest (excluding fallow), consistent at the farm- and landscape-level.

This exploratory study uses statistical models to study the socioeconomic, geographic, and demographic factors that contribute to the generation of successional vegetation in the NEA. The study estimates two cross-sectional models, for 1990 and 1999. Each reflects different time periods and conditions at the time of survey. While the models yield different levels of explanation and show varying slope coefficients, they indicate that aspects related to the proportion of forest in past years, household and plot life cycle, accessibility, and socioeconomic characteristics such as off-farm employment, males, and education are related to secondary forest at different stages of the colonization.

The NEA is a region that has been deeply influenced by oil activity. This activity has

contributed to the development of infrastructure, urbanization, a floating population of migrant labor, and cultural change in indigenous population (Holt et al. 2004). Landscape change, and, in this case, the dynamics of successional vegetation, is, in part, caused by activities related to the oil industry and its impact on the transportation network, the growth of towns, and rising employment opportunities for farmers and young adults.

As shown in the statistical analysis, there are a variety of factors that contribute to the generation of secondary vegetation, and although this study does not include data on price of coffee, the drastic decrease in agricultural commodity prices that begun in the late 90s and continued since contributed to the abandonment of coffee “pushed” farmers to seek alternative incomes in the oil industry and in towns. Push factors from the farm and “pull” factors to non-agricultural activities can promote farm abandonment (something heretofore relatively rare in the NEA), which could promoted the regeneration of forest and fallow in previously cultivated sites. While too early to tell if such a transition will occur, anecdotal evidence suggests that the process of farm and agricultural parcel abandonment has begun in the NEA. If correct, an increase in secondary forest and fallow is likely to occur at a scale observable through remote sensing systems and identifiable through socio-economic and demographic surveys.

## **CHAPTER 4**

### **Characterizing the Spatial Dependence and Spatial Heterogeneity of the Drivers of Land Change in the Northern Ecuadorian Amazon**

#### **4.1. Introduction**

Land cover change is one of the core problems of global environmental change. Although the environmental consequences of land cover change can be traced to colonial times (Grove 1992), significant advances have been made in the last two decades in the understanding of spatial and temporal dimensions of change at regional and global scales (Ramankutty et al. 2006), direct and underlying causes (Geist and Lambin 2002; Lambin et al. 2001), economic factors (Barbier and Burgess 2001; Cancian 1989; Kaimowitz and Angelsen 1998), ecological changes (Dirzo and Raven 2003; Sauders et al. 1991; Turner 1996), and socio-cultural consequences of habitat modification (Godoy et al. 2005b).

One of the most devastating impacts following ecosystem change with minimal management to agricultural extensification is loss of species and populations extinction (Brook et al. 2003; Laurance et al. 2002). Furthermore, it is not only direct habitat destruction, but broad degradation of habitat quality through forest fragmentation (Fahrig 2003; Laurance et al. 2002) and edge effects (Woodroffe and Ginsberg 1998) in surrounding areas that affect biotic communities and ecosystems. Rapid land use and land cover change also has negative feedbacks to the livelihoods of local populations. The advance of the

agricultural frontier is linked to technological and cultural change, engagement to markets (Godoy et al. 1997; Godoy and Wilkie 1997), and reduction of the natural resource base of indigenous populations (Cannon 1995). Deforestation and the associated land cover changes negatively affect not only the local physical template, including effects to the microclimate (Bruijnzeel 2004) and soil erosion (Bruijnzeel 2004), but also to larger Earth system by contributing to global warming through the release of large amounts of carbon to the atmosphere (Fearnside 2000; Lewis 2006).

One of the challenges of global environmental change is the mismatch between the scale of management and the scale of assessment (Cash and Moser 2000). The assessment of the drivers of land cover change, in great part, has been supported by statistical methods that generalize relationships across regions, landscapes, or study areas, in this paper also called *global regression* models. Global regression analysis may be misleading, if one assumes that the relationships are constant or invariant across space (or exhibit stationarity), but, in fact, are *heterogeneous* across space (Fotheringham et al. 2002). Specifically in the Amazon Basin, characterized by its very high biological and cultural diversity, the advance of the agricultural frontier and the natural systems are characterized by a high degree of heterogeneity across space. For example, the variability in land-use strategies among colonist farmers (Pichón 1996), different types of human adaptation to similar environments (Coomes 1992; Moran 1991), and the heterogeneity of soils and landforms (Williams et al. 2002; Zender et al.) show striking differences across space. Even in the political arena, the homogeneity of the Amazon, which was a traditional assumption within governments of the region for many decades, is now characterized as just another myth (Amazonic Cooperation Agreement 1994). Thus, it should not be surprising that the assumption of processes working

identically across geographical units (e.g., colonization areas) is not supported by global statistical models, because they are missing some local characteristics that might be relevant for successful sustainable development or conservation.

In addition to the heterogeneity of the relationships that might exist across space, there are localized processes or factors that influence the behavior (or decision-making process) of agents, as well as localized errors in the data, which create local influences and produce clusters of similar characteristics in the landscape. This is conceptualized as *spatial dependency*, or the extent to which the value of an attribute in one location depends on the values of the attribute in nearby locations (Anselin 1988; Fotheringham et al. 2002; Moran 1948). The challenge is to distinguish spatial dependence from spatial heterogeneity; in other words, the difficulty is to distinguish whether a location is different because it is impacted by its neighboring values or is different because the processes have different intensities or directions at a geographic location (GeoDa 2007).

The objectives of this paper are therefore: (1) explore the spatial dependency and spatial heterogeneity of the drivers of deforestation and agricultural extensification in the Northern Ecuadorian Amazon, and (2) determine how the intensity, type, and direction of the factors that control land change are affected and differ across space within the region. This research links remotely-sensed land use and land cover data to household survey information, and assesses spatial dependency and spatial heterogeneity of the relationships through the use of Ordinary Least Square regressions (OLS), Spatial Lag Models (SLM), and Geographically Weighted Regression models (GWR). In the results section, besides the exploration of spatial dependence and spatial heterogeneity, this research briefly discusses the implications of the factors that contribute to land change and illustrates alternative representations of these

drivers.

#### **4.2. The Northern Ecuadorian Amazon (NEA)**

The study area is located in the colonization area of the northeastern portion of the Ecuadorian Amazon (Figure 1). The region covers an area approximately 7,300 km<sup>2</sup> and exhibits a variety of ecosystems (Palacios et al. 1999) and ethnic groups (Holt et al. 2004) that include colonist farmers with distinct origin and different histories of settlement and indigenous populations of ancestral and recent presence in the region. The Ecuadorian rainforest is among the most biologically diverse and unique environments in the world. It has been considered one of the world's ecological hotspots, an area with extraordinary levels of biodiversity, and at the same time, at risk from high human demand for land conversion and development (Myers 1988; Orme et al. 2005). This region has experienced considerable LULC change primarily through deforestation and agricultural extensification on household farms that are generally located along roads.

The discovery of petroleum in the region in the early 1960s helped define two periods in the history of the NEA. Prior to the exploitation of petroleum, the natural landscape was essentially intact and populated mainly by indigenous populations and some colonists devoted primarily to subsistence agriculture. Using roads built by the petroleum industry to explore, lay pipelines, and extract oil, colonists began arriving in the early 1970s and began converting land from forest to agriculture on 50-ha farms to initially support themselves with subsistence agriculture, followed by the commercial cultivation of coffee, and eventually to raise cattle for sale. Virtually all the colonization has been spontaneous. Colonist, household farms in the Ecuadorian Amazon extend up to 8-lineas (i.e., development lines) or 16 km from the nearest primary road, which links farms to market towns and population centers.

Population growth was 8-percent, 6-percent, and 4-percent per year in the intercensal periods 1974-1982, 1982-1990, and 1990-2000, respectively (Bilsborrow 2003). Migration from the Sierra and Costa regions of Ecuador, and recently from the neighboring Colombia, is among the main factors contributing to population growth in the NEA. As a result, the NEA has one of the highest rural population densities in the entire Amazon Basin. More recently, population growth has been induced subdivision of property into smaller farms and the formation of solares (non-agricultural plots), which has decreased the percentage of properties with full legal titling, from 50-percent in 1990 to 34-percent in 1999 (Bilsborrow et al. 2004). Off-farm employment (OFE) of members of farm households in emerging urban centers contributes to land transformations, as does the direct and indirect effects of communities as they expand their core services and influence land use patterns on nearby farms. In our longitudinal survey of 405 farms, 35-percent of our respondents in 1990 reported some household member engaged in OFE, whereas in 1999 this increased to 51-percent. During the same time period, hired labor decreased from 60-percent to 41-percent (Bilsborrow et al. 2004) .

Prior studies have found deforestation on farms in the NEA to be linked to farm labor (i.e., more male workers per household) (Marquette 1998), duration of settlement, soil quality, road access, education (Pichón 1997; Pichón et al. 2002), and household socio-economic and demographic characteristics (Pan and Bilsborrow 2005; Pan et al. 2004).

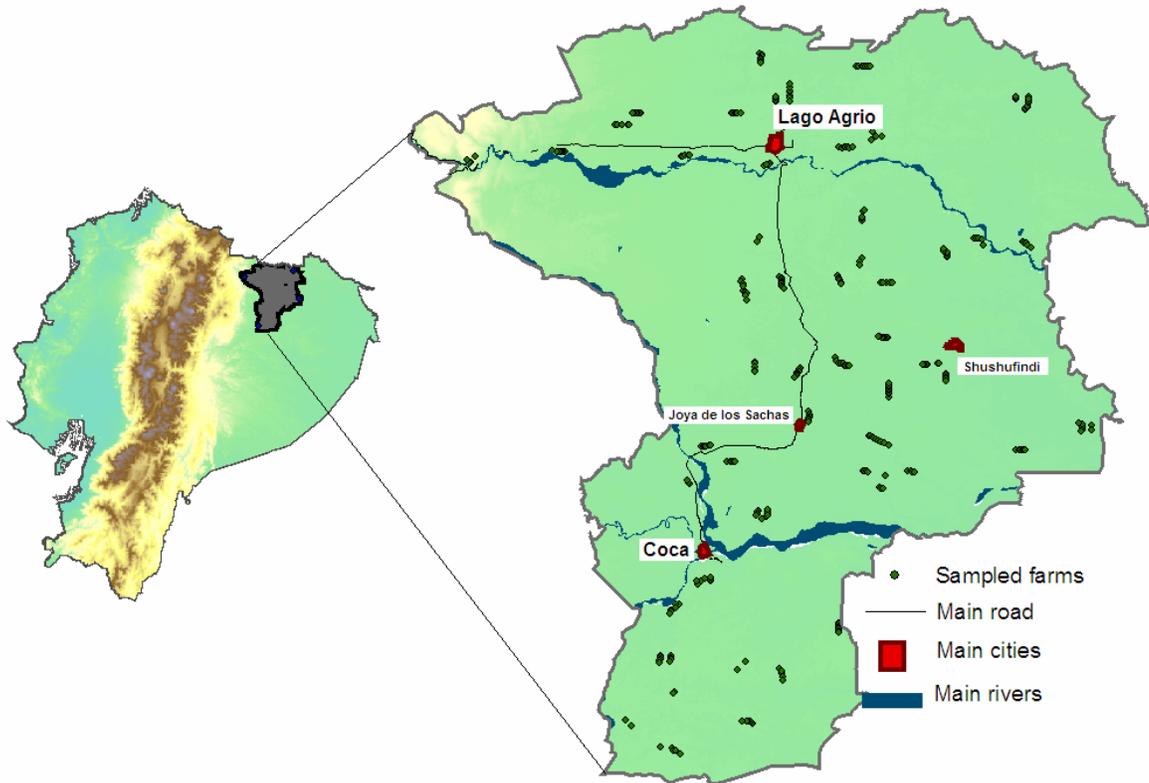


Figure 4.1. The Northern Ecuadorian Amazon.

### 4.3. Theoretical Considerations

#### 4.3.1 Drivers of Land Use and Land Cover Change in Tropical Regions

The complexity of the drivers and processes of land change, which emerges due to the many factors involved, their feedbacks and thresholds, and the co-evolution of human and natural systems, have impeded the generation of an integrated theory of land use change. Progress in land change studies, however, lies in the integration of different theoretical approaches and the understanding of how these have proven to be useful (Lambin et al. 2006). In tropical areas, the nature and drivers of land use and land cover change has been explored by an expanding body of literature that deals with the direct and indirect consequences of land use conversion (Geist and Lambin 2002; Rudel 2005) and the policy

implications of the rapid anthropogenic land use change and associated environmental degradation (Goetz et al. 2004). It is widely accepted that there is no single overarching land change driver; deforestation, for example, responds to localized demographic, socioeconomic, and biophysical processes that have global connections, and where historical, political, and cultural contexts are very important (Geist and Lambin 2002; Moran 1993; Rudel 2005; Rudel and Roper 1997). In the Northern Ecuadorian Amazon, a relatively new agricultural frontier with no additional space for expansion, land change drivers include population growth, internal and external population fluxes, the changing nature of labor and agricultural markets, and expansion of infrastructure.

In the early 1970s demographic approaches were used to explain the effects of uncontrolled population growth on the global environment (Meadows et al. 1972; Pestel 1989), based on the connection between population growth and environmental degradation, originally advocated two centuries ago by Malthus (1803). Relevant to land change, neo-Malthusian theories are built on the assumption that land productivity is fixed, therefore, it is necessary to expand agricultural lands to feed the growing populations (United Nations Organization 2001). An observation made by Malthus is that the most productive land is generally used first and consequently, newer agricultural lands tend not to be as productive. In the NEA areas occupied in the later stages of colonization have disadvantages through constraints associated with geographic accessibility, land security, and access to technology that renders these lands less suitable for highly productive agriculture. The assumption that land productivity is fixed is also taken in to consideration by classical agricultural economics. The law of diminishing returns (Ricardo 1887) argues that when land is fixed, increased applications of labor inputs generate a decrease in the productivity of the mean output per

worker (Bilsborrow and Carr 2000). In the NEA, a region with relatively infertile soils, decreases in soil fertility and the availability of a growing agricultural labor market might contribute to the extensification of agriculture. Within the NEA, demographic factors, such as temporal and permanent population flows also have consequences for the advancing deforestation front and urban center growth (Barbieri and Carr 2005) that may more important than the population growth per se.

In contrast to the Malthusian view, Boserup (1965; 1981) challenges the Ricardian and Malthusian assumption of fixed land productivity. She argues that more people create technological changes that intensify land use, so higher populations per unit area can be supported without overall resource decline in living standards. Boserupian theory is important in that it describes the role of population pressure on natural resources as a catalytic component in the process of land use intensification. According to Boserup, the increase of input labor per unit of land through time creates the stages of intensification that range from low to high intensity. Although not always linked to population change, modern conceptualizations of land use intensification are associated with increases in input variables, for example, chemical fertilizers, pesticides, and output intensification, that measures the increases in production against constant units of land area and time (e.g., calories/hectares/years) (Bilsborrow and Geores 1992; Lambin 2000). Critics of the Boserupian view argue that the endogenous character of the intensification process only applies to particular settings, relatively rich areas where investments in new technologies are possible or areas where population density is relatively low with an extraordinary capacity to change tenure regimes (Lee et al. 2000). In the Northern Ecuadorian Amazon, two different types of intensification scenarios are present. First, in colonist environments, where the

population pressure on natural resources emerges recently in the form of farm subdivisions, the decrease in soil nutrients in small intensely used areas coupled with the expense of compensating technology (e.g., fertilizers) makes the process of further intensification unsustainable for long periods of time and ends with the decline of natural resource base. Second, in indigenous territories, where exogenous forces (e.g., reduction of ancestral territory due to colonization) and endogenous factors (e.g., high fertility) create population pressures on the natural resource base, the intensification is produced by decreasing fallow periods in *chacras* (i.e., gardens) across the different ethnic groups.

The household life cycle theoretical approach argues that changes in extent/intensity of agricultural activities are dependent on the household life cycle. Chayanov (Cancian 1989; Chayanov 1966) explored the size and age structure of households and their affect on the proportion of land cultivated. He observed, in the early 20<sup>th</sup> century on isolated farmland in Russia, that older households with a greater number of adults created a higher local labor force, the necessity and means for generating increases in cultivated land. In recent years, studies have extended and adapt Chayanov's findings to the Brazilian Amazon. Several studies (McCracken et al. 1999; Perz and Walker 2002; Walker and Homma 1996) identify stages of a household life cycle of small farmers in the Brazilian Amazon that are closely linked to the extent of forest, cattle ranching, and annual and perennial crops. In the NEA, the space for future agricultural expansion is extremely limited as the total area is relatively small and geographic accessibility to the region remains a constraining factor to settlement and development. Land scarcity has produced little farm abandonment in the region and a process of farm subdivision is on-going. When young adults marry, they claim a portion of the farm for their own agricultural activities and new households are created that begin using

portions of the farm. Although, these young adults might leave to work temporarily outside the farm, the subdivision remains with relatively active agricultural production.

There are a wide range of economic theories and models that explore relationships between human activities and agriculture at different levels of organization (e.g., households, firms). Microeconomic models, generally, see households as a singular type of firm, where relationships with markets and inputs are simplified in different degrees, almost always, following a profit maximizing assumption. Small open economy models of land use in rural areas assume that (1) all relevant prices are exogenous, which indicates that the actions and behavior of agents of land use change (i.e., farmers and households) do not have an effect on prices, and (2) markets fully determine how farmers value their resources and inputs (Kaimowitz and Angelsen 1998). Labor markets have a significant effect on the farm's economy, labor markets also impacts the demographic-economic models, such as neo-Chayonovian and neo-Malthusian, because households are not only dependent on household demographic characteristics and land constraints, but they can opt to hire and work outside of the farm. Specifically for the NEA, the relevance of these models is that they support the quantification of the effects produced by exogenous factors, such as the demand for off-farm employment produced by the oil industry and in other agricultural farms, current markets decline and prices of agricultural products, and at the same time, consider some fixed characteristics of the population.

The role of poverty in rural areas is important to explain small-holding LULC change, but this relationship is complex and non-linear. It can be viewed from different contrasting perspectives: first, rural populations are often impoverished by a declining resource base, and as a consequence, they are forced by circumstances to further degrade the environment,

creating a cycle difficult to break. In addition, short-term attention to current needs takes precedence over long-term stewardship of resources (de Sherbinin 2000). The second perspective shows that small farmers with increasing amounts of cultivated land tend to have the capital, access to technology, education, and subsidies necessary to succeed (Marquette 1998; Pichón 1997). The political and economic inequalities in the larger society, where urban systems are incapable of assimilating demographic growth, may compel poor, dispossessed peasants to seek livelihoods on the margins of society in the rainforest (Rudel and Horowitz 1993). At the same time, it creates the need to better understand the role of institutional and household level factors in influencing the observed variation in forest clearing strategies (Pichón 1997).

A theoretical approach that deals with the institutional relationships between state, local communities, individuals, and natural resources is the study of regimes of property rights. A regime of property rights is the structure of rights to natural resources and rules under those rights are exercised (Hanna et al. 1996). The study of property rights is important, because the change of property rights is the preferred alternative by which governments and international organizations improve ecosystems management. Bromley (1992) defines property as the social relationship that defines the property holder with a benefit stream (i.e., natural resource). Open access (i.e., non-owner) resources has been strongly linked to environmental degradation. Individuals tend to exploit natural resources on open access lands without concern for the cost to society, according to what is called the “Tragedy of the Commons” (Hardin 1968). It holds that as long as incentives exist to privatize open access resources, there will be a tendency at the societal level to over-exploit available resources. Hardin assumes that an individual in his or her self-interest will try to

maximize gains despite the negative effects on society. In the Ecuadorian Amazon, the process of agricultural colonization shows the evolution of the perceptions about property rights regimes among colonist, indigenous people, and the state. In the early stages of colonization, the NEA was seen by local authorities, international development agencies, and poor colonists as an open access regime, and, therefore, played a central role in the *reforma agraria* (agrarian reform) and larger development scheme (Barsky 1984). When farmers settle, the colonization processes favor forest clearing to access property rights, specifically, privatization of lands that induces a cycle of excessive land clearing and inadequate soil conservation (Southgate 1990). Only 40-percent of farmers have legal title over their lands (Ruiz 2000), however, despite the absence of land titles, farmer holds an informal private regime or effective possession that consists of the physical delimitation of the property and recognition from neighbors. Rudel (1995) has found that the lack of title does not contribute to deforestation in the central Ecuadorian Amazon. It is also important to note that in the Ecuadorian Amazon, the legal title or *escritura* is central to the access of agricultural or non-agricultural credits. State and private banks grant loans to support agricultural activities (e.g., cattle raising, coffee production) and other non-agricultural activities (e.g., acquisition of small trucks to be used as taxis).

#### **4.3.2 Spatial Dependence and Spatial Heterogeneity in the Drivers of Land Use**

Land use patterns generally exhibit spatial autocorrelation that is generated by the distribution of landscape features and gradients of environmental conditions (Verburg et al. 2006). Much of the analysis of the drivers of land change use statistical multivariate techniques to estimate the significance and magnitude of the relationships (Kaimowitz and Angelsen 1998). The problem with using conventional statistical methods, like regression, in

spatial land use analysis is that these methods assume that the data are statistically independent, when in reality the variables are space-dependent (Overmars et al. 2003). The justification to include spatial dependence in statistical models emerges from theory-driven specifications (i.e., there are diffusion networks, neighborhood or other spatial processes in the phenomenon studied) or from data-driven specifications, when the information collected is dependent on location (Anselin 2002).

Multivariate statistical models thus assume spatial stationarity that represents situations where the nature of the relationships is fixed over space (Brunsdon et al. 1998). Social and ecological processes, in general, appear to be non-stationary: the relationship depends in part on *where* it occurs (Fotheringham et al. 2002; Pickett and Cadenasso 1995). If non-stationarity is evident, global techniques provide an unrealistic or "average" summary that implies that a local modeling approaches may be more appropriate (Foody 2004a). In land use and land cover change analysis, some global statistical approaches, such as multilevel models (Pan and Bilborrow 2005) that represent processes across hierarchical spatial scales, the addition of variables that represent spatial domains, or geo-coding of land change processes to represent spatial regimes (Mertens and Lambin 2000; Nelson et al. 2001), assume an a priori definition of discrete sets (Brunsdon et al. 1998; Fotheringham et al. 2002). This assumption implies that relationships or behaviors are different once the artificial boundaries (e.g., community limits, political boundaries) are crossed.

In statistical modeling, there are several reasons why one might expect measurements of relationships to vary over space (Fotheringham et al. 2002): (a) the social or natural relationships between factors are intrinsically different across space, (b) the estimation of parameters is made using spatially different subsamples of a larger dataset, (c) the model and

the estimated relationships are a misspecifications of reality, in that relevant variables should either be omitted or represented incorrectly. In the Northern Ecuadorian Amazon all of these factors may be of concern. This research hypothesized that, first, processes of land change are non-stationary and the relationships change across space. Within this colonization area, that has a relatively homogenous population (i.e., migrant colonists), local processes can have different intensities and directions, because pre-cooperatives, towns, and localities have different paths of development that are influenced by different process of settlement, as well as social and cultural conditions (Uquillas 1984). Therefore, different farms in different sectors may have different paths of adaptation, as well as opportunities and challenges in the use of their land and resources. Second, it is hypothesized that there are local influences that affect changes on the land and the associated drivers. For example, deforestation in one plot will promote deforestation in the adjacent plots, because previous forest clearing has created easier access to plots close to the edge. Specific to this research is the manner in which the initial sampling was made (i.e., clustered sample farms) that might affect the results of the land change study. A final caveat is that the process of land change is affected by a multiplicity of very dynamic factors, and, as much, this research can only present a partial picture of the land change process in the NEA. The comparison of the GWR and SLM modeling approach indicates processes that are present/missing and the nature of their correlation to location.

#### **4.4. Methodology**

##### **4.4.1 Data**

*Household Survey Data:* This analysis was performed on 316 finca madres, farms colonized by initial settlers of approximately 50-ha in size. This set of farms is a sub-sample

of all farms surveyed in 1990 (i.e., 405 farms) and 1999 (i.e., 715 farms), because geospatial data and Landsat imagery were available. The original sample of farms, collected in 1990, was derived from a two-stage sample design and a 6-percent probability sample of all sectors within the development region. The first stage was the selection of sectors, or “pre-cooperatives,” groups of individual farms. A list of official settlement sectors was compiled from maps of IERAC (Ecuadorian Institute for Agrarian Reform and Colonization). A random sample of 64 sectors was drawn from this list. The second stage of sampling was the selection of individual farms: 5-10 contiguous farms were randomly selected from each sector using a probability proportional to the size of the sector (Bilsborrow 1991 unpublished report; Pichón 1997). The sample farms as viewed from a regional perspective form clusters. This pattern generated the interest in the study of spatial dependence. Beyond the data collection, the settlement process has created pockets of farmers that share similar characteristics of origin and time since settlement and, therefore, similar adaptation processes.

The data collected in the 1990 and 1999 household longitudinal surveys cover many topics, including land use and agriculture, socio-economic and demographic aspects, and technical assistance. The independent variables accordingly consist of a set of socioeconomic, technological, biophysical, and geographical characteristics. Table 4.1 shows the set of selected independent variables used in this study, their definitions, and mean and standard deviation. Additional variables (e.g., household size, number of subdivisions, annual income, distance to rivers, technical assistance, etc.) were assessed and excluded, because of the high correlation with other variables or endogeneity.

Table 4.1. Selected independent variables used in the regression models.

Variable	Definition	1990		1999	
		Mean	SD	Mean	SD
Male	Number of males on the farm, older than 12 years	2.68	(1.71)	5.03	(4.93)
Female	Number of females on the farm, older than 12 years	2.10	(1.47)	3.88	(3.76)
Child	Number of children on the farm, younger than or equal than 12 years old	2.82	(2.35)	4.64	(4.66)
Age	Mean age of the head of households within the farm	44.56	(12.39)	45.20	(10.49)
PriEduc	Any primary education (binary) of the head of household	0.89	(0.31)	0.82	(0.38)
SecEduc	Any secondary education (binary) of the head of household	0.05	(0.23)	0.13	(0.34)
Walk	Walking distance to main road (km)	2.68	(3.36)	1.04	(1.62)
Road	Distance to reference city by the main road (km)	20.85	(14.15)	11.64	(11.96)
Access	Car access to the farm (binary)	0.50	(0.50)	0.55	(0.50)
SecRoad	Distance to the main road by secondary road (km)	2.11	(4.08)	6.47	(7.77)
Soil	Black soil on the farm (binary)	0.65	(0.48)	0.56	(0.50)
Fertility	Farmer reports soil fertility decrease in the farm (binary)	0.86	(0.35)	0.79	(0.41)
Flat	Flat land on the farm (binary)	0.42	(0.49)	0.48	(0.50)
Wetland	Wetlands on the farm (binary)			0.58	(0.49)
Hlabor	Hired labor on the farm in the last year (binary)	0.54	(0.49)	0.61	(0.48)
Ofe	Off farm employment on the farm in the last year (binary)	0.34	(0.48)	0.68	(0.46)
Title	At least some of the farm under legal title (binary)	0.33	(0.46)	0.37	(0.48)

**Remotely Sensed Data:** The proportion of land use and land cleared or in various uses on farms, used as an independent variable, were obtained using remotely-sensed data. This analysis uses a hybrid supervised-unsupervised classification of Landsat TM images for 1986, 1996, and 2002, with a resolution of 30 meters. As described by Walsh et al. (2002), the classification approach was designed to be repeatable across images in the assembled time-series. It uses image characteristics assessed through fieldwork, Global Positioning System (GPS) data collection, air photography interpretation, and statistical methods. The hybrid approach begins with a supervised classification using the ISODATA classifier to

define approximately 500 “naturally” occurring spectral classes. Using output statistics such as the transformed divergence and divergence statistics, the 500 spectral classes are reduced by approximately 50-percent. A supervised classification is applied using a maximum likelihood classifier to relate unclassified pixels to the 250 classes (i.e., the training data) defined through the unsupervised classification approach (Messina and Walsh 2001). This approach relies upon a hierarchical classification scheme to characterize the LULC types in the study area. The resulting classifications are based on a central LULC scheme that includes 16 land cover types that were grouped depending on relative categories of "economic activity" and deforestation (Table 4.2). Farm boundaries were constructed using field data from GPS surveys, official IERAC (Ecuadorian Institute of Agrarian Reform and Colonization) maps, and topographic maps that were used to clip the classified imagery.

Table 4.2. Central and Grouped Classification Schemes.

	CENTRAL SCHEME	GROUPED SCHEME
1	Primary Forest	Forest
2	Swamp	
3	Secondary Forest	Succession
4	Rastrojo	
5	Pasture No Trees	Pasture
6	Pasture Few Trees	
7	Pasture Many Trees	
8	Coffee	Mostly Cash Crops or small scale agriculture
9	Cacao	
12	Banana	
13	Corn	
10	Palmito	
11	African Palm	Alternative crops and industrialized agriculture or large scale agriculture
14	Barren	Barren/Urban
15	Urban	
16	Water	Water
17	Unclassified	Unclassified

#### 4.4.2 Methods

The methodology followed in this study includes the following phases: (a) an analysis of the local indicators of spatial dependence, (b) generation of an Ordinary Least Square (OLS) regression model and assessment of spatial dependence, (c) generation of Spatial Lag Models (SLM) and analysis of the magnitude, direction, and significance of relationships, and (d) a generation of Geographically Weighted Regression model (GWR) that includes a Monte Carlo test for the significance of spatial non-stationarity.

Spatial dependence is the extent to which the value of an attribute in one location depends on the values of the attribute in nearby locations (Anselin 1988; Fotheringham et al. 2002; Moran 1948). This analysis includes a global (or regional) Moran's I test (test for clustering) and a local Moran's I (test for clusters) (Anselin et al. 2006) that are available in GeoDa<sup>15</sup>. The local indicators of spatial autocorrelation are well situated for identifying the existence of hotspots or local spatial clusters and assessing assumptions of spatial stationarity (Longley and Tobon 2004). Results of the global and local Moran's I are displayed graphically. In the case of global Moran's I, the standardized variable (on the x axis) is regressed against its spatially-lagged version (y-axis). The spatially-lagged variable is obtained by multiplying the value of each neighboring location by the spatial weight and the products summed. The slope of the regression is the global Moran's I values. Every sample farm, within a 5-km area, was considered as a neighbor of the “target” farm, and, therefore, the definition of neighborhood captured all farms from the corresponding cooperative or sector. The exploration of local spatial correlation or clusters within the region is computed

---

<sup>15</sup> GeoDa 0.9.5-I is a software package (<https://www.geoda.uiuc.edu/>) developed by the Spatial Analysis Lab at the University of Illinois and led by Dr. Luc Anselin. GeoDa will be also used to explore the spatial dependency of OLS models and to create the spatial lag regression models.

using local Moran's I values and represented in maps of direction of the spatial autocorrelation and statistical significance, based on a permutation test (Anselin et al. 2006).

Three regression model types, OLS, SLM, WGR, are used to explain LULC change between 1986-1996 and 1996-2002 for the entire colonization area (Figure 4.1). The dependent variables in the regressions are the proportion of land change, at the farm level, specifically: deforestation (proportion of forest cleared), proportion of pasture, proportion small scale agriculture, and proportion large scale agriculture, generated in both periods (1986-1996 and 1996-2002). The set of independent variables, described in Table 4.1, originate from the household surveys carried out in 1990 and 1999. The intention was to build models in which the independent variables were collected approximately in the middle of each time period.

The objective of the OLS models is to serve as a baseline for the assessment of the models. If the OLS model is biased due to spatial dependence, it will be corrected using a spatial parameter within the spatial lag models. Thus the general form of the linear multiple (OLS) regression model is:

$$y = X\beta + \varepsilon$$

where,  $X$  is a matrix of predictor variables,  $\beta$  is a vector of regression coefficients,  $y$  is the vector of response variables and  $\varepsilon$  is a vector of independent random errors.

OLS model diagnostics are used to assess the assumptions of normality of errors (Jarque-Bera test), heteroskedasticity (Breusch-Pagan test and Koenker-Bassett test), and multicollinearity (condition number). Spatial dependence within the OLS regression model is assessed using Moran's I, the Lagrange Multiplier, and the Robust Lagrange Multiplier test (Anselin 1988; Anselin 2002; Anselin et al. 2006) that will indicates the type of dependence.

Spatial lag models will be used to obtain the magnitude and significance of the relationships between land change and the drivers of deforestation. SLM are global regressions that generalize the relationships across the region, but take into consideration the spatial dependency of the relationships. SLM uses a weighted neighbor matrix  $W$  that characterizes neighbors and their relative weights. The definition of neighbors, therefore, changes the degree of spatial autocorrelation. The spatial lag model is defined as (Anselin 1988; Anselin 2002):

$$y = \rho Wy + X\beta + \varepsilon$$

where  $y$  is the dependent variable,  $\rho$  is the autoregressive parameter,  $Wy$  is the spatially lagged dependent variable,  $X$  the set of independent variables,  $\beta$  the vector of their coefficients, and  $\varepsilon$  the vector of random error terms. The estimation of coefficients is by maximum likelihood (Anselin and Bera 1998). The SLM provides a solution to the problem of parameterization of a model taking into consideration the neighborhood effects or the spatial interactions among agents. Spatial regressions have been widely applied in spatial econometrics models (Florax and Van der Vlist 2003) and more recently in landscape ecology (Gustafson et al. 2005), land cover change (Mena et al. 2006b), and medical geography (Mobley et al. 2006).

The last phase of the methodology is the use of GWR models to capture the spatial heterogeneity of the relationships. This technique has been found useful in detecting spatial trends in relationships that may be missed in a typical global regression analysis (Foody 2004a). GWR generate spatially explicit regression coefficients and standard errors that make possible the mapping of the direction of the relationships and their statistical significance. Geographically Weighted Regression can be expressed as (Brunsdon et al. 1998;

Fotheringham et al. 2002; Fotheringham and Wegener 2000):

$$y_i = \beta_o(u_i, v_i) + \sum_k \beta_K(u_i, v_i) x_{ik} + \varepsilon_i$$

where  $y_i$  is the observation of the dependent variable at the location  $i$ ,  $(u_i, v_i)$  represents the coordinates of the  $i$  in space, and  $\beta_k(u_i, v_i)$  is the realization of the continuous function  $\beta_k(u, v)$  at point  $i$ .

The basic assumption of this model is that locations nearer to  $i$  will have more influence on the estimation of the parameter  $\beta_k(u_i, v_i)$  than those farther from  $i$ . Under this assumption, a continuous surface of parameter values is estimated. The geographical weighting is accomplished using an adaptive Gaussian kernel or moving window that defines the geographical weights ( $w_{ij}$ ) using:  $w_{ij} = (1 - (d_{ij}/b)^2)^2$ , where  $d_{ij}$  is the distance between  $i$  and  $j$  and  $b$  is the bandwidth (Figure 4.2). In practice, the selection of the kernel type is not as important as the selection of the bandwidth. The bandwidth, which increases where data points are sparser (Figure 4.2), is defined following a procedure that finds the minimum Akaike Information Criterion (AIC) (Fotheringham et al. 2002). The minimization of AICs provides optimal values for the trade-off between goodness-of-fit and degrees of freedom. Within GWR, dividing the local estimates by their corresponding standard errors allows the mapping of pseudo t-statistics that are necessary to estimate the significance of the independent variables. GWR has been applied in the social sciences (Calvo and Escobar 2003; Longley and Tobon 2004; Yu 2006) and the natural sciences (Atkinson et al. 2003; Foody 2003; Foody 2004b; Wang et al. 2005) to explore the spatial heterogeneity of relationships.

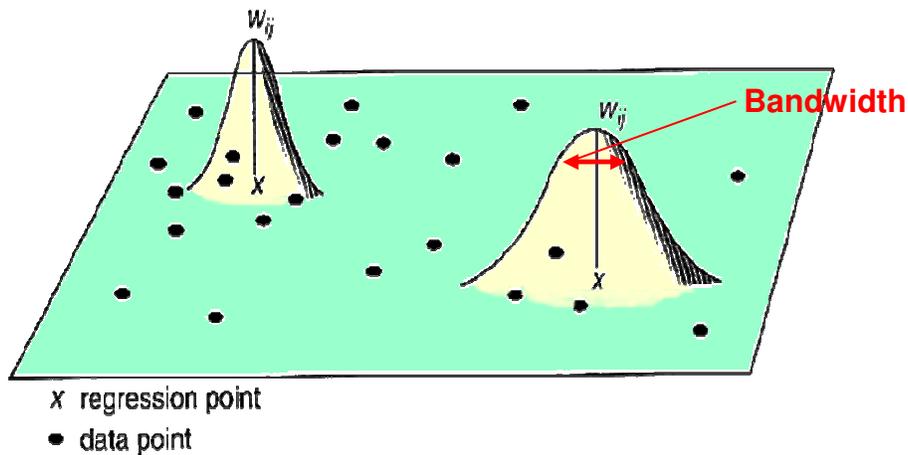


Figure 4.2. Two adaptive moving weighting kernel.

#### 4.5. Results

This section reviews, first, the results of the exploratory spatial analysis, followed by the diagnostic test of the OLS regression model. The results of the global regression model (spatial lag) are then presented, and finally the results of the GWR model are shown. Figure 4.3 and Figure 4.4 show the global Moran's I for selected variables for the 1990 and 1999 models respectively. Both figures show measures of clustering for the dependent variables (i.e., deforestation, pasture, small- and large-scale agriculture) and for the four independent variables that had the highest spatial autocorrelation (i.e., soil, flat, road, and walk). The upper-right quadrant and lower left quadrant in the graphs indicate positive spatial autocorrelation or association of high values surrounded by high values (high-high) or low-low values, respectively. Upper-left and lower-right quadrants indicate negative spatial autocorrelation or high-low and low-high values, respectively. Values range from 0 (no spatial autocorrelation) to 1 (full spatial autocorrelation). Figure 4.3 shows that for the proportion of change between 1986 and 1996 for forest, pasture, small and large agriculture

have relatively low positive spatial autocorrelation. The highest value is in small scale agriculture (Moran's  $I=0.4$ ) followed by deforestation (Moran's  $I=0.27$ ). The values for the selected independent variables are much higher, geographically accessibility measures (road and walk) over 0.93 and terrain characteristics over 0.41.

Figure 4.4 shows measures of global spatial autocorrelation for land change between 1996 and 2002 and terrain and geographic accessibility characteristics for 2001. In general, spatial autocorrelation values are similar to those in the earlier period. Noticeable differences include the decrease in positive spatial autocorrelation for small scale agriculture that suggests the spread of small agriculture plots (not necessarily extensification) and also improvements in accessibility characteristics, the latter of which might be triggered by better connectivity for farms.

The representation of local spatial autocorrelation within regions is illustrated using (uni- or bi-variate) maps. Unfortunately, the modeling presented here contains 13 independent variables and four dependent variable for each period, therefore, making a challenge to include all the maps for individual local Moran's  $I$  values in this chapter. As result, all the maps were visually examined to find clusters and outliers, and two examples were chosen and presented in Figure 4.5 and Figure 4.6. Figure 4.5 is the analysis of the proportion of deforestation between 1986 and 1996, and Figure 4.6 represents local spatial autocorrelation for the variable walking distance to main road (*walk*). For deforestation (in the period 1986-1996), the global or regional Moran's  $I$  indicates a relatively low global spatial autocorrelation, whereas Figure 4.5 indicates the presence of clusters dispersed across the region. *Walk* on the other hand, had very high values of global spatial autocorrelation and Figure 4.6 indicates that there are very well defined clusters with the exception of farms

located closed to the main two cities, Lago Agrio and Coca, which are not significant. Despite the fact that the initial sampling frame created different sets of clusters of sample farms (within pre-cooperatives of settlement), not all of the sampled farms share similar patterns of deforestation or accessibility characteristics, even if they belong to the same sample clusters.

The results of the OLS regression model for land change (1986-1996) and (1996-2002) are shown in Table 4.3 and Table 4.4, respectively. Both tables contain four models, where the dependent variables are the proportions of the change in forest cover (deforestation), pasture, small scale agriculture, and large scale agriculture within the respective period. Although there are statistically significant variables in all the models, the focus of this portion of the analysis is the diagnostic test of the models. One of the more important tests is for normality of the errors. The Jarque-Berta test is not significant for six models indicating a normal distribution of errors. The exceptions are the small-scale agriculture (1986-1996) and large-scale agriculture in (1996-2002), models that were later modified using transformations to correct the non-normality. The large scale agriculture model was corrected after a square-root transformation<sup>16</sup>. The normality assumption is important, because diagnostics of spatial dependence and heteroskedasticity depend on this assumption, and models with non-normal errors should be viewed with caution (Anselin 2002; Longley and Tobon 2004). The condition number, although not a test for collinearity, helps to identify problems related to the high degree of correlation between variables in a regression (Anselin 1990). Regressions with a condition number higher than 30 are

---

<sup>16</sup> The other dependent variables were normally distributed and did not show improvement when using transformations.

considered to contain collinearity problems (Anselin 2005). The OLS equations in Tables 4.3 and 4.4 have condition numbers approximately 20 and 21, respectively, that indicate the absence of serious problems with collinearity. Some degree of collinearity is expected, because many of the processes considered and measured by the household survey, specially in frontier environments, are related. For example, isolation (or distance to city) is indirectly related to labor, farms closer to cities have easier access to non-agricultural jobs located in towns. The Breusch-Pagan tests for heteroskedasticity, used when the errors are normally distributed, are not significant in all the OLS models. The Koenker-Bassett test for heteroskedasticity when non-normality is suspected is significant for the small scale agriculture (1986-1996) model. Some degree of heteroskedasticity is the product of spatial dependence.

Moran's I, the Lagrange Multiplier (LM), and the Robust LM show that the models are statistically significant, and spatial dependence exist across the models. Within GeoDa, Lagrange Multiplier (LM) and Robust LM were applied in each regression model to investigate the spatial dependence in the lagged variable and in the residuals. Robust LM (Lag) was always more significant than LM (Error) (not shown here), and, therefore, spatial lag models were constructed (Anselin 2005). This suggests that the spatial dependence, created by the relationships among farms (within a 5-Km distance neighborhood) is stronger than the spatial dependence created by the error in the data. The only model that is not spatially correlated is large-scale agriculture (1996-2002) after being subject to a square-root transformation to normalize the errors. This indicates that this particular OLS model offers a good specification and spatial regression is not necessary.

Table 4.3. OLS Regression Results -- Land Change (1986-1996).

OLS Regression Results -- Land Change (1986-1996)												
Variable	Deforestation			Pasture		Small Scale Ag.			Large Scale Ag.			
	Coefficient	Std.Error		Coefficient	Std.Error	Coefficient	Std.Error		Coefficient	Std.Error		
Constant	33.8848	(4.4089)	***	11.9987	(2.1824)	***	4.3231	(0.8214)	***	6.3278	(1.7408)	
Age	-0.1777	(0.0603)	***	-0.1112	(0.0299)	***	0.0013	(0.0112)		0.0001	(0.0234)	
Child	-0.2996	(0.3359)		-0.5224	(0.1663)	***	0.1285	(0.0626)	**	0.0785	(0.1306)	
Fertility	-1.1602	(2.2051)		-2.0111	(1.0915)	*	0.0649	(0.4108)		0.2469	(0.8487)	
Prieduc	0.3380	(2.2301)		0.1780	(1.1039)		0.2552	(0.4155)		0.1866	(0.8690)	
Flat	4.1707	(1.5339)	***	0.5524	(0.7593)		1.2320	(0.2858)	***			
Soil										1.0390	(0.6204)	*
Male	1.1343	(0.4840)	**	0.7336	(0.2396)	***	0.0570	(0.0902)		0.0172	(0.1840)	
Female										-0.1208	(0.0839)	
Walk	-0.7526	(0.2154)	***	-0.4092	(0.1066)	***	-0.1729	(0.0401)	***	0.0005	(0.0210)	
Road	-0.1485	(0.0515)	***	-0.0259	(0.0255)		-0.0371	(0.0096)	***	0.7165	(0.5699)	
Ofe	1.7087	(1.4646)		1.9688	(0.7250)	***	-0.1944	(0.2729)		-0.0420	(0.0379)	
Hlabor	1.9528	(1.4030)		1.0252	(0.6945)		0.0887	(0.2614)		-0.3502	(0.5843)	
Tenure	1.8038	(1.5093)		0.5328	(0.7471)		-0.0320	(0.2812)		6.3278	(1.7408)	
Akaike info criterion		2365.7400			1941.0100			1350.8100			1781.0000	
Condition Number		20.3000			20.3000			20.3000			20.4500	
Jarque-Bera		1.6817			0.2032			8.9322	*		2.8200	
Breusch-Pagan test		18.3008			12.8077			26.0981	*		19.4261	*
Koenker-Bassett test		22.1255	**		13.1385			29.0353	*		22.2264	*
Moran's I (error)		0.211707	***		0.1391	***		0.2612	***		0.1276	***
Lagrange Multiplier (lag)		51.6794	***		25.6832	***		66.6465	***		16.0404	***
Robust LM (lag)		23.0797	***		16.8137	***		9.0494	***		5.3514	***

Statistically significant at 1% (\*\*\*), 5%(\*\*), and 10%(\*)

Table 4.4. OLS Regression Results -- Land Change (1996-2002).

OLS Regression Results -- Land Change (1996-2002)												
	Deforestation			Pasture			Small Scale Ag.			Large Scale Ag.		
Variable	Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error	
Constant	9.0593	(3.0232)	***	6.9473	(2.1227)	***	5.4397	(1.2312)	***	1.1060	(0.5847)	**
Male	0.1265	(0.1237)		0.0520	(0.0868)		0.1267	(0.0504)	**	-0.0188	(0.0206)	
Fertility	-1.3861	(1.1795)		-1.0044	(0.8281)		-0.3657	(0.4803)		0.0579	(0.2281)	
Flat	3.3634	(1.0363)	***	2.3451	(0.7276)	***	0.6296	(0.4220)		0.3655	(0.1923)	**
Age	-0.0724	(0.0483)		-0.0329	(0.0339)		-0.0317	(0.0197)		0.0024	(0.0098)	
Walk	-0.3365	(0.2975)		-0.2860	(0.2089)		-0.0265	(0.1211)		-0.0718	(0.0496)	
Child	0.2384	(0.1280)	*	0.0430	(0.0899)		-0.0130	(0.0521)		0.0222	(0.0199)	
Road	0.0119	(0.0392)		-0.0491	(0.0275)	*	-0.0115	(0.0160)		-0.0043	(0.0076)	
Prieduc	1.5469	(1.2424)		-0.4077	(0.8723)		0.1433	(0.5059)		0.3279	(0.2333)	
Ofe	-1.4658	(1.0744)		-0.8936	(0.7543)		-0.7710	(0.4375)	*	-0.0135	(0.2139)	
Tenure	0.2609	(1.0499)		0.7284	(0.7371)		0.2943	(0.4275)		0.4174	(0.2101)	**
Hlabor	2.4701	(1.0114)	**	1.3168	(0.7101)	*	1.0439	(0.4119)	**	0.0431	(0.2047)	
Akaike info criterion	2069.68			1861.0300			1539.6400			305.6500		
Condition Number	21.8910			21.8910			21.8910					
Jarque-Bera	1.2788			1.9449			4.4206			0.9410		
Breusch-Pagan test	6.6720			9.4624			11.7893			17.2680 *		
Koenker-Bassett test	5.8111			9.2587			13.7960			19.4854 *		
Moran's I (error)	0.0597 ***			0.1171 ***			0.0870 ***			0.0220		
Lagrange Multiplier (lag)	8.0860 ***			17.4292 ***			8.4259 ***			0.5468		
Robust LM (lag)	12.8851 ***			12.8792 ***			3.8514 ***			0.9985		

Statistically significant at 1% (\*\*\*), 5%(\*\*), and 10%(\*)

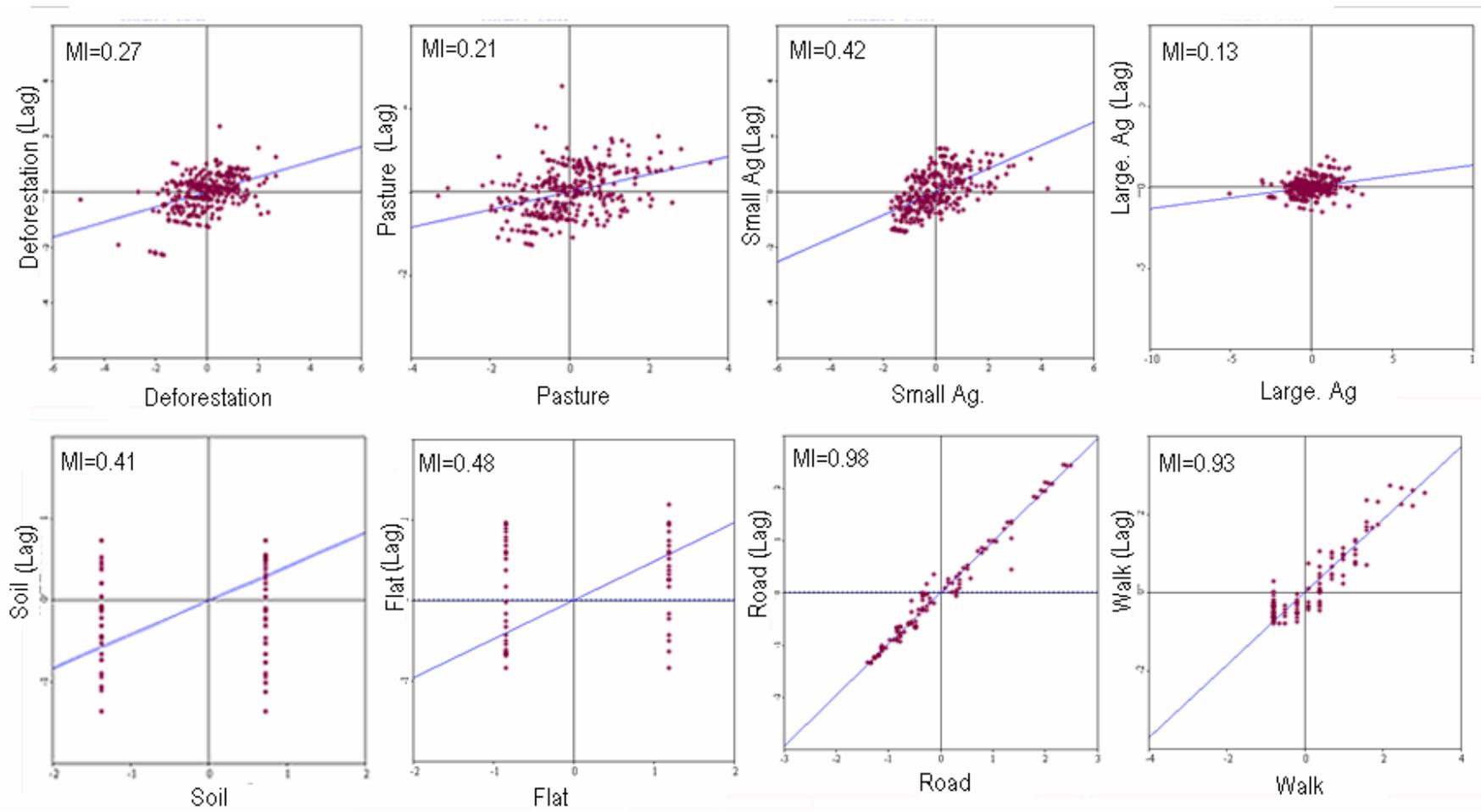


Figure 4.3. Moran's I Index for selected variables for 1990.

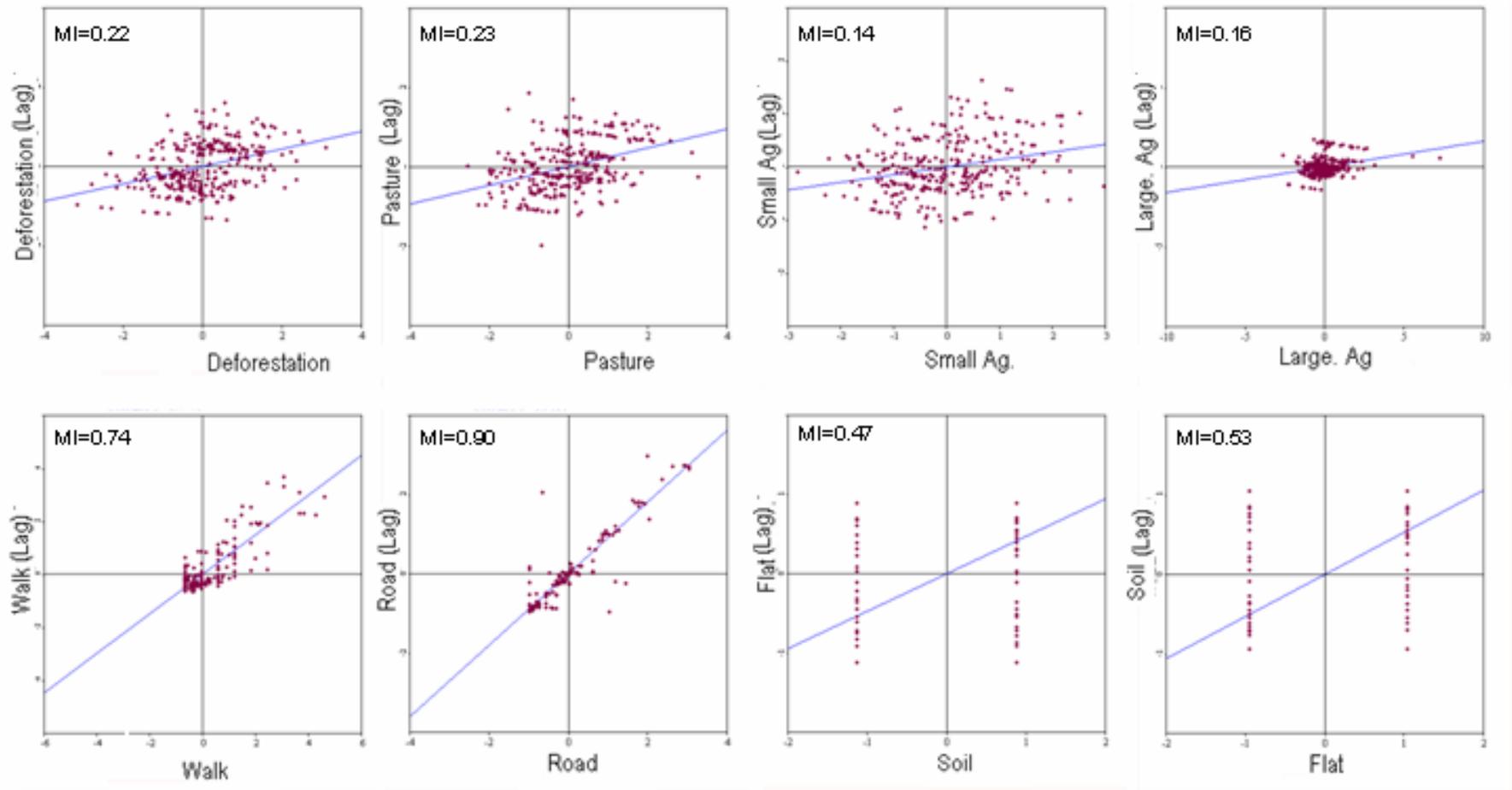


Figure 4.4. Moran's I Index for selected variables for 1999.

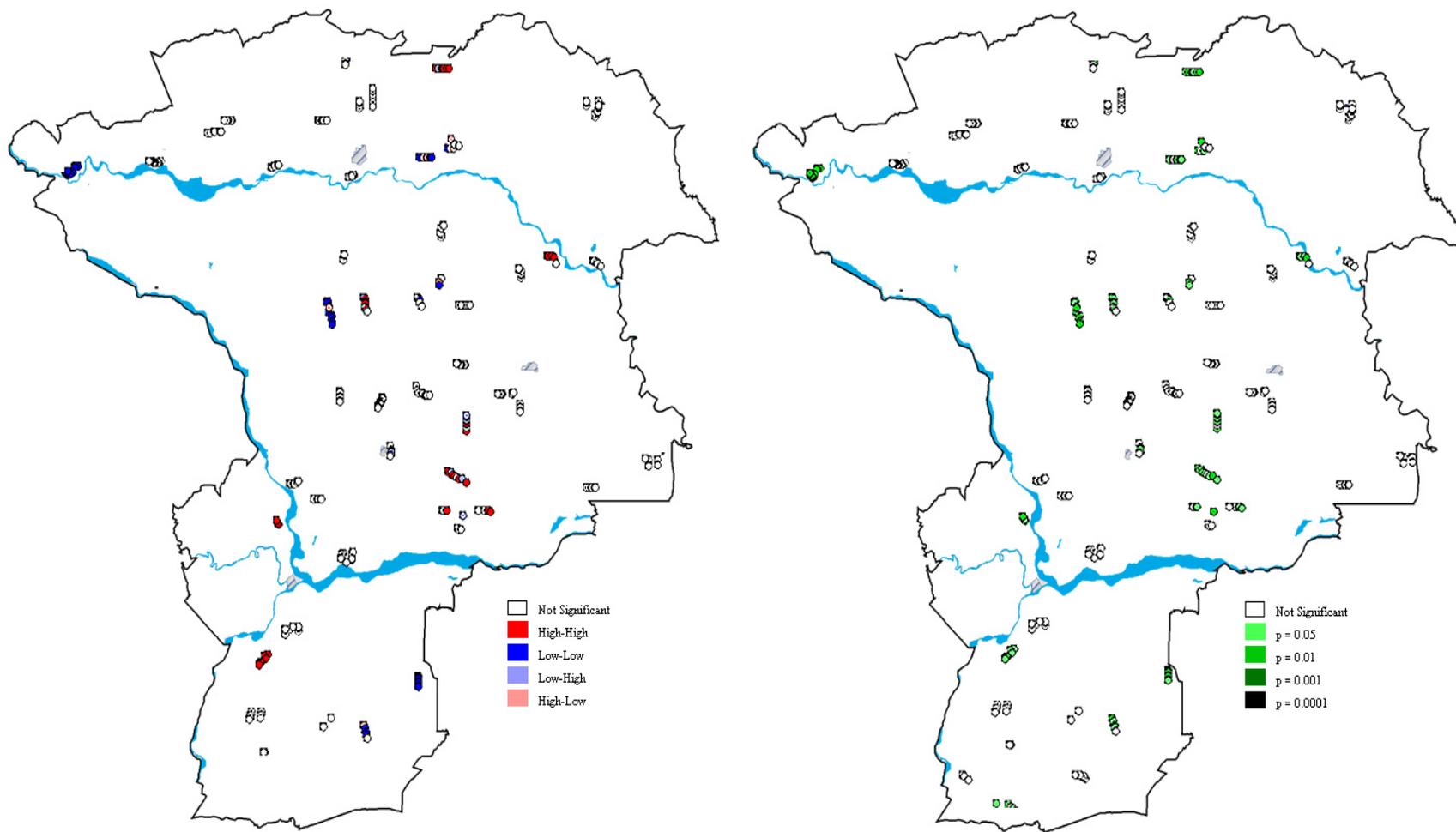


Figure 4.5. Local indicators of spatial autocorrelation for the variable *deforestation* in the period 1986-1996.

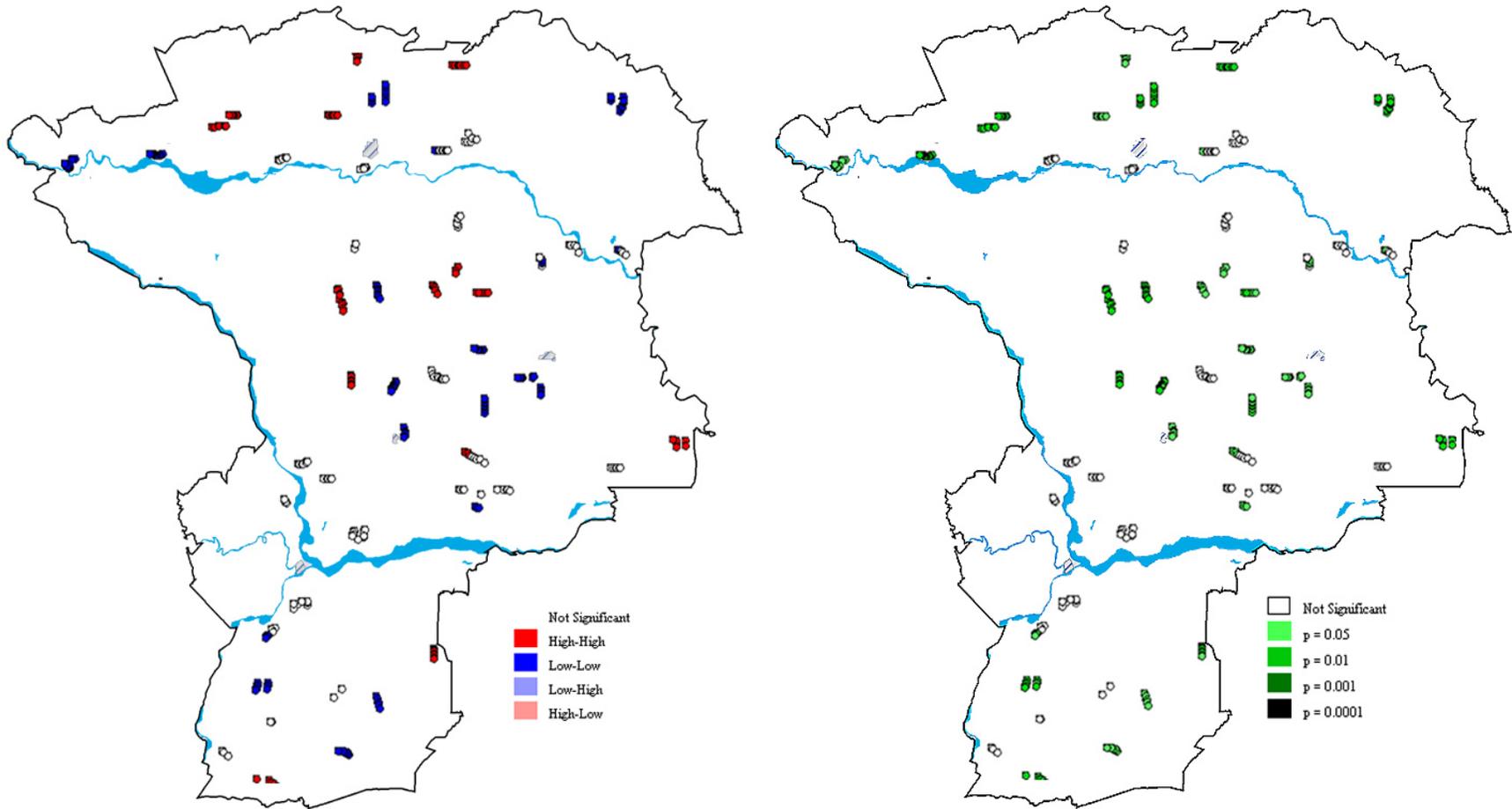


Figure 4.6. Local indicator of spatial autocorrelation for the variable WALK (walking distance to the main road) in 1990.

Table 4.5 and Table 4.6 show the results of the spatial regression models for land change in 1986-1996 and 1996-2002 respectively. For deforestation in the first period (Table 4.5), age of the head of household (*age*), walking distance to the road (*walk*), and distance by road to the reference city (*road*) are negatively related to deforestation. Older households and more distant households tend to deforest less over time since most is done in the early years. For the same period, number of male adults (*male*) and flat topography on the farm (*flat*) are statistically significant and positively related to deforestation. Farms with better land and with more working adults contribute to deforestation. For deforestation in the second period (Table 4.6), the variables *age* and *flat* are still statistically significant and negatively related to deforestation. However accessibility and number of males is not significant. Additionally, hired labor (*hlabor*) is significant and positively related to deforestation in the second period. Farms with older heads of households that hired agricultural labor and possessed flat land deforested more in the period 1996-2002.

For pasture in the first period, the variable *age*, number of children on the farm (*children*), farms that reported a decrease in the soil fertility (*fertility*), and *walk* are negatively related to the change in proportion of area in pasture. Number of males (*male*) and off farm employment (*ofe*) are significant and positively related to proportion of pasture. In the second period, hired labor (*hlabor*) and flat topography (*flat*) are the only variables significant and positively related to pasture. For the first period, demographic and accessibility variables are important controls on pasture, but hired labor becomes more important in the second studied period.

Small-scale agriculture in the first period is positively associated and statistically significant to the number of children on the farm (*children*) and flat land (*flat*) and

negatively related to the accessibility variables (*road* and *walk*) that are also statistically significant. Small scale agriculture for the second period is positively related to hired labor and male adults and negatively related to off-farm employment. While in the earlier period of colonization, there is a signal of the Chayonovian perspective on land use, in the second period, when accessibility becomes more homogenous, access to labor markets is more important and promotes a decrease in small scale agriculture.

In the case of large scale agriculture for the period (1986-1996), the OLS model shows that black soil on the farm (*soil*) is positively related and statistically significant (Table 4.3). This OLS regression reports very strong spatial dependence, but when the lagged variable was introduced, *soil* is not statistically significant, thus this spatial lag model is not relevant. In the second period, the spatial dependence tests for the model of the large scale agriculture (1996-2002) show that there is no significant spatial dependence and, therefore, a SML is not needed. The OLS results indicate that *flat* land and land tenure are positively related to the increase in area in large scale agriculture and statistically significant.

Table 4.5. Spatial Lag Model Results -- Land Change (1986-1996).

Spatial Lag Model Results -- Land Change (1986-1996)									
	Deforestation			Pasture			Small Scale Ag.		
	Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error	
$\rho$	0.4176	(0.0615)	***	0.3201	(0.0691)	***	0.4617	(0.0568)	***
Constant	21.3822	(4.5080)	***	8.9276	(2.1362)	***	2.1716	(0.8002)	***
Age	-0.1460	(0.0546)	***	-0.0962	(0.0281)	***	0.0005	(0.0099)	
Child	-0.1727	(0.3042)		-0.4604	(0.1563)	***	0.1416	(0.0553)	**
Fertility	-1.5613	(1.9969)		-1.7931	(1.0266)	*	-0.0931	(0.3633)	
Prieduc	0.3417	(2.0189)		0.4695	(1.0374)		0.1851	(0.3674)	
Flat	2.3251	(1.3928)	*	0.1681	(0.7137)		0.7477	(0.2552)	***
Male	0.9082	(0.4382)	**	0.6686	(0.2251)	***	0.0339	(0.0797)	
Walk	-0.4837	(0.2001)	**	-0.2942	(0.1032)	***	-0.0970	(0.0370)	***
Road	-0.0920	(0.0479)	*	-0.0219	(0.0240)		-0.0198	(0.0089)	**
Ofe	1.7992	(1.3260)		1.8460	(0.6814)	***	0.0286	(0.2414)	
Hlabor	1.8167	(1.2700)		1.0209	(0.6526)		0.1416	(0.2312)	
Tenure	0.8668	(1.3663)		0.2063	(0.7020)		-0.2936	(0.2487)	
Akaike info-criterion	2331.9100			1924.2400			1306.0000		

Statistically significant at 1% (\*\*\*), 5%(\*\*), and 10%(\*)

Table 4.6 Spatial Lag Model Results -- Land Change (1996-2002).

Spatial Lag Model Results -- Land Change (1996-2002)									
	Deforestation			Pasture			Small Scale Ag.		
	Coefficient	Std.Error		Coefficient	Std.Error		Coefficient	Std.Error	
$\rho$	0.2176	(0.0762)	***	0.2942	(0.0720)	***	0.2199	(0.0776)	***
Constant	7.7721	(2.9741)	***	5.8245	(2.0440)	***	4.5296	(1.2318)	***
Male	0.0994	(0.1191)		0.0486	(0.0823)		0.1128	(0.0485)	**
Fertility	-1.1427	(1.1371)		-0.8610	(0.7851)		-0.3790	(0.4627)	
Flat	2.6327	(1.0177)	***	1.5556	(0.6980)	**	0.4829	(0.4095)	
Age	-0.0804	(0.0465)	*	-0.0422	(0.0321)		-0.0324	(0.0189)	
Walk	-0.2665	(0.2877)		-0.1966	(0.1991)		-0.0063	(0.1167)	
Child	0.1968	(0.1235)		0.0150	(0.0852)		-0.0128	(0.0502)	
Road	0.0093	(0.0377)		-0.0383	(0.0263)		-0.0095	(0.0154)	
Priedu	1.6031	(1.1965)		-0.3233	(0.8266)		0.1663	(0.4872)	
Ofe	-1.2188	(1.0354)		-0.7052	(0.7149)		-0.7446	(0.4216)	*
Tenure	-0.0207	(1.0113)		0.6431	(0.6988)		0.2989	(0.4117)	
Hlabor	2.2398	(0.9745)	**	1.2144	(0.6732)	*	0.9757	(0.3968)	**
Akaike info-criterion	2064.5600			1848.9700			1539.4900		

Statistically significant at 1% (\*\*\*), 5%(\*\*), and 10%(\*)

Finally, the results of the GWR models are presented. The GWR's power resides in the presentation of results in a spatially explicit way. This approach, however, makes it somewhat impractical to present each variable map of the four models, taking into consideration that each variable has a map of the parameter and a map of t-test values. GWR results for significant variables in the SLM and other relevant independent variables are presented in Figures 4.7 to 4.12. Deforestation (1986-1996) and deforestation (1996-2002) are presented in Figures 4.7 and 4.8, respectively. Pasture in (1986-1996) and (1996-2002) is presented in Figure 4.9 and Figure 4.10, respectively. Small scale agriculture for (1986-1996) and (1996-2002) are displayed in Figure 4.11 and Figure 4.12, respectively. Consistent with postmodern approaches that emphasize local context, the main objective of GWR is to detect local patterns. The results emphasize the strong variation of coefficients and the statistical significance across space within the NEA. This suggests that the region does not have homogenous processes of land change across space, and land change is non-stationary. There are some spatial patterns that can be explored at the region level. First, in some cases, the influence on the core versus periphery of the effects on the main towns are evident (e.g., the parameter for *male* in the 1986-1996 deforestation model or *walk* and *road* in the 1986-1996 small scale agriculture model), while in other cases, there are differences between the north and south, that have different biotic characteristics (e.g., hired labor is always statistically significant in the north portion of the study area).

The results of a more formal statistical test, a Monte Carlo test of significance for spatial variation, are presented in Tables 4.7 and 4.8. Variables that are not significant indicate a high probability that the variation occurred by chance. Accessibility measures, topographic and soil characteristics, and market labor for specific models have statistically

significant spatial variability. These are strong indicators of spatial non-stationarity and further modeling should pay close attention to issues of spatial heterogeneity in the relationships.

Table 4.7. Results of Monte Carlo test for the spatial variability of parameters in land change models (1986-1996).

Parameter	Deforestation		Pasture		Small Agriculture	
Constant	0.1700	n/s	0.3100	n/s	0.2700	n/s
Age	0.4400	n/s	0.1100	n/s	0.1300	n/s
Child	0.9500	n/s	0.6700	n/s	0.8600	n/s
Fertility	0.2500	n/s	0.1000	n/s	0.6500	n/s
Prieduc	0.7200	n/s	0.7600	n/s	0.4300	n/s
Flat	0.1700	n/s	0.2200	n/s	0.2000	n/s
Male	0.9800	n/s	0.4900	n/s	0.6700	n/s
Walk	0.0000	***	0.0000	***	0.2200	n/s
Road	0.0000	***	0.0000	***	0.0000	***
Ofe	0.1700	n/s	0.6700	n/s	0.0000	***
Hlabor	0.1700	n/s	0.2400	n/s	0.2000	n/s
Tenure	0.2900	n/s	0.6300	n/s	0.0700	n/s

Table 4.8. Results of Monte Carlo test for the spatial variability of parameters in land change models (1986-1996).

Parameter	Deforestation		Pasture		Small Agriculture	
Constant	0.6900	n/s	0.0300	*	0.2200	n/s
Male	0.1500	n/s	0.3300	n/s	0.0300	*
Fertility	0.5600	n/s	0.8400	n/s	0.0100	**
Flat	0.0500	*	0.0700	n/s	0.2700	n/s
Age	0.5000	n/s	0.4700	n/s	0.1700	n/s
Walk	0.5200	n/s	0.1400	n/s	0.8800	n/s
Child	0.8100	n/s	0.6700	n/s	0.3600	n/s
Road	0.2000	n/s	0.0200	*	0.1900	n/s
Priedu	0.1300	n/s	0.0800	n/s	0.6700	n/s
Ofe	0.0900	n/s	0.3400	n/s	0.1300	n/s
Tenure	0.0200	*	0.1700	n/s	0.4400	n/s
Hlabor	0.3300	n/s	0.0500	*	0.1400	n/s

Statistically significant at 1% (\*\*\*)

It is clear from the analysis that the large scale agriculture model for (1986-1996) is not well specified. None of the variables is statistically significant after controlling for spatial

dependence. On the other hand, the large scale agriculture models for 1996-2002 do not have significant spatial dependence, and the Monte Carlo test suggests that the model does not have spatial variation across the study site. Both of these results indicate that more research is needed. The residuals of the GWR for large scale agriculture (1996-2002) in Figure 4.13 indicate that higher errors within the model are produced around the main road that connects Lago Agrio and Coca. It is possible that, for large scale agriculture, this is a problem of accessibility not being captured by the variables (e.g., transportation cost) or that other types of variables that are at work outside the household level (e.g., Market prices of agricultural products) control the changes in the study area.

The Akaike information criterion, measures of the goodness of fit, for the GWR models are as follows: for deforestation, 2343.43 (1986-1996) and 2073.40 (1996-2002); for pasture, 1916.59 (1986-1996) and 1862.80 (1996-2002); and for small scale agriculture, 1345.71 (1986-1996) and 1543.81 (1996-2002). In all cases, SLM provides better results than the GWR models, which indicates that SLM provides a better goodness-of-fit. However, SLM and GWR might be complementary, where GWR provides an exploration of the factors that are dynamic in space or which are not seen can bias the results of SLM.

Finally, Figure 4.14 and Figure 4.15 are 3-dimensional representations of two selected parameters. Elevation is the value of the parameter across space. In Figure 4.14, colors represent parameter values. In the case of Figure 4.15, colors represent t-test values for local regressions. This alternative representation of the parameters is helpful to spatially visualize the results of statistical models.

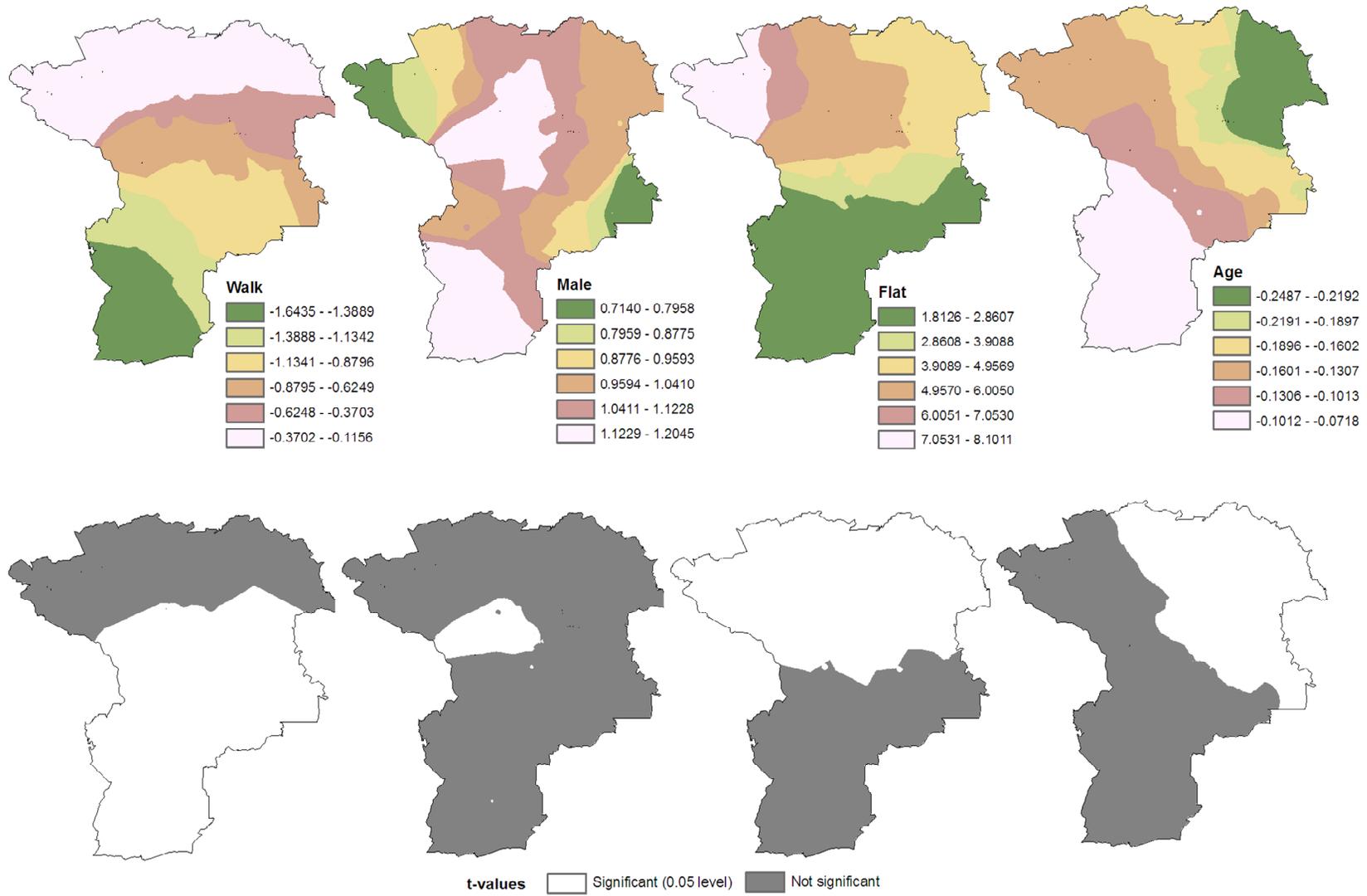


Figure 4.7. GWR results for selected significant variables in the Deforestation (1986-1996) model.

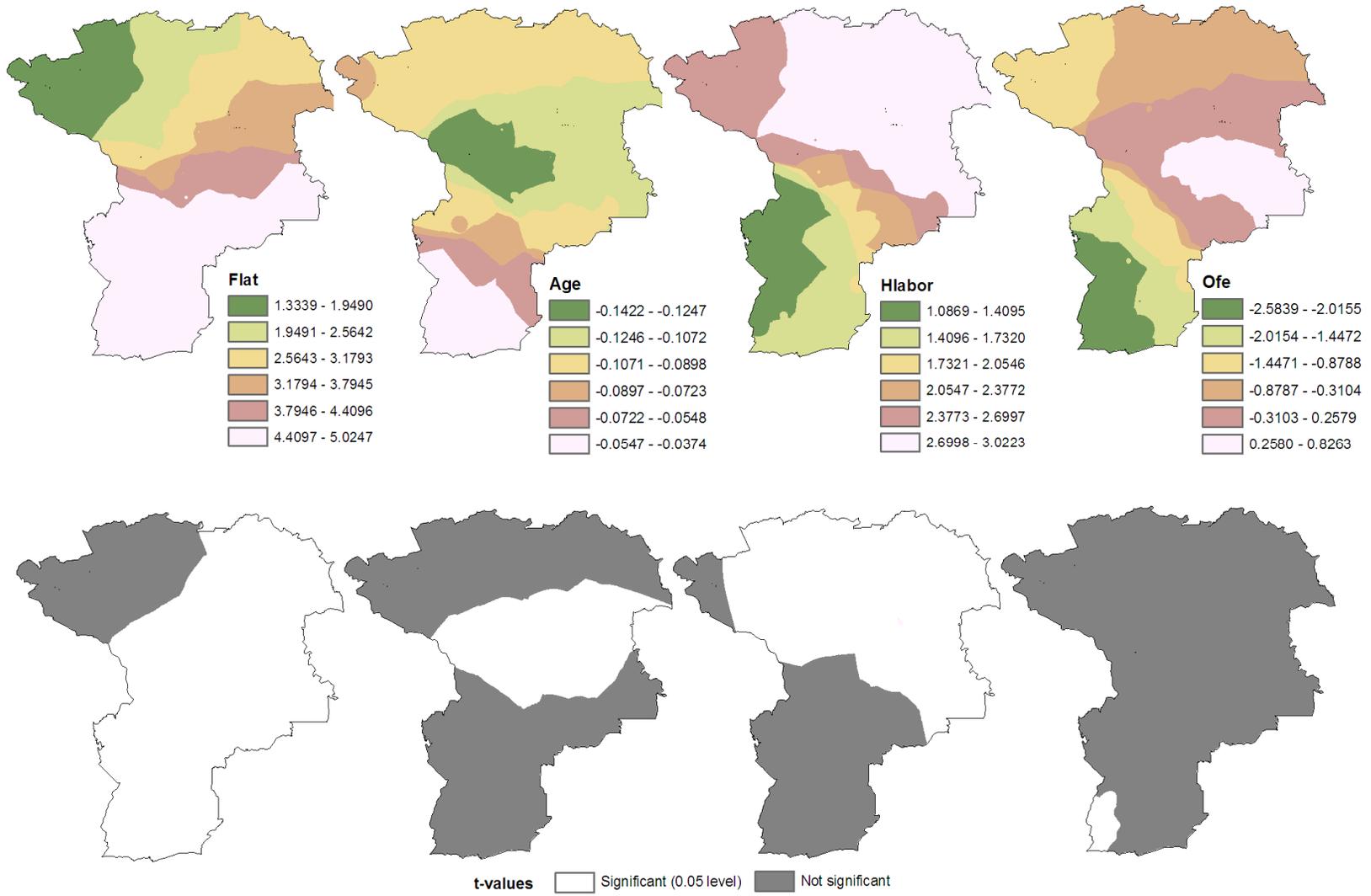


Figure 4.8. GWR results for selected significant variables in the Deforestation (1996-2002) model.

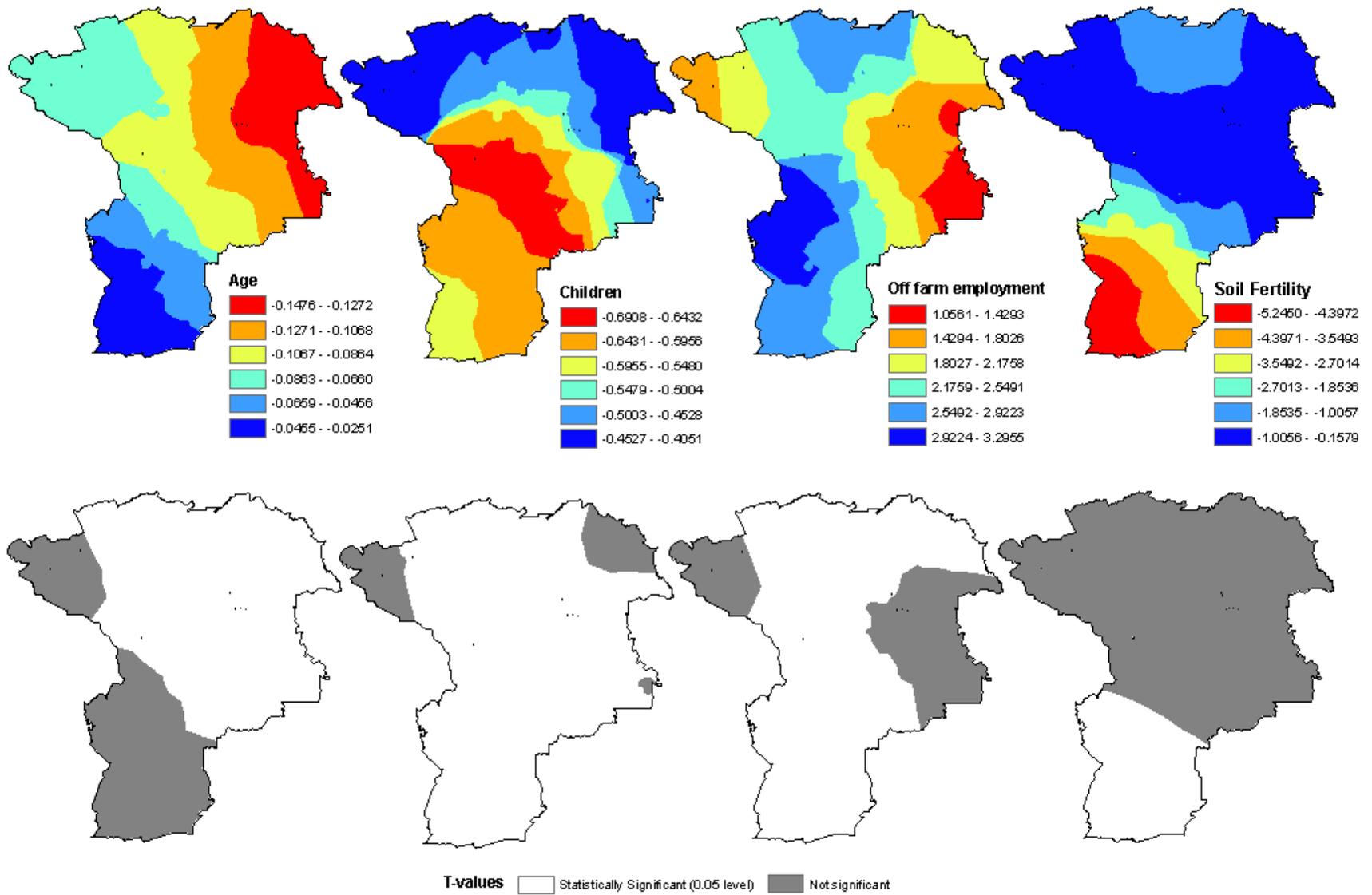


Figure 4.9. GWR results for selected significant variables in the Pasture (1986-1996) model.

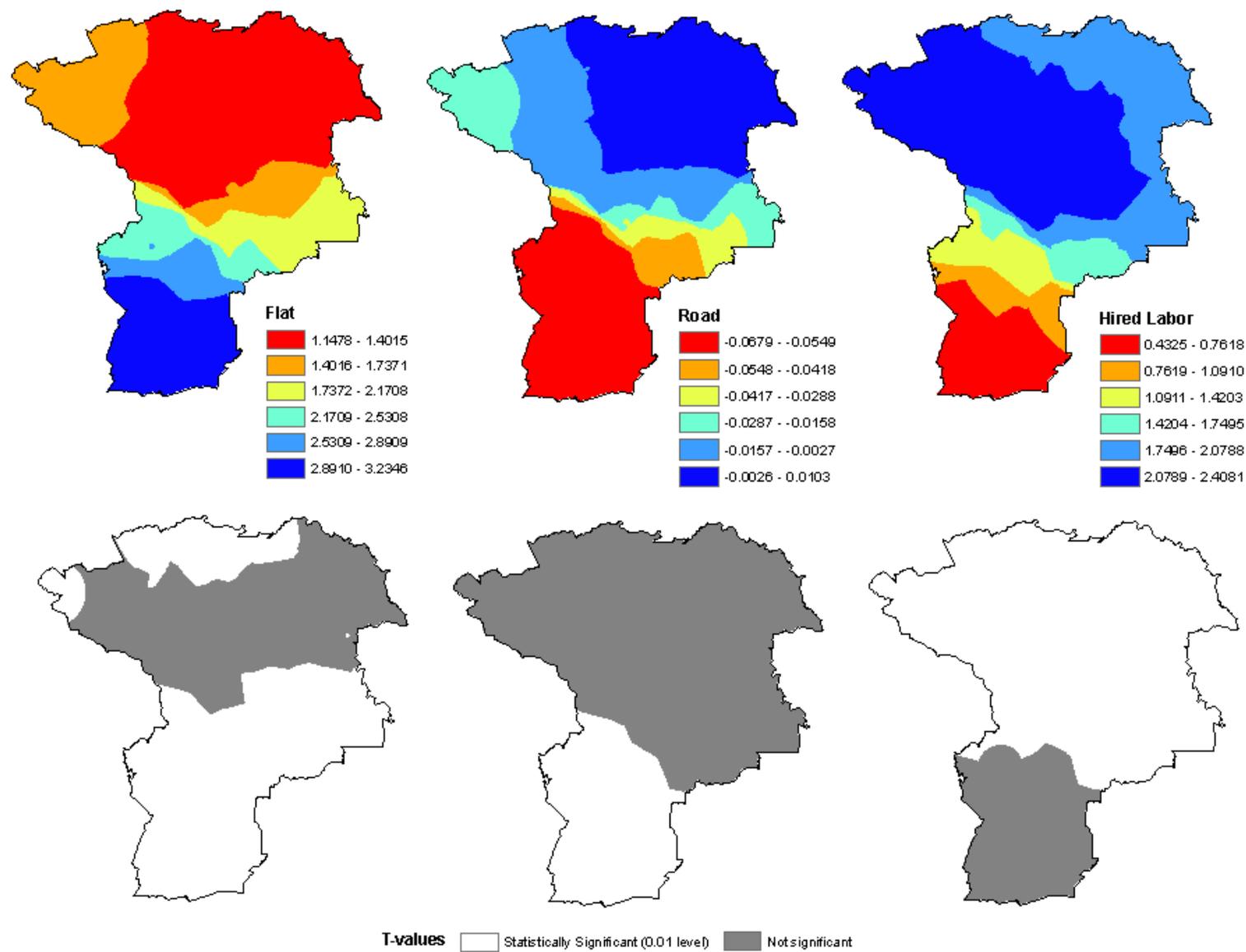


Figure 4.10. GWR results for selected significant variables in the Pasture (1996-2002) model.

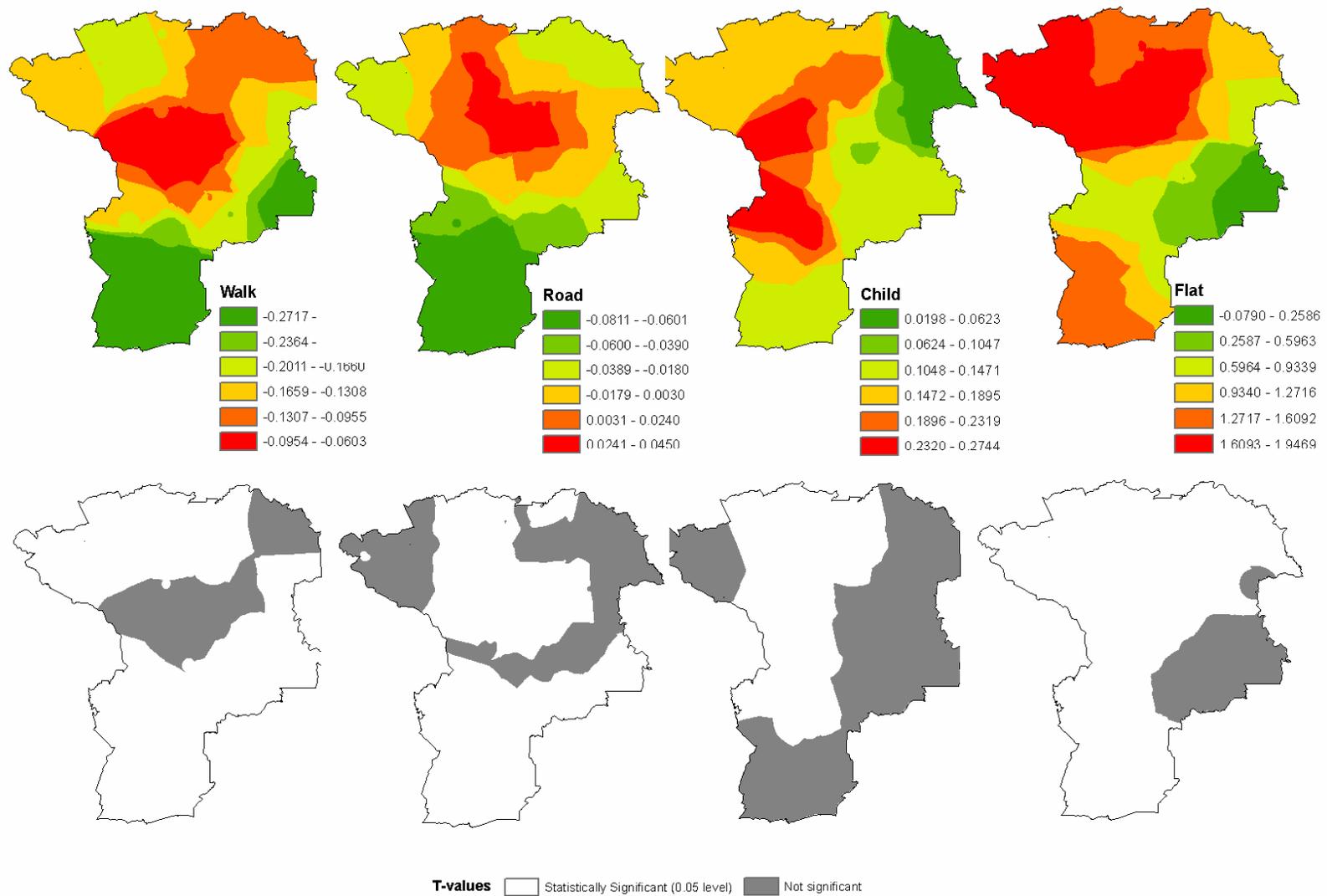


Figure 4.11. GWR results for selected significant variables in the small scale agriculture (1986-1996) model.

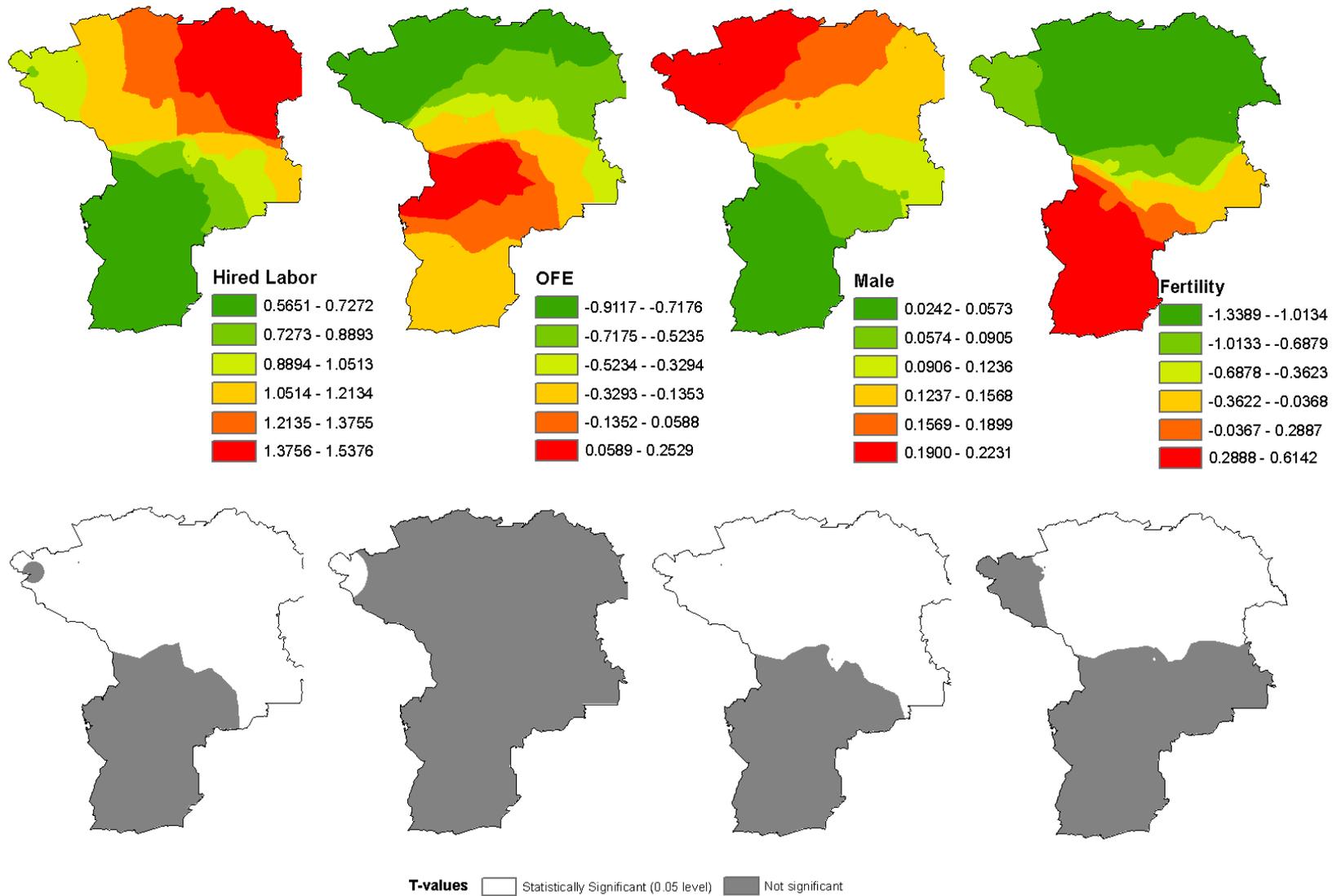


Figure 4.12. GWR results for selected significant variables in the small scale agriculture (1996-2002) model.

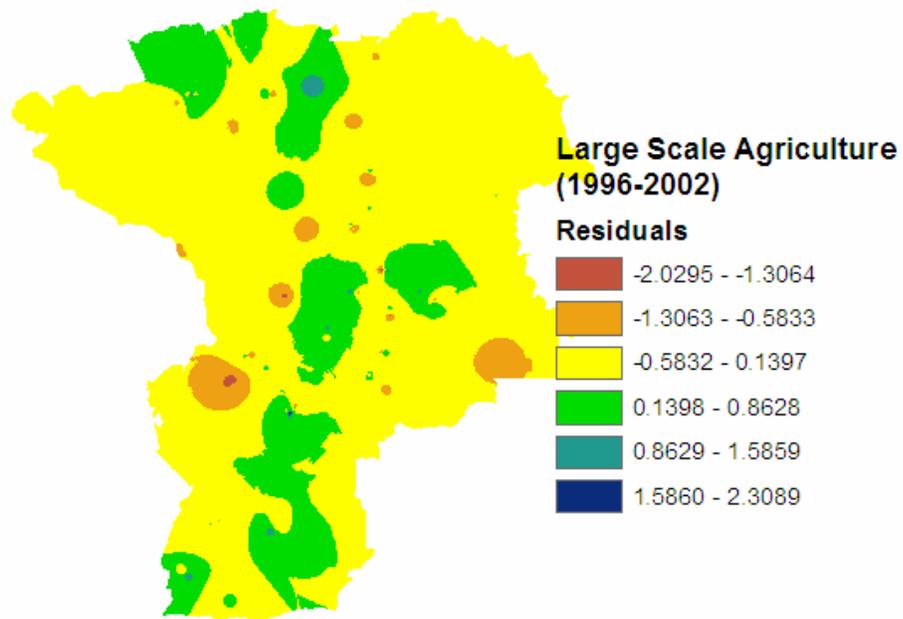


Figure 4.13. Residuals of the Large Scale Agriculture Model (1996-2002)

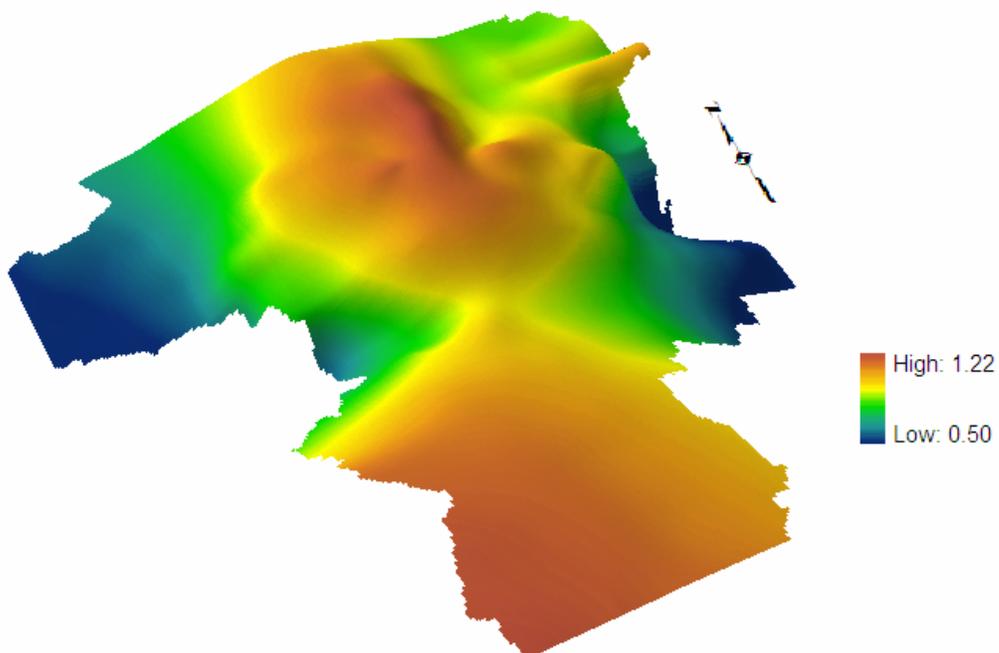
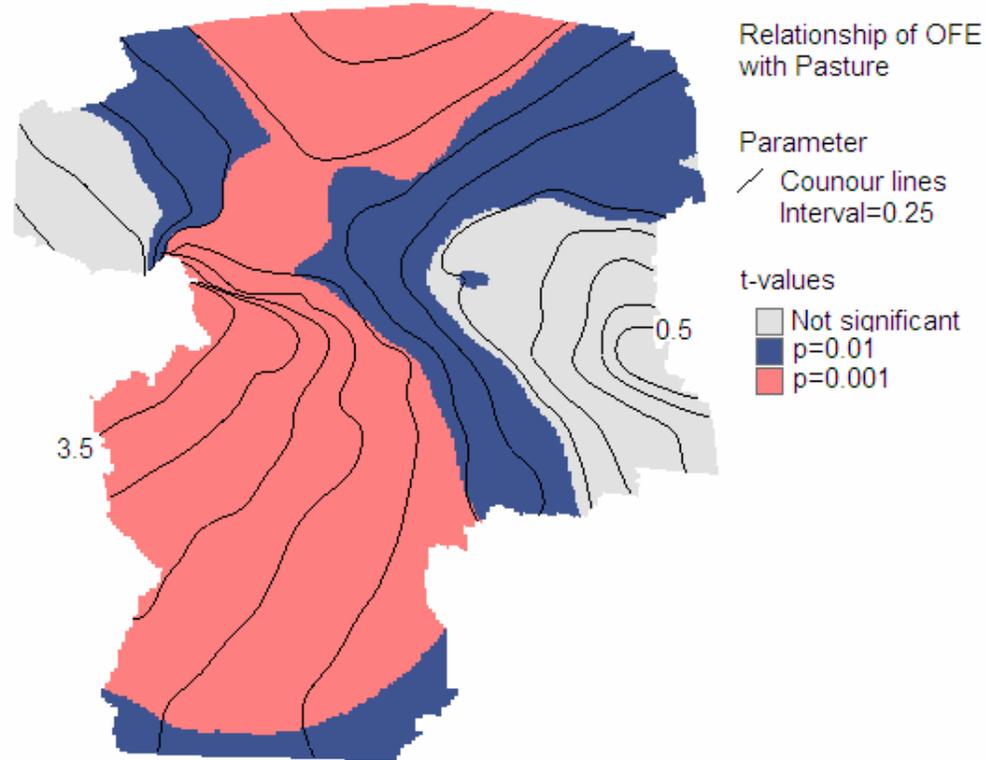


Figure 4.14. 3-D representation of the effect of the variable *male* on the proportion of deforestation for the period 1986-1996.



**Figure 4.15. 3-D representation using contour lines of the effect of the variable child on pasture for the period (1986-1996): The colors represent t-test values in the GWR model**

#### 4.6. Conclusions

This research has explored the use of different techniques to explore spatial dependence and spatial heterogeneity within the drivers of land change. This study determined how the relationships between different socioeconomic, demographic, and biophysical factors and land change are non-stationary across the Northern Ecuadorian Amazon. The issue of non-stationarity has implications for environment and development policy and management. The limitations of the study are related to the lack of information to explain processes that maybe less related to small households farming and more related to agro-industrial plantations (i.e., large scale agriculture, including cultivation of African palm and *palmito*). Processes that are related, for example, to the patterns of consumption of

African palm within Ecuador. From the methodological perspective, this research successfully links remotely-sensed and households survey data to provide information that can help guide spatially-explicit modeling efforts that examine local effects (e.g., cellular automata) opposed to regional trends.

The Northern Ecuadorian Amazon is an agricultural frontier where different actors with different histories of settlement have followed different processes of adaptation. Although, the diverse conditions under which migrant colonist operate are sometimes recognized in studies of LULC change, the statistical models used generalize the drivers of land change across a study area. This generalization is necessary to generate new knowledge paradigms or for policy implications. Unfortunately, the different intensities of the relationships over space are thereby "washed out" and the importance of place is overlooked. This research analyzes the spatial heterogeneity within the drivers of LULC change across space and demonstrates how factors, such as accessibility, impact with different intensities across the in the study area. For example, for deforestation in the period 1986-1996, walking distance to main road (*walk*) is more important in the southern portion of the study area. Obviously, efforts devoted to halt deforestation through access to roads should be focused in the southern portion, since in the North there are already so many primary and secondary roads and conservation efforts should be devoted to restoration of degraded forests.

The problem of spatial dependence and heterogeneity can be seen as a problem of geographic scale. Using the same data, global models find relationships a level higher than the observed data, while local models (e.g., GWR) find relationships at a lower levels than the global regressions. At this level, "pockets" of different conditions can be found (Longley and Tobon 2004). From the methodological point of view, Anselin and Bera (1998) argue

that spatial dependence can arise due to certain misspecifications, specifically, when there is a mismatch between the unit of measurement and the unit within the process. In this analysis, for example, despite the fact that the models are carried out at a very basic level of geographic organization (i.e, farm), several households might control (formally or informally) different portions of land that exist within farms and such relationships are not captured in this research performed on 50 hectares *finca madre*. Unfortunately, there are data limitations in terms of lack of geodetic surveys of the subdivisions and satellite imagery.

Specific for the NEA, this research indicates that there is strong spatial dependence in the effects of many of the explanatory variables. The analysis shows that the spatial dependence must be caused by processes at work in the NEA rather than produced by spatially autocorrelated errors in the data. However, this study used farms as the unit of analysis. It is obvious that the results of this research cannot be extended to areas where urban or suburban processes are at work. The study area does not include protected areas or indigenous territories, but may include the effects of migrant indigenous groups that have settled as pre-cooperatives but still manage their land as a community. This case also should be excluded. The use of GWR and SLM (or error models) provides a good synergism to explore the spatial dependence and spatial heterogeneity of the relations between drivers of land use and land cover change.

Finally, one of the outcomes of the analysis is related to representation. The benefit of having images and maps to represent relationships of the drivers of LULC have benefits for communicating the results of statistical models to policy-makers. Of course the visual representation does not replace the need to communicate exact parameters of relationships to scientific audiences.

## **CHAPTER 5**

### **Simulating Land Cover Trajectories, Spatial Heterogeneity, and Local Variation through Cellular Automata Modeling in the Northern Ecuadorian Amazon**

#### **5.1. Introduction**

Land-based anthropogenic processes, such as agricultural expansion, deforestation, urbanization, and desertification, have altered the earth system in significant ways during the past century. A better understanding of these processes and their feedbacks are indispensable for the better management and sustainability of human actions (National Research Council 1999a). These processes are “place” based, thus providing a conceptual and operational framework within which progress in integrative understanding and management are possible (National Research Council 1999b). Spatial analysis, which plays an important function in the study of land resources, is fundamental in the modeling of human decision making regarding the use of space, or human preferences for land attributes (Bell 2005). Coupled with insights from complexity theory and complex adaptive systems, spatial analysis and modeling offer a novel way to capture the spatial dimensions, amounts, and rates of the complex interactions. The theoretical and applied links between spatial analysis techniques and complex systems concepts separate spatial analysis from traditional positivist modeling and supports the development of less deterministic models that better represent the realities of an uncertain world.

The objective of this research is to create a spatially-constrained Cellular Automata (CA) model that captures uncertainty, neighborhood change and spatial heterogeneity to explore the effects of land transitions (i.e., agricultural extensification and urbanization) in the Northern Ecuadorian Amazon (NEA). This model is empirically-based and uses satellite imagery, a geographic information systems, household survey data, national census data, and other datasets to generate parameters that influence landscape transitions, manage uncertainty, and generate suitability surfaces to affect land transformations in the NEA, primarily due the actions of colonists settlers, whose decision-making and conditions are mediated by a complex set of exogenous and endogenous forces.

### **5.1.1 Cellular Automata and the Spatially-Explicit Modeling of Land Cover Change**

CA models are examples of mathematical systems constructed from many simple, identical components that together are capable of complex behavior. From their analysis, CA can, first, generate specific models for particular systems, and second, abstract general principles applicable to a wide variety of complex systems (Wolfram 1984). CA involves a regular division or tessellation of space into cells, each characterized by a state that represents the actual condition of the cell; the state changes according to a transition function that depends on the initial conditions, states of neighboring cells, and the initial state of the focal cell (Badalamenti et al. 2002). CA is not used to describe a complex system with complex equations, but instead allows complexity to emerge by the interaction of simple "individuals" following simple rules. The essential properties of a CA are: first, a regular n-dimensional lattice (in most cases of one or two dimensions), where each cell has a discrete state, and second, a dynamical behavior, described by growth or transition rules. These rules describe the state of a cell for the next time-step, depending upon the states of the cells in the

defined neighborhood. From a methodological point of view, White and Engelen (1993; 1994) and White (1997) defined the components of a CA as: (1) the cell, the basic element of a CA and works as a memory element and stores states; (2) the lattice, cells arranged in a spatial web; and (3) neighborhoods, defined by the rules that perform changes of the state in the cells depending on the neighboring cells. Cells, cell arrangements, and neighborhoods are easily defined within Geographic Information Systems (GIS), which provide the basic tools to create datasets that input the model.

Cellular automata has been used in various studies that address the pattern-process relations and dynamics of natural and social systems, including fisheries (Badalamenti et al. 2002), forest fires (Bendicenti et al. 2002), urban land use change (Batty et al. 1999; Clarke and Gaydos 1998; de Almeida et al. 2005; de Almeida et al. 2003; Ward et al. 2000), and deforestation (Alonso and Solé 2000; Messina and Walsh 2001; Silveira et al. 2002). CA cannot, however, model all types of spatial phenomena. CA models are more useful if used in conjunction with other modeling techniques (White and Engelen 1994) and several pure- and pseudo-CA models have been created using empirical data and different types of methods to calibrate land use transitions. For example, Wu (2002) used a sequential process that combines data-driven global and local probabilities to generate transition rates, updated at each step of the simulation. Li (2002) generated a CA that used a three-layer neural network to calculate conversion probabilities for competing multiple land uses that simulate gradual land use conversion processes. Xu et al. (2006) integrated CA with genetic algorithms to find optimization functions that define land class proportions. The theoretical basis of the quantification of the neighborhood functions for the CA models is relatively poor (Verburg et al. 2004). The model developed in this research overcomes this problem by using

Geographically-Weighted Regression (GWR) to explore and address the spatial heterogeneity of the drivers of land cover change, based on household survey data.

### **5.1.2 Complexity and Complex Systems**

In science, social processes are usually regarded as complex outcomes of interactions between social structures and human agency, while natural processes are usually regarded as determined by laws of nature (Blackman 2000). Currently, there is a certain convergence in the study of coupled social and natural systems supported by developments in the fields of complexity theory, complex adaptive systems, vulnerability, and resilience (Hollings and Sanderson 1996). To define complexity theory and complex systems is not an easy task, in the sense that there is no identifiable complexity theory per se. Different disciplines and theories concerned with complex systems are positioned under the banner of complexity research (Manson 2000). To understand how complexity and complex systems contribute to this research, it is necessary to review some concepts related to the foundation of complexity science.

Complexity theory is a type of systems theory that approaches explanation in terms of causes and effects, but it is not deterministic. According to Blackman (2000), the basic principles of complexity can be summarized as: (1) system-environment interactions that allow feedbacks, (2) systems of social and environmental signatures that have multiple and interacting causes with non-linear trajectories of change occurring within a phase-space of possible attractors, (3) certain parameters that govern the general properties of a system and its trajectory in phase-state, and (4) system states that are not predictable in the long-term, but the generic class to which they belong can be described, investigated and perhaps anticipated. Dynamics emerging from local nonlinear feedbacks can constrain the evolving

patterns or create the emergence of new landscape structures that create additional feedback mechanisms on subsequent activities (Walsh et al. In Press-a).

The origin of systems theory in social (Von Bertalanffy 1950) and natural (Patten 1959; Watt 1966) sciences is the basis for the development of several concepts related to complex systems, among them feedback mechanisms. Chorley and Kennedy (1971) defined feedbacks as the property of systems that, when changes are introduced via one of the system variables, transmission through the structure directs the effect of the change back to the initial variable, i.e., circularity of action. With a negative feedback the system is maintained in a steady-state by self-regulation processes, termed morphostatic; with a positive feedback, the system is characterized as morphogenetic, changing substantially, its characteristics and effects over time.

Complexity conceptualizes the outcome of processes as states of the system. It conceives a system as either reproducing its current state (i.e., stable state) via negative feedbacks with the environment or moving along trajectories from one state to another (i.e., state cycle) as a result of positive feedbacks (Blackman 2000). In this research, the states of the system are the land classes that change across time or remain the same. A state cycle (also known as a system phase) embodies all the possible states for a system in a possible environment. In this research, the system phase is the possible land trajectories.

A Complexity theory analysis of land use and land cover (LULC) change aims at understanding the dynamics of LULC change patterns in terms of a state-space within which the system functions. Characteristics of complexity in this state space may include thresholds that cause rates of change to vary; bifurcations that can cause systems to diverge from similar states; folds that lead to jumps of state; and various stability conditions. All are constraints on

LULC dynamics and future trajectories. A relevant topic within complexity is the concept of self-organizing systems: spatially-extended, dynamic, systems can self-organize to generate order.

Environmental change (e.g., the construction of a road or the implementation of a new policy) can cause perturbations to the system that can slow its development by a negative feedback or develop into a chaotic behavior with a positive feedback, thereby, generating change along a trajectory within the system's state-space. Complexity theory can be applied to the analysis of LULC transitions, because landscape frontiers (e.g., the NEA) are emergent phenomena resulting from human-environment interaction at local scales and manifested at regional scales.

It is expected that complexity will provide a framework for two important features in the NEA agricultural system: feedbacks and uncertainty. Positive and negative feedbacks need to be accounted for in the spatially-explicit and dynamic models; important positive and negative feedbacks include the existence and creation/improvement of accessibility, subdivision of plots, and immigration to the area. In terms of uncertainty in complex systems, it can be classified in stochastic and epistemic uncertainty. Stochastic, or irreducible uncertainty describes the inherent variation associated with the system or the environment under consideration, while epistemic, or reducible uncertainty describes the lack of information or knowledge in any phase or activity of the modeling process (Oberkampff et al. 2004). Sources of uncertainty are numerous. In the case of agricultural frontiers, there is uncertainty related to the scarcity of information small farmers in the agricultural frontier face within their decision-making space that does not allow a clear maximizing strategy for planting food or cash crops (Ortiz 1973). In this model, there is also uncertainty related to the

data, for example how well initial satellite classifications of land use capture the initial conditions. Spatially-explicit models of complex systems generate spatial patterns that can be very sensitive to slight differences in processes or initial conditions, i.e., path dependence (Brown et al. 2005). The type of uncertainty addressed here is the stochastic type, using random elements that generate a degree of variation in the outcome. The model developed here does not focus on prediction that might generate overfitting, but emphasizes patterns to capture process at work in the study area.

The challenge and major weakness of the CA models is the difficulty they have to capture processes at a level of social organization where the land change decision-making actually occurs, which in the NEA is at the household level. The CA model works at the cell level but human decisions are made by households and implemented at the farm level. Therefore, CA models capture only indirectly the main decisions that influence LULC change. This research tries to overcome this challenge by incorporating the drivers of LULC change at the household-level by using spatially-explicit statistical models and Geographical Weighted Regression (GWR), that are capable of characterizing and managing the heterogeneity of relationships.

## **5.2. The Study Area: The Northern Ecuadorian Amazon**

Ecuador had the highest deforestation rate in South America over the last twenty years (Food and Agriculture Organization 2001; Food and Agriculture Organization 2005). The NEA is the second deforestation front within the Ecuador, after the Choco Region in North Western Ecuador (Sierra 2000). This oil rich region covers an area of approximately 7,000 km<sup>2</sup> and comprises three provinces: Sucumbios, Orellana, and Napo. The Napo rainforest, where the NEA is located, is among the most biologically diverse and unique environments in the

world, and it is considered one of the world's hotspots—areas with high biodiversity and under high human pressure (Myers 1988; Myers 1990; Orme et al. 2005). The NEA has experienced considerable LULC change primarily through deforestation, agricultural extensification, and urbanization.

The discovery of petroleum in the region in the early 1960s helped define two periods in the history of the NEA. Prior to the exploitation of petroleum, the natural landscape was essentially intact and populated mainly by indigenous populations and some colonists devoted primarily to subsistence agriculture. Using roads built by the petroleum industry to explore, lay pipelines, and extract oil, colonists began arriving in the early 1970s and began converting land from forest to agriculture on 50-ha farms, to initially support themselves with subsistence agriculture, followed by the commercial cultivation of coffee and eventually to raise cattle for sale. Virtually all the colonization has been spontaneous. Population growth between 1974 and 1982, 1982 and 1990, and 1990 and 2001 increased at rates of 8%, 6%, and 5% per year respectively (Bilsborrow 2003) —almost double those of the national population. As result, the total population grew from 384,616 in 1990 to 548,419 in 2001 (ECORAE 1996). The tenancy of legal titles of colonist decreased from 50 to 34 percent among colonist farmers in the region between 1990 and 1999 (Bilsborrow et al. 2004).

The CA-based, spatial simulation is developed for a smaller portion of the colonization area in the Northern Ecuadorian Amazon. This area is the Northern Intensive Study Area (NISA), shown in Figure 5.1. The NISA covers an area of 80,260 hectares and contains the largest city in the Ecuadorian Amazon: Lago Agrio (or Nueva Loja), which had a population of 34,000 inhabitants as the 2001 population census. The NISA is an excellent place to apply the CA model, because it contains two major land change processes:

agricultural extensification and urbanization. This CA model, because it captures the heterogeneity of the relationships between the drivers of land change across space, can be applied to any area of the NEA

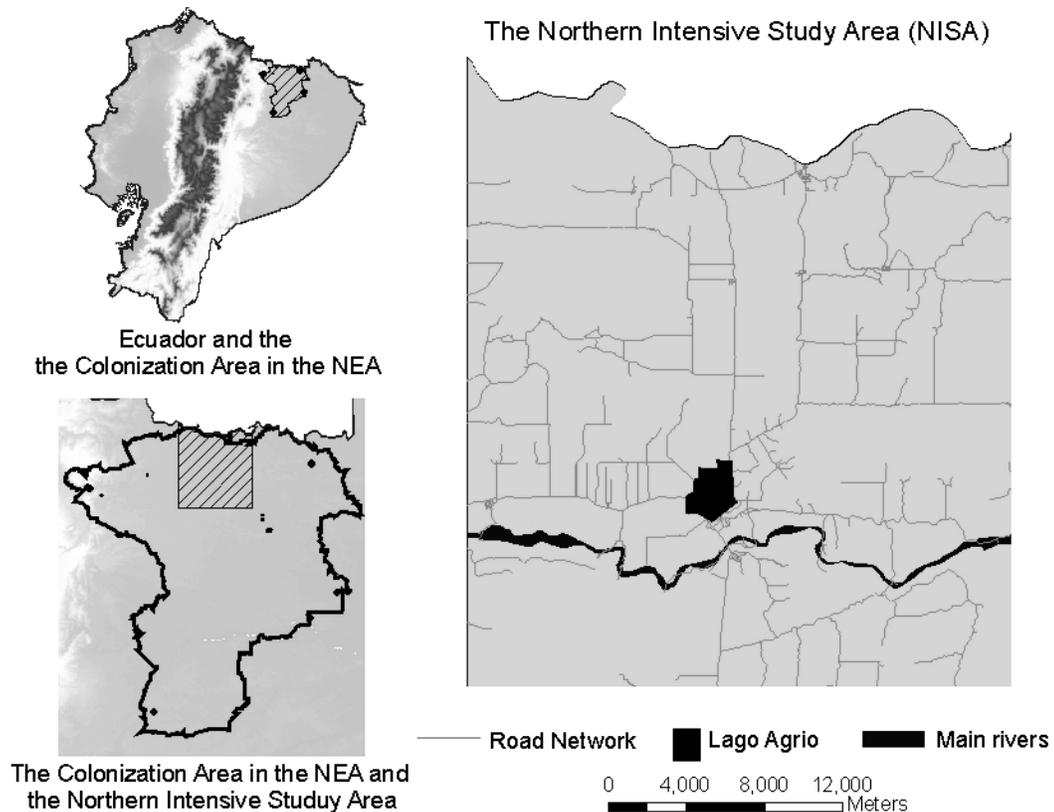


Figure 5.1. The North Intensive Study Area (NISA) within the colonization area of the Northern Ecuadorian Amazon.

### 5.3. Cellular Automata Models in the Ecuadorian Amazon

Considerable advances in the field of spatially-explicit simulation modeling have been made using the Ecuadorian Amazon as the setting and using complexity as the theoretical framework. The first generation of CA models in the Amazon, described in Messina and Walsh (2001) and Messina (2001), set the basis for further development of the

CA models by applying three elements used in modified form in later models: initial conditions, random number generation, and growth rules. The predictive emphasis of these initial models explains the use of autoregressive techniques to quantify errors in the products and the lack of socioeconomic information to generate growth rules. Further development of this model (Messina and Walsh 2005) includes the generation of a flux class, also used in the model presented here, where classes are combined before the simulation and separated after growth rules are applied. These set of models include a more sophisticated form of calibration that uses satellite image-based transition probabilities that tune the parameters of the model. This model also includes the use of geographical accessibility, a dimension of socioeconomic condition. There is, also, an evolution from the software used to code the model, initially Erdas Imagine software and Spatial Modeling Language were used because they have strong capabilities for processing satellite images, but limited spatial and statistical analysis functions. Later models, including the model presented here, use IDL (Interactive Data Language) to code and run simulations. IDL provides vast potentials to generate spatial simulations, including the use of established statistical functions.

Other advances include models explained in Walsh et al. (In Press-a; In Press-b). Although these models contain similar elements as earlier models, the use of household socioeconomic data is emphasized. The source of socioeconomic data includes household survey and national census data. The use of socioeconomic data allows the construction of different scenarios of future LULC change based on changes in some socioeconomic characteristic. Specifically, this model hypothesizes that an increase in accessibility will create negative feedback by generating better access to towns and consequently more opportunities for off-farm employment that creates higher income on farms and accelerates

the process of deforestation.

The advances of the model presented here in relation to earlier models are based on two key characteristics: (a) the use of Geographically Weighted Regression (GWR) to create spatial regimes that control the random seeding that creates a semi-constrained stochastic uncertainty in the system; and (b) the direct use of household survey data to parameterize the model by providing data to create spatially-explicit parameters in the GWR model.

#### **5.4. The Simulation Process**

The spatially-explicit simulation uses a cell-based, dynamic modeling approach based on cellular automata principles to calculate change for several land cover classes in annual time steps. The model is grounded in empirical data obtained from a longitudinal household survey in the Northern Ecuadorian Amazon conducted in 1990 and 1999. One of the key elements of this model is that the *relationships* between socioeconomic and demographic factors and LULC change, obtained for discrete points (i.e., sample households), are transformed in continuous surfaces using Geographically Weighted Regression (GWR). In broad terms, the simulation process is divided into three components: (a) determination of the initial conditions and rules within the system, (b) dynamics of the land change processes: dilation and seeding, and (c) suitability for transitions and resolution of conflicts. Figure 5.2 illustrates the main components in the process defined to simulate land change for Year 1 of the 20-year simulation period that begins in 1986.

The initial conditions of the system are represented by an initial land cover classification (Land Classes in Year  $t$ ), here represented by the 1996 Landsat classification generated using a hybrid classification approach (Messina and Walsh 2001; Walsh et al. 2003) and explained in Chapter 2. In this initial classification and in the simulated LULC

surfaces, the classes used are: primary forest, succession, pasture, agriculture, urban/barren, and water. Three other initial parameters are designated to capture the local and regional dynamic: a growth kernel, neighborhood threshold, and a random seeding coefficient. The growth kernel neighborhood is a moving window of 3 x 3 cells (1 cell = 90m<sup>2</sup>), where the central or focal cell is susceptible to change based on the values of its neighbors. The neighborhood threshold is an integer that indicates the minimum number of cells that must be from the same class to generate a change or transition of the central cell to another class. For instance, if a center cell is forest and it is surrounded by agriculture, it is highly likely that the state of the cell will be switch to agriculture during the next interaction of the model.

*Seeding* is the process by which random cells are distributed across the landscape to represent the possibility that landcover may change in less predictable ways and in isolated locations. Seeding, in this case, is not completely random, it is partially controlled by the generation of spatial regimes. Geographically Weighted Regression (GWR) is used to create spatial stratifications of the landscape. GWR is designed to capture the spatial heterogeneity of relationships, and, in this study, is applied to create spatial regimes in the relationships influencing the drivers of land change. GWR generates spatially-explicit regression coefficients that define the spatial distribution and direction of relationships and their statistical significance. Geographically Weighted Regression (Brunsdon et al. 1998; Fotheringham et al. 2002; Fotheringham and Wegener 2000) can be expressed as:

$$y_i = \beta_o(u_i, v_i) + \sum_k \beta_K(u_i, v_i)x_{ik} + \varepsilon_i$$

where,  $y_i$  is the observation of the dependent variable at the location  $i$ ,  $(u_i, v_i)$  that represents the coordinates of  $i$  in space, and  $\beta_k(u_i, v_i)$  is the realization of the continuous function  $\beta_k(u, v)$  at point  $i$ . The basic assumption of this model is that locations nearer to  $i$  will have more

influence on the estimation of the parameter  $\beta_k(u_i, v_i)$  than data points farther from  $i$ . Under this assumption, a continuous surface of parameter values is estimated. Detailed information of how the GWR models were created and the variables used is provided in Chapter 4. The dependent variables are the proportion of land change (i.e., agriculture, pasture, and succession) that occurred between 1986 and 1996 at the farm-level, calculated from the Landsat classifications. Table 5.1 shows the set of independent variables generated using the 1990 household survey and used in the GWR model. The model was generated for the entire NEA using 314 farms and the area that corresponds to the NISA was extracted.

The dilation or growth of land classes in this CA model is captured by three basic processes that are based on principles of complex systems modeling, and described by Messina and Walsh (2005) and Walsh and Messina (In Press-b). The basic processes include: (1) the dilation (or growth) coefficient for the urban class, (2) the dilation coefficient for the flux class (i.e., the grouped set of classes: succession, agriculture, and pasture), and (3) the transition probabilities to separate the flux class at the end of each model iteration. Dilation is the propensity of one class to “flip” to another class based upon a defined threshold of LULC class frequencies within a defined filter window or kernel. Dilation is used to fill holes or add pixels along a boundary. The equations for these processes can be expressed as (Messina and Walsh 2005; Seul et al. 2000):

$$I^{dc}(i_0, j_0) = \begin{cases} \text{on, if } I(i_0, j_0) = \text{off, and } \emptyset(i, j, \eta) \geq T_{\emptyset}, \\ \text{and } x(i, j, \eta) (>, <, =) T_x \\ \text{off, otherwise;} \end{cases}$$

where  $I$  is the image, the main element;  $(i, j)$  represents all the pixels;  $\eta$  represents the

neighborhood around the center pixel;  $(i_0, j_0)$  = on or off pixels;  $I$  is the main element;  $T_\emptyset$  is a growth kernel threshold;  $T_x$  is a neighborhood threshold.

Table 5.1. Set of independent variables from 1990 used to parameterize the GWR model.

Variable	Definition	1990	
		Mean	SD
Male	Number of males in the farm, older or equal than 12 years old	2.68	(1.71)
Female	Number of females in the farm, older or equal than 12 years old	2.10	(1.47)
Child	Number of children in the farm, younger than 12 years old	2.82	(2.35)
Age	Average age of the head of households within the farm	44.56	(12.39)
PriEduc	Any primary education (binary)	0.89	(0.31)
SecEduc	Any secondary education (binary)	0.05	(0.23)
Walk	Walking distance to main road (km)	2.68	(3.36)
Road	Distance to reference city by the main road (km)	20.85	(14.15)
Access	Car access to the farm (binary)	0.50	(0.50)
SecRoad	Distance to the main road by secondary road (km)	2.11	(4.08)
Soil	Black soil on the farm (binary)	0.65	(0.48)
Fertility	Farmer reports fertility decrease in the farm (binary)	0.86	(0.35)
Flat	Flat land on the farm (binary)	0.42	(0.49)
Wetland	Wetlands on the farm (binary)		
Hlabor	Hired labor on the farm in the last year (binary)	0.54	(0.49)
Ofe	Off farm employment in the farm on the last year (binary)	0.34	(0.48)
Title	A portion of legal title on the farm (binary)	0.33	(0.46)

The separation of the flux class is made using transition probabilities of land classes across time and space that incorporate a Markovian process. The transition probabilities were derived from summary cross-tabulations of land class areas for the 1986 classification and standardized to represent the probability of those classes to exist in the next year. The last step of the model deals with the calculation of a suitability score that allows the resolution of

conflicts that occur when a cell has been changed and activated for different types of land transitions. For example, when the dilation process has flipped a cell to urban, but the seeding has designated the same cell as succession, the difference of suitability scores for each land class then indicates the type of change that should be applied to the cell in question. When the differences of suitability scores are too small, the change is random. The suitability scores are calculated using a set of biophysical and socioeconomic variables shown in Table 5.2.

The process mentioned in the preceding paragraphs is carried out for the initial year. The results serve as the inputs for the next iteration of the model. The same cycle is repeated for each of the years modeled. Obviously, the more years modeled, the higher the uncertainty related to how well the model represents reality and how new un-modeled processes that impact LULC. The CA results presented here model land changes only to the year 2010.

Table 5.2. Layers used to characterize the suitability for flux class change or urban change. The sign indicates the direction of the relationship.

Flux Class Suitability	Urban Class Suitability
Travel distance to main towns (-)	Travel distance to main towns (-)
Euclidean distance to nearest road (-)	Euclidean distance to nearest road (-)
Population density (+)	City Gravity Model (+)
Slope (-)	
Topographic moisture index (-)	

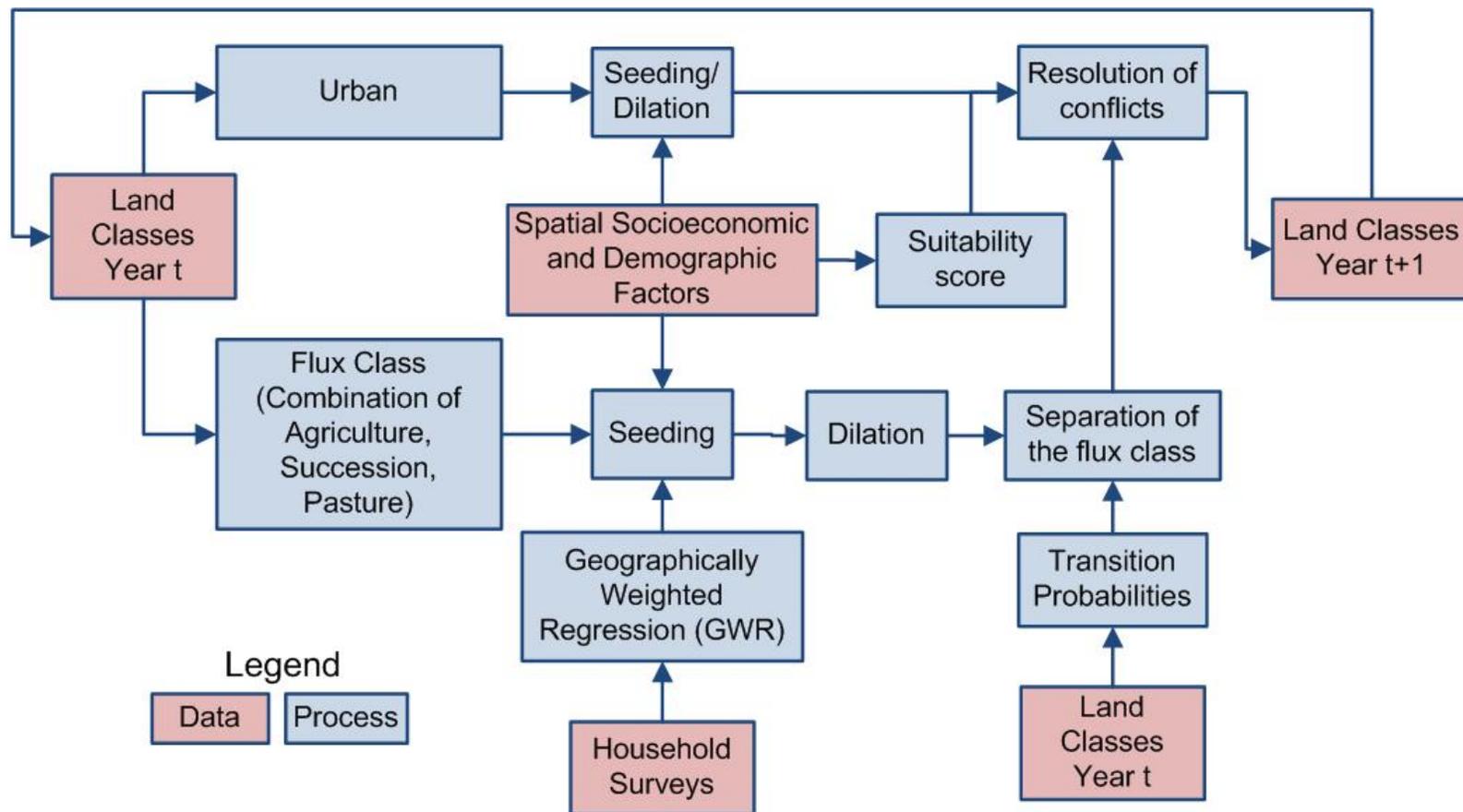


Figure 5.2. Main components in the process of land change using the CA model.

## 5.5. Results

The spatial simulation process builds a set of predictive maps based on a set of initial conditions that include biophysical, socioeconomic, and demographic factors. Figure 5.3 (a) indicates the initial land cover conditions of the system, while Figure 5.3(b) shows one of the various possible outcomes for the simulation at the year 2010. This final year of the model run shows changes in the composition and spatial pattern of land cover that are simulated to occur over space and time. The linear features (colonization lines) that exist in 1986 are the main axis of agricultural extensification through the time series.

There are several random elements at work in the simulation that are included to capture some of the uncertainty contained in the land change decision-making at different levels of social organization, as well as our imperfect understanding of the system. Figure 5.4 shows the results of 100 runs of the model that simulates land cover through the year 2010. The variability of the results for each run is evident; however, all the results are within a reasonable range of outcomes. For primary forest, for example, there is a difference of 1,250 hectares between the maximum and minimum simulated area. This is to be expected, because the model also includes stochastic processes, so no model run is identical and, hence, results can vary in subtle and less than subtle ways.

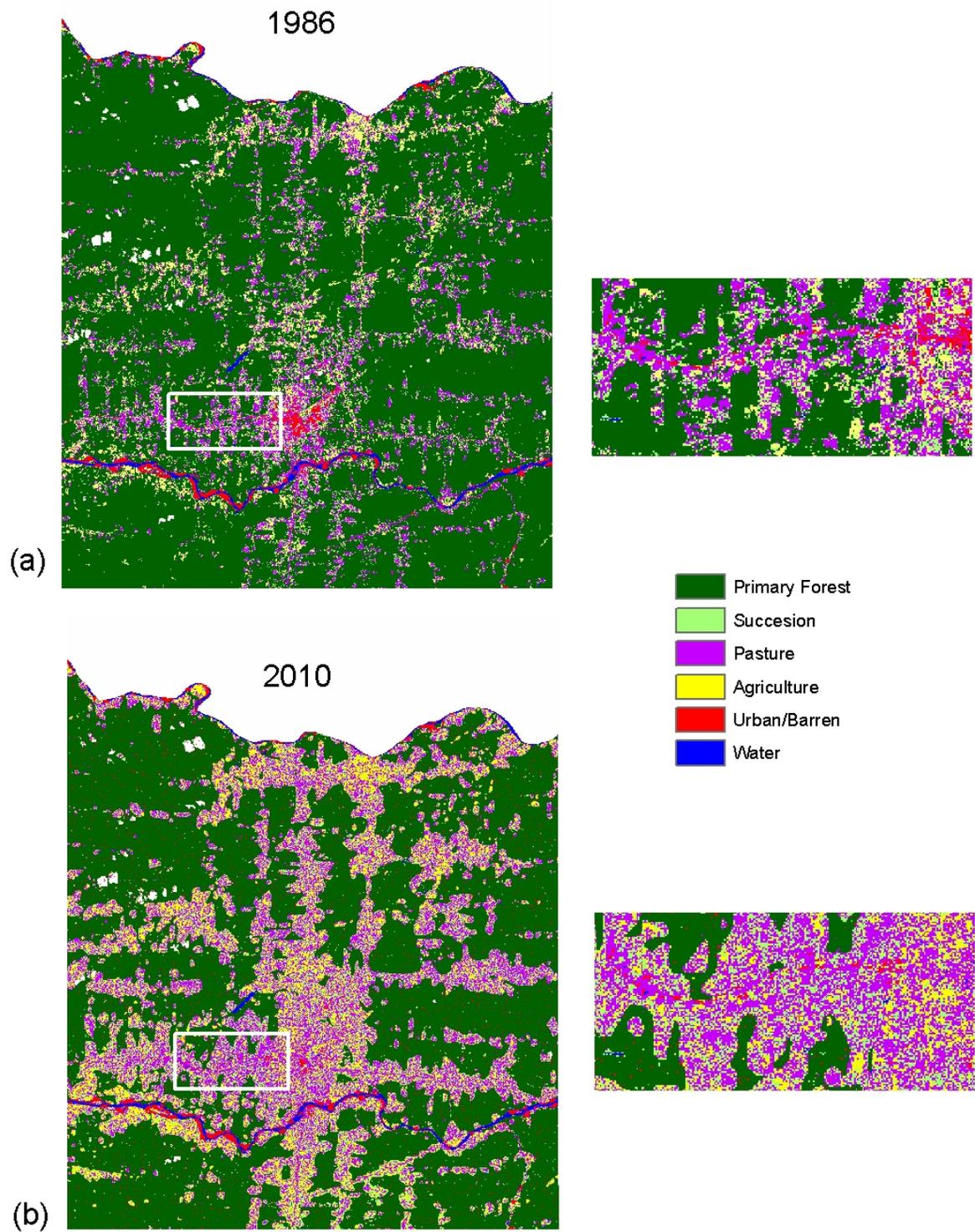


Figure 5.3. Simulation results: (a) the initial land cover in 1986, and (b) the simulated land cover in 2010.

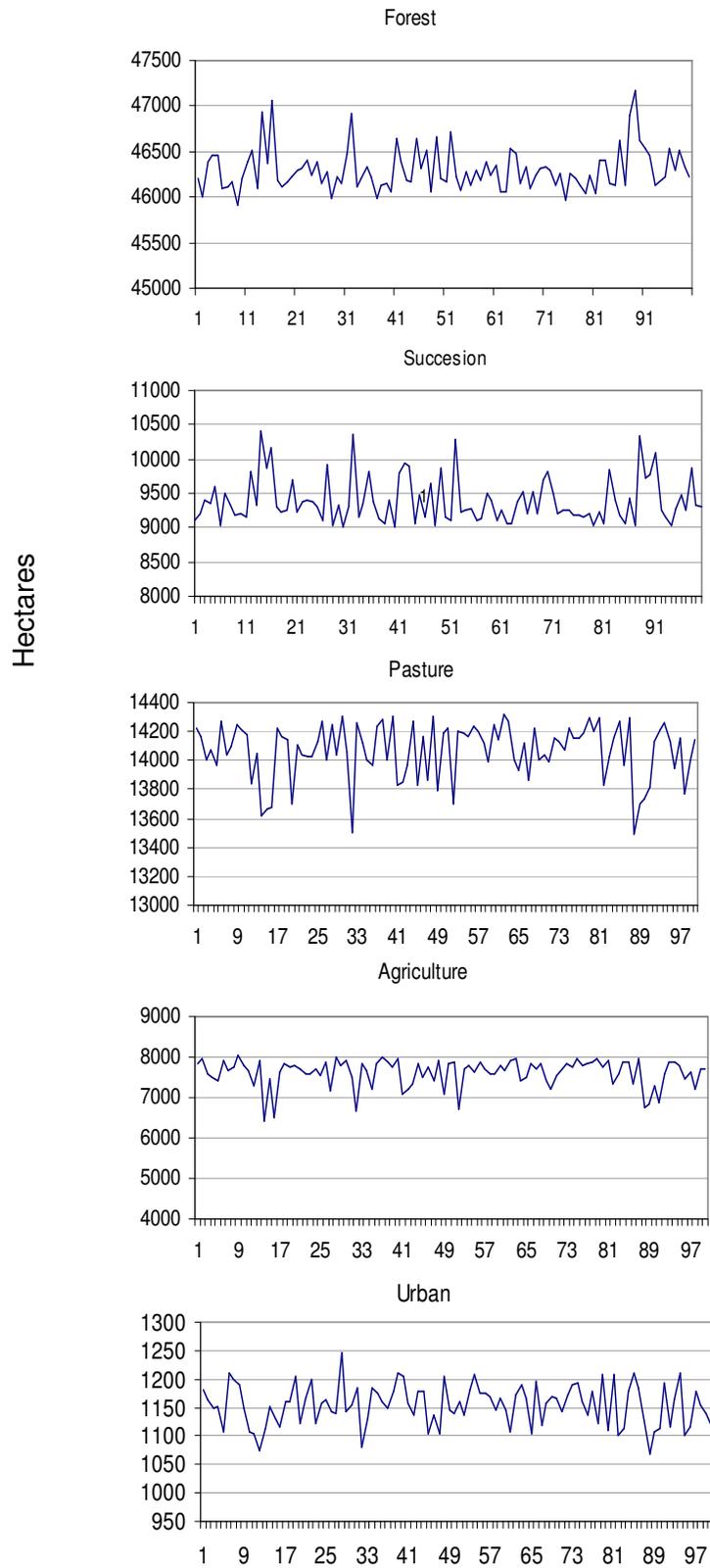


Figure 5.4. Results of 100 runs of the model for the year 2010 for different land classes.

Figure 5.5 specifies the yearly simulation for different land classes. In this case deforestation occurs at 1.9%/year for the period 1986-1996 and 0.8 %/year for the period 1996-2002, which is consistent with deforestation rates reported in other studies (Mena et al. 2006b). The simulation captures a sustained advance of the deforestation front as seen in Figure 5.5, where pasture and agriculture are non-linear, and the shape of a exponential function  $a^y=x$  (with  $a>1$ ), where  $y$  is area of the land class and  $x$  is time.

Different components of the simulation are compared to a classification of LULC using Landsat imagery for 2002. Table 5.3 shows the results of the comparison of class areas for that year. In general, the model performs well, taking in consideration that tuning, or calibration of the model, has not been implemented. The major deficiency is the under-estimation of agriculture (11% of the landscape) in the model when compared to the classification. This obviously has implications for the amount of forest remaining that differs by approximately 8% between modeled and classified tabulations. The assumption is that the Landsat classification is perfectly and absolutely correct, an assumption that is tenuous at best.

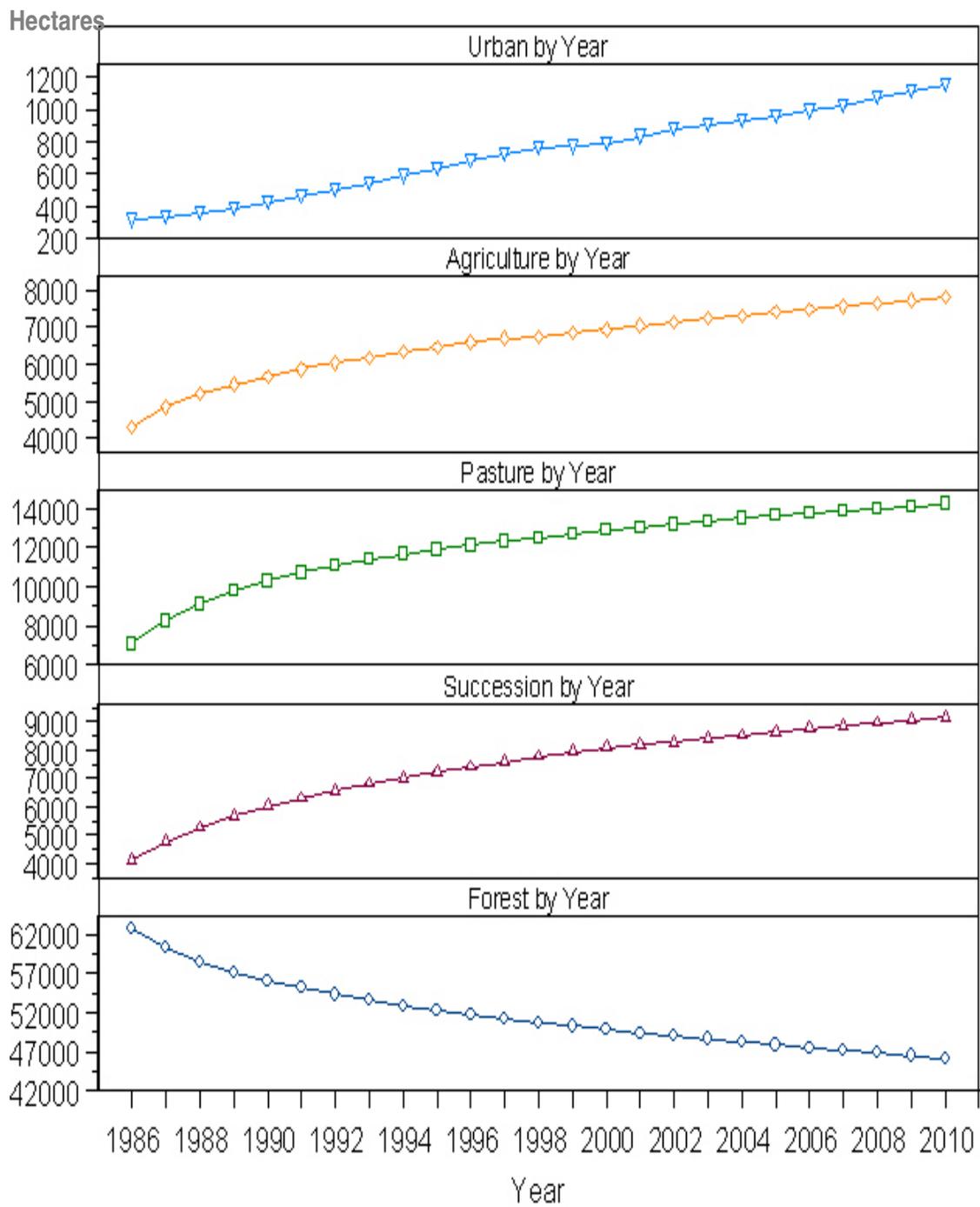


Figure 5.5. Areas of land cover generated by the model between 1986 and 2010.

Table 5.3. Comparison of the total land class areas and percentage of the landscape obtained using Landsat Classification and Simulations for the year 2002.

Land Cover	Classification		Simulation	
	Ha	%	ha	%
Forest	35807.49	39.61	49010.49	47.70
Succession	10400.22	11.50	8281.08	8.06
Pasture	14688.45	16.24	13188.33	12.83
Agriculture	16619.85	18.38	7149.24	6.95
Urban/Barren	1195.11	1.32	1477.62	1.43
Water	543.78	0.60	753.48	0.73

The spatial pattern of the simulation was also compared to the spatial pattern generated by the Landsat classification. Several pattern measurements were used: number of patches in the landscape (Patches), the number of patches per 100 ha (Patch Density), the percentage of the landscape comprised by the largest patch (Largest Patch Index), patch shape complexity measured by the fractal dimension (Perimeter-Area Fractal Dimension, higher than one indicates complex shapes), and measurement of aggregation of the patches (Contagion is 100 when the patches are completely aggregated).

The results indicate that the model performs poorly in terms of configuration of the patches in space. Table 5.4 shows that the simulation creates fewer and larger patches. Contagion, a measurement of landscape aggregation, indicates that the simulation tends to produce patches that are clumped together or clustered. The only index that shows a good performance is related to the complexity of the patch shape measured by the perimeter-area dimension. The poor performance related to spatial pattern of land use is the result of the randomness created when the flux class is divided using transition probabilities. The model however, should improve with additional tuning.

Table 5.4. Comparison of relevant spatial pattern indices obtained from Landsat Classification and Simulations for the year 2002.

Spatial Pattern Indices	Classification	Simulation
Patches	106147	52760
Patch Density	117.42	51.35
Largest Patch Index	4.31	18.36
Perimeter Area Fractal Dim	1.64	1.64
Contagion	32.61	49.86

## 5.5. Conclusions and Discussion

This chapter explains how a CA model for the Northern Ecuadorian Amazon has been created and shows its application to a smaller area (NISA). This CA model is based on demographic, socioeconomic, and biophysical characteristic of the study area collected through household surveys, census data, and geographic information systems. The manner in which the agricultural frontier and urbanization processes advance across space and time emphasize the creation of a morphogenetic model that emphasizes positive feedbacks within the system, feedbacks or forces that change substantially the nature of the land cover through time.

In this CA model, the positive feedbacks can be explored at different levels. The more general positive feedback occurs when the land classes produced in an early iteration generate a higher probability of land change in current or future years. Other specific feedbacks occur when the different biophysical, demographic, and socioeconomic factors reinforce or constrain the seeding and dilation processes and increase or decrease the suitability scores and transition probabilities.

This model, on one hand, conserves different random elements that seek to capture uncertainty in the interactions across time. On the other hand, the model attempts to account

for the observed processes using statistical models and other user-defined parameters. Therefore, the model is not completely deterministic, but is also not chaotic either. The millions of interactions across cells and across time allow complexity to occur, but it is restricted by spatial regimes and follows empirically-based rules.

The relatively low degree of coherence in the spatial pattern as compared to satellite data should not be considered a major problem. This present simulation is only a base or initial model, which will undergo modifications and fine-tuning. The further development of this model is related to general options including: the generation of a knowledge system or the generation of a predictive model. A knowledge system would emphasize the processes at work in the study area, and aims to test different theoretical approaches and methodologies. This knowledge system is less able to capture land change outcomes that mimics reality, its objective is to capture the processes behind the patterns. A predictive system, on the other hand, would emphasize accurate outcomes that have relevance for environmental policy and management. In this context, a tuning or modification of the transition rules is needed to generate outcomes closer to reality. The key is that when the model forces a "more" real or likely outcome, it also generates a more deterministic model, which is contrary to a complex model where the interactions generate spatial pattern.

The potential of this particular CA model is that it lays the groundwork for the development of a set of scenarios relevant to theory or policymaking. Scenario analysis is a useful tool to test incentives, measures, or planning regulations according to different policy objectives (Reginster and Rounsevell 2006). Beyond, traditional land use management prediction and its impact on terrestrial ecosystems, land change scenarios is essential for the prediction of climate change and global warming (Feddema et al. 2005) and is basic to

address the tradeoff, for example, between environmental change and human health (Patz et al. 2004). Different CA models have already demonstrated an ability to address a range of regional planning issues, but spatial accuracy and scale sensitivity (Jantz et al. 2003) and path dependence (Brown et al. 2005) need to be addressed. This CA model can be used in combination with other modeling techniques (e.g., agent based models) to model how short term human decision-making affects the long term stability of human and ecosystem health.

## **CHAPTER 6**

### **Conclusion**

#### **6.1. Revisiting Research Questions**

This research has shown that agricultural frontier regions are heterogeneous and complex entities. Stea (1996) characterizes frontiers in three senses: as a region, as a cutting edge separating regions, and as an intellectual territory. The agricultural expansion of the Northern Ecuadorian Amazon (NEA) responds to the advance of perpendicular and parallel lines, roads, and edges that open into forested areas, but the region that these lines engender is far from geometric, homogenous, or constant. The chapters included in this research show that: (a) the NEA can be characterized and modeled by the LULC trajectories, (b) different combinations of factors control the regeneration of forests, (c) there is non-stationarity in the underlying processes that drive LULC trajectories within the region, and (d) spatially-explicit models can simulate the emergence of broad LULC patterns from the interactions at low levels of geographic organization. The intellectual territories, the different kinds of spatial representation of the NEA shown in this research, are the result of the synergism between spatial analysis, statistics, remote sensing, and complexity theory.

This research links four interconnected research questions whose answers seek to generate new insights in the processes of land use and land cover change in the Ecuadorian Amazon. The first question, treated in Chapter 2, deals with the composition and spatial

configuration of the LULC transitions in the NEA between 1986 and 2002. The intent of this section is to find temporal patterns and logical or regular cycles in land use change when analyzed through classified satellite time-series. This question also explores the spatial organization of the LULC trajectories in the colonization area. It is hypothesized that the land use and land cover transitions in the Northern Ecuadorian Amazon have spatial and temporal patterns that emerge according to the lines of colonization and urban center influence.

Chapter 3 characterizes secondary forest succession, its extent, and the socioeconomic, demographic, and biophysical factors that effort forest generation. As in the first research question, the analysis is restricted to the period 1986-2002, when satellite imagery was available. This chapter analyzes whether a transition to forest is controlled, for example, by accessibility, demographic characteristics, or biophysical conditions. The aim of this question is to clarify the temporal nature of the relationship between people and secondary forests and to infer future positive and negative feedbacks between social, geographical, and biophysical considerations of reforestation as revealed in the sequence of changes captured in the LULC trajectories. It was hypothesized that the production of secondary forest is less intense at the early stages of the settlement where initial positive feedbacks to farmers (e.g., high productivity and rents) promote deforestation and conservation of agricultural lands. In the latter period, however lands decrease in soil fertility and forest resources, thereby, pushing farmers to seek other strategies (e.g., off-farm employment ) to cope with exogenous changes.

Chapter 4 is devoted to the analysis of the spatial heterogeneity of the relationships between socioeconomic, demographic, and biophysical drivers and LULC in 1990 and 1999.

The intent of this question is to identify the spatial non-stationarity of the relationships between explanatory factors and LULC change. Non-stationarity or spatial heterogeneity is created when a stimulus provokes different responses in different locations of the study area. It is hypothesized that the region has intrinsic differences in the farmer's typology and their natural resource base; therefore, they show different intensities across the NEA. This analysis uses Geographically Weighted Regression (GWR) and Spatial Lag Models (SLM) to identify spatial dependence and heterogeneity within relationships. There is also an emphasis on new spatial representations of the parameters resulting from regression analysis that facilitates the communication of results generated through statistical analysis.

Chapter 5 deals with the development of a Cellular Automata (CA) model for the Northern Intensive Study Area (NISA). This CA model, based on previous models generated for the NEA, simulates LULC trajectories using pixels, neighborhoods, and spatial regimes that interact to produce broad LULC patterns. It is hypothesized that it possible to model farms and farmer's behavior using cells that are influenced by socioeconomic, geographic, biophysical, and demographic factors in a changing environment with feedbacks between actors and the environment. Specifically, LULC patterns emerge from rules that control interactions among cells, neighborhoods and other spatial regimes. The model presented here will serve as the basis for the construction of a predictive tool or a process-based model suitable for the construction of theoretical scenarios with LULC change outcomes.

## **6.2. Main Findings, Applications, and Contributions**

The work on the LULC trajectories (Chapter 2) provides an exploratory assessment of LULC change patterns in the Northern Ecuadorian Amazon. This section of the research shows the complex and diverse nature of the sets of LULC trajectories derived for the agricultural

frontier of the NEA. Different patterns were identified using different types of statistical analyses: descriptive statistics, cluster analysis, and spatial logistic regression. Within the NISA and the NEA, trajectories were aggregated and stratified by different spatial units, stages of deforestation, and census sectors. The analysis of LULC transitions has suggested a “core and periphery” pattern of transitions in the NEA. The agricultural and forest trajectories occurring in urban or semi-urban places and marginal lands are sufficiently different to produce diverse responses. From this analysis, practical implications for environmental management can be made. For example, the design of corridors for conservation will be more effective if the stability of LULC transitions is taken into consideration. Clusters with forest stability or areas with low probability of transitioning to other land uses should be considered to form components of corridors and patches for restoration efforts. From a methodological point of view, Chapter 2 contributes through a novel methodology to extract broad or general patterns from pixel histories that come from classifications of unknown accuracy. The key elements in this method are the elimination of LULC trajectories that are not consistent with the realities and history of the study area, the stratification by geographic units, and the application of a clustering algorithm. This approach supports the further exploration of trends in areas where historical control data are not available.

Chapter 3 deals with the analysis of secondary forest. It was found that the succession of vegetation in the NEA is an incipient increasing process, but at increasing rates. At the farm-level, farmers reported that the proportion of successional vegetation of 5.2-percent in 1990 and 11.2-percent in 1999. For the entire NEA, remotely-sensed data indicates that the area of secondary forest increased between 1986 and 1996 (i.e., by 49,400 ha), but the

decreased by 19,400 ha between 1996 and 2002. Conversely, the area in *rastrojo* (or young succession) maintained relatively constant values between 1986 and 1996, but increased from 5,457 ha in 1996 to 16,796 ha in 2002. Although the information provided by farmers through the longitudinal survey, and that obtained through remotely sensed methods, are not directly comparable, both sources show that in the late 1990s there was an increase in the relative proportion of secondary forest, consistent at the farm- and landscape-levels.

The dynamics of secondary vegetation is partially caused by activities related to the oil industry and broad development efforts, specifically the impact on the transportation network, the growth of towns, and rising employment opportunities for farmers and young adults. There are a variety of factors that contribute to the generation of secondary vegetation, and although this study does not include data on prices of coffee and cacao, the drastic decrease in agricultural commodity prices starting in the late 1990s contributed to some abandonment of long-standing coffee crop and served to “push” farmers to seek alternative income in the agricultural labor or oil industry and in towns. "Push" factors from the farm as well as “pull” factors from growing towns can promote plot abandonment that promoted the regeneration of forest and fallow in previously cultivated sites. In practical terms, this research shows that some factors (e.g., off-farm employment) can contribute to the regeneration of forest and these results can be used as the basis for development and restoration programs that take into consideration the socioeconomic situation. From a theoretical point of view, this research shows that despite the fact that secondary forests are increasing in the NEA, the drivers of change are not likely to be compatible with those advocated in the Forest Transition theory. In the NEA, secondary forest is not the result of “development” per se, but occurs as a consequence of a series of factors, including land

abandonment, biophysical conditions, and off-farm employment.

In Chapter 4, this research has explored the use of different techniques to explore spatial dependence and spatial heterogeneity within the drivers of land change. This study determined how the relationships between different socioeconomic, demographic, and biophysical factors and land change are non-stationary across the Northern Ecuadorian Amazon. This implies that the intensity of the drivers of LULC change is different across space. This study has shown that important characteristics of the relationships can be simplified by “global” statistical models. In the NEA, for example, road accessibility affects LULC in different ways for different places. Discussions about the impact of roads on forests should take this into consideration: access affects deforestation in different ways depending upon geographic location. From a methodological point of view, Anselin and Bera (1998) argue that spatial dependence can also arise due to certain misspecifications, specifically, when there is a mismatch between the unit of measurement and the unit within the process. This research indicates that in the NEA there is strong spatial dependence for some variables, but that spatial dependence is caused by processes at work in the NEA, rather than produced by spatially-autocorrelated errors in the data or sampling issues. The advances in Land Change Science are centered on the use of spatial statistical models, i.e., Geographically Weighted Regression (GWR) and Spatial Lag Models (SLM), to explore the spatial dependence and spatial heterogeneity of the drivers of land use and land cover change, and to provide alternate ways of representation of parameters and outcomes.

Chapter 5 explains how a CA model for the Northern Ecuadorian Amazon has been created, with application to a smaller area, the NISA. The CA model simulated change in forest, pasture, agriculture, and urban/barren classes from 1986 to 2010. The main advance

and contribution of this CA model, and the difference with previous versions, is the direct use of demographic, socioeconomic, and biophysical variables collected through household surveys. This is possible due to the application of GWR and the use survey data to create spatial regimes that partially control CA dynamics. The synergism between GWR and spatial simulation methods has strong potential, especially when socioeconomic information (i.e., household survey data) is scattered across the landscape at survey farms used for the estimation of spatially-explicit models.

This CA model used methods to develop spatially continuous models derived from household information. The method is not an interpolation per se, but the use of spatial regimes is created according to the intensities of the drivers of LULC across space. The use spatial regimes can have utility in the implementation of other spatial simulations (e.g., agent based models) that are built using discrete units in space.

### **6.3. Main Challenges**

The challenges addressed in this research have several dimensions, specifically related to data, methods, and theoretical approaches. The first problem, and probably the main obstacle, was related to data and involves the accuracy of the Landsat image classifications. Commonly encountered, particularly in the multi-temporal analysis of frontier environments, is the lack of multi-temporal control data for the quantification of the error produced within the land use classification for earlier periods. The classifications used in this research were generated by the Ecuador Project Team using an hybrid method of classification (Frizzelle 2004; Messina and Walsh 2001; Walsh et al. 2002; Walsh et al. 2004). Unfortunately, the lack of ground control points for an overall accuracy assessment of the time-series is a limiting factor common to the Land Change Science and remote sensing

communities. Although ground control points were collected at various points in time between 1999 and 2004, which in practice would support an analysis of the accuracy for the 2002 classification, there is no exact match between ground control points and the 2002 image. The situation for the classifications for the period 1973-1996 is more severe because ground control points do not exist and other ancillary data (e.g., aerial photography) are inconsistent with the years of the classifications.

Thus analyses made at the pixel level should be interpreted with caution. The study of the LULC trajectories attempts to overcome the lack of a rigorous accuracy assessment and possible errors in the classification by identifying the main patterns after the extraction of illogical trajectories. New retrospective data, acquired in the field in 2007 about the age of secondary forest, coffee, and cacao farm patches, will support the development of an accuracy assessment to help improve estimates, especially related to secondary forest.

Other limitations of this research are related to the lack of information to explain processes that are less related to small household farms than to agro-industrial plantations (i.e., large scale agriculture, including African palm and *palmito*). Although this research makes use of the most comprehensive data source available for the Ecuadorian Amazon, the 1990 and 1999 longitudinal household data, these data are not sensitive to several processes that have occurred after 1999, specifically between the period 1999-2002 and beyond. These processes include the advance of the agro-industrial sector, specifically African palm and palmito plantations that are developed by small to medium scale entrepreneurs or companies. These plantations affect the landscape in significant ways but not always obey endogenous and exogenous factors related to households, more related to small or large commercial operations.

The issue of spatial scale is also important. In this analysis, despite the fact that the statistical models are carried out at a very basic level of geographic organization (i.e, farms), several different households often control (formally or informally) different portions of land within the farm, as in the case of subdivisions of "finca madres". Different management strategies may thus exist within the same farm, which are not captured in this research. Unfortunately, there are data limitations in terms of the lack of geodetic GPS data to precisely identify the subdivisions boundaries. Additionally, observations based on satellite imagery depend on their spatial resolution, which set the level of detail or scale of analysis.

The results of this research focus on small-farmer agricultural land use and land cover change. As such, the results of this research cannot be extended to areas where urban or suburban processes are at work in the NEA. The study area does not include protected areas or indigenous territories, but the NEA may include the effects of migrant indigenous groups that have settled as pre-cooperatives but still manage their land as a community (e.g., the Sardinas and Alama communities in Sucumbios).

In the case of the cellular automata simulations, the inability to replicate spatial patterns indicated by satellite data is related to the tradeoff between an improved predictive accuracy and a more theoretical deterministic model. This present model tries to conserve the complexity and not over-parameterize the model. However, this base model can be modified and fine-tuned to generate a more predictive model. Another challenge is the use of a flux class, a temporal class that encompasses agriculture, pasture, and succession within the simulation. The flux class was designed in earlier versions of the Ecuador CA model (Messina and Walsh 2001; Messina and Walsh 2005; Walsh et al. In Press-b) to capture nonlinearities and randomness in the system. However, land use classes within the flux class

respond to stimulus in different ways (i.e., direction and intensity) and the generation of scenarios is often limited.

#### **6.4. Rethinking Agricultural Frontiers**

This research finds that the processes of land use and land cover change in the Northern Ecuadorian Amazon, including the drivers of change and the spatial-explicit responses, are extremely diverse and heterogeneous across space and time. This is not a surprise, in a place characterized by its very high biological and cultural diversity. However, there is the perception that colonist areas are homogenous entities produced along deforestation fronts. This research has shown that there is high spatial heterogeneity in the transformation of land and in the drivers of such transformations. Frontiers are not static or homogenous, but they have different types of stratifications, in the case of the NEA, variations from core-periphery patterns in the land use systems to different spatial regimes in the factors that drive land change. The homogeneity of the Amazon Basin, a traditional assumption for many decades within governments of the region, is now characterized just as another myth (Amazonic Cooperation Agreement 1994). This characterization can be extended to specific colonist areas such as the NEA. The processes related to the advance of an agricultural frontier (i.e., migration and population growth, deforestation, socioeconomic and cultural change) create an area that is diverse. Although, the need for generalization is deeply rooted in scientific paradigms, the generation of models that capture intra-regional variability related to site-specific patterns will help to understand localized necessities for conservation and development hence assist in developing appropriate local policies.

#### **6.5. Implications to Future Research**

The vision for future research related to this dissertation lies within a population-

environment framework in broad terms, but in which this framework not only emphasizes demographic and socioeconomic factors and land use change but stresses the integration of the human-natural system. The study of population- environment relationships within the NEA will thus have two dimensions: first, a continuation of the research in the Ecuador Project that revolves around household survey design and data collection for statistical analysis and spatial simulation, and remote sensing and a second dimension, more applied to development and conservation with implications to everyday life of the inhabitants of the region. What follows is a review of research topics to be pursued and how they connect to this research.

Remote Sensing of Tropical Forests: The experience acquired during the analysis of remotely-sensed products suggests that the study of LULC in the Amazon, using “classical” classification schemes (e.g., supervised classification), is difficult to implement. On the other hand, it is widely accepted that the structure, condition, and dynamics of tropical forest is important to advance knowledge related to ecosystem productivity, landscape dynamics, and climate change, among others (Widlowski et al. 2004). Remote sensing is key to defining tropical forest parameters (Kerr and Ostrovsky 2003). The emphasis of future research will be on the analysis of the biotic characteristics of tropical forest, including biodiversity. The Ecuadorian Amazon offers unlimited opportunities for remote sensing, because the diversity of forested ecosystems (e.g., upland forest, forested wetlands, and cloud forests) occurs with different degrees of intervention (from pristine primary forest to heavily managed secondary forest). The analysis of the structure and dynamics of tropical forest will be easily extended to practical applications. For example, the development of an early warning system to control and monitor illegal selective logging, prevalent even in the Cuyaveno Reserve and the

Yasuní National Park, can be designed that includes use of image processing methods, such as mixture models and object-based image analysis.

Rural Households, Mobility, and Migration: Questions and hypothesis that extends from this research include the spatial and social characterization of internal and international migration and their effects on households, agriculture, and the environment. This research shows the strong effects of off-farm employment in land use and land cover change. Furthermore, different stages of fieldwork have demonstrated the cultural, social, and economic value of labor and the impacts that temporary migration (mobility) and international migration have on the conditions of rural households. While the effects of international migration on the environment via remittances is a topic that has received renewed attention (e.g., Hecht et al. 2006; Orozco 2002; VanWey et al. 2005), international migration into the Amazon is a relatively new phenomenon and new research on the topic is needed. The hypotheses revolve around the potential opportunities that different types of migration generate and how they influence the wellbeing of ecosystems and households. For example, the role of off-farm employment and forest regeneration, on the one hand, and how private and governmental oil companies can catalyze forest restoration through labor, on the other, is an important concern. A second example includes the study of the “mobilization” of indigenous communities within protected areas that respond to governmental or private strategies beyond the control of the communities.

Inequality, Vulnerability, and Resilience: Inequality, vulnerability, and resilience are intrinsically linked to issues of poverty and environmental degradation. Economic inequality is an essential component of different processes of degradation of ecosystems (Gray and Moseley 2005; Mikkelson et al. 2007) and an intrinsic component of the impoverishment of

communities. The different dimensions of vulnerability are difficult to quantify (Fussler 2007; Mioduch 1994); however, new conceptualizations of resilience of human-natural systems (e.g., Berkes and Seixas 2005; Walker et al. 2006) provide better alternatives to characterize how poverty, inequality, and the environment are related.

This research, and other advances within the Ecuador Project, provides a framework for the development of a more applied assessment of the geography of small farming communities (colonist and indigenous) in the Ecuadorian Amazon. Future research can usefully focus on specific communities located within or near protected areas with an emphasis in qualitative, spatial, and biotic data collection.

### **6.5.1 Spatially-Explicit Simulations**

The emphasis of spatial analysis and simulations can be developed within the context of inequality, vulnerability, and resilience, using Agent Based Models (ABM) as the primary tool. This research proposes to integrate and extend existing quantitative modeling methods in an innovative fashion to investigate complex human behavior in the context of an ABM that allows the generation of future scenarios. The approach also uses complexity theory as a framework to incorporate multiple behavioral models of human behavior in a simulation model to explore a number of plausible future scenarios involving environmental and population change and the emergence of economic opportunities. In the ABM work, specific aims will provide descriptive information on (1) the demographic system, (2) the ecological systems, and (3) the socio-economic system. Data collection and analysis will include: the analysis of demographic change using existing and proposed household survey data (1990, 1999, and 2008), and national census data, and analysis of land use and land cover change using remote sensing methods. ABMs will be used to integrate the endogenous and exogenous

factors and feedbacks among the three systems so that we can examine, for example, land abandonment, off-farm employment, migration, and tourism development scenarios.

## **6.6. Summation**

This research shows that agricultural frontier regions are heterogeneous and complex entities. This dissertation linked four interconnected questions that sought to generate new insights into the processes of land use and land cover change in the Northern Ecuadorian Amazon. The four papers included in this research demonstrate that the composition and spatial configuration of the land use and land cover (LULC) trajectories in the NEA have temporal and spatial patterns that emerge due to the effects of the combinations of different factors across time and space. This study has implications for broad theoretical and applied problems of spatial analysis, land change science, conservation, and development. For the author, this research is only the beginning of a lifetime set of applications of geographical knowledge to seek a better understanding of humans and the environment.

## REFERENCES

- Allen, T. F. H., and Starr, T. B. (1982). *Hierarchy: Perspectives for Ecological Complexity*, Chicago University Press, Chicago.
- Alonso, D., and Solé, R. (2000). "The DivGame Simulator: a stochastic cellular automata model of rainforest dynamics." *Ecological Modelling*, 133(1-2), 131-141.
- Amazonic Cooperation Agreement. (1994). *Amazonia Without Myths*, Amazonic Cooperation Agreement, Colombia.
- Anselin, L. (1988). *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers, Dordrecht.
- Anselin, L. (1990). "Spatial Dependence and Spatial Structural Instability in Applied Regression Analysis." *Journal of Regional Science*, 30(2), 185-207.
- Anselin, L. (2002). "Under the hood: issues in the specification and interpretation of spatial regression models." *Agricultural Economics*, 27(3), 247-267.
- Anselin, L. (2005). "Exploring Spatial Data with GeoDa: A workbook." Spatial Analysis Laboratory, University of Illinois, Urbana-Champaign.
- Anselin, L., and Bera, A. (1998). "Spatial dependence in linear regression models with an introduction to spatial econometrics." *Handbook of Applied Economic Statistics*, A. Ullah and D. Giles, eds., Marcel Dekker, New York, 237-289.
- Anselin, L., Syabri, I., and Kho, Y. (2006). "GeoDa: An Introduction to Spatial Data Analysis." *Geographical Analysis*, 38(1), 5-22.
- Atkinson, P. M., German, S. E., Sear, D. A., and Clark, M. J. (2003). "Exploring the relations between Riverbank Erosion and Geomorphological controls using Geographically Weighted logistic Regression." 35(1), 58(25).
- Badalamenti, F., D'Anna, G., Di Gregorio, S., Pipitone, C., and Trunfio, G. A. (2002). "A first Cellular Automata Model of Red Mullet Behaviour." *Emergence in Complex, Cognitive, Social, and Biological Systems*, G. Minati and E. Pessa, eds., Kluwer Academic, New York.
- Barbero, M., Bonin, G., Loisel, R., and Quézel, P. (1990). "Changes and disturbances of forest ecosystems caused by human activities in the western part of the mediterranean basin." *Plant Ecology*, V87(2), 151-173.

- Barbier, E. B., and Burgess, J. C. (2001). "Tropical Deforestation, Tenure Insecurity, and Unsustainability." *Forest Science*, 47(4), 497-509.
- Barbieri, A. F., Bilsborrow, R. E., and Pan, W. K. (2005). "Farm Household Lifecycles and Land Use in the Ecuadorian Amazon." *Population & Environment*, V27(1), 1-27.
- Barbieri, A. F., and Carr, D. L. (2005). "Gender-specific out-migration, deforestation and urbanization in the Ecuadorian Amazon." *Global and Planetary Change*, 47, 99-110.
- Barsky, O. (1984). *La Reforma Agraria Ecuatoriana*, Corporacion Editora Nacional, Quito.
- Batty, M., Xie, Y., and Sun, Z. (1999). "Modeling urban dynamics through GIS-based cellular automata." *Computers, Environment and Urban Systems*, 23(3), 205-233.
- Bell, K. P. (2005). "Spatial Analysis and Applied Land Use Research." *Land Use Problems and Conflicts*, S. Goetz, J. Shortle, and J. Bergstrom, eds., Routledge, New York.
- Bendicenti, S., Di Grogorio, F. M., and Iezzi, A. (2002). "Simulations of Forest Fires by Cellular Automata." *Emergence in Complex, Cognitive, Social, and Biological Systems*, G. Minati and E. Pessa, eds., Kluwer Academic, New York.
- Berkes, F. (2002). "Cross-scale Institutional Linkages: Perspectives from the Botton-Up." *The Drama of the Commons*, E. Ostrom, T. Dietz, N. Dolsak, P. C. Stern, S. Stonich, and E. U. Weber, eds., National Academy Press, Washington, DC.
- Berkes, F., and Seixas, C. S. (2005). "Building resilience in lagoon social-ecological systems: A local-level perspective." *Ecosystems* 8, 967-974.
- Bilsborrow, R. E. (2003). "Cambios Demográficos y Medio Ambiente en la Región Amazónica de los Países Andinos." *Amazonia: Procesos Demográficos y Ambientales.*, C. E. Aramburu and E. Bedoya, eds., Consorcio de Investigación Económica y Social, Lima, Peru.
- Bilsborrow, R. E., Barbieri, A., and Pan, W. (2004). "Changes in population and land use over time in the Ecuadorian Amazon." *Acta Amazonica*, 34(3), 635-647.
- Bilsborrow, R. E., and Carr, D. L. (2000). "Population, Agricultural Land Use and the Environment on Developing Countries." *Tradeoffs or Synergies? Agricultural Intensification, Economic Development and the Environment*, D. R. Lee and C. B. Barrett, eds., CABI Publishing, New York.
- Bilsborrow, R. E., and Geores, M. (1992). *Rural Popualtion Dynamics and Agricultural Development: Issues and Consequences in Latin America*, The Cornell International

- Institute for Food, Agriculture and Development, Ithaca, New York.
- Bilsborrow, R. E., McDevit, T. M., Kossoudji, S., and Fuller, R. (1987). "The Impact of Origin Community Characteristics, on Rural-Urban Out-Migration in a Developing Country." *Demography*, 24(2), 191-210.
- Bilsborrow, R. E., and Okoth-Ogendo, H. (1992). "Population-Driven Changes in Land Use in Developing Countries." *Ambio*, 21(1), 37-45.
- Blackman, T. (2000). "Complexity Theory." *Understanding Contemporary Society: Theories of the Present*, G. Browning, A. Halcli, and F. Webster, eds., Sage Publications, London.
- Boserup, E. (1965). *The Conditions of Agricultural Growth. The Economics of Agriculture under Population Pressure*, Earthscan, London.
- Boserup, E. (1981). *Population and Technological Change*, The University of Chicago Press, Chicago.
- Bromley, D. (1989). *Economic Interests and Institutions: The Conceptual Foundation of Public Policy*, Blackwell Publishers, Oxford.
- Bromley, D. W. (1992). "The Cosmos, Property, and Common-Property Regimes." *Making the Commons Work: Theory, Practice, and Policy*, D. W. Bromley, ed., ICS Press, San Francisco, CA.
- Brook, B. W., Sodhi, N. S., and Ng, P. K. L. (2003). "Catastrophic extinctions follow deforestation in Singapore." *Nature*, 424(6947), 420-426.
- Brookfield, H. (2004). "American geography and one non-American geographer." *GeoJournal*, V59(1), 39-41.
- Brown, D., Page, S., Riolo, R., Zellner, M., and Rand, W. (2005). "Path dependence and the validation of agent-based spatial models of land use." *International Journal of Geographical Information Science*, 19(2), 153-174.
- Brown, L. A. (1991). *Place, Migration, and Development in the Third World: An Alternative View*, Routledge, London and New York.
- Brown, S., and Lugo, A. E. (1990). "Tropical secondary forests." *Journal of Tropical Ecology*, 6, 1-32.
- Bruijnzeel, L. A. (2004). "Hydrological functions of tropical forests: not seeing the soil for

- the trees?" *Agriculture, Ecosystems & Environment*, 104(1), 185-228.
- Brunsdon, C., Fotheringham, S., and Charlton, M. (1998). "Geographically Weighted Regression." *Journal of the Royal Statistical Society: Series D (The Statistician)*, 47(3), 431-443.
- Burel, F., and Baudry, J. (2003). *Landscape Ecology: Concepts, Methods, and Applications*, Science Publishers, Plymouth, UK.
- Bürgi, M., Hersperger, A. M., and Schneeberger, N. (2005). "Driving forces of landscape change — current and new directions." *Landscape Ecology*, V19(8), 857-868.
- Calvo, E., and Escolar, M. (2003). "The Local Voter: A Geographically Weighted Approach to Ecological Inference." *American Journal of Political Science*, 47(1), 189-204.
- Cancian, F. (1989). "Economic Behavior in Peasant Communities." *Economic Anthropology*, S. Plattner, ed., Stanford University Press, Stanford, CA, 128-170.
- Cannon, T. (1995). "Indigenous peoples and food entitlement losses under the impact of externally-induced change." *GeoJournal*, V35(2), 137-150.
- Cao, C., and Lam, N. S. (1997). "Understanding the Scale and Resolution Effects in remote Sensing and GIS." *Scale in Remote Sensing and GIS*, D. A. Quattrochi and M. F. Goodchild, eds., CRC Press, New York.
- Cash, D. W., and Moser, S. C. (2000). "Linking global and local scales: designing dynamic assessment and management processes." *Global Environmental Change*, 10(2), 109-120.
- Castro, K. L., Sanchez-Azofeifa, G. A., and Rivard, B. (2003). "Monitoring secondary tropical forests using space-borne data: implications for Central America." *International Journal of Remote Sensing*, 24(9), 1853-1894.
- Center for International Forest Research. (2002). "Secondary Forest: a Neglected Resource." *CIFOR News*, 1.
- Chayanov, A. V. (1966). *Theory of Peasant Economy*, Richard Irwin, Homewood, Illinois.
- Chokkalingam, U., and De Jong, W. (2001). "Secondary Forest: a working definition and typology." *International Forestry Review*, 3(1), 1926.
- Chokkalingam, U., Smith, J., De Jong, W., and Sabogal, C. (2001). "A conceptual framework for the assessment of tropical secondary forest dynamics and sustainable development

- potential in Asia." *Journal of Tropical Forest Science*, 13(4), 577-600.
- Chomitz, K. M., and Gray, D. A. (1996). "Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize." *The World Bank Economic Review*, 10(3), 487-512.
- Chorley, R. J., and Kennedy, B. A. (1971). *Physical Geography: A System Approach*, Prentice-Hall, London.
- Chowdhury, R. R., and Turner, B. L. (2006). "Reconciling Agency and Structure in Empirical Analysis: Smallholder Land Use in the Southern Yucatán, Mexico." *Annals of the Association of American Geographers*, 96(2), 302-322.
- Clark, W. A. V., and Hosking, P. L. (1986). *Statistical Methods for Geographers*, Wiley, New York.
- Clarke, K. C., and Gaydos, J. C. (1998). "Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore." *International Journal of Geographical Information Science*, 12(7), 699 - 714.
- Coomes, O. T. (1992). "Blackwater Rivers, Adaptation, and Environmental Heterogeneity in Amazonia." *American Anthropologist*, 94(3), 698-701.
- Coomes, O. T., Grimard, F., and Burt, G. J. (2000). "Tropical forest and shifting cultivation: secondary forest fallow dynamics among traditional farmers of the Peruvian Amazon." *Ecological Economics*, 32, 109-124.
- Cramer, W., Bondeau, A., Schaphoff, S., Lucht, W., Smith, B., and Sitch, S. (2004). "Tropical forests and the global carbon cycle: impacts of atmospheric carbon dioxide, climate change and rate of deforestation." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 359(1443), 331-343.
- Crews-Meyer, K. A. (2002). "Characterizing landscape dynamism using paneled-pattern metrics." *Photogrammetric Engineering and Remote Sensing*, 68(10), 1031-1040.
- Crews-Meyer, K. A. (2004). "Landscape Change and Stability: Historical Patch-Level Analysis." *Agriculture, Ecosystems, and Environment* 101, 155-169.
- Davis, K. (1963). "The Theory of Change and Response in Modern Demography History." *Population Index*, 29(4), 345-666.
- de Almeida, C., Monteiro, A., Soares, G., Cerqueira, G., Pennachin, C., and Batty, M. (2005). "GIS and remote sensing as tools for the simulation of urban land-use

- change." *International Journal of Remote Sensing*, 26(4), 759-774.
- de Almeida, C. M., Batty, M., Vieira Monteiro, A. M., Camara, G., Soares-Filho, B. S., Cerqueira, G. C., and Pennachin, C. L. (2003). "Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation." *Computers, Environment and Urban Systems*, 27(5), 481-509.
- De Jong, W., Freitas, L., Baluarte, J., Van de Kop, P., Salazar, A., Inga, E., Melendez, W., and Germana, C. (2001). "Secondary forest dynamics in the Amazon floodplain in Peru." *Forest Ecology and Management*, 150(136-146), 135-146.
- de Koning, C. H. J. (1999). "Spatially Explicit Analysis of Land Use Change: a case study for Ecuador," Doctoral Thesis, Wageningen Agricultural University, Wageningen, The Netherlands.
- de Sherbinin, A. (2000). "Population, Development, and Human Security: a micro-level perspective." *Aviso*, an information bulletin on global environmental change and human security, 9-15.
- Dirzo, R., and Raven, P. H. (2003). "Global State of Biodiversity Loss." *Annual Review of Environment and Resources*, 28(1), 137-167.
- ECORAE. (1996). *Estadísticas Básicas de la Región Amazónica Ecuatoriana*, ECORAE, Quito.
- Ehrhardt-Martinez, K. (1998). "Social determinants of deforestation in developing countries: a cross - national study." *Social Forces*, 77(2), 567-572.
- Energy Information Administration. (2003). "Recent estimations of world crude reserves, <http://www.eia.doe.gov/emeu/international/reserves.html> 10/1/03."
- Entwisle, B., and Stern, P. C. (2005). "Population, Land Use, and Environment: Research Directions." National Academy Press, Washington, DC.
- Fahrig, L. (2003). "Effects of habitat fragmentation on biodiversity." *Annual Review of Ecology, Evolution, and Systematics*, 34(1), 487-515.
- Fearnside, P. M. (1993). "Deforestation in Brazilian Amazonia: The effect of Population and Land Tenure." *Ambio*, 22(8), 537-545.
- Fearnside, P. M. (1996). "Carbon uptake by secondary forest in Brazilian Amazon." *Forest Ecology and Management*, 80, 35-46.

- Fearnside, P. M. (2000). "Global Warming and Tropical Land-Use Change: Greenhouse Gas Emissions from Biomass Burning, Decomposition and Soils in Forest Conversion, Shifting Cultivation and Secondary Vegetation." *Climatic Change*, V46(1), 115-158.
- Feddema, J. J., Oleson, K. W., Bonan, G. B., Mearns, L. O., Buja, L. E., Meehl, G. A., and Washington, W. M. (2005). "The Importance of Land-Cover Change in Simulating Future Climates." *Science*, 310(5754), 1674-1678.
- Florax, R. J. G. M., and Van der Vlist, A. J. (2003). "Spatial Econometric Data Analysis: Moving Beyond Traditional Models." *International Regional Science Review*, 26(3), 223-243.
- Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., and Snyder, P. K. (2005). "Global Consequences of Land Use." *Science*, 309(5734), 570-574.
- Food and Agriculture Organization. (2000). "Commented Bibliography: Forest cover changes in Ecuador." Food and Agriculture Organization, Rome.
- Food and Agriculture Organization. (2001). "Global Forest Resource Assessment 2000." FAO, Rome.
- Food and Agriculture Organization. (2005). "Global Forest Resource Assessment 2005." FAO, Rome.
- Foody, G. M. (2002). "Status of land cover classification accuracy assessment." *Remote Sensing of Environment*, 80(1), 185-201.
- Foody, G. M. (2003). "Geographical weighting as a further refinement to regression modelling: An example focused on the NDVI-rainfall relationship." *Remote Sensing of Environment*, 88(3), 283-293.
- Foody, G. M. (2004a). "GIS: stressing the geographical." *Progress in Physical Geography*, 28(1), 152-158.
- Foody, G. M. (2004b). "Spatial nonstationarity and scale-dependency in the relationship between species richness and environmental determinants for the sub-Saharan endemic avifauna." *Global Ecology and Biogeography*, 13(4), 315-320.
- Foody, G. M., and Curran, P. J. (1994). "Estimation of tropical forest extent and regenerative stage using remotely sensed data." *Journal of Biogeography*, 21, 223-

- Fotheringham, A. S., Brunson, C., and Charlton, M. (2002). *Geographically Weighted Regression*, Wiley, West Sussex, England.
- Fotheringham, A. S., and Wegener, M. (2000). "New Spatial Models: Achievements and Challenges." *Spatial Models and GIS: New potential and new models*, A. S. Fotheringham and M. Wegener, eds., Taylor & Francis, Philadelphia.
- Frizzelle, B. G. (2004). "NASA-Ecuador Image Rectification Overview." Spatial Analysis Unit - Carolina Population Center, Unpublished Report, 1.
- Fussler, H.-M. (2007). "Vulnerability: A generally applicable conceptual framework for climate change research." *Global Environmental Change*, 17(2), 155-167.
- Gardner, R. H. (1998). "Pattern, Process, and the Analysis of Spatial Scale." *Ecological Scale: Theory and Applications*, D. L. Peterson and V. T. Parker, eds., Columbia University Press, New York.
- Gaston, K. J., Blackburn, T. M., and Goldewijk, K. (2003). "Habitat conversion and global avian biodiversity loss." *Proceedings of the Royal Society B: Biological Sciences*, 270(1521), 1293-1300.
- Geist, H. J., and Lambin, E. F. (2001). *What Drives Tropical Deforestation? A meta-Analysis of proximate and underlying causes of deforestation based on subnational case study evidence.*, Lucc International Project Office, Louvain-la-Neuve.
- Geist, H. J., and Lambin, E. F. (2002). "Proximate Causes and Underlying Driving Forces of Tropical Deforestation." *BioScience*, 52(2), 143-150.
- GeoDa. (2007). "GeoDa Glossary." Spatial Analysis Lab, University of Illinois, Urbana-Champaign, Ill.
- Geoghegan, J., Cortina-Villar, S., Klepeis, P., Mendoza, P. M., Ogneva-Himmelderger, Y., Chowdhury, R. R., Turner, B. L., and Vance, C. (2001). "Modeling tropical deforestation in the southern Yucatan penninsular region: comparing survey and satellite data." *Agriculture Ecosystems and Environment*, 85(1), 25-46.
- Godoy, R., and Contreras, M. (2001). "A Comparative Study of Education and Tropical Deforestation among Lowland Bolivian Amerindians: Forest Values, Environmental Externality, and School Subsidies." *Economic Development and Cultural Change*, 19(3), 555-574.

- Godoy, R., O'Neill, K., Groff, S., Kostishack, P., Cubas, A., Demmer, J., McSweeney, K., Overman, J., Wilkie, D., Brokaw, N., and Martinez, M. (1997). "Household determinants of deforestation by amerindians in honduras." *World Development*, 25(6), 977-987.
- Godoy, R., Reyes-Garcia, V., Byron, E., Leonard, W. R., and Vadez, V. (2005a). "The effect of market economies on the well-being of indigenous peoples and on their use of renewable natural resources." *Annual Review of Anthropology*, 34(1), 121-138.
- Godoy, R., Reyes-Garcia, V., Byron, E., Leonard, W. R., and Vadez, V. (2005b). "The effect of market economies on the well-being of indigenous peoples and on their use of renewable natural resources." *Annual Review of Anthropology*, 34(1), 121-138.
- Godoy, R., and Wilkie, D. (1997). "The Effects of Markets on Neotropical Deforestation: A Comparative Study of Four Amerindian Societies." *Current Anthropology*, 38(5), 875-878.
- Goetz, S., Shortle, J., and Bergstrom, J. (2004). *Land Use Problems and Conflicts: Causes, Consequences and Solutions*, Routledge, London.
- Goodchild, M. F., and Quattrochi, D. A. (1997). "Scale, Multiscaling, Remote Sensing and GIS." Scale in Remote Sensing and GIS, D. A. Quattrochi and M. F. Goodchild, eds., CRC Press, New York.
- Gradus, Y., and Lithwick, H. (1996). "Frontiers in Regional Development." Rowman & Littlefield, Lanham, MD.
- Gray, L. C., and Moseley, W. G. (2005). "A geographical perspective on poverty-environment interactions." *The Geographical Journal*, 171(1), 9-23.
- Grove, R. (1992). "Origins of Western Environmentalism." *Scientific American*, 267(1), 42-47.
- Gunderson, L. H., and Hollings, C. S. (2002). *Panarchy: Understanding Transformations in Human and Natural Systems*, Island Press, Washington, DC.
- Gustafson, E. J. (1998). "Quantifying Landscape Spatial Pattern: What is the State of the Art?" *Ecosystems*, 1, 143-156.
- Gustafson, E. J., Hammer, R. B., Radeloff, V. C., and Potts, R. S. (2005). "The Relationship between Environmental Amenities and Changing Human Settlement Patterns between 1980 and 2000 in the Midwestern USA." *Landscape Ecology*, 20(7), 773-789.

- Hanna, S., Floke, C., and Mäler, K.-G. (1996). "Property Rights and the Natural Environment." *Right to Nature: Ecological, Economics, Cultural, and Political Principles of Institutions for the Environment*, S. Hanna, C. Floke, and K.-G. Mäler, eds., Island Press, Washington, DC.
- Hardin, G. (1968). "The Tragedy of the Commons." *Science*, 152, 1248.
- Hecht, S. B., Kandel, S., Gomes, I., Cuellar, N., and Rosa, H. (2006). "Globalization, Forest Resurgence, and Environmental Politics in El Salvador." *World Development*, 34(2), 308-323.
- Hollings, C. S., and Sanderson, S. (1996). "Dynamics of (Dis)harmony in Ecological and Social Systems." *Right to Nature: Ecological, Economics, Cultural, and Political Principles of Institutions for the Environment*, S. Hanna, C. Floke, and K.-G. Mäler, eds., Island Press, Washington, DC.
- Holt, F. L., Bilsborrow, R. E., and Oña, A. (2004). *Demography, Household Economics, and Land and Resource Use of Five Indigenous Populations in the Northern Ecuadorian Amazon: A Summary of Ethnographic Research*, Carolina Population Center Occasional Paper, Chapel Hill, NC.
- Houghton, R. A., Skole, D. L., Nobre, C. A., Hackler, J. L., Lawrence, K. T., and Chomentowski, W. H. (2000). "Annual Fluxes of Carbon from Deforestation and Regrowth in the Brazilian Amazon." *Nature*, 403(20 January), 301-304.
- Idrisi. (2006). *Idrisi Andes Manual*, Clark Labs, Worcester, MA.
- Jantz, C. A., Goetz, S. J., and Shelley, M. K. (2003). "Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area." *Environment and Planning B*, 30, 251-271.
- Kaimowitz, D., and Angelsen, A. (1998). *Economic Models of Tropical Deforestation: A Review*, Center for International Forestry Research, Bogor, Indonesia.
- Kammesheidt, L. (2002). "Perspectives on Secondary Forest Management in Tropical Humid Lowland America." *Ambio*, 31(3), 243-250.
- Kaufman, L., and Rousseeuw, P. J. (1990). *Finding groups in data. an introduction to cluster analysis*, Wiley, New York.
- Kerr, J. T., and Ostrovsky, M. (2003). "From space to species: ecological applications for remote sensing." *Trends in Ecology & Evolution*, 18(6), 299-305.

- Keshari, K., Bilborrow, R. E., and Murphy, L. (1996). "Deforestation, Land Use, and Women's Agricultural Activities in the Ecuadorian Amazon." *World Development*, 24(8), 1317-1332.
- Kimes, D. S., Nelson, R. F., Salas, W. A., and Skole, D. (1999). "Mapping Secondary Tropical Forest Age from Spot HRV data." *International Journal of Remote Sensing*, 20(18), 3625-3640.
- Kimes, D. S., Nelson, R. F., Skole, D. L., and Salas, W. A. (1998). "Accuracies in Mapping Secondary Tropical Forest Age from sequential Satellite Imagery." *Remote Sensing of Environment*, 65, 112-120.
- Klooster, D. (2003). "Forest Transitions in Mexico: Institutions and Forest in a Globalized Countryside." *The Professional Geographer*, 55(2), 227-237.
- Kratsas, R., and Parnell, J. (2001). "An industrial Perspective on Environmental and Social Issues in Oil and Gas Development." *Footprints in the Jungle*, I. Bowles and G. Prickett, eds., Oxford University Press, Oxford.
- Krugman, P. R. (1991). "Increasing returns and economic geography." *Journal of Political Economy* 99, 483-499.
- Lambin, E. F. (2000). "Are Agricultural Land-Use Models Able to Predict Changes in Land Use Intensity?" *Agriculture, Ecosystems and Environment*, 82, 321-331.
- Lambin, E. F., Geist, H., and Rindfuss, R. R. (2006). "Introduction: Local Process with Global Impacts." *Land-use and Land-cover change: Local processes, global impacts*, L. E.F. and G. H, eds., Springer, Berlin.
- Lambin, E. F., Turner II, B. L., Geist, H. J., Agbola, S., Bruce, J., Coomes, O., Dirzo, R., Fischer, G., Folke, C., George, P., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E., Mortimore, M., Ramakrishnan, P., Richards, J., Skanes, H., and Steffe, W. (2001). "The causes of land-use and land-cover change: moving beyond the myths." *Global Environmental Change*, 11, 261-269.
- Laurance, W. (2004). "Forest-climate interactions in fragmented tropical landscapes." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 359(1443), 345-352.
- Laurance, W. F., Lovejoy, T. E., Vasconcelos, H. L., Bruna, E. M., Didham, R. K., Stouffer, P. C., Gascon, C., Bierregaard, R. O., Laurance, S. G., and Sampaio, E. (2002). "Ecosystem Decay of Amazonian Forest Fragments: a 22-Year Investigation." *Conservation Biology*, 16(3), 605-618.

- Lee, D. R., Ferraro, P. J., and Barrett, C. B. (2000). "Introduction: Changing Perspectives on Agricultural Intensification, Economic Development and the Environment." Tradeoffs or Synergies? Agricultural Intensification, Economic Development and the Environment, D. R. Lee and C. B. Barrett, eds., CABI Publishing, New York.
- Levin, S. A. (1992). "The Problem of Pattern and Scale in Ecology: The Robert H. MacArthur Award Lecture." *Ecology*, 73(6), 1943-1967.
- Levy, P. E., Friend, A. D., White, A., and Cannell, M. G. R. (2004). "The Influence of Land Use Change On Global-Scale Fluxes of Carbon from Terrestrial Ecosystems'." *Climatic Change*, V67(2), 185-209.
- Lewis, S. (2006). "Review. Tropical forests and the changing earth system." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 361(1465), 195-210.
- Li, X., and Yeh, A. G.-O. (2002). "Neural-network-based cellular automata for simulating multiple land use changes using GIS." *International Journal of Geographical Information Science*, 16(4), 323 - 343.
- Longley, P. A., and Tobon, C. (2004). "Spatial Dependence and Heterogeneity in Patterns of Hardship: An Intra-Urban Analysis." *Annals of the Association of American Geographers*, 94(3), 503-519.
- Lu, D., Mausel, P., Brondizio, E., and Moran, E. (2004). "Change detection techniques." *International Journal of Remote Sensing*, 25(12), 2365-2407.
- Lunetta, R. (1999). "Applications, Project Formulation, and Analytical Approach." Remote Sensing Change Detection: Environmental Monitoring Methods and Applications., R. Lunetta and C. Elvidge, eds., Taylor and Francis Ltd., London.
- Malthus, T. R. (1803). *On Population (First Essay on Population, 1798)*, Reprint, Modern Library of Random House, New York.
- Manson, S. M. (2000). "Simplifying complexity: a review of complexity theory." *Geoforum*, 32, 405-414.
- Marquette, C. (1998). "Land use patterns among small farmers settlers in the Northeast Ecuadorian Amazon." *Human Ecology: An Interdisciplinary Journal*, 26(4), 573(2).
- Mather, A. S. (2000). "North-south challenges in global forestry." Forest transition and deforestation: global perspectives, M. Palo and H. Vanhanen, eds., Kluwer Academic Publisher, Dordrecht.

MathSoft. (1999). *S-Plus 2000 Guide to Statistics*, MathSoft, Seattle, Wa.

Mayle, F., Beerling, D., Gosling, W., and Bush, M. (2004). "Responses of Amazonian ecosystems to climatic and atmospheric carbon dioxide changes since the last glacial maximum." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 359(1443), 499-514.

McCracken, S., Brondizio, E., Nelson, D., Moran, E., Siqueira, A., and Rodriguez-Perraza, C. (1999). "Remote Sensing and GIS at the Farm Property Level: Demography and Deforestation in the Brazilian Amazon." *Photogrammetric Engineering and Remote Sensing*, 65(11), 1311-1320.

McGarigal, K., Cushman, S. A., Neel, M. C., and Ene, E. (2002). "FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps." University of Massachusetts, Amherst, MA.

Meadows, D. H., Meadows, D. I., Randers, J., and W.W., B. (1972). *The Limits to Growth*, Universe Books, New York.

Mena, C. F., Barbieri, A. F., Walsh, S. J., Erlie, C. M., Holt, F. L., and Bilsborrow, R. E. (2006a). "Pressure on the Cuyabeno Wildlife Reserve: Development and Land Use/Cover Change in the Northern Ecuadorian Amazon." *World Development*, 34(10), 1831-1849.

Mena, C. F., Bilsborrow, R. E., and McClain, M. E. (2006b). "Deforestation in the Napo Basin: Socioeconomic Factors, Spatial Patterns, and Metrics." *Environmental Management*, 37(6), 802-815.

Mertens, B., and Lambin, E. F. (2000). "Land-Cover-Change Trajectories in Southern Cameroon." *Annals of the Association of American Geographers*, 90(3), 467-494.

Messina, J. P. (2001). "A Complex Systems Approach to Dynamic Spatial Simulation Modeling: Landuse and Landcover Change in the

Ecuadorian Amazon," University of North Carolina, Chapel Hill.

Messina, J. P., and Walsh, S. J. (2001). "2.5 Morphogenesis: modeling landuse and landcover dynamics in the Ecuadorian Amazon." *Plant Ecology*, 156(1), 75-88.

Messina, J. P., and Walsh, S. J. (2005). "Dynamic spatial simulation modeling of population-environment matrix in the Ecuadorian Amazon." *Environment and Planning B: Planning and Design*, 32, 835-856.

- Mikkelsen, G., Gonzalez, A., and Peterson, G. (2007). "Economic Inequality Predicts Biodiversity Loss." *PLoS ONE* 2(3), e444.
- Mobley, L., Root, E., Anselin, L., Lozano-Gracia, N., and Koschinsky, J. (2006). "Spatial analysis of elderly access to primary care services." *International Journal of Health Geographics*, 5(1), 19.
- Mocduch, J. (1994). "Poverty and vulnerability." *American Economic Review*, 84(2), 221.
- Moran, E. F. (1991). "Human Adaptive Strategies in Amazonian Blackwater Ecosystems." *American Anthropologist*, 93, 361-382.
- Moran, E. F. (1993). "Deforestation and Land Use in the Brazilian Amazon." *Human Ecology*, 21(1), 1-21.
- Moran, E. F., Brondizio, E. S., Tucker, J. M., da Silva-Forsberg, M. C., McCracken, S., and Faldesi, I. (2000). "Effects of soil fertility and land-use on forest succession in Amazonia." *Forest Ecology and Management*, 139(1-3), 93-108.
- Moran, P. A. P. (1948). "The Interpretation of Statistical Maps." *Journal of the Royal Statistical Society B*, 10(2), 243-251.
- Myers, N. (1988). "Threatened Biotas "Hot Spots" in Tropical Forest." *The Environmentalist*, 8(3), 187-208.
- Myers, N. (1990). "The Biodiversity Challenge: Expanded Hot-Spots Analysis." *The Environmentalist*, 10(4), 243-156.
- National Research Council. (1999a). *Human Dimensions of Global Environmental Change: Research Pathways for the Next Decade* National Academy Press, Washington, DC.
- National Research Council. (1999b). *Our Common Journey: A Transition Toward Sustainability* National Academy Press, Washington, DC.
- Nelson, G. C. (2002). "Introduction to the special issue on spatial analysis for agricultural economists." *Agricultural Economics*, 27(3), 197-200.
- Nelson, G. C., Harris, V., and Stone, S. W. (2001). "Deforestation, Land Use, and Property Rights: Empirical Evidence from Darien, Panama." *Land Economics*, 77(2), 187.
- Oberkampf, W. L., Helton, J. C., Joslyn, C. A., Wojtkiewicz, S. F., and Ferson, S. (2004). "Challenge problems: uncertainty in system response given uncertain parameters." *Reliability Engineering & System Safety*, 85(1-3), 11-19.

- Ochoa-Gaona, S., and Gonzales-Espinosa, M. (2000). "Land use and deforestation in the highlands of Chiapas, Mexico." *Applied Geography*, 20, 17-42.
- Orme, C. D. L., Davies, R. G., Burgess, M., Eigenbrod, F., Pickup, N., Olson, V. A., Webster, A. J., Ding, T.-S., Rasmussen, P. C., Ridgely, R. S., Stattersfield, A. J., Bennett, P. M., Blackburn, T. M., Gaston, K. J., and Owens, I. P. F. (2005). "Global hotspots of species richness are not congruent with endemism or threat." *Nature*, 436(7053), 1016-1019.
- Orozco, M. (2002). "Globalization and Migration: The Impact of Family Remittances in Latin America." *Latin American Politics & Society*, 44(2), 41.
- Ortiz, S. (1973). *Uncertainties in Peasant Farming*, Athlone Press, London.
- Overmars, K. P., de Koning, C. H. J., and Veldkamp, A. (2003). "Spatial Autocorrelation in Multi-scale Land Use Models." *Ecological Modelling*, 164(2-3), 257-270.
- Palacios, W., Ceron, C., Valencia, R., and Sierra, R. (1999). "Formaciones Naturales del la Amazonía Ecuatoriana." Propuesta Preliminar de un Sistema de Clasificación de Vegetación para el Ecuador Continental, R. Sierra, ed., Proyecto INEFAN/GEF-BIRF y EcoCiencia, Quito, Ecuador.
- Pan, W., and Bilborrow, R. (2001). "Changes in ecuadorian farm composition over time - population pressures, migration, and changes in land use." Carolina Population Center, Cahpel Hill.
- Pan, W. K. Y., and Bilborrow, R. E. (2005). "The use of a multilevel statistical model to analyze factors influencing land use: a study of the Ecuadorian Amazon." *Global and Planetary Change*, 47(2-4), 232-252.
- Pan, W. K. Y., Walsh, S. J., Bilborrow, R. E., Frizzelle, B. G., Erlie, C. M., and Baquero, F. (2004). "Farm-level models of spatial patterns of land use and land cover dynamics in the Ecuadorian Amazon." *Agriculture, Ecosystems and Environment*, 101, 117-134.
- Parayil, G., and Tong, F. (1998). "Pasture-led to logging-led deforestation in the Brazilian Amazon." *Global Environmental Change*, 8(1), 63-79.
- Patten, B. C. (1959). "An Introduction to the Cybernetics of the Ecosystems: The Trophic-Dynamic Aspect." *Ecology*, 40(221-231).
- Patz, J. A., Tabor, P. D. G. M., Aguirre, A., Pearl, M., Epstein, J., Wolfe, N. D., Kilpatrick, M., Foufopoulos, J., Molyneux, D., and Bradley, D. J. (2004). "Unhealthy

- Landscapes: Policy Recommendations on Land Use Change and Infectious Disease Emergence " *Environmental Health Perspectives*, 112(10), 1092-1098.
- Perz, S. G. (2007). "Grand Theory and Context-Specificity in the Study of Forest Dynamics: Forest Transition Theory and Other Directions." *The Professional Geographer*, 59(1), 105-114.
- Perz, S. G., and Skole, D. (2003a). "Secondary Forest Expansion in the Brazilian Amazon and the Refinement of Forest Transition Theory." *Society and Natural Resources*, 16(4), 277-294.
- Perz, S. G., and Skole, D. (2003b). "Social Determinants of Secondary Forest in the Brazilian Amazon." *Social Science Research*, 32(1), 25-60.
- Perz, S. G., and Walker, R. T. (2002). "Household Life Cycles and Secondary Forest Cover Among Small Farmer Colonist in the Amazon." *World Development*, 30(6), 1009-1027.
- Pestel, E. (1989). *Beyond the Limits to Growth*, Universe Books, New York.
- Pichón, F. (1997). "Settler Households and Land - Use Patterns in the Amazon Frontier: Farm - Level Evidence from Ecuador." *World Development*, 25(1), 67-91.
- Pichón, F., and Bilsborrow, R. E. (1999). "Land Use Systems, Deforestation, and Demographic Factors in the Humid Tropics: Farm-Level Evidence from Ecuador." Population and Deforestation in the Humid Tropics, R. E. Bilsborrow and D. Hogan, eds., International Union for the Scientific Study of Population, Liege, Belgium.
- Pichón, F., Marquette, C., Murphy, L., and Bilsborrow, R. E. (2002). "Endogenous Patterns and Processes of Settler Land Use and Forest Change in the Ecuadorian Amazon." Deforestation and Land Use in the Amazon, C. Wood and R. Porro, eds., University Press of Florida, Gainesville, FL.
- Pichón, F. J. (1996). "The forest conversion process: A discussion of the sustainability of predominant land uses associated with frontier expansion in the Amazon." *Agriculture and Human Values*, V13(1), 32-51.
- Pickett, S. T. A., and Cadenasso, M. L. (1995). "Landscape ecology: spatial heterogeneity in ecological systems.(Frontiers in Biology: Ecology)(Cover Story)." (*Frontiers in Biology: Ecology*)(Cover Story), v269(n5222), p331(4).
- Pitman, N. C., Terborgh, J. N., Silman, M. R., Nunez, P., Neill, D., Ceron, C., and W.A.Palacios. (2003). "A Comparison of Tree Species Diversity in Two Upper

- Amazonian Forests." *Ecology*, 83(11), 3210-3224.
- Pitman, N. C. A., Jorgensen, P. M., Williams, R. S. R., Leon-Yanez, S., and Valencia, R. (2002). "Extinction-Rate Estimates for a Modern Neotropical Flora." *Conservation Biology*, 16(5), 1427-1431.
- Puyravaud, J.-P. (2003). "Standardizing the calculation of the annual rate of deforestation." *Forest Ecology and Management*, 177(1-3), 593-596.
- Ramankutty, N., Graumlich, L., Achard, F., Alves, D., Chhabra, A., DeFries, R., Foley, J. A., Geist, H., Houghton, R. A., Klein Goldewijk, K., Lambin, E. F., Rasmussen, K., Reid, R., and Turner, B. I. (2006). "Global land cover change: Recent progress, remaining challenges." *Land-use and Land-cover change: Local processes, global impacts*, L. E.F. and G. H, eds., Springer, Berlin.
- Reginster, I., and Rounsevell, M. (2006). "Scenarios of future urban land use in Europe." *Environment and Planning B*, 33(4), 619-636.
- Ricardo, D. (1887). *Letters of David Ricardo to Thomas Malthus, 1810-1823.*, Clarendon Press, London.
- Rignot, E., Salas, W. A., and Skole, D. L. (1997). "Mapping Deforestation and Secondary Growth in Rondonia, Brazil, Using Imaging Radar and Thematic Mapper Data." *Remote Sensing of Environment*, 59, 167-179.
- Rindfuss, R., Entwisle, B., Walsh, S., Mena, C., Erlien, C., and Gray, C. (In Press). "Frontier Land Use Change: Synthesis and Next Steps." *Annals of the Association of American Geographers*.
- Rudel, T. (1995). "When Do Property Rights Matter? Open Access, Informal Social Controls, and Deforestation in the Ecuadorian Amazon." *Human Organization*, 54(2), 187-194.
- Rudel, T. (2005). *Tropical forests: regional paths of destruction and regeneration in the late twentieth century*, Columbia University Press, New York, NY.
- Rudel, T., Bates, D., and Machinguiashi, R. (2002). "A Tropical Forest Transition? Agricultural Change, Out-Migration, and Secondary Forests in the Ecuadorian Amazon." *Annals - Association of American Geographers*, 92(1), 87-102.
- Rudel, T., and Horowitz, B. (1993). *Tropical Deforestation: Small Farmers and Forest Clearing in the Ecuadorian Amazon*, Columbia University Press, New York.

- Rudel, T., and Roper, J. (1997). "The Paths to Rain Forest Destruction: Cross-national Patterns of Tropical Deforestation, 1975-1990." *World Development*, 25(1), 53-65.
- Ruiz, L. (2000). *Amazonia Ecuatoriana: escenario y actores del 2000*, EcoCiencia - UICN, Quito.
- Runge, F. (1992). "Common Property and Collective Action in Economic Development." *Making the Commons Work: Theory, Practice, and Policy*, D. W. Bromley, ed., ICS Press, San Francisco, CA.
- Sala, O. E., Chapin, F. S., III, Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Hueneke, L. F., Jackson, R. B., Kinzig, A., Leemans, R., Lodge, D. M., Mooney, H. A., Oesterheld, M., Poff, N. L., Sykes, M. T., Walker, B. H., Walker, M., and Wall, D. H. (2000). "Global Biodiversity Scenarios for the Year 2100." *Science*, 287(5459), 1770-1774.
- Saunder, D., Hobbs, R., and Margules, C. (1991). "Biological Consequences of Ecosystems Fragmentation: A Review." *Conservation Biology*, 5(1), 18-32.
- Seul, M., O'Gorman, L., and Sammon, M. J. (2000). *Practical Algorithms for Image Analysis: Descriptions, examples, and Code*, Cambridge University Press, Cambridge.
- Sierra, R. (2000). "Dynamics and Patterns of deforestation in the Western Amazon: The Napo Deforestation Front, 1986-1996." *Applied Geography*, 20(1), 1-16.
- Silveira, B., Coutinho, G., and Lopes, C. (2002). "DINAMICA - a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier." *Ecological Modelling*, 154(3), 217-235.
- Smith, J., Ferreira, S., Van de Kop, P., Palheta Ferreira, C., and Sabogal, C. (2003). "The persistence of secondary forest on colonist farms in the Brazilian Amazon." *Agroforestry System*, 58, 125-135.
- Song, C., and Woodcock, C. E. (2003). "Monitoring forest succession with multitemporal Landsat images: factors of uncertainty." *Geoscience and Remote Sensing, IEEE Transactions on*, 41(11), 2557-2567.
- Song, C., Woodcock, C. E., and Li, X. (2002). "The spectral/temporal manifestation of forest succession in optical imagery: The potential of multitemporal imagery." *Remote Sensing of Environment*, 82(2-3), 285-302.
- Southgate, D. (1990). "The causes of land degradation along expanding agricultural frontiers

- in the Third World." *Land Economics*, 66(1), 93-101.
- Southgate, D., and Whitaker, M. (1994). *Economic Progress and the Environment: One Developing Country's Policy Crisis*, Oxford University Press, Oxford.
- Southgate, R., Sierra, R., and Brown, L. (1991). "The causes of Tropical Deforestation in Ecuador: a Statistical analysis." *World Development*, 19(9), 1145-1147.
- Stea, D. (1996). "Romancing the Line: Edges and Seams in Western and Indigenous Mindscapes with Special Reference to Bedouin." *Frontiers in Regional Development*, Y. Gradus and H. Lithwick, eds., Rowman & Littlefield Publishers, London.
- Taylor, P., and Garcia-Barrios, R. (1995). "The social analysis of ecological change: from systems to intersecting processes." *Social Science Information*, 34, 5-30.
- Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W. H., Simberloff, D., and Swackhamer, D. (2001). "Forecasting Agriculturally Driven Global Environmental Change." *Science*, 292(5515), 281-284.
- Tokola, T., Lofman, S., and Erllila, A. (1999). "Relative Calibration of Multitemporal Landsat Data for Forest Cover Change Detection." *Remote Sensing of Environment*, 68, 1-11.
- Turner, I. M. (1996). "Species loss in fragments of tropical rain forest: a review of the evidence." *Journal of Applied Ecology*, 33(2), 200-209.
- Turner, M. G. (1989). "Landscape Ecology: The Effect of Pattern on Process." *Annual Review of Ecology & Systematics*, 20, 171-197.
- Turner, M. G., Dale, V. H., and Gardner, R. H. (1989). "Predicting across scales: Theory Development and Testing." *Landscape Ecology*, 3(3-4), 245-252.
- United Nations Organization. (2001). "World Population Monitoring 2001: Population, Environment and Development." Population Division, Department of Economic and Social Affairs, United Nations Secretariat, New York.
- Uquillas, J. (1984). "Colonization and Spontaneous Settlement in the Ecuadorian Amazon." *Frontier in Expansion in Amazonia*, M. Schmink and C. Wood, eds., University of Florida Press, Gainesville.
- Urban, D. L., O'Neil, R. V., and Shugart, H. H. (1987). "Landscape Ecology: a hierarchical perspective can help scientists to understand spatial patterns." *BioScience*, 37, 119-127.

- VanWey, L. K., Tucker, C. M., and McConnell, E. D. (2005). "COMMUNITY ORGANIZATION, MIGRATION, AND REMITTANCES IN OAXACA." *Latin American Research Review*, 40(1), 83-107.
- Verburg, P. H., Kok, K., Pontius, R. G. J., and Veldkamp, A. (2006). "Modeling Land Use and Land Cover Change." Land-use and Land-cover change: Local processes, global impacts, L. E.F. and G. H, eds., Springer, Berlin.
- Verburg, P. H., Schot, P. P., Dijst, M. J., and Veldkamp, A. (2004). "Land use change modelling: current practice and research priorities." *GeoJournal*, 61(4), 309-324.
- Vieira, I. M. G., Silva de Almeida, A., Davison, E. A., Stone, T. A., Reis de Carvalho, C. J., and Guerrero, J. B. (2003). "Classifying successional forest using Landsat spectral properties and ecological characteristics in eastern Amazonia." *Remote Sensing of Environment*, 87, 410-481.
- Von Bertalanffy, L. (1950). "An Outline of General System Theory." *British Journal of Philosophy of Science*, 1, 134-165.
- Wade, T. G., Riitters, K. H., Wickham, J. D., and Jones, K. B. (2003). "Distribution and causes of global forest fragmentation." *Conservation Ecology* 7(2), 7 [online] URL: <http://www.consecol.org/vol7/iss2/art7/>.
- Waggoner, P. E., and Stephens, G. R. (1970). "Transition Probabilities for a Forest." *Nature*, 225(5238), 1160-1161.
- Walker, B. H., Gunderson, L. H., Kinzig, A. P., Folke, C., Carpenter, S. R., and Schultz, L. (2006). "Handful of heuristics and some propositions for understanding resilience in social-ecological systems." *A Ecology and Society*, 11(1), 13(online).
- Walker, R. T., and Homma, A. K. O. (1996). "Land use land cover dynamics in the Brazilian Amazon: an overview." *Ecological Economics*, 18, 67-80.
- Walsh, S. J., Bilsborrow, R. E., McGregor, S. J., Frizzelle, B. J., Messina, J. P., Pan, W. K. Y., Crews-Meyer, K. A., and Taff, G. N. (2002). "Integration of Longitudinal Surveys, Remote Sensing Time-Series, and Spatial Analyses: Approaches for Linking People and Place." *Linking Household and Remotely Sensed Data: Methodological and Practical Problems*, J. Fox, V. Mishra, R. R. Rindfuss, and S. J. Walsh, eds., Kluwer Academic Publishers, Boston.
- Walsh, S. J., Evans, T. P., and Turner II, B. L. (2004). "Population-environment interactions with an emphasis on LULC dynamics and the role of technology." *Geography and Technology*, S. D. Brunn, S. L. Cutter, and J. Harrington Jr, eds., Kluwer Academic

- Publishers, Boston, 491-519.
- Walsh, S. J., Evans, T. P., Welsh, W. F., Entwisle, B., and Rindfuss, R. R. (1999). "Scale-Dependent Relationships between Population and Environment in Northeastern Thailand." *Photogrammetric Engineering & Remote Sensing*, 65(1), 97-105.
- Walsh, S. J., Malanson, G. P., Messina, J. P., Brown, D. G., and Mena, C. F. (In Press-a). "Biocomplexity." *Handbook of Biogeography*, M. Jumlal, G. MacDonald, A. Millington, and U. Schickhoff, eds., Sage Publishers, London.
- Walsh, S. J., Messina, J. P., Crews-Meyer, K. A., Bilborrow, R. E., and Pan, W. K. Y. (2003). "Characterization and Modeling Patterns of Deforestation and Agricultural Extensification in the Ecuadorian Amazon." *Linking People, Place, and Policy*, S. J. Walsh and K. A. Crews-Meyer, eds., Kluwer Academic Publishers, Boston.
- Walsh, S. J., Messina, J. P., Mena, C. F., Malanson, G. P., and Page, P. H. (In Press-b). "Complexity theory, spatial simulation models, and land use dynamics in the Northern Ecuadorian Amazon." *Geoforum*.
- Walsh, S. J., Moody, A., Allen, T. R., and Brown, D. G. (1997). "Scale Dependence of NDVI and Its Relationship to Mountainous Terrain." *Scale in Remote Sensing and GIS*, D. A. Quattrochi and M. F. Goodchild, eds., CRC Press, New York.
- Wang, Q., Ni, J., and Tenhunen, J. (2005). "Application of a geographically-weighted regression analysis to estimate net primary production of Chinese forest ecosystems." *Global Ecology and Biogeography*, 14(4), 379-393.
- Ward, D. P., Murray, A. T., and Phinn, S. R. (2000). "A stochastically constrained cellular model of urban growth." *Computers, Environment and Urban Systems*, 24(6), 539-558.
- Watt, K. E. F. (1966). *System Analysis in Ecology*, Academic Press, New York.
- White, R., and Engelen, G. (1993). "Cellular automata and fractal urban form: a cellular modeling approach to the evolution of urban landuse patterns." *Environment and Planning A*, 25, 1175-1199.
- White, R., and Engelen, G. (1994). "Urban Systems Dynamics and Cellular Automata: Fractal Structures between Order and Chaos." *Chaos, Solitons & Fractals*, 4, 563-583.
- White, R., Engelen, G., and Uljee, I. (1997). "The use of constrained cellular automata for high-resolution modelling of urban land-use dynamics " *Environment and Planning*

- B, 24(3), 323-343.
- Widlowski, J. L., Pinty, B., Gobron, N., Verstraete, M. M., Diner, D. J., and Davis, A. B. (2004). "Canopy Structure Parameters Derived from Multi-Angular Remote Sensing Data for Terrestrial Carbon Studies." *Climatic Change*, 67(2), 403-415.
- Wiens, J. A., Stenseth, N. C., Van Horne, B., and Anker, R. I. (1993). "Ecological Mechanisms and Landscape Ecology." *Oikos*, 66, 369-380.
- Williams, M., Shimabukuro, Y. E., Herbert, D. A., Lacruz, S. P., Renno, C., and Rastetter, E. B. (2002). "Heterogeneity of Soils and Vegetation in an Eastern Amazonian Rain Forest: Implications for Scaling Up Biomass and Production." *Ecosystems*, V5(7), 692-704.
- Wolfram, S. (1984). "Cellular automata as models of complexity." *Nature*, 311(October).
- Wood, C. H., and Skole, D. (1998). "Linking Satellite, Census, and Survey Data to study Deforestation in the Brazilian Amazon." *People and Pixels: linking remote sensing and social science*, D. Liverman, E. F. Moran, R. R. Rindfuss, and P. C. Stern, eds., National Academy Press, Washington D.C.
- Woodroffe, R., and Ginsberg, J. R. (1998). "Edge Effects and the Extinction of Populations Inside Protected Areas." *Science*, 280(5372), 2126-2128.
- Wu, F. (2002). "Calibration of stochastic cellular automata: the application to rural-urban land conversions." *International Journal of Geographical Information Science*, 16(8), 795-818.
- Xu, X., Zhang, J., and Zhou, X. "Integrating GIS, cellular automata, and genetic algorithm in urban spatial optimization: a case study of Lanzhou." *Geoinformatics 2006: Geospatial Information Science*, 64201U-10.
- Young, O. R. (2002). "Institutional Interplay: The Environmental Consequences of Cross-Scale Interactions." *The Tragedy of the Commons*, E. Ostrom, T. Dietz, N. Dolsak, P. C. Stern, S. Stonich, and E. U. Weber, eds., National Academy Press, Washington, DC.
- Yu, D. L. (2006). "Spatially varying development mechanisms in the Greater Beijing Area: a geographically weighted regression investigation." *The Annals of Regional Science*, V40(1), 173-190.
- Zender, C. S., Newman, D., and Torres, O. (2003). "Spatial heterogeneity in aeolian

erodibility: Uniform, topographic, geomorphic, and hydrologic hypotheses." *Journal of Geophysical Research*, 108(D17), 4543.