DEVELOPMENT OF INTEGRATED PROGNOSTIC MODELS OF LAND USE/LAND COVER CHANGE: CASE STUDIES IN BRAZIL AND CHINA

By

Yushuang Zhou

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ABSTRACT

DEVELOPMENT OF INTEGRATED PROGNOSTIC MODELS
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Human beings are transforming significant portions of the earth's land surface, which has been of central concern to the international research community for most of the past century. The conversion of natural forest biomass to agricultural activities plays a significant role in global climate change, while the loss of agricultural land as results of urban sprawl brings more concern about global food security. This dissertation aims to improve the understandings of land use/land cover change (LUCC) dynamics, to investigate activities and factors that control LUCC processes at various scales, and ultimately, to build integrated prognostic models that can provide scientific projections for land use/land cover change as reference to future policy designs in developing countries.

Case studies are carried out in the Brazilian Amazon and the East Region of China. As an agricultural frontier in Brazil, the Amazonia is chosen to be a representative case to study the consequences of agricultural activities on a primarily forested landscape. In contrast, the East Region of China is a rather developed area with a long history of agricultural development. It is selected to be a case for studying the change of agricultural landscape in highly urbanized areas. The State of Rondonia in the Brazilian Amazon and the

Shanghai Municipality located in the East Region of China are further studied to account for the spatial variations of land use/land cover change.

Remote sensing technique is applied to measure the magnitude and rate of land use/land cover change, and various modeling method are developed for different modeling purposes and based on data availability. A multinomial logit model of cultivated land use change in the East Region of China shows a declining pace of cultivated land loss that is highly subject to government policy intervention. A principal component regression model is developed to examine how much agricultural land will be taken over by urban sprawl in Shanghai, and how the frontier of urban sprawl is advancing deeper into the far suburb areas. Results of the systematic model of land use/land cover change in the Brazilian Amazon and the State of Rondonia demonstrate an accelerating speed of deforestation in the coming decades. Nearly one third of the standing forest in the Amazonia will be cleared within next twenty years, and more than 70% of primary forest for Rondonia, a frontier state of agricultural development, will disappear from sight.

DEDICATION

To my family

For their infinite love and constant inspiration

And to my husband Gao

For being a wonderful spouse

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Introduction

Land use/land cover change (LUCC) is one of the three most important global environmental changes along with increasing carbon dioxide concentrations in the atmosphere and alterations in global nitrogen cycle (Vitousek, 1994). Human beings have transformed significant portions of the Earth's land surface, with ten to fifteen percent of land being dominated by agricultural or urban-industrial areas, and six to eight percent being pasture (Vitousek et al. 1997).

The scientific community's call for studies on land use/land cover changes could date back to the Stockholm Conference on Human Environment in 1972, and later at the United Nations Conference on Environment and Development (UNCED) in 1992. After that Turner, Moss, and Skole (1993) surveyed many international programs and organizations that expressed the need for addressing land use/land cover changes as a research priority. Since then the subject of land use/land cover change has been of central concern to the environmental research community and drawn considerable attentions from various disciplines. It is now a science that brings together the human social processes of land use change and the physical processes of environmental change under a single conceptual umbrella in an effort to understand the fundamental processes of global environmental change (Turner II et al, 1994).

Land use/land cover changes are results from multidimensional interactions of biophysical and socioeconomic processes (Frohn et al, 1996; Fischer et al, 1996). Land cover is the physical and biotic character of the land surface while land use denotes the purposes for which human beings employ or exploit land cover (Turner II et al, 1994; Lambin, 1994). Most of the early studies focused on the biophysical processes that drive land cover change without accounting explicitly for land use changes driven by human demands and economic activities (Fischer et al, 1996). However, past decades have witnessed a growing recognition of human interventions as a major force shaping the biosphere - as much as 40% of the global net primary production has been appropriated by human activities (Vitousek et al, 1986). Geographers are among the first scientists to realize that it is the human actions rather than natural forces that are the sources of most contemporary change in the status and flows in the biosphere, and to sound the alarm that human-induced land use changes are beginning to threaten the balance of life (Turner II et al, 1994). This is how the human dimension became a major theme in the agenda of global change research (Gallopín, 1991;IGBP&HDP, 1993, 1995; Turner II et al, 1995).

This dissertation work aims to improve the understanding of the dynamics of land use/land cover change process, investigate factors that control land use/land cover change processes at various scales, and explore the interlinkages of different factors and different land types. The major theme is to monitor and model the spatial-temporal dynamics of land use/land cover change as well as its relationship with the human socio-economic driving forces using GIS, remote sensing and different modeling techniques.

This report is structured in five chapters as follows:

Chapter one provides an introduction to the background of LUCC research, discusses the importance of LUCC as a link with global environmental change and food security, and outlines the most important research questions to be addressed in LUCC studies.

Chapter two presents a study of agricultural land use change in the East Region of China, where conflicts between urban and agricultural land use are the dominant subject of controversy. This chapter is designed to analyze what drives the rapid loss of cultivated land in highly urbanized areas. Based on this, a multinomial logit model is constructed to predict future land use change in the East Region of China.

Chapter three zooms into Shanghai, the largest city in the East Region of China. It closely examines the phenomena of urban sprawl and agricultural land loss in metropolitan Shanghai. Remote sensing technique is applied to monitor the magnitude, rate and pattern of land use/land cover change. A principal component regression model is constructed to link remotely sensed observations of land use/land cover change to the understanding of processes that resulted in the LUCC changes.

Chapter four is a study on deforestation and secondary growth in the Brazilian Amazon Basin. It studies the consequences of agricultural development and various other tropical activities on a primarily forested landscape. A systematic model is constructed by linking remotely sensed land classification and census data to simulate future land use/land cover changes in the Brazilian Amazon. The model is applied to the State of Rondonia as well.

Chapter five summarizes the empirical and theoretical findings from the land use/land cover change studies in China and Brazil. It also addresses the implication of the studies and suggests avenues for future research.

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CHAPTER 1

LUCC Monitoring and Modeling

1.1 Land Use/Land Cover Change

Broadly speaking, there are three main types of land: urban, agricultural and forest. The term land use/land cover change can refer to any type of change that occurs within each land type (such as agricultural intensification and forest thinning) or between two different land types (for example, deforestation and urban sprawl). This project will focus on the second category of change, that is, changes between different land types. Given the irreversibility of urban land use, there are four possible types of changes that form an LUCC triangle: (1) change from forest to agricultural land; (2) change from agricultural land to urban use; (3) change from forest to urban land; and (4) change from agricultural land to forest (Figure 1.1).

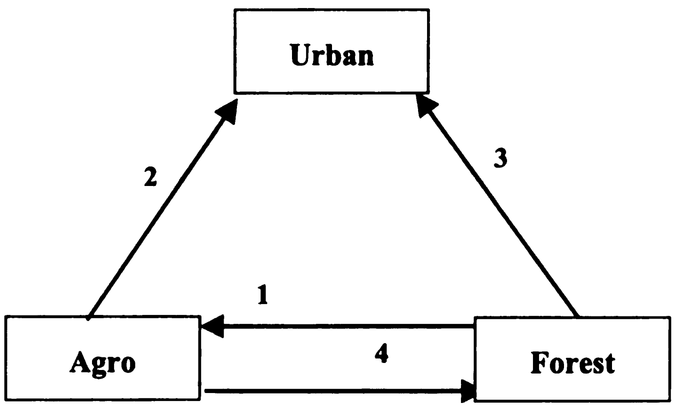

Figure 1.1: LUCC Triangle with Four Major Types of Changes: 1- Agricultural land encroaching on forest; 2 - Urban sprawling over agricultural land; 3 - Urban taking over forest directly; and 4 - Agricultural land turning into forest.

Most studies focused on one type of land use/land cover change. These fragmented studies do not integrate different land use/land cover change types, therefore are not able to account for the dynamic interlinkages between different land types as shown on the LUCC triangle. As a science whose research subjects across both social and natural sciences, geography has a unique advantage and rich heritage of thinking systematically. By its very nature, geography is a discipline that seeks to integrate and synthesize knowledge, and to bring together and integrate the area association and spatial organization of both natural and anthropogenic phenomena on the earth's surface. This has put geography in a position of advantage to study land use/land cover change in an integrative way.

1.2 Study Areas and Research Tasks

This dissertation work aims to understand the major types of land use/land cover change and their interlinkages across space and over time. The East Region of China and the Brazilian Amazon are selected to be the main study areas. The Shanghai Municipality located in the East Region of China and the State of Rondonia in the Brazilian Amazon are further studied to account for spatial variations of land use/land cover change (Figure 1.2).

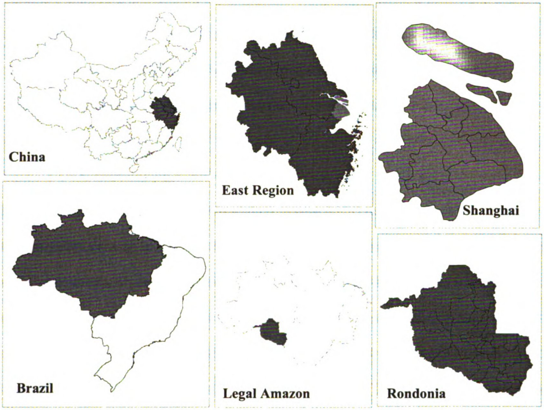

Figure 1.2: Maps of Study Areas: (1) the East Region of China and the Shanghai Municipality; (2) the Legal Amazon of Brazil and the State of Rondonia

Though both belonging to developing countries, the East Region of China and the Amazonia in Brazil have very different levels of development and different types of landscape as well. The Amazonia is an agricultural frontier in Brazil, and it is chosen to be a representative case to study the consequences of agricultural activities on a primarily forested landscape. In contrast, the East Region of China is a rather developed area with a long history of agricultural development. It is selected to be a case for studying the change of agricultural landscape in highly urbanized areas.

There are three general research tasks in this dissertation work: to monitor land use/land cover change using remote sensing and GIS, to understand the process of land use/land cover change and to model land use/land cover change based on remotely sensed observations and theoretical understandings of the processes.

1.2.1 LUCC Monitoring

Remote sensing and geographic information system (GIS) techniques are the powerful tools to fulfill the task of land use/land cover change monitoring (Downton, 1995; Coppin and Bauer, 1996). Since remote sensing data can be collected at multiple scales and at multiple times, they provides a great opportunity to characterize and map land use/land cover distribution and change patterns with great details that is not possible by using census data or field surveys alone (Townshend et al, 1991). Together with data available from ground-based observations or surveys, remotely sensed data can be used to monitor changes in space and time, to develop and validate dynamic models of regional development and to forecast future land use patterns and changes (Moran et al, 1994; Frohn etal, 1996; Wood and Skole, 1998). This unique advantage of remote sensing has stimulated a growing interest in making scientific progress through the use of remotely sensed data in social science research community, so-called "Pixelize the Social" (Pritchard et al, 1996; Schweik and Green, 1999).

What makes remote sensing more appealing to land use/land cover change studies is that remote sensing provides an opportunity to measure landscape attributes and record data in accurate digital maps and files that can be stored and managed in Geographic Information System (GIS). GIS has the capability to readily combine, integrate and analyze remote sensing data within a spatial framework (Liu et al, 1993; Martin, 1996). It is the combination of remote sensing and GIS that makes data input and computational limits for dealing with temporal sequences of land use/land cover information a less significant issue (Lambin, 1994).

1.2.2 From Pattern to Process

However, monitoring the magnitudes and patterns offers only a partial picture of land use/land cover change; it cannot provide much insight into the processes. We need to move from pattern description to process understanding, to find out what processes are involved that change land use/land cover, and what are the underlying driving forces.

Understanding the relationships between pattern and process at landscape scales was the focus of the earlier works in ecology (Baker, 1989; Gardner, 1991). But most recent land use studies tend to focus on spatial aspects of patterns rather than the processes that resulted in the patterns (Grainger, 1995; Sklar and Costanza, 1991). Recent development in landscape ecology has reemphasized the important relationships between spatial patterns and processes (Turner 1990; Naveh and Lieberamn, 1998). The pattern to process approach allows us to consider how spatial patterns of land use/land cover change are resulted from social-economic and ecological processes, and how the processes are influenced by the changing patterns.

1.2.3 LUCC Modeling

With the understanding of pattern and process, LUCC models can be built to link pattern to process by quantifying the contribution from each driving force and representing the sensitivity of land use/land cover change to economic, ecological or locational factors. LUCC modeling has become a popular practice since policy makers and the public became increasingly concerned about quantifying the environmental impacts of human socio-economic activities on land use/land cover change (Lambin, 1994).

Well-defined quantitative models can play an essential role in our efforts to untangle the complexities of what drive land use/land cover change and to generate projections for future land use/land cover changes. As a caricature and deliberate simplification of reality, models simplify the multidimensional land use/land cover change processes by highlighting the important variables as well as the causal/impacts relationships involved in the processes. Good modeling skill may help us move closer to the reality and represent the qualitative factors in a better manner; and good model projections may contribute to the design of policy responses to land use/land cover changes.

1.3 Spatial and Temporal Dimension of LUCC

Land use/land cover changes have two dimensions: space and time. Geographers have special interests and unique advantages in dealing with the spatial component. The basic spatial question is "what is where": what is the magnitude of different types of land? What is the rate of different types of land use/land cover change? And where are the changes? The spatial pattern is also called into close attention because of its essential importance in understanding land use/land cover change process as well as its environmental impacts on key ecological processes (Dunn et al, 1991). Since landscapes are in constant changes, it is important to go beyond the spatial dimension to account for the temporal dynamics of land use/land cover change: how is land use/land cover changing over time? And in the long term, do we know enough to generalize the trend of land use/land cover change?

1.3.1 Spatial Dimension

Bid-rent function offers a powerful analytical approach for exploring the spatial component of land use/land use change. As early as in 1826, Von Thunen started to account for the spatial distribution of economic activities upon agricultural landscape using a bid-rent function, which shows that the most productive activities will compete for locations with the highest accessibility, and activities not productive enough will be located further. In Von Thunen's agricultural land use model, urban area is a dimensionless central point. Later geographers such as Alonso (1964) and Fujita (1989) succeeded in generalizing and reviving Von Thunen's bid-rent function and applying it in an urban context to account for the structure and dynamics of industrial and residential land use changes. Muth (1961) was the first one to use bid-rent functions to account for land use change in regional context where urban residential area growth pushes the city limit into the agricultural hinterland. However, the agricultural land area in Muth's land use model is not bounded; therefore, there is no land conversion between urban (or agricultural) land and natural land. Walker et al. (1997), Walker and Homma (1996) and Walker and Solecki (1999) described possible adaptations of the bid-rent models to land cover change. Walker (2001) introduced natural land into the bid-rent function of land cover change, a dynamic process in which forestry, agriculture and urban industry compete for space.

Assuming a homogenous region like that of Von Thunen's isolated state, we can imagine a concentric zone model where the region is comprised of a set of concentric zones with each zone devoted to a particular type of land use (Figure 1.3). An urban land zone is located in the center as the core of the region, surrounded by an agricultural land zone in a less intensively used manner, with forest area (natural wildness) as the outmost zone. The bid-rent for urban land use is higher than that of agriculture near the urban core area, but falls below agricultural rent at a sufficient distance from the city. The bid-rent for agriculture exceeds that of forestry within certain distance to urban market, but becomes profitless as it moves further away from the urban center.

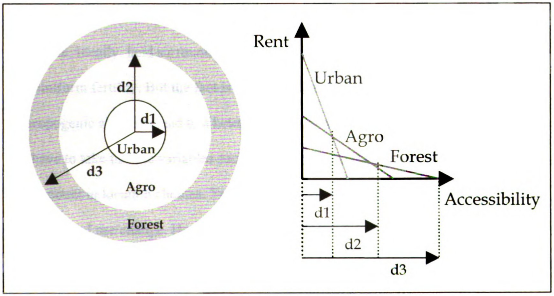

Figure 1.3: Bid-Rent Theory of Land Use/Land Cover Change

The changing landscape patterns can be described in the following processes. As the city grows over time, urban land area will exert pressure on the agricultural zone immediately surrounding it. Outward expansion of the urban area will invade agricultural area and cause agricultural area to expand outward into forestry areas. Therefore the agricultural land is the advancing edge of urban sprawl and forestry land is at the threat of agricultural expansion. The process will continue with each successive zone moving further from the center, but not in an unlimited way because of the environmental pressure as the result of diminishing forest area.

The concentric zone model is a simple representation of a region's land use patterns, i.e., an idealized model of land use and social spatial structure. There are many exceptions to and variations on this theme, and there is no particular region that actually and precisely fits this pattern. The introduction of realities such as local physical situation variables, transport routes and multiple city centers will cause distortions of the concentric pattern (Isard, 1956). The most plausible assumption of the concentric model is homogeneity of the region. Ideally, land surrounding the urban core area is assumed to be entirely flat with uniform fertility. But the fact is that interactions between physical, biological and anthropogenic elements lead to a heterogeneous mosaics of landscape (Froman, 1995). We have to take the site variables such as physical situation and transportation network into account in location choices. Transportation accessibility is the decisive factor affecting land use change. Hoyt (1939) developed the sector theory to account for the impacts of major transportation routes on land use change. He theorized that cities tend to grow in wedge-shaped patterns, emanating from the central business district (CBD) and centered on major transportation routes. Therefore land use tends to conform to a pattern of sectors rather than concentric rings. However, Harris and Ullman (1945) argued that economic activities are built around several centers of nuclei rather than one single center. Cities of greater size develop substantial suburban areas, some of which reach significant size, develop into smaller business districts and act as satellite nodes, or nuclei, of activity around which land use patterns formed.

1.3.2 Temporal Dimension

In terms of the temporal component of land use/land cover change processes, diffusion theory provides a useful tool to capture the spread effects of land use/land cover change process which can be viewed as moving across landscape in diffusion waves as the passage of Hagerstrand's (1953) innovation diffusion profile.

There are three general types of diffusion process: expansion diffusion, hierarchical diffusion and relocation diffusion (figure 1.4). Expansion diffusion is a contagious spreading process operated by a distance decay function. Urban sprawl and deforestation are two good example of expansion diffusion. The further away from the source of expanding, the less likely a parcel of land will be changed. Hierarchical diffusion works in a "jumping" manner where simple linear distance is not always the strongest influence on a diffusion pattern. For example, logging activities will leap over intervening places following a path that concentrates initially only on regions with high quality wood, and from there spreading to regions in the lower hierarchy. Shifting cultivation is an example of relocation diffusion. Forestry land is cleared and crops are grown and harvested for a couple of years till the fertility of the land is exhausted. Then the land will be abandoned and farmers will move to a new location for new clearance. However, many diffusion processes in reality represent a combination of expansion, hierarchical and relocation diffusion, especially the combination of expansion with either hierarchical or relocation diffusion (Robinson, 1998).

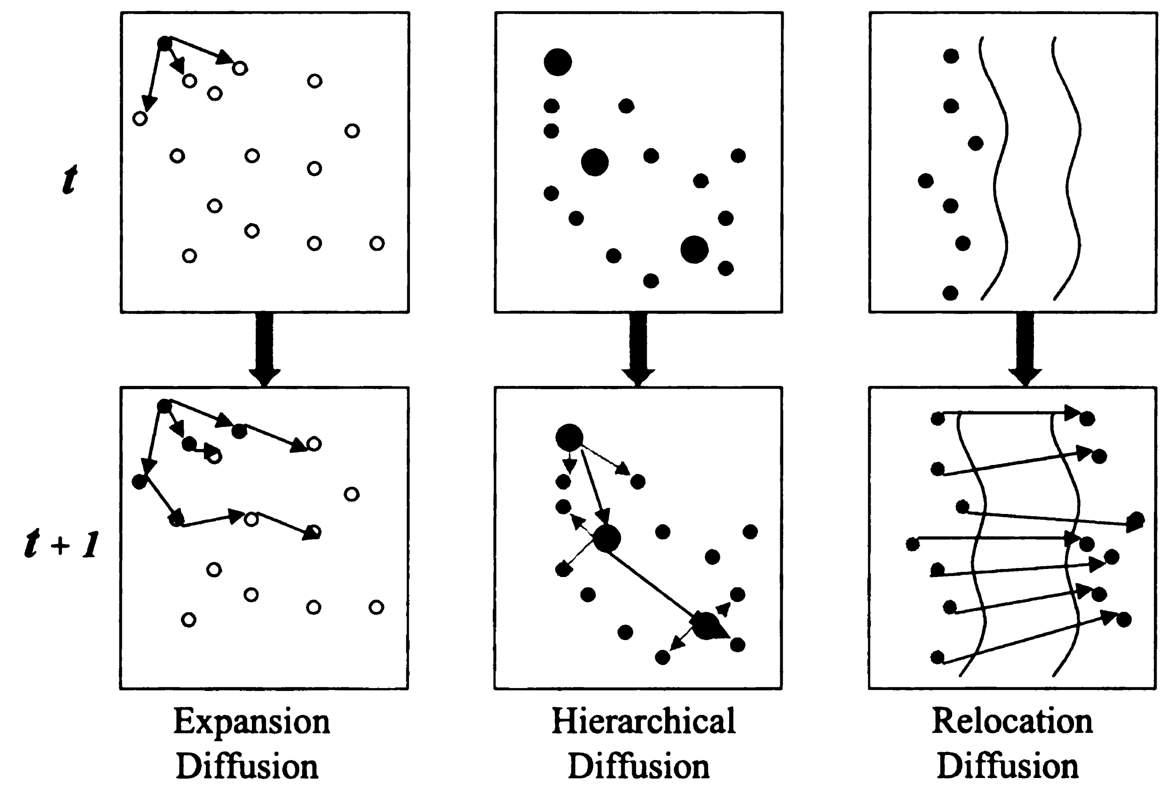

Figure 1.4: Three Major Types of Diffusion Processes: Expansion Diffusion, Hierarchical Diffusion and Relocation Diffusion

Land use/land cover change is a built-up process. The contemporary urbanized landscapes started a long time ago when agricultural and cattle ranching were the main economy activities; agricultural expansion and deforestation were the major types changes of land. It is through the built-up process that very advanced and complex levels of landscape have been obtained with dominant presence of buildings and infrastructures (Folch, R., 1997). Land use/land cover change processes start with a primary slow increase stage, followed by a rapid increase stage, then a slow condensing stage again before finally reaching a saturation stage. As time goes along, we can expect the following general transitional trends for different land types (Figure 1.5).

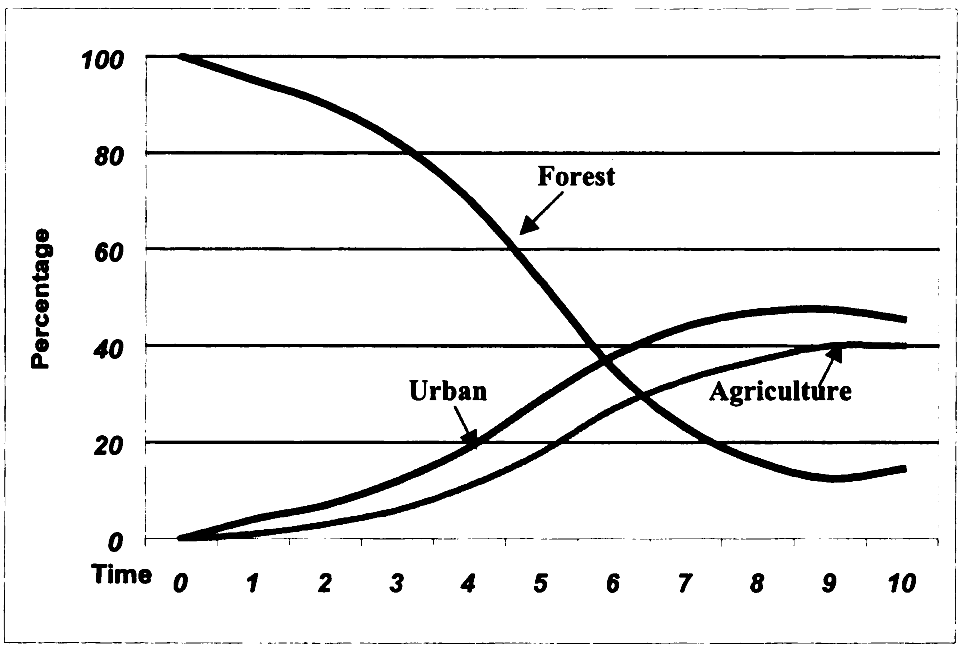

Figure 1.5: Land Use/Land Cover Change Diffusion Processes

Urban land grows slowly at the primary stage with a small urban population, but starts to accelerate (the urban sprawl stage) when the region steps into an industrialization age, and finally reaches a saturating stage marked by a slowing and eventual cession of the urban growth process. Agricultural land has a rapid initial expansion due to the increasing demand for agricultural products, reaches a peak size of agricultural area and then starts to shrink as more and more agricultural land being encroached by urban land and other uses. Forest area starts with an initial high stock, followed by shrinkage in size as it being converted to agricultural or other uses. But forest cover will eventually experience a slight increase due to environmental awareness and forest reconstruction projects. In the land use transitional stages, only the shapes of the trends are universal, the slopes (parameters) are dependent on specific region's economy type and development stage.

The literature of forest transition theory was derived from the concept of the environmental Kuznets curve, which says that environmental impacts of natural resource use initially grow but later decline as income increases (Arrow et al., 1995; Mather et al., 2000; Stern et al., 1996). Similarly, forest transition theory indicates that forest cover would exhibit a U-shaped transition pattern; an initial decline in forest cover due to deforestation is later reduced, offset, and eventually outweighed by secondary forest expansion (Drake, 1993; Mather, 1992; Walker, 1993).

Regional level land use data from The Food and Agriculture Organization (FAO) supported the general trends of these land use/cover changes. The Brazilian Amazon is now experiencing a slight increase of urban land, a rapid expansion of agricultural land, and a fast declining of forest area. This is very different from what is happening in China, where agriculture system has been developed for thousands of years and industry has been developing very fast more recently. Urban land in China is undergoing a rapid expansion period at the cost of both agricultural land and forest area, and agricultural land is taking over forest area due to the increasing tension between the supply and demand of agricultural land. The land use transitional stage for highly developed regions such as Shanghai bears much similarity to that of the USA, where urban area is still growing, but with a tendency to stabilize. Forested area is also experiencing a slow growth as its importance of being a vital environmental resources being increasingly recognized, and the government is making massive efforts on aforestation projects.

1.4 LUCC Significance

1.4.1 Urban Sprawl and Agricultural Land Loss

From an economic perspective, change of agricultural land is a major concern due to its explicit ties with agricultural production and food security (Simpson, 1993). Urban sprawl has been blamed for eliminating productive agricultural land and imperiling food production at an alarming pace (Berry, 1990).

Loss of prime farmland has been repeatedly reported worldwide (Nelson, 1992; Levia, 1998; Yeh and Li, 1997, 1999; Li, 1998). An estimated 5 million to 7 million hectares of farmland are disappearing from the world each year. The United States lost nearly 400,000 hectares of farmland each year to urban sprawl (Feder, 1997), which also took over about one million hectares of agricultural land in China each year between 1987 and 1992 (Tyler, 1994). Arable land per capita in many developing countries has declined sharply. The average arable land of developing countries as a whole dropped from one half of a hectare per person in 1961 to less than one fifth of a hectare in 1992. If current trends in population growth and land use continue, the amount of arable land will be a little over one-tenth of a hectare per person in 2050 (Robey, 1997). This situation has brought the international attentions to the concern of food security, "a state of affairs where all people at all times have access to safe and nutritious food to maintain a healthy and active life" (FAO, 1996). By this definition, about one-third of world population lacks food security. FAO estimates that world food production would have to double to provide food security for the 8 billion people projected for 2025 (Robey, 1997).

The amount of land that could be cultivated to improve food production was estimated to be 2 billion hectares, or about 40% more than what is currently being cultivated (Robey, 1997). However, most of the uncultivated land has marginal productivity because of poor soil quality or inappropriate weather condition. Without substantial new financial investments or unforeseeable improvements in technology, increases in food production will have to come from the existing agricultural land. Therefore, it is of great importance to protect the existing agricultural land from being encroached by urbanization. This is notably a challenge for heavily populated countries such as China, one of the nations with the lowest per capita land resources in the world (CCICED, 1996; Yang and Li, 2000; Bai, 2000). As populous agricultural areas become even more crowded, arable land is likely to come under increasing pressure of being developed. While the overall agricultural land area in China is slightly increasing, agricultural production ability is decreasing due to the fact that most agricultural land being lost is likely to have been fertile prime farmland located on the periphery of major cities and towns, yet most agricultural land newly brought into cultivation constitutes inferior land whose productivity is for the time being far less than what has been lost (Ash and Edmonds, 1998; Smil, 1999; NACOC, 1999). Thereby, the offset in quantitative changes of agricultural land does not necessarily justify a similar conclusion regarding the production capability of agricultural land and food security.

Besides its economic significance, urban growth related land use change also has significant impacts on the ecological sustainability. According to the World Wildlife Fund in China, at least 20 percent of all plant and animal species in China are threatened, well over the world's average of 10 to 15 percent. At least 156 of the 640 species listed on the International Convention on the Trade of Endangered Species of Flora and Fauna are found in China. Nowhere is the threat more evident than in Shanghai, where urban expansion projects have forced hundreds of species of wild birds and reptiles from their natural environments (United Press International, 2000). Chapter three and chapter four will proceed to explore urban sprawl and agricultural land use change in the East Region as well as the Municipality of Shanghai in China.

1.4.2 Agricultural Expansion and Deforestation

From an ecologic perspective, however, loss of forest land is of greater importance due to its significant role in global carbon cycle, ecological complexity and biodiversity preserving (Skole and Tucker, 1993; Adger and Brown, 1994). Most deforestation is for agricultural development purposes.

Deforestation has a profound effect on the global carbon cycle by increasing the amount of CO_2 in the atmosphere, which has increased by more than 25% during the last two centuries and has largely contributed to climate change and global warming. From 1850 to 1990, deforestation worldwide released 122 billion metric tons of carbon into the atmosphere, while the current rate is approximately 1.6 billion metric tons per year. In comparison, fossil fuel burning releases about 6 billion metric tons of carbon per year, so deforestation makes a significant contribution to the increase of atmospheric CO_2. Houghton, Skole, and Lefkowitz (1991) emphasized the importance of land use/land cover data in calculating the global carbon balance. According to Houghton and Skole (1990), approximately 30% of the current net flux of carbon dioxide is biogenic and related to anthropogenic land cover changes. Long-term historical release of carbon dioxide from human alterations of land use/land cover has been approximately equal to the release of carbon from fossil fuel burning.

Most biotic carbon before the 20th century came from deforestation in northern hemisphere temperate zone; but since mid-20th century, the biotic carbon emission center has shifted to southern tropical areas (Ojima et al., 1994). Repetto (1990) reported an accelerating pace of tropical forest resources depletion. The Food and Agriculture Organization (FAO) estimates that 53,000 square miles of tropical forests were destroyed each year during the 1980s, with an estimated 21,000 square miles of annual deforestation in South America, mostly in the Amazon Basin. If the current rate of deforestation continues, the world's rainforests will vanish within 100 years. Besides its significant role in global environmental change, tropical deforestation also imposed great threat to biodiversity preservation and ecological sustainability (Meyer and Turner II, 1994). Covering only 7% of the total dry surface of the Earth, tropical forests have the highest ecological complexity, holding over half of all the species in the world. Many of the rainforest species require a special habitat to live in, therefore are vulnerable to deforestation. Alarming discoveries of the relationship between tropical deforestation and global warming and biodiversity preservation has stimulated a rising interest in land use/land cover change researches in tropical areas, especially in the Brazilian Amazon, the world's largest piece of contiguous tropical forest reserve that contains about 40% of the world's remaining tropical rainforest (Houghton et al, 1987; Houghton et al, 1991; Henderson-Sellers, 1994; Adger and Brown, 1994). . Farmers slash an area of forest, burn the tree trunks and grow agricultural product on the cleared land, so-called slash and burn agriculture. Chapter four will study land use/land cover change in the Brazilian Amazon and the State of Rondonia as the results of agricultural and other tropical development activities.

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CHAPTER 2

Cultivated Land Use Change Analysis and Modeling in the East Region of China

2.1 Introduction

It will be a challenge for China to feed more than 20% of the world's total population with less than 10% of the world's total arable land. As one of the most important grain producers in the world, China has only 13-14% of its landmass under cultivation, in contrast with 55% in India and 20% in the USA (Information Office of State Council in China, 1995). Moreover, cultivated land per capita in China is only half that of India, one-ninth that of USA, and about half that of the world average.

With its large population and low ratio of cultivated land per person, there is growing pressure on China's agricultural system, particularly for grain production. While population is growing at a rapid rate of about 15 million per year, cultivated land is increasingly being converted to orchards or fishponds in response to changes in diet preferences, and to built-up areas for industrial and residential uses. The State Land Administration (SLA) of China reported that 1.73 million ha of cultivated land were lost between 1988 and 1995. To put this magnitude in perspective, it is more than a third of Japan's total cultivated land area. Assume the average grain yield to be 4.5 tons/ha, and the grain consumption for each rural person to be 0.25 ton/year (China Statistic Yearbook, 1997), the loss of land area was equivalent to a loss of grain production capacity of 7.8 million tons, or enough to feed a rural population of more than 30 million for one year.

The problem of cultivated land loss and food security in China has drawn considerable international attention. Growing disparities between land supply and demand has brought the specter of a Malthusian crisis, and aroused the debatable question of whether China can feed itself in the future. For example, a recent report from the Worldwatch Institute has predicted that, with economic modernization, China would lose a significant proportion of its cultivated land in the coming two decades, which would result in a major food security crisis and force China onto the international food market to import food (Brown, 1995). The Chinese government has also realized the importance of food security. “Hunger breeds discontent” is a frequently used idiom within official and public discourse (UNDP, 1996). The Government regards food security as one of its top priorities for attaining social order and political stability. National policies have been promulgated to protect arable land to ensure grain self-sufficiency since 1990s. In 1995 the central government initiated a new grain policy giving provincial governors primary responsibility for maintaining the "grain bag" by stabilizing sown area and allaying urban residents’ concerns about grain supply.

This study addresses some of the key issues related to land use change and food security. It uses a case study of the East Region of China in the 1980s and 1990s to explore the driving forces of China’s cultivated land loss problem within a socio-economic and environmental framework. The use of political ecology as a conceptual and analytical framework enables a reevaluation of the importance of shifting regimes -- from centralized planning to free market, from collective to individual action – for understanding the roles of social relations within which land users interact and land uses are changed. Quantitative models can help simplify the complex and multidimensional processes of land use and land cover change by highlighting the important variables as well as the causal relationships involved in the processes. The study also applies a well-defined model to untangle the complexities of physical and social-economic driving forces of land use/land cover change, and to quantitatively forecast future land use changes and loss of cultivated land in the East Region of China.

2.2 Study Area: the East Region of China

We adopt a regionalization scheme used by the International Institute for Applied System Analysis (IIASA). It divides China into eight economic regions: North, Northeast, East, Central, South, Southwest, Plateau and Northwest regions. This study examines the East Region, which had the highest percentage of cultivated land loss, though the Northwest Region had the largest area of land lost from cultivation. As seen from Figure 2.1, every economic region has experienced losses of cultivated land from 1988 to 1995, except for a minor increase in the Plateau Region.

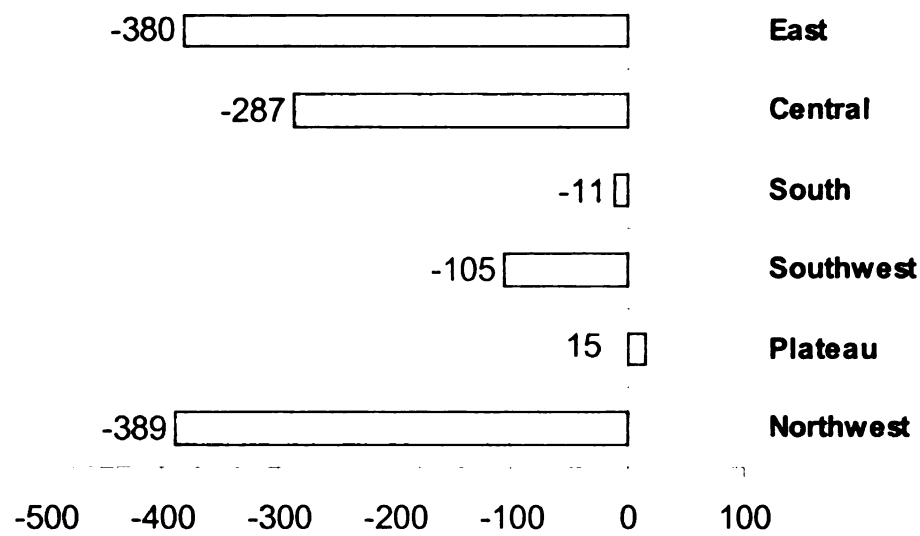

Figure 2.1: Balance of Cultivated Land for Eight Economic Regions of China (1988-1995) Unit: 1000 ha. Data Source: State Land Administration. Edited from Fischer et al

The East Region is located in the lower reaches of the Yangtze River (Figure 2.2), including the Shanghai municipality and Jiangsu, Zhejiang and Anhui provinces. It is an important economic region for both agriculture and industrial development. The total land area of the East Region is less than 4% of the national territory, but it accounts for 12% of China's cultivated land area and 18% of the total population. Also, it produces 18% of the agricultural output and generates 63% of the national rural industry output. The topography of north part of East Region is low plains, while the south part is fairly mountainous. The plain areas have rich agriculture resources with fertile land and abundant water resources. Roughly 80% of the cultivated land area is irrigated, the highest of any region in China (Streets et al., 1995). It permits a multiple cropping system of two or three crops per year, producing an average yearly grain output of 15 -18.75 tons/ha.

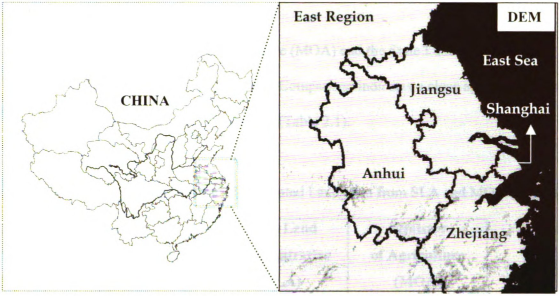

Figure 2.2: Study Area: the East Regions of China (Shanghai,Jiangsu, Zhejiang and Anhui Provinces). The graph on the right side is the Digital Elevation Model (DEM).

Historically, Jiangsu and Zhejiang provinces were known as China's "home for fish and rice". Now these two provinces are among China's most developed areas. Anhui province by contrast is less developed and remains mostly rural. The city of Shanghai is the most important industrial, commercial and financial center of China. As a metropolis of over 13 million people, Shanghai has little natural resources of its own. The peripheral provinces provide most of its labor and raw materials supplies. Demographic statistics show that approximately 75% of the immigration into Shanghai in the 1980s was from the peripheral provinces of East Region itself. Shanghai's booming economy has brought the East Region rapidly into an industrial and technological age in advance of other regions. It is playing a key role in China's "economic development with Chinese characteristics". Thus, what is happening here is a prototype for what may happen in other regions.

2.3 Land Use Data

Data sets from the Ministry of Agriculture (MOA) and the State Land Administrative (SLA) of China, were used in this study. Comparison indicates a close agreement between the land use data from these two sources (Table 2.1).

Table 2.1 Comparison of Cultivated Land Data from SLA and MOA (1990)

Province	State Land Administrative (SLA)	Ministry of Agriculture (MOA)
Shanghai	324	343
Jiangsu	5,069	5,482
Zhejiang	2,357	2,559
Anhui	6,023	5,472
EAST REGION	13,771	13,857

Unit: 1,000 ha

Each of these data sets has its own advantages and disadvantages. Data from the MOA are available at the county level, thus have a higher spatial resolution than data from the SLA, which is provided at the province level. However, the MOA data set differentiates eight types of land use (cultivation, horticulture, forest, grassland, settlement, transportation, water and unused land) for only two dates, 1980 and 1990. By comparison, the SLA data set covers eight years (1988-1995) with detailed land conversion information, which enables an analysis of the dynamics of cultivated land change. The combination of these two data sets provides a good picture of the land use changes in the East Region of China.

2.4 Distribution and Changes of Cultivated Land

The average per capita cultivated land in the East Region was 0.087 ha/capita in 1980. It declined to 0.080 ha/capita in 1990, far below the national average of 0.117 ha/capita. According to a study by the United Nations Food and Agriculture Organization (FAO), a minimum of 0.053 ha of cultivated land per person is required to ensure self-sufficiency in food supply, even with the existence of advanced agriculture production techniques (State Land Administrative Research Project for Cultivated Land Protection, 1998). Yet 48 of 237 counties in the East Region were below this minimum level in 1980, increasing to 74 by 1990 (Table 2.2). Except for Anhui province, all provinces in this region experienced an expansion in the number of counties with per capita cultivated land lower than the FAO minimum requirement. Zhejiang province was the most critical case, with more than 60% of the counties below the minimum level in 1990.

Table 2.2 Four Classes of Cultivated Land Per Capita

Province Name	Total County Number*	<0.053 ha/capita		0.053 – 0.117 ha/capita		0.117 – 0.250 ha/capita		> 0.250 ha/capita	
		1980	1990	1980	1990	1980	1990	1980	1990
Shanghai	9	1	3	8	6	0	0	0	0
Jiangsu	75	10	15	54	46	10	13	0	0
Zhejiang	73	18	45	48	29	1	0	7	0
Anhui	80	19	11	34	40	27	29	0	0
East Region	237	48	74	144	121	38	42	7	0
(%)	(100)	(20)	(31)	(61)	(51)	(16)	(18)	(3)	(0)

Data Source: Ministry of Agriculture (MOA). Note 1: Since the county boundaries vary over time, data of 1980 are re-coded to match the county administrative codes for 1990. Note 2: Two counties (Jinhua and Daishan) in Zhejiang Province are excluded from the analysis due to data inconsistency.

Figure 2.3 shows the spatial distribution of cultivated land per capita by county. Dark red represents counties with cultivated land less than the FAO minimum requirement for grain self-sufficiency (< 0.053 ha/capita). Light red is for counties with an average cultivated land of more than self-sufficiency level but lower than the national average level (0.053 – 0.117 ha/capita). Light green indicates counties with per capita cultivated land larger than the national average level, but lower than the world average level (0.117 – 0.250 ha/capita). And dark green shows counties where per capita cultivated land is higher than the world average (>0.250 ha/capita).

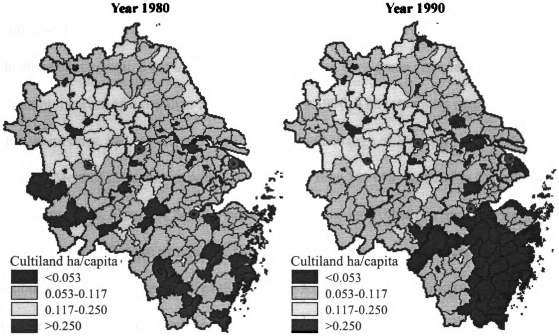

Figure 2.3: Distribution of Cultivated Land Per Capita by County. Data Source: Ministry of Agriculture (MOA)

In 1980, the cultivated land per capita for most counties was between 0.053 – 0.250 ha. Counties with cultivated land per capita less than the FAO minimum requirement were located mainly in the mountainous areas of Zhejiang and Anhui provinces, but also in the urban areas of Jiangsu and Zhejiang provinces. There were only a few counties in Zhejiang province whose cultivated land per capita was higher than the world average. From 1980 to 1990, what emerges most strikingly is that counties with cultivated land per capita of less than 0.053 ha became concentrated on the east and northwest part of Zhejiang province. Another striking observation is that by 1990 no counties have a per capita cultivated land of above the world average, while several did in 1980. Counties within the group 0.053 – 0.250 ha/capita still led the predominant majority.

Figure 2.4 shows the spatial distribution of the net change in cultivated land. Dark red indicates counties with a net loss of more than 3% and dark green represents counties with a net increase of more than 3% during 1980 - 1990. The remaining counties, shown as the white ones, had experienced a relatively small change of less than 3% in either direction. Most of the counties with a loss of more than 3% were located in the southwest mountainous area, along the boarder between Zhejiang and Anhui provinces as well as in the coastal part of Jiangsu province. Land newly brought under cultivation was distributed unevenly to the north of the Yangtze River, mostly clustered in Anhui province. This spatial distribution is very disproportionate to Anhui's share of national cultivated acreage and its importance of agriculture development.

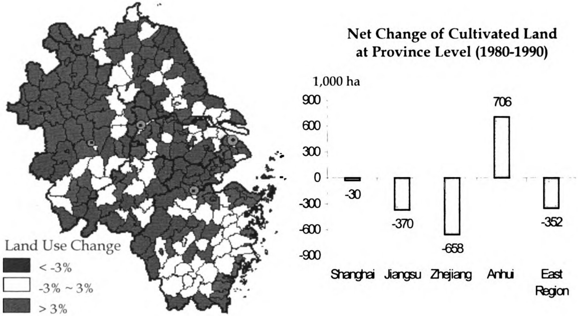

Figure 2.4: Net Changes of Cultivated Land by County and by Province. Data Source: Ministry of Agriculture (MOA)

Analyses of cultivated land use change between 1980 and 1990 shows the change is the net result of loss of cultivated land in Shanghai (30 thousand ha), Jiangsu (370 thousand ha) and Zhejiang provinces (658 thousand ha), and new addition of cultivated land in Anhui province (706 thousand ha). The total net loss of cultivated land for the East Region is 352 thousand ha during the period. However, the decline in productivity resulting from this land loss was not proportional to the decrease in area; most cultivated land loss is from encroachment of urban and rural development on the periphery of cities and results in the loss of above-average quality land (Ash and Edmonds, 1998). At the same time, most cultivated land newly brought into cultivation does not have equal quality. For example, reclamation is by far the most important means of obtaining new cultivated land (Guenther et al, 1998) and a large proportion of reclaimed land constitutes inferior land, whose productivity is far less than what has been lost.

2.5 Driving Forces of LUCC

From our land use database, in particular the SLA data, we can ascertain the direct causes of cultivated land use change. We estimated the magnitude of cultivated land loss and the associated uses for converted land for each province during the period 1988 – 1995. Figure 2.5 groups the cultivated land use change into four conversion processes.

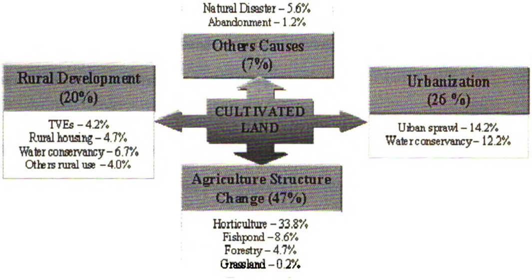

Figure 2.5: Conversion Processes of Cultivated Land. Data Source: State Land Administration (SLA)

Between 1988 and 1995, the total land area converted from cultivation to non-cultivation uses was 526.7 thousand ha. The dominant source of change was conversion to other forms of agriculture due to agricultural structure change, accounting for nearly half of the total conversion (47%). The most important activity in this category was conversion to horticulture, which alone accounted for 34% of all the conversions. The second most important contributor was urbanization, including sprawl of urban areas into once cultivated land and water conservancy for urban use. Urbanization accounted for 26% of the loss of cultivated land. The third source of change was rural development, which included rural housing construction, water conservation projects and Township & Village Enterprise (TVE) development. This accounted for 20% of all conversions. The remaining 7% were due to other causes such as natural disasters and cultivated land abandonment. Among these land use changes, urban construction, rural housing and Township & Village Enterprises (TVEs) are irreversible losses. Depending on the degree to which natural disasters and abandonment are irreversible losses, as much as 50% of the loss of cultivated land during the period was permanent.

2.5.1 Agriculture Structure Change

Agriculture structure change is the most important cause of cultivated land loss in the East Region. Of the 526.7 thousand ha of cultivated land conversion occurred between 1988 and 1995, 246.7 thousand ha was due to agriculture structure change, which was the result of changes in the overall agricultural production system as the government policy and planning embraced a more market-oriented economy.

In the past, the Chinese production system had been organized around a farming team system, under which the government decided what and how much to plant, and teams of farmers were assigned points based on their participation in the system. Points were then used as the basis for income distribution. But the adoption of the Household Production Responsibility System and later the transition from a centrally planned economy to a market-oriented economy have allowed farm households to decide what and how much agricultural commodities to produce, i.e., the decision making at the farm level are now being guided by household economic returns rather than directives from the government. Thus, farmers who had been used to a fixed-price system were rapidly pushed into a market system. Without appropriate guidelines and regulations, overreaction to market signals often occurred, which lead to a rush to produce high-priced agricultural commodities, such as horticultural products, over staples and grains crops.

An increasing proportion of land has been taken out of crop cultivation and put into other agricultural uses that provide higher economic returns. Table 2.3 presents land use change statistic compared with net economic value for various land uses in the region. It is clear that the highest gains occurred to land uses with the highest economic potential, resulting in net replacement of cultivated lands by land uses with as much as a 3-fold more economic value.

Table 2.3 Economic Assessment of Agricultural Structure Change

Agriculture Type	Net Economic Return (yuan/ha)*	Land Use Change (1,000 ha)
Fishpond	14,970	46
Horticulture	8,265	179
Grassland	585	1
Forestry	555	25
Cultivation	5,535	-250

Note*: Edited from the National Office of Regional Planning for Agricultural Resources (1997). 1 Yuan ≅ 8.3 US$

From these statistics, it is apparent that the process of land use change from cultivation to horticulture and fishponds has by itself improved the region's agricultural economic output by approximately 900 million yuan during the period of 1988-1995. Economic returns from grassland and forestry land are as low as 585 yuan/ha and 555 yuan/ha respectively. However, the land converted from cultivation to grassland or forestry generally had a low productivity either because of being infertile or environmental degradation. But even if we assume these lands originally had the average cultivated land productivity, we can still conclude that the total agricultural structure change has produced a substantial net economic benefit of 800 million yuan for the East Region, an economic benefit with the price of losing important land for grain and cereal production.

2.5.2 Urbanization

Urbanization associated with industrialization is well known as one of the most important driving forces for land use/land cover change. Most metropolitan areas around world have experienced massive land use change associated with rapid urban sprawl. This is also the case for the four capital cities in the East Region -- Shanghai (Shanghai municipal), Nanjing (Jiangsu province), Hangzhou (Zhejiang province) and Hefei (Anhui province). Table 2.4 provides a summary of urban expansion and population growth for the four capital cities during the period 1986 - 1996. The ratio of urban land growth rate to urban population growth rate is defined as the elastic ratio of urban area expansion. The urban population of Hangzhou increased dramatically, more than 160% over this ten-year period. Shanghai's population increased by 1.2 million within ten years. Nanjing as well as Hefei also experienced rapid population growth. Correspondingly, the urban areas of these cities grew rapidly. Shanghai's urban area expanded from 20 thousand ha to 36 thousand ha, 8-fold faster than population growth. The urban area of Nanjing increased from 12 thousand ha to 17 thousand ha, and Hangzhou expanded from 63 km^2 to 102 km^2. Detailed urban area data about Hefei during 1986-1996 is not available for this study. For the East Region, the overall urban population grew from 43.7 million in 1980 to 50.4 million in 1990, an increase of 15.3% during within ten years. The urban area increased from 34095 km^2 to 35751 km^2, an increase of 3.7%.

Table 2.4 Urban Population Growth and Area Expansion

City Name	Urban Population[1] (million)			Urban Area[2] (1000 ha)			Elastic Ratio of Urban Growth
	1985	1995	Change (%)	1986	1996	Change (%)	
Shanghai	12	14	10	20	36	78	8.1
Nanjing	2	3	29	12	17	36	1.2
Hangzhou	2	4	164	6	10	62	0.4
Hefei	1	1	44	n/a	n/a	n/a	n/a
All Cities	44	50	15	3448	3575	4	0.2

Note1: from Population Projection of United Nation (1998); Note2: from State Land Administration Research Project of Cultivated Land Protection (1998). Urban areas for Shanghai, Nanjing and Hangzhou are based on remote sensing satellite images.

Besides population growth, urban development is another important contributing factor to urban area expansion. Large areas of cultivated land were arbitrarily zoned for development. However, oversupply, unbalanced and mismatched development, as well as spiraling inflation are causing considerable problems in China's development economy (Chan, 1997). Consequently, large areas of cultivated land have been cleared and zoned for urban development and yet lie idle without any subsequent development.

2.5.3 Rural Development

China is still a nation of farmers. Before the economic reforms of 1978, nearly the entire rural labor force was engaged in agriculture, contributed more than 70% of the rural gross products. As agricultural production becomes more intense and economic reforms encourage the development of rural-based industry, the economic structure in rural areas became more diversified. Urban industrialization was extended to rural areas with the Township & Village Enterprises (TVEs). In mid-1980s, the rural Township & Village Enterprise (TVE) industry output contributed about 50% of the gross output of the rural areas in the East Region, whereas Shanghai had the highest percentage (Table 2.5). By 1995, each province had experienced significant increases in TVE output. TVEs contributed 85% of the rural total output, and became a dominant source of rural income in the East Region. The pace of TVE development far exceeds agriculture growth rates.

Table 2.5 Rural Economy Structure in the East Region

Province	1985			1995		
	Agro Output	TVE Output	TVE % of Rural Output	Agro Output	TVE Output	TVE % of Rural Output
Shanghai	31	94	75	182	1520	89
Jiangsu	289	352	55	1687	8890	84
Zhejiang	174	200	54	892	7478	89
Anhui	198	41	17	980	3012	75
East Region	692	687	50	3661	20900	85

Unit: 100 million yuan, in current price. Data Source: China Statistical Yearbook, 1986 and 1996.

The construction of TVEs explained about 13 % of the land withdrawn from cultivation between 1988-1995. In addition to the land that was lost as the result of rural industry construction, TVEs are responsible for other long-term impacts on cultivated land use change:

First of all, the development of TVEs stimulates rural home construction. Although agriculture continues to provide work for the majority of rural population, growth of rural industry has created more disposable income available for improving living standards. As a result, the development of TVEs has stimulated increased demand for rural housing construction.

Secondly, TVEs cause land degradation. Most rural industries are low technology oriented and highly polluting activities. The intrusion of these industries into rural areas has resulted in rural environmental pollution that causes major crop losses and land degradation.

Thirdly, the development of TVEs increases land abandonment. The development of TVEs is necessarily accompanied by a steep decline in the rural labor force involved in agricultural activities. The labor force leaving agriculture production is mostly comprised of younger and better-educated individuals. An increased industrial labor force has come at the expense of the rural labor force, and this has intensified the shortage of human capital in agricultural sector, leading to the abandonment of cultivated land.

Finally, TVEs lead to an "invisible" loss of cultivated land. As the economy develops, the opportunity cost of crop farming increases. Farmers become less interested in labor-intensive multiple-cropping systems. Double or triple cropping, a practice which once played an important role in rice production, has declined in Zhejiang, Shanghai and Jiangsu provinces (Figure 2.6).

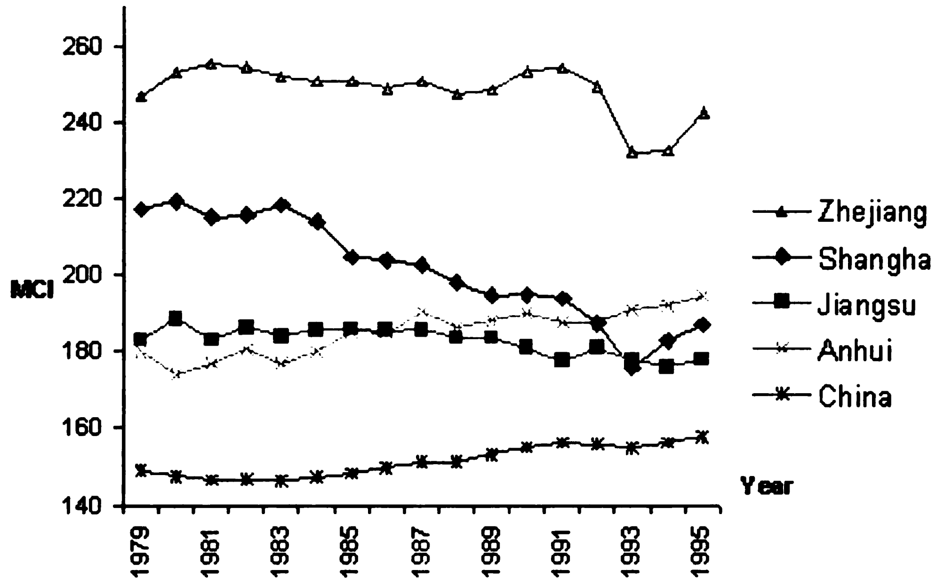

Figure 2.6: Change of Multiple Cropping Indices over Time. Source: Statistical Yearbook of China, 1980-1996. MCI is calculated by dividing sown area by cultivated area.

2.5.4 Other Causes

Two other striking contributors to cultivated land loss are natural disaster and soil erosion. Between 1988 and 1995, 29.3 thousand ha of cultivated land in the East Region were destroyed as the result of natural disaster. In 1991 alone, 11.3 thousand ha of farmland were forced out of cultivation by such natural disasters. Another 6 thousand ha were abandoned due to various other reasons such as soil erosion.

Located in the lower level of the Yangtze River, the East Region has suffered a lot from natural disasters, particularly floods, which inundate and degrade vast tracts of cultivated land every year. According to the 1995 China Environment Yearbook, deforestation in the upper reach of the Yangtze River has resulted in a 40% increase in silt accumulation in the Yangtze River since 1950s, which has caused the riverbeds in the lower reach to rise several meters higher than the surrounding farmland, causing flood almost every year. Much of the soil erosion can be attributed to the region's topography. More than half of the land territory is made up of mountainous areas, where top soil is typically thin and unstable. Coupled with a semi-tropical climate, erosion has been accelerated by the rains in these areas.

2.5.5 Summary

The forces driving changes in land use and cultivated land loss can be categorized into four components: agricultural structural change, urbanization, rural development and others factors related to land degradation and land abandonment. Figure 2.7 illustrates the influence of these factors.

For Shanghai, the dominant sources of change are urban construction and rural housing/industry development. In 1988, agriculture structural change explained about 40% of the total cultivated land loss in Shanghai. These sources of change fit well with Shanghai's changing economic and demographic profile of rapid urban sprawl and rising output from TVE initiatives. The dominant factor in Jiangsu province is agriculture structural change. Freshwater fish production in fishponds and horticulture are very important agricultural income sources in Jiangsu, and increasing rapidly. Zhejiang also has felt the impact of agriculture structural change, as well as rapid urbanization. Here natural disaster appears to be more prevalent than other provinces. In Anhui, agriculture structural change, urban construction and rural development have approximately equal levels of importance as sources of cultivated land loss.

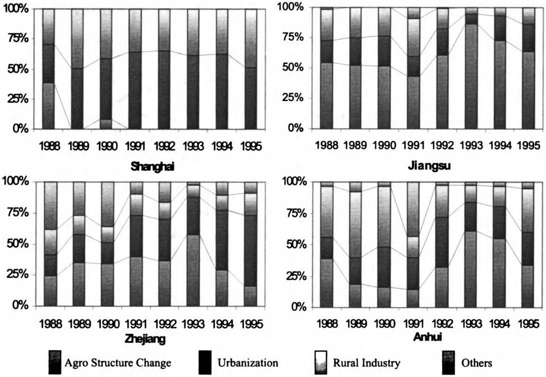

Figure 2.7: Explanatory Power of the Driving Forces in Each Province. Data Source: SLA

2.6 Land Use Change Model

Now we present a model of future changes of cultivated land use for the East Region. The East Region of China can be viewed as an ecological-economic system integrating urban, rural, agricultural and natural subsystems (Figure 2.8). The driving forces of land use change described above are factored into this model to project future cultivated land use change. Since the region is already intensively used, an expansion in urban area, rural housing, industry land or horticulture land is accompanied by a loss of cultivated land or, to a lesser degree, natural land. Urban and rural built-up areas are assumed to be irreversible.

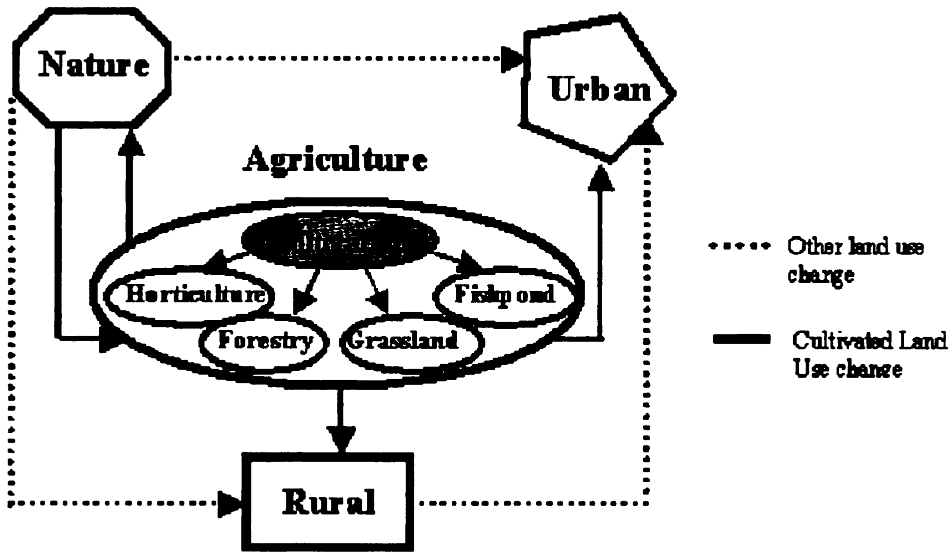

Figure 2.8: A Conceptual Model for Cultivated Land Use Change

The general modeling approach of this study integrated both Von Thunen and Ricardo land use models. Traditional Von Thunen model regards proximity to commodity markets as the prime determinant for economic returns of different land uses, while the Ricardo model describes potential returns in terms of specific land quality characteristics. The land use change model in this study has two major explanatory components: a Thunen component representing the impacts from the regional urban centers, and a Ricardian component representing the local physical conditions. Land rents are regarded as a function of the spatial proximity to city as well as land characteristics such as elevation, slope or soil quality, which measure the land suitability to different uses (Geoghegan et al, 2001). These two components are combined in an integrated model to predict land use changes between urban, agriculture and nature (Konagaya et al, 1999).

Spatial proximity to commodity markets is commonly used in empirical land use models (Capozza and Helsley 1989, Ludeke et al, 1990, Chomitz and Gray, 1996, Bockstael, 1996, Turner et al, 1996, Nelson and Hellerstein 1997, Cropper et al 1999). For example, Ludeke et al. (1990) found strong relationships between the deforestation pattern and the road accessibility as well as the proximity to a house or shelter. Many other research results also illustrated the strong spread effect and the importance of accessibility in land cover change.

There are three groups of driving variables being included in the land use model in this study: (1) Urban situation variables (distance-weighted central urban population and local urbanization level); (2) Rural situation variable (rural industry output per capita) and (3) Site variables (mean elevation and mean slope). Four land use types are distinguished in the model: (1) urban and rural built-up land area; (2) cultivated land area; (3) horticultural land area and (4) natural land area (including forest, grassland, water and other unused land). We differentiate horticulture from cultivation land use because of the dramatic conversion between these two land use types as the result of agriculture structural change.

The observation units of the model are counties.

The urban situation variables play an important role in determining the influence of urban centers. Variables that simply measure the population of selected cities do not describe how the impact from each city changes as its proximity to land varies. Shi et al (1997) include a gravity index as an explanatory variable in a county-level hedonic model of agricultural land price to account for urban influences. In this study, a gravity urban population index is also developed to integrate the impacts of both population and proximity. Urban population of the four capital cities in the East Region is associated with each county in proportion to the inverse of the distance between the county under study and the capital cities. A county with a shorter travel distance to the provincial capitals is said to have higher accessibility, and thus experience a greater influence from that urban center. The calculation can be made using equation 1:

$$Y_i = \sum_{j=1}^{4} P_{ij} = \sum_{j=1}^{4} \{[(1/d_{ij})/\sum_{j=1}^{4}(1/d_{ij})] * P_j\} \qquad (1)$$

Where:

Y_i ---- distance-weighted central urban population for county i

i ------ county number (i = 1, 2, 3,..., 237)

j ------ urban centers (1 = Shanghai; 2 = Nanjing; 3 = Hangzhou; 4 = Hefei)

P_{ij} ---- urban impact of county i from capital city j

P_j ---- urban population for capital city j

d_{ij} ---- distance between county i and capital city j concentric zones of accessibility extending from Shanghai to the west is apparent. This spatial pattern resembles very much the distribution of Township & Village Enterprises (TVEs) as depicted by Figure 2.9.2, which suggests that rural industry would spread to the west in the future. In fact this appears to be the case today as shown in Figure 2.9.2. Figures 2.9.3 and 2.9.4 show the average elevation and slope for each county. Most of the high elevation and high slope land is in the south of the region.

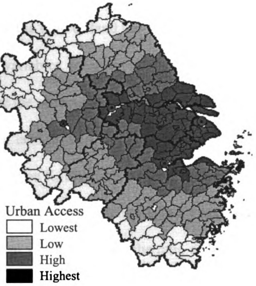

Figure 2.9.1: Urban Accessibility

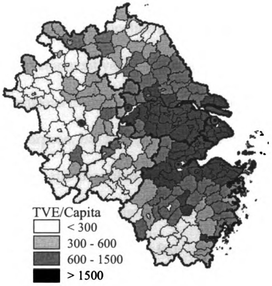

Figure 2.9.2: Rural Industry Output

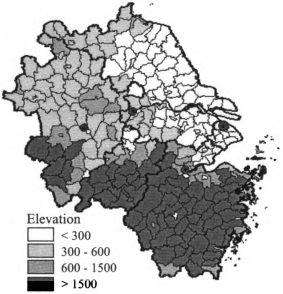

Figure 2.9.3: Elevation

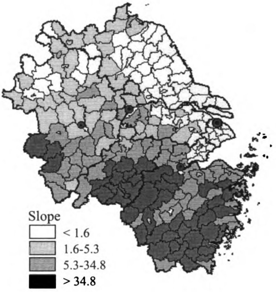

Figure 2.9.4: Slope

These spatially articulated variables (accessibility, elevation and slope and rural industry output) are incorporated into a land use change model in the following manner: for each county i, the ratio of land use type c is defined as an exponential function of the urban impact variables, local physical variables and rural development variable (Equation 2). Because the observation units (counties) are heterogeneous in size, the absolute extents of different land uses are not appropriate for modeling purpose. Instead, the ratio of each land use type $K_i(c)$ is used as the dependent variables. It also describes the probability of a given land use type occurring in a given county and at a certain point in time. Since the dependent variable $K_i(c)$ is the ratio of land use type c in county i, all the four land use types in county i should add up to 1 (Equation 3). The equations are specified as follows:

$$\begin{cases} K_i(c) = k_{0i}(c)\{\exp[a_1(c)*Y_i+a_2(c)*X_i]\}*\{\exp[a_3(c)*Z_{1i}+a_4(c)*Z_{2i}]\} \\ \qquad * \exp[a_5(c)*R_i] & (2) \\ \sum_{c=1}^{4} K_i(c) \equiv 1 & (3) \end{cases}$$

i ------ county number (i = 1, 2, 3,..., 237)

j ------ urban centers (1 = Shanghai; 2 = Nanjing; 3 = Hangzhou; 4 = Hefei)

c ------ land use type (1 = Cultivate; 2 = Built-up area; 3 = Horticulture; 4 = Nature)

$K_i(c)$ -----ratio of land use type c in county i

K_{0i} --- constant term

Y_i----- distance-weighted central urban population as defined by equation (1)

X_i ----- ratio of urban population to total population for county i

Z_{1i} ---- mean elevation of county i

Z_{2i} ---- mean slope of county i

R_i ----- per capita rural industry output in county i

$A_n(c)$-- model parameters for land use type c

The parameters, from a_1 to a_5, are estimated from the transformations:

$$Ln[K_i(c)] = Ln[k_{0i}(c)] + a_1(c)*Y_i + a_2(c)*X_i + a_3(c)*Z_{1i} + a_4(c)*Z_{2i} + a_5(c)*R_i \quad (4)$$

Equation 4 is a multinomial logit model, where the dependent variable is a four-dimensional vector of land use ratios for cultivated land, built-up areas, horticultural land and natural areas. Statistical significance of a logit model is tested using likelihood ratio (P^2) test statistics, which follow a Chi-square distribution with t degrees of freedom (t = number of parameters been estimated in the model). The likelihood ratio index is similar to the determinant coefficient (R^2) of a regression model that is used to examine the goodness of fit of a model. $P^2 = 1$ when the model estimate fits the observed data perfectly, and when $P^2 = 0$, it means that the explanatory variables do not explain the dependent variables at all.

Figure 2.10 shows sources from which data are obtained for the model. County-level land use data come from the land survey conducted by the Ministry of Agriculture, China. Urban population data are taken from United Nation urban population projection. Urban accessibility is generated in a GIS, using the Euclidian distance between county centroids and urban centers. Rural industrial production data came from regional statistic yearbook published by the Statistic Bureau of China. Elevation and slope data are derived from a

Digital Elevation Model (DEM) of USGS. All the data are geo-coded to county-level administrative boundary coverage.

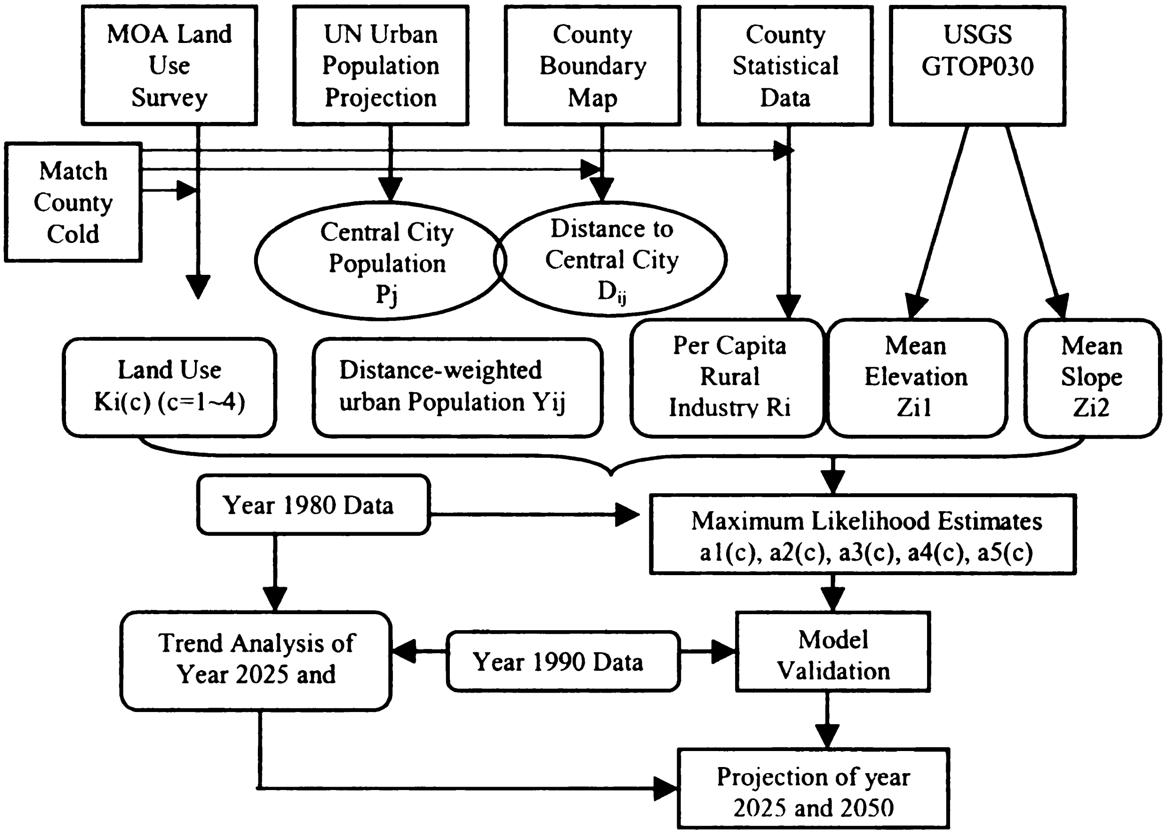

Figure 2.10: Flow Chart for Data and Modeling Methodology

Figure 2.10 also shows the major steps of model estimate. Land use data as well as the corresponding explanatory variables for year 1980 are used to estimate the parameters of the model using maximum likelihood method. Assuming the parameters remain constant over time for each land use type, we apply the data of 1990 to the model and compare the model-estimated results with the observed data to examine the explanatory power of the model. Explanatory variables for 2025 and 2050 were projected by trend extrapolation, i.e., with an underlying assumption that the current trend for either urban population growth or rural industry development will continue through the projection year. Finally we use the multinomial logit model to project future land use change for the years 2025 and 2050.

2.7 Modeling Results

We ran the model in the Guide to Available Mathematical Software (GAMS). The model explains land use in 237 counties of the East Region with a $P^2 = 0.793$. All parameters were statistically significant at a =0.05. The modeling results are as follows:

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$$K_i(1) = 2.41\ [\exp(-0.65*Y_i - 1.58*X_i)]\ [\exp(-0.87*R_i)]\ [\exp(0.11*Z1_i - 0.74*Z2_i)] \quad (4.1)$$

$$K_i(2) = 1.89\ [\exp(1.90*Y_i + 1.58*X_i)]\ [\exp(2.17*R_i)]\ [\exp(-0.95*Z1_i - 0.19*Z2_i)] \quad (4.2)$$

$$K_i(3) = 1.26\ [\exp(0.97*Y_i + 0.73*X_i)]\ [\exp(5.76*R_i)]\ [\exp(-0.37*Z1_i + 0.48*Z2_i)] \quad (4.3)$$

$$K_i(4) = 2.16\ [\exp(-1.37*Y_i - 4.34*X_i)]\ [\exp(0.47*R_i)]\ [\exp(0.04*Z1_i - 0.42*Z2_i)] \quad (4.4)$$

Equations 4.1 – 4.4 are the land use model for cultivated land, built-up area, horticultural land and natural land respectively. Taking a close look at the parameters for the equations, we can note that impacts from the four provincial capital cities as well as the local urban population will negatively affect a county's cultivated land ratio and natural land ratio, but positively related to built-up area as well as the horticulture land ratio. This supports the hypothesis that urbanization will lead to a loss of cultivated and natural land.

A more urbanized regional landscape will have more built-up area, more high-profit horticultural land, but at the cost of less cultivated land and natural area.

The model results also suggest the importance of rural industrial development as a driving force for regional land use changes. The influence of rural industry is negative on cultivated land, but positive on all other three types of land use. As analyzed previously in the study, the development of TVEs in rural areas is essentially a part of the urbanization process. Increased TVE development will bring more built-up area and create a higher demand for horticultural land, as the result, impose a threat for the loss of valuable cultivated land. However, equation 4.4 shows that rural industry development has a positive coefficient for natural land use. This may be attributed to the environmental reconstruction projects (for example, reforestation) sponsored by TVEs as part of community constructions.

With respect to local physical variables, slope is negatively related to cultivated land ratio, while elevation is positive. National guidelines for proper cultivation practices stresses that cultivation is best on land with a slope less than 30% because of the high correlation between slope and soil erosion. Therefore, any area with a slope greater than 30% is unlikely to be developed for cultivation. The positive sign of elevation may be explained by the fact that land on high elevation will still be reclaimed in a densely populated area like the East Region. It might also suggest that physical variables are a less important constraint in regional development than other factors such as accessibility and demographics.

Figure 2.11.1-2.11.4 compare observed cultivated land data with model estimates for both 1980 and 1990. Comparison indicates that the model captures the pattern of cultivated land distribution very well. For 1980, counties with more than 48% of cultivated land were mainly located in the plains of the East Region. Counties with cultivated land less than 32% or even 16% were mostly in the southern mountainous areas. Counties with cultivated land between 32-48% can be found in a conversion belt in between the former ones. When comparing observed cultivated land data in 1990 with 1980, we observe a decrease in the number of counties with a high percentage (>48%) of cultivated land, and an increase in the number of counties with a medium percentage of (36-48%). Evaluating the model with the driving force variables for 1990, there is good correspondence between model results and the observed spatial distribution.

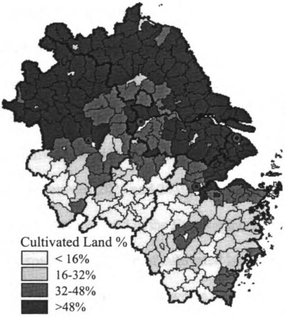

Figure 2.11.1: 1980 Estimated

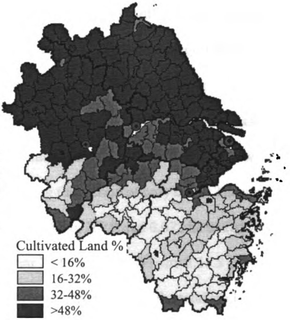

Figure 2.11.2: 1980 Observed

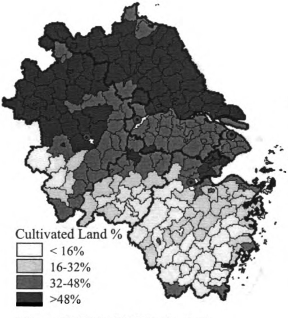

Figure 2.11.3: 1990 Estimated

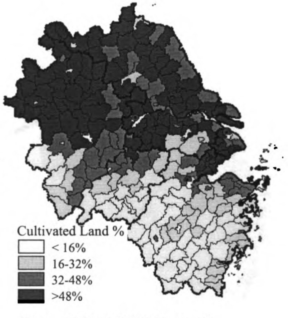

Figure 2.11.4: 1990 Observed

The model is used to project future land use changes for the East Region. Model projection shows a reduction of cultivated land to the level of 12.3 million ha by the year 2025, a total loss of 1.24 million ha from year 1990, accounting for an average annual loss of 35.3 thousand ha. Between 2025 and 2050, another 113.3 thousand ha of cultivated land is estimated to be lost. In percentage terms, the model predicts a decrease of cultivated land by 9.2% from 1990 to 2025. The rate of cultivated land loss will slow during between 2025 and 2050, with a total loss during this period of only 0.9%. The per capita cultivated land in the East Region will be 0.073 ha in 2025, and 0.072 ha in 2050. The spatial distribution of cultivated land in the year 2025 and 2050 (Figure 2.11.5 and 2.11.6) shows that counties with a high cultivated percentage (>48% of the total land area) will be clustered in the north part of Jiangsu and Anhui provinces. Most counties in Zhejiang province, and the hilly part of Anhui province will have cultivated land of less than 32%; half of those counties will have a percentage of cultivated land less than 16%.

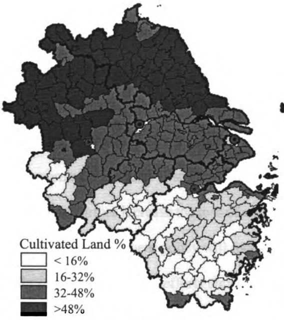

Figure 2.11.5: 2025 Estimated

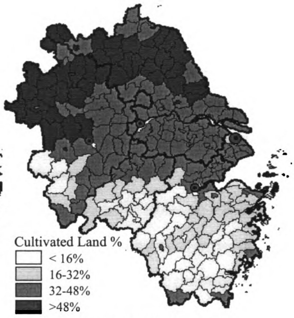

Figure 2.11.6: 2050 Estimated

2.8 Conclusions and Discussions

This study shows that urbanization, agriculture structural change, rural development and local physical environment have all played important roles in the cultivated land use change process in the East Region of China and will continue to be important determinants in the future. Results from prognostic modeling analysis suggest that cultivated land will continue decreasing at a rapid rate for another two decades before it reaches a stabilization level of 0.0727 ha/capita. This value exceeds the self-sufficiency level defined by FAO (0.053 ha/capita), so we conclude that food security should not be a large problem in the East Region.

Because all driving factors of cultivated land use change are susceptible to policy intervention at least to some degree, policy-makers will have some flexibility in addressing the cultivated land loss problem and food security issue. Urban development has enjoyed a high priority in the national agenda for about half a century, and the government has realized the need to slow urban expansion as a measure to reduce its encroachment on arable land. Structural adjustment in the agriculture sector and promotion for rural industry development are more recent policy priorities. Directly associated with policies for agriculture structural change and rural industry development are government's efforts to stimulate increases in farmers' income, which have the potential to further increase the loss of cultivated land in the future. However, it is quite possible that government policy will focus on the fundamental economic objective of grain self-sufficiency and efforts aimed at guaranteeing ample domestic grain supply.

Such policy positions might lead to more restrictive regulations, hence limiting land uses which result in conversion of cultivated land.

In this study we used county-level survey data to quantify land use change. Spatial articulation was resolved at the county level, and hence we may have underestimated the importance of considerable local variation. In addition to these issues of scale, underreporting in land use data from government sources is another important concern (Ash, 1998; Yeh and Li 1997). To resolve both issues we suggest the use of remote sensing data for future analyses. Remote sensing data with high spatial resolution can be a powerful tool for refining the measurements of the rate, extent and spatial pattern of and use/land cover change. It is an efficient means of monitoring land use change, providing fine resolution data of land use/land cover, and enabling spatially explicit quantitative analysis and modeling of land use/land cover change. Since we can collect remote sensing data at multiple scales and at multiple times, we are able to analyze various land use changes synoptically from local to regional scales through time, and to consider the real spatial arrangements of landscape from remote sensing scenes, characterizing and mapping the land use pattern with a great detail that is not possible by using the census data alone.

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CHAPTER 3

Urban Sprawl and Land Use Change in Shanghai, China

Urban sprawl has been reported to be one of the most significant development issues globally and held responsible for a host of problems such as rapid loss of farmland, natural vegetation and open spaces, profligate energy consumption, rising infrastructure costs and decline of social fabric (Tjallingii, 2000; Yeh and Li, 1998). This study will focus on its detrimental impacts on land use/land cover change. Shanghai, a fast-growing metropolitan area in China that has little unused arable land and a fragile ecosystem, is selected to be a case for studying urban sprawl and its impact on rural landscape change.

The study will proceed in five sections. Section one introduces the process of urban sprawl and the consequent economic and ecological significances. Section two outlines the urban sprawl problem in Shanghai and how urbanization and sub-urbanization drive urban sprawl and land use/land cover change dynamics. Section three uses remote sensing to monitor the magnitude, rate and pattern of land use/land cover change in Shanghai. Section four constructs a land use/land cover change model using Principal Component Regression modeling method that combines the remotely sensed satellite data and statistical data. Section five draws conclusion from monitoring and modeling results, discusses the limitations of the study and shows future research direction.

3.1 Introduction

Over the last half century, widespread emergence of urban sprawl has characterized city growth patterns for major metropolitan areas in the world. An estimated 5 million to 7 million hectares of farmland are disappearing from the world each year due to urban sprawl. Natural areas, such as forests, wetlands and other ecosystems, are also being sacrificed to urban development such as residential estates, industry and tourism.

Although the amount of land converted to urban uses may be far smaller globally than the amount of natural lands being lost to agricultural activities and grazing, urban sprawl has more profound impacts on people's lives. Cities are at the heart of a changing global economy, playing an increasingly important role in the economic standing of nations. Urban build-up area occupies only 1-2% of the Earth's land surface, yet it houses nearly half of the world's population and uses three quarters of the resources we take from the earth, marking the most massive change in the flows of energy, water and materials (Douglas, 1994). For historical reasons, cities are often located on prime agricultural land with abundant natural resources or valuable ecosystems near water bodies. Yet residential and commercial development is replacing these valuable lands at an unprecedented rate. In terms of urban sprawl, it is the type rather than the scale of land being changed that is more important (WRI, 1997).

Urban growth generally experienced two major stages: urbanization and sub-urbanization. The evolution of urbanization and suburbanization has been amply documented. It is also well understood that cities exert centripetal and centrifugal forces at different stages of their history that attract people to the cities or push them toward the periphery (Zhou and Ma, 2000). Urbanization began roughly around the turn of the 19th century when large-scale industries took root in urban centers in developed countries and attracted massive population movement into cities. Urban residents represented only 3% of the world's total population in 1800, yet the percentage rose to 14% by the beginning of the 20th century, 29% in 1950 and 49% in 1998. Researchers at World Resources Institute estimated that worldwide movement towards cities is growing at three times the rate of population expansion worldwide; in ten years from now, two thirds of human beings will be living in the cities. 90% of the urban population growth will occur in the developing countries where urbanization started at a much later time but at a unprecedented fast pace (WRI, 1997). Urban growth in developed countries arrived at a sub-urbanization stage in the middle of the 20th century when oversized urban population, high land price, severe environmental pollution and crowd transportation situations in urban centers drove the location of urbanization centers away from the central cities to suburb areas. This new urban growth stage was also facilitated by the modern age of transportation network and automobile that made it possible for suburbs to gradually take the place of the central cities as the area with the fastest growing population and economic development.

Both urbanization and sub-urbanization consume large amounts of land. Rural landscapes surrounding most of our cities and towns are being converted to urban uses at an accelerating rate. The land conversion pressures are especially high in developing countries where cities are growing at least twice as fast as those of the developed world.

The general pattern of urban growth in developing countries today is marked by rapid growth of urban population and expansion of urban area, not much different from what occurred a century ago in the developed world. What is unprecedented is that, in some major developing world cities like Shanghai, China, urbanization is still at its most intensive stage while sub-urbanization has started to play its role on stage, a case in which urban growth would exert double pressures on the neighboring land, therefore, have far-reaching impacts on land use/land cover changes (UNESCAPE, 2001; Zhou and Ma, 2000.

In order to ensure food security and compensate the agricultural production due to the loss of agricultural land, crop production on the remaining land has to be more intense, a practice that is heavily dependent on substantial new financial investments or technology improvements (Ash and Richard, 1998). An alternative is to reclaim more land into cultivation. But reclamation can push agriculture to frontier areas with marginal productivity and entail high ecological risks for fragile ecosystems by forcing birds and animals from their natural habitats and surroundings. Large-scale reclamation projects in Shanghai have forced hundreds of species of wild birds and reptiles from their natural environments (United Press International, 2000). Although the city government has passed environmental laws aiming at protecting the wildlife, developers have flagrantly violated the laws, and the number and variety of wildlife species in Shanghai had declined by 10 percent in the past year.

This study aims to explore the impacts of urban growth on land use/land cover change, with a case study in Shanghai, China where rapid development of industry and the expansion of the city have systematically taken over large areas of agricultural land, seized limited green land and natural reserve, threatening the urban economic and ecological environment. There are two main research tasks in this project: to monitor urban sprawl using remote sensing and GIS, and to model land use/land cover change based on remotely sensed observations and theoretical understandings of land use/land cover change processes.

LUCC monitoring intends to determine the pattern and magnitude of urban sprawl and rural land use change. Remote sensing provides a strong tool to visualize the spatial patterns and temporal sequence of urban growth patterns, and to convey how the progress of modern urbanization and sub-urbanization can result in profound changes to the landscape (Dai et al, 1996; Li, 1997; Mei, 1992). The priority task of this project is LUCC modeling based on the understanding of LUCC processes as results of urban growth. The LUCC model can play an important role to generate projections for future land use/land cover changes by simplifying the multidimensional processes and highlighting the important variables as well as the causal/impacts relationships involved in the processes. Good model projections may contribute to the design of policy responses to urban growth management.

3.2 Shanghai: Urbanization and LUCC

The Shanghai municipality is located at the mouth of the Yangtze River Delta, bordered by the Jiangsu province on the north and west and Zhejiang province on the south (Figure 3.1). It includes fifteen districts (Huangpu, Nanshi, Luwan, Xuhui, Changning, Jing'an, Putuo, Zhabei, Hongkou, Yangpu, Pudong New Area, Minhang, Jiading, Baoshan and Jinshan) and five counties (Nanhui, Fengxian, Songjiang, Qingpu and Chongming). With an area of only 6,340 km^2, Shanghai houses a population of 16.74 million (data of March, 2001), therefore, is one of the world's most populous urban areas.

Figure 3.1: Study Area: the Shanghai Municipality

3.2.1 Urban Sprawl

Like in most other metropolitan areas over the world, rampant urban sprawl has characterized the urban growth patterns for Shanghai during the past half century (Chen et al, 2000; Mei, 1992). Despite the administrative criteria that make a clear distinction between rural and urban areas (Zhang and Zhao, 1998), urban space in Shanghai has expanded dramatically outwards to encroach on the countryside, and rural space has been transformed into an extension of the urban landscape. Among all the large metropolitan areas in China, Shanghai has the highest rate of agricultural land loss. Study of Chen et al (2000) shows that the build-up area in Shanghai has expanded rapidly from 91 km^2 in 1947 to 364km^2 in 1996, a four-fold urban area expansion within half a century (see Figure 3.2).

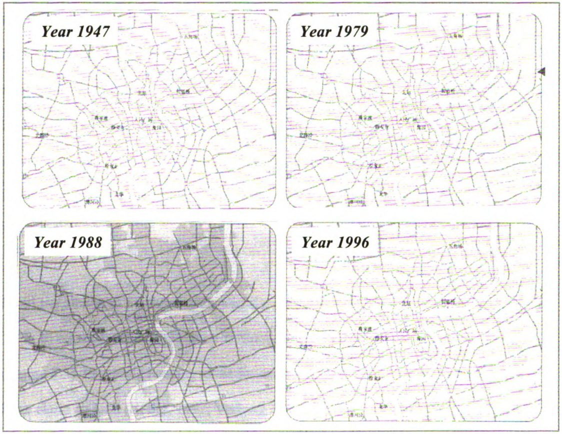

Figure 3.2: Urban Area Expansion for the Central City of Shanghai, 1947 – 1996. Source: The Atlas of Shanghai.

3.2.2 Urbanization and Suburbanization

As the largest city of China and one of the world's most important industrial, commercial and financial centers, Shanghai has long been the largest urban economy and domination over China's commerce (Murphey, 1953; Johnson, 1995). But urbanization in Shanghai remained modest until the communist victory in 1949 (Atash and Wang, 1990; Chang, 1963), since when it has become an administrative entity directly subordinate to the central government and enjoyed high policy priority on government investment. It is now a leading model in the modernization of China and an industrial giant whose products supply China's growing domestic and international markets (Yeung and Sung, 1996). Except for policy incentives, many of the driving forces of urbanization in Shanghai remain the same as what occurred a century ago in the developed world, with the most important ones being the shifting job opportunities from agriculture to industry and services, and the concentration of economic opportunities in urban areas (Fung, 1982). It is the large scale of immigration into the city that keeps the overall population of Shanghai growing.

Rural population in Shanghai grew slightly from 3.2 million in 1959 to 3.5 million in 1998. In contrast, urban population in Shanghai increased from 7.2 million to 9.5 million (Figure 3.3). Providing housing alone for such a large urban population would make a large claim on land (Heilig, 1997; Verburg et al, 1999). Besides removing agricultural land from cultivation as the city expands, urbanization also affects rural land use change by reducing the farmland area as more farmers move to cities or start to work for Town and Village Enterprises (TVEs). Guildin (1997) argues that the indirect effects of urbanization may cause a larger loss of agricultural land than physical conversion into build-up areas. The booming of TVEs in Shanghai was resulted from the spill-out effects of urban industry, and it has extended the urban industrialization to rural areas in Shanghai, so-called rural sprawl (Zhou, 1997).

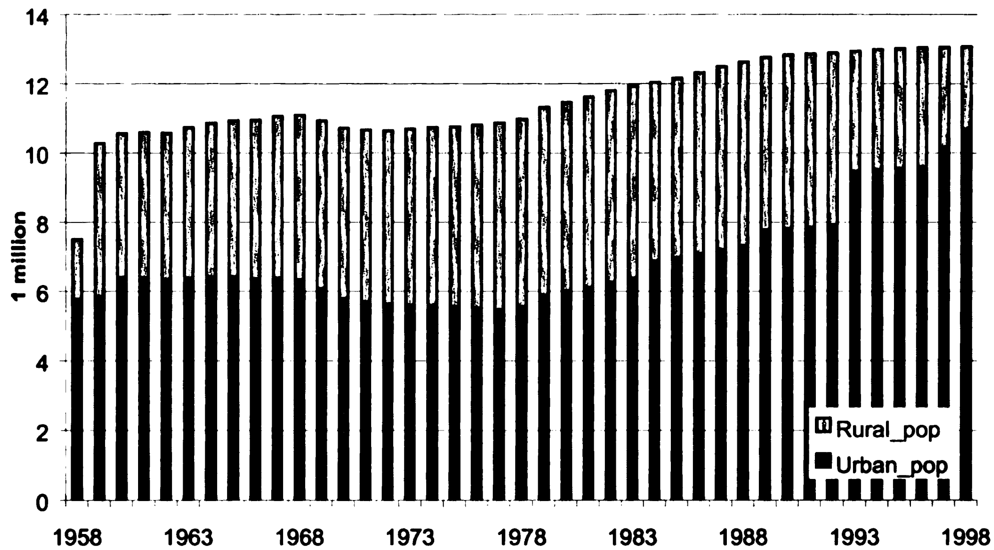

Figure 3.3: Urban and Rural Population Growth in Shanghai Municipality, 1959 – 1998

Decades of urbanization helped Shanghai to form a ring-structured spatial pattern that corresponds remarkably well with the boundary of the city's master plan (Zhou and Ma, 2000; UNESCAP, 2001). The central city, including the ten districts of Huangpu, Nanshi, Luwan, Xuhui, Changning, Jing'an, Putuo, Zhabei, Hongkou and Yangpu, is the core area of urban growth (Figure 3.4). It covers an area of 280.8 km^2, accounting for 4.4% of the total area. The first ring out of the urban core area is near suburbs, including the districts of Pudong New Area, Minhang, Jiading and Baoshan. With an area of 1777 km^2 (26% of the total area), the near suburb ring is the major supplier for fresh vegetable, sideline food and crops. Outside for that is the far suburbs (including the district of Jinshan and five counties - Nanhui, Fengxian, Songjiang, Qingpu and Chongming), a ring of fresh water fishery, bases for fruits and crops, where intensively cultivated fishponds and orchards hold a substantial percentage.

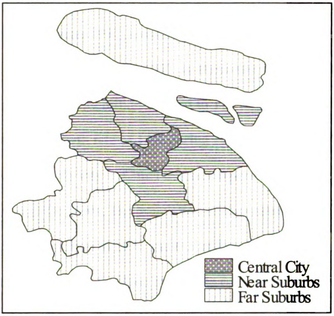

Figure 3.4: The Ring Structure of Urbanization in Shanghai Municipality, China

Most of the early urban growth was concentrated in the central city (UNESCAP, 2001; Ning and Yan, 1995). However, severe environmental pollution and high transportation pressure started to force many industrial plants to relocate from the city center to the outlying suburb areas in the 1980s. The rapid growth of Township & Village Enterprises (TVEs) in the later 1980s further dispersed the urban growth center away from the central city; and the grand opening of the Pudong New Area under the strong support of the central government in 1993 marked the beginning of a new suburbanization stage.

Suburbs started to take the leading role as the most active urban economic growth areas. Figure 3.5 shows the distribution for the percentage of annual GNP value and population in the three concentric rings of Shanghai. We can observe the decline of the central city and the accompanied growth of the suburb areas, especially the near suburbs. The GNP in the suburbs of Shanghai increased from 26 billion yuan in 1985 to 102 billion yuan in1992 and 389 billion yuan 1997, indicating an annual GNP growth rate of 40% during 1985 – 1992, and 56% during 1992 - 1997. In the meanwhile, the GNP for the central city experienced a growth from 59 billion in 1985 to 116 billion in 1992 and 153 billion in 1997, with an annual growth rate of 14% during 1985 – 1992, and 6% during1992 – 1997. Shanghai is the only city in China that has experienced a negative natural population growth in the1990s. The population of the central city declined from 6.7 million in 1985 to 6.4 million in 1993 and 6.3 million in 1997, while the population for the suburbs increased from 5.4 million in 1985 to 6.5 million in 1993 and 6.7 million in 1997.

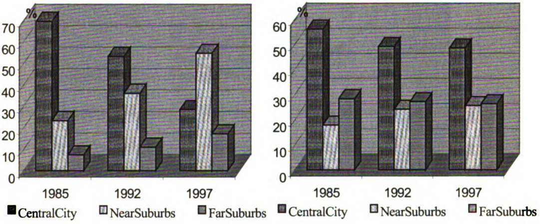

Figure 3.5: Distribution GNP Value and Population for 1985, 1992 and 1997

However, suburbanization in Shanghai is still at its primary stage despite the high speed of development in the suburb areas (Zhou and Ma, 2000; UNESCAPE, 2001; Yusuf and Wu, 1997). With nearly half of the municipality's population and one third of the municipality's GNP, the central city still shows strong attractions for investment. Therefore, the urban growth pattern in Shanghai since 1993 can be characterized as rapid suburbanization in the near suburbs along with intense urbanization in the central city. With the double pressures, Shanghai experienced the most extensive urban sprawl. Figure 3.6 displays the growth of urban build-up areas since the 1970s, with a ring-structured fashion of urban sprawl. The river running through the scene is the Huangpu River, and the central city of Shanghai is located to the west of the river bank. Most urban sprawl took place during the 1990s when the suburbs established most of its transportation networks, housing complexes, parks as well as other recreational facilities.

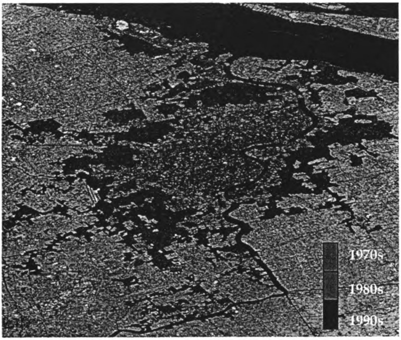

Figure 3.6: Urban Sprawl in Shanghai, 1970s – 1990s. Source: Jiangnan Remote Sensing Institute, China

3.2.3 Land Use Change Dynamics

In order to examine the impacts of urban growth on land use change, we cannot isolate the change of urban land from that of agricultural land or natural land; instead, we need to look at the dynamic conversions between these land types as a coherent system. Figure 3.7 shows the dynamics of land use system in Shanghai.

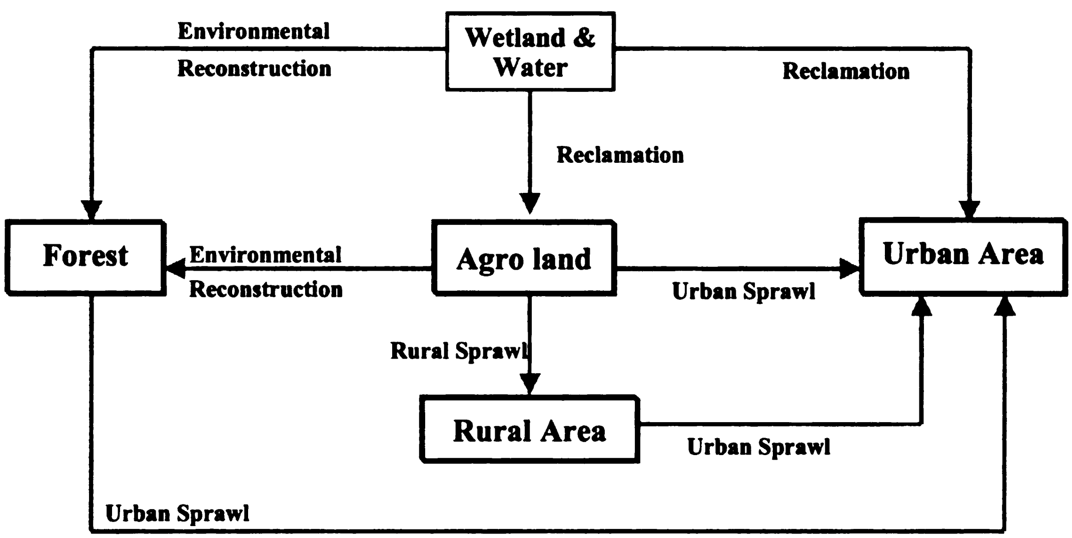

Figure 3.7: A Systematic View of LUCC in Shanghai, China

There are four major activities contributing to the LUCC dynamics in Shanghai: urban sprawl, rural sprawl, reclamation, and environmental reconstruction. As urban sprawl forces large areas of prime agricultural land at the city edge out of cultivation, it also took over neighboring rural communities and green open space.

But urban sprawl is not the sole contributor for the loss of agricultural land. Rural sprawl, caused by the construction of rural Township & Village Enterprise (TVEs), takes more agricultural land out of cultivation. In order to compensate the loss of agricultural land and also to meet the growing demand for urban land use, Shanghai, "a city on the sea" in Chinese, reclaims land from the sea on an annual basis. Since 1949, Shanghai has reclaimed more than 660 km^2 of land from the sea, an area equals to nearly two-thirds of the total areas used in construction projects in the past decades (IIASA, 1999). A large proportion of the reclaimed areas are developed into farmland, and others are developed into port or industrial construction use. For example, reclamation has played an important role in the development of Chongming Green Food Zone, China's first state-level pollution-free food production center on the Chongming island. The construction of Baoshan Iron & Steel Co. on reclaimed land is another often-cited example of land reclamation in Shanghai.

Environmental reconstruction programs also play an important role in Shanghai's land use change. A nice environment with green open space is very important in the city's bid for modernization. It can improve the urban environment by preserving water and soil, adjusting the temperature and humidity of air, preventing pollution and dust, purifying air and eliminating noises. The government of Shanghai municipality is making major efforts to improve its environment by increasing the greenness percentage for the region. The green coverage of the city has reported to increase from 8.2% in 1978 to19.1% in 1998.

3.3 LUCC Monitoring

The analysis of Chinese land use statistics is difficult due to large inconsistencies between sources and the absence or unreliability of many critical variables. Official statistics in China are generally assumed to have under-report problems (Verburg et all, 1999; Smil, 1995; Brown, 1995; Ash and Richard, 1998; Crook, 1991 and 1993). In this project, we use remote sensing to estimate different land use types over time so as to monitor urban sprawl and land use/land cover changes in Shanghai. Four scenes of Landsat TM data with path of 118, row of 038 from 1987 to 2000 are acquired, with the acquisition dates of 05/18/1987; 04/08/1990; 08/04/1998 and 06/15/2000. Each scene is pre-processed and then classified. Filed validation is carried out for the scene of year 2000. Post-classification analysis is performed to analyze the magnitude, rate and pattern of land use/land cover change.

3.3.1 Image Pre-Processing

Each TM imagery is co-registered (with RMS values less than 0.8 pixels) to a Universal Transverso Mercator (UTM) map projection, and geo-referenced to north-up by using the four corner points provided in the DDR as Ground Control Points (GCPs) to define the linear transformation. Image rectification is performed using nearest neighbor resampling technique to minimize convolution of the data. An image enhancement step (contrast manipulation) is performed to increase the visual distinction between features in a scene in order to increase the amount of information that can be visually interpreted from the data (Ahern and Sirois, 1989).

False color composites are generated displaying bands 4, 3 and 2 as red, green, and blue respectively (see figure 3.8). In this color combination, old urban build-up areas (buildings, pavement etc.) appear with dark bluish tones, while new urban areas are much brighter from all the reflective pavement and roofs. Pre-construction land appeared to be medium gray-green, while construction land appears to be totally bright because of the high reflectiveness of bare soil. Rural build-up areas have very similar reflectance like that of urban build-up areas, but with very different spatial patterns that are easily distinguishable from Landsat images. Rural villages are usually small clusters of single-family buildings among agricultural fields, while urban residential areas rarely have single-family buildings except in few recent exceptional western-style suburban areas. Photosynthesizing vegetation always adds a red tint on false colored TM images. The red component corresponds to variation in vegetation, including agricultural land and greenness area. There are two major types of agricultural area: crop cultivation land and horticultural gardens. Cultivation land has more seasonal variation than horticultural gardens. The April 1990 image was taken between harvest and the growth of the next crop so there were less red tones on the crop fields, while the August 1998 image was taken during the growing season, and it showed healthy crops with reddish reflectance. Forestry and parks have the most intense vegetation, therefore appear bright red. For the class of water, most water appeared to blue, while some others appears almost black because the scatter less light back to the Landsat sensor.

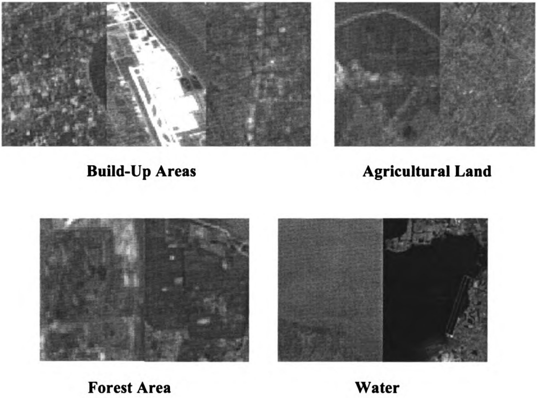

Figure 3.8: False Color Composition of Different Land Types in Shanghai, Landsat TM

3.3.2 Classification and Editing

There are two basic methods for multi-temporal satellite data analysis: a pixel-to-pixel combination of multi-temporal scenes without classifying individual scenes, or a comparison of individually classified scenes of different dates (Singh, 1989; Yeh and Li, 1997). This project uses the post-classification comparison method because it can facilitate the generation of land transition matrices and provide spatially explicit information on "from-to" class changes. Each scene is individually classified, using spectral image classification to aggregate the spectral response for different objects within a pixel into three thematic features of land: build-up areas, agriculture land and water/wetland.

A hybrid classification methodology is adopted by using an iterative, self-organizing, unsupervised (ISO) clustering technique along with a knowledge-based classifier (Skole et al, 1998). For the ISO analysis, a new band is created by calculating the ratio of band 4 (NIR) to band 2 (RED), which expresses the increasing difference between red and near-infrared reflectance with increasing green leaf area index. The unsupervised classification uses only band 3 and this new band NIR/RED. An ISO algorithm is applied to assign the 45 output clusters. The statistical mean spectral values of clusters are shifted to locate the actual spectral statistics for each cluster. This step is repeated until 95% of the pixels are not reassigned to new clusters during the iterations that shift the cluster means. Assignment of individual pixels to a cluster is accomplished using a minimum spectral distance decision rule such that all pixels are assigned to one of the 45 output clusters. These output clusters are then recoded into a new classification containing three classes by overlaying the 45 clusters on the original imagery to aggregate the 45 spectral clusters into final land use/cover classes. The output classification is converted from ERDAS file format to an ARC/INFO raster format (GRID file). The GRID file is then converted to vector format in ARC/INFO. Polygons that are misclassified are identified using visual interpretation and recoded into GIS. Vector coverages are plotted and checked for further editing. These plotting and editing steps are repeated until the classification is completed.

Post-classification look-up tables are constructed for the magnitude of different land types at different dates, and for the rate of different type of land use/land cover changes over time. Urban growth pattern change over space and time are also analyzed. The structure of land use, according to the land use/land cover classification based on Landsat TM images from 1987 – 2000 is shown on table 3.1.

Table 3.1 Land Use/Land Cover Types for Shanghai Municipality, 1978 - 2000

Year	Land	Build-Up Area	Agro Land	Forest	Water/Wetland
1987	Area (km^2)	1625	3701	589	273
	%	(26.3)	(59.8)	(9.5)	(4.4)
1990	Area (km^2)	1799	3572	600	195
	%	(29.1)	(57.7)	(9.7)	(3.2)
1998	Area (km^2)	2393	3047	630	119
	%	(38.7)	(49.2)	(10.2)	(1.9)
2000	Area (km^2)	2570	2864	638	118
	%	(41.5)	(46.3)	(10.3)	(1.9)

Comparison of Shanghai's land use from 1987 to 2000 demonstrates that build-up area grew from 1625 km^2 to 2570 km^2, and build-up area percentage increased from 26.3% to 41.5%. In the meanwhile, there was 837 km^2 of agricultural land being converted to urban uses, accounting for 22.6% of the total agricultural land area in 1987. Agricultural land percentage decreased from 59.8% to 46.3%. Forested area experienced a slight increase from 9.5% to 10.3%, and water/wetland area decreased from 4.4% to 1.9%. By the year 2000, the region's overall urban land held a percentage of 41.5% while the percentage for agricultural land, forested area and water/wetland was 46.3%, 10.2% and 1.9% respectively. Table 3.2 illustrates the spatial variation of land use distribution for the three rings of Shanghai municipality. The urban core area has a build-up percentage of as high as 89%, while the near suburbs and far suburbs have 68.9% and 31.1% of land under urban uses respectively. In contrast, the percentage of agricultural land is the highest in far suburbs where 56.4% of land is under agricultural use, while in the urban core area there is no land remains in agricultural use.

Table 3.2 Spatial Variation of Land Use Distribution

Urban Rings	Year	Build-Up Area	Agro Land	Forest	Water
Urban Core	1987	82.8	10.5	5.0	1.7
	2000	89.0	0.0	11.0	0.7
Near Suburbs	1987	30.1	62.0	6.1	1.8
	2000	68.9	19.7	9.5	1.9
Far Suburbs	1987	22.7	61.2	10.8	5.3
	2000	31.1	56.4	10.5	2.0

Unit: %

3.3.3 Field Validation

In order to ensure accurate classification, ground truthing is carried out on the study sites using GPS. Because satellite system can typically acquire voluminous amounts of data that can be spatially rectified and processed, characterizing the temporal dynamics of large areas may be easier with remote sensing than through traditional field approaches.

Fieldwork is often necessary, however, especially when new or different relationships must be established between the remote sensing data and field conditions. After such relationships being established, much fieldwork can be eliminated and restricted to a spot- checking of selected sites (Wood and Skole, 1998). A random stratified sampling procedure is used to select points for classification accuracy assessment, with 50 points for each class of build-up area and agricultural land, and 25 points for each class of forest and water/wetland. The overall classification accuracy was 82%. Table 3.3 shows the results for accuracy assessment.

Table 3.3 Accuracy Assessment for Land Use/Land Cover Classification

Reference	Classification				Row Total	% Correct
	Build-Up	Agro	Forest	Water		
Build-Up	**42**	3	1	4	50	84
Agro	2	**41**	5	2	50	82
Forest	2	4	**19**	0	25	76
Water	2	1	1	**21**	25	84

3.4 LUCC Modeling Method and Data

The modeling method in this project is a two-step Principal Component Regression (PCR), which basically consists of Principal Component Analysis (PCA) followed by Multivariate Linear Regression (MLR). Eigenvectors and component scores of the explanatory variables are calculated in the Principal Component Analysis step. Then the scores are regressed against the land use data using Multivariate Linear Regression method.

A cross-sectional panel data at county/district level for the years of 1987, 1990 and 1998 are used for model parameter estimates. Table 3.4 lists the variables being used in the model, including land use data derived from remote sensing satellite images and demographic and socio-economic data from the Yearly Statistic Book for Shanghai, County-level Statistic Yearbook for China as well as the National Population Survey (July 1, 1990).

Table 3.4 List of Variables Used in Principle Component Regression

Variable Name	Description	Unit
Land Use Types		-
Urban	Ratio of build-up areas, including land for settlement, industry and transportation	-
AgroLand	Ratio of agricultural land areas, including land for cultivation, horticulture other agricultural uses	-
Forest	Ratio of forested land, including woodland, economic forest, wind-protection forest and forestry parks	-
Water	Ratio of water bodies and wetland, including lakes, rivers, beaches, reservoirs and marshlands	-
Explanatory Variables		
PopDens	Population density	10000 person/km^2
UrbanPop	Urban population percentage	-
PopGrowth	Population growth rate	1/10000
RuralActive	Active rural labor percentage	-
AgroLab	Rural labor in agricultural production	-
RurInduLab	Rural labor in industry production	-
InduOPT	Urban industry output percentage	-
RurInduOPT	Rural Industry output as percentage of rural output	-
GrainProd	Grain production as percentage of agricultural output	-
RuralOPT	Rural output as percentage of GNP	-
Machinery	Percentage of land ploughed by machine	-
Forestry	Percentage of forestry production in rural economy	-
Fishery	Percentage of Fishery production in rural economy	-

Principal Component Analysis (PCA) involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller group of uncorrelated variables called principal components. The objectives of performing PCA are to reduce the multilineairty and dimensionality of the data set, and to identify new meaningful underlying variables for land use changes. The factor scores of thee components being extracted from PCA are calculated using the following equation:

$$S_{n\times 1} = F_{m\times n}{}^{T} X_{m\times 1} \qquad (1)$$

Where $\boldsymbol{S}$ is an $\boldsymbol{n \times 1}$ matrix of score values for all of the explanatory variables, $\boldsymbol{F^T}$ is the transpose of the $\boldsymbol{m \times n}$ factor matrix $\boldsymbol{F}$, while $\boldsymbol{X}$ is an $\boldsymbol{m \times 1}$ matrix of the explanatory variables. The dimensions of the matrices are m representing the total number of explanatory variable included in the PCA ($\boldsymbol{m}$ = 13), and n being the number of components extracted from PCA ($\boldsymbol{n}$ = 3).

After obtaining the score matrix $\boldsymbol{S}$ from the PCA analysis, a Multivariate Linear Regression (MLR) step is performed to regress the land use data on the PCA scores. The model equation is therefore:

$$L_{k\times 1} = A_{k\times 1} + B_{k\times n} S_{n\times 1} + E_{k\times 1} \qquad (2)$$

where $\boldsymbol{L}$ is a $\boldsymbol{k \times 1}$ land use matrix where the dimension $\boldsymbol{k}$ is the number of land use types under study(in this study $\boldsymbol{k}$ = 3, including build-up areas, agricultural land and forested area). $\boldsymbol{S}$ is an $\boldsymbol{n \times 1}$ matrix of the scores from the PCA model, $\boldsymbol{A}$ is a $\boldsymbol{k \times 1}$ matrix of regression intercepts, $\boldsymbol{B}$ is a $\boldsymbol{k \times n}$ matrix of the regression coefficients, and $\boldsymbol{E}$ is a $\boldsymbol{k \times 1}$ matrix of estimate errors. The $\boldsymbol{A}$ intercept matrix and $\boldsymbol{B}$ coefficients matrix are solved by Ordinary Least Square (OLS) regression.

Finally, by combining the MLR regression equation (2) with the PCA scores equation (1), the final PCR model equation emerges:

$$L_{k\times 1} = A_{k\times 1} + [B_{k\times n} (F_{m\times n})^T]\, X_{m\times 1} + E_{k\times 1} \qquad (3)$$

where $\boldsymbol{L}$ is a $\boldsymbol{k \times 1}$ land use matrix, $\boldsymbol{A}$ is a $\boldsymbol{k \times 1}$ matrix of regression intercepts, $\boldsymbol{B}$ is an $\boldsymbol{k \times n}$ matrix of the regression coefficients, $\boldsymbol{F^T}$ is the transpose of a $\boldsymbol{m \times n}$ factor matrix, $\boldsymbol{X}$ is a $\boldsymbol{m \times 1}$ matrix of explanatory variables, and $\boldsymbol{E}$ is a $\boldsymbol{k \times 1}$ matrix of estimate errors. If we put the resulted matrix of $[B_{k\times n} (F_{m\times n})^T]$ as $C_{k\times m}$:

$$C_{k\times m} = B_{k\times n} (F_{m\times n})^T \qquad (4)$$

Then equation 3 becomes an equation like that of the ordinary least square regression:

$$L_{k\times 1} = A_{k\times 1} + C_{k\times m}\, X_{m\times 1} + E_{k\times 1} \qquad (5)$$

Thus the Principal Components Regression combines Principal Component Analysis and Ordinary Least Squares Regression to estimate the matrices of $A_{k\times 1}$ and $C_{k\times m}$.

3.5 LUCC Modeling Results

3.5.1 PCA Results

All the thirteen explanatory variables are included in the PCA analysis. Three components with eigenvalues larger than one are extracted (Table 3.5). The first component includes six variables: population density, urban population percentage, population growth rate, urban industry output percentage, rural agricultural output percentage as well as machinery plough level. This component accounts for as much as 45% of the variability in the data set. It can be referred to as the urbanization component because all the variables are highly correlated with urbanization level. Population density, urban population, urban industrial output and machinery plough level are positively correlated with urbanization level, while population growth rate and rural agricultural output have negative correlations.

The second component accounts for an additional 18% of the total variance of the explanatory variables. This is a component indicating the level of rural agricultural production. It consists rural active labor, rural agricultural labor, grain production, rural industrial labor and rural industrial output percentage, where rural active labor, rural agricultural labor, grain production are variables positively correlated with rural agricultural production, while rural industrial labor and rural industrial output have negative correlations. Spill-out effects of urban industry lead to the development of industry in rural areas, driving rural labors to abandon their land to work for Town and Village Enterprises (TVEs). Regions with higher output of rural industry tend to have lower agricultural production and higher pressure for agricultural land to be converted to other uses.

The third component, including forestry and fishery productions explains another 14% of the total variance. Forestry and fishery are two important forms of rural economy in

Shanghai that are heavily dependent on natural resource endowment. Therefore this component will be addressed as natural resource-based rural economy.

Table 3.5 Component Matrix Extracted by Principal Component Analysis

Variables	Component 1	2	3
PopDens	**.801**	-.150	-.394
UrbanPop	**.936**	-.067	-.035
PopGrowth	**-.640**	.486	-.647
RuralActive	.053	**.814**	-.269
AgroLab	-.115	**.841**	.258
RurInduLab	.337	**-.823**	.054
InduOPT	**.841**	-.389	-.001
RurInduOPT	.468	**-.777**	-.111
GrainProd	-.464	**.479**	-.487
RuralOPT	**-.865**	.259	-.257
Machinery	**.578**	-.011	.539
Forestry	-.063	-.042	**.494**
Fishery	-.173	.212	**.836**

Note: Extraction Method-Principal Component Analysis. Rotation Method-Varimax with Kaiser Normalization. Rotation converged in 4 iterations

3.5.2 MLR Results

Remotely sensed land use data are used to regress against the factor scores of from the three components extracted from the principal component analysis. The results are presented in table 3.6. All the regression models have high overall significance level, and the explanatory powers for the land use models are reasonably good. The R^2 is 0.703 for the urban land model, 0.646 for the agricultural land model and 0.447 for the forest land model.

Table 3.6 Multivariate Linear Regression Results

Dependent Variable	R^2	Coefficient & Significance	Constant	Independent Variables (Component Scores)		
				1	2	3
Urban	.703	ß	.326	.1030	-.0678	-.0372
		Std. ß	-	.670	-.442	-.243
		Sig.	.000	.000	.001	.044
AgroLand	.646	ß	.554	-.0963	.0449	.0203
		Std. ß	-	-.716	.333	.151
		Sig.	.000	.000	.013	.236
Forest	.447	ß	.095	-.0001	.0140	.0109
		Std. ß	-	-.030	.527	.410
		Sig.	.000	.848	.002	.015

Note: ß is the unstandardized regression coefficient from MLR while Std. ß is the standardized coefficient. Sig. indicates regression significance.

For the urban land use model, all three components are significant at the level of 5%. The urbanization level (component one) has a positive partial coefficient that is highly significant, which shows that urbanization level contributes directly to the expansion of urban areas as discussed throughout the first part of this study. The regression coefficients for component two (development of agriculture) and component three (development of other natural resource based rural economy) are both negative, which means that areas with more traditional rural production (such as cultivation, fishery and forestry) and less rural industry tend to have less urbanized area.

In the agricultural land use model, component one is negatively related with agricultural land ratio and the coefficient is statistically significant. This supports the hypothesis that high urbanization level will be accompanied by lower ratio of agricultural land area. Both component two and three have a positive relationship with agricultural land use, but the coefficient for component two is significant at the level of 1.3% while the coefficient for component three is not. Thus, agricultural cultivation and rural industry development contribute to variation in agricultural land area, but other rural economy forms such as forestry and fishery do not have a significant statistical relationship with agricultural land area.

For forest area, component one is negatively correlated while component two and three have a positive relationship. But the probability of significance for component one is as high as 0.848, so urbanization level is not a statistically significant contributor to forest area. But both components two and three are significant, which means rural areas tend to have more land covered by forest areas.

3.5.3 PCR Results

The final step is to combine the MLR regression equation with the PCA component matrix to estimate the coefficients of each explanatory variable. The resulted estimates are listed in table 3.7.

(1) Intercept

The constant terms for urban land, agricultural land and forest area are 0.326, 0.54 and 0.095 respectively. If all the explanatory variables are set to be zero, agriculture will take up a majority of 54% of the total area, urban will account for 32.6% of the land and forest area will be 9.5%.

(2) Component one

There are three variables (population density, urban population percentage and urban industrial output) in component one that contribute positively to urban build-up areas, but are negatively related with agricultural land and forest area. For example, one unit of growth in population density would lead to an increase of 0.087 for the ratio of urban build-up areas, in the meanwhile, a decrease of 0.078 units of agricultural land and 0.003 units of forest area. All other explanatory variables can be interpreted in the same way. Rural output percentage and population growth rate are two variables that contribute negatively to urban land but positively to agricultural and forest area. More rural production implies more agricultural land area and more forest area but less build-up area, and region with higher population growth rate tend to have lower urban area ratio. Machinery plough level is the only variable in component one that has a positive relationship with urban land and forest ratio, but a negative relationship with agricultural area.

(3) Component Two

Rural active labor ratio, agricultural labor ratio and grain production are three variables in component two that contribute negatively to urban area, but positively to agricultural and forest area. On the contrary, rural industrial labor and output are two variables that contribute positively to urban build-up land but negatively to agricultural and forest area. Therefore, regions with more agricultural activities maintain a higher percentage of agricultural and forest area, yet regions with more rural industry development have more land being converted into build-up areas.

(4) Component Three

Both the variables (fishery and forestry) in component three contribute negatively to urban land ratio, but positively to both agricultural and forest land. This is because fishery and forestry are only important in the far suburbs where urbanization level is much lower than the urban core area. The growth of these lines of agricultural activities tends to prevent agricultural land and forest area from being encroached by urban uses.

Table 3.7 Parameter Estimates of LUCC Model Using PCR Regression

Model	LAND	Intercept
1	Urban	0.326
2	Agro	0.554
3	Forest	0.095

Model	LAND	Component One				
		PopDens	UrbanPop	PopGrowth	InduOPT	RuralOPT
1	Urban	0.087	0.102	-0.104	0.113	-0.097
2	Agro	-0.078	-0.094	0.079	-0.099	0.090
3	Forest	-0.003	-0.002	0.014	-0.006	0.002

Model	LAND	Component Two				
		RuralActiv	AgroLab	GrainProd	RurInduLab	RurInduOPT
1	Urban	-0.040	-0.079	-0.062	0.089	0.105
2	Agro	0.026	0.054	0.056	-0.068	-0.082
3	Forest	0.008	0.015	0.002	-0.011	-0.012

Model	LAND	Component Three	
		Forestry	Fishery
1	Urban	-0.022	-0.063
2	Agro	0.014	0.043
3	Forest	0.005	0.012

The statistical relationships show that urbanization (in both urban and rural areas) takes place at the cost of agricultural land and forest area, but agricultural activities (including traditional cultivation, fishery and forestry) tend to preserve agricultural and forest area. A comparison of the coefficients for agricultural land model and forest area model shows that the coefficients for agricultural land are generally larger than that of the forest area, which means urban sprawl will be more of a threat to agricultural land than to forest area.

One limitation of the Principal Component Regression model, though, is the fact that it cannot calculate the statistical significance of each individual variable like in Multivariate Linear Regression. Therefore it is impossible to determine the statistical significance for individual explanatory variables.

3.5.4 Land Use Projection

The models are used to estimate land use ratios of different types using statistical data of year 2000. The results are compared with observed land use data of the same year from satellite image classification for model validation purpose. Trend analysis of time series demographic and socio-economic data enables the forecasting of the explanatory variables for year 2025, which are then used to project land use types for year 2025. Tables 3.8.1 – 3.8.3 present the model validation and projection results.

(1) Urban land

In 2000, the overall urban land ratio for Shanghai was 41.5% while the model estimate is 43.8%, with a marginal estimate error of 2.3%. The estimate error percentage is the lowest in the near-suburb areas, where there is generally a high agreement of more than 99% between the model estimates and remote sensing observations. The model tends to underestimate the urban area by 4.4% in the central city, and overestimate by 4.4% in the far-suburb areas. The error percentage at the county/district level ranges from 0.0% in the central city to 6.7% in Fengxian county.

According to the urban land use model projection, build-up areas will take over an additional 10% of the land area in Shanghai and lead a majority of 51.5% by year 2025. While all the counties and districts will experience a positive growth of urban area, the growth is not evenly distributed over space. The urban growth rate between 2000-2025 is 4.1% for the central city, 7.0% for the near suburbs and 11.2% for the far suburbs. Therefore the urban are center will gradually shift away from the old city in the next two decades. Rural industry development are penetrating into far suburb areas, bringing more urban and industrial activities into the remote regions.

A closer examination at the counties/district level shows spatial variations of the urban area growth rate, ranging from 2.8% in the Pudong New Area and 16.6% in Songjiang county. Counties with the highest urban land growth rate (Songjiang, Jinshan and Chongming) are all located in the far suburbs of Shanghai Municipality. Jiading is the only near suburb county where the urban land area will grow by more than 10% during 2000-2025.

Table 3.8.1 Model Results Validation and Projection for Urban Build-Up Area

Zones	County/ District	2000 Observed	2000 Estimated	Estimate Error %	2025 Estimated	Urban Area Growth % (2000-2025)
Center	**Central City**	**89**	**84.6**	**-4.4**	**93.1**	**4.1**
Near Suburbs	Minhang	83	83	0.0	90.4	7.4
	Jiading	50.3	53.7	3.4	61.5	11.2
	Pudong	72.5	67.6	-4.9	75.3	2.8
	Sub-total	**68.9**	**68.3**	**-0.6**	**75.9**	**7.0**
Far Suburbs	Jinshan	27.1	27.8	0.7	42.4	15.3
	Nanhui	43.5	45.4	1.9	52.1	8.6
	Fengxian	37.6	44.3	6.7	46.1	8.5
	Songjiang	33.8	37.9	4.1	50.4	16.6
	Qingpu	35.6	41.5	5.9	40.7	5.1
	Chongming	19.5	20.8	1.3	32	12.5
	Sub-total	**31.1**	**35.5**	**4.4**	**42.3**	**11.2**
Shanghai TOTAL		**41.5**	**43.8**	**2.3**	**51.5**	**10.0**

(2) Agricultural land

The agricultural land model estimates the overall percentage of agricultural land area in Shanghai to be 46.3% in 2000, approximately the same as what was detected from satellite images (46.2%). A comparison of model estimates with remotely sensed land use data at the county/district level show a general overestimate of agricultural land in the central city and near suburbs(except for the county of Jiading), and an underestimate in the far suburbs.

Model results also show that agricultural land percentage will fall to 39% by year 2025. Therefore, an additional 16% of agricultural land will be lost within next 25 years. In terms of land area, this means a loss of 456 km^2 of agricultural land, equivalent to 2.3 times of the central city area. Spatial distribution of agricultural land use change shows that only the central city and Pudong New District will have a slight increase in agricultural area, all other counties and districts will lose part of their agricultural land stock. Songjiang, Jiading and Chongming are the counties that will have the highest rate of agricultural land loss. The far suburbs will lose 10% of the agricultural land. Again, this agrees with the trend that urbanization is slowing down in the central city, and suburbanization is spreading from near suburbs to far suburb areas.

Table 3.8.2 Model Results Validation and Projection for Agricultural Land

Zones	County/ District	2000 -O	2000 -M	Estimate Error %	2025 -M	Agro Land Growth % (2000-2025)
Center	**Central City**	**0.4**	**8.6**	**8.2**	**1.8**	**1.4**
Near Suburbs	Minhang	5	8.8	3.8	4.6	-0.4
	Jiading	40.5	37.4	-3.1	29.8	-10.7
	Pudong	14.6	24.6	10.0	17.7	3.1
	Sub-total	**19.7**	**23.4**	**3.7**	**17.2**	**-2.5**
Far Suburbs	Jinshan	54.9	51.5	-3.4	47.1	-7.8
	Nanhui	46	45.3	-0.7	38.5	-7.5
	Fengxian	51.3	46.2	-5.1	43.6	-7.7
	Songjiang	54.2	53	-1.2	40.1	-14.1
	Qingpu	56.2	48.5	-7.7	47.8	-8.4
	Chongming	66.5	66	-0.5	56.6	-9.9
	Sub-total	**56.4**	**53.7**	**-2.7**	**47.2**	**-9.2**
Shanghai TOTAL		**46.3**	**46.2**	**-0.1**	**38.9**	**-7.4**

(3) Forest area

The observed forest coverage in Shanghai was 10.3% in 2000, while the model estimates a similar percentage of 10.0%. Despite the slight increase of forest coverage from 9.5% in 1978 to 10.3% in 2000, the forest model shows that Shanghai's total land under the class of forest will fall to 9.6% by 2025. The distribution of forest area growth has more spatial variations than urban or agricultural land change. The forest coverage in the central city will decrease by 5.8% percent. In the near suburbs, Minghang and Pudong Near Area will also have a decrease of forest coverage rate, while Jiading will experience a slight increase. In the far suburbs, Jinshan and Chongming are the two counties that will have less land under forest cover, while Nanhui, Fengxian, Qingshan and Qingpu will have more forest area.

Table 3.8.3 Model Results Validation and Projection for Forest Area

Zones	County/ District	2000 -O	2000 -M	Estimate Error %	2025 -M	Forest Area Growth % (2000-2025)
Center	**Central City**	**11**	**6.8**	**-4.2**	**5.2**	**-5.8**
Near Suburbs	Minhang	10	8.2	-1.8	5.1	-4.9
	Jiading	7.5	8.9	1.4	8.7	1.2
	Pudong	10.9	7.8	-3.1	6.9	-4.0
	Sub-total	**9.5**	**8.3**	**-1.2**	**6.9**	**-2.6**
Far Suburbs	Jinshan	14	10.7	-3.3	10.5	-3.5
	Nanhui	8	9.3	1.3	9.4	1.4
	Fengxian	9	9.6	0.6	10.3	1.3
	Songjiang	9	9.1	0.1	9.5	0.5
	Qingpu	8	10.1	2.1	11.5	3.5
	Chongming	13	13.1	0.1	11.4	-1.6
	Sub-total	**10**	**10.7**	**0.7**	**10.6**	**0.6**
Shanghai TOTAL		**10.3**	**10**	**-0.3**	**9.6**	**-0.7**

3.6 Conclusions

This project demonstrates an application of the remote sensing technology to the study of land use dynamics related to human socio-economic activities. Temporal remote sensing data are used to characterize urban land use change. Since underreporting of agricultural land area has been a long tradition in Chinese statistics as the consequence of linkage between the statistical system, the tax system and the production quota (Crook, 1991; Verburg et al, 1999), remote sensing provides a more objective tool for measuring the magnitude and rate of land use change. It also provides a strong visual portrayal of recognized growth patterns, and dramatically conveys how the progress of modern urbanization results in profound changes to the landscape (Ward et al, 2000).

Land use models are developed using Principal Component Regression modeling method. This is a method that combines the advantages of principal component analysis and multivariate linear regression to explore the relationship between land use changes and the driving forces. Remotely sensed data on urban extent, agricultural land and forest area along with statistical data on urban and rural population growth and economic development are used to calibrate the land use models. Model validation shows high agreements between the model-estimated and remotely sensed land use data.

The land use models are used to project future land use changes and the regional pattern of urbanization. Modeling results show urban build-up areas will keep eating up a large amount of land, mostly agricultural land, in the next twenty-five years. The growth of the central city has stepped into an old age. Market economies as well as a deeper recognition of environmental protection have urged factories to leave urban areas through land exchange, promoting the decentralization of urbanization. The booming of rural industry in the suburb areas further disperses the region's urban growth. As the result, the frontier of urban sprawl is advancing deeper into the far suburb areas. As the process advances, the agricultural land loss problem that has perplexed Shanghai for many years is expected to deteriorate. Therefore, it is of great importance for the municipality government to strengthen its land use regulation and planning in order to protect its limited agricultural land resources.

Despite the government's propaganda on afforestation efforts, the increase for forest coverage in the region was very modest during 1978 – 2000. The forest model projects a slight decrease of forest area ratio during the next 25 years. In order to alleviate the environment problem and achieve sustainable development in the region, more intensive measures for afforestation work have to be taken immediately.

Land use/land cover changes are results from multidimensional interactions of biophysical and socioeconomic processes. The metropolitan area of Shanghai is very plain with little spatial variation in the terrain and soil quality. Therefore none of the biophysical variables are included in the modeling framework of this project. Transportation is has long been known as an important driving force of land use change. It is a crucial variable that changes the concentric shape of land use zones and facilitates the process of urban sprawl. However, little information about transportation development at the county/district level is available for this study, so it is not included in any of the modeling component. A more thorough analysis of model performance is highly recommended as soon as more transportation information becomes available.

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CHAPTER 4

Land Use/Land Cover Change

in the Brazilian Amazon and the State of Rondonia

The Brazilian Amazon is an agricultural frontier. It is chosen to be a representative case to study the consequences of agricultural activities on a primarily forested landscape. The main objective of this chapter is to understand the complex factors of human socio-economic activities as they control processes of land use/land cover change (LUCC). Based on this analysis, projections of future land use/land cover change in the region are made using a process-based systematic model that links remotely sensed observations of LUCC to the demographic and economic data.

This chapter will proceed through the following sections: the first section describes the background and main themes of this study, starting with the environmental significance and global attentions to land use/land cover change in the Brazilian Amazon, followed by the importance of LUCC monitoring, process understanding as well as LUCC modeling. The second section outlines a systematic modeling scheme, with elaborations on the advantages of dynamic system modeling method and the importance to integrate remotely sensed land cover information with census data. The third through fifth sections construct a systems model of land use/land cover change by integrating land cover change with the region's demographic and socioeconomic structures, as well as land use behaviors. The LUCC systematic model is comprised of a land cover change model, a socio-economic model and a population model, with multi-interactions between each modeling component. The sixth section performs sensitivity analyses to examine the model behavior, and also to determine some critical model parameters that are subject to high uncertainties. Section seven presents major modeling results and model validation. The last section addresses the implication of the study and possible improvements for future modeling work.

4.1 Introduction

Research on tropical deforestation is important because of its significant role in the global carbon cycle, its relation to ecological complexity, and its impact on changes in biodiversity. As the world's largest contiguous tropical forest biome covering an area of approximately 500 million hectares and containing 40 percent of the world's remaining tropical rainforest, the Brazilian Amazon has come into the international spotlight over the past two decades because of concerns for its high deforestation rate, currently at an average of nearly 2 million hectares per year (Houghton et al, 2000).

Land use/land cover change (LUCC) is well known as an important driver of ecological change in Amazonia, with large influence on hydrology, climate, and global biogeochemical cycles (Houghton 1991; Crutzen and Andreae 1990; Houghton and Skole 1990, Salati and Vose 1984, Shukla et al. 1990). As the results, there has been rapid growth in empirical social science research on LUCC in Amazon.

This study aims to understand the impacts of human land use activities on land cover changes and to project future land use/land cover change in Amazonia based on the understanding. Three related questions are raised within this content: What changes have happened to the land? How did these changes occur? And what will happen in the future? In order to address these questions, this study proposed three theme activities with the applications of different research tools. Theme one is to monitor land cover change with remote sensing satellite images, which offers an objective quantitative approach to measure the magnitude and rate of land cover change. Theme two is understand the land use/land cover change process and underlying driving forces. In a human-dominate landscape, it is the human actions rather than natural forces that are the sources of most contemporary change in land. Economic and demographic theories are applied to explain land use/land cover change processes. Theme three is to develop a land use/land cover change model that links remotely sensed land cover change with the demographic and socio-economic understanding of land use processes. The model is then used to project what changes would happen to the land in the Brazilian Amazon.

4.1.1 LUCC Monitoring

The general interest in land use/land cover change is stimulated by current global change concerns, yet empowered by the new capacity of landscape monitoring with the earth observing systems. Satellite remote sensing has been used extensively to map the magnitude and rates of deforestation in Amazonia (e.g. Tucker et al. 1984, Malingreau and Tucker 1988, and Skole and Tucker 1993). These studies have been successful at documenting deforestation rates using remote sensing analyses that measure changes in forest versus non-forest covers. However, we should consider more than only forest versus non-forest when considering land use/land cover change in the Amazonia. The simplistic view of forest versus non-forest overshadows some interesting dynamics which are only recently being observed.

New research in Amazonia has shown land use/land cover change as a highly dynamic process of clearing, abandonment and re-clearing (Alve and Skole, 1996; Steininger, 1996; Houghton et al, 2000). It has documented high frequency of secondary vegetation regeneration following deforestation, generally vigorous regrowth of forests on former pastures and agricultural land. Recent studies have mapped the extent and temporal dynamics of secondary vegetation at landscape level (e.g. Alves and Skole 1996, Mausel et al. 1993, Skole et al. 1994, Adams et al. 1995, Steininger 1996, Foody et al. 1996). A satellite analysis in Rondonia by Alves and Skole (1996) showed that secondary growth accounted for over 40% of the deforested areas. Almost 60% of the areas in secondary growth in 1986 were re-cleared at least once by 1992, and over 55% of the deforested areas in 1986 were abandoned into secondary growth by1992. This analysis and other similar satellite based analyses (Brondizio et al. 1994, Moran et al, 1994; Steininger, 1996, Foody et al. 1996) are useful for characterizing the dynamics of the landscape change resulting from tropical land use. By the year 1986, around 6% of the primary forest in the Brazilian Amazon had been deforested, an area of 23.8 million ha (including 16.8 million ha of deforestation and 7.0 million ha of secondary growth). In 1992, more than 9% of the trees were deforested, representing an area of 34.7 million hectares (including 23.9 million hectares in deforestation and 10.8 million hectares in secondary growth). By 1999, the overall deforested area had reached 47.3 million hectares, of which secondary growth was 15.9 million hectares. Given the widespread vegetation succession and its carbon sequestration potential, secondary growth has become a large and rapidly changing carbon pool. The balance of atmospheric carbon in Amazonia depends nearly as much on succession in the wake of disturbance as on deforestation.

4.1.2 Process Understanding

Observing the magnitudes and patterns of landscape change can provide detailed information on "what changes have happened at when and where", but it does not lead much insight into the question of "why do the changes occur". We need to move from pattern description to process understanding, to find the mechanisms which govern the land use/land cover process. It is very important to understanding the factors that influence land use/land cover changes. Controlling deforestation is difficult until we know more about the causes and processes being involved.

It is important to distinguish between two categories of causes for land cover change: the proximate sources of changes and underlying driving forces of changes (Turner et al, 1990). Proximate sources are human activities that make use of, and hence change or maintain, attributes of land cover dynamics, such as agricultural expansion and cattle ranching. They are activities directly responsible for the physical changes in the land. Large-scale deforestation in Amazonia did not begin until the early 1970s, when the Brazilian government introduced ambitious road construction and colonization programs intended to develop the remote Amazonia, which stimulated massive movement of ranchers, farmers, loggers and miners into the region and caused dramatic changes in land cover as results of their land use activities such as agricultural development, logging and mining (Schmink and Wood 1992).

Underlying driving forces contribute to the changes of land indirectly by motivating and constraining production and consumption, therefore give rise to proximate sources of land changes. The identification of driving forces is a more complex subject than that of the proximate causes (Lambin, 1994; Angelsen and Kaimowitz, 1999). There are many factors, including social-economic, physical-ecological and political-institutional factors that may influence the magnitude of the proximate source activities and help generate or release the environmental pressures on the process of land use/land cover change. Candidate forces driving land use/land cover changes include population growth, level of affluence, technology development, property right regime, political economy and government policies, international trade and debt, and attitudes and values (Turner and Meyer 1991; Stern et al. 1992; Burgess, 1993). The challenge is to design a manageable yet realistic model that can incorporate the effects of the key driving variables of land use/land cover change.

4.1.3 LUCC Modeling

From pattern observation and process understanding, the next step is to build an LUCC model, an important endeavor for projection of "what would happen in the future" which are beyond the reach of direct observations from satellite remote sensing.

Little attention was paid to LUCC modeling until the late 1980s, since when various models have been developed to answer such questions as how changes in land use influence changes in land cover, how different configurations of economic development and technological level influence deforestation, and what is the relative importance of these factors in driving deforestation (Lambin, 1994). Answering these questions requires an understanding of the mechanisms of land use/land cover change, and the design of models that are able to incorporate both the proximate sources and the associated driving forces. A range of LUCC models has already existed in literature. Extensive reviews can be found in Lambin (1994), Angelsen and Kaimowitz (1999) and Agarwal and Green et al (2000).

Modeling has become the key to project long-term trends of tropical deforestation. However, most LUCC models concerned about the fate of tropical forest. Few of them addressed the issue of secondary growth. Walker (1999) developed an LUCC model to predict the fallow times of secondary regrowth as well as the areas of regrowth associated with each regrowth cohort as a function of family size. But the model was focused only on the subsistence economy of shifting cultivators, therefore did not provide a complete accounting for economic activities of other major land use agents in the Amazonia.

The existing LUCC models are focused either on field-level understanding of land use change in small areas, or on basin-wide land cover projection without the detailed accounting for land use change. Without basin-scale land use and land cover change projection, the future of the Amazonia remains uncertain. A recent research effort led by

Laurance et al (2001) was to develop a basin-wide GIS model to project future land cover change in the Brazilian Amazon. By integrating GIS data layers on deforestation, logging, mining, highways and roads, navigable rivers, vulnerability to wildfires, protected areas, and existing and planned infrastructure projects, the GIS model was used to predict the pattern and pace of forest degradation and what road construction would do to Brazil's rainforest over the next 20 years. Modeling results showed strikingly extensive deforestation even under the optimistic scenario, therefore, sounded alarms for development plans in the Amazonia. However, like in most land use/land cover change models to date, the driving forces in this model (population growth, industrial logging and mining, changing spatial patterns of deforestation and wildfire) were treated as simple explanatory variable layers that are exogenous from outside of the land use/land cover change process. There was no explicit internal interaction or feedback built into the models (Lawrance et al, 2001). Therefore the models did not adequately account for the mechanism complexity of land use/land cover change.

This study adopts a systems modeling method to simulate the dynamic structure and behavior of land use/land cover change as complex systems with interactions, feedback loops and reciprocal effects between the proximate sources and driving forces of land use/land cover change. It aims to model the dynamic processes of how forests become deforested, how deforested areas grow into secondary vegetation and what is the fate of this secondary growth. Land cover changes are largely caused by human being's land use practices for socio-economic purposes. In a human-dominate landscape, the influence of all economic forces must be recognized for a model to be scientifically predictive (Turner, 1990; Braat and Lierop, 1987; Parks, 1991).

4.1.4 Study Areas

Two studies were undertaken in this chapter: a region-wide analysis for the Amazonia and a smaller-scale case study for the state of Rondonia, the region's newest frontier (see figure 4.1). By definition, the Brazilian Amazon include the states of Acre, Amapa, Para, Rondonia, and Roraima, plus part of Mato Grosso, Maranhao, and Tocantins. The State of Rondonia is located in the western portion of the Brazilian Amazon with an area of 243,044 km^2. It has developed an economy that is centered on agriculture, timber extraction and mining (Dale et al, 1993). Rondonia is selected to be a case study site because it has patches of soil, vegetation and climatic conditions that represent large areas of the Amazon Basin, but it has the most intensive deforestation among all the states in the Brazilian Amazon. It is the most recent state to undergo the transformation from a remote intact forest to a nearly developed agricultural frontier.

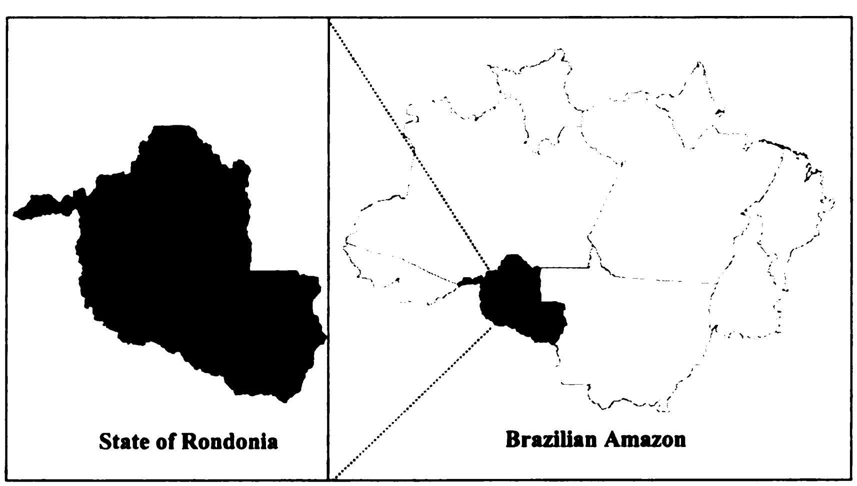

Figure 4.1: Study Areas: the Brazilian Amazon and the State of Rondonia

4.2 Modeling Method and Data

4.2.1 Conceptual Model

To understand the dynamics of land cover change in a particular region, we have to regard the region with the context of its population structure, socio-economic structure and land use structure, treating these components as a coherent system that cannot really be understood from its separate components.

In this study, the Brazilian Amazon is assumed to be a coherent system in three parts: a land subsystem, a population subsystem, and a socio-economic subsystem which consists of proximate sources and driving forces (see Figure 4.2).

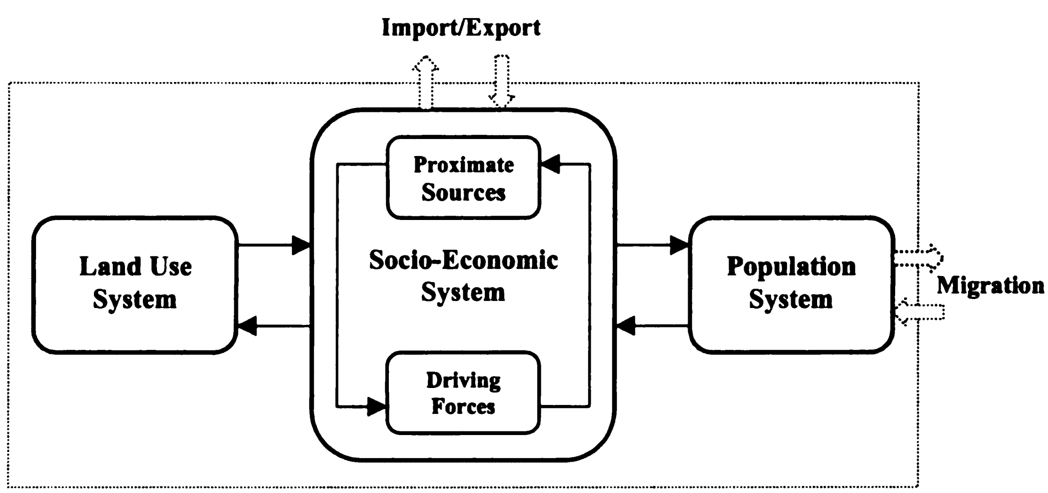

Figure 4.2: A system of LUCC with a land use system, a socio-economy system (with sources and causes) and a population system. Interactions between the system and its environment include both population migration and goods import/export.

Five major proximate sources of land use/land cover change will be analyzed in this study: agricultural development (including farming and cattle ranching), logging, mining, fire, and road construction. The driving forces of land use change are categorized into variables that affect the demands for land (population growth, consumption behavior and income) and variables that control the intensity of land exploitation (technology and soil fertility). Population migration and agricultural product import/export are two other variables that indicate the interactions between the system and its environment.

As the landscape is changed by human activities through various socio-economic processes, the land use system is highly dependent on changes taking place in the population system and the socio-economic system in general. It is the dynamic interactions between the proximate sources and driving forces that lead to the dynamics of land use/land cover change process. This study adopts a systematic modeling method to explicate these interactions and feedbacks behaviors. It develops a systematic model of land use/land cover change based on regional economic development and demographic dynamics.

4.2.2 Modeling Method

Traditional economic models are limited in their power to adequately explain or predict nonlinear, dynamic complexity of the land use system in the Brazilian Amazon. Instead, dynamic system modeling is a useful tool to simulate the dynamic structure and behavior of complex systems with interactions, feedback loops and reciprocal effects. The concept of dynamic feedback has a rich history in ecological modeling that dates back to the early 20^{th} century when Volterra used now-classic differential equations to show how the interaction between predator and prey could drive sustained oscillations (Hannon and

Ruth, 1997). Ecological science has had a profound influence on economists' understanding of the concepts of system stability and the complex relationship between economics and the environment (Perman et al, 1998). Since the 1970s, the systems approach has been applied in economic modeling and later in integrative economic-ecological modeling (Braat and Lierop, 1987).

A systems-based modeling approach can yield more accurate projections of changes in land by taking into account the multidimensional interactions between humans and their environment by clarifying how the economy operates and how the environment reacts therefore allowing for better decision-making and policy optimization. However, the prerequisite for developing of a dynamic systems model is that the processes and mechanisms of land use/land cover change for a given situation are well understood (Lambin, 1994). Building a systematic model is essentially a process of formalizing and articulating, in a comprehensive manner, the cause/effect relationships that have been described in prior studies. The main point of dynamic system modeling is to understand the land use/land cover change process within a system, and to express the structure of a system as mathematical relationships. But no single modeling approach can be expected to elucidate the full range of socio-economic processes affecting land use/land cover change. Statistical methods will be used as a supplement to the systematic modeling method to parameterize the model and quantify the empirical relationship between different variables. Simulation was developed within the STELLA modeling environment, a graphic-based dynamic modeling method developed by High Performance Systems, Inc.

4.2.3 Modeling Data

There are two major types of data in this study: remotely sensed data on land cover change and census data on agricultural land use, demographic and other socio-economic situations. When large areas are studied, census and statistic data are virtually the only regional wide sources that contain extensive sets of data on socio-economic and demographic characteristics of population (Wood and Skole, 1998). Integration of census and statistical socio-economic data with remotely sensed land cover data have been found useful to some modeling work regarding land use/land cover change (e.g., Reis and Margulis, 1992; Wood and Skole, 1998; Moran et al, 1994).

Information regarding land types is derived from LANDSAT satellite data. TM imageries of the Brazilian Amazon Basin for the years 1986, 1992 and 1999 are available from the Tropical Forest Information Center (www.trfic.msu.edu). An iterative, self-organizing (ISO) unsupervised clustering technique was applied to the geo-referenced imageries with a knowledge-based classifier. Seven thematic features of land classes are extracted for each scene: forest, deforestation, secondary growth, water, cloud, cloud shadow and cerrado. The classification is based on a series of thresholds used to isolate each class. In general, visible bands are used to discriminate between forest and non-forest, whereas, the near infrared bands are used to separate forest from early secondary growth forests. The classification is then converted from raster to vector format and input into the project GIS. In the GIS the vectors are checked using visual interpretation by overlaying the vectors on the 1:250,000 scale colorfire photoproducts and on the digital data. The vectors are edited until they match the interpreter's visual assessment. The results are then registered to the tile system to facilitate data manipulation and analysis. Scenes were edge-matched and merged to form a seamless land cover data set for the entire Brazilian Amazon basin (see figure 4.3). In this study, water, cloud, cloud shadow and cerrado are grouped into one category "other" to yield four categories of features (forest, deforestation, secondary growth and other).

Figure 4.3: Land Cover Data in the Brazilian Amazon Based on Landsat Satellite Image Classification for Year 1986 and 1992

The socio-economic data set was fetched in ASCII format from the anonymous FTP site (www.prc.utexas.edu) at the Population Research Center at the University of Texas at Austin. It contains indicators of the social, demographic and economic characteristics of the Legal Amazon and the State of Rondonia in 1980 and 1991. Data for year 1986 were calculated by geometric interpolation. Indicators for demographic characteristics were derived by aggregating the individual-level characteristics of the population reported in the 25 percent sample of the 1980 demographic census of Brazil, and the 10 percent sample of the 1991 demographic census. Data for agricultural production came from 1980 agricultural census of Brazil, 1989 agricultural production annual and 1990 cattle and extractive production annuals of Brazil. An important value of agricultural census reports is that they provide data not available from remote sensing, such as crop type, production and other useful information related to land use and management. Skole et al (1994) showed a comparability of census-derived and satellite-derived estimates of total area deforested, suggesting an important role of agricultural census data in land use/land cover change modeling.

The LUCC systems model consists of a land cover change model, a socio-economic model and a population model. The next three sections will explore each model component in more details.

4.3 Land Cover Change Model

Most land cover change models to date have been focused on the conversion between forest and non-forest covers. However, we should consider more than only forest versus non-forest when considering land use/land cover change in the Brazilian Amazon. There are three types of land cover of interest in this study: forest, deforestation and secondary growth. Forest is tropical rainforest with a closed canopy; deforestation is forest clearing and conversion to agricultural and other uses while secondary growth refers to vegetation regeneration following the reduced use of agricultural land.

Associated with these three types of land cover are four processes of change that form a sequential loop: deforestation, agricultural land use reduction, secondary growth re-clearing, and forest and vegetation regeneration. The land cover change model aims to capture the dynamics of the processes of forest conversion, regeneration, and re-cycling or re-clearing of regeneration vegetation (see Figure 4.4).

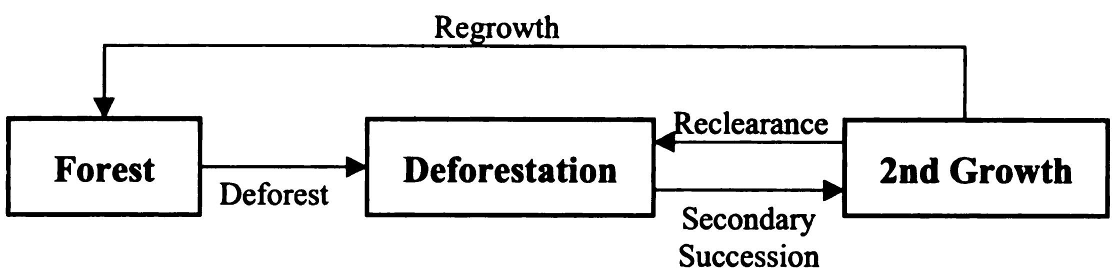

Figure 4.4: Diagram of Land Cover Change Model with Four LUCC processes: deforestation, secondary succession, forest regrowth and secondary growth reclearance.

Upon the arrival of agricultural colonists, parcels of forest are cut and burned. Crops and pastures are grown on the cleared land until the fertility of the land is exhausted, after that the colonists will move forward to clear forested area in new locations, while the land with exhausted fertility will be left fallow for several years. The fallow land will grow into secondary vegetation with critical contributions from factors such as soils, nutrients and land use history (Salomão et al 1996; Moran et al. 1996). Most likely, secondary growth will be recleared again for agricultural use once the fallow land regains fertility, therefore will not revert back to forest (Scatena et al, 1996). Alves and Skole (1996) used multi-temporal Spot XS imagery for a site in Rondonia, Brazil to show that only 42% of the areas in secondary vegetation in 1986 remained in secondary vegetation over the following 6 years. But if left alone, secondary growth will increase its biomass and canopy density, and finally succeed to forest. The reflectance characteristics of secondary growth will eventually become indistinguishable from those of mature, undisturbed forest (Mausel et al. 1993, Boyd et al. 1996).

The land cover change model is simulated in STELLA (figure 4.5). The mathematical expression is formulated using linear algebra in equations 1.01 – 1.05 as shown on table 4.1. Initial areas for the forest, deforestation and secondary growth pools are set at 360,308,500 hectares, 168,041,200 hectares and 7,024,400 hectares respectively in the Brazilian Amazon basin, 20,338,140 hectares, 1,633,760 hectares and 363,310 hectares in the state of Rondonia. These are land cover data derived from satellite images analysis of the year 1986. The annual rate of deforestation (*Deforest*), abandonment (*total_abandonment*) and the rate at which secondary forests are converted back to pasture and agriculture (*total_reclearance*), therefore, the rate of vegetation regeneration *(regrowth_rate1)* are left undefined in this part of the LUCC model. The following text will introduce the factors and processes that control the relative magnitude of forest clearing and agricultural land abandonment, which will finally lead to the development of a LUCC model that can track the land use/land cover change on an annual basis.

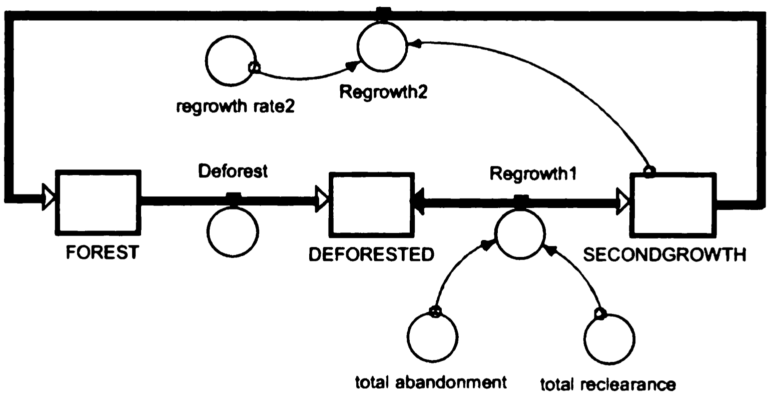

Figure 4.5: A Diagram for the Land Cover Change Model. Regrowth1 is a biflow between two state variables DEFORESTED and SECONDGROWTH. If total_abandonment is larger than total_reclearance, the flow goes into SECONDGROWTH; else the flow goes into DEFORESTED.

Table 4.1 Equations for the Land Cover Change Loop

No.	Equation Specification
1.01	$FOREST(t) = FOREST(t - dt) + (Regrowth2 - Deforest) \times dt$
1.02	$DEFORESTED(t) = DEFORESTED(t - dt) + (Deforest - Regrowth1) \times dt$
1.03	$SECONDGROWTH(t)$
	$= SECONDGROWTH(t - dt) + (Regrowth1 - Regrowth2) \times dt$
1.04	$Regrowth\_1 = total\_abandonment - total\_reclearance$
1.05	$Regrowth\_2 = SECONDGROWTH \times regrowth\_rate2$

4.4 Socio-Economic Model

The socio-economic model links between the land cover change model and the population model. The influence of socio-economic forces must be recognized for a model to be scientifically predictive in a human-dominate landscape (Turner, 1990; Braat and Lierop, 1987; Parks, 1991; Kaimowitz et al, 1997). Unlike most systematic models that view land as an ecological system that will eventually produce some economic benefits, the socio-economic model in this project will explicitly account for the socio-economic processes as well as their impacts on land use/land cover change. Figure 4.6 and equation 2.01 illustrate how the magnitude of deforestation is determined by the five major sources of land use/land cover change, including agricultural development (farming and cattle ranching), logging, fire, mining and road construction.

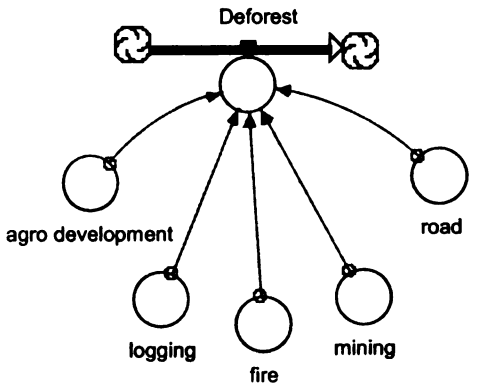

Figure 4.6: Sources of Deforestation in the Brazilian Amazon: agricultural development, logging, fire, mining and road construction

Table 4.2 Equations for Source Activities of Deforestation

No.	Equation Specification
2.01	Defor = agro_development + logging + fire + mining + road

4.4.1 Importance of Agricultural Development

The major cause of deforestation in the Brazilian Amazon is agricultural development, especially large-scale cattle ranching operations (Hecht, 1985; Moran et al, 1994; Walker et al, 2000). Fearnside (1993) attributed 70 percent of deforestation in Amazonia to cattle ranching. Estimates of Walker et al (2000) in the State of Para supported the general view that cattle ranching might be held accountable for a large proportion of forest clearing. While the links between cattle ranching and tropical deforestation have been widely acknowledged, there is a growing realization for the role of small farmers, the largest socio-economic group who produced 80 percent of the total food production in Amazonia (Scatena et al, 1996). Faminow (1998) estimated that small farmers created at least half of the deforestation area in Amazonia.

In this study, eleven agricultural products are analyzed in the agricultural developing system, including ten types of crop cultivation (rice, sugarcane, soybean, corn, manioc, beans, coffee, banana, cacao, black pepper) and cattle ranching. It is the conversion of closed forest canopy to pasture and cropland that accounts for most of the landscape dynamics (Fearnside, 1993; Southgage, 1994; Moran et al, 1994; Parayil and Tong, 1998).

4.4.2 Agricultural Economic Processes

Figure 4.7 illustrates three dynamic agricultural economic processes (demand expansion, inventory correction and expectation adjustment) which interact to generate the equilibrium between the supply and demand for each agricultural product, and a Cobb-Douglas production function that determines the amount of land needed as input to the agricultural production system.

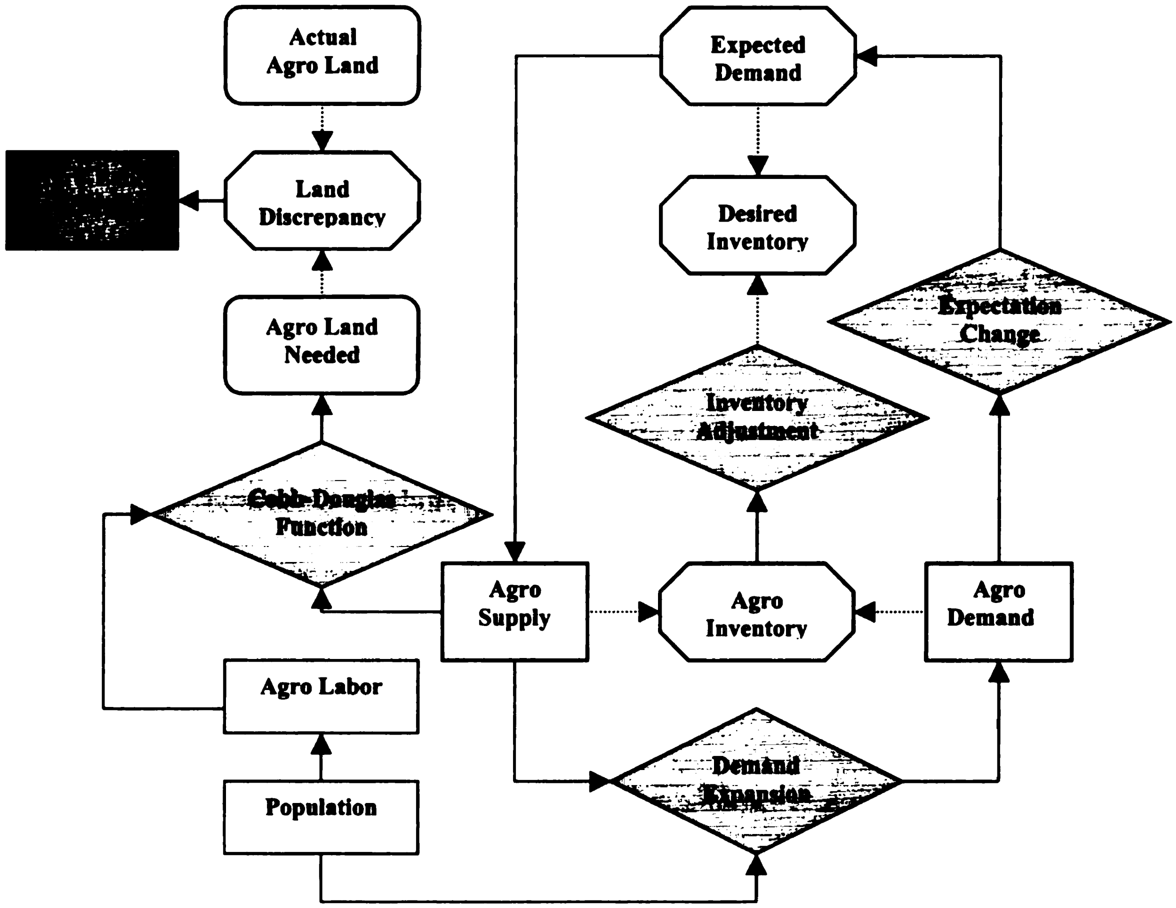

Figure 4.7: Dynamic Agricultural Economic Growth Processes (demand expansion, inventory correction and expectation adjustment) and agricultural land demand through a Cobb-Douglas Production Function

If the demand for agricultural products of an economy increases for reasons such as population growth, agricultural producers will increase the production, which will lead to increased incomes. On one hand, increased income will increase the demand for agricultural goods. In economic terms, this is known as induced consumption that causes an expansion in demand. On the other hand, increased income will increase the further ability of agricultural supply. In macro economy, an initiative that leads to an increase in demand will ripple through the economy. By the time the ripples die out, total expansion in demand can greatly exceed the initial increase.

Expectation adjustment is a process that seeks to eliminate the discrepancies between expected demand and actual demand. Agricultural producers will adjust their expectations for agricultural demand based on the difference between expected demand and actual demand so as to avoid oversupply.

The difference between agricultural supply and demand is agricultural inventory. An inventory correction process is to adjust the production behaviors so as to eliminate the discrepancies between actual and desired inventory.

A Cobb-Douglas production function links the agricultural economy system with agricultural land uses. It describes an empirical relationship between specified inputs and outputs. The agricultural economy is conceived as a machine that transforms the input factors into agricultural outputs through a Cobb-Douglas function, which determines the amount of land needed to produce a certain amount of agricultural supply.

The difference between needed agricultural land and existing agricultural land is agricultural land discrepancy. People will alter their land use behaviors as responses to the discrepancy level. More land will be cleared if the actual land area is short of the needed land area; on the contrary, more land will be abandoned if less land is needed for production.

4.4.3 Modeling Agricultural Land Use Processes

Figure 4.8 shows the model architecture for these components. The arrays in Figure 4.8 have a dimension of agricultural type with the eleven major agricultural products. Equations 2.01 – 2.18 on table 4.3 are the mathematical expressions for the diagram.

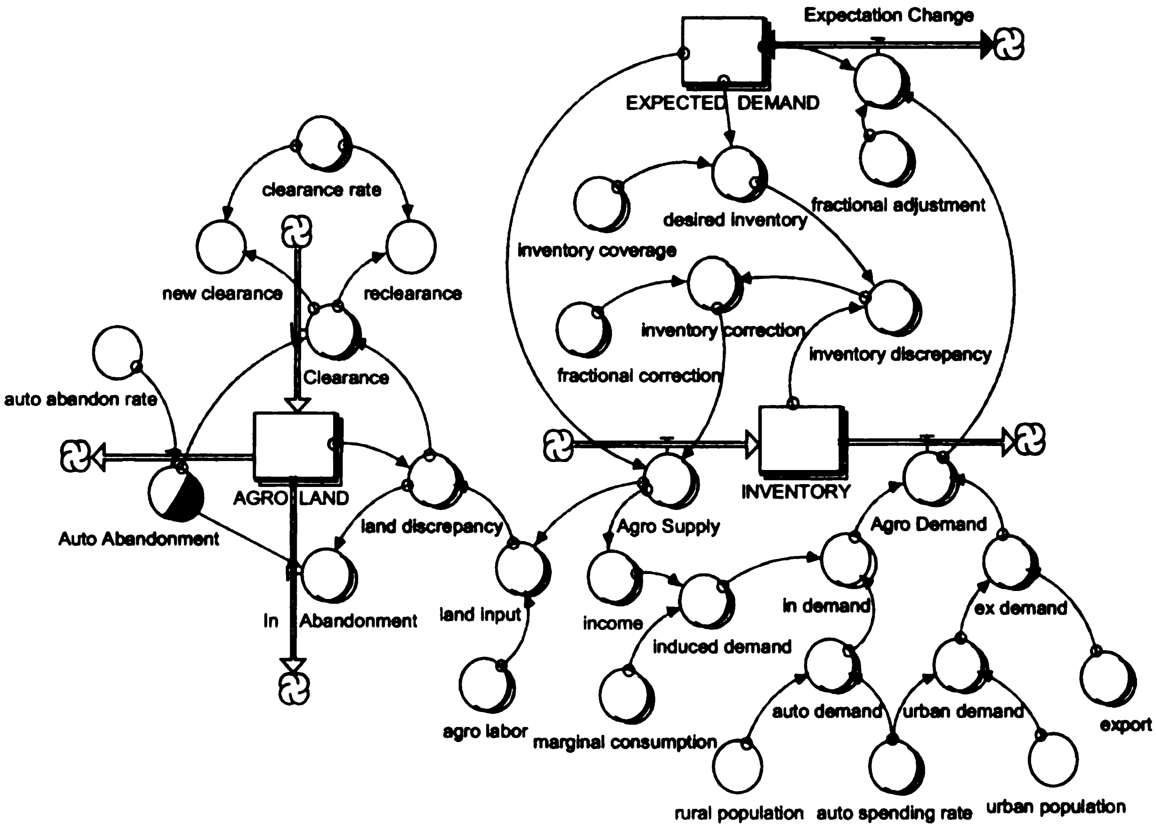

Figure 4.8: Diagram of Agricultural Development and Land Use Change

Table 4.3 Equations of Agricultural Economic Processes for the Socio-Economic Model

No.	Equation Specification
(1) Demand expansion	
2.01	$Agro\_Demand_p = in\_demand_p + ex\_demand_p$
2.02	$in\_demand_p = auto\_demand_p + induced\_demand_p$
2.03	$auto\_demand_p = rural\_pop \times auto\_demand\_rate_p$
2.04	$induced\_demand_p = income_p \times marginal\_consumption_p$
2.05	$income_p = AGRO\_SUPPLY_p$
2.06	$ex\_demand_p = urban\_demand_p + export_p$
2.07	$urban\_demand_p = urban\_pop \times auto\_demand\_rate_p$
2.08	$export_p = Agro\_supply * export\_ratio$
(2) Expectation adjustment	
2.09	$EXPECTED\_DEMAND_p(t)$
	$= EXPECTED\_DEMAND_p(t - dt) + (Expectation\_Change_p) \times dt$
2.10	$INIT\ EXPECTED\_DEMAND_p$
	$= auto\_demand_p/(1 - marginal\_consumption_p)$
2.11	$Expectation\_Change_p$
	$= (AgroDemand_p - EXPECTED\_DEMAND_p) \times fractional\_adjustment_p$
(3) Inventory Correction	
2.12	$INVENTORY_p(t)$

$= INVENTORY_p(t - dt) + (Agro\_Supply_p - Agro\_Demand_p) \times dt$

2.13 INIT $INVENTORY_p = desired\_inventory_p$

2.14 $desired\_inventory_p = EXPECTED\_DEMAND_p \times inventory\_coverage_p$

2.15 $inventory\_discrepancy_p = desired\_inventory_p - INVENTORY_p$

2.16 $inventory\_correction_p = inventory\_discrepancy_p \times fractional\_correction_p$

2.17 $Agro\_Supply_p = EXPECTED\_DEMAND_p + inventory\_correction_p$

(4) Cobb-Douglas Production

2.18 $land\_input_p = \exp [(\ln(Agro\_Supply_p) - \ln(c_p) - b_p \times \ln(agro\_labor_p))/a_p]$

(5) Agricultural Land Use Change

2.19 $land\_discripancy_p = land\_input_p - AGROLAND_p$

2.20 $AGROLAND_p(t)$

$= AGROLAND_p(t - dt)$

$+ (Clearance_p - Auto\_abandonment_p - In\_abandonment_p) \times dt$

2.21 $Auto\_abandonment_p = AGROLAND_p \times auto\_abandon\_rate_p$

If $land\_discrepancy_p >= 0$

2.22.1 $Clearance_p = land\_discrepancy_p + Auto\_abandonment$

2.23.1 $In\_abandonment = 0$

If $land\_discrepancy_p < 0$

2.22.2 $Clearance_p = Auto\_abandonment_p$

2.23.2 $In\_abandonment_p = -(land\_discrepancy_p) - Auto\_abandonment_p$

2.24 $New\_clearance_p = Clearance_p \times clearance\_rate_p$

2.25 $Reclearance_p = Clearance_p \times (1\text{-}clearance\_rate_p)$

Note: p is the dimension for the array of agricultural type, representing rice, sugarcane, soybean, corn, manioc, beans, coffee, banana, cacao, black pepper and cattle (in order).

(1) Demand Expansion

Demand for each agricultural product comes from two sources: an internal demand and an external demand (equation 2.01). The internal demand is to satisfy the needs for farmers living within the agricultural production system, while the external demand comes from outside of the system.

The volume of the internal demand is a function of the internal population size and consumption behavior. It is comprised of an autonomous demand and an induced demand (equation 2.02). Autonomous demand is independent of the consumers' income (equation 2.03), while induced demand is dependent on consumer's income and marginal propensity to consume (equation 2.04). Farmers allocate some fraction of their income to the purchase of goods and service. Since they derive their income from agricultural activities, their income is a function of agricultural production (equation 2.05). When incomes change, consumers will vary their spending in the proportion to the change, called the marginal propensity to consume. Increased agricultural supply will lead to an increased income so as to increase the internal demand for agricultural goods.

External demand came from outside of the agricultural production system. It consists of demand from urban residents in Amazonia and demand from people outside of the region (equation 2.06). Agricultural demand from urban residents is dependent on the size of urban population (equation 2.07). There is an active market for agriculture goods in areas outside of the Legal Amazon area, where not much land is available for agricultural use. The semi-open access status of the vast amount of tropical forestry in the Amazon basin makes it more subject to be converted to agricultural use. Since no reliable data source for agricultural commodity export exists, export ratio is assumed to be 10% of total agricultural supply in this model (equation 2.08).

(2) Expectation Adjustment

Expectation adjustment is a process that seeks to eliminate the discrepancies between expected demand and actual demand. The expected demand is adjusted by expectation change (equation 2.09), with the initial expected demand set to be a function of the autonomous demand and the marginal propensity to consume (equation 2.10). The expectation change is the fractional adjustment times the difference between actual agricultural demand and expected demand (equation 2.11).

(3) Inventory Adjustment

The difference between agricultural supply and demand is agricultural inventory (equation 2.12). Initially, inventories for all agricultural products are set at their desired inventory levels (equation 2.13). Desired inventory is the coverage fraction of expected demand (equation 2.14), and inventory discrepancy is the difference between desired inventory and the actual inventory (equation 2.15). The inventory correction process is to adjust the production behaviors so as to eliminate inventory discrepancies (equation

2.16). Producers will regulate their production activities to make supply conform to the volume of demand. A negative feedback loop uses the discrepancy from equilibrium agricultural production to control supply responses, which equals the expected agricultural demand adjusted by inventory correction (equation 2.17).

(4) Cobb-Douglas Production Function

The economic processes of demand expansion, expectation adjustment and inventory correction work together to decide how much agricultural products will be produced each year in order to meet the changing demand. Then a transformed Cobb-Douglas function is used to calculate how much land is needed to produce the amount of agricultural products (equation 2.18).

For simplicity, we consider agricultural production with only two inputs: land and labor. The agricultural economy is conceived as a machine that converts the input factors into agricultural outputs through a Cobb-Douglas function, which is defined as the following:

$$Y = c f\{N, L\} = c \times N^a \times L^b$$

Where Y is agricultural output, N is agricultural land, and L is agricultural labor. c is a constant scaling parameter that accounts for technological progress, while the exponents a and b are elasticity ratios that give estimates of the percentage change in agricultural output for one percent change in the corresponding agricultural input (land and labor). Given data on quantities of agricultural inputs and outputs, we can estimate the parameters of the Cobb-Douglas production function by taking logarithms to transform it into a linear relationship, then regressing the log of the quantity produced on the logs of the input quantities and a constant term.

Take logs of both side of the function, the Cobb-Douglas functions is transformed into:

$$\ln(Y) = \ln(c) + a \times \ln(N) + b \times \ln(L)$$

The Ordinary Least Squares (OLS) method is employed to estimate the parameters (constant c and exponents a, b) of the Cobb-Douglas production function for each agricultural product. With known agricultural output and labor, we can calculate needed land as input to agricultural production based on the following equation:

$$N = \exp\left[(\ln(Y) - \ln(c) - b \times \ln(L))/a\right]$$

(5) Agricultural Land Use Change

The difference between needed agricultural land and existing agricultural land is agricultural land discrepancy (equation 2.19). There are three processes that change the stock of agricultural land area: autonomous abandonment, induced abandonment as well as clearance (equation 2.20).

Land abandonment is the combined results of both autonomous and induced abandonment. The largest part of the Amazonian soils has a low fertility as far as nutrients for plants are concerned. Autonomous abandonment is the land taken away from agricultural production as the result of soil fertility exhaustion, no matter what is the level of agricultural land discrepancy (equation 2.21). Induced abandonment and clearance amount are determined by the discrepancy level of agricultural land demand. When the land discrepancy is larger than zero, that is, when more agricultural land is in need, more land will be cleared and added to the agricultural land stock to make up the land deficiency cause by land discrepancy and autonomous abandonment (equation 2.22.1), and no land will be induced to be abandoned (equation 2.23.1). On the contrary, if the discrepancy is less than zero, in another word, existing agricultural land exceeds the needed land, people tend to reduce the land stock. No new land will be cleared (equation 2.22.2), and more land will be abandoned (equation 2.23.2). Once the amount of annual clearance is determined, equations 2.24 and 2.25 are used to divide between new clearance of primary forest and reclearance of secondary growth, two important sources of new agricultural land.

4.4.4 Other Proximate Sources

In addition to agricultural development, logging, fire, mining and road construction are four other proximate sources of deforestation. Figure 4.9 illustrates the interactions among these source activities, and the interactions between these sources and agricultural development as well as population.

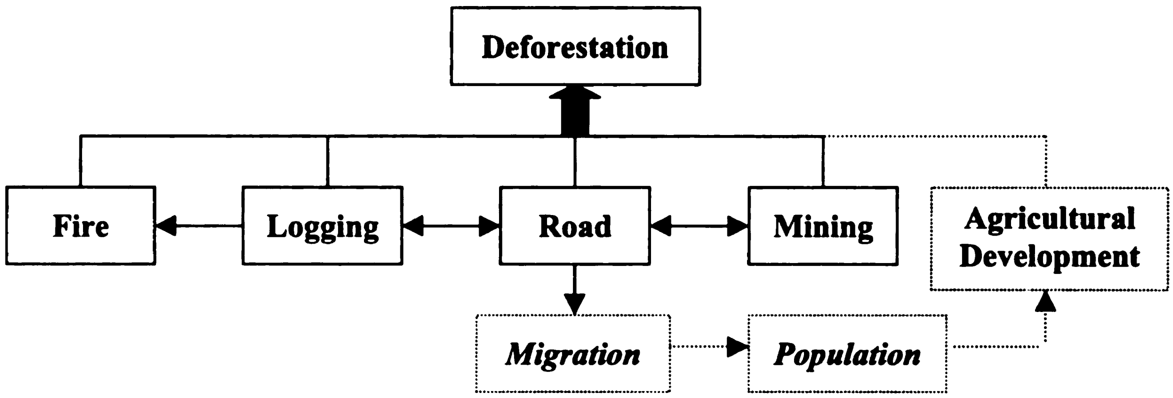

Figure 4.9: Interaction Loops between Deforestation Source Activities

(1) Logging

The Amazon basin is an enormous warehouse of tropical timber with an estimated 50 billion cubic meters of standing wood. Logging is becoming an increasingly important activity in the Brazilian Amazon; it is by far the most extensive forms of human activity in Amazonia (Parayil and Tong, 1998). Basin-wide estimates of logging area vary widely. Nepstad et al. (1999) used survey data to estimate a total logged area of 9,000-15,000 km^2 in 1996-1997, nearly equal the area of forest converted to pasture or agriculture. Krug (2000) estimated a logging rate of 1,561 km^2/year using visually interpreted Landsat prints. Matricardi et al (2001) developed an automatic remote sensing analysis along with visual interpretation and quantified the selective logging area in the Amazonia to be 5,627 km^2 by 1992, which increased to 9,449 km^2 by 1996 and 23,379 km^2 by 1999.

Logging was considered as forest degradation as opposed to a source of deforestation until recently (Panayotou and Sungsuwan, 1994; Houghton et al, 1991). With only a few marketable species, logging in the Brazilian Amazon is highly selective. Current logging practice generally removes timbers in a volume range of around 60 cubic meters per ha (~ 2-10 trees per ha) out of a total of up to 300 trees above 10cm diameter. But as many as 27 trees can be damaged for each tree harvested as a high level of collateral damage (Verissimo et al. 1992). Besides damage to nearby trees, selective logging have far more detrimental environmental consequences by increasing fire susceptibility and stimulating road construction.

(2) Road Construction

Road construction that provides access to remote forested areas is a critical source of deforestation, but with more serious effects than the road construction activities themselves. It is a main factor driving the vicious feedback cycles that threaten Amazon ecosystems (Cochrane et al, 1999). A major component of the colonization programs in the Amazonia was road construction and improvement (Laurance et al, 2001; Dale et al, 1993; Pfaff, 1997; Frohn et al, 1990). Highways were paved amid much controversy regarding the potential environmental impacts. Financed road construction programs have stimulated a massive shift in investment from southern Brazil to the Amazonia. Besides facilitating timber transportation, roads opened for logging stimulated immigration, which in turn brings more logging, more agricultural development and subsequently more deforestation to the area. Uncontrolled exploration by loggers catalyzes deforestation by opening roads into unoccupied forest area that are subsequently colonized by ranchers and farmers (Verissimo et al. 1995).

(3) Forest Fire

Forest fire is an important deforestation source that is closely related with logging. Logging changes forest structure and increases forest flammability (Holdsworth and Uhl, 1997). Fires are frequent because of the accidental spread of fire from nearby pastures. The fire susceptibility is subject to human disturbance. According to Uhl and Kaufman (1990), the flammability of forest ecosystems is highly dependent on the structure of the vegetation that determines the microclimate of the stands. A primary forest with undisturbed canopies does not reach flammable levels even in periods of more than 30 rainless days. A 15-year-old secondary forest need a period of 8-10 rainless days to have flammable conditions, and a pasture needs only 24 rainless hours. The selectively logged forest, with artificially open canopies, becomes flammable in 5-6 rainless days. Research of Cochrane et al (1999) shows that fire in highly degraded areas are significantly more severe in all respects of flame height, intensity, depth, residence time and rate of spread.

(4) Mining

Mining is also an active source of deforestation. The Brazilian Amazon has significant mineral resources including coal, gold and the ores of iron, aluminum, copper, tin, kaolin and some rare minerals such as niobium. There were 530 mineral extraction establishments and 3,161 mineral processing establishments in 1980. Like logging establishments, these mining establishments are responsible for road constructions leading to mineral-rich areas, providing a rapidly growing economic impetus for road building in the Amazon (Laurance et al, 2001). While mineral extraction may destroy hundreds to thousands of hectares of forest directly, mineral processing can consume even larger areas of forest. Fearnside (1989) explored substantial destruction of forested areas in the eastern Amazon to provide raw materials for charcoal to be used in smelting pig iron.

(5) Modeling

Figure 4.10 shows the structure of this part of the model. Equations 2.26 to 2.31 are the mathematical representations of the model.

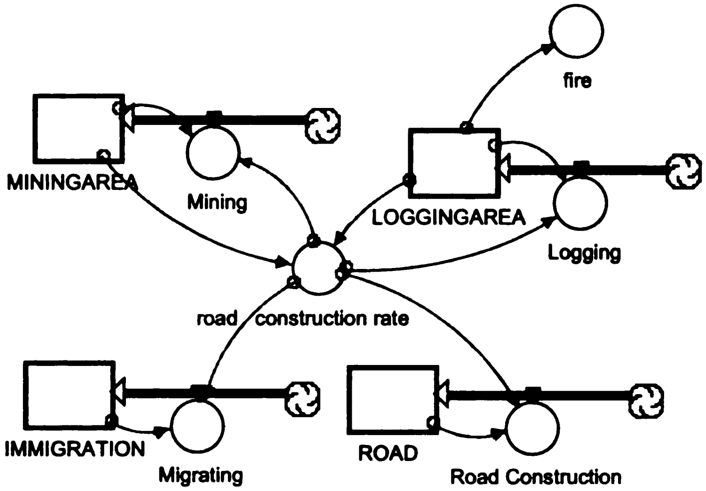

Figure 4.10: Modeling Other Proximate Sources of Deforestation - Logging, Road Construction, Mining and Forest Fire

Table 4.4 Equations of Other Proximate Sources of the Socio-Economic Model

No.	Equation Specification
2.26	ROAD(t) = ROAD(t - dt) + (Road_Construction) * dt
2.27	Road_Construction = ROAD * Road_Construction_rate
2.28	Road_Construction_rate = a + b* LOGGINGAREA +c* MININGAREA
2.29	LOGGINGAREA(t) = LOGGINGAREA(t - dt) + (Logging) * dt
2.30	Logging = LOGGINGAREA * Road_Construction_rate
2.31	fire = LOGGINGAREA * random (min, max)
2.32	MININGAREA(t) = MININGAREA(t - dt) + (Mining) * dt
2.33	Mining = MININGAREA * Road_Construction_rate
2.34	IMMIGRATION(t) = IMMIGRATION(t - dt) + (Migrating) * dt
2.35	Migrating = IMMIGRATION * Road_Construction_rate

Equations 2.26 to 2.28 model road construction. New road constructions extend the road network in Amazonia by adding more roads (equation 2.26 and 2.27). The annual rate for road construction is determined by logging and mining activities (equation 2.28). The parameters a, b, and c in equation 2.28 are estimated using municipal-level data on logging, mining and road construction. Annual logging area, mining area and population migration are all defined as functions of road construction (equations 2.29 – 2.34). Fire is a function of logging (equation 2.35). Areas with more logging are subject to a higher probability of catching fire. A random function with a minimum probability of 0.1 and a

maximum probability of 0.5 is used to defined the magnitude of forest fire caused by logging.

4.5 Population Model

The population model estimates changes in population and associated demographic characteristics based on historic records and projections. There is a popular notion in literature that associates land use/land cover change with demographic pressure (Bilsborrow and Okoth-Ogendo, 1992; Mather, 1996; Wood and Perz, 1996). Most of these studies showed a significant correlation between population size (or density) and land use/land cover change, and used the statistical evidence to theorize the argument that demographic pressure is the most important driving force for land use/land cover change (Meyer and Turner II, 1992).

Intuitively, there is a positive correlation between population and deforestation. Fulfilling the resource requirements of a growing population ultimately requires some form of land-use change to provide enough land for food production. In a dynamic perspective, this implies a positive relationship between population growth and deforestation. However, land use/land cover change is a more complex problem than simply because of too many people (Skole et al, 1994). The intensity of the relationship between population and land use/land cover change can vary considerably because it is mediated by a series of socio-cultural, economic and ecological factors (Andersen and Reis, 1997). Malthusian and neo-Malthusian demographic theory offers an over-simplistic understanding of the complex relationship of resources and population. Population in Amazonia should be analyzed in a more comprehensive way that extends beyond a sheer size of population size, which represents only one important variable in the complex relationship between population and resources.

This study proposes a dynamic population system model that considers at least the following demographic factors: (1) age structure and gender composition, (2) population distribution (urban vs. rural), (3) occupation, and (4) population growth mode (natural population growth vs. migration).

4.5.1 Age Structure and Gender Composition

Population age structure, along with the gender composition, matters in determining the impacts of population on land use/land cover change. The effect of population growth on land use/land cover change, via increases in food consumption, is maximum when children reach adolescence, i.e., with a time lag of approximately 15 years (Lambin, 1994). In the same way, age structure decides the degree of participation in agricultural production. Population within the age range of 15-65 is the main labor pool that is economically active. Together with population's gender composition, age structure can influences the region's population growth. Women of age 15-60 are the main fertility group that contributes to the natural growth of population.

The population pyramids (Figure 4.11) show the relative population size of each age group and gender category. The youngest age group is at the bottom and the oldest is at the top; males are on the left and females are on the right. Each horizontal bar represents the number of people in a 5-year age group as shown by the labels on the left. The triangle-shaped pyramid of the Brazilian Amazon is typical of many developing countries. The wide bottom of the pyramid indicates a high population growth rate as well as a gradual shift in the age structure in favor of the economically active population. Besides this, young people are more likely than their older counterparts to migrate, primarily as they leave the parental home in search of new opportunities. As a result, given the relatively large younger generation, we might anticipate an increasing level of migration and urbanization.

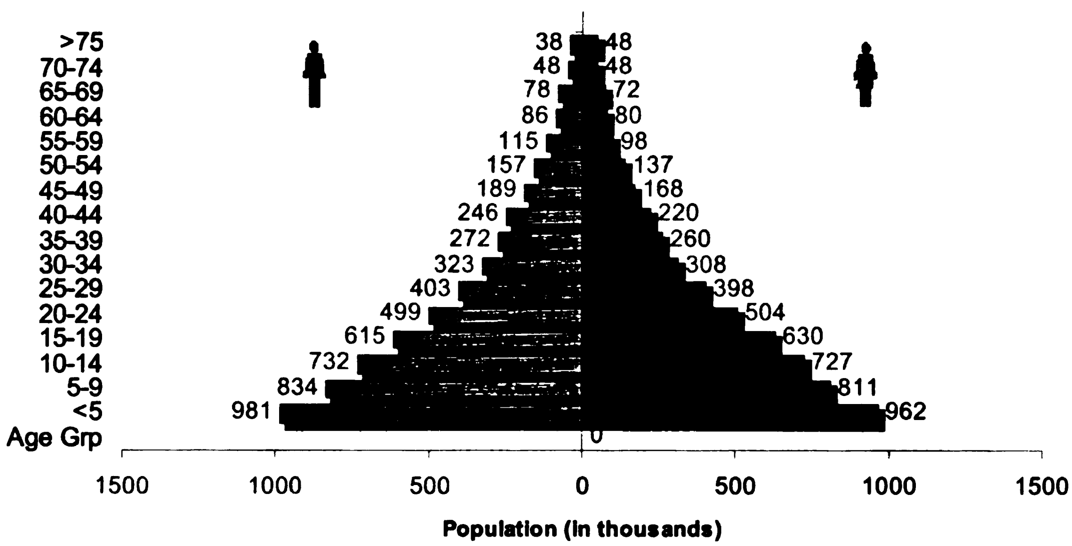

Figure 4.11: Population Pyramid in the Brazilian Amazon, 1990. Data source: IBGE (Brazilian Geographic and Statistical Institute)

4.5.2 Population Distribution: Urban and Rural

The general picture of Amazonia is rural and wildness. However, more than half of its population is living in urban areas. Total population in the Brazilian Amazon grew at an average annual rate of 4.0% during the period 1970-1991. Urban population grew much faster than that of rural, leading to a dramatic change in the composition of the population (Andersen and Reis, 1997). According to demographic census, urban population percentage had increased from 27.7% in 1940 to 55.6% in 1989 (Figure 4.12).

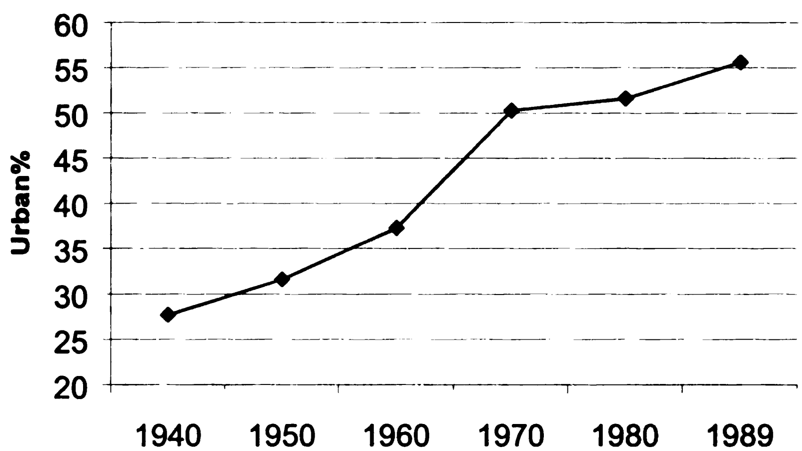

Figure 4.12: Growth of Urban Population Percentage (1940 – 1989). Data source: IBGE (Brazilian Geographic and Statistical Institute) census.

Urban and rural population has different production and consumption behaviors, therefore the ways in which population is distributed among urban and rural areas can affect land use change (Andersen and Reis, 1997; Moran, 1999). Therefore it is important to differentiate these two groups of population and to model their behaviors separately. A traditional rural family lives on a farm, where the demand for land comes both from agricultural production and consumption, while an urban family typically lives in urban areas and works in the service sector with no direct impact on deforestation. However, urban residents will have an indirect effect through the demand for agricultural goods in the form of both raw materials and food consumption.

4.5.3 Occupation

Occupation is an important linkage between the population system and the economic system. Economically active population work with different occupations, therefore have different production functions and different requirements for land as an input to production. It is the human economic actions undertaken by different population groups or agents (such as small farmers, cattle ranchers and loggers etc) that are directly responsible for land use/land cover change. The overall human impacts on land use/land cover change will depend on the relative size of each occupational group and its production behavior. Cattle ranchers account for 6-8% of the rural population, roughly 10% of small farmers, who are the predominant majority of rural working force. But cattle ranchers have far more impacts on the process of land use/land cover change than small farmers (Hecht, 1985; Moran et al, 1994; Fearnside,1993). As seen from figure 4.13, cattle ranching area is much larger than small farm cultivation area.

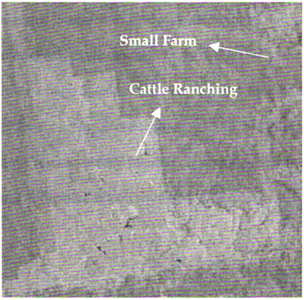

Figure 4.13: Different Land Use Patterns for Different Occupational Groups. LANDSAT TM image (path 230, row 69, 05/15/99)

4.5.2 Population Growth: natural population growth vs migration

The population in the Brazilian Amazon increased from 7.3 million in 1970 to 16.6 million in. About 40% of the increase was caused by migration into the area, so the number of immigrants in the period is 3-4 million (Andersen and Reis, 1997). Both natural population growth (the excess of births over deaths) and migration will lead to an increase in population size, but with different mechanisms. Migration is facilitated by road construction, while natural population growth is more a function of the region's existing population. In order to have a better picture of the future population size in the Brazilian Amazon, we need to examine these two components of population growth separately.

Migration has been a driving force for extensive land use/land cover change. Large numbers of migrants in search of land and employment entered the area, as well as firms that wanted to establish cattle ranches. Early in the 1960s, the Brazilian government decided to initiate a huge development program that should integrate the Amazon region into the rest of the economy. Since then, around 60,000 kilometers of roads were constructed in the region, several hundred thousand people were helped to settle along these roads, and millions of others followed without official help (Andersen and Reis, 1997).

4.5.5 Modeling Population Growth and Distribution

The population growth model is a discrete-time model that describes four ecological processes: age growth, reproduction, mortality and migration. It is used to generate the region's intrinsic rate of overall population growth and the proportion of each age class. All population is disaggregated into six age cohorts: (1) below 15; (2) 15-29; (3) 30 – 44; (4) 45-59; (5) 60 – 74; (6) 75 and up. As shown on figure 4.14, population of each age cohort is an array with a gender dimension. Equations 3.01 – 3.05 are the mathematical expressions of the population growth model, where i represents the population cohort number ($i = 1, 2, 3, 4, 5, 6$), and j is the population gender dimension ($j = 1$ for male; $j = 2$ for female).

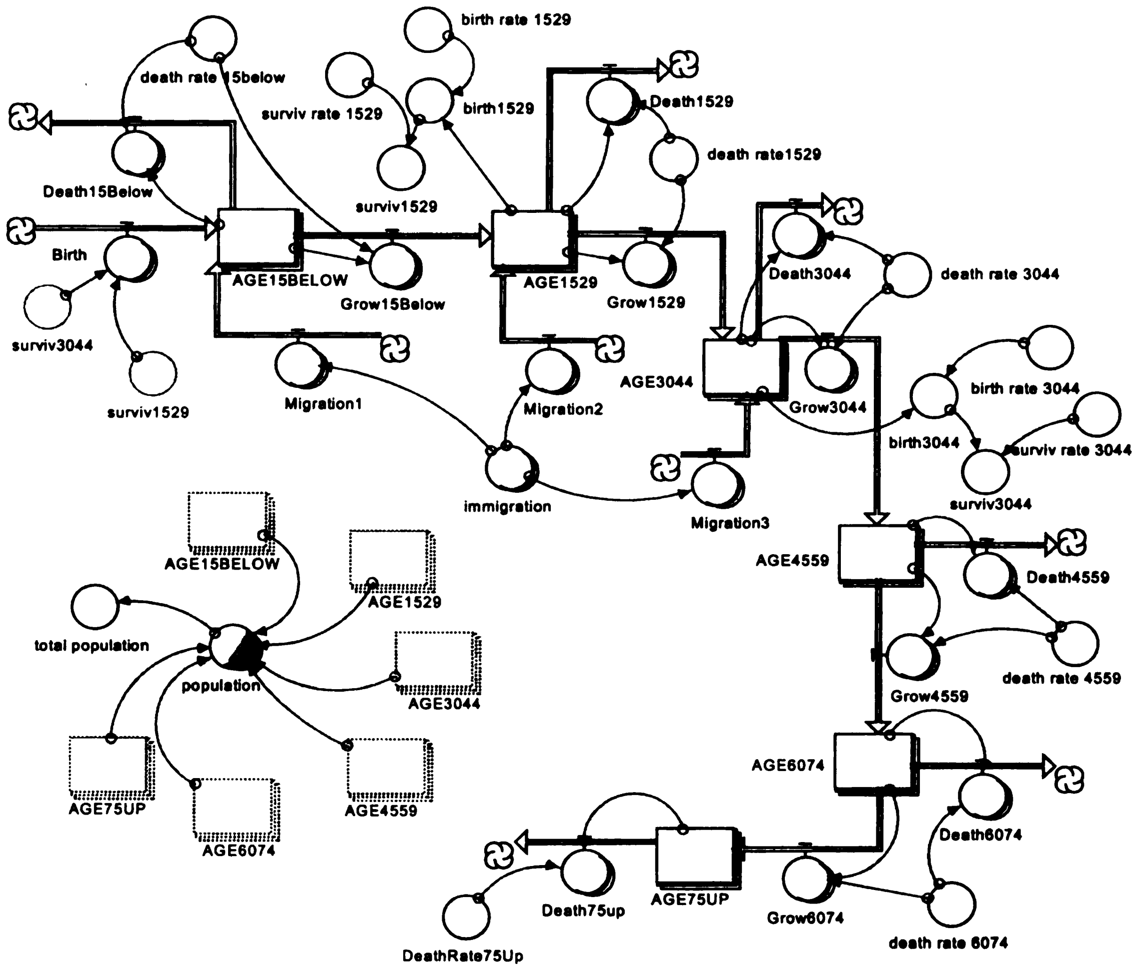

Figure 4.14: Population Growth Model with Four Ecological Processes: age growth, age-specific reproduction and mortality, and migration.

Table 4.5 Equations of the Population Growth Model

No.	Equation Specification
3.01	$AGE_{i,j}(t) = AGE_{i,j}(t\text{-}dt) + (Grow_{i-1,j} + Migration_{i,j} - Grow_{i,j} - Death_{i,j}) \times dt$
3.02	$Death_{i,j} = AGE_{i,j} \times death\_rate_{i,j}$
3.03	$Grow_{i,j} = AGE_{i,j} \times (1 - death\_rate_{i,j}) \times (1/x_i)$ (for all i > 0)
3.04	$Grow_{0,j} = \sum_{i=2}^{4}(AGE_{i,2} \times birth\_rate_i \times surviv\_rate_i)/2$
3.05	$total\_population = (\sum_{i=1}^{6}\sum_{j=1}^{2} AGE_{i,j})$

Note: i represents the population cohort number (i = 1, 2, 3, 4, 5, 6), and j is the population gender dimension (j =1 for male; j = 2 for female).

Population in one cohort moves up into the next cohort by the growing process as part of the progress through the life cycle. Equation 3.01 shows that the number of population in age cohort i at time t+1 equals to the number of population in the same cohort of the previous time t, plus the population grown from the prior age cohort i-1 and the migrated population into the age group, minus the population grown into the next age cohort i+1 and the population that die within the age cohort i.

Equation 3.02 calculates the number of population who dies within the age group. The mortality rate varies across all age cohorts. The last cohort is moved out of the population system at above age 75.

For an age cohort with an x-year interval, nearly the whole cohort is moved to the next stage within x years. Since the time step for the model simulation is one-year, we assume the transfer coefficient of the age development process to be 1/cohort size, that is, 1/x of the survived population in an x-year cohort will grow to the next cohort (equation 3.03).

In equation 3.04, we assume that only female population in the age range of 15 to 59 years old (cohort number 2, 3 and 4) have reproduce capability that varies among different age groups. We assume that the birth rate, death rate, and mortality rate will remain at the current level. We need to model the reproductive rule such that each fertile cohort reproduces at the age-specific birth rate multiplied by the size of the corresponding female population. Statistics shows the survival rate for a new-born is dependent on the mother's age, so the actual number of population adding to the age cohort i = 0 (below 15 years old) is adjusted by new-born survival rate. We also assume half of the survived newborns will add to the female population and the other half will add to the male population.

The total number of population is summed over all age cohorts and gender dimension in equation 3.05.

The population number of each age group as well as the corresponding birth rate, death rate and new-born survival rate is available from the census data. Yet the number of population migrated into the region is undefined at this point. We will project the annual population migration based on road construction and economic development in the socio-economic model.

The following part of the population model deals with the region's urban/rural distribution and occupational compositions (see figure 4.15 for model structure and table 4.6 for model specification). The number of people living in either urban or rural area is determined by the urbanization level (equation 3.06 and 3.07). Only people within the above age 15 and below age 75 are considered as economically active (equation 3.08), based on which we calculate the active employment of both urban and rural areas (equation 3.09 and 3.10). Equation 3.11 generates the number of agricultural labors that works as farmers (k=1), as cattle ranchers (k = 2) or as day labors (k = 3).

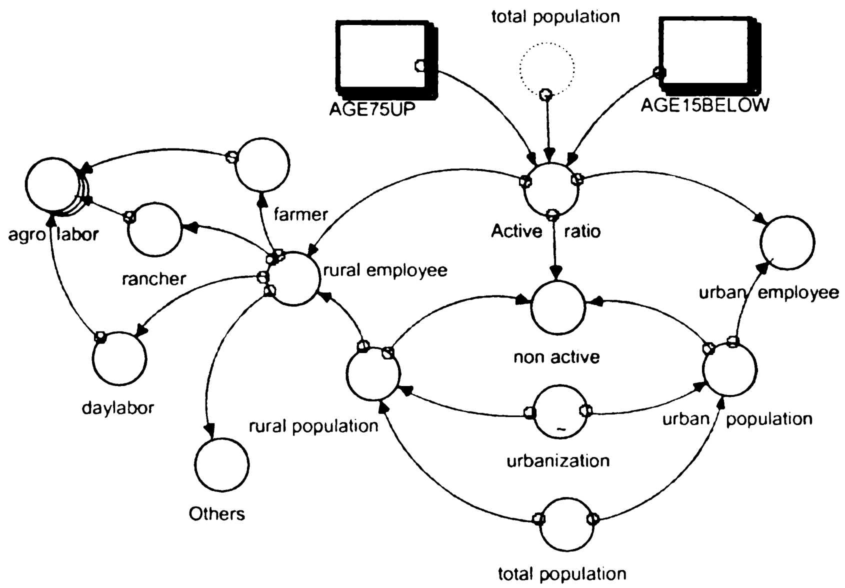

Figure 4.15: Population Urban/Rural Distribution and Occupational Composition

Table 4.6 Equations of Population Distribution Model

No.	Equation Specification
3.06	urban_population = total_population × urbanization
3.07	rural_population = total_population × (1- urbanization)
3.08	active_ratio = [total_population $- \sum_{j=1}^{2}(AGE_{1,j} + AGE_{6,j})$] / total_population
3.09	urban_employee = urban_population × active_ratio
3.10	rural_employee = rural_population × active_ratio
3.11	$agro\_labor_k$ = rural_employee × $labor\_ratio_k$

4.6 Sensitivity Analysis

Sensitivity analysis is a useful tool for model evaluation. It helps build confidence in the model by studying the uncertainties that are often associated with parameters in models. There are three critical parameters subject to high uncertainties in the model: the succession rate of undisturbed secondary growth to forest (regrowth_rate2), the autonomous abandonment rate of agricultural land with exhausted fertility (auto_abandon_rate) and the ratio of new clearance on primary forest (clearance_rate). Parameter sensitivity analyses are performed to determine how sensitive the model is to changes in the value of these parameters, and to indicate which parameter values are reasonable to be used in the model.

4.6.1 Secondary Growth Regrowth Rate

If secondary growth is not disturbed, its reflectance characteristics will eventually become indistinguishable from those of mature, undisturbed forest (Mausel et al. 1993, Boyd et al. 1996). But the question of how long it takes secondary growth to revert to mature forest remains quite uncertain. Brown and Lugo (1990) showed that secondary forest recovered most of its biomass during the first thirty years, after which biomass accumulation slows considerably. Analysis of Vieira (1996) concluded that secondary forest recover only thirty five percent of mature forest biomass after twenty years. Saldarriaga et al. (1988) found a steady biomass increase for older secondary vegetation, but even after eighty years biomass remained substantially less than primary forest. In a similar analysis. Houghton and Skole (2000) indicated that abandoned agricultural land recovered 70 percent of their original biomass in 25 years and the remaining 30% over the next 50 years. But they realized that the assumption that "forests are fully regrown after as little as 75 years are probably not valid". In this analysis, we selected four possible forest regrowth rates for sensitivity analysis: 1/25, 1/50, 1/75 and 1/100, implying the assumptions that undisturbed secondary growth will recover most of its biomass stock and take similar spectral reflectance and structural quality like that of a primary forest canopy in 25, 50, 75 or100 years.

4.6.2 Autonomous Abandonment Rate

The largest part of the soil in Amazonian has a low fertility. Autonomous abandonment is the land taken away from agricultural production as the result of soil fertility exhaustion. is independent of the agricultural economic process. The autonomous abandonment rate is also subject to high variability. According to a Landsat TM image analysis by Skole et al (1994), approximately 11% of the active agricultural land was abandoned each year between 1986 and 1988. However, between 1988 and 1989 when there was more than a twofold increase in forest clearing, 22% of the agricultural land was abandoned annually. The amount of land being abandoned is the combined results of both autonomous and induced abandonment. It is not easy to determine how much land is abandoned autonomously because of ecological constraints, and how much abandonment is induced by economic concerns. In this analysis, we assume the autonomous abandonment rate has a lower bound of 10% and an upper bound of 20%. Five runs of sensitivity analyses were performed on an incremental basis, where the autonomous abandonment rate was set to be 0.1, 0.125, 0.15, 0.175 and 0.2 respectively.

4.6.3 Clearance Rate

Clearance of primary forest and reclearance of secondary growth are two important sources of new agricultural land. The agricultural economic processes help to determine how much more land is needed to put into production, but they couldn't provide information on the percentage of land coming from cutting primary forest and percentage of land from reclearing secondary growth. Satellite TM image analyses by Skole et al (1994) showed that 42% of the new agricultural land in the Amazonia was created from clearing of secondary growth between 1988 and 1989. The clearance rate in this study is set to be 0.50, 0.55, 0.60 and 0.65 for each sensitivity analysis run, assuming that 50%, 55%, 60% or 65% of the clearance will come from deforestation on primary forest.

4.6.4 Sensitivity Analysis Results

Running sensitivity analyses on the specified model parameters show that specific parameter values can change the magnitude of deforestation and secondary growth, but not at a highly significant level. Results of sensitivity analyses are compared with remotely sensed land cover data to choose which parameter values are reasonable to use in the model. If the model behaves as expected from real world observations, it gives some indication that the parameter values reflect the real system behavior, so it is reasonable to use the estimated parameter value in the model. Based on this rule, the secondary growth regrowth rate in the final model was set to be 1/75, the autonomous abandonment rate was 0.125, and the ratio of new agricultural land cleared from primary forest was 0.60.

Despite the magnitude difference of LUCC, there were no significant changes in the overall system behavior. Dynamic system models are general insensitive to many parameter changes. It is the structure of the system, not the parameter values, that has most influence on the behavior of the system. By showing that the system does not react greatly to changes in parameter value, it reduces the modeler's uncertainty in model behavior. In addition, it gives an opportunity for a better understanding of the dynamic behavior of the system.

4.7 LUCC Modeling Results and Validation

The LUCC model is applied to the Brazilian Amazon and to the State of Rondonia as well. The base year for model simulation is set to be 1986. The model projects the region's population, economic growth as well as land use/land cover change into year 2020 at a one-year time step. Remotely sensed land use/land cover data for years of 1992 and 1999, agricultural census data for year 1990 and demographic census data for year 1991 are used to validate model results.

4.7.1 Population Modeling Results and Validation

Figure 4.16 shows the exponential population growth pattern for the Brazilian Amazon basin and for the State of Rondonia as well. Based on model projection, population of the Brazilian Amazon will reach 31.2 million by year 2020, nearly twice the population size of year 1991. During 1986 – 2020, the average annual rate of population growth in the Brazilian Amazon basin is 3.87%. According to IBGE census data, population growth rate during1980 – 1990 was 4.69%. Therefore we can expect a slower population growth rate in the Amazonia in the next two decades. For the State of Rondonia, the population size will grow from 1.1 million in 1991 to 3.8 million in 2020, with an annual population growth rate of 10.3%. The population growth pattern for the State of Rondonia resembles that of the whole basin, but with a faster pace.

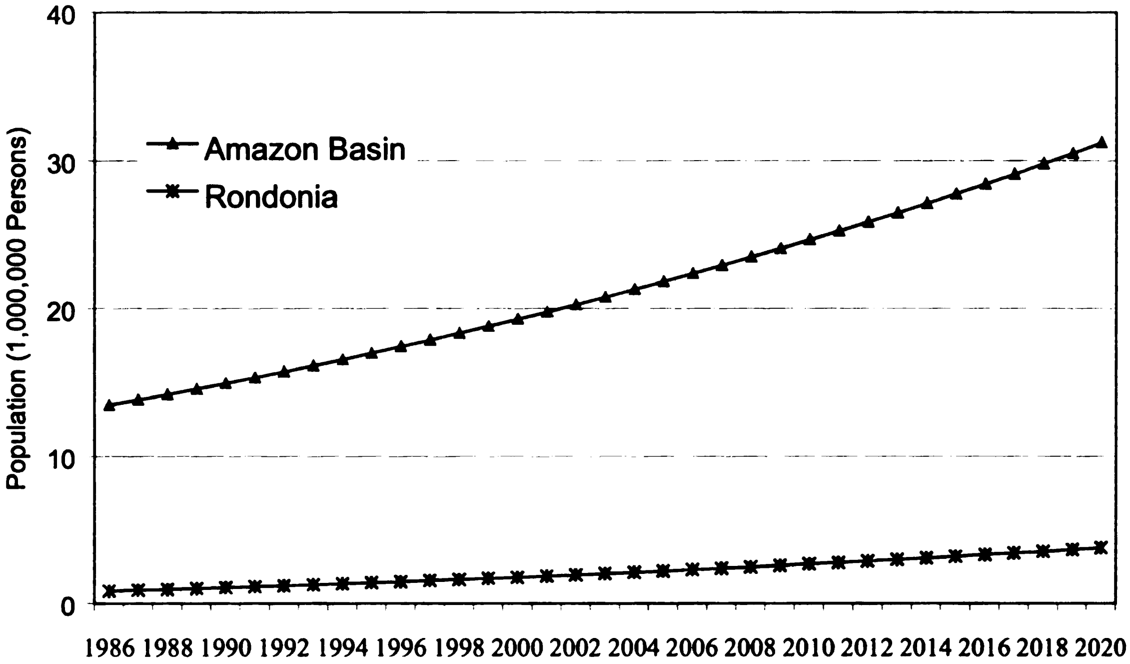

Figure 4.16: Population Growth in the Brazilian Amazon and the State of Rondonia (1986 – 2020)

According to the demographic census, 52% of the population lived in the urban areas of the Brazilian Amazon in 1991. Urbanization level in Rondonia is higher, with 58% of population lives in urban area in 1991. Figure 4.17.1 and figure 4.17.2 illustrate the different growth pattern for urban and rural population in the Brazilian Amazon and in Rondonia. On both figures, urban population keeps an exponential growing pattern like that of the total population, while rural population grows in a linear fashion. Therefore urban population tends to play a more and more important role in the region's economic development. Compare the urban/rural distribution figure of the basin with that of Rondonia, we can see the rural population in Rondonia grows faster than that of the whole basin. So rural economy in Rondonia might have more important impacts on the landscape change process.

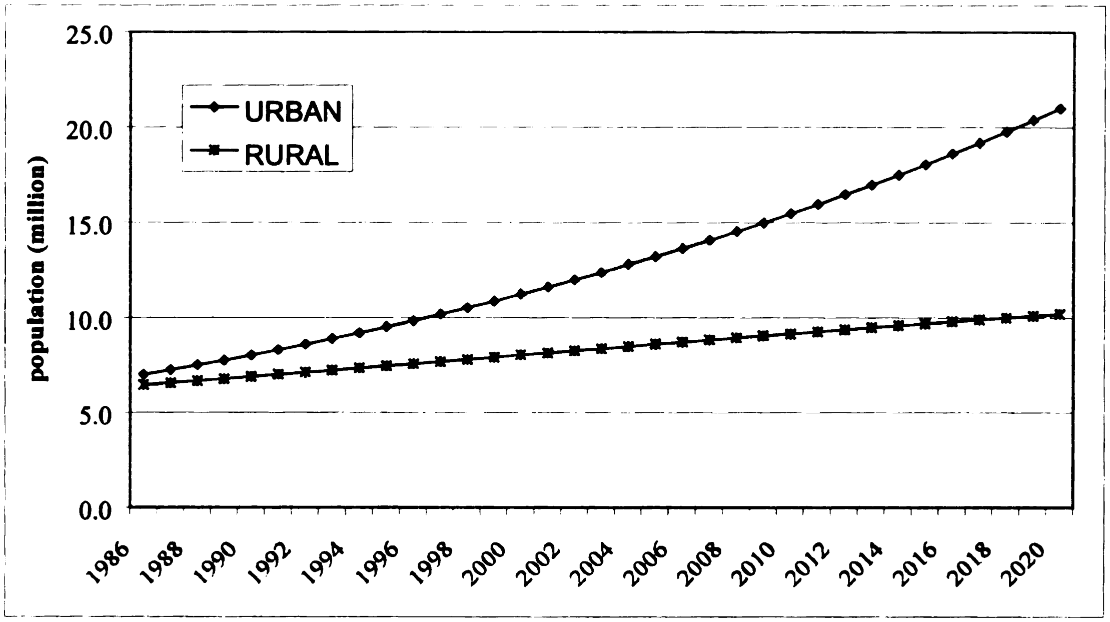

Figure 4.17.1: Urban vs. Rural Population in the Brazilian Amazon (1986 – 2020)

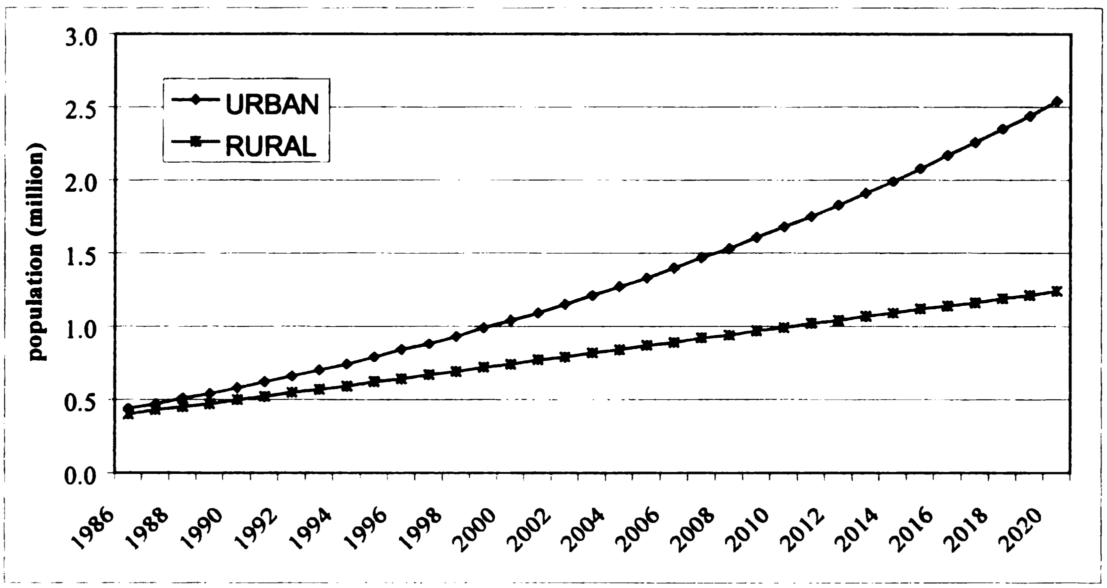

Figure 4.17.2: Urban vs. Rural Population in the State of Rondonia, Brazil (1986 – 2050)

Table 4.7 shows the model validation for projected population of different age group. It compares the model-estimated population size of 1991 with the observed population data from demographic census in 1991 to examine the fitness of the model.

Table 4.7 Validation Table for Population of Different Age/Gender Groups

			< 15	15-30	30-45	45-60	60-75	>75	Total
Brazilian Amazon (1991)	Male	Census	3,309.9	2,179.2	1,281.4	650.5	303.5	100.9	7825.4
		Model	3180.1	2193.7	1301.9	662.4	306.2	96.6	7740.9
		Error %	-3.92	0.67	1.60	1.83	0.89	-4.26	-1.08
	Female	Census	3,235.8	2,172.3	1,250.3	612.2	285.5	91.9	7648.1
		Model	3136.3	2180.4	1,273.9	624.4	286 2	92.1	7593.3
		Error %	-3.07	0.37	1.89	1.99	0.25	0.22	-0.72
State of Rondonia (1991)	Male	Census	233.7	172.4	105.1	50.4	21.4	3.4	586.3
		Model	234.1	168.0	112.3	47.8	19.4	3.4	585.0
		Error %	0.17	-2.55	6.85	-5.16	-9.35	0.00	-0.22
	Female	Census	224.7	167.2	95.8	41.3	14.8	3.2	547.0
		Model	229.0	162.9	105	40.6	14.6	2.6	554.7
		Error %	1.91	-2.57	9.60	-1.69	-1.35	-18.75	1.41

Unit: 1000 persons. Validation data source: 1991 Demographic Census

Error percentages for the Brazilian Amazon range from 0.22% (female, age older than 75) to –4.26% (male, age older than 15). The overall population size for year 1991 was 15.4 million, while the model projected population size is 15.3 million, an estimate with a marginal error of -0.9%. In the State of Rondonia, error percentages of population estimates range from -0.00% (Male, age older than 75) to –18.75% (Female, age older than 75). The total population of Rondonia was 1.133 million in 1991 while and model estimate was 1.139 million. The overall error percentage of population model estimate in Rondonia is as low as 0.57%.

4.7.2 Socio-Economic Model Results and Validation

Figure 4.18.1 and figure 4.18.2 show the expansion of agricultural land area in the Brazilian Amazon and in the State of Rondonia during the period of 1986 - 2020. The land areas of rice, sugarcane, soybean, corn, manioc, beans, coffee, banana, cacao, black pepper are grouped into one class called cultivation area.

According to the model projection, total agricultural land area in the Brazilian Amazon will increase from 16.7 million hectares in 1986 to 44.8 million hectares in 2020, among which cattle ranching area will increase from 8.5 million ha to 20.8 million hectares. As seen from figure 4.18.1, basin-wide agricultural cultivation area and cattle ranching area will experience similar level of growth during the study period. For the State of Rondonia alone, the total agricultural area will grow from 1.63 million hectares in 1986 to 7.33 million hectares in 2020, with cattle ranching area growing from 1.13 million hectares to 5.28 million hectares. Compare figure 4.18.1 with figure 4.18.2, we can tell that Rondonia will experience faster speed of agricultural expansion, especially for cattle ranching, than the whole region of Amazonia basin. Figure 4.18.2 shows that cattle ranching area in Rondonia grows as much as twice faster than the agricultural cultivation area. It is the cattle ranching activities that account for most of the area expansion of agricultural land in Rondonia.

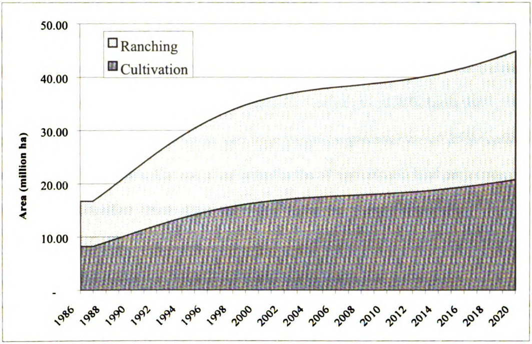

Figure 4.18.1: Agricultural Land Area Projection for the Brazilian Amazon (1986 -- 2020)

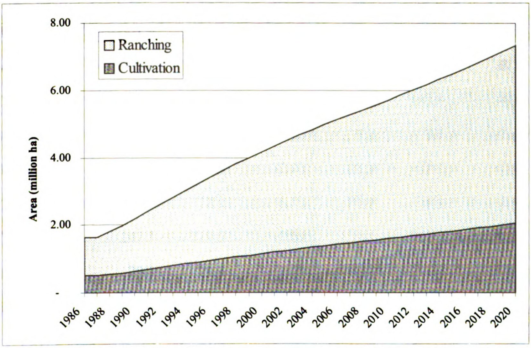

Figure 4.18.2: Agricultural Land Area Projection for the State of Rondonia (1986 – 2020)

Table 4.8 shows the model validation for different agricultural land areas using agricultural census data in 1990. Comparison shows the generally, the model estimated agricultural land areas have a very good fitness with the agricultural land census data. The error percentage ranges from -1.62% (area for manioc) to 10.90% (area for sugarcane) for the Brazilian Amazon, and from 0.00% (sugarcane) to –10.25% (coffee) for the State of Rondonia. The marginal error for the all agricultural land projection is –7.09% for the Brazilian Amazon and only –0.69% for the State of Rondonia.

Table 4.8 Validation Table for Agricultural Land Areas

	Brazilian Amazon (1990)			**State of Rondonia (1990)**		
	Census	**Model**	**Error %**	**Census**	**Model**	**Error %**
Rice	2,351.0	2,470.6	5.09	149.6	149.8	0.13
Sugarcane	4,565.7	4,068.2	-10.90	0.4	0.4	0.00
Beans	341.3	334.9	-1.88	122.1	112.9	-7.53
Manioc	493.4	485.4	-1.62	28.6	28.4	-0.70
Corn	1,236.1	1,209.1	-2.18	158.0	151.6	-4.05
Soybeans	1,747.0	1,587.1	-9.15	9.2	9.1	-1.09
Banana	102.8	100.5	-2.24	21.9	21.7	-0.91
Cacau	82.5	77.4	-6.18	38.5	38.3	-0.52
Coffee	247.3	229.5	-7.20	138.5	124.3	-10.25
Black Pepper	29.4	29.9	1.70	0.0	0.0	n/a
Cattle	12,699.8	11,609.1	-8.59	1541.0	1556.0	0.97
TOTAL	**23,896.3**	**22,201.7**	**-7.09**	**2207.8**	**2192.5**	**-0.69**

Agricultural land area unit: 1,000 ha. Validation data source: 1990 agricultural census

4.7.3 Land Cover Change Modeling Results and Validation

Based on the demographic model and the socio-economic economic model, future land use/land cover changes are projected for the whole basin as well as for the State of Rondonia only. Figure 4.19.1 and figure 4.19.2 present the model results for different land types. As shown on the figures, forest area in both cases will decline steadily while deforestation and secondary growth areas will increase significantly, indicating massive deforestation as well as extensive growth of secondary vegetation in the years to come.

According to remote sensing TM image analysis, the basin-wide deforestation area in 1986 was 15.8 million hectares, and a secondary growth area was 7.02 million ha. The LUCC model projected that, by year 2020, deforestation area in the Brazilian Amazon will grow to 50.5 million hectares, and secondary growth will reach 60.5 million hectares. Total deforested area (including areas under deforestation and secondary growth) will account for 29% of the previously forested area of the Brazilian Amazon in 2020. The basin-wide estimates are compatible with the results from Laurance et al's (2001) GIS model, which showed that 28% of the Brazilian Amazon will be deforested or heavily degraded by year 2020 under the optimistic scenario, and 42% of the region will be deforested under their non-optimistic scenario. The situation is worse in the State of Rondonia, where there were 1.6 million hectares of deforestation area and 0.63 million hectares of secondary growth in year 1986, but model results show that deforestation area will rise to 9.4 million hectares; and secondary growth will be 7.0 million hectares in year 2020. According to this projection, 73% of the primary forest area will disappear from Rondonia by 2020 (figure 4.19.2).

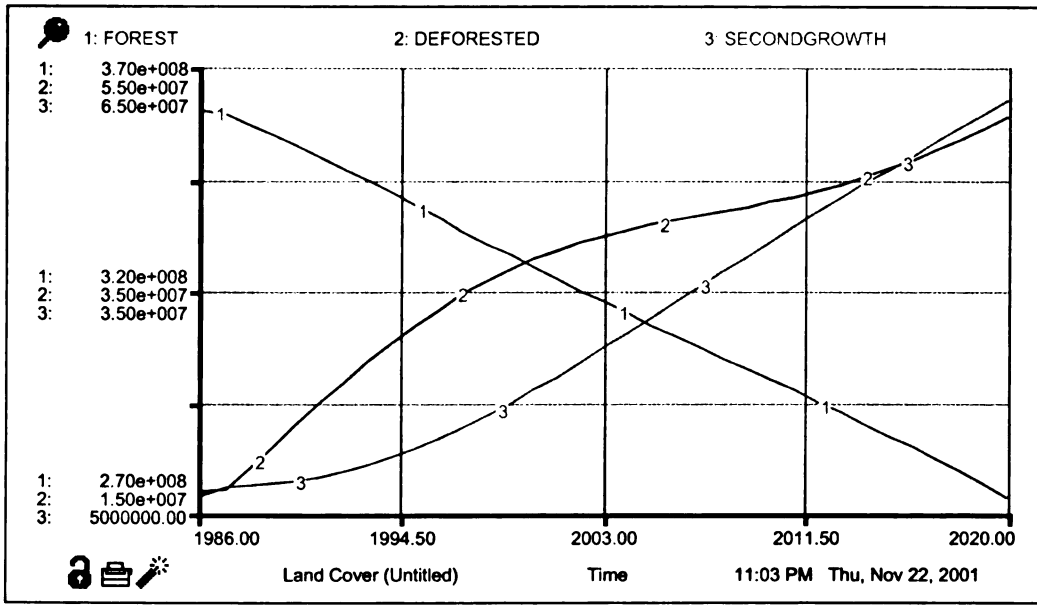

Figure 4.19.1: LUCC for the Brazilian Amazon (1986 – 2020)

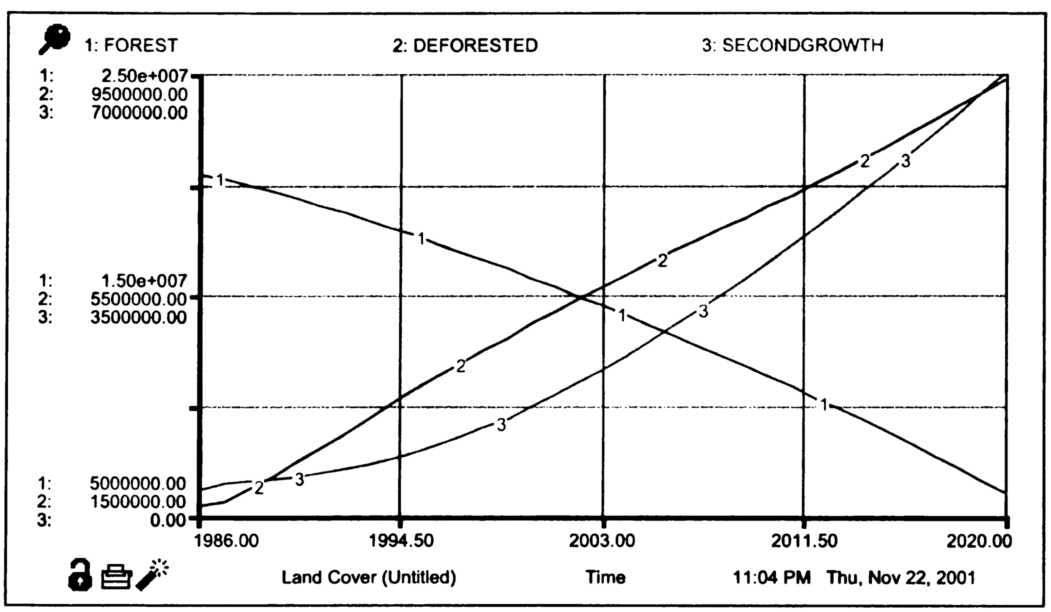

Figure 4.19.2: LUCC for the State of Rondonia (1986 – 2020)

Though both deforestation and secondary growth areas will experience significant increase during 1986-2020, it seems clear that the magnitudes and rates of their changes are quite different. Here we define the annual growth rate for deforestation growth rate and secondary growth in the following manner:

$$AnnualDeforRate_t = (DEFORESTED_t - DEFORESTED_{t-1})/DEFORESTED_{t-1} * 100$$

$$AnnualRegrowRate_t = (SECONDGROWTH_t - SECONDGROWTH_{t-1}) \\ /SECONDGROWTH_{t-1} * 100$$

As shown on figure 4.20.1, deforestation area growth for the Amazonia starts with a high growth rate of 11% in 1988, which lowers down to a bottom threshold rate of 0.92% in 2009, after that the deforestation growth rate starts to head up again to the level of approximately 2%. The curve of secondary growth exhibits a very different pattern. It starts with a low rate of 2%, which quickly rises to nearly 10%, after that its growth rate began to decline to the level of 3%. The annual growth rate for deforestation fells below that of secondary growth for the first time in year 1992, after that regrowth rate remains higher than deforestation rate throughout the temporal horizon of model projection.

Similar patterns are found in the case of Rondonia (figure 4.20.2), where deforestation growth rate declined from 13.38% in 1988 to 2.75% in 2020, and secondary growth increases by a percentage of 6.48% in 1988, which rises to 12.44% in 1996 and later drops down to 4.85% in 2020. However, unlike that of the basin-wide curve, the deforestation growth rate in Rondonia keeps declining throughout the model period, and the annual growth rate of secondary growth starts to exceed that of deforestation in 1992.

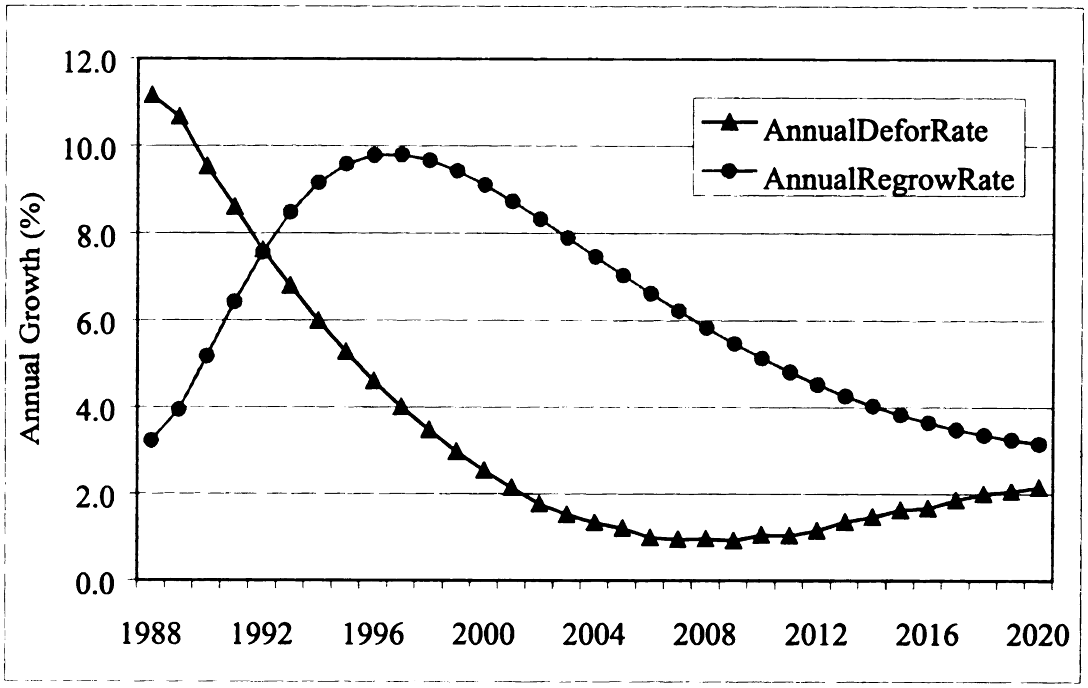

Figure 4.20.1: Annual Deforestation Rate and Secondary Growth Rate in the Brazilian Amazon (1986 – 2020)

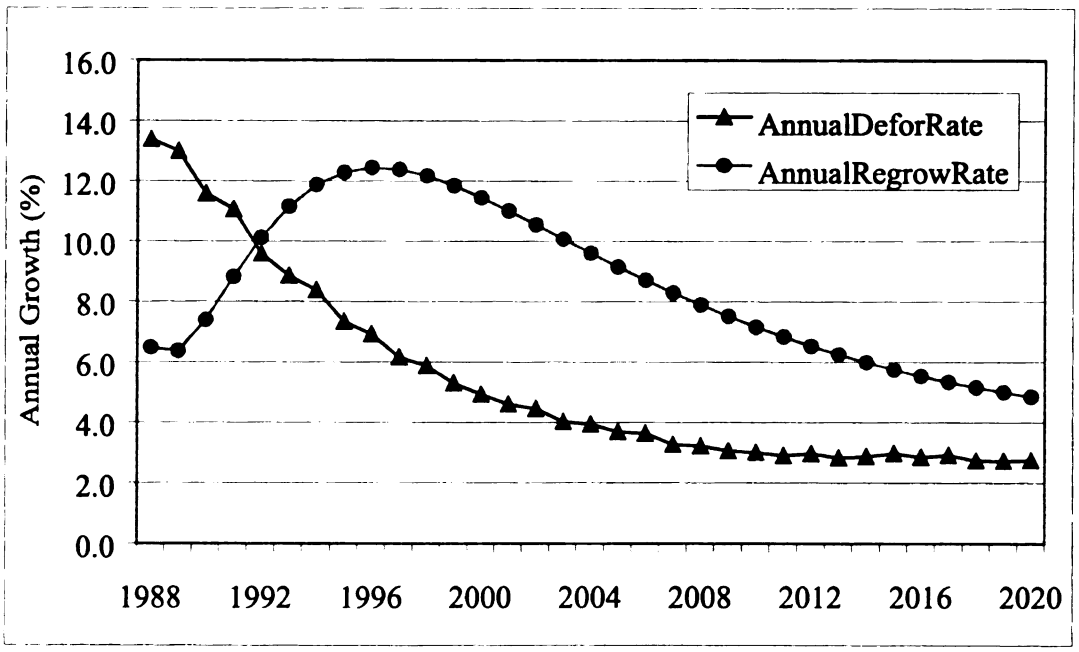

Figure 4.20.2: Annual Deforestation Rate and Secondary Growth Rate in the State of Rondonia (1986 – 2020)

Land use/land cover data derived from remote sensing image classification of year 1992 and 1999 are used to validate the model results. Remote sensing data show that deforestation area in the Brazilian Amazon was 23.9 million hectares in 1992 and 31.4 million hectares in 1999; secondary growth was 10.8 million in 1992, which grew to and15.9 million hectares in 1999. In comparison, modeling results shows that deforestation area is 26.7 million hectares in 1992 and 36.9 million hectares in 1999, while secondary growth area is 10.4 million hectares in 1992, and 19.6 million hectares in 1999. The difference between the observed and model estimated deforestation areas was 2.8 million hectares in 1992, and 5.5 million hectares in 1999 (see Figure 4.21.1).

For the State of Rondonia, there were 2.2 million hectares of deforestation and 1.0 million hectares of secondary growth in the year 1992 based on remote sensing image classification. In 1999, deforestation area grew to 4.3 million hectares and secondary growth area increased to 1.3 million hectares. Modeling results for the state of Rondonia shows that deforestation area is 2.9 million hectares in 1992 and 4.7 million hectares in 1999, while secondary growth area is 0.7 million hectares in 1992, and 1.5 million hectares in 1999. The difference between the observed and model estimated deforestation areas was 0.7 million hectares in 1992, and 0.3 million hectares in 1999 (see Figure 4.21.2).

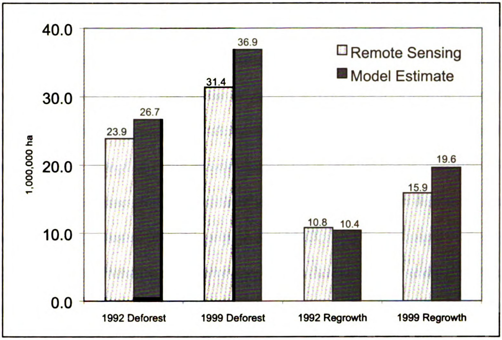

Figure 4.21.1: Validation Chart for Land Types of the Brazilian Amazon, 1992 and 1999

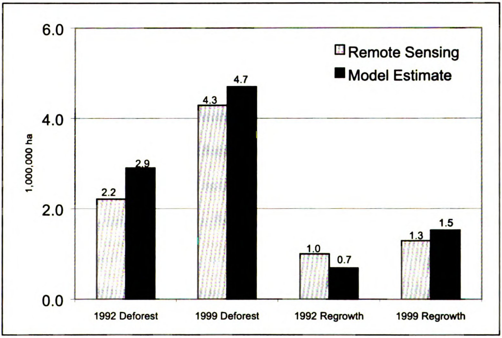

Figure 4.21.2: Validation Chart for Land Types of the State of Rondonia, 1992 and 1999

The differences between the observed deforestation and model estimates may originate from the fact that a lot of deforestation caused by activities such as logging or mining may not be easily detectable from satellite images. The difference might also result from the uncertainty caused by cloud and cloud shadows in satellite image classification. Land areas under the classes of cloud and cloud shadows may actually be deforested areas, but those areas are excluded from this project. The LUCC model only considers three types of land: forest, deforestation and secondary growth. It assumes active deforestation only takes place on forested land or secondary growth. But the fact is that some agricultural land is cleared from other types of land such as cerrado, which may further complicate the land use/land cover change process.

4.8 Conclusions and Discussions

Land cover changes associated with land use practices have exerted great influences on global environmental change (Houghton and Skole, 1990; Houghton, 1991). In addition to a need for refinements in measurements of the rate, extent and spatial pattern of deforestation, it is important to understand the processes of human land use and other socio-economic behaviors as well as their consequent impacts on land cover changes; and based on these, to make projections for future land use/land cover change in Amazonia.

Most LUCC models are mainly focus on deforestation issues rather than the land use/land cover change dynamics. The forest versus non-forest view overshadows some very interesting dynamics which are only recently being observed and discussed. This analysis not only addressed the problem of how forests become deforested, it also studied the process of how deforested areas grow into secondary vegetation and what is the fate of this secondary growth. By analyzing the dynamics of forest clearing and abandonment in the Brazilian Amazon, this study will significantly enhance the understanding of land use/land cover change process

Instead of using traditional statistical modeling method, this analysis adopts a systems modeling approach to simulate the dynamic structure and behavior of land use/land cover change as a complex system with interactions, feedback loops and reciprocal effects between population groups, economy sectors and land use system. Most land use/land cover change view land as an ecological system without explicitly incorporating the socio-economic process; a few have incorporated the socio-economic process, but in a limited way (Parks, 1991). Though the extent and frequency of land use/land cover change are the results of a multitude of human decisions and physical constraints, it is possible to identify the key role-players and driving forces for land use/land cover change processes, to understand how the major determinants interact to drive land cover change and how projections about them could be used to project future patterns of land use, future rates of land cover change, and future states of land cover. Unlike any black-box or abstract LUCC models that do not clearly identify the agents and actions being modeled, the systematic LUCC model in this project is built upon theoretical and empirical understanding of the factors and processes that control the relative magnitude of forest clearing and agricultural land abandonment, leading to the development of a diagnostic LUCC model that tracks the perturbations and responses of agricultural economy on an annual basis. The process-based LUCC model can be linked to other carbon or ecosystem process models to account for carbon emission or ecosystem disturbance in Amazonia.

Remotely sensing data collected at multiple times are used as initial inputs to the LUCC model and also as data for modeling results validation. Remote sensing provides a great opportunity to characterize and map land use/land cover distribution and change patterns with detail that is not possible using census data or field surveys alone. This unique advantage of remote sensing has stimulated a growing interest in making scientific progress through the use of remotely sensed data in social science research community, so-called "Pixelize the Social" (Turner II, 1997). Linking remote-sensing data sets to the human driving forces of land use and cover change permits the development of empirically-based diagnostic models of important land use/land cover changes such as tropical deforestation and secondary growth.

Model validations show that the systematic LUCC model is a powerful tool for projecting future land use/land cover change for the Brazilian Amazon as a whole region, and for the State of Rondonia as well. This will help to move toward an integrated modeling scheme at various scales, where a global land use/land cover change model can be able to scale down to a landscape model paradigm to account for the local socio-economic dynamics yet retain its global focus, while a landscape model can be able to scale up to global level to address the geobiophysical issues such as global change but still be able to account for local spatial dynamics (Clark, 1985; Gallopín, 1991; Mather and Sdasyuk, 1991; Turner II et al, 1993). Developing models of land use/land cover change at the local-to-regional scales allows for better estimations of future rates, pattern and locations of LUCC change, which are very important to integrated regional and global models of land use in the future. Since land use/land cover changes are local in domain, but are replicable globally (Turner et al, 1990), the dynamic system modeling approach in the Brazilian Amazon may provide insights into modeling land use/land cover changes that are taking place in other regions around the world.

The basin-scale or state-level analysis elucidates the interannual variations in deforestation and secondary growth, but it is not able to draw a detailed map to provide information on where the land cover changes are mostly likely going to happen. The limitation of little spatial articulation is attributed to the reason that most socio-economic data are only available on aggregated geographic units, which restricts the opportunity for behavioral interpretations of land cover change. Such aggregations conceal the spatial variations of land use practices. The rates at which land is cleared or abandoned are highly dependent on local land use practice. In some cases, deforestation and secondary succession exist as a tightly coupled system in which secondary growth is continually recycled back into farmland. In other cases, active land management maintains the land in agriculture, or the lack of active land management or population displacement results in long-term succession. Aggregations can also conceal the dynamic balance between gross deforestation and regrowth, which together define net forest loss. Finer scale study at the level of the farming household overcomes certain of these inherent limitations to more aggregate analyses (Walker and Homma, 1996; Leinbach and Smith 1994). Future research can apply this model to finer scales so as to include local variations and produce temporal-spatial maps of land use/land cover change.

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CHAPTER 5

Conclusions

This dissertation work aims to monitor and model the interlinkages of land use/land cover change as well as its relationship with the human socio-economic driving forces using GIS, remote sensing and various modeling techniques. It is designed to better understand the complexity of causes and mechanisms governing land use/land cover changing processes, and to investigate the environmental impacts of socio-economic activities and to quantify the built-up process of landscape change.

The interactions between different land use types as shown on the LUCC triangle call for a need to conceive a general modeling framework of land use/land cover change to integrate several model components which account for the main categories of land use/land cover change at different stages of development, for example, deforestation driven by agricultural expansion, forest regrowth due to land abandonment, deforestation at urban fringe, farmland loss as the result of urban sprawl etc. In each geographical context at a certain timing stage, one or more components of the model would take prominence on the others, to reflect the dominant driving forces and resulted land use/land cover change types in that region (Lambin, 1994).

The East Region and the Shanghai Municipality of China are selected to be the cases for studying the change of agricultural landscape in highly urbanized areas, while the Brazilian Amazon Basin as well as the State of Rondonia in Brazil is a representative case to study the consequences of agricultural activities on a primarily forested landscape. Remote sensing technique is applied to detect the magnitude and pattern of land use/land cover change, and future land use/land cover change are projected by taking into account the factors that cause or control these changes, with an ultimate objective to provide scientific projections of land use/land cover change as reference to future policy design in developing countries.

There are various types of model that have already existed in land use/land cover change research literature. We need to decide what type of model is the best to simulate the pattern and processes of land use/land cover change, and how to incorporate both the spatial and temporal dynamics for a model to be predictive across space and over time. In terms of modeling method choice, the necessary properties and requiem for a good model have been known as transparency, robustness, reasonable data needs and appropriate spatial-temporal resolution and inclusion of key policy variables as outlined by Lee (1973).

There are three basic types of land use/land cover change models being used in this dissertation work: analytical model, statistical/empirical model and systematic model. Each modeling method has its own advantages and limitations. Analytical models are abstract, theoretical constructs with no empirical data; but they can provide an important supplement to abstract propositions because it has more ability to map the complex causal connections, including feedback loops and reciprocal effects etc. (Turner et al 1991). Therefore analytical models have been developed in each case study of this dissertation work.

Statistical/empirical models quantify the relations between variables based on empirical historical or cross-sectional data. This approach has standardized methods and is easy to apply and interpret. It is a powerful tool to identify the key driving force variables with the strongest association with the LUCC process under study. A multinomial logit model is constructed for the agricultural land use change study in the East Region of China, with both socioeconomic and biophysical variables included in the model. In the case of urban sprawl study in Shanghai, China, a principal component regression method is applied to explore the multidimensional relationships between the demographic and socio-economic driving forces of land use change. No biophysical variables are included in the model because of the relatively homogenous landscape characteristics of a small plain region like Shanghai.

However, most statistical/empirical models are intrinsically descriptive. They can only provide insights into the empirical relationships over a system's history or at a particular point in time, but is of limited use for analyses of a system's future development under alternative management schemes (Agarwal et al, 2000). So we have to be very cautious to extrapolate beyond the range of the original observations. Another limitation of the statistical/empirical approach is that it does not adequately account for the complexity of, and relationships among, socioeconomic and environmental factors; its explanatory variables are treated as exogenous factors from outside of the land use/land cover change process, and rarely is there any internal interaction or feedback explicitly included in the models. Therefore, this type of models is limited in the power to adequately explain or predict the nonlinear, dynamic complexity of the land use/land cover change processes.

Instead, a systematic model is developed for the case study of Brazilian Amazon basin and the State of Rondonia. Systematic models are useful tools to simulate the dynamic structures and behaviors of complex systems with interactions, feedback loops and reciprocal effects. Unlike the empirical statistical models that focus on specific process affected by a defined set of variable, systematic models examines land use/land cover change as one component of an economic-ecological system. Models are built on the belief that the processes and mechanisms by which a system operates in a given situation have been well understood; building a systematic model is essentially to formalize and articulate, in a comprehensive manner, the causal/effect relationships and the system's operating mechanism (Lambin, 1994). The systematic modeling approach has an advantage over statistical/empirical modeling method because it builds into the representation of a phenomenon those aspects of a system that we know actually exists. It doesn't rely on historic data to reveal statistical or empirical relationships. It is desirable to introduce the mechanisms of human social economic activities directly into a model of land use/land cover change, and to build an integral systematic model. This advantage also allows dynamic models to be used in more applications than empirical models. Systematic models are often transferable to new applications because the fundamental concepts on which they are built are present in many other systems as well (Agarwal et al, 2000). However, rich data sets are often required for a systematic model to deal with multidimensional feedbacks among system components. Another challenge of systematic modeling approach is the difficulty in deciding how to incorporate model complexity without jeopardizing either model feasibility or model reality.

Like all other environmental problems, land use/land cover changes are deep-rooted in development. While it is development that causes most of the environmental problems, it is also development that can solve them. The only possible answer is sustainable development. The challenge of achieving sustainable development in the context of global environmental change is particularly acute for developing countries such as Brazil and China, two of the world's largest nations under increasing pressure to modify their development strategies so as to reduce the adverse impacts of global environmental change. Scientific modeling projections of land use/land cover change can provide important reference to future policy design and land management in these countries. Land use model of the East Region of China show a rapid pace of cultivated land loss in the next half century, therefore, raise serious concerns for the Malthusian type question of whether China can feed itself. Urban sprawl in Shanghai will take over more agricultural and forest area in Shanghai municipality, threatening the region's food security and ecological stability. The problem of tropical deforestation in the Brazilian Amazon has been a primary focus of the international environmental research community. Results of the systematic model of land use/land cover change in the Brazilian Amazon demonstrate an accelerating speed of deforestation in the coming decades. Nearly half of the standing forest will be cleared within next fifty years; all the primary forest in the state of Rondonia, a frontier state of agricultural development, will disappear from sight within less than forty year. Projections of annual deforestation and secondary growth in the

Brazilian Amazon can bring more insights into the missing carbon sink of the global carbon cycle.

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