Land use Change Detection Methodologies and Techniques for Remotely Sensed Images

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Abstract

The increasing land use changes leading to urban expansion have attracted the researches. Urbanization has become a recent growing trend in many cities around the world. In most cases to estimate the urban expansion with the conventional survey and mapping techniques is expensive and time consuming. Remote sensing is increasingly used for detection and analysis of urban expansion since it is cost effective and technologically efficient. This paper aims to give the taxonomy of various methods and techniques to analyze the land use change detection through remote sensing images in an effective manner. One of the most important functions of remote sensing data is Land Use and Land Cover maps managed through image classification. This describes the various classifiers, software and image digitization techniques that are used in estimating the urban changes. Wide database of images has been used to test the algorithms. Hence, an in-depth study of existing work related to land use change detection will help to accelerate research in the field of urban change. This paper presents a systematic analysis of work done in land use change detection area. We also present a Comparison of existing methods and techniques used for land use change detection. Based on this analysis, we finally presented a few future research directions related to land use change detection through remote sensing images, which will be reduce uncertainties in the image-processing chain to improve classification accuracy.

Keywords: Land Use Land Change, Remote Sensing, Random forest, CHAID, Maximum likelihood algorithm, SVM, KNN.

1. INTRODUCTION

The earth's surface has been changed considerably over the past decades by humans because of urbanization, deforestation and agriculture. Even though the conversion of land to agriculture and deforestation rates vary across the world, the number of people residing in cities has been increasing continuously. Urbanization has been increasing since World War II, and has not shown any sign of decline and is likely to continue into the twenty-first century (Oğuz, 2004).Generally, land use change (LUC) is the modification of a piece of land. This change is based on the purposes of need, which is not necessarily only making the change in land cover but also change in intensity and management(Verburg *et al*. 2000). Land use/land cover changes are critical issue that degrade biodiversity and create impact on human life. The International Geosphere-Biosphere Program (IGBP) and the International Human Dimension Program (IHDP) initiated a joint international program to study the land use/land cover change (LULCC) considering the enormous impacts and implications generating from the changes of land use/land cover. They commended the necessity of improved understanding, modeling and projections ofland dynamics from global to regional scale and focusing particularly on the spatial explicitness of processes and outcomes (Geoghegan *et al*. 2001). The land use change in large city area is a complicated process; several factors have influences on this process, including both physical aspects and human aspects. On the one hand, accelerated urban expansion is usually associated with and driven by the social-economic factors; on the other hand, the process of urbanization has a considerable impact on the economics of the society in that area (He, 2006; Mahesh, 2008).

A serious problem for modelling urban land use change has been the lack of spatially detailed data. GIS and remote sensing have the potential to support such models, by providing data and analytical tools for the study of urban environments. The work emphasizes spatial relationships between various geospatial, land-use, and demographic variables characterizing fine zones across and around regions. Land use change is a complex process that encounters sophisticated parameters. The interpretation of aerial photography provides a variety of ways to develop digital land use information which is basis for land use planning. For this reason, government is planning to develop land use maps on a regular timetable and store and manage this information in a GIS (Tayyebi, A., M.R. Delavar, S. Saeedi, J. Amini and H. Alinia, 2008). The status and trends of urban land cover and land use significantly impact the quality of human life and urban ecosystems. Accurate, up-to-date and spatially explicit data on urban land cover and land use are required to support urban land management decision-making, ecosystem monitoring and urban planning (Ridd, 1995).The use of remotely-sensed data in natural resources mapping and as source of input data for environmental processes modeling has been popular in recent years. With the availability of remotely sensed data from different sensors of various platforms with a wide range of spatiotemporal, radiometric and spectral resolutions has made remote sensing as, perhaps, the best source of data for large scale applications and study. In this review, we summarize some of the most commonly used methodologies and techniques used for land use change detection through remote sensing images.

2. THEORETICAL FOUNDATIONS

Land use and land cover change has been recognized as an important driver of environmental change on all spatial and temporal scales (Adepoju et al., 2006), as well as emerging as a key environmental issue and on a regional scale is one of the major research endeavors in global change studies. These changes encompass the greatest environmental concerns of human populations today, including climate change, biodiversity loss and the pollution of water, soils and air. Monitoring and mediating the negative consequences of LULC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world. In this chapter, pervious related published works are discussed in order to strengthen this specific study.

The world is undergoing the largest wave of urban growth in history. According to the United Nations Population Fund (UNFPA, 2013), rapid population growth has been concentrated in towns and cities of the world. The report also projected that by the year 2030 the vast majority of this growth will be observed in the developing world of Africa and Asia where urban growth is highly concentrated. Because cities offer a lot of opportunities such as jobs and sources of income than the corresponding rural areas, they attracted a lot of people. Following the rapid increase of population in urban areas, the growth of the world's rural population has shown a slowly decreasing pattern as indicated in figure 2.1 below.

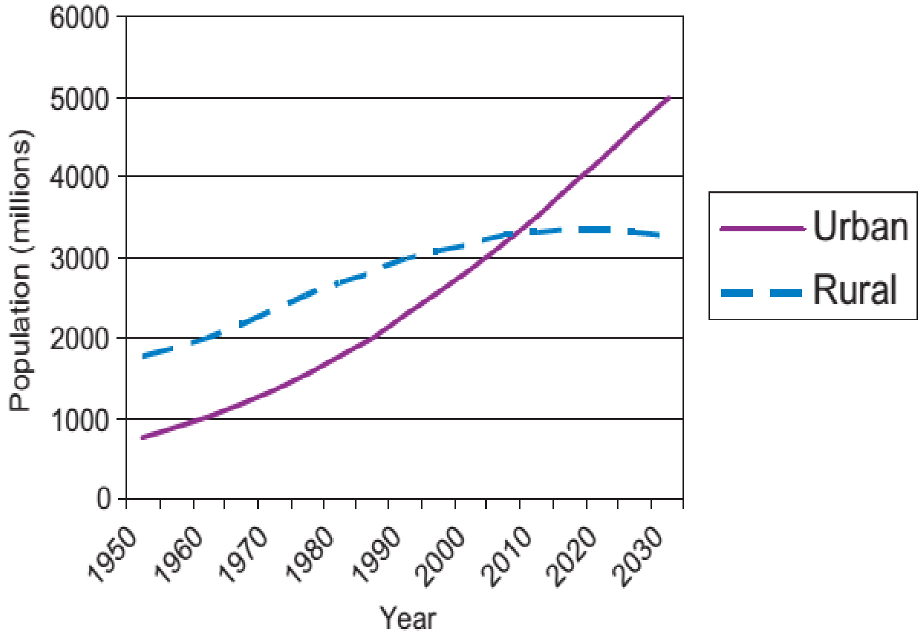


Figure 2.1: World's urban and rural population size estimated and projected, 1950–2030, (Source: Cohen, 2006).

It is clearly shown in figure 2.1 that when the world's urban population increased four-fold between 1950 and 2003, the world's rural population less than doubled going from 1.8 billion in 1950 to 3.2 billion in 2000 (Cohen, 2006). Regarding to projection of population growth, the world's urban population is expected to increase by almost 2 billion over the next 30 years, whereas the world's rural population is actually expected to decline slightly falling from 3.3 billion in 2003 to 3.2 billion in 2030.

2.1 Change Detection Categories

Two main categories of land cover changes:

- Conversion of land cover from one category to a different category.
- Modification of the condition of the land cover type within the same category

2.2 Applications of Change Detection Techniques

- Land-use and land-cover (LULC) change
- Forest or vegetation change
- Forest mortality, defoliation and damage assessment
- Deforestation, regeneration and selective logging
- Wetland change, forest fire and fire-affected area detection
- Landscape change, urban change
- Environmental change, drought monitoring, flood monitoring, monitoring coastal marine environments, desertification, and detection of landslide areas.
- Other applications such as crop monitoring, shifting cultivation monitoring, road segments, and change in glacier mass balance and facies.

2.3 Considerations before Implementing Change Detection

Before implementing change detection analysis, the following conditions must be satisfied:

- Precise registration of multi-temporal images;

- Precise radiometric and atmospheric calibration or normalization between multi-temporal images.
- Selection of the same spatial and spectral resolution images if possible.

2.4 Good change detection research should provide the following information:

- Area change and change rate
- Spatial distribution of changed types
- Change trajectories of land-cover types
- Accuracy assessment for change detection results.

2.5 Land use and Land cover Changes

The definition of land use and land cover has been used interchangeably in the land use research community because of the availability of many existing information systems. However, these two terms explain two different issues and meanings. Land cover refers to the observed biophysical cover on the earth's surface including vegetation, bare soil, hard surfaces and water bodies. Whereas land use is the utilization of land cover type by human activities for the purpose of agriculture, forestry, settlement and pasture by altering land surface processes including biogeochemistry, hydrology and biodiversity (Di Gregorio and Jansen, 2000). Conversion and modification are the two forms of land cover changes described by Meyer and turner (1992) where the former is a change from one class of land cover to another (e.g. from grassland to cropland). The latter is, however, a change within a land cover category (e.g. thinning of a forest or a change in composition). Land cover changes due to human activities drive land use and hence a single class of cover could support multiple uses (forest used for combinations of timbering, slash and burn agriculture, fuel wood collection and soil protection). On the other hand, a single system of land use can maintain several covers (as certain farming systems combine cultivated land, improved pasture and settlements).

Changes in land use and land cover caused through direct and indirect consequences of human activities on the environment for the purpose of having better life. One of the direct impacts of humans is population growth where its increase and decrease have effects on land use especially in developing world at longer time scales. According to Lambin et al (2003), it can also be caused by the mutual interactions between environmental and social factors at different spatial and temporal scales as land use and land cover change is a complex process. Verburg et al (2002) showed that causes of land use and land cover change can be categorized as direct (proximate) or indirect (underlying). The direct causes comprise human activities that could arise from the continuous use of land and directly alter land cover which reflect that human are driving forces. They are generally operated at local levels and explain how and why local land cover and ecosystem processes are modified directly by humans. On the other hand, indirect causes are fundamental forces that strengthen the more direct causes of land cover changes. These causes are resulted due to the complex interaction of social, political, economic, technological and biophysical variables.

Land use and land cover changes have significant consequences on climate change, hydrology, air pollution and biodiversity. Meyer and Turner (1992) mentioned in their study that it caused a various microclimatic changes. The rise in global surface temperature is associated with deforestation through changes in land use. This in turn caused a strong warming in urban environment called urban heat island. Their study also showed water pollution occurred due to land cover changes from cultivation to settlement (urban areas). It has been reported also that loss of forest species has wide range of effects on biodiversity. Identifying the causes and impacts of land use and land cover change require understanding both how people make land-use decisions and how specific environmental and social factors interact to influence these decisions (Lambin et al, 2001). In order to understand the impacts of dynamic land use and land cover changes, the use of land use change models become an advantage since they provide information of land use trajectories by projecting for the future.

2.6. Urban Land use Changes

From a broader point of view urbanization is one of the ways in which human activities altering global land cover. Although urbanization trend is global, according to the reports of the United Nations Centre for Human Settlements (Habitat, 2001), it has showed most remarked changes in developing countries associated with the migration of rural people to cities for better opportunities. Following this there had been estimated a rapid growth of population in urban areas at an average rate of 2.3% per year between 2000-2030 (Nations, 2001). However, its importance becomes unbalanced with impacts on ecosystem, greater economic differences and social fragmentation. It can be defined as the rate of increase in urban population. Dynamic processes due to urban change, especially the tremendous worldwide expansion of urban population and urbanized area, affect both human and natural systems at all geographic scales (Brockerhoff, 2000). The ability to monitor urban land cover and land use changes is highly desirable by local communities and policy decision makers. Due to the increased availability and improved quality of multi spatio-temporal data and new analytical techniques, nowadays it is possible to monitor urban land cover and land use changes and urban sprawl in a timely and cost-effective way (Yang et al, 2003). Therefore, the use of satellite data provides for regional planning and urban ecology.

2.7. The Role of Remote Sensing on Land use and Land cover Changes

Maktav et al (2005) showed that traditional data collection methods such as demographic data, census and sample maps were not satisfactory for the purpose of urban land use management. Accurate information of land use and land cover change is therefore highly essential to many groups. To achieve this information, remotely sensed data can be used since it provides land cover information. Remote sensing refers to the science or art of acquiring information of an object or phenomena in the earth's surface without any physical contact with it. And this can be done though sensing and recording of either reflected or emitted energy or the information being processed, analyzed and applied to a given problem (Campbell, 2002). Remote sensing is important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation and many other landscape-level phenomena. Such useful information can be then integrated into many regional to global scale models, including those that are used to develop parameters for carbon fluxes and hydrological cycles. Therefore, remote sensing data can be used as the basis for answering important ecological questions with regional to global implications (Vogelmann et al, 2001). Herold et al (2005) also noted that one of the advantages of remote sensing is its ability to provide spatially consistent data sets covering large areas with both high detail and high temporal frequency, including historical time series.

Over the past decades almost all the remote sensing researches have given more attention to natural environment than urban areas. The reason was that urban areas have complex and heterogeneous by nature (Melesse et al, 2007). However, Herold et al (2005) reported that with the availability of high resolution imagery together with suitable techniques, urban remote sensing become a rapidly gaining interest in the remote sensing community. Supported by advanced technology and satisfying social needs, urban remote sensing has become a new field of geospatial technology and applicable in all socioeconomic environments (Melesse et al, 2007).

Following this, a number of applications of remote sensing for urban studies have shown the potential to map and monitor urban land use and infrastructure. Moreover, Herold and Menz (2001) showed urban land use information in high thematic, temporal and spatial accuracy, derived from remotely sensed data, is an important condition for decision support of city planners, economists, ecologists and resource managers. Generally, land use and land cover changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and functions (Rimal, 2011). Therefore, the use of remote sensing data and analysis techniques provide accurate, timely and detailed information for detecting and monitoring changes in land cover and land use.

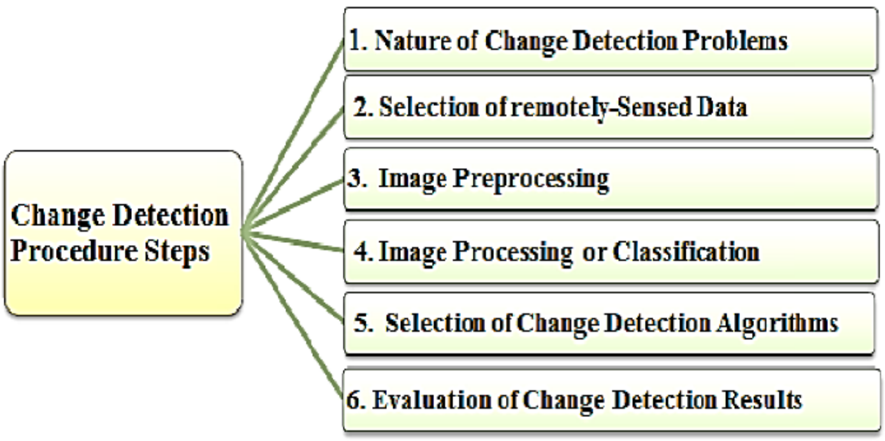
3. CURRENT ONGOING WORK ON LAND USE CHANGE DETECTION

In recent years a number of algorithms developed for machine learning have been adopted for remote sensing applications. These include neural networks, support vector machines, boosting, and random forests. Traditionally, remote sensing classification methods rely on statistical models to determine how radiance values recorded by a sensor should be grouped into a number of categories or classes (e.g., land cover type). These statistical approaches work on the assumption that an appropriate data model is being used and parameters for the model can be approximated from the data (Elith et al. 2008). For example, when using the maximum likelihood classifier the model assumes that the image data for each class and therefore the training data used to parameterize the model are normally distributed. A machine learning approach, on the other hand, does not start with a data model but instead learns the relationship between predictor and response data (L. Breiman 2001).By removing the need for data to fit a specific model, machine learning algorithms offer the opportunity to incorporate a diverse variety of data layers in addition to image data (e.g., digital elevation models, soil type, and climate data) into the classification algorithm.

4. METHODS AND TECHNIQUES

4.1 Change Detection

Detecting and analyzing Land Use Land Cover Change(LULCC) over large geographic areas as well as over regional areas have been highlighted both in a manner of discrete long-time span and in sequential time series with high temporal resolution remote sensing satellites through a process commonly called ‘change detection’ (Coppin, Bauer 1996). Change detection has been defined as a “process of identifying differences in the state of an object or phenomenon by observing it in different times” (Singh 1989b). This is considered an important process in monitoring LULCC because it provides quantitative analysis of the spatial distribution of the population of interest and this makes LULC study a topic of interest in remote sensing applications (Song et al. 2001, Gallego2004). Using remotely-sensed data to detect LULC changes, six main steps are important as mentioned by Jensen in 2005 (see figure 1).



Figur1. Major Change Detection Procedure Steps

4.2. Image Classification

In order to examine and asses environmental and socioeconomic applications such as: urban change detection and socioeconomic variables, image classification results with better accuracy are mandatory. Image classification refers to the extraction of differentiated classes or themes, usually land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). Image classification using remote sensing techniques has attracted the attention of research community as the results of classification are the backbone of environmental, social and economic applications (Lu and Weng, 2007). Because image classification is generated using a remotely sensed data, there are many factors that cause difficulty to achieve a more accurate result. Some of the factors are:

- The characteristics of a study area,
- Availability of high resolution remotely sensed data,
- Ancillary and ground reference data,
- Suitable classification algorithms and the analyst's experience, and
- Time constraint.

These factors highly determine the type of classification algorithm to be used for image classification. There are various image classification methods that can be applied to extract land cover information from remotely sensed images (Lu and Weng, 2007). However, their application depends on the methodology and type of data to be used. Some of these methods are: artificial neural networks, fuzzy-sets and expert systems. In a more specified way, image classification approaches can be categorized as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel and per-field. Some of the most commonly used image classification methods are discussed below.

4.2.1. Pixel-Based Image Classification Methods

Pixel-based classification methods automatically categorize all pixels in an image into land cover classes fundamentally based on spectral similarities (Qian et al, 2007; Weng, 2012). These types of classifiers develop a signature by summing up all pixels. Thus, the developed signature contains the necessary things found in the training pixels but does not contain the influence of mixed pixels (Weng, 2012). According to Tadesse et al (2003), there are two primary types of pixel-based classification algorithms applied to remotely sensed data: unsupervised and supervised. Unsupervised image classification algorithms are based on categorizing each pixel to unknown cluster centers and then moving from one cluster center to another in a way that the Supervised Spatial Encoder (SSE) measure of the preceding section is reduced data. Whereas in the case of supervised image classification the analyst has previous knowledge about pixels to generate representative parameters for each land cover class of interest. The Maximum Likelihood classification, under the category of supervised classification, which is the most widely, used per-pixel method by taking in to account spectral information of land cover classes (Qian et al, 2007). Although pixel based classification methods have been widely accepted and applicable, however, there are limitations in including spatial pattern during classification. This happened especially in Maximum Likelihood classification methods where they consider only spectral information by neglecting contextual and texture information (Zhou and Robson, 2001; Dean and Smith, 2003).

4.2.2. Object-Oriented Image Classification Methods

This method of image classification is based on identifying image objects, or segments with similar texture, color and tone of spatially contiguous pixels (Gao and Mas, 2008; Weng, 2012). This approach allows for consideration of shape, size, and context as well as spectral content (MacLean and Congalton, 2012). The classification stage starts by grouping the neighboring pixels into meaningful areas. Qian et al

(2007) noted that in object oriented classification approach, single pixels cannot be classified rather homogenous image objects are extracted during segmentation step. Image analysis in object-oriented is based on contiguous, homogeneous image regions that are generated by initial image segmentation.

4.2.3. Contextual Image Classification Approaches

In the case of maximum likelihood classification technique the pixels are assigned to represent classes taken in to consideration and this is done through observing of each pixel. However, there could be misclassification errors especially during the presence of random noise which causes different classes to be appeared similar (Sharma and Sarkar, 1998). To avoid such problems, contextual classification techniques have been chosen which exploits spatial information among neighboring pixels. These techniques are based on the assumption that the response and class of two spatially neighboring pixels are highly related. The advantage of using contextual techniques will improve image classification results by reducing error rates related to spectral properties (Weng, 2012).

4.3. Land use Change Detection Analysis

Change detection can be defined as the process of identifying differences in the state of object or phenomena by observing them at different times by using remote sensing techniques (Singh, 1989). Essentially, it also involves the ability to quantify temporal effects using multi-temporal data sets. Because of repetitive spatial coverage at short time intervals and consistent image quality, change detection is considered as one of the major applications of remotely-sensed data obtained from Earth-orbiting satellites (Singh, 1989).

Change detection has a wide range of applications in different disciplines such as land use change analysis, forest management, vegetation phenology, seasonal changes in pasture production, risk assessment and other environmental changes (Singh, 1989). The main objective of change detection is to compare spatial representation of two points in time frame by controlling all the variances due to differences in non target variables and to quantify the changes due to differences in the variables of interest (Lu et al, 2004). A change detection research to be good, it should provide the following vital information: area change and rate of changes, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results. Quantifying land use and land cover changes and applying suitable change detection methods highly depend on the type of changes that happened in landscapes and how those changes are noticeable in images. The changes could be continuous or categorical. According to Abuelgasim et al (1999), change detection in continuous land cover changes focuses on measuring the degree of changes in amount or concentration through time. However, in the case of categorical land cover changes, the goal of change detection is to identify new land cover classes and changes between classes through time.

4.4. Change Detection Techniques using a remotely Sensed Data

The selection of suitable method or algorithm for change detection is important in producing a more accurate change detection result since constraints such as spatial, spectral, thematic and temporal properties affect digital change detection. Some techniques such as image differencing can only provide change or non-change information, while some techniques such as post classification comparison can provide a complete matrix of change directions. According to Bekalo (2009), different change detection methods could produce different changes of maps depending on the algorithm they followed. Although there are many change detection methods in remote sensing of image classification, recently researchers divided in to image ratio, image regression, image differencing and the method of change detection after classification (post classification method) (Xu et al, 2009; Bekalo, 2009). The classification of methods mainly depend on data transformation procedures if exists and analysis techniques applied. So, based on these conditions the current common methods of change detection are discussed below:

4.4.1. Image Regression Method

In image regression method of change detection, pixels from time t1 are assumed to be a linear function of the time t2 pixels (Singh, 1989). Under this assumption, it is possible to find an estimate of image obtained from t2 by using least-squares regression. According to Abuelgasim et al (1999), image regression technique takes in to account differences in the mean and variance between pixel values for different dates. This consideration minimizes the influence of differences in atmospheric conditions. In detecting changes of urban areas the regression procedure has more advantage than image differencing technique.

4.4.2. Image Ratio Method

In image ratio method, images must be registered beforehand and rationed band by band. The results of image ratio are interpreted with a threshold of values. If the ratio of the two images is 1, it means that there is no change in the land cover classes where as a ratio value of greater or less than 1 indicates a change in land cover classes (Singh, 1989; Bekalo, 2009). This method rapidly identifies areas of changes in relative terms.

4.4.3. Image Differencing Method

Image differencing is one of the most extensively applied change detection method. It can be applied to a wide variety of images and geographical environment. In this technique, images of the same area, obtained from times t1 and t2, are subtracted pixel wise. It is generally conducted on the basis of gray scale which used to show the spatial extent of changes in the two images. A threshold value is required for the gray of difference image in order to examine the changed and unchanged regions (Xu et al, 2009).

4.4.4. Post Classification Method

This method is the most simple and obvious change detection based on the comparison of independently classified images (Singh, 1989). Maps of changes can be produced by the researcher which shows a complete matrix of changes from times t1 to time t2. Based on this matrix, if the corresponding pixels have the same category label, the pixel has not been changed, or else the pixel has been changed (Xu et al, 2009).

4.5. Introduction to Land use Change Modeling

Land is utilized for multiple purposes and it is critical that land cover change be monitored and evaluated for both its negative and positive consequences. Dynamic urban land use and land cover change processes caused due to human activities have a wide range of effects on the global climate change either directly or indirectly (Herold et al, 2001; Lambin et al, 2001). It also affect human and natural systems and contribute to changes in carbon exchange and climate through a range of feedbacks. Its future changes are also a function of numerous driving variables (Lambin et al, 2003; Veldkamp and Lambin, 2001). Some of these drivers are population change, economic activity and growth as well as biophysical conditions and are most important at a range of geographic scales.

Bhatta (2010) noted that, the first and foremost reason for urban growth is an increase of urban population. Urban areas attained rapid growth as a result of natural increase in population. This is due to uncontrolled family planning where birth rate is greater than death rate. The second one is migration to urban areas. Migration is defined as the movement of people from rural to urban areas within the country. Therefore, modeling of urban growth is a very essential step for further improvement of urban planning and land use management. The rising awareness and importance of land- use models in the land use and land cover research community has led to the development of a wide range of land-use change models (Verburg et al, 2002).

4.6. Land use Change Models

The significance impacts of land use and land cover changes, the use of land use change models become important to understand these changes and driving factors (Verburg et al, 2004). Models are representations of the real world, based on theoretical assumptions that represent systems (Verburg et al, 2002). Over the past decades, a range of land use change models have been invented by the land use modeling community for the land management needs as well as to analyze and project impacts for the future. Lambin et al (2001) described integrated modeling in a wider scale is an important technique in order to predict future scenarios. Land use change models are tools which support the analysis of the causes and consequences of land use changes. They provide better understanding of the dynamics of systems to develop hypotheses that can be tested empirically. Verburg et al (2004) reported that they are useful for extracting complex driving forces that affect the spatio-temporal pattern of land use changes and impacts.

Literature has described a number of models depending on different disciplines such as on: landscape ecology, urban planning, statistics and geographic information science (Veldkamp and Lambin, 2001; Verburg et al, 2004). Comparing the performance of models is a complex issue because of its high dependency on disciplinary perspectives, applied methods, data types used and modeling goals. For example: the GEOMOD model simulates change between two land categories where as Markov chain and the cellular automata Markov model simulate change among several categories (Brown et al, 2004). According to Wainger et al (2007), for different applications of land use change modeling, models were categorized in to three major types as: spatially explicit econometric models, spatial allocation (GIS neighborhood rules) and agent-based models as shown in figure 2.2 below. The criteria to group these models are based on structure and methodologies. Structure in this case refers to the spatial relationships between the components of a landscape.

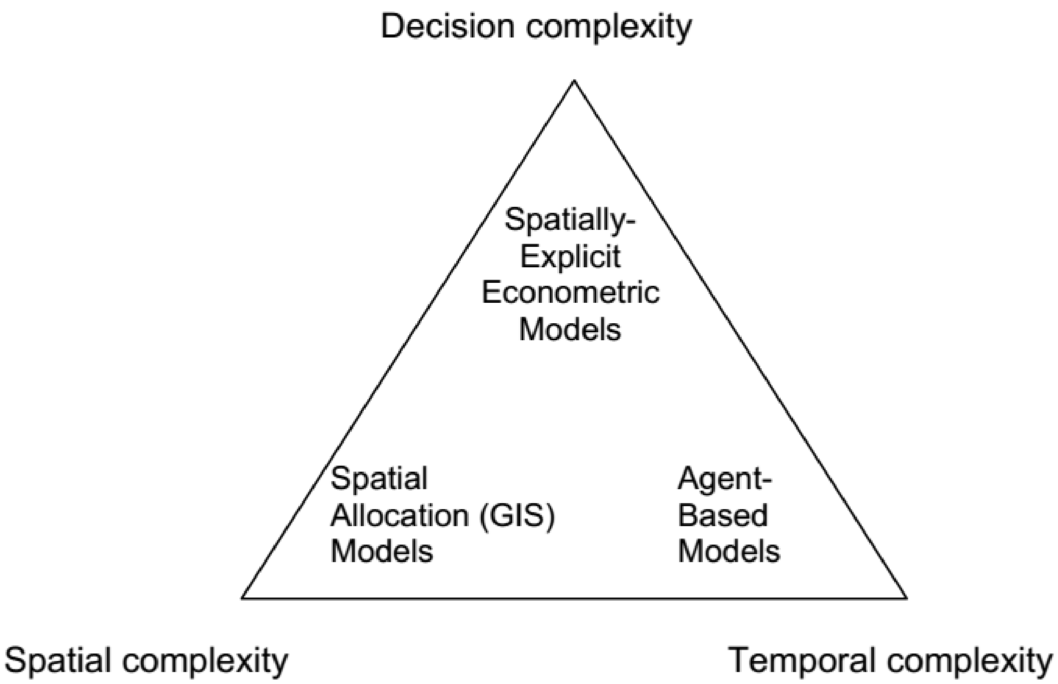


Figure 2.2: Classification of Models based on structure.(Source: Wainger et al, 2007)

4.6.1. Spatially-Explicit Econometric Models

Spatially-explicit econometric models were developed by economists for the purpose of characterizing decisions of agents converting land between uses. The spatially explicit economic models are known by conceptualization of the conversion decision as an economic transaction where expected payoff must exceed costs. The advantage of these types of models is that its ability to share explanatory variables with other types of models developed by other disciplines (Irwin and Geoghegan, 2001). However, these models have limitations of detailed data of regionally consistent formats and also unable to model conditions that deviate from historic norms. Suarez-Rubio et al (2012) reported that such models provide information by projecting spatial distribution of land use conversion by using transaction data. This enables to determine the maximum profits by considering factors that affect the expected result. Understanding how likely land development is changing with different policy scenarios is one of the expected importances of spatially-explicit econometric models.

As mentioned in previous topics, the availability of infrastructure and better developments as well as recreational areas allowed urban growth is towards to urban-rural fringe driven by increase of population. Suarez-Rubio et al (2012) showed that urban-rural fringe development in metropolitan areas has showed a growth of more than twice as fast as development in metropolitan urban areas. Their study also emphasized that urban-rural fringe development by the year 2000 covered about 25% of the contiguous United Sates. Modeling the trend of urban-rural fringe areas therefore important for better management and mitigate the consequences. Thus, spatially explicit models become a good choice to predict land use changes since they consider social and environmental causes and consequences (Cabral and Zamyatin, 2009).

4.6.2. Spatial Allocation Models

Spatial allocation models have been developed for the purpose of identifying neighborhood conditions that have connections with land conversion specifically for residential and commercial development. They can also used for generating future land use changes. A transition rule is required for modeling the drivers of changes of new land use. Verburg et al (1999) also noted that the spatial pattern of land use through time can be determined by the components of landscape such as: human factors (population, technology and economic conditions) and biophysical constraints (soil, climate and topography). In order to describe the relationships between these factors, a decision rule is used. These models have the capability of generating a diffusion of growth near the areas of existing urban centers. Thus, there should be sufficient growth rules which help to generate new urban centers by limiting the diffusion otherwise variables that recognize patterns of land use must be considered (Wainger et al, 2007).

4.6.3. Agent-Based Models

Agent-based models comprises of simulation models where much attention has been given by the land use research community. They characterize systems in terms of independent but interconnected “agents” that have the ability to make “decisions” based on changing conditions. For most of the agent based models which used for land use modeling, higher temporal complexity could be taken as accurate criteria to be chosen (Parker et al, 2002). The majority of these models are referred to as cellular models which include spatial modeling techniques such as cellular automata and Markov models. However, Parker et al (2003) showed they have different applications as cellular models focused on landscapes and transitions, where as agent-based models focused on human actions. Agent based models have a wide range of applications such as archaeological reconstruction of ancient civilizations, modeling of infectious diseases as well as modeling of economic processes. Matthews et al (2007) have identified the five purposes of agent based models in the land use modeling community. These are policy analysis and planning, participatory modeling, explaining spatial patterns of land use, examining social science concepts and demonstrating land use functions.Cellular Automata (CA) is a discrete dynamic system in which space is divided into regular spatial cells and time progresses in discrete steps. CA models can generate complex global patterns based on transition rules for simulation processes. The transition rules determine how a cell will evolve under certain conditions. These models have been widely used for simulating urban sprawl and land use dynamics (Cao et al, 2013). This study has integrated Markov chain model and Land Change Modeler. The descriptions and approaches of these models are discussed below.

4.7. Markov Chain Models

Markov chain models are relatively simple and more powerful to model complex processes and changes in land use for planning purposes. They provide better information for analyzing time series of system evolution (Levinson and Chen, 2005). A Markovian process is one in which the state of a system at time t2 can be predicted by the state of the system at time t1given a matrix of transition probabilities from each cover class to every other cover class. A stationary property is one of the importances of these models since it integrates a transition probability matrix. This property is critical to Markov chain model especially for future predictions of land use. The stationary of the transition matrix in turn helps to inspect the validity of the model (Iacono et al, 2012). The MARKOV module in IDRISI can be used to create such a transition probability matrix (Eastman, 2012).

Markov Chain model to be considered as a system, it has to satisfy the following properties:

- The sum of the rows of the probability matrix must be one
- The probabilities of the transition matrix must be the same for any two periods
- Probabilities have no memory, that is, the state tomorrow depends only on the state today (the Markov condition)
- Time periods must be uniform in length or duration.

Markov chain model has a good quality of simplicity. It can also describe complex and long-term process of land use conversion in terms of simple transition probabilities.

4.8. Land Change Modeler

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI oriented to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation. It was developed by Clark Labs for the purpose of assessing a variety of land change scenarios and contexts. This model adopts the Markov Chains analysis for time prediction, but with an automatic Multi-Layer Perceptron for a spatial allocation of simulated land cover scores (Eastman, 2012). In LCM, according to Eastman (2012), tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment and planning interventions. Also, there is a facility in LCM to support projects aimed at Reducing Emissions from Deforestation and Forest Degradation (REDD). The REDD facility uses the land change scenarios produced by LCM to evaluate future emissions scenarios. Because of its ability to integrate various transitions involving same explanatory variables in to a single sub model, LCM is applied in this study.

5. CONCLUDING REMARKS

Land use and land cover changes have wide range of consequences at all spatial and temporal scales. Because of these effects and influences it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and its drivers over space and time is important to predict future developments, set decision making mechanisms and construct alternative scenarios. Models of land use change are tools to support the analysis of the causes and consequences of land use changes in order to better understand the functioning of the land use system and to support land use planning and policy. Models are useful for monitoring the complex suite of socio-economic and biophysical forces that influence the rate and spatial pattern of land use change and for estimating the impacts of changes in land use.

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