

Masters Program in Geospatial Technologies

URBAN LAND USE CHANGE ANALYSIS AND MODELING: A CASE STUDY OF SETÚBAL AND SESIMBRA, PORTUGAL

Master Thesis

By

Yikalo Hayelom Araya

Institute for Geoinformatics

University of Münster

Münster

March 2, 2009

URBAN LAND USE CHANGE ANALYSIS AND MODELING: A CASE STUDY OF SETÚBAL AND SESIMBRA, PORTUGAL

By

Yikalo Hayelom Araya

Supervisor:

Prof. Dr. Edzer Pebesma (University of Münster, Germany)

Co-supervisors:

Prof. Dr. Pedro Cabral (New University of Lisbon, Portugal)

Prof. Dr. Mario Caetano (New University of Lisbon, Portugal)

Prof. Dr. Michael Gould (University Jaume I Castellon, Spain)

Declaration of originality

This is to certify that the work is entirely my own and not of any other person, unless explicitly acknowledged (including citation of published and unpublished sources). The work has not previously been submitted in any form to the University of Münster or to any other institution for assessment for any other purpose.

Signed _____

Date 02/03/2009_____

Abstract

In this paper urban land use change analysis and modeling of the Concelhos of Setúbal and Sesimbra, Portugal is accomplished using multitemporal and multispectral satellite images acquired in the years 2000 and 2006 and other vector datasets. The LULC maps are first obtained using an object-oriented image classification approach with the Nearest Neighbour algorithm in Definiens. Classification is assessed using the overall accuracy and Kappa measure of agreement. These measures of accuracies are above minimum standard accepted levels. The land use dynamics, both for pattern and quantities are also studied using a post classification change detection technique together with the following selected spatial/landscape metrics: class area, number of patches, edge density, largest patch index, Euclidian mean nearest neighbor distance, area weighted mean patch fractal dimension and contagion. Urban sprawl has also been measured using Shannon Entropy approach to describe the dispersion of land development or sprawl. Results indicated that the study area has undergone a tremendous change in urban growth and pattern during the study period. A Cellular Automata Markov (CA_Markov) modeling approach has also been applied to predict urban land use change between 1990 and 2010 with two scenarios: MMU 1ha and MMU 25ha. The suitability maps (change drivers) are calibrated with the LULC maps of 1990 and 2000 using MCE and a contiguity filter. The maps of 1990 and 2000 are also used for the transition probability matrix. Then, the land use maps of 2006 are simulated to compare the result of the “prediction” with the actual land use map in that year so that further prediction can be carried out for the year 2010. This is evaluated based on the Kappa measure of agreement (Kno, Klocation and Kquantity) and produced a satisfactory level of accuracy. After calibrating the model and assessing its validity, a “real” prediction for the year 2010 is carried out. Analysis of the prediction revealed that the rate of urban growth tends to continue and would threaten large areas that are currently reserved for forest cover, farming lands and natural parks. Finally, the modeling output provides a building block for successive urban planning, for exploring how and when urban growth is occurring, and for helping subsequent research works.

Acknowledgments

To the most High God be glory great things He has done. I acknowledge Your great provisions, protections and support throughout the duration of this course and my life.

I remain indebted to my supervisors Prof. Dr. Edzer Pebesma, Prof. Dr. Pedro Cabral, Prof. Dr. Mario Caetano and Prof. Dr. Michael Gould for the discussions and guidelines provided.

I would like to express my deepest gratitude to the Portuguese Geographic Institute, Remote Sensing Unit in general and Prof. Dr. Mario Caetano and Antonio Nunes in particular for providing me all the data required for the study and arranging all the infrastructures to collect the data. I would also like to express my heartfelt gratitude to Prof. Dr. Marco Painho, Prof. Dr. Pedro Cabral and Dr. Filomena Caria for arranging the facilities during my stay in Lisbon for data collection. I am also grateful to Paulo Morgado and Sofia Morgado at the University of Alameda for providing me information related to the legislation. I thank also my friend Nick for helping me during my stay in Lisbon.

I remained indebted to Prof. Thomas Kohler, Prof. Steve Drury, Robert Burstcher, Dr. Christoph Brox, Mohamed Bishr and Prof. Dr. Werner Kuhn for their moral support through out the duration of the program. I am also grateful to all Erasmus Mundus 2007 intake classmates.

I am also grateful to my friends Francis Mwambo and Benedict Mugambi for supporting me during collecting samples for accuracy assessment.

Last but not least I would like to express my heartfelt gratitude to my beloved parents, brothers and sisters who encouraged me morally in my school life.

Table of Contents

Abstract	iv
Acknowledgements	v
List of tables	ix
List of figures	x
Acronyms	xi
CHAPTER 1	1
INTRODUCTION	1
1.1: Study background	1
1.2: Statement of problem	2
1.3: Study area.....	2
1.3.1: The Concelhos of Setúbal and Sesimbra	3
1.3.2: The Natural Park of Setúbal and Sesimbra	3
1.4: Aim and objectives.....	4
1.5: Research hypothesis and questions	5
1.6: Dissertation structure	5
1.7 Tools used in the study	6
1. 8 Significance of the study	6
CHAPTER 2	7
REMOTE SENSING IMAGE ANALYSIS AND CLASSIFICATION	7
2.1: Introduction.....	7
2.2: Remote sensing for urban studies	8
2.3 Spatial data and processing	8
2.3.1: Baseline and charactestics of data used	9
2.3.2: Pre-processing and Minimum Mapping Unit (MMU).....	10
2.4: Image classification paradigm for image analysis	11
2.4.1: Pixel-based paradigm	12
2.4.2: Object-based paradigm.....	12
2.4.3: Advanced classification approaches.....	12
2.5: Image classification and validation method used	13

2.5.1: Multi-resolution segmentation	13
2.5.2: Image classification algorithms	14
2.5.3: Image classification validation.....	15
2.6: Results and evaluation of classification	15
2.6.1: Land use classification	15
2.6.2: Evaluation of classification results using descriptive analysis	18
2.7: Discussions.....	21
CHAPTER 3	212
URBAN LAND USE CHANGE DETECTION AND ANALYSIS	22
3.1: Introduction.....	22
3.2: Urban land use change detection	23
3.2.1: Change detection: conceptual framework.....	22
3.2.2: Application and approaches of detection techniques.....	23
3.3: Post-classification detection technique used.....	24
3.4: Results of change detection in Setúbal and Sesimbra.....	24
3.5: Urban land use change analysis	25
3.6: Quantification and description of urban land use in Setúbal and Sesimbra....	26
3.6.1: Class Area (CA).....	26
3.6.2: Number of patches	27
3.6.3: Edge Density (ED).....	27
3.6.4: Largest Patch Index (LPI).....	27
3.6.5: Area Weighted Mean Patch Fractal Dimension (FRAC_AM)	27
3.6.6: Euclidean Mean Nearest Neighbour (ENN_MN).....	28
3.6.7: Contagion.....	28
3.7: Analysis of landscape indices in the Concelhos of Setúbal and Sesimbra	28
3.8: Urban sprawl measurement using Shannon entropy.....	30
3.8.1: Urban sprawl: built up areas as indicator of urban sprawl.....	30
3.8.2: Measurement of urban sprawl in Setúbal and Sesimbra	31
3.9: Urban sprawl in Setúbal and Sesimbra	33
3.9.1: The on-going sprawl in Setúbal and Sesimbra.....	33
3.9.2: Population density and urban sprawl	34
3.10: Discussions.....	35

CHAPTER 4	37
URBAN LAND USE CHANGE MODELING	37
4.1: Introduction.....	37
4.2: Land use change models	37
4.2.1: Urban land use models.....	37
4.2.2: Cellular Automata.....	38
4.3: Modelling in Idrisi	40
4.4: Modeling urban land use in Setúbal and Sesimbra.....	41
4.4.1: Introduction.....	41
4.4.2: Model description	42
4.5: Model Calibration	42
4.5.1: Original data and criteria development.....	43
4.5.2: MCE: the Boolean approach.....	44
4.5.3: MCE: standardization and weighting of factors	45
4.6: Model implementation and validation	49
4.6.1: Model implementation.....	49
4.6.2: Model validation	50
4.7: Urban land use prediction for the year 2010.....	51
4.8: Discussions.....	53
CHAPTER 5	54
CONCLUSIONS AND PERSPECTIVES.....	54
5.1: Conclusions.....	54
5.2: Perspectives and future works.....	55
REFERENCES.....	57

List of tables

Table 2.1 Characteristics of the satellite data used	9
Table 2.2 Land cover classes	11
Table 2.3 Error matrix: image classification of 2006 (MMU 25ha)	20
Table 2.4 Error matrix: image classification of 2000 (MMU 1ha)	20
Table 2.5 Error matrix: image classification of 2006 (MMU 1ha)	20
Table 3.1 Spatial metrics adopted and used	26
Table 3.2 Landscape indices and percentage of changes	29
Table 3.3 Shannon's Entropy values of Setúbal and Sesimbra.....	33
Table 3.4 Differences of Shannon Entropy	34
Table 3.5 Population size and built-up areas (Freguesia-based).....	35
Table 4.1 Existing urban land use models	39
Table 4.2 Transitional probability matrix	42
Table 4.3 Boolean approach criteria development.....	45
Table 4.4 Fuzz Module: standardization of variables	46
Table 4.5 Weights assigned to the variables	48
Table 4.6 Results of the validation analysis.....	51
Table 4.7 Urban class area of the reference and simulated maps	51

List of figures

Figure 1.1 The AML with the Concelhos of Setúbal and Sesimbra	3
Figure 1.2 The natural parks “protected areas” of Setúbal and Sesimbra.....	4
Figure 1.3 Dissertation structure	5
Figure 2.1 Methodology employed to classify images and validate their accuracy ...	7
Figure 2.2 The Four spectral bands (palette gray) and RGG of LISS-III.....	10
Figure 2.3 Image classification methods.....	12
Figure 2.4 Segmented image.....	14
Figure 2.5 LULC maps of 1990, 2000 and 2006	16
Figure 2.6 Simplified LULC maps of 1990, 2000 and 2006.....	17
Figure 3.1 Methodology employed to detect and analyze changes	22
Figure 3.2 Urban land use change maps	25
Figure 3.3 Temporal urban growth signatures of spatial metrics.....	29
Figure 3.4 Buffer zones around the city of Sesimbra.....	32
Figure 3.5 Buffer zones around the city of Setúbal	32
Figure 3.6 The 11 “Freguesia” of Setúbal and Sesimbra.....	33
Figure 3.7 Three Year’s entropy values.....	34
Figure 3.8 Differences in entropy values in each pair of years.....	34
Figure 3.9 Population density in each “Freguesia”	35
Figure 4.1 Neighborhood relationship	40
Figure 4.2 Components of Cellular Automata (CA).....	40
Figure 4.3 Model Calibration and validation methods.....	42
Figure 4.4 Map variables derived after standardization.....	47
Figure 4.5 The rating assigned to each of the factors considered	48
Figure 4.6 Suitability map.....	49
Figure 4.7 Actual and predicted land use maps of 2006	50
Figure 4.8 Predicted land use maps of 2010	52

Acronyms

AML:	Greater Metropolitana de Lisboa “Lisbon Metropolitan Area”
CA:	Cellular Automata
CA_Markov:	Cellular Automata Markov Chain Analysis
CA/TA:	Class/total area
DEM:	Digital Elevation Models
DGRUPD:	Directorate General of Regional Planning and Urban Development
ED:	Edge Density
EEA:	European Environmental Agency
EIA:	Environmental Impact Assessments
ENN_MN:	Euclidean Mean Nearest Neighbour Distance
FRAC_AM:	Area Weighted Mean Patch Fractal Dimension
GIS:	Geographic Information Systems
IPG:	Portuguese Geographic Institute
IRS:	Indian Remote Sensing
LIP:	Largest Patch Index
LULC:	Land Use/Land cover
MCE:	Multi-Criteria-Evaluation
MIR:	Mid Infrared
MMU:	Minimum Mapping Unit
NRSA:	National Remote Sensing Agency
NIR:	Near Infrared
NP:	Number of Patches
RS:	Remote Sensing
SWIR:	Short Wave Infrared
TIR:	Thermal Infrared

CHAPTER 1

INTRODUCTION

1.1: Study background

The history of urban growth indicates that urban areas are the most dynamic places on the Earth's surface. Despite their regional economic importance, urban growth has a considerable impact on the surrounding ecosystem (Yuan et al., 2005). Most often the trend of urban growth is towards the urban-rural-fringe where there are less built-up areas, irrigation and other water management systems. In the last few decades, a tremendous urban growth has occurred in the world, and demographic growth is one of the major factors responsible for the changes. By 1900 only 14% of the world's population was residing in urban areas and this figure had increased to 47% by 2000 (Brockerhoff, 2000). The report also revealed that by 2030, the percentage of urban population is expected to be 60%. Urban growth is a common phenomenon in almost all countries over the world though the rate of growth varies. Currently, these are the major environmental concerns that have to be analyzed and monitored carefully for effective land use management. The rapid urban growth and the associated urban land cover changes have also attracted many researchers.

A substantial amount of data from the Earth's surface is collected using Remote Sensing (RS) and Geographic Information Systems (GIS) tools. RS provides an excellent source of data from which updated land use/land cover (LULC) information and changes can be extracted, analyzed and simulated efficiently. RS in the form of aerial photography provides comprehensive information of urban changes (Bauer et al., 2003). It is not, however, without limitations: costs of the acquisition and the analogue data format are the most obvious problems. The cost of acquiring data causes many analysts to remain sceptical about the potential of remotely sensed data (Rowlands and Lucas, 2004). It should also be noted that LULC mapping using remote sensing has long been a research focus of various investigators (Civco et al., 2002).

Recent advancement in GIS and remote sensing tools and methods also enable researchers to model and predict urban growth more efficiently than the traditional approaches. Several modeling approaches have also been developed to model and forecast the dynamic urban features. One of the approaches is the Cellular Automata-CA. CA is a dynamical discrete system in space and time that operates on a uniform grid-based space by certain local rules (Alkehder and Shan, 2005, Hand 2005). The CA is consisting of cells and transition rules are applied to determine the state of a particular cell. Its ability to represent complex systems with spatio-temporal behaviour from a small set of simple rules and states made it very interesting for urban studies (Alkehder and Shan, 2005). In this study an integrated approach of GIS, RS and modeling has been applied to identify and analyze the patterns of urban changes and provide quantitative and spatial information on developments of urban areas.

1.2: Statement of the problem

On a global basis, nearly 6.8 million km² of forest, woodlands and grasslands have been converted to other land uses in the last three centuries (Agarwal et al. 2002) and most of the changes were into urban land use. These changes in land use have significant implications on the Earth's resources and climate.

On a local basis, the expansion of the city of Lisbon to its highly rural outskirts, overtaking the wide, highly productive basalt plains as well as alluvial areas mostly used for horticultural products, has entailed a systematic abandonment of transitional agricultural practices (Carlos 2002). The land use change analysis carried out by the IGP between 1990 and 2000 also verified these facts. This would have significant impact on the surrounding ecosystem: loss of farming land, forest cover, water depletion, and on the benefits generated from the land. Being located in the coastal areas of the country, the study site attracted various human induced activities, which in return resulted in a loss of land resources. As part of the land use management of the Greater Metropolitana de Lisboa (Lisbon Metropolitan Area or AML), attempts are still made and some green spaces are currently being planned. The Portuguese government has also created several protected areas aiming to reduce and control building speculation, and to protect the natural heritage (Carlos 2002). It has to be noted that some kind of urbanization is still continuing in the protected areas of the region. This reveals that the rate of urban growth is still high in the region. Thus, consideration and careful assessment are required for monitoring and planning land management, urban development and decision making.

1.3: Study area

The study was carried out in two administrative areas in Portugal: Setúbal and Sesimbra. Both administrative areas belong to the AML (Figure 1.1). *The AML is a public collective person of associative nature, and of territorial scope that aims to reach common public interests of the 18 Concelhos "Counties": Alcochete, Almada, Amadora, Barreiro, Cascais, Lisbon, Loures, Mafra, Moita, Montijo, Oeiras, Palmela, Sesimbra, Setúbal, Seixal, Sintra and Vila Franca de Xira* (AML 2005). The AML has the largest population concentration in Portugal and a dramatic population growth has occurred since the year 1960 (Cabral 2006). This situation became serious with the great urban sprawl that took place from 1940 to 1960 as a result of a general migration from rural areas (Carlos 2002). The urbanization increased tremendously when Portuguese inhabitants of the overseas ex-colonies returned during the 1970's (Cabral 2006). Based on the Portuguese census data of 2001, the population of the AML is around 2.6 Million-approximately ¼ of the entire Portuguese population. The total area of the AML is also about 2,957.4km² (AML 2005).

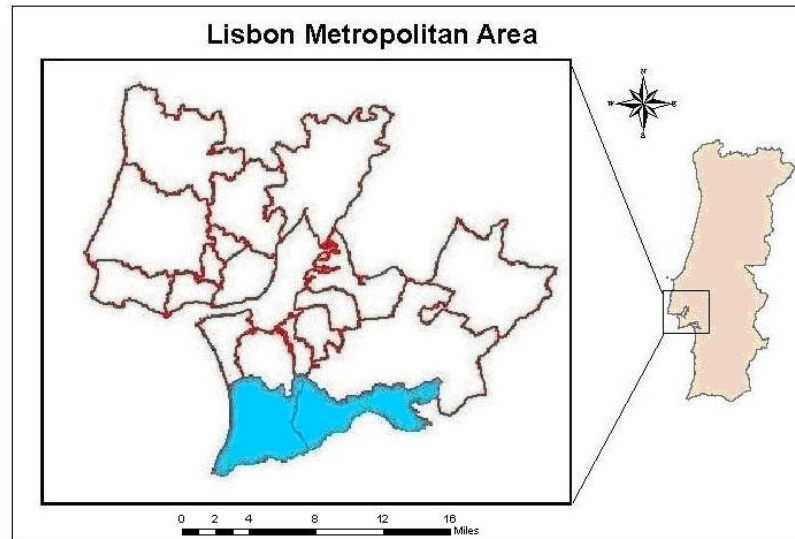


Figure 1.1: The AML with the Concelhos of Setúbal and Sesimbra

1.3.1 The Concelhos of Setúbal and Sesimbra

The study area is located in the southern part of Portugal, specifically in the districts of Setúbal and Sesimbra (Figure 1.1). *Setúbal is an urban area, differentiated from a town, village, or hamlet by size, population density, importance, or legal status*¹. It is located just beneath the capital Lisbon and on the River Sado. As the capital has grown over the years, it has become wealthier and more urbanized, now essentially being a suburb of Lisbon². It is located about 40km south of Lisbon with approximately 100,000 inhabitants.

The Concelho Sesimbra is another municipality of Portugal in the district of Setúbal. It lies about 40km south of Lisbon and is situated at the foot of the hills of Arrabida Park (discussed below) with a total area of 195.7km² and a total 37,567 inhabitants³. Due to its particular position near the mouth of the Sado River and its natural harbour, it attracts the attention of many human activities.

1.3.2 The Natural Park of Setúbal and Sesimbra

The study site is well characterized by the natural reserve “Serra da Arrabida”. *The “Serra da Arrabida” lies between Setúbal and the coast, miles of vast limestone ridges and forests of oaks, bay trees and plant life unique to the peninsula* (AML 2005). Arrabida is a natural park that covers 108km² area and the Arrabida Hills and Mediterranean-like vegetation and microclimate of the region. *The natural reserve surrounding the river Sado provides all manner of wetland wonders from migratory birds and interesting fish species to unique agricultural and natural landscapes*⁴.

¹ <http://en.wikipedia.org/wiki/>

² <http://www.enterportugal.com/>

³ <http://www.travel-in-portugal.com/>

⁴ <http://www.travel-in-portugal.com/>

Moreover, the natural reserve of the Sado Estuary occupies a total area of 23,160 ha, integrated into the Concelhos of Setúbal, Ballina and Palmela. The reserve was created by law due to pollution affecting the estuary of Sado and the danger of damaging the natural heritage of interest existing fauna and flora. It is also a place of nesting for various birds such as storks, flamingos and ducks, and spawning, growth and development of various fish⁵.

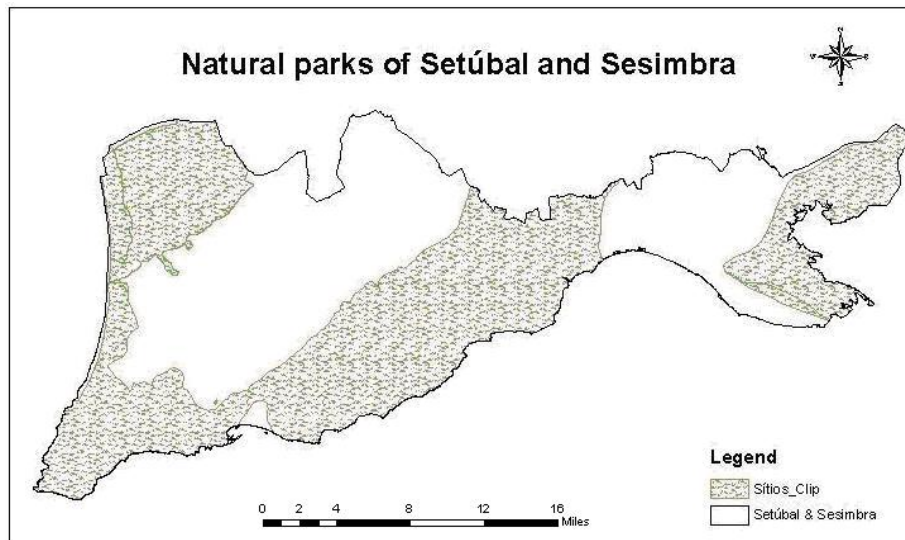


Figure 1.2: The natural parks “protected areas” of Setúbal and Sesimbra

1.4: Aim and objectives

The principal aim of this paper was to apply remotely sensed data, geospatial and modeling tools to detect, quantify, analyze, and forecast urban land use changes.

The following were also some of the specific objectives of the paper:

- Quantify and investigate the characteristics of urban land use over the study area based on the analysis of satellite images;
- Identify whether there have been and will be significant urban land use changes;
- Analyze and examine the changes using selected spatial metrics;
- Assess the accuracy of the classification techniques using error matrix and Kappa statistics;
- Identify and analyze urban sprawl using Shannon entropy approach;
- Predict and assess urban future land use changes;
- Analyze the specific issues of the urban environment and put forward a recommendation or set of recommendations that may form the basis for a sound solution for sustainable land management.

⁵ <http://en.wikipedia.org/wiki/>

1.5: Research hypothesis and questions

This study is based on the hypothesis that there have been considerable urban land use changes in the study area. It also tests two research assumptions:

- 1) It is possible to use RS and GIS tools along with modeling techniques to study urban growth analysis and modeling
- 2) There was a significant urban land use changes and urban sprawl in the study area during the study period

In order to assist the analysis, the following research questions will also be posed:

- Have there have been major changes in the urban environment of the study areas?
- What was the spatial extent of the land cover change and where was the highest rate of changes?
- What will be the extent of the land use changes in the future?
- What were the major deriving forces for the changes?

1.6: Dissertation structure

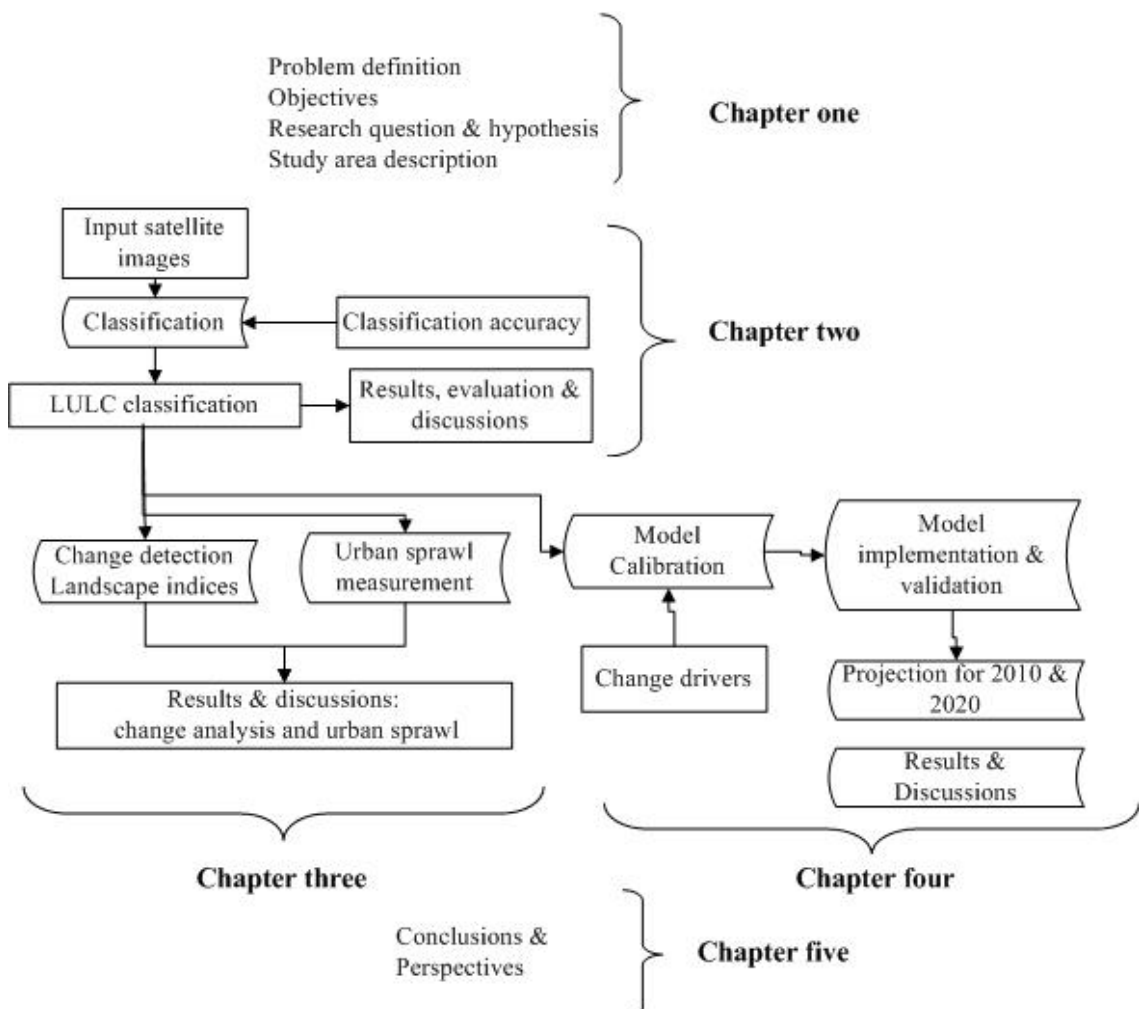


Figure 1.3 Dissertation structure

1.7: Tools used in the study

Various software programs have been used in this study to process, quantify, analyze and model the spatial dataset. For the preliminary data processing, extracting the study area and mosaicing satellite images, ArcGIS 9.2-ArcInfo version was used. An object-oriented image classification was implemented using Definiens 5.0. In order to calculate the metrics, Fragstats was also applied. For the modeling part, CA_Markov chain analysis embedded in Idirisi Kilimanjaro has been used.

1.8: Significance of the study

One of the major impacts of urban land cover dynamics is a shrinking amount of cultivated land through the development of infrastructures and various development projects. Therefore, urban land use change studies are important tools for urban or regional planners and decision makers to consider the impact of urban sprawl. The results of this study would provide information relevant to contribute in the environmental management plans and improve urban planning issues. It is also expected to:

- Provide information on the status and dynamics of the urban land use of the area and the use of remote sensing from satellite imagery for such analysis for planners.
- Assist environmentalist, regional (urban) planners, and decision makers to consider the potential of geospatial tools for monitoring and planning urban environment
- Provide elements for long term bench-mark monitoring and observation relating to resource dynamics
- Provide a base line for eventual research follow-up, by identifying specific and important topics that should be considered in greater detail by those interested in the area

CHAPTER 2

REMOTE SENSING IMAGE ANALYSIS AND CLASSIFICATION

2.1: Introduction

The theoretical and practical aspects of urban land use change analysis and modeling applied in this study involve different approaches and datasets. The first step for understanding the dynamic nature of LULC was to generate surface information using remote sensing approaches. In the first place, different datasets such as existing land use maps, satellite data, Digital Elevation Model (DEM), road maps and other vectors maps were acquired from the IGP, remote sensing unit⁶. Basically, CORINE land cover maps for the years 2000 and 2006 with a Minimum Mapping Unit (MMU) of 25ha and a national land cover map with a MMU of 1ha for the year 1990 were obtained. In addition, the satellite data, for the years 2000 and 2006, used in the study were pre-processed and an object-oriented image classification was employed to generate surface information. The following section presents the overall image processing phases applied to generate LULC information and assess the accuracy of the classification. Figure 2.1 also describes the methodology applied to classify the images, assess and analyze the classification.

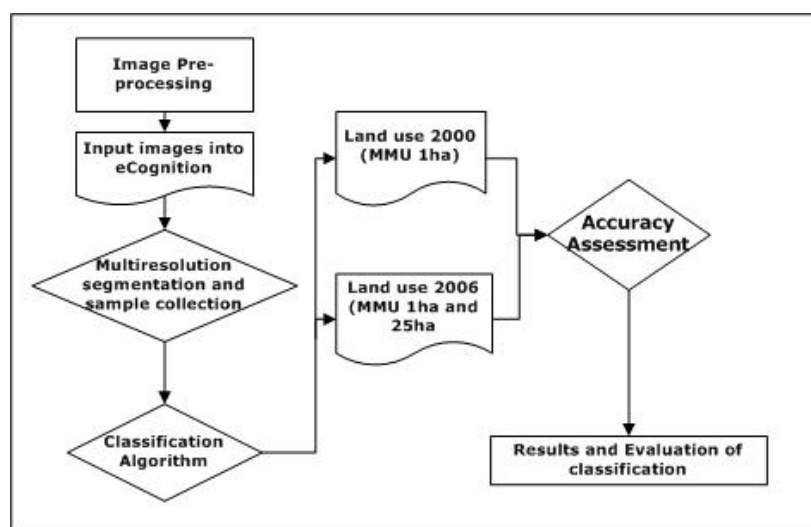


Figure 2.1 the methodology employed to classify images and validate their accuracy

⁶ Remote sensing unit of the IGP is a research and development department integrated in the Geographical Information Research and Management Services Directorate (DSIGIG), which is one of the central operational services of the Portuguese Geographic Institute (IGP). The unit develops its activity in the framework of the mission and functions of IGP, which is a National Agency of the Central Public Administration with the main objective of ensuring the execution of the geographic information policy at a national level.

2.2: Remote sensing for urban studies

GIS and RS are land-related and therefore are very useful in the formulation, implementation and monitoring urban development in the move towards sustainable development strategy detection (Yeh and Li 1997). GIS is a systematic process of spatial data collection and processing. It can be used to study the environment by observing and assessing the changes and forecasting the future based on the existing situation (Ramachandra and Kumar 2004). RS, on the other hand, is the process of data acquisition through space or air borne sensors without having any contact with the target objects. It allows the acquisition of multispectral, multiresolution and multitemporal data for the land use change analysis and modeling. Both RS and GIS tools have been applied in a number of urban studies to detect, monitor and simulate urban land use changes.

Because of their cost effectiveness and temporal frequency, RS approaches are widely used for change detection analysis (Im et al. 2008). It has also great potential for the acquisition of detailed and accurate surface information for managing and planning urban regions (Herold et al. 2002). However, computer assisted production of spatially detailed and thematically accurate LULC information from satellite image continues to be a challenge for the remote sensing research community (Civco et al. 2002). This is due to the heterogeneous nature of urban environment, which makes discriminating land cover classes difficult. It could also be due to the absence of appropriate classification techniques. However, recent advances in GIS and RS tools and methods have enabled researchers to analyze and detect the dynamic nature of urban features in a more efficient way. Some recent researches have also been directed toward quantitatively describing the spatial structure of urban environments and characterizing patterns of urban structure through the use of remotely sensed data (Herold et al. 2002).

2.3: Spatial data and processing

Satellite data are the bases for various environmental studies and have been used in different application areas (e.g. mapping and detecting of land use changes). However, consideration must be given to the impacts of the sun's inclination, season of image acquisition and cloud cover. This is because these factors would affect the quantitative analysis of the changes. The impact of the differences of sun's angle may partially be reduced by selecting data belonging to the same time of the year (Singh 1989). The availability of multitemporal data to produce land cover changes is also useful because it solves the problems associated with single dated land cover information. In this study, multiresolution and multitemporal time series including historical satellite imagery, aerial photographs and other vector datasets were used to determine LULC changes over the study period between 1990 and 2006. In order to analyze the time-series dataset and generate surface information, different approaches were also employed.

2.3.1 Baseline and characteristics of data used

The urban land use change analysis and modeling was based on three LULC maps: 1990, 2000 and 2006 with different MMU, and various ancillary data. In the first place, CORINE⁷ land cover maps for the years 1990 and 2000 with a MMU of 25ha were acquired from the IGP. A national land cover map with a MMU of 1ha for the year 1990 was also obtained from the IGP. This map was derived from historical Landsat TM images by the remote sensing unit of the IGP⁸. Moreover, land cover maps with a MMU of 1ha (2000 and 2006) and 25ha (2006) presented at the end of this chapter were derived from the Landsat image of the year 2000, and LISS-III (summer) and SPOT (spring) images of the year 2006. LISS-III is a multi-spectral camera operating in four spectral bands, three in the visible and near infrared (NIR) and one in the short-wave infrared (SWIR) region. The new feature in LISS-III camera is the SWIR band (1.55 to 1.7 μ m), which provides data with a spatial resolution of 23.5m (NRSA 2003). Similarly, the SPOT-4 is acquired both in the panchromatic and multispectral mode at 10m and 20m resolution, respectively. In the multispectral mode, it acquires images three in the visible and NIR, and one in the SWIR. The spring and summer images were used to better discriminate some land cover classes. The characteristics of the satellite data used in this study are summarized in the Table below.

Satellites	Spectral bands	ground pixel size)	Spectral resolutions	Acquisition time
Landsat TM	P: panchromatic	15	0.50-0.90 μ m	August 24, 2000
	B1: Blue	30	0.45-0.52 μ m	
	B2: Green	30	0.52-0.60 μ m	
	B3: Red	30	0.63-0.69 μ m	
	B4: Near-infrared	30	0.76-0.90 μ m	
	B5: SWIR	30	1.55-1.75 μ m	
	B6: thermal-infrared	120	10.40-12.50 μ m	
LISS-III	P: panchromatic	5.8	0.50-0.75	August 11, 2006
	B1: Green	23	0.52-0.59 μ m	
	B2: Red	23	0.62-0.68 μ m	
	B3: NIR	23	0.77-0.86 μ m	
	B4: SWIR	23	1.55-1.70 μ m	
SPOT-4	P: panchromatic	10	0.61-0.68 μ m	May 24, 2006
	B1: Green	20	0.50-0.59 μ m	
	B2: Red	20	0.61-0.68 μ m	
	B3: NIR	20	0.78-0.89 μ m	
	B4: SWIR	20	1.58-1.75 μ m	

Table 2.1 Characteristics of satellite data used in the study

⁷ CORINE land cover uses a unique combination of satellite images and other data to reveal all kinds of information on land sources-information which has a broad range of application: from nature conservation to urban planning (EEA, 2000). Computer-assisted image interpretation of earth observation satellite images is used to map the whole European territory into standard CORINE Land cover categories.

⁸ www.igeo.pt

In order to view and discriminate the surface features clearly, all the input images were composed using the RGB color composition. This is also important for generating a segmented image because the algorithm considers all the input images for segmentation. The four spectral channels that can be generated using the LISS-III and SPOT-4 sensors are similar to bands 2, 3, 4 and 5 of the TM or ETM+ sensors. This reveals that both LISS-III and SPOT-4 are not operating in the blue band. Figure 2.2 shows an example of gray palette of the four spectral bands and RGB composition of the study area in the LISS-III sensor.

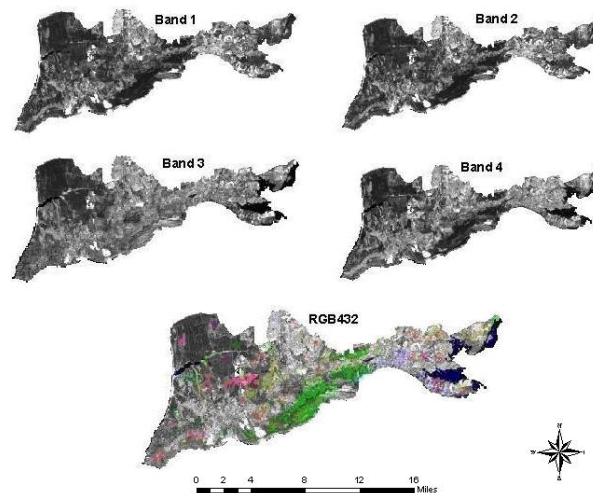


Figure 2.2 the four spectral bands (palette gray) and RGB432 of LISS-III

Furthermore, ancillary data such as major road axis maps, existing land cover maps, DEM, high resolution aerial photographs and Google map were integrated in the study. Population data for the census year of 2001 was also used to describe and analyze the pattern of urban sprawl or growth.

2.3.2 Pre-processing and Minimum Mapping Unit (MMU)

➤ Pre-processing:

Satellite data obtained from various sensors undergo some degree of geometric and radiometric distortions due to Earth rotation, platform instability, atmospheric effects, etc. Accurate spatial registration or rectification of the images is thus essential for effective LULC change analysis. This necessitates the use of geometric rectification algorithms that register the images to each other or to a standard map projection (Singh 1989). The input images were corrected and resampled by the Remote Sensing Unit of the IGP. Initially, the satellite data were provided in composite images and as a pre-processing phase, individual bands were extracted in ArcGIS. Consequently, all the bands (4bands-LISS-III, 4bands-SPOT and 6bands-Landsat TM) were obtained for further processing and analysis. The spatial extent covering the entire study area (Setúbal and Sesimbra) was then extracted from the images using spatial analyst tool in ArcGIS. Since a single spring image was not covering the whole study area, two scenes of spring images of the year 2006 were also mosaiced on a band by band basis using Mosaicing tool.

➤ *Minimum Mapping Unit (MMU):*

MMU is the smallest area that can be mapped. It is selected as close as possible to the original data resolution so as to reduce the loss of specificity introduced in the resampling process. *Since only large MMU changes resulted in significant differences in the accuracy estimates, an analyst may have the flexibility to select from a range of MMU that are appropriate for a given application* (Knight and Lunetta 2003). It was also argued that a possible MMU for a classification created from ETM+ may be 8100m² or 90*90 m (3*3 pixels) (Knight and Lunetta 2003). As stated, the MMU for the available land cover maps was 1ha (national land cover-1990) and 25ha (CORINE1990 and 2000). The LULC maps were therefore derived with a MMU of 25ha for the year 2006 and 1ha for the year 2000 and 2006.

➤ *Land cover nomenclature*

The European nomenclature distinguishes 44 different types of land cover classes and each country can supplement the categories with a more detailed level (EEA 2000). The datasets, the land cover maps used in the study, were provided along with the 44 land cover classes. For the sake of simplicity on one hand and because the focus of the study was on urban area on the other hand, the 44 classes were simplified into 7 major classes. The land cover classes used and their descriptions are given in Table 2.2. The urban/developed areas exhibit spatially heterogeneous features and discrimination of some of the features still remain a problem. This is because such surface features tend to have similar spectral response. In this case, the “urban class” includes all forms of built structure including commercial, residential, road and other impervious features.

	Land cover classes	Descriptions based on the CORINE land cover classes
1	Urban or Built up areas	This classes both continuous and discontinuous urban fabric, industrial, commercial, transportation and other related built up areas
2	Green urban areas	This contains only the Green urban areas
3	Non-irrigated arable land	It comprises non-irrigated arable land, annual and permanent crops, complex cultivation patterns, agriculture with natural vegetation, etc
4	Irrigated land	This mainly contains permanently irrigated land, rice fields, fruit trees and berry plantations
5	Forest cover	This is the dominant land cover class in the area and comprises: broad-leaved forest, coniferous forest, mixed forest, transitional woodland/shrub, etc
6	Bare land	Sand plains and dunes, bare rock, are considered as bare land
7	Water bodies and marsh area	Water related features such as water courses, water bodies, estuaries, salt marshes are include in this class

Table 2.2 Land cover classes

2.4 Image classification paradigm for image analysis

RS research focusing on image classification has attracted the attention of many researchers (Lu and Weng 2007) and a number of researches have been conducted using different classification algorithms. It should be noted that valuable surface information extraction and analysis is also well performed using image classification. Image classification is the process of assigning pixels of continuous raster image to predefined land cover classes. It is a complex and time consuming process, and the result of classification is likely to be affected by various factors (e.g. nature of input images, classification methods, algorithm, etc). In order to improve the classification accuracy, thus, selection of appropriate classification method is required. This would

also enable analyst to detect changes successfully. In various empirical studies, different classification methods are discussed and Figure 2.3 summarizes the different types of classification techniques using different criteria for categorization. Two classification paradigms: pixel and object-based as well as advanced classification approaches are discussed below in detail.

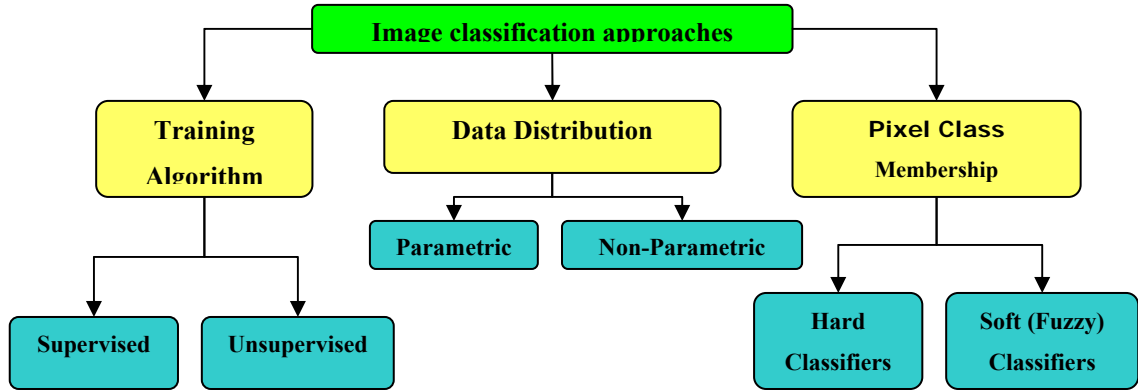


Figure 2.3: Image Classification methods

2.4.1 Pixel-based paradigm

In this method, each pixel is classified based on the spatial arrangement of edge features in its local neighbourhood (Im et al. 2008). Image classification at pixel level could be supervised or unsupervised; parametric and hard classifiers. In a supervised classification method (e.g. maximum likelihood), the analyst is responsible for training the algorithm. Input from analyst is very limited in an unsupervised method i.e. specifying number of clusters and labelling the classes. The statistical properties of training datasets from ground reference data are typically used to estimate the probability density functions of the classes (Santos et al. 2006). Each unknown pixel is then assigned to the class with the highest probability at the pixel location. However, a pixel-based method is associated with the mixed-pixel problem and it might not clearly show the required classes of interest, although they are the most commonly used technique. Hence, change detection using this approach may not be effective.

2.4.2 Object-based paradigm

The advent of object-oriented approaches provides a tool for mapping detailed land uses (Mori et al. 2004). This approach considers group of pixels and the geometric properties of image objects. It segments the imageries into homogenous regions based on neighbouring pixels' spectral and spatial properties. It is based on a supervised maximum likelihood classification. Thus, an object-oriented method has been applied in this project in to avoid the mixed pixel problems. The overall procedure is described below.

2.4.3 Advanced classification approaches

Recently, various advanced image classification approaches have been widely used (Lu and Weng 2007). These include artificial neural networks, fuzzy-set theory,

decision tree classifier, etc. The pixel-based approach is referred to as a “hard” classification approach and each pixel is forced to show membership only to a single class. Soft classification approach is thus developed as an alternative because of its ability to deal with mixed pixels. The soft classification method provides more information and produces potentially a more accurate result (Jensen et al. 2005).

2.5 Image classification and validation techniques used

Analyses of the literature reviewed and analyst’s personal experiences revealed that pixel-based classification produces inconsistent “salt and pepper” output. This is true not only with coarse resolution images but also with fine resolution images (e.g. IKONOS). As stated, recent studies indicated that an alternative object-oriented approach produces better and effective result than the pixel-based does. This is because the world is not pixelated rather it is arranged in objects (Araya and Hergarten 2008). The object-oriented processing technique segments the images into homogenous regions based on neighbouring pixels’ spectral and spatial properties. Image analysis techniques that consider both the measured reflectance values and neighbourhood relations (object-oriented analysis) are available in Definiens and SPRING software packages. Such object-based schemes are essential for urban growth studies (Moeller et al. 2004).

In this study, the Definiens 5.0 software has been used to classify the Landsat, LISS-III and SPOT images. According to the software manufacturer the guiding principle for the land use classification is that objects should be generated as large as possible and as fine as necessary (GmbH 2001)⁹. The software is based on an object-based processing and classification of remote sensing imagery. It has the capabilities to import images from different data formats, generate object of segments, collect training samples, classify and perform mapping operations. It also supports different methods to train the algorithm and build up resource- and knowledge-based image classification. The image segmentation and object-oriented classification method for change detection holds much promise (Civco et al. 2002). Moreover, object-based analysis offers great potential and opportunities for identifying and characterizing LULC change processes.

2.5.1 Multi-resolution segmentation

The Landsat (bands1-5 and band7), SPOT (four bands) and LISS-III (four bands) images were loaded into Definiens as image layers. One way to include spatial dimensions in image analysis is to identify relatively homogenous regions and treat them as objects using the process of segmentation. Although segmentation is not a new concept, segmentation-based image classification has significantly increased recently (Blaschke 2004). The segmentation process in eCognition is known as a “multi-resolution segmentation” and is based on “region growing approach”. That is a bottom-up region merging approach, where the smallest objects contain single pixels. In the process, smaller objects are merged into larger objects based on the scale parameters defined and spectral properties. The segmentation process stops when the

⁹ www.definiens-imaging.com

smallest growth of an object exceeds a user defined threshold or scale parameter (Im et al. 2008). The formation of the objects is also carried out in such a way that an overall homogeneous resolution is kept (Mansor et al. 2002). Image segmentation in Definiens 5.0 requires some parameters to be set:

- *Image layer weights*: varying between 0 to 1 indicating the importance of a layer in the segmentation process;
- *Scale parameter*: determines the average size of image objects;
- *Color*: determines the homogeneity of the image;
- *Shape*: controls the degree of object shape homogeneity

There is no specific agreement or guideline on the rules to be set and these parameters are often set in a trial and error mode as well as visual analysis of the segmented images. In this case, all the image layers were given equal importance 1 and different scale parameters were attempted based on visual analysis of the segmentation results. Figure 2.4 shows one of the segmented images for the Landsat image of 2000.

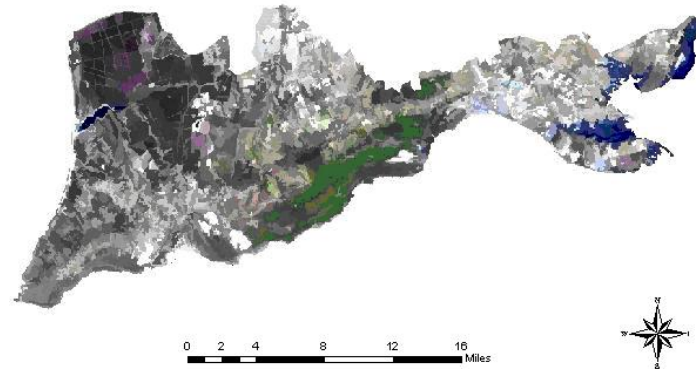


Figure 2.4 segmented image

For the analysis and classification of image objects, in Definiens 5.0, the land cover classes (Table 2.2) has to be defined in a class hierarchy. Sample objects which are typical representatives of the classes were collected using high resolution images and existing land cover maps.

2.5.2 Image classification algorithm

Land use classification requires a classification scheme and algorithms. As mentioned above, the CORINE land cover classification scheme has been applied to define the land cover classes. The Definiens offers two different classification algorithms: Nearest Neighbour and Membership Functions. The Membership Functions are soft classifiers that are based on a fuzz classification systems, in which the feature values of arbitrary range were translated into a value between 0 (no membership) and 1 (full membership) (Benz et al. 2004). The Nearest neighbour classification is similar to supervised classifications in common image analysis software. The classifier was applied by using the Edit Standard Nearest Neighbour Feature Space Tool. For each class, the standard nearest neighbour expression was inserted. After constructing the resource based sample collection, a standard nearest neighbour algorithm was applied

to produce the land cover map. Based on these procedures, land cover maps of the study area have been produced.

2.5.3 Image classification validation

Accuracy assessment is a process used to estimate the accuracy of image classification by comparing the classified map with a reference map (Caetano et al. 2005). It is critical for a map generated from any remote sensing data. Although accuracy assessment is important for traditional photographic remote sensing techniques, with the advent of more advanced digital satellite remote sensing the necessity and possibility of performing advanced accuracy assessment have received new interest (Congalton 1991). Currently, accuracy assessment is considered as an integral part of any image classification. This is because image classification using different classification algorithms may classify pixels or group of pixels to wrong classes. The most obvious types of error that occurs in image classifications are errors of omission or commission.

The common way to represent classification accuracy is in the form of an error matrix. An error matrix is a square array of rows and columns and presents the relationship between the classes in the classified and reference maps. Using error matrix to represent accuracy is recommended and adopted as the standard reporting convention (Congalton 1991). In this paper, overall, producer's and user's accuracy were considered for analysis. The Kappa coefficient, which is one of the most popular measures in addressing the difference between the actual agreement and change agreement, was also calculated. The Kappa statistics is a discrete multivariate technique used in accuracy assessment (Fan et al. 2007).

The reference data used for accuracy assessment are usually obtained from aerial photographs, high resolution images (e.g. IKONOS, QUICKBIRD, and aerial photo), and field observations. In this case, the assessment was carried out using high resolution (50cm) aerial photograph as a reference. A set of reference points has to be generated to assess accuracy and 240 stratified random points were generated for each derived maps. These points were verified and labelled against the reference data. Error matrices were then designed to assess the quality of the classification accuracy of all the maps. The error matrix can be used as a starting point for a series of descriptive and analytical statistical techniques (Congalton 1991). The overall, user's and producer's accuracies, as well as the Kappa statistic were then derived from the matrices. By introducing the methodologies employed to classify the images and assess the accuracy in the study, the results are presented in the following section.

2.6 Results and evaluation of classification

2.6.1 Land use classification

In order to facilitate the task of mapping relatively homogeneous areas over different time periods to enable spatio-temporal analysis, geospatial tools are very essential. The presence of multitemporal satellite data also provided an opportunity to generate

land cover maps of the areas with different MMU and observe the changes in urban characteristics. The figures shown below have been derived using an object-oriented image analysis to detect, quantify and simulate the changes.

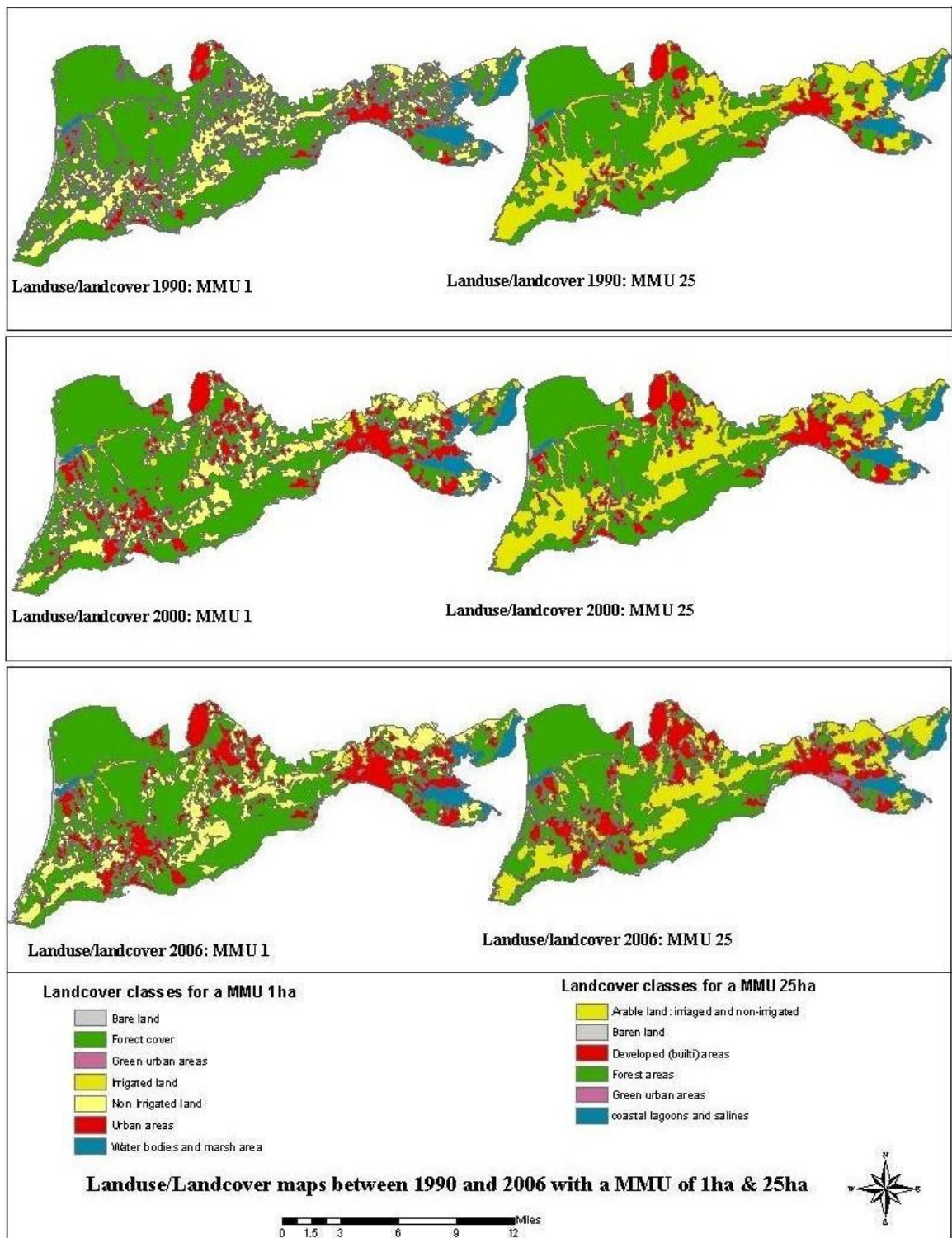


Figure 2.5 LULC maps of 1990, 2000 and 2006 with a MMU 1ha and 25ha

Furthermore, in order to examine the nature and spatial extent of built-up areas, the LULC maps were also simplified into two broad classes (Figure 2.6). This simplified graphic presentation enables a direct visual comparison of urban land use change.

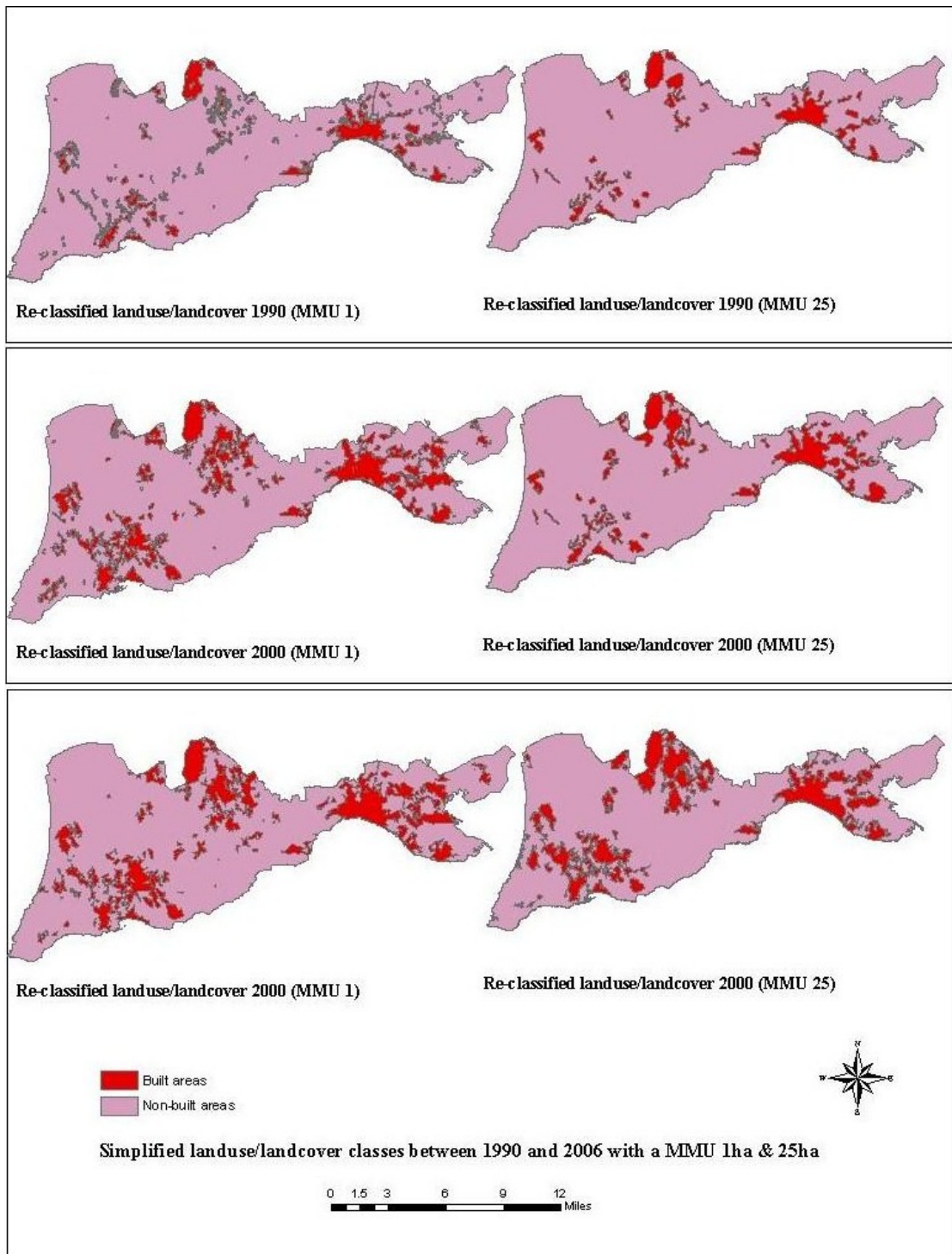


Figure 2.6 Simplified LULC maps of 1990, 2000 and 2006 With a MMU of 1ha & 25ha

2.6.2 Evaluation of classification results using descriptive analysis

In order to use the derived land cover maps for further change analysis, the errors need to be quantified and evaluated in terms of classification accuracy. As stated, an accuracy assessment was carried out and the result of the matrix is presented in Tables 2.3, 2.4 and 2.5. The technique provides some statistical and analytical approaches (in the form of user's, producer's and overall accuracies) to examine the accuracy of the classification. The Kappa analysis was also calculated from the error matrix.

➤ Overall accuracy

This is computed by dividing the total correct number of pixels (i.e. summation of the diagonal) to the total number of pixels in the matrix (grand total). The overall accuracies for the maps of 2000 and 2006 with a MMU of 1ha were 92.51% and 87.68%, respectively. Similarly, the overall accuracy of the 2006 map with a MMU of 25ha was 89.17%. Various standard threshold levels were applied to the lower and higher tail of each distribution in order to find the threshold value that produced the highest change classification accuracy (Mas 1999). In some empirical studies (Anderson et al., 1976), it is noted that a minimum accuracy value of 85% is required for effective and reliable land cover change analysis and modeling. Therefore, the classification carried out in this study produces an overall accuracy that fulfils the minimum accuracy threshold defined by Anderson.

➤ Producer's accuracy

This refers to the probability of a reference pixel being classified correctly. It is also known as omission error because it only gives the proportion of the correctly classified pixels. It is obtained by dividing the number of correctly classified pixels in the category by the total number of pixels of the category in the reference data. The overall result of the producer's accuracy ranges from 60% to 100%. The lowest producer's accuracy exists in the land cover classes "arable" and "urban areas". This is probably attributed to the similar spectral properties of some of the land cover classes (e.g. bare land with urban areas, green urban areas with forest cover, arable during dry season with bare land, etc).

➤ User's accuracy

This assesses the probability that the pixels in the classified map or image represent that class on the ground (Congalton 1991). It is obtained by dividing the total number of correctly classified pixels in the category by the total number of pixels on the classified image. User's accuracy of individual classes ranges from 63% to 100%. From user's accuracy point of view, urban areas and bare land presented low accuracy for the land cover map 2000 (1ha MMU). The "urban class" and bare land were, to some extent, misclassified as "non-irrigated land" and urban areas, respectively. This is probably caused by the spectral signature of the features.

➤ *Kappa coefficient*

The Kappa coefficient, which is a measure of agreement, can also be used to assess the classification accuracy. It expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification (Congalton 1991). The Kappa statistic incorporates the off-diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. The Kappa coefficient is calculated using the information in Tables 2.3, 2.4 and 2.5 and the following formula given by Congalton, 1991.

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} \times X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} \times X_{+i})},$$

(Adopted from Congalton 1991)

Where:

r = is the number of rows in the matrix

X_{ii} = is the number of observations in rows i and column i (along the major diagonal)

X_{i+} = the marginal total of row i (right of the matrix)

X_{+i} are the marginal totals of column i (bottom of the matrix)

N is the total number of observations.

It is not uncommon that the Kappa coefficient appears to be low, giving the impression that the classification of remote sensing performed better than chance only by K point of proportion (Muzein 2006). It was calculated to be 0.86, 0.86 and 0.83 for the land cover maps of 2006 (MMU 25), 2000 (MMU 1ha) and 2006 (MMU 1ha), respectively. These Kappa results are considered to be a good result.

		Reference map							User's accuracy
		Urban areas	Green urban	Arable	Forest cover	Bare land	Water bodies & marsh areas	Grand Total	
Classified map	Urban areas	140		4	12	4		160	88.00
	Green urban	24	210	6				240	88.00
	Arable	2		34	4			40	85.00
	Forest cover			10	190			200	95.50
	Bare land				10	70		80	88.00
	Water bodies & marsh areas	3		3	6	3	105	120	88.00
Grand Total		169	210	57	222	77	105	840	
Producer's accuracy in %		83.00	100	60.00	86.00	91.00	100		

Table 2.3 Error matrix: image classification of 2006 (MMU 25ha)

		Reference map							User's accuracy
		Urban areas	Non-irrigated land	Irrigated land	Forest cover	Bare land	Water bodies & marsh areas	Grand Total	
Classified map	Urban areas	29	11	3	2	1		46	63.04
	Non-irrigated land	3	126		12	3		144	87.50
	Irrigated land			32	8			40	80.00
	Forest cover	10	5		530			545	97.25
	Bare land	6				18		24	75.00
	Water bodies & marsh areas						56	56	100
Grand Total		48	142	35	552	22	56	855	
Producer's accuracy in %		60.61	88.73	91.42	96.01	81.81	100		

Table 2.4 Error matrix: image classification of 2000 (MMU 1ha)

		Reference map							User's accuracy
		Urban areas	Non-irrigated land	Irrigated land	Forest cover	Bare land	Water bodies & marsh areas	Grand Total	
Classified map	Urban areas	240	30		6			276	86.95
	Non-irrigated land	20	180	10	10			220	81.81
	Irrigated land		8	24				32	75.00
	Forest cover	2	8		202			212	95.28
	Bare land					3		3	100
	Water bodies & marsh areas		7				70	77	90.10
Grand Total		262	233	34	218	3	70	820	90.90
Producer's accuracy in %		91.60	77.25	70.59	92.66	100	100		

Table 2.5 Error Matrix: image classification of 2006 (MMU 1ha)

2.7 Discussions

One of the applications of remote sensing image analysis is mapping and monitoring urban land use. It is applied to estimate various surface features and provide spatially consistent datasets that cover large areas with high level of details and temporal frequency. The availability of multitemporal and multiresolution satellite images also provides the opportunity to identify and detect urban features. Mapping of urban areas can be accomplished at different spatio-temporal scales. A wide variety of image classification schemes and techniques have also come to exist. The heterogeneous nature of urban environment, however, makes the discrimination of some urban surface features difficult. There is also still an argument on the potential of remote sensing techniques for urban studies (i.e. pixelizing urban environment is not a simple process). Nevertheless, the recent advances in context- or object-based remote sensing approach using Definiens provide a means to obtain better and reliable information. The study also realized that Definiens is powerful tool for generating contextual based surface information but requires subjective manipulation of input parameters.

In this chapter, different classification techniques have been reviewed and presented. It was found out that pixel-based approach does not clearly present an object of interest and may not be appropriate for delimitating urban areas. In this study, a more effective classification paradigm, object-oriented paradigm, has been applied. This method successfully avoided the problems associated with pixel-based paradigm. The approach aided the process of classification by segmenting imageries into homogenous regions. During segmentation, consideration must be given to the parameters because they have a significant role in defining the desired class objects though defining parameters is not straightforward. Considering these facts, LULC covers maps of the study area were obtained. Besides, it should be noted that assessing the accuracy of image classification is fundamental in urban land use studies. This is because maps derived from remote sensing data contain inevitable errors due to inefficient number of training sites or lack of reference data. Accuracy levels that are acceptable for certain tasks may not be acceptable for others. Hence, 85% classification accuracy is defined as minimum classification accuracy for effective LULC change analysis and modeling. The results obtained from classification and the validation statistics were higher than the minimum validation threshold defined. Therefore, it was reasonable to employ the derived maps for further change analysis studies. In the next section, the nature and trend of urban land use changes in the Concelhos of Setúbal and Sesimbra is studied.

CHAPTER 3

URBAN LAND USE CHANGE DETECTION ANALYSIS

3.1: Introduction

Despite their regional economic importance, the growth of the size of cities, often at rates exceeding the population growth rate, and the accompanying loss of agricultural lands, forests, and degraded environments, is of growing concern to citizens and public agencies responsible for planning and managing urban development (Bauer et al. 2003). The trend of such urban growth has a tremendous impact particularly on the outskirts of urban areas. It has also to be noted that the use of unsuitable methods for development may cause harm both to the natural environment and human life (Yeh and Li 1997). As pointed by (Lavalle et al. 2001), understanding the urban dynamics is one of the most complex tasks in planning sustainable urban development while also conserving natural resources. Therefore, urban development requires a careful assessment and monitoring to provide planners with information on the tendency of urban change in the future. In order to examine the urban land use changes, a post-classification change analysis was employed and the changes were quantified. Urban sprawl measurement was also studied to examine the sprawl in the study area. Figure 3.1 describes the methodology applied to detect changes and analyze the dynamics.

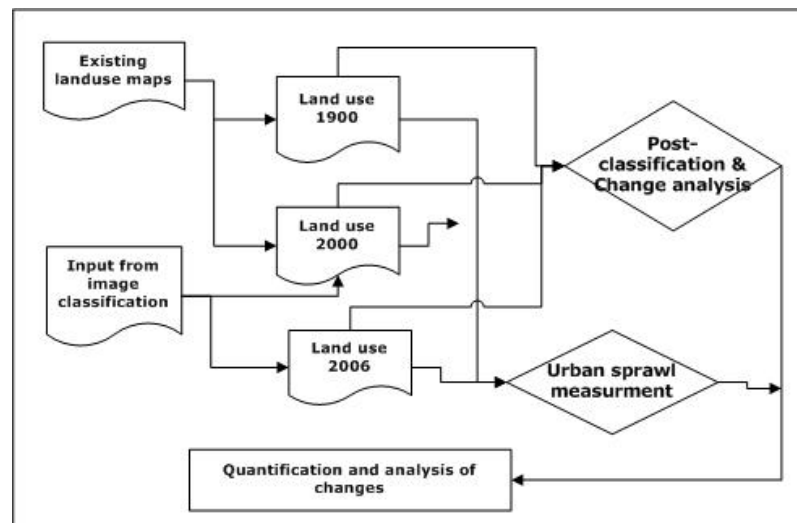


Figure 3.1 the methodology employed to detect and analyze changes

3.2: Urban land use change detection

3.2.1 Change detection: conceptual framework

Change detection is the process used in remote sensing to determine changes in the land cover properties between different time periods. It is also viewed as:

- the process of identifying differences in the state of an object by observing it at different times (Singh 1989).

- the measure of thematic change information that can guide to more tangible insights into underlying process involving LULC changes than information obtained from continuous change (Ramachandra and Kumar 2004).
- the process for monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution in the area of interest (Tardie and Congalton 2004).

3.2.2 Applications and approaches of change detection

Change detection has been applied in different application areas ranging from monitoring general land cover change using multitemporal imageries to anomaly detection on hazardous waste sites (Jensen et al. 2005). One of the most common applications of change detection is determining urban land use change and assessing urban sprawl. This would assist urban planners and decision makers to implement sound solution for environmental management.

A number of approaches have emerged and applied in various studies to determine the spatial extent of land cover changes. It is also reviewed that different methods of detection produce different change maps (Araya and Cabral 2008). The selection of an appropriate technique depends on knowledge of the algorithms and characteristic features of the study area (Elnazir et al. 2004), and accurate registration of the satellite input data. Change detection approaches based on expert systems, artificial networks, fuzzy sets and object-oriented methods are also available in different software platforms (Jensen et al. 2005). In addition, various researchers (Singh 1989; Mas 1999; Belaid 2003; Jensen et al. 2005; Berkavoa 2007) have attempted to group change detection methods into different broad categories based on the data transformation procedures and the analysis of techniques applied. According to (Berkavoa 2007), for example, change detection can be divided into two main groups: pre-classification and post-classification methods. The following section discusses some of the techniques that are available in various software platforms.

➤ Image differencing:

Image differencing is one of the widely used change detection approaches and is based on the subtraction of images acquired in two different times. This is performed on a pixel by pixel or band by band level to create the difference image. In the process, the digital number (DN) value of one date for a given band is subtracted from the DN value of the same band of another date (Singh 1989; Tardie and Congalton 2004). Since the analysis is pixel by pixel, raw (unprocessed) input images might not present a good result.

➤ Image ratioing:

In this method, geo-corrected images of different data are ratioed pixel by pixel (band by band). It also looks at the relative difference between images (Eastman 2001). Ratio value greater or less one reflects cover changes.

➤ *Image regression:*

This method is based on the assumption that pixels from Time₁ are in a linear function of the Time₂ (Singh 1989; Ramachandra and Kumar 2004). The regression technique accounts for differences in the mean and variance between pixel values for different dates.

➤ *Vegetation index differencing:*

This method is applied to analyze the amount of change in vegetation versus non vegetation by computing NDVI. NDVI is one of the most common vegetation indexing method and is calculated by

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where NIR is the near infrared band response for a given pixel and RED is the red response

➤ *Post classification comparison:*

This is the most obvious, common and suitable method for land cover change detection. This method requires the comparison of independently classified images T₁ and T₂, the analyst can produce change map which show a complete matrix of changes (Singh 1989).

3.3 Post-classification detection technique used

There are a number of detection techniques but the most common approach is the simple technique of post classification comparison (Blaschke 2004). A post-classification comparison, which is the most straightforward technique, has been applied in this study. The land cover maps for the years 1990, 2000 and 2006 were first simplified into two classes: built and non-built areas. The post-classification comparison was then applied by overlaying the corresponding reclassified maps to generate change maps. The change map of two images will only be generally as accurate as the product of the accuracies of each individual classification. The result of the detection change entirely depends on the accuracies of each individual classification. Image classification and post-classification techniques are, therefore, iterative and require further refinement to produce more reliable and accurate change detection results (Fan et al. 2007).

3.4 Results of change detection in Setúbal and Sesimbra

Preliminary results from the multi-date visual change detection indicate that urban land use has changed significantly over the period from 1990 to 2000 in Setúbal-Sesimbra (Figure 3.2). This trend continued in the period from 2000 to 2006. Notably, most of the changes occurred in the peripheries of the existing urban areas. Some of the observed types of change revealed by the study were urban expansion and densification. Besides, the results of the image classification and change map would provide an estimate of the extent, pattern and direction of urban land cover changes in the study site.

In spite of this, there has also been conversion of built areas into non-built areas. It is less likely to have such kind of conversions and these are questionable results. These discrepancies or errors might have been caused by differences in class definition, spectral responses of some features (e.g. built areas and bare land), mapping inconsistencies and smoothing or generalization applied. To alleviate such discrepancies in the change analysis, new land cover maps for the years 2000 and 2006 (with classes of built and non-built) were generated by summing the reclassified land cover maps of the years 1990 and 2000, and 2000 and 2006, respectively.

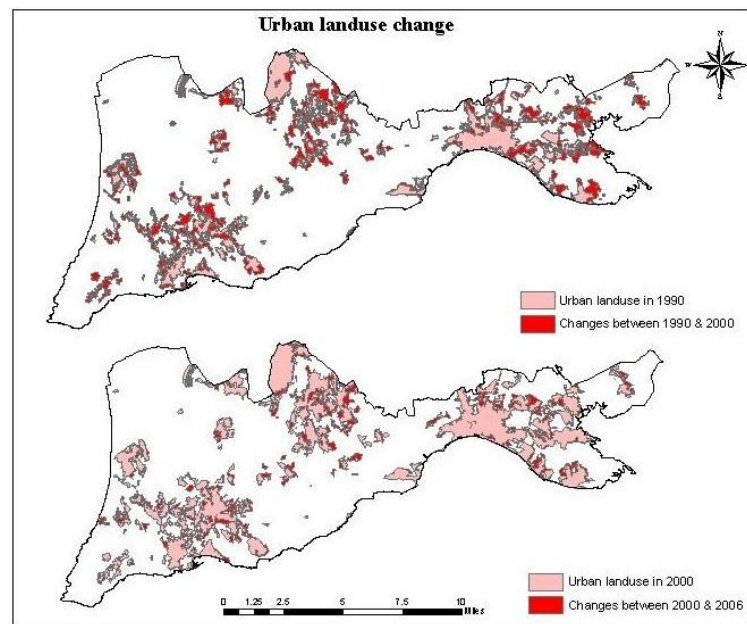


Figure 3.2 Urban land use change maps

Based on this time scale series analysis, the urban growth has occurred in almost all part of the study site except in the southern, north-western part and to some extent in the eastern part of the study area. These areas can be characterized as “Zone of Discard”, which hinders further urban development, as oppose to “Zone of Assimilation” as far as Urban Geography is concerned. These areas are characterized by forest cover, marsh and coastal areas.

3.5 Urban land use change analysis

Monitoring urban land cover changes requires careful analysis of the change using different tools (e.g. change analysis and modeling). A change in urban land use structures can also be well described using information from spatial or landscape metrics. Spatial metrics are quantitative indices used to describe the structures and patterns of landscape (Herold et al. 2002). They were employed to analyze and model urban growth and landscape changes in different urban studies (Herold et al. 2003, Cabral et al. 2005). Understanding the deriving forces is also imperative for further analysis of the changes. In addition, MURBANDY (monitoring urban dynamics) was developed to provide means to measure the extent of urban areas and their progress towards their sustainability (Lavalle et al. 2001). The model was presented based on

the creation of land use database for various European cities. The approach is an element of the MOLAND (monitoring land use/ land cover change dynamics) project aimed at monitoring urban changes in European cities. Some attempts have also made to apply the model in some developing countries. Like any kind of urban change analysis, the data for the project were derived from imageries and aerial photo.

3.6: Quantification and description of urban land use changes in Setúbal and Sesimbra

The differences in representation of a space have led to a wide variety of spatial metrics for the description of spatial structure (Herold et al. 2003). The spatial metrics are algorithms used to quantify spatial characteristics of patches, class areas and the entire landscape (Cabral et al. 2005). They enable us to quantify the spatial heterogeneity of classes and identify the changes in the pattern of urban growth. In this study, the changes in urban landscape (e.g. development of discontinuous urban areas or urban fragmentation) are measured and analyzed using the FRAGSTATS¹⁰ tool and thematic maps that represent both built and non-built spatial patches.

A number of metrics have been developed to describe and quantify elements of patch shape complexity and spatial configuration relative to other patch types. However, it is not clear which will prove to be the most informative and interpretable over large areas (EPA 2000). In this paper, seven spatial metrics (class area-CA, Number of patches – NP, Edge Density – ED, Largest Patch Index – LPI, Euclidian Mean Nearest Neighbour Distance – EMN, Area Weighted Mean Patch Fractal Dimension-FRAC_AM and Contagion) which have already been used in various publications are adopted and used for analyzing the urban land cover changes (Table 2.4) The selection of the metrics was based on their applications in previous research works on urban areas.

Metrics	Descriptions
CA/TA Class Area	CA measures total areas of built and non-built areas in the landscape
NP Number of Patches	It is the number of built and non-built-up patches in the landscape
ED-Edge Density	ED equals the sum of the lengths (m) of all edge segments involving the patch type, divided by the total landscape area (m ²)
LPI Largest Patch Index	LPI percentage of the landscape comprised by the largest patch
MNN-MN Euclidian Mean Nearest Neighbour Distance	Equals the distance (m) to the nearest neighbouring patch of the same type, based on shortest edge-to-edge distance
FRAC_AM Area weighted mean patch fractal dimension	Area weighted mean value of the fractal dimension values of all urban patches, the fractal dimension of a patch equals two times the logarithm of patch area (m ²), the perimeter is adjusted to correct for the raster bias in perimeter
Contagion	The index describes the heterogeneity of a landscape and measures to what extent landscapes are aggregated or clumped

Table 3.1 Spatial metrics adopted and used (McGarigal et al., 2002)

3.6.1 Class Area (CA/TA)

CA is the simplest measure of total area or landscape composition. It indicates how much of the area is comprised of a particular urban patch type. It equals the sum of the

¹⁰ FRAGSTATS, a public domain spatial metrics program, was developed in the mid 1990s and has been continuously improve since (McGarigal et al., 2002)

areas (m²) of all patches of the corresponding patch type, divided by 10,000 (to convert to hectares), i.e. total class area (McGarigal et al. 2002). It is given by Eq. 3.1

$$CA = \sum_{j=1}^n a_{ij} \left(\frac{1}{10,000} \right) \quad (3.1)$$

Where a_{ij} is the area (m²) of urban patch ij

3.6.2 Number of Patches (NP)

The NP quantifies the number of individual urban patches in the landscape. This index has limited interpretive values by itself because it does not address any information about area, distribution or density of patches (McGarigal et al. 2002). However, it addresses if there were new urban patches in the landscape. It is given by Eq. (3.2)

$$NP = N \quad (3.2)$$

Where N is the total number of urban patches in the landscape

3.6.3 Edge Density (ED)

The ED is a measure of the total length of the edge of the urban patches divided by the total landscape area (m²), multiplied by 10,000 (to convert to hectares). In other words, it measures the length of the urban boundary divided by the total landscape area E.q (3.3).

$$ED = \frac{E}{A} (10,000) \quad (3.3)$$

Where E is the total length (m) of edge in landscape and
A is the total landscape area (m²)

3.6.4 Largest Patch Index (LPI)

This index is a simple measure of the proportion of total landscape area comprised by the largest urban patch. It equals the area (m²) of the largest patch of the corresponding patch type divided by total area covered by urban (m²), multiplied by 100 (to convert to percentage) E.q (3.4).

$$LPI = \frac{\max(a_{ij})}{A} (100) \quad (3.4)$$

Where $\max(a_{ij})$ is the area (m²) of largest urban patch ij and
A is the total landscape area (m²)

3.6.5 Area Weighted Mean Patch Fractal Dimension (FRAC_AM)

The FRAC_AM measures the average fractal dimension of all components of urban patches weighted by the major components in the landscape (E.q 3.5). The fractal dimension varies between 1 and 2. It also describes the complexity and fragmentation of a patch by a perimeter–area proportion (McGarigal et al. 2002). Low values are derived when a patch has a compact rectangular form with a relatively small perimeter

relative to the area. If the patches are more complex and fragmented, the perimeter increases and yields a higher fractal dimension (Herold et al. 2002).

$$FRAC_AM = \sum_{i=1}^m \sum_{j=1}^n \left[\left(\frac{2 \ln(0.25 p_{ij})}{\ln a_{ij}} \right) \left(\frac{a_{ij}}{A} \right) \right] \quad (3.5)$$

Where: m-number of patch elements or types (in this case: built and non-built classes); n-number of patches in the same class; p(ij)-perimeter of urban patch ij; a(ij)-area of urban patch ij and A-total landscape area.

3.6.6. Euclidean Mean Nearest Neighbour (ENN_MN)

The ENN_MN represents the average minimum distance between the individual built areas (urban) blob. The metrics measures the distance (m) the nearest average Euclidean urban patch (3.6).

$$ENN_AM = h_{ij} \times \frac{\sum_{j=1}^n x_{ij}}{n_i} \quad (3.6)$$

Where h_{ij} is the distance (m) of the urban patch ij to the nearest urban patch; x_{ij} is the urban patches and n_i is the total number of patches in the landscape.

3.6.7 Contagion

The index describes the heterogeneity of a landscape and it measures the extent to which the landscapes are aggregated or clumped (Herold et al. 2003). It also indicates the overall probability that an urban pixel to be adjacent to pixels of the same class (urban), multiplied by 100 (Eq. 3.7). The values range from 0 to 100. A value close to 0 indicates that the patch of the landscape is very fragmented while value close to 100 describes less fragmentation (Cabral 2006).

$$Contagion = \frac{\sum_{j=1}^m \sum_{k=1}^m \left[p_i \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right] \times \left[\ln \left(p_i \right) \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right]}{2 \ln(m)} \times 100 \quad (3.7)$$

Where P(i) is the proportion of the landscape occupied by patch type i (built area); g_{ik} is the number of adjacencies between pixels of classes i and k (in this case classes built and non-built and m is the number of patch types (urban patch in this case)

3.7 Analysis of landscape indices in Setúbal and Sesimbra

The indices described above, as qualitative measures of spatial structure, were calculated for the “urban/built-up” class. Table 3.2 contains a summary of statistics from the spatial metrics of the changes obtained using the Fragstats. These indices provide information on the nature of each index in the study site. As it is evident from the table, there has been a tremendous growth in the built-areas and spatial pattern of regional economic developments in the study area. Analysis of the metrics indicates that urban land cover was increased significantly during the study period. The trend of the growth was typically into the outskirts of the urban areas and this could be probably due to the improvements in infrastructures.

Metrics	Spatial metrics during the study period			Change in urban structure	
	1990	2000	2006	$\Delta\%90-00$	$\Delta\%00-06$
CA/TA	3487.50	6665.06	7087.7296	91.11	6.34
NP	234	114	134	-51.28	17.54
LPI	1.9264	4.1435	3.0687	115.09	-25.94
ED	12.4501	15.8027	15.5501	26.93	-1.60
FRAC_AM	1.1272	1.1656	1.1514	3.41	-1.22
ENN_MN	271.3556	359.5010	309.6645	32.48	-13.86
Contagion	0.7395	0.8103	0.8200	9.57	1.20

Table 3.2: landscape indices and percentage of changes calculated in Setúbal Sesimbra

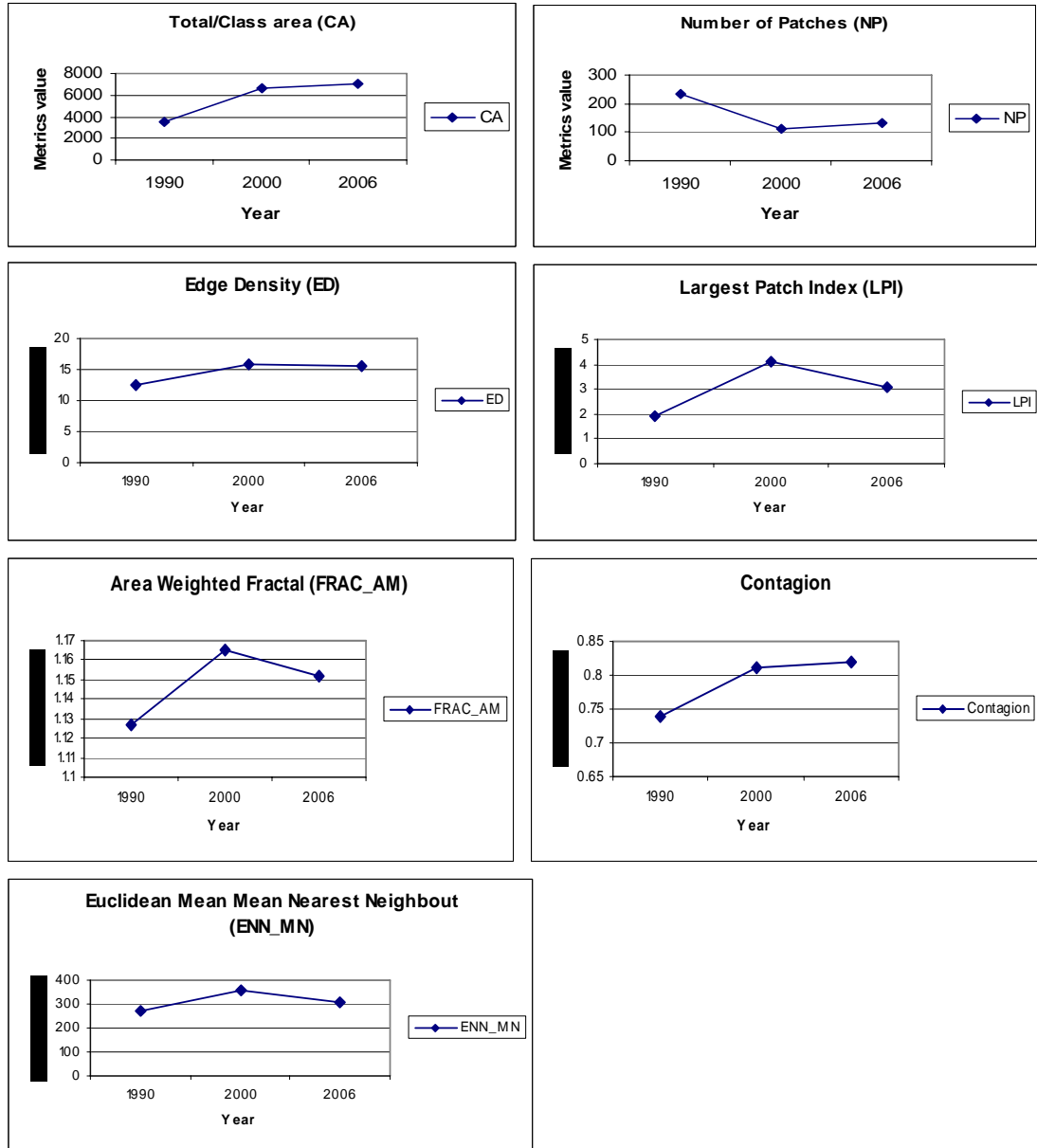


Figure 3.3 Temporal urban growth signatures of spatial metrics for the study area

The class area (CA/TA) index is a good starting point to analyze urban developments. Generally speaking, urban land use has greatly changed over the study period. The built-up areas have increased by 91.11% between 1990 and 2000. Similarly, urban growth has increased in the period between 2000 and 2006 though the rate of growth was relatively slow (i.e. 6.34%).

The number of patches, urban blocks in this case, has decreased considerably (51.28%) in the study period between 1990 and 2000. This reveals development of urban features in open spaces and it also indicates that urban growth has been occurred gradually in the surrounding of the existing developed areas. However, there has been an increase in the number of urban patches by 6.34% between 2000 and 2006.

The LPI has increased by 115% between 1990 and 2000. It seems to represent a considerable growth of the historical urban core. However, the size of the LIP has decreased by 25.94% and this is probably affected by the development of discontinuous urban features in the period after 2000. It is also likely that the result might have been affected by the result of the classification.

The ED has increased by 26.93% and this proves an increase in the total length of the edge of the urban patches. The total length of the edge of the land use patches (urban patch) increases with an increase in the land use fragmentation and development of continuous urban features. There has been a decrease in ED between 2000 and 2006. This is less likely to happen but it might have been affected by generalization applied for the land use map of 2006.

A fractal dimension which is greater than one indicates an increase in shape complexity (Cabral et al., 2005). The FRAC_AM of built areas, however, exhibit more or less no significant change during the study period. This indicates that an increase in CA, LPI and ED, in this context, does not affect the complexity of the shape.

The ENN_MN is considered a measure of the open space between urbanized areas (Herold et al., 2003). An increase in ENN_MN by 32.48% between 1990 and 2000 shows an increment in the distance between the urban patches. The value of ENN_MN after 2000 shows a decrease by 13.86% and this indicates reductions in the distance between the built-up patches.

3.8 Urban sprawl measurement using Shannon entropy

3.8.1 Urban sprawl: built-up areas as indicator of urban sprawl

Urbanization takes place either in radial direction around a city center (Center business District –CBD) or linearly along major road networks. Such dispersed nature of urban development along major road networks or surrounding city center is often referred to as sprawl (Yeh and Li 2001; Barnes et al. 2002; Sudhira et al. 2004). Urban sprawl is also defined as a complex phenomenon, which has both environmental and social impacts (Barnes et al. 2002; Sun et al. 2007). Some of the major factors responsible for urban sprawl are population growth, proximity to major resources,

services and infrastructure. The pattern of sprawl has to be identified and analyzed effectively to help urban and regional planning. In order to analyze the sprawl, spatial dataset such as urban land use maps, location of city center or road network and a buffer ring around city center or roads are required.

As noted by (Sutton 2003), there is no specific, measurable or accepted definition of urban sprawl because public perception of sprawl might vary. This would make identifying indicators of urban sprawl difficult. It has been, however, mentioned that the area covered by impervious surfaces such as asphalt and built areas is a measure of development (Barnes et al. 2002). It is also apparent that built-areas have greater proportions of impervious surfaces. Population growth in the region is also another good indicator of sprawl. Hence, the proportion of the total population in a region to the total built-up of the region can be obtained to measure and quantify sprawl.

3.8.2 Measurement of Urban sprawl

Many attempts have been made to measure sprawl (Leta et al. 2001; Yeh and Li 2001; Sun et al. 2007). One of the most commonly used approaches, in most urban sprawl studies, is to integrate Shannon's Entropy with GIS tools. This is relatively straight forward and efficient approach to analyze urban sprawl. In this study, urban sprawl over the period of 1990 to 2006 was determined by computing the area of all the built lands from the land cover maps. The Shannon's entropy along with GIS tools was also applied to measure the sprawl during the study period. Shannon's entropy is used to measure the degree of spatial concentration and dispersion defined by geographical variable (Leta et al. 2001; Yeh and Li 2001; Sudhira et al. 2004). In order to make the measurement of the three years of sprawl, the three land use maps for the years 1990, 2000 and 2006 and Shannon entropy approach was employed. The entropy value varies from 0 to 1. If the distribution is maximally concentrated in one region, the lowest value of entropy 0 is obtained while an evenly disperse distribution across space give a maximum value of 1. The dispersion of built-up areas from a city centre or road network leads to an increase in the entropy value. This gives a clear idea to recognise whether land development is more dispersed or compact. The Shannon's entropy (E_n) is given by,

$$E_n = \sum_i^n p_i \log(1 / p_i) / \log(n) \quad (3.8)$$

Where $p_i = x_i / \sum_1^n x_i$ and x_i is the density of land development, which equals the amount of built-up land divided by the total amount of land in the i th zone in the total zone of n zones. The number of zones means the number of buffer zones around the city center or around selected roads. Since entropy can be used to measure the distribution of a geographical phenomenon, the difference in entropy between two different periods of time can also be used to indicate the change in the degree of dispersal of land development or urban sprawl (Yeh and Li 2001).

$$\Delta E_n = E_n(t + 1) - E_n(t) \quad (3.9)$$

Where ΔEn is the difference of the entropy values between two time periods; $En(t+1)$ is the entropy value at time period (t+1); $En(t)$ is the relative entropy value at time period t.

Since we are interested in the urban land use only, the three land cover maps the years 1990, 2000 and 2006 were first simplified into two major classes: built and non-built areas. In addition, two scenarios were attempted to calculate the entropy:

- 1) 15 and 16km concentric buffer rings around city center were needed to cover all parts of Setúbal and Sesimbra, respectively. This scenario treated the Concelhos of Setúbal and Sesimbra separately (Figure 3.4 and 3.5).
- 2) The 11 number of “Freguesia” (administrative division) of the study area was treated as a zone. The Setúbal and Sesimbra were considered as one region in this case (Figure 3.6).

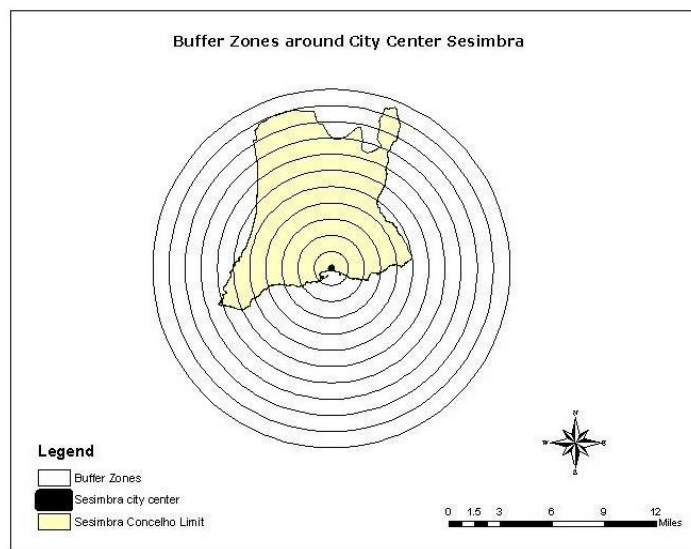


Figure 3.4 Buffer zones around the city of Sesimbra

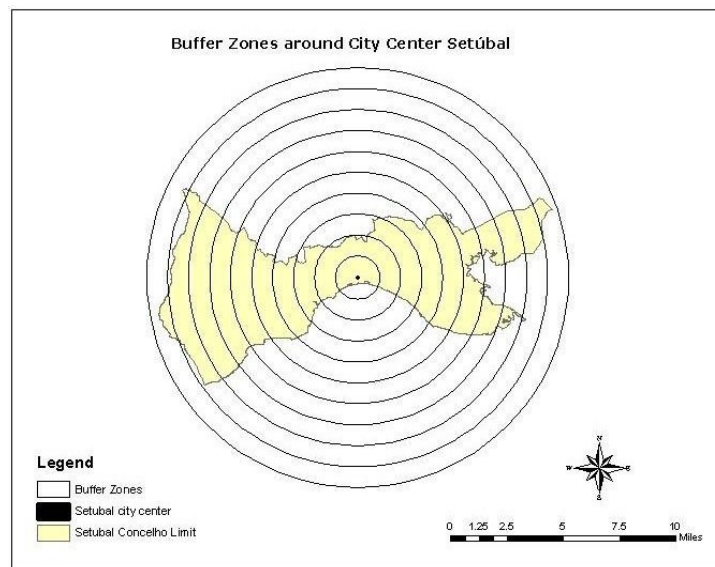


Figure 3.5 Buffer zones around the city of Setúbal

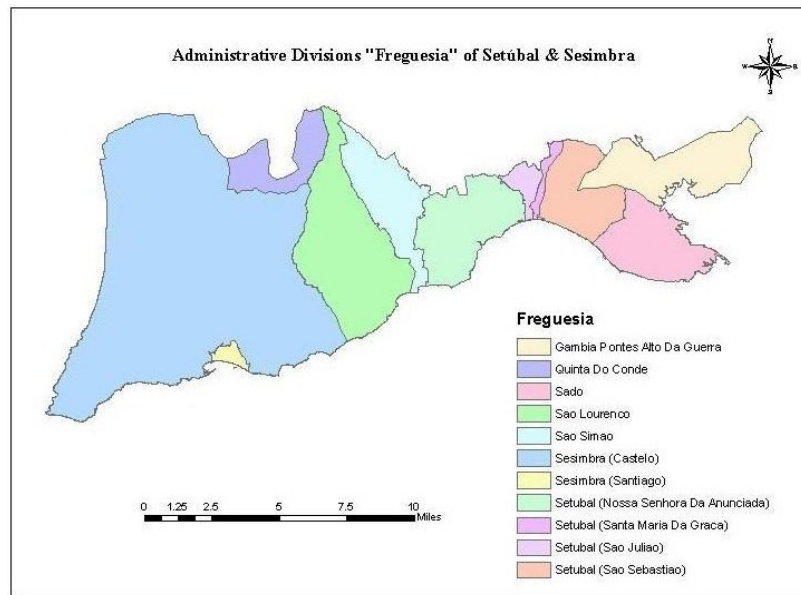


Figure 3.6 The 11 administrative divisions “Freguesia” of Setúbal-Sesimbra

Both scenarios have their own limitations; the buffer ring, for example, includes area outside the study limit though it is good approach of measuring sprawl. The second scenario is likely to be affected by the size of the Freguesia. Nonetheless, both scenarios were attempted to measure sprawl.

3.9 Urban sprawl in Setúbal-Sesimbra

3.9.1 The on-going sprawl in Setúbal-Sesimbra

The entropy was calculated using Equation 3.8, the one km buffer zones and the eleven (11) number of “Freguesia”. The results of the entropy calculation are shown in Table 3.3 and Figure 3.7. The results indicate that both sites: Setúbal and Sesimbra have undergone a significant urban sprawl between 1990 and 2006. The entropy measure also indicates the study site “all freguesia” has undergone a considerable sprawl. As it is evident from Table 3.3, the entropy value for the years 1990, 2000 and 2006 for Setúbal, Sesimbra and “all Freguesia” was above 0.50 and indicating high rate of sprawl. The entropy value for the year 2006, however, shows a highly dispersed development in both scenarios compared to the entropy value in 1990 and 2000. Figure 3.7 also reveals a marginal increase in the level of sprawl and this indicates the study site was continuing to sprawl between 1990 and 2006. Such high entropy values also reveal that land development was spreading over the urban fringe and to the surrounding rural area.

	1990	2000	2006
Setúbal	0.729917625	0.827029415	0.88275902
Sesimbra	0.732641422	0.801504817	0.894718755
All Freguesia	0.879942588	0.910748821	0.944373107

Table 3.3 Shannon’s Entropy values of Setúbal and Sesimbra in the 3 years

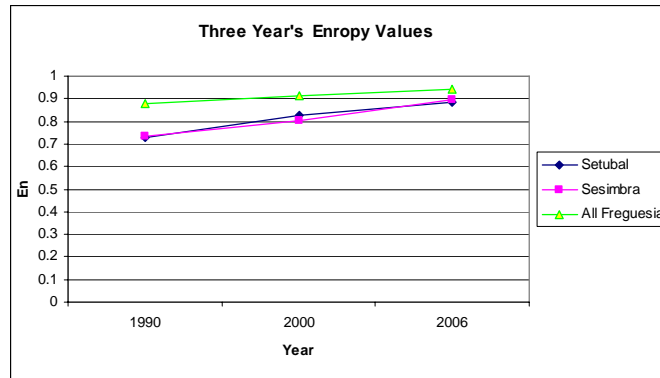


Figure 3.7 Three year's entropy values

Furthermore, the measurement of the difference on entropy between (t) and t+1 was also obtained using Equation 3.9 to indicate the temporal change in the degree of dispersal of land development or urban sprawl. The change in the entropy values is given in Table 3.4 and Figure 3.8. The overall difference “all Freguesia” however presents a gradual increase in the sprawl.

	ΔEn		
	Setúbal	Sesimbra	All Freguesia
1990-2000	0.097111791	0.055729605	0.030806233
2000-2006	0.068863395	0.093213938	0.033624286

Table 3.4 Differences of Shannon Entropy

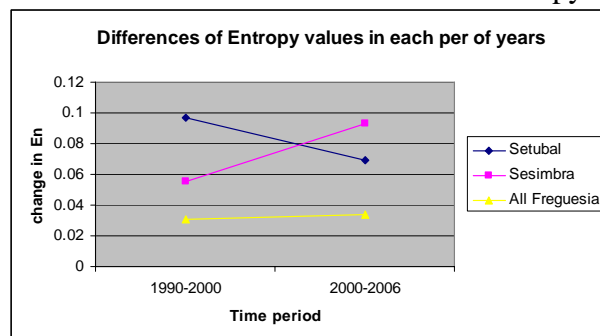


Figure 3.8 Differences in entropy values in each pair of years

3.9.2 Population density and urban sprawl

In order to better understand the situation, the population density in each “freguesia” was calculated considering two aspects: population density A and population density B. The population density A (Table 3.5) is the population of the “freguesia” divided by the total area of the “freguesia” and the population density B was calculated by dividing the population of the “freguesia” to the built-up area of the ward. This shows how much pressure has been given to the available land.

	District name	Total area in ha	Area ha (built areas)	Pop. 2001	% of built-up	Pop. Den. A (Pop./total area)	Pop. Den. B (Pop./built areas)
1	Sesimbra (Castelo)	17907	1175	22871	6.56	1.28	19.46
2	sesimbra (Santiago)	199	101	6960	50.75	34.97	68.91
3	Quinta Do Conde	1395	649	23429	46.52	16.79	36.10
4	Setúbal S. Anunciada	2699	331	23429	12.26	8.68	70.78
5	S. S. maria da Graca	225	117	15751	52.00	70.00	134.62
6	S. Sao julio	405	151	23255	37.28	57.42	154.01
7	Sao Lourenco	4724	565	15835	11.96	3.35	28.03
8	S. Sao-Sebastiao	1909	902	62023	47.25	32.49	68.76
9	Sao Simao	2207	312	10019	14.14	4.54	32.11
10	Gambia Pontes	2768	194	7496	7.01	2.71	38.64
11	Sado	2247	570	8160	25.37	3.63	14.32

Table 3.5 Population size and built-up areas (Freguesia-based)

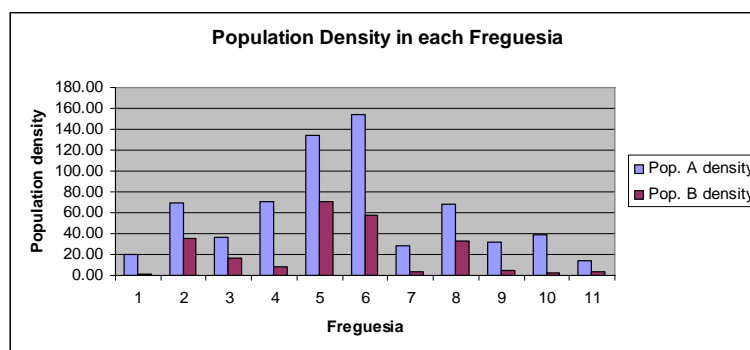


Figure 3.9 Population density in each freguesia

3.10 Discussions

In this chapter, land use detection techniques, landscape indices and urban sprawl measurement have been studied and presented. A wide variety of change detection approaches are available to characterize LULC changes and each has a set of strengths and weakness (EPA, 2000). Nevertheless, all the approaches enable analyst to explore the structural variations among different land cover patterns and explore land use change (Long et al., 2007). A study was carried out on spatio-temporal change analysis in the Concelhos of Setúbal and Sesimbra with the most common change detection approach. Results of the analysis indicate that there have been a remarkable urban land use changes during the study period. However, the method presents only the spatial extent of urban land use changes. It is also likely that successful change detection from satellite images depends on the success of image pre-processing and classification (Shalaby and Tateishi, 2007). In order to better describe the changes in pattern and structure of urban areas, the study was supplemented by the use of selected landscape indices.

Each of the metrics provided information on the nature of each index in the study site. Analysis of the CA index indicates that there has been a remarkable growth in the spatial extent of built-up areas and spatial pattern of regional economic developments in the area. The NP indicates the aggregation or disaggregation in the landscape. There was a decrease in NP between 1990 and 2000 and hence some degree of aggregation of landscape was evident. The decrease in NP between the years 2000 and

2006 shows the development of a number of isolated, fragmented or discontinuous built-up areas. An increase in LPI between 1990 and 2000 is pertained to the contagion of small and isolated urban patches into the largest patch and development of other urban areas around the existing largest patch. The FRAC_AM and Contagion measure the complexity or shape of urban classes. If the patches are more complex and fragmented, the perimeter increases and yields a higher FRAC_AM. The shape of the urban patch would become more complex as well. FRAC_AM greater than 1 indicates increase in shape complexity (McGarigal et al. 2002). In addition, when the shape of the patch becomes more complex and fragmented, the value of the Contagion would also become close to 0. There was a marginal change in the FRAC_AM and Contagion but it can be argued that there were no significant changes in shape and complexity. Finally, the ENN_MN measure the distance between urban patches and thus increase in distance between the years 1990 and 2000 reveals dispersed urban growth and some of patches might have developed at distance places. A decrease in distance between urban patches after the year 2000 addresses that urban patches were getting closer to each other between the years 2000 and 2006.

Furthermore, urban sprawl has been measured using Shannon entropy. If the distribution is maximally concentrated in one region, the lowest entropy value (0) is obtained while an evenly disperse distribution across space give a maximum value of 1. The dispersion of built-up areas from a city centre leads to an increase in the entropy value. This gives a clear idea to recognise whether land development is towards a more dispersed or compact. Thus, an increase in the entropy value in Sesimbra indicates an increase in urban sprawl and more dispersed development. Despite the marginal sprawl between the years 1990 and 2006, there has been a decrease in the rate of sprawl in Setúbal area. This indicates that the rate of dispersion between the years 2000 and 2006 was not as extensive as the period between 1990 and 2000. However, the overall difference “all freguesia” presents a gradual increase in sprawl. The driving forces behind the sprawl could be many but one of the major factors is population growth particularly in the period after 1970 with the end of Portuguese overseas colonies. Urban sprawl is increasingly considered as a significant and growing problem that entails a wide range of social and environmental problems. Furthermore, some of the “Freguesia” are facing high population density compared to others e.g. Sesimbra (Santiago), Setúbal Maria da Graca, Setúbal Sao Julio and Setúbal Sao Sebastiao. Most of these are located close to the major urban areas of the Concelhos.

CHAPTER 4

URBAN LAND USE CHANGE MODELING

4.1: Introduction

Modeling land use change plays a significant role for understanding the impacts of the changes. This would also help for effective environmental management, sustainable resources use, development plans and decision making. In order to achieve all this, a number of modeling approaches have come to exist. In this chapter, the role of GIS, RS and modeling technique in urban land use dynamics is studied. To accomplish this, the following questions were posed:

- (1) Is it possible to model urban land use changes using geospatial techniques?
- (2) What would be the degree of certainty of the model output?

To address the first question, different LULC models were reviewed and studied. There exist various types of models and employ different techniques to predict urban land use changes. They also vary from each other depending on the type of data input, assumptions, number of classes, decision rules, data format, etc. The choice of modeling type also depends on the purpose of the model, analyst's preferences and skills. It is not however easy to decide which model to apply for a given location (Pontius and Malanson 2005). One of the commonly used models, Cellular Automata Markov (CA_Markov), is applied in this study. To answer the second question, the model output was compared and validated with a reference land use map. Once the result of the validation was found to be successful, the model has been applied for further simulations.

4.2: Land use change models

The term "model" has been used in different context and in a number of application areas. It is broadly defined as abstraction or approximation of reality achieved by simplification of complex real world relations to the point that they are understandable and analytically manageable (Batty 1976; Briassoulis 1999). In practical situation (e.g. land use studies), models are used to predict the future state of land use patterns considering various physical and socio-economic elements.

4.2.1 Land use change models

Dynamic urban features, rapid expansion of urban population and urban areas affect natural and human systems at all geographic scales (Brockerhoff 2000). Traditional planning approaches have been used by various communities to monitor these impacts and the approach was complemented with analytical decision making tools (EPA 2000). Recent technological advances in the spatial modeling also allow communities to examine environmental dynamics and decision-making. Moreover, GIS along with modeling tools provide an opportunity to simulate land use change and assist land use planning. As the need for modeling has intensified, the use of computer-based models

of land use change and urban growth has greatly increased, and become an instrument in urban planning and management support (Herold et al. 2003).

The existing models may differ from each other depending on the purpose they are designed, spatial scale, temporal dimension, data availability, expertise knowledge, etc. Some models are simple and provide user-friendly tools that someone can apply with limited experiences (e.g. GEOMOD in IDRISI). There are also technically complex models which require advanced programming and expertise knowledge (e.g. agent-based modeling-CA). Thus, assessment and selection of the desired model requires consideration of a number of factors. Table 4.1 presents some of the existing urban land use models available on the Web but their comprehensive description is out of the scope this research. However, the most commonly used modeling approach (CA) is reviewed in detail in the following section.

4.2.2 Cellular automata (CA)

CA is a dynamical discrete system in space and time that operates on a uniform grid based space (Batty 1976; Alkheder and Shan 2005; Hand 2005). It was first introduced in the 1940's by John Von Neumann, the founder of the game theory¹¹, and Stanislaw Ulam, who worked in the Manhattan project¹² and made intensive research in the field of Monte Carlo Simulation (Hand 2005; Pinto and Antunes 2007). Since its advent, it has been used to model a wide range of phenomena due to its ability to represent spatial process ranging from forest fires to epidemics, from traffic simulation to regional-scale urbanization (Pinto and Antunes 2007). It has also been implemented in various land use models to simulate multiple land use types and provides a powerful tool for modelling the dynamic nature of the land use change.

There are, however, profound challenges to CA-based urban simulation: complex urban system and cells are usual defined by a binary state (Xie 2003). The term CA itself is evolved from the fact that it consists of cells and transition rules that are applied to determine the state of a particular cell. Each cell depends on its state in the previous period and the state of its immediate neighbor according to the rules applied. This rule is applied to all cells on the grid. The neighboring cells are often defined as the entire set of eight adjacent cells (Moore neighborhood) or as a set of four adjacent cells usually located in the main cardinal points (von Neumann neighborhood) (Hand 2005). The von Neumann and Moore neighborhoods relationships are shown in Figure 4.1.

¹¹ Game theory is a branch of applied mathematics that is used in the social science, biology, engineering, political science, international relations, computer science and philosophy. It is also the study of the ways in which *strategic interactions, mathematically, among rational players produce outcomes* with respect to the *preferences (or utilities)* of those players, none of which might have been intended by any of them (Ross, 2006).

¹² The Manhattan Project was the project to develop the first nuclear weapon (atomic bomb) during World War II by the United States, the United Kingdom and Canada (<http://en.wikipedia.org/wiki/>).

Model name	Model type	Purpose	Target user group	Spatial resolution	Spatial extent	Temporal resolution	Temporal extent (future and past)
SLEUTH	Cellular automata	Project urban growth and examines how new urban areas consume surrounding land and impact the natural environment	Academic and government researchers, planners	User defined	User defined	Yearly	As far into the past or future as available data will allow
CURBA	Urban growth	Evaluates the possible effects of alternative urban growth patterns and policies on biodiversity and natural habitat quality	Land use planners, policy makers and environmentalist	One hectare (100*100m) grid cells	Scale and can be customized for users needs	User defined	User defined
IRPUD Model	<ul style="list-style-type: none"> • Travel demand model • Urban economic/ use market models 	Projects the impacts of long-range economic and technological change on housing, transportation, public policies, land uses, and infrastructure	Regional transportation and land use planners, researchers	300 zones	Local or regional level	User defined	User defined into the future
LTM (Land Transformation Model)	GIS Urban impact Neural network	Integrates a variety of land use change driving variables to project impact on land use on a watershed level	Watershed stakeholders (resource managers, landowners, planners)	Parcel (30*30), plat (100*100m), block (300*300m) and local (1*1km)	User defined	5 or 10 years	20-50 years into the future
DELTA	Urban economic/land use market	Projects changes in urban area including the location of households, population, employment, and the amount of real estate development	Politicians, policy makers, planners	User defined	Customized for users needs (typically for cities with population 250,000+)	1 year increments recommended	User defined

Table 4.1 Examples of existing urban land use change models (adopted from EPA, 2000 and Agarwal et al., 2002)

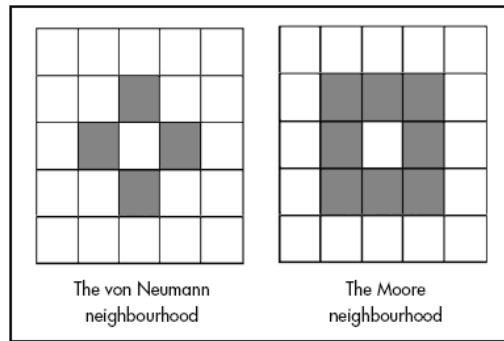


Figure 4.1 the most common neighborhood relationship (Source: Hand, 2005)

The CA integrates four basic components, as shown in figure 4.2, to simulate changes: grid cells (lattice), rule, state, and neighbor (Clarke and Gaydos 1998; Xie 2002; Sun et al. 2007). Most CA models also require GIS-based inputs in image format such as land use maps, road maps, protected areas, etc. Besides, the ability that CA has to represent complex systems with spatial/temporal behaviours from a small set of simple rules and states made this technique very interesting for geographers and urban researchers (Alkheder and Shan 2005).

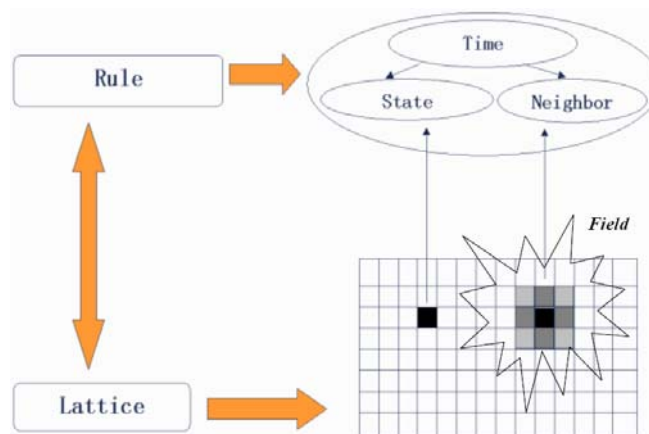


Figure 4.2 Components of CA (adopted from Xie, 2002)

4.3: Modeling in Idrisi

IDRISI is the industry leader in raster analytical functionality covering the full spectrum of GIS and RS needs (Eastman 2001). Some of the functionalities included in the package are image analysis, change and time series analysis, spatial modeling, decision support system, etc. These are essential for environmental modeling and natural resource management. Despite the highly sophisticated nature of these capabilities, the system is easy to use and inexpensive to buy (Eastman 2001). Some of the modeling techniques embedded in Idrisi Kilimanjaro are logistic regression, stochastic choice, GEOMOD and CA_Markov chain analysis.

As mentioned above, CA operates on a grid based cells and transition rules are applied to determine the state of a cell. Markov Chain Analysis, on the other hand, is a system in which the future state of a system is modelled on the basis of the immediate preceding state. A Markov chain, named after Andrey Markov¹³, is a stochastic process. It is based on the principle that given the present state, future states are independent of the past states. In order to explore land use dynamics, this study employed CA_Markov chain analysis integrated with raster-based remote sensing. The CA_Markov is a combination of both CA and Markov chain. These two are termed as the two geosimulation techniques used to produce land use predictions (Sun et al. 2007). The geosimulation refers to the process of land use change between two points in time and extrapolating this change into the future (Eastman 2001).

4.4: Modeling of urban land use in Setúbal and Sesimbra

4.4.1 Introduction

In this study, a CA_Markov Chain analysis for simulating urban land use was implemented in IDIRIS Kilimanjaro. CA_Markov has the ability to predict transition among any number of classes unlike GEOMOD which operates only with two numbers of categories (e.g. built and non-built). The CA_Markov uses a Multi-Criteria-Evaluation (MCE) to generate the decision rules in the form of suitability maps. The transition rules were based on the factors that have impacts on urban growth. These include distance from built-up areas, distance from major road axis, slope and other reserved areas (e.g. natural parks or water bodies). The effects of these factors were first evaluated using MCE (criteria developments) transition rules and resulted in generating potential “suitable” areas for urban expansion. In order to calibrate the model and simulate land use change for the year 2006, these drivers along with the land use maps of the years 1990 and 2000 were used. The predictive model output for 2006 was then validated using a “real” land cover map for the year 2006. After validating the performance of the model, the urban land use map for the year 2010 was simulated using the same procedures. Figure 3.4 describes the methodology applied to calibrate, simulate and validate the model.

¹³ Andrey Markov, was a Russian Mathematician, is best known for his work on theory of stochastic process (<http://en.wikipedia.org/wiki>).

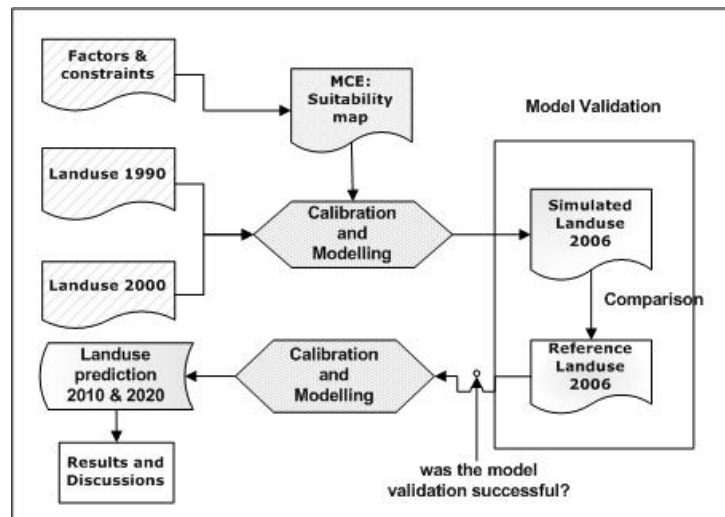


Figure 4.3 Model calibration and validation methods

4.4.2 Model Description

CA provides a powerful tool for modeling the dynamic nature of land use and is a commonly used method to take spatial interaction into consideration (Clarke and Gaydos 1998; Verburg et al. 2004; Houet and Hubert-Moy 2006). There are different many CA models in various software platforms and are different options to implement: using an existing model or developing a new model. The later requires extensive and advanced programming knowledge. This study is based on the existing modeling technique “CA_Markov”. The CA_Markov integrates two techniques: Markov Chain Analysis and Cellular Automata Analysis. The Markov Chain Analysis describes the probability of land use change from period to another by developing a transition probability matrix between t1 and t2. The probabilities may be accurate on a per category basis but there is no knowledge of the spatial distribution of occurrences within each land use classes (Eastman 2001). This is the inherent problem of the Markov Analysis. In order to add the spatial character to the model, therefore, Cellular Automata (CA) is integrated to the approach. In the CA analysis, the land use was treated as a dynamic system in which space, time and the states of the system were treated discretely (Yeh and Li 2001). The Cellular Automata component of the CA_Markov model allows the transition probabilities of one pixel to be a function of neighbouring pixels (Pontius and Chen 2006).

4.5: Model Calibration

The first step in CA_Markov analysis is to develop a transition probability matrix using the Markov module in Idrisi. The transition probability matrix¹⁴ (Table 4.2) for each land cover classes was developed between 1990 and 2000, and hence used as input for projecting land use change. The off-diagonal elements indicate the number

¹⁴ A transition probability matrix records the probability that each land cover category will change to every other category.

of cells that are expected to change from each existing land use class in 1990 to each new class in 2000.

In this study, two land use model scenarios: with a MMU of 1ha and 25ha were carried out. This was to assess the impact of MMU in model output. The first scenario employed land use maps for the years 1990 and 2000 with a MMU of 1ha. The second scenario used CORINE land cover maps for the years 1990 and 2000 with a MMU of 25ha. For both scenarios, land cover map for the year 2006 was generated for validating the model output.

Cells in	Urban areas	Green urban areas	Non irrigated land	Irrigated land	Forest cover	Bare land	Water bodies
Urban areas	8162	23	1373	251	1691	61	19
Green urban areas	15	8	0	0	0	0	0
Non-irrigated land	3083	5	5666	668	3274	58	14
Irrigated land	485	0	729	965	457	3	94
Forest cover	3645	0	4905	1310	22101	463	144
Bare lands	141	0	85	2	389	536	5
Water bodies	207	0	14	183	300	42	1787

Table 4.2 Transition probability matrix with a MMU of 1ha

Using the outputs from the Markov Chain Analysis, specifically the Transitions Area matrix¹⁵, CA_Markov applies a contiguity filter and suitability drivers to examine the land use change. The following sections present the overall calibration procedures applied to predict the change.

4.5.1 Original data and Criteria Development

The calibration of CA_Markov requires different dataset including land use data, suitability maps, constraints (e.g. protected areas), etc. The information used for calibration should be at or before some specific point in time t1 (2000), which is the point in time at which the predictive extrapolation starts. In this paper, land cover maps for the years 1990 and 2000 with a MMU of 1ha and 25ha, major road axis, protected areas, slope, water bodies, and built areas were used. In order to determine lands to be considered for development, a set of criteria has to be determined and two types of criteria: constraints and factors have been used. All the criteria are expressed as raster images.

➤ Constraints

There are many factors responsible for urban growth and urban land use change such as urbanization, population growth, industrialization, land allocation policy, etc. In spite of this, there are some constraints for the urban development. The most obvious constraints are topography, water bodies and existing urban areas. Local administrators may also pose protection of urban development towards water bodies and preserved green areas (e.g. urban parks). Three major constraints: water bodies,

¹⁵ A transition area matrix also records the number of pixels that are expected to change from each land cover type to each over next time period.

existing urban areas and the natural parks were considered in this study. Constraints are the Boolean criteria that limit the expansion of urban land use. They are characterized by their “hard” rule of 0 and 1 and are criticized for not considering the degree of suitability of the transitions potential.

➤ *Factors*

Unlike the constraints, factors define some degree of suitability and provide alternatives in terms of a continuous measure of suitability (e.g. a byte scale of 0 to 255). These criteria do not absolutely constrain development, but enhance or detract from the relative suitability of an area for development (Eastman 2001). The criteria are often obtained from urban planners, administrators, environmentalist or legislations. In order to develop the criteria for MCE and implement the CA_Markov model, the factors affecting urban expansion were first identified based on the literatures reviewed and “Directorate General of Regional Planning and Urban Development- DGRPUD: restrictions of Public utility, Lisbon, 1988”. The factors considered are:

- i. *Land use factor*: this determines the location and spatial extent of the amount of land available for development. This is based on the land use maps obtained.
- ii. *Distance from road networks*: the major road axis obtained from the IGP was used and its effects are determined by the distance function. The influence of road network is measured in terms of accessibility and areas close to road access have greater probability to be changed into urban. This is because development closer to road reduces development costs.
- iii. *Slope*: most often urban development undergoes in a relatively flat areas than hilly areas. Slope is represented in terms of percent or degree (0 represents flat land while cells with a value of 100% represent steep sided). The slope factor was acquired from DEM and obtained by “surface” module.
- iv. *Distance from water bodies or protected areas*: this describes the more the cells close to the preserved areas or water bodies; the less is the probability of change into urban areas. This was also calculated by the distance function in Idrisi.
- v. *Distance from developed “built” areas*: this also shows that urban development takes places in the adjacent developed or vacant areas (i.e. cells close to the developed surface have high probability of being urban). Distance function had been applied to derive this factor.

4.5.2 MCE: The Boolean approach Criteria development

The first step to solve the problem of MCE is to develop a Boolean image of all the criteria. All the criteria (constraints and factors) have standardized to Boolean values of 0 and 1. The table below describes the criteria used to generate the Boolean suitability maps. The suitable areas have a value of 1 while unsuitable areas have a value of 0. The Boolean standardization was based on the legislation defined by (DGOTDU 1988).

Change Drivers	Descriptions
Land use factor	Based on the trend of land use change between 1990 and 2000, and visual interpretation of the changes; agricultural land and bare lands are considered as the possible land use types available for development while all other land use: urban area, water body and irrigated lands are treated as completely unsuitable.
Distance from roads factor	Areas within 500m from major road networks are considered suitable (Rocha et al. 2007). Thus, the continuous image of distance from roads was reclassified to a Boolean expression such that areas within 500m of the road are suitable while areas beyond 400m are unsuitable.
Slope factor	Areas that have low slopes (less than 15%) are suitable for development while areas greater than 15% are not suitable
Distance from water bodies	A protection buffer of 50m from the sea and navigable waters was created and areas within 50m of the water bodies are considered unsuitable while areas beyond 50 are suitable.
Distance from built areas	Areas close to developed areas are more suitable for urban development than areas far from built-up areas.
Distance from protected areas	To preserve the natural park a protection zone of 50m is stated in the legislations and areas within 50m of the protected areas are considered unsuitable while areas beyond 50m are suitable.

Table 4.3 Boolean approach criteria development

Initially, transition rules (suitability maps) were developed in a binary scale “Boolean approach” of 0 and 1. However, a value of 1 in the final suitability image is only possible where all the criteria have a value of 1 and a value 0 is the result even if once criterion has a value of 0. This is a “hard” rule because a location is considered suitable by exactly meeting all the criteria. In addition, in the Boolean approach all the factors were given equal importance in the final suitability map. However, some criteria may be more important than others to determining the overall suitability. Therefore, the Boolean approach was further standardized to represent the probability (range from 0 to 255) of a cell to be suitability for urban land use using weighting factor discussed below.

4.5.3 MCE: Standardization and weighting of factors

➤ Standardization of Factors

In order to overcome the “hard” rule of Boolean approach, a “soft” or “fuzzy” approach has been applied. In this case, all the criteria were standardized to a continuous scale of suitability from 0 (the least suitable) to 255 (the most suitable). The constraints, however, retained their “hard” Boolean character because these are considered completely unsuitable for further development.

The fuzzy membership function in Idrisi is provided for the standardization of factors using a whole range of fuzzy set membership functions. It varies from a complete “non-membership” to full “membership” expressed in either a binary scale (0 and 1) or in a byte scale (0 to 255). The byte scale is recommended because the MCE module is optimized for a 0-255 level standardization (Eastman 2001). The higher the value of the standardized scale, the higher is the suitability of the land. The fuzzy module embedded in Idrisi Kilimanjaro, which provides the function of standardization of continuous variable is applied. Three fuzzy scaling approaches: Sigmoidal, J-shaped and Linear functions are also employed in setting the critical points for the set of membership function. The selection of the parameters for standardization (membership function type and shape as well as control points) is

subjective and depends on analyst knowledge and experiences. The following table describes the membership functions used for standardizing the variables.

Variable-factors	Membership function type/shape	Control points	Descriptions/observation
Distance from the major road axis	J-shaped decreasing	50/500m	Areas within 500m of roads are identified as suitable. It is stated that areas within 50m are the most suitable and areas beyond 50 meters as having a continuously decreasing suitability that approaches 0 but never reaches 0. This is typical characteristics of J-shaped function because the function never reaches 0.
Distance from water bodies and marsh areas	Linear increasing	50/12000 m	Suitability is low within 50m and beyond 50m, suitability increases with distance. Thus, the linear increasing function has been applied because suitability increases with increase distance from water body but the minimum control points should be 50m.
Distance from the developed/ built areas of 2000	Linear Decreasing	0/6500	Linear decreasing function is considered because as distance from built-areas increases, its suitability decreases. The values of the control points are, respectively, the amount of minimum and maximum distance of the original map variable.
Distance from the protected areas	Linear increasing	50/6500	Monotonically increasing function is applied because as distance from the protected areas increases, the suitability increases equally. The minimum and maximum distance of the original map variables are considered as control points.
Slopes	Sigmoidal decreasing	0/15%	Slope greater than 0 is considered suitable but the suitability should not go beyond 15%. Beyond 15%, suitability is again equal. The minimum and maximum thresholds are not longer the minimum and maximum of the input values. Rather, the first control point (0) is the value at which suitability begins to rise sharply above zero and the second control point (15) is the value at which suitability begins level off and approaches a maximum of 255.

Table 4.4 Fuzzy Module: standardization of variables

The figure below shows the map variables derived by standardizing the criteria in a continuous scale from 0 (the least suitable) to 255 (the most suitable).

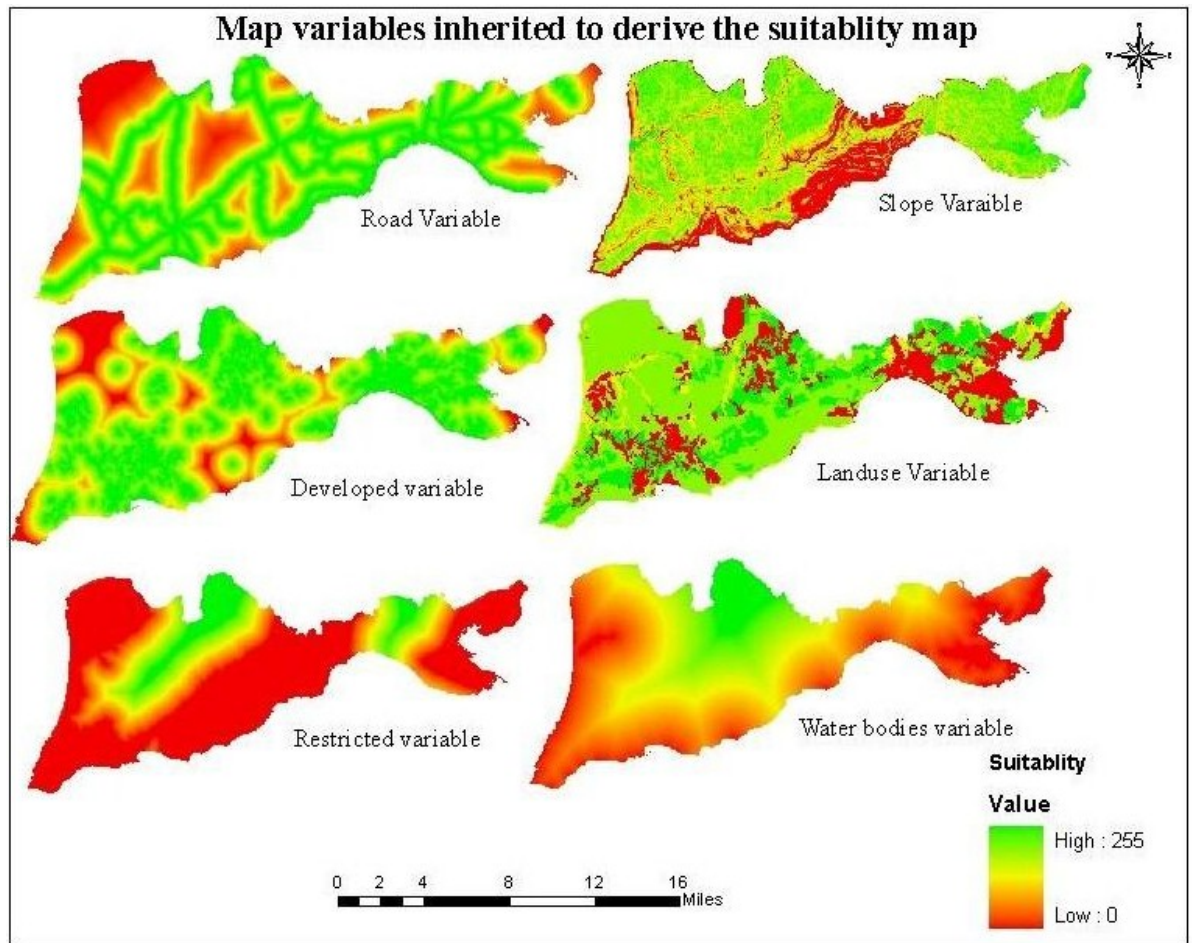


Figure 4.4 map variables derived after standardization

➤ *Weighting factors*

The next step was to establish a set of weights for each of the factors studied and the analyst has to fill out the pairwise comparison matrix using the WEIGHT module in Idrisi. The pairwise comparison¹⁶ was developed by (Saaty 1977) in the context of a decision making process known as the Analytical Hierarchy Process (AHP). This module uses a pair-by-pair technique to compare the relative importance of one factor (e.g. road) against another factor (e.g. slope). The rating ranges from “extremely less important” (1/9) to “extremely more important” (9). The rating is subjective and entirely depends on the analyst. The analyst compares every pair and assigns the rating into the matrix as shown below.

¹⁶ Pairwise comparison generally refers to any process of comparing entities in pairs to judge which of each pair is preferred, or has a greater amount of some quantitative property.

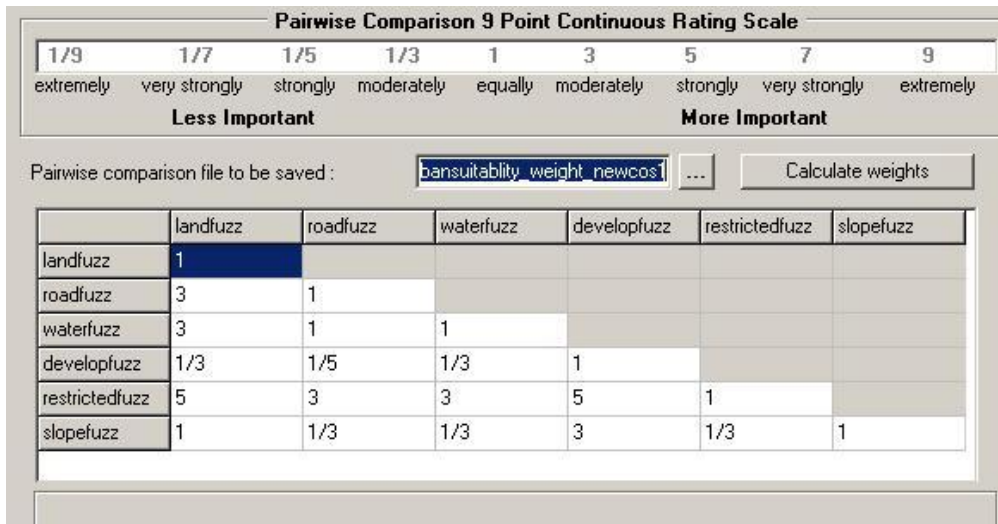


Figure 4.5 the rating assigned to each of the factors considered

The weights derived from the pairwise comparison matrix and assigned to each of the suitability variables discussed above are summarized in 4.5.

Map variables	Weight
Land use	0.0823
Distance from road axis	0.2015
Distance from water bodies	0.1870
Distance from developed areas	0.0453
Distance from restricted areas	0.3932
Slope	0.0907

Table 4.5 Weights assigned to the variables

➤ *Undertaking MCE using Weighted Linear Combination (WLC)*

Once the pairwise comparison was filled, a consistency ratio (CR) was calculated to identify inconsistencies and develop the best fit weights in the complete pairwise comparison matrix. As noted by (Saaty, 1977), CR is the procedure by which an index of consistency can be produced. It also indicates the probability that the matrix ratings were generated randomly and shows possible inconsistencies in the matrix. It is argued that, a consistency ratio greater than 0.1 should be re-evaluated. In this case, the CR was calculated to be 0.04.

Once the criteria maps and weights have been developed and established, respectively, the module MCE in the form of a weighted linear combination (WLC) was applied to combine the standardized factors and constrains. With a WLC, each standardized factor image is multiplied by its weight, then the results are summed and then multiplied by the product of the constraints (i.e. Boolean constrain maps are applied to limit areas under consideration in the final analysis). The resulting suitability map has a range from 0-255.

The result of the suitability map derived using the MCE is presented in the following figure.

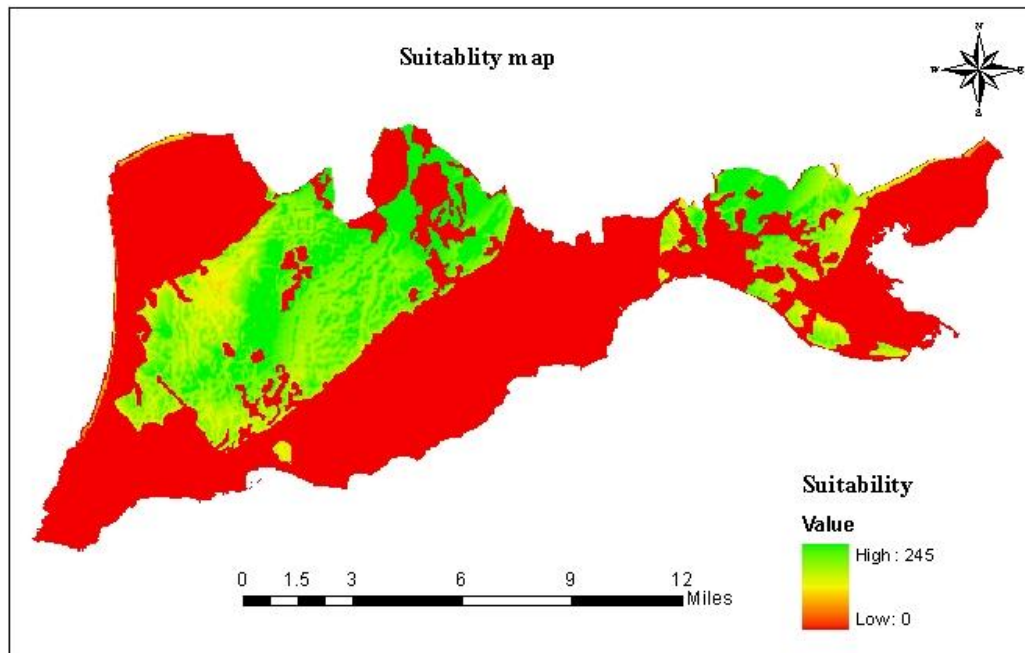


Figure 4.6 suitability map

4.6: Model implementation and validation

4.6.1 Model implementation

The Cellular automata Markov analysis is accomplished using the CA_Markov module in Idrisi Kilimanjaro. The module uses the following elements to determine the location of changes:

- Base land cover image (land use map for 2000)
- The transition areas matrix.
- Transition suitability collections: this is a raster group file created using the six (6) suitability maps using the collection editor module. The module is used to create the collection or define members of a raster group file collection.
- A contiguity filter: the Markov module is based on the 1st law of Geography by using a contiguity rule (Cabral and Zamyatin 2006). The rule states a pixel that is near one land use category (e.g. urban areas) is more likely to become an urban pixel than a pixel that is farther. The definition of nearby is determined by a spatial filter that the user specifies. In this study, the default contiguity filter in Idrisi "5*5" was applied. The 5*5 contiguity filter considers the predicted land use change to be within two pixels of the edge including the diagonal.

Based on these inputs, the module determines the location of change, the number of pixels that must undergo each transition and selects the pixels according to the largest suitability for a particular transition. The initial analysis used the 1990 and 2000 land cover maps to "predict" for the year 2006. Due to their unsuitable nature

for urban further development, three land cover classes: water bodies and marsh areas, developed areas and protected areas were considered as a constraint. These were created from the land use map of the year 2000, which was used as a base for simulation. The following figures present the “actual” and simulated land use maps for the year 2006 based on the MMU of 1ha and 25ha.

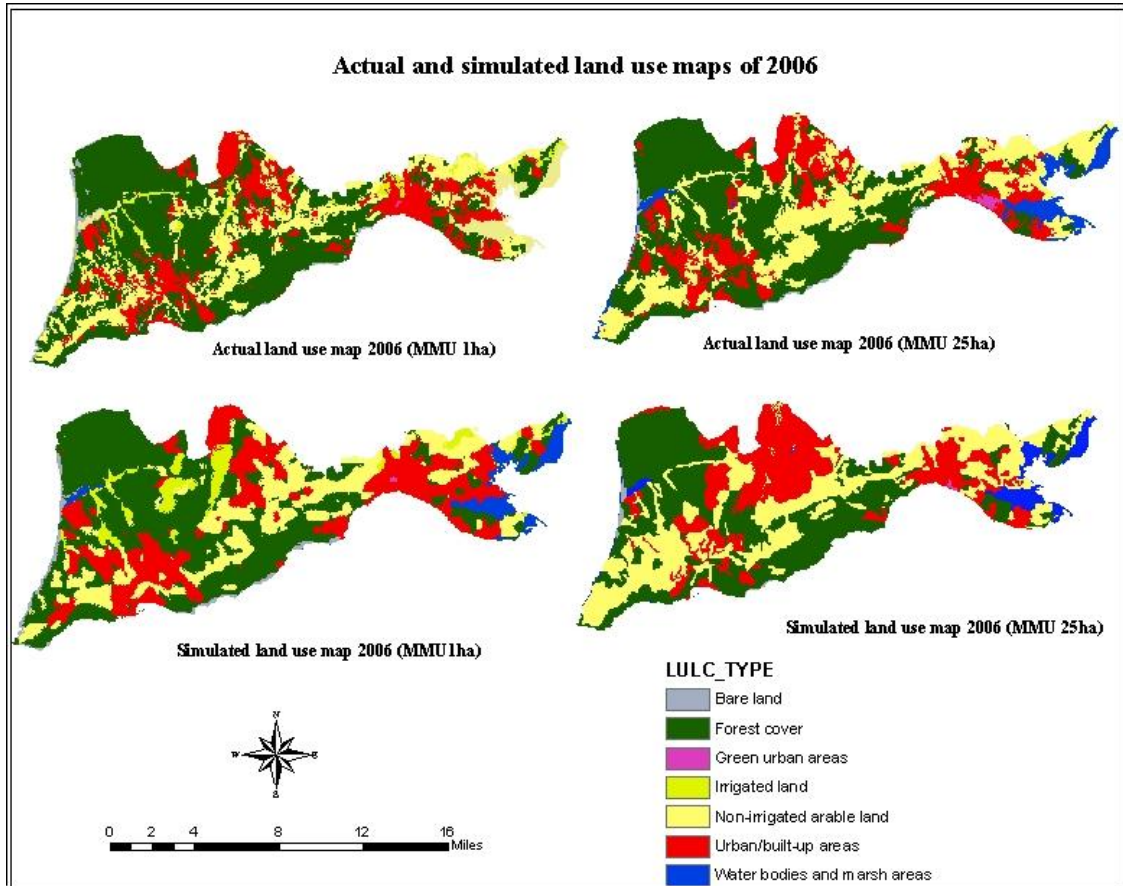


Figure 4.7 “Actual” and “predicted” land use map of 2006

4.6.2 Model validation

It should be noted that validating the projected land use is an important step in the modeling process because results of the simulation would give a misleading result. However, the issue of model validation is still one of the challenges in land use modeling (Verbeeten et al. 2007). This is because there is no agreed criterion to assess the performance of different land use models (Pontius and Chen 2006). It is not easy, therefore, to come out with an accurate and precise evaluation of land use models. The only way to quantify the predictive power of the model is to compare the result of the prediction for time t2 (2006) to a reference map of time t2 (2006). The reference map is usually considered more accurate of the study site at time t2 (Dushku and Brown 2003; Pontius and Chen 2006).

The land use maps for the year 2006 were simulated to compare the result of the “prediction” with the actual land use map in that year so that further land use

prediction can be carried out for the years 2010. Visual analysis of the results reveals that the simulated maps are close to the “actual” map for the year 2006. The predicted land use map also shows a number of development trends that can be found in the “actual” land use map of 2006. However, a more detailed analysis can be carried out based on the Kappa analysis. The Validate module in Idrisi is thus applied to calculate the Kappa index of agreement: Kno, Klocation and Kquantity in order to compare the 2006 “prediction” with the “actual” land use map more effectively. The result of the validation is given in Table 4.6.

Variations	Values for the map with a MMU 1ha	Values for the map with a MMU 25ha
Kno	0.8348	0.8474
Klocation	0.8694	0.8776
Kquantity/standard	0.8348	0.8476

Table 4.6 Results of the validation analysis

➤ *Kno*

The *Kno* indicates the proportion classified correctly relative to the expected proportion classified correctly by a simulation with no ability to specify accurately quantity or location (Pontius, 2000). It is therefore a variation of the standard Kappa index of agreement that gives the overall accuracy of a simulation. In this case, the *Kno* is calculated to be 0.8348 and 0.8474 for the MMU of 1ha and 25ha, respectively.

➤ *Klocation*

The *Klocation* indicates the success due to the simulation’s ability to specify location divided by the maximum possible success due to a simulation’s ability to specify location perfectly (Pontius, 2000). It validates the simulations ability to predict location and the *Klocation* was 0.8694 and 0.8776, respectively, for MMU of 1ha and 25ha.

➤ *Kquantity*

It is the success due to the simulation’s ability to specify quantity divided by the maximum possible success due to a simulation’s ability to specify quantity perfectly (Pontius, 2000). It is a measure of validation of the simulations to predict quantity and the *Kquantity* for MMU 1ha and 25ha was 0.8348 and 0.8476, respectively.

4.7: Urban land use predictions for the year 2010

As noted by (Pontius, 2000), values above 0.80 indicate a good agreement between the “actual” and predicted map. Based on this criterion for agreement, the predicted land use 2006 was successful. After calibrating the model and assessing its validity, it was interesting to examine the pattern and tendency of the change in long-time forecasting. Therefore, a real “prediction” for the year 2010 was carried out in the same way considering: land use maps for the years 1990 and 2000, the transition areas matrix, a contiguity filter and the transition suitability collection. In Figure 4.8, the expected land use changes for the year 2010 using the two scenarios, MMU of

1ha and 25ha, are presented. It is obvious that the short-term predictions are more reliable than the long term.

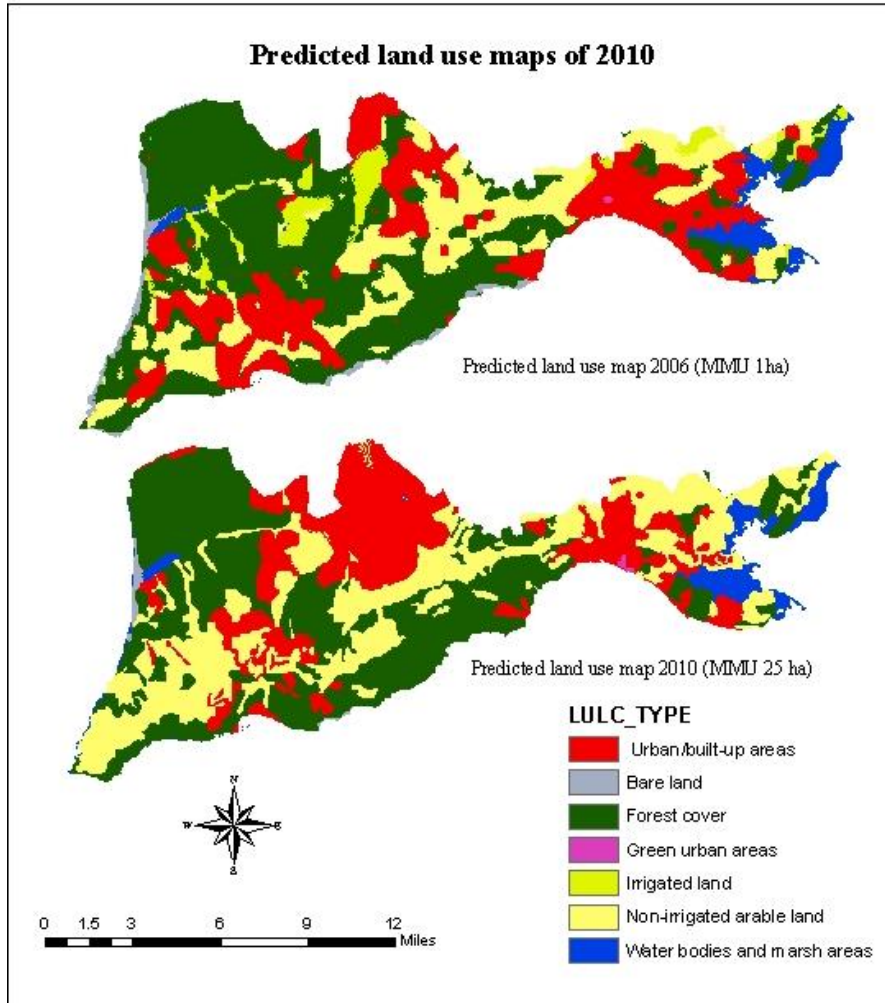


Figure 4.8 Predicted land use map of 2010

A much clearer urban land use change trend can be detected when comparing the predicted land use map 2010 with the land use map of 2000. Visual analysis of the simulated maps reveals that urban/built-up areas will occur at very high rate of growth. This is particularly true in the area surrounding the existing developed regions. In order to better understand the trend of the change in the future time period, the simulated land use maps were studied with reference to the class area metrics. Table 4.7 contains a summary of statistics of the class area obtained using Fragstats for the simulated land use maps.

	Class area index in ha	
	Built	Non built
2000	6665.06	30007
2010	8957	27716

Table 4.7 class area for land use maps of 2000 and 2010

The results of the simulation, both scenarios, indicate that there will be a significant urban land use changes in the future. The current trend of urban growth would have a

considerable impact on the surrounding ecosystems particularly on arable farming land and forest cover. Both visual analysis of the simulation and the result of class area metrics verify that the MMU has significant impact on simulation outputs. The prediction using MMU 25ha produced less reliable result compared to MMU 1ha. Based on these facts, therefore, it is sensible to argue that analyst should consider the impact of MMU for simulation and if at all possible avoid using maps with large MMU (e.g. 25ha). Otherwise it would give a misleading result. This would have also an impact on the land use management plan.

Furthermore, it should be noted that the result of the simulation might be affected by a number of factors: suitability maps, accuracy of the image classification and the level of generalization applied. Specifically, the suitability maps had a great influence on the land use predictions. This is because the suitability maps acted as the rules for the CA model.

4.7: Discussions

The purpose of this chapter was to simulate urban land use change in the future time period and assess the impact of the changes in the surrounding ecosystem. The model applied in this study, CA_Markov, allow us to predict and project the urban land use change. The focus of this study was only on urban land use but it should be noted that the CA_Markov model considers all the input land cover classes for simulation. The Markov chain analysis predicts the future land use pattern only on the basis of the known land use patterns of the past (Eastman, 2001). It is also supplemented by the CA approach and a number of change drivers to better understand the change. Considering these facts, the approach was implemented to “predict” land use map for the year 2006 with two scenarios: MMU 1ha and MMU 25ha. The result of the simulation has also been validated using the “actual” land use map for the year 2006. Visual interpretation of the simulation and result of the validation (kno, klocation, kquantity) produced a satisfactory level of accuracy. However, it is still easy to see discrepancies between the “real” and simulated land use maps. The reason for such discrepancies could be inadequate suitability maps to model the phenomenon, the MMU employed, the generalization applied during classification, the shape of the contiguity filter and to some extent the result of image classification. The suitability maps have been used as rules during the prediction process and it is apparent that they had a great influence on the result of the prediction. Regardless these, the land use maps for long-time forecasting was carried out and the result indicates that the urban areas will continue to expand further in the next few years. It is also evident that short term prediction is more reliable than long term though it is not easy to assess the accuracy of the simulation. It was also explored that MMU has significant role in predicting land use change. Land use maps with large value “MMU” would produce less reliable simulation output than small MMU.

CHAPTER 5

CONCLUSIONS AND PERSPECTIVES

5.1: Conclusions

The current trend of urban growth has the most obvious environmental impacts on the surrounding ecosystems, land resources, structure and pattern of the urban area and hence quality of life. The selected study area is part of the AML and is located south of the capital Lisbon. The area is situated in the productive alluvial plains and attractive coastal areas of the country and hence drew the attention of many people to make their settlement. Besides, the area is underwent large urban land use changes in the last few decades. It was also figured out that some kind of urbanization is undergoing in the protected areas of the region. Given these underlying facts, the principal objective of this study was to detect, assess and predict the trend of urban land use changes in the study site. The methodology employed in this study involved four phases: (1) defining the problem associated with the current trend of urban growth and stating the research objectives (2) classifying, analyzing and validating satellite images, (3) detecting and characterizing the spatio-temporal dynamics using landscape indices and measuring urban sprawl; (4) projecting urban land use in the next few years.

In order to accomplish this, an integrated approach of GIS, remote sensing and modeling tools have been applied. The overall research findings can be summarized in three sections. In the first section, the theoretical and practical aspects of image classification and validation were presented to provide valuable information to assess the dynamics. Although the purpose of the study was on built-up areas, LULC maps of the study areas were first obtained. The derived LULC maps had an overall accuracy above the minimum threshold. They also provided new information on spatial and temporal distributions of built-up areas. Therefore, it was reasonable to use the derived LULC maps for further change analysis and modeling.

In the second section, a critical analysis of the change detection techniques was addressed and results of changes were discussed. Though there are a number of detection techniques, it was concluded that post-classification comparisons is the most effective approach for effective detection. The nature of urban change structure was also studied and quantified using the landscape metrics. Such indices are an instrument to assess the impact of urban structure. Based on these findings, the study area has undergone considerable changes in the pattern and structure of urban features. The landscape analysis has also been supported by the urban sprawl measurement. The results of the sprawl measurement indicated that there has been high rate of sprawl and dispersed nature of urban development between 1990 and 2006. This in return would have a significant impact the urban fringe.

In the third section, the adopted modeling approach was calibrated to predict land use change in the future. In order to use the model for short-and long-term forecasting,

the predictive ability of the model was also assessed. Once the predictive ability of the model was evaluated, a long-term land use change forecasting was carried out. Regardless of the factors that might have had an impact on the simulation output, it was inferred that the current trend of urban growth will continue in the next few years. Being located in the attractive coastal areas of the country, large area of non-built features is expected to convert to built-up areas. Unless some preservation mechanism is overtaken, the trend of urban growth would have undeniable impact on the land resource and natural parks of the area. The study suggested Smart Growth as a means to preserve the protected areas of the region. The study also addressed that using large value of MMU e.g. 25ha would produce unreliable results and hence affect the subsequent planning process.

Finally, it was important to examine the research hypothesis of the study. The first hypothesis was “it is possible to use RS, GIS and Modeling techniques for urban growth analysis”. The complexity of urban environment is one of the most challenging areas for remote sensing change analysis and modeling (Muzein, 2006). However, the advent of contextual based or object-oriented remote sensing approach provides an opportunity to derive reliable surface information. The GIS tools were also powerful for analyzing and assessing land use change and measuring urban sprawl more effectively. Finally, the modeling approach in this study might have been affected by the suitability maps but still the validity and predictive ability of the model was satisfactory. Therefore, it was reasonable to support the first hypothesis. The second hypothesis argued that there was a significant urban land use changes and urban sprawl during the study period. This is was also evident from the analytical detection analysis, landscape indices and urban sprawl measurement. It was also sensible to support the second hypothesis of the study.

5.2 Perspectives and future works

The thesis addressed the potential of remote sensing, GIS and modelling tools for predicting land use change in the future. It pointed out that the current trend of urban land use and on-going urban sprawl would have remarkable impacts on the surrounding land resources. It would also contribute to improve our understanding of the dynamics of urban land use and urban sprawl in the Concelhos of Setúbal and Sesimbra. The study may assist environmentalist and planners to consider the impacts of urban development by identifying the current trend of urban land use and sprawl.

Urban land use change and sprawl are some of the major environmental concerns currently seen in the world and their social and environmental impact is becoming evident. In order to minimize the impacts of urban growth, a policy oriented urban development strategy “Smart growth” is suggested by the (EPA, 2000). The strategy advocates the implementation of higher residential densities. Smart growth is a development strategy that serves the economy, community and the environment (EPA, 2001). Considering the on-going urban land use changes and sprawl in the study site, it would be important to consider smart growth for the efficient and effective use of newly developed land (e.g. vertical development or expansion of

areas to preserve natural environment). For effective urban developments, Environmental Impact Assessment (EIA) and public participation in decision making are also recommended. These are essential to assess the likely impacts of urban development on the surrounding ecosystems. Finally, urban growth and urbanization involves different governmental and non-government agencies. Therefore, institutional coordination among those various ministerial offices at different administrative hierarchy is required for sustainable development and environmental management.

Although results of the prediction presented a satisfactory output for short term forecasting, it is important to mention that the modeling approach applied in this study may not be the best approach for long term forecasting. It should be noted that the model considers all the input classes, not only urban areas, for simulation and may not provide a reliable output when it is applied for long term forecasting. In addition, the model was calibrated with limited number of change drivers (suitability maps) and most of them were generated from the land use maps. This is because the analyst was not able to get data to derive change drivers (e.g. lack of reliable and complete road dataset). The future work will consider all these limitations and apply advanced modeling approach that would allow us for long-term forecasting.

REFERENCES:

- Agarwal, C., Green, G., Grove, J., Evans, T. and Schweik, C. (2002). A Review and Assessment of Land-use Change Models: Dynamics of Space, Time, and Human Choice, US Dept. of Agriculture, Forest Service, Northeastern Research Station.
- Alkheder, S. and J. Shan (2005). Cellular Automata Urban Growth Simulation and Evaluation-A Case Study of Indianapolis. Geomatics Engineering, School of Civil Engineering, Purdue University [online] <http://www.geocomputation.org/2005/Alkheder.pdf> [Accessed May 2008].
- AML (2005). Área Metropolitana de Lisboa [online]. www.aml.pt [Accessed Oct. 2008].
- Anderson, J., Hardy, E., Roach, J. and Witner, R. (1976). A Land Use and Land cover Classification System for Use with Remote Sensor Data, Geological Survey Professional paper 964, United States Government Printing Office.
- Araya, Y. and Cabral, P (2008). Urban land cover change detection analysis using GIS and remote sensing: a case study of Asmara, Eritrea (peer-reviewed paper)
- Araya, Y. and Hergarten, C (2008). A comparison of pixel and object-based land cover classification: a case study of the Asmara region, Eritrea
- Barnes, B., Morgan J., Roberge M. and Lowe, S. (2002). Sprawl development: its patterns, consequences, and measurement. Center for Geographic Information Services, Towson University Towson, Maryland. [online] http://chesapeake.towson.edu/landscape/urbansprawl/download/Sprawl_white_paper.pdf (Accessed Dec. 2008).
- Batty, M. (1976). Urban modelling, Cambridge University Press.
- Bauer, M., Yuan, F., and Sawaya, K. (2003). Multi-temporal Landsat image classification and change analysis of land cover in the Twin cities (Minnesota) metropolitan area.
- Belaid, M. (2003). Urban-Rural Land use Change Detection Analysis Using GIS and Remote Sensing Technologies. 2nd FIG Regional conference, Marrakech, Morocco.
- Benz, U., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing **58**: 239-258.
- Berkavoa, V. (2007). Application of Remote Sensing and GIS for Change Detection from Various Data Type of Remote Sensing.
- Blaschke, T. (2004). "Towards a framework for change detection based on image objects." Erasmí, S., Cyffka, B. and M. Kappas (eds.): Göttinger Geographische Abhandlungen **113**: 1-9.
- Briassoulis, H. (1999). Analysis of Land Use Change: Theoretical and Modeling Approaches, Morgantow, PA (EUA)].

- Brockerhoff, M. P. (2000). "BULLETIN." Population.
- Cabral, P. (2006). ÉTUDE DE LA CROISSANCE URBAINE PAR TÉLÉDÉTECTION, SIG ET MODÉLISATION Le cas des Concelhos de Sintra et Cascais (Portugal).
- Cabral, P., Geroyannis, H., Gilg, J., Painho, M. (2005). Analysis and modeling of land-use and land-cover change in Sintra-Cascais area. [online] http://plone.itc.nl/agile/Conference/estoril/papers/06_pedro%20Cabral.pdf [Accessed Oct 2007]
- Cabral, P. and Zamyatin, A (2006). Three land change models for urban dynamics analysis in Sintra-Cascais area.
- Caetano, M., Mata, F., Freire, S. and Campagnolo, M. (2005). "Accuracy assessment of the Portuguese CORINE Land cover map." Global Developments in Environmental Earth Observation from Space, Milpress.
- Carlos, S. (2002). Some points in the management of natural spaces in the Lisbon Metropolitan Area. [online] <http://www.fedenatur.org/docs/docs/58.pdf>. [Accessed Dec. 2008]
- Civco, D., Hurd, J., Wilson, E., Song, M and Zhang, Y (2002). A comparison of land use and land cover change detection methods.
- Clarke, K. C. and Gaydos, L. J. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington. Baltimore International Journal of Geographical Information Science **12**: 699-714.
- Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment **37**(1): 35-46.
- DGOTDU (1988). Direção Geral de Ordenamento do Território e Desenvolvimento Urbano Serviços e Restrições de Utilidade Pública.
- Dushku, A. and Brown, S. (2003). Spatial Modelling of Baselines for LULUCF Carbon Projects: The GEOMOD modelling approach International Conference on Tropical Forests and Climate Change. Manila.
- Eastman, R. (2001). IDRISI 32 Guide to GIS and Image Processing Vol. 1 y 2. Clark University, Worcester **332**.
- EEA (2000). CORINE Land cover technical guidelines. European Environmental Agency.
- Elnazir, R., Xue-zhi, F. and Zheng, C. (2004). Satellite remote sensing for urban growth assessment in Shaoxing City, Zhejiang Province. Journal of Zhejiang University SCIENCE **5**(9).
- EPA (2001). What is Smart Growth? United States Environmental Protection Agency [online] <http://epa.gov> [Accessed Dec. 2008]

- EPA, U. S. (2000). Projecting Land-Use Change: A Summary of Models for Assessing the Effects of Community Growth and Change on Land-Use Patterns. Cincinnati, OH, USA. US Environmental Protection Agency, Office of Research and Development **264**.
- Fan, F., Weng, Q. and Wang, Y. (2007). Land Use and Land cover Change in Guangzhou, China, from 1998 to 2003, Based on Landsat TM/ETM+ Imagery. Sensors **7**: 1323-1342.
- GmbH, D. I. (2001). eCognition Object Oriented Image Analysis–User Guide, Munich, Germany.
- Hand, C. (2005). Simple Cellular Automata on a Spreadsheet. Economics **17**.
- Herold, M., Goldstein, N and Clarke, C. (2003). The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sensing of Environment **86**(3): 286-302.
- Herold, M., Scepan, J. and Clarke, C. (2002). The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. ENVIRONMENT AND PLANNING A **34**(8): 1443-1458.
- Houet, T. and Hubert-Moy, L. (2006). Modelling and projecting land-use and land-cover changes with a cellular automaton in considering landscape trajectories: an improvement for simulation of plausible future states. EARSeL eProceedings **5**(1): 63-76.
- Im, J., Jensen, J. and Tullis J. (2008). "Object-based change detection using correlation image analysis and image segmentation." International Journal of Remote Sensing **29**(2): 399-423.
- Jensen, R., Gatrell, J., and Mclean, D. (2005). Geo-spatial technologies in urban environments, Springer.
- Knight, J. F. and Lunetta, R. S. (2003). An experimental assessment of minimum mapping unit size. Geoscience and Remote Sensing, IEEE Transactions on **41**(9): 2132-2134.
- Lavalle, C., Demicheli, L., and Turchini, M. (2001). Monitoring megacities: the MURBANDY/MOLAND approach. Development in Practice **11**(2-3): 350-357.
- Leta, M., Prasad, K., Bandarinath, K., Raghavaswamy, R. and Rao, S. (2001). Measuring urban sprawl: A case study of Hyderabad. Map India.
- Long, H., Tang, G., Li, X. and Heilig, G. (2007). Social-economic driving forces of land use in Kunshan, the Yantze river delta economic area of China. Journal of Environmental Management **83**: 351-364.
- Lu, D. and Weng, Q (2007). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing **28**(5): 823-870.

- Mansor, S., Hong, W., and Shariff, A. (2002). Object oriented classification for land cover mapping. Proceedings of Map Asia: 7-9.
- Mas, J. F. (1999). Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing **20**(1): 139-152.
- McGarigal, K., Cushman, S., Neel, M. and Ene, E. (2002). "FRAGSTATS: spatial pattern analysis program for categorical maps." University of Massachusetts, Amherst, MA.
- Moeller, M. S., Stefanov, W. L. and Netband, M. (2004). Characterizing Land cover Changes in a Rapidly Growing metropolitan Area Using Long Term Satellite Imagery.
- Mori, M., Hirose, Y. and Li, Y. (2004) Object-based classification of IKONOS data for Rural Land use Mapping.
- Muzein, B. S. (2006). Remote Sensing & GIS for Land cover/Land Use Change Detection and Analysis in the Semi-Natural Ecosystems and Agriculture Landscapes of the Central Ethiopian Rift Valley.
- NRSA (2003). India Remote Sensing (IRS)-P6, National Remote Sensing Agency [online] http://www.euromap.de/download/P6_data_user_handbook.pdf. [accessed Oct. 2008]
- Pinto, N. N. and Antunes, A. P. (2007). Cellular Automata and urban studies: a literature survey. ACE **1**(3).
- Pontius, G.R. (2000). Quantification error versus location error in comparison of categorical maps. Photogrammetric Engineering and Remote sensing **66**: 1011-1016
- Pontius, G. R. and Chen, H. (2006). GEOMOD Modelling: Land use and cover change modelling tutorial.
- Pontius, G. R. and Malanson, J. (2005). Comparison of the structure and accuracy of two land change models. International Journal of Geographical Information Science **19**(2): 243-265.
- Ramachandra, T. V. and Kumar, U. (2004). Geographic Resources Decision Support System for land use, land cover dynamics analysis.
- Rocha, J., Ferreira, C., Simoes, J., Tenedorio, A. (2007). Modelling Coastal and Land use evolution patterns through Neural Network and Cellular Automata integration. Journal of Coastal Research, 50.
- Ross, D. (2006). Game theory: Stanford encyclopaedia of philosophy [online] <http://plato.stanford.edu/entries/game-theory/> [Accessed Dec. 2008]
- Rowlands, A. P. and Lucas, R.M. (2004). Use of hyperspectral data for supporting the classification of agricultural and semi-natural vegetation using multi-temporal satellite sensor data. Proceeding of the Airborne imaging spectroscopy Workshop-Bruges.

- Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology **15**(3): 234-281.
- Santos, T., Tenedorio, J., Encarnacao, S and Rocha, J. (2006). Comparison pixel vs. object-based classifiers for land cover mapping with Envista-Meris Data.
- Shalaby, A. and Tateishi, R. (2007). Remote sensing and GIS for mapping land cover and land use changes in the Northwestern coastal zone of Egypt. Applied Geography **27**: 28-41.
- Singh, A. (1989). "Review Article Digital change detection techniques using remotely-sensed data." International Journal of Remote Sensing **10**(6): 989-1003.
- Sudhira, H. S., Ramachandra, T.V. and Jagadish, K.S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. International Journal of Applied Earth Observations and Geoinformation **5**(1): 29-39.
- Sun, H., Forsythe, W. and Waters, N. (2007). Modeling Urban Land Use Change and Urban Sprawl: Calgary, Alberta, Canada. Networks and Spatial Economics **7**(4): 353-376.
- Sutton, P. C. (2003). A scale-adjusted measure of "urban sprawl" using nighttime satellite imagery. Remote Sensing of Environment **86**(3): 353-369.
- Tardie, P. S. and Congalton, R. G. (2004). A change-detection analysis: using remotely sensed data to assess the progression of development in Essex country, Massachusetts from 1990 to 2001.
- Verbeeten, E., Poulter, B., Braimoh, A, Herrmann, S., Cabral, P. and Balogun, A (2007). Modeling Global Land-Use Decision Making. Eos Trans. AGU **88**(49): 546.
- Verburg, P. H., Schot, P. P. Dijst, M. J. and Veldkamp, A. (2004). "Land use change modelling: current practice and research priorities." GeoJournal **61**(4): 309-324.
- Xie, Y. (2002). "Projecting Urban land use change: DUEM-dynamic urban evolution modeling, USGS-GLSC." from <http://www.casa.ucl.ac.uk/duem/DuemHelp.pdf>.
- Xie, Y. (2003). Integrated Dynamic Urban Evolution Modeling.
- Yeh, A. G. and Li, X. (1997). "An integrated remote sensing and GIS approach in the monitoring and evaluation of rapid urban growth for sustainable development in the Pearl River Delta, China." International Planning Studies **2**(2): 193-210.
- Yeh, A. and Li, X (2001). "Measurement and monitoring of urban sprawl in a rapidly growing region using entropy." Photogrammetric engineering and remote sensing **67**(1): 83-90.
- Yuan, F., Sawaya, K., Loeffelholz, B. and Bauer, M. (2005). Land cover classification and change analysis of the Twin cities (Minnesota) Metropolitan Area bz multitemporal Landsat remote sensing of Environment. Remote sensing of Environment **98**: 317-328.