ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Elaheh ZADBAGHER

MODELLING LAND USE/COVER CHANGE IN SEYHAN BASIN, TURKEY USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEM

DEPARTMENT OF REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEM

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on 30/11/2017.

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ABSTRACT

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Land use/cover (LULC) changes affect many environmental factors such as soil, water, biodiversity, climate, which are related to human lives. Therefore, LULC change has become an important agenda to manage land use and environment. One of the effective way to analyses LULC change is using of modeling approaches. In this study, CA-Markov model that combines the Cellular Automata and Markov chain models, was used to predict LULC changes in the Seyhan Basin for 20-year period, up to 2036. Remote sensing multispectral imagery acquired in 1995, 2006 and 2016 were classified using the object-oriented classification approach and fed into the CA-Markov model. Subsequently, post-classification comparison technique was used to detect historic change. Markov Chain analyses and Multi-Criteria Evaluation (MCE) were used to produce transition probability matrixes and suitability maps, respectively. The model was validated using Kappa index of agreement which resulted in an overall accuracy of 77 %. Finally, the future LULC changes of 2036 based on transition rules and transition area matrix was predicted and mapped. LULC prediction for 2036 showed 50% increase of built-up area, 7% decrease of open spaces in comparison to 2016. 8% increase of agricultural land was predicted in 2036. No significant changes were modelled for wetland and water body category. 4% increase of shrub land and 5% decrease of forest were predicted.

Keywords: Land use/cover change, CA-Markov model, Seyhan Basin

ÖZ

YÜKSEK LİSANS TEZİ

SEYHAN HAVZASI ARAZİ KULLANIM/ÖRTÜSÜ DEĞİŞİMLERİNİN UZAKTAN ALGILAMA VE COĞRAFİ BİLGİ SİSTEMLERİ KULLANARAK MODELLENMESİ

Elaheh ZADBAGHER

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Arazi kullanım/örtüsü değişimleri, toprak, su, biyo-çeşitlilik, iklim gibi insan hayatını etkileyen birçok çevresel faktörleri etkiler. Bu nedenle, arazi kullanım/örtüsü değişimleri hakkında bilgi sahibi olmak, çevre yönetimi ve arazi kullanım planlaması için giderek önem arz etmektedir. Bu bilgileri elde etmenin etkin yollarından biri de modelleme yaklaşımlarını kullanmaktır. Bu çalışmada, geleceğe yönelik Seyhan havzasının arazi kullanım/örtüsü değişimlerini tahmin ve simule etmek için Markov zinciri ve Hücresel özişleme modellerinin birleşiminden oluşan CA-Markov modeli kullanılmıştır. 1995-2006 ve 2016 yıllarına ait uydu görüntülerinden elde edilen arazi kullanım/örtüsü haritaları CA-Markov modeli ile entegre edilmiştir. Daha sonra, arazi kullanım/örtüsü haritaları üretmek için obje tabanlı sınıflandırma tekniği ve değişim analizleri için sınıflandırma sonrası karşılaştırma tekniği kullanılmıştır. Geleceğe yönelik uygunluk haritaları ve geçiş olasılık matrisleri sırasıyla Çok Kriterli Analiz ve Markov Zinciri kullanılarak elde edilmiştir. Doğrulama sürecinde, model için %77 kappa değeri elde edilmiştir. Son olarak, geçiş kurallarına ve üretilen geçiş matrislerine dayalı olarak, 2036 yılının gelecekteki arazi kullanım/örtüsü değişimleri haritalandırılmıştır. 2036 yılı için arazi kullanım/örtüsü tahmini, 2016 yılına ait arazi kullanım/örtüsü haritası ile kıyaslandığında, yerleşim alanlarında %50, tarım alanlarında %8, çalılık alanlarında %4 artış görülürken az ya da hiç bitki örtüsü içermeyen açık alanlarda %7, ormanlık alanlarda %5 düşüş görülmektedir fakat su ve sulak alanlar için belirgin bir değişim görülmemektedir.

Anahtar Kelimeler: Arazi kullanım/örtüsü değişimleri, CA-Markov modeli, Seyhan havzası

EXTENDED ABSTRACT

Human usually used land to meet various and numerous needs. Land use/cover change is resulted from the human activity and using of land resources for various purpose. Therefore, land use/cover change has become an important topic to manage land use and environment. In order to find out the relationship between land and human, the analysis of land use change is necessary. LULC change can be caused by multiple driving forces that control some environmental, social and economic variables. In order to comprehensively understand LULC changes, it is need to identify and monitor the texture and location of LULC changes, to understand the interactions of the leading factors that cause changes, to use technologies to predict future changes, to identify the results of the changes on ecosystems.

One of the effective way to analyses LULC change is using of modeling approaches. The models bring together different techniques and approaches for understanding the dynamics of LULC systems. By using models the future LULC changes at various scenario conditions is predicted. Models are used to find out what purpose, where, and how often the land is used, under different boundary conditions, supporting land use and policy decisions, as well as the analysis of drivers and processes. The models are applied to identify problems and concepts in a complete and clear way, to analyze the connections between data and to generate predictions. LULC change models are effective approaches to evaluate LULC changes and imposing factors, evaluating the ecological impacts of change and decision-making for land use planning. Remote sensing data sources supply the data to geographic information systems allowing for advanced analysis and monitoring of LULC change. Capturing and analyzing information by the RS and GIS tools provides timely, accurate and detailed data to monitor and detect the changes in LULC.

In this research, Seyhan basin was chosen as a case study, where is one of the most important regions in Turkey in aspect of agricultural activities such as dry farming, irrigated farming and animal husbandry. In view of the biologic diversity, the basin is one of the richest regions in the world. Thus, the objective of this study was to simulate and predict future LULC changes in Seyhan basin based on the historic change trends of LULC change by using CA-Markov model that combines the Cellular Automata and Markov chain models.

Remotely sensed data acquired in 1995, 2006 and 2016 were classified with the object-oriented classification approach. This method is performed four step of perform multi-resolution segmentation, select training areas, define statistics and classify. The object-based approach has advantages over the pixel-based approach in terms of classification features and classification units. Within-class spectral variation is decreased by changing classification units from pixels to objects. Also, salt-and-pepper effects that are typical in pixel-based classification is removed by the object-based method. LULC classes were determined according to level 2 CLC classification including 7 classes (water bodies, forests, shrub and/or herbaceous vegetation association, open spaces with little or no vegetation, built-up areas, wetlands and agricultural areas). The statistical index Kappa and confusion matrices was used to determine the classification accuracy. The Kappa indices for the years of 1995, 2006 and 2016 were 87%, 88% and 90% respectively.

Then post-classification comparison technique was used to detect historic change. This method is based on classifying images belonging to different dates and by this way creating the change map and it is also important in terms of obtaining and giving "from-to" information about the changes. The change between 1995-2006 and 2006-2016 was analyzed. The overview of changes in land use showed an increase of built-up areas for both periods because of the growth population and migration. Also, it showed an increase of agricultural areas that the majority of this class conversion was from shrub land and open space area.

In this research a CA-Markov model was applied to simulate the future LULC changes of Seyhan Basin. This approach convert the quantity results of the Markov Chain by a CA function to spatially explicit outcomes. Markov Chain analyses and Multi-Criteria Evaluation (MCE) were used to produce transition probability matrixes and suitability future maps, respectively. Transition probability matrix represents the probability of each land use change to another within a new period compared to the previous one which it is obtained using cross tabulation of two images of different time. MCE involves two types of criteria including constraints, Boolean criteria, limiting analysis of some regions and factors defining suitability of all regions. It is the application of decision-making rules to determine different criteria in order to combine the criteria in the form of GIS layer, into a single map. Natural factors including slope, soil, elevation and distance to the water along with the socioeconomic variables including population, distance to urban and distance to the road network were determined as a model variables. To predict the spatial pattern of change the variables were standardized between 0 – 255 using fuzzy approach based on their influence on the subjected LULC change and then weighted using AHP technique. Based on pairwise comparisons that are obtained according to different parameters significance, AHP determines the weight of importance for different land use. In validation process, the model was validated using Kappa index of agreement which resulted in overall accuracy 77 %.

Finally, after acquiring acceptable k-standard, the land use/cover changes of 2036 based on transition rules and transition area matrix was predicted and mapped. The result showed the most increase in the built-up class that majority of the expansion was in the population centers It also showed the disappearing of open spaces with little or no vegetation and forest that might be converted into built-up area and agricultural area. Consequently, the findings of this research provide useful information for land use managing and planning in future of the Seyhan basin.

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LIST OF ABBREVIATIONS

AHP	: Analytic hierarchy process
CA	: Cellular Automata
CLUE	: Conversion of Land Use and its Effects
CLUE-s	: Conversion of Land Use and its Effects at Small regional extent
CORINE	: Coordination of Information on the Environment
CLC	: CORINE Land Cover
DEM	: Digital Elevation Model
DN	: Digital Number
EEA	: European Environment Agency
GIS	: Geographic Information Systems
GRASS	: Geographic Resources Analysis Support System
IPCC	: Intergovernmental Panel on Climate Change
KIA	: Kappa Index of Agreement
LCM	: Land Change Modeler
LULC	: Land Use and Land Cover
LUCAS	: Land Use Change Analysis System
MBP	: Man and the Biosphere Program
MC	: Markov Chain
MOLAND	: Monitoring Land use and land cover Dynamics
MCE	: Multi-Criteria Evaluation
MSS	: Multispectral Scanner
NN	: Nearest Neighbor
OLI	: Operational Land Imager
ROC	: Relative Operating Characteristic
SRTM	: Shuttle Radar Topography Mission

SLEUTH	: Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade
TM	: Thematic Mapper
TOA	: Top of Atmosphere
TUIK	: Turkish Statistical Institute
USGS	: United States Geological Survey
UPLAN	: UPLAN Urban Growth Model

1. INTRODUCTION

Human usually used land to meet various and numerous needs. Land use change is resulted from the human activity and using of land resources for various purpose. The impact of the change can be undesirable or desirable. In order to find out the relationship between land and human, the analysis of land use change is necessary (Ames, 2014). For the last years, rapid urbanization caused to conversion of natural lands such as wetlands and forests to urban and agricultural lands. Such rapid land use/cover (LULC) change imposes significant effect on natural environments and human. Specifically, it affects air and land resources, radiation budgets, livelihoods, water quality, carbon cycling and biodiversity at all scales (Riebsame et al., 1994; Xu, et al., 2013).

LULC changes are the results of many interacting processes. Therefore, studies on understanding of LULC change within the cause and effect relation as well as the prediction of future land uses to support decision making process have been of great importance for the last decades (Verburg et al., 2006). Satellite remote sensing is used to obtain multi-temporal and multi-spectral data that can be utilize to quantify the type, amount, and location of LULC change. GIS is used to store, display and analyze digital data that is need to detect changes.

Briefly, remotely sensed data sources supply the data to GIS allowing for advanced analysis and monitoring of LULC change. (Yu et al., 2011). Capturing and analyzing this information by the remote sensing and GIS tools provides timely, accurate and detailed data to monitor and detect the changes in LULC (Reis, 2008; Araya, 2009; Chen et al., 2013). However, unresolved issue remains prediction of future LULC change. Some theories and models have been developed to predict the changes (Ames, 2014). Models are used to find out what purpose, where, and how often the land is used, under different boundary conditions, supporting land use and policy decisions, as well as the analysis of drivers and processes (Heistermann et al., 2006).

Models also allow to understand the complexity of the world, reduce uncertainty, update the environmental knowledge and orient the vision towards the occurrence possibility of simulated scenarios. Seyhan Basin as a study area of this research, is one of the largest and fertile basin in Turkey and provides both agricultural and economical resources to people. Additionally, this basin has a high richness of biodiversity species. Therefore, there is a need to understand the LULC system within the basin to assess its impacts on the overall basin dynamics. This study will provide a comprehensive insight about the LULC change of basin using remote sensing, GIS and modeling techniques.

1.1. Land use/cover

Land cover is defined as the bio-physical characteristic that can be observed on the earth. The characteristics can be involved both the features originated from human activity and the natural features on the surface of Earth. It includes soil, water ice, vegetation, and physical features such as settlements and mines. The settlements and mines are features that made by human (Turner et al., 1994; Lambin et al., 2003). 'Land use' term describes the human's uses of biophysical or ecological properties of land cover. Land uses is an effect of modification of the natural land cover for agriculture, settlements, and other purposes. One distinct class of land use in current years is the designation of nature reserves for conservation. In other words, Land use represent the human activity and human's use of the land **(**Lambin et al., 2001; Fonji and Taff, 2014).

Therefore, land cover shows the biological groups, chemical and physical characteristics on the land, for example; concert, forest and grassland while land use represents the human decisions about the land surface, for example; urbanization, ranching and recreation (Meyer et al., 1994). Although land cover can be directly shown and detected by data obtained from remote-sensing, land use usually is concluded from a combination of information gathered from local knowledge, remote sensing data in situ observations and other information (Sohl and Sleeter, 2012).

1.2. LULC change

Land use change is a complex and dynamic model (Verburg et al., 2002). The models show the conversion of natural land to urban along whit the competition of the two factors. To meet various needs, human usually use land. In addition, it can be for different purposes. Desirable and undesirable effects can be imposed on land when human decide to use resources of land (Ames, 2014). As it was reported by Riebsame, et al., (1994), land cover is influenced by land use which is influenced by land cover changes. It is possible that land cover change don't cause to degradation of the land. Changes in land use pattern can be originated from various social factors. The changes show significant impact on trace gas emissions, biodiversity and other factors affecting biosphere and climate (Turner II and Meyer, 1994).

Conversion and modification are two type of LULC changes. The conversion represent the replace one type of LULC to another one (for example forest can be converted to grassland) while modification represent the change of function or structure without a total replacement of one type by another one. The last one can be involved alteration in phenology, biomass, productivity and so on (Skole, 1994; Lambin et al., 2003). LULC conversion takes place through some stages including deforestation, desertification, agricultural intensification, transformation of natural land to transport or industrial uses and urbanization.

These processes can be grouped in view of modification or conversion, rate and amount of change. Recently, rapid urbanization caused to changes in land use, also, the changes have negatively affected ecosystems (Xu et al., 2013). Due to the rapid urbanization a lot of natural land (for example wetland and forest) have been replaced by agricultural lands and many agricultural lands changed to urban. The rapid changes affected the natural environments and human life (Riebsame et al., 1994). Today, 50% of the world's surface has been changed because of direct human uses, such as agriculture, grazing, forestry, industrialization, urban development and transportation networks. Due to intensifying human activities, the world has entered a process in which hydrological, climatological and biological changes are quite different from the past in terms of size, magnitude and violence (Erdogan, 2011). surveys about LULC, which is considered to be one of the most important formations in the world, and is being conducted by the International Geosphere and Biosphere Program (IGBP) and International Human Dimension Programme on Global Environmental Change (IHDP), LULC change has been determined as priority work.

1.3. Driving forces of LULC changes

LULC changes are the result of many interacting processes. Each of these processes operates over a range of scales in space and time. These processes are driven by one or more of variables that influence the actions of the agents of LULC change (Verburg et al., 2002). LULC change can be caused by multiple driving forces that control some environmental, social and economic variables.

Two main categories affect the LULC change: direct driving forces and indirect (underlying) driving forces. Direct driving forces include the immediate actions or activities that cause changes (Geist and Lambin, 2001) such as infrastructure expansion, wood extraction, agricultural expansion and other causes that change the physical state of land cover (Meyer and Turner, 1996). These driving forces usually operate at the local scale (i.e. individual farms, householders, or communities). In other words these drivers are related to the occurrence of natural environment and so called bio-physical drivers such as weather and climate variations, topography, soil types and drainage patterns. In contrast, indirect driving forces are fundamental socioeconomic and political processes. Underlying drivers generally operate at a larger scale, such as national and the regional level. These underlying driving forces include demographic, economic, technological and institutional factors such as population density, family structure, local customs, market, and the related policies and rules (Turner et al., 1994; Geist and Lambin, 2001). Both direct and underlying factors interact with each other continuously (Mehdi et al., 2012).

Changes in air quality, water quality, habitat, and the life quality are some of economic, social and environmental concerns related to LULC change. Change in land use can have various consequences on natural resources like effects on hydrological externalities, change in plant and animal populations and change in physical soil characteristics. LULC change influences climate in the area, loss of biodiversity and the sustainability of human environment interactions (Lambin et al., 1999). Sustainable land resource management can be managed using accurate knowledge of LULC features and relative risk of environmental hazards (Turner and Meyer, 1994).

In order to be able to make appropriate policy and plan for LULC changes, it is necessary to understand the causes of these changes. Driving factors that cause LULC changes determine the quality and quantity (shape and amount) of changes (Verburg et al., 2002). In order to comprehensively understand LULC changes, it is need to identify and monitor the texture and location of LULC changes, to understand the interactions of the leading factors that cause changes, to use technologies to predict future changes, to identify the results of the changes on ecosystems (Defries et al., 2004). Understanding the complexity of LULC changes and their drivers at a local or landscape level is essential to better understand the relationship between human and the environment.

1.4. LULC Modelling

A model is simplified representation of a system or process in the real world (Turner et al., 2001). Generally, models can be in different forms, including both abstract forms and physical forms. An example for physical form is miniature replicas of real systems. The abstract one include verbal models made from words, graphical models displayed as pictorial representation and mathematical models defined by symbolic notation. Mathematical models is the approach adopted in this thesis.

The models bring together different techniques and approaches for understanding the dynamics of LULC systems. By using models the future LULC changes at various scenario conditions is predicted. The models are applied to identify problems and concepts in a complete and clear way, to analyze the connections between data and to generate predictions. LULC change models are effective approaches to evaluate LULC changes and imposing factors, evaluating the ecological impacts of change and decision-making for land use planning. In other words, it provides information about how the system and process will behave under a number of conditions that may arise as a result of changes (Verburg et al., 2004; Zhongming et al., 2010).

LULC changes happen in time and space because of interaction of natural factors and socio-economic factors associated with humans. According to this, LULC changes are in three dimensions as time and space that provide the biophysical and human processes and human decision-making. Scale and complexity of model are considered as important attributes for these dimensions. In modeling studies, the scale is addressed with resolution and extent concepts. The resolution is defined as the smallest unit considered in the measurements and analyzes in the models and the sensitivity of the models is determined according to the resolution (Agarwal et al., 2001). The simulation of LULC spatial pattern reveal the driving factors, various scenarios and rate of LULC change in order to predict future land use demand (Han et al., 2015).

Generally, models describe a relationship between landscape changes and features based on an analysis of observed past changes in order to make prospective simulations (Martínez et al., 2015). LULC change models are mainly used to answer at least one of the questions of "why", "where", "how much" and "when" the land uses will change. So, modeling land use changes helps to resolve the following issues: (Veldcamp and Verburg, 2004)

- Identification of the socio-economic and bio-physical drivers that cause land use changes.
- Identification of the locations influenced by land use changes.
- Determination of the temporal progress rate at which LULC change, and
- Predicting future LULC structure in a given area of interests

The general steps of the modeling can be as following: (Turner et al., 2001)

1. Define the problem; the first step of the modeling process begins with the identification of the problem. At this stage, the reasons for creating the model and the objectives of the model are detected.
2. Develop the conceptual model; at this phase, the conceptual framework for the system to be modeled is being developed in the direction of the model's purpose. Also, the boundaries of the system to be modeled, the properties of the model components and the interactions between these properties and the behavior expected from the model are determined.
3. Select the model type; at this stage, the type of model to be used (non-spatial-spatial, Stochastic-deterministic, etc.) is determined according to the of the interactions nature and nature of the processes in the system and the expected results from the model
4. Model development; at this step, the equations and/or logical operations is written to be performed by the model. Various statistical techniques and mathematical formulations can be used.
5. Computer implementation; taking into account available computer resources and usefulness of different programming language this stage

involves writing code, translating words or diagrams into equations in computer.

6. Parameter estimation; at this step, values of model parameters, model inputs and initial values of the state variables in the model are selected. All values must be consistent with the aim and equations of the model representing the area of interest.
7. Model evaluation; at this stage, the performance of the model is evaluated including both comparisons of model results with data and understanding the sensibility of the model.
8. Experimentation and prediction; after the model validation, the model can be used for different applications and determined for the future estimates.
9. Flowchart of the steps in building a model is given in Figure1.1.

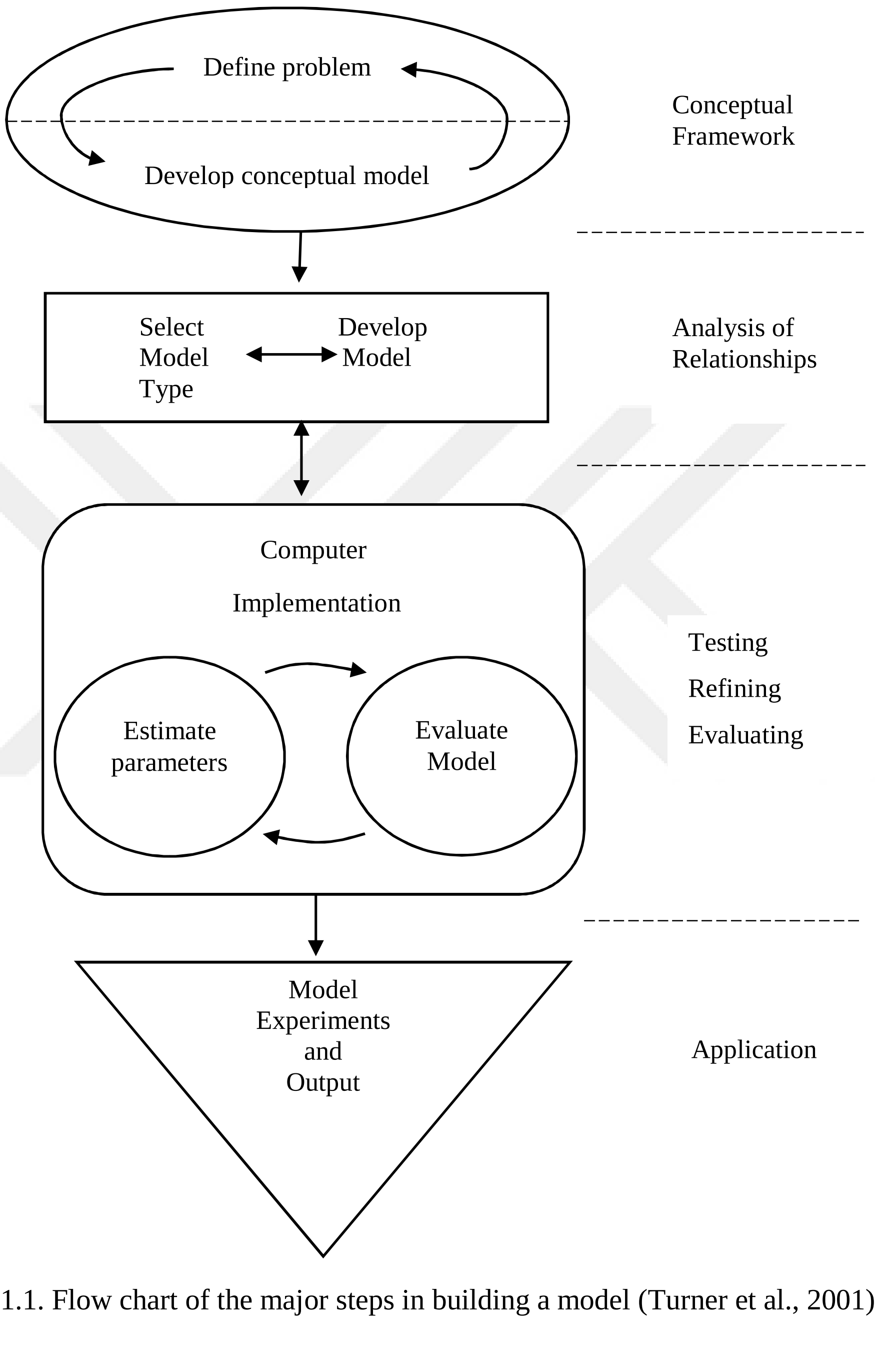


Figure1.1. Flow chart of the major steps in building a model (Turner et al., 2001)

1.5. Types of LULC change models

In landscape planning studies, processes that take place at different temporal and spatial scales should be analyzed together with the spatial structure of the landscape.

Use of appropriate tools and methods is necessary to analyze the complex structure of the landscape. For this reason, the models have begun to be widely used in recent years. Hundreds of LULC change models have been explained in the literature in the various field such as geography, landscape ecology, urban planning, computer science, economics, statistics, GIS, etc. Categorizing of models are very complicated because the goal of models, accessibility of data and methodological approaches are very different.

The change models are divided into three main categories including individual-based models, process-based models and stochastic models (Brown et al., 2012). Individual-based models that bring together measurements of a single entity or individual to model changes. The individuals can be plants, people, vehicles, animals and etc. that have a set of behaviors and attributes. Process-based models that predict LULC changes by modeling of processes and their interactions with the system environment and each other over time. In this approach, the base of each process is defined by a set of equations. Stochastic models have some inherent randomness and the same input conditions cause different results in every simulation. In these models, changes are modeled depending on the characteristics of spatial configuration and transition probability of the patches for different situations. Another categorization of LULC change models including 19 type of model is offered by Agarwal et al. (2002). The models were designed based on dimensions of time, space, and human decision-making. The models were also identified according to the degree of complexity and scale that they acted on three dimensions.

Another categorization of the approaches for modeling LULC change is proposed by The National Research Council. The categorization was based on methods used, application type and theoretic concepts. This category includes six classes, ranging from pattern-based models to the agent-based models of change. This category includes six classes, ranging from pattern-based models that consider patterns o of LULC change to the agent-based models that focus on process and mechanisms of change.

To make the future simulation, pattern-based models explain the relation between LULC changes and features depending on analysis of historical changes. Usually, LULC maps acquired from satellite imagery, population censuses and landscape variables are used for these models. Process-based approaches are based on modeling the mechanisms of change and frequently used in social sciences (Martínez, et al., 2015). The modeling approaches are as following:

1. Machine-learning and statistical approaches the evidence and information of the historic LULC changes is applied by machines and Statistical tools to calibrate nonparametric and/or parametric relations between the changes.
2. Cellular approach, this approach combines suitability maps of LULC along with information about the quantity of change anticipated and neighborhood effects to predict future changes.
3. Sector-based economic approach utilizes local and global stability constructive models to describe land demand by sectors of economy in the areas due to trade and economic activity.
4. Spatially disaggregate economic approach, to detect the causal relationships impressing the spatial stability of land systems, this approach predicts decreased and structural form econometric models.

5. Agent-based approach, to get LULC changes in the land system, the nonhomogeneous decisions and actions of the actors which interact with each other and the land surface are simulated.
6. Hybrid approaches, different approaches of application are integrated into the modeling frame or a single model.

1.6. LULC change models

Numerous models have been developed based on the scale, field, and purpose of the research and the scientific experience of the researchers for modeling LULC changes. Nevertheless, there is a need for reliable and acceptable modeling approaches that are generally tested and verified in order to provide explanations, modeling, and future predictions of the worldwide LULC changes that have different characteristics. In this section, the general characteristics of some models including SLEUTH, What If?, LUCAS, MOLAND, CLUE and CLUE-s, Markov Chain, CA-Markov have been summarized as below.

SLEUTH

The SLEUTH model is a cellular automata model that is used in the simulation of urban development and land cover change. The name of SLEUTH indicates the first letter of the data required to run the model: Slope, Land Use, Exclusion, Urban extent, Transportation and Hillshade. The SLEUTH model predicts urban growth based on various growth rules, the order of urban pixels, and their interaction with their environment (Lizhong Hua et al., 2014). The model predicts over time the probability of urbanization of the pixel (iterative). The SLEUTH model, a probability model, produces many growth simulations using the Monte Carlo program. Application of the model include three steps that consist preparation of inputs, calibration and prediction. Calibration of model is performed based on trend of historical urban growth and this past growth is applied to the future prediction. The model needs at least four urban maps, two LULC maps and two transportation maps in different time periods, a slope map and an excluded region map. The input data must be in a raster format because of the spatial framework raster-based model. (Zhao and Chung, 2006; Anil Tanriover, 2011). By using this model, many different estimates can be developed to test the effects of different growth plan forecasts and the effects of land use /cover change scenarios. The SLEUTH model decides whether or not a pixel can be transformed into an urban area. Urban dynamics is simulated as four types of growth using SLEUTH:

1) Spontaneous growth
2) New spreading center growth or diffusive
3) Organic growth
4) Road-influenced growth

These four growth rules are applied sequentially in each growth period and are controlled by five growth parameters. These parameters are diffusion, slope resistance, breed (growth at new settlements), road gravity (promoting new settlements near transportation networks) and spread (Anil Tanriover, 2011; Lizhong et al., 2014). The value of each of these parameters is between 0-100. These parameters are evaluated together with the excluded regions to determine the probability that a given location is a city. Areas excluded from growth are determined by the user for areas where development cannot be entirely or in part. This model simulates changes from non-urban to urban land use based on local factors (such as existing urban, topography and roads), random factors and temporal factors (Erdogan, 2011; Jones, 2005).

What IF

What if? Model is a model that is used to assess urban change scenarios, particularly in fast-growing urban, and is associated with geographic information systems. The objective of the model is to test the correctness of assumptions about what to do and what to do if the specified policy preferences are to be applied, rather than predicting future conditions. For this reason, What if? model is defined as a policy-oriented planning tool. Assumptions of the model can be considered for the future are population and employment trends, expected density development and default households properties (Klosterman, 1999).

The model consists of three modules, the growth module, the suitability module, and the allocation module. The suitability module determines the suitability of the units for different area LULC patterns by applying standard weight and ratio based on the user defined LULC criteria. The growth module generates projected demands including settlement, industry, commercial, conservation and locally focused uses for each LULC type for four future time periods according to the projected growth. In the case of the allocation module, the estimated area is based on the LULC request allocation, the unit's suitability for LULC types, demands, infrastructure, area utilization plans. The model needs detailed local growth information (number of households, regional employment, etc.) as well as policy makers that will influence the future. The model needs a lot of local information about socioeconomic factors. However, gather the data would require a fairly wide effort. In addition, the assignment of weights would likely require guidance from the developer to obtain convincing results (Jones, 2005).

LUCAS

LUCAS (Land Use Change Analysis System) was developed as a multi-disciplined land use management tool supported by Man and the Biosphere Program (MBP) in 1994. LUCAS, a spatial simulation model, is used to demonstrate the effects of alternative land use management policies. In the model, regional LULC change patterns are considered as a function of social preferences and regulatory approaches. In addition, LUCAS can be used to compare the effects of alternative ecosystem management strategies and to investigate the impact of LULC changes on natural resource availability and local income. LUCAS that programmed in C++ uses the public-domain GIS, GRASS (Geographic Resources Analysis Support System), to forecast changes in land cover and the resulting impact on the environment (Hazen And Berry, 1995; Rauscher and Potter, 2001).

The LUCAS model is structured in the base of three modules associated with a general database: the socioeconomic module, the landscape change module, and the environmental impacts module. The socio-economic model is related to LULC changes. The probabilities are calculated as a function of socio-economic variables including transportation networks, slope and elevation, ownership (characteristics of landowners), land cover and population density. The transition probability matrix, the outcome product of the socio-economic model, is used as an input to the landscape change model. The landscape change module allocate land cover changes to the landscape by using the output probabilities. In the third module, the results of the landscape change model are used to predict the effects of selected environmental factors and resource-supply variables (Berry et al., 1996; Jones, 2005).

MOLAND

MOLAND (Monitoring Land use/cover Dynamics) is a research project including activities for urban and regional developments. The project is aimed at preparing, defining and monitoring the European union environmental policy and legislation. The aim of the MOLAND model is to evaluate, monitor and model urban and regional developments of Europe in terms of sustainable development perspective by creating a database for LULC and transportation for various cities and regions (Lavalle et al., 2004).

The MOLAND methodology consists of three parts including change, comprehension and prediction. In the change phase, the LULC changes are measured in the selected areas. In this phase, which takes account of a period of 50 years, four different time periods of data are used, one of which is current and the other is past LULC. Socio-economic data are combined with LULC maps to detect the change that has taken place over time. In the comprehension phase, environmental indicators are defined to measure the sustainability of urban and urban periphery. Indicators are used to compare development potentials of different cities. In this way, it is possible to evaluate the social, economic, environmental and landscape characteristics of urban and regional developments. In the prediction phase, urban development scenarios are presented for selected areas (Erdogan, 2011). This stage consists of dynamic spatial models operating at macro and micro geographic levels. Macro-level modeling framework combines multi-component sub-models that present natural, social and economic subsystems that symbolize the workspace. These models are associated with each other within interacting networks. At the micro level, cellular automata based model is used. In this model, depending on the types of activities in the areas adjacent to the individual, institutional, and environmental characteristics of the area, the future situation of the area is detected.

The model uses five kinds of digital maps for geographic areas of interest including actual land use types, accessibility to the transport network, inherent suitability for different land uses, zoning status (legal restrictions) and socio-economic characteristics (production, population, income, employment) of the area (Lavalle et al., 2004).

CLUE and CLUE-s

The CLUE (Conversion of Land Use and its Effects) modeling approach is a grid-based, multi-scale, dynamic and spatial domain LULC change model. It uses actual and historical land use patterns be based on socio-economic and biophysical factors to study land use changes in the near future. The model was first applied to Costa Rica (Veldkamp and Fresco, 1996).

The CLUE model is developed for national and continental scales models past, current and near-future LULC changes. The model combines spatial analysis with dynamic modeling approaches where numerical relationships between LULC and driving factors are quantified. The model consists of three main modules including demand module, population module and allocation module. The demand module calculates changes in demands based on socio-economic factors such as agricultural production, population growth at the national level. Modeling approach makes demand module, population module, product module and value assignment module. This calculation can be based on socio-economic factors such as agricultural production, population growth. In the population module, changes taking place in population and related demographics are calculated based on projections and past growth rates. In the allocation module, the changes in the distribution of different land use types are calculate at the national level (Verburg et al., 1999).

Since the CLUE model is developed for national and continental scale work and due to differences in data representation and other characteristics of regional applications, the CLUE model cannot be applied at the regional scale. For this reason, this model was modified with CLUE-s (Conversion of Land Use and its Effects at Small regional extent) model (Verburg et al., 2002).

CLUE-s model which was built upon the CLUE model by Verburg and other scholars in 2002, relies on simulation of the changes that occur in the demand for land use/cover and spatial dynamics of land use system. The model consists of two sub-modules including non-spatial demand and the spatial explicit allocation module. In the non-spatial module, the area of change is determined separately for each area of LULC types. In the second part of the model, these demands are converted to land use changes at different locations within the study area by utilizing a raster-based system.

The demand for LULC is determined separately for each year and is used as direct input data for the allocation module. The spatial part of the model, which has an iterative structure, is a combination of spatial analysis and dynamic modeling techniques. Spatial analysis reveals the relationships between the spatial allocation of LULC and driving factors that affect this allocation (Verburg et al., 2002; Zhou et al., 2013).

Markov Chain

Markov chain model proposed by Andrei Markov that explains the possibilities of movement consisting of separate states of an individual in a system. The Markov Chain is a random process based on Markov property that is any subsequent state depends only on the current state. Markov Chain usually defines a finite set of states and time as discrete values when it is applied to varied applications. Transitions between the states are shown as a transition matrix. Each element in this matrix expresses the probability of transition from one state to another. In the Markov chain model, LULC change between two time periods is determined and the transition probability matrix is obtained by analysis of the images. The results of this process are used to generate predictions of future changes (Anil Tanriover, 2011; Iacono et al., 2012). If the transition probabilities can be defined regularly, highly efficient estimates can be made. In many cases, probability matrixes include all the land use classes at different times and are applied for modeling in wide local scale. To create transition probability matrix, the Markov module in IDRISI can be used (Eastman, 2012). The Markov chain model is a useful tool in modeling the LULC change when it is difficult to define processes and changes in the landscape (Erdogan, 2011).

The basic assumption of the Markov chain is that land use in the future (t+1) can be assigned as a function of current land use (t), that is, the future change will only depend on the existing change and it can be modeled mathematically (Iacono et al., 2012). The prediction of land use changes is calculated by the following equation;

$$S(t+1) = \mathrm{P}_{ij} \times S(t)$$

where $S(t)$, $S(t+1)$ are status of the system at the time of t and t +1; P_{ij} is the transition probability matrix in a state. (Sang et al., 2011). With the Markov Chain model following issues should be considered: (Sahalu et al., 2014)

- In the transition probability matrix, the sum of the rows must be one.
- For any two periods, the probabilities of the transition matrix must be the same.
- On the basis of the Markov condition, the state tomorrow depends only on the state today.
- The length or duration of time periods should be uniform.

CA-Markov

The CA-Markov model integrates both the CA (Cellular Automata) and Markov Chain models. The Markov Chain focuses on the quantity in predictions for land use changes. For this model, the spatial parameters are weak. Since the Markov chain model does not have a spatial structure, it is usually used with cellular automata. CA model is a grid dynamical model in which time, space, and state are all discrete, and spatial interaction and temporal casual relationship are both local, and it is able to simulate the temporal and spatial evolution process of complicated systems. The parts constituting CA are called as cells and each cell has a state which can only be a concentrated finite state. The states of the cells change with time and are determined according to local transition rules (Li et al., 2007), also the CA model could simulate complicated natural phenomena and established the basis of CA theory. CA is defined as a discrete dynamical model which can evolve a global change pattern in terms of time and space, through local behaviors among individuals (Wolfram, 1984). The CA model can be expressed as follows:

$$S(t, t+1) = f(S(t), N)$$

where S is the set of limited and discrete cellular states, N is the Cellular field, t and t + 1 indicate the different times, and f is the transformation rule of cellular states in local space. A cellular automation system usually consists of four elements cells, neighborhoods, states and rules. The cell state can be altered according to transition rules. These transition rules are defined by neighborhood functions and other suitability criteria (Jacoba et al., 2008).

CA model has been widely applied in LULC change, urban growth, fire, ecology, traffic flow, and simulation in other relevant areas. CA also adopts a bottom-to-top modeling concept with strong spatial modelling and computing capacity and is thus able to effectively simulate spatial changes of systems, but it chiefly concentrates on the interaction of the cells local neighborhood. During the simulation process, it emphasizes the elements of the natural environment. However, it fails to consider complicated spatial decision-making behaviors and humanistic factors, thus presenting certain limitations. During LULC change simulation, for solving limiting conditions of CA model it is combined with other models and techniques (Yang et al., 2014). The CA model has a strong space conception with complex space systems.

The CA-Markov model is about space and the time series for the advantages of estimating. Markov Chain model can be used to model changes over time among LULC categories with use of transition probabilities while spatial dynamics are controlled by local rules through a CA mechanism taking into consideration either transition probabilities or neighborhood configuration, thus CA-Markov model can achieve better simulation for temporal and spatial patterns of LULC changes in quantity and space (Sang et al., 2011).

By using this approach, the quantity results of the Markov Chain is converted to spatially explicit outcomes by a CA function. The CA-Markov model can be used for spatial simulations and reconstructions of LULC also, this approach is able to simulate several land categories at the same time (Yang et al., 2015). The CA-Markov module in IDRISI integrates the functions of CA filter and

Markov processes, using conversion tables and conditional probability of the conversion map to predict the states of land use changes, and it may be better to carry out LULC change simulations. The Markov Chain analysis is able to predict changes in terms of the quantity and unable to obtain the change degree of the land use types from a spatial view; whereas CA model has strong dynamic simulation ability to present spatial and temporal changes so it is often used in conjunction/ associate with cellular automata (Yuan et al., 2015).

In this research, Seyhan basin was chosen as a case study, where is one of the most important regions in Turkey in aspect of agricultural activities such as dry farming, irrigated farming and animal husbandry. In view of the biodiversity, the basin is one of the richest regions in the world. In addition, according to the preliminary studies performed by the Intergovernmental Panel on Climate Change (IPCC), the Seyhan Basin has been identified as the most sensitive and vulnerable region in the Mediterranean against climate changes. Thus, the objective of this study was to simulate future LULC changes in Seyhan basin based on the historic change trends of LULC change by using remote sensing and geographic information system. For this purpose The CA-Markov model was adopted for the future simulation that the model has not been applied previously in Seyhan basin. The use of CA-Markov model in the LULC change studies, compared to other models for the similar task, has its advantage and limitations. It terms of advantage, CA-Markov model has high efficiency, simple to calibrate and high ability to simulate complex relationships of LULC (Memarian et al. 2012). It enables a more comprehensive simulation as compared to other LULC change models (Mas et al., 2007).

2. LITERATURE

The earth's surface has been changed because of human uses such as agriculture, forestry, industrialization and urban development for the past years. To identify and understand the impact of these changes on the environment and to simulate the changes, modelling techniques and different models are used. Detection of LULC changes and prediction of future changes by CA-Markov model have been reported in several studies as:

Fan et al., (2008) used CA-Markov model to analyze LULC changes in the Pearl River Delta in China. They detected spatial and temporal LULC changes 1998 to 2003. In addition, they predicted level of urbanization from 2008 to 2013 by using the model. The result of the research showed both changing of many farmland to urban and changing grass field to farmland. they concluded that the model was appropriate model to predict LULC expansion according to accuracy assessment.

Wu et al., (2006) performed a research to predict LULC change for 2012 by the CA-Markov Model in Beijing, China. They integrated RS and GIS with the CA-Markov Model in this research. Result of the research showed that the integration was very useful way to predict of land use change.

Chang and Changchin (2006) studied vegetation cover of Jiou Jiou Mountain by SPOT data at times period of 1999- 2005. Then they predict spatial and temporal changes of vegetation cover by using CA-Markov model. According to the result of the research they approved that the CA-Markov model was appropriate model to simulate vegetarian cover change.

Opeyemi (2006) predicted LULC changes of the Ilorin region in Kwara state using Markov Chain and Cellular automata models for the year of 2015. He used MSS, ETM and TM data of between 1972 and 2001. The result showed a rapid growth in built-up land for period of 1972-1986 while the period of 1986-2001 showed a decrease in built-up class. It was also observed that change 2015 likely follow the trend of between 1986 and 2001. He evaluated socioeconomic implications of the predicted change obtained from LULC map at different periods.

Falahatkar et al., (2011) used ETM +, TM and MSS images and aerial photos of Isfahan and its environs in IRAN to provide land cover maps. Also, they used a combination of supervised and unsupervised classification (hybrid classification) method for image classification and CA-Markov model for simulating LULC maps. In order to validate of model and evaluate accuracy of the simulated map they used three methods including chi-square goodness-fit test, agreement and disagreement table and an error matrix. The result of prediction showed a fast and unplanned development for Isfahan and its environs where urban area was growing without any consideration of the landscape types that are being transformed. Finally, they could conclude that if change of land cover remain constant and fixed, CA-Markov model predicts following the years changes with validation less than 70% for the study area.

Wang et al., (2011) detected land use distribution and studied temporal and spatial change for 10 years in Xi and Guanzhong-Tianshui region of china. For this purpose, they applied the data from Landsat TM images of 2000 to 2010. Then in order to predict the land use in 2020 and 2030 CA-Markov model. The result of this research showed that land use change of the region during 2000-2010, the changes include decrease of farmland and grassland, increase of construction area. Therefore they concluded that the model can predict overall distribution ratio without predicting exactly where land use changes occur.

Kim et al., (2011) predicted future land use changes using CA-Markov model and logistic regression in the Soyang River basin to compare future land use change patterns with past land use change patterns. They used 1995 and 2000 land use maps. Variables, which influence land use change, and predicted future land use changes include natural-environmental and socio-economic factors were extracted. The prediction map was validated with the map of actual land use for 2006 to test the applicability of the land use prediction model, using Relative

Operating Characteristic (ROC) and variations of the Kappa index of agreements for major land use classes (urban, forest, agriculture). The forest class had a high accuracy for both distribution ratio and spatial agreement, while urban and agriculture classes had a high accuracy for their distribution ratio and a low accuracy for spatial agreement. The results demonstrated that the model can predict overall distribution ratio without predicting exactly where land use changes occur.

Roy et al. (2012) used multi-temporal Landsat imagery to generate LULC maps for the years of 1989, 2003 and 2014 for analyzing the spatial distribution; temporal changes and prediction of LULC categories in the southeastern hill tracts of Bangladesh. In the first step, a total seven LULC categories were derived using the integration of NDVI and conventional supervise classification techniques which were further evaluated using the error matrix table and kappa statistics. The accuracy assay of the results showed the accuracy up to 90% for all three years. They carried out a rigorous change analysis using Land Change Modeler (LCM) where dramatic changes were noticed in hilly forest, shrub land and crop land categories for 1989-2014 time span. From 1989 to 2014 hilly forest decreased while shrub land and cropland increased. In the second stage, they used CA-Markov model to predict LULC in the study area. After successful validation of observed and predicted LULC maps of 2014 (Overall accuracy 91.43%), the combined procedure was employed to simulate LULC for 2028 and 2042. The simulated result of 2014-2042 shown a dramatic decrease in hilly forest and water reservoirs whereas a significant increase was noticed in the shrub land, crop land and settlement area. All these findings from the research could offer an opportunity for the more skillful management and policy making on biodiversity, forest, land and other environmental resources in the study region.

Kaveh and Ebrahimi (2013) used CA-Markov model in detection and simulating LULC changes over 65 km of Aghbolagh River. LULC map was prepared using 1956, 1969, 1998 aerial photos and 2006 satellite images. Then river, riparian area, agriculture and bare lands around it were illustrated and LULC maps of each year were drowned and overlaid through cross routine to evaluate model validation. Finally, the conditions of these classes were forecasted using CA-Markov model for 2016. Results of forecasting future changes based on 1969 and 1998 maps showed that in 2016, arable lands will have the most stability while the river is the most vulnerable land cover to change.

Al-Sharif and Biswajeet (2014) simulated urban land use change of Tripoli, Libiya by using CA-Markov model. In addition, they project spatial patterns in Tripoli, Libya. They employed the satellite images obtained from SPOT 5 and Landsat TM to provide maps of land use for 1984-2010. In this research, land use change was simulated by Markov chain model then dynamic spatial patterns of changes was simulated by CA model. Using the CA-Markov model, land use change of urban for 1984-2010 was modeled. Then the future land use change was predicted. In this research accuracy analysis showed accuracy of more than 85 %. The result of this research exhibited that the model was reasonable and appropriate model. These research group showed that the CA-Markov model can be appropriately used to model cities in North African.

Yang et al., (2015) used CA-Markov model to reconstruct LULC in the 1930s in Northeast China based on the assumption that current spatial patterns of land use are dynamically dependent on a historical pattern and factors for land suitability do not change over time. They used the three map comparison technique for accuracy assessment of the model. The result of assessment showed that the major differences among the three maps have less to do with the simulation model and more to do with the mismatches among the land classes during the study period. The model could perform retrospective projections by analyzing LULC changes in recent years. The results of reconstruction indicated that in the 1930s most of the study area was occupied by grasslands, followed by wetlands and arable land. They concluded that the CA-Markov modelling approach can be simultaneously applied to spatial reconstructions of various land cover types.

Huang et al., (2015) used remote sensing data (Landsat TM) from 1999 to 2005 to analyze LULC pattern in Wuhan city in China. They applied CA-Markov model to predict and simulate urban land use change in the study area. To predict the urban land use change, they determined locally restrained and globally restrained conditions and a random variable as the transition rules for the model. According to the experiment results, the feasibility and validity of the CA-Markov model were confirmed. Not only the model helped to understand the complexity of the components of spatial systems, but also supplied reference and theories for land resource management and land planning.

Berberoğlu et al. (2016) applied three different CA based modelling approaches including SLEUTH, Markov Chain, Dinamica modelling with the Regression Tree, Logistic Regression and Artificial Neural Networks to forecast the urban growth of Adana city. They used 1967-1977 CORONA aerial photos, 1987-1998 SPOT and 2007 ALOS AVNIR-2 satellite images to calibrate and validate models and to project future growth for the year 2023. They assessed the results to find the most appropriate model for the study area. The SLEUTH model and Markov Chain resulted in the largest overall accuracy of 75 % and 72 % respectively. Considering the gain and loss of built values, SLEUTH and Markov models were the most consistent models with the real data in terms of allocation maps and Artificial Neural Networks had the highest disagreement value compared with other models. Thus, they provided a guide for urban sprawl modelling by using the empirical results and findings of various approaches

Vazquez et al., (2016) used Markov Chains and Cellular Automata models to analyze change dynamics of temperate forests land use in the region of Pueblo Nuevo, Durango, Mexico. They classified Landsat images of the years 1973, 1990 and 2014 by using supervised classification to generate land use maps. The models showed constant changes in land use. Also, changes in the temperate forest size of the study area were indicated that pine forests areas can be reduced continuously until 2028. The results could provide quantitative information for managing of ecosystems of temperate forest and taking action to mitigate their degradation.

Hyandye and Martz (2016) simulated LULC change of Usangu Catchment (Tanzania), in 2020 based on LULC of 2000, 2006 and 2013 using Markov Chain and Cellular Automata Analysis. Social, edaphic, climatic and landscape geomorphology factors governing the LULC change and distribution were used to prepare LULC suitability maps in geographical information system. The relative importance of LULC change factors was determined using the AHP and aggregated using weighted linear combination under multi-criteria evaluation approach. The model was validated using simulated and observed LULC 2013. The predicted LULC 2020 scenario showed the increase in urban area and a major decrease in forestland and shrubs. About 19.6% grassland and 8.5% of agricultural land in 2013 will be converted to urban land by 2020. The 2020 LULC simulation model of Usangu provided some useful information for future LULC scenarios and data for water balance models and preparation of future ecological conservation plans.

3. MATERIALS AND METHODS

3.1. Study area

The Seyhan Basin is one of the most fertile and the largest basin in Turkey. The Seyhan Basin is located in the Eastern Mediterranean Region of Turkey, between latitudes of 36° 30’ and 39° 15’ north, and longitudes of 34° 45’ and 37° 00’ east. The Seyhan Basin is bordered by Tecer Mountains (1600 m) to the North, Tahtalı Mountains (3075 m) the East, Melendiz and Bolkar Mountains (3524 m) to the west, and Mediterranean to the South. The basin covers an area of 21760 km^2 and constitutes of the 2.07% of Turkey. It is consist of six provinces. The largest part of the basin is under administration of the Adana and Kayseri provinces (over %50). The rest of the basin’s area is under Sivas and Kahramanmaraş, Mersin and Niğde provinces. The study area is given in Figure 3.1.

The Seyhan Basin consist of 24 districts including Yuregir, Seyhan, Cukurova, Karaisalı, Sarıçam, Karataş, Aladağ, Pozantı Feke, part of İmamoglu and Kozan, Tufanbeyli and Saimbeyli districts of Adana, Pınarbaşı, Tomarza and Sarız districts and the part of Develi and Yahyalı districts of Kayseri, and Ulukışla and Çamardı districts of Niğde, the part of Tarsus district of Mersin as shown in Figure 3.2.

Zamantı, Göksu and Seyhan rivers are main rivers in the basin. The Seyhan river is the largest and longest of rivers flowing into the Mediterranean. Seyhan river formed from the unification of Zamantı and Göksu rivers that collect the water of upper basin. The length of Seyhan River is 560 km. The length of Zamantı which originates in the eastern section of Central Anatolia is 306 km. The length of Göksu river is 199 km, which originates in Eastern Anatolia (Megar, 2009). The physiography of the Seyhan Basin varies from south to north, the south side is characterized by lowlands while the north is represented by harsh topography.

Actually, the Seyhan Basin can be subdivided into the upper and lower basin. The upper section is predominantly mountainous, while lower section has plain topography, and is used as agricultural land. There is no significant lake formation in the basin but there are reservoirs of Seyhan and Çatalan dams as artificial lakes. The basin also has rich biodiversity and various ecologically important areas. There is one national park (Aladaglar NP) and 7 wildlife reserve sites, including Seyhan Dam, Pozantı Karanfildağ, Çamardı Demirkazık, Tarsus Hopur Topaşır, Hançerderesi, Tuzla lake and Akyatan lake which are as internationally important wetlands in basin (Zeydanli and Ulgen, 2009).

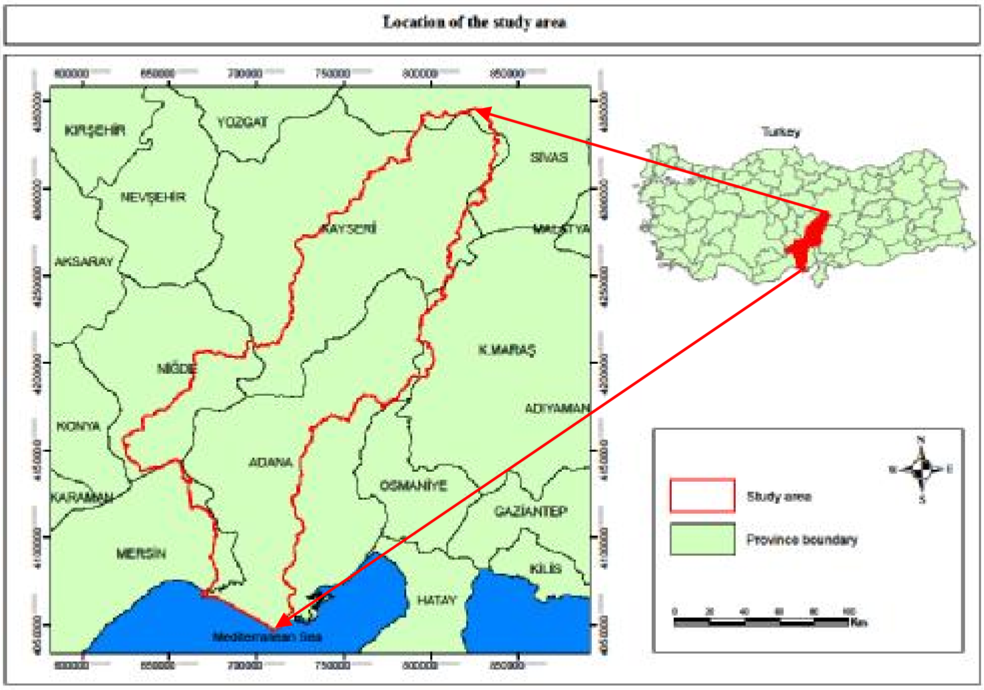


Figure 3.1. Location of the study area

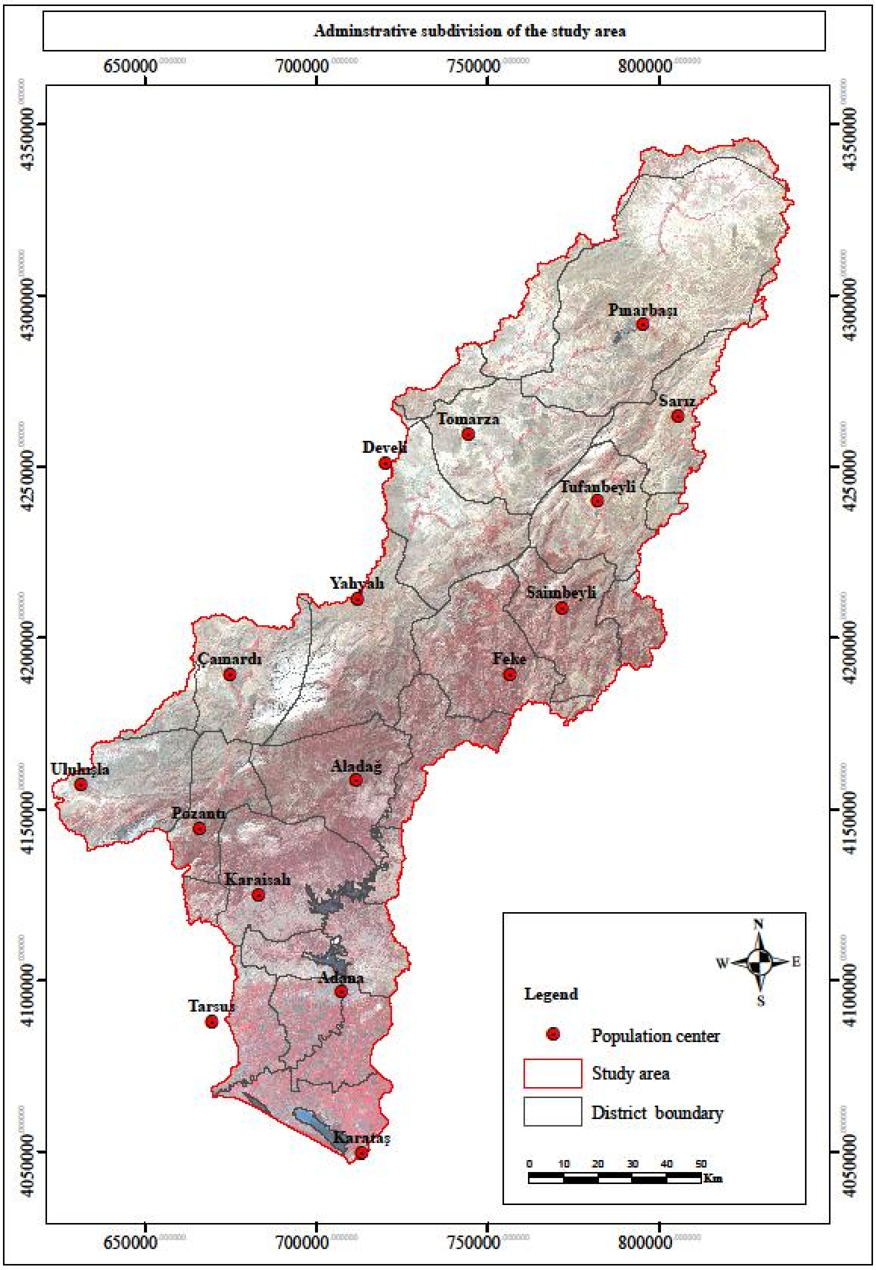


Figure 3.2. Administrative subdivision of the study area

3.1.1. Population

The population density in the upper Seyhan basin is not so high, only there are some small settlements in the borders of Kayseri. The settlements in the lower Seyhan basin are much bigger and population is much denser. Lower basin is facing with the rapid urbanization due to developing agricultural and industrial facilities. Adana, one of the biggest cities of Turkey, places in this basin. Also it is the fifth largest province of Turkey in terms of population making up 2.7% of the country's population. According to the results of Population Census carried out by the Turkish Statistical Institute (TUIK) the populations of the population centers between 1990 and 2016 are given in Table3.1

Table 3.1. Population of the district centers between 1990 and 2016 (TÜİK)

		Total Population in year				
Province	**District**	**1990**	**2000**	**2007**	**2010**	**2016**
Adana	Yuregir	369529	453799	522265	422529	419902
	Seyhan	672121	849283	1007992	723277	797563
	Saricam*	No data	No data	10929**	120325	156748
	Cukurov*	No data	No data	271344**	347941	362351
	Karaisali	37584	35122	28740	22981	21250
	Kratas	26450	32375	21485	21260	21867
	Pozanti	23040	21756	19896	20279	19362
	Aladag	23207	23579	17506	17169	16333
	Feke	21751	20890	19489	18996	17033
	Saimbeyli	20700	17149	17775	17355	15239
	Tufanbeyli	22672	20171	18279	18072	17558
Kayseri	Tomarza	42669	35808	28697	27130	22818
	Sariz	19255	14596	12705	11758	9558
	Pinarbasi	47822	35388	30898	28983	23658
	Develi	72825	70893	65695	64836	64422
	Yahyali	44047	43203	37834	36348	36077
Nigde	Camardi	21432	20302	15293	15245	12773
	Ulukisla	29434	32928	21754	22728	19883
Mersin	Tarsus	290633	348205	318553	312573	329464

***** Cukurova and Saricam districts were separated from Seyhan and Yuregir districts in 2008 respectively. The data presented by ** are related to 2008

3.1.2. Geology and Soil

Upper Seyhan basin has a complicated geological structure. Early Cambrian aged deposit of sandstone-siltstone-quartzite-limestone is widely observed near the proposed Feke Dam and its vicinity. There are deposits of Middle Cambrian aged limestones, Late Cambrian-Ordovician aged shale-siltstone, and Early Devonian aged sandstone-shale- limestone near Feke district. Besides, Middle Devonian aged limestone- Dolomitic limestone deposits cover a wide range of area between Feke, Saimbeyli and Tufanbeyli districts. In the lower basin, the geological formations from Cambrian to Devonian period are widely observed. Permian Carboniferous and Mesozoic aged formations lie through the southwest direction and more young deposits follow these formations in the south direction. This deposit has been interrupted by the tectonic movements along the south direction. Claystone, shale, quartzite, ophiolitic rocks and limestone are observed in the basin of Zamanti and Goksu. Dominant soil types of the Seyhan basin are leptosols for grasslands and forests and fluvisols/vertisols for croplands. The two main soil texture categories of clay loam and light clay cover 54% and 42% of the study region, respectively (Eswaran et al. 2010).

The general soil structure of the Seyhan basin is mainly composed of rough and rocky red or brown Mediterranean soils, brown earth and non-limestone brown earth soils in middle of the basin as well as brown and non-limestone brown soils in north of basin. Along Goksu Valley, alluvial deposits only exist in places where major tributaries join Goksu River. On the other hand, alluvial deposits with a width of 100 m and thickness of 6-7 m are observed in the upper sections of Zamanti Valley. The basin consists of 12 major soil groups shown in Table3.2. (Dokayeng, 2010; SHKEP, 2011)

Table 3.2.Distribution of major soil groups in the study area

Major soil groups	Distribution %
Brown soils	18.1
Red Brown soils	1
Chestnut soils	3.8
Red Mediterranean soils	1.8
Red-Brown Mediterranean soils	2.1
non-limestone Brown soils	11.5
Brown earth soils	23.5
non-limestone Brown earth soils	23.9
Rendzina soils	0.12
Hydromorphic soil	0.36
Alluvial soils	6.6
Colluvial soils	3
Vertisol soils	1.2

3.1.3. Climate and Vegetation

The climatic conditions in the Study Area display transition characteristics between the Mediterranean climate and continental climate of the Central Anatolia Region. The lower basin is dominated by the Mediterranean climate, while the middle and upper basins are influenced by the continental climate. Mediterranean climate is Characterized by are hot and dry summers, cool and rainy winters. Because the Taurus Mountains traverse the middle Seyhan Basin, the lower Seyhan Basin is not affected by northern winds. Therefore, the summers are quite hot (Dokayeng, 2010).

Mild and rainy winters and hot and dry summers are typical across the study region with a mean annual rainfall of about 800 mm 75% of which are received in autumn and winter. Mean annual air temperature is 19^{o}C with mean minimum and maximum values of 8^{o}C in January and 30^{o}C in July, respectively (Eswaran et al., 2010). Prevailing wind directions are north and northeast December to March, south in March and September, and southwest in June, July and August. The winds in the direction of north and northeast are dry. However, these winds decrease the air temperature considerably in winter. The Seyhan Basin is rich in diversity of the plant species and it has fertile agricultural lands from the slopes of the Taurus Mountains to the Mediterranean. Dominant forest cover of the study area is characterized by old-growth Mediterranean evergreen needleleaf forest with pure and mixed stands of the following dominant tree species: Taurus fir (Abies cilicica), Crimean pine (Pinus nigra), Turkish pine (Pinus brutia), Lebanese cedar (Cedrus libani) and Juniper (Juniperus excelsa) (Evrendilek et al., 2006). Mixed forest is generally composed of P. brutia and P. nigra; P. brutia and J. excelsa; P. nigra and A. cilicica; and C.libani and A. cilicica stands. Main crop products of the area comprise corn, cotton, citrus, water melon and soybean.

3.1.4. Livelihood and Economy

Adana city is located in the center of Cukurova. The Ceyhan and Seyhan rivers have brought Seyhan, Kozan and Catalan dams to the province and these rivers have provided very fertile alluvion lands. Not only the geographic location but also suitable climate made an advantage for the agriculture. Adana is ranked as the eighth province in Turkey in terms of socio-economic development. Productive agricultural lands constitutes 39% of the total area. In this regard, agriculture – cotton cultivation in particular is the main economic activity in the region. 15% of Turkish cotton production is provided from this region. Animal husbandry, on the other hand, is not as much developed as agricultural activities since meadow and grass lands are quite few. However, animal husbandry is more developed than agriculture in the mountainous areas. Besides, mountain tourism is another livelihood for the people living in the upper north side of Adana Province.

In Kayseri Province, almost 50% of the land area is used for agriculture. However, insufficient irrigation adversely affects the fertility of the lands. Wheat is the major agricultural output, followed by barley and sugar beet. Animal husbandry is also practiced in the province. Poultry and beekeeping are more prevalent. Industry and trade have the largest shares in the economy of the province. As a consequence of increasing investments and better infrastructure, the province has achieved a remarkable industrial growth since 2000 and has become a favorable environment especially for small and medium enterprises. Kayseri is ranked as the nineteenth province in Turkey in terms of socio-economic development (Dokayeng, 2010).

3.2. Datasets

The data for this study comprised Landsat 5 and Landsat 8 satellite imagery acquired 1995, 2006 and 2016 with 30 m spatial resolution. They were obtained from the United States Geological Survey (USGS) and the Earth Observation Link (EOLi) that is the European Space Agency's client for Earth Observation Catalog and Ordering Services. The following Table 3.3 summarizes the characteristics of each of the images used in the present study.

Table 3.3. Characteristics of satellite images used in the study

Satellite	**Sensor**	**Acquisition Date**	**Path/Row**
Landsat 5	TM	27.08.1995	175/33
Landsat 5	TM	27.08.1995	175/34
Landsat 5	TM	27.08.1995	175/35
Landsat 5	TM	10.09.2006	175/33
Landsat 5	TM	10.09.2006	175/34
Landsat 5	TM	10.09.2006	175/35
Landsat 8	OLI	04.08.2016	175/33
Landsat 8	OLI	04.08.2016	175/34
Landsat 8	OLI	20.08.2016	175/35
Landsat 8	OLI	11.08.2016	176/34

In addition to digital elevation model (DEM) data of 30 m resolution (downloaded from SRTM website), 1:25000 soil maps, Google Earth®-image, transportation networks and population censuses data obtained from TUIK were used in this study.

3.3. Methods

The workflow of the study can be summarized in the following six stages;

1) Data collection
2) Data pre-processing
3) Object-oriented classification
4) Change detection analysis with the post-classification technique
5) LULC simulation using CA-Markov model and preparation of suitability maps with MCE
6) Validation process

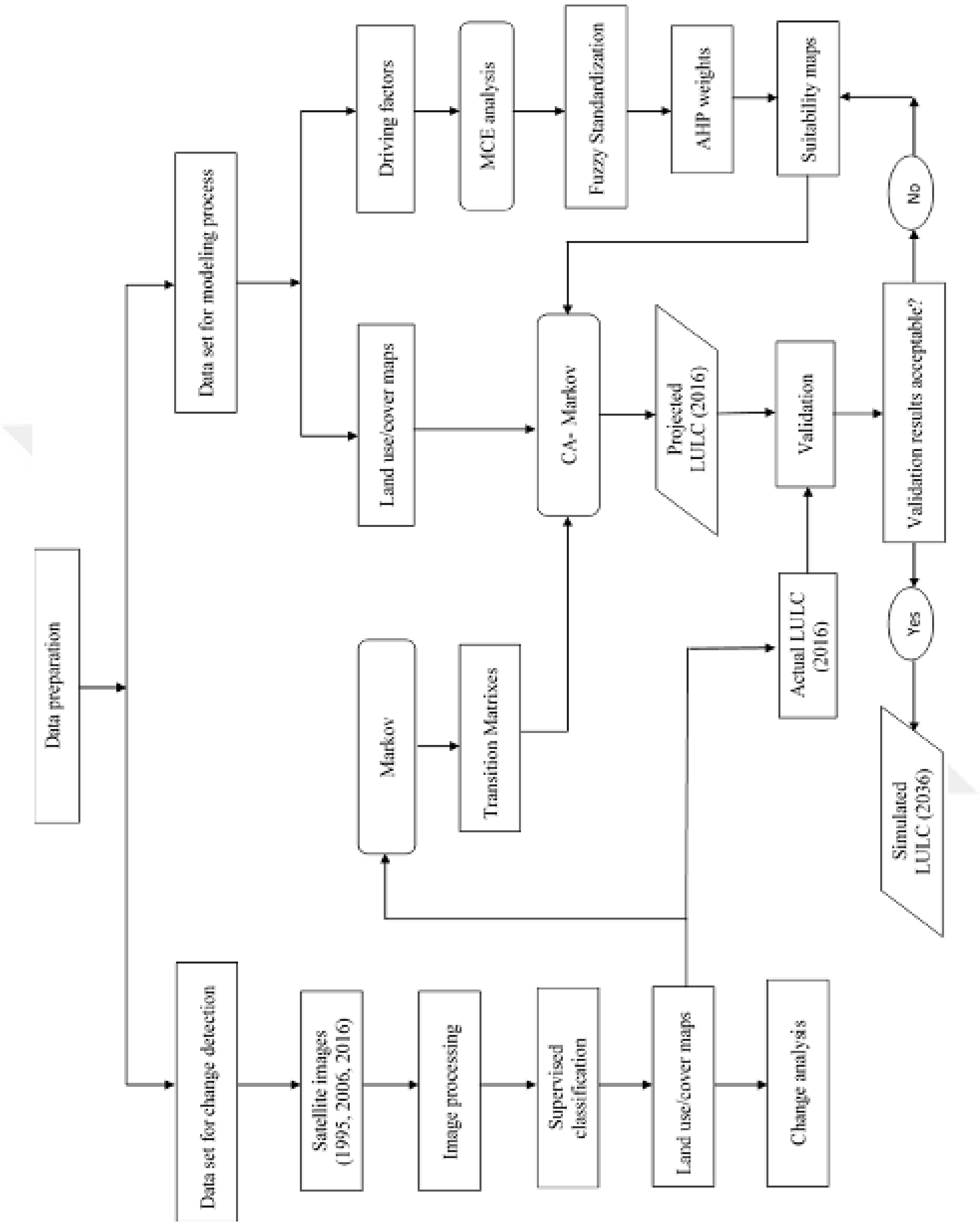


Figure 3.3.Workflow of the study

3.3.1 Image pre-processing

In remote sensing, the electromagnetic energy from the energy source exhibits some effects such as absorbing, scattering, reflection and emitting when it is passed through the atmosphere due to the existence of particles and aerosols in the atmosphere and effect of the sun's elevation and azimuth. Because of these effects, there is a difference between the actual energy emitted or reflected from the surface and the energy recorded by sensors. To reduce or correct the systematic and atmospheric errors, radiometric corrections need to be performed (Song et al., 2001). Atmospheric correction is an important pre-processing for remote sensing applications such as detection of LULC changes, identification of land cover types, and merging of images obtained from different sensors. In the radiometric normalization process, the pixel values (DN) of the satellite image are converted into a spectrum that is spectrally comparable. For this purpose the surface reflectance values are used (Lu et al., 2002). The images were radiometrically corrected. The radiometric conversion for the Landsat TM sensor was performed in two-steps including convertion of DNs to radiance values and converting these radiance values to reflectance values using Eq. (3.1) and Eq. (3.2).

$$L_\lambda = \big((LMAX_\lambda - LMIN_\lambda) / (QCALMAX - QCALMIN)\big) * (QCAL - QCALMIN) + LMIN_\lambda \quad (3.1)$$

Where L_λ is the spectral radiance, QCAL is digital number; QCALMIN and QCALMAX are the minimum and maximum quantized calibrated pixel value, respectively. $LMIN_\lambda$ is spectral radiance scales to QCALMIN; $LMAX_\lambda$ is spectral radiance scales to QCALMAX.

$$\rho_\lambda = \pi * L_\lambda * d^2 / ESUN_\lambda * \cos\theta_S \quad (3.2)$$

Where ρ_λ is the unitless planetary reflectance; d is the distance from earth to sun; $ESUN_\lambda$ is mean solar exoatmospheric irradiances, and θ_S is the solar zenith angle.

In the case of the data from the Landsat OLI, the radiometric conversion was performed applying Eq. (3.3):

$$\rho_\lambda = \frac{(M_\rho Q_{CAL} + A_\rho)}{\sin \theta_{SE}} \tag{3.3}$$

where ρ_λ is the top of the atmosphere (TOA) reflectance, with a correction for the solar angle, and θ_{SE} is the local sun elevation angle; M_ρ is the band-specific multiplicative rescaling factor taken from the metadata of the image; A_ρ is the Band-specific additive rescaling factor taken from the metadata and Q_{CAL} is Quantized and calibrated standard product pixel values.

Then mosaics of the images were generated for three deferent times (1995, 2006 and 2016) then the study area was extracted from the mosaics by using the software ArcMap 10.3 and ERDAS 2014. In the next step supervised classification was carried out.

3.3.2. Image Classification

Object-based classification with the Nearest Neighbor (NN) method was applied using eCognition software for LULC classification. One of the common classification methods is the nearest neighbor classification. Classification of remote sensing data can be performed by pixel based classifications (unsupervised and supervised) that uses the spectral information of the grey value of pixel. This method do not consider the textural information but focus on topological information, individual pixels and so forth. Analysis of object-based image is founded on data from a set of similar pixels called objects. Image objects are groups of pixels that are similar to one another based on a measure of size, texture, spectral properties, shape, and context from a neighborhood surrounding the pixels. Object-based image analysis supports multi-band use for classification and multi-resolution segmentation (Modi et al., 2014). In this method after multi-resolution segmentation, the user identifies sample sites for each land cover class. The statistics to classify image objects are defined. Then Software finds objects similar to the samples and the statistics defined, then assigns those objects to proper class. So this method was performed in four steps including multi-resolution segmentation, selection of training areas, defining statistics and classification.

CORINE (Coordination of Information on the Environment) Land Cover Classification (CLC) scheme was used for the LULC classification. CORINE is a European program initiated in 1985 by the European Environment Agency (EEA), aimed at gathering information relating to the environment on certain priority topics for the European Union (air, water, soil, land cover, coastal erosion, biotopes, etc.). The CORINE land cover nomenclature comprises three levels, the first level consist of five major classes of land cover including artificial surfaces, agricultural areas, forests and semi-natural areas, wetlands, water bodies while second level and third level include 15 and 44 sub-classes for LULC respectively (Table 3.4). In this research, LULC classes were determined according to Level 2 CLC classification including 7 classes (water body, forest, shrub and/or herbaceous vegetation association, open space with little or no vegetation, built-up area, wetland and agricultural area).

Table 3.4. CORINE Land Cover Classes

Level 1	**Level 2**	**Level 3**
Artificial surfaces	Urban fabric	Continuous urban fabric
		Discontinuous urban fabric
	Industrial, commercial	Industrial or commercial units
		Road and rail networks and associated land
		Airports
	Mine, dump, and construction sites	Mineral extraction sites
		Construction sites
	Artificial non-agricultural vegetated areas	Green urban areas
		Sport and leisure facilities
Agricultural areas	Arable land	Non-irrigated arable land
		Permanently irrigated land
		Rice fields
	Permanent crops	Vineyards
		Fruit trees and berry plantations
		Olive groves
	Pastures	Pastures
	Heterogeneous agricultural areas	Complex cultivation patterns
		Land principally occupied by agriculture, with significant areas of natural vegetation

Table 3.4. (Continued)

Forests and semi-natural areas	Forests	Broad-leaved forest
		Coniferous forest
		Mixed forest
	Shrub and/or herbaceous vegetation	Natural grasslands
		Sclerophyllous vegetation
		Transitional woodland-shrub
	Open spaces with little or no vegetation	Beaches, dunes, sands
		Bare rocks
		Sparsely vegetated areas
Wetlands	inland wetlands	Inland marshes
	Coastal wetlands	Salt marshes
Water bodies	Inland waters	Water courses
		Water bodies
	Marine waters	Coastal lagoons
		Sea and ocean

3.3.3. Classification Accuracy

The statistical index Kappa and confusion matrices was used to determine the classification accuracy. Kappa index is a multivariate method that used for comparing LULC classes through a matrix and determining the degree of similarity between actual and mapped values of LULC. Kappa values equal to one and equal to zero indicate a 100% and 0% similarity between real and mapped values, respectively (Prieto et al., 2016).

Kappa is represented by Eq. (3.4).

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} * X_{+i})} \quad (3.4)$$

where K is the Kappa index, X_{ii} is the observation number on column i and row i (along the diagonal), r is the total number of matrix rows, X_{i+} and X_{+i} are total marginal for row i and column i, respectively and N is the total number of observations.

The matrix is also used to calculate user's accuracy, producer's accuracy and overall accuracy. Overall accuracy is calculated by dividing the sum of the diagonal in the error matrix (correctly classified sample) by the total number of sample in the entire error matrix. The producer's accuracy that represents the individual category accuracy, is calculated by dividing the total number of correct sample by the total reference data. User's accuracy is calculated by the total number of correct pixels from a specific class divided by the total number of pixels classified. A group of sample points (260 points) in the study area was employed to estimate the Kappa index.

3.3.4. Change Detection

Change detection method identifies variations in the state of an object or phenomenon by observing it at different times. In order to better use and manage, it is necessary to understand relation between environment and human, for this purpose, it is need to detect changes of land's features accurately. Many change detection techniques have developed recently; the most commonly used are image differencing, principal component analysis and post-classification comparison (Fan, 2008; Pathak, 2014).

The post-classification comparison change detection method was used in this study by simply comparing classified images. Post-classification comparison that is pixel-based method, is commonly used in change detection studies. This method is based on classifying images belonging to different dates and by this way creating the change map and it is also important in terms of obtaining and giving "from-to" information about the changes (Pathak, 2014). The general flow chart of the method is given in Figure 3.4.

In the study, classified image pairs of two different decades including 1995-2006 and 2006-2016 were compared using cross-tabulation in order to detect changes for the periods.

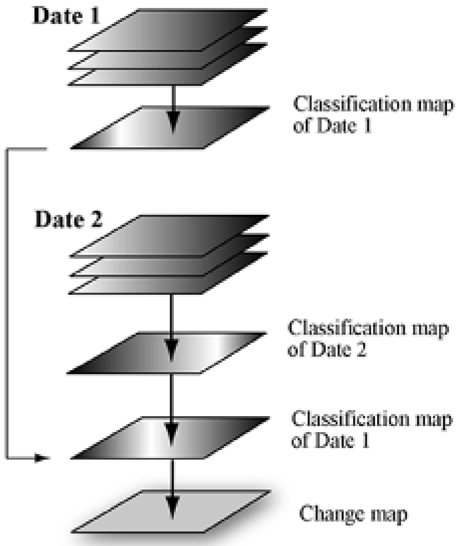


Figure 3.4.Post-classification comparison change detection

3.3.5. CA-Markov model

In this research a combination of Markov chain (MC) and a hybrid cellular automata (CA) called CA-Markov was applied to simulate the future LULC changes of Seyhan Basin.

The CA model is:

$$S (t, t + 1) = f (S (t), N) \tag{3.5}$$

where f is the transformation rule of cellular states in local space, N is the Cellular field, t and t + 1 indicate the different times and S is the set of limited and discrete cellular states. The Markov Chain model is a theory based on the process of the formation of Markov random process systems for the prediction and optimal control theory method. Based on the conditional probability Formula-Bayes, the prediction of land use changes is calculated by Eq. (3.6).

$$S(t+1) = \mathrm{P}_{ij} \times S(t) \tag{3.6}$$

where $S(t)$, $S(t+1)$ are the system status at the time of t or t +1; P_{ij} is the transition probability matrix in a state which is calculated as follows.

$$\mathrm{P}_{ij} = \begin{bmatrix} \mathrm{P}_{11} & \mathrm{P}_{12} & \cdots & \mathrm{P}_{1n} \\ \mathrm{P}_{21} & \mathrm{P}_{22} & \cdots & \mathrm{P}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \mathrm{P}_{n1} & \mathrm{P}_{n2} & \cdots & \mathrm{P}_{nn} \end{bmatrix}$$

$$\left(0 \le \mathrm{P}_{ij} < 1 \; and \; \sum_{j=1}^{N} \mathrm{P}_{ij} = 1\, , (i, j = 1,2, \ldots, n)\right)$$

where n is the number of LULC types in the target area, and i, j is the LULC type of the first and second time period.

Spatio-temporal Markov Chain model can be used to model changes over time among LULC categories with use of transition probabilities while spatial dynamics are controlled by local rules through a CA mechanism taking into consideration either transition probabilities or neighborhood configuration. Thus coupling of transition matrices and CA models LULC change over space and time can provide a better understanding of the historical landscapes. This model was based on using and evaluating land use layers of previous years and further predicting the spatial distribution of land uses in the future using GIS (Sang et al., 2011). This approach convert the quantity results of the Markov Chain by a CA function to spatially explicit outcomes (Yang et al., 2015). The model was applied to predict LULC distributions in 2016 (to validate the model) and 2036. IDRISI software was used for the CA-Markov model. The stages of this model is as follow:

Transition area matrix and transition probability matrix was calculated with Markov chain analysis. Transition area matrix represents the number of pixels that are expected to change from an LULC class to another class during a time period. Transition probability matrix represents the probability of each land use change to another within a new period compared to the previous one which it is obtained using cross tabulation of two images of different time (one belonging to the past and the other one belonging to the present time) (Nouri et al., 2014; Jalerajabi et al., 2013). LULC maps dated 1995 and 2006 were used to calculate transition probability matrix in order to project LULC for the year 2016.

In this study, a standard 5 × 5 filter was applied that calculates the neighborhood pixels. Usually, the procedure of filtering includes moving a 'window' of a few pixels in dimension (e.g. 3 × 3, 5 × 5, etc.) over each pixel in the image. The central pixel is replaced with a new value that is mathematically calculated by the pixel values under the window. The window is moved along in both the row and column one pixel at a time and this calculation is done until the entire image has been filtered. Filters can be designed to enhance or suppress different types of features such as low-pass and high-pass filters by varying the calculation performed and the weightings of the individual pixels in the filter window. The CA filter is used to develop a spatially explicit contiguous weighing factors to change the state of cells based on its neighbors so that the pixels that are far from the existing LULC class have lower suitability than the pixels that are near. Contiguity filter used in CA- Markov is:

$$\begin{matrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{matrix}$$

Also the CA number of iterations and the starting point as a base map was determined. At the end of each repetition, a new land use map was produced through overlapping the whole results obtained in the previous steps (Vazquez et al., 2016). Here, the years of 2006 and 2016 were chosen as a starting point for predicting of LULC 2016 and 2036 respectively.

3.3.6. Preparing suitability maps

The suitability maps were produced for each of LULC categories separately by using Multi-Criteria Evaluation (MCE). MCE is a mathematical tool that compares different scenarios or alternatives in regard to several criteria to help the decision maker towards reasonable choices. MCE technique is usually applied for analysis of land suitability. It is the application of decision-making rules to determine different criteria in order to combine the criteria in the form of GIS layer, into a single map (Raddad, 2016).

3.3.6.1. Identifying the criteria

Multi-criterion evaluation analysis involves two types of criteria including constraints, Boolean criteria, limiting analysis of some regions and factors defining suitability of all regions. On other words, constraints are criteria that exclude areas from the analysis while factors are criteria affecting (enhance or detract) the viability of the objective. They define areas or alternatives in aspect of a continuous measure of suitability. In this research one constraint layer and different factors like distance to water, distance to road, slope, elevation, soil, etc., was determined for each LULC categories in the GIS environment. The layers were continuous and categorical (Pramanik et al., 2016).

3.3.6.2. Standardization of the criteria

Data may be expressed according to different units as well as in different scales (interval, ratio and ordinal) of measurements. However, all of the criteria should be expressed on a similar scale. Standardizing the criteria allows the rescaling of all the evaluation dimensions between 0 - 1 and 0 - 255 that 0 represents low suitability, 1 and 255 represent high suitability. This permits within and between criteria comparisons. During this stage, the factors were stretched from 0 to 255 using different fuzzy functions and control points. The constraint images were standardized as Boolean images (0-1). The value of 0 represented areas restricted for suitability analysis while 1 represented the suitable areas.

Fuzzy logic is made up of mathematical principles based on the degree of membership for displaying information rather than the crisp membership of classical binary logic. Unlike two-valued Boolean logic, fuzzy logic is multi-valued. It deals with degrees of membership and degrees of truth. Fuzzy logic uses the continuum of logical values between 0 and 1. Instead of only white and black, it utilizes the spectrum of colors, accepting that things can be partially false and partially true simultaneously. Some of the fuzzy membership function types are sigmoidal, J-shaped and linear membership functions (Eastman, 2001; Eastman, 2009; Mandal et al., 2012).

3.3.6.3. Weighting of criteria

Analytic hierarchy process (AHP) was used for weighting of the criteria. AHP is one of the most popular multipurpose decision-making techniques that was firstly developed by Saaty (1980). AHP establishes a hierarchical structure to a set of criteria or sub-criteria by weighting each criterion incomplete decision-making process (Kiker et al., 2005). Based on pairwise comparisons that are obtained according to different parameters significance, it determines the weight of importance for different land use.

This technique can be adopted when it comes to decisions or several competing options ahead. In this method a decision tree hierarchy is provided. The decision tree hierarchy depicts the factors compared and evaluates the competing alternatives. Then a series of paired comparisons are made. These comparisons outline the weight of each factor in order to determine the competing options. Finally, the AHP logic integrates the matrices of pairwise comparison in a way that the optimal decision is achieved. Then, weights for the each selected criterion were estimated using AHP and after that weighted overlay method was adopted to establish the suitability map (Muller and Middleton, 1994; Bunruamkaew et al., 2011).

3.3.7. Validation

Several methods for the model validation are available in the literature. Such methods include, Chi-Square–F-test of two images for variance method (Katana et al., 2013; Weng, 2002), kappa coefficient k and Cramér’s V and quantity disagreement and allocation disagreement approaches (Pontius and Millones 2011; Baysal 2013). In order to evaluate the model accuracy, 2006 LULC map was considered as the base map. All the suitability maps and transition area matrix developed for projecting 2016 land use/cover map was utilized as inputs in the CA-Markov module. Actual and simulation maps of 2016 were compared to validate the model. This comparison was carried using Kappa Index of Agreement (KIA) technique. There are three indicators of KIA including (i) Kno is the measure of the overall proportion correctly classified versus the expected proportion correctly classified, (ii) Kstandard is the proportion assigned correctly versus the proportion that is correct by chance and (iii) Klocation is the measure of the spatial accuracy due to correct assignment of values also validate the location between the actual and simulated maps. The possible values of the statistic range of those 3 indices from 0 to 1, where 1 means perfect agreement and 0 means no agreement beyond that expected by chance. The model validation is an important stage in the development of any predictive change model (Eastman, 2012; Pontius, 2000; Pontius and Hao, 2006).

4. RESULTS AND DISCUSSIONS

4.1. Image pre-processing

Atmospheric corrections were performed to reduce the atmospheric effects. In this study radiometric correction was necessary to detect changes in surface reflectance. In the first step equation (3.1), the digital number of the images were converted into the satellite radiance values for each band with image header file and in the second step, the obtained radiance values were converted into reflectance values by using the equation given in (3.2) and (3.3). As a result of these transformations the effects of atmospheric and sun's elevation and azimuth was corrected.

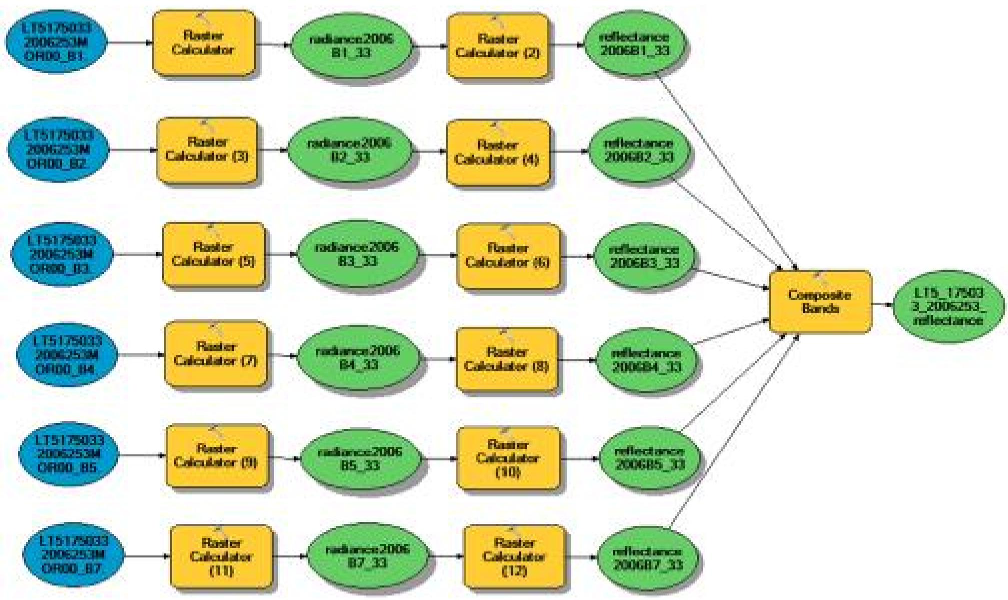


Figure 4.1. Model used in radiometric correction for image in10.09.2006

It can be seen that the original image is darker compared to radiometrically corrected image and image reflection is evenly spread as seen in the following Figure 4.2.

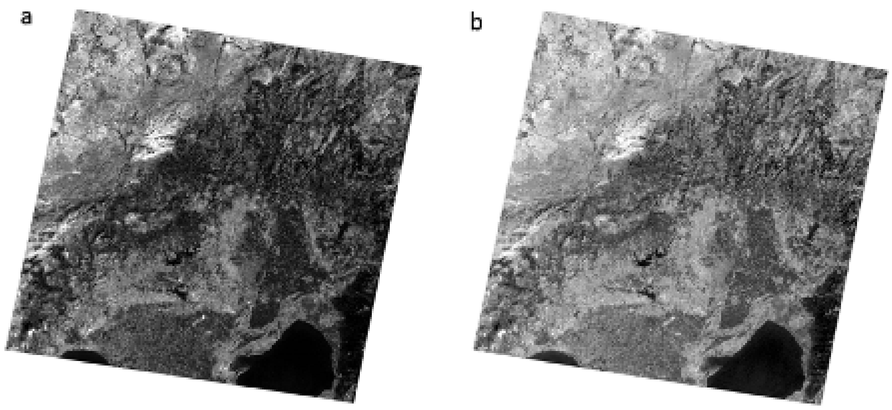


Figure 4.2.a) original image, b) radiometrically corrected image

4.2. Image classification

LULC maps were produced for the years of 1995, 2006 and 2016 by using object-based classification and nearest neighbor algorithm and seven classes including water body, forest, shrub and/or herbaceous vegetation association, open space , built-up area, wetland and agricultural area were identified. Also quantity of each class was calculated (km^2). The process of object-based classification is usually divided into two main workflows of multi-resolution segmentation and classification of the segments. The object-based approach has advantages over the pixel-based approach in terms of classification features and classification units. Within-class spectral variation is decreased by changing classification units from pixels to objects. Also, salt-and-pepper effects that are typical in pixel-based classification is removed by the object-based method. A large set of features characterizing objects' spatial, contextual and textural properties can be derived as complementary information to the direct spectral observations to potentially improve classification accuracy (Liu and Xia, 2010). However, it is possible to correct errors of classes manually after classification. In this way, classification errors are edited systematically. For the years of 1995, 2006 and 2016 LULC maps are shown in Figures 4.3, 4.4 and 4.5 respectively. The area occupied by each LULC is given in Figure 4.6.

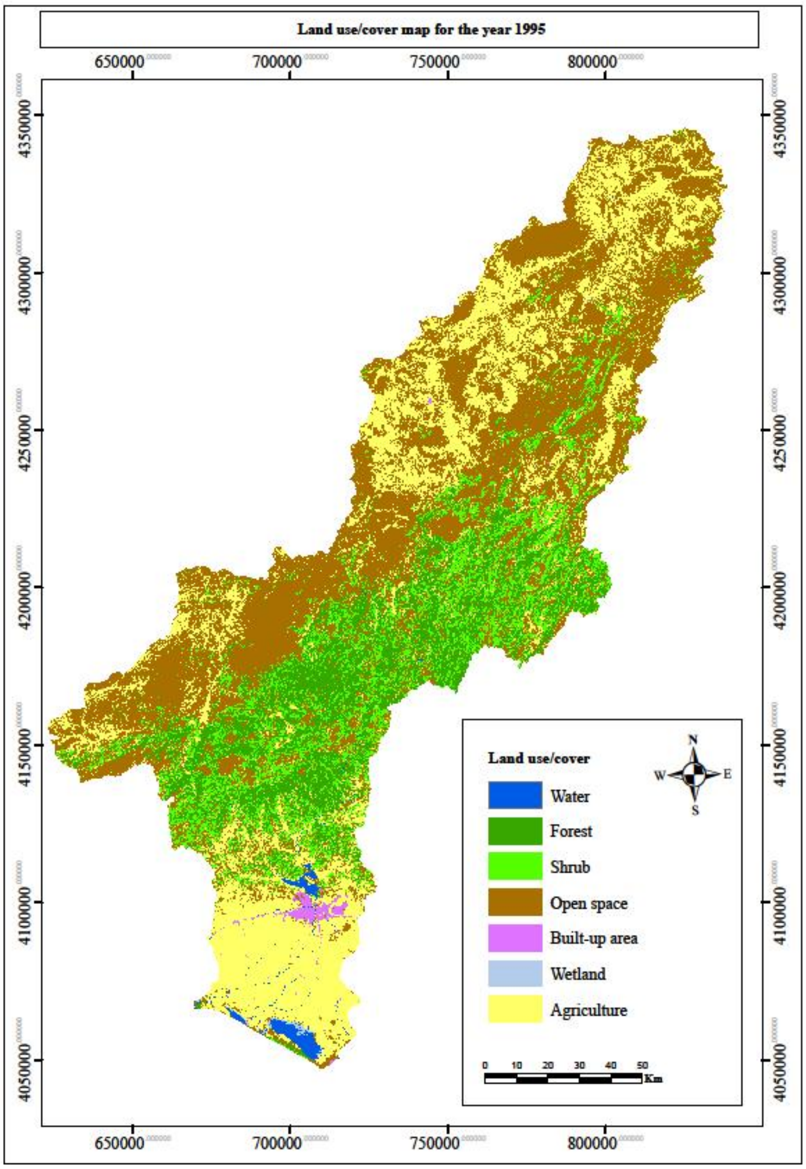


Figure 4.3. Land use/cover map of 1995

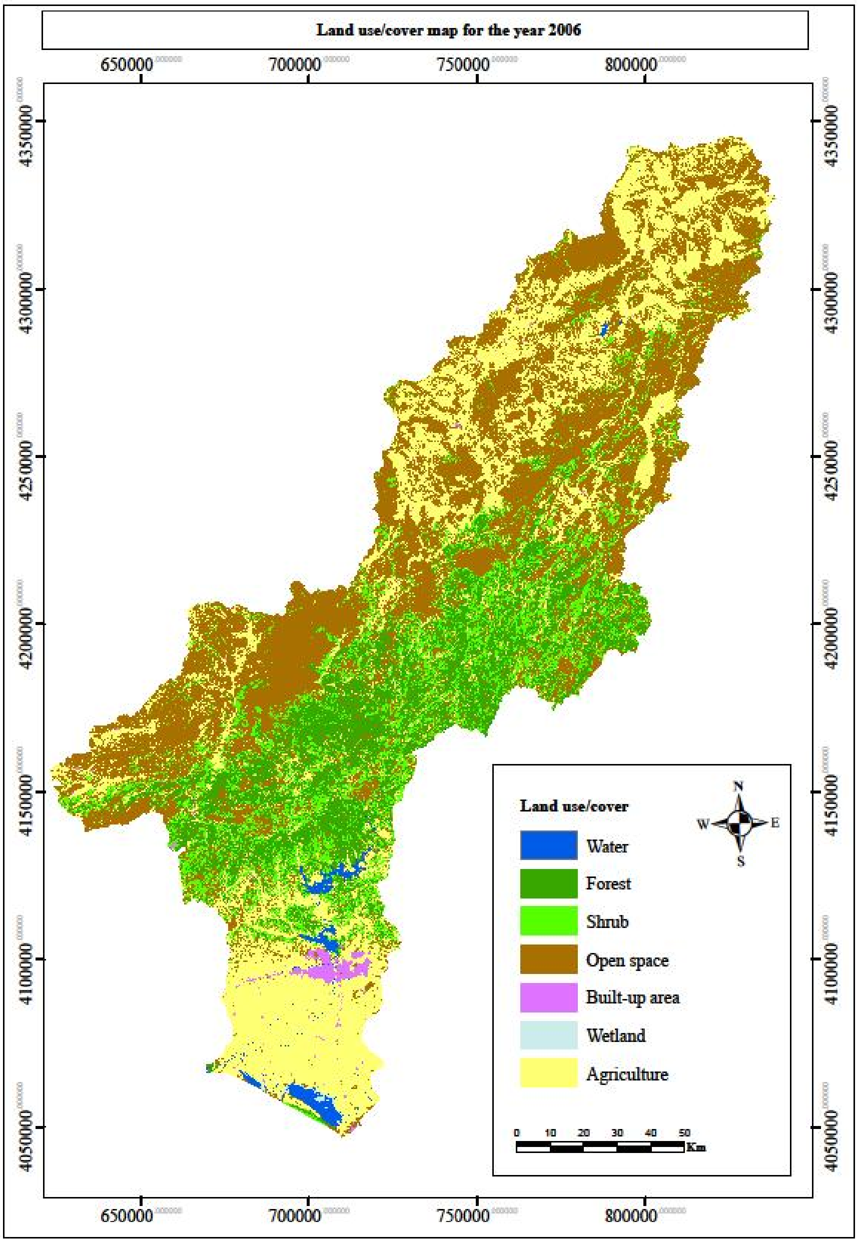


Figure 4.4. Land use/cover map of 2006

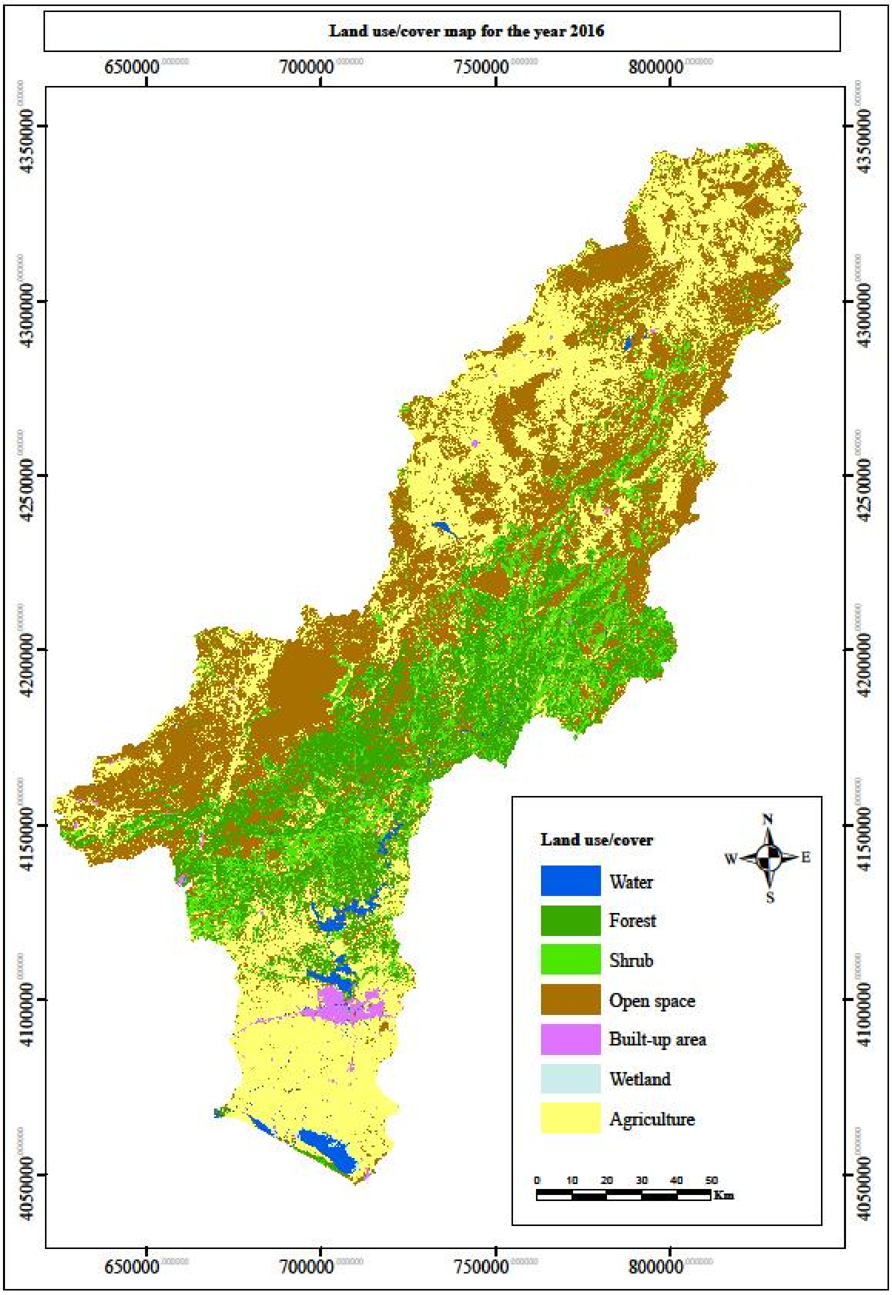
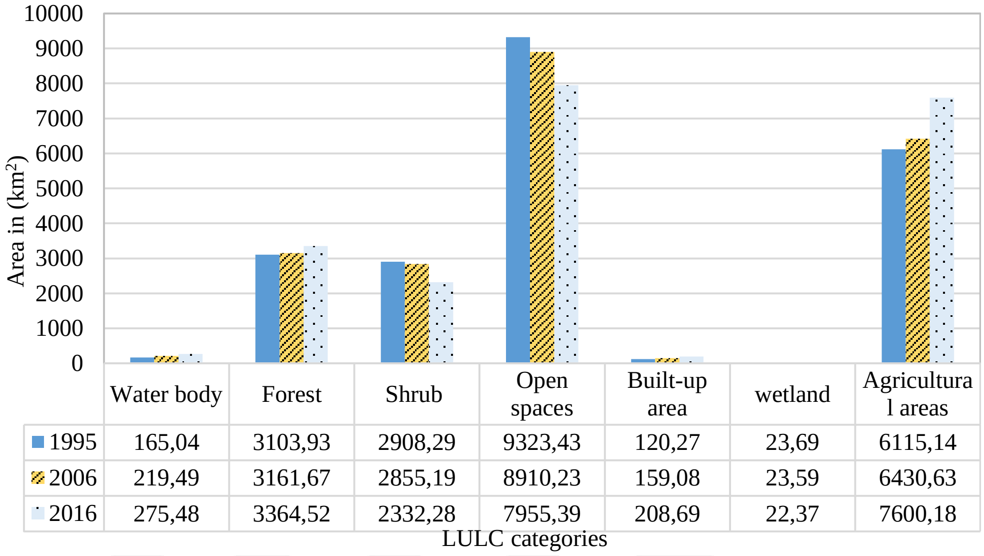


Figure 4.5. Land use/cover map of 2016



	Water body	Forest	Shrub	Open spaces	Built-up area	wetland	Agricultural areas
1995	165,04	3103,93	2908,29	9323,43	120,27	23,69	6115,14
2006	219,49	3161,67	2855,19	8910,23	159,08	23,59	6430,63
2016	275,48	3364,52	2332,28	7955,39	208,69	22,37	7600,18

Figure 4.6. Comparison of areas occupied by each LULC in 1995, 2006 and 2016

4.3. Classification Accuracy

The kappa coefficient and overall accuracy were derived for all maps. Overall accuracies calculated for 1995, 2006 and 2016 maps were 91%, 90% and 91% respectively. The Kappa indices for the years of 1995, 2006 and 2016 were 87%, 88% and 90% respectively. These values are above the minimum threshold value (85%) of interpretation accuracy in the description of the remote sensing data for LULC categories (Cabral and Zamyatin, 2009). The lowest precisions were presented by the classes of shrub and forest. User accuracy for all classes together with Kappa index for the years 1995, 2006 and 2016 are given Table 4.1.

Table 4.1. Accuracy figures of the classified LULC maps

Land use/cover	**Precision**		
	1995	**2006**	**2016**
Water body	1.00	1.00	1.00
Forest	0.82	0.83	0.78
Shrub and/or herbaceous vegetation association	0.76	0.71	0.65
Open space with little or no vegetation	0.93	0.87	0.99
Built-up area	1.00	1.00	1.00
wetland	1.00	1.00	1.00
Agricultural area	0.91	0.95	0.97
Kappa Index	**0.87**	**0.88**	**0.90**

4.4. Change Detection

Cross tabulation is an approach by which quantities of conversions from a particular land cover to another land cover category can be determined (Alphan et al., 2009). In order to understand land encroachment for different land categories the change matrices based on post classification comparison were obtained. This matrix compares the cells on the diagonal and the cells outside the diagonal which gives information on whether the class area is the same on both dates or change to a new class. Tables 4.2 and 4.4 show the results of the cross-tabulation analysis for the seven LULC classes for two date range (1995-2006 and 2006-2016).

Percentage of LULC changes in total of study area and net change for land classes are shown in Tables 4.3 and 4.5. Net change for each class was calculated by subtracting the value of the class later time from the amount of class (km^2) present in earlier time. To visualize the changes that occurred in periods, a simple technique was used to create a final change map for LULC classes (Figures 4.7 and 4.8).

4.4.1. Changes between 1995 and 2006

Table 4.2 shows the changes of different LULC classes from 1995 to 2006. Water body class area was increased by 54.45 km^2 which is resulted from artificial lake called Çatalan in the Seyhan basin. The Çatalan dam constructed between 1982 and 1996 and was opened in 1996 (Fakioglu, 2005). The built-up area covered 165.04 km^2 in 1995 and 219.49 km^2 in 2006, so the net gain of built-up area was calculated 38.81 km^2 which of the 40.95 km^2 of agricultural area and 12.78 km^2 of open space are converted to built-up area. Due to the growth population and migration, especially in Adana, residential and industrial areas was expanded. During this period agricultural areas were increased by 315.48 km^2. The class of open spaces with little or no vegetation showed the largest loss of 413.20 km^2 despite 1679.65 km^2 of agricultural areas converted to open spaces. Also, Table 4.3 shows the positive and negative changes of the LULC and the percent of LULC change for all classes in the total study area.

Table 4.2. LULC change matrix in period of 1995–2006 (km^2)

1995

	Class	1	2	3	4	5	6	7	Total (1995)
	1	137.2437	2.6010	1.1169	3.3849	0.4752	4.5657	15.6510	165.0384
	2	2.5461	2441.9511	289.3536	257.1534	0.0585	0.0297	112.8366	3103.9290
2006	3	19.5561	544.2948	1284.0066	725.5683	1.1916	0.2070	333.4572	2908.2816
	4	11.4930	99.3186	1006.5339	6239.3049	12.7791	1.6173	1952.2872	9323.3340
	5	0.2970	0.0819	0.3339	3.5577	103.6161	0.0000	12.3795	120.2661
	6	3.0204	0.1962	0.0117	1.4661	0.0000	15.6762	3.3237	23.6943
	7	45.3321	73.2276	273.7926	1679.6556	40.9545	1.4904	4000.6161	6115.0689
	Total(2006)	219.4884	3161.6712	2855.1492	8910.0909	159.0750	23.5863	6430.5513	

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.built-up area, 6.Wetlands and 7.Agricultural area

Table 4.3. LULC changes in period of 1995-2006

Class	**Net change (km^2)**	**Change (%)**
Water body	54.45	0.25
Forest	57.74	0.27
Shrub and/or herbaceous vegetation	-53.10	-0.24
Open space with little or no vegetation	-413.20	-1.90
Built-up area	38.81	0.18
Wetland	-0.11	0.00
Agricultural area	315.48	1.45

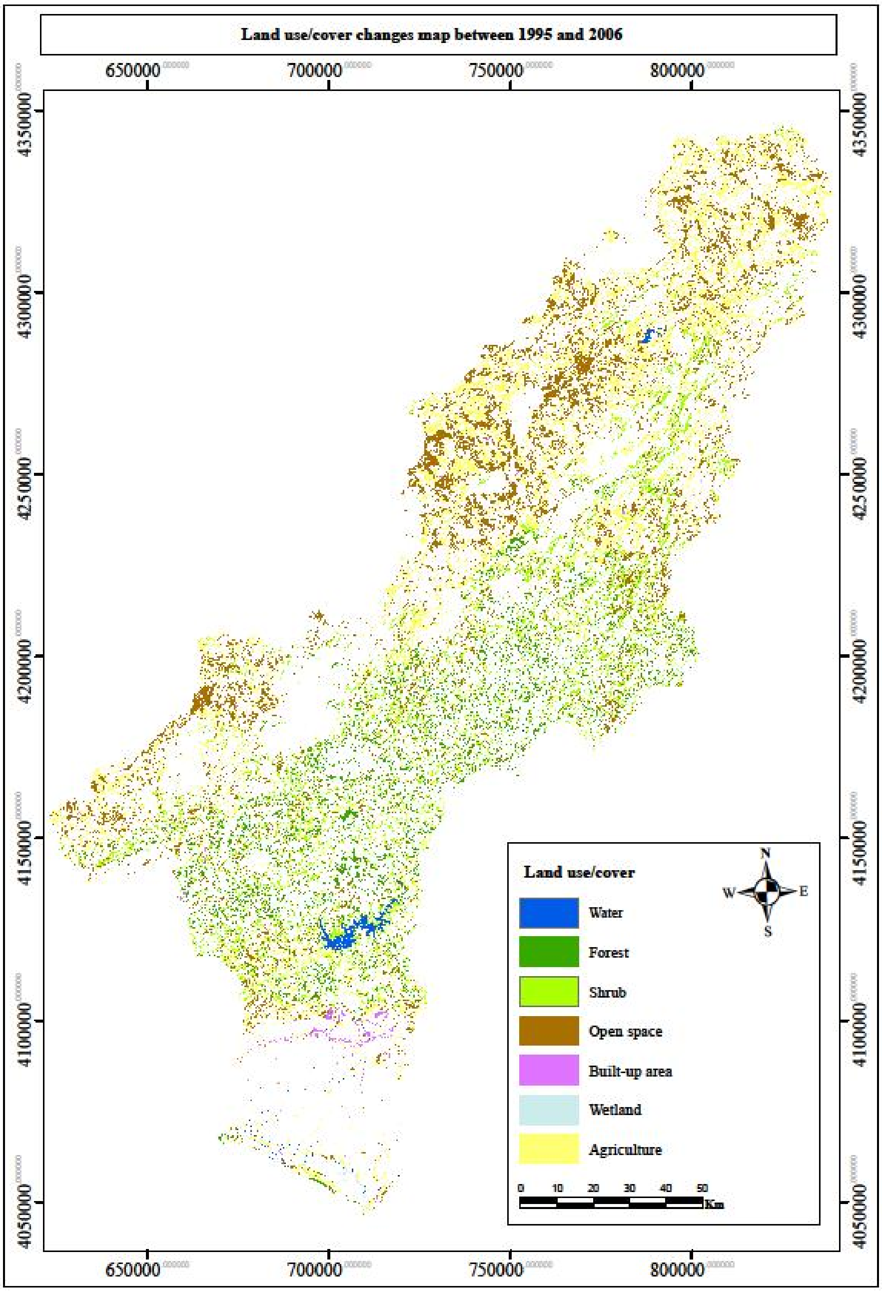


Figure 4.7. LULC change map of 1995 – 2006

4.4.2. Changes between 2006 and 2016

According to change area matrix given in Table 4.4 from 2006 to 2016 the water body class and the class of forest increased by 55.98 km^2 and 202.85 km^2, respectively. The open space loss of 954.91 km^2 was the result of conversion to agricultural area and shrub lands. The overview of changes in land use between 2006 and 2016 showed an increase of built-up area and agricultural lands. The net increase in built-up and agricultural classes were determined as 49.61 km^2 and 1169.55 km^2 respectively during this period. The reasons of increase in built-up class were the rapid urban growth and migration. In the study area, the wetland has slightly decreased from 23.59 km^2 in 2006 to 22.37 km^2 in 2016. Forest cover increased by 202.85 km^2. The reason for increase in forest class was protection and the reforestation activities. The total loss of shrub and/or herbaceous vegetation was 522.91 km^2, which was converted mostly to agricultural land (21.06 km^2) and open space from 2006 to 2016. Small portion of these changes resulted from classification error especially mixing forest and shrub cover. Table 4.4 gives the negative and positive changes of LULC and the percent of LULC change for all classes. Table 4.5 gives the positive and negative changes occurred in the LULC and the percent of LULC change for all classes in the study area.

Table 4.4. LULC change matrix in period of 2006–2016 (km^2)

		2006							
	Class	1	2	3	4	5	6	7	Total (2006)
2016	1	206.6058	1.4616	0.1476	2.9268	0.4176	1.2402	6.6438	219.4434
	2	18.1521	2635.8111	276.8067	192.3066	0.2448	0.0198	38.2509	3161.592
	3	7.5123	381.9924	1119.4281	872.3331	3.6639	0.0099	470.1492	2855.0889
	4	7.8192	247.7844	619.2684	5742.1764	14.9643	3.1932	2274.4890	8909.6949
	5	0.5301	0.1080	0.3690	3.3183	140.9553	0.0000	13.7898	159.0705
	6	6.6645	0.1008	0.2070	1.0737	0.0000	14.1507	1.3905	23.5872
	7	28.1925	97.2630	316.0368	1141.2126	48.4434	3.7575	4795.3674	6430.2732
	Total(2016)	275.4765	3364.5213	2332.2636	7955.3475	208.6893	22.3713	7600.0806	

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.Built-up area, 6.Wetland and 7.Agricultural area

Table 4.5. LULC changes in period of 2006-2016

Class	**Net change (km^2)**	**Change (%)**
Water body	55.98	0.26
Forest	202.85	0.93
Shrub and/or herbaceous vegetation	-522.91	-2.40
Open space with little or no vegetation	-954.84	-4.39
Built-up area	49.61	0.23
Wetland	-1.21	-0.01
Agricultural area	1169.55	5.37

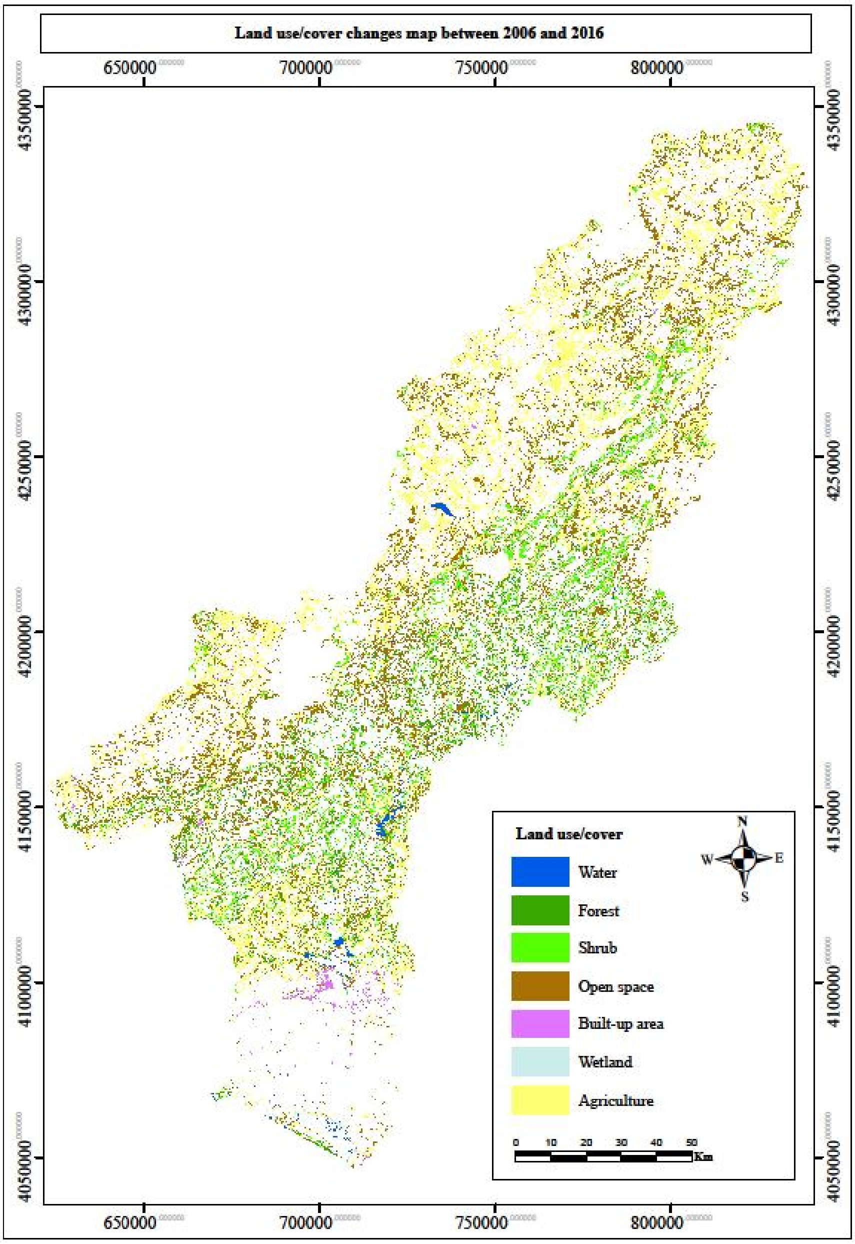


Figure 4.8. LULC change map of 2006 – 2016

4.5. Prediction by CA-Markov model

In order to use the CA-Markov model and predict the land use changes, the IDRISI Selva software was used. The CA-Markov module needs LULC dataset to show the initial states, matrix of transition probabilities calculated with Markov model, suitability map for all LULC categories, a starting point as base map, a contiguity filter and CA number of iterations.

4.5.1. Calculation of transition matrix

Transition probability matrixes and transition area matrixes were derived from Markov chain analysis of LULC maps for time periods of 1995-2006 and 2006-2016. The transition probabilities matrix explains the possibility that each land cover category will change to another category. The transition area matrix explains the number of pixels that are expected to shift from one land cover type to another land cover type on the specified time units (Kityuttachai et al., 2013). Transition areas matrixes and transition probability matrixes for time periods of 1995-2006 and 2006-2016 are given in Tables 4.6, 4.7, 4.8 and 4.9.

Table 4.6. Transition areas matrix for each LULC class from 1995 to 2006

Class	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	19476	681	290	828	128	1313	4381
2	438	266151	56153	47406	0	6	20139
3	2556	71812	139525	95838	124	18	42463
4	1424	11748	152842	641324	1699	229	291137
5	85	25	71	1042	14567	0	3840
6	467	25	0	205	0	1738	513
7	7190	11071	42353	272162	6575	234	454062

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.Built-up area, 6.Wetlands and 7.Agricultural area

Table 4.7. Transition probability matrix for each LULC class from 1995 to 2006

Class	1	2	3	4	5	6	7
1	0.7188	0.0251	0.0107	0.0306	0.0047	0.0485	0.1617
2	0.0011	0.6819	0.1439	0.1215	0	0	0.0516
3	0.0073	0.2038	0.396	0.272	0.0004	0.0001	0.1205
4	0.0013	0.0107	0.1389	0.5828	0.0015	0.0002	0.2646
5	0.0043	0.0013	0.0036	0.0531	0.7421	0	0.1956
6	0.1583	0.0084	0	0.0695	0	0.5897	0.1741
7	0.0091	0.0139	0.0534	0.3429	0.0083	0.0003	0.5721

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.Built-up area, 6.Wetlands and 7.Agricultural area

Table 4.8. Transition areas matrix for each LULC class from 2006 to 2016

Class	1	2	3	4	5	6	7
1	27181	879	81	1554	200	679	3417
2	4144	294495	63620	44404	63	6	8794
3	822	42272	96102	96207	392	3	52207
4	1114	34799	86743	537691	2115	450	318773
5	191	34	115	1157	19325	0	4878
6	967	14	29	158	0	1408	203
7	5921	20552	66534	239557	10144	778	595071

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.Built-up area, 6.Wetland and 7.Agricultural area

Table 4.9. Transition probability matrix for each LULC class from 2006 to 2016

Class	1	2	3	4	5	6	7
1	0.7997	0.0259	0.0024	0.0457	0.0059	0.02	0.1005
2	0.01	0.7087	0.1531	0.1069	0.0002	0	0.0212
3	0.0029	0.1468	0.3337	0.334	0.0014	0	0.1813
4	0.0011	0.0354	0.0884	0.5477	0.0022	0.0005	0.3247
5	0.0074	0.0013	0.0045	0.045	0.7519	0	0.1898
6	0.3481	0.005	0.0104	0.0568	0	0.5069	0.0729
7	0.0063	0.0219	0.0709	0.2552	0.0108	0.0008	0.634

Class: 1.Water body, 2.Forest, 3.Shrub and/or herbaceous vegetation association, 4.Open space with little or no vegetation, 5.Built-up area, 6.Wetlands and 7.Agricultural area

4.5.2. Compilation of suitability maps

One of the steps in predicting of LULC changes is to produce suitability maps. Therefore, the suitability maps were produced for each LULC classes using MCE after selecting constraints and factors based on existing literature and opinion of experts. To predict the spatial pattern of change the variables were standardized between 0 – 255 and then weighted using fuzzy approach based on their influence on the subjected LULC change. The value 0 indicates the restricted areas where as value of 255 shows the higher suitability.

The functions that have probability use to show a fuzzy set are as follows:

- The sigmoidal (s-shaped) function that is a combination of linear and cos2 functions is probably the most commonly used function in fuzzy set theory
- J-shaped functions, that are similar to the sigmoidal membership function
- Linear functions**,** that are similar to the J-shaped function but they have linear sides, and are simple to calculate and have a fixed and well-defined extent (Mandal et al., 2012). The types of membership function are shown in Figure 4.9.

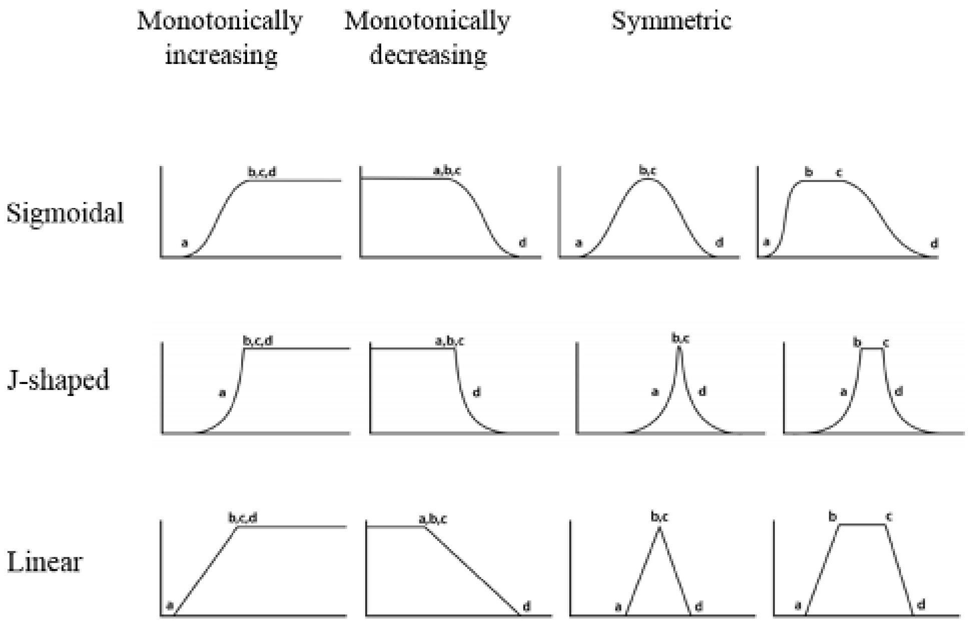


Figure 4.9. Membership function types of fuzzy (Mandal et al., 2012)

a=membership rises above 0 , b=membership becomes 1
c=membership falls below 1 , d=membership becomes 0

Selection of the function type is depended on the information to understand fuzzy membership and on the information about the relationship between the criterion and the decision set. Usually, linear and sigmoidal functions are sufficient.

Natural factors including slope, soil, elevation and distance to the water along with the socioeconomic variables including population, distance to urban and distance to the road network were determined as model variables. Maps of the distance to urban, distance from the road, elevation, slope, distance to water, population density and soil are given Figures 4.10, 4.11, 4.12, 4.13, 4.14, 4.15 and 4.16 respectively.

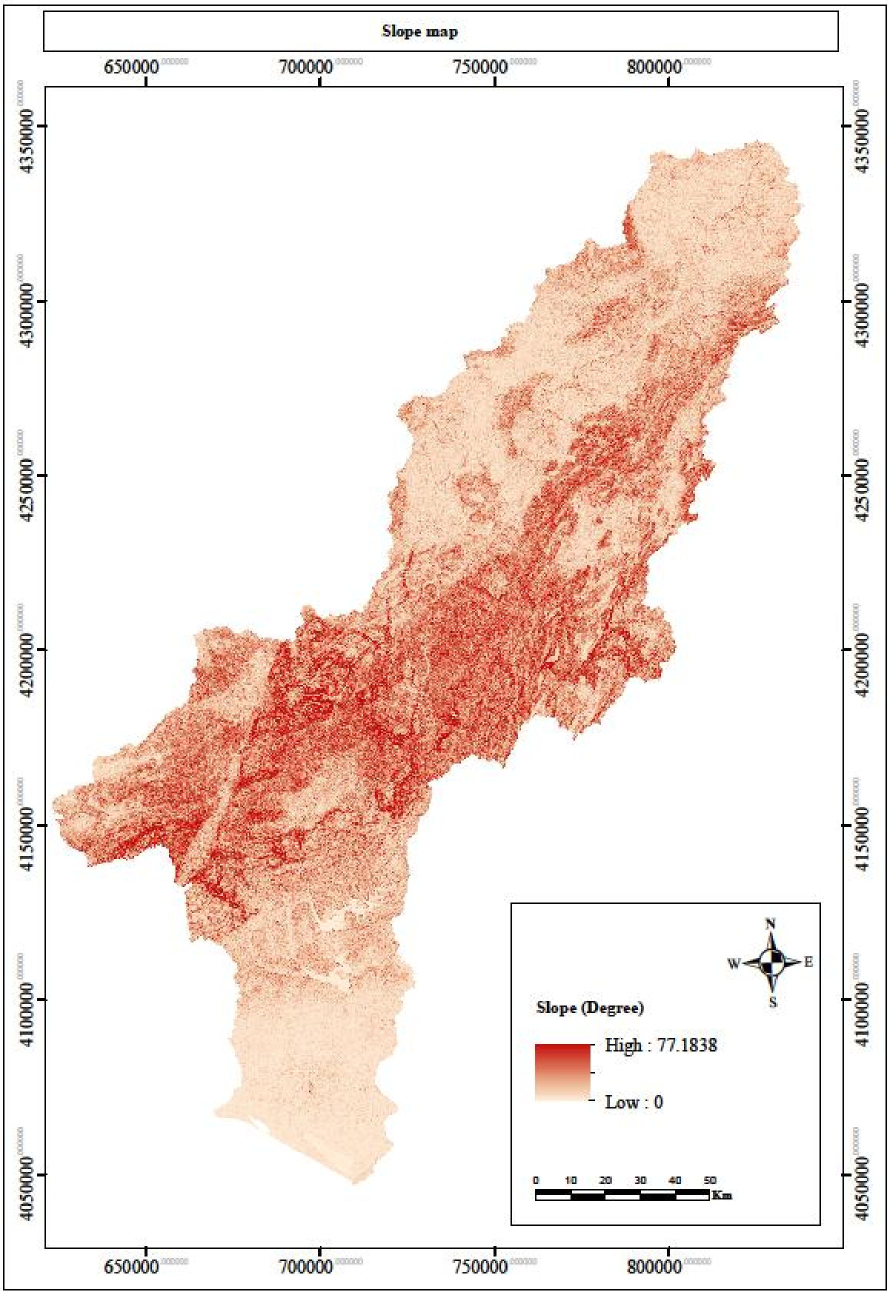


Figure 4.10. Slope map of the study area

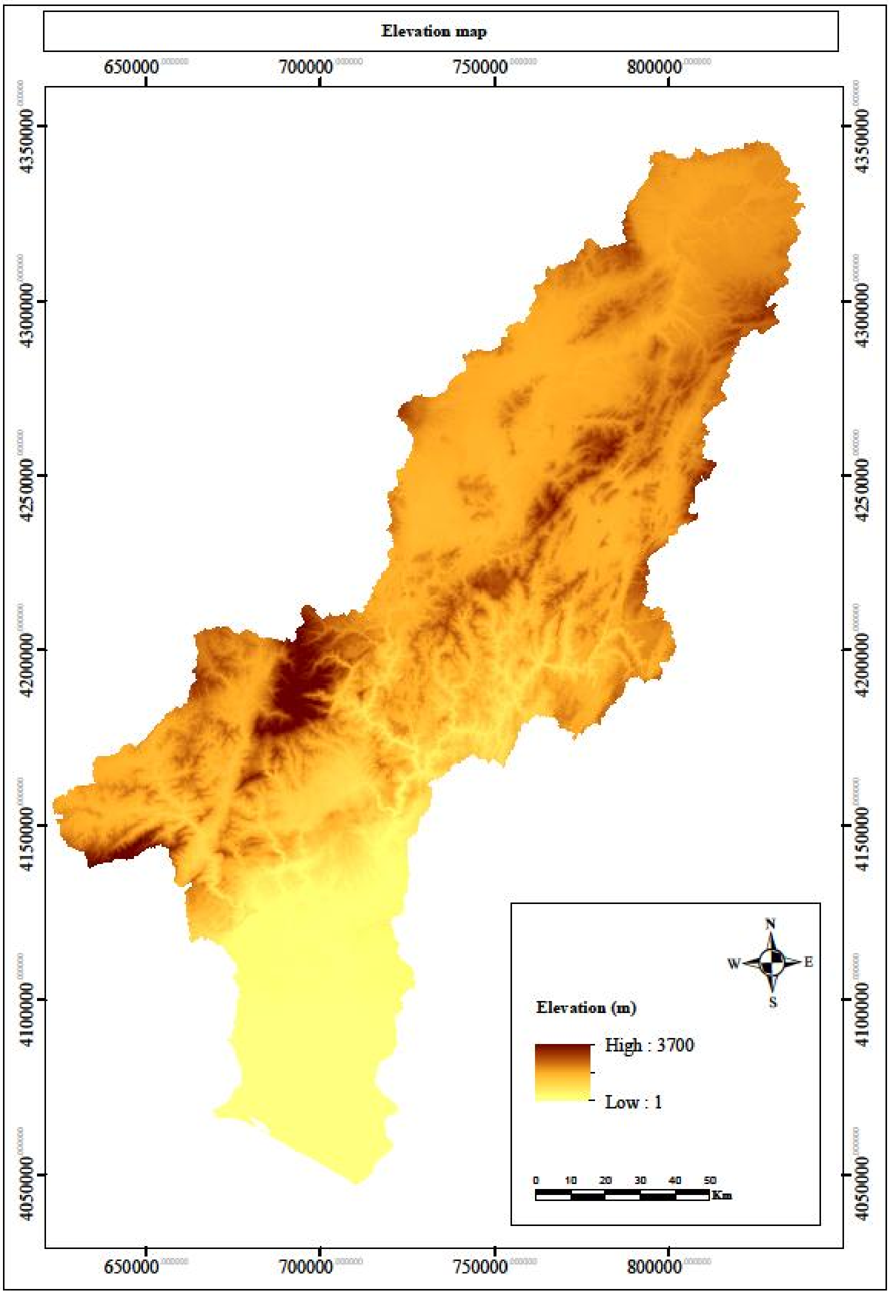


Figure 4.11. Elevation map of the study area

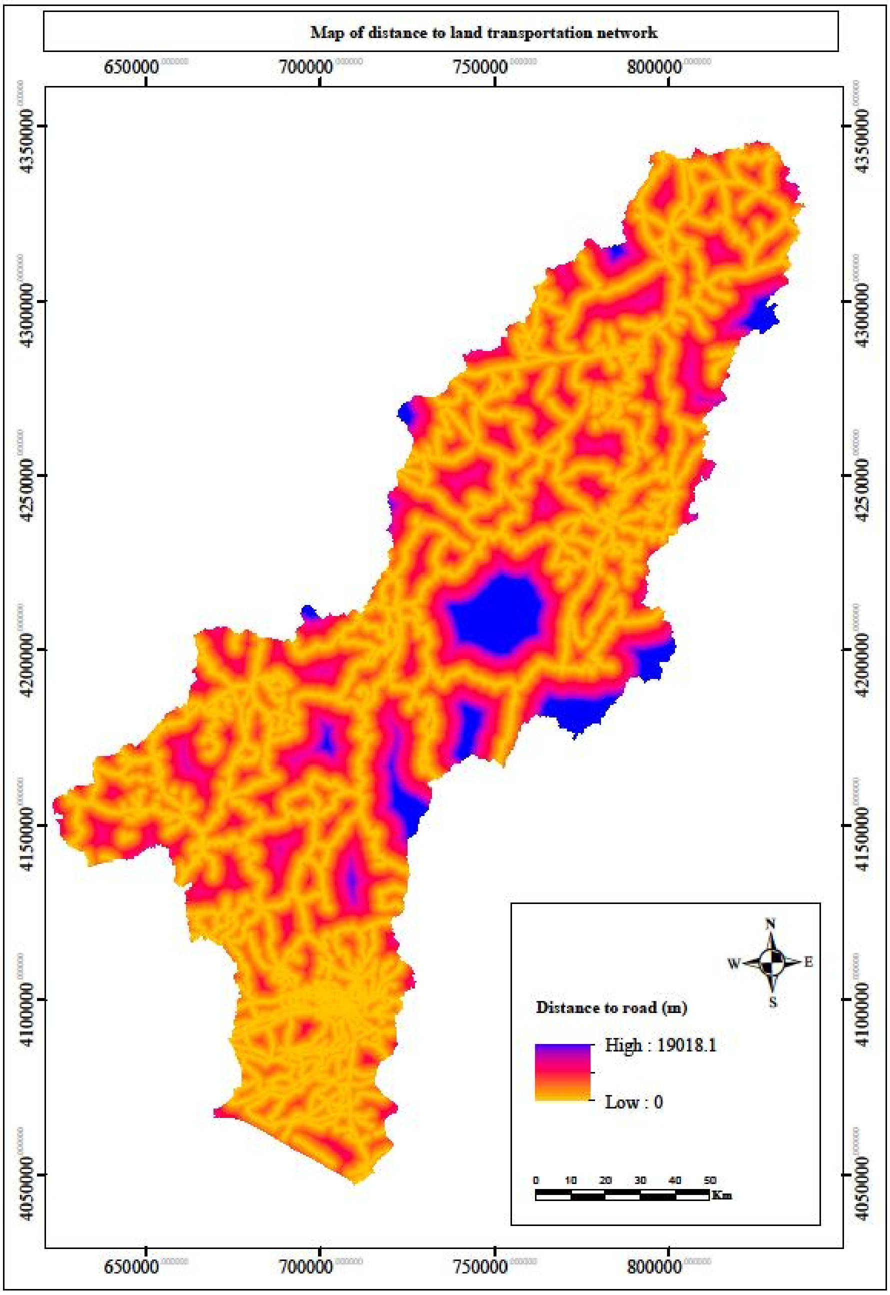


Figure 4.12. Map of distance to land transportation network

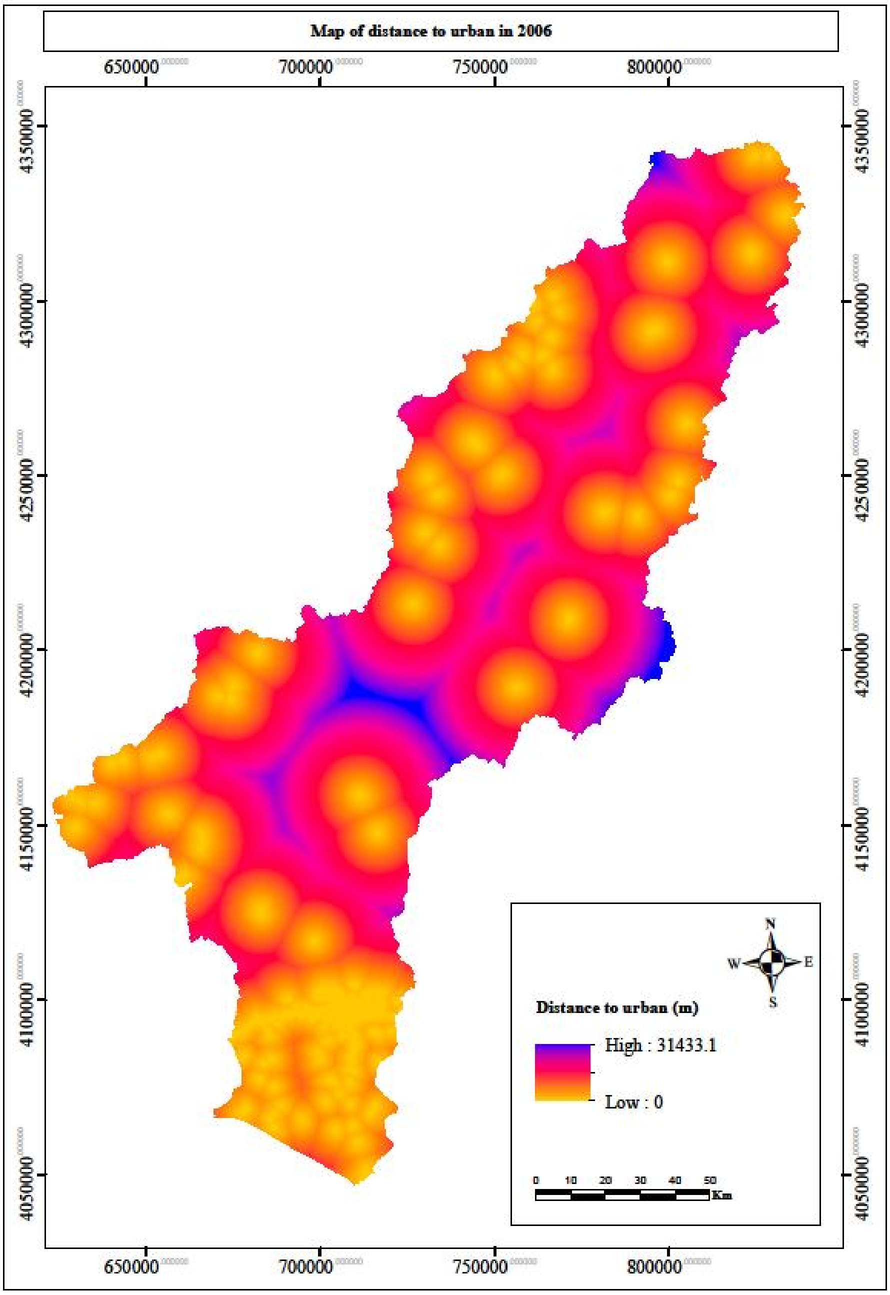


Figure 4.13. Map of distance to urban in 2006

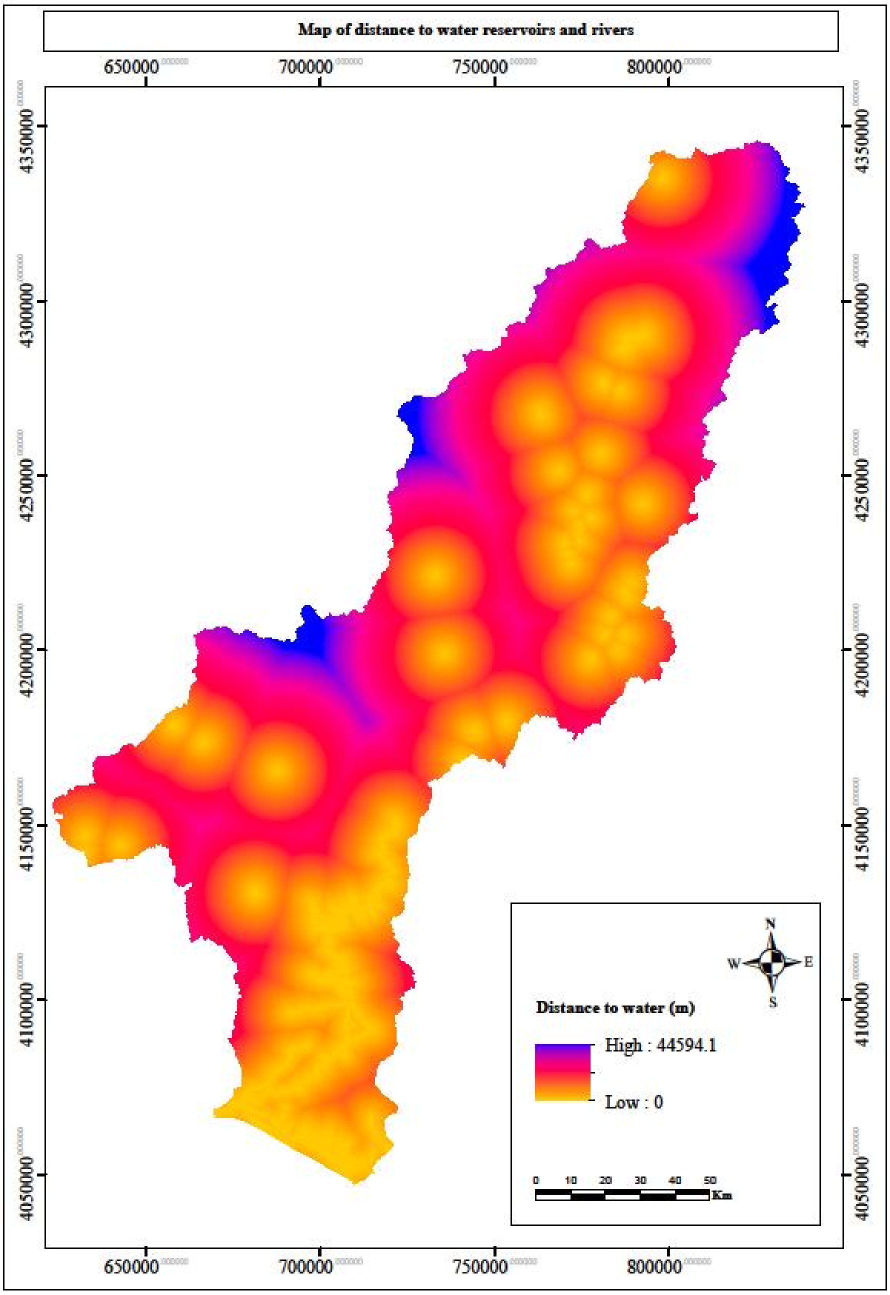


Figure 4.14. Map of distance to water reservoirs and rivers

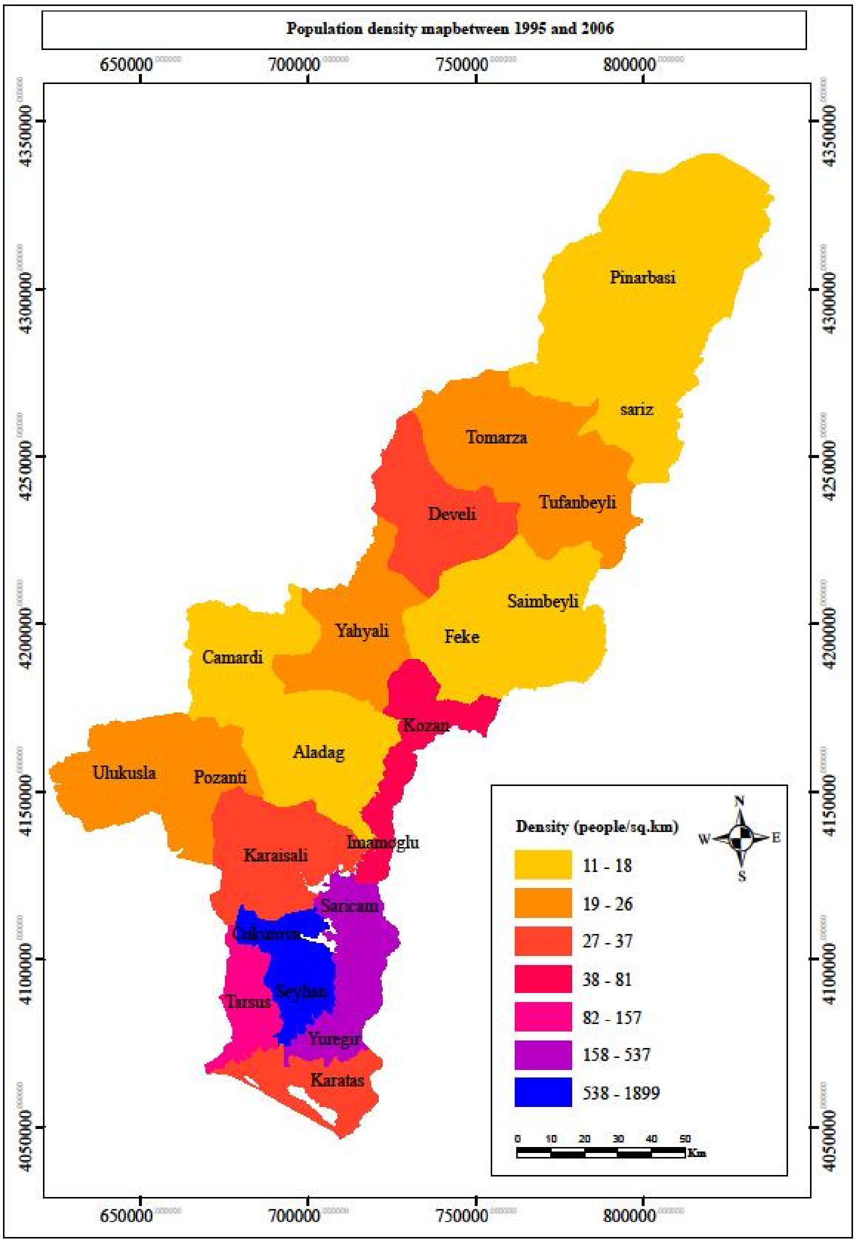


Figure 4.15. Map of population density between 1995 and 2006

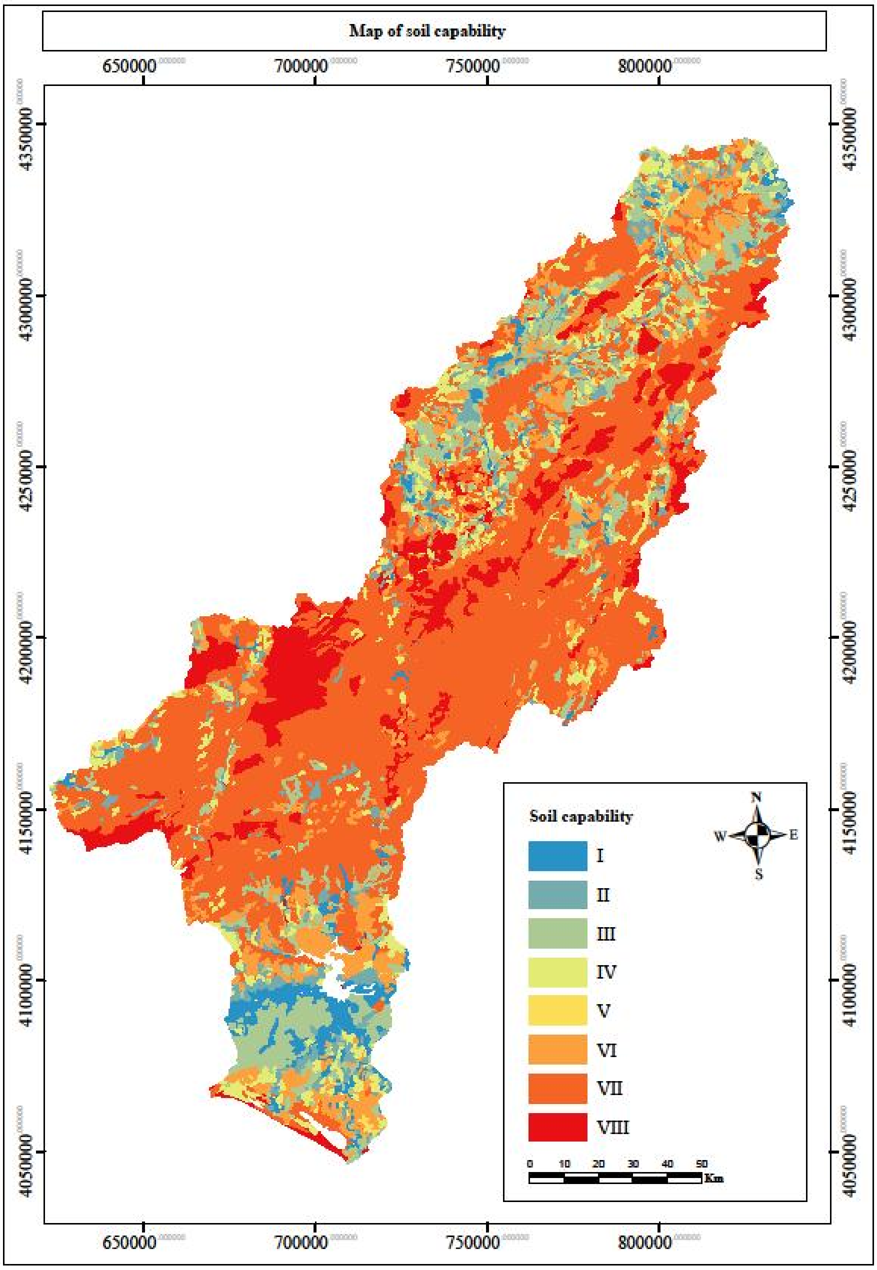


Figure 4.16. Soil map of the study area

4.5.2.1. Suitability map for built-up area

Six factors namely slope, elevation, road distance, water distance, urban distance and population were used to produce suitability map of the built-up class. The factors of distance to urban and road were obtained as the most important factors. In addition, existence water and wetland areas and current built-up class were considered as restricted areas.

Map of distance to urban was created by masking urban class from LULC map. Urban development is mainly achieved through growth from the existing settlement boundary, for this reason, the distance from the boundary of the urban was selected instead of distance to city center. The probability of settlement area in the future is high for the pixels near the existence settlement while it is low for the pixels that are far from settlement area. That means there is direct relation between distance to urban and development of urban. So, chances of conversion to settlement area decrease as the distance increase to settlement area.

A similar work was applied for the roads where thedistance map was derived from digitized images. In urban development, the roads are very important. As a result, the probability of settlement area is high for the locations near the roads while it is low for the areas that are far away from roads. Generally, places with high elevation are not suitable areas for settlement. Considering that chance of becoming settlement area reduces with increase of elevation. Slope map was generated using DEM data.There is an inverse proportion between slope data and the probability of becoming settlement. A buffer (100 m) was created around water bodY then the map of distance to water was produced. The probability of settlement area is high for areas that are near the water. By taking into account of the above mentioned information the factors were standardized as:

Linear monotonically decreasing function was used for distance to urban. The maximum distance from the urban was 31433.1 m. The chances of the pixels turning into the settlement in the future are diminished with increasing distance to urban. Therefore, value 0 shows the highest suitability and 31433.1 shows the lowest suitability of distance. J-shaped monotonically decreasing function was applied for distance to road. The maximum distance from road was 19018 m. The value 100 was defined as the most suitable value and the maximum distance value was chosen as an unsuitable value. The sigmoidal monotonically decreasing function was used for the slope map. Values of 0 and 77.1838 degrees were defined as minimum and maximum value respectively. Linear monotonically increasing function was used for population factor.

The six factors selected for the suitability map of built-up area were weighted using AHP technique. The distance to urban and distance to road were weighted most heavily as they have most influence on the urban development. The variables and weighting values for built-up area are shown in Table 4.10.

Table 4.10. Factors and weight value derived from AHP for built-up area

Factors of suitability map	**Value of AHP weighting**
Slope	0.04
Elevation	0.08
Distance to road	0.41
Distance to water	0.11
Distance to urban	0.30
Population density	0.06

4.5.2.2. Suitability map for water and wetland

Existing wetlands and water bodies were kept during the modelling process. The change in water bodies is mostly due to seasonal effects so no change was forecasted for the future. That is the existing water bodies and wetlands were selected as the factors of multi-criteria evaluation.

4.5.2.3. Suitability map for agriculture

The factors soil, elevation and distance to water was used to produce suitability map of agriculture. Agricultural applications are restricted in areas where elevation is high so monotonically decreasing fuzzy function was used for elevation factor. The soil map was standardized according to groups including eight group (Figure 4.13). Agricultural suitability increases from I group to IV group and decreases toward VIII group. Areas that are near water body are more suitable for agriculture. Sigmoidal symmetric function was chosen for the soil factor, however sigmoidal monotonically decreasing function was used for elevation and distance to water factors. Weighting values of the elevation, distance to water and soil maps used in determining suitable areas for agriculture are given in Table 4.11.

Table 4.11. Factors and weight value derived from AHP for agricultural area

Factors of suitability map	Value of AHP weighting
Soil	0.35
Elevation	0.20
Distance to water	0.45

4.5.2.4. Suitability map for open space

For open spaces, existence open space, slope and road distance factors were taken into account. Locations with high slope and closeness to existing open space were considered as the most suitable places. The probability to be open space in the areas farther away from roads are high. Sigmoidal monotonically increasing function was used for slop and elevation factors and linear increasing function was used for existence open space. The weights of the factors are given in Table 4.12.

Table 4.12. Factors and weight value derived from AHP for open space

Factors of suitability map	Value of AHP weighting
Slope	0.38
Distance to Road	0.33
Elevation	0.09
Existence open space	0.20

4.5.2.5. Suitability map of forest

The factors slope and distance to road was selected for the forest. Slope of existence forest in the study area was about between 1 and 50 degrees. By taking into account of this slope range and selecting appropriate fuzzy function (linear symmetric), suitability map for the forest was produced. Similar procedure was applied for shrub land.

4.5.3. CA filter and number of iteration

After generating the suitability maps for each LULC class a suitable image collection was produced with grouping all of the suitability maps together (Figure 4.17) and was used as input for the CA-Markov model. To obtain a spatially explicit contiguity-weighting factor to change the state, CA filter (5 × 5) was used. This is performed to change the state of cells according to its neighbors. The suitability of a pixel is obtained by the pixel values within this filtering kernel. The more pixels of the same category of LULC exist in the neighborhood, the more the suitability value for that particular land cover type increases. Otherwise the pixel value remains the same (Eastman, 2009). Iterations was set to 10 (time lag between 2006 and 2016) in order to predict 2016 LULC map and it was set to 20 for predicting 2036 LULC map. Thus, the time interval between modelling was set to be for yearly. During each iteration, pixels with the highest transition probability and highest suitability score for a particular class transition to a new class while pixels with lower probabilities and lower suitability scores remain unchanged (Eastman, 2006). To achieve the best result, model many (seventeen) times was run with different factors and different weight of factors and results of model validation were compared. Predicted LULC map for the year 2016 is given in Figure 4.18.

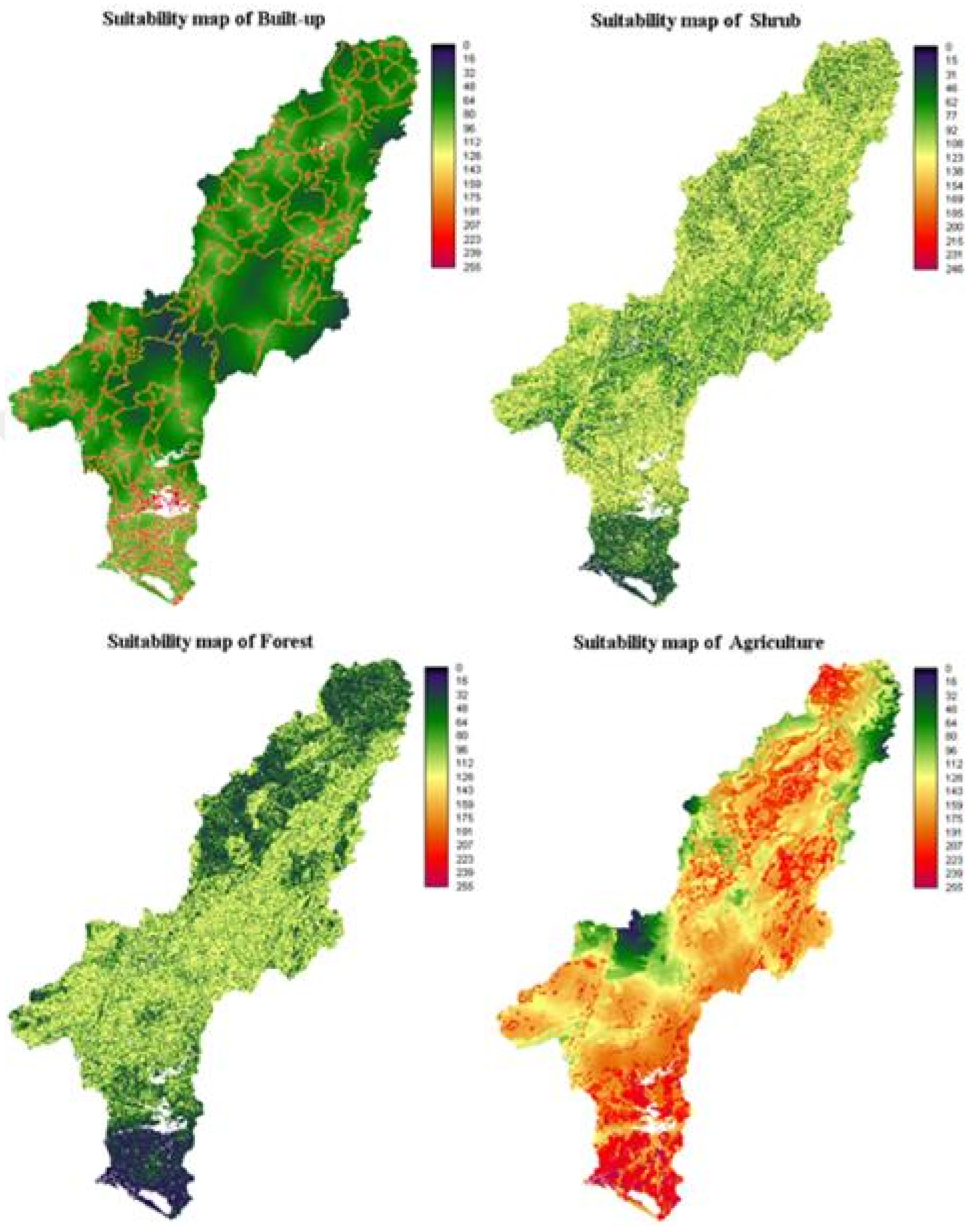


Figure 4.17. Suitability maps of built-up, shrub, forest and agricultural areas

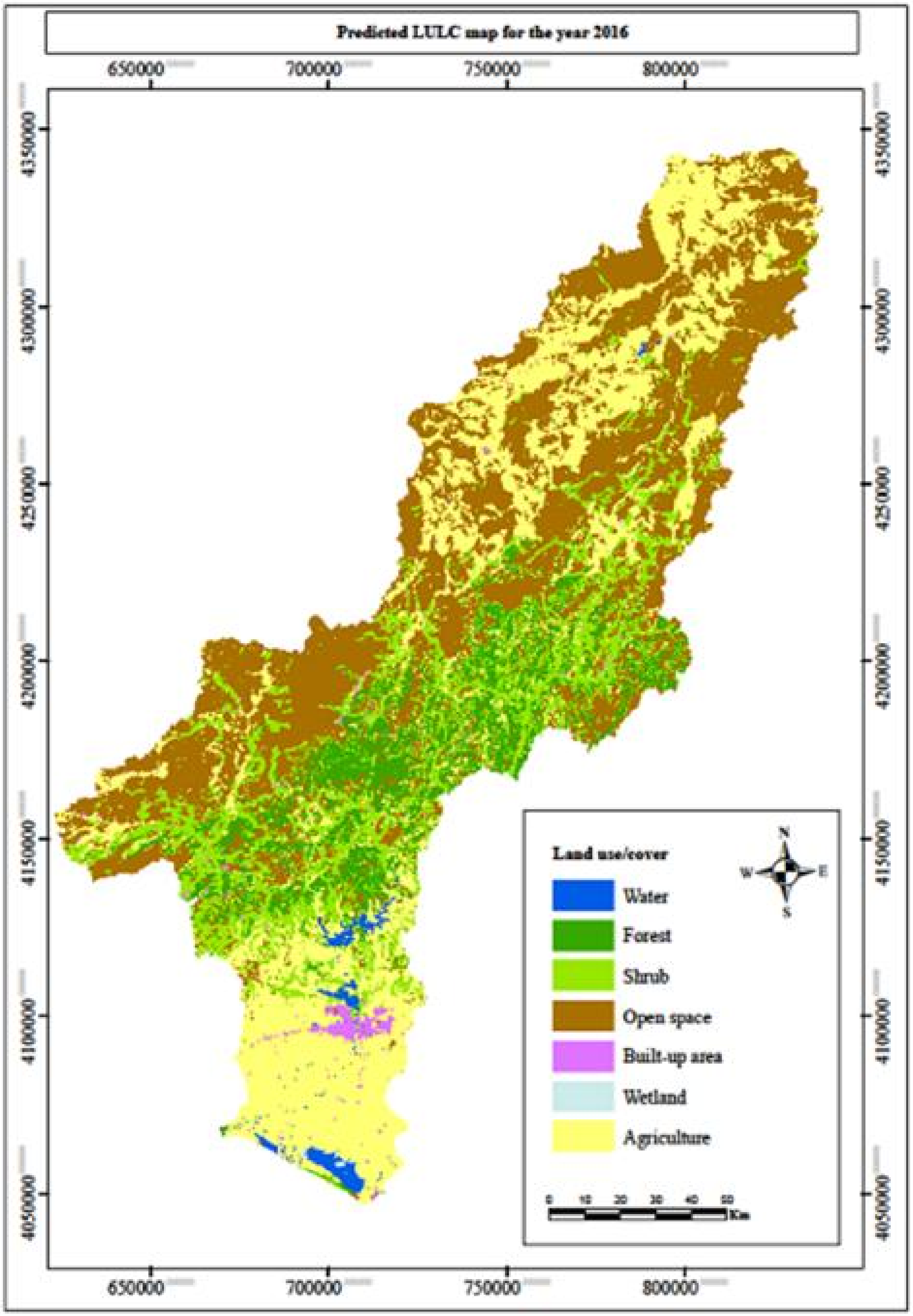


Figure 4.18. Predicted LULC map of 2016

4.6. Model validation

Similarities between actual image and simulated image were compared using the KIA approach for the model validation. The standard Kappa index is used to check whether the model is valid or not (usually the Kappa Index for a valid model is >70%) (Wen, 2008). The KIA approach gave the standard Kappa of 0.7698, Kappa for no information of 0.8613, Kappa for grid-cell level location of 0.8217 and Kappa for stratum-level location of 0.8217 which indicates results of model validation are reasonable (Table 4.13). Overall disagreement and the overall agreement were obtained 0.12 and 0.8786 respectively (Table 4.14). The overall agreement consists of agreement due to chance, agreement due to quantity and agreement due to grid cell level location. Another factor commonly used in the literatures which measures of agreement between maps called M(m) (Pontius, 2006). It describes the agreement between the reference map and the unmodified comparison map. It is the proportion of grid cells classified correctly. It confounds agreement due to quantity and agreement due to location. Here the M(m) obtained a value of 0.8786 which was considered a good matching (Table 4.14). After acquiring reasonable results for the 2016 simulation, LULC prediction was performed for the year 2036.

Table 4.13. Kappa Index of Agreement of ability to predict 2016 LULC

Statistic	**Index**
Kno	0.8613
Klocation	0.8217
KlocationStrata	0.8217
Kstandard	0.7698

Table 4.14.Agreement/disagreement components resulted from validation analysis

Information of Allocation	No[n]	Medium[m]	Perfect[p]
Perfect[P(x)]	P(n)= 0.4609	P(m)= 0.9667	P(p)= 1
PerfectStratum[K(x)]	K(n)= 0.4609	K(m)= 0.9667	K(p)= 0.9995
MediumGrid[M(x)]	M(n)= 0.3705	M(m)= 0.8786	M(p)= 0.8775
MediumStratum[H(x)]	H(n)= 0.1250	H(m)= 0.4729	H(p)= 0.4738
No[N(x)]	N(n)= 0.1250	N(m)= 0.4729	N(p)= 0.4738
AgreementChance			0.1250
AgreementQuantity			0.3479
AgreementStrata			0.0000
AgreementGridcell			0.4058
DisagreeGridcell			0.0880
DisagreeStrata			0.0000
DisagreeQuantity			0.0333

4.7. Prediction

The optimal transition rules for the model can be calculated using determined iterations number then used to predict LULC in 2036. CA-Markov model was employed to predict LULC for the year 2036 after acquiring reasonable results for the 2016 simulation. The transition area matrixes and transition potential maps, the future patterns of LULC were predicted by using the 2016 LULC as base map, as shown in Figure 4.19. The prediction showed expansion of built-up area in the population centers especially Adana province. The expansion might be happening because the lower of basin area is suitable for the development of built-up area since it is low to moderate elevation and flat slope and growth of population or in-migration. It also showed the disappearance of open spaces with little or no vegetation and forest that might be converted into built-up area and agricultural area. It showed 8% increase of agricultural land, no significant changes for wetland and water body category. The most increasing area was built-up area, about 50% from 2016 to 2036.

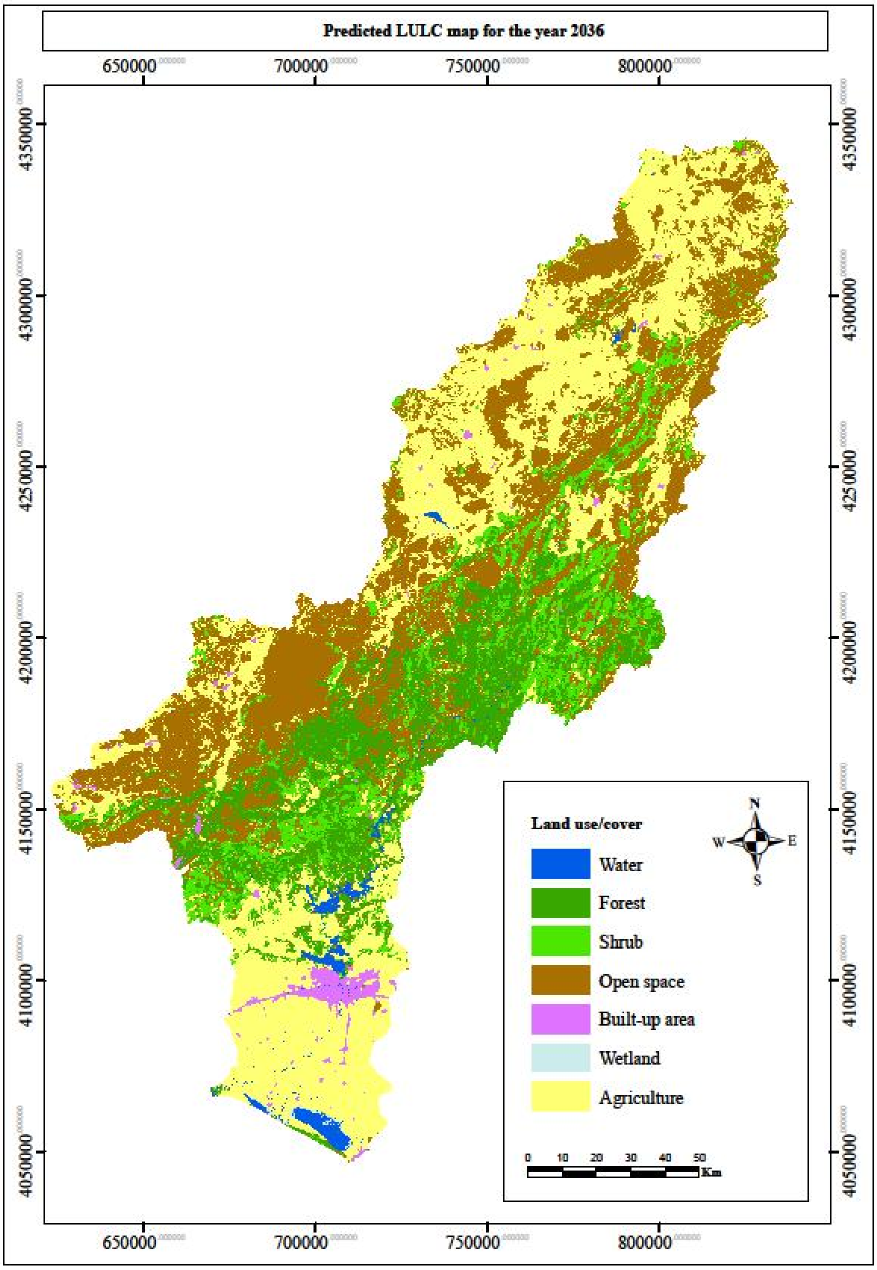


Figure 4.19. The predicted LULC map of 2036 by CA-Markov

5. CONCLUSIONS

In this study, the LULC changes in Seyhan basin were modelled and simulated using classified LULC maps of 1995, 2006 and 2016, and integrated CA-Markov model that combines the cellular automata and Markov chain models. Several Landsat images were used to generate LULC maps and to acquire the LULC change patterns. Firstly radiometric correction was applied on the images then classified using object-oriented classification technique to produce LULC maps for different years (1995, 2006 and 2016) based on CORINE classification scheme. The accuracy of the classification results is crucial for both the change analysis and the modelling approaches. A post-classification comparison technique which is one of the most commonly used methods of change analysis in the literature was employed, for performing change detection. A pixel-based comparison was used to produce change information on pixel basis and thus, interpreted the changes more efficiently by taking the advantage of ‘‘from-to’’ information. The change between 1995-2006 and 2006-2016 was analyzed.

The overview of changes in land use showed an increase of built-up areas for both periods because of the population growth and migration. It showed an increase of agricultural areas from shrub land and open space area. The results showed an increase of forest cover during the period of 2006-2016 because of protection and the reforestation activities. A spatio-temporal transition matrix was constructed from the classified images and applied in the proposed model to simulate land use changes in the study area. Setting transition rules in the form of suitable maps based on MCE allowed for consideration of various factors that are commonly used in land use planning and decision-making. The creation of the suitability maps has been a time-consuming process and it is related to the used digital data as well as user's level of knowledge about the study area. In order to achieve accurate future LULC results, an expert understanding of the interactions and the influence of the factors with LULC was very important in assessing and aggregating weighted maps (criterion) during the MCE process. So, this study provided an important contribution to LULC change analysis by integrating both natural (slope, soil, elevation, and distance to the water bodies) and population, distance to urban and distance to the road networks variables into the CA-Markov model. The overall modelling success (k-standard) was obtained 77 % for projected LULC map in 2016 and the overall agreement (M (m)) that is the proportion of grid cells classified correctly, with a value of 88%. The accuracy assessment of the simulated LULC was based on the transition matrix results. Such approach suggests that attention should be paid during the time of preparation of suitability maps as well as the transition matrices. Once the suitability maps, as well as the transition matrices are accurately prepared, then, accurate results of predicted future LULC are ensured.

The CA-Markov approach is frequently used for LULC in the literature. When the earlier studies are examined, it has been found a good performance of this model. In a similar study, Hyandye and Martz (2016) simulated LULC change of Usangu basin (Tanzania), in 2020 based on LULC of 2000, 2006 and 2013 using CA-Markov. Social, edaphic, climatic and landscape geomorphology factors governing the LULC changes and distribution were used to prepare suitability maps that it is different from the used factors in this study. It was obtained the values of 67% and 91% for the standard kappa coefficient (k-standard) and overall agreements respectively. Roy et al., (2012) used CA-Markov to model and predict LULC the southeastern hill tracts of Bangladesh. They used multi-temporal Landsat imagery to generate LULC maps but in the simulation process, some important parameters like physical and existing policy were excluded due to the lacking of data and they just used population growth and climate factors. They carried out change analysis using Land Change Modeler (LCM) technique. The result obtained from the validation process presented an overall accuracy of 90 %. In another study, Berberoglu et al. (2016) applied CA-Markov model to forecast the urban growth of Adana city. Aerial photos and satellite images with different resolution ranging from 2 to 10 meters were used to calibrate and validate models and future growth was projected for the year 2023. The result obtained from the validation process presented an overall accuracy of 72 %.

Finally, the LULC trends were simulated for the year 2036 through the use of CA-Markov model. The result showed that the areas of built-up in Seyhan basin increased by 50% from 2016 to 2036. So, built-up area increased from 208.69km^2 in 2016 to 314.93 km^2 in 2036. Majority of this expansion was in the population centers. During this period, forest and open space lands decreased by 5% and 7% respectively. It showed 8% increase of agricultural land, no significant changes for water body and wetland areas. The results showed that the combination of satellite remote sensing, GIS and CA-Markov model provided useful information to predict LULC dynamics for future which could be consequently be used for land use planning. One good advantage of applied CA-Markov chain model is that the model needs limited data to simulate and predict any future land use change explicitly, i.e. at least two land use maps in different time spans. On the other hand, the CA-Markov model absorbs the benefits from the time series and spatial predictions of the Markov and CA theory, and it can be used to carry out the spatio-temporal pattern stimulation. So, a CA-Markov model is a robust approach in the spatial and temporal dynamic modelling of land use changes because GIS and RS can be efficiently incorporated. It was assumed that model prediction results would be in agreement with past change trends so the accuracy of maps used for the modelling is important to obtain an accurate result. In this study, the application of remote sensing, GIS and modelling was proven as an effective means for LULC change analysis and produced meaningful information about land use system of Seyhan basin. However, it involves some limitations, such as; Challenges in acquiring cloud free satellite sensor imagery with an appropriate spatial resolution, difficulty in differentiating the signature of some LULC features.

It always requires to consider many factors like socioeconomic, physical, existing policy and so on, to get more accurate result from the simulation of LULC.

It is essential to consider the changes in conditions affected by these factors, when predictive models are adopted to figure out the trends and rates of land use change in the future. Otherwise, the results of the model would be away from the reality. The experiences obtained from this work put forward some recommendations for future research. High-resolution satellite images can be used to increase simulation accuracy. Another factor such as metrological data can be used in combination with the factors used in this research within the model (CA-Markov) or by integrating another model like logistic regression. It is possible to get better understanding of LULC changes. This research can be compared with another model such as CLUE-s model as further study.

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