Modeling Land-Use Changes in the South Nation Watershed using Dyna-CLUE

by

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A Thesis

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To my wife Reine and my son Peter

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ABSTRACT

The South Nation watershed is located in Eastern Ontario, Canada and managed under the authority of the South Nation Conservation (SNC). The watershed covers an area of 400,000 hectares with four dominant categories of land-use classes (60% agriculture, 34% forest, 5% mixed urban, and 1% other). Water quality is a great concern for the SNC as many anthropogenic activities generate harmful pollutants (such as heavy metals, nitrogen, phosphorus, and pesticides) that are discharged to the river through surface and groundwater flow. The discharge patterns of these pollutants are mainly driven by land-use distribution within the watershed which has been constantly evolving with urbanization and intensification of agriculture. Major changes in land-uses can potentially offset current SNC efforts to mitigate water pollution.

The objective of the current study is to predict land-use series of maps for the South Nation watershed starting from 1991 to 2020. The prediction is carried out using the land-use allocation algorithm of the Dyna-CLUE (Dynamic Conversion of Land-Use and its Effects) model which is implemented for local regions. Dyna-CLUE is a spatially explicit hybrid land-use allocation model that combines estimation and simulation models, and its allocation procedures predict future trends of land-use surface (estimated from historical trends). The binary logistic regression is used to link preferences of land-use classes and potential demographic and geographic driving factors. Expert judgment was used to select a set of spatial driving factors believed to be responsible for changes in land-use distribution in the South Nation watershed. Three different scenarios for future development of the region were considered, with different initial conditions and conversion restrictions. The simulation

results were evaluated using visual and statistical validation techniques to assess the performance of the model in generating maps similar to reality.

The Dyna-CLUE model was successfully applied to the South Nation watershed. It was observed that the simulated maps generated from the model were in good agreement with the reality maps. This was confirmed through statistical validation via map pair analysis (error matrix) used to assess the overall accuracy of the model predictions. Results showed that the model was sensitive to land-use restrictions. Such type of modeling can be valuable for assessing the land-use changes at the local level, and setting up a decision support system for the South Nation Conservation towards sustainable land-use management in the watershed. Better results are expected to be achieved with more reliable datasets (i.e., accurate classification of land-use types in reality maps). Data availability and quality were the main obstacles that faced this research work. Our work has the merit to be the first application of CLUE model in Eastern Ontario.

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LIST OF ABBREVIATIONS

AnnAGNPS	Annualized Agricultural Non-Point Source
BLR	Binary Logistic Regression
CLUE-S	Conversion of Land-Use and its Effects at Small regional Extent
Dyna-CLUE	Dynamic Conversion of Land-Use and its Effects
FPF	False Positive Fraction
GIS	Geographic Information System
ROC	Relative Operating Characteristic
SN	South Nation
SNC	South Nation Conservation
SPSS	Statistical Package for the Social Sciences
TPF	True Positive Fraction

CHAPTER 1

INTRODUCTION

1.1. Background

Land cover is the layer of soil and biomass including natural vegetation, crops, and infrastructures that cover the land surface. Land-use is the means through which humans exploit the land cover (Verburg *et al.*, 2000). Land-use change is the modification in the purpose of the land cover, which is not only the change in land cover, but also changes in management. Change detection is a process of identifying and analyzing the differences of a phenomenon through monitoring at different times. The detection and analysis of changes in multi-temporal remote-sensing data have achieved remarkable success in several application domains (Soepboer, 2001).

In the last three decades, the South Nation (SN) watershed has accomplished an outstanding economic growth, which was reflected in an increase in the urban areas and decrease in the rural areas. This urbanisation expansion resulted in continuous conversion of some agricultural land-uses to urban uses including residential, industrial and infrastructure projects (SNC, 2006). Consequently, many questions arise such as; how does this process occur? Which type of land-use is more likely to be replaced by urban? Where and how fast does that urbanisation expansion occur? Which driving factors are behind such process? Modeling can be employed to answer these questions and also to predict land-use conversions. Several types of models have been developed, however most of them are at the descriptive level rather than at the predictive level (Tian *et al.*, 1993).

1.2. Types of Models

Mulligan and Wainwright (2004) classified models into two major types: physical (or hardware) and mathematical models. Physical models are scaled-down versions of real-world situations that are used when mathematical models would be complex, uncertain and/or inapplicable due to lack of knowledge. Several mathematical models simulate land-use changes based on human activities and socio-economic drivers. The most known ones are Conversion of Land-Use and its Effects (CLUE) (Veldkamp and Fresco, 1996), Cellular Automata (CA) (White *et al.*, 1997), and Land-Use Cover Changes (LUCC) (Lambin and Geist, 2002).

1.3. Research Problem and Objectives

Land-covers have major effects on natural resources, productivity and rural living conditions which directly influence our lives through the changes of the landscape and living environment (Palang *et al.*, 2000). Those changes are often caused by socio-economic driving factors (Riebsame *et al.*, 1994). The study area (South Nation watershed) had undergone significant land-use changes during the last three decades (SNC, 2006). It is necessary to investigate the changes in land-use pattern to have better understanding of this process. Spatial simulation of land-use changes is very important to determine and quantify the interaction between land-use dynamic changes and potential drivers causing changes in the area under investigation. In this research work, we will investigate the following points:

- The evolution of land-use in the SN watershed in the near and far future.
- The most significant driving factors behind land-use changes in the SN watershed.
- The impact of land-use restriction policy on the conversions of land-use covers.

1.4. Specific Research Objective

The specific objective of this research work is to generate future land-use maps of the SN watershed which can serve in the future as input data in the AnnAGNPS (Annualized Agricultural Non-Point Source) model (Bingner *et al.*, 2007). From the land-use modeling software available in the literature, the dynamic version of CLUE model, known as Dyna-CLUE, was selected to model the land-use changes in the SN watershed, for the following reasons:

- Dyna-CLUE is a hybrid model that combines estimation and simulation models, which uses the parameters from the estimation model to predict the spatial pattern of land-use changes that could occur under different conditional scenarios;
- Dyna-CLUE is an empirical model that aims to quantify the relationships between variables using empirical data and statistical methods;
- Dyna-CLUE is a multi-scale land-use change model developed for understanding and predicting the impact of bio-physical and socio-economic forces that drive land-use changes;
- The model projects and displays cartographically the future land-use patterns that result from the continuation of current land-use or actual land-cover map;
- The model can simulate and locate 'hot-spots' of land-use changes at fine local scale of spatial resolution; and
- The modeling outcome of Dyna-CLUE can be used by land-use planners to make decisions about the land-use planning desired for the future.

- Dyna-CLUE has been successfully used in several case studies with a local to regional extent and at resolution ranging from 20 to 1000 meters (Veldkamp and Fresco, 1996; Verburg *et al.*, 2002; Verburg and Veldkamp, 2003).

1.5. Methodology

This study aims to combine remote sensing Geographic Information System (GIS), and Dyna-CLUE spatial simulation modeling approach to detect changes in land-use pattern of the SN watershed throughout a period of 30 years (1990-2020). The model has been applied based on resolution of 250 meter data in which each pixel contains a single land-use class. The model helps to visualize future land-use scenarios with different hypotheses of the SN watershed. Demographic and socio-economic drivers were integrated to study their impacts on the changing process of land-use patterns. The methodology through which the Dyna-CLUE model was applied needs to consider the following four parts:

(1) Land-use requirements: they represent the land-use demands in the surfaces of each land-use class available in the study area. These requirements are calculated outside the Dyna-CLUE model using Microsoft Excel.

(2) Location characteristics and suitability: in Dyna-CLUE model, the location suitability is a major determinant of the competitive capacity among land-use classes at a specific location, and it is based on empirical analysis of preferences between land-use classes and potential driving factors. In the present study, the stepwise method in the logistic regression analysis is used in the Statistical Package for the Social Sciences (SPSS) software to indicate the probability of a certain cell to be devoted to a land-use class given a set of potential driving factors.

(3) Spatial policies and restrictions: the Dyna-CLUE model accounts for the spatial policies and restrictions given for any place or land-use class in the study area. The model protects the restricted area by assigning specific codes to restricted pixels.

(4) Land-use specific conversion settings: for all land-use classes in the study area, conversion settings are defined and implemented into the model in two forms: a matrix of conversions and a set of elasticity coefficients. In the matrix, the possible conversion ways between land-use classes are assigned a value of 1, and those which are not allowed to be converted are assigned a value of 0. In addition, to avoid easy conversions between land-use classes, each class is assigned an elasticity coefficient value that represents the resistance of that class to conversion. The elasticity coefficient ranges from 0 to 1, where values close to 0 mean easy conversion, and those close to 1 mean difficult conversions.

1.6. Organization of the Thesis

This thesis consists of six chapters that discuss the major components of this research work. In Chapter One, the problem statement and the main objectives of the study were defined. Chapter Two presents some key definitions and concepts used in most land-use studies. This chapter also covers a brief literature review on: land-use modeling software and their historical development, the CLUE model, and a description of the Dyna-CLUE version including multiple case studies where the model had been used. Chapter Three deals with the implementation of the Dyna-CLUE model, and covers the steps required to run the model. Chapter Four describes the procedures through which the results were visually and statistically validated. In Chapter Five, both the application (with simulated results) and validation (with real land-use maps) of the developed model are presented. Additionally, the essential driving factors behind land-use changes in the SN watershed are identified based on the results of the logistic regression models. Chapter Six covers the discussion of the results as well as the conclusions, contributions, and suggestions proposed for future research.

CHAPTER 2

LITERATURE REVIEW

2.1. Outline

This chapter covers four sections including: (1) basic terminologies and concepts used in land-use studies; (2) theory of modeling and the types of models used for simulating land-use changes; (3) the CLUE model and implemented case-studies worldwide; and (4) the history and characteristics of the South Nation study area.

2.2. Basic Terminologies and Concepts

2.2.1. Land

Briassoulis (2000) defined land as "*an area of the earth's terrestrial surface, encompassing all attributes of the biosphere immediately above or below this surface, including those of the near-surface climate, the soil and terrain forms, the surface hydrology, the near-surface sedimentary layers and associated groundwater reserve, the plant and animal populations, the human settlement pattern and physical results of past and present human activity*".

2.2.2. Land-Cover

According to Turner *et al.* (1995), land-cover is the observed bio-physical cover on the earth's sub surface. It includes vegetation, water bodies (surface and ground water), desert, ice, soil, topography and human-made landscaping.

2.2.3. Land-Use

Di Gregorio (2005) defined land-use as "*the intended management activities underlying human exploitation of a land-cover including any arrangements of a certain land-cover to produce, change, or maintain it*".

2.2.4. The Concept of Land-Use Change

Carter (1981) described the concept of land-use change as a "*wide mix of land-uses where changes among land-uses are subject to many variations driven by a complex set of socio-economic drivers*". Alternatively, Verburg *et al.*, (2002) defined the concept of land-use change as "*a complex and dynamic model which is not only the conversion from non urban land to urban land, but also the existence of competition between the drivers*".

2.2.5. The Concept of Driving Factor

Van den Berg (1984) described the concept of driving factor as the influence of one or more centrifugal or centripetal forces. Accordingly, he categorized the driving factors to two classifications: centrifugal driving forces (drive for outside the area) and centripetal driving forces (drive for inside the area). For example, in any study area, the pressure coming from any activity related to ruralisation (gardening, landscaping, horticulture, horse-riding schools, etc) is called centripetal driving force. On the opposite side, some urban land-users (or owners) who are not able to operate in central locations (for example, in the urban zones) are forced to leave their locations towards other more tolerable ones (rural zones) due to centrifugal drivers such as noisy, smelly or dangerous industries. In both classifications (centrifugal or centripetal driven forces), two main categories of driving factors are distinguished: the bio-physical and the socio-economic drivers. The bio-physical drivers are related to the occurrence of natural environment such as weather conditions, climate variations, topography, volcanic eruptions, soil types, and drainage patterns. The socio-economic drivers are related to demographic, social, economic, political and institutional factors such as population density, industrial structure and change, technology and technological change, the family, the market, and policies (Turner *et al.*, 1995).

2.3. Theory of Modeling

The definition of modeling had confused researchers for a long time, until 1972 when Meadows *et al.* defined it as follows: "*modeling has one purpose which lies in the need of communication. In another way, modeling can help people to communicate with each other more easily*". Models allow us to understand the complexity of the world, to reduce uncertainty, and to update our knowledge and orient our vision towards the occurrence possibility of simulated scenarios (Benders, 1996). Models can provide the user with important assistance for present and future decision-making. In addition, modeling works as experimental labs where different types of experiments and proposed theoretical hypotheses could be tested and evaluated (Cheng, 2003).

2.3.1. Modeling Land-Use Changes

Models in land-use changes are used to improve our understanding of the dynamics of land-use, and also to predict and evaluate various scenarios of activities (Brown *et al.*, 2004). Modeling land-use changes helps to resolve the following issues (Lambin, 2004):

- Identification of the socio-economic and bio-physical drivers that cause land-use changes.

- Determination of the locations which are affected by land-use changes.
- Determination of the temporal progress rate at which land-use and land-cover change.

2.3.2. Types of Models

Mulligan and Wainwright (2004) classified models into two major types: physical (or hardware) and mathematical models. Physical models are scaled-down versions of real-world situations, and are used when mathematical models are complex, uncertain and/or inapplicable due to lack of knowledge. On the other hand, mathematical models are more common and represent rates of change according to mathematical rules. This class of models is divided into three types: empirical, conceptual and physical models. Empirical models describe behaviour between variables on the basis of observations and relations between variables with high predictive power but low explanatory depth. Conceptual models explain the same concept but they describe the relationship between the variables. Physical models are derived based on the above two types of models, are capable of producing more reliable results.

In general, empirical models which use regression techniques are classified as non-spatial models (which are also called multivariate statistical models), and spatial models (which combines multivariate statistical models with GIS) (Lambin, 2004). The aim of spatial empirical models is to quantify the relationships between variables using empirical data and statistical methods, then project and display cartographically the future land-use patterns that result from the projection of current land-use. This type of models is developed to describe the relationship between the dependent variable (land-use class) and the independent variables (driving factor) (Lambin *et al.*, 2000).

2.3.3. Development of Land-Use Models

Most of the developed models were initially created to simulate urbanisation processes. In the 1960s, models' developers from the USA and Europe started to implement urban models in combination with other discipline knowledge such as ecology, geography, mathematics, regional science, economics, and many other disciplines. As a result, many larger socio-economic models emerged during that period, such as the modeling projects of "*Pittsburgh*" in Pennsylvania, and the model of "*Peen-Jersey corridor*" in San Francisco (Torrens, 2000).

Modeling researches conducted by Turner *et al.* (1995), Veldkamp and Fresco (1996); Lambin *et al.* (2000), Verburg *et al.* (2002), and Verburg and Overmars (2007; 2009) had led to the development of wide ranges of land-use models. Those new models were able to explain and simulate spatial and non-spatial scenarios for deforestation and land-use conversions from agriculture intensification to urbanisation.

2.3.4. Available Land-Use Models

Several land-use models were based on human activities and socio-economic drivers to simulate land-use changes, including: Cellular Automata (CA) (White *et al.*, 1997), Land-Use Cover Changes (LUCC) (Lambin and Geist, 2002), and Conversion of Land-Use and its Effects (CLUE) (Veldkamp and Fresco, 1996). Table 2.1 presents a brief overview and assessment of each of the above models that are classified as simulation, estimation and hybrid models, respectively.

Table 2.1: Comparison between major models of land-use changes (modified from Kaimowitz and Angelsen, 1998).

Model Category	Characteristics	Advantages	Disadvantages
Simulation model: Cellular Automata (CA)	A mathematical model in which the system behaviour is generated by a set of specific rules that determine the discrete state of a cell based on the states of neighbouring cells.	Instructive and offer practical approach to understand interaction among individual agents used to determine regional patterns of urbanization.	Simulation often yields complex and highly structured patterns. Not very useful for land-use planning and policy making.
Estimation Model: Land-Use Cover Changes (LUCC)	Focus on deforestation aspects that are derived from remotely sensed data. Explanatory variables are deducted from diverse sources such as remote sensing and GIS measures.	Identify spatially the location of changes and explicitly the proximate causes of land-cover changes based on multivariate analyses.	Less successful in explaining human behaviour that may cause land-use changes.
Hybrid Model: Conversion of Land-Use and its Effects (CLUE)	A hybrid model in which the simulation model uses the parameters from the estimation model to predict the spatial pattern of land-use change that could occur under different imposed scenarios.	Cover a wide range of bio-physical and human drivers at different temporal and spatial scales. Predict land-use changes where attributes of one grid unit affect land-use outcomes in another unit.	Successful in determining human behaviour that leads to changes in land-use covers.

2.4. The CLUE Model

2.4.1. Development of CLUE Model

CLUE framework model was developed by Veldkamp and Fresco (1996). It simulates land-use change using empirically quantified relations between land-use and its driving factors in combination with dynamic modeling of competition between land-use types. The model was developed for the national and continental level and has been applied in more than 30 countries in Central America, Ecuador, China, and Indonesia. For larger study areas, the spatial resolution is represented through assigning dominant land-use class per pixels level.

For smaller study areas, the spatial resolution is usually based on homogeneous polygons or even classified at the pixels level. The CLUE modeling approach was later modified by Peter Verburg in collaboration with some colleagues at the Department of Environmental Sciences at Wageningen University in The Netherlands, and the modified version was called CLUE-S (Conversion of Land-Use and its Effects at Small regional extent) (Verburg *et al.*, 2002). Other versions were later developed in the same department; for example: Dyna-CLUE (Verburg and Overmars, 2009) and CLUE-Scanner (Perez *et al.*, 2010). CLUE's versions are freeware licensed programs that can be downloaded from the following link http://www.ivm.vu.nl/CLUE. Appendix A provides a summary of the development and structure of CLUE model and its versions.

2.4.2. CLUE Worldwide Case Studies

This section describes the performance of CLUE model (CLUE-S and Dyna-CLUE versions) in eight case studies at different regions of the world. The model was applied to broad ranges of land-use change scenarios including agricultural intensification, deforestation, land abandonment, and urbanisation.

2.4.2.1. Sibuyan Island - Philippines 2001

Soepboer (2001) applied the CLUE-S modeling software to simulate land-use changes of the Sibuyan Island located in the Philippines. The study area represented a total surface of approximately 45,600 hectares where agricultural, mining, and residential activities were localised in the coastal parts of the island. In addition, the area is characterised by steep mountain slopes covered with forest canopy. The model was used to explore land-use changes starting from 1997 to 2012 at a spatial resolution of 250×250 meter which means the surface of one grid cell was fixed to 6.25 hectares. All analyses of geo-processing were made on the Geographical Information System software platform ArcGIS 9.3. Thirteen driving factors were used and classified under three categories: (1) geographic drivers (distance to sea, road, city, and stream); (2) bio-physical drivers (diorite rock, ultramafic rock, sediments, no erosion, moderate erosion, elevation, slope, and aspect); and (3) demographic driver (mean population density). Binary logistic regression analysis was conducted on the statistical software SPSS 13.0 using stepwise method. The performance of the resulting regression models between land-use classes and expected driving factors were evaluated by referring to the ROC method (Relative Operating Characteristic) applied by Pontius and Schneider (2001). The results showed that the CLUE-S model had the potential to support the decision-making in land-use planning and natural resource management. The model was found to be very sensitive to small changes in the input of the demand module. Visual comparison between simulated map and true map of the same year was used to decide which simulations were the best.

2.4.2.2. Selangor River - Malaysia 2002

Engelsman (2002) applied the CLUE-S model to study the development of urbanisation in the Selangor river basin located in Malaysia. The study area covered a total surface of 161,700 hectares with high population density and variable landscape diversification. The objective was the prediction of land-use changes for 15 years, starting from 1999 to 2014. In that study, 15 driving factors were considered: (1) nine bio-physical drivers (altitude, four types of soil textures, and four types of suitability class soils); (2) four geographic drivers (distances to road, river, centre of residence, and centre of forest); and (3) two demographic drivers (population density, and agricultural labour forces). Binary logistic regression analysis was conducted by using SPSS with the stepwise method, and the goodness of fit of the logistic regression model was measured using the ROC method. The geo-processing analyses were made on ArcGIS 9.3 using pixels of 750 ×750 meter as unit of observation. Results showed that the CLUE-S model was able to perform different simulations based on the range of realistic demands. The model was found sensitive to the use of different matrix settings between land-use classes. However, the author did not perform any validation approaches to assess the obtained results.

2.4.2.3. Achterhoek - The Netherlands 2007

Verburg and Overmars (2007) used the CLUE-S model to simulate land-use changes in the Achterhoek region in the Netherlands. The study region covered a surface area of 42,000 hectares, where dairy farming was considered as the main land-use activity. The model was used to compare between two scenarios; the first one described land-use changes without spatial policies, whereas in the second one, ecological spatial policies were applied to preserve part of the landscaping area. The time horizon of the modeling process was from 2000 to 2018, and the spatial resolution was set to 50×50 meter. The driving factors used were classified into two categories; (1) geographic (distances to highway, provincial road, cities, and streams); and (2) bio-physical (slope, elevation, soil characteristics, and groundwater level). The binary logistic regression analysis was performed using the stepwise method. Researchers applied the ROC method to test the performance of the resulting regression models between land-use classes and expected driving factors. Results showed that the model was able to respond to designated policies and converted the dairy farming and grazing activities to other potential locations, where the degree of biodiversity losses in land degradation was less significant. Authors used visual observation between simulated and true map of the same year to select the best output. They concluded that the CLUE-S model could be a useful tool to assess, discuss, and adjust policies in land-use changes, and they also recommended using the model in further comparable studies.

2.4.2.4. Taips County - China 2007

The CLUE-S model was used by Jinyan *et al.* (2007) to model land-use changes at the Taips County in China. The study area covered a total surface of 341,500 hectares, where farming and pasturing were considered as the main agricultural activities. Three categories of driving factors were considered: (1) stable controlling drivers (elevation, degree of slope, aspect, landform, and soil texture); (2) seasonal changing drivers (annual changes of air temperature, and precipitation); and (3) socio-economic drivers. The spatial resolution used was 100×100 meter with a grid surface of 1 hectare. The binary logistic regression analysis was performed using the stepwise method. The performance of the resulting regression models between land-use classes and driving factors was evaluated using the ROC method. The results demonstrated significant correlation between land-use changes and their driving factors, and allowed the decision-maker to select the best sustainable development strategy for the Taips County.

2.4.2.5. Pennsylvania County - USA 2009

Batisani and Yarnal (2009) applied the CLUE-S model to study the transition of agricultural land to urban in the Pennsylvania County in the United States. The Pennsylvania County covered an area of 288,700 hectares, and was rated as a retirement destination. Over the years the number and size of farms had decreased as the number of rural non-farm residents had increased in the county. The researchers considered a list of bio-physical factors such as topography, soil suitability for agricultural production, and population density as the major driving factors behind urbanisation of the county. The map analyses were made on ArcGIS 9.3 at spatial resolution of 100×100 meter, and the SPSS 13.0 was used to conduct the binary logistic regression analysis. The performance of the resulting regression models was evaluated via the ROC method, and the model was calibrated by adjusting its parameters. Results showed that land-use changes in the county were dominated by transitions from agricultural to urban land-use, and by exchanges in location between forest and others land-use classes. Researchers proved that the model was able to simulate urban land-use changes at the county level.

2.4.2.6. Northern Thailand - Thailand 2010

Trisurat *et al.* (2010) studied the deforestation activities in Northern Thailand using Dyna-CLUE model. The study area extended over a total surface of approximately 17,300 hectares, and consisted of flat forests in the lower north and mountainous forests in the west and upper north of the region. The time horizon covered in this case study was between 2002 and 2050, and the spatial resolution was set to 500×500 meter. The researchers considered 13 driving factors which were classified into three main categories: (1) bio-physical drivers (annual precipitation, soil texture, altitude, aspect, and slope); (2) geographic (distances to available water body, main road, stream, river, village, and city); and (3) socio-economic drivers (population density, and income). The simulated map for 2050 indicated that forests would mainly persist in the west and upper north of the region, which is rocky and not easily accessible. In contrast, the highest deforestation occurred in the lower north where flat areas were impacted by commercial logging. Authors found that the model was very useful, not only in simulating land-use allocation, but also in visualizing the landscape patterns of remaining forests. Additionally, the model was able to identify the "*hot zones*" of deforestation and important areas for biodiversity conservation. The authors recommended adding more driving factors related to socio-economic variables as they noticed that this category of drivers had the largest influence on deforestation.

2.4.2.7. Sangong Watershed - China 2010

Luo *et al.* (2010) applied the CLUE-S model to study the Sangong watershed in China. The Sangong River drains the Tianshan Mountains into the southern Junggar Basin in Xinjiang with a total catchment area of 167,000 hectares. The watershed consisted of six land-use classes including farmland, woodland, grassland, residential, waters, and other lands. During the past 50 years, land-use covers in the watershed had changed dramatically due to reclamation, irrigation and cultivation, as well as the application of fertilizers across the Sangong watershed (Luo *et al.*, 2003). The time frame of the study extended from 2004 till 2030 with a spatial resolution of 50×50 meter. Researchers stated that demographic and socio-economic drivers were behind land-use changes in the watershed, and considered the population density, livestock density, water consumption, and crop production as main driving factors behind land-use changes in the watershed. Results showed that the model was able to allocate the land-use demand taking into consideration the effect of land-use suitability and spatial policies. In addition, the model was able to highlight the location of the "*hot spot*" which are the first areas were conversions might occur in the future. Researchers concluded that the methodology adopted was able to simulate virtual cases of "*What-If*" scenarios, which provided scientific support for land-use planning and management of the watershed.

2.4.2.8. Pengyang County - China 2010

Zhu *et al.* (2010) applied the CLUE-S model to evaluate the implementation of the project policy "*Grain for Green Project*" conducted by the Chinese government in the Pengyang County. The project aimed to simulate the effects of the implementation of an ecological agriculture policy between 1993 and 2005. The study area covered a surface of 252,900 hectares of mountains with forest, grassland, cropland, and others as main land-use classes, and the resolution applied was set to 100×100 meter as unit of observation. Natural and socio-economic driving factors such as slope, aspect, elevation, distance to road, soil types, and population density were proposed as the main forces behind land-use changes in the county. Results indicated that the model was capable of simulating the policy-dominated areas.

2.4.2.9. Current Research

In previous case studies, CLUE's versions (CLUE and Dyna-CLUE) were used to model the process of land-use changes in eight case studies at different regions of the world. The spatial units of observation applied ranged from 50 to 750 meter where each land-use class was represented by one dominant pixel. Two categories of demographic and geographic driving factors were used to highlight the probability of changes in land-use classes as a result of those drivers. Inspired by the previous successful applications of the CLUE model to forecast land-use changes, the present study apply this methodology to model land-use changes in the South Nation watershed under the effect of various geographic and demographic driving factors.

2.5. Study Area

2.5.1. Location

The South Nation (SN) watershed is located in Eastern Ontario between latitude 44°44′-45°38′ North and longitude 75°32′- 74°22′ West (Figure 2.1). It covers an area of approximately 400,000 hectares and includes 15 municipalities. The watershed is drained by the South Nation River flowing North-East before joining the Ottawa River near Plantagenet. Over its course, the South Nation River drops only 85 meters creating a flat landscape which leads to poor drainage and consequently encourages the formation of several wetlands. The SN watershed is under the authority of the South Nation Conservation (SNC) that is governed by a board of directors made up of 13 representatives elected from across the watershed. Together, the SNC, municipalities, government and individual landowners work to maintain and improve the natural resources which consist one of the largest watershed in Ontario (SNC, 2006).

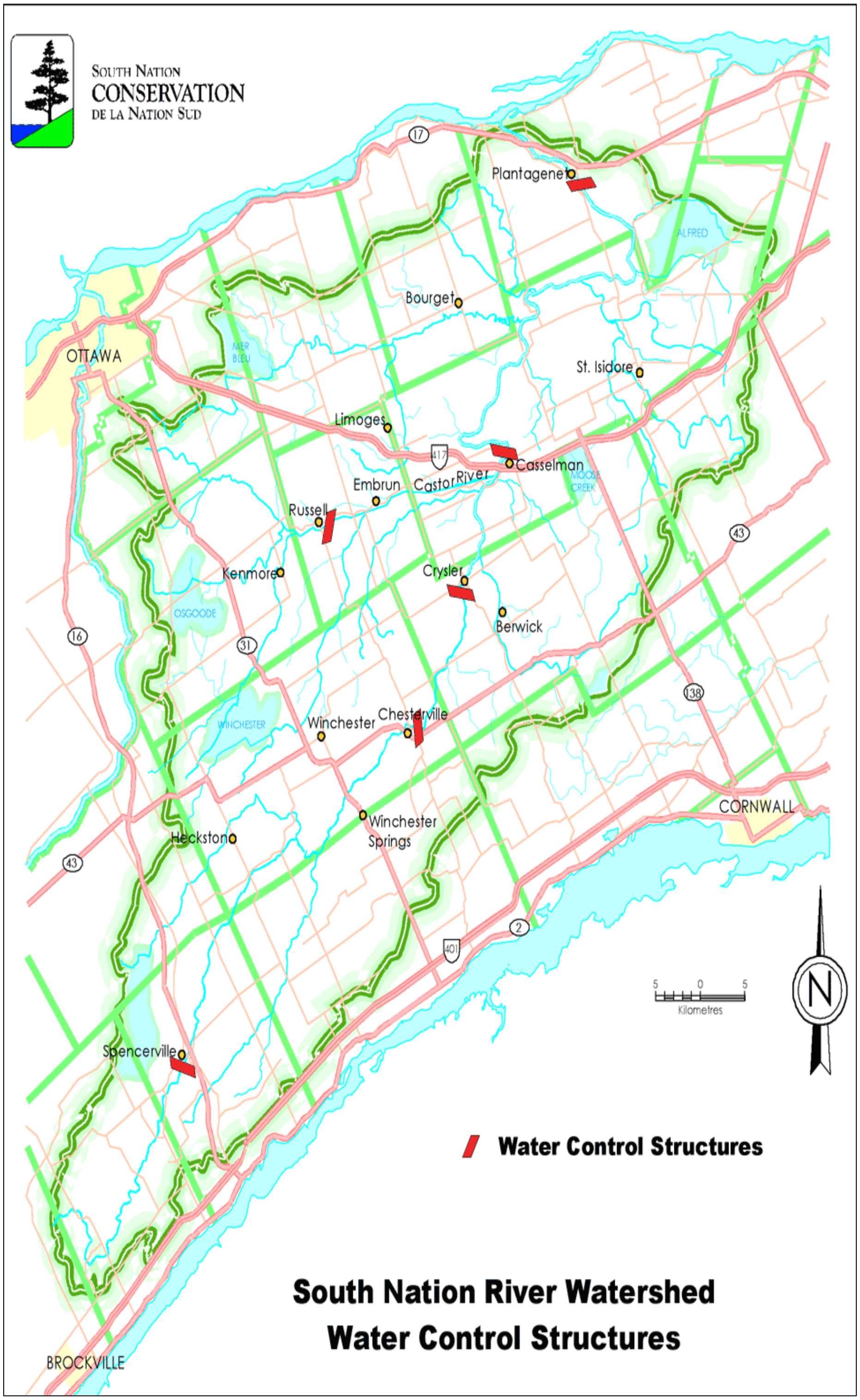

Figure 2.1: The South Nation watershed (adapted from SNC, 2006).

2.5.2. History

In the early 1800s, migration to the South-Eastern Ontario started due to the development in logging, agricultural, and industrial activities (Diogo and Jeena, 1995). As the demand for lumber grew in Britain, USA, and locally (to supply demands of new settlements), larger areas of land in the SN watershed were deforested and commercial lumbering operations were established throughout the entire area. Steamboats travelled the South Nation River to backup the trade taking place on both sides of the Ottawa River. Later in the 1850s, a railroad network was built and used as a new transport chain for goods and woods access to and from the region. Wheat was the first crop grown in the area until the 1840s when the farmers were forced to diversify their farming practices into livestock husbandry and dairying. During the early 1900s, more demands for milk and butter were needed, and therefore farmers introduced new techniques to improve their production (Coyne, 2001). The introduction of electricity in the 20th century brought many changes to the SN watershed area where power lines were constructed and electrical motors were introduced in farming activities to increase production. As a result, farming activities became more efficient, and the economies and agro-industrial activities in the area were significantly improved (Diogo and Jeena, 1995). Deforestation and intensive farming practices were observed where forests and wetland land-use classes had been converted into other land-use classes. Additionally, the increased number of villages in the area had dramatically affected the natural character of the SN watershed as well as the river itself, which had contributed to increased incidences of spring flooding and summer drought. On the other hand, the effect of deforestation and flooding had also caused mass erosion of topsoil into the river banks. Since the early settlement of the SN watershed till today, these problems have remained and the area is still subjected to wind and water erosion, summer droughts, and spring flooding. From the recent natural occurrences affecting the watershed, the most severe ones include the ice storms in 1942 and 1998, and the two landslides that occurred in 1971 and 1993 which moved around 70 and 50 acres of land, respectively (Coyne, 2001).

2.5.3. Trends in Land-Use Covers

Historically, land-use covers in the SN watershed had faced dramatic changes, and accordingly, some of the land-use classes had been converted. The changes in land-use covers occurred periodically and could be related to many driving factors as follows:

Forest: in the early 1800s when the lumbering industry started, forests in the SN watershed had suffered significant environmental degradation. By 1920, little original forest remained in the area where agriculture became the main farming activity. Today, lumbering is carried out using more sustainable forestry methods (Coyne, 2001).

Agriculture: in late 1800s, due to the exponential growth in population density and consequent increase in demands for food, many wetlands were converted to farming activities. In 1996 census, agricultural lands covered roughly 59% of the watershed, where 70% of the farming activity consisted of cropland (mainly wheat) (Coyne, 2001).

Wetlands: in 1800, the wetland areas in the SN watershed covered 47.6% of the total surface, while they only covered 15.6% in 1982. The major cause of wetland losses within the watershed was the conversion to agriculture farming activities. Today, the total area of wetlands within the SN watershed is around 180 km^2 (Coyne, 2001).

2.5.4. Current Land-Use Covers

The actual land-use covers in the SN watershed include 60% agricultural, 34% forest, and 6% mixed urban (SNC, 2006). Compared to the last 200 years, it can be clearly noticed that those three main land-use covers had faced dramatic conversions which allowed for the existence of other land-use covers (bare and urban).

2.5.5. Specific Characteristics

The SN watershed is characterised by a large diversity of rural and urban characteristics described as follows:

Population: the population of the SN watershed is a complex between urban and rural categories. It represents a model of people with different cultural and professional backgrounds living in the same geographical area and sharing the same environmental conditions. Over the last 20 years, due to the geographical location of the SN watershed nearby the capital and surrounded by well developed network of highways, migration occurs and new comers come to reside in the SN watershed where they are engaged in multiple economic activities.

Social Characteristic: the local residents of the SN watershed spend most of their time working in the fields at regular intervals determined by agricultural seasons and/or holidays. Different socio-economic classes between residents can be distinguished compared to areas between suburbs and countryside.

Economic Characteristic: among the agricultural activities in the SN watershed, cropping vegetable contributes in developing the agro-industrial sector. As a result, the economic structure in some areas of the SN watershed has evolved rapidly from rural to agro-industrial activities (SNC, 2006).

2.5.6. Driving Factors

Based on the historical trends of land-use conversions that occurred in the SN watershed; two major categories of driving factors could be distinguished:

Demographic Driving Factors: since it is under the authority of the South Nation Conservation; the SN watershed is subject to different governmental policies and engineering plans. Also, the variation in population density has been found to influence the spatial pattern of land-use changes of the watershed.

Geographic Driving Factors: the existence of a well developed public transportation system in the capital region had encouraged people to no longer prefer to live in the urban centre (capital) where high levels of stress and pollution existed, and motivated them to move towards rural areas. In parallel, the rapid development of high technology offered more employment opportunities and accelerated the migration of farmers from the rural areas towards urban centre. As a result, agricultural lands were abandoned and conversions of agricultural lands towards other land-use classes were most likely to occur.

CHAPTER 3

PRINCIPLES OF LAND-USE SIMULATION USING DYNA-CLUE

3.1. Outline

This chapter describes the Dyna-CLUE model which is used in the present study to predict land-use changes in the South Nation watershed. It covers three sections which are model description, statistical analyses, and Dyna-CLUE model's parameters.

3.2. Dyna-CLUE Model Description

3.2.1. Model Structure

The Dyna-CLUE model (Dynamic Conversion of Land-Use and its Effects) is divided into two levels: the non-spatial and the spatial analysis (Figure 3.1). The non-spatial analysis calculates the area demands at the aggregate level, while the spatial analysis translates the yearly demands into land-use changes at different locations within the time frame period of the study area. Land-use is represented in a grid system where each pixel only contains one land-use class. The structure of Dyna-CLUE model was developed with the objectives of:

- Providing a clear view of the spatial variability of land-use changes under the effect of driving factors;
- Indicating the locations of "*hot-spots*" areas that may be converted under realistic scenarios; and
- Analysing the relationships between the driving factors and land-use covers in spatial representation.

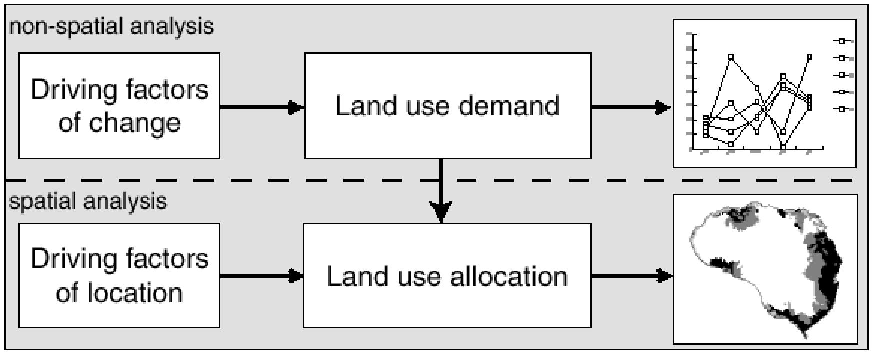

Figure 3.1: The structure of Dyna-CLUE model (adapted from Verburg and Overmars, 2009).

3.2.2. Iteration Procedure

In order to run the Dyna-CLUE model, four types of data are required including: (1) spatial policies and restrictions; (2) land-use type specific conversion settings; (3) land-use requirements (demands); and (4) location characteristics (Figure 3.2).

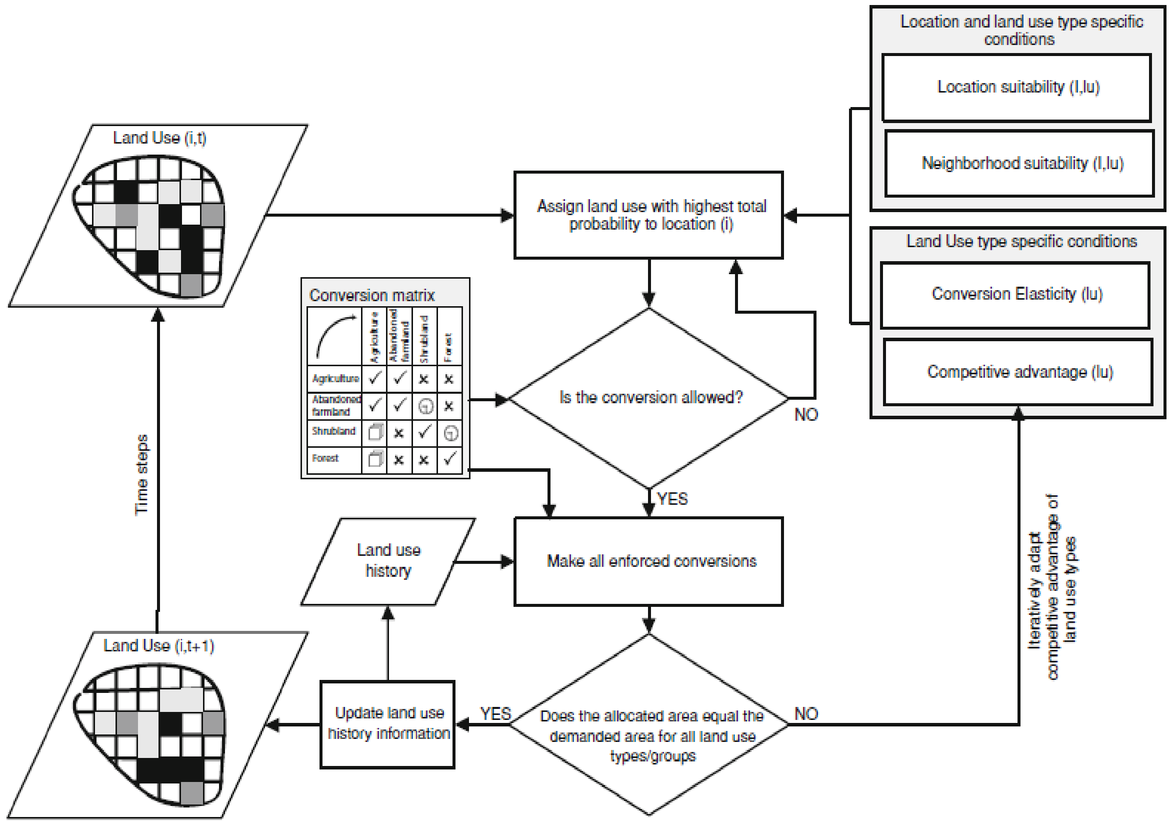

Figure 3.2: Flow chart of the allocation procedure in Dyna-CLUE model (adapted from Verburg and Overmars, 2009).

3.2.2.1. Spatial Policies and Restrictions

Restricted areas, shown in Figure 3.3, are specific pixels of land-use classes located in the study area that are not allowed to be converted into any other class. Such restriction is represented in Dyna-CLUE model with the following codes:

0 **:** code for active cells which are the only cells allowed to be converted;

-9999 **:** code for "*No Data*" value(s); and

-9998 **:** code for restricted area.

Figure 3.3: Maps of restricted areas (in black) in Dyna-CLUE model (adapted from Verburg and Overmars, 2009).

Once created, grids of restricted areas should be converted into ASCII format and must be saved under the code name "*region_park1.fil*" (Figure 3.4) in the same directory where the model is installed (Verburg and Overmars, 2009).

```
region_park1.fil - Notepad
File Edit Format View Help
ncols         128
nrows         108
xllcorner     436000
yllcorner     1356000
cellsize      250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999
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-9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 -9999 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

Figure 3.4: Example of a restricted area in ASCII format for Dyna-CLUE model (adapted from Verburg and Overmars, 2009).

3.2.2.2. Land-Use Type Specific Conversion Settings

Land-use type specific conversion settings is an A×A matrix where A equals the number of land-use classes available in the study area. It determines the temporal dynamics of the simulations, and indicates the sequences of possible and impossible conversions among land-use classes. For example, in a case study of five land-use classes (forest, coconut, grassland, rice fields, and others), the dimensions of the matrix will be 5×5 where rows and columns represent the present and potential future land-use classes, respectively. If the conversion is allowed, the value "1" is assigned to the corresponding cell, while if the conversion is not allowed, the value "0" is used instead. This matrix (e.g. shown in Table 3.1) is first created in Microsoft Excel, then converted to a text file and saved under the code name "*allow.txt*" in the same directory where the model is installed.

Table 3.1: Example of a conversion matrix in table format.

	Forest	Coconut	Grassland	Rice fields	Others
Forest	1	0	0	0	0
Coconut	1	1	1	1	0
Grassland	1	1	1	1	0
Rice fields	1	1	1	1	0
Others	1	1	1	1	1

3.2.2.3. Land-Use Requirements

Land-use requirements (demands) are time series of projected surfaces of land-use classes available in the study area. The land-use demand could be calculated using several methods such as the linear extrapolation of historical trends, and the socio-economic models. To generate a land demand, the following steps must be conducted in the following order:

- Create a table in an Excel sheet and specify the land surface (in hectare) of each land-use class for each simulation year. The sum of the values in each row should be equal to the total surface of the initial land-use map of the study area (Table 3.2);
- Convert the table into a text file, and insert the total number of years to be simulated at the top line of the table (Figure 3.5); and
- Save the text-formatted table under the code name "*demand.in** " (where * indicates the number of demand file scenario in use) in the same directory where the model is installed.

Table 3.2: Example of a demand file created in Excel.

	Bare	Cropland	Urban	Other	Forest	Water	Total Surface Hectares
1991	39172	223743	3478	1718	112680	702	381493
1992	38872	223443	3678	1618	113180	702	381493
1993	38572	223143	3878	1518	113680	702	381493
1994	38272	222843	4078	1418	114180	702	381493
1995	37972	222543	4278	1318	114680	702	381493
1996	37672	222243	4478	1218	115180	702	381493
1997	37372	221943	4678	1118	115680	702	381493
1998	37072	221643	4878	1018	116180	702	381493
1999	36772	221343	5078	918	116680	702	381493
2000	36472	221043	5278	818	117180	702	381493
2001	36172	220743	5478	718	117680	702	381493
2002	35872	220443	5678	618	118180	702	381493
2003	35572	220143	5878	518	118680	702	381493
2004	35272	219843	6078	418	119180	702	381493
2005	34972	219543	6278	318	119680	702	381493
2006	34672	219243	6478	218	120180	702	381493

demand.in1 - Notepad

16

39172	223743	3478	1718	112680	702
38872	223443	3678	1618	113180	702
38572	223143	3878	1518	113680	702
38272	222843	4078	1418	114180	702
37972	222543	4278	1318	114680	702
37672	222243	4478	1218	115180	702
37372	221943	4678	1118	115680	702
37072	221643	4878	1018	116180	702
36772	221343	5078	918	116680	702
36472	221043	5278	818	117180	702
36172	220743	5478	718	117680	702
35872	220443	5678	618	118180	702
35572	220143	5878	518	118680	702
35272	219843	6078	418	119180	702
34972	219543	6278	318	119680	702
34672	219243	6478	218	120180	702

Figure 3.5: Example of a demand file in text format for Dyna-CLUE model.

3.2.2.4. Location Characteristics

Land-use conversions are expected to occur at certain grid cells that have special location characteristics, including: (1) selected cells that share the same pixel basis; and (2) land-use class having the highest "*preference*" of suitability. The preference is determined from the iteration procedure that occurs mainly between land-use classes and driving factors. Mathematically speaking, the preference is a binomial "*logit*" model (Binary Logistic Regression) of probabilities that are calculated from the relationships between each land-use class (dependent variable), and the expected list of driving factors (independent variables). The stepwise regression method is used to select the relevant factors from the list of expected driving factors. For each land-use class of the study area, only driving factors with significant statistical Beta (β) values are included in the final regression equation (Eqn.3.1) as described in the following "*logit*" equation model (Verburg and Overmars, 2009):

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=0}^{n} \beta_j X_{j,i} \quad \textbf{(3.1)}$$

Where:

P_i **:** probability of a grid cell to be allocated with a specific land-use class in a specific location;

$ß_0$ **:** constant obtained from the binary logistic regression model;

$ß_j$ **:** coefficients of driving factors estimated through the binary logistic regression model; and

$X_{j,i}$ **:** the (j^{th}) location factor affecting the suitability of land-use (i).

The preparation of the "*logit*" models is conducted outside the Dyna-CLUE model using certain statistical software (e.g. SPSS).

3.2.3. Allocation Procedure

Once the location preferences for each land-use class are calculated, the following allocation steps are taken to assign the suitable land-use changes:

1. Determination of all grid cells that are allowed to change by excluding those which are parts of protected areas.
2. For each grid cell (i), the total probability (*TPROBi,u*) is calculated for each of the land-use class (u) according to the following equation:

$$TPROB_{i,u} = P_{i,u} + ELAS_u + ITER_u \quad \textbf{(3.2)}$$

Where:

$P_{i,u}$ **:** the suitability of location (i) for land-use class (u) based on the "*logit*" model;

$ELAS_u$: the conversion elasticity for land-use (u); and

$ITER_u$ **:** an iteration parameter.

3. A preliminary allocation is made for all land-use classes by allocating the land-use class with the highest total probability to the considered grid cell. This allocation process will cause a certain number of grid cells to change land-use class. The total allocated area of each land-use is then compared to the land-use demand areas presented in the demand file. When the allocation predicted by the model is equal to demand area required for each land-use class, the ultimate map of the year in question is generated, and saved in the same directory where the model is installed. If not equal, steps 2 and 3 are repeated until the demands are correctly allocated. After that, the model continues to the next time step of its yearly simulation.

3.3. Statistical Analyses

3.3.1. Logistic Regression

Binary Logistic Regression (BLR) is a form of statistical regression that is used when the dependent variable is dichotomous (0 or 1) and the independent variables are continuous or categorical. For example, land-use classes are the dependent variables which could have a value of 0 or 1 to indicate the absence or presence of a land-use class in a specific grid cell. The BLR applies a maximum likelihood estimation to maximize the odds before transforming the dependent variable into a "*logit*" variable. The odd of an event is defined as the probability of the event occurring divided by the probability of the event not occurring. The logistic regression equation with several independent variables is represented in the following form:

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=0}^{n} \beta_j X_{j,i} \tag{3.3}$$

Where (P_i) is the probability of a grid cell for the occurrence of the considered land-use class and the (*X's*) are the driving factors. The beta coefficients (β) are estimated through logistic regression using the actual land-use pattern as dependent variable and drivers as independent variables (Garson, 2005).

From the output of the BLR method, only ß-values of 0.01 and above for each independent variable will be incorporated in each logistic regression model (logit equation 3.3). It should be noted that a positive ß-value indicates that the higher the value of this variable (driving factor), the more likely to find this land-use class in that location. While a negative ß-value indicates that the higher the value of this variable (driving factor), the lower the probability to find this land-use class in that location (Garson, 2005).

3.3.2. Evaluation of the Logistic Regression Models

The results of the logistic regression models can be evaluated by applying the method of "*ROC Curve*" (Relative Operating Characteristic). ROC Curve was introduced by Lusted (1971) in the field of medical decision making, and was also used for the analysis of radar signal detection during World War II (Obuchowski, 2003). A ROC Curve is a plot of true positive fraction (TPF) plotted on the y-axis versus its false positive fraction (FPF). The area under the curve is the ROC value which demonstrates the diagnostic accuracy; the ROC value varies from 0.5 at the diagonal line (indicating a completely random model) to 1.0 (indicating a perfect model) (Figure 3.6) (Dodd, 2003). It is worth mentioning that in 2001, Pontius and Schneider applied the ROC Curve method to quantitatively validate a land-use change model. Similarly, as an example, Figure 3.6 shows an ROC Curve that was generated by Verburg and Overmars (2009) in their land-use study. The area under the curve is 0.868, which means that the logistic regression model used between the land-use class and its driving factors was quite efficient in predicting the probability of occurrence of such land-use change scenarios.

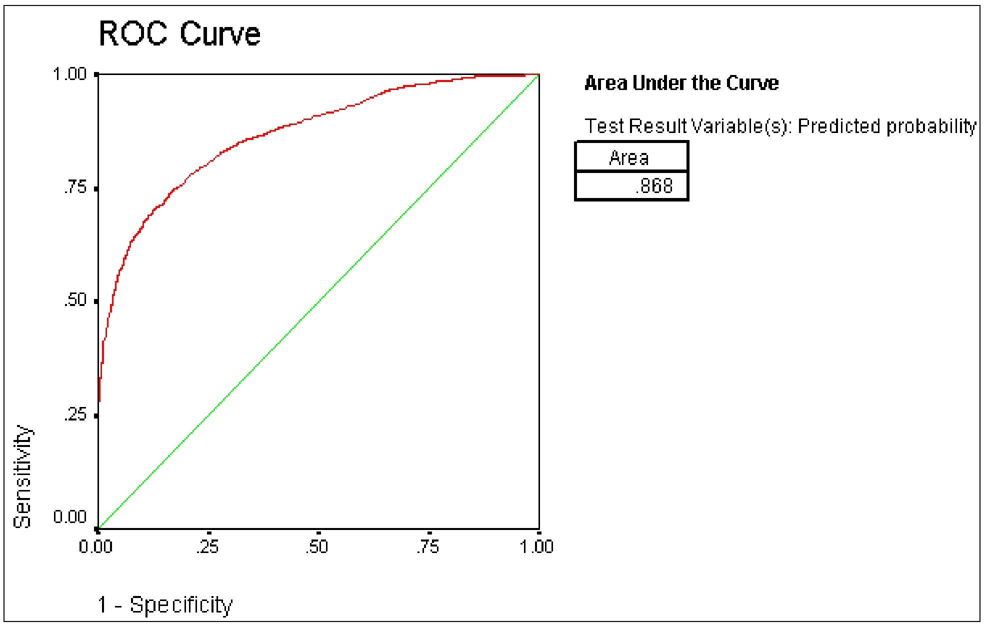


Figure 3.6: Example of an ROC Curve generated in SPSS (adapted from Verburg and Overmars, 2009).

3.4. Dyna-CLUE Model's Parameters

Dyna-CLUE model contains 20 parameters saved in a text file (main.1) in the same directory where the model is installed. These parameters have two essential functions: (1) to configure the model, and (2) to calibrate the model (Verburg and Overmars, 2009).

3.4.1. Model Configuration

In order to configure the model to the new application (case study), the *main.1* text file must incorporate 20 parameters including: the number of land-use classes, the number of expected and significant driving factors, the iteration variables, among others so as to represent the area of study. Appendix B describes each of the 20 parameters required to configure the model (Verburg and Overmars, 2009).

3.4.2. Model Calibration

Out of the 20 parameters, two parameters (initial land-use age of pixels, and elasticity coefficients) are used to calibrate the model (Verburg and Overmars, 2009).

3.4.2.1. Initial land-Use Age of Pixels

An initial land-use age of pixels is a grid map of the study area that may be either randomly generated by the model itself or created by the user. In that grid map, each pixel is assigned with a certain value (before the beginning of simulations) that represents the period (in year) that a specific class had been using this specific pixel location.

3.4.2.2. Elasticity Coefficients

Elasticity coefficients are values assigned by the user for land-use classes to indicate the resistance of each class to the conversions. It is a scale that ranges from 0 (indicative of easy conversion) to 1 (indicative of hard conversion, i.e., irreversible change). In other terms, the closer the values to 0 the easier is the land-use conversion, and the closer the values to 1 the harder is the land-use conversion.

The calibration of Dyna-CLUE model is performed by running the model several times using an initial land-use age of pixels (either generated by the model or created by the user) with a set of elasticity coefficients for land-use classes assigned by the user. The initial land-use age of pixels and the elasticity coefficients of the simulation that gives the most reliable results will be retained as the ones to be used in the final model. This calibration process is not performed automatically by the model, and it mostly relies on the user's judgement, knowledge, and experience.

CHAPTER 4

VALIDATION OF RESULTS

4.1. Outline

This chapter demonstrates two types of validation techniques: statistical and visual validation, both of which will be used to validate simulated maps obtained from the runs of Dyna-CLUE model.

4.2. Concept of Validation

Simulation models are being increasingly used to solve problems and to aid in decision-making. The developers and users of these models are concerned with whether a model and its results are "*correct*", and this concern is addressed through model validation. Model validation is defined as "*proof that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model*" (Mulligan and Wainwright, 2004). The proof that a model is valid is generally considered to be a process and is usually part of the total model development process.

4.3. Validation Techniques

This section introduces two validation techniques intended to be applied to judge on the results obtained from the runs of Dyna-CLUE model. The model performance was assessed by applying the following validation techniques:

4.3.1. Visual Validation

This technique is based on visual assessment of agreement between a simulated map (generated from the model) and a reference map (reality map) of the same year (Visser, 2004). The visual examination allows the user to identify the similarities between images; however this technique is not very useful to accurately detect both agreement and disagreement between maps (Pontius *et al.*, 2004). Therefore, to be more realistic in assessing the performance of the model, it is better to rely on statistical methods of validation.

4.3.2. Statistical Validation

The aim of this method is to measure the association between different pairs of GIS layers based on their measurement scales. Based on the type of data (nominal, ordinal, and/or interval), an adequate method(s) is (are) proposed. The mathematical methods used to evaluate the agreement of two maps (reference and simulated) are presented in Table 4.1

Table 4.1: Methods applied to measure the association between different pairs of GIS layers (adapted from Bonham-Carter, 1994).

	Nominal	Ordinal	Interval / Ratio
Nominal	Chi-square, Error Matrix, …etc	Median by nominal class (Box plot)	Mean by nominal class (Box plot)
Ordinal		Rank correlation coefficient	Rank correlation coefficient
Interval / Ratio			Covariance, Correlation coefficient

Chi-square test is used to assess the difference between an actual sample and another hypothetical distribution (i.e., may be expected due to chance or probability). Chi-square test is usually easier to compute but it requires a large number of observations to ensure convergence. Box plot is a way of graphically depicting groups of numerical data through their five-number summaries: the smallest observation (sample minimum), lower quartile (Q1), median (Q2), upper quartile (Q3), and largest observation (sample maximum). Box plots display differences between populations without making any assumptions of the underlying statistical distribution. Rank correlation coefficient measures the extent to which, as one variable increases, the other variable tends to increase though not necessarily according to a linear relationship. Rank correlation coefficient is commonly seen as an alternative to Pearson's coefficient, which is used either to reduce the amount of calculation or to make the coefficient less sensitive to non-normality in distributions. Covariance is a measure of how much two random variables change together (i.e. if the variables tend to show similar behavior). If the greater values of one variable mainly correspond with the greater values of the other variable, and the same holds for the smaller values, and vice versa for the opposite case. The sign of the covariance therefore shows the tendency in the linear relationship between the variables. The correlation coefficient measures the covariation in the magnitudes of two variables. However, this covariation is only to reflect on the population (or universe) from which the observations were taken (Wasserman, 2004). In the present study, the data generated by the Dyna-CLUE model includes maps in ASCII format, which are considered nominal type of data (i.e., classes of land-uses). Therefore, based on Table 4.1, the method which will be utilized to measure the association between pair of nominal maps (simulated and reality maps) can be Chi-square and the error matrix. Further information of the error matrix is illustrated below.

4.3.2.1. Mathematical Description of the Error Matrix

An error matrix is a square array of data classified in rows and columns representing the number of sample units which could be pixels, clusters or polygons. Generally, the columns represent the reference data (which can be generated from aerial photography, airborne video, ground observation or ground measurement) while the rows represent the classification of generated data (from model simulations). Each cell in the error matrix is assigned a number based on the number of sample units assigned to a given land-use class in the reference and generated data. The error matrix is an effective method to calculate multiple accuracy parameters, such as: overall accuracy, producer's accuracy, and user's accuracy of any nominal set of GIS pair of data (Congalton and Green, 1999).

4.3.2.2. Mathematical Representation of the Error Matrix

This section presents the error matrix in mathematical terms needed to perform the statistical analyses in Chapter 5. Figure 4.1 shows the mathematical representation of an error matrix where:

(n): total number of samples distributed into ($k \times k$) matrix of cells where each sample is assigned to one of:

(k) categories in the remotely sensed classification (rows of the matrix). In this case study, (k) cells are generated from the Dyna-CLUE model; and

(k) categories in the reference data set (columns of the matrix). In this case study, (k) cells are those cells in the reality maps.

(n_{ij}): number of samples classified into category (i) (i = *1, 2,…, k*) in the remotely sensed classification (rows), and category (j) (j = *1, 2,.., k*) in the reference data set (columns).

(n_{i+}): the total number of samples classified into category (i) (i = *1, 2,.., k*) in the remotely sensed classification (rows).

		j = columns (reference)			
		1	2	k	row total n_{i+}
i= rows (classification)	1	n_{11}	n_{12}	n_{1k}	n_{1+}
	2	n_{21}	n_{22}	n_{2k}	n_{2+}
	k	n_{k1}	n_{k2}	n_{kk}	n_{k+}
column total n_{+j}		n_{+1}	n_{+2}	n_{+k}	n

Figure 4.1: Mathematical representation of an error matrix (adapted from Congalton and Green, 1999).

The total number of samples classified into category (i) in the remotely sensed classification (rows) is computed as follows:

$$n_{i+} = \sum_{j=1}^{k} n_{ij} \qquad \textbf{(4.1)}$$

Where (n_{+j}) refers to the total number of samples classified into category (j) (j = *1, 2,…, k*) in the reference data set (columns). Next, the number of samples classified into category (j) in the reference data set (columns) is computed as follows:

$$n_{+j} = \sum_{i=1}^{k} n_{ij} \qquad (4.2)$$

4.3.2.2.1. Overall Accuracy

The overall accuracy is the sum of the diagonal in the error matrix (Figure 4.1 and 4.2), divided by the total number of sample units (n) in the entire error matrix. The overall accuracy is computed as follows:

$$\text{Overall Accuracy} = \frac{\sum_{i,j=1}^{k} nij}{n} \qquad (4.3)$$

Where (n_{ij}) represents the diagonal of the matrix (Congalton and Green, 1999).

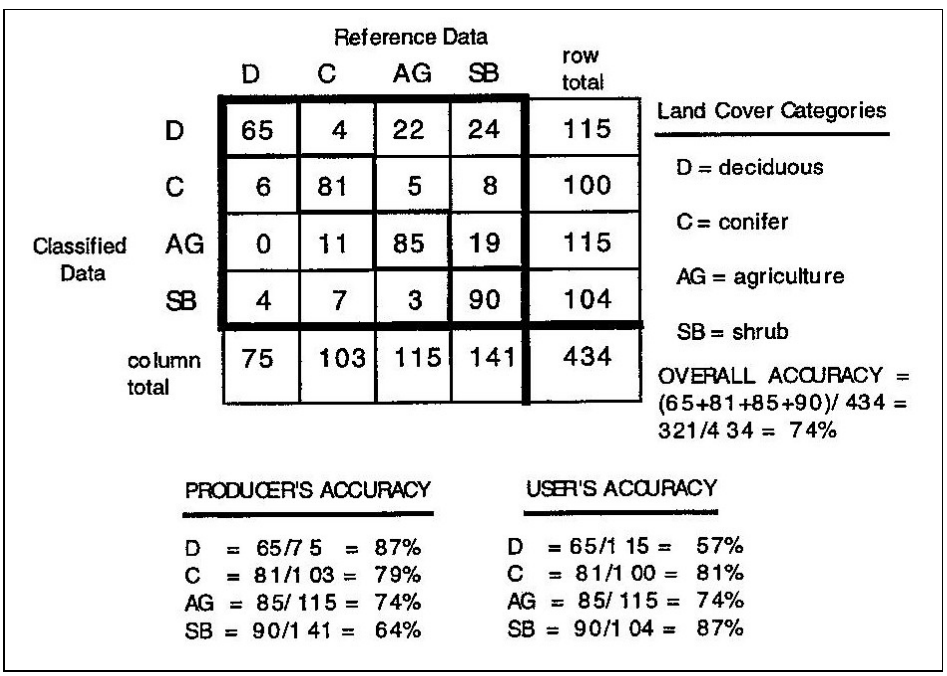


Figure 4.2: Example of an error matrix (adapted from Congalton and Green, 1999).

4.3.2.2.2. Producer's Accuracy

The producer's accuracy represents the individual category of accuracy instead of the overall classification of accuracy. It is calculated by dividing the total number of correct sample units (shared in the diagonal) by the total reference data. The producer's accuracy is computed as:

$$\text{Producer's Accuracy} = \frac{n_{jj}}{n_{+j}} \quad \textbf{(4.4)}$$

Where (n_{jj}) represents the total of shared correct samples in the diagonal (n_{ij}), and (n_{+j}) represents the sum of total reference data of that specific class (column) (Congalton and Green, 1999).

4.3.2.2.3. User's Accuracy

Similar to the producer's accuracy, the user's accuracy represents the individual category of accuracy instead of the overall classification of accuracy. It is calculated by dividing the total number of correct pixels (shared in the diagonal) by the total number of classified pixels. The user's accuracy is computed as:

$$\text{User's Accuracy} = \frac{n_{ii}}{n_{i+}} \quad \textbf{(4.5)}$$

Where (n_{ii}) represents the total of shared correct samples in the diagonal (n_{ij}), and (n_{i+}) represents the sum of total classified data of that specific class (row) (Congalton and Green, 1999).

4.3.2.3. Interpretation of the Error Matrix

Larger value of the overall accuracy indicates that the two maps (reality map and simulated map) are similar. Likewise, larger values of the producer's accuracy and/or the user's accuracy are indicative of great spatial similarity among the pair of classes tested (in reality map and simulated map). For example, Figure 4.2 shows an overall accuracy of 74%, which means that, the generated and the reality maps (references) are similar. The accuracy of the class "*deciduous*" is calculated by the producer accuracy for that specific class. This calculation is performed by dividing the total number of correct sample units in the deciduous category (i.e., 65) by the total number of deciduous sample units as indicated by the reference data (i.e., 75); see Figure 4.2. This results in a good producer's accuracy of 87% for the "*deciduous*" class. Additionally, the user's accuracy of "*deciduous*" class is computed by dividing the total number of correct pixels in the "*deciduous*" class (i.e., 65) by the total number of pixels classified as deciduous (i.e., 115) which results in a value of 57%; see Figure 4.2. In conclusion, 87% of the deciduous areas have been correctly identified as "*deciduous*", and only 57% of the areas considered "*deciduous*" on the map are actually deciduous on the ground (Congalton and Green, 1999).

CHAPTER 5

APPLICATION AND RESULTS

5.1. Outline

In this chapter all GIS data were brought together with the same spatial reference that represents the location of the South Nation watershed (e.g., NAD_1983, UTM_Zone 18 N, and D_North_American_1983). All analyses of geo-processing were made with ArcGIS 9.3 using pixels of 250 × 250 meter as unit of observation.

5.2. Methodology

Figure 5.1 illustrates the five main sections of the methodology applied. The first section introduces and defines the implementation of different scenarios proposed to evaluate the model performance. The second section presents the essential files required to run the model, and also the results from the statistical analyses. The third section includes the implementation of data files needed to run each scenario separately. The fourth section presents the total number of simulated maps generated from the runs of the three scenarios. Additionally, in this section simulated maps are sorted and grouped per scenario according to their potential in testing the proposed hypotheses. The last section presents the statistical methods used to validate results obtained in each scenario. Discussion on the results and on the performance of the model is covered in Chapter 6.

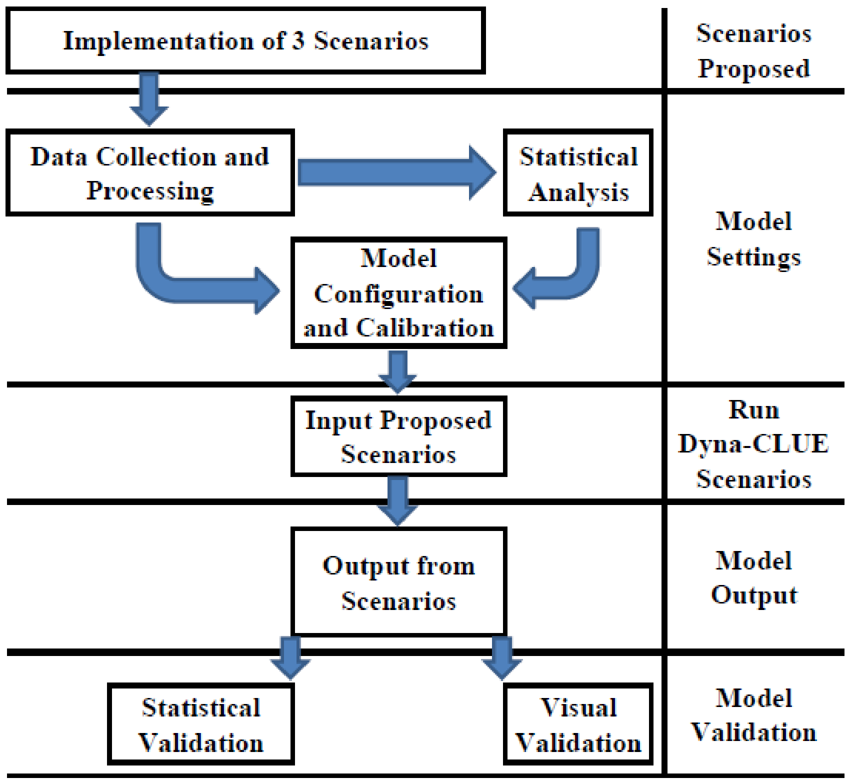


Figure 5.1: Flowchart of the methodology used.

5.3. Scenarios Proposed

Three scenarios are prepared to simulate land-use changes of the SN watershed based on the reality map of 1991.

Scenario 1 uses the linear trend calculated from year 1991 till 2020 with "*no area restriction*" and with an "*initial land-use age of pixels*" generated by the model itself. The purpose of this scenario is to assess the accuracy of the Dyna-CLUE model to generate maps similar to reality.

Scenario 2 uses the same files as in scenario 1, but with an "*area restriction*" created by the user on bare land-use class. The purpose of this scenario is to evaluate the performance of the model in responding to applied policy.

Scenario 3 uses the same files as in scenario 1, but with an "*initial land-use age of pixels*" created by the user. The purposes of this scenario are to: (1) evaluate the model sensitivity to the change of one of the main calibrating parameters (i.e., initial land-use age of pixels), and (2) evaluate the accuracy of the model to generate maps similar to reality.

5.4. Model Settings

5.4.1. Data Collection and Processing

5.4.1.1. Available Land-Use Maps

Five land-use maps in raster format covering Eastern Ontario boundary were collected from different sources, and had been reclassified into six land-use classes as shown in Table 5.1.

Table 5.1: Available land-use maps of the SN watershed (adapted from Seidou and Lapen, 2010).

Year	Source	Land-Use Classes
1991	REIS.1991 (Regional Environmental Information System)	Bare - Cropland - Urban - Other - Forest - Water
1995	Ontario Ministry of Natural Resources	
1998	REIS.1998 (Regional Environmental Information System)	
2000	Agriculture and Agri-Food Canada	
2005	Agriculture and Agri-Food Canada	

It should be noted that the map of 1991 was selected to be the baseline map from where the simulations will start. In addition, only maps of year 1998 and 2005 were chosen as reality maps to validate the model predicted results.

Using ArcGIS, each of the selected maps (1991, 1998, and 2005) was extracted by mask tool according to the administrative limit of the SN watershed and reclassified assigning the codes 0, 1, 2, 3, 4, and 5 to bare, cropland, urban, other, forest, and water, respectively (Figures 5.2, 5.3, and 5.4, respectively). Each of the reclassified rasters was then converted into ASCII format as required by the Dyna-CLUE model. During the conversion, the code "*cov_all.0*" (shown in Figure 5.5) is assigned to the output ASCII file of year 1991. To document the applied procedures and repeatability, the procedures of "*Extraction by Mask*", "*Reclassification*", and "*Conversion Raster to ASCII*" are programmed in the model builder (Figure 5.5).

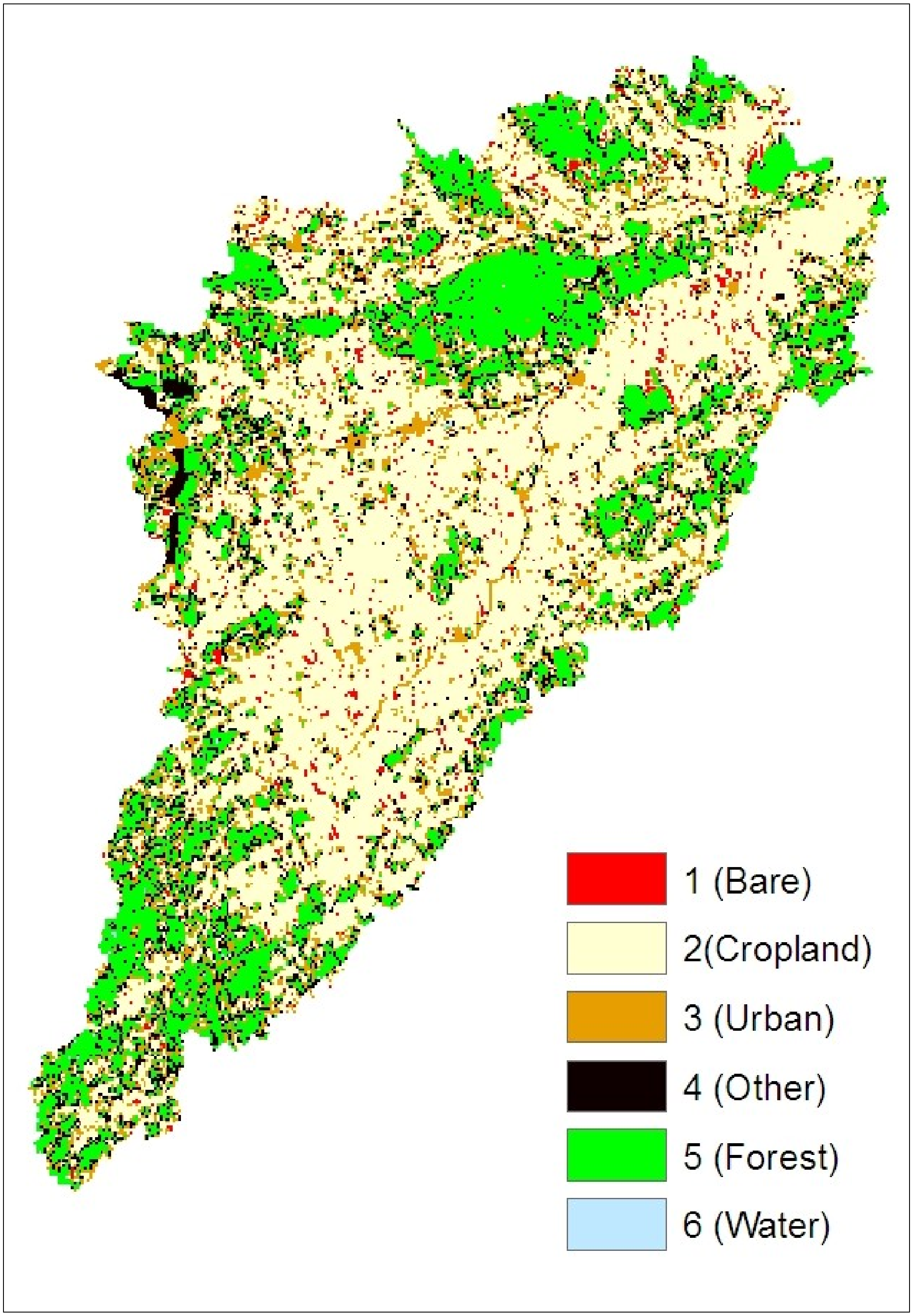


Figure 5.2: Initial land-use map of 1991.

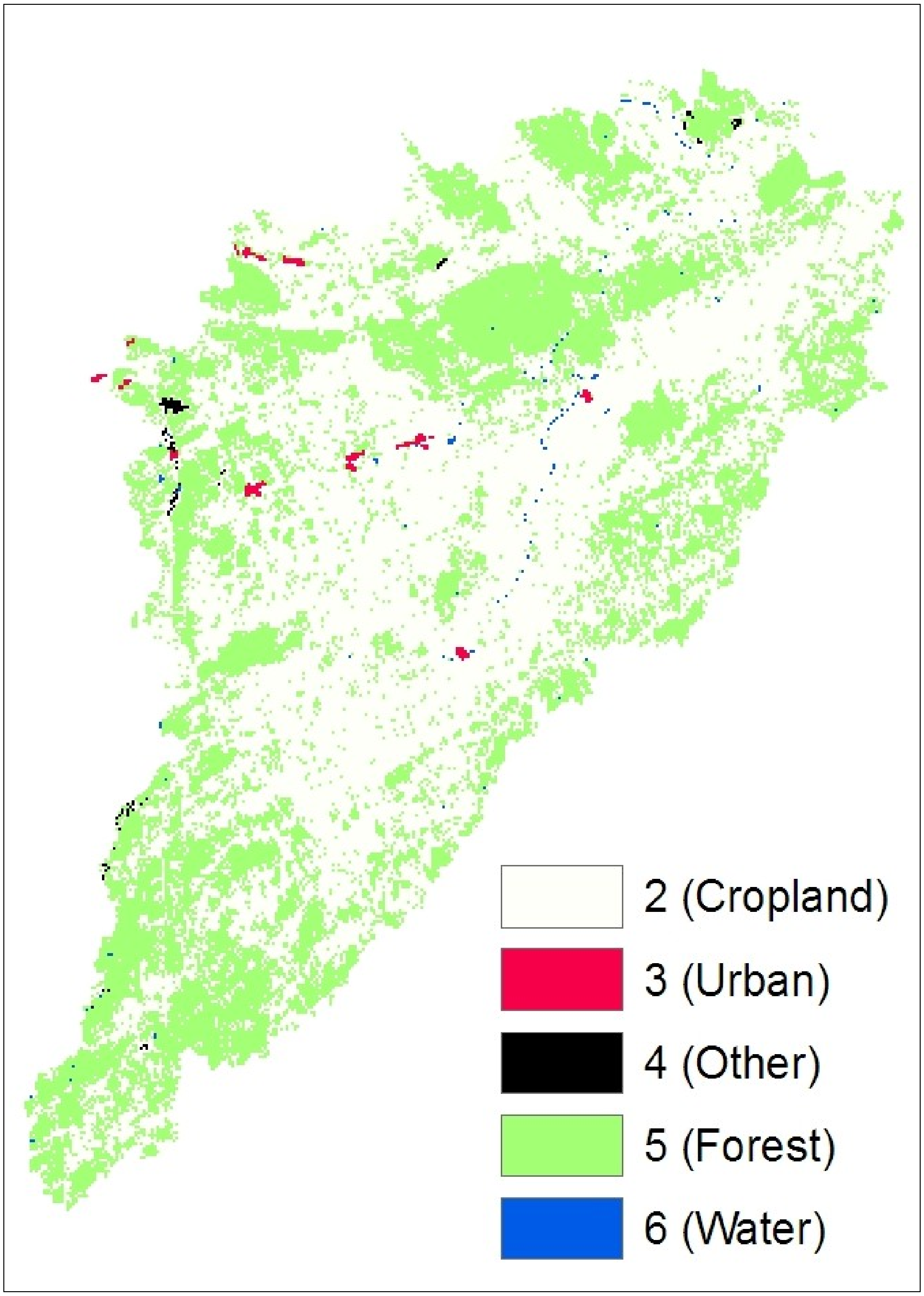


Figure 5.3: Reality land-use map of 1998.

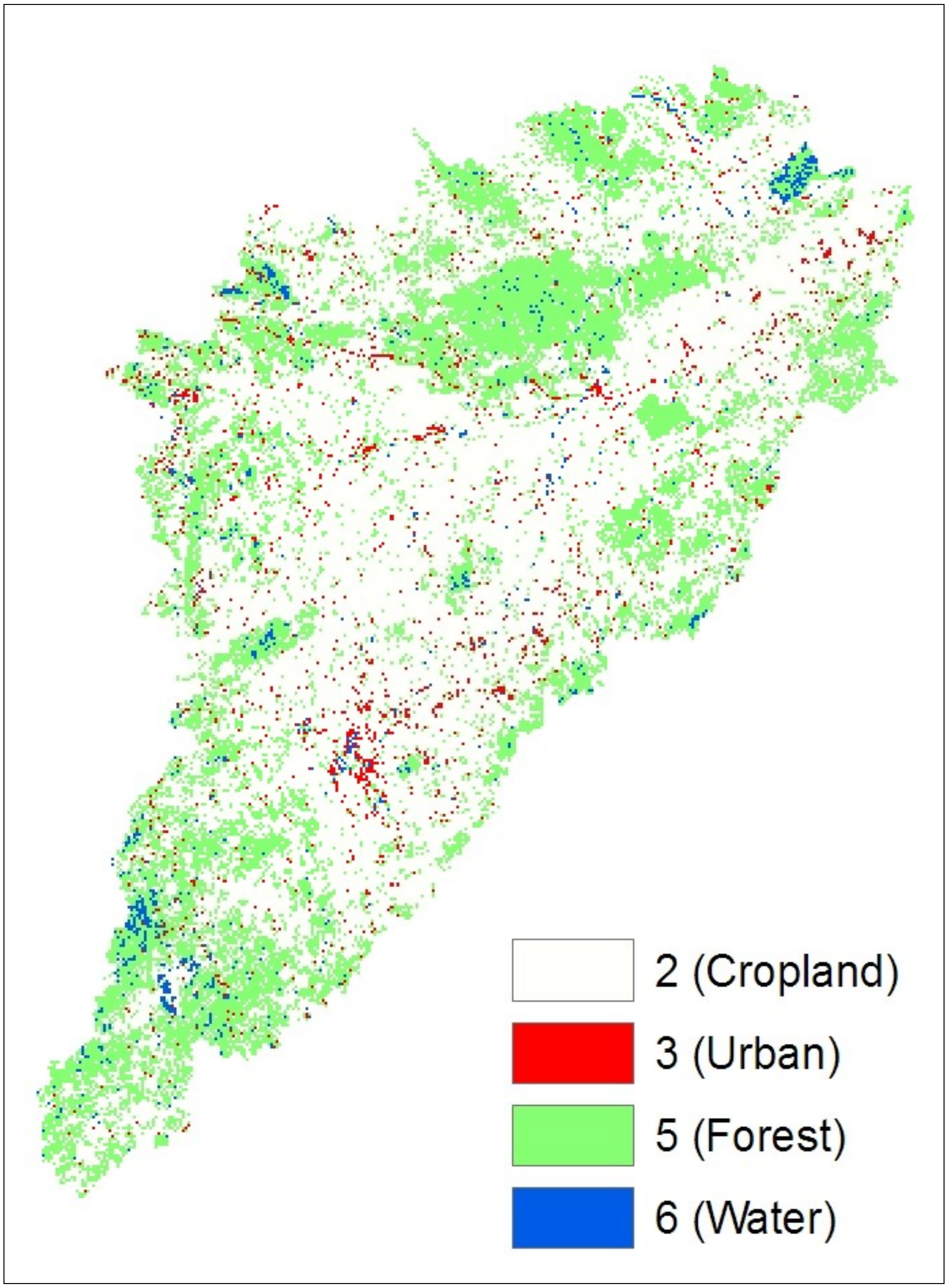


Figure 5.4: Reality land-use map of 2005.

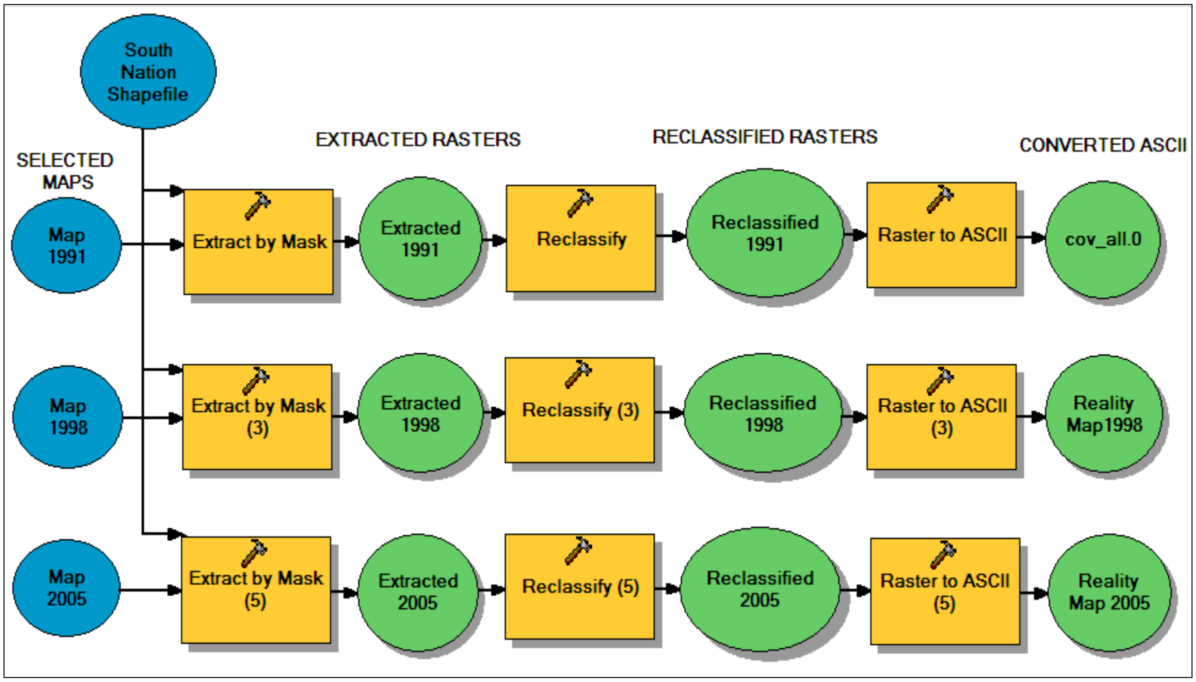
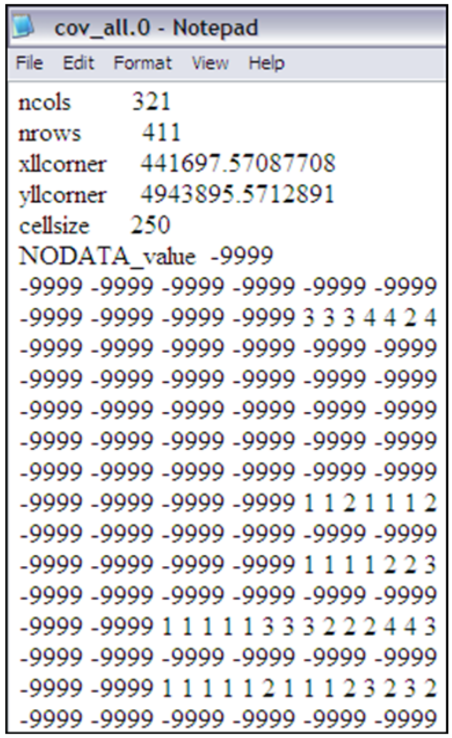


Figure 5.5: Designed model in Model Builder for extraction by mask, reclassification, and conversion of the rasters to ASCII in ArcGIS.

5.4.1.2. Initial Land-Use Map

The ASCII file (cov_all.0), shown in Figure 5.6, generated from above model builder represents the baseline map from where the simulation will start. It contains the codes 0, 1, 2, 3, 4, and 5 that represent each of the land-use classes of bare, cropland, urban, other, forest, and water, respectively. Once created, this file should be saved in the same directory where the model is installed.



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cov_all.0 - Notepad
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yllcorner    4943895.5712891
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-9999 -9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999 -9999
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-9999 -9999 -9999 -9999 -9999 -9999
-9999 -9999 1 1 1 1 1 2 1 1 1 2 3 2 3 2
-9999 -9999 -9999 -9999 -9999 -9999
```

Figure 5.6: Initial land-use map in ASCII format for Dyna-CLUE model.

5.4.1.3. Maps of Individual Land-Use Classes

Maps of individual land-use classes as rasters must be extracted from the initial map of 1991. Each raster contains the code of one of the six classes available in the initial land-use map. The extraction is carried out using the tool "*Extract by Attributes*", and then the extracted rasters are converted into ASCII format. During the conversion, the code names "*cov1_0.0*, *cov1_1.0*, *cov1_2.0*, *cov1_3.0*, *cov1_4.0*, and *cov1_5.0*" are assigned to bare, cropland, urban, other, forest, and water land-use classes, respectively (Figure 5.7). The model of model builder shown in Figure 5.7 displays the steps followed starting from the extraction to the conversion.

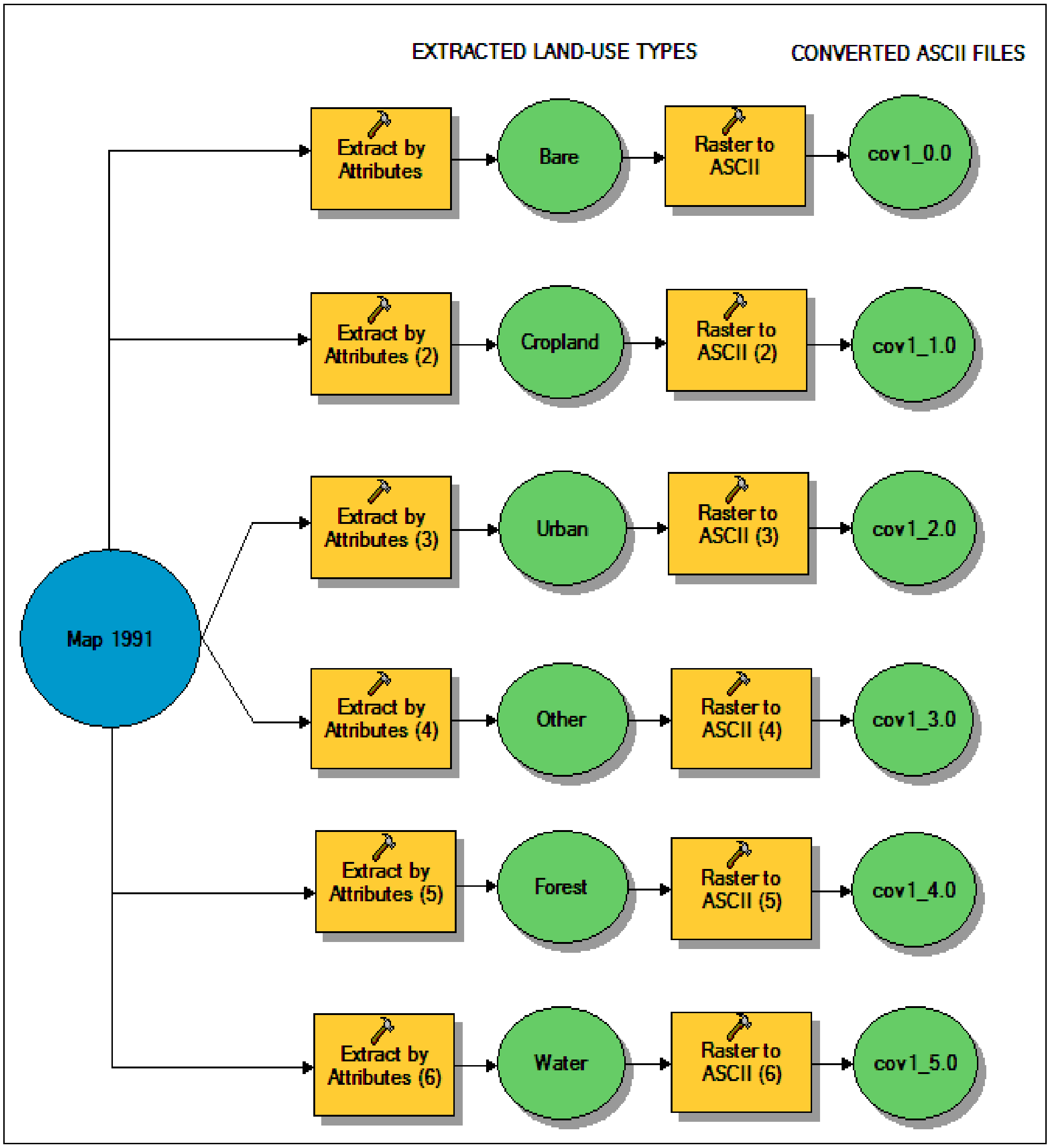

Figure 5.7: Designed model in Model Builder of extraction by attributes and conversion raster to ASCII of land-use classes in ArcGIS.

Created ASCII files (Figure 5.8) are to be saved in the same directory where the model is installed and will be used to run the logistic regression analyses.

cov1_0.0 - Notepad

File Edit Format View Help

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```

cov1_1.0 - Notepad

File Edit Format View Help

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-9999 -9999 1 1 1 1 1 1 1 -9999
-9999 -9999 -9999 1 1 1 1 1 1 1
-9999 -9999 1 1 1  -9999 -9999
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```

cov1_2.0 - Notepad

File Edit Format View Help

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```

cov1_3.0 - Notepad

File Edit Format View Help

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3 3 3 3-9999 -9999 -9999 -9999
-9999 3 3 3 3-9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
```

cov1_4.0 - Notepad

File Edit Format View Help

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nrows        411
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yllcorner    4943895.5712891
cellsize     250
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-9999 -9999 -9999 -9999 -9999
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-9999 -9999 -9999 -9999 -9999
4 4 4 4-9999 -9999 -9999 -9999
4 4 4 4-9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
```

cov1_5.0 - Notepad

File Edit Format View Help

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-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 5 5 5 5 5 5 5
-9999  -9999 -9999 -9999  5 5 5
```

Figure 5.8: Individual land-use maps converted into ASCII format for Dyna-CLUE model.

5.4.1.4. Demand File

It was assumed that the total surface area of water in 1991 (250 hectares) will remain constant during the whole period of simulations. The remaining surfaces of land-use classes follow linear trends as shown below in Table 5.2 and Figure 5.9.

Table 5.2: Surfaces of land-use classes for time series: 1991, 1995, 1998, 2000, and 2005.

	Bare	Cropland	Urban	Other	Forest	Water	Total Surface (Hectares)
1991	9106	194975	54619	42800	79781	250	**381531**
1995	256	171775	58306	44531	102168	4493	**381531**
1998	0	236900	1150	768	141893	818	**381531**
2000	2756	202393	6956	0	168362	1062	**381531**
2005	0	246868	10781	0	117312	6568	**381531**

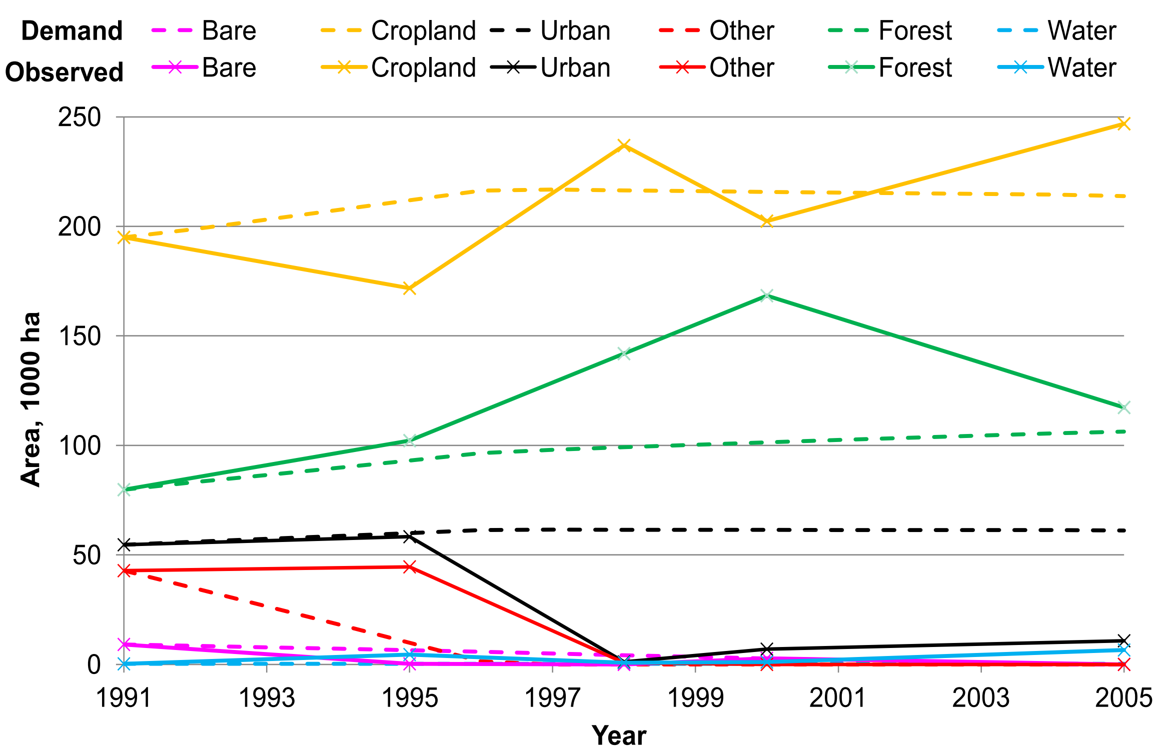


Figure 5.9: Linear trends of land-use classes for 1991, 1995, 1998, 2000, and 2005.

Observed linear trends in the surfaces of each land-use class had been projected from year 1991 to fit the 30 years time horizon of simulations which ended in year 2020. Table 5.3 lists the demands in surfaces projected for the six land-use classes for 30 years.

Table 5.3: Demand in surfaces of land-use classes starting from 1991 to 2020.

Year	Bare	Cropland	Urban	Other	Forest	Water	Total Surface (Ha)
1991	9106.25	194975	54618.75	42800	79781.25	250	381531.25
1992	8478.11	198831	56052.47	34697	83222.67	250	381531.25
1993	7814.97	203132	57341.76	26523	86469.52	250	381531.25
1994	7173.42	207488	58647.39	18246	89756.44	250	381531.25
1995	6463.31	211899	59969.68	9863	93086.26	250	381531.25
1996	5774.46	216367	61308.95	1372	96458.84	250	381531.25
1997	4982.25	216782	61499.61	0	98017.39	250	381531.25
1998	4194.51	216428	61469.80	0	99188.94	250	381531.25
1999	3430.93	216084	61440.91	0	100325.41	250	381531.25
2000	2690.42	215751	61412.89	0	101426.94	250	381531.25
2001	1971.93	215428	61385.71	0	102495.61	250	381531.25
2002	1274.52	215114	61359.32	0	103533.41	250	381531.25
2003	597.25	214810	61333.70	0	104540.30	250	381531.25
2004	0	214479	61299.04	0	105503.21	250	381531.25
2005	0	213833	61172.26	0	106275.99	250	381531.25
2006	0	213207	61049.40	0	107024.85	250	381531.25
2007	0	212600	60930.28	0	107750.97	250	381531.25
2008	0	212011	60814.73	0	108455.52	250	381531.25
2009	0	211439	60702.60	0	109139.65	250	381531.25
2010	0	211419	60682.60	0	109179.65	250	381531.25
2011	0	211399	60662.60	0	109219.65	250	381531.25
2012	0	211379	60642.60	0	109259.65	250	381531.25
2013	0	211364	60627.60	0	109289.65	250	381531.25
2014	0	211349	60612.60	0	109319.65	250	381531.25
2015	0	211334	60597.60	0	109349.65	250	381531.25
2016	0	211324	60587.60	0	109369.65	250	381531.25
2017	0	211314	60577.60	0	109389.65	250	381531.25
2018	0	211306	60569.60	0	109405.65	250	381531.25
2019	0	211298	60561.60	0	109421.65	250	381531.25
2020	0	211292	60555.60	0	109433.65	250	381531.25

Next, the highlighted red selection in Table 5.3 is copied to a text file, and saved under the code name "*demand.in1*" in the same directory where the model is installed. It should be noted that a line should be insert at the top of this file indicating the number of years of simulations (30 years in this case study) (Figure 5.10).

demand.in1 - Notepad

File Edit Format View Help

30

9106.25	194975	54618.75	42800	79781.25	250
8478.11	198831	56052.47	34697	83222.67	250
7814.97	203132	57341.76	26523	86469.52	250
7143.42	207488	58647.39	18246	89756.44	250
6463.31	211899	59969.68	9863	93086.26	250
5774.46	216367	61308.95	1372	96458.84	250
4982.25	216782	61499.61	0	98017.39	250
4194.51	216428	61469.80	0	99188.94	250
3430.93	216084	61440.91	0	100325.41	250
2690.42	215751	61412.89	0	101426.94	250
1971.93	215428	61385.71	0	102495.61	250
1274.52	215114	61359.32	0	103533.41	250
597.25	214810	61333.70	0	104540.30	250
0	214479	61299.04	0	105503.21	250
0	213833	61172.26	0	106275.99	250
0	213207	61049.40	0	107024.85	250
0	212600	60930.28	0	107750.97	250
0	212011	60814.73	0	108455.52	250
0	211439	60702.60	0	109139.65	250
0	211419	60682.60	0	109179.65	250
0	211399	60662.60	0	109219.65	250
0	211379	60642.60	0	109259.65	250
0	211364	60627.60	0	109289.65	250
0	211349	60612.60	0	109319.65	250
0	211334	60597.60	0	109349.65	250
0	211324	60587.60	0	109369.65	250
0	211314	60577.60	0	109389.65	250
0	211306	60569.60	0	109405.65	250
0	211298	60561.60	0	109421.65	250
0	211292	60555.60	0	109433.65	250

Figure 5.10: Demand trend values for areas of land-use classes in text file format for Dyna-CLUE model.

5.4.1.5. Conversion Matrix

Possible ways of conversions between the six land-use classes (bare, cropland, urban, other, forest, and water) are indicated in Table 5.4, where "1" stands for possible conversions and "0" for impossible ones. After that, the highlighted red selection in Table 5.4 is copied to a text file, and saved under the code name "*allow.txt*" (Figure 5.11) in the same directory where the model is installed.

Table 5.4: Land-use conversion matrix.

		Future Land-Use Classes					
		Bare	**Cropland**	**Urban**	**Other**	**Forest**	**Water**
Present Land-Use Classes	**Bare**	1	1	1	0	1	0
	Cropland	1	1	1	0	1	0
	Urban	0	0	1	0	0	0
	Other	1	1	1	1	1	0
	Forest	1	1	1	0	1	0
	Water	0	0	0	0	0	1

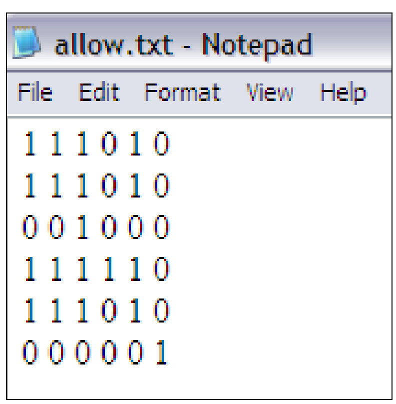


Figure 5.11: Land-use conversion matrix in text file format for Dyna-CLUE model.

5.4.1.6. Map of No-Restriction Area

The map of "*no restriction area*" is a raster created from the grid of the baseline map of 1991 where the six land-use classes are reclassified by assigning them with the code "0". After the reclassification, obtained raster is converted into ASCII format and given the code name "*region_nopark.fil*" (Figure 5.12). For simplicity, the steps of reclassification and conversion are programmed as a model in the model builder (Figure 5.12).

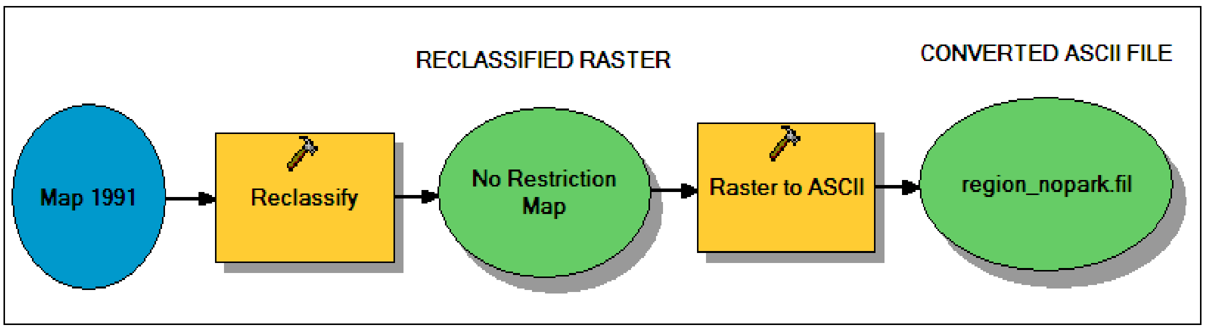
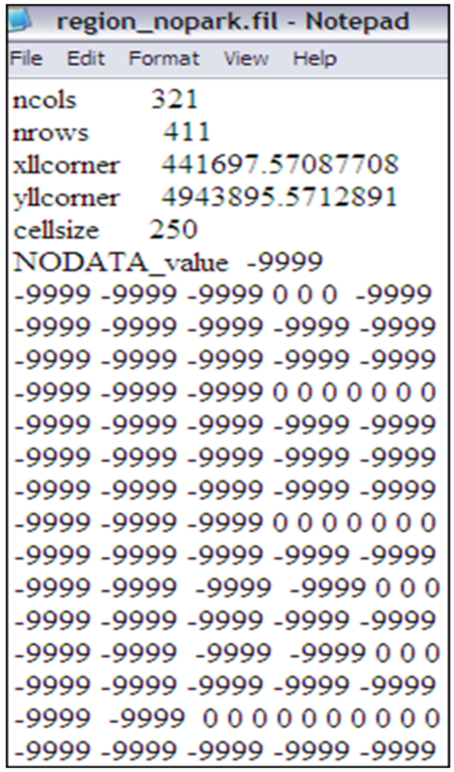


Figure 5.12: Designed model in Model Builder used for the creation of no-restriction area in ArcGIS.

The obtained ASCII file (region_nopark.fil) should be saved in the same directory where the model is installed (Figure 5.13).



region_nopark.fil - Notepad

File Edit Format View Help

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-9999 -9999  -9999  -9999 0 0 0
-9999 -9999 -9999 -9999 -9999
-9999  -9999  0 0 0 0 0 0 0 0 0 0
-9999 -9999 -9999 -9999 -9999
```

Figure 5.13: No-restriction area in ASCII format for Dyna-CLUE model.

5.4.1.7. Expected Driving Factors

Seven maps of land-use drivers have been proposed as the expected forces behind land-use changes in the SN watershed. These drivers were classified into two categories: geographic and demographic as shown in Table 5.5.

Table 5.5: List of expected driving factors behind land-use changes in the SN watershed (adapted from Seidou and Lapen, 2010).

Category	Description of Driving Factors	Codes of Driving Factors in ArcGIS
Demographic	Mean density population	DENSITY
Geographic	Distance to the closest city	TO_CITY
	Distance to the closest major city	TO_M_CITY
	Distance to the closest small city	TO_S_CITY
	Distance to major road	TO_M_ROAD
	Distance to paved road	TO_PAVED
	Distance to water body	TO_WATER

These drivers cover the Eastern Ontario boundary and are extracted according to the administrative limit of the SN watershed. The extraction is performed using the tool "*Extracted by Mask*" in ArcGIS. Then, the extracted rasters (density, distance to closet city, major city, small city, major road, paved road, and water body) are converted to ASCII format and assigned with the code names "*sc1gr0.fil*, *sc1gr1.fil*, *sc1gr2.fil*, *sc1gr3.fil*, *sc1gr4.fil*, *sc1gr5.fil*, and *sc1gr6.fil*", respectively (Figure 5.14). The following model in model builder (Figure 5.14) illustrates the steps from the extraction to the conversion.

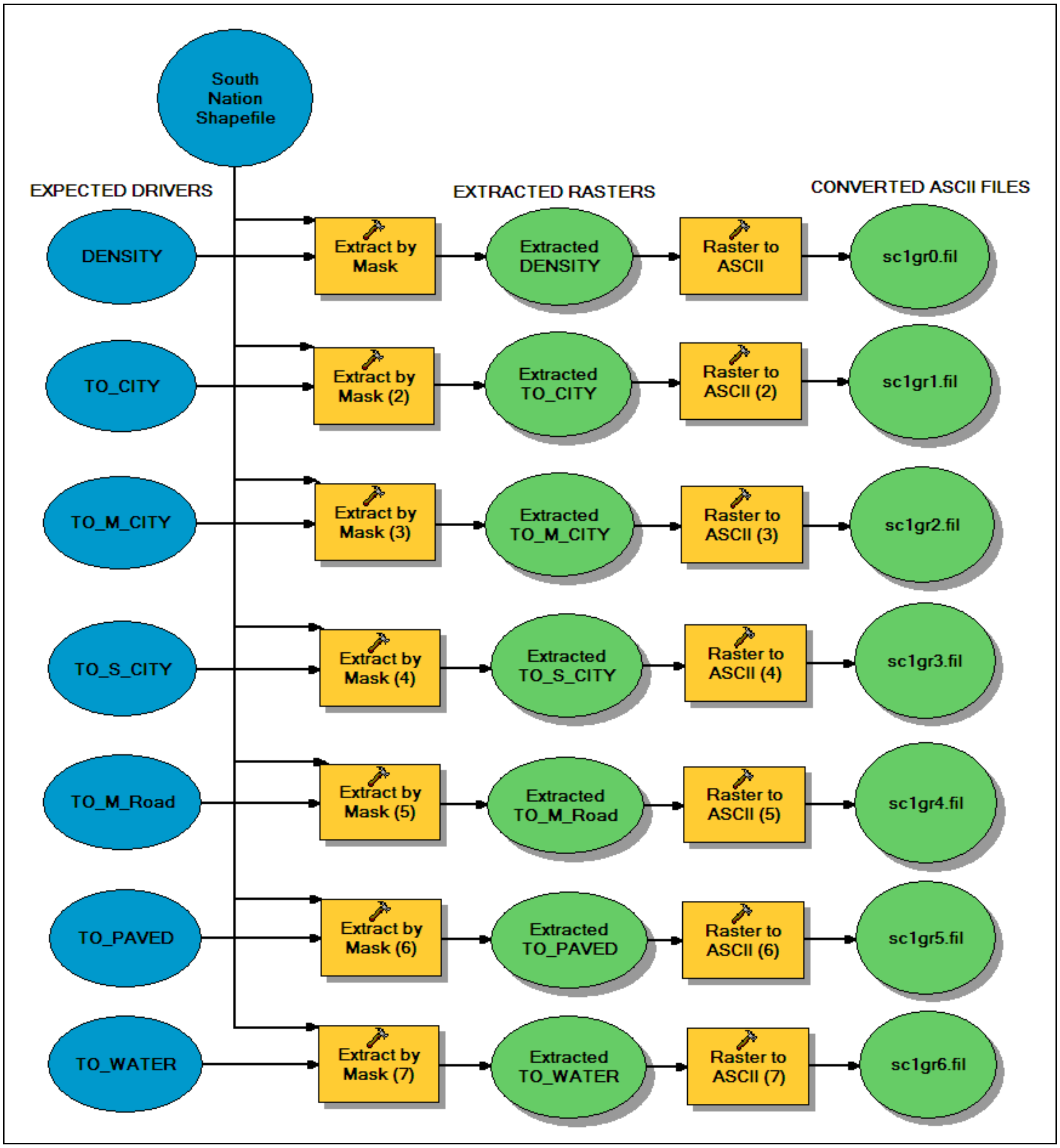
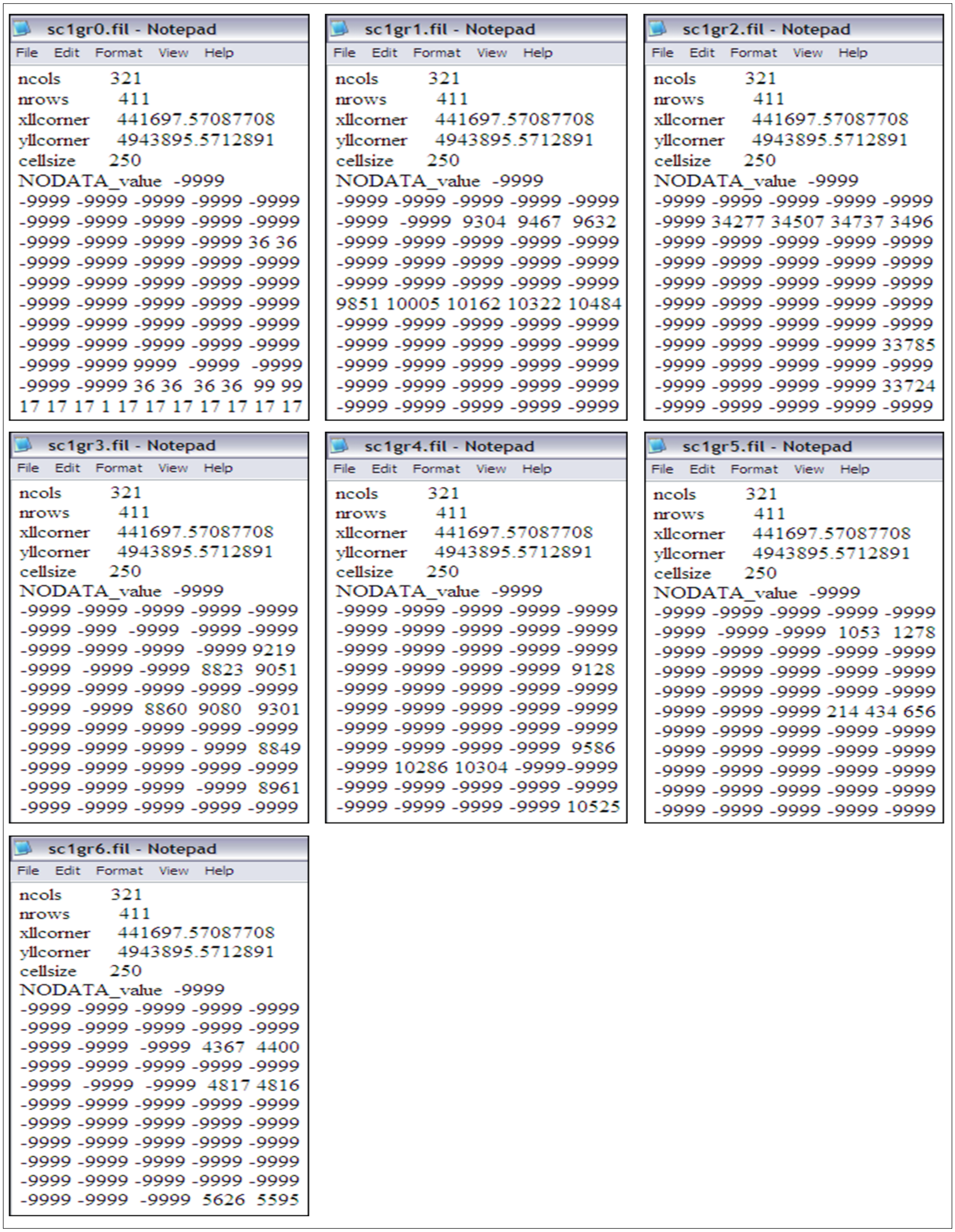


Figure 5.14: Designed model in Model Builder used to extract and convert expected driving factors in ArcGIS.

Created ASCII files of driving factors (Figure 5.15) are saved in the same directory where the model is located.



sc1gr0.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 36 36
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 9999  -9999  -9999
-9999 -9999 36 36  36 36  99 99
17 17 17 1 17 17 17 17 17 17 17
```

sc1gr1.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999  -9999  9304  9467  9632
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
9851 10005 10162 10322 10484
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
```

sc1gr2.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 34277 34507 34737 3496
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 33785
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 33724
-9999 -9999 -9999 -9999 -9999
```

sc1gr3.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 -999  -9999  -9999 -9999
-9999 -9999 -9999  -9999 9219
-9999  -9999 -9999  8823  9051
-9999 -9999 -9999 -9999 -9999
-9999  -9999  8860  9080  9301
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 - 9999  8849
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999  -9999  8961
-9999 -9999 -9999 -9999 -9999
```

sc1gr4.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999  9128
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999  9586
-9999 10286 10304 -9999-9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 10525
```

sc1gr5.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999  -9999 -9999  1053  1278
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 214 434 656
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
```

sc1gr6.fil - Notepad

File Edit Format View Help

```
ncols        321
nrows        411
xllcorner    441697.57087708
yllcorner    4943895.5712891
cellsize     250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999  -9999  4367  4400
-9999 -9999 -9999 -9999 -9999
-9999  -9999  -9999  4817 4816
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999  -9999  5626  5595
```

Figure 5.15: Expected driving factors in ASCII format for Dyna-CLUE model.

5.4.1.8. ROC Evaluation

Binary logistic regression analyses were conducted with the statistical software SPSS using the stepwise method. The purpose of these analyses is to identify the effective driving factors which were behind land-use changes in the SN watershed. The regression confidence degree used in these analyses was set to 99% ($\alpha = 0.01$), and the beta coefficients which did not satisfy this condition were excluded. Only regression models that showed ROC values above 50% are listed in Table 5.6, and their related ROC curves are presented in Appendix C.

Table 5.6: Calculated beta coefficients and ROC values of binary logistic regression for land-use classes of 1991 in SPSS.

Driving Factor	Bare	Cropland	Urban	Other	Forest
Mean density population	0.001104	0.001246	0.008669	0.008195	0.000167
Distance to closet city			0.000331	0.000165	0.000071
Distance to closet major city	0.000015	0.000024	-0.000012	-0.000180	-0.000019
Distance to major road	0.000010	0.000054	0.000100	0.000372	-0.000082
Distance to paved road	-0.000362	-0.000667	-0.008321	-0.002709	0.001082
Constant	-2.606497	-1.445821	-5.042388	-3.845015	0.561357
ROC value	**0.827**	**0.913**	**0.821**	**0.759**	**0.867**

The "*logit*" model equations (Eqn.3.1), for each of the five land-use classes, can be written as follows:

Probability [Bare] = -2.606497 + 0.001104 [Density] + 0.000015 [To closet major City] + 0.00001 [To major roads] - 0.000362 [To paved roads]

Probability [Cropland] = -1.445821 + 0.001246 [Density] + 0.000024 [To closet major City] + 0.000054 [To major roads] - 0.000667 [To paved roads]

Probability [Urban] = -5.042388 + 0.008669 [Density] + 0.000331 [To closet City] - 0.000012 [To closet major City] + 0.0001 [To major roads] - 0.008321 [To paved roads]

Probability [Other] = -3.845015 + 0.008195 [Density] + 0.000165 [To closet City] - 0.00018 [To closet major City] + 0.000372 [To major roads] - 0.002709 [To paved roads]

Probability [Forest] = 0.561357 + 0.000167 [Density] + 0.000071 [To closet City] - 0.000019 [To closet major City] – 0.000082 [To major roads] + 0.001082 [To paved roads]

To implement the results of the logistic regression equations into Dyna-CLUE model, the above equations are encoded in a text file (alloc1.reg) and saved in the same directory where the model is installed (Figure 5.16).

alloc1.reg - WordPad

File Edit View Insert Format Help

```
0
        -2.606497
4
        0.001104 0
        0.000015 2
        0.000010 3
        -0.000362 4

1
        -1.445821
4
        0.001246 0
        0.000024 2
        0.000054 3
        -0.000667 4

2
        -5.042388
5
        0.008669 0
        0.000331 1
        -0.000012 2
        0.000100 3
        -0.008321 4

3
        -3.845015
5
        0.008195 0
        0.000165 1
        -0.000180 2
        0.000372 3
        -0.002709 4

4
        0.561357
5
        0.000167 0
        0.000071 1
        -0.000019 2
        -0.000082 3
        0.001082 4
5
        0.7
```

Figure 5.16: Results of the logistic regression equations in a text file format for Dyna-CLUE model.

5.4.2. Model Calibration

After four runs of the model using the "*initial land-use age of pixels*" (generated by the model) combined with sets of elasticity coefficients for land-use classes specified by the user to define the resistance of each land-use class to conversion. During each run, simulated map of 1998 was compared to the reality map of the same year. It was found that the most reliable results depend on the following elasticity coefficient set of values 0.2, 0.4, 1, 0.2, 0.9, and 1, for bare, cropland, urban, other, forest, and water, respectively. For now, these values were taken as the elasticity coefficients that represent the resistance of land-use classes to the conversion.

5.5. Run Dyna-CLUE Scenarios

5.5.1. Run of Scenario 1

Before running this scenario, the user must make sure that all the ASCII and text files (baseline map of 1991, demand file, matrix of conversion, map of no restriction area, driving factors, and regression results) are saved in the same directory where the Dyna-CLUE model is installed.

5.5.2. Run of Scenario 2

Scenario 2 is based on the same files used in scenario 1, but with an area restriction created by the user on bare land-use class, as follows:

5.5.2.1. Bare Restricted Area

The procedure followed to create the bare restricted area was to reclassify the baseline map of 1991 by assigning the code "-9998" (code of area restriction in Dyna-CLUE model) to bare pixels, and the code "0" to the remaining active cells. Once the reclassification is done, obtained raster must be converted into ASCII format and assigned the code name "*region_park1.fil*". For simplicity, the steps of reclassification and conversion from raster to ASCII are programmed as a model in the model builder (Figure 5.17).

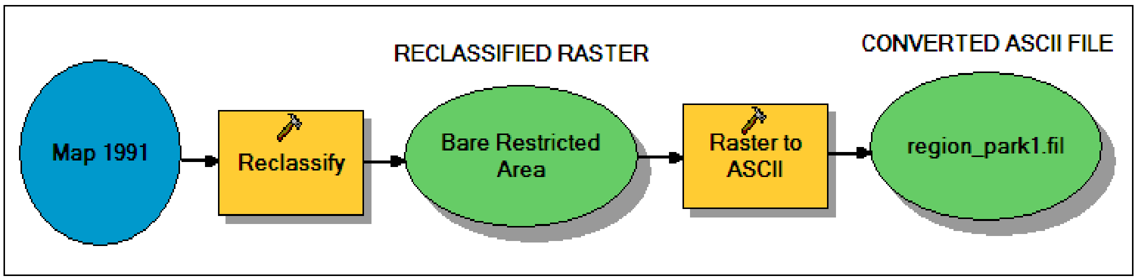
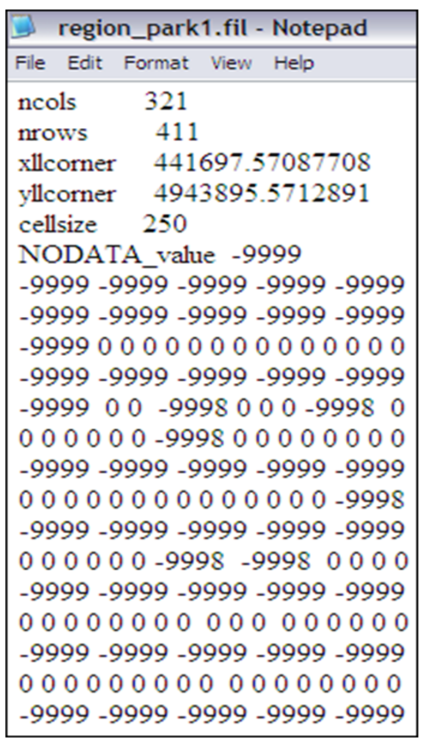


Figure 5.17: Designed model in Model Builder used for the creation of bare reserved area in ArcGIS.

Obtained ASCII file (region_park1.fil) should be saved in the same directory where the model is installed (Figure 5.18).



region_park1.fil - Notepad
File Edit Format View Help

```
ncols        321
nrows         411
xllcorner     441697.57087708
yllcorner     4943895.5712891
cellsize      250
NODATA_value  -9999
-9999 -9999 -9999 -9999 -9999
-9999 -9999 -9999 -9999 -9999
-9999 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-9999 -9999 -9999 -9999 -9999
-9999  0 0  -9998 0 0 0 -9998  0
0 0 0 0 0 0 -9998 0 0 0 0 0 0 0 0
-9999 -9999 -9999 -9999 -9999
0 0 0 0 0 0 0 0 0 0 0 0 0 0 -9998
-9999 -9999 -9999 -9999 -9999
0 0 0 0 0 0 -9998  -9998  0 0 0 0
-9999 -9999 -9999 -9999 -9999
0 0 0 0 0 0 0 0  0 0 0  0 0 0 0 0 0
-9999 -9999 -9999 -9999 -9999
0 0 0 0 0 0 0 0 0  0 0 0 0 0 0 0 0
-9999 -9999 -9999 -9999 -9999
```

Figure 5.18: Bare reserved area in ASCII format for Dyna-CLUE model.

Before running scenario 2, the user must make sure that the ASCII and text files (baseline map of 1991, matrix of conversion, driving factors, regression results, map of bare restriction area, and demand.in2 file) are saved in the same directory where the model is installed.

5.5.3. Run of Scenario 3

Scenario 3 is based on the same input files used in scenario 1, but an "*initial land-use age of pixels*" prepared by the user is now used (instead of the "*initial land-use age of pixels*" generated by the model) in the run of this scenario.

5.5.3.1. Initial Land-Use Age of Pixels

The procedure used to create an "*initial land-use age of pixels*" is to reclassify land-use classes in the baseline map of 1991 by assigning bare, cropland, urban, other, forest, and water with the code values of "2", "5", "80", "3", "25", and "100", respectively. Each of these code values is assumed by the user for each land-use class, and represents the number of years spent at a given pixel prior to the start of the simulations (i.e., before applying the Dyna-CLUE model). For simplicity, the steps of reclassification and conversion are programmed as a model in the model builder (Figure 5.19).

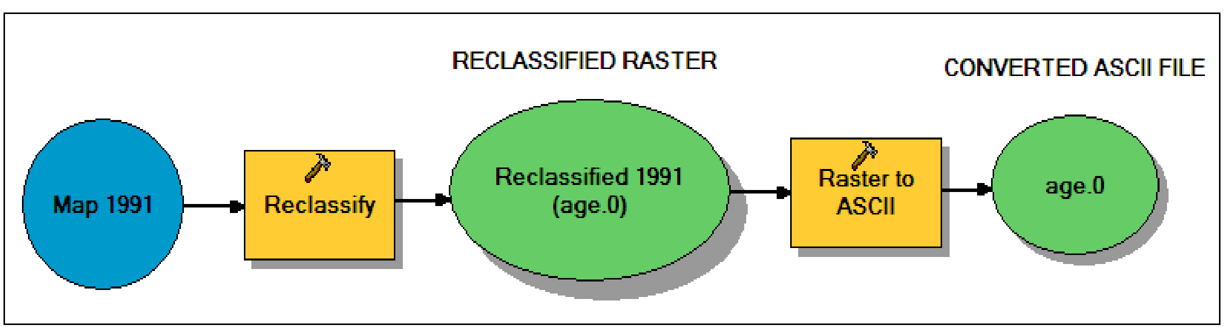


Figure 5.19: Designed model in Model Builder used for the creation of initial land-use age of pixels in ArcGIS.

The obtained ASCII file (age.0) should be saved in the same directory where the model is installed (Figure 5.20).

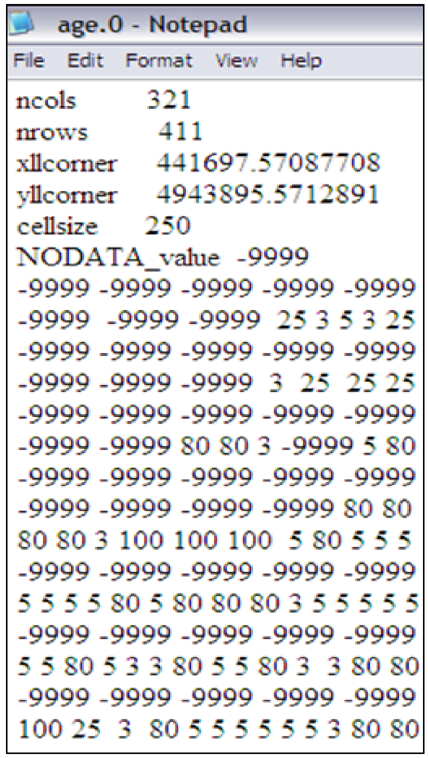


Figure 5.20: Initial land-use age of pixels in ASCII format for Dyna-CLUE model.

Before running this scenario, the user must make sure that the ASCII and text files (baseline map of 1991, demand file, matrix of conversion, map of no restriction area, driving factors, regression results, and created initial land-use age of pixels) are saved in the same directory where the Dyna-CLUE model is installed.

5.6. Model Output

Overall, Dyna-CLUE model generates a total of 90 maps of simulations from the runs of the three scenarios. The main output maps are those of the years at which reality maps are available for comparison (as described in section 5.3 and 5.4).

5.6.1. Simulated Maps from Scenarios 1 and 3

Taking into consideration the existence of reality maps for the year 1998 (the 7th year of simulations) and 2005 (the 14th year of simulations), only simulated maps of those years (i.e., 1998 and 2005) are selected to undertake the error matrix tests as shown below in sections 5.7.1.1 and 5.7.1.3.

5.6.2. Simulated Maps from Scenario 2

Only maps of year 2005 (the 14th year of simulations) and 2020 (last year of simulations) are selected to undertake the error matrix tests with the baseline map of 1991 (section 5.7.1.2).

5.7. Model Validation

Dyna-CLUE generates maps in ASCII format (without projection) with numbering codes for land-use classes which start from class "zero". In order to compare between simulated and reality maps, selected maps must be converted from ASCII to raster, then the projection parameters of obtained rasters must be adjusted to fit the geographical location of the SN watershed (e.g., NAD_1983, UTM_Zone 18 N, and D_North_American_1983). After that, the land-use classes in projected rasters are reclassified with code numbers starting from a value of "1".

5.7.1. Statistical Validation

5.7.1.1. Validation of Results Generated from Scenario 1

The geo-processing procedures (i.e., the ASCII/raster conversion, raster projection, reclassification, and computation of the cross-tabulation area between simulated and reality maps of 1998 and 2005) were programmed as a model in model builder (Figure 5.21). Next, the error matrices between simulated and reality maps of 1998 and 2005 are computed and presented in Tables 5.7 and 5.8, respectively. Discussion on results is covered in Chapter 6.

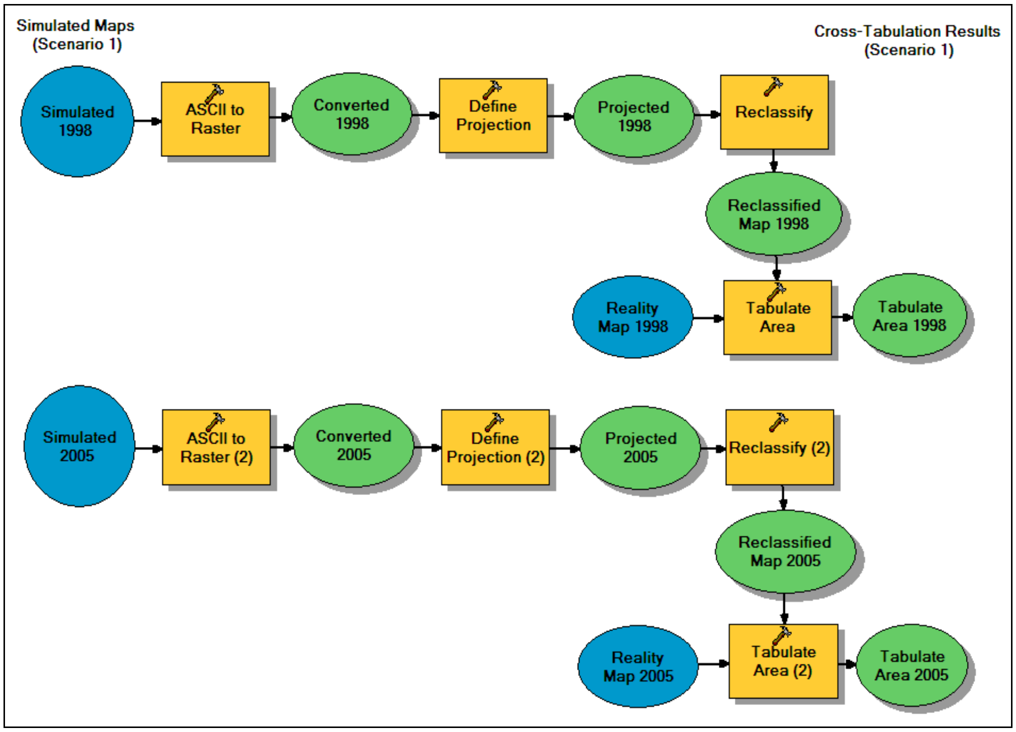


Figure 5.21: Designed model in Model Builder used in scenario 1 to compute the cross tabulate area between reality and simulated maps of 1998 and 2005 in ArcGIS.

Table 5.7: Accuracy results of simulated and reality maps of 1998 obtained from scenario 1.

Observed Classes from Reality Map of 1998

Generated Classes from Simulated Map of 1998

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare		35812500	62500	500000	4937500	0	41312500	
Cropland		1811000000	1312500	4750000	343687500	3187500	2163937500	0.84
Urban		381937500	9937500	1750000	219125000	2250000	615000000	0.02
Other							0	
Forest		139750000	187500	687500	849937500	2000000	992562500	0.86
Water		500000	0	0	1250000	750000	2500000	0.30
$n_{.j}$	0	2369000000	11500000	7687500	1418937500	8187500	3815312500	
Producer's Accuracy		0.76	0.86		0.60	0.09		

Overall Accuracy	0.70

Table 5.8: Accuracy results of simulated and reality maps of 2005 obtained from scenario 1.

Observed Classes from Reality Map of 2005

Generated Classes from Simulated Map of 2005

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare							0	
Cropland		1801312500	389500000		277687500	187500	2468687500	0.73
Urban		64500000	29625000		13562500	125000	107812500	0.27
Other							0	
Forest		251500000	186062500		734500000	1062500	1173125000	0.63
Water		14062500	9750000		40750000	1125000	65687500	0.02
$n_{.j}$	0	2131375000	614937500	0	1066500000	2500000	3815312500	
Producer's Accuracy		0.85	0.05		0.69	0.45		

Overall Accuracy	0.67

5.7.1.2. Validation of Results Generated from Scenario 2

The geo-processing procedures (i.e., the ASCII/raster conversion, raster projection, reclassification, and computation of the cross-tabulation area between simulated and reality maps of 2005 and 2020) are programmed in the model builder (Figure 5.22). Next, the error matrices between the simulated and reality maps of 2005 and 2020 are computed and presented in Tables 5.9 and 5.10, respectively. Discussion on results is covered in Chapter 6.

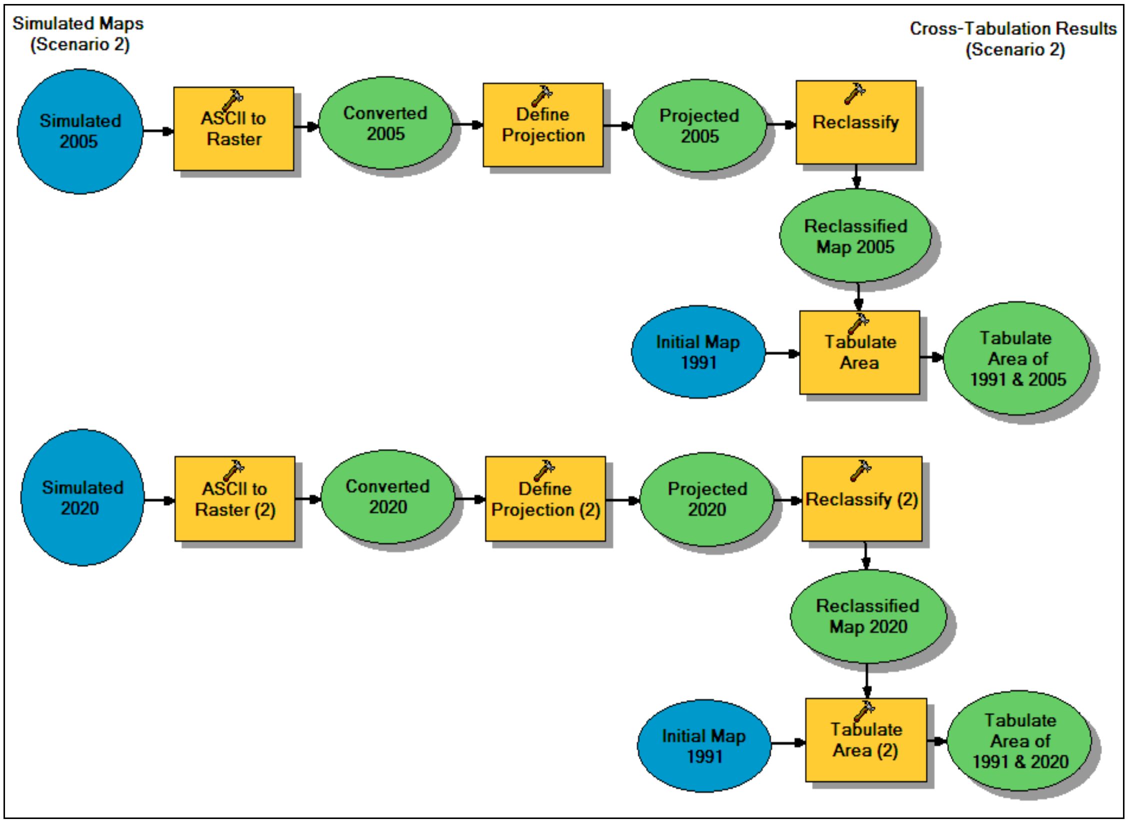


Figure 5.22: Designed model in Model Builder used in scenario 2 to compute the cross tabulate area between map of 1991 and simulated maps of 2005 and 2020 in ArcGIS.

Table 5.9: Accuracy results of map of 1991 and simulated map of 2005 obtained from scenario 2.

Observed Classes from Map of 1991

Generated Classes from Simulated Map of 2005

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare	91062500	0	0	0	0	0	91062500	1.00
Cropland	0	1857437500	0	255687500	13625000	0	2126750000	0.87
Urban	0	33062500	546187500	35687500	0	0	614937500	0.89
Other							0	
Forest	0	59250000	0	136625000	784187500	0	980062500	0.80
Water	0	0	0	0	0	2500000	2500000	1.00
$n_{.j}$	91062500	1949750000	546187500	428000000	797812500	2500000	3815312500	
Producer's Accuracy	1.00	0.95	1.00		0.98	1.00		

Overall Accuracy	0.86

Table 5.10: Accuracy results of map of 1991 and simulated map of 2020 obtained from scenario 2.

Observed Classes from Map of 1991

Generated Classes from Simulated Map of 2020

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare	91062500	0	0	0	0	0	91062500	1.00
Cropland	0	1834500000	0	255687500	13625000	0	2103812500	0.87
Urban	0	33062500	546187500	35687500	0	0	614937500	0.89
Other							0	
Forest	0	82187500	0	136625000	784187500	0	1003000000	0.78
Water	0	0	0	0	0	2500000	2500000	1.00
$n_{.j}$	91062500	1949750000	546187500	428000000	797812500	2500000	3815312500	
Producer's Accuracy	1.00	0.94	1.00		0.98	1.00		

Overall Accuracy	0.85

5.7.1.3. Validation of Results Generated from Scenario 3

The geo-processing procedures (i.e., the ASCII/raster conversion, raster projection, reclassification, and computation of the cross-tabulation area between simulated and reality maps of 1998 and 2005) are programmed in the model builder (Figure 5.23).

Next, the error matrices between the simulated and reality maps of 1998 and 2005 are computed and presented in Tables 5.11 and 5.12, respectively. Discussion on results is covered in Chapter 6.

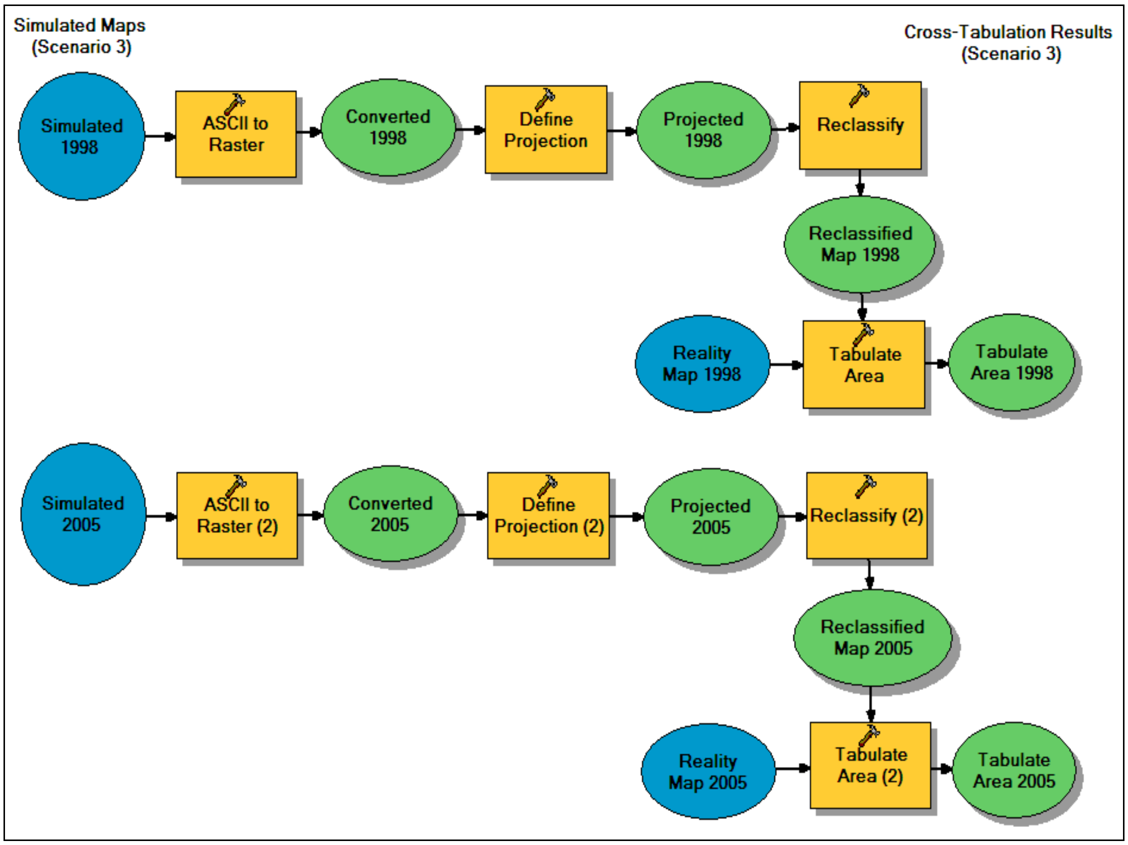


Figure 5.23: Designed model in Model Builder used in scenario 3 to compute the cross tabulate area between reality and simulated maps of 1998 and 2005 in ArcGIS.

Table 5.11: Accuracy results of simulated and reality maps of 1998 obtained from scenario 3.

Observed Classes from Reality Map of 1998

Generated Classes from Simulated Map of 1998

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare		35812500	62500	500000	4937500	0	41312500	
Cropland		**1811000000**	1312500	4750000	343687500	3187500	2163937500	0.84
Urban		381937500	**9937500**	1750000	219125000	2250000	615000000	0.02
Other							0	
Forest		139750000	187500	687500	**849937500**	2000000	992562500	0.86
Water		500000	0	0	1250000	**750000**	2500000	0.30
$n_{.j}$	0	2369000000	11500000	7687500	1418937500	8187500	3815312500	
Producer's Accuracy		0.76	0.86		0.60	0.09		

Overall Accuracy	0.70

Table 5.12: Accuracy results of simulated and reality maps of 2005 obtained from scenario 3.

Observed Classes from Reality Map of 2005

Generated Classes from Simulated Map of 2005

CLASS	Bare	Cropland	Urban	Other	Forest	Water	$n_{i.}$	User's Accuracy
Bare							0	
Cropland		**1801312500**	389500000		277687500	187500	2468687500	0.73
Urban		64500000	**29625000**		13562500	125000	107812500	0.27
Other							0	
Forest		251500000	186062500		**734500000**	1062500	1173125000	0.63
Water		14062500	9750000		40750000	**1125000**	65687500	0.02
$n_{.j}$	0	2131375000	614937500	0	1066500000	2500000	3815312500	
Producer's Accuracy		0.85	0.05		0.69	0.45		

Overall Accuracy	0.67

CHAPTER 6

DISCUSSION AND CONCLUSIONS

6.1. Outline

This chapter focuses on the performance of the Dyna-CLUE model in simulating land-use changes of the South Nation watershed. In order to test the hypotheses proposed in scenarios 1 and 3, the simulated maps of 1998 and 2005, generated from both scenarios, were used to conduct the error matrices with the reality maps of the same years. To test the hypothesis proposed in scenario 2, the simulated maps of 2005 and 2020 were used to conduct the error matrices with the baseline map of 1991. At the end, a visual comparison between the three scenarios is conducted for the last simulated maps (maps of year 2020) so as to identify the best scenario(s) in predicting realistic simulations for the SN watershed.

6.2. Results from Scenario 1

6.2.1. Error Matrix of 1998

Table 5.7 shows the results of the error matrix computed between the reality and simulated maps of 1998. The overall accuracy computed was 70%, which means that the model was able to agreeably predict the simulated map of year 1998 (Figure 6.1). Table 5.7 shows that the cell values on the diagonal (of bare and other land-use classes) had pixel count of empty cells (no matching between reality and simulated maps of 1998). This means that, in some year before 1998, both land-use classes had been completely converted. This could have occurred due to two reasons:

1. The elasticity coefficients were set up for those classes at the lowest values (0.2 for each) compared to the remaining land-use classes (0.4, 1.0, 0.9, and 1.0 for cropland, urban, forest, and water, respectively). Consequently, those land-use classes will be the first to undergo the conversion; and
2. The conversion matrix set up for the six land-use classes, allows such type of conversion.

The calculation of the producer's accuracy of cropland, forest, and water land-use classes showed that 76% of cropland, 60% of forest, and 9% of water land-use areas have been correctly identified in the reality map of 1998 (Table 5.7). The calculation of the user's accuracy, of the same classes, showed that 84, 86, and 30% of the areas denoted as cropland, forest, and water land-use classes respectively in the simulated map of 1998 were correctly detected compared to the real situation (Table 5.7). This could be attributed to the following reasons:

1. As discussed previously, bare and other land-use classes had been converted to cropland, forest, and water land-use classes since they had the lowest elasticity coefficients (0.2 for each); but
2. Based on the conversion matrix, this could be performed to all land-use classes except for the "water" land-use class which had been identified as a static class at the beginning of the simulations.

The producer's accuracy of urban land-use class showed that 86% of the urban areas have been identified as urban in the reality map of 1998 (Table 5.7). On the other hand, the calculation of the user's accuracy of the same land-use class showed that only 2% of the areas determined as "urban" in the simulated map of 1998 are actually urban on the ground (Table 5.7). This might happen if the urban land-use class was misclassified in the reality map of 1998.

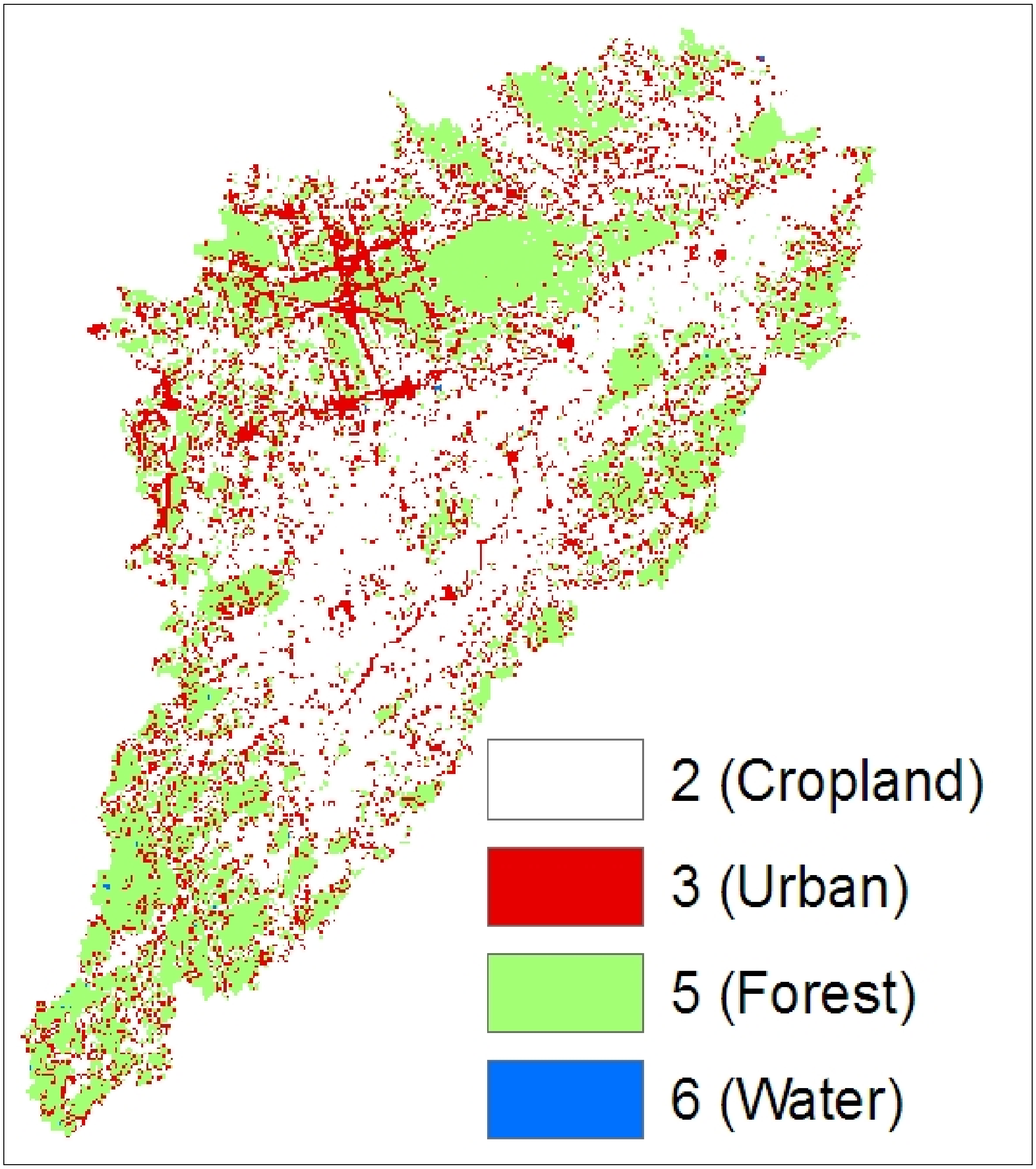


Figure 6.1: Simulated map of 1998 for the SN watershed generated from scenario 1.

6.2.2. Error Matrix of 2005

Table 5.8 shows the results of the error matrix computed between the reality and simulated maps of 2005. The overall accuracy of the model was 67%, which means that simulated map of 2005 (Figure 6.2) was fairly close to the reality map of the same year.

The producer's accuracy computed for the model predictions of cropland, forest, and water land-use classes have shown that 85% of cropland, 69% of forest, and 45% of water land-use areas have been correctly identified in the reality map of 2005 (Table 5.8). While, the calculation of the user's accuracy for the same classes showed that only 73% , 63%, and 2% of the areas identified as cropland, forest, and water land-use classes in the simulated map of 2005, were actually cropland, forest, and water land-use classes, respectively, on the ground (Table 5.8). This could be explained by the reason that cropland, forest, and water classes might have been misclassified in the reality map of 2005.

The calculation of the producer's accuracy of urban land-use class showed that only 5% of the urban areas have been identified as "urban" in the reality map of 2005 (Table 5.8). While, the calculation of the user's accuracy, of the same land-use class, showed that 27% of the areas determined as "urban" in the simulated map of 2005, are actually urban on the ground (Table 5.8). Since this scenario was run with an initial land-use age of pixels generated by the model (randomly selected by model), it can be concluded that:

1. The randomized initial land-use age of pixels has played the main role of synchronizing the rate of conversion among land-use classes;

2. Among the remaining land-use classes (cropland, forest, and water), the elasticity coefficient of cropland was set up at the lowest value (0.4). Therefore, it will be the first land-use class to undergo the conversion; and

3. The matrix of conversion set up for the six land-use classes allows such type of conversion.

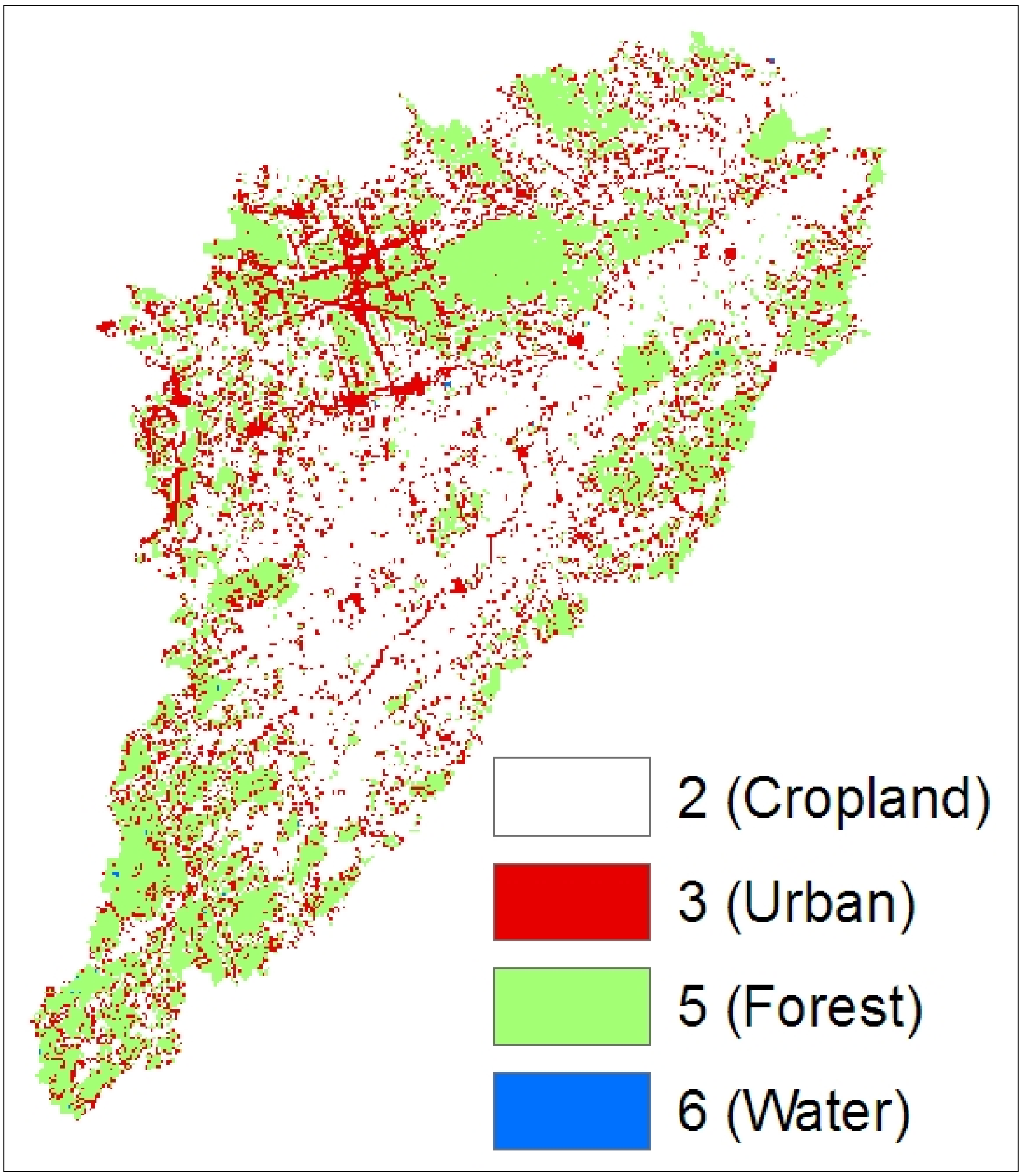


Figure 6.2: Simulated map of 2005 for the SN watershed generated from scenario 1.

6.2.3. Summary from Scenario 1

The results from both error matrices of 1998 and 2005 proved that the Dyna-CLUE model was able to simulate maps fairly close to reality. It should be noted that the accuracy of prediction could have been increased with the precision in the reclassification occurred to original land-use classes of the reality maps of 1998 and 2005. Results are in agreement with studies conducted by: Verburg and Overmars (2007); Trisurat *et al.*, (2010); Luo *et al.,* (2010); and Zhu *et al.,* (2010) which reported that the model was capable of generating simulated maps quite similar to reality.

The model was found very sensitive to changes in the elasticity coefficients set up for land-use classes, which conform to the findings of Soepboer (2001); Batisani and Yarnal (2009); and Luo *et al.,* (2010). The randomized initial land-use age of pixels played a significant role in synchronizing the rate of conversion among land-use classes, as well as, its direct effect on calibrating the model's iteration process. In addition, the combination between the statistical results of the error matrices and the performance of the model allowed the user to detect possible misclassification among land-use classes in the reality maps of 1998 and 2005. In conclusion, the hypotheses proposed for the run of scenario 1 was proved true.

6.3. Results from Scenario 2

6.3.1. Error Matrices of 2005 and 2020

In the error matrices presented in Tables 5.9 and 5.10, the producer's and user's accuracies for the predictions of bare land-use were equal to 100%, which indicates that bare land-use type have not undergone any conversions and was stable during the whole simulation period. In addition, validation by visual observation between the baseline map of 1991 and the simulated maps of 2005 and 2020 confirmed that bare areas remained intact during the simulation period (Figure 6.3).

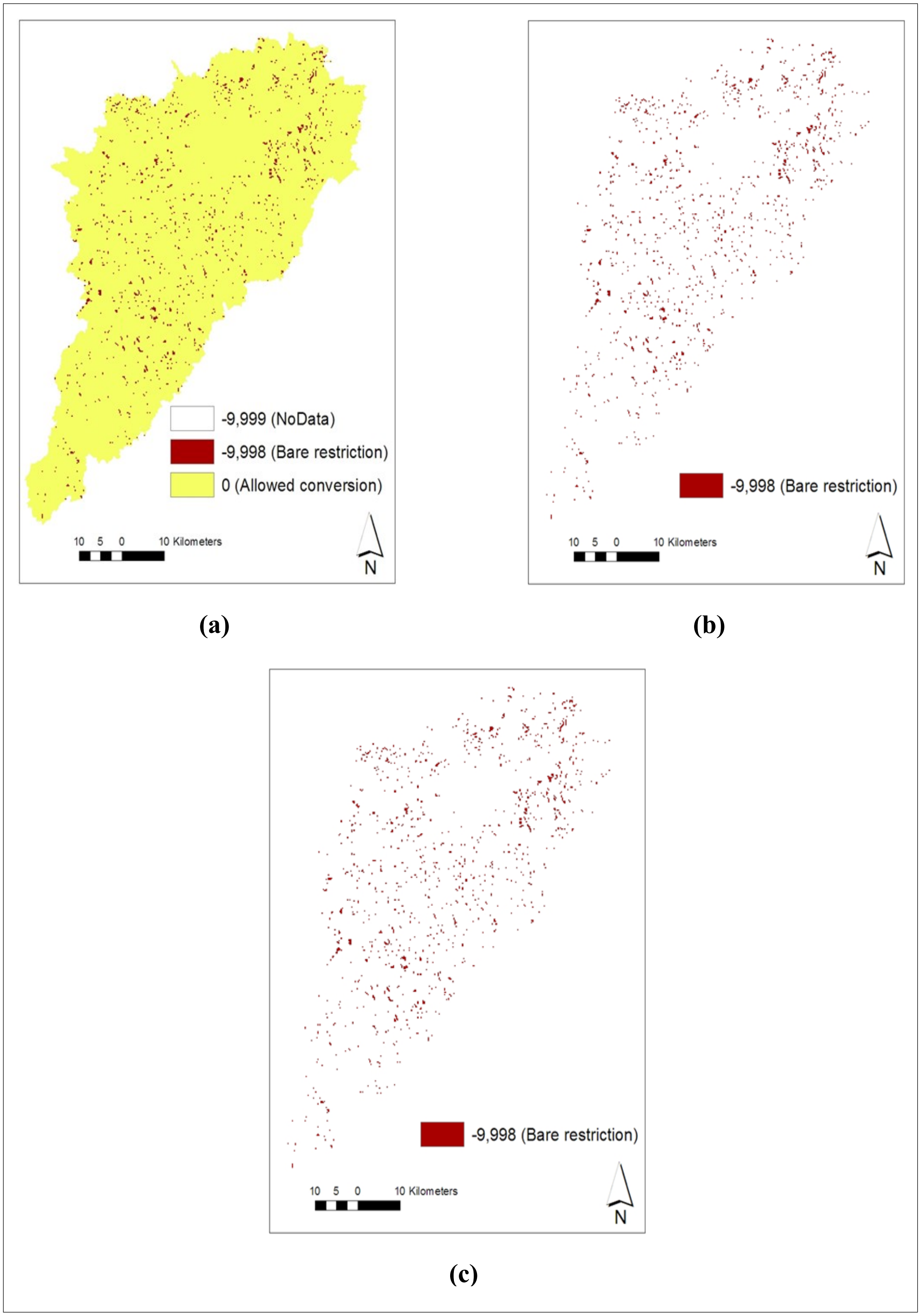


Figure 6.3: Bare reserved areas in map (a) 1991, (b) 2005, and (c) 2020.

6.3.2. Summary from Scenario 2

The results of statistical and visual validation conducted between the baseline map of 1991 and the simulated maps of 2005 and 2020 proved that the Dyna-CLUE model was able to respond to any planned policies (such as that proposed in scenario 2). Results are in agreement with the findings of Soepboer (2001); Verburg and Overmars (2007); Luo *et al*., (2010); and Zhu *et al.*, (2010) who reported that the Dyna-CLUE model is generally capable of respond and protect policy-making of any reserved areas. In conclusion, the hypotheses proposed for the run of scenario 2 was verified.

6.4. Results from Scenario 3

6.4.1. Error Matrices of 1998 and 2005

Tables 5.11 and 5.12 shows the same results of the error matrices as observed in tables 5.7 and 5.8 computed between the reality and simulated maps of 1998 and 2005, respectively. Such results proved that the initial land-use age of pixels created by the user and implemented in the run of scenario 3 was found not to play a role in synchronizing and prioritizing the sequences of conversions among land-use classes as was expected.

6.5. Comparison between Scenarios

This comparison covers only the results generated from scenarios 1 and 2, since scenario 3 was found identical to scenario 1.

Scenario 2 was conducted as a test to assess the ability of the Dyna-CLUE model to respond to a proposed policy. Therefore, the following conclusions can be drawn:

1. The Dyna-CLUE model was able to fairly simulate/predict reality maps (scenario 1).

2. The model was found sensitive to changes in the elasticity coefficients of land-use classes.
3. When created by the user, the initial land-use age of pixels could not play a significant role in calibrating the model and prioritizing the sequence of conversions among land-use classes as predicted which means that the model was found not sensitive to the changes of initial land-use age of pixels (scenario 3).
4. The statistical analysis (by means of the error matrix) allowed the user to detect possible misclassifications among land-use classes in reality maps (scenario 1).

In conclusion, scenario 1 was found able to predict land-use changes in the SN watershed. Therefore, it can be predicted that the land-use changes map of the SN watershed in the year 2020 will be expected to be similar to the map predicted by the Dyna-CLUE model as shown in Figure 6.4.

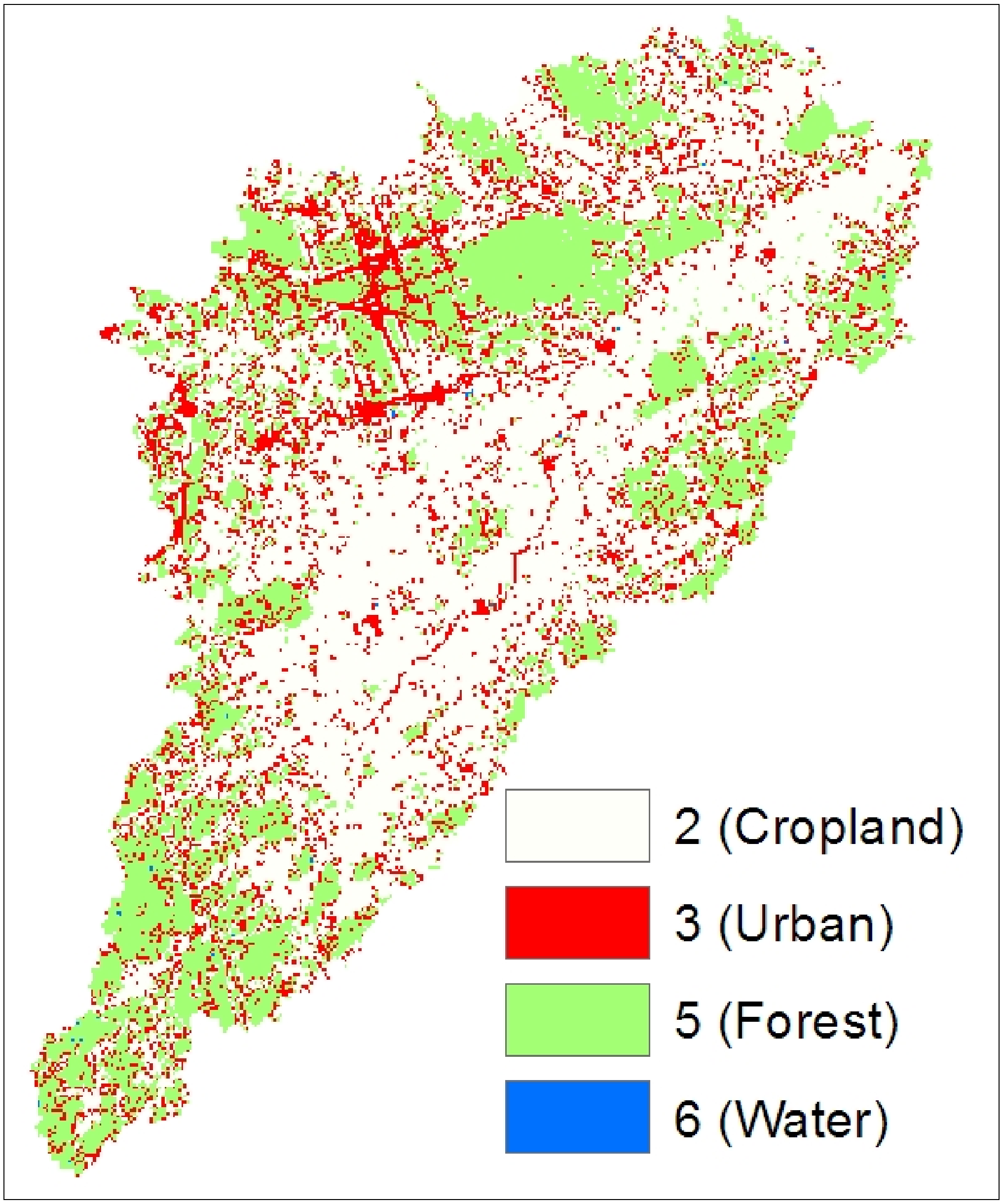


Figure 6.4: Predicted map of 2020 for the SN watershed generated from scenario 1.

6.6. Conclusions

The Dyna-CLUE model was applied to the South Nation watershed with three different runs of scenarios in order to have a better understanding of the development of the region. Based on the simulations performed in the present study, it should be noted that the application of the Dyna-CLUE model is not straightforward since data preparation and conversions require significant time (months). In addition, basic knowledge and expertises in statistical software (SPSS or other) and ArcGIS are required to run statistical analyses and geo-processing procedures.

The interpretation of the results of this study proved that, the Dyna-CLUE model was able to: (1) simulate land-use maps quite close to reality, and (2) respond to proposed policies such as certain area restrictions. It was found that the model was not sensitive to the implementation of an initial land-use age of pixels either randomized by the model or created by the user. It was also found that the model is very sensitive to changes in the elasticity coefficients set up for various land-use classes. However, further studies and applications may contribute to better predict future land-use changes of the region.

6.7. Thesis Contribution

This work is the first application of the Dyna-CLUE model in Eastern Ontario. The research work in the present study has added the following contributions:

1. Proving that the Dyna-CLUE model was not been affected by implementing an initial land-use age of pixels created by the user. Results observed were the same compared to those obtained from a run with a randomized initial land-use age of pixels generated by the model.

2. Enhancing the common statistical validation procedures of the model by calculating the error matrix (map pair analysis) between simulated and reality maps at a given year.

6.8. Future Work and Recommendations

Based on the observations and findings of this study, the following recommendations are proposed for future work intended to apply the Dyna-CLUE modeling software:

1. The conservation authority of the South Nation watershed should develop and enforce sustainable policies, such as: specify park zones with forestry regions, agricultural zoning and recreational/tourism zoning, so as to better control the urbanization growth in the watershed.
2. For future studies of the South Nation watershed, the modeller must consider implementing some socio-economic drivers (e.g., income and gross domestic product) as well as bio-physical drivers (such as soil erosion susceptibility).
3. In the calculation of the land-use demands, the modeller must rely on socio-economic trends to project future allocated areas since those trends are more realistic in figuring out the situation rather than historical trends.

APPENDIX A

ADDITIONAL INFORMATION FOR CLUE VERSIONS

Model General Information	
Model Name	Conversion of Land Use change and its Effects.
Model Abbreviation	CLUE, CLUE-S, Dyna-CLUE and CLUE-Scanner.
Model General Summary	The objective of CLUE model is to make a spatially explicit, multi-scale, quantitative description of land use changes through dynamic modelling and the quantification of the most important (assumed) bio-geophysical and human drivers based on either knowledge of the land use system or empirical analysis of observed land use patterns.
Model Home Page	http://www.ivm.vu.nl/CLUE

Information on Model Development	
Model Developers / Owners	Peter H. Verburg, Koen Overmars, Tom Veldkamp and other contributors Department of Environmental sciences Landscape Centre at Wageningen University (www.cluemodel.nl).
Model History	Mid 1990s - ongoing.
Target Group / Users	The CLUE model has been used by a large number of both universities and governmental research institutes from all over the world.
Calibration	Calibration is based on observed land use patterns and, if possible, based on historic data. For some case studies calibration is helped by interviews with land managers.
Validation	Validation is based on historic land use changes for various case studies. Pontius *et al.*, 2007. Comparing the input, output, and validation maps for several models of land change.

	Model Dimension
Thematic coverage	• Agriculture • Land use • Urbanization
Input data	• Land use maps, remote sensing of land cover or census data on land use • Demographic change • Land use requirements (based on trends, scenarios, or macro-economic modelling) • Spatial policies • (Assumed) location factors
Output data	• Land use change

APPENDIX B

MAIN PARAMETERS OF DYNA-CLUE

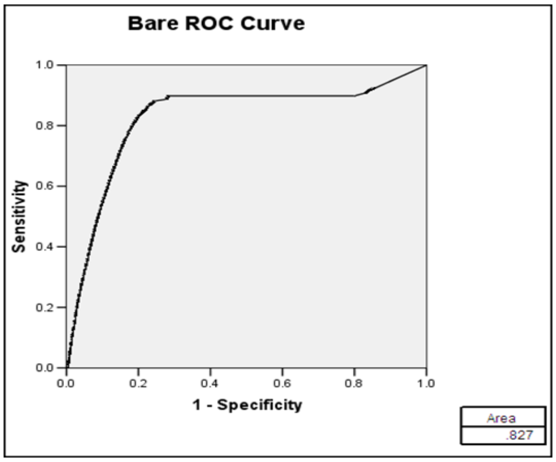
Line	Title	Description	Format	Example
1	Number of land-use types	Maximum 12 different land-use types can be identified in this version	Integer	5
2	Number of regions	By default is 1 and the maximum number of regions is 3 in this version	Integer	1
3	Maximum number of driving factors in a regression equation	The model can handle 20 variables as maximum	Integer	11
4	Total number of driving factors	The model can handle 30 files as maximum	Integer	13
5	Number of rows	Number of rows of the input grids. The maximum extent is 1000 rows in the demo version, which means a maximum northing of 1000 times the Grid Size	Integer	108
6	Number of columns	Number of columns of the input grids. The maximum extent is 1000 columns in the demo version, which means a maximum easting of 1000 times the Grid Size	Integer	128
7	Cell area	The cell area of the grid cells. The cell area should be expressed in Hectares	Float	6.25
8	xII coordinate	X coordinate of the lower left corner, this is also indicated in the header of the ArcView and ArcGIS ASCII files	Float	436000
9	yII coordinate	Y coordinate of the lower left corner, this is also indicated in the header of the ArcView and ArcGIS ASCII files	Float	1356000
10	Number coding of the land use types	The number coding of the land use types. The coding should start with 0 for the first land use type, 1 for the second land use type, etc.	Integer	0 1 2 3 4
11	Codes for conversion elasticities	The codes for the allowed changes and behaviour of the land use types (conversion elasticities) have to be indicated for each land use type, following the order of line 10. This must be a value between 0 and 1	Float	0.8 0.2 0.2 1 1

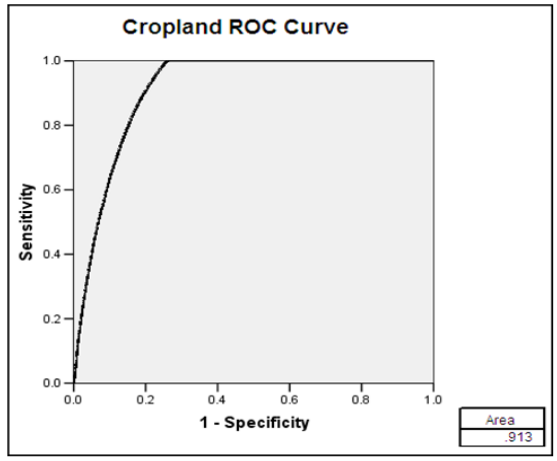
Line	Title	Description	Format	Example
12	Iteration variables	1) Iteration variables: three numbers should be specified: Iteration mode. Options: o, which means that convergence criteria are expressed as a percentage of the demand; 1, which means that convergence criteria are expressed as absolute values (units of demand, so hectares) 2) First convergence criterium: average deviation between demanded changes and actually allocated changes (default for % : 0.35; for the absolute iteration mode at least the cell area divided by the number of land use types) 3) Second convergence criterium: maximum deviation between demanded changes and actually allocated changes (default for % : 3)	Float	0 0.35 3
13	Start and end year of simulation	Start year and end year of the simulation	Integer	1999 2009
14	Number and coding of explanatory factors that change every year	Number of Dynamic Driving Factors, e.g., population density. This number should be followed by the coding of these explanatory factors, e.g. 2 9 11 . This means that there are 2 dynamic driving factors: driving factors 9 and 11 are dynamic and have input files for each year	Integer	0
15	Output / input file choice	Choice for the type of output file: 1. ArcView headers will be printed in output files; 0. No headers in output files (suited for e.g., Idrisi). -2. No headers in output files. 2. ArcView headers will be printed in output files. 3. ArcGIS/ArcMap extensions Note: if the ArcView - ArcGIS file type is chosen, all input grid files should contain an ArcView - ArcGIS header	1, 0, -2 OR 2	1
16	Region specific regression choice	Choice for a region specific regression: 0 No different regressions for different regions 1 Different regressions for different regions 2 Different regressions with different demands The default is value 0	0, 1 OR 2	0

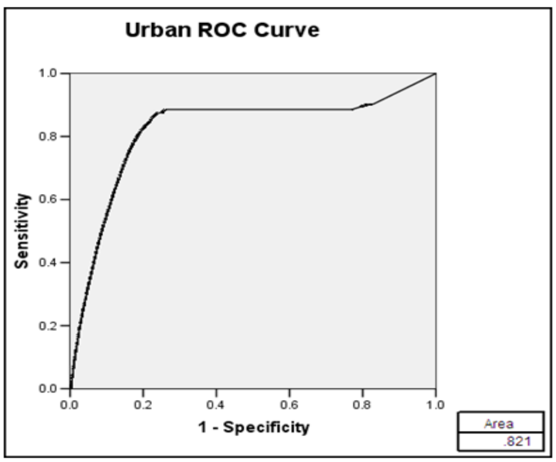
Line	Title	Description	Format	Example
17	Initialization of land use history	0 the initial land use history will be read from file age.0, which should contain a grid with, for every pixel, the number of years that the pixel is used for the current land use type 1 a random number will be assigned to all pixels to represent the number of years that the current land use is already found at that location according to the standard seed for the random number generator. with this option two runs will result in the same random number, which is useful for comparison 2 a random number will be assigned to all pixels to represent the number of years that the current land use is already found at the location with a different random number generator. For option 1 or 2 an additional number should be added that indicates the maximum number of years that can be generated by the randomizer (5 in the example below)	0, 1 OR 2	1 5
18	Neighbourhood calculation choice	Choice for using the neighborhood function: 0 Neighbourhood function is not used 1 Neighbourhood function is used in simulation 2 Only the influences are calculated	0, 1 OR 2	2
19	Location specific preference addition	Variables for location specific preference addition. The first number is a switch: activate the function (1) or not (0). If the switch is set to 1 , it should be followed by, for each land use type, the fraction of the preference addition that is added to the probability as calculated in the regression	Integer	0
20	Optimal iteration parameter	Iteration parameter. If no value is supplied 0.05 is assumed which works well with most applications. The value of this parameter should be between 0.001 and 0.1. With a somewhat higher value (e.g. 0.06) the iteration is more stabile and more likely to find a solution. A lower value (e.g. 0.01) will give a faster convergence although instability is more likely	Float	0

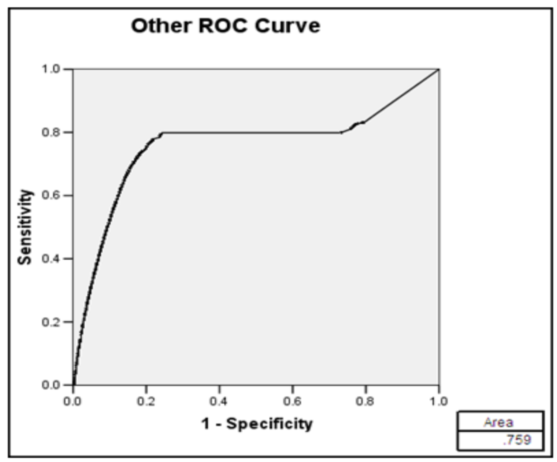
APPENDIX C

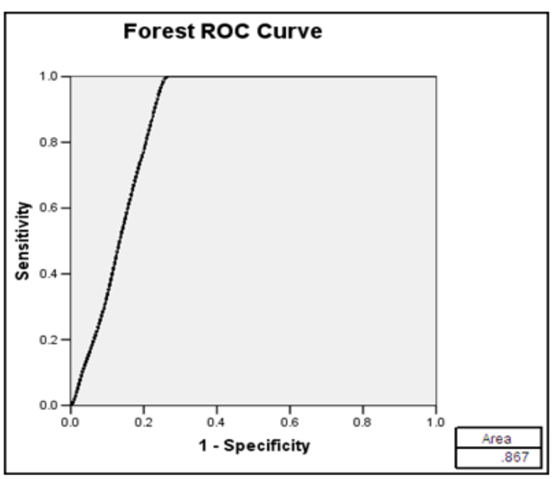
ROC CURVES FROM THE REGRESSION ANALYSIS











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