SIMULATING LAND USE CHANGE FOR ASSESSING FUTURE DYNAMICS OF LAND AND WATER RESOURCES

by

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Simulating Land Use Change for Assessing Future Dynamics of Land and Water Resources

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Abstract

Models of land use change fall into two broad categories: pattern based and process based. This thesis focuses on pattern based land use change models, expanding our understanding of these models in three important ways.

First, it is demonstrated that some driving variables do not have a smooth impact on the land use transition process. Our example variable is access to water. Land managers with access to piped water do not have any need for surface or groundwater. For variables like this, a model needs to change the way that driving variables are represented. The second important result is that including a variable which captures spatial correlation between land use types significantly increases the explanatory power of the prediction model. A major weakness of pattern based land use models is their inability to model interactions between neighbouring land parcels; the method proposed in this study can be an alternative to account for spatial neighbourhood association.

These innovations are applied using the CLUE-S (**C**onversion of **L**and **U**se and its **E**ffects at **S**mall regional extent) system to the Deep Creek watershed in the Southern Interior of British Columbia. The results highlight the challenge of balancing the protection of agricultural land and conserving forest and natural areas when population and economic growth are inevitable. The results also demonstrate the implications of land use change on existing land use policies.

The calibrated model was validated using remote sensing data. A series of discriminant functions were estimated for each land use type in the recent period and these functions were then used to classify. The calibrated model was run in reverse, back to the generated land use classification, and results compared. Fit was reasonable with error rates falling below ten percent when radii beyond 2.5 km were considered.

Another important contribution is demonstrating the importance of modelling dynamic variables. Some important drivers are changing continuously and others depend on land use change itself. Failure to update these variables will bias model forecasts. Spatial neighbourhood association, an endogenous variable governed by land use change itself, is again used as the example dynamic variable. The study demonstrates the importance of updating all associated information.

Keywords: CLUE-S; discriminant function; endogenous variables; food security; pattern based land use models; remote sensing images; simulation; spatial association; water district.

Preface

This thesis documents the contribution for one of the three well identified global changes - "Ongoing land use change". The research was a component of a larger project "Water Sustainability under Climate Change and Increasing Demand: A One Water Approach at the Watershed Scale" funded by the Natural Sciences and Engineering Research Council of Canada (NSERC). The research described herein was implemented under the supervision of Dr. Johannus (John) Janmaat in Economics, unit 8, I.K. Barber School of Arts and Sciences, The University of British Columbia (Okanagan) and Dr. Adam Wei and Dr. Craig Nichol from the Department of Earth and Environmental Sciences and Physical Geography in my supervisory committee were also advisors and guided for this research. This work is primarily my own and completely original unless the appropriate reference is made. I am responsible for all the intellectual content.

The thesis encompasses six chapters. The first chapter mainly focuses on the research issues and research gaps existing in land use modelling research. It also presents the academic contributions that this thesis makes. The main body of research is presented in chapters 2 to 5 in manuscript form and the major findings are summarized at the end of each chapter.

The model parameterization is presented in chapter 2. Part of this chapter has been submitted to *Western Geographers* in October 2015 as:

> **Anputhas, M.,** J. Janmaat, C. Nichol, and Wei X.A, (2015). Simulating Land Use Change in a Southern Interior Watershed in British Columbia, *Western Geographers*, *(Submitted).* Dr. Wei provided the groundwater level shape file for the study area.

Chapter 3 describes the model validation. It is planned for submission to the *Journal of Land Use Science* in January to February 2016 as: Validation of Land Use Projection Output with the Aid of Satellite Images: A Discriminant Function Characterization and Backcasting of Land Use

Change. Dr. Janmaat contributed to perform the accuracy assessment based on multi resolution technique.

Simulation of land use change under varying scenarios is explored in chapter 4. This manuscript is prepared in the format for submission to the *Journal of Global Environmental change* in February to March 2016 as: "Food Sovereignty or Forest Conservation: A trade-off between agricultural and environmental priorities and their implication on existing land use policy." Dr. Nichol contributed to set the major focus of this manuscript and gave useful inputs to improve this paper. This work was presented in the *4th IUFRO* (International Union of Forest Research Organization) *International Conference on Forest and Water in a Changing Environment, Kelowna, BC, Canada, July 6 - 9, 2015.* The presentation was recognized for "*Most Innovative*" award of all the students' poster presentations.

Chapter 5 details the methodological innovations proposed to account for spatial neighbourhood association. This manuscript has currently been under review by the *Journal of Environmental Management* (submitter in June 2015) as:

- Anputhas, M., J. Janmaat, C. Nichol, and Wei X.A, (2015). Modelling Spatial Association in Pattern Based Land Use Simulation Models, *Journal of Environmental Management*.

The conclusions presented in chapter 6 synthesize the research findings and describe the contribution made to the broader body of land use modelling and simulation literature. The chapter makes several recommendations for future land use modelling research. The study wraps up by highlighting the limitations in this research and the future directions that one may pursue.

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Acronyms

AAFC	Agriculture and Agri-Food Canada
ALR	Agricultural Land Reserve
AR	Area Restriction scenario
BAU	Business As Usual scenario
BC	British Columbia
BCMAFF	BC Ministry of Agriculture, Food and Fisheries
BCMAL	BC Ministry of Agriculture and Land
BCMFLNRO	BC Ministry of Forests, Lands and Natural Resource Operations
BCMFML	BC Ministry of Forests, Mines and Lands
BCMFR	BC Ministry of Forests and Range
BCMOA	BC Ministry of Agriculture
BCMOE	BC Ministry of Environment
BCMOF	BC Ministry of Finance
BCPALC	BC Provincial Agricultural Land Commission
C	Conservation scenario
CAR	Conservation and Area Restriction scenario
CLUE-S	Conversion of Land Use and its Effects at Small regional extent
CSRD	Columbia Shuswap Regional District
DF	Discriminant Function
GHG	Greenhouse Gases
MEA	Millennium Ecosystem Assessment
NSERC	Natural Sciences and Engineering Research Council of Canada
NRC	Natural Resources Canada
OBWB	Okanagan Basin Water Board

OCDI	Okanagan Climate Data Interpolator
OCP	Official Community Plan
RDNO	Regional District of North Okanagan
ROC	Receiver Operating Characteristic
RS	Remote Sensing
TM	Thematic Mapper
USGS	United States Geological Survey

Glossary

Aquifer	An aquifer is a underground formation containing sufficient saturated permeable material to generate significant amounts of water to wells and springs.
BCStats	The main statistical agency of British Columbia, providing provincial related statistical information to support decision making and policy derivation
Exogenous variable	Outside variables that influence a process or the model.
Endogenous variable	The variables found within the system or model and governed by inter-connection or process within it.
GeoBC	The provincial agency generate and manage the geospatial information and offers consultancy services for natural resources sector
GloVis	The USGS Global Visualization Viewer that provides online satellite data for any area of interest across the Globe.
iMapBC	The web-based data portal to BC Provincial government geographical information systems spatial data. It also provides geographic information online for maps and products, one can view, verify and use it. It provides topographic, administrative and other spatial data products
LandSat	System of satellites providing real time imagery coverage of planet on daily basis to help resources managers and policy makers to arrive well informed decision to manage resources and environment wisely
Official Community Plan	A policy document developed to manage land use at lowest level of government administration such as municipalities, townships and regional districts within the province of British Columbia.

Pattern based land use models	One of few major categories of land use modelling systems that are used to assess future land use change with the use of factors that drives the change. Spatial information is mostly used and land owners' behavioral related information is generally not used in this model type.
Thematic mapper	One of the earth observation sensors used by the Landsat space missions. The sensor gathers information featuring seven bands, generally at 30 meter resolution. Of the seven bands, three bands are in the visible range of wavelengths
Water utility / districts	Water delivery system that supplies water within a demarcated area for domestic, agricultural, industrial and other purposes.

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I would like express my sincere gratitude to my advisor Dr. Johannus (John) Janmaat. John, I am truly grateful for offering me this wonderful opportunity to work with you as a graduate student. Your continued in-depth questions and suggestions shape my research to pan out well. John, thank you very much for your mentorship, advice, comments, support and importantly your patience throughout this learning process. The weekly research group meeting you initiated is very useful and motivating. I am sincerely fortunate to gain and learn from your intelligence and academic communications. John, I have greatly benefitted and thank you very much for all these.

I would like to thank my research supervisory committee of Dr. Adam Wei and Dr. Craig Nichol for their constant advice and suggestions during research. My special thanks goes Dr. Wei for his patience when my component is moving relatively slowly in the larger project "Water Sustainability under Climate Change and Increasing Demand: A One Water Approach at the Watershed Scale ". Adam, my research has truly benefitted from your suggestions and your comments on the draft thesis helped me to organize the thesis with good flow. Craig, I am very grateful for asking me the question "on the role of water districts ", which turned out to be the first attempt of assessing water district influence in modelling land use change. This thesis benefitted from the constructive comments that you provided on each chapter. My sincere appreciation is also extended to Dr. Lael Parrott, university examiner, for her valuable comments and suggestions. I am extremely grateful to Dr. Eric Koomen, for being external examiner in my final defence examination. His constructive criticisms and valuable suggestions immensely helped to improve this thesis.

This research is a component of an interdisciplinary study on "Water Sustainability under Climate Change and Increasing Demand: A One Water Approach at the Watershed Scale" sponsored by the Natural Sciences and Engineering Research Council of Canada. Additional funding was provided by The University of British Columbia. The author is grateful to the funding bodies for their support.

Data acquisition assistance was provided by the British Columbia Ministry of Agriculture and Lands and Okanagan Basin Water Board. Dr. Denise Neilsen of the Pacific Agri-Food Research Centre (PARC) of Agriculture and Agri-food Canada supplied access to the climate grid data and climatic scenario related information for the watershed. The assistance of these agencies is gratefully recognized.

The services provided from the University of British Columbia library, IT and Writing Services are gratefully acknowledged. My special mention goes to Barbara Sobol and Amanda Brobbel for their assistance during this work. This research is also benefitted from many open source and trial versions of software, web sites and online discussion groups. The time and energy behind all these sources are earnestly valued and appreciated.

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All my sisters and their families helped me in various ways to accomplish this task. I know your unconditional love and commitment was / is / will be always there for me and I believe this is the appropriate moment to recognize all that. I am profoundly indebted to my wife for her understanding, patience and support as I was away for so long and I have no words to thank my little son who sacrificed for me to complete this work at his age of two months. All of you deserve the appreciations and accolades that come from this work as much as I do.

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To my father Eliyathamby Markandu for his ....

Chapter 1. Introduction

1.1 Problem Statement

One of the major challenges for sustainability is how to manage land resources in an environmentally meaningful way while meeting growing human needs. Vitousek (1994) points out that "three of the well-documented global changes are: increasing concentrations of carbon dioxide in the atmosphere; alterations in the biochemistry of the global nitrogen cycle; and ongoing land use change." Although he noted this problem more than two decades ago, these changes continue. Land use change contributes to the other two changes directly or indirectly. For example, loss of forest is believed by many scientists to be an important contributor to those other changes. Ramankutty and Foley (1999) found that 120 million hectares of forest and woodland were converted to various other land use purposes across the globe in the past three centuries. Vitousek et al., (1997) found that nearly 10 – 15 % of the global surface has been converted to agricultural crops (row-crop) or urban / industrial areas while 6 – 8 % has been put into pasture land. Further, agriculture is the biggest contributor to climate change (Foley et al., 2011). Multiple factors such as market demand, technological change and capacity, social influences, and environmental characteristics determine land use changes (Verburg et al., 2004 b,c). Human actions and behaviours are the reasons for the dynamic transformation of land use in a landscape (Turner et al., 1990). As these variables change, land use patterns evolve. In addition to land use driving factors, climate change is likely to impact both land use change and its driving factors. A theory of land use change needs to conceptualize the relations among the driving forces of land use change, their mitigating factors (such as policies and management), and human behaviour and organization.

Land use change has important impacts on the functioning of socioeconomic and environmental systems with significant tradeoffs for sustainability, food security, biodiversity and the vulnerability of people and ecosystems. More specifically, the loss of biodiversity, changes in habitat, depletion of forests, and changes in hydrological processes are major impacts within a system. Land use change can also, indirectly, influence the vulnerability of places and people to climatic, economic or socio-political perturbations (Kasperson and Kasperson, 2001; Kasperson, et al., 1995). However, land use change is inevitable as the population continues to grow and the demand for various uses of land increases. As such, it is important to predict likely future changes in order to manage land resources in economically, socially, and environmentally efficient ways, thereby sustaining limited resources for future generations. Hence, projecting the spatial pattern of land use change is important for assisting future management of this important resource.

Land use change is driven by changes in other driving factors. Broadly speaking, these drivers are population growth, economic growth and change, climatic changes, and technological innovations (Figure 1.1). Many more specific and locally relevant drivers can be identified within these broad categories. Some of these driving factors are static, while others are changing over time. For example, elevation of a land parcel is unlikely to change, while the road network in the local area is likely to. Some land use drivers are endogenous, their level depending on the pattern of land use. They change as the land use pattern changes. Groundwater level in an area is generally influenced by the land use found on the surface. If the existing land use is replaced by a more water demanding land use, the new land use in turn alters the water resource uses by consuming more water and accordingly influences the groundwater level (Figure 1.1). Thus, identifying the land use drivers for each use, properly accounting for their interactions and feedbacks in modelling, and the way in which these drivers influence land use change (static versus dynamic) should be clearly understood to effectively simulate future land use change.

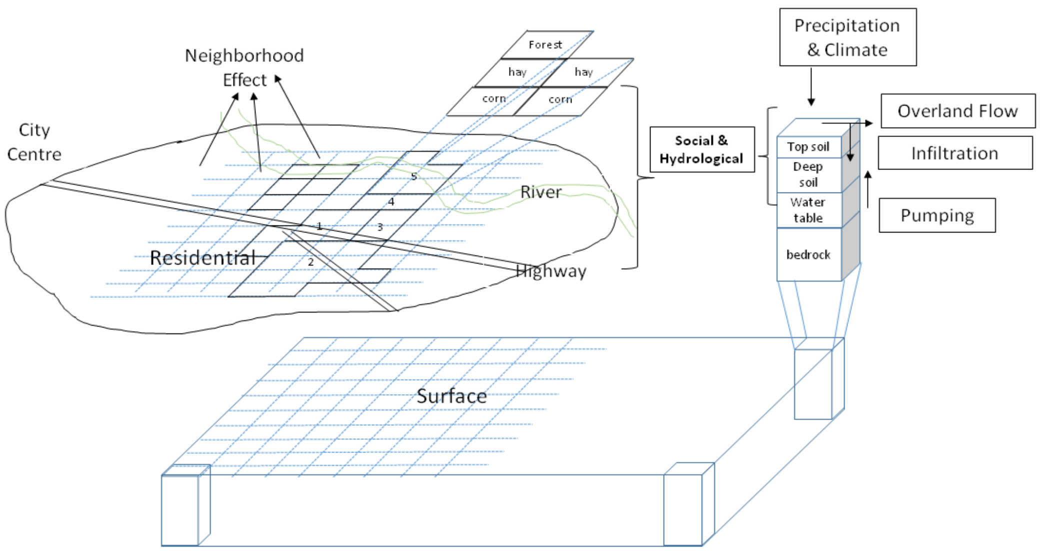


Figure 1.1: Conceptual model for land use changes driven by interactions among socioeconomic, hydrological and other factors

This study contributes to a few research gaps that have been identified in the literature. First, there are reasonable number of studies that investigate the role access to water has in determining patterns of land use change. Water resource (availability and access) is an important factor that influences land use decisions. Surface water influences on land use decisions are well documented (Lin et al., 2007a; Verburg and Overmars 2004; Verburg and Veldkamp 2004; Verburg et al., 2002) while the impact of land use change on groundwater is also extensively examined (Keilholz et al., 2015; Wijesekara et al., 2012; Jinno et al., 2009;

Dams et al., 2008; Lin et al., 2007b). In addition, the influence of groundwater on land use decisions is examined in a reasonable number of studies (Park et al., 2011; Luo et al., 2010; Valbuena et al., 2008; Verburg et al., 2004 c,d). Depth to groundwater is included in our examination of driving factors, and found to be important in several situations.

Further, water services provision is very common in many countries and supplies water for residential, industrial, commercial, irrigation and other purposes. Generally, availability and access to surface water and groundwater resources influences land use decisions. In an area where water service infrastructure is available, distance or depth to water sources has no role to play in land use decisions. As such, it is important to account for the effect of water services infrastructure on both groundwater and surface water resources in any land use modelling and simulation exercise. No land use studies, to my knowledge, have considered the role of water services infrastructure. This study contributes to fill this research gap existing in land use simulation exercise.

It is well known that land uses are spatially correlated, correlation which typically persists even after controlling for driving factors. However, few studies make use of this correlation in their forecasting models (Verburg et al., 2004a). I develop a simple measure to capture this correlation, find it to be an important driver, and included it in the forecasting models. Further, this correlation is endogenous in a landscape and the association between land parcels changes with the land use change itself.

The land use modelling community has identified the importance of spatial association in modelling land use change. Cellular automata models use transition rules to model the neighbourhood association, though they are mostly technology driven (Torrens and

O'Sullivan, 2001). On the other hand, agent based land use models are based on behavioral theories and treat the agents as autonomous decision making entities. Further, agent based models exclusively consider the spatial neighbourhood process in their modelling exercise (Parker, and Filatova, 2008; Parker et al., 2003).

Conversely, pattern based land use models have limited ability to account for neighborhood association. Few pattern based land use studies have applied standard statistical approaches to model the neighbourhood association. Lin et al. (2008) used spatial auto correlation (Moran's statistics) to examine the dependency of spatial patterns in their study though spatial association was not directly used as a driving factor. Geographically weighted regression was used to model the effect of spatial instability of driving factors on land use change in Tongjun, China (Liao et al., 2010). Luo and Wei (2009) used global logistic regression and geographically weighted logistic regression to model the land use variables in their simulation exercise and demonstrated that the geographically weighted logistic regression results (which accounts for spatial association) showed better predictability. The methods used in the above studies are based on traditional spatial statistical procedures and the assumption for normality. However, the response variables used in pattern based land use modelling research are categorical variables and require a more appropriate approach to account for the spatial association and its associated endogeneity along with other predictor variables.

Hagoort et al. (2008) found that the methodology developed by Verburg et al., (2004a) provides a useful basis for modelling the neighbourhood this far. The method proposed by Verburg et al., (2004a) accounts for the local neighbourhood association in relation to the proportion of grids occupied by given land use type. However, the method calculates neighbourhood association values in terms of each land use type for grids, which shows multicolinearity issues thereby causing problem for interpretation. As an alternative, I propose a methodology, analogues to the spatial autocorrelation measures, to account for neighbourhood association.

Projected land use changes can provide information that may be useful for developing land management policies. Projection results are helpful to refine zoning for residential use within an administrative area and other land use designations. Projections can assist planning for: waste management (one of the prime responsibility of the municipalities and the townships); controlling above and below surface pollution; carbon emission reduction and forestry conservation; maintaining the hydrological balance; and water resources management. Moreover, the spatial distribution of forest area will assist for any reforestation planning. The estimation of water demand at local and regional levels is one of the important results from land use change simulation exercises. It is also possible to estimate water deficit / vulnerability and their spatial distribution within the study domain and thereby the pressure on groundwater and surface water resources can be assessed. In addition, different land use scenarios can be tested to evaluate the best scenario to manage land resources efficiently.

Any land use change simulation is not complete without a meaningful validation exercise. Validation of the land use change projection establishes its credibility and builds trust among users of simulation result. Many land use researches do not perform model validation. I undertake an extensive validation of the model. I use remote sensing data to develop a historic land use map. To compare my model projection and the historic map, I use both a grid by grid, as well as the strongly recommended but little used multiscalar approaches.

Validation is not often performed for land use simulations due to the lack of land use information for historic time periods. Further, the resources and skill required to process existing information like aerial photographs restricts this exercise. Though the remote sensing information is used to derive land use maps extensively by various researchers (Amato et al., 2013; Riveiro-Valino et al., 2009; Thenkabali et al., 2004; Jimenez and Landgrebe,1998), the use of remote sensing is limited in land use modelling and validation exercise (Sohl and Sleeter, 2012). Few studies have used remote sensing information in their validation work recently (Wang et al., 2013; Castella and Verburg, 2007). In this study, I use satellite information to perform the validation in the absence of an actual land use map for the historic period. I use a discriminant function based land use classification which is common in remote sensing disciplines (Amato et al., 2013; Riveiro-Valino et al., 2009, 2008; Davidson et al., 2007).

Pontius (2000) pointed out that limited methods were used in validation exercises and elaborated that most of the studies used to assess projection accuracies failed to recognize the quantification error versus the location error. These authors also stressed the importance of recognizing the "near misses" and "far misses" and called for a multi resolution evaluation (described in Chapter 03) instead of grid by grid comparison (Pontius et al., 2004; Pontius et al., 2002). Hence, in this study I first use a discriminant function based land use classification to produce the land use map with the aid of satellite information and then perform multi resolution based validation to assess the model fit.

Pattern based models generally assume that driving factors remain fixed over the duration of the model run. I demonstrate that this assumption can introduce bias into model forecasts, a result not found in many previous works. Land use simulations are executed for a longer period of time and simulation exercises keep the initial land use map and driving factors unchanged throughout the simulation period (Liu et al., 2013). In reality, these factors are not going to be static for that long. The initial land use map passes through a number of land use change transitions before the end of the simulation and this should be accounted for in the simulation. Further, certain variables are endogenous, changing with the change of land use. Hence, this information should be updated at a regular interval to obtain accurate model forecasts.

There are a few studies that have implemented a dynamic simulation. Cellular automata models have addressed these issues (Engelen et al., 2007; Geertman et al., 2007; Engelen et al., 2004). Verburg et al., (2006) typically update driving factors and land use information biannually while Liu et al., (2013) used the single exponential smoothing of model parameters to implement the dynamic simulation annually. Verburg and Overmars (2007) describe the use of annual updating for neighborhood characteristics in a pattern based model for Kuala Lumpur, and Koomen et al. (2010) documents software that enables updated maps of driving factors. Recently, Verburg et al., (2011) and Perez-Soba et al., (2010) implemented the dynamic simulation for their work to assess biodiversity conservation in Europe. However, they did not provide a structured comparison between simulation results from static and dynamic simulations. This research indentifies this issue in a dynamic simulation and illustrates the necessity of dynamic simulation in detail. In this study, I update the land use map and the temporal land use demand at regular intervals in each simulation steps. In addition, measure of spatial association, an endogenous variable that is a function of the land use pattern - was regularly updated. This variable served as an example dynamic driving factor for land use change. Very few simulations have, as far as I know, been implemented like this before in pattern based land use models. Clear illustration of dynamic variable calculation and the comparison between static and dynamic simulation output will clearly demonstrate the need of dynamic simulation to encourage and strengthen the future effort of dynamic simulation.

1.2 Research Question

This study contributes to the overall effort to understand future land use change dynamics. The land use change is simulated in a small watershed by identifying and modelling important driving factors. The simulation is implemented under four land use management scenarios. This thesis is constituted of four manuscripts that answer five research questions. The studies examine future land use change by specifically studying major land use categories found in the study area. Detailed spatial land use survey data, along with other spatial and non spatial information, are used. In addition to projecting future land use dynamics, the thesis also addresses a few unique methodological, data availability and data usage issues. The thesis also demonstrates the integration and application of several advanced analysis methods. I illustrate various spatial land use management issues faced in the future by: successfully implementing the land use model; simulating the land use change; and assessing the impact on major land use policy.

This research was a component of an interdisciplinary research titled “Water Sustainability under Climate Change and Increasing Demand: A One Water Approach at the Watershed Scale” funded by a NSERC Strategic Grant. The goal of this project was to use MIKE-SHE to assess impacts of climate change and increased demand on water resources (including both surface water and groundwater). To forecast climate change impacts, a forecast of water demand was required, and this in turn required an understanding of how land use evolves. Land use will respond to several factors. One is certainly the change in opportunities that result from climate change. However, population growth pressures and changing economic conditions, some of which are a consequence of climate change, will also play an important role. This investigation aims to: forecast how land use responds to these forces; examine various land use scenarios; provide input for estimation of water demand due to land use change; and assess an integrated surface and groundwater model of the watershed to estimate overall water resources within the domain. In essence, this research serves two main purposes: 1) contributing to the overall understanding of future land use dynamics, 2) supplying information to other components of a larger multidisciplinary study.

The four papers included in this thesis aim to address five research questions or methodological improvements. The research questions answered in this thesis are:

1. What will the future land use pattern look like and how can the dynamics of the change process be modeled spatially and quantitatively?
2. How can the spatial association existing in landscape be accounted for and modeled?
3. How credible are the simulated future land use change results?
4. What are the possible land use options to manage land use resources in a socially and environmentally meaningful way?
5. Why it is important to account for the dynamics of driving variables in land use simulations?

The first research question focuses on the driving factors of land use change and specifically provides insight into the influence of water service providers on land use change. The modelling issues of water district influences on the role of surface water and groundwater variables are addressed. I take advantage of spatial information available for the study area. The second research question deals with spatial association / neighbour effects on land use change. Various methodologies available in the literature are carefully reviewed before proposing my own methodology. The credibility issue of simulation results is answered through a validation exercise (research question 3). The validation exercise for land use simulation is seldom performed. The difficulties to obtain the spatial land use data are detailed and illustrate the use of remote sensing information for this purpose. Modern spatial information coupled with the use of an advanced spatial statistical approach is used to complete this exercise. The accuracy assessment of validation also addresses the methodological issues before presenting the results. The fourth research question examines different land use scenarios. It identifies the future spatial dynamics of land use change to address the tradeoff among land use types. Analysis also provides insight of future land use change impacts on existing major land use policy to support policy makers in future policy formulation. The final question focuses on the importance of updating information dynamically. It illustrates a dynamic simulation, as a proof of concept, to elaborate the necessity to update dynamic and/or endogenous driving variables at regular intervals during the simulation. Further, data is not available presently for future time step. The study illustrates how the future data can be derived to update the information at regular intervals. The study highlights the use of endogeneity of driving factors for this purpose.

The research is applied to a case study of the Deep Creek watershed, which is located in the Southern Interior of British Columbia, Canada. The watershed lies in a semi arid mountainous region with high variation in topography. The Deep Creek watershed shows significant variations in climate, land cover and soil types. The productive land area available for agricultural purposes is limited due to topography and soil suitability. The region is one of the fastest growing locations in Canada, leading to increased demand for land for development purposes. Further, water demand for various activities including the agricultural sector is relatively higher compared to the national usage, which is of the things that make the watershed unique. The groundwater aquifers are complex in nature with strong surface water and groundwater interaction. The complexities found in the watershed makes this a unique case to be an example location to understand land use dynamics and its impacts.

1.3 Study Location

The Okanagan is a semiarid region in the southern interior of British Columbia, Canada. It is a growing region with changing land use patterns and potential environmental consequences. The dry, relatively warm climate makes the Okanagan Valley an attractive destination for tourists and retirees, and this temporary and permanent movement of population generates demands for goods and services. The valley has among the highest rates of population growth of any region in Canada (Statistics Canada, 2012 a,b). Deep Creek is a small watershed in the northern part of the Okanagan Valley, located between the latitude of 50° 19' 56" to 50° 38' 29“ N and longitude of 119° 1' 58“ to 119° 19' 59“ W (Figure 1.2). It covers an area of 230 Km^2 and includes the City of Armstrong and Township of Spallumcheen. It cuts across the boundary of the Columbia-Shuswap regional district (CSRD) and the regional district of North Okanagan (RDNO). Salmon Arm, Armstrong and Vernon are the major cities that can be easily access from within the watershed (Figure 1.2 and Appendix A-1). The elevation of the southern part of the watershed ranges between 340

– 520 meters, while the northern part of the creek ranges from 370 – 1575 meters above sea level (Ping et al., 2010).

Climate

The average annual precipitation is 468 mm and 592 mm in valley bottom and the mountainous regions respectively, based on the Okanagan Climate Data Interpolator (OCDI) (Neilsen et al., 2010; Duke et al., 2008). Mean annual temperature and potential evapotranspiration are 8 ˚C and 890 mm respectively (Ping et al., 2010). Both precipitation and temperature show an upward trend between 1970 and 2010, confirming that the watershed is impacted by climate change (Appendix A-2). Precipitation has increased and, in particular, winter snowfall (Ping et al., 2010). Daily minimum temperature has also increased noticeably (Cohen and Kulkarni, 2001). The frost free period increased by nearly 3.1 days per decade during the 20th century, and now ranges from 120 – 150 days (Zbeetnoff, 2006). These changes in climate will lengthen the growing season, reducing the risk of extreme minimum winter temperatures (Cohen et al., 2006).

Water resources

Surface water and groundwater are linked within the Deep Creek watershed. The hydrograph of the Deep Creek watershed is freshet dominated with a peak flow of 1 – 2 m^3 / sec during freshet while the discharge rate is 0.1 – 0.3 m^3 / sec during the non-freshet period (Ping et al., 2010). A long term, constant, average low flow rate (0.15 – 0.30 m^3 / sec) is experienced during mid – September to March. Groundwater flow provides a larger portion of Deep Creek discharge during this period when the groundwater withdrawal is at its minimum (Nichol, 2011). Upwelling groundwater contributes (0.13 – 0.18 m^3 / sec) to Deep Creek from Otter lake to the head of Okanagan lake (Appendix A-1). The watershed also gains water through lateral groundwater flow (0.06 to 0.07 m^3 / sec) from outside of the Deep Creek watershed, specifically from the boundary of Deep Creek and Fortune Creek (Nichol, 2011). Estimated mean annual recharge (spatially and temporally) throughout the watershed is 61.9 ± 30.7 mm / year, representing about 10 % of the precipitation (Assefa and Woodbury, 2013, 2011). The future climate change and increasing water demand are expected to reduce the groundwater storage change in depth by 54 % over the next three decades (Assefa et al., 2011).

The geology of the North Okanagan Valley has recently been reviewed by Nichol et al. (2015). The aquifer system in the watershed is very complex (Ping et al., 2010). Surface water and groundwater exchange both ways in the Hullcar and Sleepy Hollow areas of Deep Creek watershed (Appendix A-1). Groundwater springs add flow to Deep Creek south of Otter Lake. The aquifer system in the watershed is composed of valley bottom unconsolidated aquifers surrounded by bedrock highlands of variable composition, geological history and geometric configuration. Shallow, moderate, and deep aquifer systems are found in the study area (Nichol et al., 2015; Ping et al, 2010). Recharge from adjacent mountainous areas can include components of both diffuse and localized recharge. Mountain system recharge is a major contributor to the deep regional aquifers and is frequently the dominant source of recharge (Ping et al., 2010). The annual groundwater level follows a seasonal pattern and remains nearly constant from October to March. The water level starts declining from April and reaches its lowest level during July and August before it starts reversing from mid or late September (BCMOE, 2013). Groundwater levels drop in the summer due to irrigation pumping in all shallow and moderate aquifers (Ping et al., 2010).

Groundwater levels have dropped in the last 30 years in the majority of the aquifers due to withdrawals (BCMOE, 2013) (Appendix A-3).

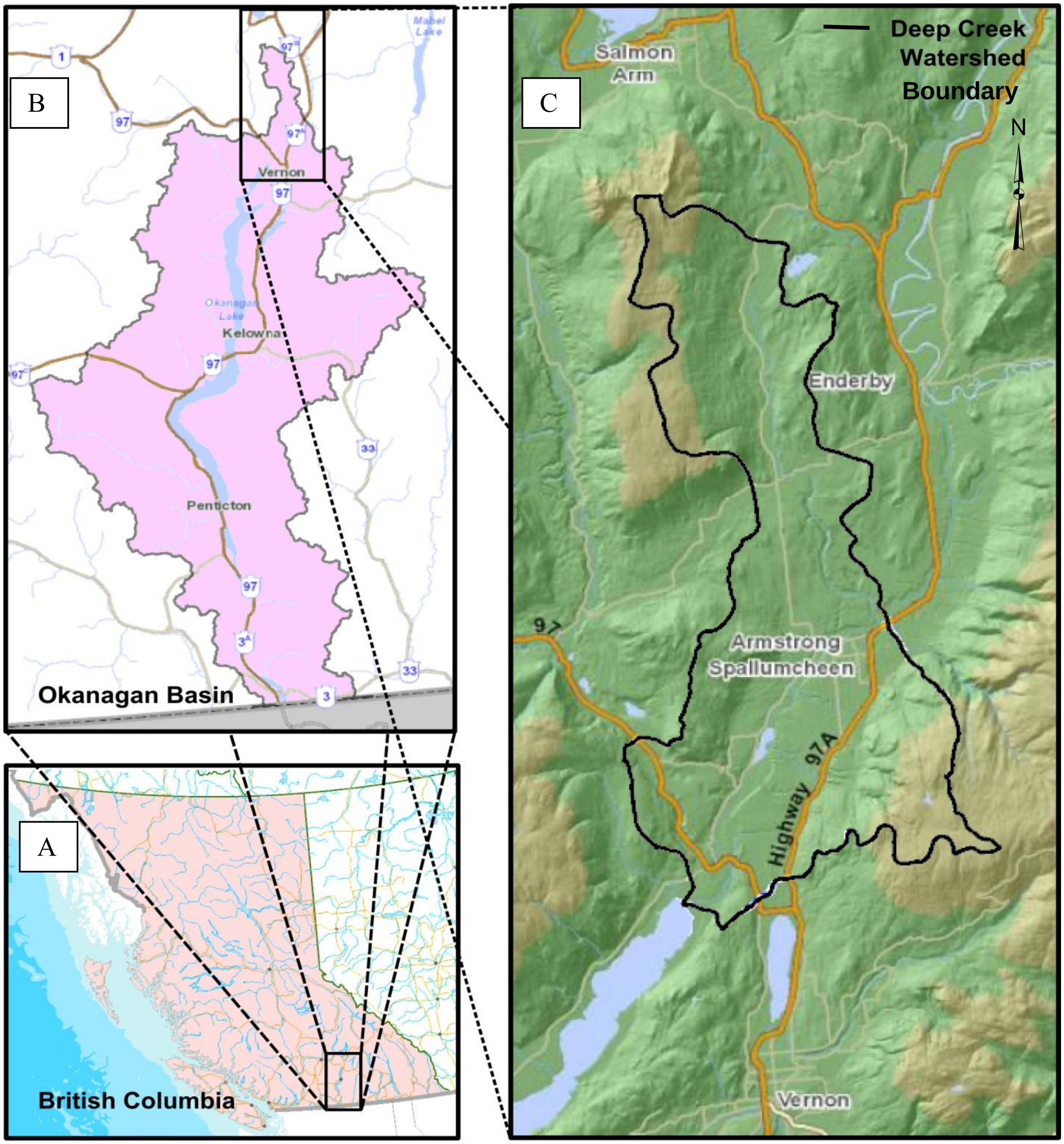


Figure 1.2: Location of A) Okanagan Basin in British Columbia, Canada; B) Deep Creek watershed in Okanagan Basin; C) major road network, cities and towns in and around the watershed. Images generated using iMap BC (2014)

Groundwater in the study area is used for domestic water supply, irrigation, commercial and industrial purposes. Groundwater irrigation requirements for most of the Spallumcheen Township extend from the beginning of May to the second week of September, or a period of 130 days. Roughly 12% (1,950 ha) of the total farmland in the Township of Spallumcheen is currently irrigated, predominantly from groundwater (Zbeetnoff, 2006). The variability in water supply and demand is an important characteristic of in the watershed. So, the seasonal variability in both supply and demand, the differences that exist from place to place (highland mountainous region and the valley bottom) within the watershed, and the annual variability in both supply and demand also affects the availability of water resources both spatially and temporally.

Based on the water licences that have been issued, surface water within the watershed is pretty much completed allocated and almost no new users can be licensed (Nichol et al., 2011). This scenario leaves groundwater as the alternative source within the watershed. Forty-eight licenses for surface water use were identified in the Deep Creek watershed (Ping et al., 2010). Irrigation districts and municipalities' withdrawal of surface water is very low within the Deep Creek watershed but private permit holders remove nearly 3 Mm3 / year mostly for irrigation purposes (Nichol et al., 2011). However, significant amounts of surface water are withdrawn from adjacent Fortune Creek. Some irrigation districts withdrawing from Fortune Creek actually supply water to users within the Deep Creek watershed (Ping et al., 2010). Fourteen water districts operate in the study area and eight of them use surface and groundwater as their source of water supply and six districts solely rely on groundwater resources (Table 1-1). Only half of the water utilities operating in the study area provide service for agricultural enterprises. The influence of water district (utilities) on land use should be accounted for any land use modelling exercise.

Table 1.1: Water supply and usage information for water districts within the study area

District Name	Water Supply Source	Water usage	Extent covered in Ha
Canyon	Groundwater	Domestic, some farms	100
City of Armstrong	Surface water, Groundwater	Domestic , others	750
Eagle Rock	Groundwater	Domestic, farms	225
Grandview	Groundwater	Domestic, others	1250
Greater Vernon	Surface water, Groundwater	Domestic, agriculture	150
Highland Park	Surface water	Domestic , others	200
Lansdowne	Surface water	Domestic , others	225
Larkin	Groundwater	Domestic, farms, industrial	1525
Liard	Groundwater	Domestic, big farm, others	25
Meighan Creek	Surface water	Domestic , others	50
Okanagan Indian Band	Surface water	Domestic, others	550
Otter Lake	Groundwater	Domestic, Irrigation, farms	1175
Stardel	Surface water	Domestic , others	200
Steele Springs	Surface water spring	Domestic, chicken farms	325

Socioeconomic

The population trends for the City of Armstrong, Township of Spallumcheen (Armstrong – Spallumcheen local health area) and regional districts of Columbia – Shuswap and North Okanagan show a steady positive growth (Figure 1-3; BC Stats, 2014). The population of the City of Armstrong was 4850 in 2011 and the population change from 2006 to 2011 was 13.4

% while the population of the Township of Spallumcheen was 5050 and the population growth was 1.9 % during the same period (Figure 1-3) (Statistics Canada, 2012 a,b). Forestry, agriculture, manufacturing and tourism are all important economic activities in the watershed areas. Agriculture is the most important industry in this area. Cattle farming are the most common operation representing about 21% of all agricultural operations in the township. Other relatively important farm types include hay and forage operations (17.2%), horse and pony (15.2), poultry (6.8), and dairy (6.1%) (Zbeetnoff, 2006).

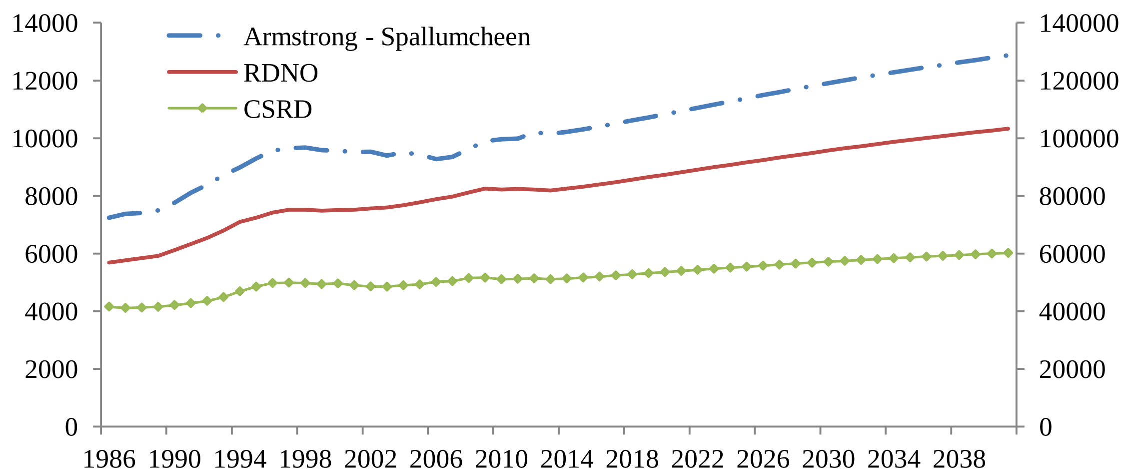


Figure 1.3: Estimated (1986 – 2013) and projected (2014 – 2041) population change in Armstrong – Spallumcheen (primary axis), Regional District of North Okanagan (RDNO) and Columbia Shuswap Regional District (CSRD) (both in secondary axis)

Land cover

Land use types within the watershed can broadly grouped into agricultural, development and forest lands. Agriculture includes crops, pasture land and livestock enterprises. Commercial greenhouses, golf courses and gravel processing units are some of the example for diverse land use types found within the study area. At present, more than half of Deep Creek watershed area is occupied by forest and range land. Montane forest types of Douglas Fir, and lodge pole pine are extensively found in the study area (Demarchi, 2011). Wildfires and a recent outbreak of mountain pine beetle have caused considerable forest damage (BC Ministry of Forests, Lands and Natural Resource Operations [BCMFLNRO], 2011).

Governance

Land resources management is a provincial responsibility under the Canadian constitution. Several land use policies have been imposed by the provincial government ministries and agencies to protect and manage the land resources. Major land use policies in the province of British Columbia include the Agricultural Land Reserve (ALR) act (British Columbia Provincial Agricultural Land Commission [BCPALC], 2010), the Forest and Range Practices act (BCMFLNRO, 2004) and Crown land policy (BCMFLNRO, 2015). The most important land use policy that controls land use management within the watershed is the ALR. The ALR is a zone demarcated by provincial agencies inside which the priority is given to agricultural related activities. Introduction of the ALR in 1974 was an attempt to protect farmland from urban and suburban sprawl as development related activities are discouraged within this zone. The land capability classification (BCPALC, 2013) is the prime criteria for selecting land to be included in the ALR. Land does not have to be actively farmed, nor ever have been farmed, to be included in the ALR. The land owner can apply for inclusion, exclusion, subdivision for their lands and also can apply for non-agricultural purposes. However, all changes of this nature are approved or denied by the provincial Agricultural Land Commission, which administers the ALR. The area coming under the ALR within British Columbia is nearly 4.7 million hectares, which encompasses both public and private lands, and approximately 5% of this is located in Okanagan region.

The ALR in the RDNO accounts for 9 % (69,705 ha, as of January, 2008) of the regional district's overall area. Almost 39 % of all ALR land in the Okanagan is located within RDNO (BCMAL, 2008). The middle part of the Deep Creek watershed is mainly demarcated as ALR zone and nearly 44 % of the study area is covered by ALR restrictions.

The land use simulation exercise implemented in this study is the first in this kind for the Okanagan region to my knowledge. Only a few land use change projection exercises have been executed within the province. However, several studies related to climate change have been found (Neilsen et al., 2010; Duke et al., 2008; Cohen et al., 2006; Cohen and Kulkarni, 2001). Dale (1997) argued that land use change impacts more on ecological variables than climate change and human influence on land use change is greater than the climate change influence. Dale (1997) describes how climatic factors along with other factors are required to understand the management of the ecological functions. Hence, the contribution from this research strengthens the existing body of literature that can be used by the regions elsewhere in the world with the similar characteristics.

Many land use simulation exercises use land use policy to derive land use scenarios to assess the future dynamics of land use change while others assess the impacts of land use change on land use policy (Lin et al., 2007b; Wassenaar et al., 2007; Verburg et al., 2005; Verburg and Veldkamp 2004; Verburg et al. 2002). The policy instruments are not causal factors for land use change. Policies include the desires of the society and policy makers but the land use conversion pressures are driven by both internal and external forces. As such, I use the ALR policy demarcation area to assess the impact of future land use change on ALR rather than as a land use change driver.

A mountainous watershed, located in a semi arid climate with higher population growth faces many resources related problems. Forest area is found in the major parts of watershed. The limited amount of prime agricultural land faces considerable land use change pressure due to population growth. This situation demands more space for development and may create problems for agricultural land as well as natural space for environmental protection. The uniqueness found in a watershed like Deep Creek offers the opportunity to explore future land use dynamics under various scenarios. The exercise also provides an opportunity to assess the impacts of land use change on existing land use policies, especially ones like the ALR. The knowledge and experience gained through this research can provide useful insights to the regions that share similar characteristics.

1.4 Thesis Structure

Figure 1.4 broadly explains the research implemented and how the thesis is organized.

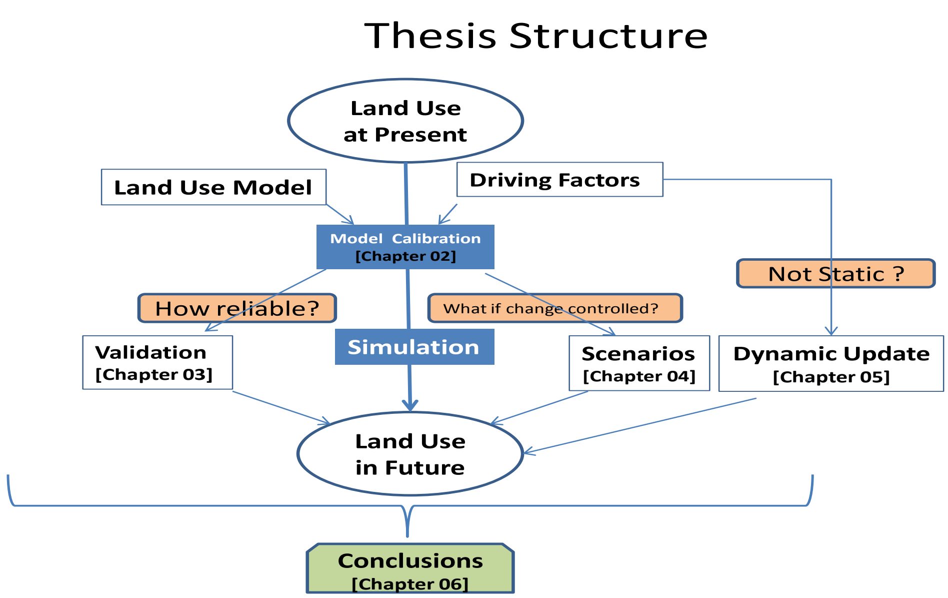


Figure 1.4: Layout used to organize thesis

The overall goal of this research is to project the land use change from 2010 to 2050. This chapter represents the research questions and a study site description. The driving forces behind the land use change and the modelling of these forces are discussed in chapter 2. The question of credibility of the modelling process and accuracy of the projection are detailed in chapter 3. Scenario based land use change projections provide flexible options to take appropriate action to manage the landscape. Different scenarios also present the opportunity to assess the impacts of land use change. Chapter 4 documents this information. The variables used for modelling is kept unchanged during the simulation in many land use projections. However, it is not the case in reality and chapter 5 explores some implications of this common weakness found in many land use simulations by updating the land the information at regular intervals. This is only a proof of concept because a number of driving factors that change during the simulation are not updated. The conclusion chapter (chapter 6) synthesizes the findings from all the chapters and highlights the uncertainties in this research before giving direction for future work.

Chapter 1: Introduction

This chapter describes the general research issues in land use change studies and identifies the research gaps to be filled. It also states the research objectives to be achieved and the intended contribution to the literature on land use change. A study area description was also provided in this chapter before presenting the outline of the thesis (Figure 1.4).

Chapter 2: Evolving Land and Water Use in an Arid British Columbia Watershed

This chapter is based on a manuscript prepared with the major focus on model calibration. It examines various land use models in use to project land use change and selected the appropriate one for this study. The chapter identifies the important land use change driving factors and illustrates the importance of the inclusion of water district influences on land use change. A measure of spatial association is also included as one of the driving factors. Predictive models are fitted to identify the significant driving factors for each land use category and draw inferences from the modelling exercise. These fitted models serve as the fundamental models throughout the thesis.

Chapter 3: Validation of Land Use Projection Output with the Aid of Satellite Images: A Discriminant Function Characterization and Backcasting of Land Use Change

The manuscript presented in this chapter examines the accuracy of the land use simulation output. This chapter describes how remote sensing information can aid to derive a land use map for land use modelling and validation purposes. Further, this chapter demonstrates how available information can be better used to derive historical land use maps for a region with limited land use information. Details of the backcasting of historical land use are also presented in this chapter. The manuscript examines various validation methods and performs single resolution and multi resolution validations to assess the projection accuracy.

Chapter 4: Food Sovereignty or Forest Conservation: A trade-off between agricultural and environmental priorities and their implication on existing land use policy

The manuscript in this chapter presents the land use management problem faced by residents of a watershed located in a mountainous region. This chapter explores different land use management scenarios and examines implications for existing land use policy. The manuscript examines the consequences of giving preference to a particular land use over the others. Results are presented under different scenarios and the implications are discussed in the broader context relevant to Pacific Northwest region.

Chapter 5: Modelling Spatial Association in Pattern Based Land Use Simulation Models

This manuscript proposes a methodology to account for spatial association in pattern based land use models. A measure of spatial association is used as one of the driving factors in the model calibration in chapter 2. This chapter explains the calculation procedure of the method for incorporating spatial association and demonstrates how it can be computed to use as a predictive variable. The paper further stresses the importance of accounting for the dynamic nature of driving factors and illustrates how important it is to update these variables regularly. The measure of spatial association is used as an example dynamic variable as a proof of concept to illustrate some results.

Chapter 6: Conclusions and Recommendations

This chapter synthesizes the research findings of the four manuscripts and makes recommendations for the future. Some of the important contributions summarized in this chapter are the assessment of role of water service infrastructure on land use change and accounting for spatial association in land use model by an alternative methodology. The chapter finally presents the future directions where research focus should be given.

Chapter 2. Evolving Land and Water Use in a Semi Arid British Columbia Watershed

2.1 Overview

In this chapter we document the development of a land use forecasting model of the Deep Creek watershed, and highlight a number of issues pertinent to our model, and to many other land use change modelling efforts. Our first challenge is selecting a land use change modelling approach. We discuss the difference between pattern based and process based models, and explain our choice of the CLUE-S system. We next turn to the identification of important driver variables that influence land use change in the watershed. Within the watershed, access to water is important for agricultural land uses. We find that the presence of piped water from a water provider, which renders depth to groundwater and distance to surface water unimportant for water users, is an important predictor. Unlike previous work, we model the presence/absence of water infrastructure, rather than the common practice of including distance to the infrastructure as the driver. Distance to infrastructure makes strong assumptions about the way that infrastructure will be expanded, and we suggest that this may not be the appropriate way to consider the role that infrastructure has in driving land use change. We also pay special attention to spatial neighbourhood effects. We use a measure of spatial association that we develop (detailed in chapter 5) which we find to be significant for many of our land use types. We suggest that failing to include measures of neighbourhood effects risks biasing forecasting results by placing inappropriately high weight on those driving variables which are included. Finally, we discuss our results in the context of the provincial Agricultural Land Reserve policy, an effort by the province to promote food sovereignty by protecting agricultural land from development.

Just over 32 % of British Columbia's 925,000 km^2 land area can be considered arable, in the broadest sense of that term. However, prime agricultural land accounts for only 1.1% of this total, and most of that is located in valley bottoms, typically near major urban centers (BCPALC, 2013). The Okanagan Valley is one of the areas with prime agricultural land, and it is facing increasing development pressures. The valley has among the highest rates of population growth of any region in Canada (Statistics Canada, 2012 a,b).The dry, relatively warm climate makes the Okanagan Valley an attractive destination for tourists and retirees, and those migrants generate demands for goods and services. This growth is placing pressure on natural resources, particularly water and agricultural land, both of which are in scarce supply. One consequence of this pressure is ongoing land use change. Land use change has important implications for food sovereignty, agribusiness viability and landscape scale environmental processes. Within British Columbia, various aspects of land use change are under the jurisdiction of different levels of government, levels of government that do not always communicate or coordinate their decisions.

Climate change is likely to intensify the resource pressures already being experienced in the Okanagan Valley. To date, annual precipitation, particularly winter snowfall, has increased (Ping et al., 2010) along with daily minimum temperatures (Cohen and Kulkarni, 2001). The frost free period has lengthened by more than three days per decade, and now ranges from 120 to 150 days (Zbeetnoff, 2006). Warmer winter temperatures are likely to result in an earlier freshet with higher peak flows and significant reductions in late season flows (Merritt et al., 2006). There is some suggestion that total annual flows will also decline (Cohen and Kulkarni, 2001). In lower elevation areas, this effect will probably to be more pronounced.

Milder winters may increase the land area suitable for many crops, particularly perennials such as tree fruits (Neilsen et al., 2001). The precise pattern of these changes depends to a large degree on the microclimates created by the complex topography of the region (Cohen et al., 2006). The longer growing season and warmer temperatures will increase water demand, precisely at the time when surface flows and groundwater recharge is reduced (Neilsen et al., 2001). Reservoir storage is an important part of water management systems in many parts of the Okanagan; earlier peak flows and lower late season flows will increase the need for water storage (Merritt et al., 2006). Overall, climate change is likely to exacerbate the environmental impacts of current water use patterns, with those impacts becoming even more significant if water use increases.

The Okanagan Basin extends from the US border some two hundred kilometers north in the southern interior of British Columbia. In the rain shadow of the Coast and Cascade mountains, the valley bottom receives relatively little precipitation (330 – 450 mm / year) (Neilsen et al., 2010; Duke et al., 2008). Deep Creek drains a small watershed in the northern part of the Okanagan. This watershed exemplifies many of the challenges related to land use change with British Columbia and in other areas facing similar issues. Its water yield is comparatively small, making groundwater an important resource (Ping et al., 2010). Surface-groundwater interactions are also strong in the study area, with groundwater contributing significantly to the lower reaches of Deep Creek and as an important source of water for Okanagan Lake (Ping et al., 2010). Flow rates at peak freshet are 1 – 2 m^3 / sec while non-freshet flow is 0.1 to 0.3 m^3 / sec (Nichol et al., 2011). Withdrawals of groundwater from aquifers feeding Deep Creek may therefore have significant effects on flow rates, and on habitat conditions within the creek. These withdrawals can be substantial. For example, almost 2,350 ha in the Township of Spallumcheen is currently irrigated, predominantly with groundwater (British Columbia Ministry of Agriculture and Lands [BCMAL], 2008). Consumptive water uses as direct withdrawals for supply from Deep Creek are also significant, with documented withdrawals of 2.1 Mm^3/year for domestic and commercial use and almost 3.0 Mm^3/ year for irrigation purposes (Ping et al., 2010), the large majority of which is used in July and August. New water licences are not being issued for Deep Creek (British Columbia Ministry of Forest, Lands and Natural Resources Operations [BCMFLNRO], 2011). However, climate change is expected to cause an earlier freshet and a longer low flow period, the period when peak demands occur.

Land use change is a dynamic process driven by a combination of economic, social, environmental and technological forces (Verburg et al., 2004 b,c; Turner et al., 1990). Different land uses provide different land use or ecosystem functions (de Groot, 2006; Wiggering et al., 2006; Millennium Ecosystem Assessment [MEA], 2005; de Groot, 1992). Many land uses are multi-functional. For example, farmland may produce aesthetic and biodiversity values along with food production (MEA, 2005). Changing land use affects not just the primary purpose, but a range of functions. Changing land use patterns can also affect the vulnerability of places and people to climatic, economic or socio-political perturbations (Kasperson and Kasperson, 2001; Kasperson et al., 1995). Forecasting land use change can support planners and decision makers with protecting important environmental resources and addressing social and economic vulnerabilities.

A model that forecasts land use change in the Deep Creek watershed can help policy makers to better understand and anticipate changing pressures on both land and water resources in the watershed. Water use is closely tied to land use. A land use model can highlight where water withdrawals are likely to increase. Where such increases can adversely affect environmental resources, alternatives can be sought.

Agricultural land is relatively abundant in the Deep Creek watershed, but scarce in the province as a whole. The provincial Agricultural Land Reserve (ALR) was established to prevent good agricultural land from conversion to other uses (British Columbia Agricultural Land Commission [BCPALC], 2010; Seabrooke et al., 2004; City of Richmond, 2002). However, land can be removed from the ALR. A land use forecasting model can help identify those areas where development pressure is the greatest, areas where the model predicts development will occur. Planners can then act in anticipation of these pressures. Possible responses may include strengthening the protection of agricultural land or managing infrastructure development and zoning to provide other outlets for development pressure.

In the following section we discuss our choice of the CLUE-S modelling system. We then describe in greater detail the study site and the drivers that were included in the model, together with a brief description of the CLUE-S data requirements. The subsequent section presents the results. This is followed by a more in depth discussion of the results and their implications. The final section wraps up the paper with a brief summary.

2.2 Method

The choice of modelling strategy depends primarily on the purpose of the modelling exercise. One of our modelling objectives was to develop a model that incorporated the role of surface and groundwater sources on the evolution of land use. A variety of approaches to modelling land use change have been developed, reflecting differing research objectives and data availability. They can be divided into those that seek to model the process of land use change and those that project from observed patterns of land use. Agent-based models (ABM) belong to the former category (Parker and Filatova, 2008; Polhill et al., 2008; Alexandridis et al., 2007; Robinson et al., 2007; Parker et al., 2003) while many spatially explicit simulation models belong to the latter (Pijanowski et al., 2005; Verburg and Veldkamp, 2004; Verburg et al., 2002; Kok and Veldkamp, 2001;Schotten et al., 2001; Hilferink and Rietveld, 1999; Landis et al., 1998; Berry et al.,1996).

We reviewed a range of models, including SAMBA (Castella et al., 2005a,b; Boissau and Castella, 2003), cellular automata models (Clarke et al., 1996; Kirtland et al., 1994), the Mathematical Programming based Multi Agent System – MPMAS (Berger, and Schreinemachers, 2009), GEOMOD (Pontius and Malanson, 2005; Pontius and Spencer, 2005; Pontius et al., 2001), an econometric (multinomial logit) model (Chomitz and Gray, 1996), a general ecosystem model (Fitz et al., 1996), the **C**onversion of **L**and **U**se and its **E**ffects - CLUE model (Kok and Veldkamp, 2001; Verburg et al., 1999; Veldkamp and Fresco, 1996), and the **C**onversion of **L**and **U**se and its **E**ffects in **S**maller scale- CLUE-S model (Verburg and Veldkamp, 2004; Verburg et al., 2002).

The intended application of our land use change forecasting results was a spatial forecast of changes in water demand, which would be accomplished by applying crop water demand relationships for the agricultural land use types in our model. This forecast would enable policy makers to identify areas where the pressure on water resources would be greatest, and provide the opportunity to mitigate these effects. Given that there are multiple land uses and a large range of activities being undertaken in the watershed, collecting enough data to calibrate a process based model to a reasonable degree of accuracy would be challenging. Further, the forecast precision would likely be low. Using a pattern based approach will not illustrate the role of drivers like crop price, nor allow the influences of policies such as subsidies and taxes on land use decisions. While of considerable interest, evaluating alternative policies such as subsidies and taxes was not part of our research objective. A pattern based model can be calibrated using more readily available spatial data, and will likely capture many of the spatial influences that drive activities to particular locations in a landscape. From among the various pattern based models available, CLUE-S has proven to be an effective tool for modelling fairly fine scale land use change. It has been used as a land use change projection tool in African, Asian, American and European locations (Neumann et al., 2011; Hurkmans et al., 2009; Wassenaar et al., 2007; Castella et al., 2005b; Verburg et al., 2005).

The model evolves a gridded map of the study landscape forward, changing land use of individual grid cells using a probabilistic transition algorithm (Appendix B-1). The transition probabilities are impacted by the driving factors that have been included in the model. Many CLUE-S applications are calibrated with observations of land use and a range of possible driving factors for each grid cell. The observed land use, together with the driving factors, are used to develop a model of transition probabilities for each cell with that relationship assumed to remain constant over the length of the simulation and across the landscape. The system uses this model to choose which grid cells will change, to match an externally determined trend for aggregate land use change over the simulation period. The final step in the analysis is visualizing and mapping the result. Further information about the CLUE-S system can be found in Verburg (2010).

A CLUE-S model requires three main inputs: 1) trend changes in total area for each land use type; 2) logistic regression coefficients relating land use type to the explanatory variables; and 3) transition characteristics. Trend changes are generated prior to a model run outside CLUE-S, and provided as input to the system. The trend forecasts may be informed by population growth and other large scale variables, or simply capture historic trends.

The second input required by CLUE-S is a set of coefficients from a logistic regression for each land use type on the driving variables. The driving variables will be selected for a given study based on, among other factors, land use types considered in the simulation and study area characteristics. These regressions are estimated prior to starting the simulation, and serve to compute the transition probabilities. One regression is run for each land use type. Each regression predicts the probability that the land use of each cell will be of that land use type, as a function of the included driving variables. The success of the model will depend in part on identifying the right driving variables for each land use category in the study area. By including distance to surface water and depth to groundwater level as driving variables in these regressions, we both empirically estimate the role of these drivers on land use change, and incorporate these influences into the simulation model.

The transition characteristics capture the direction of change and the inertia against change. For example, land that changes from forest to any other land use is likely irreversible, just as land use change from almost any use to residential is. Some land uses, such as perennial crops, may be more 'sticky' than others. The transition characteristics included in CLUE-S (elasticity and iteration probability) reflect these properties. Readers are referred to Verburg (2010) for additional information.

Spatial restrictions can also be imposed on a model. Such restrictions can reflect land use policies which specify that certain lands are to be protected, for example as parks. Consultations with local government staff, along with examining zoning bylaws and other relevant documents, can help identify land use restrictions that should be implemented. Spatial restrictions can be used to test how the influences of land use policies in one part of the study area impact on the evolution of land use throughout the study area. Such a detailed analysis is presented in chapter 4.

2.2.1 Study Site

The Deep Creek watershed is located in the northern part of the Okanagan Valley, a semi-arid valley in the southern interior of British Columbia (Figure 1-2). The watershed covers an area of 230 km^2 and includes the communities of Armstrong and Spallumcheen. It cuts across the boundary of the Columbia-Shuswap regional district (CSRD) and the regional district of North Okanagan (RDNO). The elevation of the southern part of the creek ranges between 340 – 520 meters above sea level, while the northern part ranges from 370 – 1575 meters above sea level (GeoBC, 2000). Forestry, agriculture, manufacturing and tourism are all important economic activities in the watershed. The area included within the boundaries of the Township of Spallumcheen overlaps to a large degree with the boundaries of the Deep Creek watershed. Within the township, the share of employment in agriculture is among the highest in the province (British Columbia Ministry of Agriculture, Food, and Fisheries [BCMAFF], 2002). The agriculture overview of the Township of Spallumcheen reports an average farm size of 38.1 ha with cropped area covering more than half (52 %) of the farmed area and pasture (managed and unmanaged) area occupying 44 %. Among livestock enterprises, there are 11,100 cattle on 155 farms and 44 % of the dairy herd in Okanagan Valley is found within the township limits (BCMAL, 2008). Poultry farming has significantly intensified. There were 325,000 birds on 150 farms in 1996, while in 2006 there were 909,000 birds on 99 farms. Irrigated area has also increased, from 8 % of total farm land in 1996 to 14 % in 2006 (BCMAL, 2008). Unless irrigation efficiency was improved by at least 43% over the same period, this increase in irrigated land will have increased total water use.

The North Okanagan area has an average annual precipitation of 468 mm on the valley floor and 592 mm on the surrounding mountains (Neilsen et al., 2010; Duke et al., 2008). The basin has a semi-arid climate with a bimodal precipitation pattern. Summers are warm, with irrigation necessary for many crops. A winter peak reflects the migration of Pacific storms across the region, while convective storms result in another peak in the early summer (Late May / Early June) (Merritt et al., 2006). Daily minimum temperature has increased noticeably, as has precipitation, particularly winter snowfall. (Cohen and Kulkarni, 2001). The frost free period has increased ~~a~~nd these changes in climate are lengthening the growing season, reducing the risk of extreme minimum winter temperatures (Cohen et al., 2006).

A history with multiple glaciations has resulted in a complex system of aquifers (Nichol et al., 2015). Some of these aquifers are recharged by precipitation that falls on the surrounding hills and mountains. From these sources, groundwater flows through fractures in the bedrock, recharging some deeper aquifers that are themselves in contact with the bedrock. Other aquifers are recharged by local precipitation or by exchange with surface waters, and may be isolated from groundwater that originates in the hills and mountains. Some wells pump from relatively shallow, unconfined aquifers, with pumping potentially impacting stream flows. Other wells pump from deeper confined, and sometimes artesian, aquifers. A recent numerical modelling study indicated that usage of groundwater during the summer period is 17 % of the total through flow of the aquifer system when the pumping is at its maximum (Ping et al., 2010). Groundwater levels drop during the summer and year over year the levels have been dropping in most of the aquifers (Ping et al., 2010).

Presently, more than half of the Deep Creek watershed is covered by forest and range land. Montane forest types of Douglas Fir and lodge pole pine are found in the study area (Demarchi, 2011). Wildfires and the recent outbreak of mountain pine beetle have caused considerable forest damage (BCMFLNRO, 2011). Forest and range lands are the undeveloped land use in the watershed. Generally, land use demand is filled by converting forest and range land to other uses. This reduces the extent of forest and range land, thereby decreasing the ecosystem services provided by these lands.

Agricultural land is relatively rare in British Columbia, and public interest in food sovereignty led the province to introduce the Agricultural Land Reserve Act (ALR) in 1974 (BCPALC, 2010). Land zoned as inside the ALR has development controlled to give priority to agricultural activities. In total, almost 4.7 million hectares of both public and private lands are included in the ALR, about 5% of which is in the Okanagan. Before the ALR was established nearly 6000 ha of farm land per year was lost. In 1997 the area lost was a much smaller approximately 500 ha. As of January, 2008 about 9 % (69,700 ha) of the Regional District of North Okanagan’s overall area and almost 39 % of all land in the ALR in the

Okanagan is located in the regional district (BCMAL, 2008). Nearly 44 % of the Deep Creek watershed is included in the ALR.

2.2.2 Data Requirements and Processing

There are a variety of data sources that were used to build the model. Some data were supplied by government agencies, while other data were obtained from organizations active in the study area. For the CLUE-S simulation, the data need to be organized on the simulation grid, with each variable used having a value for each grid cell. A substantial amount of data processing (aggregation and interpolation) was required to generate a dataset suitable to the modelling task.

CLUE-S simulates a gridded landscape, with the computational burden increasing rapidly as the number of grid cells increases. With the application of these modelling results being an integration with climate change projections, we chose a 500m × 500m grid size (25 hectares) that matches with the highest resolution future climate data that will be used (gridded climate surface data generated by OCDI). This grid size is also loosely consistent with average farm size in the Township of Spallumcheen, which was 36.8 ha in 2001, and 62.5 ha in 2006 for the Regional District of North Okanagan (BCMAFF, n d.; BCMAL, 2008). Gridding the landscape also meant representing all polygon based data as grid cells. Standard tools in ArcGIS™ (9.3) were used to generate a grid map that overlays the watershed boundary polygon. The resulting grid contains 1112 cells. The remaining data processing consisted of scaling data to be consistent with the simulation grid.

A key ingredient of CLUE-S is a land use map. To generate the base map, land uses have to be aggregated down to a limited number of land use types, and single land use types have to be assigned to each grid cell. A recently concluded land use survey map for Okanagan basin, obtained from BCMAL, covered much of the study site (Van der Gulik et al., 2010). The land use survey was conducted during the summer of 2007 and 2008, and was made available in 2010 after processing the collected information. A second, slightly older map, also available from BCMAL, was used to patch the missing areas. Most of these missing areas were in the north part of the watershed.

A raster map of the land use data was generated at a 100 m^2 resolution. A land use was assigned to the grid cell, where a majority of the 2,500 pixels in each grid cell were a single land use. More than 40% of grid cells had only one land use and 18% had only two. Almost 82% had one land use accounting for the majority of pixels in the grid cell. Less than 5% of grids had the dominant land use in the cell accounting for less than one third of the pixels in the grid. The two most dominant land use/cover types were woodland (102.8 km^2) and grassland (18.0 km^2), together accounting for nearly half of the grid cells.

There were 42 major land uses found over the 1112 grid cells. Many were only represented by one or a few cells. It is not possible to estimate a regression model with fewer observations than independent variables. So, land use types with too few observations were aggregated into other groups. Further, attempts to precisely forecast land use change with many land use categories are subject to error. We therefore grouped the land use types into three broader categories – undeveloped, agriculture, and urbanized area – and further divided the agriculture category into three more, pasture and forage, cultivation land, and livestock farm. Each grid was then assigned the dominant land use from those of the cells it contained (Figure 2-1).

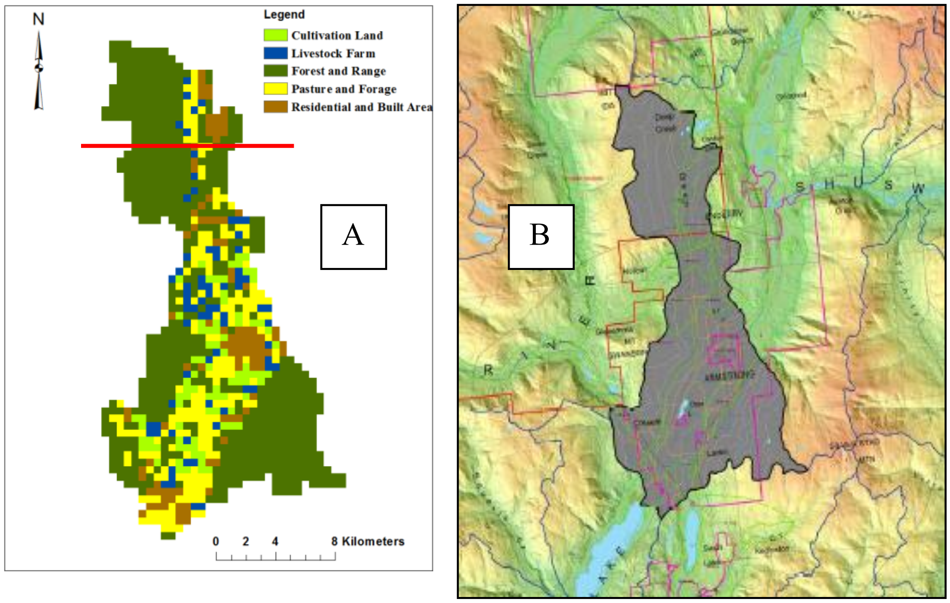


Figure 2.1: (A) Major land uses and their spatial distribution in 2010. Area above red line used as land use change restricted area in the scenarios. (B) Locations of the towns of Armstrong (inside the watershed) and Enderby (outside the watershed), the boundaries of the Township of Spallumcheen, and the Agricultural Land Reserve (ALR) areas

The physical variables included as potential land use change drivers were: elevation, slope, aspect, soil depth, sand percentage, silt percentage, depth to groundwater, and distance to surface water. Elevation, slope and aspect are important determinants of the local climate conditions. To calculate average elevation, slope and aspect for each cell, contour map information provided by the provincial government was used (GeoBC, 2000). This data was used to generate a raster map with 25 meter pixels. ArcGIS™ (ESRI, 2012) functions were used to convert polygon data to raster data and to generate values for the different drivers that will be included in the model. This process calculated an elevation in meters above sea level, a percentage slope and an aspect in degrees from North for each pixel. The elevation and slope for the 400 pixels within each grid cell were then averaged to generate slope and elevation values for the 500m × 500m grid cell. Orientations of North, East, South or West were assigned to each pixel by dividing the compass at 45˚, 135˚, 225˚ and 315˚. The orientation (aspect) of the grid cell was then set as the majority orientation of the contained pixels.

Access to transportation and markets is important for many activities. Farmers need roads to access markets for inputs and to deliver products for sale. Residents use roads to access employment and retail. Much of the Deep Creek watershed is rural residential, with many jobs located in the cities of Vernon and Salmon Arm, both just outside the watershed (Figure 1.2). Distance to urban centers and access to transportation are expected to be drivers for land use change. Using distance to roads implicitly assumes that the process by which the road network is expanded is uniform with respect to the existing road network. This is somewhat inconsistent with the fact that road network decisions are typically important policy choices. However, we follow this conventional approach. Distances from the centroid of each 25m pixel to the nearest urban center (Vernon or Salmon Arm), nearest highway and nearest paved surface were calculated. These were averaged for the pixels in each grid cell to generate distance measures for each grid cell.

Soil depth, sand and silt percentages are important components of the agricultural capacity of the land. Soil depth, sand and silt percentages (measured at 10 cm depth) were generated using a soil map available from Soil Landscapes of Canada version 3.2 (Agriculture and Agri-Food Canada [AAFC], 2012). A raster map of these variables was generated and averages calculated for each grid cell as done for elevation and slope.

Given the semi-arid climate, many agricultural activities cannot occur without irrigation. Irrigators holding surface water licenses – generally long established farmers – are able to draw from surface sources. Those who do not have a license or are too far away from a source to make conveyance of water practical can use groundwater. For irrigators relying on their own water supply, the cost of access – increasing with distance or depth – are likely to affect the choice of agricultural activities. Further, the nature of the aquifer (unconfined / confined) also plays the role in the cost of accessing groundwater.

Distances to both flowing (streams and rivers) and non-flowing (lakes and reservoirs), sources of surface water, were calculated. For each 25 meter pixel, the distance between the centroid of the pixel and the nearest point on the respective water body was measured. The average distance for each grid cell was then calculated as the distance measure for the grid cell. This adjusts for the relatively course resolution of a 500 meter grid cell, which in a number of cases will have a stream or similar feature passing through it. Recognizing the increasing cost of conveyance with distance, grid cells with an average distance of more than a kilometer from a surface source were assumed not to use surface water, and a flagging variable was also calculated that marked each grid cell as more than a kilometer from a surface water source.

Surface water bodies are licensed. Groundwater is not. Any land owner can drive a well and pump as much water as desired and as available, with the only cost being that for drilling and for lifting the water. To approximate depth to groundwater, data for the elevation of groundwater at the known wells was used. A raster map of simulated groundwater level elevation was generated using results from Ping et al. (2010). The groundwater level elevation at each grid was calculated in the same manner as it was calculated for elevation. The depth of potentiometric surface was calculated using the difference between the elevation of the grid and the elevation of the depth of static groundwater level of that particular grid. Negative values of the static groundwater table, represents locations where the simulated data predicts artesian flows and were assigned a depth of zero. Less than 5 % of the grids (46) were interpolated to have negative depth to groundwater.

There are a number of water utilities in the watershed that provide water for residential and agricultural purposes (Figure 2-2). In those areas where water is available from a water utility, distance to surface water and/or depth to groundwater is less likely to be a relevant driving variable. Of the 14 water districts, eight water districts use groundwater as their source of water supply and six districts rely exclusively on groundwater.

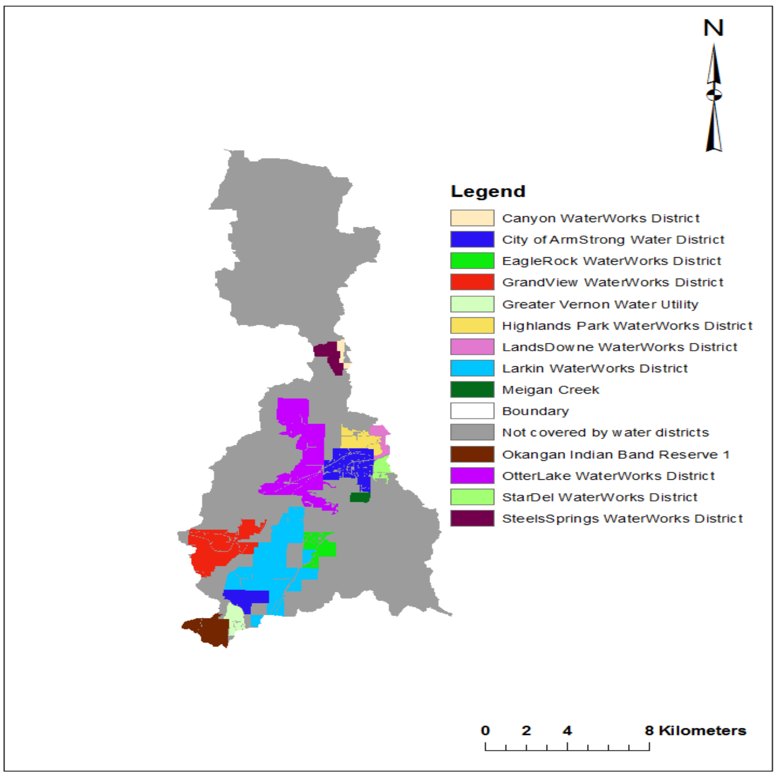


Figure 2.2: The spatial coverage of water districts operating within the study area

Only half of the water utilities operating in the study area provide water for agricultural purposes. Polygons representing the areas serviced by each water provider were obtained from the Okanagan Basin Water Board.

These polygons were used to assign each 25 meter pixel as supplied or not supplied by a water provider. If the majority of pixels within a grid cell were included in a water provider polygon, then the cell was marked as supplied by a water provider. This flagging would be used to turn off the role of distance or depth to water as a driving factor. The flagging also differentiated between areas with water providers that primarily supplied residential potable water and those that supplied irrigation water.

Finally, we recognize that land use tends to be clustered. In addition to the drivers already described, we expect that a patch of land is likely to convert in the direction of the most common land uses nearby. Land use change can be influenced by neighbourhood characteristics (Verburg et al., 2004a). To capture this effect, we calculate a spatial "neighbourhood strength" that reflects the relative dominance of the cell under consideration within its immediate neighbourhood. In our method, we divide the share of the local Moore neighbourhood (Verburg et al., 2004a) occupied by cells with the central cell type by the average share for the central cell land use type over the entire study area. The details of this derivation are described more fully in Chapter 5. We expect that this neighbourhood association will capture spatially correlated effects that may not be reflected by the levels of the other included driving variables.

2.2.3 Simulation

CLUE-S requires three major inputs, aggregate land use change, coefficients from a logistic regression of land use types on driving factors, and land use change propensities. The regression parameters are described in the results section. Forecast changes in agricultural land use types were based on past trends. Changes in residential land use area were assumed to follow projected population growth. Projections were based on information in the Census of Agriculture (British Columbia Ministry of Agriculture, 2011; BCMAL, 2009; BCMAL, 2008; BCstats 2006). Overall, changes for cultivation land, livestock farm, pasture and forage land, and residential and built area are projected to be, respectively, 0.50, -0.67, 0.95, and 1.12 percent per year, with these changes made up for by a corresponding reduction in forest area. The "free to change" (total conversion pressure is applied on Forest and Range area) demand for 2050 was used in this simulation (Figure 2-3).

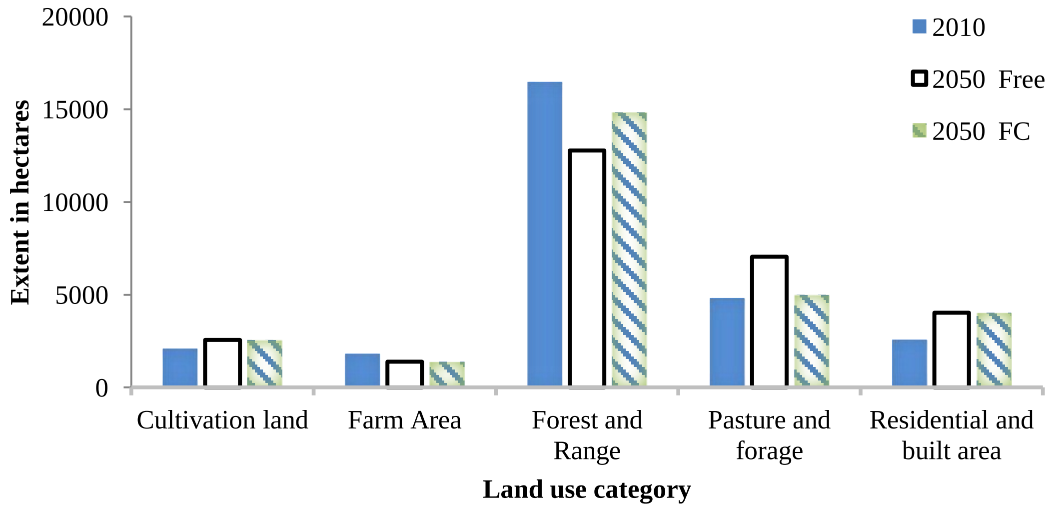


Figure 2.3: Aggregated land use demand in 2010 and 2050 under "free to change" (Free) and "forest conservation" (FC) scenarios

The land use change propensities are reflected in two sets of parameters, the conversion elasticity and the conversion sequence (Verburg, 2010). Conversion elasticity values range between zero and one, and measure the 'inertia' of a land use type, how difficult it is to convert it to another land use type. After reviewing the literature and consulting with local experts from the regional districts, elasticity values were set at 0.65, 0.75, 0.80, 0.85 and 0.95 for pasture and forage, cultivation land, forest and range, livestock farm and residential and built respectively. This captures the fact that pasture and forage is relatively easy to convert to a range of other land uses, while residential and built areas are much more difficult to convert. The conversion sequence captures the fact that land use change is typically ordered. For our simulations, conversion was possible between all land use types except residential and built areas. All types could convert to residential and built areas, but once a grid cell is of this type, it could not convert to any other type.

2.3 Results

2.3.1 Summary Statistics

Summary statistics for each land use category are presented in Table 2-1. Nearly half (48.5 %) of residential and built area is supplied with water for domestic and other purposes by water districts while residential and built area receives services from water districts for agricultural purposes, domestic use, and other purposes is only 16.5 % (Table 2-1). Nearly a third of grids occupied by the cultivation land use category are supplied water for agricultural purposes by the water districts while 31.5 % of farm area in 2010 are supplied water by water districts / utilities for agricultural purposes. A minor proportion (4.4 %) of the forest and range land was also supplied water by water districts for agricultural purposes (Table 2-1). This reflects the aggregation process, where some grid cells assigned to the forest and range land use type contain some land that is developed and connected to a water supply. On average, the depth to groundwater level is greater for areas supplied by water utilities, consistent with the idea that water utilities are created to supply water where it is too difficult or costly for individual land owners to develop their own source. However, the average depth of the potentiometric surface for grids not supplied water by water districts was not significantly different between land use categories except for forest and range land irrespective for the purpose to which they receive water from water districts. But, the average depth of the potentiometric surface (areas where water districts do not supply water for agricultural purpose) for cultivation land, and pasture land is nearly 30 meters while it is closer (189m) to ground surface for forest and range land (Table 2-1).

Table 2. 1: Comparison of explanatory variables used in the logistic regression analysis for each land use category for 2010 (Means with the same letters are not significantly different from each other)

Variable	**Cultivation Area**	**Livestock Farm**	**Forest and Range**	**Pasture and Forage**	**Residential and Built Area**
Distance to highway (m)	2042^{a}	3148^{b}	4049^{c}	2307^{a}	1863^{a}
Distance to urban centre (m)	15047^{c}	$11545^{a,b}$	10459^{a}	12103^{b}	$10862^{a,b}$
Distance to paved path (m)	258^{a}	263^{a}	1766^{c}	617^{b}	767^{b}
Population density (per km^2)	22.17^{a}	29.47^{a}	2.74^{a}	11.34^{a}	209.81^{b}
Slope (%)	3.96^{a}	3.52^{a}	10.68^{b}	3.68^{a}	4.46^{a}
Spatial association	0.36^{b}	0.27^{a}	0.85^{d}	0.47^{c}	0.47^{c}
Depth of groundwater level (m)	36.42^{a}	38.24^{a}	191.70^{b}	35.01^{a}	33.30^{a}
Depth of groundwater level[1] (m)	21.74^{a}	16.92^{a}	183.96^{b}	19.08^{a}	20.97^{a}
Depth of groundwater level[2] (m)	30.78^{a}	23.46^{a}	189.40^{b}	30.06^{a}	24.95^{a}
Distance to lake / reservoir (m)	569^{a}	640^{a}	958^{b}	466^{a}	518^{a}
Distance to lake / reservoir[2] (m)	384^{a}	428^{a}	942^{b}	371^{a}	461^{a}
Distance to river (m)	491^{a}	429^{a}	1082^{b}	$749^{a,b}$	700^{a}
Distance to river[2] (m)	444^{a}	457^{a}	1079^{b}	$728^{a,b}$	642^{a}
Water supplied for domestic and other[3]	16 (19.1)	10(13.7)	25(3.8)	45(23.3)	33 (32.0)
Water supplied for all purpose[4]	27 (32.1)	23(31.5)	29(4.4)	44(22.8)	17 (16.5)

1–Depth / Distance computed for area not serviced by water districts for domestic and other water purposes;

2–Depth / Distance computed for area not serviced by water districts for agricultural purposes;

3 -No. of grid cells that have access to receive water supply from water district for domestic and other purposes;

4 -No. of grid cells that have access to receive water supply from water district for all purpose (domestic, agriculture, and others);

Values in the parenthesis are the percentage of the total grids in given land use category.

The surface water resources variables interacted with land use type similar to the way that groundwater does, except for the livestock farm land use type. Distance to river is not significantly different for cultivation land, livestock farm, and residential and built area land use types, while being significantly larger for forest and range lands, with pasture and forage falling between, and not significantly different from any of the others. The average distance to lake / reservoir (after including the water district effect) is not significantly different across all the land use categories except forest and range land (Table 2-1). This is consistent with the fact that development has occurred on the valley floor, which is closer to the main water bodies.

2.3.2 Regression Results

A logistic regression was fit for each land use type (Table 2-2 and 2-3). The models were fitted using forward conditional stepwise regression. Receiver Operator Curves (ROC) were used to diagnose the strength of each land use model (Pontius and Schneider, 2001. Parameter estimates that were not significant at the 95% level have been dropped, except where noted. Table 2-2 and 2-3 present the coefficient estimates and goodness of fit measures (model Chi-square, pseudo R^2, and the area under the ROC curve). Table 2-2 presents parameter estimates when water provider service area was considered, while Table 2-3 shows results when these adjustments were not made. Model fit was best for the forest and range land use type, the type with the greatest number of observations, and poorest for the livestock farm land use type. All the models are significant at 0.1 % error level (prob< 0.001). These ROC values are in the range reported for similar models, where they vary within the range of 0.735 to 0.983 (Lin et al., 2007a).

Table 2.2: The parameter estimates, level of significance, Chi – square values, and R^2 values of logistic regression output and ROC values for each land use category in the study area

Variables	**Cultivation land**	**Livestock farm**	**Residential & built area**	**Pasture &Forage**	**Forest &Range**
Distance to highway	–	–	-0.0004 (0.00009)[1]	–	0.0002 (0.00005)
Distance to urban center	0.0002 (0.00004)	–	-0.0002 (0.00003)	–	–
Distance to paved surface road	-0.0007 (0.00025)	-0.0009 (0.00026)	–	–	0.0007 (0.00019)
Population density	-0.0035 (0.00184)	–	0.0162 (0.00274)	-0.0105 (0.0031)	-0.0189 (0.00459)
North direction of aspect				0.4893 (0.2295)	–
South direction of aspect	0.7856 (0.28459)	–	–	–	–
East direction of aspect	–	0.6468 (0.27153)	–	–	–
Slope	-0.0750 (0.03561)	-0.1874 (0.04910)	–	-0.1565 (0.0275)	0.2046 (0.02491)
Percentage of sand	–	0.0261 (0.00732)	0.0146 (0.00695)	–	–
Depth of ground water level	-0.0056 (0.00266)	-0.0076 (0.00330)	-0.0094 (0.00245)	-0.0106 (0.0015)	0.0100 (0.00155)
Distance to river in buffer zone	0.0020 (0.00062)	–	–	–	-0.0004 (0.00014)
Distance to lake and reservoir	–	–	-0.0006 (0.00030)	–	0.0004 (0.00020)
Spatial association	0.7852 (0.39938)	0.8911 (0.41908)	–	0.9928 (0.3086)	–
Constant	-5.2086 (0.72637)	-2.5627 (0.43893)	0.4663 (0.56595)	-0.4821 (0.2520)	-3.0141 (0.26166)
Number of grids / cells	84	73	103	193	659
Model Chi-Square value	167	117	241	262	792
Pseudo R^2 (Cox & Snell)	0.14	0.10	0.20	0.21	0.51
ROC value	0.88	0.84	0.93	0.84	0.89

All variables are significant at $p < 0.05$ except the population density that is significant for cultivation land at $p < 0.10$. [1]-Values in the parenthesis are standard error and "-" implies insignificant.

Table 2.3: The parameter estimates when water resources variables are unadjusted for water providers influence, level of significance, Chi – square values, and R^2 values of logistic regression output and ROC values for each land use category in the study area

Variables	**Cultivation land**	**Livestock farm**	**Residential & built area**	**Pasture &Forage**	**Forest &Range**
Distance to highway	–	0.0001 (0.00007)[1]	-0.0005 (0.00009)	–	0.0002 (0.00005)
Distance to urban center	0.0002 (0.00004)	–	-0.0002 (0.00003)	–	–
Distance to paved surface road	-0.0020 (0.0004)	-0.0020 (0.0004)	–	–	0.0007 (0.00019)
Distance to major cities	0.0001 (0.00004)				
Population density	-0.0050 (0.0022)	–	0.0159 (0.0028)	-0.0106 (0.0031)	-0.0189 (0.00459)
North direction of aspect				0.4761 (0.2308)	–
South direction of aspect	0.6226 (0.2866)	–	–	–	–
East direction of aspect	–	NS	–	–	–
Slope	NS	-0.2034 (0.0463)	–	-0.1477 (0.0277)	0.2046 (0.02491)
Percentage of sand	–	0.0154 (0.0078)	0.0204 (0.0074)	–	–
Depth of ground water level	-0.0096 (0.0025)	NS	-0.0104 (0.0024)	-0.0117 (0.0016)	0.0100 (0.00155)
Distance to river	0.0012 (0.0003)	0.0010 (0.0003)	–	–	-0.0004 (0.00014)
Distance to lake and reservoir	–	–	-0.0006 (0.0003)	–	0.0004 (0.0002)
Spatial association	1.1387 (0.4005)	1.0338 (0.4247)	–	1.0455 (0.3109)	–
Constant	-6.9249 (1.2410)	-2.6682 (0.4620)	0.3598 (0.5789)	-0.4318 (0.2534)	-3.0141 (0.26166)
Number of grids / cells	84	73	103	193	659
Model Chi-Square value	175	117	245	269	792
Pseudo R^2 (Cox & Snell)	0.15	0.11	0.20	0.22	0.51
ROC value	0.88	0.84	0.89	0.85	0.93

All explanatory variables are significant at $p < 0.05$ error level. [1]Values in the parenthesis are standard errors. NS-denotes variable that is insignificant for water resources variables were not adjusted for water providers but significant when adjusted for it. "-" implies insignificant.

Depth to groundwater is not significant without considering the water provider service area for the livestock and farm land use category. For the remaining three land use categories where service area is considered, adding this variable significantly increases the fit of the model, based on the incremental Chi-squared test. In a regression with both depth to groundwater and depth to groundwater interacted with being outside of a service provider area is significant for cultivation, livestock farm and residential and built area (change in chi-square value are 4.85, 5.87, 4.60 respectively, relative to a significant cutoff value of 3.84). In addition, the level and significance of a number of other variables also changes when the influence of water provider services area is considered. There is no difference for the forest and range land use type because the influence of water provider service area was not considered. Given both the statistical support and the logical consistency of including this influence, the regression results with water service provider influence were used.

Distance to urban centre, spatial association (neighbourhood strength), distance to river (within the 1 Km buffer zone) and south orientation are positively correlated with the cultivation land use type. Distance to paved surface, population density, slope and depth to groundwater are negatively correlated (Table 2-2). Cultivation land tends to be located close to urban centers, reflecting proximity to markets. The negative influence of population density and paved surface is consistent with residential and built areas being a higher value use, driving cultivation land to be close to, but not too close to, settled areas. Slope and depth to groundwater have the expected signs, as does spatial association. Steep land is hard to work, and there are benefits of being near other cultivation land cells that are not captured by the driving variables, reflected in the significance of the spatial association variable. The sign on distance to river is opposite to expectations, but may reflect water table or flooding issues not captured by the included variables.

Residential and built areas are negatively associated with distance to highway, distance to urban center, distance to lake / reservoir and depth of groundwater table, while population density, and percentage of sand have a positive influence. Spatial association (neighbourhood strength) does not have a strong enough effect to be retained in the model. For the livestock farm land use type, distance to paved surface, depth to groundwater and slope are negatively correlated, while easterly orientation, percentage of sand and measure of spatial association are positive.

Pasture and forage land use is the second largest land use found in the study area (Table 2-2). Population density, slope and depth to groundwater are negatively associated with this land use type, while northerly orientation and spatial association (neighbourhood strength) are positive. Where water is not available from a utility, access to water is important, which is consistent with the influence of depth to groundwater. Flatter land is preferred. The influence of northerly orientation may occur because pasture is a superior use on some sites, where microclimates are not suitable for cultivating higher value, heat loving crops. The very high influence of spatial association (neighbourhood strength) suggests that there are other spatial drivers that have not been included in the model.

The residual land use class is forest and range, the land use that would occur were land not converted to other uses. Hence, the influence of the driving variables reflects the fact that the land remaining as forest and range is less attractive for those other uses. Distance to highway, to paved surface roads, and depth to groundwater and distance to a lake or reservoir have a positive influence, while population density and distance to a river are negative. Highways and road networks are built to connect settlements and enable conversion of land to other uses, so the negative association with these variables makes sense. The influence of depth to groundwater and distance to lake or reservoir is consistent with the fact that most of the land development has occurred on the valley bottom, where lakes and reservoirs are located, and where groundwater is easier to access. In an agricultural area like the Deep Creek watershed, settlement patterns are related, at least historically, to agricultural activities, consistent with the influence of population density. The negative influence of distance to flowing surface water, within the one kilometer band of that water, may reflect topographic constraints that limit other land uses in some of those areas.

Note that spatial association (neighbourhood strength) was not included in the forest and range model. When included, the coefficient became negative, and the signs and magnitudes of the other variables were unreasonable. Forest and range is not so much an actively chosen land use type, but rather that land use type for land that has not been converted to one of the other four uses. Where spatial association captures the propensity to convert a parcel of land to be similar to its neighbours, such an effect is not relevant for land that is not actively converted.

2.3.3 Simulation Results

Table 2-4 reports the aggregate changes between 2010 and 2050, broken out to show the conversions from one land use type to another. Each row represents a land use, and the total of the row is the number of cells of that land use type in 2010. Likewise, the sum of each column is the total number of cells of that land use type in 2050. Each cell contains the number of cells that were of the row type in 2010 and of the column type in 2050. Numbers along the diagonal count the cells that had the same land use in 2010 and 2050. The off diagonal numbers show the loss (row land use) / gain (column land use) from land use change. By construction of the elasticities, all the residential lands in 2010 remained residential in 2050. Seven agricultural cells will be converted to residential uses, five that are currently of the livestock farm type. This is a two percent loss of presently farmed agricultural land. The vast majority of the area that is predicted to become residential land is converted from forest and range. Most of the predicted decline in the livestock land use type is taken up as pasture and forage. Overall, nearly 85 % of the watershed will remain the same in 2050 (Figure 2.4). In chapter 4 we consider the impact on land use conversion when policies are implemented that restrict land conversion for part of the watershed.

Table 2.4: Land use types status (remain same / changed) in year 2050

		2050						
		Cultivation Area	Livestock Farm	Forest and Range	Pasture and Forage	Residential and Built area	In 2010	Remain as Original (%)
2010	Cultivation Area	83 (76)	0	0	0	1 (1)	84 (77)	99 (99)
	Livestock Farm	0	56 (51)	0	12 (12)	5 (5)	73 (68)	77 (75)
	Forest and Range	19 (14)	0	510 (28)	79 (55)	51 (19)	659 (116)	77 (24)
	Pasture and Forage	0	0	0	192 (173)	1 (1)	193 (174)	100 (99)
	Residential and Built area	0	0	0	0	103 (61)	103 (61)	100 (100)
	In 2050	102 (90)	56 (51)	510 (28)	283 (240)	161 (87)	1112 (496)	85 (87)

Values in the parenthesis are the number of grids coming within the ALR boundary

Table 2-4 also shows the number of grid cells that are in the Agricultural Land Reserve (ALR), for each land use type, and how many of these change. A grid cell is in the ALR if at least 50% of the area of the cell is in the ALR. Some of the ALR numbers seem counter intuitive. However, given the assignment of land use types, a cell can be more than 50%

built, but if some of that built area is on parcels that are in the ALR, it can also be more than 50% in the ALR. The numbers also highlight the certain parcels that are not used for farming activities also inside the ALR. Of the 659 forest and range cells, 116 are at least 50% included in the ALR. Most of these lands are not being actively farmed, but are considered to be of sufficient quality to be farmed, and are therefore protected.

The model does not include the ALR as a driver of land use change. The ALR is a policy that has a process for excluding land from the ALR to enable development. The results predict that seven actively farmed grid cells, all of which are at least 50% in the ALR, will be converted to residential uses. Of the 51 forest and range cells that are converted, more than one third are included in the ALR. Taken together, more than half of the new residential and built area takes place on land that is presently in the ALR. Thus, while seven of 350 actively farmed grid cells are lost to development, 2%, 26 of 496 grid cells that are in the ALR, 5.2% are converted to residential and build area. While much of this land is not presently profitable to farm, its conversion does represent a negative impact on the potential for food production in the future. We examine these impacts under different scenarios in chapter 4.

The expansion of residential and built areas occurs largely in the far northwest and the south of the watershed, areas close to Salmon Arm and Vernon, and close to a highway corridor (Figure 2-4). Much of this new build area is converted from forest and range, some comes from livestock land use types, and smaller amounts are converted from other land use types (Table 2-4). The simulation results predict that a large share of the expansion of built areas will occur along the interface between agricultural uses and the forest and range lands, consistent with the impact of the ALR. The largest expansion of built areas into agricultural

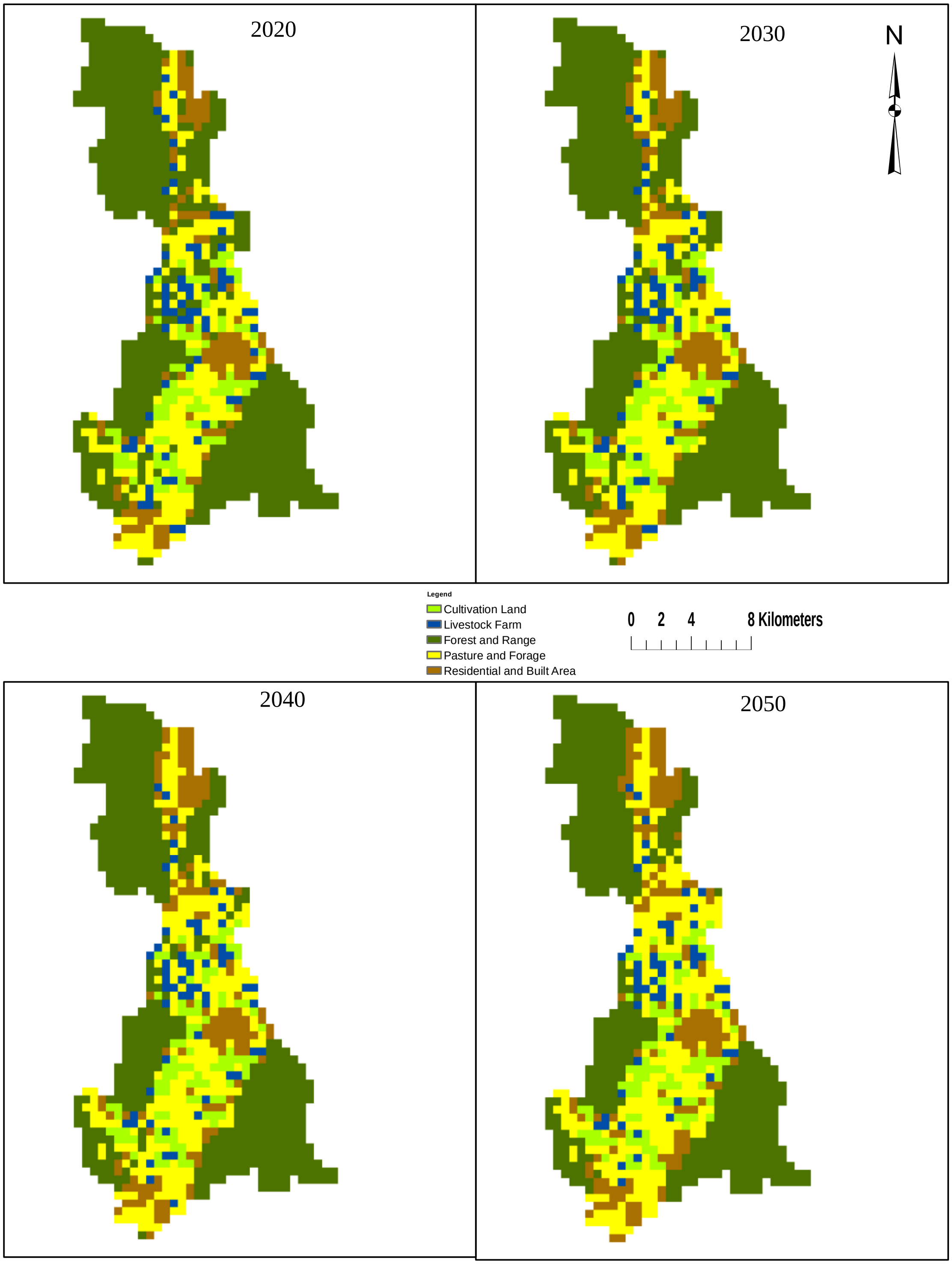


Figure 2.4: Land use changes in the Deep Creek watershed from 2020 to 2050

land uses is predicted to occur along the southern part of the watershed, which is close to Vernon, and where there are two important highway corridors. In this area there is less forest land available to convert, and that which there is has a steep slope, making it less attractive. The livestock land use area declines throughout the watershed but this does not necessarily mean that livestock numbers will decline by the same amount. If livestock intensity is increased, then there is a need to dispose of animal waste. Much of this will be spread on land that is classified as cultivation land and in particular pasture and forage land. Likewise, pasture and forage land is intimately connected to livestock operations, as these areas produce the feed consumed by the livestock. The simulation suggests that most of the remaining livestock operations will be concentrated in the central part of the watershed, north of Armstrong. Waste disposal will likely be concentrated in these areas.

The increase in cultivation land and pasture and forage is largely accommodated by the reduction in the livestock land use and conversion of forest and range land along the margins between this land use and the agricultural land use types. Forest fragments that are currently scattered around the watershed, particularly in the central region where most of the current livestock land use type is also concentrated, are predicted to be largely gone by 2050. Much of this forecast expansion in cultivation land and pasture and forage land is in areas not presently serviced by water utilities. Thus, this expansion will likely be accompanied by increased withdrawals of groundwater, unless the utilities expand their service areas.

A simple 'expert' validation of the model results was done by consulting the official community plan for the Township of Spallumcheen, and by direct communications with Columbia – Shuswap regional district staff. The general directions of the changes are consistent with the community plan (RDNO, 2012; CSRD, 2011). However, the community plan does not resolve between different agricultural land types, but rather between large and small holdings. Large holdings are generally consistent with commercial agricultural enterprises, while small holdings are more often hobby farms. Township staff were shown the land use maps, and given the opportunity to point out where the model predictions were inconsistent with their professional expectations. After incorporating some of their suggestions such as high density development closer to Gardom lake (Appendix A-1) area and inclusion of spatial association (neighbourhood strength), the final simulation results were seen as reasonable.

2.4 Discussion

Four important results are highlighted by this work. First, the extent of water supply infrastructure needs to be expressly considered to ensure that water related variables are properly reflected in the model. Second, a measure of spatial association is an important predictor and should be considered in building models like this. Third, continued population growth will put increasing pressure on agricultural lands, particularly near the urban centers of Vernon and Salmon Arm. Fourth, increased areas of cropped agricultural land will likely increase groundwater withdrawals, which may impact on water quality and quantity in Deep Creek.

Access to water resource is an important factor in land use decisions, particularly in semi-arid areas. Proximity and access to surface water has been incorporated into numerous models (Park et al., 2011; Valbuena et al., 2008; Lin et al., 2007a; Verburg and Veldkamp, 2004). Groundwater variable was also used in number of studies (Park et al., 2011; Luo et al., 2010; Verburg et al., 2004c,d), though many researchers discuss the impact land use has on groundwater resources. No land use model results could be found that considered the extent of water supply infrastructure on land use change.

In our model, access to surface and groundwater resources was only modeled for cells that were either close to a surface water source or that were not serviced by a water utility. When the model was fit without considering water utilities, parameters related to surface and groundwater resources were often not significant or had signs inconsistent with expectations. Farmers with access to water from a utility do not need access to groundwater or surface water sources. Including their land in the regressions would result in biased estimates.

Including a spatial association measure in a forecasting model is a way of incorporating the influence of drivers that vary over space but were not included in the model. Ideally all these drivers could be measured and a richer model estimated. However, often the data do not exist or cannot be measured at a fine enough resolution. Failure to include spatial association effects will attribute a greater influence to the other driving variables included in the model, resulting in a simulation that spreads development too strongly in response to these other drivers. The longer the length of the simulation, the larger this influence will be. Using a spatial association measure is consistent with the spatial lag regression (strong spatial correlation) models used in various land use analysis (Aguiar et al., 2007; Gellrich and Zimmermann, 2007; Overmars et al., 2003). Our proposed methodology demonstrates that the effect of spatial association for a categorical variable, like land use type, can be modelled effectively. Our results highlight that assuming all important spatial affects are captured by the included driving variables can miss important effects. In chapter 5, we consider the impact of dynamic updating of the spatial association measure on CLUE-S model forecasts.

The extent of water infrastructure is a variable that has not often been considered in land use change modelling. There are a number of infrastructure types where a parcel either is or is not connected. Examples include electricity, telephone, roads, and railways. Some of these, such as roads and railways, can be accessed privately, with a cost that increases with distance from the infrastructure. For others like electricity and telephone, substitutes are imperfect or unavailable, and distance to the infrastructure may proxy for the likely expansion of that infrastructure. Including distance to such infrastructure as a driver implicitly assumes that the way this infrastructure is expanded does not change the role of these variables over the landscape as a whole. This may be a strong assumption when infrastructure expansion decisions are often important policy choices. Water infrastructure provides a somewhat unique relationship. The alternative to connecting to a piped supply is access to groundwater or surface water. Cost of access, reflected by distance or depth, will be important for those who do not have access to a piped supply, while it will be irrelevant for those who do. Distance to the infrastructure is likely less important a driver for water than for roads or electricity, where such a clear substitute does not exist. Therefore, the role of water related infrastructure is somewhat unique, and calibration of models like CLUE-S must be careful to include drivers in a way that accurately reflects how they do drive land use change.

Surface water resources are completely allocated for Deep Creek [BCMFLNRO, 2011]. While groundwater resources are to be regulated under the recently enacted BC Water Sustainability Act [BCMOE, 2013], the regulations have not yet been released. Restrictions on new groundwater withdrawals may change how land use changes, with the expansion of the service area for water utilities being necessary for agricultural expansion. However, if the new groundwater regulations are not sufficiently strict, the forecast land use changes will result in increased groundwater withdrawals. For groundwater withdrawals from aquifers that are connected to surface sources, the forecast land expansion can lead to reductions in stream flow, even where water is not being directly withdrawn from the stream. Such effects may adversely affect those with surface water rights, and will affect environmental flows and the biota that depend on those flows.

Accessibility variables (distance to highway, distance to urban center), distance to lake / reservoir, groundwater level, population density, and percentage of sand are the important drivers for residential and built area. Highways are generally built to connect population centers, and the existence of those highways tends to enable development at the margins of urban centers. The influence of distance to highway and distance to urban center are consistent with these facts, and agrees with other studies (Aguiar et al., 2007; Mertens et al., 2002). Residents in the town have water supplied by a utility, so distance to lake / reservoir and depth to groundwater likely capture other effects, as is probably the case for percentage of sand. These may reflect suitability of the town site for building. The strong influence of population density reflects the fact that built areas are where people live, and thus population density is likely positively correlated.

Distance to paved surface road, groundwater level, easterly orientation, sand % and spatial association (neighbourhood strength) are significant drivers in the model for livestock farm. Livestock operations prefer flat, well drained land with easy access to groundwater – where water is not available from a utility. They also tend to be located with easy access to transportation. That distance to transportation influences the likelihood of livestock related land use types was also found in a study conducted in Western Montana (Headwaters Economics, 2008). Further, Gellrich and Zimmermann (2007) found that agricultural land located farther away from the road network is more likely to be abandoned. Access to the road network reduces the cost of transporting agricultural inputs and outputs, and facilitates the movement of equipment and similar activities.

Our spatial association measure was insignificant for residential and built areas, where we might expect it to be the strongest. One possible explanation is the size of the grid cells. Residential and build areas are typically composed of land parcels much smaller than 25 hectares, often smaller than one hectare. The coarse resolution may simply mean that the regression model cannot capture the neighbourhood effects occurring at this finer scale.

Population density was based on geolocated addresses, those addresses having been harvested from an online directory (www.411.ca). These telephone directory based postal addresses do not reveal the number of people living at the address, and also fails to capture those who have an unlisted number, or a mobile phone that is not attached to a physical address. Any systematic differences between rural and urban areas in terms of the number of household occupants and the likelihood of having a mobile phone instead of a land line will compromise the validity of this measure for population density.

The role of distance to surface water is an approximation. Ideally, each parcel that has a water licence attached to it would be marked as having access to surface water. However, having a licence attached to a parcel does not mean that surface water is actually being used. Throughout the Okanagan, many water sources are seriously over allocated, when licensed withdrawals are compared to average discharge. However, in most years licence holders use far less than the volume that they are entitled to use. Further, some licences are not used at all, but remain active so long as the owner continues to pay a nominal annual rental.

Therefore, as appealing as the idea of using presence of a water licence as a measure of access to surface water, on reflection it is not clear that it would be superior to the distance band approach we have used.

Several policy solutions suggest themselves. One solution may be expansion of the area serviced by water utilities. If water utilities expand into the areas where more water-using agricultural activities are or are forecast to occur, farmers may choose to connect to the utility rather than accessing groundwater. Provided that the water source being accessed by the water utility has less impact on surface waters than a private well, connecting to the water utility will have a lower environmental impact. A further advantage of centralizing groundwater withdrawals is that it is easier to regulate a few large pumpers than it is to regulate a large number of smaller pumpers. If utility connections are not too costly for the farmers, then prohibiting groundwater withdrawals in certain areas may not be met with too much resistance.

A second solution is to provide people with assistance to increase the efficiency of their water use. Improvement in water use efficiency in residential, commercial and industrial sector can be achieved by adopting more water efficient technology and by changing behaviors. Within agriculture, there is substantial scope for increasing the yield per unit of water through the use of more water efficient technologies, improved water management strategies, and choosing less water consuming crops. Investing in increased water efficiency does not always result in aggregate water savings in agricultural sector (Pfeiffer and Lin, 2014; Dumont et al., 2013). The rebound effect tends to offset the gains, whereby greater efficiency increases the profit per unit of water used, thereby creating an incentive to use more water, particularly in agricultural sector. However, in the Deep Creek watershed, water may not be the only limiting resource. Relatively flat, productive land is largely limited to the valley floor. Significant agricultural expansion in response to increased water availability, beyond the valley bottom lands, is therefore unlikely. Further, the cost of water is typically not a deciding factor in most agricultural decisions. Most Okanagan water utilities do not charge volumetric prices, creating little incentive for conservation and little additional burden if water use is increased. Thus, subsidizing water conserving practices – moving to high efficiency irrigation for example – is likely to reduce impacts on groundwater resources.

The simulation results also show that development pressures on agricultural land are likely to be strong in the areas closest to Vernon and Salmon Arm. Much of the agricultural land that is highly productive is protected in a provincial level Agricultural Land Reserve (ALR) zone. To a large degree, land within this zone can only be used for agricultural activities. However, owners can apply to exclude land from the ALR, and if successful are able to develop it in other ways. Such exclusions often bring large windfall profits to the owner.

The lands near Vernon and Salmon Arm that the simulation suggests will be converted to the residential and built land use type will almost certainly be subject to applications for exclusions. If the communities in and around the Deep Creek watershed want to protect the agricultural land within the watershed, then they should be cautious about investing in infrastructure that facilitates conversion, such as expansion of the road network, in areas that are agricultural (Aguiar et al., 2007; Mertens et al., 2002). Likewise, if areas that are less valuable agriculturally are made easily accessible for development, pressure on agricultural land will be reduced. Further, policies that directly increase the profitability of farming, from preferential tax treatment through assistance with marketing to payments for ecosystem services can all reduce the incentive to convert land (Adelaja et al, 2010; Duke and Johnston, 2010; Findeis et al, 2010; Haaren and Bills, 2010).

Our land use forecasts suggest that the demand for water will increase, particularly in the part of the basin north of Armstrong. Absent expansion of water utilities, this increased water demand will likely be from increased groundwater pumping. This will likely exacerbated by the drier, warmer climate expected with global warming (Green et al., 2011; Shah, 2009; Loáiciga et al., 2000). Even without the effects of climate change, this increased pumping is likely to impact flows in Deep Creek, particularly during the late summer low flow period (Nichol et al., 2015; Ping et al., 2010). Climate change promises to further reduce late season flows and increase the duration of low flows (Mantua et al., 2010; Rood et al., 2008; McMahon and Finlayson, 2003; Smakhtin 2001). Proactive measures to offset the anticipated impacts of land use change will be needed earlier to adapt to climate change.

Additional climate change impacts, such as changes in forest fire risk and impacts on global food markets, will also impact on the Deep Creek watershed. The model predicts that much residential development will occur on what is currently forest and range land. Some of this will be expansion into the forest interface area. In anticipation of climate change, fire risk management should be considered (Flannigan et al., 2009; Millar et al., 2007). Likewise, potential increases in food demand may significantly change the value of agricultural land. Protecting agricultural land may therefore have a role in climate change adaptation.

2.5 Summary

As a small, semi-arid watershed in the Okanagan Valley, the Deep Creek area is experiencing pressures from population and economic growth that are pushing land use change. Access to transportation and proximity to urban centers are important driving forces, particularly for conversion to residential and built areas from other uses. For conversion to and between agricultural land use types, depth to groundwater is an important driver in those areas not serviced by a water utility. Failure to account for the difference between areas serviced by a water provider and those not serviced can generate misleading results. Spatial association, a measure of spatial correlation, was also an important predictor in three of the four models where it was included. The importance of spatial association implies that land use is more clustered than would be predicted if spatial association is not included in the model. Failure to include it will therefore result in a more dispersed pattern of land use change than is actually likely to occur.

The simulation results identify where land use change is likely to occur. Most of the increase in residential and built areas will happen near the urban centers of Vernon and Armstrong, close to major highways. Near Vernon, some of this new development is forecast to occur on land presently used for agricultural purposes. If the provincial Agricultural Land Reserve is enforced, then this development may not happen. However, the simulation results suggest that applications to exclude land from the ALR are likely in these areas. Conversions of forest land to agricultural uses and conversions between agricultural uses are likely to increase groundwater withdrawals in some parts of the watershed. This may have adverse environmental impacts, where connections between groundwater and surface water are strong. Expansion of water utility services into these areas may be a way to protect in stream flows. Changing groundwater regulations implemented under the new Water Sustainability Act may also limit the conversion of land use where groundwater is connected to surface water or the capacity of the aquifer is being reached. Overall, pressures for land use change in the Deep Creek watershed are likely to exacerbate several environmental issues, and our simulation results highlight spatially where some of these issues are likely to be the most serious.

Chapter 3. Validation of Land Use Projection Output with the Aid of Satellite Images: A Discriminant Function Characterization and Backcasting of Land Use Change

3.1 Overview

This chapter reports on an assessment of the validity of the forecasting model developed previously (Chapter 2). Our largest challenge when validating our model was the absence of two observations of land use types across our study watershed at different points in time. In many studies we reviewed, the absence of two such maps means that the model is not validated. We overcame this problem by developing a model to classify land use types using LANDSAT spectral information. This classification model is 'trained' using the land use map that was the initial condition for the forecasting model, and applies it to historic spectral information to generate a historical land use map. We then ran the forecasting model backwards to 'forecast' the historic land use map. Another significant challenge was choosing a method to compare the two historic maps. Our approach introduces two sources of error, one from the forecasting model and a second from the classification model. We compare the conventional cell by cell approach with a recently suggested multiscalar approach, and demonstrate the validity of our model increases rapidly as the scale over which it is assessed increases.

The Deep creek watershed is a semi arid watershed located in the Southern Interior region of British Columbia, Canada. The watershed experiences a bimodal precipitation pattern, with relatively higher precipitation in December / January and June (Merritt et al., 2006; 2003;

Nicholson et al., 1991). Total annual precipitation is 468mm on the valley floor and 592mm on the surrounding mountains (Neilsen et al., 2010; Duke et al., 2008). The semi arid climate together with agricultural and land development activities applies tremendous pressure on local water resources, particularly groundwater. Forecasting land use change and the resultant changes in the spatial distribution of water demand can help decision makers anticipate and mitigate consequences of these changes. In an earlier chapter (Chapter 2), we reported on the development and calibration of a land use forecasting model for the Deep Creek watershed. In this chapter we describe how the validity of this model was tested. A significant hurdle for our validation was the lack of land use maps for two points in time, we only have a map for 2007. We used remote sensing data (LANDSAT reflectance bands) calibrated on the known land use map to classify land uses from the remote sensing data collected in 1993. We then run our simulation backwards from 2007 to 1993, and compare the model backcast with the generated land use map.

A forecasting model is validated to gain some insight into how much confidence can be placed future projections (Law and Kelton, 1991). By definition, future projections cannot be truly validated until the future arrives. Therefore, the ability of a model to project from one set of historic data to another is typically used to validate its predictive capability. However, the scarcity of historic data, data inconsistencies, and limited validation techniques means that forecasting models are often not validated (Wassenaar et al., 2007; Pontius et al., 2004).

For our validation, we will run the model in reverse, which for conciseness we will call 'backcasting'. Generally used definitions of forecasting and backcasting are: "forecasting (or explorative) scenarios always look to the future based on forward induction and answer the question what might happen? Backcasting (or normative) scenarios are proactive, based on wildcard trends that break assumptions, and backward induction from the future to the present to answer the question how can a specific situation be reached?" (Houet et al., 2010). Our use of the term 'backcasting' is not precisely consistent with this definition, but shares the general notion that the model is run in reverse. In forecasting, the maps are developed in forward direction of time with the use of a predictive model consisting of land use change drivers (Lambin et al., 2003; Pijanowski et al., 2002). Historic maps either can be generated using the predictive model in reverse or using historical forecasting (Ray and Pijanowski, 2010). In general, modelling land use change forward or backward has many aspects in common but, the backcasting of land use has an important difference that historical information (cadastre map, census and other data) can be added into the model to generate a historical land use map (Rhemtulla and Mladenoff, 2007).

Validation of land use models typically starts with a minimum of two known land use patterns at different times. The simulation model is calibrated using at least one map, and then run to generate a predicted map for a different time. The simulation map and actual map are then compared to see how accurately the simulation reproduced the actual outcome. Validation can be accomplished by calibrating the model using older data and then running it forward to younger data, or by calibrating it using younger data and backcasting the model to an older data time. Since forecast error increases with the number of time periods over which the simulation runs, calibration using data as close to the start of the forecast period is preferable. Hence, validation requires two actual maps. The study area has the actual map for 2007 for the entire area but an actual map for another period for the study area was not available. We therefore had to generate a historic land use map from other information sources.

Land use classification using remote sensing information is very well studied and documented (Teferi et al., 2010; Sun et al., 2009; Thenkabali et al., 2005; Roberts et al., 2003). However, few studies have used remote sensing information to validate a simulated land use map (Wang et al., 2013; Castella and Verburg, 2007). Remote sensing information is often available in image form, where the images contain spectral information. To generate a land use map, this spectral information is used to assign a land use to parcels or grid cells on the land map. In general the quality of both the historic land use maps and the remote sensing data get worse the further back one goes. The calibration of remote sensing information can be done with older but less accurate maps and then use the calibrated model in forward time step to classify remote sensing information to obtain a newer map, with validation a comparison of the forecast map with the recent land use map. Alternatively, one can use the latest remote sensing information and land use maps to develop a classification (calibration) model and use that to generate a historic land use map by applying the developed model in reverse to produce a land use map for the past. Given that we do not have a historic land use map, we adopt the later approach.

While using alternative data to generate a historic land use map is not often used in land use modelling, (Pontius et al., 2003; Aspinall and Hill, 2000), some have suggested that this approach can useful (Grossinger et al., 2007; Ray et al., 2006). Ramankutty and Foley (1999) used a backcast historical land use map to assess how much natural vegetation was converted to agricultural and other purposes across the Globe. Ray and Pijanowski (2010) used the backcasting approach in their land use validation exercise in Muskegon River watershed in the USA. For our purposes, we take advantage of publically available LANDSAT™ data to generate an estimate of historic land use types. We then use this generated historic map to validate a backcast for a CLUE-S simulation model.

3.2 Background

3.2.1 Validation methods used with land use change models

The planned application of our forecasting model was the generation of a land use change map that could be used to predict changes in water use. Developing detailed representations of the process through which land use change occurs was beyond the scope of this project. We decided that CLUE-S (**C**onversion of **L**and **U**se and its **E**ffects in **S**maller scale), a popular pattern based land use modelling system, would be appropriate to our task. . Spatially explicit simulation models developed using CLUE-S have proven to be an effective tool for modelling fairly fine scale land use change (Verburg, 2010; Verburg and Veldkamp 2004; Verburg et al., 2002)

There are a number of validation methods that have been used. Examples include visual comparison (Castella and Verburg, 2007), the use of expert knowledge (Wassenaar et al., 2007), zonal validation methods (Castella and Verburg, 2007), single resolution methods (Pontius, 2002), random model and null model approaches (Pontius et al., 2004), the multi resolution approach (Kok et al., 2001), the null resolution approach (Pontius et al., 2008; 2004) and the "figure of merit" approach (Thapa and Murayama 2011, p.29). The key distinction between single and resolution and muti-resolution approaches is that the latter is forgiving of near misses. We will use both single and multi-resolution methods in our validation.

3.2.1.1 Single Resolution Methods

Single resolution methods are the most common approach to forecasting model validation (Pontius et al., 2004). One approach is to use the full map. Each grid cell of the simulated map is compared to the actual or reference map for a match. This comparison yields a contingency table with the percentage of grids that are correct for each land use category used as a measure of goodness of fit. The column and rows show the comparison between the simulated and actual land use map output. Further analysis can be performed with Chi-square, Kappa and other statistics (Pontius, 2002). Additional statistics such as producer's and user's accuracy are used in the area of remote sensing and geography (Congalton and Green, 1999). Producer's accuracy is the ratio of correctly predicted changes relative to total observed changes, while user's accuracy is the ratio of correctly predicted changes relative to total predicted changes (Pontius et al., 2008).

Sometimes grid by grid comparison is not possible, such as when historical data are not available for the entire study area. Further, the nature of the area, such as having mountainous areas or large water bodies within the forecast area may not permit grid by grid comparisons, or may make the results appear unreasonably accurate as these areas do not change. Random cell (grid) comparisons can be used in such situations (Wear and Bolstad, 1998). In this approach, the areas that do not have land use information or the physical obstacles are removed. Individual cells (grids) or groups of cells (grids) – strata – are randomly selected and compared for accuracy. Contingency tables and statistics can be calculated as well, with the reliability of these measures depending on the sampling techniques employed.

Single resolution methods are relatively simple and not computationally burdensome (Pontius et al., 2004; Pontius, 2002). However, they do not account for partial success. A partial success or "near miss" occurs when the simulation model predicts land use types for grids (cells) near the actual location, but fails to place it at the right place. Since some portion of the observed land use pattern is due to idiosyncratic randomness – a house is first built on the right side of the road rather than the left – such near misses should not be taken as a serious challenge to the validity of a simulation model (Pontius, 2002). Multi resolution approaches take care of many of these limitations.

3.2.1.2 Multi Resolution Methods

These methods also use a reference and simulated map. The multiple resolutions range from the smallest size used in projection, the individual grids, to the largest, comparing the maps as a whole (Pontius et al., 2004). At each change of resolution, fit measures are generated based on resolution specific collections of cells (grids). This is repeated for a selected number of resolutions, with validity measures calculated for each of these resolutions. If the single resolution method mismatch is due to near misses, then the fit should improve rapidly as the resolution for the fit measures becomes coarser. Various techniques have been proposed to assess the fit as the resolution levels are changed (Pontius, 2002; Kok et al., 2001).

3.2.2 Watershed Characteristics and Historical Land Use Data

3.2.2.1 Deep Creek Watershed

A detailed description of the Deep Creek watershed can be found in Ping et al. (2010), and details about the land use classification in Chapter 2. A few of the main features relevant to the validation exercise are described here. The Deep Creek watershed lies at the northern end of the Okanagan Valley, in the semi-arid southern interior of British Columbia (Figure 1-2). The watershed covers 230 km^2 and includes the town of Armstrong and the Township of Spallumcheen. Elevations in the south range between 340 – 520 meters above sea level, and in the north from 370 – 1575 meters (Ping et al., 2010). Forestry, agriculture, manufacturing and tourism are all important economic activities in the watershed. Cattle farming are the most common agricultural activity, accounting for about 21% of all agricultural operations in the Township of Spallumcheen. Other relatively important farm types include hay and forage operations (17.2%), horse and pony (15.2), poultry (6.8), and dairy (6.1%) (Zbeetnoff, 2006). For simulation purposes, the variety of land use activities were condensed into five land use categories, one forest related, three agriculture related, and one built area related.

3.2.2.2 Historical data availability for Deep Creek

Comparable land use maps at two different times are necessary to validate a simulation model. We considered aerial photographs, government land use maps and satellite photographs. There were a limited number of aerial photographs available for the study area (1993 and 1987). Most of the aerial photos were monochrome (Natural Resources Canada [NRC], 2013), and would have been difficult to translate into a land use map. For such photographs, the classification process likely could not be automated, and the accuracy would probably be low. Aerial photos were therefore not used for the validation. Government land use maps, such as vineyard maps and tree fruit maps, were inconsistent as the maps were generated for particular purposes, and therefore land use classifications differed across the different historic maps. A government land use survey map was used for model calibration purposes (Van der Gulik et al., 2010). However, a map for an earlier period with land use classifications consistent with the calibration map could not be found. Absent aerial photographs or government maps, we turned to satellite data.

Satellite data provided the coverage and consistency necessary for land use identification. Unfortunately, the satellite data do not directly provide land use classifications. Therefore, generation of a historic land use map requires mapping the calibration map onto the satellite data for the calibration period, and then generating land use classifications from the satellite data for the validation period. Roberts et al. (2003) and Thenkabali et al. (2005) are examples where satellite data were used to generate land use classification maps. SPOT satellite data were used by Castella and Verburg (2007) to validate a CLUE-S model projection using a classified map for Cho Don district of Vietnam.

3.2.3 Land Use Characterization for Deep Creek

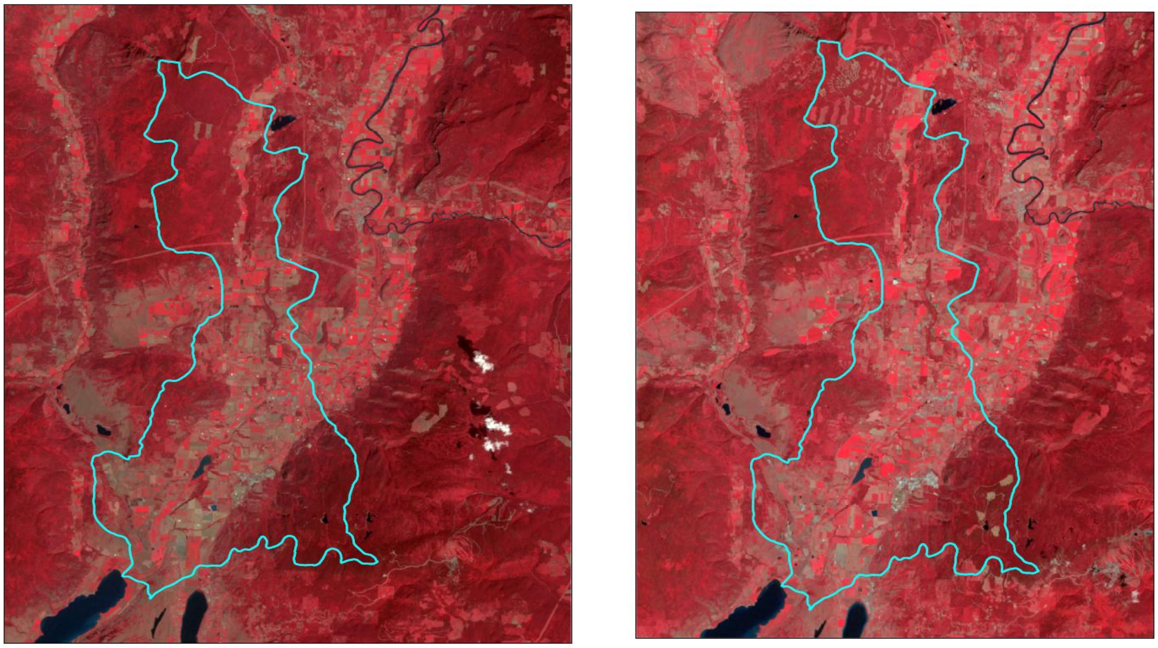
3.2.3.1 Use of Remote Sensing Images for Land Use Classification

The United State Geological Survey (USGS) provides a wide range of data that can be used for land use and land change studies. Landsat 5 TM (Thematic mapper) images provide the information necessary for our characterization of land use types. The images covering the study area were acquired for 2007 and 1993 (Table 3-1). Each image contains seven layers, each one with the reflectance for a unique color wavelength. We did not make any corrections for cloud cover or solar angle as the acquired images were already corrected for atmospheric errors. For details on the correction procedure, one can refer Chen et al. (2012) and Richter and Schläpfer (2014). A quick inspection of the images shows that land use has changed, and particularly obvious is the impact of forestry activities in the northwest part of the watershed in 2007 that were not there in 1993 (Figure 3-1).

Table 3.1: Information of Landsat image available for 1993 and 2007

Image date	Julian Date	Cloud Cover (%)	Sun Elevation	Sun Azimuth
07/04/2007	97	53	43.9	153.6
25/05/2007	145	56	57.6	148.2
12/07/2007	193	11	57.6	143.7
14/09/2007	257	0	40.8	156.5
18/05/1993	138	15	53.3	137.3
06/08/1993	218	2.4	49.5	136.4
23/09/1993	266	0	35.3	149.5

Distinguishing between different land use types using images with well developed crop canopies is difficult. Using two or more periods, when differences in the growth, canopy cover and/or post harvest impacts are apparent, increases the accuracy of the classification (Lu et al., 2003). In the study area, peak canopy cover occurs during the months of July and August, the mid cropping season (British Columbia Ministry of Agriculture, Food and Fisheries [BCMAFF], 2001). The images from these months, August 6, 1993 and July 12, 2007, were used for classification, with the images from other months used to improve the land use classification accuracy.



1993, Julian date 218. 2007, Julian date 193.

Figure 3.1: Red green and blue colour composite of bands 4, 3 and 2 for path 45 raw 25 in year 1993 and 2007 of Landsat 5 TM obtained from USGS. The outlined area indicates the Deep Creek watershed

3.2.3.2 Classification of Remote Sensing Images into Land Use Classes

3.2.3.2.1 Selection of classification approach

There are two broad types of land use classification, supervised and unsupervised (Foody, 2002). Unsupervised classification is performed in the absence of known classifications or when there is no land use map available, while supervised classification is used when the land use pattern for the area under study is known (Jimenez and Landgrebe, 1998). For supervised land use classification, either a land use map for the entire area or randomly surveyed points from the area are used. We conducted a supervised classification using information for 2007, building a discriminant function that was then be applied to the reflectance data for 1993 (Figure 3-2). The land use map for 2007 was based on a survey conducted by AAFC and BCMAL (Van der Gulik et al., 2010). This was the same land use map that served as the initial conditions for the simulation that is being validated.

The 2007 land use survey was conducted for the entire Okanagan basin as a part of estimating agricultural water demand for the region (Van der Gulik et al., 2010). The survey initially obtained the cadastre information from the regional districts and other local government agencies. The cadastre information was digitized and divided into polygons linked to a database created to enter the information about each property. The basin was subdivided into four regions and a ‘windshield’ survey was conducted during the summers of 2006 and 2007. Each property was viewed from the nearest public access and the crop, irrigation system, etc. for the parcel recorded. This comprehensive land use map was a unique resource that we were able to take advantage of for calibrating and for validating our model.

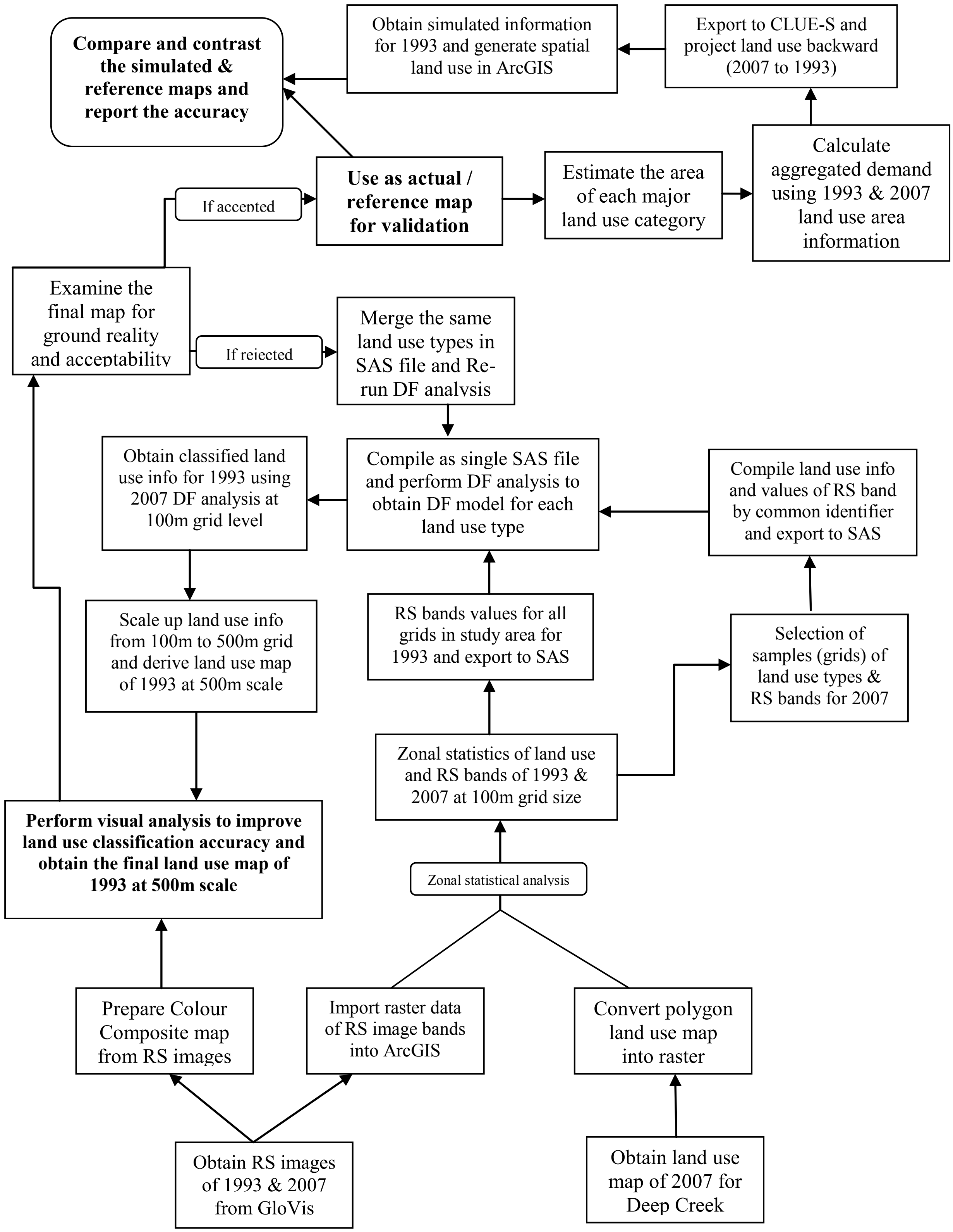


Figure 3.2: Schematic representation of land use change validation methodology applied in Deep Creek watershed

While some researchers use all seven Landsat reflectance bands, the reflectance values for bands 1-5 and 7 are most commonly used for classification (Thessler et al., 2008). Band 6 is a thermal band with larger pixels, providing little information relevant for vegetation / crop classification (USGS, 2013; Thessler et al., 2008). The Normalized Difference Vegetation Index (NDVI), calculated as (Band 4 – Band 3) / (Band 4 + Band 3), has also proved useful for distinguishing differences in plant canopies. We used bands 1-5 and 7, together with the NDVI, to build our discriminant function.

Among classification algorithms, the standard (Fisher's) discriminant function (DF) analysis is commonly used for supervised classification (Amato et al., 2013; Riveiro-Valino et al., 2009; 2008; Davidson et al., 2007; Thenkabali et al., 2004; Legendre and Legendre, 1998; Lobo et al., 1998). Discriminant function analysis is a parametric multivariate statistical technique. The analysis generates a discriminant function, a linear combination of the assumed continuous characteristics (spectral reflection / bands or signature patterns and indexes) for each of the categories being classified (Chatfield and Collins, 1980). The discriminant function (y) of k^{th} land use type can be written as a linear combination of variables:

$$y_k = C_k + (a_{k1} \times x_1) + (a_{k2} \times x_2) + \cdots + (a_{kp} \times x_p) \qquad 3-1$$

Where, y_k is the discriminant function of k^{th} land use type. $x_1 - x_p$ are the characterizing variables used in the discriminant function. The discriminant coefficients of characterizing variables are $a_{k1} to\ a_{kp}$, while C_k is the constant of k^{th} land use type for the discriminant function.

The resulting discriminant functions can be used to classify data for unclassified samples (in our case pixels in the 1993 images) into the known categories. Classification is performed by calculating a set of discriminant scores for each element (grid cell), using the estimated discriminant functions, and assigning the element that land use which has the highest score (Cingolani et al., 2004; Chatfield and Collins, 1980). This process permits us to generate a land use map for 1993, based on the image data for 1993. This map can then be used to validate the simulation results.

The gridded land use simulation map for the Deep Creek watershed had 1112 grid cells of a 500m×500m grid size. A few major land use types occupied majority of the grids, and 42 prominent land use types were found within the study area (Table 3 – 2). Typically, supervised classification retains the heterogeneity in land use types in the initial classification before aggregating the closely related land use types to increase the classification accuracy. However, at the 500m×500m grid size, there were insufficient observations for some of the land use types. We therefore constructed the discriminant functions using a 100m×100m grid size, and likewise conducted the classification using this grid size, and then aggregated the resulting land use map to the coarser size of the simulation map.

3.2.3.2.2 Computation of Spectral Values of Grids and Assign Land Use Types

The land use map for 2007 was overlain with a 100m×100m grid. Each grid cell was assigned a land use type that represented the dominant land use for the grid. For the final land use map used in the simulation, all of the land use types in the original data were aggregated into 5 land use categories (Chapter 2). However, for the discriminant function classification, the analysis retained the 100m×100m grid throughout, until the final aggregation of the classified 1993 land use types to the same five used for the simulation.The remote sensing images were processed similar to the 2007 land use map, also on the 100m × 100m resolution grid, (25156 grid cells in total). For each grid cell and each reflectance band, the reflectance values for all the pixels within each grid were averaged to generate one value for each grid. Each grid cell then has six average reflectance values, together with the calculated NDVI value.

The homogeneity of land use types in the 100m×100m resolution grid computed using the land use survey conducted during the summers of 2007 and 2008 (Van der Gulik et al., 2010). Almost 74.4% of the 100m × 100m grids are occupied fully by a single land use type and 97.7% are at least 50 % covered by a single land use type (Table 3 – 2). More than 90 % of the grids have only one or two land use types.

Table 3.2: Number of land uses in a single 100m × 100m grid and the number grids occupied by majority land use type at varying area proportion of a single grid computed using land use survey conducted by provincial ministry in 2007 and 2008

Number of land-use types in a single grid (100m×100m) area	**Number of grids**	**Percentage of total study area**	**Number of grids occupied by dominant (majority) land-use at different intervals (% of area covered by dominant land use in a single grid)**		
			> = 66	**> = 50**	**<= 33**
Single land use type	18711	74.38	18711	18711	0
Two land use types	4302	17.10	3206	4302	0
Three land use types	1498	5.95	706	1221	0
Four land use types	502	2.00	111	296	17
Five land use types	120	0.48	12	44	11
Six land use types	21	0.08	1	4	3
Seven land use types	2	0.01	0	0	0
Total	25156	100.00	22747	24578	31

Sample size, degree of homogeneity of grids, and number of land use types used in the discriminant function analysis for each estimation land use type are provided (Table 3 – 3).

Table 3.3: Land use type and their constitution in the 100m × 100m grid and the study area

Land use type	Number of Land use types in single grid 1	2	3	4	Total number of grids used in DF analysis	% of area of a grid occupied by single dominant land use	Percentage of grids used for DF Analysis
Cultivation land							
Apples (1)	7	10	2	0	19	>=75	79.2
Asparagus (2)	48	0	0	0	48	100	75.0
Oats (3)	10	8	2	1	21	>=72	75.0
Grains, Ginseng, cereals and oilseeds (4)	15	4	3	0	22	>=73	66.67
Cropland (4)	116	0	0	0	116	100	35.15
Vegetated (Cultivated) areas (4)	333	0	0	0	333	100	55.13
Cultivated land (4)	54	0	0	0	54	100	48.21
Nursery/trees (4)	55	0	0	0	55	100	63.95
Fallow land (4)	23	0	0	0	23	100	63.89
Misc. Vegetables (4)	19	0	0	0	19	100	61.29
Barley (4)	273	0	0	0	273	100	56.99
Trees (plantation) (4)	49	0	0	0	49	100	63.64
Strawberries (4)	10	8	2	1	21	>=72	87.50
Livestock Farm							
Farm structures (5)	57	0	0	0	57	100	43.5
Farmstead (5)	570	0	0	0	570	100	46.8
Beef Cattle Farm (5)	97	0	0	0	97	100	66.9
Farm yard area (5)	82	0	0	0	82	100	57.3
Forest and Range							
Abandoned or neglected farm land (6)	325	0	0	0	325	100	59.5
Treed Forest (6)	565	0	0	0	565	100	54.2
Non productive woodland (7)	133	0	0	0	133	100	47.3
Other Forest (8)	484	0	0	0	484	100	64.4
Productive woodland (9)	9268	0	0	0	9268	100	87.6
Range (10)	55	0	0	0	55	100	67.1
Unimproved pasture and rangeland (11)	377	0	0	0	377	100	53.2
Pasture and Forage							
Grass (12)	1038	0	0	0	1038	100	55.2
Herbaceous vegetation (13)	84	0	0	0	84	100	60.0
Improved pasture and forage crops (14)	649	0	0	0	649	100	76.2
Legume (15)	787	0	0	0	787	100	51.7
Forage corn (16)	169	0	0	0	169	100	67.1
Pasture and Forage (16)	228	0	0	0	228	100	44.6
Residential and Built Area							
Industrial Use (17)	44	0	0	0	44	100	48.4
Wood processing facility (18)	24	0	0	0	24	100	66.7
Municipal / regional open spaces/parks (18)	10	8	3	0	21	>=70	75.0
Residential (18)	222	0	0	0	222	100	40.2
Outdoor recreation (18)	44	0	0	0	44	100	46.3
Golf fairway and green (18)	15	3	3	0	21	>=64	70.0
Urban Built Area (19)	97	0	0	0	97	100	56.1
Total	16436	41	15	2	16494	>=64	69.6

Land use type denoted by same values are merged and given same name for which major LU it belongs to in the final DF analysis

Thirty-seven land use types were represented by enough observations that a discriminant function could be calculated, with 25 of these accounting for nearly 93% of the watershed area (Table 3 – 3). For most of these, the sample could be restricted to grids with only a single land use type. However, for some of the less common land use types, the grids used in the estimation were not all completely covered. The lowest coverage used was just under two thirds (64%) for golf fairways and greens. The land use types included in the discriminant function analysis are found in more than 90% of the grid cells, and the grid cells used in the estimation account for 65.6 % of the study area. Within this sample, 65.3% of the grid cells include only one land use type. The sample was further refined by aggregating together 'similar' land use types into nineteen distinct categories, with 19 discriminant functions therefore generated.

3.2.3.2.3 Discriminant Functions and Classification of Land Use Types for Year 1993

Discriminant function analysis was conducted in SAS (version 9.2). The discriminant functions generated by comparing 2007 image data and the BCMAL land use map were then used to classify land use on the same 100m × 100m resolution grid, using the 1993 reflectance data. While the primary classification was based on the August 6, 1993 images, discriminant functions were also used to assign land use types based on the May 18, 1993 and September 23, 1993 images, which were then checked to assure accuracy of the main results. These results were then scaled up to the 500m × 500m resolution used for the simulation by identifying the majority land use within each of the 500m grids. To align with the simulation, aggregating to the larger grid size also required reducing the number of land uses from nineteen to five, which required further grouping.

3.2.4 Backward Simulation of Land Use Status

The CLUE-S model being validated is described in greater detail in Chapter 2, with more detail about CLUE-S itself found in Verburg (2010). CLUE-S is calibrated using a gridded landscape map for a single period. For each land use type to be included in the simulation, a logistic regression is estimated that generates a probability for each grid cell being of a specific land use type. The logistic functions include exogenous driving variables, which for the Deep Creek simulation included distance to the nearest highway, paved surface road, and urban center, population density, slope and aspect, percent sand in the root zone, depth to groundwater, distance to surface water and a measure of spatial association. The depth to groundwater and distance to surface water was adjusted for water utilities service areas. Water utilities provide services for domestic, industrial, commercial and irrigation purposes, rendering access to surface or groundwater unimportant (see Chapter 2 for more details). While different variables were significant in each of the logistic regression functions, signs and magnitudes tended to fall within reasonable bounds. These logistic regression functions were then used to generate transition probabilities between land use types – qualified by some controlling variables – that were used to assign land use changes.

The CLUE-S system does not estimate how much land use change will occur, but rather takes a given aggregate representation of land use change and assigns where that change will occur. This aggregate representation of the land use changes is therefore a critical input. The aggregate area for each major land use category for the land use classification map generated for 1993 was used as input for the backcasting run of the CLUE-S simulation. This meant that there was no aggregate forecasting error, only error in the placement of land use types.

The area occupied by forest and range increases, while all other areas decrease. In percentage terms, the largest decrease is for residential and built areas (Figure 3 – 3).

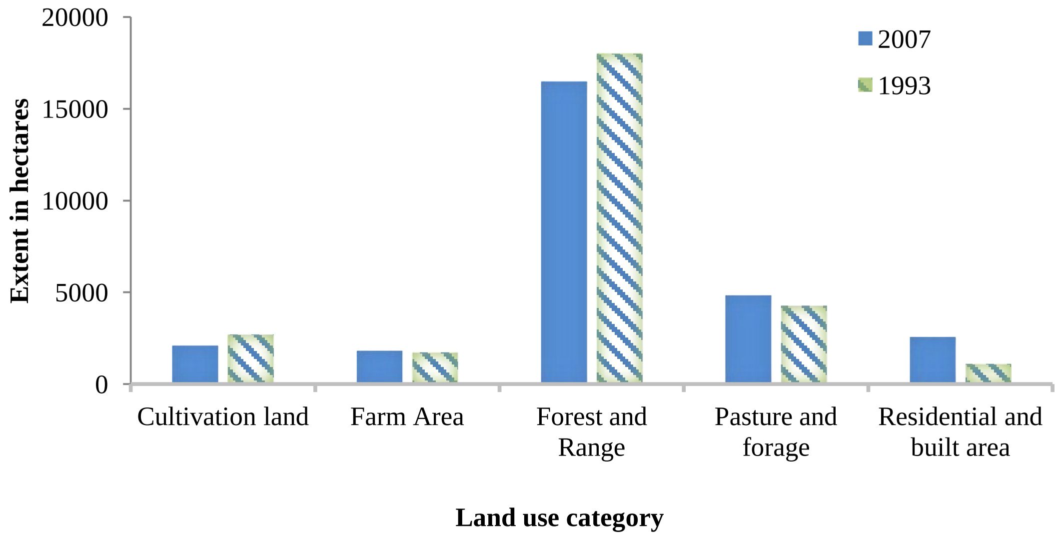


Figure 3.3: Aggregated land use demand in 2007 and 1993

3.2.5 Validation of Land Use Projection by CLUE-S

The simulated and reference maps of 1993 were examined for prediction accuracy. Both single and multi resolution techniques were used. In the single resolution technique, pixel by pixel (grid by grid) comparisons are performed. In addition, the Kappa statistic was computed to examine the level of agreement for the major land use categories (Munroe et al., 2002). Kappa statistics are used to measure the agreement between expected and actual data relative to what would be expected by chance matching (Cohen, 1960). The Kappa coefficient, level of significance and the confidence interval for each major land use category were computed using proc freq of SAS (version 9.2). The Landis and Koch's (1977) categorization scheme for agreement was adopted to interpret the projection accuracy. Following this scheme, the Kappa coefficient values are divided into six categories of agreement at 0.2 intervals starting from zero and ending at one. The higher the value of the Kappa coefficient, the greater the agreement between the data being compared.

The multi resolution technique assesses the accuracy of the simulation map by progressively making the grid coarser. The approach used here was to center a circle on each grid cell. The total number of cells of each land use type with each circle were compared between the classification map and the backcast map. Given that the aggregate change was the same for both the classification and simulation maps, when the multi resolution radius had increased to incorporating the entire study area, the error would be zero. We used both the single resolution and multi resolution approaches to assess the validity of our CLUE-S model for the land use change in the Deep Creek watershed.

3.3 Results

3.3.1 Discriminant Function Analysis

The comprehensive land use map provided us with enough observations to estimate discriminant functions for 37 land use types, representing majority of the study area. However, to get reasonable quality for the estimates, these 37 land use types were aggregated down into 19 land use types for the final discriminant analysis.

The bands 1 and 5 along with NDVI are positive, while all other bands and constants are negative in the model irrespective of the land use types (Appendix C – 1). The error count estimate of the discriminant function model for year 2007 is 0.3882, i.e. the accuracy of the model is 61.2 %. Considering the number of land use types used to classify the model and the number of characterizing variables (bands information and vegetation index) used in the model, these results are consistent with other work (Cingolani et al., 2004; Thenkabali et al., 2004; Bunce et al., 1996b; Paola and Schowengerdt, 1995).

The totals for each major land use type served as input into the backcast CLUE-S simulation (Table 3 – 4). Not surprisingly, when the grid size is increased, those land use types with small areas are often absorbed into other land use types when a single land use is assigned to the larger grid. The most striking visual difference between the 1993 classification and 1993 simulation (Figure 3 – 4), is that the back simulation removes much of the residential and built land from the southern portion of the watershed, while leaving it in the northern region. The simulation also locates more pasture and forage land in the central part of the watershed, while the reference map indicates there was more in the southwest corner. We turn to numeric summary measures to examine how different they are.

Table 3.4: Total assignment across the 100m×100m and 500m×500m resolution grids for the 19 land use types used in the discriminant function. Area occupied each land use type after classification and up scaling in 1993

Land Use Type	Area of each land use type based on DF analysis at 100×100 grid size(Ha)	Area after scaling to 500×500 grid size (Ha)
Apples (1)	5	0
Asparagus (2)	0	0
Oats (3)	6	0
Cultivation land (4)	2788	2700
Cultivation land	2799	2700
Farm area (5)	3064	1725
Livestock Farm	3064	1725
Forest and Range (6)	3230	3400
Non productive woodland (7)	1924	2050
Other Forest (8)	2130	2300
Productive woodland (9)	5367	6175
Range (10)	104	25
Unimproved pasture and rangeland (11)	3084	4050
Forest and Range	15839	18000
Grass (12)	1957	1675
Herbaceous vegetation (13)	3	0
Improved pasture and forage crops (14)	5	0
Legume (15)	2282	2275
Pasture and Forage (16)	841	325
Pasture and Forage	5088	4275
Industrial Use (17)	320	425
Residential and built area (18)	314	25
Urban Built Area (19)	429	650
Residential and Built Area	1063	1100
Total	27853	27800

Cultivation land (4) is the combination of grains, ginseng, cereals and oilseeds, cropland, vegetated (cultivated) areas, Cultivated land, nursery / tress, fallow land, misc. vegetables, barley, trees (plantations), and strawberries; Livestock farm (5) includes farm structures, farm stead, beef cattle farm, and farm yard area; Forest and Range (6) are merging of abandoned or neglected farm land, and treed forest; Pasture and Forage (16) comprise of forage corn, and pasture and forage; Residential and built area (18) consist of wood processing facilities, municipal and regional open spaces and parks, residential, golf fairway and green, and outdoor recreation.

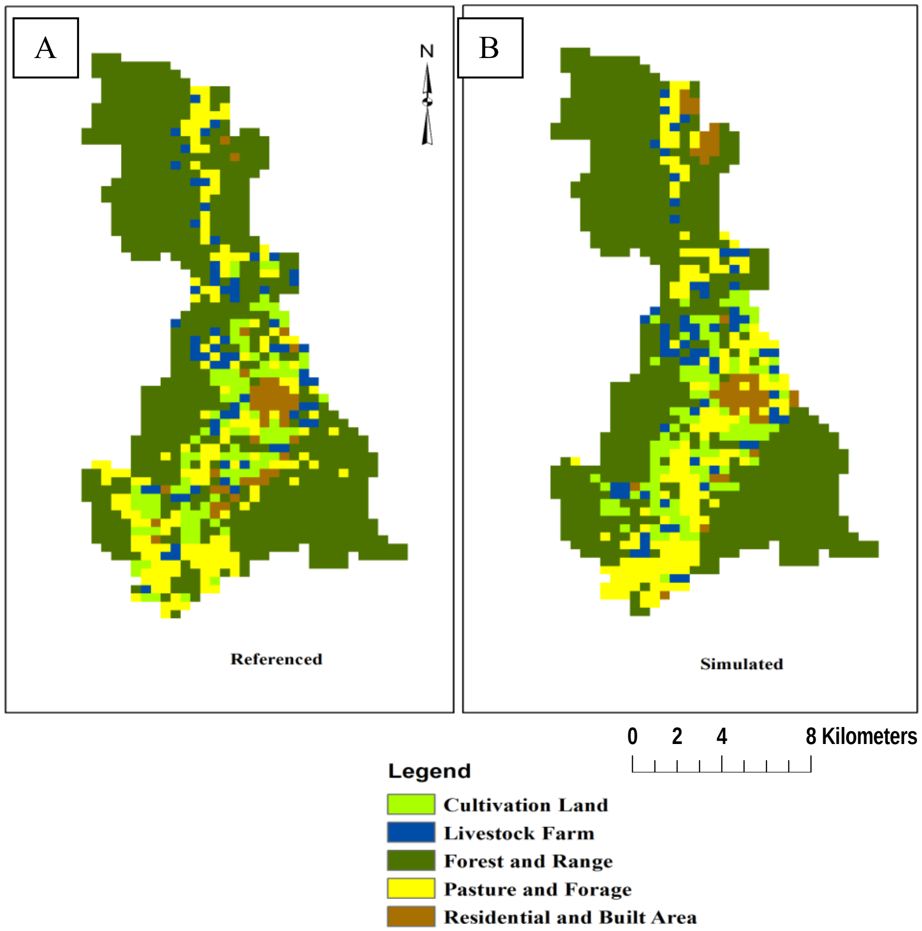


Figure 3.4: Land use maps of the Deep Creek watershed in 1993 based on (A) classification using discriminant function analysis and (B) simulation by CLUE-S

3.3.2 Single and Multi Resolution Validations

Several numeric measures were used to compare the two maps. Based on the confusion matrix (Congalton and Green, 1999; 1993), the overall error in projection is 21.2 % i.e. the land use projection accuracy is about 78.8 %. However, much of this is dominated by the forest and range land use type, which accounts for by far the largest area in the watershed.

The individual land use errors reveal the difference in spatial inaccuracy between the actual and simulated maps. The projection error in the spatial area is the lowest for the forest and range land use, while it is the highest for the residential and built area. As noted by Castella and Verburg, (2007), it is not unusual for error estimates to be higher for some land use types and lower for the others. Castella et al. (2007) also argued that the capacity to adopt land use change rules and scenarios is more important than the ability to accurately predict land use change. The Kappa coefficient measures the degree of agreement between the two maps for each land use category, as the difference between the observed agreement and that expected by chance alone. The cultivation land and forest and range categories showed substantial agreement between the simulated and reference maps, while other land use categories showed moderate agreement (Table 3 – 5). All the coefficients are significantly different at 0.001 error level.

Table 3.5: The Kappa coefficient and their confidence interval for each land use category

Major land use category	Kappa Coefficient*	Confidence Interval	
		Lower	Upper
Cultivation Land	0.6344	0.5561	0.7128
Livestock Farm	0.5519	0.4492	0.6547
Forest and Range	0.7006	0.6565	0.7446
Pasture and Forage	0.4864	0.4154	0.5573
Residential and Built area	0.5031	0.3727	0.6335

**All the coefficients are significant at p<0.001*

Figure 3 – 5 reports a multi resolution assessment of the fit between the simulation and reference maps. At each radius value, for each grid cell in the study area, the count of cells of each land use type in a circle of the indicated radius was calculated for both the reference and simulated maps. The level of agreement between these values, as a percent error, was calculated. This was repeated for each grid cell, and the average error rate over the whole

grid was calculated. This was then repeated for each radius, to generate the plot in Figure 3–5. The relative error decreases with the increase in radius and at the radius of 6 grid cells (3 kilometers), the relative error has fallen below 10%. The CLUE-S simulation places land use in ‘approximately’ the right location, although it is not precisely accurate.

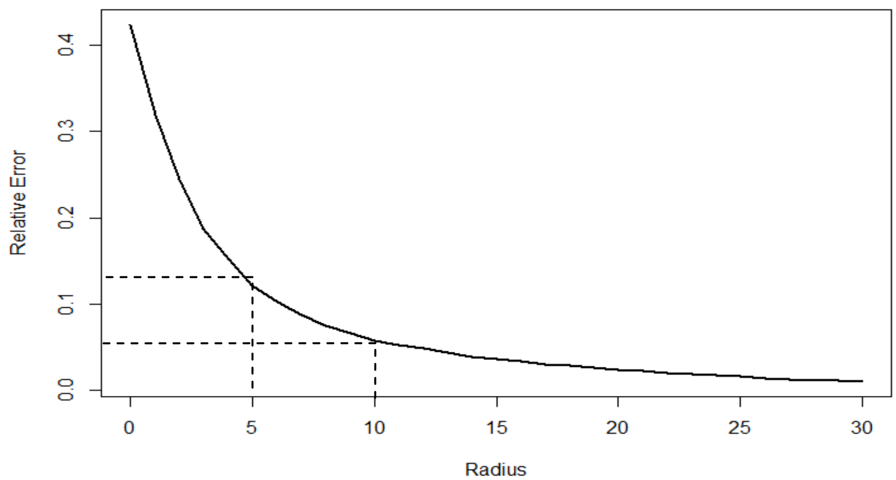


Figure 3.5: Relative change in error between simulated and referenced map with the increase of radius (number of [500m×500m] grids)

3.4 Discussion

Generally, supervised classification of remote sensing images requires actual data representing the ground reality. Usually ground information is not collected for the entire area of interest in any study because of the cost and resources required. This study used land survey data collected for the Okanagan region in 2007 as ground level information to perform the land use classification. The survey data cover nearly the entire study area and this information is used in our discriminant function analysis. This coverage allows us to generate a more complete set of discriminant functions, each of which uses more data, than would be the case with a less complete land use map. Many investigations have not had the luxury of such a complete land use map, giving us a greater degree of confidence in our historical classification.

Having a comprehensive land use map enabled us to use 19 land use types for classifying historic land use and generating the historic land use map. However, these 19 land use types were an aggregation from 37 land use types. Further, the 37 land use types ignored a number of land use types that were represented by too few observations to estimate a discriminant function. This invariably introduces some error into the historic land use map, as incorrect assignments, and as the absence of and representation of the land use types for which a discriminant function could not be generated. One approach would be to move to an even finer grid, perhaps 50m on a side or even 25m on a side. However, then any benefits resulting from the averaging across pixels within a grid cell diminishes. Exploring the impact of different rastering scales for generating a land use map from remote sensing data are left for future work.

Aggregating the data into a courser grid (moving from 100m×100m to 500m×500m resolution) generally introduces the Modifiable Areal Unit Problem (MAUP) (Heywood, 1988). The MAUP problem causes under or over estimation of the area for each land use category, which may result in propagation of errors and subsequently affect the accuracy assessment. We expect that this is an issue for our simulation and for our generation of a historic land use map, and this needs to be kept in mind when interpreting our results.

Unlike some other classification models that use a large number of characterizing variables (e.g. Bunce et al., 1996a), we restricted ourselves to six of the seven Landsat TM5 spectral bands and one derived vegetation index. Our data did include biophysical variables such as elevation, slope and soil characteristics, variables that have been used elsewhere for classification of land use (Wulder et al., 2004). However, as these variables were used as drivers in our land use change model, we opted not to use them in the classification model, to reduce the risk that a correlation would be created between the model results and classification results which would make our model look to have a better fit than it actually does. Exploring the impact of different classification variables on our validation is also left for further work.

In Chapter 2 we discussed the importance of the dynamic nature of some of the driving variables used in the model. The impact of these dynamic aspects is explored further in Chapter 5. The parameter estimates used to backcast to the 1993 land use change were based on their 2007 levels. A number of these variables, such as distance to road, access to piped water, etc. would not have been the same in 1993. Changes in these variables are important policy choices, and estimation of their influence should account for this. Other variables, such as measure of spatial association, are themselves functions of the land use pattern, and therefore change as the land use pattern changes. These too were assumed constant for the backcast. As we discuss further in Chapter 5, failing to account for the dynamic nature of these variables likely biases the results.

A further complication for forecasting and backcasting is that at least some of the land use changes we are trying to model are influenced by policy and planning decisions. How the road network expands and where residential development is permitted to occur is a consequence of the interaction between local government land use planning decisions and decisions of the provincial Agricultural Land Commission, which is responsible for administering the Agricultural Land Reserve (ALR) (BCPALC, 2010). The ALR is a provincial level zoning classification intended to protect agricultural land. Moving land out of the ALR zone and enabling development of that land requires the successful application for an exclusion from the ALR (BCPALC, 2010). On the other side of the land use process, much forest and range land is owned by the crown. The provincial government must choose to dispose of crown land if it is to move into private ownership, the first stage in its development. These decisions are heavily influenced by politics and by changes in community preferences, driving forces that are not captured in our model.

We agree with the suggestions made by Pontius et al. (Pontius et al., 2004; Pontius, 2002) that near misses and far misses need to be differentiated, and that a multi resolution approach to assessing model validity is appropriate. We have implemented this, something that is seldom done, on account of the computational challenges (Castella and Verburg, 2007; Pontius et al., 2004; Pontius et al., 2002).Pontius also suggests that it is important to differentiate between quantity and location errors (Pontius, 2000). The CLUE-S system does not estimate total land use change, but rather takes the aggregate changes for each land use type as input and locates those changes. We did not have an estimation model for our aggregate changes, but rather relied on public forecasts or projected trends in these aggregate variables. This means that for our model, there is no source of quantity error. Any quantity error in the validation would have been due to errors in the classification process. We therefore used the aggregate change measured in the classification process as input into the CLUE-S backcast, making the validation assessment strictly an analysis of location error.

Our validation exercise indicates that the CLUE-S model we developed can generate a valid land use forecast. However, as Pontius et al., (2004) pointed out, it is not professional to claim that our modelling exercise is accurate. There is always room for improvement, and above we have described some of the limitations and directions for further work. The final assessment of the usefulness of our results rests with the stakeholders and policy makers who will decide if our projections are useful for their purposes.

3.5 Summary

The validation results for the Deep Creek watershed model suggest that within the assumptions of the model, it provides a credible forecast of land use change in the watershed. Unlike many other validation exercises, we did not have comparable land use category maps at two different points in time to provide anchors for our validation. We therefore turned to remote sensing data and discriminant function analysis to construct a historic land use map. Using the single resolution cell-by-cell measure, our forecast model has an error of slightly over 20%. When we consider a multi resolution approach, we find that the error decreases rapidly as the resolution is increased. The single resolution results are reasonable in relation to other studies that have been done. The multi resolution evaluation has been suggested in the literature, but has seldom been used. Our results suggest that much of the error in our forecast will be due to ‘near misses’, where the model predicts well the general trend of land use change, but does not precisely predict the changes at the level of each cell.

Chapter 4. Food Sovereignty or Forest Conservation: A trade-off between agricultural and environmental priorities and their implication on existing land use policy

4.1 Overview

In this chapter we turn to the application of the forecasting model. Forecasting land use change and testing various land use change options can support planners and decision makers in the region by highlighting future land use management issues and enabling the longer term impacts of policy options to be evaluated. We use the model we have developed to examine four different policy scenarios, scenarios reflecting different levels of protection for undeveloped land. Comparing the results reveals how greater protection for undeveloped land pushes development onto land that is currently used for agriculture. In a mountainous province with scarce agricultural land and a public desire to promote food sovereignty, our results point out that there are tradeoffs. The existence of these tradeoffs, and the interactions that create them, highlights the problems that are created when authorities responsible for decisions that affect land use do not work together. As in many places, decisions that affect land use are made by different overlapping jurisdictions and different levels of government. There is often no requirement for communication, let alone coordination, between these authorities, and therefore the interactions and tradeoffs are not considered. Recognition of the existence of these tradeoffs by all relevant authorities is the first step in moving towards more integrated landscape management, and we hope that our results contribute to this recognition.

Forest conservation is an important part of protecting biodiversity and reducing atmospheric carbon (Millennium Ecosystem Assessment, 2005; Tilman, 2002). Forested lands also provide many other services, such as: reducing soil erosion; improving infiltration of precipitation and regulating groundwater recharge; mitigating some environmental impacts of farming; and providing natural habitats. The agricultural land base is essential for food production. British Columbia is a mountainous province, and as many mountainous regions around the globe (e.g. nearby Oregon and Washington states which have similar amounts of forest, see Bradley et al., 2007; BCMAL, 2006; Daniels and Nelson, 1986), it has a limited agricultural land base. Population growth, economic development and technological progress all put pressure on the land base, pressures typically manifested as conversion of agricultural and/or undeveloped land to different uses. Faced with such changes to their landscape, and to the services provided by that landscape, governments often pursue policies to protect undeveloped land and at the same time undertake efforts to protect agricultural land.

The Food and Agricultural Organization of the United Nations (1996) defines food security as "….a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life". Worldwide, 925 million people suffer with undernourishment (used as proxy for food insecurity) (FAO, 2010), and one in seven people are unable to get sufficient energy and protein from their food (Godfray et al., 2010). Protection of forest and range land transfers development pressure to agricultural land and causes reduction in food supply for human needs. Reduction in food supply in some parts of the world have caused food crisis and lead to social unrest. While these issues are not directly relevant to a high income country like Canada, reduced local food production increases

Canadian demand for imported food. Further, some climate change projections suggest substantial reductions in food production capacity for tropical countries, making protection of temperate food production ability an important issue. Hence, to meet the forest conservation and food supply, a balance must be found to accommodate both environmental and agricultural priorities.

British Columbia is one of the lowest green house gas emitters in North America (British Columbia Ministry of Environment [BCMOE], 2010). Major land use issues in the province, in addition to limited availability of agricultural land, are loss of natural habitats, and sustaining the forest industry. Much of the province is mountainous. The most productive forest land, the most biologically productive and diverse habitats, and the best agricultural land are often in close proximity, if not coincident. As such, development pressure exerts land use conversion pressure on these lands. In this chapter we examine how different approaches to protecting undeveloped land impacts on where development occurs, and in particular the impact on agricultural land, in the Deep Creek watershed of the northern Okanagan Valley in British Columbia.

As a mountainous province, British Columbia has a small amount of arable land, largely concentrated in the valley bottoms that are also most convenient for conversion to other uses. As an affluent province, food security is not an issue for most of the population. However, there is popular public support for protecting agricultural land and sustaining as high as possible a degree of food sovereignty. At present, almost 50 % of the provincial food requirement is imported (BCMAL, 2006). The province imports 80% of all fresh field vegetables and 85% of processed field vegetables from the US and 72% of that is supplied by California alone (Baumbrough et al., 2009). The price and availability of fresh produce in

British Columbia is therefore very sensitive to both climatic and economic shocks in California, a vulnerability that is highlighted by those most concerned about local food sovereignty. Environmentally, the average food imports travels about 4500 Km to reach the BC consumer (Provincial Health Services Authority, 2008), which is expected to increase if California becomes a less reliable source. The provincial population is expected to increase from 4.5 million at present to 6.1 million in 2036. This will increase demand for local production and imports (BC Stats, 2010). Prime agricultural land covers only 1.1 % of the province, although 32 % of the British Columbia's land can be considered arable (BCPALC, 2013). With the current population, the per capita farmland requirement is 0.524 ha (BCMAL, 2006). Efforts to sustain or increase food production are therefore constrained by agricultural land availability. Recognition of these facts has led the province to attempt to protect agricultural land from development.

In 1974, with the public alarmed by the rapid pace of development on agricultural land, the government implemented the Agricultural Land Reserve (ALR) act. This act aimed to make the conversion of agricultural land to non-agricultural uses more difficult (BCPALC, 2010). Under the ALR policy, all land with a sufficient agricultural capacity is included in a special provincial ALR zoning classification. Land within the ALR cannot be converted to a non-agricultural use without passing a review process, a process managed by the Agricultural Land Commission. The increasing prices of land that is available for development motivates land owners to apply to have their land excluded from the ALR. It has been noted that this has the cumulative effect of "…death by a thousand small cuts to the very land that can produce food locally" (RDNO 2008). In addition, the high cost of farmland, coupled with lower returns from farming, discourages new entrants to farming (Penner, 2008) and leads to sales of these valuable agricultural lands to people who hold the land with little interest in its use for agricultural purposes. This concern is not unique to British Columbia. Conversion of farmlands to urban development has reduced the amount of land available for food production in Washington State (Lubowski et al., 2006). Further south in Oregon, the state implemented a land use planning program to protect farm land from unregulated and unplanned development (Kline and Alig, 1999; Gustason et al., 1982). Effective protection of agricultural land and the services that land provides is a significant issue in many areas, with governments in many of these areas searching for effective policy solutions.

Forest land accounts over 55 % of the total land base in British Columbia. This land provides various useful environment and ecosystem related amenities addition to its major timber production function (BCMAL, 2006). The forest land in BC supplies lumber for local and international markets, while providing job opportunities for residents in the province. The forested area also regulates the water supply and provides space for habitats for animal and plant species. In addition to development pressure, forest and range lands are also threatened by wildfire, pests and diseases, the most significant at present being the mountain pine beetle. Wildfire has affected an average of 98,450 Ha per year in BC during 2000 – 2010 (BC Ministry of Forests and Range [BCMFR], 2012). The latest outbreak of mountain pine beetle has caused approximately 17.5 million Ha of forest damage as of 2009 (British Columbia Ministry of Forests, Lands and Natural Resource Operations [BCMFLNRO], 2011). These natural influenced, likely intensified by climate change, have raised the urgency of protecting undeveloped forest lands, both in British Columbia and elsewhere. Searchinger et al., (2008) noted the same issues in Washington state, while Oregon has also demarcated places of importance for protecting forest land (Kline and Alig, 1999; Gustason et al., 1982).

Few policies are in place to protect the forest land in British Columbia. The Forest and Range Practices Act was introduced on January 31, 2004 (BCMFLNRO, 2004). The policy instrument sets out the requirement for activities such as planning, infrastructure expansion, harvesting of forest, management of grazing and reforesting. The act also gives attention to the water bodies and natural habitats within forest and range land to ensure their protection. The stipulated compliance and enforcement mechanisms are intended to induce management practices that ensure forest and range resources are available for future generations. However, nearly 6,200 Ha of forest land was deforested in 2007. In 2010 the provincial government introduced the “Zero Net Deforestation Act,” intended to bring the net loss of forest area to zero and increase afforestation (British Columbia Ministry of Forest, Mines, and Lands [BCMFML], 2010). This policy was also seen to contribute to reduced greenhouse gas emissions (Parfitt, 2010).

4.2 Background

4.2.1 Site Characteristics

The Deep Creek watershed is located in the northern portion of the Okanagan Valley, in the southern part of British Columbia (Figure 1-2). The valley has one of the highest rates of population growth in Canada (Statistics Canada, 2012 a,b). The dry, relatively warm climate makes the Okanagan Valley an attractive destination for tourists and retirees, and those migrants generate demands for goods and services. The Deep Creek watershed covers an area of 230 Km^2 and includes the City of Armstrong and Township of Spallumcheen. The elevation of the watershed varies from 340 to~1575 meters (Ping et al., 2010). Forestry, agriculture, manufacturing and tourism are all important economic activities in the watershed. Agriculture is particularly significant in the valley bottom. Livestock farming is the most common category of farming, representing about 21% of all agricultural operations in the Township of Spallumcheen. Other relatively important farm types include hay and forage operations (17.2%), horse and pony (15.2), poultry (6.8), and dairy (6.1%) (Zbeetnoff, 2006). The Deep Creek watershed falls under the North Okanagan basin eco-section of Thompson – Okanagan Plateau eco-region (Demarchi, 2011). Montane forest types of Douglas fir, and Lodgepole pine are extensively found in the study area (Demarchi, 2011).

A recent geological history with multiple glaciations has resulted in a complex system of aquifers. Some of these aquifers are recharged by precipitation that falls on the surrounding hills and mountains. Shallow, moderate, and deep aquifer systems are found in the valley bottom; groundwater levels have dropped in the last 30 years in the majority of the aquifers, with withdrawals exacerbating influences of climate change on natural recharge rates (Ping et al., 2010).

Groundwater in the study area is used for domestic water supply, irrigation, commercial and industrial purposes. The irrigation season for most of the Spallumcheen Township area extends from the beginning of May to the middle of September, a period of approximately 130 days. Roughly 12% (1,900 ha) of the total farmland in the Township of Spallumcheen is currently irrigated, predominantly using groundwater (Zbeetnoff, 2006). Water yield of the watershed is comparatively small and the water rights for surface water are fully allocated (BCMFLNRO, 2011), making groundwater an important resource for irrigation (Ping et al., 2010). Forty-eight licenses for surface water use are active in the Deep Creek watershed (Ping et al., 2010). Irrigation districts and municipalities withdrawal (of surface water) is limited. However, private licensees remove nearly 3 Mm^3 / year, mostly for irrigation

(Nichol et al., 2011). Significant amounts of water are withdrawn from the adjacent Fortune Creek watershed. Irrigation districts, withdrawing from Fortune Creek, supply water within the Deep Creek area (Ping et al., 2010), on account of the close proximity between the creeks and little height of land separating them. Fourteen water districts operate in the study area. Eight of these use surface and groundwater as their source of water supply, while the remaining six rely solely on groundwater. Only half of the water utilities operating in the study area provide water to agriculture.

4.2.2 Model Selection

Various pattern based and process based land use models were reviewed. A pattern based model can be calibrated using more readily available spatial data, and will likely capture many of the spatial influences that drive activities to particular locations in a landscape. From among the various pattern based models available, the Conversion of Land Use and its Effects in Smaller scale (CLUE-S) (Verburg, 2010; Verburg et al., 2002) has proven to be an effective tool for modelling fairly fine scale land use change. It has been used as land use change projection tool in African, Asian, American and European locations (Neumann et al., 2011; Hurkmans et al., 2009; Wassenaar et al., 2007; Castella et al., 2005b; Verburg et al., 2005). We adopted the CLUE-S model for our purposes.

A CLUE-S model evolves a gridded map of the study landscape forward, using a probabilistic transition model to forecast land use changes of individual grid cells. CLUE-S is parameterized using an observation of the landscape at one point in time, with multiple variables measured for each grid cell. The observed relationship between land use and the explanatory variables is assumed to continue forward in time and to be constant across the landscape. Changing trends in aggregate land use types across the study are taken from other sources. The land use type of individual grid cells changes as the simulation progresses, to match the provided aggregate changes. Thus, CLUE-S does not model how much land use will change, but rather where changes will take place. The main elements of the model development, data usage and implementation are summarized here and additional details can be obtained from chapter 2.

Within CLUE-S, spatial restrictions can be imposed to reduce land use change or protect a particular land use in an area of the simulated landscape. For example, political zoning imposed in the Brazilian Amazon reduced deforestation (Aguiar et al., 2007; Mertens et al., 2002). In this study, our goal is to examine the impacts of two different spatial land use policies on the evolution of land use in the Deep Creek watershed. While the model is specific to this location, the interactions and potential conflict highlighted by our model is are common issues. In our specific case, the conflict is between protection of agricultural lands and protection of forest lands and natural areas – undeveloped land - in the face of continuing immigration and development.

4.3 Method

4.3.1 Data Requirement

The required data came from a variety of sources, including government agencies (e.g.: BCMAL), internet sources (e.g.: www.411.ca) and other projects implemented in the same area (e.g.: various projects implemented by Okanagan Basin Water Board [OBWB]). One planned use for our land use forecast was contributing spatial water demands to a simulation of the impact of climate change on the hydrologic processes in the Deep Creek watershed. The downscaled climate data were available on a 500m × 500m grid. We chose the same resolution, to match with the climate change data. This resolution resulted in the watershed being covered by just over one thousand grid cells, keeping the computational demands for running the CLUE-S simulations reasonable.

Determining the major land uses for each grid

A land use land cover map was obtained from the BC Ministry of Agriculture and Land (Van der Gulik et al., 2010 and BCMAL, 2005) (Chapter 2, Figure 2-1). The various land use types were aggregated into five major land use categories. Each grid was assigned the dominant land use from those of the grids it contained. The final five major categories of land use are cultivation land, livestock farm, forest and range land, pasture and forage land, and residential and built area. The total area covered by each major land use category was estimated for year 2010 and this information served as initial input for the aggregated land use demand projections. Logistic regression functions were estimated for each land use type, providing a means of predicting the probability that a grid cell will be of a particular land use type, conditional on the values of the included driving variables. These regression functions are used by CLUE-S to choose the locations where land use change will occur in the simulation, together with the initial period land use maps, measures of the 'inertia' related to particular land use types, and the overall aggregate changes that are to occur over the length of the simulation.

Computing values for explanatory variables

Biophysical, socio-economic, soil related, and water resources variables were used in the analysis to identify the important drivers of land use change. The variables such as elevation, slope, and aspect represent the biophysical variables while population density, distances to town centers, cities, and road networks covers the socio – economic variables. The sand, and silt percentages were used for soil related variables. The distance to surface water and depth to groundwater levels measure access to water. Irrigators holding water licenses – generally long established farmers – are able to draw from surface sources. Those who do not have a license, or are too far away from a source to make conveyance of water practical, use groundwater. However, as water license holders do not have to report their actual water use, knowing whether a parcel has a water license appurtenant to it does not indicate what the water source for that parcel actually is. We therefore did not use water licenses as a driving variable. For irrigators relying on their own water supply, the cost of access – increasing with distance or depth – are likely to affect the choice of agricultural activities. There are a number of water utilities in the watershed that provide water for residential and agricultural purposes. In those areas where water is available from a water utility, distance to surface water and / or depth to groundwater is less likely to be a relevant driving variable. We therefore flagged those cells where piped water is available, and allowed the influence of depth to groundwater or distance to surface water to be zero. We found that this significantly improved the model fit (see Chapter 2 for more detail). Driving variables were calculated for each 500m × 500m for each grid cell in the study area. Details on the aggregation to the grid cell scale are available in Chapter 2.

We did not use the area of a grid that is included in the Agricultural Land Reserve (ALR) as a driving variable. The ALR is at best a soft constraint that increases the cost of developing land for non-agricultural uses (BCPALC, 2010). Instead, we use the ALR area as a measure of where development pressure is likely to occur under the policy scenarios that we compare. The ALR is a reflection of the public desired to protect and promote food sovereignty for British Columbia, and if policy choices lead to additional pressure to remove agricultural designation from land presently zoned as part of the ALR, then we can comment on the conflict between these policy choices and the agricultural land protection goal. To make this comparison, we designate a grid cell as being part of the ALR if at least half the area of a grid is land within the ALR   For the study area as a whole, 45 % of grid cells are more than 50% within the ALR, while 30 % of grid cells are 100 % covered by the ALR. From the five land use categories used in our simulation, we take the three agricultural categories as consistent with the ALR. Our interest is then in how much land is that is currently within the ALR and used for agricultural purposes is converted to residential and built area.

4.3.2 Land use change simulation in Deep Creek

4.3.2.1 Test of scenarios and area restrictions

We chose trend extrapolation as our method to project aggregate land use demand. The change in residential and build area was expected to match population growth trends. The aggregate changes in the three agricultural land use categories were expected to continue past trends. The area in the forest and range category was taken to be the source for the aggregate increase in land devoted to the other categories. These aggregate changes were the same for all the scenarios examined.

Two policies restricting the conversion of undeveloped land to other uses were considered. In one of these, the "forest conservation" policy, where after 2030 no further conversion of undeveloped land to other uses was permitted. The other policy, "area restriction", does not allow undeveloped land in the northern part of the watershed to be converted to other uses for the duration of the simulation. With these two policies, there are four possible combinations, and these are the four scenarios we examine. See figure 4.1 for a tabular description.

		Forest and Range land	
		Free to Change	Conserved
Area Restriction	Not imposed	Business As Usual (BAU)	Conservation without area restriction (C)
	Imposed	Area restriction without Conservation (AR)	Conservation with area restriction (CAR)

Figure 4.1: Land use scenarios tested for Deep creek watershed in this study

The policy scenarios are inspired by various government documents. The "forest conservation" option considers the local governments' Official Community Plan (OCP) coupled with provincial and federal government commitments towards carbon emission control (BCMOF, 2012; Government of Canada, n.d.; RDNO, 2012; CSRD, 2011). The "area restriction" policy reflects the policy direction of the Columbia Shuswap Region District (CSRD). The Official Community Plan (OCP) of the district seeks to contain development within the lower elevation parts of the watershed, protecting undeveloped land, most of which is at the higher elevations (CSRD, 2011).

4.4 Results

4.4.1 Driving Variables

Full details on the model calibration can be found in Chapter 2, with model validation in Chapter 3. An overview of some of the results is presented here. The logistic models predicting the probabilities for the different land use types were all significant at 0.10 % error level ($P < 0.001$) or better. The livestock farm model had the smallest pseudo R^2 value (less model strength) while the forest and range land gave the highest pseudo R^2 value (better model strength) for the logistic regression models fitted (Table 2-2). The Receiver Operating Characteristic (ROC), which evaluates the goodness of fit, showed best fit for forest and range land while other land use categories also showed relatively good fit (higher area value). The overall fits for the regression model are consistent with results found elsewhere.

The distance to paved surface road was negatively correlated for the cultivation land and the livestock farm categories, while it was positively correlated to the forest and range land use category. Population density was positively correlated for the residential and built area, while it had a significant negative influence on land use change for all other land use categories, except for the livestock farm (insignificant). All the significant land use categories, except the residential and built area, were usually far away from the populated areas. Access to surface and groundwater resources was only modeled for grids that were either close to a surface water source or that were not serviced by a water utility. When the model was fit parameters related to surface and groundwater resources were often significant.

In addition to the conventional drivers, we also included a measure of spatial association (Chapter 5). This measure captured the relative concentration of the land use type of the grid cell in relation to neighboring cells. Including spatial association permits the influence of factors – neighborhood effects – that may be driving land use change but are not measured or included in the regressions. The measure of spatial association was a significant and positive predictor for the pasture and forage land, the cultivation land and the livestock farm while it was not significant for the residential and built land use category. Spatial association (neighbourhood strength) was not included as a predictor for conversion of forest and range land, as this land use category is the 'residual' category. It is the source of land for conversion to the other land use types, and as such it is not the result of an active choice. When the spatial association was included, parameter estimates became inconsistent with normal expectations, reflecting this fact.

4.4.2 Simulation results

The aggregate changes between 2010 and 2050 were divided to show the conversions from one land use type to another (Table 4-1). In table 4-1, each row represents a land use, and the total of the row is the number of grids of that land use type in 2010. The sum of each column is the total number of grids of that land use type in 2050. Each grid contains the number of grids that were of the row type in 2010 and of the column type in 2050. The values within the parenthesis denote grids inside the ALR boundary.

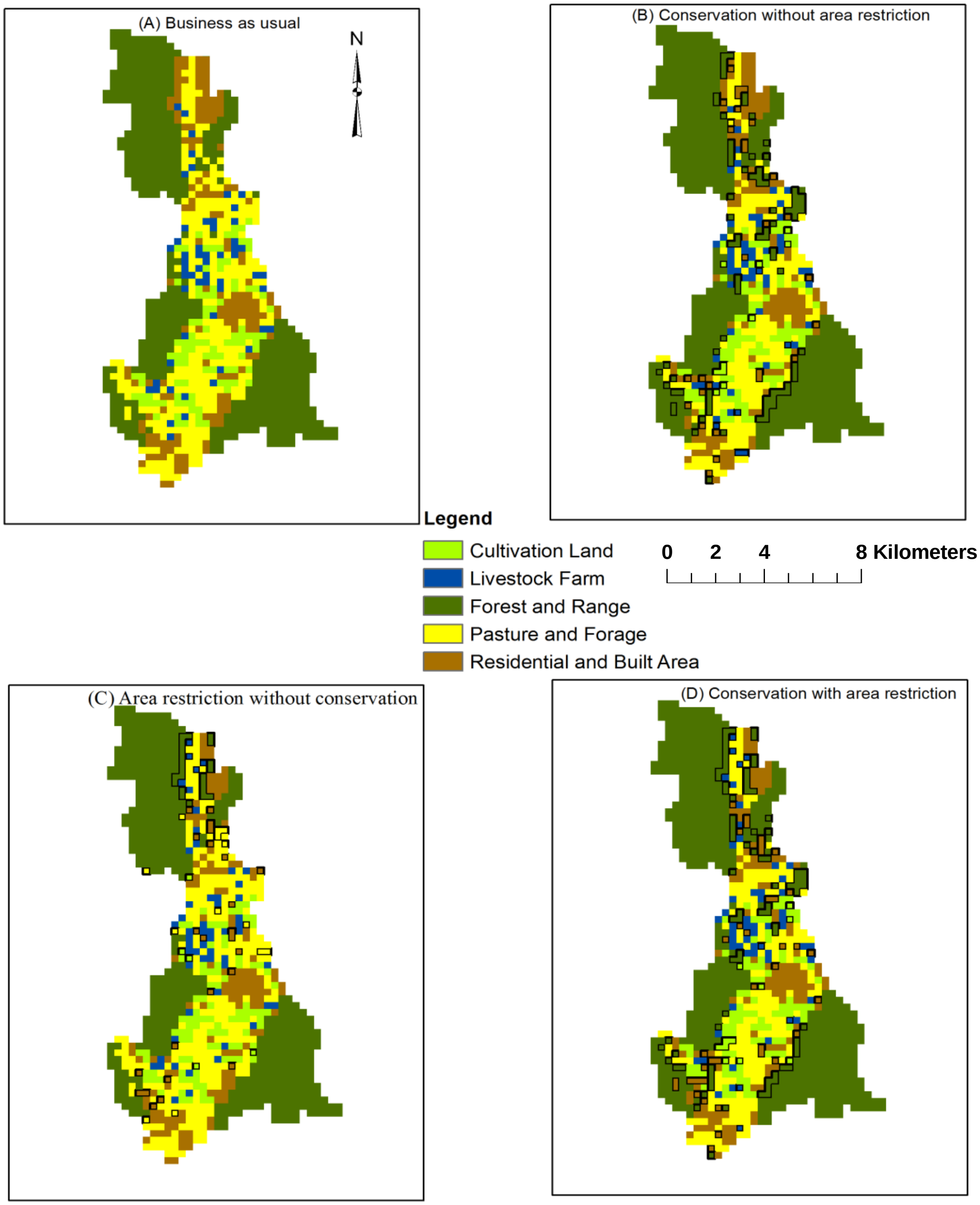


Figure 4.2: Projected Land use changes at 2050 under four varying scenarios. Grids with difference in land use from BAU are indicated by surrounding borders for other scenarios

Numbers along the diagonal count the grids that had the same land use in 2010 and 2050 (Table 4-1). The off diagonal numbers show the loss (row land use) / gain (column land use) from land use change. All the residential lands in 2010 remained unchanged in 2050 irrespective of the scenarios.

Table 4.1: Land use types status (remain same / changed) in 2050 under varying scenarios

		2050			
	Land use Category	Agriculture land	Forest and Range	Residential and Built area	Remain as Original in %
		Business as usual - BAU			
2010	Agricultural land	343 (312)[1]	0 (0)	7 (7)	98 (98)
	Forest and Range	98 (69)	510 (28)	51 (19)	77 (24)
	Residential and Built area	0 (0)	0 (0)	103 (61)	100 (100)
	In 2050	441 (381)	510 (28)	161 (87)	86 (81)
		Conservation without area restriction - C			
2010	Agricultural land	308 (288)	8 (6)	34 (25)	88 (90)
	Forest and Range	50 (43)	585 (61)	24 (12)	89 (53)
	Residential and Built area	0 (0)	0 (0)	103 (61)	100 (100)
	In 2050	358 (331)	593 (67)	161 (98)	90 (83)
		Area restriction without conservation - AR			
2010	Agricultural land	345 (314)	0 (0)	5 (5)	99 (98)
	Forest and Range	92 (62)	510 (26)	53 (28)	77 (22)
	Residential and Built area	0 (0)	0 (0)	103 (61)	100 (100)
	In 2050	441 (376)	510 (26)	161 (94)	86 (81)
		Conservation with area restriction - CAR			
2010	Agricultural land	312 (289)	4 (4)	34 (26)	89 (91)
	Forest and Range	46 (40)	589 (59)	24 (17)	89 (51)
	Residential and Built area	0 (0)	0 (0)	103 (61)	100 (100)
	In 2050	358 (329)	593 (63)	161 (104)	90 (82)

[1] *Values in the parenthesis are the number of grids coming within the ALR boundary.*

This follows from the specification of the conversion elasticities as input to the CLUE-S model (see Chapter 2). Effectively, we imposed the assumption that land which has been converted to residential and build area will not be converted to other uses. The loss of presently farmed agricultural land varies between 1 – 12 % across the scenarios. Overall, nearly 85 - 90 % of the watershed will remain the same in 2050 irrespective of the scenarios (Table 4-1).

Business as usual (BAU)

Livestock farming is expected to decline and cease their operation in the mountainous region and the valley bottom (because of intensification and more efficient management) whereas it is expected to continue as at present in the central area (closer to Armstrong) (Figure 4-2 A). The expansion of residential and built area is most prominent in the north-east and in the valley bottom of the watershed (Figure 4-2 A). The expansion of residential development in this area may be due to the development pressure arising from proximity to the major population centers -Salmon Arm and Vernon – just outside the watershed. These areas are effectively on the urban fringe of these population centers. Road networks (paved surface road and highways) are one of the significant driving factors in the model. The location of conversion to residential and built area also reflects the location of major roads in the watershed.

Conservation without area restriction (C)

In this scenario, the total area of forest and range remained the same from 2030. This restriction results in a larger number of grid cells that remain forest at the end of the simulation (593 cells instead of 510, an increase of 83 forest cells). The total amount of conversion to residential and built area is the same at the end of each scenario (161 cells). Thus, with the conservation scenario, the increase in undeveloped area drives the 83 cells that are converted to residential and built area onto cells that were included in one of the three agricultural categories. Restricting conversion of undeveloped land has driven development onto agricultural land. This development occurs largely on grid cells that are near those in the BAU scenario, substituting development of agricultural land near the forest and range land that is forecast to be built on when there are no changes. Proximity to these urban centers and to the transportation network continue to be the important drivers, subject to the imposed restriction.

Area restriction without conservation (AR)

The area restriction, when imposed on its own, does not change the aggregate conversion that is forecast to occur in the simulation. This restriction prevents conversion of forest and range land to other uses in the northern part of the watershed. The decline of forest area therefore shifts to the south-west part of watershed (Figure 4-2 C). This puts increased pressure on forest land, particularly low elevation forest land in the center of the watershed. This land is particularly suitable for agricultural uses, and is in effect substituted for agricultural land that is developed for residential and built area in the northern part of the watershed. The restriction drives residential and built area conversion from the forest and range land to agricultural land in the area where the restriction is in place. This means that the growth in cultivation and pasture and forage land must occur elsewhere in the watershed. The importance of the proximity to urban areas and the proximity to transportation are what keep the residential and built area development from moving too far. Given the scarcity of suitable land, residential and built area conversion in the north part of the watershed does move south, closer to the border between CSRD and RDNO, compared to the BAU. These results agree with the OCP of RDNO, in which these areas are medium holding lands reserved for development, including the residential and built area (RDNO, 2012).

Forest conservation with land use restriction - (CAR)

Combining the two restrictions means that forest and range land in the north part of the watershed cannot be developed for the duration of the simulation, and conversion of the remaining forest and range land does not occur after 2030. Consequently, the 89 grid cells that are not converted from forest and range to other uses must all be accommodated in the agricultural land portions of the watershed, and primarily in the southern part of the watershed. Proximity to urban areas and distance to transportation continue to be the important drivers for conversion to residential and built area. This means that what conversion to agricultural uses or conversions between agricultural uses work together to expand agricultural area significantly in the central part of the watershed, farthest from the major urban centers and somewhat distant from the highway connecting these centers.

4.4.3 Simulation results and land use policy

In the BAU scenario, 19 % of the total grids found inside the ALR will be converted from one use to the other (Table 4-1). Of the forest and range area converted into residential and built area, 47 % of them will be in the northern part of the watershed while 35 % of them will be in valley bottom. The loss of forest and range land is significant under this scenario and there is significant conversion of land presently in the ALR to other uses. The loss of natural land cover contributes to environmental problems.

In the C scenario, 2.3 % of the agricultural lands are expected to remain as forest and range land. The forest and range land converted to residential and built area will be reduced by nearly half while the agricultural land converted for development purposes will be five times higher compared to the BAU scenario (Table 4-1). A 42 % increase in development pressure will be expected to occur inside the ALR area compared to the BAU scenario. Of the conversion from forest and range to residential and built area, more than 70 % will be expected to take place in the northern and valley bottom parts of the watershed and more than 50 % will be in the northern part alone under this scenario (Figure 4-2). The development pressure is concentrated more on agricultural land under this scenario (Figure 4-3).

In the AR scenario, the land converted for development purposes inside the ALR will be expected to increase by 21% compared to the BAU scenario while it will be reduced by 12% under this scenario compared to the scenario C (Table 4-1 and Figure 4-3). Hence, the area restriction will apply more development pressure inside the ALR area. Of the forest and range land converted to the residential and built area, 23% of them are expected to take place in the Northern part while nearly 50 % of them are in the central area (Figure 4-2).

BAU	C
• 61 % of conversions will take place inside the ALR. • All AG lands and 60 % of the FR land converted for development will be inside the ALR. • ~27 % of the total conversion inside ALR is not the approved land use conversion, i.e. for development use. • FR land converted into AG land inside the ALR, > 90 % of them in the central / VB. Of the AG land converted to RB area, > 70% of them will be either in the Northern part or in the VB.	• 9.7 % of the AG lands will be put in for development purpose. • Of the FR land converted, > 2 / 3 of them will be put into AG land. • ~ 1/3 conversion reduction from FR land to AG land will be inside the ALR compared to the BAU scenario. • Of the FR converted to AG land inside the ALR, 42 % & 51 % are in central part or in the VB respectively. About 80 % of the conversion for development purpose from AG land is either in the Northern part or in the VB of the watershed.
AR	**CAR**
• 1.4 % of AG land and ~33% of FR land converted for development purpose – inside the ALR. • FR land converted to AG land inside the ALR is the least compared to the BAU & C. • FR land converted to the AG area, 45 % & 39 % of them – in the middle & the VB area respectively. • Of the conversion from AG land to the RB area, all the conversion – in the central & the VB.	• ~ 10 % of the AG lands converted to RB area and of the FR land converted to other uses inside the ALR, 70 % be AG land • Of the lands converted to RB area, 74 % of them – inside the ALR. • AG land converted to RB area, 56 % is in the VB. FR land converted to the AG land, 40 % and 55 % of them are in the central and VB areas respectively. • Conversion for development use inside the ALR from all other uses will be in the central (44 %) and VB (47 %) areas.

AG - Agriculture; FR - Forest and Range; RB - Residential and Built area; VB - Valley Bottom

Figure 4.3: Land use conversion, spatial location of change and its influence on ALR area in 2050 under different scenarios

However, the conversion of this type that will occur inside the ALR area, half of them will be closer to the city of Armstrong. The area restriction in the northern part of the basin drives the development pressure from areas closer to Salmon Arm to areas surrounding the City of Armstrong and the border of CSRD and RDNO (Figure 4-3). Hence, more development pressure is expected for ALR lands near Armstrong.

The total amount of forest and range land remaining at the end of the simulation is the same for the C and CAR scenarios (593 grid cells). Among all the scenarios, the lands converted inside the ALR for development purposes and from agricultural use is the highest under this scenario. Combining these two policies as done in this scenario puts the greatest pressure on land presently protected for agricultural purposes.

4.5 Discussion

Several results are important to emphasize from this study. First, development will exert pressure on both agricultural and forest and range land if land use conversion continues as at present. Second, protecting forest and range land from conservation will transfer development pressure to agricultural lands, lands which the public in British Columbia has expressed a strong desire to protect. Third, efforts to protect presently undeveloped land will make it more challenging to protect land that is presently zoned for agriculture, the ALR, which is the implementation of the public desire to protect agricultural land. Fourth, restricting development of public forest and range lands – part of the AR scenario – will transfer development of forest lands to private lands, much of which are lower elevation lands. These lands may be important low elevation patches that provide scarce habitat and/or act as corridors for movement of wildlife. Fifth, the overlapping jurisdictions and decision making authorities need to recognize that their decisions are often not independent, and may interact in ways that conflict with important public goals. Decisions about what lands to protect or turn over to development, where to expand the road network, etc. have effects across the landscape, effects that decision makers should consider.

In this analysis, we have focused on four policies that restrict the development of forest and range land, and show the impacts on land use change throughout the watershed. This land use modelling exercise started as part of a project aiming to forecast the impacts of climate change on the Deep Creek watershed. Our forecasts of land use change can be used to predict changes in water demand. Since groundwater is an important water source in the watershed, these changes in water demand are likely to translate into changes in groundwater withdrawals. The scenarios therefore can also be used to examine the spillover effects of restricting the conversion of forest and range land on the hydrologic processes elsewhere in the watershed. Increased concentrations of irrigated cultivation lands and forage and pasture lands in the central part of the watershed, as in the CAR scenario, suggest that there will be substantial increases in groundwater pumping. This in turn may adversely affect natural springs which are important for environmental quality, particularly salmonid fish species survival during the warm summer. The details of this further assessment are left for future work.

There are important feedbacks between the pattern of land use and some of the driving variables which has not been considered in our simulations. Several studies have assessed the impact of land use change on hydrologic processes, and in particular on groundwater (Keilholz et al., 2015; Wijesekara et al., 2012; Jinno et al., 2009; Dams et al., 2008; Lin et al., 2007b). Land use change leads to changes in groundwater pumping, which in turn changes the depth to groundwater throughout the watershed. To the extent that pumping costs and groundwater availability are important determinants of land use choice, this should feed back to the land use change process. Our modelling assumption that the depth to groundwater did not change over the duration of the simulation may be too strong an assumption. One approach, which we explore in Chapter 5, adapts a pattern based simulation system to accommodate dynamic variables. An alternative would be development of an integrated model that couples the hydrologic processes with the processes driving land use change.

Such a model would relate the land use choice, via the demand for water and the cost of pumping, to the depth to groundwater, and relate the depth to water to the pumping decisions made by land managers. Development of such a model is left for future work.

While in British Columbia protection of agricultural land in the face of development is an important policy objective, in some other locations the expansion of agricultural land into forested areas is seen as an important issue. Foley et al., (2011) focused their analysis on agricultural and environmental context and argued that agricultural expansion should be stopped by improving land productivity, reducing yield gaps, increasing cropping efficiency, reducing waste and other means to protect forest from depletion. Rudel and Meyfroidt (2014) also argued for increasing agricultural land productivity without expanding in extent of cropping area as the way to solve the food security, climate change and biodiversity crises. But, Angelsen (2010) found that deforestation in developing countries increased agricultural land only by 0.3 % in last 20 years and played down the influence of agricultural expansion on deforestation. In mountainous regions with scarce agricultural land, the expansion of agriculture into forested or natural areas is less of an issue. Agriculture land area cannot expand much. However, with immigration and development, land will invariably be converted, and the question then becomes one of deciding whether that land is going to come from forested areas or agricultural areas. The scarcity of agricultural land and landscapes is what has contributed to the public demands to protect agricultural land in jurisdictions such as British Columbia and Oregon state, and public concerns with these issues can be found in many areas that are similarly mountainous.

The scenarios involving “Forest conservation” (scenarios C and CAR) highlight the complexity of efforts to mitigate climate change. These scenarios are inspired in part by expressed government intentions to use forest preservation as climate change mitigation strategy (BCMOF, 2012). Recent experience with efforts to encourage biofuel highlighted the fact that expansion of crop area targeted at biofuel production reduces the land available for food production, and resulted in an increase in the price of some food commodities. These results suggest a similar policy dilemma when dealing with climate change. If forest protection is the strategy followed, then the expansion of agricultural land will be limited, and with continued development for other purposes, we can expect the area of agricultural land to fall. Absent offsetting increases in the productivity of agricultural activities – actions that may themselves contribute to climate change – forest protection as a large scale strategy may also result have effects on the price of food.

The land demarcated as ALR area in the Deep Creek watershed may face considerable conversion pressure. Forest and range land inside the ALR that may be converted into other land use categories, mostly becomes agricultural land under all scenarios. While the development related conversion activities are restricted under ALR policy, our analysis found that absent a strict enforcement of the ALR policy, land use conversion into residential and built area will occur within the ALR area. The forest conservation scenarios (C and CAR) demonstrate how protecting forest land will put more pressure on agricultural land. Owners of land within the ALR can apply for exclusion of their land from the ALR, and if successful they can develop the land. Restrictions that limit the availability of non-ALR land for development will increase the profit potential for development, and therefore increase the efforts of land owners to have their land excluded from the ALR. While our simulation focus has been on the Deep Creek watershed, the ALR is a provincial policy, as are provincial efforts to protect forest land. Recent changes in the ALR, which make it easier to have land excluded and/or allow activities that traditionally, were not considered agriculture may reflect this pressure (BCPALC, 2010). Thus, land use restrictions to achieve one objective may have impacts on the evolution of regulations related to other objectives.

Simulation exercises such as this can also highlight conflicts between the development plans of government bodies and the likely spatial patterns of development pressures. For example, residential development near Gardom lake (Appendix A-1) in the BAU scenario contradicts the official community plan of the CSRD (Figures 1-2 and 4-2; CSRD, 2011) and with the ALR boundary. The OCP shows a plan to keep residential development away from this area, while the simulation results suggest that development pressure will be high in this area. Official community plans are meant to express the overall long term desired form of the community. The actual path of development reflects economic forces and the willingness of local government politicians to follow the plan when land owners appeal for a change to the plan that enables them to realize a greater profit from their land. It would be interesting to revisit the land use pattern in the future, to see if development proceeded in line with the OCP, or responded more closely to the pressures suggested by our simulation results. Work by Kline and Alig (1999) in Oregon suggests that the results are not obvious. They found that the land use planning program initiated in Oregon focused development pressure in urban boundaries. However, it is not clear what the impacts of this policy were in more rural areas. It should also be noted that the simulation results are based on a projected increase in developed land. The simulation does not choose how much development will occur, but where it will occur. A possible, but unlikely, situation would be that both agricultural land and forest land are conserved, so that immigration is accommodated by increased density.

All four scenarios illustrate the importance of proximity to urban centers and the role of the road network in where land will be converted to residential and built uses. Distance to urban centers is not a policy leaver. However, where to extend the road network is. Our results emphasize the importance that decisions about the road network have on the way that development proceeds. While this result is not new (Aguiar et al., 2007; Mertens et al., 2002), it is all too often ignored by transportation experts within government who are not charged with considering the interaction between transportation development and impacts on the landscape as a whole.

Another source of interactions relates to the management of watersheds for ecological and community drinking water purposes. In our simulations, more than 22 % of the forest and range land is expected to be lost by 2050 if forest and land conversion is not restricted. Within forested watersheds, the rule of thumb is that 'mature' forest should cover no less than 70% of the watershed (for watersheds greater than 100 Km^2). This limits the adverse effects of cleared area on hydrologic processes of the watershed (Zhang and Wei, 2014; Zhang, et al., 2012; Wei and Zhang, 2010). The focus of these rules is generally on forestry activities. However, conversion of land out of forestry reduces the forested area of the watershed. Management of forestry activities, management of wildfire risk, and response to fire damage, may all have to be changed if the hydrologic benefits of mature forest are to be protected. Most of this impact would likely be as a reduction in the amount of timber harvesting that should occur in the watershed. This would adversely impact the forest sector, a sector that is presently experiencing a reduction in the allowable harvest, following the impacts of the pine beetle (Abbott et al., 2009).

Our analysis, using a pattern based land use system, has limited scope for policy analysis, beyond restrictions on land use change. In the following chapter we discuss extensions that may allow a better incorporation of dynamic drivers, which could include a richer analysis of policy. If clear land use objectives are specified, then it would be possible to run multiple scenarios and search for the optimum, from among the set of policies that can be analyzed. Looen et al. (2007) suggest that such optimization can help determine how various important functions of the landscape can be maintained or enhanced, and point towards policies that can support this optimization (see also Seixas et al., 2007;Seppelt and Voinov, 2002 and Aerts, 2002 for additional discussions of optimizing landscape form). An important future direction for land use change modelling is a tighter integration with the policy process, such that the analysis can help identify the optimal mix of land use that reflects a full accounting of the multifunctionality of the landscape.

4.6 Summary

Landscapes are complex systems with many interactions and feedbacks that even when understood are often not considered while making land management decisions. Our results highlight this interaction for two important issues in British Columbia, and in many other areas where publics are concerned both with local food production and with protecting presently undeveloped land. We show that implementing policies that protect undeveloped land can increase the pressure to convert agricultural land to residential and built areas. Within British Columbia, there is a strong public desire to promote local food sovereignty, and our results point out that protecting undeveloped land may be in conflict with policies that are meant to protect agricultural land. While our model focuses exclusively on these two issues, we point out that there are further environmental effects, via the hydrologic cycle, impacts on habitat connectivity, and efforts to mitigate climate change, implied by land use change.

British Columbia is not atypical in that land use decisions are regulated by a variety of overlapping jurisdictions with responsibility for different decisions on the landscape. These different jurisdictions are typically not required to consider the impacts of their decisions on objectives outside of their immediate authority. They may seldom communicate, and consequently decisions may often interact in ways that do not support important community goals. We suggest that greater attention should be paid to these interactions and to the cumulative effects of collections of individual decisions, so that land use can be better managed to be more consistent with overall social goals.

Chapter 5. Modelling Spatial Association in Pattern Based Land Use Simulation Models

5.1 Overview

Structures arranged in any space are influenced by the neighbourhood characteristics (Verburg et al., 2004a,c). For example, urban area expansion occurs more in the urban fringe than anywhere else. Conversion of crop land from one use to another typically occurs where cultivation is being practiced. Farmers exhibit imitating behaviour when they make crop choices, as they are influenced by the surrounding farmers' crop choices.

Land use types in a given area are associated with its neighbourhood surroundings and its interactions. Neighbourhood characteristics have mostly been examined for urban development theories and in land use modelling frameworks (Verburg et al., 2004a,c). However, land use models dealing with various land use categories often use bio-physical, accessibility and socio-economic variables, while neighbourhood effects / spatially correlated shocks (unobserved variables) are limited in use in the modelling process, particularly in land use pattern based models.

Various studies have demonstrated that spatial auto correlation is evident in land use data (Anselin, 2002; Munroe et al., 2002). These studies argue that land tenure arrangements or spatial processes, such as effects of agglomeration in land use for housing purposes or the imitation effect among farmers, are the major causes for spatial patterns. They argue that it is necessary to account for these phenomena in land use modelling. Indeed, results of linear regression models are inaccurate (Walsh et al., 1997) if the spatial association between land use types is not accounted for (Overmars et al., 2003). Verburg et al. (2002) demonstrated that spatial stratification can reduce the spatial auto correlation considerably and improve accuracy.

Spatial association has received considerable attention among modellers using cellular automata, agent based modelling and related frameworks, (Berger et al., 2006; Parker et al., 2003; Jenerette and Wu, 2001; Torrens and O'Sullivan, 2001). Cellular automata models are applied in urban and rural land uses by many researchers (Candau, 2000; Ward et al., 2000; White and Engelen, 2000). The transition from one land use to another is modelled using neighbourhood rules. Neighbourhood characteristics are used as one of the driving factors. Torrens and O'Sullivan, (2001) argued that the cellular automata models are mostly technology driven. Cellular automata models are limited in use because of the problems associated with the definition of neighbourhood transition rules, arbitrariness of these rules, and larger number of combinations of rules required to model land use in many situations (Torrens and O'Sullivan, 2001).

Agent based models, which directly model the decision processes leading to land use change, use the process and context involved in decision making in their modelling framework. Agent based models are built on a bottom-up approach to explore the system (Magliocca et al., 2012; Batty, 2009; Crooks, 2006). Spatial association flows from the decision process being made by the agent. Berger et al., (2006) developed an agent based model to account for technological innovations adopted by farmers in their cultivation practices. Agent based models are mainly limited by difficulties in setting initial conditions and defining the interaction rules, which are often somewhat arbitrary (Couclelis, 2002). Further, overall model complexity and extensive computational requirements limit the usefulness of these models in many situations.

Pattern based models are spatially data intensive models and are popularly used by geographers and environmental scientists. Land use data obtained in spatial form and satellite land use images available for multiple time periods at low cost favours land use pattern based models. A major weakness of many current versions of these models is their limited ability to account for neighbourhood effects, particularly updating these variables as the simulation proceeds. Since the land use pattern is changing over time, influences that result from this pattern –neighbour effects – also change over time. As such, a timely update of variables that are derived from this pattern should be an important component in any land use simulation.

Inclusion of neighbourhood effect is a major weakness in pattern based models. This challenge in our modelling is addressed by proposing a methodology to account for neighbourhood effects. Our proposed method is free from complexity; easy to interpret; and accounts for relative differences in spatial association between the global and local scale. Our next issue is that driving factors keep changing as the simulation progresses. These should be updated as the simulation proceeds. We illustrate how future changes of driving factors can be calculated and updated. We use our results to explore the impact updating driving variables can have on model results. We perform a grid by grid comparison between results obtained from regular updating of driving factors and those generated without updating. The proposed methodology is demonstrated using a CLUE-S model of a watershed in the North Okanagan region of British Columbia.

5.2 Background

5.2.1 Sources of Neighbour Effects

Neighbour effects are the result of: environmental characteristics; actors whose decisions are influenced by the local context; and institutional arrangements that are local in nature. Agro-ecology and physical geography cause natural constraints and spatial connections. Each parcel or unit of land is characterized by soil and climate conditions that favour certain agricultural activities or natural vegetation. That local soil and climate conditions are evaluated when recommending agricultural land uses is testament to the importance of local physical conditions. The spatial correlation in these physical factors will create spatial patterns in land use. When all relevant spatially correlated physical drivers are not accurately measured and/or not included in simulation models, bias will be introduced. A measure of spatial association between land use types can account for these missing drivers, improving model fit.

An individual's behaviour can influence others who are 'close by' (neighbours). Adoption of a new technology (e.g.: an improved crop variety) by one farmer can influence the choices of farmers in the surrounding area. Farmers observe each other and consider what they see in their own choices. Conlisk (1980) linked this behaviour to the cost of decisions and explained that the costly decisions were imitated from better informed individuals. Alessie and Kapteyn (1991) explained that individual demand increases with the average demand of a studied group when holding prices fixed in consumer demand models. Manski (1993) describes how observed correlations between choices made by individuals can be caused by endogenous, exogenous (contextual), and/or correlated effects. Statistical separation of these causes can be challenging. For predictive purposes however, establishing the cause of a spatial pattern is less important than ensuring that the influence of omitted drivers is reasonably accounted for in the predictions. When the ability of individuals to form expectations, gather information, and/or compare alternatives is limited, it is rational to consider the decisions of others when making choices (Manski, 2000). Agents (neighbours) thereby affect each other through altering preferences, expectations and constraints. These sources of neighbour effects are likely important drivers for observed patterns of land use change.

With unlimited resources for data collection and modelling, all relevant drivers could be included, and incorporation of measure(s) of spatial association into a model would not be necessary. However, this is typically not the case. Therefore, measuring spatial association between land use types and its influence on land use change is important for capturing these influences. Further, since spatial associations are a function of the land use pattern, as this pattern changes, so does the measured spatial association. This dynamic process should be accounted for. In what follows we describe one simple measure of spatial association and demonstrate a process for incorporating it into a land use change model.

5.2.2 Modelling Spatial Relationships

There are a variety of approaches to test for and model spatial relationships. Versions of Moran's I (Anselin, 1995), which measures spatial autocorrelation, are used to account for the spatial association in land use change projections (Lin et al., 2008). The G*i* – statistic is popular among geographers and remote sensing professionals for spatial analysis as the estimation method is built in ArcGIS 9.2 and later versions. This statistic (Getis and Ord,

1992) is typically used to identify where spatial clustering is stronger than expected by chance. Statistically, the G*i* statistic is not appropriate for categorical variables, which land use classifications typically are. Geographically Weighted Regression (GWR) allows regression parameter estimates to vary spatially (Fotheringham et al., 2002; 2001). Each spatial point receives its own regression function estimate, where the individual parameters are varied according to a spatial weighting process. Such methods have been developed for ratio scale and/or ordinal variables (e.g. temperature, plant growth, count of individuals, etc.). Any statistical analysis using such methods is questionable where categorical variables, such as land use type, are used. A few studies have used binomial logistic regression techniques to account for neighborhood effects in their estimation, and report conducting simulations with annual updating of these variables (Verburg and Overmars, 2007). Another recent approach, implemented in the component of multi-scale, multi-model land use modelling system EU-ClueScanner, uses multinomial logistic regression to model the neighborhood effects, and enables driving factors to change over time (Koomen et al., 2010).

One approach to including categorical variables was used by Hagoort et al., (2008). Hagoort et al., (2008) argues that the spatial "enrichment factor" developed by Verburg et al., (2004a) provides an appealing method to model the interaction between surrounding land uses. These authors defined "spatial enrichment" by focusing on the square neighbourhoods of each cell. Their measure was calculated as the proportion of grids in the square consisting of a given land use type in relation to the proportion of grids occupied by the same land use within the study area. The number of spatial enrichment values for a given grid cell equals the number of land use types in the study area. Hagoort et al., (2008) used this approach to derive empirically based neighbourhood rules for their cellular automata study. As such, the methodology developed by Verburg et al., (2004a) was comprehensively examined for our modelling purpose.

5.3 Method

5.3.1 Proposing Method for Pattern Based Land Use Models

Verburg et al. (2004a) proposed an “enrichment factor” to account for the spatial association of land use types at a given location on a land use map. It measures the representation of land use classes in relation to neighbourhood land use class arrangements. This “spatial enrichment” is defined as “the occurrence of a land use type in the neighbourhood of a location relative to the occurrence of that land use type in the study area as a whole” (Verburg et al., 2004a, p 671). Mathematically, it is

$$F_{k,i,d} = \left(\frac{n_{k,i,d}/n_{i,d}}{N_k/N}\right) \quad (5-1)$$

Where $n_{k,i,d}$ is the number of cells of land use k in the neighbourhood d of location i. The total number of cells in neighbourhood d of location i is $n_{i,d}$ while N_k is the total number of cells of type k within the study area and N is the total number of cells in the study area.

The value of $F_{k,i,d}$ will be greater than one if land use type k is more abundant within neighbourhood d than it is for the study area as a whole, and less than one if it is locally less abundant. The value therefore identifies local concentrations and absences of individual land use types. Common neighbourhoods are square groups of grid cells centered on the location of interest. These will have size of 3 × 3, 5 × 5, 7 × 7, etc. grid cells, and one can calculate these measures for a range of different perimeters, observing how the "spatial enrichment" changes as the size of the neighbourhood grows. While useful, we suggest that focusing on the land use type at location i and adjusting the calculation of the spatial enrichment so that it always lies between zero and one provides a more intuitive measure, a measure that is loosely analogous to an autocorrelation coefficient.

Calculation of our measure ("neighbourhood strength") of spatial association proceeds through a series of steps. We begin by defining $\theta_{i,d}$ as the numerator of the Verburg et al. (2004a) "spatial enrichment",

$$\theta_{i,d} = n_{k(i),i,d} / n_{i,d} \qquad (5-2)$$

To focus on the land use type at location i, $\theta_{i,d}$ is calculated for the land use type $k(i)$ at location i.

Rather than using the total cell counts in the denominator, we instead will use averages based on the numerator ratio. The first part of this denominator is the average of $\theta_{i,d}$ for all those cells where the land use at location i is k,

$$\bar{\theta}_{k,d} = \sum_{i \in N_k} \theta_{i,d} \Big/ N_k \qquad (5-3)$$

where N_k is either the set of cells with land use type k or the number of cells with land use type k, as indicated by the context. There will be one value of $\bar{\theta}_{k,d}$ for each land use k. The second part of the denominator is the mean of all values of $\theta_{i,d}$ over all grid cells:

$$\bar{\theta}_d = \sum_{i \in N} \theta_{i,d} \Big/ N \qquad (5-4)$$

which results in one value for the entire study area.

Analogous to the spatial enrichment of Verburg et al., (2004a), we calculate a "neighbourhood strength" value $\tau_{i,d}$ for each location i as:

$$\tau_{i,d} = \frac{n_{k(i),i,d}/n_{i,d}}{\bar{\theta}_{d,k}/\bar{\theta}_{d}} = \frac{\theta_{i,d}}{\bar{\theta}_{d,k}/\bar{\theta}_{d}} \qquad (5-5)$$

This is the measure we will use in what follows to include a spatial effect in a land use forecasting model.

With a bit of manipulation, we can establish that $0 < \tau_{i,d} < 1$. That $\tau_{i,d}$ is greater than zero follows immediately from the fact that all terms in the definition are positive. Replacing all the elements of the definition of $\tau_{i,d}$ by their definitions, in terms of primitives alone, we get

$$\tau_i = \frac{n_{k,i}/n_i}{\left[\sum_{j\in N_k}(n_{k,j}/n_j)/N_k\right]/\left[\sum_{j\in N}(n_{k,j}/n_j)/N\right]} \qquad (5-6)$$

Where to simplify the exposition we have dropped the subscript d and the location argument for k. j indexes grids of type k when $j \in N_k$ and indexes all grids when j∈N. Rearranging yields

$$\tau_i = \left(\frac{n_{k,i}}{n_i}\right)\left(\frac{N_k}{N}\right)\left(\frac{\sum_{j\in N}(n_{k,j}/n_j)}{\sum_{j\in N_k}(n_{k,j}/n_j)}\right) \qquad (5-7)$$

For this number to be less than one, the denominator must be larger than the numerator, or the difference,

$$N n_i \sum_{j\in N_k}(n_{k,j}/n_j) - N_k n_{k,i} \sum_{j\in N}(n_{k,j}/n_j) \qquad (5-8)$$

must be positive. If we assume that the interior of the grid is large relative to the edges, or that the grid wraps a sphere so that there are no edges, then n_j is constant and can be factored out of the sums. After factoring, we are left with

$$N \sum_{j \in N_k} n_{k,j} - N_k \left(\frac{n_{k,i}}{n_i}\right) \sum_{j \in N} n_{k,j} \tag{5 – 9}$$

The upper bound of the left sum is $N_k n_i$ and for the right sum it is $N n_i$. Inserting these upper bounds and we get the difference as

$$N N_k n_i - N N_k n_{k,i} \tag{5 –10}$$

which is greater than or equal to zero, as $n_{k,i} \leq n_i$. This therefore establishes that our measure cannot exceed one.

As an example, consider Figure 5-1. We can calculate the "spatial enrichment" measure of Verburg et al., (2004a) and components of our proposed method for three land use types. Consider only the shaded area is as our area of interest in Figure 5.1. The number grids occupied by each land use and the total numbers of grids in our area of interest are $N_1 = 4, N_2 = 3, N_3 = 2\ and\ N = 9$ respectively (Equation 1). We also include a surrounding ring of land use types in our calculations for edge effects.

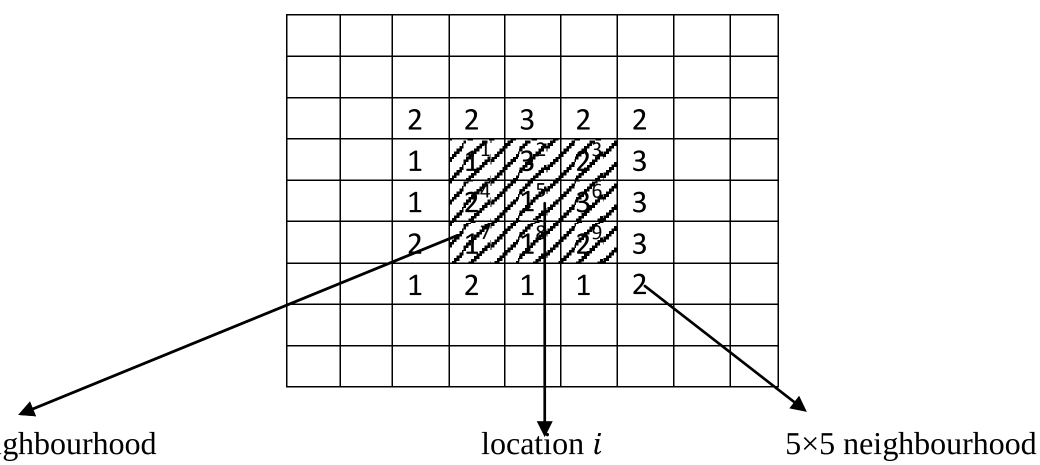


Figure 5.1: Hypothetical land use arrangement in an area for three land use types (Superscript in the shaded area refers the grid ID)

The values for average neighbourhood association of each land use types at 3 × 3 neighbourhood are $\bar{\theta}_{d,1} = 0.5278, \bar{\theta}_{d,2} = 0.2593\ and\ \bar{\theta}_{d,3} = 0.4444$ and the overall average neighbourhood association for our area of interest at 3 × 3 neighbourhood is $\bar{\theta}_d = 0.4198$ (Equations 5-3 and 5-4; Figure 5-1). The "neighbourhood strength" proposed in this study shows, these values are always ≤ 1 (Table 5-1).

Table 5.1: The "spatial enrichment" and the spatial association measures for Verburg et al., (2004a) and our methods to explain the calculation steps

Grid ID	$k(i)$	Verburg et al., (2004a) measures				$\theta_{i,d}$	$\tau_{i,d}$
		V1	V2	V3	V(i)		
1	1	1.00	1.00	1.00	1.00	0.44	0.35
2	3	0.50	1.33	1.50	1.50	0.33	0.31
3	2	0.25	1.00	2.50	1.00	0.33	0.54
4	2	1.50	0.67	0.50	0.67	0.22	0.36
5	1	1.00	1.00	1.00	1.00	0.44	0.35
6	3	0.50	0.67	2.50	2.50	0.56	0.52
7	1	1.50	1.00	0.00	1.50	0.67	0.53
8	1	1.25	1.00	0.50	1.25	0.56	0.44
9	2	1.00	0.67	1.50	0.67	0.22	0.36

As an example, consider Figure 5-1 again. At location i, in the center, the land use type is pasture (1). This is $k(i)$. There are four cells with this land use type in the 3×3 local neighbourhood, resulting in $\theta_{1,3} = 4/9$, where '3' indicates the neighbourhood (equation 5-2). Moving to the 5×5 local neighbourhood, $\theta_{1,5} = 9/25$. Similarly, one can calculate for number of neighbourhood dimension to measure the neighbourhood association.

The proposed method uses the mean spatial association of a given land use type in relation to the mean spatial association of the study area to compute the local spatial association at a given location. We see this approach as offering a simple interpretation. It is loosely analogous to a correlation measure, lying between zero and one, being equal to one if all the cells in an area are occupied by a single land use category.

The calculations can all be done using a spreadsheet. The "neighbourhood strength" value ($\tau_{i,d}$) of each grid was used as an explanatory variable in the land use category logistic regressions used as inputs for a CLUE-S land use change simulation.

5.3.2 Implementation of Dynamic Simulation

As land use patterns change over the course of a simulation, measures of spatial association will also change. If such measures are serving as drivers in the forecasting model, then they should be updated as the simulation proceeds. Figure 5-2 illustrates such a changing land use pattern, and can be used to show the consequent change in the calculated local spatial association.

Initial Pattern

P	**P**	**P**
P	**P**	**Fa**
C	**C**	**P**
C	**R**	**R**

After 3 Years

P	**P**	**P**
P	**C**	**Fa**
C	**C**	**P**
C	**R**	**R**

After 5 Years

P	**P**	**P**
P	**C**	**Fa**
C	**C**	**P**
P	**R**	**R**

After 7 Years

P	**P**	**P**
C	**C**	**Fa**
C	**C**	**P**
R	**R**	**R**

(C – Cultivation land; Fa – Farm area; Fr – Forest and range; P – Pasture and Forage; R – Residential and Built area)

Figure 5.2: Hypothetical land use change over the time in an area

After three years, the local spatial association measure based on a 3×3 neighbourhood for the cell that changed from **P** to **C** has changed, as well as for all cells of type **P** and **C** that include the one which has changed in their neighbourhood. This will be eight cells. When year five arrives, three further cells will have changed local spatial association values, and from year five to year seven, seven cells will have changed values.

For land use change models that do not enable continual updating of variables, dealing with these dynamic effects requires running the model as a sequence of short simulations, where dynamic drivers are updated between each short simulation. Implementation of this approach requires choosing how long each simulation step should be. This choice is a tradeoff between the accuracy of the dynamic variables and the burden of repeatedly updating data sets and variables and restarting the simulation. We chose to explore the impact of dynamic updating using three and five year long simulation steps, as well as running the simulation for the entire 40 year interval to 2050 with no updating. This enables us to detect any bias introduced by not updating our endogenous variable. To make the simulations consistent, we also had to break the aggregate changes projected for the 40 year simulation interval into smaller changes for each of our short simulation intervals. For example, in the case of a 5 year interval, the first simulation will be executed from 2010 to 2015 and the 2015 land use map will be used to estimate the spatial neighbourhood association (neighbourhood strength) for 2015. The estimated spatial neighbourhood strength serves as the value for land use simulation from 2016 to 2020. This step will be repeated at five year intervals to calculate the spatial neighbourhood strength values for entire simulation (Appendix E-1).

5.3.3 CLUE-S System

CLUE-S is a popular example of a pattern based land use modelling system (Neumann et al., 2011; Hurkmans et al., 2009; Castella et al., 2007; Wassenaar et al., 2007; Verburg et al., 2005). CLUE-S evolves a gridded map of the study landscape forward, changing the land use of individual grid cells consistent with a probabilistic transition model (see the manual for a complete description, Verburg, 2010). CLUE-S is calibrated using an observation of the landscape at one point in time, where multiple variables are observed for each grid cell. The observed relationship between land use and the explanatory variables is assumed to continue forward in time and to be constant across the landscape. This is unrealistic for variables that are impacted by land use, and particularly for variables that are derived from the land use pattern. Trend changes in aggregate land use types across the study are taken from other sources. The CLUE-S model changes the land use type of individual grid cells over the length of the simulation to match the provided aggregate change.

There are three main inputs required by CLUE-S: 1) trend changes in aggregate areas of each land use type; 2) logistic regression coefficients relating land use type to explanatory variables; and 3) transition and spatial characteristics. Trend changes are taken from other estimations. They might reflect population growth or simply capture historic trends. The logistic regression (forward conditional stepwise) relates observed land uses to driving variables. Local spatial neighbourhood strength is one of the drivers we use in our simulations. The Receiver Operating Characteristic (ROC) curves, which measure the sensitivity of the model, are used to diagnose the strength of each land use model (Pontius and Schneider, 2001). Identification of the important driving variables is a key part of the research challenge. The transition characteristics include the direction of change and the inertia against change. For example, in our simulation, land that changes from forest to any other land use is likely irreversible, just as land use change from almost any use to residential is. Some land uses, such as perennial crops, may be more 'sticky' than others. The transition characteristics – elasticity and iteration probability – reflect these properties.

Our measure of local spatial association (neighbourhood strength) will not be constant over the run of the simulation for the neighbourhoods of any cells where land use change occurs. In this example, we only consider the dynamics of the spatial association measure, and modify the simulation as described above to observe the impact of dynamic updating on the simulation results.

The computations were fully implemented in Microsoft Excel™. The other methods we encountered appeared to be more complex than this. For cellular automaton models, the updating is built into the models. Where statistical analysis are undertaken on forecasting results, software and skills beyond those required for spreadsheet are likely needed. Our approach is therefore simpler to implement and available to anyone undertaking a land use modelling exercise.

5.3.4 Application of the Proposed Methodology

The land use change projection was implemented for the Deep Creek watershed in the north Okanagan Valley, in the southern interior of British Columbia (Figure 1-2). The Deep Creek watershed lies between latitude**:** 50° 19' 56" and 50° 38' 29" N, and between longitude**:** 119° 1' 58" and 119° 19' 59" W. It covers an area of 230 Km^2 and includes the City of Armstrong and Township of Spallumcheen. It cuts across the boundary of Columbia-Shuswap regional district (CSRD) and regional district of North Okanagan (RDNO).

The elevation of the southern part of the watershed ranges between 340 – 520 meters, while the northern part of the watershed ranges from 370 – 1575 meters above sea level (Ping et al., 2010). Forestry, agriculture, manufacturing and tourism are all important economic activities in the watershed areas. Agriculture is the most important industry in this area. Activities that can be categorized as cattle farming are the most common, representing about 21% of all agricultural operations in the Township. Other relatively important farm types include hay and forage operations (17.2%), horse and pony (15.2), poultry (6.8), and dairy (6.1%) (Zbeetnoff, 2006).

The land use map of the study area is the heart of this study. A land use land cover map was obtained from a survey conducted by AAFC and BCMAL (2007). Where there were data gaps, other land use land cover maps (BCMAL, 2005) obtained from the provincial ministry were used, with these gaps mostly the north part of the watershed. These maps were used to derive the major land use category for each grid in the study area. For modelling purposes, the data were mapped onto a 500m × 500m grid. Further detail on how the major land use categories were determined, how variables were calculated, and how the model was calibrated is explained in Chapter 2.

We chose five main land use type categories: cultivation land, livestock farm, forest and range land, pasture and forage land, and residential and building area (Figure 2-1). The total area covered by each major land use category was estimated and this information serves as the initial input for aggregated land use demand (non spatial demand) for the simulation. This information and the historical growth of each land use category was used to extrapolate (simple trend extrapolation) to estimate the future land use demand for each land use category. The major land use category for each grid arranged in the gridded data frame was used to compute the local spatial association for each grid. Biophysical, socio-economic, soil related, and water resources variables (adjusted for the spatial extent of piped water services) were assessed for their role as land use change drivers.

5.4 Results

5.4.1 Change of Spatial Association

The mean local neighbourhood association ($\bar{\theta}_{k,d}$) and the grand mean of local neighbourhood association ($\bar{\theta}_d$) decrease with the increase in the neighbourhood dimension (Table 5-2). This reveals the fact that the spatial strength (closeness of a given land use category in its vicinity) decreases with increase of distance. However, when we considered the mean neighbourhood association ($\bar{\theta}_{k,d}/\bar{\theta}_d$) in relative terms (in relation to mean neighbourhood association of the study area) for each land use category, the forest and range land showed an increase in the mean relative ($\bar{\theta}_{k,d}/\bar{\theta}_d$) neighbourhood association with the increase of neighbourhood dimension (Table 5-2). This may be due to scattered forest fragments along the interface between forested areas and other land use types and increase in dominance of forest and range land with the increase in neighbourhood dimension.

Table 5.2: Variation in mean local neighbourhood association ($\bar{\boldsymbol{\theta}}_{k,d}$) and relative neighbourhood association ($\bar{\boldsymbol{\theta}}_{k,d}/\bar{\boldsymbol{\theta}}_d$) for each land use category at varying neighbourhood levels

Land use Category	**3 by 3**		**5 by 5**		**7 by 7**	
	$\bar{\theta}_{k,d}$	$\bar{\theta}_{k,d}/\bar{\theta}_d$	$\bar{\theta}_{k,d}$	$\bar{\theta}_{k,d}/\bar{\theta}_d$	$\bar{\theta}_{k,d}$	$\bar{\theta}_{k,d}/\bar{\theta}_d$
Cultivation Area	0.3598	0.5312	0.2586	0.4226	0.2092	0.3619
Livestock Farm	0.2755	0.4067	0.1753	0.2866	0.1437	0.2486
Forest and Range	0.8545	1.2615	0.8157	1.3332	0.7942	1.3739
Pasture and Forage	0.4721	0.6969	0.3741	0.6115	0.3227	0.5583
Residential and Built area	0.4725	0.6976	0.3503	0.5726	0.2825	0.4888
Grand Mean ($\bar{\theta}_d$)	0.6774	1.0000	0.6118	1.0000	0.5781	1.0000

5.4.2 Regression Analysis

Parameter estimates and goodness of fit measures for the logistic regression results for each land use category are presented in Table 2-2. All the models are significant at 0.1 % error level (prob< 0.001) and ROC curve results suggest that the models are appropriate for inclusion in the simulation.

Our key variable of interest is local (spatial) neighbourhood strength (Equation 5-5). In the regression results, it is significant for pasture and forage land ($\tau = 0.9928, p, 0.0013$), cultivation land ($\tau = 0.7852, p < 0.048$) and livestock farm ($\tau = 0.8911, p < 0.0335$), while it is insignificant for the residential and built land use category. The neighbourhood strength was not included in the predictive model for the forest and range land category as the results are not reasonable (sign and magnitude) for other driving factors. This is a residual category that is converted to the other land use types, making spatial association a nonsensical driver.

5.4.3 Simulation Output

The variations in mean local neighbourhood association for three year dynamic interval was plotted (Figure 5-3). The trend in the mean local neighbourhood association showed the same pattern over time for a five year dynamic interval and for static simulation though the magnitude of change is different. Recall that the static simulation is the case where the neighbourhood association measure is not updated. The mean local neighbourhood association of the livestock farm category declines over time while for all other land use categories the spatial association increases irrespective of the time interval (Figure 5-3). The decline of the mean local neighbourhood association in the livestock farm land use category is consistent with the extent of the loss of livestock farm area. Land in this category is becoming more fragmented as some is converted to other uses. The neighbourhood association value of the livestock farm category is the lowest for the initial time period and continues to be the lowest among all the land use categories. The mean local neighbourhood association of forest and range land increases over the simulation period irrespective of the time interval though the total extent of forest and range land decreases. This increase in association may be due to the conversion of scattered forests into other land use categories.

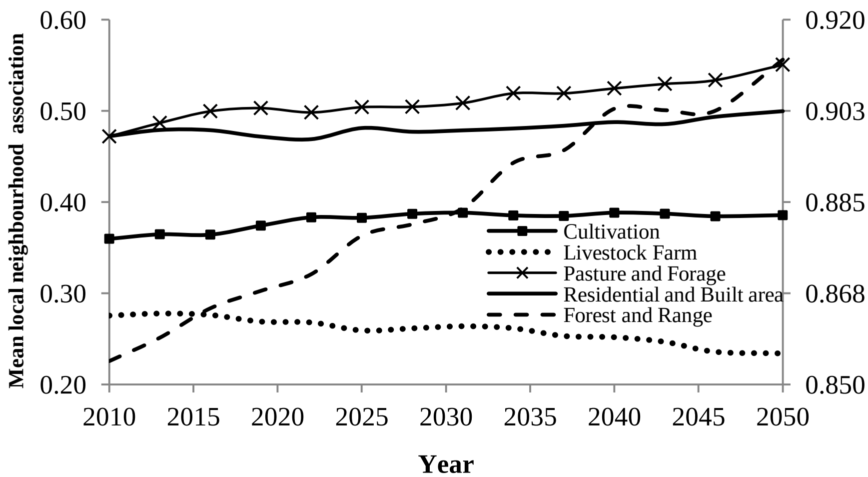


Figure 5.3: Variation of dynamic mean local neighbourhood association for each land use category over time for three year interval (Secondary y-axis for mean local neighbourhood association of forest and range land)

The projected land use change from the CLUE-S simulation is presented for the static and dynamic (three and five year intervals) simulations for 2050 (Figure 5-4). The two dynamic (regular update of information) land use changes for year 2050 (panel b, c) were compared with static (panel a) simulation results (Figure 5-4). Some variation in simulated results was observed in the maps produced in dynamic simulation compared to the static land use change maps in the north part of the watershed and middle part of the watershed. The pasture and forage land projected by the dynamic simulations is somewhat more concentrated in the

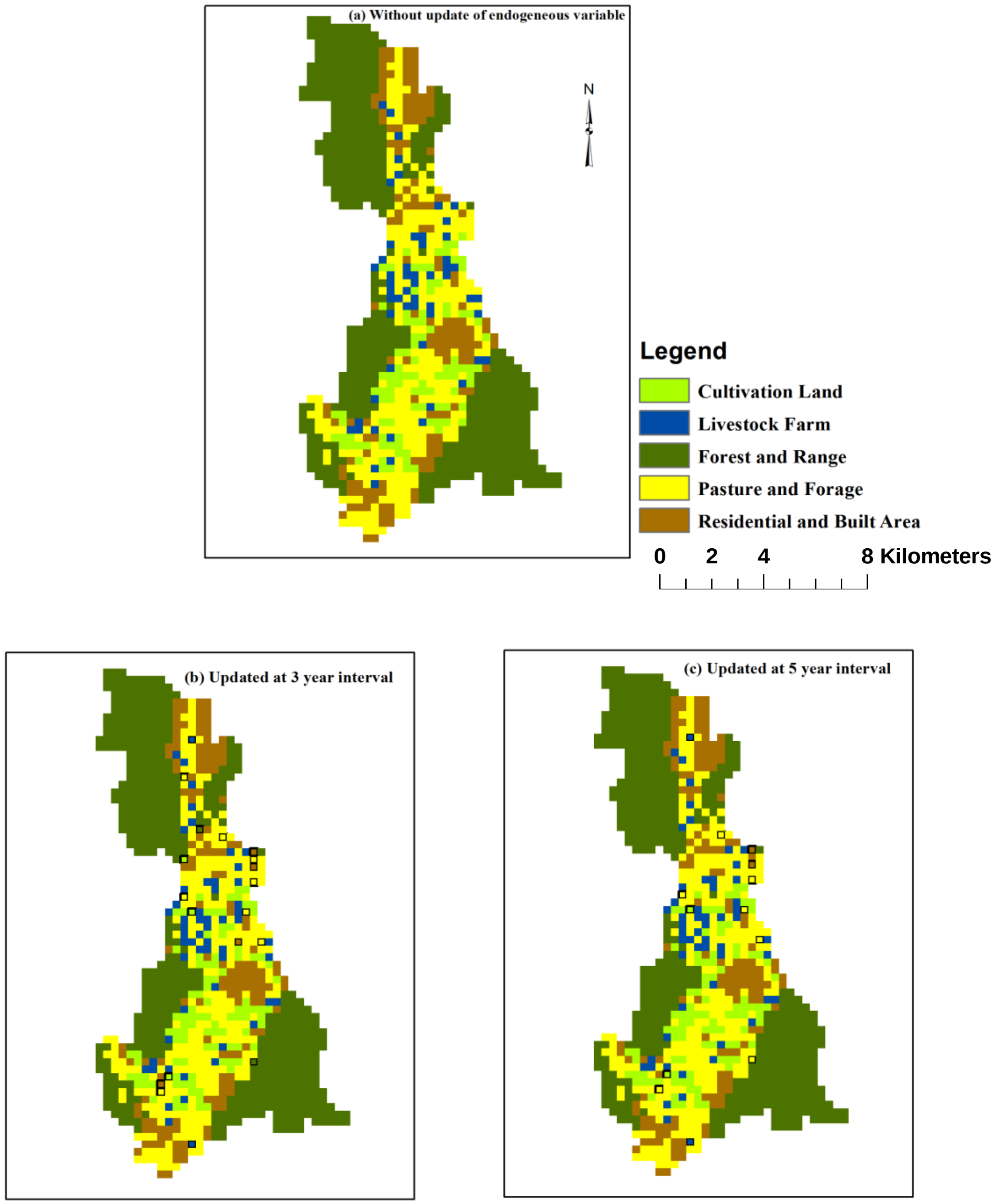


Figure 5.4: Land use change for 2050 in the Deep Creek watershed (a) without updating (static) of spatial neighbourhood strength variable and recalculating neighbourhood strength at (b) 3 year and (c) 5 year intervals. The grids that are surrounded by black lines are different in static (a) and dynamic (b.c) results

middle part of the watershed. The changes in the cultivation and residential land use categories reflect the neighborhood characteristics though the association is not as close as it is in the pasture and forage land category.

In the dynamic simulations, the question of what land use category a particular grid is going to be in the future is answered rather than whether a given cell is going to be converted or not. In essence, the dynamic simulation closely looks for the spatial change. Since the spatial land use change is different in the dynamic simulation, the dynamic and static simulation results at different temporal scales were examined to distinguish the differences. The mismatches generally increase with time, revealing the fact that the longer the projected time horizon is, the greater the mismatch (Figure 5-5). The three year dynamic update shows more mismatches than the five year update in all time intervals. The five year dynamic updates produce the same results as the static simulation in 2015 and 2030. The three year updates never match the static simulation. The 2015 result of five year dynamic simulation occurs because after five years the input into the five year update has not yet been changed. However, the reason for similar results produced in 2030 for the static and dynamic simulations with the five year update might be that the grids that were different in year 2025 changed to be a perfect match in 2030. However, what we do not know is what combination of driving factors – drivers other than spatial association – lead to this change. The percentages of mismatches to the total number of cells changed were 5.7 % and 3.9 % for the three and five year updates respectively at end of the simulation period (Figure 5-5 and Table 5-3). The mismatches observed here is only with the update of one predictive variable (measure of spatial association) with the 40 years (2010 – 2050) time horizon. This effect may be compounded if there are other dynamic variables – such as groundwater access where some land uses imply groundwater use – which are not being updated. The iteration probabilities had to be adjusted between the stepwise and static simulations. These changes were also investigated as possible sources for the deviations between the simulations, and found to have a negligible effect.

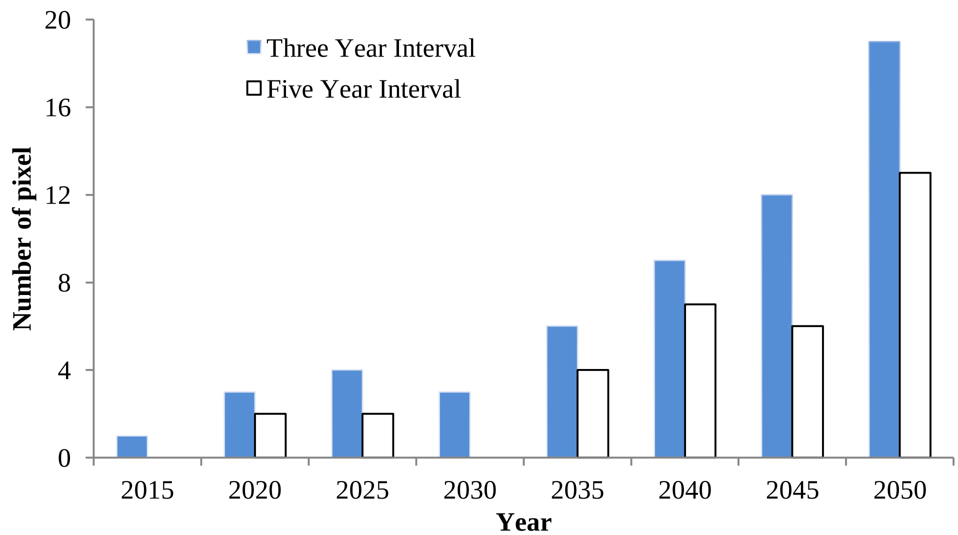


Figure 5.5: The difference (grid by grid comparison) between static and dynamic simulation (3 and 5 year intervals) projections for simulation from 2010 to 2050

Given the number of predictive variables used and the length of the time period, the aggregate mismatches are a cause for concern in such modelling. As a result, the mismatches between the dynamic and static simulations at 2050 were disaggregated across the major land use categories to examine the projection accuracy for each major land use category. The confusion matrix (Congalton and Green, 1999;1993), reporting these results, is shown as Table 5-3.

Table 5.3: The confusion matrix of static and dynamic simulation projection differences in both 3 and 5 year intervals

		Dynamic 2050					
		Cultivation	Livestock Farm	Forest & Range	Pasture & Forage	Residential & built area	Total Static
Static 2050	Cultivation	99 (100)	0 (0)	1 (0)	1 (2)	1 (0)	102
	Livestock Farm	0 (0)	54 (54)	0 (0)	2 (2)	0 (0)	56
	Forest and Range	0 (0)	0 (0)	510 (510)	2 (2)	0 (0)	512
	Pasture and Forage	2 (1)	2 (2)	1 (0)	273 (276)	3 (2)	281
	Residential & built area	1 (1)	0 (0)	0 (0)	3 (1)	157 (159)	161
	Total Dynamic	102 (102)	56 (56)	512 (510)	281 (283)	161 (161)	1112
No of grids changed 2010-50		19	17	148	89	58	331
Difference in projection (%)		15.8 (10.5)	11.8 (11.8)	1.4 (0.0)	9.0 (7.9)	6.9 (3.5)	5.7 (3.9)

Values in parenthesis represents the 5 year interval values

The diagonal values in the matrix show the number grids in agreement between the static and dynamic simulations. For example the first diagonal value, 99, shows that 99 of the 102 cultivation land use grids match between the static and 3 year updates, and 100 match for the 5 year updates. The off diagonal values show the cells that change. Reading along rows reveals what category the changed cells from each of the static simulation become. Reading down the columns reveals the source of the cells in the dynamic simulation that are not the same as in the static simulation. For example, when we consider the first row, the static simulation projects 102 grids as cultivation land use (total along the row). Of these, 99 grids at the same location are also cultivation land with the three year updating. For the three that do not match, the three year update projects one each as forest and range, pasture and forage, and residential and built area. Simultaneously, the five year dynamic interval agrees with 100 grids in the static simulation and it simulates the other two grids as pasture and forage lands.

When we read down a column in Table 5-3, we are looking at the way projections from the stepwise updating differ from the static simulation. The three and five year updates both project 102 grids as cultivation land use (total along the column). The number of grids in agreement by the dynamic and static simulations is same as in the static case. We now see that of the three grids that do not match for the three year updates, two are pasture and forage and one is residential and built area in the static simulation. For the five year updates, one is pasture and forage and one is residential and built area. When the individual differences are calculated for each land use category, the deviation is more than 10 % for the cultivation land and livestock farm categories. Disaggregating the results in this way demonstrates that for some land use categories, ignoring the evolution of dynamic spatial variables can substantially bias simulation results.

5.5 Discussion

The relative neighbourhood association ($\bar{\theta}_{k,d}/\bar{\theta}_d$) proposed in this study demonstrated that it is a fairly useful indicator of spatial neighbourhood association at varying neighbourhood dimensions. It also takes account of total neighbourhood association for a given land use category against that of the whole study area. Hence, it gives the measure of relative spatial neighbourhood strength of a given land use category in the study area. Further, it is also a useful measure for computing the value for spatial neighbourhood strength (for each analysis units / grids), which paves the way to model spatial association as an explanatory variable along with other driving factors of land use change in the regression. Thus, the relative neighbourhood association ($\bar{\theta}_{d,k}/\bar{\theta}_d$) used in this study is a useful measure for assessing spatial strength of each land use category as well as modelling the influence of spatial association on land use change.

The spatial association (neighbourhood strength) is positive and significant for three land use categories (cultivation land, livestock farm, and pasture and forage) of the four models where it was included. Moreover, the magnitude of this variable (relatively higher parameter estimates compared to other variables) explains the predictive power of this variable. The spatial association is one of most important variables among all the explanatory variables in determining the conversion of a given plot of land into these categories (Table 2-2). It was only insignificant for residential and built areas, likely because population density was included as a driving factor, and it probably captures most of the effects that would be captured by spatial association.

Including spatial association in a forecasting model is a way of incorporating the influence of drivers that vary over space but are not included in the model. Ideally all these drivers could be measured and a richer model estimated. However, often the data do not exist or cannot be measured at a fine enough resolution. Failure to include spatial association effects will attribute a proportionately greater influence to the other driving factors, resulting in a simulation that spreads development too strongly in response to these other drivers. The longer the length of the simulation, the larger this influence will be. Using a spatial association measure is consistent with the spatial lag regression models used in various land use analysis (Aguiar et al. 2007; Gellrich and Zimmermann, 2007; Overmars et al., 2003). Our results highlight that assuming all important spatial effects are captured by the included driving variables can miss important effects and lead to misleading results.

Dynamic updating of information is included in specific land use simulation studies. It is more commonly incorporated into cellular automata models that can change the parameter values during the simulation (Wijesekara et al, 2012). However, such models have been criticized for arbitrariness of these parameter values. Some papers were identified where pattern based land use models update driving factors (Verburg et al., 2011; Perez-Soba et al, 2010;Verburg et al., 2006) or change parameter estimates (Liu et al., 2013) during the simulation run. Changing the parameters relating driving factors to land use change as the model progresses means that forecast data are used to estimate a model that is then used to forecast. These approaches often include expert judgement in their specification and contain some arbitrary elements as was discussed for the cellular automata models above. Alternatively, regression analysis can be applied to help specify these dynamic relations (Koomen et al., 2010; Verburg and Overmars, 2007). Parameter changes and similar adjustments that reflect policy interventions which occur during the simulation run seem more reasonable, and would seem to be a more appropriate and useful use of these models. Our results show that the dynamic updating of driving variables help steer simulation results. We argue that researchers should carefully consider the feedbacks within the system that link driving variables with the land use pattern, and consider updating those that are clearly linked to the pattern of land use.

It is important to recognize that spatial association changes over time, and that this is just one example of a variable that changes over time. Variables like population density, road network and groundwater depths are also dynamic in nature and change over time. These variables are important drivers in most of the land use categories (Table 2-2). Hence, the effects of these variables in the projection output may be much higher and the results could be quite different from the one used at present. Failure to include all these evolving variables will therefore result in an inappropriate forecast pattern of land use change than is actually likely to occur.

Breaking simulations into short steps allows dynamic updating of endogenous and spatially defined driving variables. It paves the way to account for driving factors and land use itself that changes within a shorter time period than the overall simulation period. The spatial association (neighbourhood strength) was updated at two intervals in our study as a proof of concept. We acknowledge that many land use drivers are generally dynamic in nature and ideally should be updated regularly. This means that selecting an appropriate time interval to update the dynamic driving factors is essential to make the projection results more consistent with the underlying processes.

Ideally we would work with a fully integrated model that updates all dynamic variables continually. When choosing a modelling approach, the models we examined did not have this capability. Several driving factors that we use to model the land use are dynamic in nature: groundwater level, road network and population density. These would need a fairly sophisticated modelling approach to fully implement, something beyond the scope of the current project. In the absence of such integrated models, we suggest that iteration between short simulation intervals and driving variable updating provides an improvement over the practice of assuming all driving variables are constant for the duration of the simulation run.

These results are preliminary, based on updating one dynamic driving variable, our measure of spatial association. The results have not been compared to the one alternative measure of spatial association encountered in the literature, particularly that of Verburg et al., (2004a). A proper comparison would compare simulation results from both methods. Both sets of driving variables would be calculated, and updated at the same time intervals. This would be done for a dataset where land use maps at two dates are available. It can then be determined both if the dynamic updating does a better job of matching the observed changes, and which of the two methods for including neighbourhood association does the best job of matching the outcome.

Some studies indicate that the scale of analysis (in our case 500m × 500m) affects the influence of spatial association (Su et al., 2012; Lin et al., 2008; Verburg et al., 2004a,d). For example, a land use type that is a neighbour in a given scale might not be a neighbour at another scale. We do not examine the influence of different scales. This can be partially justified by the results presented in chapter 3, where the heterogeneity of land use types in the study area did not show much difference when the land use types were grouped into major land use categories. However, we acknowledge that this is a limitation, and something else to consider for further work.

The neighbourhood shapes can also influence the effect of spatial association on land use change. We have used square neighbourhoods to calculate the spatial neighbourhood strength. However, land parcels are generally irregular in shape. Representing the landscape as a grid of equal sized cells may not be the best way to capture the processes that generate neighbourhood effects. If the neighbourhood is defined by distance between cells, then a circular shape may be more appropriate (White and Engelen, 2000). Where mimicry by owners/managers is a driver, neighbourhoods based on property boundaries may be the best approach. However, the limited use of spatial association in land use modelling might further hinder by the use of more complex and advanced methods, particularly in pattern based land use models. As always, there is a tradeoff between the sophistication of the representation and the effort that it requires to implement. We suggest that an important first step is simply including and updating measures such as spatial association and assessing their value in improving forecast results.

5.6 Summary

This study identified spatial association as an important land use driver to use in models of land use change. We have proposed a simple way of incorporating spatial association into a land use change model, and shown how updating that variable during the simulation run can affect forecast results. Neighbourhood association is only one of a number of driving factors that may have an important influence on land use change. Our measure of spatial association was statistically significant in three of the four models where it was included. The statistical significance of spatial association implies that land use is more clustered than would be predicted by the other driving variables on their own. Failure to include it will therefore result in a more dispersed pattern of land use change than is actually likely to occur. Using a dynamic version of our land use change simulation demonstrated that updating dynamic variables as the model runs leads to a different forecast. The deviation increases both with the frequency of the dynamic updating and the number of periods elapsed in the simulation. The spatial land use change assessment performed in this study was based on a single variable update. Inclusion of all the dynamic driving variables will likely further change the results.

Chapter 6. Conclusions and Recommendations

Human influenced watersheds are complex social ecological systems. These systems evolve as a consequence of the interactions between a range of forces. To manage land use change, managers need to understand these forces, be able to predict how the interplay between these forces will influence the evolution of the observed pattern of land use, and in particular understand how manipulating these forces can change the way that land use changes. This thesis uses the Deep Creek watershed in the northern Okanagan Valley of British Columbia to explore:

1. The important factors driving land use change, with particular attention to spatial correlation between land use types;
2. Validation of a land use change model when only one land use map exists, through the use of remote sensing data;
3. The inherent conflict between different land use policy objectives; and,
4. The consequences of not including dynamic feedbacks between the pattern of land use and endogenous driving variables, using a measure of spatial correlation between land use types as an example.

My research into these four issues is documented in the four chapters that make up this thesis.

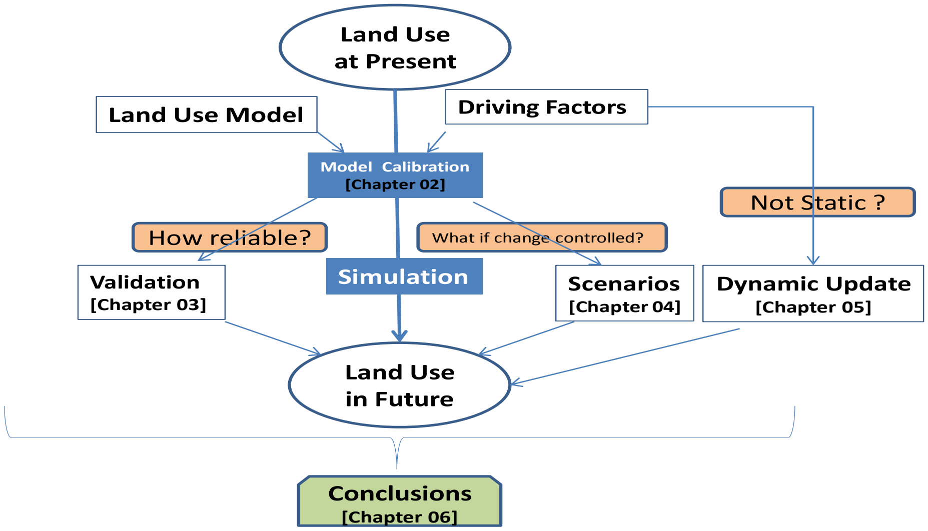


Figure 6. 1. Overview of Thesis Elements (reproduced from Chapter 1)

Figure 6.1 illustrates the components of my doctoral research. The specific objective of the project was to generate a forecast of land use for the Deep Creek watershed in the northern Okanagan Valley, a forecast which could be used together with climate change models of the area, to better forecast the impacts on the hydrology of the watershed. In addressing this specific objective, a number of more general land use modelling challenges were encountered and addressed. The way I addressed these general challenges provides insights into how to generate more effective land use forecasting models. In this concluding chapter, I will summarize my research and review these main lessons, describe some of the limitations of my results, point the direction for future research, and describe the practical application of these results for both academic and policy purposes in a number of recommendations.

6.1 Research Summary and Lessons Learned

Many findings from the four studies in this thesis present unique or incremental contribution to the existing body of literature available on land use change modelling and simulation. The following sub sections describe the findings from this research.

Model Calibration

The first challenge in any modelling exercise is deciding how the situation being studied is to be modeled, and with that which important variables will be included within the model (Chapter 2). One of my main challenges was to decide on the modelling approach. I chose a pattern based model, as pattern based models look for and build on patterns observed on the landscape. The alternative, building a process based model, would necessitate an in depth understanding of the decision processes lying behind the land uses observed on the landscape. Conducting the necessary research to identify the different types of land use decision makers and develop a reasonable representation of their decision process was beyond the scope of the specific project. By using a pattern based model, I am assuming that the underlying processes that are driving land use change are not themselves changing, at least not significantly over the length of my forecast, fifty years.

The pattern based modelling system I chose to use was CLUE-S (Verburg et al. 2002). The climate change forecasts were generated for grid cells 500 meters on a side, so I chose to develop my model to match these grids. The next step was to choose which variables to include.

As in most of the semi-arid regions of the world, water is a key input for agricultural activities in the Deep Creek watershed. Throughout much of the watershed, groundwater pumping is an important source of water for agricultural activities. There are a number of small water providers within the watershed that supply at least some water for agricultural purposes, in addition to providing potable drinking water for household uses. In my initial modelling, I used distance to surface water and depth to groundwater as driving variables. However, the results for depth to groundwater were generally affecting the model by making the other variables insignificant or having improper signs. When I differentiated grid cells based on the presence or absence of piped water – where cells with access to piped water did not have any influence from depth to groundwater or distance to surface water – model calibration improved.

Water resources are an important factor in land use decision. Both surface water and groundwater accessibility on land use change have been studied previously (Park et al., 2011; Luo et al., 2010; Valbuena et al., 2008; Verburg and Veldkamp, 2004; Verburg et al., 2004b,c). However, no land use study that included the effect of water supply infrastructure on water resources related variables in a land use change model could be found. While the presence or absence of piped water is not relevant to every land use model, all land use modellers using pattern based models should consider the underlying processes by which the variables included influence land use change. In the present case, where availability of water is an important determinant of land use choices, having access to piped water means that depth to groundwater or access to surface water are no longer important drivers of land use change. Land users simply do not need to worry about depth to groundwater or distance to surface water in their choices, as they will not be using either. The process determining land use change is different in those parts of the landscape where piped water is available. There are certainly other variables that similarly result in different land use change processes, such as access to electricity or natural gas, being on one side or the other of a natural barrier like a cliff or river, etc. *Modellers using pattern based forecasts should consider the underlying land use change processes when choosing the driving variables to include, and pay particular attention for how those processes may differ across the landscape and what variables may drive these changes.*

Another important calibration issue was the problem of omitted variables. It is not possible to identify, let alone measure, all of the important variables. If the net effect of these missing variables is equivalent to noise, then this will not be a problem. However, often omitted variable effects do not cancel out. In spatial statistical models, tests for spatial correlation in the residuals are typically conducted to test for such effects, and if they are found, forecasts can be adjusted to reflect the unexplained spatial correlation. When discrete land use types are being modeled, rather than a single continuous variable that varies over the landscape, standard statistical measures may not be valid. To account for this, I developed a simple spatial association measure, which I included as a driving variable.

The first result is that the spatial association (neighbourhood strength) was an important predictor for many land use types in the initial regressions that calibrate the forecasting system. In other words, after accounting for the explanatory power of the other variables included in the model, there was still remaining spatial correlation between land use types. This suggests that there are important driving variables that were not measured. To account for this, I then included spatial association as a driving variable in the forecast model. This is not completely valid, as the spatial association itself changes as the patterns of land use change. I address the importance of accounting for this in a later chapter.

Jacobs - Crisioni, et al., (2014) demonstrated the effect of spatial autocorrelation using spatial econometrics analysis in urban development studies. A surface suitability based weight structure was used to compute the spatial association. Dendoncker et al., (2007) stressed the importance of including neighborhood composition in the statistical model to obtain the best fit of land use distribution. These authors used a simple proportion based method along with equal weight factors to calculate neighbourhood influence. Verburg et al., (2004a) proposed "spatial enrichment" to account for spatial association in the neighbourhood. He used the proportion of land use in the immediate neighbourhood of a given grid in relation to the proportion of grids occupied by the same land use within the study area. The number of "spatial enrichment" values for a given grid cell equals to the number of land use types in the study area. Weighting methods may be arbitrary, and expanding the data set with multiple spatial enrichment measures is both confusing and likely burdened by multicollinearity. In contrast, I calculate single value for spatial association for each grid. This measure considers the relative local abundance of a cell in comparison to the average relative abundance of that cells land use type in the overall landscape. While the approach is intuitive and takes care of the weakness found in other methods, it has not been systematically compared to the other mentioned approaches. In addition, Jacobs - Crisioni, et al., (2014) demonstrated the scale and shape effect of spatial autocorrelation in urban development analysis and explained the need for small sized aerial units. The magnitude of positivity for spatial correlation expects to increase with higher resolution in landscape (Overmars, et al., 2003; Qi and Wu, 1996;

Arbia, 1989). The proposed methodology should therefore also be tested for scale and shape effects.

Failure to account for the correlation between land use types that is not explained by the included driving variables can bias results. In systems such as CLUE-S, the driving variables determine how an externally chosen total amount of land use change is distributed across the landscape. If there is remaining spatial correlation in land use types, then failing to include a measure of spatial correlation means that the distribution of the land use change is determined exclusively by the included driving variables, giving them too much weight and leading to a land use change forecast that does not properly reflect the correlation between land use types. *Modellers should check for remaining spatial correlation after controlling for the influence of their driving variables, and if correlation exists, should incorporate spatial correlation into their forecasting models.*

Model Validation

Before asserting that a model can be used to inform management, it is important to establish that the forecasts are valid (Chapter 3). The standard way to validate a model is to run the model between two periods where the pattern of land use is known at both periods. One reason why validation is often not done for land use models is that observed patterns of land use often do not exist for two different periods in a way that can be used to validate the model. The present case had this problem; only one detailed map of land use types existed. To overcome this problem, I had to generate a historic map of land use types using remote sensing data (Wang et al., 2013; Castella and Verburg 2007; Thenkabali et al., 2005; Roberts et al., 2003)

The raw land use type map used to calibrate the model had a large number of land use categories. These represented different crops, classes of build area, etc. For the forecast, these land use types were aggregated into five land use categories. To align with the remote sensing data, the raw land use types were used, except where there were too few observations. Each land use type was assumed to have an identifiable reflectance pattern, a pattern that could be used to identify land use types in historic remote sensing images where a reference land use map was not available.

To generate a historic land use map, I generated a discriminant function from the known land use map and Landsat images. I used this discriminant function to classify fine resolution grid cells on the historic Landsat images, using the same reflectance bands as used to generate the discriminant function (Amato et al., 2013; Riveiro-Valino et al., 2009; 2008; Davidson et al., 2007). With the land use types now assigned to the fine resolution grid cells, I conducted the same aggregation process on this historic assignment as I had done on the original land use map, to generate the land use map used for the forecast. I then ran the simulation model backwards, starting with the actual land use map and forecasting the placement of the aggregate changes observed between the land use map date and the generated historic land use map. Comparing the generated historic land use map with the model 'back-cast' provided me with the ability to compare model forecast results with estimated observed results, to provide an approximate validation of the model. *Land use modellers should take advantage of the widely available remote sensing data to construct estimated historic land use maps and use these to validate their models.*

In the literature, I found some debate about the appropriate way to compare two maps. The conventional approach is to compare each grid cell. This ignores 'near misses', with these being likely with a probabilistic forecasting system such as CLUE-S. CLUE-S is probabilistic, in the sense that it determines a probability of transition between land use types, based in part on a probabilistic relationship between land use types and driving factors. The observed transitions are realizations of an underlying process, realizations which are drawn from a distribution of possible transitions. Near misses – where the forecast transition occurs in a nearby grid cell with similar values for the driving variables - are a much less serious strike against the forecasting model than 'far misses' – where the forecast transition occurs for grid cells that are either spatially, or in relation to the driving variables, radically different than the observed transition. Inspired by Pontius (2002), I calculated both conventional cell by cell validation measures, as well as a set of multiscalar measures that accommodates near misses. The forecast fit, which is within the range of other modelling exercises for the cell-by-cell measures, improves rapidly as the scale is increased.

My choice of this multiscalar approach is inspired by Pontius and Millones (2001). The multiscalar approach accounts for near / far misses and is easier to execute than more complex methods like Fuzzy Kappa statistics (Hagen Zanker, 2009; Munroe and Muller, 2007; Visser and De Nijs, 2006; Pontius, et al., 2004; Hagen, 2003). Pontius and Millones, (2011) who themselves extensively worked to improve the Kappa statistics, have come to advocate for the simpler multiscalar approach. *Multiscalar validation measures offer an easy and intuitive option to assess the 'scale' of the forecast error.*

Comparison of Scenario Forecasts

With a calibrated and validated model, I was in a position to use the model for forecasting purposes (Chapter 4). This meant I had to choose policy scenarios. Scenario analysis is very common in land use change modelling (Hopkins and Zapata, 2007; Solecki and Oliveri, 2004). Scenario analyze can evaluate different future possibilities, either as different policy choices or as a way of accounting for uncertainties. The scenario results that provide information for stakeholders and policy makers which can help to improve land use management decisions (Koomen et al., 2008; Shearer, 2005; Clarke and Xiang, 2003). I chose scenarios that incorporated four different combinations of restrictions on the transitions between land use types. These scenarios loosely reflected policy goals stated in planning documents of the local governments in the area. The business as usual scenario did not implement any restrictions. One development scenario prevented the conversion of forest land to other uses in part of the watershed. A second development scenario allowed forest land conversion during the first half of the forecast period, and then prevented all further conversion of forest land. The final scenario combined the two restrictions, implementing a restriction in forest land conversion for part of the watershed from the beginning, and preventing all conversion of forest land after the first half of the forecast period.

Land suitable for agricultural purposes is limited and different measures are in place to protect agricultural land from development. Public opinion in the province strongly favors protecting a degree of food sovereignty, and to accomplish this, land within the province with the capacity to produced food has been zoned for agricultural use. This zoning puts strong limitations on the use to which land can be used. While public opinion strongly supports this zoning, it restricts what land owners can do with their land, and consequently land owners in areas where the value of putting the land to a use that is not 'compatible' with the agricultural zoning have a strong incentive to apply to have their land excluded from the agricultural zoning. Given that there is a process for removing land from the agricultural zoning (BCPALC, 2010), it is a 'weak' constraint on land use change. The agricultural zoning classification of the land was therefore not included as a driving variable. Rather, the pressure for conversion of land zoned for agriculture was compared under the different scenarios related to limiting forest conversion.

A key insight from comparing the scenario results is that stronger protection of forest (or undeveloped) land puts greater pressure on the land that has been zoned for agriculture. This interaction is not surprising when one considers the system as a whole. However, the responsibility for managing land use change is distributed between different agencies and different levels of government. The management of and disposal of provincial crown lands is not the responsibility of the same agency that manages the agricultural zoning policy. Approval of building permits and conversion of land that is outside of the agricultural zone – land which may be in use for agricultural or in an undeveloped state – is typically the responsibility of local government. My results highlight the fact that the decisions made by these different levels of government have interconnected impacts, and that effective management of land use change should consider these interactions. *Decision makers who influence the land use change process need to consider how their decisions impact on the 'multifunctional' services provided by the landscape they are influencing, rather than restricting themselves to considering only the immediate and local impact of their decisions within the confines of their mandate. Governments need to adjust the mandate of those delegated with approval authority for land use change so that impacts across the landscape and implications for a range of land use objectives are considered.*

Exploring Dynamic Variables

The spatial correlation between land use types was shown to be important during model calibration. The land use observed at one grid location is related to the land use observed at nearby grid locations. The influence of such neighbourhood relations underlies the family of cellular automata based land use models (Hagoort et al., 2008; Geertman et al., 2007; Hagoort, 2006; Engelen et al., 2003; Jenerette & Wu, 2001; Torrens & O'Sullivan, 2001; Candau, 2000). As land use evolves, measures of spatial association in the neighbourhood of changing grid cells also changes. Assuming that these spatial association measures remain constant over the duration of the forecast is therefore not valid. This is the final challenge I turn to as part of my research (Chapter 5).

Many pattern based land use forecasting systems do not allow driving variables to be updated during the forecast run. Some of these variables are endogenous, being themselves impacted by the changes in land use. To deal with this, I chose to generate the overall forecast as a sequence of short forecasts, with the spatial association updated between each of these short forecasts. I then compared the forecast without updating to that with updating every three years and every five years. The difference between the forecast without updating and those with updating increased with the number of years into the forecast, and increased more rapidly for the three year updating compared to the five year updating.

Using dynamic variables as I have done blurs the line between pattern based and process based forecasting models. Updating as I have done makes the pattern at any date dependent on the pattern at the previous date. The conventional approach does not permit this type of relationship. The specific goal of this research project sought to forecast land use change to improve the accuracy with which the impacts of climate change on the hydrology of the Deep Creek watershed could be estimated. Land use change will likely change the pattern of groundwater use across the watershed, which will impact on the level of groundwater in many parts of the watershed. The depth to groundwater is an important determinant of the cost of pumping water, which means that the depth to groundwater may influence land use change. Therefore, depth to groundwater would be a candidate for dynamic updating in my model. Variables like local pollution (noise, smell, etc.), visual impacts of land use types, shading, pollination services, and similar variables will be dependent on the pattern of land use, and will change as that pattern changes. *Land use modellers should carefully consider the feedbacks between land use change and driving variables, and where these influences are important, modify their forecasting models to accommodate dynamic updating of these drivers. Those developing land use modelling systems should incorporate procedures to update driving variables, specifically the land use change driven endogenous variables, either through internal updating functions, or by enabling linking to external programs at each step of the forecast to enable driving variables to be updated.*

6.2 Limitations and Directions for Future Work

My results, like those of many pattern based models, depend on the assumption of fixed driving variable. I have explored the consequences of this assumption being incorrect, and demonstrated that when this assumption is incorrect, bias is introduced. However, I have assumed that all but the spatial association variables are unchanging over the duration of the simulation run.

The specific project objective was to forecast land use change so that changes in water use could be more accurately represented in a model of the impacts of climate change. However, the availability of water may itself be an important driver of land use change, and that availability may change in response to the changed land use pattern. This is a feedback that ideally would be modeled in a coupled hydrologic and economic system. One direction for further work is to develop such a model. It may be possible to extend the stepwise updating that was demonstrated in Chapter 5, or it may necessitate building a more process oriented model that incorporates both the process driving land use change and the hydrologic processes of the watershed.

I have asserted that ignoring spatial association will result in a more dispersed land use pattern – or at least a stronger relationship between driving variables and the forecast land use pattern. I have not tested this. Using multiscalar measures of forecast error within the validation I conducted, and comparing tests of clustering between forecasts made with and without spatial association could provide some insight into the impact of ignoring this variable. Similar tests could be conducted to expand the simple cell by cell assessment of the impact of dynamic updating that I have reported.

In my policy analysis, I considered four different scenarios, all of which consisted of different combinations of restrictions on land use change. The aggregate changes in land use types, an input into CLUE-S, were the same for all four scenario runs. These aggregate changes were conservative estimates, based on projecting historic changes and on factors such as projected population growth. Since the past need not be a predictor of the future, it would be prudent to consider more extreme changes in these aggregate measures. For example, no population growth and double the expected population growth could be some of those. Alternative policy scenarios could also be considered. In particular, the agriculturally zoned area was not a constraint on actual land use change. Restricting agriculturally zoned land to remain a validly zoned use – which in my simulation would amount to forcing all residential and built conversion to occur on land not zoned for agriculture – would be a scenario consistent with the repeated calls for a stricter enforcement of the agricultural zoning policy.

Obviously, there are alternative ways to specify driving variables and different driving variables that could be included in the model. So there is scope for further improving the model by finding new and better driving variables. In many land use models, variables such as distance to highway, distance to nearest paved road, etc. are included. For some land use types, this reflects issues like transportation costs. However, the extent of the road network is itself an investment choice on the part of government, and as soon as the road network is changed, the driving variables have themselves changed. This suggests that expansions of the road network should be seen as scenarios, with updating similar to the dynamic updating described in Chapter 5 used to evaluate the impacts. From another perspective, the inclusion of distance variables related to roads and other physical infrastructure is based on the assumption that such physical infrastructure will be expanded smoothly along its existing margin. This suggests that an alternative to my characterization of the impact of access to piped water may be to include distance to piped water.

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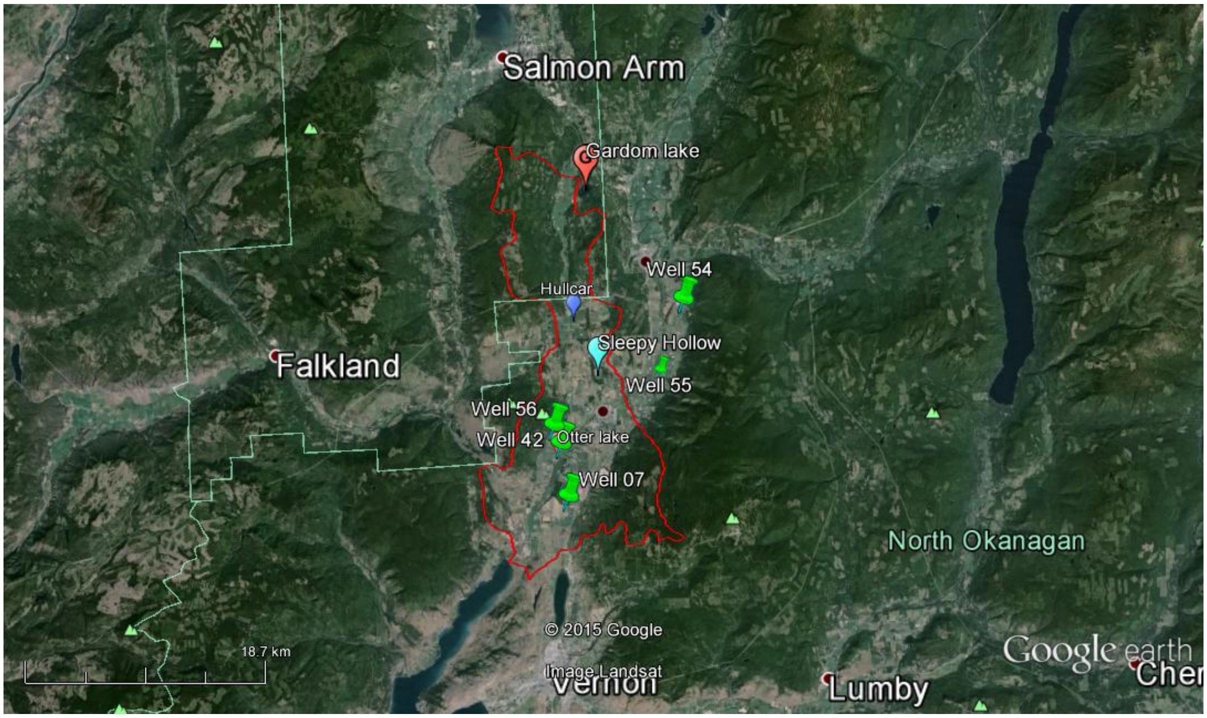
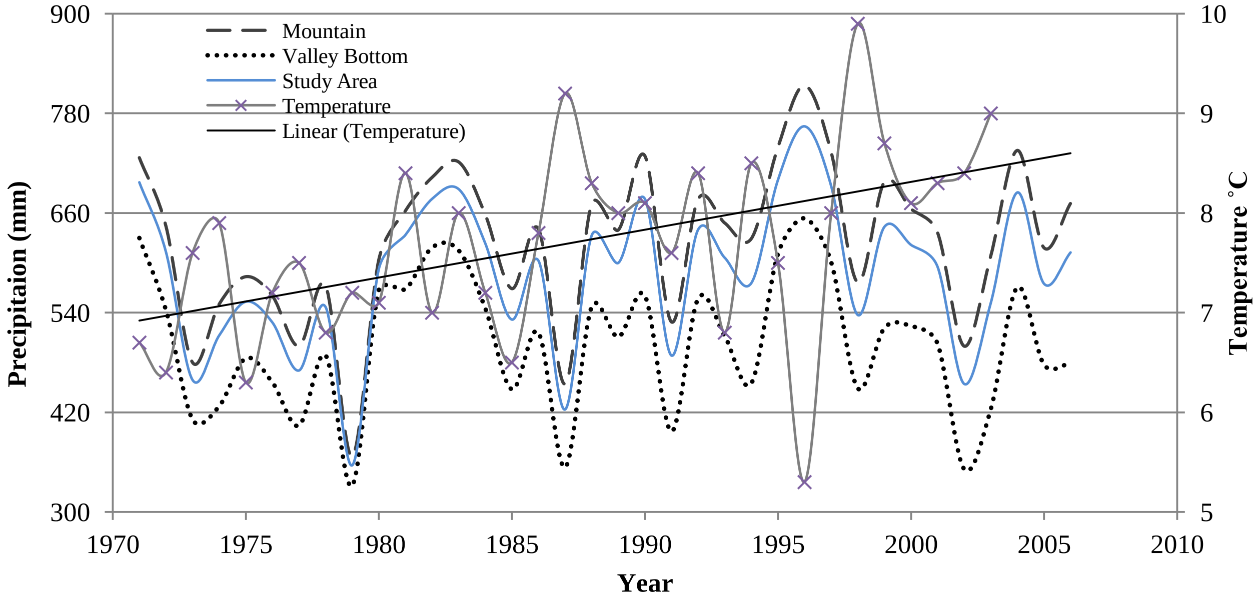
Appendices

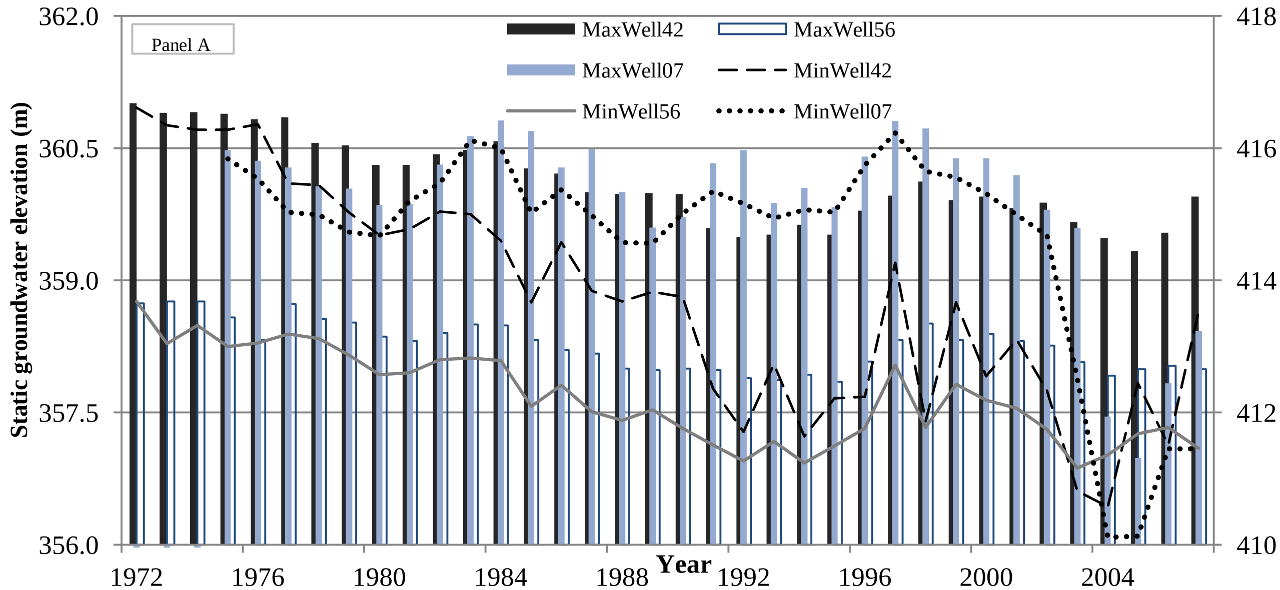
Appendix A-1: Well locations and other important locations in and around the Deep Creek watershed. Image generated using Google earth (2014)

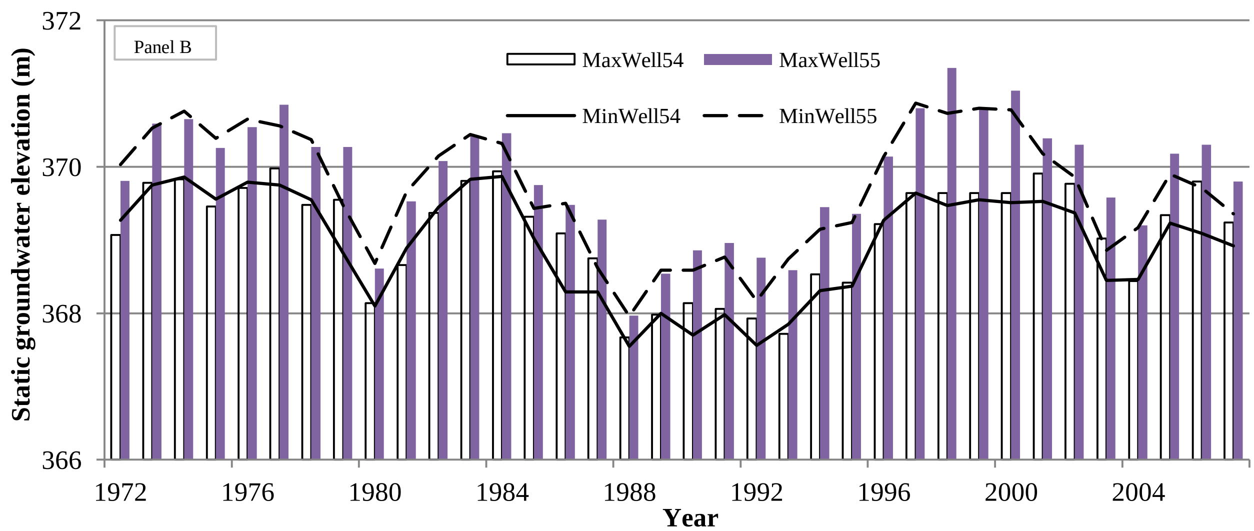


Appendix A-2: Historical variation in precipitation (mountain area, study area, valley bottom) and temperature (valley bottom) from 197 –2006 in the Deep Creek watershed



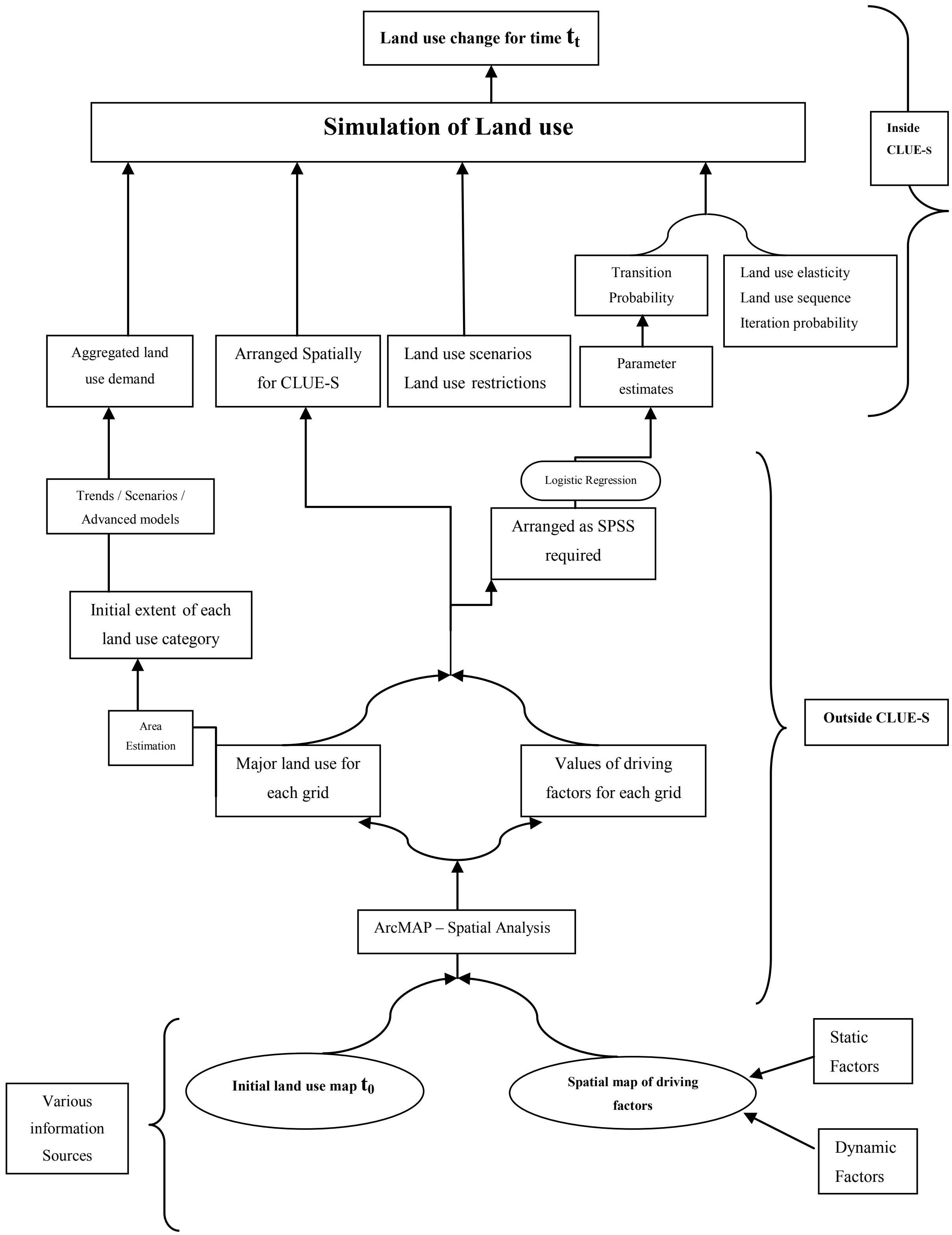
Appendix A-3: Historical variation of spring - maximum and summer minimum static groundwater levels in BCMOE monitoring wells[1] (a) 7, 42, 56 - inside the study area and (b) 54 and 55 adjacent to the study area from 1971 - 2008 (Data Source: BCMOE)





[1]Well Tag Number of wells 7, 42,54,55 and 56 are 32340, 24104,24093,24080 and 24062 respectively

Appendix B-1: Illustration of major components and key steps in the CLUE-S modelling System



Appendix C - 1: Standard linear discriminant function for 19 land use types in the study area

Land Use	Constant	Band1	Band2	Band3	Band4	Band5	Band7	NDVI
Cultivation land								
Apples (1)	-319.30	12.99	-7.85	-0.80	-1.99	2.46	-4.97	329.58
Asparagus (2)	-279.68	10.44	-2.50	-2.03	-2.04	2.06	-4.20	334.98
Oats (3)	-294.73	12.35	-7.11	-0.65	-1.88	2.25	-4.88	317.58
Cultivation land (4)	-308.16	13.27	-8.24	-1.32	-1.88	2.28	-4.49	315.86
Livestock Farm								
Farm area (5)	-304.50	13.17	-8.22	-1.44	-1.93	2.33	-4.38	321.77
Forest and Range								
Forest and Range (6)	-304.06	13.05	-7.90	-1.44	-1.95	2.37	-4.51	322.63
Non productive woodland (7)	-321.14	13.47	-7.58	-2.15	-2.04	2.25	-4.17	327.67
Other Forest (8)	-301.54	12.81	-7.32	-1.51	-2.07	2.37	-4.53	337.55
Productive woodland (9)	-282.67	12.34	-7.37	-1.06	-2.04	2.17	-4.21	346.26
Range (10)	-326.13	13.47	-7.49	-2.74	-2.04	2.37	-3.90	324.07
Unimproved pasture and rangeland (11)	-302.14	13.10	-7.95	-1.54	-1.97	2.29	-4.35	323.87
Pasture and Forage								
Grass (12)	-293.04	13.08	-8.13	-1.44	-1.84	2.35	-4.57	298.23
Herbaceous vegetation (13)	-305.88	13.00	-7.51	-1.96	-1.89	2.43	-4.49	309.77
Improved pasture and forage crops (14)	-298.61	12.84	-7.97	-1.14	-1.96	2.48	-4.77	324.33
Legume (15)	-307.63	13.35	-8.59	-1.41	-1.92	2.41	-4.52	318.95
Pasture and Forage (16)	-313.17	13.36	-8.44	-1.33	-1.96	2.38	-4.52	325.25
Residential and Built Area								
Industrial Use (17)	-349.61	13.56	-7.68	-0.72	-1.91	2.12	-4.90	312.22
Residential and built area (18)	-299.93	12.86	-7.55	-1.39	-2.00	2.27	-4.42	330.44
Urban Built Area (19)	-372.78	15.18	-9.87	-1.30	-1.93	2.53	-5.42	301.58

Cultivation land (4) is the combination of grains, ginseng, cereals and oilseeds, cropland, vegetated (cultivated) areas, cultivated land, nursery / tress, fallow land, misc. Vegetables, barley, trees (plantations),and strawberries; Livestock farm (5) includes farm structures, farm stead, beef cattle farm, and farm yard area; Forest and Range (6) are merging of abandoned or neglected farm land, and treed forest; Pasture and Forage (16) comprise of forage corn, and pasture and forage; Residential and built area (18) consist of wood processing facilities, municipal and regional open spaces and parks, residential, golf fairway and green, and outdoor recreation.

The discriminant function can be written as a linear combination of variables:

$$y_k = C_k + (a_{k1} \times x_1) + (a_{k2} \times x_2) + \cdots + (a_{kp} \times x_p)$$

All the notations are defined in the text (equation 3-1) in chapter 3.

Appendix E-1: Schematic diagram for dynamic land use change implementation