UNIVERSITY OF ALBERTA

MODELLING COMPLEXITY: COMBINING CHOICE THEORY AND MULTI-AGENT MODELLING, AGENT BASED SIMULATION OF HUNTING IN FORESTED LANDSCAPES

by

Scott Robert Heckbert ©

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Dedication

This thesis is dedicated to my lovely daughter Ashley

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CHAPTER 1 INTRODUCTION

Natural resource systems and their utilization are characterized by multiple levels of complexity in the biophysical, social, economic, spatial and temporal dimensions (Parker et al. 2001). Understanding these systems requires defensible tools that represent the individual actors at the level that their impacts occur, as it is the cumulative effect of these impacts that often can have dramatic landscape level effects in terms of resource sustainability (Boutin et al. 2002, MacKendrick et al. 2001, Weber and Adamowicz 2002). The cumulative, heterogeneous impacts over the biophysical landscape make management of resource systems a multifarious effort.

Traditional modelling representations of the system within preference based micro-economic theory may not adequately represent the system's complexity in terms of agent heterogeneity. Discrete choice modeling (Bottan 1999, McLeod 1995, Boxall and Macnab 2000, Boxall et al. 1996, Dosman et al. 2002, Haener et al. 2000, Jabs 2002, Morton 1993) offers a description of human preferences aggregately measured from the population examined. Ecological models (Bunnell et al. 2000, Cumming et al. 1998, Gunn and Sein 2000, Schneider 2002) account for biophysical attributes but lack human dimensions of resource use.

As a result, traditional modelling exercises in both economics and ecology lack important real world features which have important implications for resource management. Discrete choice modelling exercises[1] generally lack representation of heterogeneity in spatial processes, biophysical feedbacks, individual human preferences and individual perceptions of the attributes in question. Conversely, models which do well at representing ecological processes typically lack economic and social dimensions of resource use, and present simplistic representations of the human actors involved.

To properly examine resource management issues in the context of complex systems modelling, human activities need to be examined at a disaggregated individual level where agents are represented in terms of characteristics such as heterogeneity of individual preferences, heterogeneity of perceptions and agent learning. Haener et al.

[1] Such techniques generally use optimization approaches in economics, such as Nanang (2002).

(2001) identify several issues that remain to be investigated and incorporated into discrete choice models, including preference heterogeneity within the human subjects examined, and the incorporation of stated and revealed preference studies into spatially explicit models of resource use. Information about disaggregate individuals' behaviour are essential inclusions, as they offer unique insights into how cumulative impacts[2] develop over time.

Individual preferences and accuracy of perception in both the spatial and temporal context of decision making, however, have potentially important implications for resource sustainability, and should be dealt with explicitly in a modelling framework. Not representing these aspects of resource impacts presents limitations that have important outcomes for the sustainability of the resource being considered. The interaction between human behaviour and natural systems, and the levels of complexity therein, may be the root of the sustainability issue.

Modelling natural systems, particularly landscape processes and anthropogenic cumulative impacts, calls for a platform which allows for system complexity to be explicitly represented, and not 'assumed away', as in traditional methods. To properly examine the system in terms of long term resource sustainability, spatial, temporal and behavioral feedbacks must be present, as these are defining features of the real world system. To achieve this, a multi-disciplinary approach is required to properly represent the natural processes and the human dimensions of resource sustainability.

To address complexity in disaggregated systems and to present a multi-disciplinary platform, agent based modelling (ABM) has become an ever increasingly powerful tool. ABMs have been constructed to incorporate a variety of representations of human decision making, spatial interaction and temporal feedbacks (Agarwal 2002). Specifically, land use / land cover change (LUCC) models, a sub-class of ABM, typically deal with natural resource issues incorporating human decision making in spatially explicit landscapes (Parker et al. 2001). To date, however, the degree to which agent

[2] Cumulative impacts are defined as the additive and interactive impacts that may result from human activities that are repeated over time and space.

decision making is grounded in micro-economic theory and can be calibrated by data derived from real world experiments is in its infancy.

The goal of this study is to explicitly represent the complexity of a set of resource interactions in the spirit of improving resource management effectiveness and impact forecasting ability. This is done by combining a spatially explicit biophysical landscape with a multi agent system grounded in micro-economic discrete choice preference theory. As a case study, an ABM of moose hunting is constructed and analyzed to better address cumulative impacts and the resulting sustainability of game populations in forested landscapes. Sustainability refers here both to the:

- Biophysical arena, in terms of number and distribution of extirpations of moose populations, and
- Human dimension in terms of the level of hunter utility derived over time.

By using the ABM approach, a systems modelling framework can address the complexity of the resource management issue at the level that impacts occur. The individuals within the system can also be defined according to characteristics that may have important sustainability implications such as agent heterogeneity in preferences and perception and agent learning.

Resource Issue: Sustainability of Moose Populations

The issue of long term sustainability of Alberta's northern moose populations is challenged by the presence of multiple impacts resulting from hunting pressure applied by individual hunters, size and distribution of game populations across the landscape, and changes in landscape features resulting from ever increasing and additive industrial activity. Although moose populations are not considered to be at risk, concerns have been expressed by subsistence and recreational hunters about declining moose numbers (AEP 1998).

Increased industrial activity in Alberta's mixedwood boreal forest has resulted in a large number of linear disturbances on the landscape. The cumulative footprint of multiple resource users poses a unique challenge for resource managers charged with maintaining healthy forest level ecosystems and the wildlife populations within them. In the case of moose populations, where hunting is the primary population control mechanism, the increasing number of linear features provide hunters with greater access to wildlife populations. Increased hunting pressure can lead to population declines and extirpations, as has been shown with fisheries in remote lakes and game species in areas accessible to hunters. Of particular concern are the effects of increased hunting pressure to previously remote areas, an indirect consequence of the creation of cutlines, industrial roads, pipelines and other rights of way. Traditional management of industrial activity do not adequately address the problem of cumulative impacts, and rarely take account of the potential impacts of multiple and repeated activities, impacts that may be synergistic and subject to nonlinear behaviour, temporal or spatial lags, and indirect or second-order changes for removed from the original source (MacKendrick et al. 2001).

As with any human decision making, the choices of hunters are based on their preferences for attributes of feasible alternatives, in this case the characteristics of their desired hunting sites. The aggregate effect of multiple individual decisions has important implications for the sustainability of moose populations in terms of both moose population size and distribution, and the level of overall utility derived by the hunters during each hunting season. The study of disaggregated heterogeneous impacts and landscape interactions yields different conclusions on resource management relative to traditional models that do not exhibit such complexity.

Previous Research

Within the economics literature, a number of studies examine human decision making to estimate hunter preferences over landscape characteristics. Stated and revealed preference studies (SP / RP) use discrete choice analysis to determine changes in hunter utility given changes in access / impedance levels, forest industry activity, levels of hunter congestion, wildlife population characteristics, and travel cost among other variables (Bottan 1999, Dosman et al. 2002, Haener et al. 2000, Morton 1993, McLeod 1995). Although this information serves well to describe the respondents' preferences and site selection criteria, this information has not been incorporated in a spatial context that explicitly represents the dynamic biophysical feedbacks which occur within a terrestrial forested ecosystem. Furthermore, traditional preference modelling does not predict outcomes simulated for aggregated impacts resulting from individual decision making. This is a key component of presenting useful analytical tools, as the cumulative effect of disaggregated decision making is ultimately what challenges the long term sustainability of wildlife resources.

Resource managers and researchers have identified increased industrial activity as a primary concern for the future of sustainable wildlife resources, and a number of initiatives have been taken to address the issue. Under the overall goal of integrated resource management, adaptive management has been utilized to simulate and project the results of current on the ground industrial activity against best practices. As a result, a number of forest level models have been created that examine possible management scenarios and identify indicators of ecosystem health. Such models represent forest dynamics and industrial impacts, however the effects of the human dimension on wildlife populations have not been adequately incorporated.

Project Need

To understand human impacts on the environment, and the impacts of changing environments on non-timber values, the interaction between biophysical and human dimensions must be better represented. Most spatial models of multiple use or integrated resource management contain relatively simple representations of human spatial economic behaviour. In reality, spatial characteristics of the landscape are not uniform and the impacts of human decision making impact differently on each spatial component. Hence, understanding and managing the resource in terms of maintaining its sustainability should include considerations of these factors. This research project follows from initiatives to incorporate individual spatial economic behaviour into ecological models, and offers a better representation of the individuals within the system by taking into account the heterogeneity of preferences and perceptions of hunters as decision makers.

Development of simulation tools is a critical aspect of three important components of sustainable resource management in that it allows:

- Examination of outcomes arising from possible resource management scenarios,

- Representation of multiple actors with diverse types of impacts,
- Tracking the behavior and resulting effects of these individual agents on a cumulative landscape level.

Walters (1997) reports that adaptive management, as a key tool for achieving sustainable resource management, should begin with a concerted effort to integrate existing interdisciplinary experience and scientific information into dynamic models that attempt to make predictions about the impacts of alternative policies. Strategies for sustainable management require knowledge about the economic and ecological outcomes of policy decisions and management actions. With this information, 'best practices' that minimize cumulative impacts and the potential for the occurrence of irreversibilities can be identified, while maximizing the benefits accruing to users acting on the forested landscape.

This research project identifies Agent Based Modelling (ABM) as a candidate approach to achieving integration of economic behavior in ecological models. ABM involves the computational simulation of individual classes written in object-oriented programming, and allows for the spatial modelling of individuals with heterogeneous preferences and perceptions on a dynamic biophysical landscape. The ability to compute heterogeneous agents on different levels and simulate their interactions is a powerful modelling tool for examining human resource use patterns.

This project develops modelling tools, specifically the Agent Based Landuse Experiment (ABLE), to examine the effects of different resource management scenarios and representations of human agents[3]. Results describing the effect on moose populations, hunter utility and spatial impacts and decision making are generated to provide a decision support system for possible real-world management schemes. The ABLE model also examines resource sustainability implications arising from assumptions on how human decision making is represented in terms of spatial and

[3] In the ABLE model, there are several different types of agents including timber harvesters and other 'access building' agents representing impacts of such industries as oil and gas exploration and extraction. Technically each cell and the attributes within could also be thought of as agents, including the moose and roads occupying any given area. However, we are focused here on the human hunters, and as such 'agents' refers only to hunters from this point forward.

temporal complexity and agent heterogeneity. This offers an improvement on prior modeling exercises that do not represent these system characteristics, or simply assumes them away.

Research Objectives

The Agent Based Landuse Experiment aims to improve the understanding of relationships between individual preferences, perceptions and the cumulative impacts resulting from disaggregate decision making. This project also examines spatial economic behaviour for wildlife resource users given different management scenarios. The ABLE project contributes to the assessment of cumulative effects and the betterment of methodology appropriate for examining their emergence by examining both

- Assumptions applied to representing human decision making, and
- Resource management scenarios.

Table 1 outlines the four key areas of study.

Table 1: Project areas of study altering characterization of agents and resource management scenarios

	Agent Perception	Agent Preferences
Human Dimensions	1. Homogenous: Perfect information regarding agents' environment. 2. Heterogeneous at various levels: Imperfect information of environment. 3. Agent learning: The ability to improve accuracy of perceptions over time.	1. Homogenous: Agents have identical preference structures. 2. Heterogeneous at various levels: Agents each have unique preference structures.
	Access / Linear Disturbance Regeneration	**Road Decommissioning**
Resource Management	1. Overall industrial access levels and linear features remain permanent disturbances. 2. Access / linear disturbance regenerates over time, at various rates.	1. Forestry roads remain open permanently. 2. Forestry roads are decommissioned at various rates.

In this way, the ABLE model has been designed to test the effects of loosening traditional assumptions in discrete choice modelling, and applies the findings to real world management decisions. Hypotheses have been examined as to test traditional assumptions and impacts on hunter utility and resource sustainability.

Assuming that not all human agents are the same, it would be expected that within any group there are heterogeneous preferences for attributes found in various hunting sites. Therefore, what effect will various levels of preference heterogeneity have on agents' spatial decision making? What effect will such variation in preferences across the agent population have on the utility level perceived from hunting sites? How will different preference structures in the agent population affect the sustainability of moose populations across the landscape?

For heterogeneity in agents' perceptions, how will the accuracy of perceptions affect which hunting sites are visited? How will these outcomes affect the utility perceived by hunters? What effect does accuracy of perceptions have on the sustainability of moose populations? In the case where agents can learn to more accurately perceive their landscape, how will this ability alter their decision making? Again, what will be the effect of learning on hunters' utility? For moose populations, what sustainability outcomes will arise where agents are able to better perceive their environment through learning?

Upon examining the assumptions behind agent characteristics, how do agents perform upon a dynamic landscape, and what outcomes will arise under pertinent resource scenarios? Specifically, how does the time period at which forestry roads are decommissioned affect various outcomes? What effect will variable time periods of road decommissioning have for agents' spatial decision making, the utility that the landscape yields, and the effect on moose populations? Likewise, for cases where access / linear disturbance regenerates, what effect will variable time periods for such regeneration have on agents' decision making, perceived landscape utility and the sustainability of moose populations? Finally, how does the number of hunters on the landscape affect agent behaviour, the utility perceived across that landscape, and the occurrence of extirpations?

In terms of preference heterogeneity, it is hypothesized that a more diverse agent population would have a more widely distributed site selection given that hunters would hold greater diversity in values for site attributes. The utility accruing from landscape conditions as perceived by agents, however, would not be expected to change for different levels of heterogeneity, so long as the 'average' agent is characterized by the aggregate preference structure observed in SP / RP studies. In terms of sustainability of moose populations, it is hypothesized that a more heterogeneous population would most likely result in a more even application of hunting pressure across hunting sites, given that agents value attributes with increasing variety at greater level of heterogeneity. Therefore, areas that face excessive hunting pressure would be fewer, and overall, local moose populations would have a lesser risk of being 'shot out'.

The same set of hypotheses is presented for the case where agents' perceptions are heterogeneous at various levels. A population of agents with a wider variety in their ability to accurately perceive their environment will likely result in a greater distribution of site selection. The utility perceived across the landscape however, would be expected again to not deviate so long as the 'average' perception ability were not different across different levels of heterogeneity. Given greater variety in perception accuracy, it is hypothesized again that hunting pressure would be applied more evenly across the landscape, given that agents would perceive sites differently from one another. Again, it would be expected that areas that face excessive hunting pressure would be fewer, and overall, local moose populations would have a lesser risk of being 'shot out'.

Where agents are able to learn to more accurately perceive their environment, it is hypothesized that the variety of sites that agents attend will decrease. This outcome is expected given that agents will be better able to identify sites that yield the greatest utility, and a greater number of agents will attend these sites as a result. In terms of utility perceived across the landscape, it is hypothesized again that utility will not be different for agents who are able to learn. Agents may, through learning, be able to better select an ideal hunting site, but the utility perceived across the landscape would not necessarily be different from non-learning agents, as the error in their perceptions would be 'averaged out' when the landscape as a whole is perceived. In terms of the effect on sustainability of moose populations, it is expected that learning agents will become more proficient hunters, and thus increasingly select sites with large moose populations. In the case where many agents behave in such a fashion, it is expected that an increased number of areas would be 'shot out'.

Turning now to hypotheses regarding resource management scenarios, it is expected that a shorter time period at which forestry roads are decommissioned would result in a decreased variety of sites attended by hunters. This is the likely outcome, given that earlier road decommissioning would limit the number of preferred alternatives available to hunters as hunting sites become more difficult to access. Likewise, it is hypothesized that the utility perceived by hunters would be lower with earlier decommissioning as their alternatives are increasingly limited. In terms of sustainability of moose populations, the earlier decommissioning of roads is expected to result in a decreased number of areas that become 'shot out'. Because it is more difficult to reach these areas, the moose populations within would likely not face the same amount of hunting pressure, and be able to better maintain their viability over time.

For the case where access / linear disturbance is regenerated, it is expected that a similar set of outcomes would arise. For shorter regeneration time periods, a decreased variety of sites would likely be attended by hunters given that earlier regeneration would limit the number of preferred alternatives available to hunters. Likewise, it is hypothesized that the utility perceived by hunters would be lower with earlier regeneration as their preferred alternatives are increasingly limited. In terms of sustainability of moose populations, the earlier regeneration of access / linear disturbance is expected to result in a decreased number of areas that become 'shot out'. Because hunters generally prefer areas with greater overall accessibility, the moose populations within would likely not face the same amount of hunting pressure under earlier regeneration, and thus be able to better maintain their viability over time.

Lastly, for the case where there is a greater number of hunters present on the landscape, it is hypothesized that dispersion will increase as agents attempt to avoid heavily congested areas. In terms of utility perceived across the landscape, a greater number of agents is expected to decrease utility due to increased hunter congestion. It is expected that greater number of hunters will also result in greater numbers of areas being 'shot out' due to increased hunting pressure.

For each of the identified hypotheses, an agent based framework applied to moose hunting in a forested landscapes provides the opportunity to track the effects on hunter utility derived from participating in the annual hunting season, the number of extirpations of moose (areas that become 'shot out') which occur as a result of applying hunting pressure, and the spatial distribution of hunter decision making and its impacts. By doing so, the implications of traditional modelling assumptions can be evaluated in terms of both the representation of human dimensions and the consequences for natural resource management. Examining the above hypotheses within this framework offers advances to prior research that does not account for complexity in agent heterogeneity, biophysical feedbacks, and both spatial and temporal dimensions.

The ABLE model tracks data generated from simulations, and presents outcomes for hunter utility and sustainability of local moose populations for the four key areas identified in Table 1. This framework provides contributions in:

- Examining assumptions about human dimensions and their contribution to cumulative impacts
- Testing hypotheses regarding resource management scenarios
- Presenting methods of parameterizing multi-agent systems defensibly grounded in micro-economic theory
- Combining biophysical processes with economic and social dimensions to provide a multi-disciplinary decision support system

Study Presentation

This study begins in Chapter 2 with an overview of the resource situation for the case study examined here, namely the sustainability of moose populations in northern Alberta. Chapter 3 provides an overview of current initiatives and modelling platforms contributing to an understanding of the issue, and theoretical considerations behind the incorporation of human economic behaviour in ecological models. Chapter 4 describes discrete choice modelling as well as agent based modelling methodologies and outlines steps needed to parameterize, construct and simulate such models. Chapter 5 describes the Agent Based Landuse Experiment (ABLE), its structure and performance, as well as scenarios and assumptions identified in Table 1. Chapter 6 presents results and interprets model findings. The final chapter provides a summary of conclusions and recommendations for future research.

CHAPTER 2 RESOURCE DESCRIPTION

This study covers resource management concerns in Alberta's northern region, where multiple industrial uses and hunting impacts present complex management issues. The long term sustainability of moose populations and utility derived from moose hunting in particular is dependant on the effective management of the multiple impacts present in this region. The tools developed in this project therefore take into account the biophysical impacts present in this region, and the decision making of individuals who ultimately pose challenges to maintaining sustainable moose populations.

Alberta's north is home to vast forests, nine natural subregions, one of the planet's largest inland deltas between the Athabasca and Peace rivers, and sits on the Western Canadian Sedimentary Basin (WCSB), the 3rd largest oil deposit on the planet. The WCSB in Alberta and northeastern British Columbia is Canada's major oil and gas producing region as well as forestry and mining activities. Increased industrial activities in the area are "unprecedented both in their huge scale and rapidity of development" (Global Forest Watch [GFW] 2000).

The forest resource is used by companies to produce timber product for the market place and also by recreationists who use it for various activities such as hunting and outdoor recreation. These latter activities provide direct benefits through enjoyment of the forest as well as indirect benefits in the form of employment opportunities and income in the recreation and tourism sectors (Akabua et al. 2000). The area has also recently come under intense pressure from logging interests, due to the increased value of deciduous tree species for pulpwood (Marchak 1995, AEP 1998) in combination with the harvest of coniferous species which has also increased in recent years. Furthermore, the oil and gas industry continues to expand throughout the region at an unprecedented rate.

Activities of multiple users acting on the landscape present complex management dilemmas. Resource managers must address various cumulative effects arising from additive and interactive impacts arising from timber harvesting, energy sector activities, and the consumptive use of non-timber forest products such as game species. In many cases, numerous small, independent actions can eventually lead to substantial and sometimes irreversible changes in the environment. Complex systems exhibit positive feedback tendencies that can be manifested by their cumulative spatial effects. This factor is key to spatially examining individual decision making, as it can lead to very different resource use trajectories and yield different sustainability outcomes.

Public awareness of cumulative impacts is often minimal, until such time as a critical point or threshold is exceeded (MacKendrick et al. 2001). Considering that changes taking place in the boreal landscape are beyond what has been experienced in local history (Dosman et al. 2001), the future sustainability of forest dependant resources is uncertain.

The following sections discuss industrial impacts in this region, and describe the history and current on-the-ground practices that contribute to the multiple levels of environmental impacts present. The focus is the cumulative effects of these agents of landscape change, and their contribution to the complexity of managing for long-term sustainability of wildlife resources.

Industrial Impacts - Forestry

The growth of the forest industry in Alberta increased dramatically throughout the 1980s and 1990s as a consequence of government initiatives to diversify the provincial economy. The bulk of this expansion occurred in northern Alberta where vast tracts of forest were brought into industrial production for the first time (Schneider 2002).

Alberta's forest sector has grown dramatically, and is now Alberta's third largest primary economic sector. Between 1986 and 1994, the provincial forest industry made almost $4 billion worth of investment in Alberta (Alberta Environment 2001). Between 1984 and 1995, allocation of the provincial Annual Allowable Cut increased from 30 to 85 percent (AEP 1996). The total value of forest industry shipments reached approximately $4.2 billion in 1996 (Alberta Environment 2001).

The rights to harvest timber resources are allocated through Forest Management Agreements (FMA), timber quotas and timber permits which allow firms to harvest from public lands. An FMA is a long-term contractual agreement between the province and a company to establish, grow, and harvest timber on a defined area (AEP 1996). FMAs are managed to provide sustained yield given an Annual Allowable Cut (AAC), whereby the land base is managed for the maximum perpetual extraction of timber, and is subject to constraints negotiated for each individual FMA. FMAs are the largest and most comprehensive agreement offered for timber harvesting. FMAs are renewed after 20 years and give a forest company harvest rights for large areas of commercial timber.

Harshaw (2000) reports that Alberta's forests are managed predominantly for timber; however, the Canadian public values forests primarily for non-timber uses. Non-timber forest resources can be considered to be those goods, services and amenities obtained from forested areas that derive their worth independent of the economic value of merchantable timber in that same area. To this end, companies entering into a FMA are not only charged with maintaining a sustained timber supply, but also maintaining natural systems from the forest ecosystem. In certain cases, additional responsibilities require that companies strive to 'maintain viable populations of all resident wildlife species with good geographic distribution throughout their FMAs' (AEP 1992, 1998). FMA holders are responsible for their own inventory studies, road development, and forest regeneration.

Roads are cleared in forested areas in order for trucks, equipment and workers to access the cutblocks. There is a primary network of roads, intended to be permanent, and a system of in-block haul roads, which are reclaimed after the harvest operations are complete. Reclamation of in-block haul roads typically involves pulling slash, stumps or other debris across the road's entrance in an attempt to block access from other potential users. Many FMA holders plan to decommission local haul roads leading to individual stands once harvesting is complete; however, once roads are constructed it is very difficult to prevent all-terrain vehicles and snowmobiles from accessing an area (Schneider 2002).

Under the traditional system of timber harvesting, cutblocks are generally square and of fixed size, and cut in a two-pass clear cut system leading to the familiar "checkerboard" landscape pattern. Harvest methods vary across FMA holders. Some companies have adopted harvesting methods which attempt to limit the disturbance by emulating the spatial patterns of fires. Average cutblock size over the last three decades has varied from 10.9 to 24.2 ha for coniferous species, and from 13.2 to 46.0 ha for deciduous species. For spruce trees, maximum cutblock size may vary from 24 ha to 32 ha depending on the type of block. For pine and deciduous trees, cutblocks may average 60 ha and individual blocks as large as 100 ha (Alberta Environment 2001).

Industrial Impacts - Energy

The impacts caused by exploration and extraction activities of the energy industry presents a unique situation in Alberta, which produces 55% of Canada's conventional oil, 83% of natural gas, and 100% of its bitumen. Since petroleum industry features such as seismic lines, well sites, and pipelines persist on the landscape for generations, they have a greater cumulative impact than forestry industry features, most of which are immediately regenerated to forest (Schneider et al. 2002).

The forestry sector currently clears a total of 16,000 ha/year on the AlPac FMA, compared with 11,000 ha/year for the petroleum sector (Pope 2001). Likewise, Varty (2001) reports that on a per year basis, oil and gas activities in Weyerhaeuser's Edson FMA removed 1083 ha per year from the FMA while Weyerhaeuser harvested 1400 ha per year. Historically, there was no restriction on the rate of timber cutting for wellsites, seismic exploration, pipelines, or roads, and there were no requirements for road regeneration (Schenider 2002).

The primary tenure allocations in the oil and gas industries include dispositions of subsurface mineral rights, and of surface rights (MacKendrick et al. 2001) in order to access the underground resources. Subsurface mineral rights are allocated under the *Mines and Mineral Act*, and give companies the right to extract oil and gas in a specified area (Schneider 2002). Subsurface mineral rights have liability rule property rights over surface resources, and on public lands, companies must obtain a Mineral Surface Lease and License of Occupation under the *Public Lands Act* to drill wells and build roads and pipelines.

The major disturbances to terrestrial habitat involved in exploration and extraction of oil and gas include linear disturbances such as roads, seismic lines, and pipelines. Resource industries require roads to access resources, and the energy industry activities require additional linear features in the form of seismic lines and pipeline corridors.

These linear features are a significant and growing cumulative effect in the western boreal (Boutin et al. 2002).

Companies in the petroleum industry use seismic technology to locate oil and natural gas deposits by mapping the sub-surface geology using sound waves. In forested areas, conventional seismic exploration involves the cutting of linear corridors to provide access for vehicles and equipment (Schneider 2002). Often, a series of parallel lines of measurement are needed to locate a petroleum deposit. In forested areas, vegetation is cleared to allow seismic exploration, leaving long, narrow cutlines (Alberta Environment 2001). A complete seismic survey of an area typically involves a series of seismic lines running parallel to each other, usually at a distance of 400 m or more between lines (Schneider 2002). Historically, cut lines were 6-8 m in width, though the adoption of 'low impact seismic' now requires cutline width to be 5m.

Based on data from 1979-1995 in Alberta, applications were made and approved for development of almost 2.3 million kilometers of seismic lines with almost a million of those located in the 'green zone' (AEP 1998). In the 1999 fiscal year, 101,000 km of seismic lines were approved in the green zone. Of these, 71,000 km involved new cutlines, and 30,000 km involved existing cutlines (AEP 1999) The total length of seismic lines approved in the green zone is now over 1.5 million km (AEP 2001). Companies will use existing cutlines when possible. During the 1990-1994 period, about 45 percent of the exploration in the green zone used existing cutlines (Alberta Environment 2001).

These lines are often maintained for many years, but eventually they are reclaimed or naturally reforested (Alberta Environment 2001). However, as a rule seismic lines are not regenerated to forest (AEP 1999) and as a consequence, become a semi-permanent feature of the landscape. A study in northeast Alberta has demonstrated that only 11.9% of seismic lines older than 20 years (n-62) were sufficiently regenerated to meet Alberta Forest Regeneration Survey Standards (MacFarlane 1999). Similar rates of failure of forest regeneration have been described in the East Slopes. A combination of several factors is likely responsible for the observed failure in regeneration, including bulldozer damage to root systems, competition by grass species, ongoing disturbance by all-terrain vehicles and snowmobiles, and insufficient light penetration (Macfarlane 1999).

To access subsurface oil and gas deposits, a well is drilled, and an associated well pad cleared in the area. Well sites average 1.4 ha (Alberta Environment 2001) and are typically connected to an access road for workers and equipment and a 15 meter wide pipeline connected to production facilities. The clearing of trees associated with the construction of well sites, access roads, and pipelines is associated with the same list of ecological impacts described for seismic lines (Schneider 2002).

Reclamation of the land after oil and gas development is regulated by the *Environmental Protection and Enhancement Act*, which defines reclamation as a process "to return the specified land to an equivalent land capability" (MacKendrick et al. 2001). Nevertheless, well sites, roads and pipeline right-of-ways are essentially permanent features of the landscape, given their prolonged use and slow regeneration after decommissioning (Schneider 2002). These right-of-ways are all maintained in a non-forested state throughout the active life of the well. Decades later, when the well is no longer productive, the site is reclaimed, generally to grass instead of forest (AEP 1999). Since petroleum industry features, such as seismic lines, well sites, and pipelines persist on the landscape for generations, they have a greater cumulative impact than forestry industry features, most of which are immediately regenerated to forest (Schneider et al. 2002).

Cumulative Impacts

The combined footprint of forestry and the oil and gas industry in Alberta's mixedwood forest has drastically altered the overall accessibility of the region. Both industries have seen significant growth, mirrored in the increase of on-the-ground operations. Other industrial alterations of the landscape that contribute to the total amount of linear features include powerlines, hydro-electric corridors, railways, as well as the provincial road system. The resulting mosaic of actors utilize the landbase according to multiple temporal scales, overlapping property rights, and are typically regulated individually by various government departments. The result is an increased number of overlapping and sometimes incompatible demands for the land base (Haener et al. 2001).

Not only are jurisdictional boundaries often overlapping, but they rarely coincide with ecological boundaries. The current legislative system seems unlikely to address this problem, particularly due to the tendency of the provincial government to allocate the multiple resources to a range of users on the same landbase, while at the same time regulating these users separately (MacKendrick et al. 2001).

Cumulative effects are the additive and interactive impacts that may result from human activities that are repeated over time and space. In many cases, numerous small, independent actions deemed to be individually insignificant can eventually lead to substantial and sometimes irreversible changes in the environment. Public awareness of such impacts is often minimal, until such time as a critical point or threshold is exceeded. By this time, the environmental and social consequences may be considerable (MacKendrick et al. 2001). Such is the case with linear features in the boreal mixedwood; each industrial agent impacts their local area, the presence of multiple agents resulting in fragmentation of the forest as a whole.

The creation of linear disturbances is common to all industries acting on the boreal landbase because they require roads and cutlines to access resources. The overall footprint results in a multitude of linear features on the landscape. Linear features fragment the forest and create access to previously secluded areas, and the forest resources within.

Fifty years ago the forests of Alberta were still mostly free of roads and other linear access features. Today, the forests of Alberta are 83% accessed. The WCSB has 1.3 million km of linear disturbances (GFW 2000). With 73.5% of the total transportation corridors being made between the period of 1990-1995, it is likely that 100,000km of roads now persist in the region with direct replacement of an area beginning to approach 2,000km^2. Over the entire boreal forest natural region, the road density is approximately 0.21km/km^2 (AEP 1998). Projections using ALCES predict an increase in anthropogenic edge density from 1.8 km/km2 to 6.6 km/km2 within 40 years in the AlPac FMA under current practices and conservative rates of development (Boutin et al. 2002).

The increase in linear features and associated access is cumulative, as these disturbances often are not regenerated to forest. Once resource companies construct roads or seismic lines, this group of users typically resists efforts to reclaim new access routes (Schneider 2002). Oil and gas companies must obtain a reclamation certificate for roads, while forestry companies do not. Many oil and gas companies avoid reclaiming their roads by turning then over to forestry companies, as long as the forest company plans to use the roads within five years, as stipulated by ASRD (MacKendrick et al. 2001). Additionally, the continued use of trails and seismic lines by off-road vehicles and snowmobiles has been cited as a factor in delaying natural regeneration of these routes (Revel et al. 1984).

Canadian environmental assessment laws impose new requirements to identify and address cumulative effects. So far, however, considerable uncertainty exists as to how these statutory requirements will or should be carried out (MacKendrick et al. 2001). In the absence of an integrated planning framework, resource companies generally plan activities independently. There are no requirements that seismic activities be integrated with the long-term harvest plans of forestry companies. As a consequence, efforts by forestry companies to achieve ecological forest management targets are hindered (Scheneider 2002).

Currently, there is no legislation governing the use of access roads, although guidelines in the Alberta Timber and Harvest Planning and Operating Groundrules state that timber operators should cooperate with other industrial operators to "coordinate and integrate their road planning and construction" (ALPAC 2000). Both the forestry industry and energy industry require different road specifications for safety and logistic reasons and roads, as a consequence, may not be used simultaneously by both industries. Timing horizons between the two industries also constrict their ability to integrate road plans; harvesting schedules are planned years to months in advance while energy industry exploration and extraction activities are planned weeks in advance (Schneider 2002).

The root of the problem is the current system of management which lacks meaningful ecological objectives and fails to integrate the overlapping activities of resource companies (Schneider 2002). Currently in Alberta there is no legal mechanism for integrating management or reconciling land use objectives in the resource disposition process. When proposing a development, an environmental assessment may be triggered by the Canadian Environmental Assessment Act, and Alberta's Environmental Protection and Enhancement Act (Weber and Adamowicz 2002). There are no limits to maximum road / linear features density, no minimum ecological thresholds, and mitigation to impede access is not effective. Traditional environmental assessment and resource decision-making do not address adequately the problem of cumulative impacts. Such reactive, project-by-project or permit-by-permit approaches rarely take account of the potential impacts of multiple and repeated activities, impacts that may be synergistic and subject to nonlinear behaviour, temporal or spatial lags, and indirect or second-order changes far removed from the original source (MacKendrick et al. 2001).

Providing coordinated management plans, under the classification of integrated resource management (IRM), has been proposed as a policy tool for minimizing multiple use conflicts and the cumulative effects resulting from a number of actors impacting the landscape. IRM attempts to integrate forest uses such as timber harvesting, recreation, grazing, minerals, and petroleum, across space and time with as little conflict as possible. From this, the option of industrial 'best practices' has been identified as a way to minimize landscape cumulative effects. Best practices, such as minimal seismic line width, access route reclamation and forest regeneration, refers to on-the-ground operations that attempt to minimize impacts, and are feasible for implementation by current industrial users.

Proponents of IRM have identified the benefits of adopting adaptive management as a way to encourage long term sustainability of forest resources. According to MacKendrick et al. (2001), the complexity and scientific uncertainty associated with cumulative impact assessment suggests that a flexible approach incorporating monitoring, modelling, and other forms of analysis can improve assessment efforts. The management process also should be flexible enough to incorporate improved information, analytical tools and mitigation measures. Walters (2000) suggests that, adaptive management should begin with a concerted effort to integrate existing interdisciplinary experience and scientific information into dynamic models that attempt to make predictions about the impacts of alternative policies.

Linear Disturbances

Linear disturbances pose a danger to the health of forested ecosystems directly through changes in forest habitat and indirectly from changes in ecosystem dynamics. Linear features reduce forest habitat and patch size, both of which can reduce habitat suitability (Cumming and Schmiegelow 2001), and the removal of mature trees increases the proportion of young forest in the area. Ecosystem dynamics are altered through mortality due to road construction and vehicle collisions, modification of animal behaviour, alteration of the chemical environment, alteration of the physical environment, the spread of exotics, and the disruption of water and fish movements (Tombulak and Frissel 2000). In cases where such activities cause habitat loss or fragmentation, wildlife species dependent on forests may suffer population declines, reductions in range, or even extirpation (Fleming 2001).

The increase in access associated with linear developments is of particular concern for game species and other wildlife and non-timber resources that are of consumptive value to humans. Roads and cutlines facilitate access to previously remote areas, increasing the harvest pressure and mortality rate that populations face. Roads and other linear features also facilitate access for hunters, leading to higher harvest rates and population declines (Eason 1981, Girard and Joyal 1984, Eason et al. 1989, McMillan 1995, Rempel et al. 1997, cited from Courtois and Beaumont 1999). Similar effects are reported for boreal freshwater fisheries by Gunn and Sein (2000), where it is shown that when new access to fishing sites is created to previously remote areas, perhaps by forestry roads, it appears that these sites are also quickly affected by angling pressure.

Courtois and Beaumont (1999) evaluated the impact of road access on moose hunting in northern Quebec. Moose harvest rates were shown to increase after timber harvesting, sometimes remaining high for at least a decade. Hunting pressure increased in recently cut blocks but moose density and proximity from urban areas were as important as road access in influencing hunting pressure. While attracted by new roads, most hunters remained faithful to their hunting territory. The number of hunting camps, the length of large rivers, and the area of lakes were the most important variables in influencing moose harvest in the study area, more so than road densities. Coling and

Walsh (1991) report a four-fold increase in moose harvesting associated with intensity of logging. Goudreault and Milette (1999), in a study of Quebec hunters, find that moose populations began to decline after hunting pressure had exceeded a threshold level, but increased at a rate of 21% without hunting pressure (cited from: Courtois and Beaumont 1999).

Access also impacts moose populations through increased illegal hunting pressure facilitated by roads and other access routes (GFW 2000). For game species such as fish and moose, the Natural Resources Service (NRS) manages the effects of licensed hunting / angling on game populations. Regulations such as seasons, site closures, and bag limits can accomplish management goals. However, continued poaching and sale of poached meat throughout the north (Schneider 2002) lies outside of the ability of this regulatory method to ensure sustainable populations.

A 2000 report of interviews conducted with Alberta Environment NRS field staff, including fisheries and wildlife managers and conservation officer staff, reports upon the awareness of the importance of access issues. Key findings include very strong agreement that access development and management pose a significant challenge to management of fish and wildlife resources, both in Alberta as a whole, and in the local work areas of the staff interviewed (Hamilton and Stelfox 2000). Most frequently cited access issues concerns were (in order of importance): (i) licensed and non-licensed harvest of fish and wildlife, (ii) habitat loss or damage, and (ii) habitat avoidance.

Moose Hunting

Game species in Alberta can be considered regulated open access resources. Aboriginal hunters generally have open access, and licensed hunters apply for permits for the fall hunting season. Wildlife Agencies (i.e. NRS) limits human harvest of moose by setting seasons, methods and means of harvest, and bag limits. The number of permits available for licensed hunting is set by NRS staff in order to effectively manage population sizes and hunter congestion. Given the general absence of large carnivore species, hunting by both licensed and non-licensed hunters is the primary population control on moose populations. Todd and Lynch (1999) reports that 75% of moose cow mortality is caused from shooting, 20% from predation, primarily wolves, and 5% by starvation.

Although moose populations are not considered to be at risk, concerns have been expressed by subsistence and recreational hunters about declining moose numbers (AEP 1998). Population surveys in northern Alberta that have shown that the density of moose decreases with proximity to roads (Schneider and Wasel 2000). New roads facilitate access for hunters, leading to higher harvest rates and population declines (Courtois and Beaumont 1999). In response to the challenges of managing moose populations, the province is proposing to move from a simple management system appropriate for a low human population and unlimited moose supply to a more sophisticated management system appropriate for a larger and growing human population and greatly increased access to moose range (AEP 1998).

Fire suppression in the boreal mixedwood region has caused deterioration of moose habitat by favoring mature stands of timber. Forestry practices are the main source of forest rejuvenation, and cutting can enhance habitat by creating early succession forest stands. Courtois and Beaumont (1999) report that it is widely accepted that any kind of disturbance that rejuvenates the forest is beneficial to moose (Krefting 1974, Crete 1989, Timmerman and McNicol 1988, Loranger et al. 1991). This includes forest cutting, which is actually the main disturbance agent in northern forests due to the protection of the forests against wildfires (Crete 1989). This increases browse production and consequently improves the quality of moose habitat (Vallee et al. 1976, Joyal 1987). However, benefits of forest rejuvenation have rarely been realized in the form of increased moose populations. Part of the reason for this lack of response by moose populations is what ecologists call 'a predator pit' where hunting and predation keep moose numbers too low for the population to respond to increased forage availability (Osko 1999).

Summary

Forest resources in northern Alberta are under increased pressure from various users, requiring that cumulative impacts management be undertaken to maintain sustainability of moose populations, and the benefits derived from hunting. The resource issue surrounding these resources are characterized by:

- Multiple agents interacting on the same land base
- Increased and additive industrial activity, resulting in increased levels of access and linear disturbance
- Disaggregated cumulative impacts occurring at the individual hunter level
- Difficulty in ensuring effective management due to the inherent complexity existing at several levels

Modelling exercises which aim to contribute to improved management of wildlife / hunting issues must take these factors into account, and acknowledge the complexity of the system and the process by which cumulative impacts develop.

CHAPTER 3 ALTERNATIVE APPROACHES FOR SIMULATING HUNTER-WILDLIFE INTERACTIONS

Introduction

Developing an effective tool to analyze environmental impacts and the cumulative effect of multiple uses on the same landbase requires a multi-disciplinary approach that incorporates information on biophysical processes, human decision making, and feedback between the two systems. The key is to adequately represent elements of social and natural sciences, examining the intersection of the two where the human dimension directly impacts the resource.

A challenge arises when dealing with cumulative impacts resulting from the decisions of multiple actors who may impact the resource in a variety of ways. Therefore, a method of examining this complex system must be accurately represented both at an individual decision making level, and at a landscape impacts level. Specific to moose hunting in Alberta's northern forests, we are concerned about the decisions of individual hunters, and the sustainability of spatially defined populations across the landscape.

The analysis used in this project departs from previous efforts to model human – environment systems, and draws on literature in discrete choice theory, ecological modeling and agent based modeling. Applications of discrete choice theory have incorporated information of human preferences for hunting sites, ecological models have defined the spatial context of biophysical interactions, and agent based models have outlined a fashion by which the human and biophysical dimension can be linked to provide a more comprehensive multidisciplinary analysis of the issue in question.

Preference Based Economic Modelling

Adamowicz et al. (2001) report that appropriate methods for exploring hunting behavior and estimating marginal valuations can be found in resource economics research where there is a burgeoning literature on non-market valuation of non-timber forest products (Adamowicz et al. 1997, Boxall and Macnab 2000). Two approaches commonly used are revealed preference (RP) and stated preference (SP) methods. In both methodologies, the decision making of individuals is linked to their preferences for various states of the world, and econometrically measured to quantify the subject's preference structure. From this, the effects on individuals' utility derived from various possible states can be examined to predict how decision making would change under possible alternative states. Specific to hunting and wildlife resources, several RP / SP studies have examined how attributes of hunting destinations and various wildlife management policies affect hunter decision making. Given concerns regarding over-exploitation of wildlife resources through excessive hunting pressure, these studies are crucial in understanding the long term sustainability of wildlife populations, as it is individual decision makers following their unique preferences who ultimately impact the resource by harvesting wildlife.

McLeod (1995), in a RP study of Alberta moose hunters, uses a discrete choice multinomial logit model to predict site choice and associated changes in welfare estimates based on possible management polices. Marginal effects of increased access and moose densities yield positive utility changes, while increased congestion and distance from hunter origin had negative effects. Morton (1993) finds similar results for Saskatchewan moose hunters, examining how the value of a recreational hunting experience is dependant on hunting site attributes such as access level, expected size of game populations, hunter congestion, degree of impedance, presence of logging activity . Bottan (1999) presents an extensive study on Ontario moose hunters preferences and behaviors finding similar results, and expands the list of site attributes affecting hunter utility to include the presence of lakes, height of forest regeneration after logging, and forest type. Haener et al. (2001), Dosman et al. (2002) and associated papers from the same study measure preferences for hunting site attributes in Aboriginal communities in northern Saskatchewan. Using RP / SP methods and conditional logit random utility probability estimation, the marginal effect of hunter utility is measured for levels of access, driving cost, encounters with other hunters, moose density, and temporal evidence of timber harvesting. The parameter estimates for each of the attributes listed in the above studies reveal the preference structure of the subjects. Hunter behavior, as a result of preference based decision making, can therefore be estimated from the attributes of hunting sites that are chosen each year.

Findings from discrete choice random utility models have been incorporated into simulations which estimate changes in behavior under various situations. Akabua et al.

(2000) present a non-spatial moose hunting Decision Support System for Alberta estimating site choice based on environmental attributes of Wildlife Management Units. Jabs (2002) utilizes estimated preferences structures to simulate angler site selection, measuring utility changes under various management scenarios for fishing seasons in Alberta. Regulation options include access closure, quotas, site fees and restrictions on season type, all which are shown to decrease overall angler utility. This study incorporates a preference-based economic model with ecological feedbacks, with angler decision making being dependant on both fish population and site regulations.

Nanang (2002) presents an analysis of forest management problems in Alberta using optimization approach. This analysis incorporates spatial and temporal detail. Results show that there are significant tradeoffs between timber and non-timber values, and that the benefits derived by elk hunters are small compared to timber values. As such, incorporation of non-timber values only slightly affected the forest management schedules and access road development. Conversely, timber harvesting significantly influenced hunter behavior by concentrating hunters to fewer, unaccessed locations in response to the spreading out of timber harvests on the landscape (Nanang 2002). Results show a strong association between landscape characteristics and the behavioral responses by hunters. Hunter preferences are assumed to be homogenous and static.

Modelling of such human / wildlife interactions is however limited by assumptions such as preference heterogeneity across the human population, access to information regarding the landscape and hunting sites within the identified choice set, and the spatial distribution of decisions and their impacts. The RP and SP studies mentioned above assume homogenous preferences across the human population, perfect information of available fishing and hunting sites, and do not include a spatial context. Boxall et al. (2002) identify a method for accounting for groups of agents with different preference structures using latent class techniques. (cited from Haener et al. 2001) identify several issues that remain to be investigated and incorporated into SP / RP studies including the opportunity to blend SP and RP data to develop spatially explicit models of resource use, and further investigation of the preference heterogeneity within the human subjects examined. Individual preferences, accuracy of perception, homogenous preferences and spatial context of decision making however have potentially important implications to resource sustainability, and should be dealt with explicitly in a modelling framework.

Resource Focused Models

Focusing mainly on industrial effects in forested landscapes, several studies and ongoing research groups are involved in exploring moose hunting, access, and cumulative effects in the boreal forest. Some present spatially explicit models, however the human dimensions are lacking, or not grounded within economic theory. Several notable computer models have been developed for tracking cumulative effects in forested landscapes which track the impacts of industrial uses such as forestry and oil and gas impacts. The ALCES model (Stelfox 2001) tracks cumulative effects in a semi-spatial dynamic landscape subject to a suite of natural and anthropogenic disturbance events (Forem Technologies, 2002). FEEnix, a Forest Ecosystem Emulator was developed to evaluate the ecological and economic consequences of alternative forest management practices at large spatial and temporal scales (Bunnell et al. 2000). Demarchi (1998) assess the impact of forest harvesting policies on British Columbia's spotted owl in an individual based model. In a related model, Cumming (1998) describes an individual-based landscape simulation model developed for applications to forest management and habitat conservation problems in the boreal mixedwood forest.

Modelling of natural systems, particularly landscape processes and anthropogenic cumulative impacts, calls for a platform which allows for system complexity to not be 'assumed away' as is commonly done. To properly examine the system in terms of resource sustainability, spatial, temporal and behavioral feedbacks must be present, as these are defining features of the real world system. Therefore, a multi-disciplinary approach is warranted to properly represent the natural processes and the human dimension of resource sustainability.

Agent Based Modelling

Agent based modelling (ABM[4]) is increasingly being used in a variety of disciplines to understand properties of complex systems through the analysis of simulations (Axelrod 1997). Researchers in natural and social sciences, aided with advances in computational power, have added agent based modelling to their toolkit of analytical methods. ABM serves both as a substitute for, or complement to traditional research methods (Goldspink 2000). ABMs offer unique opportunities to study simulated systems resulting from micro-level interactions of multiple agents.

ABMs are computer-implementable stochastic models, which consist of a set of "micro level entities" that interact with each other and an "environment" in prescribed ways (Lane 1993). The interaction over time of the micro level entities, or agents, produces a history of the changing states of the overall system. Analysis of the history of agent-agent and agent-environmental interactions allows for system level properties to be examined.

In his *BioScience* article "New Computer Models Unify Ecological Theory", Hudson (1988) identifies modelling the interactions of individual organisms as key to understanding ecosystems. To understand the properties of systems, the interactions of the component parts must be analyzed. Agent based models can help us understand how particular aggregate properties of the modeled real-world system depend on the characteristics of the lower level process that underlie them (Lane 1993). Thus, ABM offers an appropriate platform to examine cumulative impacts in natural resource systems.

Agent based modelling offers a third method of scientific inquiry. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, an agent based model generates simulated data that can be analyzed inductively (Axelrod 1997). Models can therefore be interactive experiments in which

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[4] Many authors refer to agent based models (ABM) by various names, including artificial worlds (AW), agent-based computational economics (ACE), individual based models (IBM), Land Use / LandCover Change (LUCC) models, among others. Variations of ABMs deal with particular research interests and applications, but the principal components are the same. In direct quotations throughout this paper, I have replaced the various acronyms with the general title ABM.

scenario analysis can be completed to explore the system under examination as assumptions are altered by the modeler. Agent based models allow the researcher to conduct interactive experiments for scenario analysis, exploring the links between micro level interactions and macro level outcomes.

The components of agent based models are typically represented in object oriented programming, allowing for a modular model design. The flexibility of the platform enables examination of heterogeneity amongst decision makers in terms of preferences and perceptions, and also spatial and temporal complexity.

In terms of natural resources modelling, ABM facilitates interdisciplinary modelling by representing human dimensions included in a model of an ecological system. Thus, the system can represent spatially explicit aspects of natural science combined with theoretical social science. Defining how the system components interact over time, then simulating the outcomes allows exploration of natural resource management scenarios and provides policy relevant results.

ABMs of natural and social science offer a framework to examine biophysical representations in terms of landscape processes, and human dimensions in terms of economic and social realms. The results obtained through ABM are of use to resource managers who regulate patterns of natural resource use, researchers examining system dynamics, and policy makers who need decision support systems to accurately forecast the effects of different regulations.

Platforms

In computing science, multi-agent systems are models that allows for efficient designing and interconnection between programs (Parker et al. 2002). Various modelling frameworks have been developed that provide researchers with a set of tools suited to address common aspects of land-use systems.

For example, STELLA provides a format for dynamic modelling that has an intuitive graphical user interface, however it does not allow for spatially explicit modelling. SELES is a tool for building spatially explicit simulations to model the role of disturbance in creating and maintaining landscape structure. Models built with SELES are raster-based, semi-Markov, whole landscape models which use probabilistic disturbance spread[5]. The SWARM simulation package, has been used for modelling multi-agent systems and interactions between the agents in those systems. SWARM is a set of software tools written in Objective-C, object oriented programming (OPP). RePast is a platform similar to SWARM, but is written entirely in Java. Ascape (Epstein and Axtell 1996) is again inspired by SWARM that offers a complete user interface. CORMAS[6] is a programming environment dedicated to the creation of multi-agent systems, with a focus on the domain of natural resources (Parker et al. 2001).

Increased familiarity with code writing and greater availability of computer processing speed has also allowed many powerful multi agent systems to be developed to examine specific land use concerns. This option for building ABMs offers flexibility in defining the model operations, and the ability to represent multiple agents acting on spatially explicit landscapes, which is a defining feature of most natural resource utilization.

ABMs of Human / Wildlife Systems

A wide variety of ABMs exist, as model components depend specifically on the research question being examined. In terms of models which examine human dimensions of natural resource use, there are typically biophysical, social and / or economic components interacting within the system. Agarwal et al. (2002) examine various current land use / land cover change models, a subset of overall ABM, in terms of their spatial, temporal and human decision making complexity. Temporal complexity is examined in terms of models' time step and duration, spatial complexity in terms of resolution and extent, and human decision making (HDM) complexity in terms of agents and their domain. Agents refer to the human decision-making actors, being the smallest single decision making unit, either as individuals, households, nations, or any defined unit. Domain refers to the broadest social organization included in the model. The agent captures the concept of who makes decisions, and the domain describes the specific institutional and geographic context in which the agent acts (Agarwal et al. 2002). In

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5 www.ncgia.ucsb.edu
6 Common-Pool Resources Multi-Agent System

total, 19 models[7] are selected for comparison as being representative of a total of 136 papers describing various agent based land use / land cover change exercises.

Agarwal et al. (2002) describes the complexity of selected models in terms of temporal extend and duration, spatial scale and resolution, and representation of human decision-making. Six levels of decision-making complexity are defined as being present in the current literature as described in Table 2.

Table 2: Levels of representing human decision making complexity

Level	Representation of HDM
1	No human decision making, only biophysical variables in the model.
2	Human decision making assumed to be related determinately to population size, change, or density.
3	Human decision making seen as a probability function depending on socioeconomic and / or biophysical variables beyond population variables **without** feedback from the environment to the choice function.
4	Human decision making seen as a probability function depending on socioeconomic and / or biophysical variables beyond population variables **with** feedback from the environment to the choice function.
5	One type of agent whose decisions are modelled overtly in regard to choices made about variables that affect other processes or outcomes.
6	Multiply types of agent whose decisions are modelled overtly in regard to choices made about variables that affect other processes and outcomes; the model might also be able to handle changes in the shape of domains as time steps are processed or occurrence of interaction between decision making agents at multiple human decision making scales.

Adapted from Agarwal et al. (2002)

Examining the various spatial, temporal and human decision making complexity levels of the models reveals that most include spatial complexity, the majority do not have temporal complexity, and the majority represent HDM in a relatively simple fashion, being levels 1-3, representing HDM without environmental feedbacks, as

[7] The 19 models examined are: 1. General Ecosystem Model (GEM) (Fitz et al. 1996), 2. Patuxent Landscape Model (PLM) (Voinov et al.1999), 3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkamp and Fresco 1996a) 4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b) 5. Area base model (Hardie and Parks 1997) 6. Univariate spatial models (Mertens and Lambin 1997) 7. Econometric (multinomial logit) model (Chomitz and Gray 1996) 8. Spatial dynamic model (Gilruth et al. 1995) 9. Spatial Markov model (Wood et al. 1997) 10. CUF (California Urban Futures) (Landis 1995, Landis et al. 1998) 11. LUCAS (Land Use Change Analysis System) (Berry et al. 1996) 12. Simple log weights (Wear et al. 1998) 13. Logit model (Wear et al. 1999) 14. Dynamic model (Swallow et al. 1997) 15. NELUP (Natural Environment Research Council (NERC)–Economic and Social Research Council (ESRC): NERC/ESRC Land Use Programme (NELUP) (O'Callaghan 1995) 16. NELUP - Extension, (Oglethorpe and O'Callaghan 1995) 17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996) 18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998) 19. Cellular automata model (Clarke et al. 1998, Kirtland et al. 1994)

described in Table 3. Models which include higher level representation of human decision making (levels 4, 5, 6) account for 37% of the models examined.

Table 3: Complexity in multi-agent modelling literature, dependant on spatial and temporal feedbacks as well as representation of human decision making

Complexity Criteria	Percentage of Models Satisfying Criteria
Spatial Interaction	79%
Temporal Complexity	31%
HDM Level 1	16%
HDM Level 2	11%
HDM Level 3	37%
HDM Level 4	21%
HDM Level 5	11%
HDM Level 6	5%

Adapted from Agarwal et al. (2002)

Parker et al. (2002) present a summary of current work being done on multi agent systems of land use and land cover change, a category of agent based models involving human actors as decision makers, and their cumulative affects on a landscape level. Eight modelling projects[8] are described in terms of the types of agents examined, the decision making process of the agents, agent-environment interactions, the ecological processes included in modeled landscapes, the spatial scale of the landscapes and the temporal extent of the models. Of particular interest is the decision making criteria by which the agents base their actions. These land use / land cover change models use a variety of criteria, including simple rule based heuristics, bounded rationality, and one model which uses utility calculations in determining agent actions[9]. However, the land-use / land cover change models described, are not grounded in micro economic assumptions of individual preferences, as described in section 2.1. Incorporating discrete choice theory into this

[8] FEARLUS (Polhill et al.), MameLuke (Huigen), Multiple-agent modelling applied to agroecological development (Berger), SYPR (Manson), LUCITA (Deadman et al), LUCIM (Parker et al), The SelfCormas Experiment (d'Aquino et al.), SprawlSim (Torrens).

[9] SprawlSim was developed to examine mechanisms driving suburban sprawl in North American cities and the spatial patters that the sprawl generates (Torrens 2002), and models agent decision making based on residential location theory and urban economics. A simple weighted mathematical formula is used to describe the decision making rule for spatial development.

modelling style more accurately represents the behavior resultant from human decision making.

Focusing specifically on either outdoor recreation, wildlife consumption and hunting, we see that several agent based models have been developed to examine the behavior of individual hunters and recreationists. Bousquet et al. (2001) present "A spatially-explicit individual-based model of blue duikers population dynamics: Multi-agent simulations of bushmeat hunting in an eastern Cameroonian village". This study aims at understanding how the organization of the hunting activity between the villagers may constitute a management scheme. The model is calibrated with information from hunter surveys which is re-enacted in the simulation to explore the effect of the reported harvesting strategy on game species. The program uses CORMAS as a modelling platform, and simulates the activities of several individual hunters in a GIS data environment.

Gimblett et al. (2000), presents an agent-based model for simulating and evaluating river trip scenarios in the Grand Canyon. In this study, agents make decisions based on fuzzy logic, where visitors to a recreational or sightseeing destination make decisions regarding visitation location based on weighted formula and a probability calculation of the agent deciding on a certain action. Through this, the attempt is made to realistically express factors that affect individual decision making. Gimblett et al. (2000) incorporate GIS mapping with a multi agent system of decision making, and includes realistic visitor scheduling and recreational use policies that can be implemented through a graphical user interface.

These multi agent systems' primary contribution is in the spatially explicit modelling of natural resource utilization within an object-oriented platform. However, they fall short in terms of grounding agent decisions within micro-economic theory. Overall, the current literature describing agent based modelling of human / environmental systems contributes to adding a spatial context to examining landscape level processes, and generally includes human decision making as it affects these processes. Some ABMs are built on a sound behavioural footing, where the mental models of human agents are empirically grounded and well understood. In other cases, however, the behavioural strategies of the agents have been chosen arbitrarily in an ad-hoc manner (Batten, 2004). There is a need for further grounding of agent decision making in micro economic theory, and exploring the traditional assumptions therein.

Using Agent Based Modelling to Move Beyond Traditional Discrete Choice Modelling Assumptions

Traditional assumptions in discrete choice modelling include homogeneity of parameter estimates across the population, perfect information available to the individuals, a static understanding of landscape characteristics and do not account for spatial complexity in decision making. The inability of the study to more accurately account for individual variation is relegated to a general error term.

Ecological models of cumulative impacts traditionally lack human dimensions, or make a logical jump in assuming biophysical impacts directly relate to the sustainability of wildlife populations. Although it is individual human agents causing direct impacts on the wildlife resource, these models instead estimate the impact, for example, of roads or cutlines on moose populations, but not the individuals who use these features to access the wildlife resource. Thus, these models do not give consideration to cumulative impacts at the level on which they occur. Furthermore, these models typically assume that the human agents do not respond to the affects their activities generate.

However, the flexibility of the ABM allows for these assumptions to be explicitly represented at the individual impact level, and examined to determine the implications for the stakeholders in question. Hypotheses can be examined as to whether traditional assumptions have significant impacts on hunter utility, spatial decision making and resource sustainability. Specifically, the effect of:

- Heterogeneous perceptions of landscape attributes
- Heterogeneous preferences among individuals within a group
- An individual's ability to learn, or better understand the true state of their environment

Within this context, and by representing impacts at an individual agent level, further hypotheses can be examined which relate to resource management scenarios. Specifically, what is the effect of:

- Variable ages at which roads are decommissioned
- Variable ages at which access / linear features are regenerated

For each of the five identified hypotheses, the agent based framework chosen for this case study and applied to hunting in a forested landscape provides the opportunity to track the effects on hunter utility derived from the yearly hunting season, the number of extirpations which occur as a result of applying hunting pressure, and the spatial distribution of hunter decision making and its impacts. By doing so, the implications of traditional modelling assumptions can be evaluated in terms of both the representation of human dimensions and their consequences for natural resource management.

CHAPTER 4 METHODS

Introduction

Estimation of individuals' preferences through discrete choice modelling provides a theory of decision making firmly grounded in microeconomic theory. Agent based modelling allows for the examination of systems resulting from the actions and interactions of multiple individuals. Combining the two provides a platform by which individual preferences can be used to examine system level outcomes resulting from individual actions. Estimation of parameters for individuals' preference structures is possible through SP and RP techniques and these parameters can be taken and used as the decision-making criteria in an agent based model. The result is a modelling framework firmly grounded in well accepted theory of choice behaviour, and allows for simulation of the entire population as a composite of unique individuals.

In terms of many natural resource issues, it is the independent actions of multiple agents which ultimately can have important system level effects on the resource base. It is therefore an important advancement to be able to combine a grounded theory of individual choice with a tool that can track the outcomes of an entire population of individual decision makers. SP / RP are grounded and widely used techniques, and their combination with ABM allows for a sound basis for doing simulation to examine spatial resource issues.

Preference Based Discrete Choice Theory

The basic approach to the mathematical theories of individual preferences is that of microeconomic consumer theory. The objective of the theory is to provide the means for the transformation of assumptions about desires into a demand function expressing the action of a consumer under given circumstances (Ben-Akiva and Lerman, 1985). Neoclassical economic theory of consumer behavior is appropriate where the feasible choices are continuous variables such as the consumption of various homogenous consumption commodities. However, selection of one of many options, to the exclusion of all other options are better described as a selection of one of a finite set of discrete bundles of attributes. For such problems, discrete choice theory is a more appropriate basis for demand analysis. In particular, probabilistic choice theory that specifies the probability with which an individual will select any feasible alternative provides a potential powerful framework for analyzing discrete choice situations.

The choice problem under consideration is the subject of any decision the individual makes. Understanding and predicting the nature of individual decisions and aggregate responses is vital to the evaluation of the resulting costs and benefits. Choosing manifests itself in many ways such as supporting one outcome and rejecting others, expressed through active or passive responses (Louviere, Hensher and Swait 2000). The actual decisions made are a function of the individual's preferences, and their perceptions of possible outcomes given any constraints. Thus, following from Louviere, Hensher and Swait (2000) and Ben-Akiva and Lerman (1985), a general choice behaviour model involves:

- Decision maker facing a choice problem
- Perception of a set of possible alternatives
- Perception of attributes for alternatives
- The ability to evaluate the outcomes of each alternative by some decision rule
- Action based on the decision making rule and the feasible options
- Measurement of outcomes resulting from actions at the individual and the population level

The feasible options within the environment, as perceived by the decision maker, determine what we call the choice set of alternatives. In the natural resource context explored here, each decision is mutually exclusive and is based on collectively exhaustive alternatives, in that each hunter can only select and attend one site. Decisions therefore require selecting among sites to visit, and such decisions are best described as a selection of one of a finite set of discrete bundles of attributes. For such problems, discrete choice theory is an appropriate basis for demand analysis. In particular, probabilistic choice theory that specifies the probability with which an individual will select any feasible alternative provides a potential powerful framework for analyzing discrete choice situations (Louviere, Hensher and Swait 2000).

Discrete choice theory departs from neoclassical microeconomic theory in that utility is seen to be derived from the attributes, characteristics, or properties of a good, and not from the good itself. Using Lancaster's approach, or the concept of indirect utility, individuals define the utility function in terms of attributes which the good possess, rather than the goods themselves. Goods are used either singularly or in combination to produce the characteristics that are the source of a consumer's utility (Louviere, Hensher and Swait 2000).

$$U = U(x_{ij})$$

where x_{ij} is a vector of attributes for option i for individual j.

The probability of selecting alternative i depends on any relevant variables that affect the individual j's preferences for i. The vector x denotes consumption services or attributes, and is used to emphasize that the alternative is defined in terms of a set of attributes (Louviere, Hensher and Swait 2000) as perceived by individual j.

Random Utility Modelling

When selecting from a number of mutually exclusive options, such as the selection of a hunting site (site x_i of a set of possible sites x_n where i =1…n), hunters choose from a number of possible alternatives but ultimately only attend the site which is expected to hold the most desirable attributes, k, that generate the highest utility (U) within the feasible choice set. The utility that hunter j receives from site i is:

$$U_{ij}=U(x_{ijk}) \qquad x_{ijk} \text{ as an element of C}$$

Where x describes site i, with attributes k, perceived by hunter j. C is the set of feasible choices.

As in consumer theory, the individual is assumed to have consistent and transitive preferences over the alternatives that determine a unique preference ranking. Thus, a utility index associated with every alternative is identified, and hunters are assumed to select the utility maximizing site from their choice set:

$U_{ij} > U_{nj}$ for all sites i=1...n.

Decision makers are assumed always to choose the utility-maximizing alternatives; the choice probabilities are interpreted as the analyst's statement of the probability that of any decision maker, the utility of an alternative will exceed the utilities of all other feasible alternatives (Ben-Akiva and Lerman, 1985). In general this means a consistent and calculated decision process that displays consistent and transitive preferences in which the individual follows his or her own objectives, whatever they may be (Ben-Akiva and Lerman, 1985).

In general we can express the random utility of an alternative as a sum of observable (or systematic) and unobservable components of the total utilities. Each utility value can be portioned into two components; a systematic component, V_{ij}, and a random error component, e_{ij}, such that:

$$U_{ij} = V_{ij} + e_{ij}$$

The error component captures any unexplained factors not directly considered in systematic component of the model, such as observational deficiencies resulting from unobserved attributes, unobserved taste variations, and research error (Ben-Akiva and Lerman, 1985). Adopting this approach implies that the indirect utilities (U_{in}) are random variables, as the error can be described as a probability across all individuals. The systematic component of the indirect utility function is dependant on the relative preferences for site attributes

$$V_{ij} = \beta_1 x_i + \beta_2 x_i + \beta_3 x_i \ldots$$

where β are relevant parameters and x_{ij} are a vector of attributes of the hunting site i, as perceived by hunter j.

As decision makers are assumed always to choose utility-maximizing alternatives, choice probabilities are interpreted as the analyst's statement of the probability that of any decision maker, the utility of an alternative will exceed the utilities of all other feasible alternatives (Ben-Akiva and Lerman, 1985). Hence, the actual choice for an individual can be defined as a probability that the individual will choose any given site from within the choice set. The probability that any individual will choose site i is the probability that the selected site yields the greatest overall utility from among the alternatives:

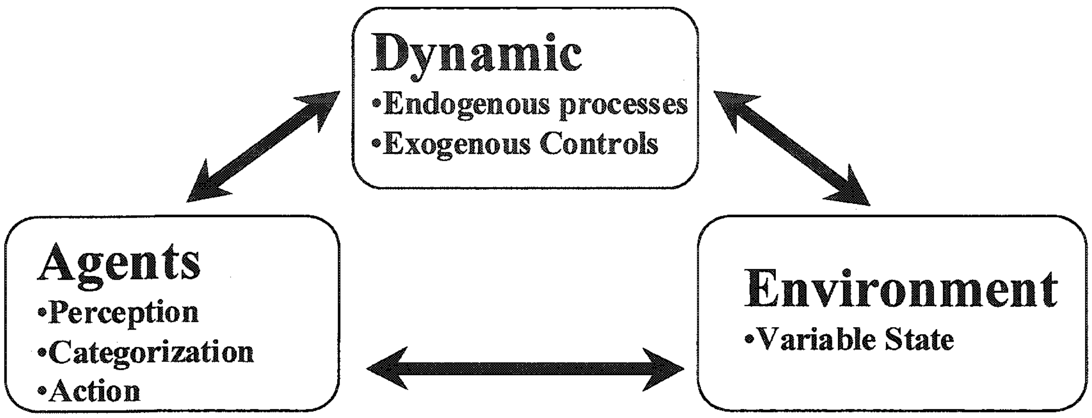
$$P(i) = Pr(U_{ij} \geq U_{nj}) = Pr(V_{ij} + e_{ij} \geq V_{nj} + e_{nj}) \qquad \text{For all n as an element of C}$$

Preference parameters are econometrically estimated at this point. Studies described in Table 5 are estimated using multinomial logit modelling, a computationally convenient representation of the probability of choosing a site.

Agent Based Modelling

ABM is the computational study of models as evolving systems of autonomous interacting agents (Tesfatsion 2002). Axtell (2000) describes agent based models as consisting of individual agents, commonly implemented in software as objects. Agent objects have states and rules of behavior. Running such a model simply amounts to initiating an agent population, letting the agents interact, and monitoring what happens. This is the inductive aspect of ABMs, which serves to examine an identified deductive hypothesis regarding expected outcomes of the system. Formally, an ABM consists of a set of micro-level entities (agents), an environment and a dynamic, as shown in Figure 1.

Figure 1: Agent Based Model Components



Each agent has attributes and modes of interaction with other agents. The environment has a state (Lane 1993). The dynamic is the control mechanism imposed by the modeler that specifies how agents interact, as well as any other exogenous controls. It is the interactions of the agents with each other and with their environment, according to the dynamic specified, that results in the simulated system under analysis. The simulation of the system is the enacting of specified rules of each of the three components. The agents and environment have internally determined actions, affected externally by the dynamic.

ABMs are often designed to emulate specific real world processes at a simplified level. Complexity which exists within system dynamics can be accurately represented by constructing program modules and defining their interactions according to the understanding of how a real world system operates. To realize this potential, the models must be realistic and their structure must be comparable to the observed structure of the population itself (Cumming 1998). Grimm et al. (1996) suggests that ecological models be designed to address specific patterns in nature: modellers should identify important observed patterns and attempt to understand and represent the mechanisms that cause the patterns. When designing and executing ABMs, Railsback (2001) suggests four steps to what he refers to as pattern oriented analysis:

- Define a set of 'testing patterns', observed patterns of system-level (or individual) responses to known stimuli that the ABM is designed to explain and reproduce;

- Build a model that includes the mechanisms and individual traits believed to drive the testing patterns;
- Pose alternative formulations for individual traits as hypotheses that will be tested. It can be interesting to pose the assumptions used in conventional aggregated models as hypothesis for individual traits;
- With the ABM, simulate the conditions under which each test pattern has been observed to occur. Repeat the simulations with each alternative formulation for individual traits. Reject hypothesized formulations that do not cause the test patterns to emerge from the model.

An agent based model generates simulated data that can be analyzed inductively (Axelrod 1997). For models with stochastic components, Cumming (1998) suggests that Monte Carlo trials be conducted to compare outcomes under different scenarios, and to allow visualization of variability about population trajectories. The history of model variables can be output to a spreadsheet file for further analysis. Statistics can also be instantly generated and displayed through the graphical user interface (GUI) as the model runs. The model tracks and reports outcomes for specific system variables of interest, as identified by the researcher, and differ depending on the system under study.

Agents

Agents generally consist of rules of behavior and type attributes. These two components define what sort of agent it is and its behavior in any given situation. An example might be a buyer/seller (the type characteristic) in a virtual marketplace, who buys and sells its goods when the price is right (e.g. Tesfatsion 2001). Another example might be species of fish that changes feeding areas dependent on the presence of predators or food availability (e.g. Railsback 2001). The agents in both examples are able to sense the state of the world around them, determine the best action to take, and act on that decision. Agent behavior can be described several ways, such as: “if - then” spatial movement rules, such as those found in the cellular automation[10] research, maximized fitness functions, internalized behavior norms, and preference structures to name a few.

The type characteristics of agents are important in determining modes of interaction with other agents and the environment. Types of agents may have different cognitive and behavioral abilities, different internally stored histories of variable states in simulation time steps, different modes of communication amongst each other, and any other characteristic required to adequately represent the system under analysis. For an ecological model, agent types might be defined by trophic level, and again for different species within that level, and perhaps again for different sub-groups within the same species. For spatial grid models with mobile agents on a landscape, the cells of the landscape itself are types of agents. The agents are heterogeneous in the sense that different agents have different behavior and beliefs, and different types and degrees of cognitive ability (Doran 2001). The agent type describes a certain class of objects in object oriented programming, and represents a certain population of unique individuals.

The cognitive ability of an agent is the means or criterion by which an agent decides to enact a certain behavior, and may be represented as a classifier system. The classifier system can be used to represent agents who 'learn' how to get what they want from their environments (Lane 1992; II). Within the computer simulated model, agents are independent units, each having its own sensor, processor and effector. Each classifier integrates perception, categorization and action (Lane, 1992). The result is a certain behavior based on information available to the agent. In this context, agents are software entities that are 'autonomous' loci of decision making that sense, decide and act (Doran, 2001).

A further breakdown of these three components identifies exactly how an agent operates. The first agent component, perception, refers to the agent's ability to view the state of the environment. Within the computer model, the agent may 'read' available

[10] Gaylord and Nishidate (1999) describe cellular automations as dynamic systems, where space, time and the states of a system are all discrete and have the following properties: Space is represented by a rectangular lattice in on, two or three dimensions, and each site, or cell, in (or on) the CA lattice can be in one of a finite number of states. The states are represented by integer number values. The computation of a CA involves the creation of a matrix of specific element values, a function, of set of functions that can be used to change the value of a matrix element, and the application of the function repeatedly to the matrix, each time changing the values of all the matrix element simultaneously.

information. The modeler determines how, and with what degree of accuracy an agent may perceive the world around them. Complete control of the access to information is held by the modeler. The fashion by which agents perceive the state of their environment is an important model specification. In a model developed to examine the emergence of resource sharing conventions, Thebaud and Locatelli (2001) enable agents a special 'field of vision'. Within the field of vision, other agents' activities are visible and each may act differently if they themselves are visible to other agents. This approach has been used to create ABMs of Hardin's (1968) Tragedy of the Commons, where agents are 'socially accountable' and do not abuse the commons when within the perception area of other agents. Controlling the perception level is an important component of modelling boundedly rational individuals. Allowing an agent an equivalent amount of information which would be available to an individual in the real world is an important modelling consideration, allowing agents to be omniscient, completely blind, or somewhere in between. The effect of altering accuracy of perceptions is one hypothesis examined in this study, as discussed in Chapter 1.

The second agent component, categorization, refers to the method by which agents determine which action to take in any given situation. Categorization is the sequencing of transition of internal states, triggered by particular patterns of perceived environmental states (Lane 1993; II). The information available to the agent is imputed as data, or instance variables, into a function defined by the modeler. The function represents observed patterns of system level (or individual) responses to known stimuli that the ABM is designed to explain and reproduce (Railsback 2001). Categorization imputes the environmental state into the behavior function and performs any calculations necessary. For example, if a boundedly rational agent must select between alternatives, categorization would involve processing environmental data according to their selection criteria.

Once the state of the environment is perceived and processed according to the defined categorization function, the agent enacts its chosen behavior. This is the final step in the perception – categorization – action process, and is where the interactions under study take place. The agent's action affects the state of the environment, and perceiving the new 'state space', it categorizes and acts again, ad infinitum as the model progresses.

The interaction over time of agents' behaviors results in the system being studied. For the model to yield valuable results, it is imperative that the decision making process of the agent be a accurate representation of real world processes. Railsback (2001) suggests developing the model around a set of defined 'test patterns', observed patterns of system-level (or individual) responses to known stimuli that the ABM is designed to explain and reproduce. Defining test patterns can be identified from existing literature of the system being studied, or posed as hypotheses for examination through the ABM. From identified test patterns, realistic representations of how an agent should perceive, categorize and act are built.

Of particular interest are ways that adaptive behavior may be included. Adaptive behavior may be at the individual level through learning, or it may be at the population level through differential survival and reproduction of the more successful individuals (Axelrod 1997). Tesfatsion (2002) identifies methods by which researchers are currently representing learning processes in agents. These include reinforcement learning algorithms, neural networks, genetic algorithms, genetic programming, and a variety of other evolutionary algorithms that attempt to capture aspects of inductive learning. Arthur (1993) explores design issues for building economic agents that behave like humans. A learning algorithm is calibrated against human learning data from psychological experiments. Here, the process involves

- Calculating the probability vector as the relative strengths associated with each action,
- Choosing one action from the set according to the calculated probabilities,
- Observing the payoff and updating the strengths of the action, and
- Renormalizing the strengths.

In order for the agent to learn, it must track the results of their past behavior and update action responses accordingly. Each agent therefore carries internally stored information regarding the history of environmental states, and the memory of results of its own actions. The payoffs associated with agent behavior over time are perceived along side the current environmental state, and are updated similarly.

Landscape

The environment in which agents interact is measured as a history of state space, with landscape variables taking on different values or states as the model progresses. For example, many spatially explicit ABMs operate on a two-dimensional grid of cells representing a landscape. Each cell, or group of cells, contains internal attributes at a current state of an environmental variable. Consider the example of an environmental variable from an optimal foraging model such as Anderson (2002). Food availability is spatially defined within each cell of the landscape and recorded over time. The range of state space for this variable is measured over the progression of the model, and is used as data for analysis of system level properties. The state space of an environmental variable is the medium through which agents interact, and functions as the feedback link between different levels of agents.

In each time step, measured in event occurrence, the state space is updated for each environmental variable affected by agent's behavior. The update function is defined by the modeler according to individual test patterns. For example, the interaction of predator and prey results in the removal of the culled individual from the prey population. The state of the prey population is then updated accordingly for the next time step. The changing level is recorded through time as data, useful for describing the system as a whole.

Dynamic

The dynamic, which may be in part stochastic, specifies the order in which interactions occur. The dynamic also imposes rules that determine when the agents die, and when new ones come into the World (and with what attributes) (Lane 1993). Control of the dynamic through manipulation by the modeler is possible, allowing for different modelling 'scenarios' under which agents perform. The dynamic also includes the initial condition and initial attributes of agents and state variables as specified by the modeler. From initial conditions, the dynamic is implemented, and a history of state space is recorded. The model then evolves over time without further intervention from the modeler (Tesfatsion 2001).

Model Complexity

The combination of agents, an environment and the rules for interaction through the dynamic allow the examination of systems that incorporate complexity on several different levels. Complexity exists within the spatial, social, and temporal dimensions through heterogeneity in terms of spatial processes, variation in agent types and system feedbacks over time steps.

Defining a multi agent system which interacts with a spatial landscape allows for spatially explicit modelling of biophysical landscape variables and location of impacts that the agents incur. In a natural resource based ABM, heterogeneity therefore exists in such areas as distribution of resources, biophysical processes and location based decisions.

Critiques of ABM

Several shortfalls of ABM have been discussed in the literature. Richardson (2002) argues that ABMs have been oversold as a tool for modelling and managing organizational complexity at the expense of other equally legitimate approaches. Richardson goes on to suggest that proponents of ABM give a false sense of realism and objectivity regarding their models, and the ability of models to identify real world causation. Indeed, Grimm (1999) points out, many ABMs have been built but relatively little has been learned about ecology or natural resource management from these models. The primary problem with ABM is perhaps the problem of properly designing and analyzing their operation. ABMs have also been criticized of lacking process theory (Parker et al. 2002).Modelers must be sure that the test patterns are emergent responses for the model, and are not hardwired in (Railsback 2001). The very nature of emergent properties makes it problematic for us, as observers of the ABM, even to formulate them, let alone discover whether or not they are in fact obtained (Lane 1993).

CHAPTER 5 AGENT BASED LANDUSE EXPERIMENT (ABLE)

Introduction

Although various styles of representing multi-agent systems exist, ABM is applied here to human-environment systems. A population of agents is generated and acts upon a landscape over multiple time steps. In this way, the human dimensions of the system can be thought to represent the 'agent' component of the system, and the landscape is represented as a spatial cellular automation of the system which interacts with the human dimension. The dynamic affects both agents and the landscape through any exogenous and endogenous effects identified.

Within this framework, the Agent Based Landuse Experiment (ABLE) was constructed specifically to examine resource focused questions regarding wildlife resources in forested landscapes, and also to present a method of combining social and natural science modelling grounded in micro-economic theory of decision making. The ABLE model simulates the activities of multiple moose hunting agents on a dynamic landscape. The model is composed of hunter agents, a landscape represented as a grid of cells, and rules by which the landscape changes.

Agents are independent decision making units able to perceive their environment, categorize preferred actions, and enact their decisions, as described in Chapter 4. The landscape is comprised of layered modules tracking biophysical variables associated with forested landscapes. These variables change over time according to internal processes and impacts incurred exogenously. A number of exogenous controls allows for examination of various resource scenarios and the resulting landscape level effects under different scenarios.

The purpose of the experiment is the examination of cumulative impacts on wildlife resources. The platform is developed using computational simulation to evaluate landscape level outcomes resulting from action and interaction of multiple individual agents affecting variables within their environment. This platform allows the modelling of complex systems of interactions between autonomous agents, and tracks system level dynamics emergent from these autonomous individual actions.

The ABLE model is a custom-built software program written in C++ which simulates individual coded classes written in object-oriented programming. The model operations are visualized through a graphical user interface (GUI) and the simulation's history is recorded for all variables in outputted text data files.

Data generated from the simulation is outputted and analyzed to examine different simulation outcomes on hunter utility levels gained from the hunting season, and also the impact of the cumulative actions on the resources of the landscape, mainly extirpations incurred through exceeding hunting pressure thresholds for local moose populations.

In accordance with discrete choice theory as discussed in Chapter 4, the ABLE model is comprised of:

- Hunters as decision making agents
- Landscape cells representing alternative sites among which hunters select sites to visit
- Perception of landscape attributes within each alternative cell
- Generation of a choice set of these alternatives
- A decision rule by which by which actions are based
- Outcomes measured for individuals and the population

The landscape grid is spatially explicit and operates at yearly time steps, simulating the outcomes of the fall moose hunting season and updating the information stored within the landscape each year. The variables of the landscape change over time through their own internal processes, defined rules and impacts of agent decisions.

Software Specifications / Model Structure

The implementation language is C++, chosen because it is an object-oriented language (OOP), produces a faster executable program, and allows for loose coupling of modules. The structure of an ABM requires modular design of many autonomous objects interacting repeatedly. ABM is inherently based on disaggregated individual actions and effects, where agents' strategies and the landscape features each represent objects. The larger number of the agents, landscape cells, and processes occurring within the combined modular construction results in objects interacting repeatedly, often recursively. This requires fast execution to produce reasonable model functioning time and the data out put generated as a result of each time step.

For every module there are two files, the header file and the implementation file. The header file (filename.h) declares the functions, classes or constant variables that are included in this module. The implementation of these declarations is found in the .cpp file with the same name. See Appendix A in attached CD to view program code.

Program code is organized into separate modules in order to optimize programming organization. Each .Cpp and .h file represents a particular module of the ABLE program. The modular construction allows the model to isolate any given portion of the program, while still having the remained function normally, referred to as loose coupling. Loose coupling also allows flexibility in altering modules of the system being modeled. For example, if a data layer is not included in a given model simulation, the module is inactive, but does not otherwise impact the operation of the other modules. Likewise, the landscape can operate without being coupled to the agent based component. Loose coupling also allows multiple simulations to be enacted while varying only one module. Therefore resource impact simulations can be compared to baseline conditions in the presence of or absence of a given ABLE module.

Loose coupling also aids in finding program bugs, as they can corrected by identifying the specific model causing an error and isolating the code within that class while correcting the problem. This essentially amounts to removing one component, repairing the code, and re-inserting it into the model structure.

Design Considerations

The architecture of the model consists of a number of interacting classes linked to the model user through an application layer. This consists of several modules, including agents, landscape, simulation and the graphical user interface (GUI).

The agent module encompasses 'Hunter' and 'HunterUtility' classes, which represent the hunter agents and the implementation of the utility calculation. Here we find:

- The utility calculator object with individual utility parameters (including standard deviation of coefficients for implementing preference and perception heterogeneity) and links to each GridUnit (cell).
- A data structure representing a memory of grid locations that have been visited, hunter age and other characteristics.

Since system memory would be prohibitive if each hunter memorized the entire Grid for multiple years, the previous year's grid is stored externally to the hunter, and is linked to the hunter to be used as an exact memory of the previous cycle. The limitation here being that the hunter only remembers the previous years landscape, but still keeps a record of how many times any site has been visited.

The landscape module encompasses several classes:

- GridUnit: The basic class containing data for each cell in the landscape
- Grid: An array of GridUnit objects
- TravelCostCalculator: Linked with RoadNode objects to calculate travel cost associated with each cell
- RoadNode: A recursive data structure representing points in the road network
- Road: A manager of RoadNodes which provides access to the RoadNode objects
- RoadManipulator: A means of building and updating a Road object
- ForestHarvester: A strategy to update the Grid and Road objects, clear cutting cells and adding forestry roads

Each landscape cell is an instance of a GridUnit class. The GridUnit class contains the landscape data and functions that operate on that data, such as forest age, moose population, congestion, access, number of visits and summed utility from hunter agents.

The road is completely decoupled from the Grid. It is constructed and updated using the RoadManipulator class. The Road class contains a list of all the RoadNode objects that form the road network, and measures distances in kilometers. The RoadNode class represents the road network using a recursive data structure containing a dynamic number of pointers to the RoadNode objects connected to it. This class provides recursive functions for traversing the network to determine travel cost.

Travel cost calculation is implemented through a strategy similar to the utility calculation. An object of the TravelCostCalculator class is passed into a function of the

RoadNode class as a path is traversed from node to node. Upon completion of the traversal, the TravelCostCalculator object will contain the total distance traveled and cost of the trip.

The RoadManipulator class facilitates the construction and updating of roads. This functionality could have been provided in the Road class, however, a separate class offers more flexibility for new functionality (loose coupling principle). The road is visualized using the RoadRenderer class which simply traverses the RoadNode objects recursively and draws lines into the image buffer.

The ForestHarvester is a strategy for cutting (setting forest age to zero) certain sections of the grid. It contains references to the current Grid and Road objects in the simulation. When the update member function is called, this class updates the Grid (clears forest) and Road (add new forestry roads) classes based on parameters given by the user.

The Simulation module is a "singleton" that provides a single point of access through member functions to key global data. This provides a single interface to global settings and calculations. For example, moose population growth rate, number of annual cut blocks, and other biophysical processes which occur each year. Simulation encompasses the ABM class, which brings all the elements of the model together, updating them and saving the data, as well as the ABMViewer class which displays the grid and road with the current user view settings.

The GUI encompasses the CWindowsApp classes, which handle windows messages and update the model based on user input. Several dialog "callback" functions are represented here that translate the user input for each of the dialog boxes and update the model accordingly through the CWindowsApp interface. This class effectively acts as a transaction center between the user and the core architecture. The graphical user interface (GUI) is the link between the coded program and the modeler, which allows the program user to input data and visually observe the operation of the model landscape as it runs. The GUI consists of the grid landscape, with pull down windows which link to data input windows.

Human Dimensions and Resource Management Scenarios

The ability to alter the operation of classes within the model presents the opportunity to examine the effect of changing one (several) variable(s) while holding others constant. Thus the landscape level effects of changes in model operation can be examined in terms of different scenarios, for both resource management and representation of the human dimensions. There are two ways under which the landscape changes from year to year: endogenous processes, and exogenous control on the state of certain landscape variables and agent attributes. These can be manipulated as the model progresses through time and simulation of scenarios are possible by altering either the initial conditions or exogenous controls.

As outlined in Table 4, resource management scenarios can be examined according to real world on-the-ground practices in terms of the effect of different time frames for access / linear disturbance regeneration and road decommissioning. Human dimensions can be examined in terms of different agent attributes, controls on preferences and perceptions. In each scenario, results have been generated for:

- The effect on hunter site selection
- Overall sum of utility perceived across all cells of the landscape
- The sustainability of local moose populations, in terms of the number of extirpations in any given grid cell, and the number of moose present across all cells on the landscape
- Other select outcomes observed in the model meta-data

Table 4: ABLE simulation scenarios implanting alternative representations of agent characteristics and resource management options

	Agent Perception	Agent Preferences
Human Dimensions	1. Homogenous vs. Heterogeneous at various levels 2. Agent learning according to age and experience	1. Homogenous vs. Heterogeneous at various levels
	Access / Linear Disturbance Regeneration	Road Decommissioning
Resource Management	1. Access / linear disturbance remain permanent features vs. regeneration over time, at various rates regenerates over time, at various rates	1. Forestry roads remain permanently open vs. decommissioning at various rates

Variable Descriptions

Variables to be included in the model were selected to represent relevant variables identified from SP / RP studies of hunter preferences, as identified in Table 5. Selection of relevant attributes was contingent on their having a significant effect on hunter decision making.

Table 5: Variables examined in hunting preference studies which are shown to have a significant impact on decision making

Study	Travel Cost / Distance	Moose Population	Hunter Congestion / Encounters	Forestry Activity	Access / Impedance	Other
Morton, 1993	x	x	x	x	x	x
McLeod, 1995	x	x	x		x	
Bottan, 1999	x	x	x	x	x	x
Dosman et al., 2001	x	x	x	x	x	
Haener et al., 2001	x	x	x	x	x	x

The results of discrete choice studies are not comparable to one another, as each study derives results from a unique set of landscape attributes and exists within a potentially unique set of institutional constraints. However, parameter estimates are comparable within each study, such that the magnitude of β^k estimates, as a percentage of the summed (absolute) β^k values, shows the comparative effect of the variable in question. By this process, the percentage of the total utility that each β^k represents is calculated as outlined in Table 6. For Each SP / RP study, the relative magnitudes of β^k are thus comparable across studies. The negative coefficients show factors that detract from the overall utility derived in the presence of that given landscape attribute.

Table 6: Agent types - β parameter calibration from various stated / revealed preference studies

Bottan 1999		Dosman et al. 2002		Haener et al. 2000		McLeod 1995		Morton 1993	
Variable	β	Variable	β	Variable	β	Variable	β	Variable	β
Intercept	-0.05364	Constant	-0.30760	Intercept	-0.25289	One Way Distance	-0.00331	Constant	-0.28112
Distance over 300Km	-0.15090	Driving cost (00's$)	-0.09000	Travel Cost	-0.00108	Access	0.18296	Cost	-0.00204
Distance <150Km	0.15090	Just harvested	-0.12236	Access 1	-0.04299	Congestion	-0.25161	Access	0.06600
Access High	0.08121	Logged 3-4 years ago	-0.05572	Access 2	0.01659	Moose Population 1	0.22050	Game	0.29945
Access Medium	0.00491	Logged 10-15 years ago	0.04123	Encounters 1	0.12506	Moose Population 2	0.21058	Congestion	-0.17216
Access Low	-0.01303	No Evidence of Logging	0.13123	Encounters 2	-0.00685	Moose Population 3	0.03752		
Encounters 4+	-0.10293	High Moose Density	0.06297	Forestry Activity	-0.00113				
Encounters 1-3	-0.00057	Medium moose density	-0.01264	Moose 1	-0.11319				
Encounters 0	0.10349	Low moose density	-0.03594	Moose 2	0.02130				
Moose (3+/day)	0.06553	Encounters occur	-0.04848						
Moose (1-2/day)	0.02757	Newer trails	-0.02424						
Moose (<1/day)	-0.09311	Old trails	-0.01766						
Regeneration >2m	-0.04551	No trails	-0.04848						
Regeneration 1-2m	0.06799								
Regeneration <1m	0.03872								

Note that the subjects in the Dosman et al. (2002) and the Haener et al. (2000) are aboriginal hunters in Northern Saskatchewan who face a different set of regulation constraint compared to the other three studies, which estimate the preference structures of licensed hunters.

Agent Based Model

Each agent represents a hunter within the model, with their own ability to observe landscape cell attributes levels, identify their preferred hunting sites, and act on that information. Specifically, the agents are capable of perception, categorization and action, as described in Chapter 4. Perception is the ability to read the current state of landscape cell attributes. Categorization refers to the agents' ability to calculate the relative utility levels associated with the cell attributes, as determined by the agent's individual preference structure. Action refers to the agent selecting the site with the highest utility across all options, and visiting that site.

This process is concurrent with discrete choice theory, where individuals identify a choice problem, perceive the set of possible alternatives, evaluate the outcomes of each alternative, choose the alternative that yields the highest level of utility, and act on that selection. Visiting a hunting site results in the hunter receiving some benefit from the experience, as measured by a parameterized indirect utility function.

Perception

From the agents' perspective, each landscape cell is a bundle of attributes as identified in Table 5, with levels of these attributes varying across different cells. The landscape cells are therefore the feasible choice set from which the agents can select their preferred alternative. The current levels or state of each variable is observable to each hunter and hence agents have perfect knowledge of their landscape.[11]

Categorization

After perceiving the landscape attributes, the associated utility for each cell in the landscape is calculated in order for the agents to evaluate the expected utility that would be derived by attending any given site. The selected site, x_{ijk}, is the cell with k attributes, that generates the highest utility (U) within the feasible choice set. The utility that hunter j receives from site i from the feasible choice set is:

$$U_{ij}=U(x_{ijk})$$

where x_{ijk} is a vector of k attributes for site i, as listed in Table 5 perceived by hunter j. The individual is assumed to have consistent and transitive preferences over the alternatives that determine a unique preference ranking. Thus, every agent is programmed with a utility function that calculates the utility level derived from potential hunting sites and comparatively ranks their expected utilities. In this fashion, a utility index associated with every alternative is identified, and hunters select the utility maximizing site from their choice set.[12] Ultimately, each agent selects the site which offers the highest calculated expected utility across alternatives.

$$U_{ij}>U_{nj} \text{ for all sites } i=1\ldots n$$

The utility calculation is portioned into two components; a systematic preference

[11] This assumption is further explored in the following sections.
[12] Although the ABLE model can eliminate cells from the choice set by not allowing hunting within any defined area, here we do not apply that ability, and hence the choice set is comprised of all cells on the landscape.

component, V_{ij}, and a perception accuracy component, ϕ_{ij} (to be discussed below).

$$U_{ij} = V_{ij} + \phi_{ij}$$

The preference component is a parameterized linear equation which draws coefficients, β^k_j, which are relevant preference parameters of hunter j for attribute k as identified from SP / RP studies.

$$V_{ij} = \sum_{k=1}^{K} \beta_j^k X_{ij}^k$$

The magnitude of the β^k coefficients represents the preference structure of the agent. The preference component is then made to be a random variable by making the β^k_j parameters random numbers that are normally distributed such that:

$$\beta_j^k \sim N(\beta^k, \sigma_{\beta^k}^2)$$

Where β^k are attribute specific parameters drawn from SP/RP studies and σ_{β^k} is the standard deviation defined by the model user. The result is a population of hunting agents who each have a unique preference structure, distributed around a mean population measure of preferences for variables described in Table 5, such that:

$$V_{ij} = \beta_j^{Tc} * Tc_{ij} + \beta_j^{Mp1} + \beta_j^{Mp2} + \beta_j^{Mp3} + \beta_j^{Cg1} + \beta_j^{Cg2} + \beta_j^{Cg3} + \beta_j^{Fa1} + \beta_j^{Fa2} + \beta_j^{Fa3} + \beta_j^{A1} + \beta_j^{A2} + \beta_j^{A3}$$

The first component ($\beta_{jTc} * Tc_{ij}$) is the preference for travel cost associated with attending a site multiplied by the calculated travel cost. The following four variables (β_j^{Mp}, β_j^{Cg}, β_j^{Fa}, β_j^{A}) represent β^k_j parameters for a cell's moose population, hunter congestion, forest age since origin and access / linear disturbance. These state variables are dummy variables (0, 1) that describe one of three possible conditions for cell attributes. The state and its β^k_j value are defined by the model user, as in Figure 2. The overall utility calculation is specified as:

$$U_{ij} = \left[\sum_{k=1}^{K} \beta_j^k X_j^k\right] + \phi_{ij(A,E)}$$

Where

$$\phi_{ij} \sim N(0, \sigma_\phi^2)$$

Agent Heterogeneity

Within the ABLE framework, calculation of the utilities derived by each hunter from the landscape cells diverges from the traditional discrete choice modeling in its inclusion of both preference and perception heterogeneity. This is done by using random variables within the utility calculation performed by each agent, and defining how these variables are distributed across the population of agents. The modeler has control over the kurtosis of the random variable distribution, and therefore the degree of variation of preferences and perceptions across the agent population.

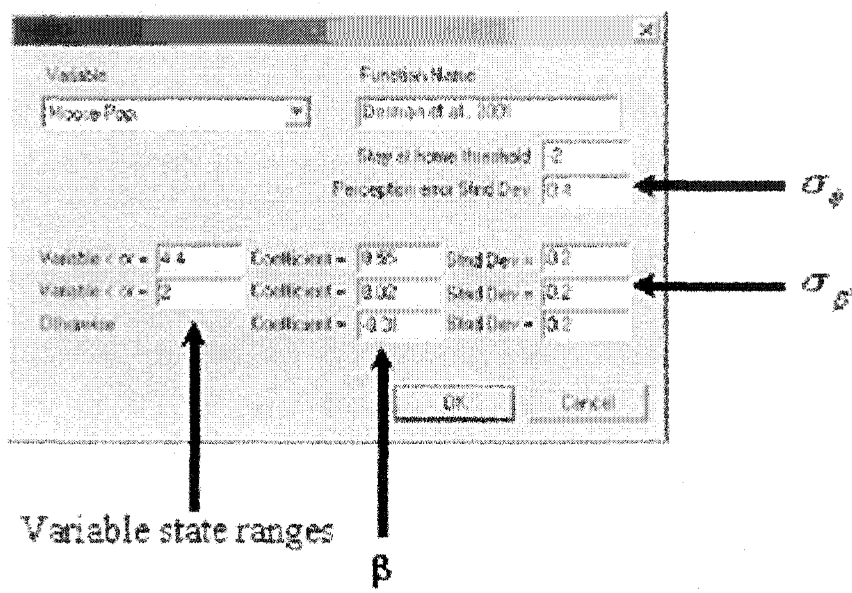
Using the ABM approach, agent preference heterogeneity is introduced through varying agents' preferences and ability to accurately perceive their landscape. The $\beta^k{}_j$ values and the perception accuracy variable (ϕ_{ij}) are both normally distributed across the population of agents, and serve to alter the level of overall utility perceived for each grid cell and the preferences of each hunter.

Heterogeneous Preferences

In traditional discrete choice modelling the researcher draws an estimate of the subjects' preferences and estimates the population level preference parameters from aggregate data. However, by varying the $\beta^k{}_j$ values used in traditional discrete choice modeling for each agent, we alter the preferences of the agents simulated in the ABLE model. The result is the generation of agents with unique individual preferences, which deviate in a normal distribution around a specified mean, $\beta^k{}_j$, and standard deviation as imputed by the modeller.

The modelling style employed here essentially reverses the traditional discrete choice estimation of parameters, by assigning a preference structure to an agent group, then deviating the $\beta^k{}_j$ parameters according to the distribution. The result is a group of agents with a mean β^k value across the population, but each agent is unique in their actual $\beta^k{}_j$ level. The parameters required are imputed through the ABLE GUI in a command box, as in Figure 2. The 'Variable' scroll down toolbar allows for switching between all landscape variables.

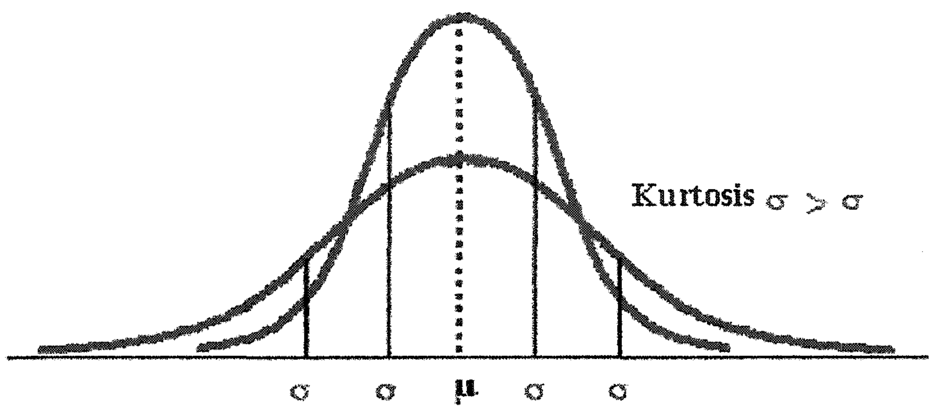
Figure 2: ABLE graphical user interface utility function specification window



The β^k parameter is estimated in RP / SP studies. Recall that when these parameters are calculated, they are a representation of the mean across the entire population studied. It is understood that in reality there is deviation across the population as to each individual's β^k estimate, but in order to mathematically determine these numbers, mean estimates for the group as a whole are calculated. Working from the other direction in the ABM framework, we start with a mean population estimate of β^k, and assign an altered value according to the normally distributed preference heterogeneity variable.

The degree of kurtosis for this distribution, or degree of variation observed in the population, depends on the magnitude of the σ_{β^k} term. The larger the σ_{β^k} term, the greater the variability in preferences across the population of agents, as described in Figure 3.

Figure 3: Kurtosis of error distribution as standard deviation changes



Heterogeneous Perception

Assumptions regarding information available to individuals have potentially important implications to how resources are impacted. Many modelling efforts assume perfect information is available. We can test whether this assumption has resource implications by altering the ability of the agents to accurately perceive their surroundings. Much the same way that a random variable is used in producing heterogeneous preferences across agents and attributes, a random variable, ϕ_{ij}, is combined with the systematic preference component of the utility calculation. Thus, each agent's utility calculated utility is 'fuzzied' by the perception error term, ϕ_{ij}. Therefore, when a hunter is 'reading' the landscape, they receive imperfect information about the current level of landscape attributes.

The degree of kurtosis for this distribution, or degree of error away from the actual state existing in the cell, depends on the magnitude of the σ_ϕ term, which is specified by the modeler through the ABLE GUI, as in Figure 2. The larger the σ_ϕ term, the greater the variability in perceptions across the population of agents. The result is that each agent will have a slightly different perceived utility level than the actual level that exists under perfect information, and also different compared to the levels perceived by other agents.

Learning

The studies described in Table 5 describe characteristics of the hunters themselves that impact decision making beyond the attributes of the hunting site. This may include demographic information, past experience at hunting sites, and a variety of other defining characteristics. Of particular interest is the effect of learning through experience, either as a function of the hunters' age, or the degree of familiarity with the hunting sites that they attend.

Exploring the concept of 'learning', and how this occurs is arguably outside of the scope of this study, but here is it proposed that learning through experience and age comes about by an individual's ability to better understand their environment over time. In this vein, learning can be thought of as the process by which the perception of site attribute information becomes more accurate, such that the individual is able to better 'read' their surroundings.

To accommodate learning over time, the number of years that each agent has been hunting is recorded. This essentially 'tags' each individual with a hunting 'age' by which it is assumed they become more experienced over time. As hunters age, they are better able to accurately perceive the state of landscape variables. The rationale here is that as a agent gets older, the better able it is to read the information available regarding attribute levels of the landscape, and thereby base decisions on this improved information. Learning through ageing applies to all possible hunting sites within the agent's choice set, with any given cell slightly more accurately perceived in each time step.

However, if an agent actually attends a site through a decision to visit the site in a given year, it may also learn of that site's attributes through direct contact. The assumption here is that hunters have better information regarding a hunting area if they actually attend the location. Therefore, direct contact with an area also increases the hunter's ability to accurately perceive the current state of the cell attributes in any given year.

Learning through age and experience is represented in the ABLE model by altering the standard deviation of the perception error term, effectively controlling how wide a distribution of perceptions exist around the actual variable state value. Recall:

$$\phi_{ij} \sim N(0, \sigma_{\phi}^{2})$$

It is possible to alter the effect of the random number on perception by varying the magnitude of the distribution standard deviation, σ_{ϕ}. This occurs as a function of the individual's age (A_j) and their number of visits, or experience, at any given hunting site i (E_{ij}), where

$$\sigma_{\phi j} = \sigma_{\phi} / (40A_j + 100E_{ij})$$

Where A_j is hunter age, in number of time steps for hunter j, and E_{ij} is hunter experience, in number of previous visits to a given site. The assumption behind the parameters, 40 and 100, assigned to A_j and E_{ij}, is that improved perception through age occurs constantly, albeit slowly across all sites on the landscape. Experience, through number of previous visits at a given hunting site, improves the hunter's ability to correctly read site attribute levels assuming that direct contact with the area offers a better 'knowledge' of the area.

Figure 4: Age and experience effects on perception standard deviation

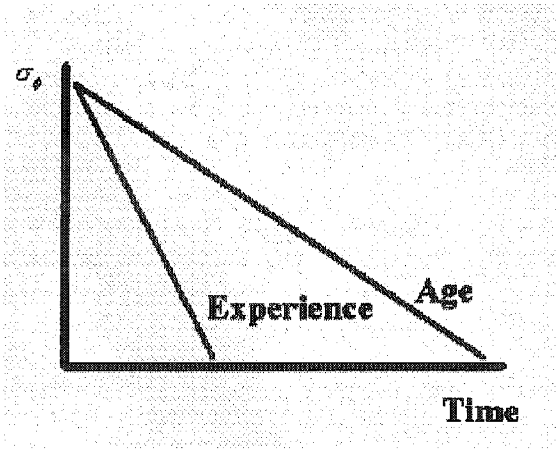


Figure 4 shows the result of age and experience effects on the distribution of error terms is to decrease the error around the mean as each of these variables increase, as in Figure 3.

The overall effect is the ability of agents to more accurately perceive correct utility measurements when selecting from among sites at the start of a hunting season. An 'older' hunter will perceive the landscape as a whole with less error than a 'young' hunter, and a hunter with experience at a given site will perceive that site with less error than sites which have not been visited.

The age and experience functions serve to accommodate the examination of different individuals that exist in the hunting community. Among the regular factors that are presented as having significant effect on hunting site choice, as listed in Table 5, the hunting literature identifies preference differences within groups in terms of hunter age, and also fidelity to certain areas that are commonly visited, or visited in the past (Bottan 1999). Here we have a subset of an agent type, one that initially has the same characteristic of all other agents, but evolves over time to accommodate learning through both experience and interaction with the environment.

Hence, through the ABLE platform, simulations can be performed where the hypothesis of whether both age and experience of hunters has a landscape level effect on both overall hunter utility and number and distribution of extirpations. This is explained further in Chapter 6. Through the GUI, the ABLE user controls the reset age function (See Figure 6 below). Learning can be turned off by setting maximum hunter age to zero. This is done to examine the effect of learning on agent decision making, and it's implications for resource sustainability.

Note that 'learning' here only covers the accuracy of the hunters' perceptions, which become clearer as the agents age and gain experience on the landscape. Another aspect of this process that is not covered in this project is a change in preferences that may accompany age and experience. As identified in the hunting literature, an individuals preference for landscape attributes may change over time, such that older hunters are less concerned about their chances of bagging a moose, are willing to travel further, and develop an affinity for certain sites for various reasons. These factors indicate that the actual preference structure of a hunter may evolve with age and experience. In this case study, the agents preferences do not evolve over time, and the relative β^k values are static throughout the simulation.

The complete utility calculation is therefore defined as:

$$U_{ij} = \left[\sum_{k=1}^{K} \beta_{ij}^{k} X_{i}^{k} \right] + \phi_{ij(A,E)}$$

Breaking the components down to show the complete operation yields:

$$U_{ij} = [V_{ij} = \beta_j^{Tc} * Tc_{ij} + \beta_j^{Mp1} + \beta_j^{Mp2} + \beta_j^{Mp3} + \beta_j^{Cg1} + \beta_j^{Cg2} + \beta_j^{Cg3} + \beta_j^{Fa1} + \beta_j^{Fa2} + \beta_j^{Fa3} + \beta_j^{A1} + \beta_j^{A2} + \beta_j^{A3}] + \phi_{j(A,E)}$$

Parameterization of Utility Functions

Parameters estimated in discrete choice models describe the preferences of the aggregate population of individuals surveyed. This is commonly identified as a limitation to modelling, in that results are aggregated across the whole population. However, in agent based modelling, the power is in tracking the cumulative effect of many independent, individual actions. Therefore, it is not reasonable for all agents to have a homogenous preference structure based on aggregate population estimates. In actuality, there is a range of preferences, such that the indirect utility function for all individuals is unique.

Coefficients used in the running of the ABLE model are identified in various discrete choice studies. From studies listed in Table 5 the β^k values of the agents' utility function is parameterized. The parameters estimated are not comparable across studies, as each is a unique snapshot of population preferences within a certain context. The magnitude of parameters within the study are however comparable to each other, showing the degree of marginal effect caused by one attribute over another. Therefore, calculating the percentage of the (absolute) sum to which each variable accounts for allows parameters to be compared across studies. The associate attribute levels can then be altered within the ABLE GUI to accommodate the unique attribute levels examined in each study, and a population of hunting agents representative of the studies in Table 5 can be generated.

In these studies, it is common for survey respondents to select between a number of (commonly three) states of a variable, for example high, low, and medium moose densities. From this, the marginal effect on utility for each attribute are determined and imputed through the ABLE GUI to represent the β^k parameters, which serve as the mean values in the random variables described above.

This is a key feature of the ABLE framework, in that parameters used in the utility calculation are easily estimated from SP / RP data, and used to build a population for examination of hypothetical scenarios. This provides a decision support system, which explicitly represents biophysical, social and economic complexity but is easily calibrated from real world data.

Action

Once each hunter has identified their preferred hunting site, the hunters visit their selected sites, impacting the cell variables accordingly. At this point, the outcome of the number of moose harvested and the congestion level realized in a given cell is recorded.

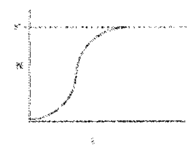
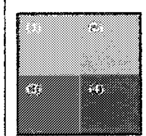
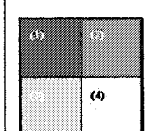
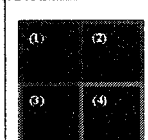
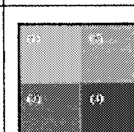
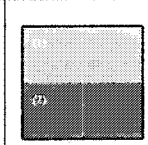
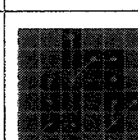
Landscape

The landscape on which the agents act is comprised of a grid of cells itself composed of the different landscape variable modules. Essentially, the environment in which the agents act is a series of layered data variables tracked over time steps. Each cell tracks the five variables listed in Table 5, with the variable's state depending on how the variables change from one year to the next. The landscape is not intended to be a re-creation of all biophysical processes in a forested landscape, but is intended to reflect the landscape in terms of hunter's perceptions of attributes that significantly affect their decision making, as identified from other studies and associated literature. As the landscape is simply a perceptual representation of the real world, from the point of view of the human agents acting upon it, other resource issues could hypothetically be represented with minor changes to the program code.

Data Layers

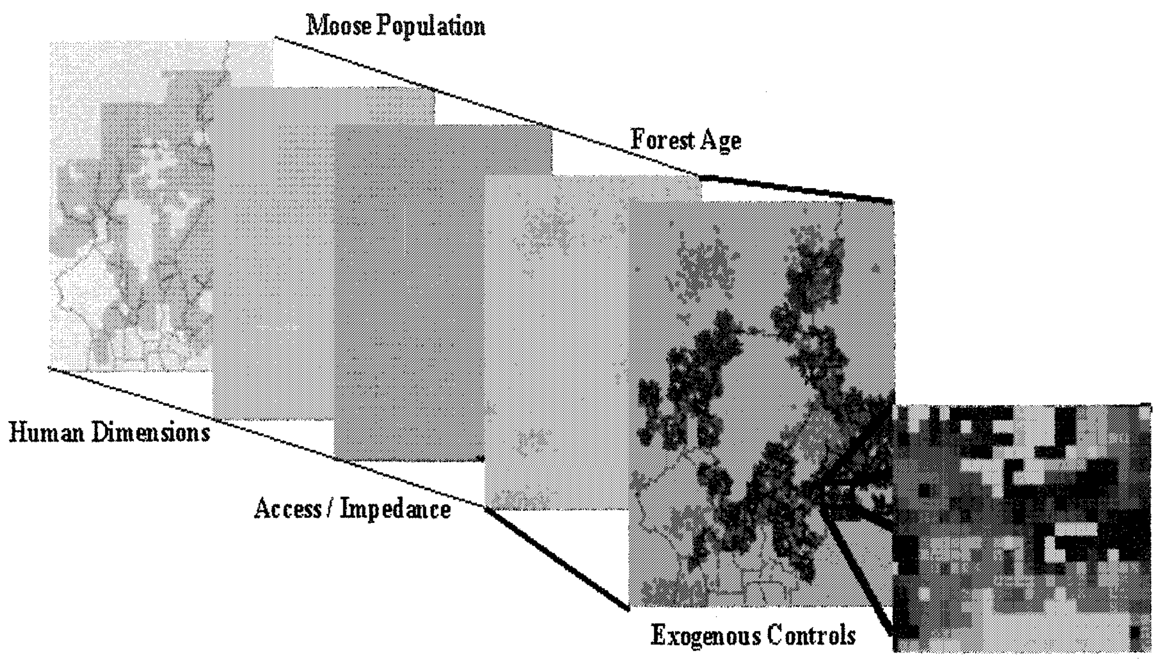
The variables included in the ABLE model represent landscape functions which change according to both endogenous and exogenous processes. Measurement, as either continuous or state variables, depends on the variable type and whether it is a spatially dependent measure, or a cell level condition, as in Table 7.

Table 7: ABLE Site Attributes and their endogenous functions, controls, graphical representation and measurement

Site Attribute	Endogenous Function	Exogenous Controls	Graphical Representation	Variable
Moose Population	 Logistic Population Growth $\partial N/\partial t = N + r(1 - N/K)N - Ht$	None		Continuous Variable: 0 to carrying capacity 1) 0 / Km^2 2) 2 / Km^2 3) 3 / Km^2 4) 4.4 / Km^2
Travel Cost	TC = 2*Distance*Operating Cost + 2*Speed*Opportunity Cost of Time	Operating cost and speed varies on type of road used	Internally stored	Continuous Variable: Computed for each grid cell to hunter origin
Hunter Congestion	Number of hunters selecting site as perceived in t - 1	None		Count: Number of Hunters 1) 1 Hunter 2) 3 Hunters 3) 6 Hunters 4) 9 Hunters
Access / Linear Disturbance	Increase to maximum level when road present	Regenerate to next lowest level after specified time		State Variable: Greater access / reduced impedance with higher level 1) Level 1 2) Level 2 3) Level 3 4) Level 4
Forest age	Ages at yearly time step	Harvest site selection based on stand age and distance		Continuous Variable: 0 to infinity 1) 70 years 2) 50 years 3) 25 years 4) 0 years
Exclude Activity	None	Externally set to exclude either timber harvesting or moose hunting		State Variable: 1) Hunting and/or timber harvesting prohibited 2) No exclusions
Roads	Roads are built to cells selected under the timber harvest strategy in the year they are cut	Can be externally set by modeler. Reclaimed after specified time if unused		State Variable: Greater access / reduced impedance with higher level 1) Level 1 2) Level 2 3) Level 3 4) Level 4

Inputting initial conditions for each data layer results in a layered set of landscape attributes that are tracked in each cell of the grid. A composite landscape comprised of these layers is depicted in Figure 5 for the AlPac FMA case study[13].

Figure 5: ABLE data layers comprising the landscape



Scale

Spatial scale refers both to the resolution and extent of the model. Although the extent of the landscape can be set by the program user through the GUI, the resolution of the scale is internally set. It is possible to alter the spatial resolution by making simple changes to the model code, although this is not available to the common user accessing the model through the regular GUI.

Determination of a proper spatial scale considers the unit of agent decision making and the units of landscape transformations that are represented in the model. The scale selection considers the spatial scale of ecological processes and the availability of spatial data which corresponds to model landscape variables. The smaller the scale, the

[13] Results from the AlPac case study are not presented in this project, rather a hypothetical case study is used for the purposes of isolating effects regarding hypotheses identified in Chapter 1

effectively larger and more complex the grid becomes, therefore scale is constrained in part by CPU operating speed.

The default scale resolution on which the grid performs is 6 miles by 6 miles, representing one 36 miles^2 township per grid cell. All landscape variables are tracked at this resolution. Therefore, if a given cell is occupied by a road node, it will register that an industrial road exists somewhere on the 36 miles^2 cell, the congestion level would report the number of hunters who attend that same 36 miles^2 cell, but not their distribution within that area.

Programming multiple scales for different variables is identified as offering statistical advantages to a homogenous scale as well as a better representation of landscape complexity. Future directions for agent base modelling should include multiple resolution scales.

With regards to temporal scale, a yearly unit was selected to examine the simulation over time. Selection of an appropriate scale to run was determined by the fact that the moose hunting season occurs once a year, over the later fall months.

Landscape Variables

The ABLE user must input the initial conditions for the agents, landscape and dynamic (as discussed in Chapter 4), or import saved or previously defined initial conditions. For agents, this amounts to selecting a population for each city[14] or point of departure. The landscape initial conditions are set by 'painted' variable levels onto the landscape. The dynamic is set internally, as with pre-described time steps, and by the modeler through the GUI by defining the parameters for exogenous controls.

Road network

The road network is represented by a series of linearly connected nodes, occurring in the centroid of the cell. There are two types of roads, the permanent provincial highway network and forestry roads. For sites with neither type of road, it is assumed that

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[14] 'City' here, is not defined by the size, or even the designation of a municipality, but is termed this way simply to identify that this is the location where hunters live, and therefore originate from when calculating the distance, and therefore travel cost, to any given hunting site. A city therefore might have 1 agent, or thousands.

hunters can still access the area through off road vehicle use or on foot. These three options for traveling to the hunting site are computed in the travel cost calculation, representing different costs per kilometer of travel, and a different opportunity cost of time due to the speeds traveled on each type of road. The travel cost calculation is identified in Table 7 and is derived from studies such Ward and Loomis (1986) and Boxall and Macnab (2000).

The travel cost for any given site is calculated from the hunter origin by determining the shortest possible route along existing roadways. This is done through a recursive function by which the model internally searches for the shortest route from the cell back to the hunter origin. The program first searches all possible branches on the road network, then eliminates routes that do not qualify as shortest possible option. After all routes have been searched, the shortest distance from origin to selected hunting site, along the different road types, is used to calculate the travel cost to that site.

The provincial road network is either imported as an .ABLE file, or defined by the model user. Forestry roads are added when a site is selected for harvesting, and decommissioned according to the forest harvesting scheduler (See Figure 6 below). Forestry road nodes are only decommissioned if they are no longer in use for hauling timber. As such, if a harvested site is occupied by a road node, additions of subsequent roads attached to this node cause the road to remain on the landscape until it is no longer in use, at which time the yearly 'countdown' to decommissioning begins.

Forest Growth and Harvesting

The forest age is tracked in the number of time steps, or years. The dynamic controls timber harvesting, represented on the landscape by resetting the age since origin of a cell's forest age to 0 years. The modeler is asked to define a minimum age and the number of cutblocks to be harvested each year (Figure 6 below). The program then makes a list of eligible cells that meet these criteria, and stores the cell locations in a list. These cells are then sorted according to the distance from that cell to the nearest road node. The cells which meet the harvesting criteria and are closest to road nodes are then harvested. A road node is added to the newly harvested cell from the nearest cell already occupied by a road node. The site's access / impedance level is upgraded to the maximum to represent the increase in passability caused by the creation of the forestry road.

By defining the timber harvesting strategy according to age and distance, the goal is not to attempt recreating the exact operations of a harvest strategy. Rather, it simply attempts to show that where possible, the closest cutblock to a connecting road will be cut first to minimize travel time and overall cost to the harvesting operation.

Moose Population

The total moose population is tracked for each cell, and changes over time according to the logistic function:

$$\partial N/\partial t = N_{(t-1)} + r\,(\,1 - N_{(t-1)} / K\,)\,N - H_t$$

Where N is the number of moose, r is the intrinsic population growth rate, k is the population carrying capacity, and H_t is the number of moose harvested in time t. Once the moose population in any given cell is reduced to zero, it will not recover, and is considered to be a extirpation.

The intrinsic population growth rate is 20% per year in the absence of hunting, as identified in Weclaw (2001) (0.2 per year) and Millette (1999) (0.21 per year, as cited in Courtois and Beaumont 1999). Osko (2000) identifies the carrying capacity as 4.4m/km^2. Hunting season outcomes data from Alberta Sustainable Resource Development from 1997 to 2000 which was provided by ASRD biologists identifies that hunters are successful in about 1/3 of their hunts. Therefore, each hunter that attends a site has a 1/3 chance at a successful hunt, represented as one moose harvested in the count of H_t from the above equation.

This logistic function is commonly used to describe population growth for various renewable resources and represents an aggregate level picture of how populations change over time. Therefore, we are tracking the total population in any given cell, not individual moose specifically. This representation of the moose population does not take into account the intricacies of population growth that would normally be present if the model were to more accurately represent moose as active agents. Factors such as age and sex ratios, the spatial distribution of highlands, lowlands and wetlands, forage availability, the presence of predators, and the behavioral changes due to landscape impacts all play a role in determining the size and distribution of moose populations. As this project focuses primarily on the representation of human hunters, and as such, has not explicitly represented these factors.

The model user is required to set the initial conditions for moose population for each landscape cell, or import default values. For the analysis presented here, a randomized moose population was initiated such that there is at least 1 moose per km^2 and a maximum of 4.4 moose per km^2 in each cell.

Access / Linear Disturbance

The accessibility within a cell is represented in terms of specific 'levels' of impedance measured in discrete states from level 0 to 3. Zero (0) representing no additional access created by human activity within the area, 3 representing full passability created by activity such as cutting of seismic lines, pipelines, in-block forestry roads, or other linear features discussed in Chapter 2.

Access level of cells change over time by being added directly by the model user, and through regeneration over time at a rate again defined by the exogenous control set up (Figure 6 below). It is assumed that regeneration occurs by natural reforestation, which sets back the access level by one unit after the specified time period has elapsed. This continues until level 0 is reached, and increases only by the user adding access through the GUI as desired.

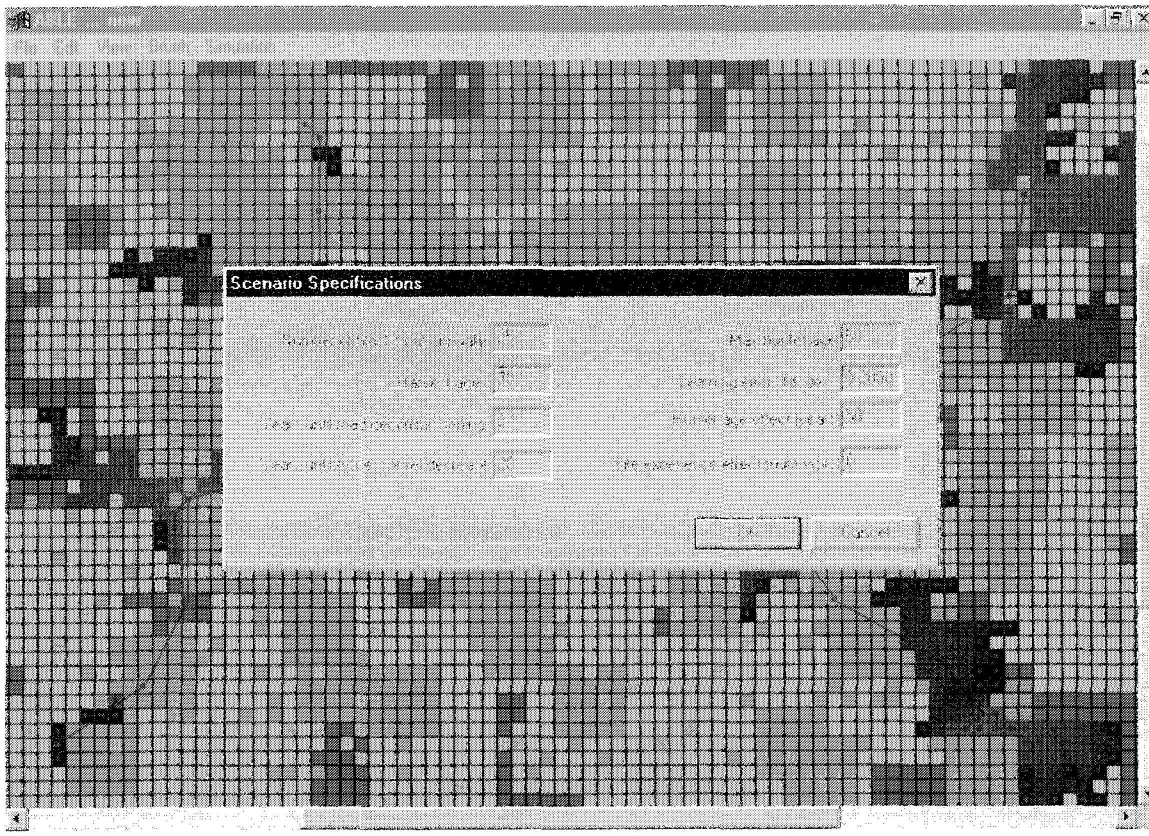
Congestion

Every year, the population of hunters each select a site to visit, based on their perception and categorization of alternatives. When the hunter selects a site, and visits it, the total number of hunters present in the cell at any given time is recorded as the measure of congestion. Hunters' preference for different congestion levels is defined in their utility function calculation. The actual congestion level perceived by the agents is recorded for any given cell from the result of the previous time step. Hunters therefore select the current preferred sites based on congestion information from the previous year's hunting season.

Dynamic

As the simulation progresses through time, the model dynamic specifies all exogenous controls and sequencing of actions. Exogenous controls are the scenario specifications identified by the model user in a pull down screen in the GUI, and specify the conditions being examined in any given model simulation as shown in Figure 6. These include specifications for timber harvesting, road and access reclamation, as well as specifications for hunter attributes connected with perception and learning. The former includes the definition of the number of cells harvested for timber each year, the minimum age of the cells which are deemed harvestable, the years until unused forestry roads are decommissioned, and the number of years until access / impedance is rolled back to the next lowest level. The latter includes the maximum age that hunters continue to operate on the landscape before being reset as a new hunter without any experience, the standard deviation of the error term associated with age and experience dependant perception, the number of years required for perfect age related perception, and the number of visits to a certain cell required for perfect experience related perception.

Figure 6: ABLE scenario specifications control window using modeler inputs to alter the simulation controls



The dynamic also specifies the event sequencing that occurs over time steps. The time step is assumed to be one year, upon which all changes in landscape variables are tracked, updated, and outputted as data for all landscape variables and hunter utility outcomes.

After all the GUI calibration of initial conditions is complete, the program initializes an agent population. Each agent is assigned their utility function, with their preferences and error functions as determined by agent type, age and experience. The site selection process proceeds, landscape variables are updated according to any outcomes for that time step, and the process repeats as the simulation progresses.

Data output

Data for all landscape variables as well as hunter utility realized in each time step are outputted in a text file for spreadsheet analysis. Data are either listed for each cell, hunter, or summed for the year. This meta-data therefore encompasses all data of every cell attribute level and outcomes for agent utility as well as the location of hunting sites attended for each year. Statistical analysis of the data is then possible as a time series across landscape variables and outcomes from hunter site selection.

Model Calibration, Verification and Validation

Structural validity of the model is proven through verification and validation of model programming. Verification refers to how well the software works, and validation refers to how well the model characterizes the system under analysis. This depends on the quality of the economic estimates and the accuracy of the representation of the system dynamics. Validation of the accuracy of the system is drawn from associated discrete preference estimation and resource literature, as identified in chapters 2 and 3. Verification is accomplished through step-by-step observation of model calculations and event sequencing within Microsoft Visual Basic C++ debugging mode.

In terms of validating the system and its functions, recall that the model landscape is constructed in terms of how hunters perceive their landscape, and comprised of variables that are shown to have a significant effect on agent decision-making. Therefore, representing the system in terms the perception of the agents whose behavior is under analysis is key. As such, it is valid to construct the landscape cells as a bundle of attributes that are shown to affect hunter decision-making. The biophysical processes that each attribute undergoes can be identified from the natural resource literature, and represented in program code to behave in this fashion from one year to the next.

Calibrating the model involves fitting initial conditions to real-world data before running the simulation. Initial conditions are again identified according to other literature and various sources of relevant spatial data. Thus, the utility function calculations and parameters are drawn from the SP /RP literature, and landscape functions and data are drawn from literature and source data from mapping such as FMA harvest maps, maps of cutline densities, moose population surveys, historical data, survey results, aerial photos, or other GIS data.

Verification was done through testing code in debugging mode, and step by step confirming that calculations are correctly derived. Outcomes are verified by running a simulation where specific modules are isolated, and output data is examined to confirm the proper functioning of each class of code by comparing data from simulations. Verification is completed through identifying source code errors through debugging modules and compiling the class files, and correcting errors until all classes are deemed to be functioning properly. Verification of the 36 $mile^2$ grid size was confirmed by testing the accuracy of model metrics inside Visual Basic C++ debugging mode. Spatial metrics were calculated for each spatial variable[15] and confirmed in this fashion.

Validation was done by running the ABLE model and examining model outcomes over different initial conditions and varying parameters, identifying how various changes alter model results. Along this vein, sensitivity analysis was accomplished through isolating and varying parameters. Altering initial conditions and exogenous controls was done within the debugging code and by running the simulation with modules both isolated and connected to examine the data produced to ensure functions were properly represented.

[15] Spatial variable exist throughout the model, and include such variables as distance between any two points, travel cost calculated for that distance, moose population carrying capacity per cell.

CHAPTER 6 RESULTS

Using the ABM approach and the framework described in Chapter 5, simulations were performed to examine hypotheses regarding the impact of alternative assumptions about agent heterogeneity and learning. Agents and their impacts were also examined in resource scenarios regarding alternative industrial practices. Output is plotted over time for:

- Landscape Utility: The sum of perceived utility across all cells by all agents in time t, as calculated from the outcomes of $t - 1$.

$$U_{ij} = \left[\sum_{k=1}^{K} \beta_{ij}^{k} X_{i}^{k} \right] + \phi_{ij(A,E)}$$

- Number of Extirpations: Landscape cells whose moose population has been reduced to zero

- Spatial Dispersion of Agents: As calculated by the Shannon Diversity Index,

$$S = \sum_{pi}(1\text{-}\log P_i)$$

Results from a hypothetical landscape were examined where simulations were conducted using identical initial conditions to examine the effects of singularly isolating and altering various variables of the model. For the following analysis, a standard grid (42 by 32) was calibrated with randomized landscape attribute levels, initiated with 300 hunting agents, and run for 80 years. A maximum of 17 grid cells a year were subject to timber harvesting each time step, providing for the minimum harvestable age, being 70 years. Road reclamation occurs after 5 years of inactivity by the forest industry, and access / linear disturbance is regenerated to forest after 20 years of the initial impact, unless otherwise stated. For simplicity, a single road is placed diagonally across the landscape, with 1 city (n=300 agents) placed in the centre of the map along this route.

The resulting model output from the ABLE simulation is plotted over time where the variables below are manipulated one at a time, including:

- Agent type
- Preference heterogeneity
- Perception heterogeneity
- Agent learning
- Resource scenarios:
    - Years until road decommissioning
    - Years until access / linear disturbance regeneration

Agent type

Five different agent types were calibrated from various SP / RP studies and examined within the ABLE framework (Dosman et al. (2002), Haener et al. (2000), Bottan (1999), McLoed (1995) and Morton (1993)), however, it was determined that the Bottan (1999) agents offered the most robust analysis. This is because the study includes the greatest number of landscape variables compared to other studies, the hunters surveyed are the best fit within the institutional constraints faced by licensed hunters, and the agent performance was deemed to result in 'middle of the road' results compared to other agent types which resulted in extreme outcomes for a variety of reasons. As a result, analyses in the sections following uses agents derived solely from Bottan (1999).

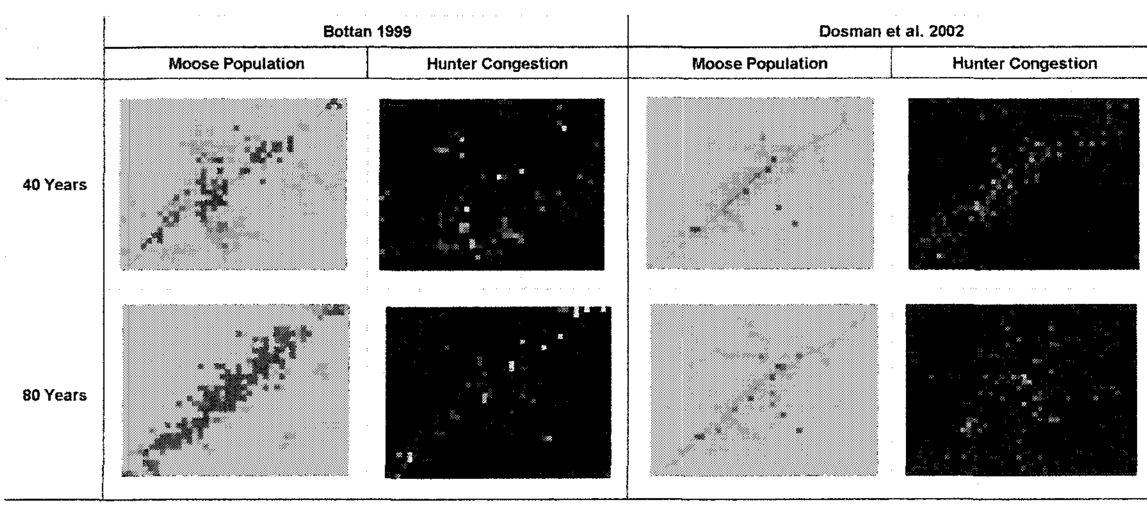
However, it is useful to examine the different outcomes from two agent types which face different institutional constraints. Here, licensed hunters from Ontario (calibrated from Bottan, 1999) are examined versus First Nations hunters from northern Saskatchewan (calibrated from Dosman et al. 2002). The parameter coefficients for each associated β^k for landscape variables are set as described in Table 6.

This first set of analyses will focus primarily on outcomes resulting from agents calibrated from Bottan (1999), which will serve to explain the 'story' of agent behaviour and the resulting resource impacts that emerge as the simulation progresses. Later sections will then focus specifically on outcomes that arise when agent heterogeneity, learning and resource scenarios are altered using the Bottan agent type.

Each agent type (Bottan and Dosman et al.) performs with 'middle of the road' heterogeneity in terms of preferences and perception, with variation around preference mean, β^k, of $\sigma_{\beta^k} = \beta^k/2$ and variation around the perception mean, ϕ_{ij}, of $\sigma_\phi = 0.1$. The following sections further describe this condition, but for the time being, this level of heterogeneity is set equally for all agents.

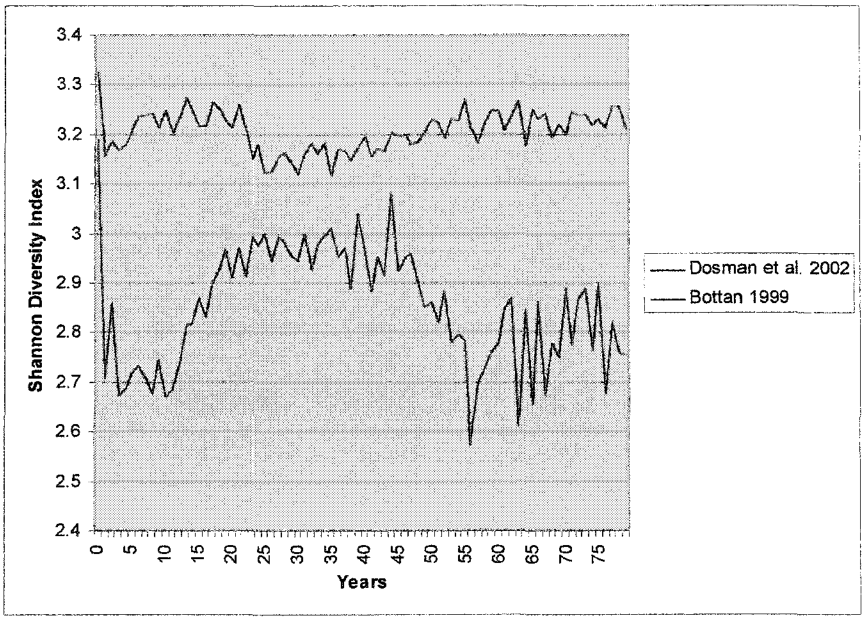
Figure 7 shows the graphical outcomes of Agents calibrated from Bottan and Dosman et al.. The figure shows outcomes for moose population and hunter congestion for year 40 and 80 of each simulation run. The blackened cells in the moose population graphic represent a extirpation, where excessive hunting pressure has reduced the moose population to 0. The lighter cells in the congestion graphic represent the level of hunter attendance in that time period, with lighter cells having a higher level of congestion.

Figure 7: Depictions of hunter agent dispersion in the grid for two agent types, lighter yellow colored cells show greater levels of agent visitation. Darker blue cells show areas depleted of their moose populations



As shown in Figure 8, The Shannon Diversity Index is calculated for each agent type over time. Agent dispersion is greater for the Dosman et al. which is observable in Figure 7 in both year 40 and 80 where there are visibly a greater number of sites visited by the agent population, but the lower brightness of the yellow cells indicate that a lesser number of agents has attended each individual site.

Figure 8: Shannon Diversity Index for two agent type populations



Whereas the diversity index for the Dosman et al. agents remains relatively constant, the Bottan agents show a general increase in dispersion (*S*) up to 20 years, then remains relatively stable until becoming increasingly erratic at 35 years before dropping to a minimum at 56 years.

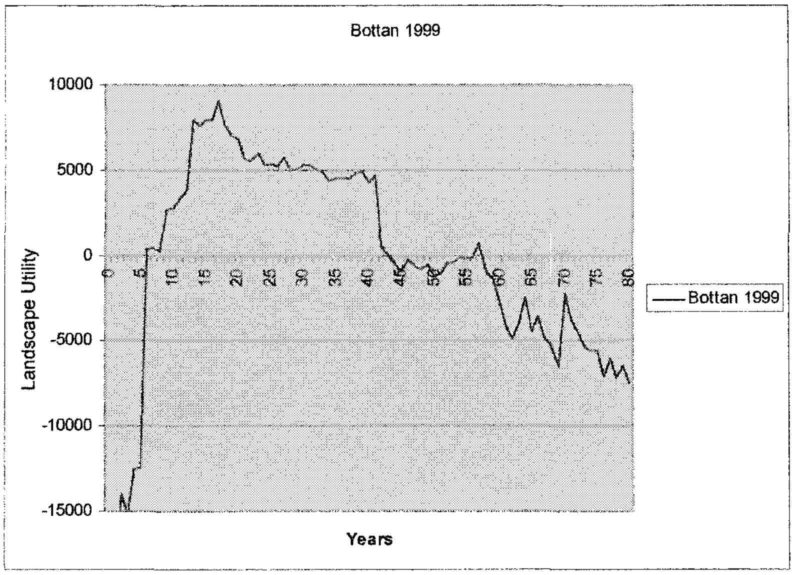
The initial increase in dispersion is explained in part by construction of forestry roads used to access merchantable forest stands. As the simulation does not begin with forestry roads already in existence, the forest harvesting strategy commences cutting blocks that are closest to the primary road system running diagonally across the grid. The increased number of roads allows for a greater number of ideal hunting sites to be accessed with a diminished travel cost (which is characterized by a negative β^k coefficient), and increases the access level in each site associated by road construction (where access has a positive β^k coefficient). Recall that decommissioning of these forestry roads is set to occur after 5 years of inactivity, and access / linear disturbance is regenerated after 20 years. As a result, there are an ever increasing number of ideal sites available for agents to attend up to about the 20 year mark, where a degree of equilibrium is achieved between the creation of new roads and access and the decommissioning and regeneration of older ones.

The decrease in dispersion of agents that reaches its minimum in year 56 is partially explained by the increased number of extirpations incurred around roadways in the earlier years of the simulation run. As we can see in Figure 7, by year 40 a pattern has already emerged whereby cells in which a extirpation has been incurred are clustered primarily around the primary road and also branch out along forestry roads that have not been reclaimed. This finding is consistent with hunting and angling literature (Gunn and Sein 2000, Courtois and Beaumont 1999) where the addition of forestry roads to previously less accessible sites is found to result in an associated increase in hunting / angling pressure.

By year 56 hunting pressure along primary and forestry roads has been sufficient to incur extirpations in nearly all cells within a given radius originating from the one central 'city'. At this point in time, the preferred hunting sites become more distant, as hunters must travel further to visit a site that still hosts a larger moose population. The further they travel, the negative travel cost coefficient increasingly plays a role in agent decision making. The result is to increasingly focus agent site selection onto cells that lie outside of this critical threshold where the radius of extirpation occurs. Agents therefore increasingly visit sites along this boundary, where travel cost is minimized, yet the size of the moose population is maximized.

Figure 9 presents the summed utility perceived across all landscape cells for the Bottan agents. As utility is ordinal and therefore not comparable across studies, results from the Dosman et al. agents are omitted.

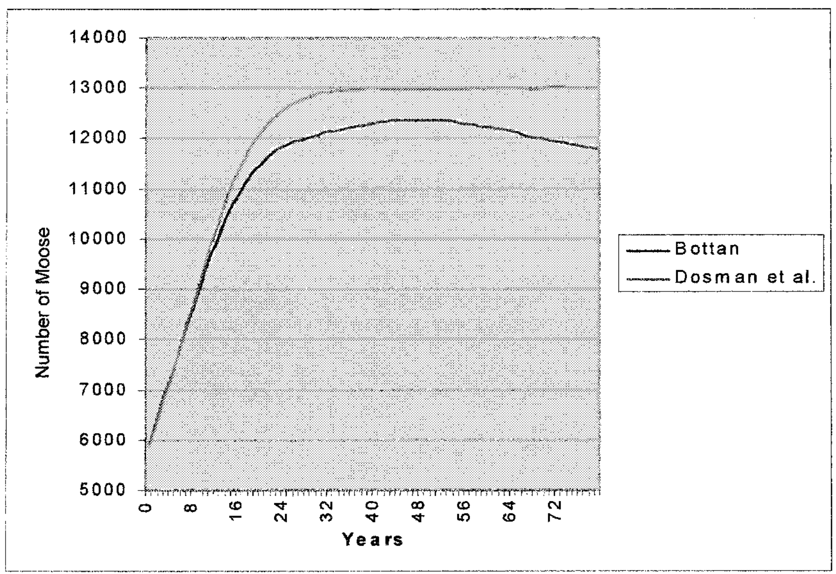
Figure 9: Landscape utility over time for agents calibrated from Bottan (1999)



Focusing on the trajectory, we see that agents initially perceive a large negative overall utility across the landscape, which increases until a maximum at approximately year 15. This is a trend that consistently occurs in all model simulations, regardless of agent type and the conditions present on the landscape, and is seen in the analysis to follow as well. This trend is explained by the fact that, upon initiation, the agents and the functions on the landscape have not had an opportunity to start performing as if it were a typical year. There are several operations in the model dependant on previous years' outcomes and a number of years are required to run before all are functioning properly.

The drastic increase in perceived landscape utility is likely driven primarily by the number of moose present on the landscape from the time of initiation until the point when some type of equilibrium comes into existence. Recall that upon initiation, all grid cells are occupied by at least 1 moose per km^2, and population levels are randomized for each cell up to the carrying capacity of 4.4 moose per km^2. As the majority of moose hunting and harvesting is concentrated in areas closer to the central 'city', there exists an area in either corner of the map which is distant from the primary road and therefore less accessible to the agents. In these areas, the moose population would therefore grow over time to its carrying capacity in the relative absence of hunting compared to those areas close to a roadway and the city. The summed utility reported in Figure 9 is a measure of perceived utility summed for all landscape cells, and therefore includes these areas distant from the city and primary highway where moose populations are reaching their carrying capacity. Therefore, for the first 20 to 25 years, the overall moose population is increasing, as is shown in Figure 10 which presents the sum of moose present in all landscape cells over time.

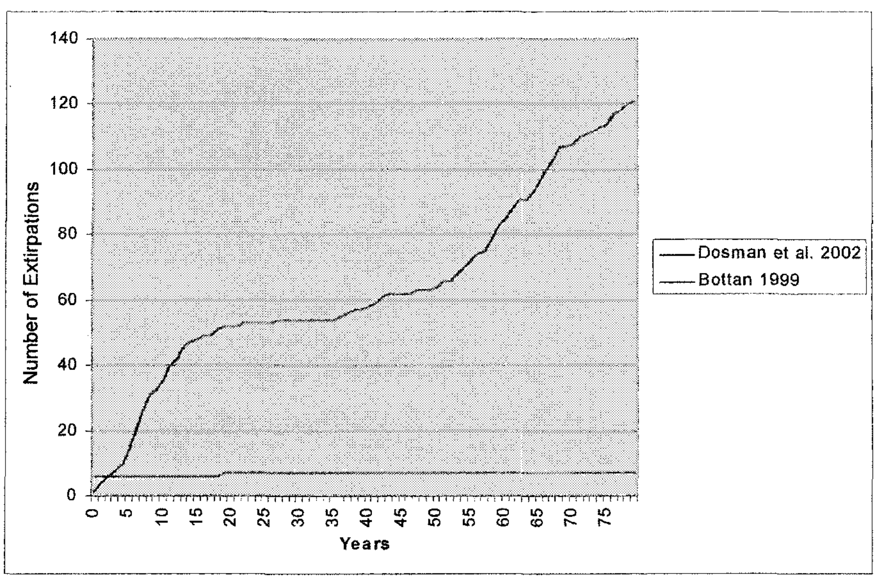
Figure 10: Landscape moose populations over time for simulations using two different agent types



Again focusing on the trajectories of the landscape utility perceived by agents as shown in Figure 9, we see the Dosman et al. agents reach a maximum at approximately year 15, followed by a slight decline and eventually leveling off for the remainder of the simulation run without major disruption. The Bottan agents on the other hand reach their maximum utility at approximately the same time as the Dosman et al. agents, followed by a gradual decline and punctuated declines at approximately years 45, 60, 67 and 73. These punctuated declines are driven by events such as decommission of roadways that have been kept in service through use by continued forest harvesting. Recall that a roadway will be kept in operation until it has not been used for 5 years during the recursive function that finds the shortest distance to the main primary roadway. As a result, long 'haul routes' develop throughout time so long as new cut blocks use this route. Once there are no more harvestable blocks along this route, or when cells closer to the primary roadway have regenerated sufficiently to again be harvested, these haul routes close, increasing the travel cost to all sites along that route. The closure of these haul routes also accounts for the decrease in S shown in Figure 8 from years 45 - 56.

The increased number of extirpations incurred as the simulation progresses explains the more gradual decline in utility over time. Figure 11 presents the number of extirpations for the different agent types. Bottan (1999) agents by far incur the greatest number of extirpations, while Dosman et al. (2002) agents incur a small number of extirpations. The graphical outcomes for this are seen in Figure 7, where the number of darkened cells for moose population are very few after both 40 and 80 years, compared to the significantly higher number for the Bottan (1999) agents.

Figure 11: Extirpations incurred over time by two different agent types



The number of extirpations over time is directly dependant on the number of hunters that may attend a site in any given year. As shown in Figure 8, the dispersion of Dosman et al. agents is much greater than the Bottan agents, resulting in relatively few cases where sufficient numbers of hunters drive cells' moose populations to zero. In this case, the moose population growth rate exceeds the harvest rate and the population is able to rejuvenate over time or without facing hunting pressure sufficient to drive the site to extirpation. Here it is important to again note that that the hunters studied in Dosman et al. (2002) are subject to a different set of institutional constraints than assumed in this analysis. Recall the simulation assumes that hunters attend their selected site on a once-a-year basis to emulate the fall licensed hunting season, and have a 1/3 chance of harvesting a moose from that cell. This is not a realistic assumption for the Dosman et al. agents, as they are calibrated from First Nations subjects who are not similarly constrained in their hunting practices.

The trajectory for Bottan agents is markedly different, showing a relatively constant rate of incurring extirpations up to year 20, followed by a relatively stable period until year 45. After this, the rate of incurring extirpations again increases and remains relatively consistent until the end of the 80 year simulation.

The initial 20 year period of high rates of incurred extirpations is explained again by the lack of forestry roads existing at the start of the simulation run. Recall that the initial landscape is devoid of forestry roads, which develop as increased numbers of cut blocks are harvested. The effect of this increasing number of roads throughout the landscape is to offer more alternative ideal hunting sites to the hunters as the relative travel cost decreases to reach previously remote sites. In the first few years, the sites that yield the highest perceived utility are therefore those in close proximity to the primary roadway running diagonally across the grid. As a result, hunting pressure that is sufficient to reduce the number of moose to zero exists within this area.

As the simulation progresses and forestry roads are constructed away from the primary roadway, the number of alternative ideal sites increases. As a result agent dispersion increases during this time period, as described in Figure 8, and the rate of incurring extirpations reduces to the 'plateau' seen in Figure 11 from years 20 to 45.

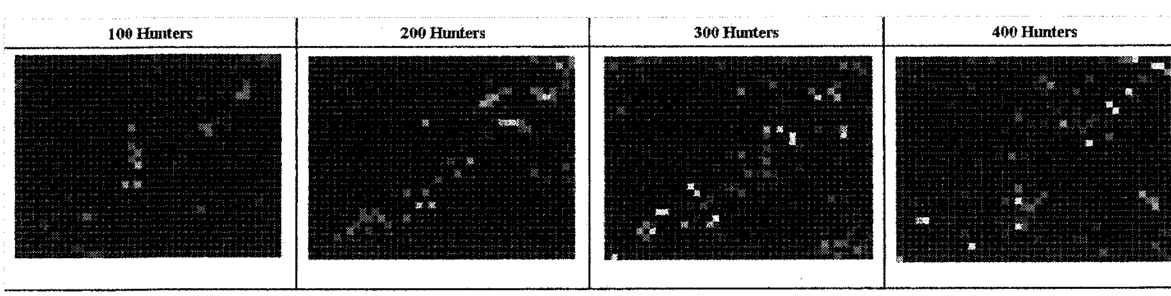
From years 45 to 80, the rate of incurring extirpations again takes a sharp increase. Recall the punctuated declines in hunter utility identified in Figure 9 associated with the decommissioning of long haul routes. Here, the number of ideal alternatives available to hunters is reduced as these routes are decommissioned, and hunting pressure is again focused more on areas closer to the primary roadway. This is supported in Figure 8 which identifies the minimum agent dispersion to occur during this time frame. From this, the decommissioning of haul routes results in increased hunting pressure in areas closer to the primary highway, resulting in increased incidence of extirpations in these areas.

It is also worth noting that the occurrence of a extirpation does not necessarily mean that hunters will no longer attend that site. The utility perceived for any given cell is a function not only of the moose population occurring there, but is also a function the four other attributes included in the utility calculation. Therefore, the effect of ideal congestion levels, travel cost, access / linear disturbance state and the forest age may outweigh the lack of moose at a site, and hunters will attend the cell anyhow.

Number of Agents

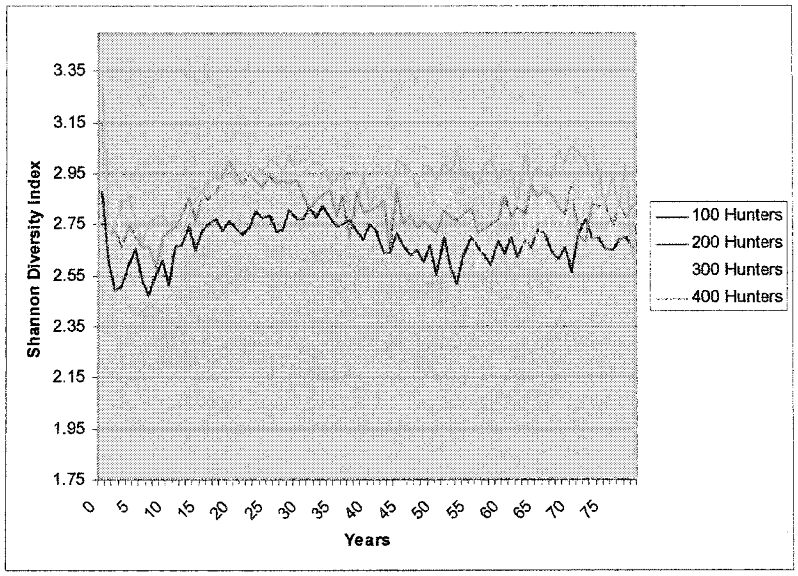
The number of individuals drawn for moose hunting licenses each year for WMUs is set by NRS biologists and managers. Here, outcomes are examined where 100, 200, 300 and 400 agents initiated on the ABLE landscape examine in this case study. Figure 12 shows the graphical outcomes at year 80 for the various simulation runs using different numbers of agents.

Figure 12: Depictions of hunter agent dispersion in the grid for different number of agents initiated on the landscape. Lighter yellow colored cells show greater levels of agent visitation.



Although there are more agents on the landscape, there does not appear to be a large difference in how the agents are distributed. This is shown in Figure 13, where the Shannon diversity index does not vary greatly for simulations using different number of agents.

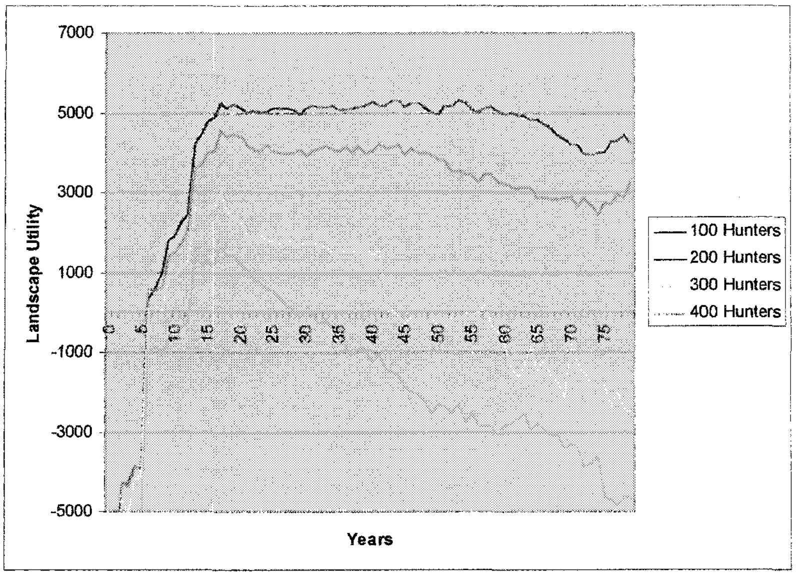
Figure 13: Shannon Diversity Index for four simulations using different agent population sizes



There appears to be a slight correlation between the number of hunters and the calculated value of S. This is driven by the fact that hunter congestion close to the main 'city' is greater for the case where there are more agents, and therefore hunters are willing to seek out more distant sites. The small variation in S across simulations is expected, given that the hunters themselves are identical; the number of hunters initiated being the only difference between simulations here. This finding is consistent with hypotheses identified in Chapter 1.

The outcomes for landscape utility, however, are notably different where the number of agents initiated varies. Figure 14 depicts the trajectories for landscape utility perceived by hunters.

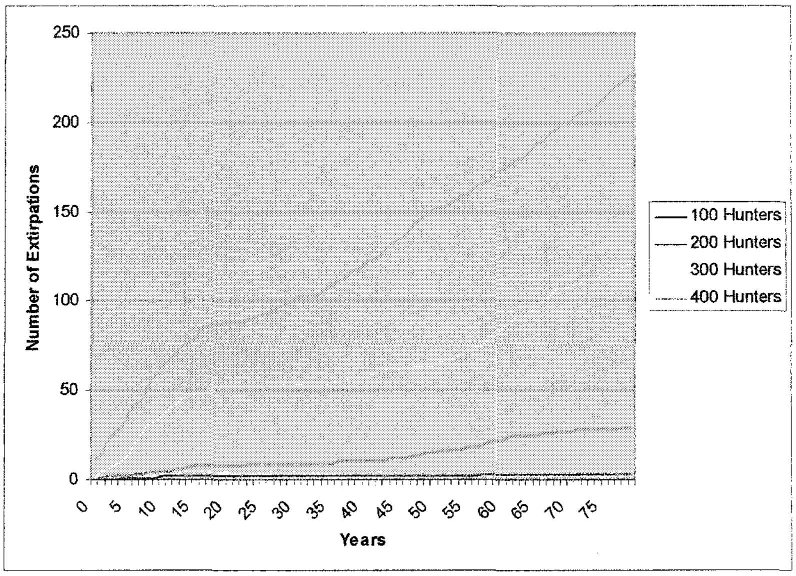
Figure 14: Landscape utility over time for four simulations agents using different agent population sizes



As landscape utility is measured as the sum of utility perceived by all agents, the output data were adjusted to account for the increased number of agents on the landscape for the case where n = 200, 300, and 400, such that the resulting measure is the utility perceived for 100 agents in any given time period. Clearly, the greater the number of agents present on the landscape, the lower the overall utility level perceived. Furthermore, all simulation runs (including those in following sections) show a gradual decrease over time in utility, yet the rate at which this decrease occurs is augmented as the number of agents on the landscape increases. This is driven by both an increased congestion reading, given the greater number of hunters, and also by the increased incidence of extirpations, and is consistent with hypotheses identified in Chapter 1.

Figure 15 depicts the number of extirpations occurring for the various simulations using different agent population sizes.

Figure 15: Extirpations incurred over time for four simulations using different agent population sizes



The number of extirpations occurring increases with the number of agents acting on the landscape. This finding is consistent with hypotheses identified in Chapter 1, where it was expected that a greater number of hunters acting on the landscape would result in increased number of areas being 'shot out'.

Heterogeneous Preferences

The following analysis now explores the relationship between the degree of heterogeneity that agent populations exhibit, and the outcomes that result therein. The degree of heterogeneity in hunters' preferences is dependant on the σ_{β^k} value as it affects the β^k_j preference coefficients as described in Chapter 5. The standard deviation, σ_{β^k} ,varies the distribution mean away from the case where the population mean, $\mu = \beta^k$. Therefore, the case where $\sigma_{\beta^k} = 0$ represents agent homogeneity in preferences. As σ_{β^k} increases, the preference structures of the hunters become more diverse across the population. Here, the σ_{β^k} value is altered over seven simulations such that $\sigma_{\beta^k} = 0$, $\beta^k/8$, $\beta^k/4$, $\beta^k/2$, β^k, β^k*2, β^k*3 holding all else constant.

Figure 16: Depictions of hunter agent dispersion in the grid for seven simulations using agents with various levels of preference heterogeneity. Lighter yellow colored cells show greater levels of agent visitation.

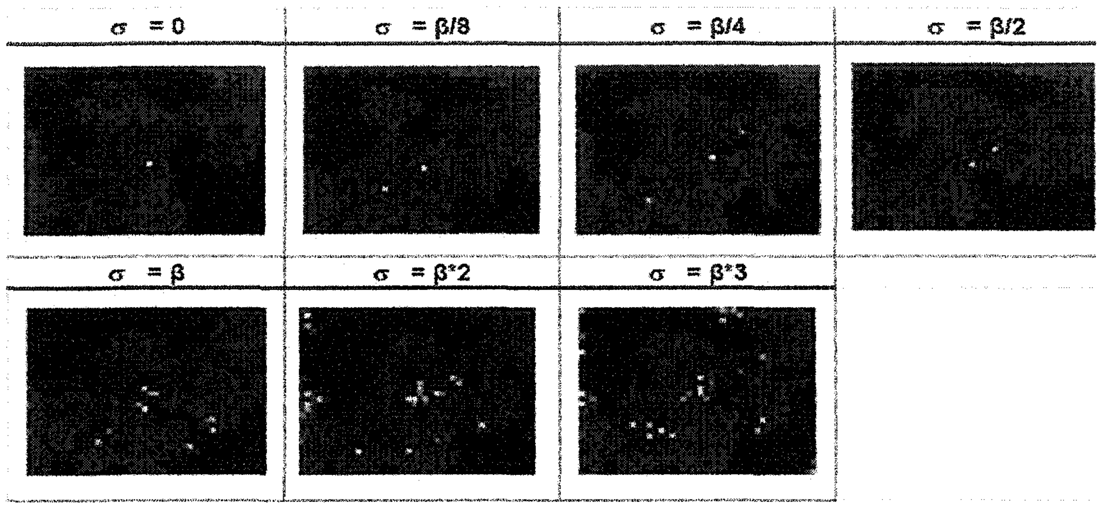
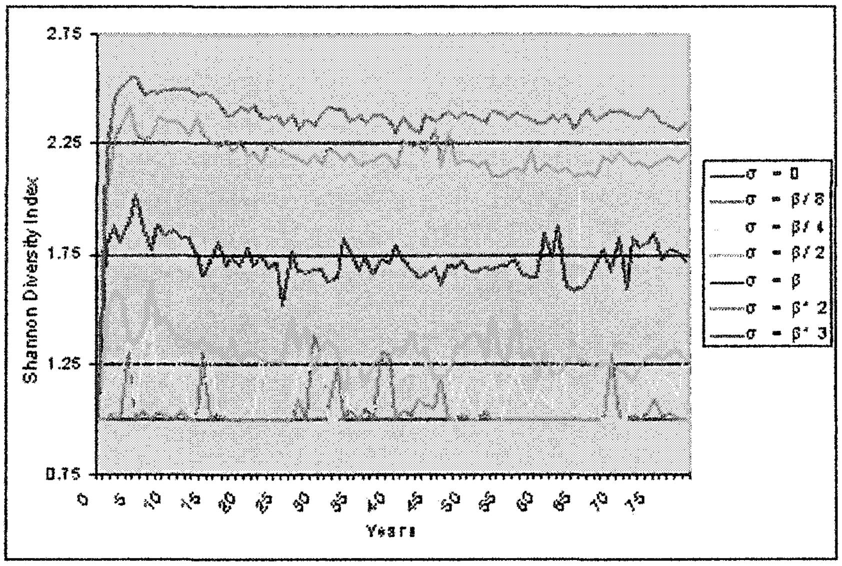


Figure 16 depicts the graphical outcomes for hunter congestion in the final simulation year for each of the model runs where preference heterogeneity is varied. There is no agent dispersion when $\sigma_{\beta^k} = 0$, resulting in all 300 agents attending the same site, whichever is calculated to yield the highest utility in that time period. Dispersion increases as σ_{β^k} increases, indicating that as the population of agents has increasingly diverse preferences, the more hunter activity is spread across the landscape. This finding supports the hypothesis identified in Chapter 1 that increased preference heterogeneity will result in greater dispersion due to a wider diversity of values for hunting sites.

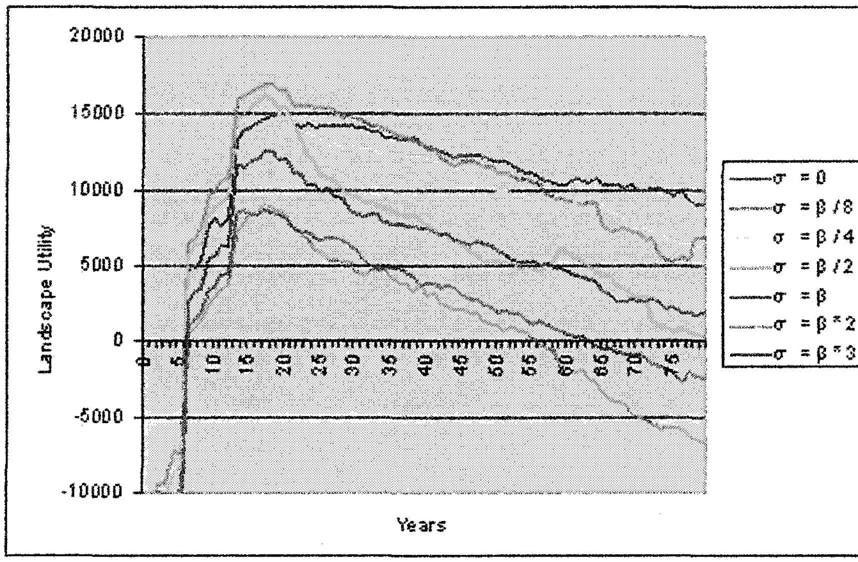
Figure 17: Shannon Diversity Index for seven simulations using agents with various levels of preference heterogeneity



When $\sigma_{\beta^k} = 0$, hunters all have identical preference structures, and therefore all select the same site, as indicated in $S = 1$ as shown in Figure 17. As σ_{β^k} increases, agents are more dispersed across the landscape, as shown with the associated increase in S. This is the expected outcome, given that as the value of σ_{β^k} increases, the distribution of the β^k preference parameter across the agent population widens, as described in Figure 3. The hunting population therefore selects a broader variety of sites as they decreasingly prefer the same bundles of attributes associated with the grid cells.

Figure 18 presents the utility perceived across all landscape cells for various distributions of the β^k value.

Figure 18: Landscape utility over time for seven simulations using agents with various levels of preference heterogeneity



In the case where hunters have homogenous preferences, $\sigma_{\beta^k} = 0$, the overall utility gained across the simulation run is greater than that of populations with heterogeneous preferences. Comparing the trajectories of the six heterogeneous populations ($\beta^k/8$ to β^k*3) shows that an increased σ_{β^k} generally results in a lower utility level over the simulation run. This contradicts the hypothesis identified in Chapter 1, where utility was not expected to change with increased heterogeneity, so long as the mean preferences for attributes did not change across heterogeneous populations examined. However, some aspect of agent behavior is in fact resulting in lower utility as heterogeneity in preferences increases.

As discussed in Chapter 5, the β^k_j values for moose population and congestion are state dependent variables. The states are defined by the model user, as in Figure 2, the highest level of congestion in this case being greater than 4 encounters. For homogenous preferences, where $\sigma_{\beta^k} = 0$, recall that all hunters attend the same site. Therefore it does not matter if 5 or 300 agents (the case existing here) attend the site, the utility calculation will return the state dependent β^k associated with maximum congestion. All other cells will register that no congestion is present at all, and therefore return the β^k value associated with the minimum congestion level. The effect of one cell registering the maximum congestion is therefore lost in the multitude of other sites which return a greater utility calculation. This limitation is imposed by the functional form used in the utility calculation. If the impact of congestion on utility were multiplicative, as with the travel cost calculation, instead of a state dependent variable, the outcomes for utility would be greatly altered. As described in Figure 17, as σ_{β^k} increases, agent dispersion increases resulting in a greater number of sites being visited. Therefore, the number of sites registering a minimum β^k value for congestion is diminished, and the landscape as a whole begins to yield lower overall utility levels.

The same effect exists for moose population, where for $\sigma_{\beta^k} = 0$, the effect of 300 agents attending one site will be to eliminate the moose population for that site. Moose populations in all other sites will grow to carrying capacity in the absence of hunting pressure and the effect of one site registering a extirpation each year is lost in the utility gained as all other landscape cells report high moose populations. Therefore, as σ_{β^k} increases, hunter dispersion increases, and the number of these 'untouched' sites is diminished. The resulting landscape utility calculation registers increased number of sites where moose harvesting has occurred, and yields a lower overall utility as perceived by hunters.

Figure 19: Extirpations incurred over time for seven simulations using agents with various levels of preference heterogeneity

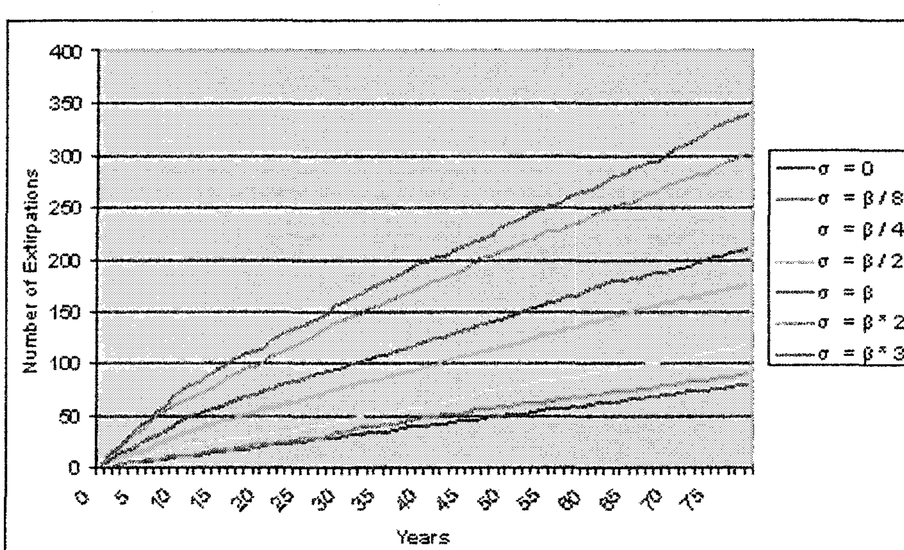


Figure 19 presents the number of extirpations resulting from hunting pressure. For the case where hunters have homogenous preferences, where $\sigma_{\beta^k} = 0$, the final number of extirpations across the simulation run is again equal to the number of years. This is the result of having 300 agents attend one site a year and eliminating the moose population present in that cell. As preference heterogeneity increases, the number of extirpations increases. This result is contrary to the hypothesis identified in Chapter 1, where it is expected that greater preference heterogeneity will result in fewer areas being 'shot out'. This result is explained by the fact that although agents select a greater variety of sites, visitation is still sufficient to eliminate the moose populations in these cells. Greater heterogeneity has therefore not resulted in sufficient agent dispersion to avoid this situation. If agents were sufficiently dispersed, we may find that the number of moose harvested in a year would eventually be lower than the growth rate of moose populations, and a extirpation would therefore not occur.

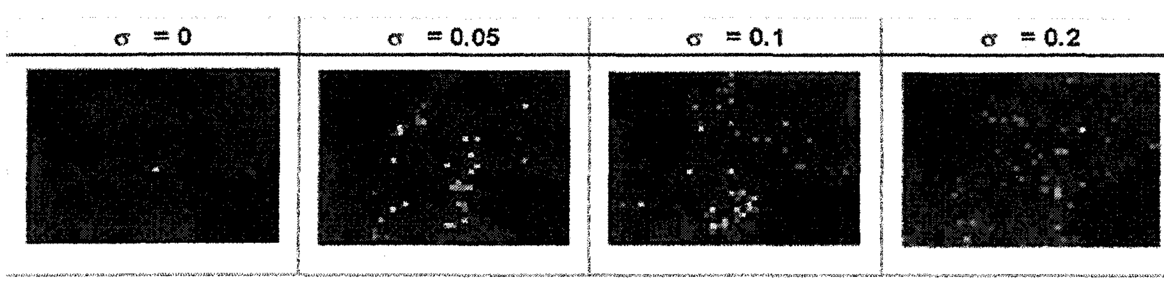
On the other hand, the fact that this trend does not arise in any of these simulations is better explained by the signs (positive or negative) of the β^k coefficients, and the basis by which a preferred site is selected. Recall that hunters select the site which yields maximum utility. Although the β^k values here are normally distributed, it would be a rare case where the signs of the coefficient sign would reverse. According to the 68% – 95% – 99.7% rule of a normal distribution's standard deviation, a reversal of β^k signs would only occur in 0.3% of cases where $\sigma_{\beta^k} = \beta^k$, 5% of cases where $\sigma_{\beta^k} = \beta^k*2$, and 32% of cases where $\sigma_{\beta^k} = \beta^k*3$. The overall effect is for the majority of agents to still attend sites with preferred attributes, and agents still seek the same attributes even if the magnitude of their preferences changes. For example, travel cost would be more diversely preferred, but still hold a negative β^k value. As such, the trend to avoid traveling further than necessary will be maintained by the average agent, thereby focusing hunting pressure on the same areas no matter how heterogeneous the preferences across the population.

Heterogeneous Perception

The ability to accurately perceive the attribute levels across landscape cells depends on the perception error variable, ϕ_{ij}, within each agent's utility calculation. The standard deviation, σ_ϕ, is altered over several simulations, holding all else constant. When $\sigma_\phi = 0$, all agents have perfect knowledge of their surroundings, and perceive the true measurement of the landscape attribute levels as discussed in Chapter 5. The larger σ_ϕ value, the wider the distribution away from the case where the population mean equals zero becomes, and heterogeneity in the population of agents is greater in terms of their perception of the actual utility level present in landscape cells.

Results were obtained for σ_ϕ values of 0, 0.05, 0.10 and 0.2, variation around the mean value of 0. Hence, if the systematic utility calculation of hunter j was 2.1 'utils' for site i, and the standard deviation for the perception error, ϕ_{ij}, is set at $\sigma_\phi = 0.1$, the hunter will have a 68%[16] chance of perceiving a utility level of between 2.0 and 2.2.

Figure 20: Depictions of hunter agent dispersion in the grid for four simulations using agents with various levels of perception heterogeneity. Lighter yellow colored cells show greater levels of agent visitation

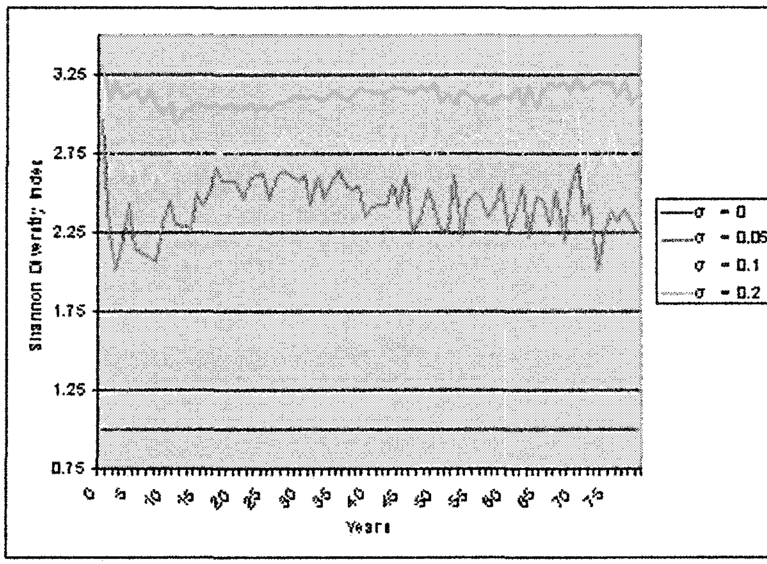


There is no agent dispersion in the $\sigma_\phi = 0$ case, with all 300 agents attending the same site. The $\sigma_\phi = 0.05$ simulation shows increased dispersion, but the number of sites selected across the agent population remains low. As σ_ϕ increases to 0.1 and 0.2, dispersion increases, resulting in more widely distributed visitation. This finding supports

[16] According to the 68 - 95 - 99.7 rule, which defines that 68% of observations will lie within one standard deviation from the mean, 95% of observations will lie within 2 standard deviations of the mean, and so on.

the hypothesis identified in Chapter 1, where it is expected that as the error of perception increases, the dispersion of selected hunting sites will also increase.

Figure 21: Shannon Diversity Index for four simulations using agents with various levels of perception heterogeneity



As shown in Figure 21, when $\sigma_\phi = 0$, hunters all have perfect knowledge of attribute levels, and therefore all select the same site, as indicated in $S = 1$. As σ_ϕ increases, agents are more dispersed across the landscape, and S increases accordingly.

Figure 22: Landscape utility over time for four simulations using agents with various levels of perception heterogeneity

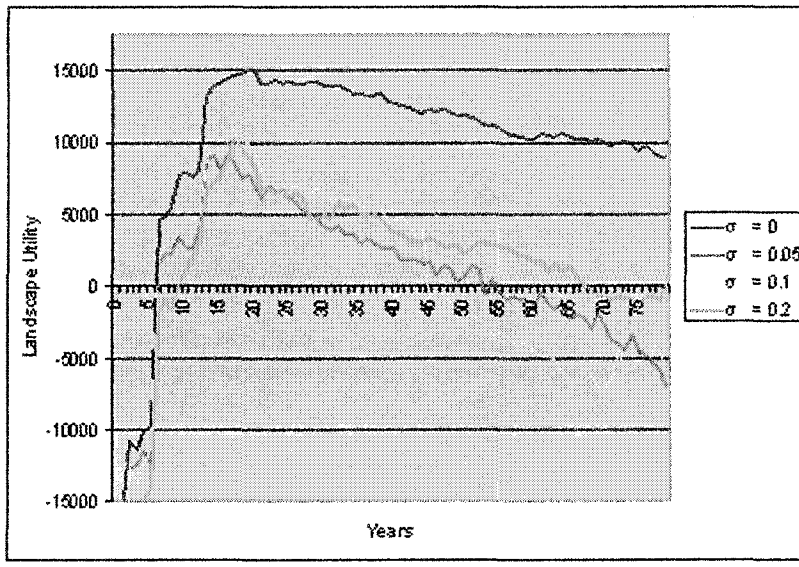


Figure 22 presents the utility perceived across all landscape cells for variable ϕij distributions. The case where hunters have the ability to perceive their environment with perfect accuracy, where $\sigma_\phi = 0$, the overall utility gained across the simulation run is greater than that of population with heterogeneous (and therefore reduced) perception accuracy, represented by $\sigma_\phi = 0.05$, 0.1 and 0.2. This result arises for the same reasons as described earlier, where all 300 agents attend one site, yet the rest of the landscape resisters no hunter congestion and high moose populations.

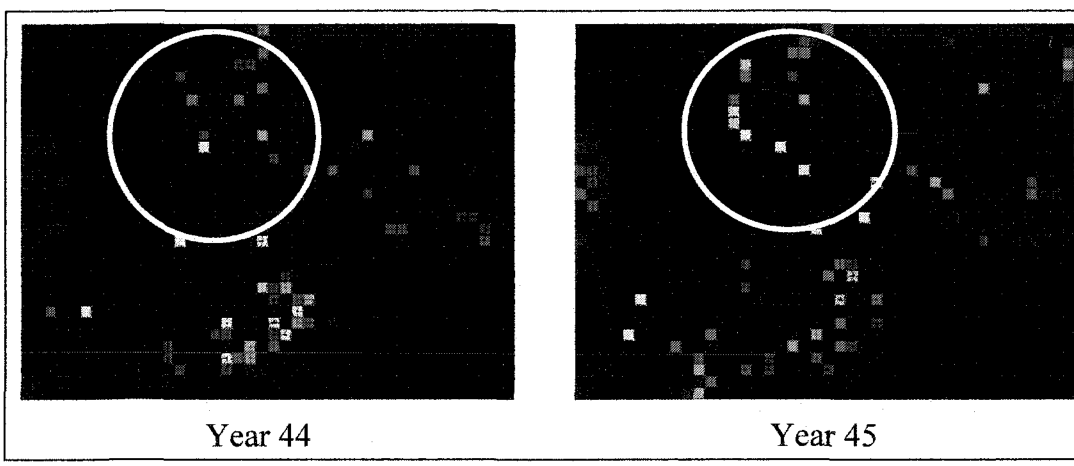
The lower utility seen here in heterogeneous agents compared to the case where perceptions are homogenous contradicts the hypothesis in Chapter 1. There, it was expected that no overall change in perceived utility would arise with increased heterogeneity, so long as the average perception accuracy was the same across agent populations. This result does not emerge due to the change in agent behavior as preference heterogeneity changes, and the resulting effect on landscape attributes.

Comparing the trajectories of the three heterogeneous populations reveals that where $\sigma_\phi = 0.2$, the case associated with the greatest heterogeneity, a higher overall utility level is maintained over time. This is explained by the presence of fewer extirpations. The greater overall visitation across landscape cells, which would be expected to decrease overall landscape utility, does not cause the overall utility to register as lower compared to the other simulation runs due to increased maintenance of local moose populations.

Where $\sigma_\phi = 0.05$, we find the next greatest overall utility, but this result is somewhat deceiving. Recall from Figure 21 that agent dispersion at $\sigma_\phi = 0.05$ is not as great as compared to the $\sigma_\phi = 0.1$ and 0.2. Therefore, the same effect causing the case where $\sigma_\phi = 0$ to yield the highest overall utility is still present here, and the number of 'untouched' sites effectively raises the landscape utility perceived by the agents.

In the case where $\sigma_\phi = 0.1$, a punctuated decrease in utility occurs in approximately year 45. This is explained by the closure of a major haul route occurring in this year, as depicted in Figure 23.

Figure 23: Depictions of hunter agent dispersion, roads and access in one simulation, showing a closure of a major haul route. Lighter yellow colored cells show greater levels of agent visitation.



This occurrence did not happen to the same degree in the other scenarios runs, and we accordingly do not see similar punctuated decreases in utility. Until this road closure depicted in Figure 23 occurs, the utility level for the case where $\sigma_\phi = 0.1$ is slightly higher than the other simulations where agents have heterogeneous populations. This results from a situation where hunters receive the 'best of both worlds' in terms of congestion and moose populations. When congestion is increasingly dispersed across the landscape, hunters perceive lower landscape utility reading. Lower landscape utility is also perceived in the cases where a greater number of extirpations occur. For the case where $\sigma_\phi = 0.1$, dispersion and number of extirpations produce mid-range results, and neither dispersion nor extirpations serves to drive a decrease in utility.

Figure 24: Extirpations incurred over time for four simulations using agents with various levels of perception heterogeneity

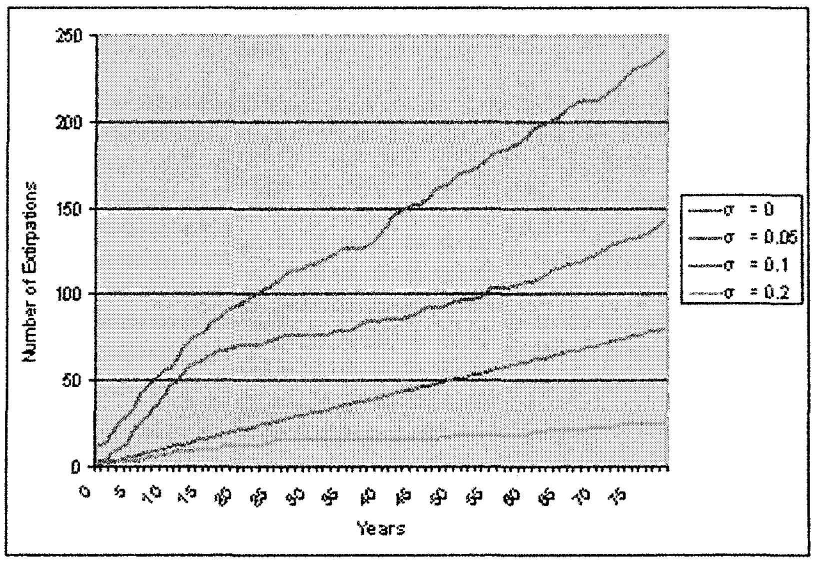


Figure 24 presents the number of extirpations resulting from hunting pressure. For the case where hunters have the ability to perceive their environment with perfect accuracy, $\sigma_\phi = 0$, the final number of extirpations across the simulation run is equal to the number of years. This is again the result of having 300 agents attend one site a year and eliminating the moose population present in that cell. As perception heterogeneity of agents increases to the case where $\sigma_\phi = 0.05$, the number of extirpations increases as groups of agents selects a greater number of sites, yet still exert sufficient hunting pressure to eliminate the moose populations in their chosen cells. The number of extirpations is lower when $\sigma_\phi = 0.1$, and again when $\sigma_\phi = 0.2$. For these values, dispersion of agent congestion has become wide enough such that hunting pressure does not necessarily exceed the capacity of the moose population to regenerate. This finding is consistent with the hypothesis identified in Chapter 1, where it is expected that greater heterogeneity in perceptions will result in a decrease in the number of areas 'shot out'.

Learning

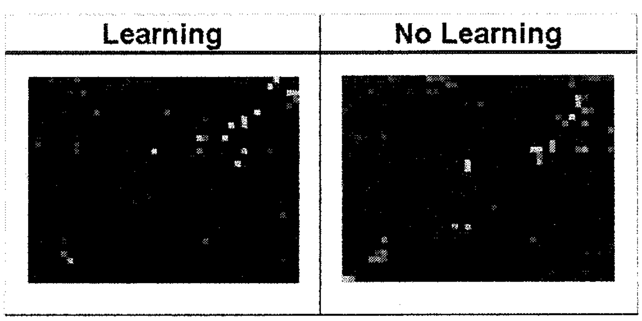
Similar to the calculations examining hunter preference and perception heterogeneity addressed above, here hunter learning is examined to see what effect learning has on agent decision making, the utility perceived by agents, and the resulting impacts on the moose population resource. Hunter age and experience, as described in Chapter 5, alter the σ_ϕ value for the perception error term, $\phi_{ij(A, E)}$.

The standard deviation, σ_ϕ of the perception error term, $\phi_{ij(A, E)}$, varies the distribution mean away from the case where the population mean equals zero. Therefore, the case where $\sigma_\phi = 0$ represents agent homogeneity in perceptions, and all agents have perfect knowledge of expected utility for each hunting site. As σ_ϕ is set at increasing levels, the accuracy of the hunters' perceptions decreases. Here, for the case where agent learning is examined, the hunters begin with a set σ_ϕ value of 0.1. Therefore, as these hunters age and gain experience their σ_ϕ value will increasingly approach 0.

As hunters age and gain experience at specific locations, the σ_ϕ value decreases according to the learning equation described in Figure 4. Agents begin with the case where age and experience = 0, and σ_ϕ is accordingly set at 0.1. The perception error term is altered through age and experience, and as σ_ϕ moves closer to 0, the greater the perception accuracy an agent will have, and hence a better ability to read actual utility levels present in landscape cells. Ages are randomized and assigned to agents at the beginning of the simulation between zero and the maximum hunter age defined by the user, as in Figure 6. The number of site visits before the hunter reaches full awareness for the specific cell visited is also defined by the model user here. For this analysis, it is assumed that hunters reach perfect knowledge for all hunting sites after an age of 50 years, or perceive perfect knowledge for individual sites after 6 visits to the specific cell in question. Once hunters reach an age of 50 years, again as defined by the model user in Figure 6, their age and experience is reset to 0 (assuming that older hunters eventually cease to hunt and are replaced with young individuals who begin hunting with no experience), and their σ_ϕ value returns to the original mean defined by the user. Until this point, σ_ϕ decreases as the hunter acts from one year to the next becoming more experienced and aged. Once hunter j has reached 50 years hunting experience, or similarly, once that hunter has visited a site 6 times, $\sigma_\phi = 0$.

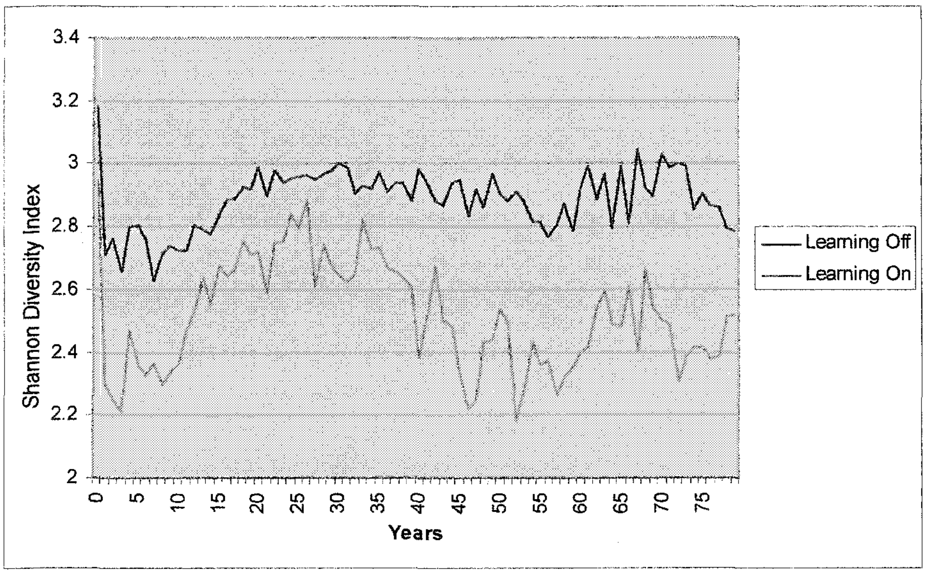
To isolate the effect of learning, two simulations were conducted, one with learning engaged according to the default values, and one where agent learning is not activated. The default values are agents with mid-range heterogeneity in preferences where β^k is determined by $\sigma_{\beta^k} = \beta^k/2$, and initial perception error before learning, ϕ_{ij}, is determined by $\sigma_\phi = 0.1$. Figure 25 shows congestion outcomes for the last year (80) run for each simulation.

Figure 25: Depictions of hunter agent dispersion in the grid for two simulations, using agents who learn and agents who do not. Lighter yellow colored cells show greater levels of agent visitation



There is greater agent dispersion in the case where agent learning is not engaged. This indicates that where agents are able to more accurately read the utility levels present in the landscape, hunter activity will be more concentrated. This finding is consistent with the hypothesis identified in Chapter 1, where it is expected that learning agents will attend a decreased variety of sites, given their ability to more accurately identify sites which yield the highest utility.

Figure 26: Shannon Diversity Index for two simulations using agents who learn compared with agents who do not learn



Learning agents are less widely dispersed across the landscape, as indicated in Figure 26 by the lower calculated S values. This is consistent with earlier findings, which show a positive relationship between σ_ϕ and S. The learning agents here each have a σ_ϕ value somewhere between 0 and 0.1, and across the population would be expected to have an average σ_ϕ value of 0.05. Thus, we would expect the trajectory in Figures 26 and 21 to closely match for the cases where learning is activated and where $\sigma_\phi = 0.05$ for all agents. This is found to be the case, where the average S values are similar.

Figure 27: Landscape utility over time for two simulations using agents who learn compared with agents who do not learn

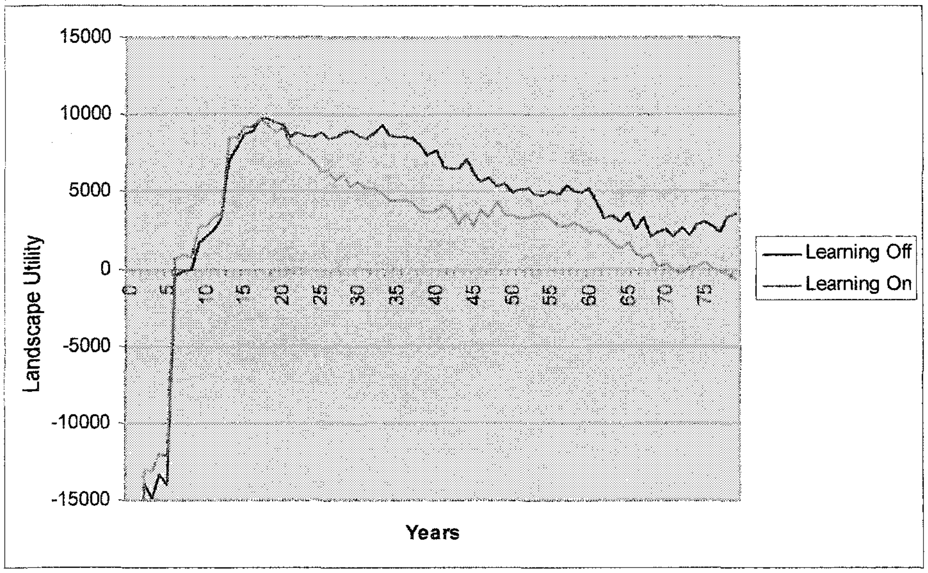
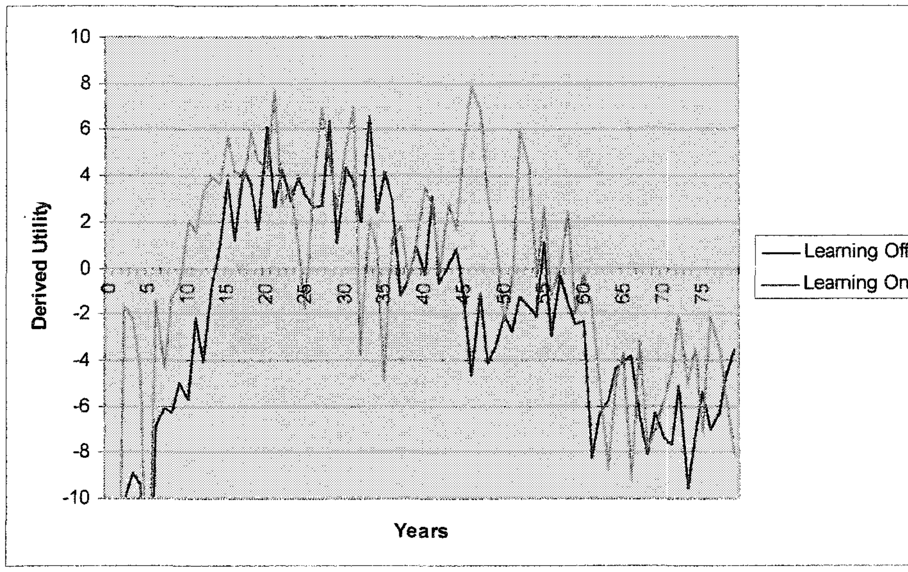


Figure 27 presents the utility perceived across all landscape cells for learning and non-learning agents. Overall utility perceived by the agents is higher for the case where agents do not learn over time. This finding seems at first to be contradictory to previous results, as we would expect the population with agents moving toward homogeneity to yield a higher utility level, as is seen in previous cases. However, this result is explained by the fact that the utility calculation is driven largely by the greater number of extirpations occurring in the case where agents learn. This finding also contradicts the hypothesis identified in Chapter 1, where it was expected that learning would not have an overall effect on landscape utility. Again, the behaviour of learning agents results in landscape impacts which serve to decrease the utility of the landscape as a whole.

Until this point, utility has only been considered in terms of the sum utility for all cells perceived on the landscape. However, if we focus solely on the utility actually derived by hunters when they attend their preferred site, we find an opposite outcome, as shown in Figure 28.

Figure 28: Utility derived from attending hunting sites by agents for two simulations using agents who learn compared with agents who do not learn



Here we see that learning agents receive a derived utility that is generally greater than non-learning agents. This is explained by the ability of learning agents to become more proficient hunters, and better select sites which yield the greatest utility. This finding is consistent with the hypotheses identified for learning agents in Chapter 1.

Figure 29: Extirpations incurred over time for two simulations using agents who learn compared with agents who do not learn

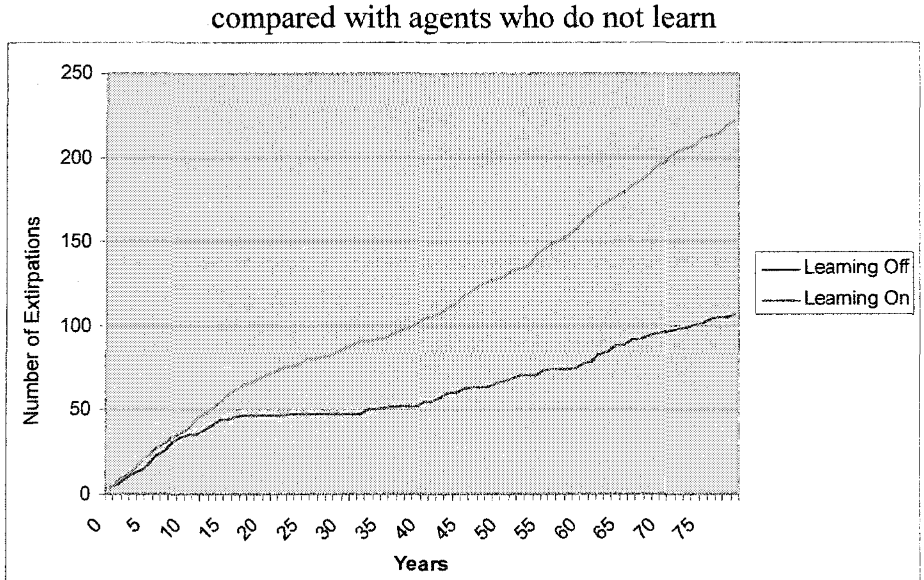


Figure 29 presents the number of extirpations resulting from hunting pressure. For the case examining learning agents, the final number of extirpations across the simulation run is higher than for agents who do not learn. This finding is consistent with the hypotheses identified in Chapter 1, where it was expected that more proficient hunters would increasingly select hunting sites with higher moose populations. The result of many agents behaving in this fashion was expected to result in an increased number of areas 'shot out' by higher hunter attendance.

Recall that we would expect the average agent to have a σ_ϕ value of 0.05, resulting from the agents having a σ_ϕ value ranging between 0.1 and 0. Thus, we would expect to see extirpations in line with Figure 24 for the case where all agents' σ_ϕ is equal to 0.05. This is indeed the case here, with 220 extirpations occurring in the case where agents learn, and 240 occurring in Figure 24.

Resource Management Scenarios

Having examined agents in terms of preference heterogeneity, perception heterogeneity and learning, simulation outcomes are now examined in response to resource management scenarios for road decommissioning and access / linear disturbance regeneration. Again, 'middle of the road' heterogeneity is set with preference coefficient, β^k, heterogeneity at $\sigma_{\beta^k} = \beta^k/2$, and perception error, ϕ_{ij}, heterogeneity at $\sigma_\phi = 0.1$.

Road Decommissioning

Four road decommissioning scenarios were analyzed, for 3, 5 and 10 year decommissioning, as well as the case where all roads are permanent.

Figure 30: Depictions of hunter agent dispersion in the grid for four simulations using various time frames for forestry road decommissioning. Lighter yellow colored cells show greater levels of agent visitation

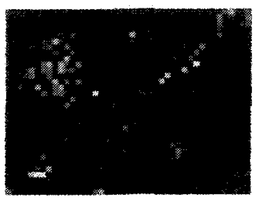
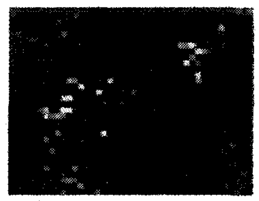
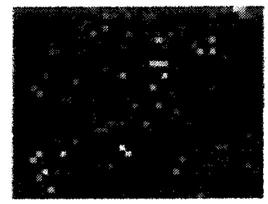
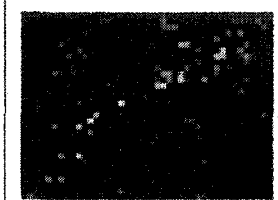
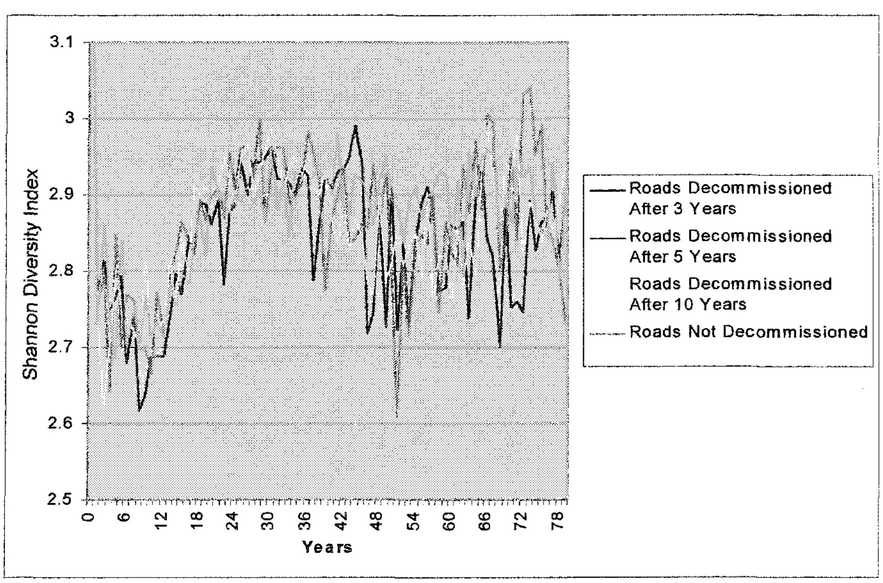
3 Years	5 Years	10 Years	Roads Not Decommissioned
			

Figure 30 shows congestion as well as roads and access (in red) in the final year of the simulation. There is increased visual presence of roads and access across the simulation runs.

Variable ages of road decommissioning do not have an overall obvious effect on agent dispersion. As shown in Figure 31.

Figure 31: Shannon Diversity Index for four simulations using various time frames for forestry road decommissioning



The relative ages of road decommissioning do not have an visible effect on the calculated value of *S* in the first half of the simulation run, however *S* increasingly fluctuates in the later half of the simulation run. Overall, however, the variable ages at which roads are decommissioned does not greatly affect the dispersion of agents. This is best explained by the fact that although individual in-block roads may be reclaimed earlier, the longer haul routes that are maintained through continued use remain present on the landscape, and the overall travel cost incurred by accessing a given remote site remains low as a result. This finding does not support the hypothesis stated in Chapter 1, where it was expected that that earlier road decommissioning would result in a decreased variety of sites attended. The persistence of haul routes that facilitates hunter travel serves to negate this expected outcome.

Figure 32: Landscape utility over time for four simulations using various time frames for forestry road decommissioning

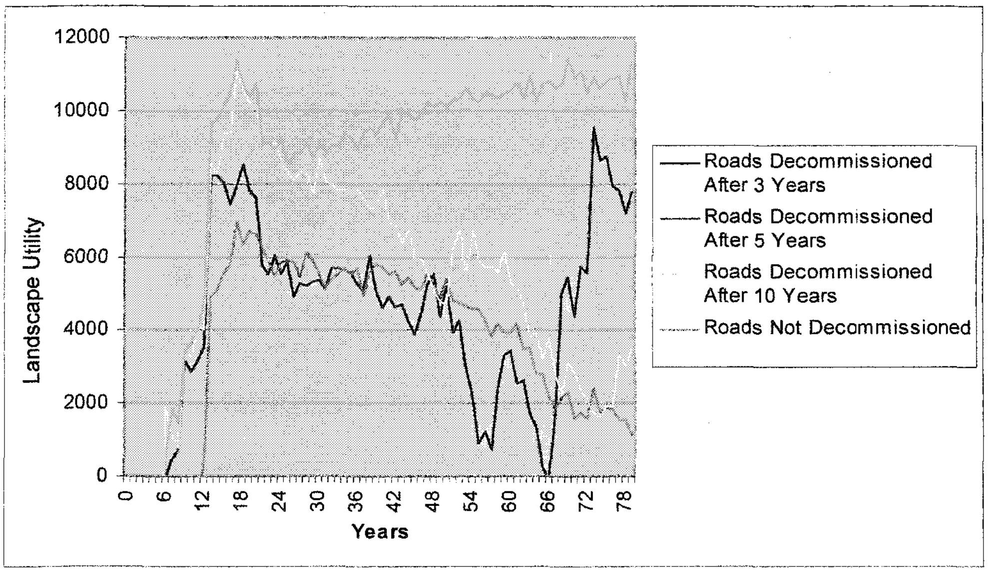
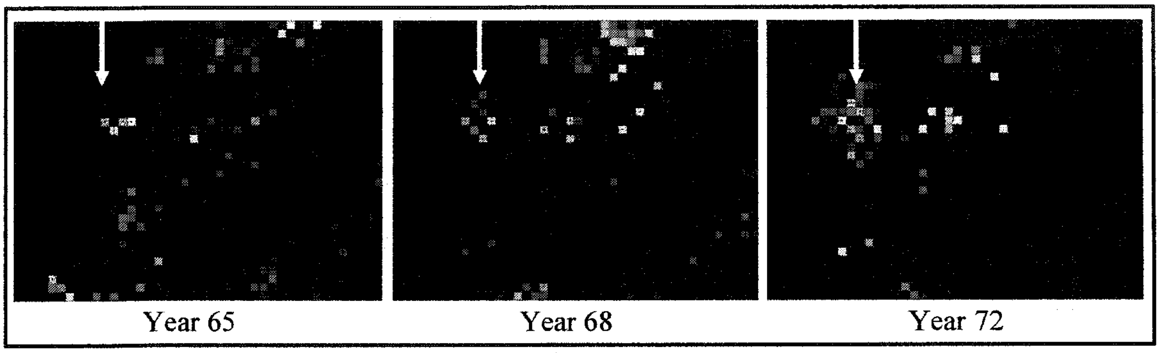


Figure 32 presents the sum of utility perceived across all landscape cells for various road decommissioning scenarios. The case where roads are not decommissioned results in the highest utility. This result is expected, given that more roads allow increased accessibility to landscape cells and a lower travel cost across the grid.

The case where roads are reclaimed in three years shows a trajectory depicting the lowest utility level until the latter few years, where a rapid increase occurs. The lower overall utility is a reasonable result given that more rapid decommissioning would increase agent's travel cost for accessing landscape cells. The rapid increase in the last 15 years of the simulation is perhaps a more mysterious finding, and cannot be explained by changes in congestion, number of moose on the landscape, or the number of extirpations. However, when examining the graphical outputs for this model simulation over time, we find that an area which was previously untouched by both high hunter visitation and timber harvesting is 'opened up' for the first time by the creation of a single haul route, as depicted in Figure 33.

Figure 33: Depictions of hunter agent dispersion in the grid for three year road decommissioning, showing a 'bubble' of new forestry activity and the ensuing increase in hunter visitation. Lighter yellow colored cells show greater levels of agent visitation.



It would appear that this 'bubble' of newly accessible cells opens up an area where moose populations are high and the new forestry roads allow for easy access. The presence of such an event in this model run, but not in the others is explained by the fact that with maintaining roads for longer periods of time allows extractive industry to easily revisit an area once the adjacent cells are deemed to be harvestable. Where roads are quickly reclaimed, these areas would become more removed from the primary road network and major haul routes. Therefore extraction activity would potentially be more concentrated after such an area was again opened up for extraction, given the lack of road nodes in proximity to other harvestable stands elsewhere on the map. Here, we see that such an area is opened up, and hunting agents quickly follow to harvest the large moose populations within.

Decommissioning in 10 or 5 years results in a steady decrease in perceived landscape utility, without the punctuated events which occur in the 3 year decommissioning simulation. Ten year road decommissioning yields a higher utility than

5 year decommissioning, which is expected given the relatively lower travel cost associated with more roads being present on the landscape. This finding supports the hypothesis identified in Chapter 1, where it is expected that earlier road decommissioning will result in a lower perceived utility across the landscape. Again, the greater persistence of roads allows for overall travel cost to be lower across the landscape.

Figure 34: Extirpations incurred over time for two simulations using various time frames for forestry road decommissioning

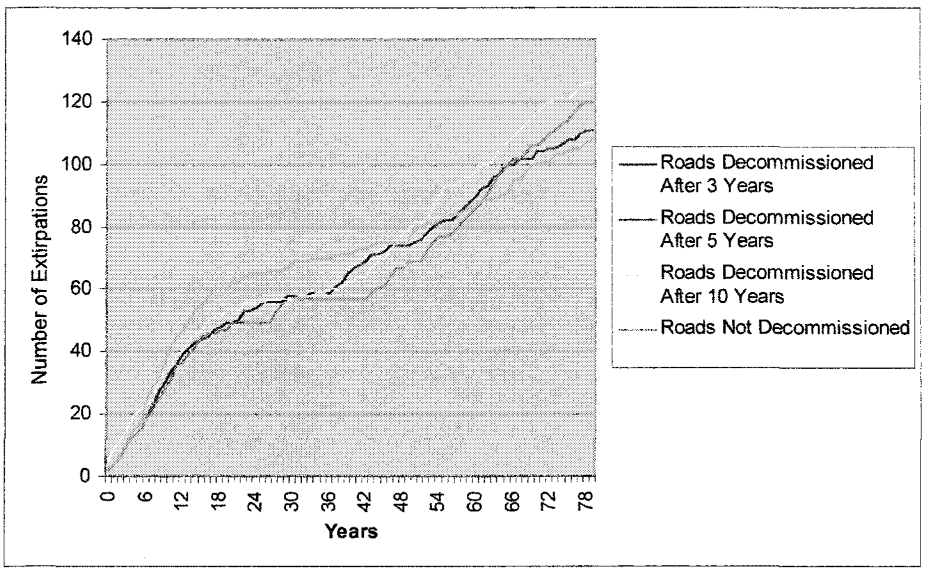


Figure 34 presents the number of extirpations resulting from excessive hunting pressure. The case where roads are not decommissioned initially records the most extirpations up to year 48, then reverses to yield the least number of extirpations by the end of the simulation run. This finding is consistent with hypotheses identified in Chapter 1, and is expected as initially roads are constructed closest to the central 'city' and are not reclaimed. Hunting pressure therefore remains high in these areas until the landscape as a whole becomes fully accessible in the latter years. This trend reverses to the point where the least number of extirpations are incurred by the end of the simulation.

For the case where roads are decommissioned at 3, 5 and 10 years, there is no large difference in the trajectories of the number of extirpations occurring, other than the 3-year scenario is inevitably overtaken first by the 10-year, and later the 5-year decommissioning scenarios. The explanation of this trend is likely driven by fact that the majority of extirpations are incurred closer to the central 'city', and maintaining roads closer to this area will hasten the occurrence of extirpations in this location.

Access / Linear Disturbance Regeneration

Four access / linear disturbance reclamation scenarios were analyzed, for 10, 20, and 30 year regeneration, as well as the case where all impacts resulting in access / linear disturbance create permanent landscape features.

Figure 35: Depictions of hunter agent dispersion in the grid for four simulations using various time frames for access / linear disturbance regeneration. Lighter yellow colored cells show greater levels of agent visitation

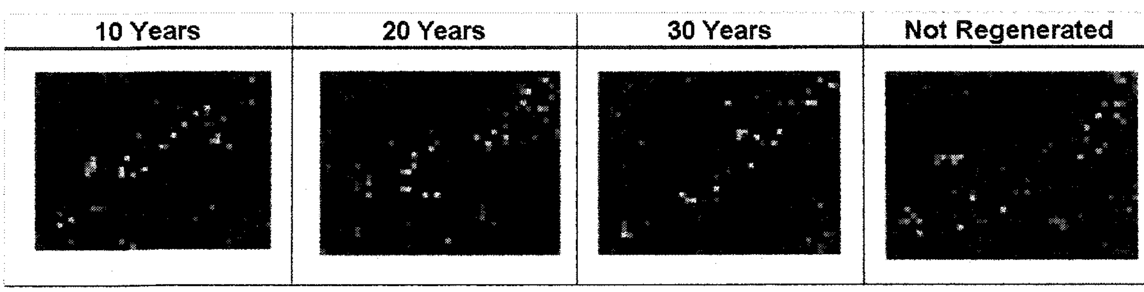
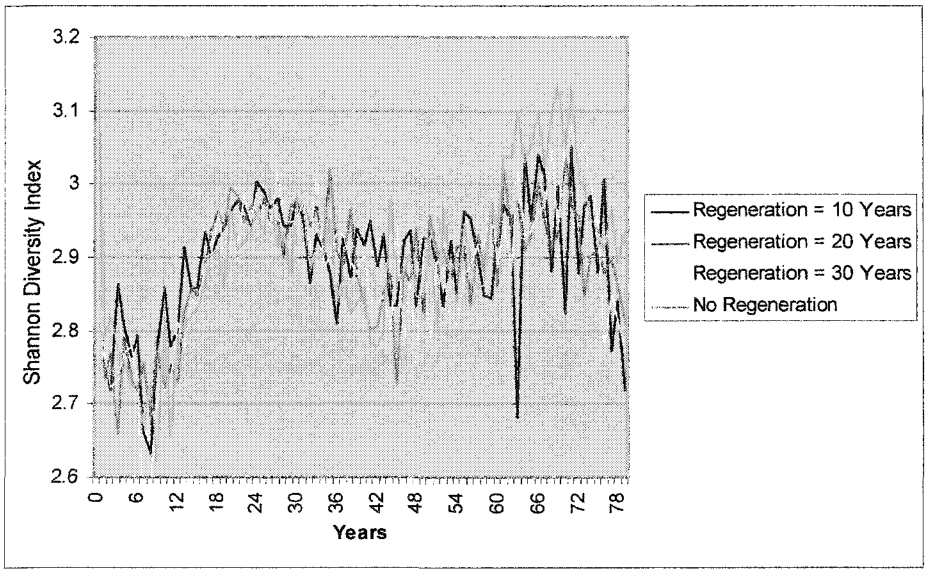


Figure 35 shows congestion, roads and access (in red) in the final year of the simulation. There is increased visual presence of roads and access across the simulation runs.

Figure 36: Shannon Diversity Index for four simulations using various time frames for access / linear disturbance regeneration



Variable ages of access / linear disturbance regeneration do not initially have an obvious effect on agent dispersion, as shown in Figure 36. The case where no regeneration occurs does however inevitably lead to the maximum dispersion observed in the latter 15 years of the simulation, and the case where regeneration occurs after 10 years leads to the minimum dispersion in this same time period. This result is expected due to a greater number 'best alternatives' available under the 'no regeneration' scenario, and lesser number of equal 'best alternatives' for the 10 year scenario. By the latter years of the simulation run, the landscape is sufficiently different between these two scenarios for this effect to emerge. This finding is consistent with the hypothesis identified in Chapter 1, where it was expected that a shorter time period for regeneration would result in a diminished variety of hunting sites attended due to fewer preferred alternatives being available.

Figure 37: Landscape utility over time for four simulations using various time frames for access / linear disturbance regeneration

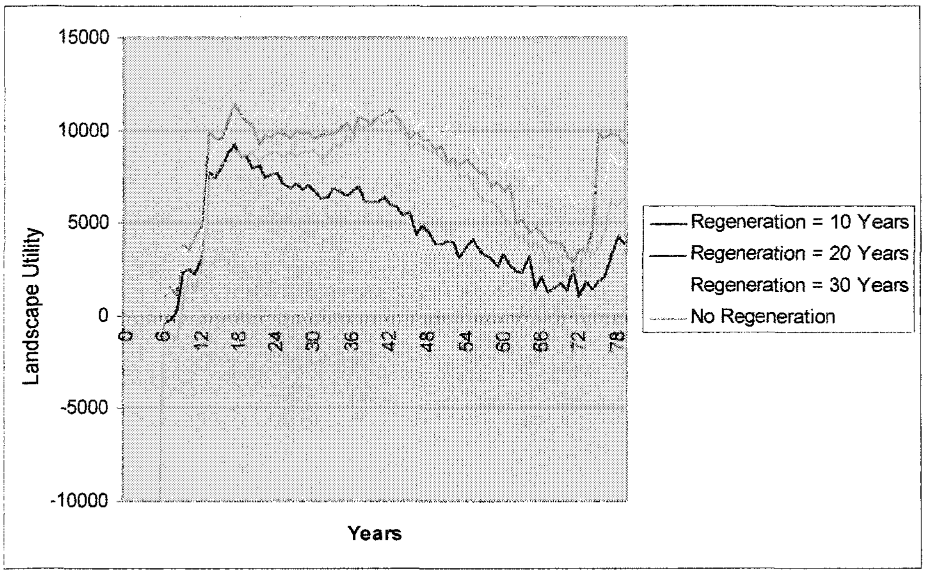


Figure 37 presents the utility perceived across all landscape cells for various access / linear disturbance regeneration scenarios. The case where areas are regenerated after 30 years yields the highest utility, while 10 year regeneration yields the lowest. The result for the 10-year regeneration is expected, as hunters prefer areas with greater access levels. These findings somewhat support the hypothesis identified in Chapter 1, where it was expected that utility perceived by agents would be lower for earlier regeneration time frames. The case where no regeneration occurs would be expected to yield the highest overall utility, but that was not found to be the case here. It is likely that the slightly larger dispersion of agents for this simulation decreased overall landscape utility through greater overall congestion, particularly in the latter portion of the simulation run. This effect negated the benefits perceived by the maintenance of higher access levels.

Figure 38: Extirpations incurred over time for two simulations using various time frames for access / linear disturbance regeneration

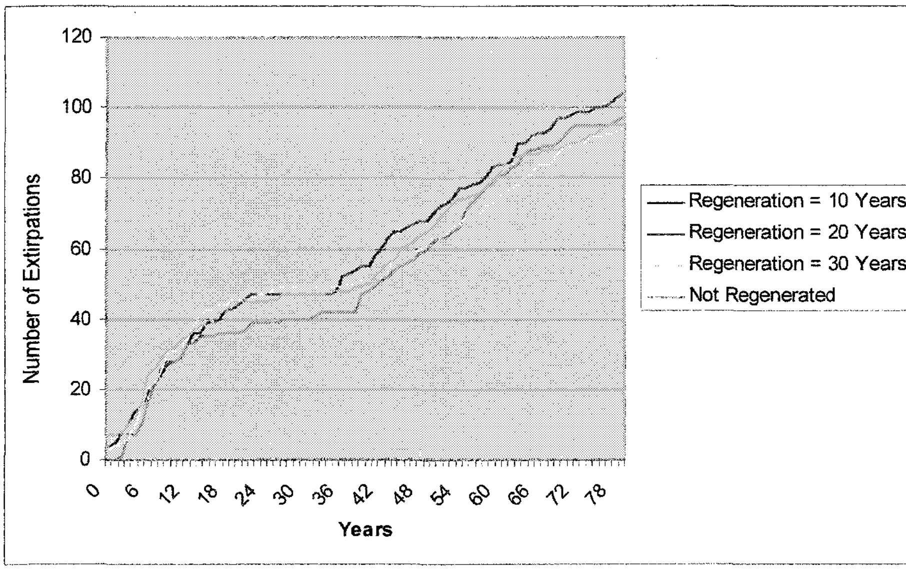


Figure 38 presents the number of extirpations resulting from hunting pressure. For the case examining different numbers of years before access / linear disturbance regeneration, there is no obvious relationship between years before regeneration and the number of extirpations occurring, except for the case where regeneration occurs in 10 years. For this scenario, the number of extirpations is consistently highest from year 40 to the end of the simulation run. This finding does not support the hypothesis identified in Chapter 1. Because hunters prefer areas of greater accessibility, it was expected that earlier regeneration would result in fewer areas being 'shot out'. This outcome was expected due to moose populations in regenerated areas being subject to lower overall hunting pressure. However, the opposite effect seems to have emerged, where earlier regeneration results in a greater number of extirpations. This is explained by the fact that given fewer 'most preferred' alternatives with greater access, hunting pressure will be increasingly focused within areas of high accessibility.

The trajectories for all simulations are very similar, except perhaps the presence of fewer extirpations in the earlier years for the case where regeneration occurs after 20 years. This result is more likely driven by particular events in the simulation progression rather than the age at which access was regenerated. It should be noted that a general trend exists where hunters tend to follow the construction of forestry roads, and the creation of these roads automatically increases the access / linear disturbance level to the maximum. Given this, it would seem that hunter activity, and the resulting extirpations is dually driven by roads and access / linear disturbance, and isolation of the singular effect of access / linear disturbance is difficult.

CHAPTER 7 SUMMARY AND CONCLUSIONS

Project Overview

Six sets of ABLE model simulations were analyzed using the ABM approach discussed in Chapter 5, where moose hunting agents were calibrated to findings from existing SP / RP studies of moose hunters' preferences. The main value of using this approach is the ability to account for complexity in terms of agent heterogeneity, agent learning, biophysical feedbacks, and spatial relationships over time. These factors are key defining characteristics of the resource system under analysis. Outcomes are examined by altering various assumptions regarding how agents are characterized, and also through alternative resource management scenarios implemented on the landscape.

The objectives of the exercise were to improve on previous modelling techniques in a multidisciplinary framework where traditional assumptions in discrete choice modelling and the inclusion of human dimensions in ecological models were explicitly represented. In this project, human decision making is grounded in micro-economic theory, and resource impacts are represented at the individual level where cumulative effects originate.

In doing so, this project contributes to sustainable resource management in that it allows the examination of outcomes arising from a variety of resource management scenarios, representing multiple actors with diverse types of impacts. The simulations track the behavior and resulting impacts of individual agents on a cumulative landscape level. This is achieved by combining biophysical processes with economic dimensions to provide a multi-disciplinary decision support system. Furthermore, defensible methods of parameterizing multi-agent systems grounded in micro-economic theory are presented and applied.

The methodology is applied here to test the effects of loosening traditional assumptions in discrete choice modelling, and applying the findings to real world management decisions. Alternative hypotheses are examined to explore the effects of

- Heterogeneous preferences among individuals within a group;
- Heterogeneous accuracy of perceived landscape utility;
- An individual's ability to better perceive their environment through learning.

Within this context resource management scenarios are examined. Specifically, the effect of:

- Variable ages at which roads are decommissioned
- Variable ages at which access / linear features are regenerated

Summary of Results

For the case where preferences are heterogeneous at various levels, a positive relationship was found to exist between heterogeneity and agent dispersion. The hunting population therefore selects a broader variety of sites as they decreasingly prefer (with increased heterogeneity) the same bundles of attributes held within these sites. A negative relationship was found to exist between perceived landscape utility and preference heterogeneity. This outcome was driven by broader visitation across the landscape, and increased occurrence of extirpations as heterogeneity increases. The increased number of extirpations is contrary to the expected findings, and emerges because sufficient agent dispersion does not arise to allow moose growth rates to exceed hunting pressure.

Simulations examining agent heterogeneity in terms of perceptions show a positive relationship between heterogeneity and hunter dispersion. As the accuracy of perceptions decreases, hunters attend a wider variety of sites. Among heterogeneous populations, the greater variation in perception accuracy yields a higher overall landscape utility. This is driven primarily by the markedly lower number of extirpations that exist as perception heterogeneity increases. In this case, hunter dispersion has become sufficiently large to allow moose populations to regenerate.

Examining the ability of agents to learn shows that learning agents are less dispersed across the landscape. This is the expected result, given that learning agents will be better able to identify ideal hunting sites, and therefore attend those specific areas in greater numbers. Learning agents perceive a lower overall landscape utility, driven primarily by the notably larger number of extirpations incurred by learning agents. Learning agents are more 'proficient' hunters, and derive a higher utility level from sites attended, while incurring a larger number of extirpations. In this sense, a 'tragedy of the commons' scenario exists, whereby each agent increasingly able to maximize their utility detracts from the overall utility available across the landscape.

Turning to resource management scenarios, overall agent dispersion was not found to be related to the time frame by which forestry roads are decommissioned. This outcome is contrary to the hypothesis presented, where it was expected that dispersion would decrease with earlier decommissioning time frames. The explanation for the lack of such an outcome comes from the fact that major haul routes that continue to be used by the forest harvester facilitate hunter travel, even though in-block haul roads are closed. As such, the overall travel cost to accessing sites is still low.

As hypothesized, landscape utility decreases with earlier decommissioning of roads. An interesting finding emerges where roads are closed after 3 years, which is the earliest time frame for decommissioning considered. In this case, the earlier closure to focus timber harvesting results in a 'bubble' of activity concentrated in one area in the latter years of the simulation. This event serves to open up an area which was previously less accessible to hunters, and agents quickly move into the area to benefit from the large moose populations, as well as new roads and access. There is a marked increase in landscape utility as this occurs.

The case where roads are not decommissioned initially results in the greatest number of moose extirpations, however this result is reversed by the end of the simulation run, yielding the least number of areas that are 'shot out'. This finding is explained by the easier travel to sites close to the main populated area as forest blocks are increasingly harvested in this area during the earlier simulation years. However, nearer the end of the simulation, the roads that persist across the landscape serves to increase the number of 'most preferred' alternatives for hunters. As a result, the rate of incurring extirpations decreases as hunters are not constrained to selecting from a fewer number of preferred sites. This result was not a hypothesized outcome, as it was expected that earlier decommissioning would result in fewer number of areas 'shot out', due to the limited accessibility available to hunters. Instead, it was found that limiting accessibility through earlier road decommissioning simply focuses hunting pressure into the fewer number of areas where roads do exists, and the number of areas that become 'shot out' therefore increases.

Turning now to outcomes resulting from various access management scenarios, we see that in the longer term, earlier regenerating of access / linear disturbances results in greater dispersion of agents. This is again due to the number of 'most preferred' alternatives available to hunters in the same fashion described above. In terms of utility perceived across the landscape, greater access / linear disturbance levels generally result in higher overall utility. Both findings are consistent with identified hypotheses. For the case where access / linear disturbances are regenerated in shorter time frames, it was found that the number of areas 'shot out' was higher. This finding is not consistent with identified hypotheses, and is explained by the reduced number of 'most preferred' alternatives available to hunters. In the manner described for earlier road decommissioning, the decrease in 'most preferred' sites serves to focus hunting pressure into fewer areas, resulting in a greater number of extirpations.

Conclusions

In the spirit of improving on previous modelling techniques, agent heterogeneity in both preferences and perceptions, agent learning, and the simulation of agents within a complex spatial context was found to result in drastically different outcomes that would have arisen using traditional assumptions. Based on these findings, decision support systems for cumulative effects management should include activities at the individual level. In order to defensibly predict outcomes for hunter utility and resource sustainability, future modelling endeavors should explicitly represent these multi-disciplinary characteristics of agent behaviour.

Based on the findings presented for preference heterogeneity, perception heterogeneity and agent learning, what characteristics would an 'optimal' population have? Findings in Chapter 6 suggest that an 'ideal' agent population would have a very wide distribution of preferences, perhaps even broader than any of the cases examined here. Such a population would also have a wide range of abilities to accurately perceive their environment, and would not have the ability to learn to improve this accuracy. Such a population would exhibit maximum dispersion, maintain a higher overall utility level, and incur fewer extirpations. The ability of resource managers to implement such a situation is perhaps questionable, and may also raise difficult moral questions in the general public. The inability to change hunter characteristics, and its resulting behaviour, is of course the basis for the current management regime of regulating the hunting season through licensing, setting quotas, seasons, and limiting the number of hunters within WMUs through the lottery system. As such, future directions of associated research should include an enhanced emphasis on representing the institutional constraints presented by alternative regulations.

In terms of managing other resource activities on the landscape, some general trends were identified across all simulations. The construction of forestry roads serves to increase hunter dispersion, and agents tend to follow the construction of new roads. This is consistent with other research in the resource management literature (Gunn and Sein 2000, Courtois and Beaumont 1999) which identifies an increase in hunting / angling pressure after the creation of new forestry roads. This result is explained by the decreased travel cost to sites once roads are built, the associated increase in access / linear disturbance levels, and the relatively lower congestion levels in prior time periods.

Although the size of moose populations is an important factor in hunter decision making, it is only one of five (or more) considerations in site selection (Bottan 1999, McLoed 1995, Dosman et al. 2002, Haener et al. 2000, Morton 1993). We therefore find that hunters will still attend a site that has registered a extirpation, even with full awareness that this has occurred.

The effect of increased dispersion generally results in decreased occurrence of extirpations, as hunting pressure is applied in a broader spatial area. Effects such as earlier decommissioning of roads and regeneration of access / linear disturbances results in increasingly concentrated hunting pressure as the number of 'most preferred' alternatives diminishes. This finding has important natural resource management implications, in that it is typically assumed that maintaining the size and distribution of moose populations requires a tighter control on site accessibility. Here we find the opposite outcome, in that a more open access landscape will yield a greater number of locally sustainable moose populations. Management that serves to limit the number of alternatives available to hunters therefore may be counter productive in attempting to maintain sustainable populations across the landscape as a whole. However, limiting accessibility closer to population centers will serve to decrease the number of areas that are 'shot out', so long as sufficient alternatives are available in more distant areas.

Given this, limiting effort, not access, is the key to achieving sustainability goals of resource management. Simply assuming that sustainability of moose populations is a function of the access levels present on the landscape is erroneous, and management must therefore account for hunter behaviour, not only the state of the landscape.

Future Extensions

Several areas remain open to further exploration in this project. Within the agent based modelling literature, the ability of agents to interact, communicate, and base their decisions on the expectations of others' actions is frequently cited as being an important aspect to the development of emergent properties. The agents' abilities to react to other agents' behaviour in this case study is limited to lagged measures of congestion, and improvement could be made in this area. The definition of leaning used in this case study does not incorporate the evolution of individual preferences over time, and future directions could include this process.

This study examines separately the effect of access management and the number of hunters on the landscape. Synergies likely exist between the two management conditions, in that the success of access management likely changes with the number of agents acting on the landscape. Access management may therefore have more beneficial effects when there are fewer hunters, but where there are 'too many' hunters it is perhaps the wrong policy instrument. Further examination should consider the effect of access management under different quota levels for hunting permits available.

Furthermore, the regulatory framework that agents face in this experiment does not accurately simulate the intricacies of repeated and continuous management of the landscape. Future directions should include a regulatory feedback mechanism that accounts for the lottery rationing of moose hunting permits, perhaps as a function of the size and distribution of moose populations in the previous time step. The case study examined here simplifies the landscape to incorporate one primary road network and one 'city' as the agent origin. Within a more explicit regulatory framework, the landscape would consist of individual WMUs, each with a method of rationing permits according to the demand from hunters in various locations and also according to the health of moose populations in these areas.

Lastly, the definition of landscape processes simplifies several processes which play into the complexity of the biophysical system under analysis. Accounting for these complexities, particularly in the representation of moose populations would better accommodate the intricacies of this system. Examples of this would include mobile moose agents, moose populations growth dependant on age and sex rations, the spatially distributed forage availability and other landscape features which have been found to alter the size and distribution of moose populations. The ability to repopulate adjacent cells once an area has been 'shot out' may or may not be appropriate, but could be a consideration in future directions.

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