Calibration of agent-based models in ecological economics

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For my wonderful children Ashley and Dante,
and with appreciation for the lessons of the four directions;
strength, tradition, new beginnings and service to mother Maka.
Abstract

Modelling human and environmental systems offers an opportunity to explore how these highly complex systems interact and influence each other. However, models are only as good as their assumptions, and rigour in calibrating models is critical. This is particularly important with agent-based models (ABM) which represent complex systems at a disaggregated scale. In this style of modelling, small details can emerge to have large consequences at the macro-scale. Many ABMs model human behaviour, and methods of empirical data collection used in social and economic sciences are thus available for use in calibrating models. To date, the use of surveys, interviews and participatory modelling have been used, and a small number of examples using experimental economics. Nevertheless, each study employs data gathering techniques and subsequent interpretation into agent behaviours according to the context of the ABM application and the style of decision making modelled. This does not offer a generalisable methodology and hence is not comparable across studies. Given the need for generalisable and consistent calibration methods using empirical data, two research questions are posed:

1. What techniques in social and economic sciences can be used to gather empirical data for model calibration, and which of these offer a generalisable methodology to allow comparability between studies?

2. Can experimental economics be integrated with ABM to gather data for calibrating models, and what benefits can be realised by integrating the two into a single platform?

In order to address research questions, six agents-based models are presented, with applications to ecological economics and specifically natural resource management and the use of market-based instruments. The results of these ABMs can inform environmental policy design, however the robustness of simulation results depends on the underlying assumptions of the model, particularly how agent decision-making functions are programmed and parameterised. The six models presented in Chapters of this thesis use calibration methods including surveys, interviews, and experimental economics. A novel approach is described using experimental economics directly integrated with a spatially explicit ABM. Experiment participants become agents
within the running simulation model, making trading decisions in a cap-and-trade market for water quality. Participant data is gathered, statistically interpreted and re-assigned to artificial agents. Integration of the ABM and experimental economics platform improves the calibration process because the experimental design and model algorithms are necessarily consistent given the direct coupling of the two techniques. Integrated experimental economics and ABM is presented as a generalisable methodology which will allow consistent and comparable results across ABM applications.
Declaration

This is to certify that

1. the thesis comprises only my original work towards the PhD except where indicated
2. due acknowledgement has been made in the text to all other material used,
3. the thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.
Acknowledgements

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Chapter 1: Introduction

1.1 Background

The field of ecological economics integrates the study of biophysical and socioeconomic systems, highlighting the connections between the two within the finite global system. Simulation modelling of integrated human-environment systems can assist in quantitatively understanding the feedbacks within and between these complex systems. A variety of complex systems modelling techniques are available, each differing in their representation of the system, such as by the scale of aggregation and whether space is explicitly represented. Issues relevant to ecological economics such as renewable resource management, conservation, sustainable development and implementing effective environmental policies are often characterised by a multitude of actors operating on the same landscape, with feedbacks between human and biophysical systems. The multitude of actions and interactions can combine to create system level emergent properties. For research questions that depend on emergent properties of complex systems, agent-based modelling (ABM) is a useful tool given the disaggregated scale at which dynamics are represented.

Ecology and economics are both concerned with interactions between organisms and their environment and the scarcity of resources that sustain livelihoods. Individuals interact along social and kinship networks and within communities, along supply chains and in markets, and within whole economies and ecosystems (Heckbert et al. 2010b). Social-ecological systems can be understood as complex systems, characterised by patterns at higher levels which emerge from localized interactions and selection processes acting at lower levels. They are formed from nonlinear relationships, feedbacks, and may show path dependency (Brown et al. 2005) and sensitivity to assumptions of initial conditions. Complex systems are recognized by the presence of patterns at a system level not reducible to characteristics at the individual level, and these patterns are emergent properties of micro-level interactions and behaviours. Here we use the definition of emergent properties as stable macroscopic patterns arising from feedbacks through local interaction of agents (Axelrod 1997; Epstein et al. 1996).
Interactions matter in complex systems. Depending on the model’s purpose, interactions can be social or environmental, and constitute feedbacks between the individual and its external conditions. Space is commonly used as the medium of interaction, particularly where human-environment feedbacks exist, as in many research areas relevant to ecological economics. ABM allows the researcher to explore how macro-level phenomena emerge from micro-level behaviour among a heterogeneous set of interacting agents (Holland 1992). In ABM, higher-order variables (e.g., commodity prices, population dynamics) are not specified, but are emergent outcomes of the multitude of interactions (Matthews et al. 2007).

This style of simulation modelling involves generating a population of artificial ‘agents’ with programmed behaviours, and examining the outcome of their collective actions through time and space. As a definition, ABM is the computational study of systems of interacting autonomous entities, each with dynamic behaviour and heterogeneous characteristics. The ‘agents’ interact with each other and their environment, resulting in emergent outcomes at the macro-scale. Interactions can be direct such as communication and physical interaction, or indirect via multiple-pathway feedbacks and from aggregate outcomes (Heckbert et al. 2010b). Dynamic behaviour of heterogeneous agents is represented by decision making functions.

This presents the issue of deciding which decision making functions to model. Human decision making itself is complex and has been shown to reveal all manner of deviations from theoretical assumptions of neoclassical economics, these deviations being the subject of behavioural economics. In order to design ABMs with robust representations of human behaviour, we can therefore turn to behavioural economics and other social sciences which have methods for eliciting and interpreting human decision making.

Researchers designing ABMs therefore have begun to use empirical methods to underpin their theoretical representations of human behaviour. Surveys, interviews, participatory modelling and more recently experimental economics have been employed to gather data for interpretation into agent behaviours.
Based on this, a number of original ABMs were constructed and are presented here, with applications to natural resource management and specifically modelling market-based instruments. The results of these ABMs can inform environmental policy design, however the robustness of simulation results depends on the underlying assumptions of the model, particularly how agent decision making functions are designed and parameterised. The calibration methods used to define and parameterise agents is discussed for each ABM presented, using a variety of techniques to bring empirical data into the development of agent behaviours. Surveys, interviews, and experimental economics are presented as techniques to calibrate ABM. The primary contribution of this thesis is the novel technique of using an experimental economics platform integrated with an ABM.

1.2 Problem statement and research questions

Agent-based models allow for macro-level spatial patterns to emerge from micro-level behaviours of autonomous agents, in order to quantitatively explain underlying processes which contribute to system outcomes. However, defensibly defining and calibrating these micro-level behaviours remains an outstanding challenge. The myriad of ways to represent decision making of agents also comes with the significant challenge of choosing the correct one. It has been argued that ABMs include too many degrees of freedom (Grimm et al. 2005), and may reflect too greatly the perspective of the modellers and users. A model built to explore a certain macro-level pattern may be ‘finding’ these patterns without ensuring the micro-interactions which cause them are indeed the correct representations. The modeller can use any number of parameters and functions, making it difficult to restrict the ranges of model parameters (Grimm et al. 2005). Along this line, Epstein (2006) also concludes the field lacks standards for model comparison and replication of results.

Calibrating and validating agent-based models is challenging due to the nature of complex systems. Defining system-level patterns and determining which underlying processes created them is difficult because of the irreducibility of these systems. Patterns created in ABMs can be compared against empirical data for validation, for example fragmentation metrics predicted in a model of deforestation can be compared
to aerial photography over time, and models can be adjusted to account for discrepancies. Some studies suggest comparing model results to empirical data on macro-scale patterns or stylized facts of a system. Grimm et al. (2005) suggests the use of patterns to guide model structure and reduce parameter uncertainty. First, alternative theories of agents’ decisions are formulated and patterns at both individual and higher levels are identified. Theories are tested by how well they reproduce the patterns, rejecting those that fail to do so. Additional patterns with more falsifiable power can be used to design experiments and analyse data. Similarly, Janssen & Ostrom (2006) suggest identifying stylized facts, and empirical evidence about behaviour and interactions is gathered which supports the selection of model functions. Model outcomes for stylized facts are compared to the evidence, and parameter sets are limited to those which reproduce the stylized facts. However, restricted parameter ranges still do not ensure the correct causal mechanisms have been represented; which of the remaining parameter combinations are the correct ones?

Criticism has been aired that model outputs rest on weak theoretical representations of human decision making. Empirical data for micro-level behaviours are often absent because data is generally collected and available only at an aggregated resolution, and key model functions may be deeply buried in lengthy code requiring great skill to develop and debug (Heckbert et al. 2010b). Model development issues aside, validating models of complex systems with their nefarious feedbacks poses unique challenges, as was identified early (for example in Janssen 2005) and remains an ongoing challenge.

The complex nature of an ABM, and its emergent properties at a system level make calibrating and validating models challenging, and some argue inherently impossible due to the irreducibility of emergent properties. Identification of underlying organization of ABMs has been hampered by the lack of an explicit strategy for coping with complexity and uncertainty. Consequently, model structure is often ad hoc (Crooks et al. 2008; Grimm et al. 2005), thus the strengths of ABMs’ flexibility to represent all manner of behaviours comes at a cost. Couclelis (2001) asks whether the benefits of that flexibility exceed the considerable costs of the added dimensions of complexity, concluding that it likely does not.
The response of many modellers is to not attempt empirical validation, and calibration rests in the theoretical domain. Moss (2008) argues that complex systems are ‘volatile’, and ‘soft’ calibration with stakeholder knowledge is perhaps the best strategy. The problem with this approach is that if different stakeholders have different subjective understandings of the system, the model might be an accurate representation of some views but an inaccurate (though precise) representation of others (Moss 2008). Subjective understandings of systems are most likely incomplete, if not incorrect. For example, Abel et al. (1998) show that mental models of graziers, scientists, and government rangeland managers are to some degree inconsistent. Given that worldviews and prejudices change, there is no guarantee that modelling the same system with similar stakeholders at different times should result in consistent modelled outcomes. The difficulty is in collecting empirical data at a system level and identifying its underlying causes. Matthews et al. (2007) argues that models can be used to organize knowledge from other studies and for developing rules-of-thumb, rather than be used as decision support systems.

Because of the difficult task of calibrating and validating complex systems models and the response of many modellers to not sufficiently address these, the field struggles with reputability, sometimes deserved. Bousquet and Le Page (2004) find some model credibility lacking, and there have been problems reported in reimplementation and replication work (Wilensky & Rand 2007). Programming errors are not uncommon, especially in early applications when ABM software platforms were not user friendly. Without a team of skilled computer scientists, early models were likely to contain unresolved bugs. Polhill et al. (2005, 2006) highlights the dramatic changes in model outcomes that can arise from floating point errors. Rouchier (2005) reports that findings of a trading market ABM were not replicable. Gintis (2007) goes further, suggesting that authors sometimes suffer from self-delusion, seeing emergent properties and explanations of model findings that cannot be supported by operations actually occurring in the code, and lists the presence of significant problems with verification, let alone attempting validation of system level outcomes.
These critiques can perhaps be viewed as birthing pains of a new methodology, and a certain amount of honest (and otherwise) errors can be perhaps be expected. Nevertheless, a consistent effort has been make over time to improve the empirical content of models. Janssen and Ostrom (2006) reports an increasing confidence in ABM as a valid technical methodology that can provide novel insights, particularly because relevant data are more available, and there is an increasing use of experiments in social sciences. To assist in comparability and replicability of models, Grimm et al. (2006) have proposed a standard protocol dubbed ODD (Overview, Design concepts, and Details), which has been used for comparing multiple ABMs of land use change in Polhill et al. (2008).

Increasingly, researchers are using multiple methods to calibrate ABMs. Techniques to empirically calibrate representations of decision making in agent-based models are discussed in Heckbert, et al. (2010b) and Heckbert & Bishop (in press). These include surveys, semi-structured interviews, existing data sources such as GIS and census data, direct participant observation, role playing games, and laboratory experiments. Existing data sets at increasingly finer resolutions are becoming available for use in spatial ABM, including satellite imagery, fine resolution GIS databases, and census and marketing data increasingly at the individual resolution. From the data gained through these sources, statistical relationships can be derived, and / or decision making rules constructed from interpretations of the data. Primary data collection is often performed when there is a gap in available data from which to generate the population of agents.

Although most models have been inspired by observation of real biological and social systems, many of them have not been rigorously tested using empirical data. In fact, most ABM efforts do not go beyond a “proof of concept” (Janssen & Ostrom 2006). Janssen & Ostrom (2006) call for efforts to develop methods that select from alternatives that fit data and are generalisable. Epstein (2006) concludes the field lacks standards for model comparison and replication of results, and Grimm et al. (2006) report that no general framework for designing, testing, and analysing ABMs has yet been established. As a result, a concerted effort has been applied to improve the defensibility of ABMs through empirical validation, with examples in Brown et al. (2005), Janssen & Ostrom (2006), Marks (2008), Moss (2008), Robinson et al.
The verification, calibration and validation process required of any robust model needs to include both validation of model outcomes, and also calibration of model functions through parameterisation. This dual focus on input (calibration) and output (validation) data allows the modeller to determine that simulated results are not only consistent with theory or observed data at a macro-level, but also that the functions generating these results are the correct ones. This is particularly important when modelling human behaviours and the underlying decision making processes.

Examples of how human decision making is represented in ABM include goal-oriented decisions such as utility seeking agents using preference functions calibrated from econometric techniques (for example Heckbert et al. 2010a; Robinson & Brown 2009), and fulfilment of aspirational thresholds (Gotts & Polhill 2009; Gotts et al. 2003). Modelling of boundedly rational agents is outlined in Ebenhoeh & Pahl-Wostl (2006), with rule-based decision making using heuristics outlined in Schlueter & Pahl-Wostl (2007), and decision trees are commonly used to work through sequential conditional decisions an individual may face, for example in Deadman et al. (2004). Decision making can also incorporate interactions in networks of agents, such as diffusion of innovation along social networks or spatial media as in Berger (2001), the effect of leaders with weighted social influence, imitation of others’ behaviours as in Polhill et al. (2001), reputation and the influence of ‘skilled’ agents in information-limited networks as in Boschetti & Brede (2009), Brede et al. (2008), and Little & McDonald (2007). These different formulations of decision making all require a set of parameterised equations programmed within each agent. The equations and parameters are often based on theoretical assumptions, interpretations of disparate data, anecdotal evidence and other sources of information available to the researcher, which do not offer a comparable and robust set of techniques across studies, and calibration methods are therefore not generalisable.

Nevertheless, techniques exist and are commonly used in social sciences and economics which can be incorporated into the calibration process of ABM. Surveys can gather information to derive individual or household behavioural models based on microeconomic theory, or to generate statistical descriptions of the attributes of agents, as described in Chapter 3.1 and Heckbert et al. (2010b). Similarly, Brown &
Robinson (2006) use econometric estimates from survey data to design agent preference functions. To learn directly why people reveal behaviour, semi-structured interviews can be used to explore drivers behind dynamic decision making. Participant observation from anthropological techniques can capture in-depth information (Huigen et al. 2006), and using the companion modelling technique, where stakeholders participate through role-playing games, while information is gathered for use in developing an ABM, as in Barnaud et al. (2008), Barreteau (2003) and Ruankaew et al. (2010).

Notably, there is recent interest in combining ABM and experimental economics to assist development and calibration of models. Chen (2007) argues that ABM matches well with experimental economics and behavioural economics, that models of software agents and human agents should not be separate entities, and that a framework combining the two will benefit economists on both sides (Chen 2007). Boscetti (2010) calls for a framework for integration involving an ABM and experimental economics in a laboratory setting, using experiments to observe and record behaviours. Barr et al. (2008) also suggest using human experiments as a calibration method to draw parameters for ABMs by fitting learning algorithms to experimental data, and then reapplying these algorithms in models. Barr et al. (2008) assert that the state of art is no longer a laboratory with only human subjects, but a lab comprising both human agents and software agents. However examples of using experiments in conjunction with ABM are limited, namely to Chan et al. (1999), Duffy (2004), Duffy and Unver (2006), Evans et al. (2006), Lopez-Paradez et al. (2008), Janssen et al. (2009), and Chen et al. (2007; 2010), although the concept of combined use of ABM and experiments has been argued as a useful methodology further in Contini et al. (2006), Barr et al. (2008), Hartig and Drechsler (2010), and Boscetti (2010), without providing actual applications. These studies are further described in Chapter 2.4. Furthermore, these studies use both techniques separately, using ABM and experiments to inform each other, which requires interpretation when re-assigning behaviours to agents. There appears to be no examples in the literature of an integrated ABM and experimental economics platform despite an exhaustive literate search.
Given the need for calibration using empirical data gathering techniques, two research questions are posed:

1. What techniques in social and economic sciences can be used to gather empirical data for model calibration, and which of these offer a generalisable methodology to allow comparability between studies?
2. Can experimental economics be integrated with ABM to gather data for calibrating models, and what benefits can be realised by integrating the two into a single platform?

The research questions are addressed through a series of case studies presenting six ABMs, each involving calibration activities using surveys, interviews and/or experimental economics. The models address issues in natural resource management including cumulative effects management, rangelands management, urban sprawl, and the use of market-based instruments in both water use and water quality cap-and-trade markets. In each case, the design and parameterization of agent decision making functions is informed by empirical calibration exercises.

The aim of this research is to advance ABM calibration methods through the use of data gathering techniques from social and economic sciences. In order to improve the rigour of calibration techniques in ABM, this body of work presents applied examples and discusses the merits various calibration techniques and determines which are generalisable. The specific contribution of this work is the application of an experimental economics platform integrated with an ABM for the purpose of gathering participant data, and in turn parameterising model functions.

1.3 Structure of thesis

The thesis is organised into three main body chapters. Chapter 2 presents an overview of ABM, its history of use, a literature summary of the use of ABM in ecological economics, and identifies calibration issues and methods. Chapter 3 presents three ABMs applied to cumulative effects management, rangelands management and urban sprawl. The design and calibration of agent decision making functions in these examples uses surveys and interviews to elicit stated preferences and behaviours from
respondents. Chapter 4 presents three ABMs which model market-based instruments for environmental management. Agricultural agents face restrictions on inputs to production and must trade in markets, requiring trading behaviours based on price-quantity decisions. Chapter 4 concludes with an example of calibrating agent behaviour from experimental economics, the primary original contribution of this thesis. Chapter 5 discusses the presented calibration methods for ABM.

All material in this thesis are original contributions by the author, including all model design, definition of equations, programming model functions, and communication of simulated results through figures. Three exceptions to this are 1) the survey design for Chapter 3.2, included in Appendix 2, which was developed by a team including the author as well as Drs. Alex Smajgl and Nadine Marshall, 2) Figure 7, which is presents rainfall data drawn from the Australian Bureau of Meteorology data drill (www.bom.gov.au/watl/) and pasture growth modelled from a biomass growth equation presented in Carlin et al. (2007), and 3) experiments conducted by Drs. John Ward and Anna Straton were used for calibrating the model in Chapter 4.1 with data provided post field experiments for model calibration, with experiments described in Ward et al. (2007). Chapters of this thesis, the calibration technique used, and resulting publications are listed in Table 1, and referenced in Appendix 1.
Table 1: Summary of thesis Chapters, the calibration method used, and publications where the research is originally presented.

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Chapter 2: Agent-based modelling in ecological economics

Many issues in ecological economics are characterised by a multitude of actors operating on the same landscape, with complex feedbacks within and between human and biophysical systems. Computer modelling of such social-ecological systems can assist in understanding how aggregate resource use affects the overall system. Among several methods of modelling such complex systems (discussed further in Chapter 2.1), agent-based modelling (ABM) represents systems at a disaggregated scale by modelling individual heterogeneous actors in space. This Chapter discusses modelling social-ecological systems as complex systems, the history and use of ABM applied to ecological economics, modelling human decision making, and methods to gather empirical evidence including surveys, interviews and experimental economics.

2.1 Complex systems modelling and history of ABM

Social-ecological systems can be modelled using a variety of techniques which vary in their structural representation of the system’s processes, including equation-based models, statistical models, Bayesian / probabilistic process models, agent-based models, and cellular automata. Many studies combine several techniques, and each has strengths in representing social-ecological systems processes in space and time. Spatial modelling of complex systems is seen as a generative, bottom-up process, and expresses patterns as emergent properties through the management of autonomous entities, their spatial relationships and behaviours over time (Benenson & Torrens 2004). Using complex systems models for ‘growing’ macro-scale patterns, and as a constructive tool for generative social science is discussed in Epstein (2006) who highlights the value of using these models to quantitatively explain theories of bottom-up processes and emergence in systems.

Feedbacks can be mathematically represented by equation-based models using variables in continuous functions. Equation-based models typically uses systems dynamics (SD) models (e.g. Vensim or Stella software), which deal in aggregate
variables for pre-defined spatial units and use a static process structure. In these applications, sub-models represented as series of continuous functions which characterize the transactions of physical stocks (such as cars, houses and people) and flows (such as fuel, waste, emissions) that describe sectors of the physical economy. Relationships between variables in equation-based models permit tractability and can be supported with measures of uncertainty around probabilistic processes. Data at aggregate scales are generally available, and statistical approaches such as regression and econometric parameter estimates are used to define relationships between explanatory and dependant variables.

Equations that describe population-level trends can appropriately describe ‘what’ happens at a system level and be validated against aggregate data, however they are limited in answering questions of ‘why’ and ‘how’ the aggregate patterns emerge and how underlying processes contribute to the overall system outcomes, leaving these to theoretical understanding of sub-system processes. Thus, equation-based models are limited to their ability to describe micro-processes within an overall statistical trend, in the same way a continuous equation for population growth describes demographic trends which are in reality a multitude of births, deaths and migrations of individuals. The equation describes the trend, rather than representing the functional scale of individuals.

Systems dynamics is certainly the most utilized modelling tool for complex systems, and ecological economics has benefitted in the ability to develop modular SD components connecting phenomena that typically are treated in isolation in some disciplines. Interconnected elements of systems, such as the biosphere, hydrosphere, atmosphere and anthroposphere can be represented and linked to allow feedbacks, as in Costanza et al. (2006). Batty & Longley (1994) use SD for modelling urban systems. Van Den Belt 92004) outlines techniques to use SD modelling in participation with stakeholders to build models directed toward participant learning, awareness and coordination across scales.

However, decisions and actions of multiple actors and potentially multiple spatial relationships are generally absent from systems dynamics models. While systems dynamics models are capable of representing complex systems, they are
fundamentally not adaptive. The equations and feedbacks in systems dynamics are structural and their ability to evolve is limited to variations in parameter values. Systems dynamics does not lay claim to representing micro-dynamics and disaggregate features, they are used to explain macro-level characteristics.

Bayesian networks can incorporate qualitative information on behaviour alongside quantitative data and statistical distributions but they do not easily represent feedbacks. A strong first criterion for choosing ABM is adaptive decision making which in turn may involve interactions with other adaptive decision makers. These dynamic aspects to modelling make outcomes at one point in time influence future events, and the linear mathematics of Bayesian networks, statistical techniques and equation-based models does not represent this well.

Emergence requires interactions, and a number of techniques exist which can explicitly represent the system at the resolution where there interactions occur. Models that explicitly represent interacting micro-dynamics include cellular automata (CA) and ABM. Both represent feedbacks through interactions of entities, being a spatial unit or grid cell in the case of CA, and an autonomous decision maker acting in space for the case of ABM. Cellular automata are a collection of cells on a grid of specified shape that evolves through discrete time steps according to a set of rules based on the states of neighbouring cells. The rules are then applied iteratively over time steps (Wolfram 2002). CA have been widely applied with increasing sophistication, to the point of ‘growing’ cities within their geographic landscape and achieving a high level of empirical accuracy (Barredo et al. 2003; Batty 2005; Clarke & Gaydos 1998; Portugali 1999; Waddell 2002; White & Engelen 1993). CA employs transition rules for the state of a cell based on neighbourhood (and beyond) spatial relationships, and these spatial transition rules can be empirically estimated from real-world data such as satellite imagery, census data linked with postal codes and GIS data of landscape features. CA can be viewed as a special case of ABM whereby the agent locations are fixed, and behaviours amount to a state change based on spatial metrics and neighbour conditions. CA rules describe observed patterns but do not necessarily explain them. ABMs’ human decision making functions require explicit assumptions about this process. Interactions may occur over space using mobile agents or over non-spatial arrangements such as social networks.
The structure of most ABM platforms is flexible enough to incorporate equations, systems dynamics and statistical techniques whereas the converse is not always the case. The disaggregated form of computation in ABM can always be aggregated up but statistics and macro-level variables cannot always be disaggregated.

Agent-based models have been widely used in ecology where they tend to be termed individual-based models (IBM) (Grimm 1999). They have contributed significantly to ecological theory, including population dynamics, group behaviour and speciation, forestry and fisheries management, conservation planning and species re-introductions (DeAngelis & Mooij 2005). ABMs have also been widely used in economics, although perhaps to a lesser extent than in ecology. The field of agent-based computational economics has explored features of economies as complex systems by representing economic agents in computer models as autonomous and interacting decision makers (Judd & Tesfatsion 2006). This opens the possibility to explore assumptions about economic decision making beyond that of self-interested rational and fully informed actors.

The ability of ABM to explicitly represent adaptive decision making and interactions provides an opportunity to explore issues in ecological economics which are defined by heterogeneity, feedbacks through interactions, and adaptation. Topics that could benefit are market dynamics, changes in consumer attitudes, consumption and sustainable behaviour, and psychological aspects such as subjective wellbeing (Costanza et al. 2007), natural resource management and land use change (Parker et al. 2003), common pool resource use (Janssen & Ostrom 2006; Schlueter & Pahl-Wostl 2007), and dynamics of urban systems (Batty 2005, 2008; Brown & Robinson 2006).

In recent years a number of ABM reviews summarising a common body of work have been published attempting to summarize experiences and categorize general trends. Grimm (1999) is among the first collection of learning from the field, coming from the perspective of ecology which uses the term IBM, addressing systems of interacting individuals but with little dynamic decision making. In social sciences, initial summaries include Levin (1992), Arthur et al. (1997), Gilbert and Troitzsch
Advances in modelling decision making of human agents led to the uptake of ABM in a variety of social sciences, with Tesfatsion (2002, 2002, 2003, 2007) providing a review of models applied to agent-based computational economics. Human agents within an environmental context are reviewed in Parker et al. (2003) focusing on land use and land cover change (LUCC) including models with varying degrees of refinement of interactions and human decision making. Notably, LUCC models provide the opportunity to simulate a system where economic tradeoffs with spatial environmental systems can occur. Janssen (2003) and Bousquet and Le Page (2004) review and categorize applications in natural resource management and ecological economics, presenting overviews of issues relating to the growing field of ABM that are still relevant today, particularly validation of models. The ‘handbook’ of Judd and Tesfatsion (2006) contributes to ABM through presenting accessible methodology for computational economics, and more broadly to macro dynamics of social systems including institutions.

Agent-based models have been applied to natural resource management and land use change, with examples in Bithell & Brasington (2009) which models cropping and forestry in subsistence farming communities, Schlueter & Pahl-Wostl (2007) examining resilience of irrigated cropping and fishing systems under different governance arrangements. A review of land use change and natural resource management models using consistent communication framework is presented in Polhill et al. (2008). Fuelwood harvest and giant panda habitat conservation is modelled in An et al. (2005), and testing the effect of various agricultural policies has been explored by Happe & Kellermann (2007) and Happe et al. (2006) for agriculture in the EU and the effect of farm business structure from agricultural subsidies. Little and McDonald (2007) examine the role of social networks and information on resource exploitation. Interestingly, this study finds that introducing ‘skilled’ agents in an information-limited system has the effect of producing hierarchical performance amongst agents.

Through this history, ABM has increasingly moved from exploratory models with theoretically based representations of underlying processes to face the rigor of empirical validation. Standards in presenting models have begun to emerge through efforts such as the Object Design Details ODD framework (Grimm et al. 2006),
making publications better communicated, comparable in their fundamental purpose, and models easier to replicate. Rouchier et al. (2008) presents an overview of efforts to compare and replicate ABM models with contributions from a number of researchers in the field. On the technical front, ABM software has greatly improved in recent years, from initial models which required extensive programming skills, to software packages which are accessible to researchers in multiple fields (Railsback et al. 2006). ABM has also improved its ability to represent space through integration with GIS, with examples in Heckbert and Bishop (in press), Heckbert (in press), Brown, et al. (2005), Crooks et al. (2008), Manson & Evans (2007), and Robinson & Brown (2009). These reviews of ABM show a progressive story of an improving methodology, with refinement of tools, targeted applications, increasingly concise and comparable communication of models, and evidence of increased experience of using ABM across disciplines.

Expanding on the reviews and journal papers listed above we can view a progress of ABM over time into various disciplines. ABM has roots in ecology’s individual-based models which represents non-human entities interacting within ecological systems (Grimm & Railsback 2005), whereas ABM generally refer to human decision makers. Individual-based models gained attention with early applications such as Boids (Reynolds 1987) which demonstrated how realistic flocking behaviour of birds can be recreated using simple interaction rules. Ecology recognized the advantages of modelling systems of autonomous agents (Huston et al. 1988), with early IBM able to reproduce familiar macro-scale outcomes based on simple interaction rules between individuals within a population. Most applications represent animals and plants as autonomous ‘particles’ with simple interaction rules, but there is increasing sophistication of representing individuals and advancing to cross-scale relationships (Grimm et al. 2005). Some studies suggest the distinctions between social systems and ecological systems is the information-processing capacity of human actors, and the ability to engage in purposeful action and reflexive learning (Schlueter & Pahl-Wostl 2007), however ABMs are increasingly taking into account adaptive decision of animals and plants (Polhill et al. 2008).

Many ABM applications have explored economic choices within urban environments (Batty 2005; Baynes & Heckbert 2010; Brown & Robinson 2006). Cities provide rich
territory for research into the complex relationships between decision making and landscapes affected by human activity. In cities there is a concentration of features that match well with the strengths of ABM: heterogeneity (in households, businesses, neighbourhoods, land use); autonomous decision making (e.g. by residents, industry, utilities); direct and indirect interactions (e.g. in property markets, planning and policy); and cross-scale effects (from local development choices to urban expansion). In the same arena, ecological economics has questions about the loss of environmental amenity, equitable access to resources (land, education, employment), and the intergenerational effects of development. Guzy et al. (2008) use ABM to incorporate urban containment and non-urban land-use policies in Oregon. Brown and Robinson (Brown & Robinson 2006) found that agent heterogeneity augments the potential for landscape change. Zellner et al. (2009) used a combination of ABM and game theory to represent the characteristics and priorities of neighbouring municipalities and demonstrated how zoning policy games can emerge from inter-municipal interactions.

In economics, ABM has had wide use in markets given the appropriate individual scale and focus on interactions which is analogous to traders within a market, with examples in Chan et al. (1999), Duffy (2004), Duffy & Unver (2006; 2008), Hailu & Thoyer (2007), Chen (2007), Heckbert et al. (2007), LeBaron & Tesfatsion (2008), Chen et al. (2010), Hartig and Drechsler (2010), and Heckbert (in press). ABMs have also been used directly to simulate markets related to natural resources. Filatova et al. (2009) use rules from standard urban economics to model price formation and market transactions in an urban land market. Applications in economics are presented in an accessible fashion in Judd & Tesfatsion (2006) with agent-based computational economics presented as a constructive methodology to explore economies as emergent systems and to understand how micro-interactions lead to persistent observed regularities at the level of society. The ability to represent decision making functions and interactions in markets opens the door for ecological economics research domains of market dynamics, consumer attitudes, adoption of sustainable behaviour and psychological aspects of human wellbeing.

Markets have been implemented in ABMs in McBride (2007) which developed an ABM of the ‘zero-intelligence’ trading market of Gode and Sunder (1993). Duffy and Unver (2008), Tesfatsion (2007), and LeBaron and Tesfatsion (2008) present
applications where agents trade in markets and form pricing decisions. With respect to markets for environmental management, Hailu and Thoyer (2007) present an ABM to test the effectiveness of different multiple-unit auction designs for water quality auctions. Weidlich et al. (2008) model electricity and emission trading where agents communicate and trade in power markets and markets for emission allowances.

### 2.2 Agent-based modelling of human decision making

ABMs represent individual decision makers as autonomous objects within a simulation. Programmed functions underlie an agent’s behaviour. In the case where the agent is a human, the ability to encapsulate the decision making functions allows theories from social sciences and microeconomics to be applied. ABM can explicitly formalize simple to complex representations of human decision making (Robinson & Brown 2009), can be used to test assumptions and theories of human decision making, and are valuable for providing a sound empirical and theoretical basis for understanding and predicting behaviour (Bousquet & Le Page 2004; Gilbert & Troitzsch 2005). Controlled experiments test alternative hypotheses of the behaviour of interacting agents, revealing how dynamics of systems from molecules to ecosystems and economies emerge from bottom-level processes (Grimm et al. 2005).

Human behaviour itself can be complex and adaptive. Assumptions of human decision makers as a homogenous pool of rational, self-interested economic agents, termed Homo economicus, is challenged by a wealth of evidence, notably from laboratory economic experiments demonstrating that human decision makers routinely depart from rational and fully informed behaviour (Heckbert et al. 2010b). People are at best boundedly rational (Simon 1997), typically using heuristics rather than optimization for making decisions, and also show a series of consistent ‘behavioural anomalies’.

Apart from neoclassical representations of fully informed and rational decision making, decisions are usually based on incomplete information, and preferences and behaviours which underlie decision making can change as new information becomes available. The field of behavioural economics has shown all manner of human
behaviours to exist in decision making, highlighting that neoclassical representations are the exception in decision making of humans. Herein lies the strength of ABM in the ability to encapsulate decision making, allowing for dynamic behaviour, adaptation, and learning.

The notion of autonomy of non-modifiable units drives the explicit representation of agents, quite like the classical Greek notion of an ‘atomic’ particle as the smallest non-divisible functional unit. The requirement to explicitly define decision making and resulting behaviour of agents opens the door to representing all manner of human decision making and behaviour. Within each instanced agent, explicit decision making functions are programmed, and the behaviours can be based in empirical evidence from behavioural economics.

Neoclassical assumptions are now challenged by experimental findings which show that in many circumstances people consistently deviate from narrowly defined rational, self-interested behaviour. For example, people tend to be risk averse, and behave differently when faced with losses or gains (Kahneman & Tversky 1984). Traits such as risk aversion are not constant, but vary between individuals, and people vary in their skills and preferences. Gintis (2000) finds that people have different discount rates depending on the decision making context, are not solely self-regarding, and are strong reciprocators who cooperate and also retaliate against free-riders even at personal cost.

Risk aversion plays a large part in individual decision making. For example, a fully rational economic agent is indifferent between one option that is certain and one option which is uncertain but with the same expected value. However experiments reveal that most people are risk averse to some extent, and would prefer the certain outcome even if the expected payoff is the same (Reeson 2009). The degree of risk aversion varies between individuals, some are risk seeking, preferring the riskier option with the higher payoff, and risk aversion varies as well as with context and the amount at stake (Reeson and Dunstall 2009).

Related to risk aversion is loss aversion, where people tend to give potential losses greater weight than potential gains. The way in which a decision is framed can
determine whether an outcome is seen as a potential loss or gain. People are generally risk averse for gains but actually become risk seeking where losses are concerned (Kahneman and Tversky 1984). Related to this is the endowment effect, where people value what they already hold more than equivalent things they do not have (Thaler 1980). In this case, willingness-to-pay to acquire something is less than the willingness-to-accept compensation to part with it. Endowment effects are not observed in professional traders, but are prevalent among their less experienced traders (List 2004). The more unfamiliar and uncertain the situation, the more likely people are to show this anomaly (Reeson and Dunstall 2009). Human decision-making under risk also displays the overweighting of certainties and small probabilities compared to intermediate probabilities (Kahneman and Tversky 1984). Certainty is greatly valued even though the difference in the expected payoff is the same.

People are fearful of losses, handle risk inconsistently, are prone to procrastination, tend to stick with the status quo and are easily swayed by irrelevant numbers (Reeson and Dunstall 2009). To deal with the challenge of making good decision with limited cognitive time and ability, people seldom calculate the consequences of each alternative, but rather tend to use heuristics, or rules of thumb, which give the right decision most of the time, and greatly simplify the decision-making process (Reeson and Dunstall 2009). Heuristics do not involve optimisation, but they should not be considered as a second best solution, nor a symptom of irrationality. They enable people to make quick, effective decisions. Human decision-makers should be considered as boundedly rational (Simon 1956), making good decisions within cognitive constraints.

The encapsulation of decision making in ABM allows representations of agent decision making as observed in behavioural economics. Examples of how human decision making is represented in ABM include goal-oriented decisions such as utility seeking agents using preference functions calibrated from econometric techniques as in Heckbert et al. (2010a) and Robinson & Brown (2009), and agents seeking to fulfil aspirational thresholds (Gotts & Polhill 2009; Gotts et al. 2003). Modelling of boundedly rational agents is outlined in Ebenhoeh & Pahl-Wostl (2006), with rule-based decision making using heuristics as in Schlueter & Pahl-Wostl (2007), and
decision trees are commonly used to work through sequential conditional decisions an individual may face as in Deadman et al. (2004). Decision making can also incorporate interactions in networks of agents, such as diffusion of innovation along social networks or spatial media (Berger 2001), the effect of leaders with weighted social influence, imitation of others’ behaviours as in Polhill et al. (2001), reputation and the influence of ‘skilled’ agents in information-limited networks as in Boschetti & Brede (2009), Brede et al. (2008), and Little & McDonald (2007).

Encapsulating decision making in agents opens the door to loosening assumptions in contravention of the Homo economicus paradigm. Behaviours and patterns seen in socio economic systems are open for explanation. For example, people routinely show social preferences, valuing the welfare of others in addition to their own. Participants in laboratory experiments are motivated by fairness and reciprocity, and are more trusting than Homo economicus (Berg et al. 1995; Gintis 2000). They are particularly concerned by equity, proving highly averse to inequitable outcomes (Fehr & Fischbacher 2002). It is also clear outside the economics laboratory that most people do not act in a purely self-interested manner, and notions of fairness and reciprocity may be represented within their utility functions. It is necessary to understand heterogeneities in social preferences in order to understand many key questions in economics. While the Homo economicus paradigm may provide a reasonable approximation of behaviour in impersonal competitive market settings, it is of far less relevance to many of the questions of interest to ecological economics. Imagine the outcomes of Homo economicus participating in the classic example of the tragedy of the commons, rather than an empathetic, skilled, and learned agent. Along this line Jager et al. (2000) present the ‘consumat’ agent as an alternative to Homo economicus, which includes features of decision making such as social comparison, imitation and repetitive behaviour (habits) under agents’ limited cognitive resources. The challenge however is to defensibly represent these behaviours, and methods for gathering empirical data can support the selection and calibration of these representations.
2.3 Behaviours drawn from surveys, interviews and participatory methods

The desire to incorporate findings from behavioural economics into decision making functions represented in ABM specifically addresses research question #1, whether techniques in social and economic sciences can be used to gather empirical data, and whether these offer a generalisable methodology to allow comparability between studies.

Surveys can gather information to derive individual or household behavioural models based on microeconomic theory, or to generate statistical descriptions of the attributes of agents (Heckbert et al. 2010b). Brown and Robinson (2006) use econometric estimates from survey data to design agent preference functions. To learn directly why people reveal behaviour, semi-structured interviews can be used to explore drivers behind dynamic decision making. Participant observation from anthropological techniques can capture in-depth information (Huigen et al. 2006). Techniques to gather, interpret and define parameters for the agent population is outlined in Berger and Schreinemachers (2006). They present a way to parameterize ABMs using a common sampling frame to select observation units for both biophysical measurements and socioeconomic characteristics drawn from surveys, which are then extrapolated over the landscape and agent population based on probability functions. The resulting landscape and agent population are statistically consistent with empirical data (Berger & Schreinemachers 2006).

Surveys and other data sets can gather information to derive individual or household behavioural models based on microeconomic theory and to generate statistical descriptions of the attributes of agents. Survey data can identify types of agents based on cluster analysis, and provide information on the distributions of characteristics, beliefs and preferences within a group. Surveys are good for sampling and extrapolating to the population level (Robinson et al. 2007).

Survey data are frequently collected for stated preference discrete choice experiments. These surveys ask participants to make selections between sets of choices, with the
aim of isolating the preferences for certain attributes of the choice. A well-designed survey can produce data for analysis using regression to infer causal links between attributes of the landscape and the choices made.

Data collected in surveys capture a snapshot in time and within a certain context of agent characteristics and behaviour, and surveys do not easily reveal motivations and strategies. To learn directly the motivations behind people’s behaviour, semi-structured interviews can be used to explore drivers behind dynamic decision making. Often in addition to surveys, interviews, focus groups, field interviews, and participant observation have been used to guide definitions of agent decision making.

Whereas surveys gather stated preferences and behaviours, techniques have been developed that begin to elicit revealed preferences from participants. This is important because what respondents report in surveys and interviews may differ from actual behaviours. Behaviours that depart from otherwise rational decision making are often couched in the context of a specific decision making situation. The goal of these activities is to identify factors influencing decision making by providing research participants with a controlled setting that represents contextual elements of the system.

Participatory modelling using ABM has been conducted using the companion modelling technique, where stakeholders participate in model development through role-playing games. Participants play their roles while information is gathered to be used in developing the associated ABM, with examples in Barnaud et al. (2008), Barreteau (2003), and Ruankaew et al. (2010). Behavioural functions are evaluated by stakeholders and transformed into rule-based agents in the model. The information collected in companion modelling on stakeholder behaviour is evaluated by the stakeholders, including post-game interviews and cross-checks, then transformed into rule-based agents in models. This process can offer system-level awareness building and an opportunity to observe agent-agent interactions, but is limited by issues of objective knowledge of stakeholders, subjective interpretation of behaviours by researchers, and has been criticized for playing a role in re-enforcing power relationships in the stakeholder groups of case studies, often in developing countries (Maru et al. 2009).
A further option in the development of experimental platforms lies in the option of using visualization technology to provide subjects with a realistic representation of the environment in which decisions are to be made (Heckbert and Bishop in press). This potentially increases the level of association of the subject with the environment and hence the ability to observe responses to contextual information. It also potentially increases the degree to which options and hence future conditions, under particular choices, are effectively communicated to the stakeholder.

2.4 Experimental economics for calibrating agent decision making

This section presents the possibility to inform ABMs using experimental economics, discussed in Heckbert et al. (2007), Heckbert (2008; 2009) and Heckbert & Bishop (in press). Whereas landscape visualization and companion modelling provide a context-rich medium, laboratory experiments can be used to strip away contextual influences and test human behaviour in very controlled decision making settings. Experimental economics uses participants in laboratory settings to study economic behaviour and test theories of decision making. This relates specifically to research question #2, whether experimental economics platforms can be integrated with ABM to gather data for parameterising the model.

Laboratory experiments and ABM each have much to gain through combined use given they both are concerned with decision making at the individual level; the former elicits decisions, the latter represents them explicitly in model code. Firstly, agent behaviours can be calibrated from results of experiments to create a population of simulated agents whose behaviours are consistent with the experiment participants. In this way, experiments can be used to bring empirical data into the ABM from data of observed behaviour. Second, experiments can help choose between possible sets of decision making algorithms a modeller may be considering (Epstein 2006).

Laboratory experiments and agent-based modelling can be used together to derive model functions that represents human behaviours with parameters calibrated from
The resulting population of agents have behaviours consistent with empirical data, provided the experiment design is sufficient to capture it and recorded data interpreted to behaviours appropriately.

The use of combined ABM and experiments is limited but increasing. ABMs have been designed with the results of lab experiments in mind by using experiments to better select agent behaviours, calibrate decision making functions based on revealed behaviours, and validate outcomes of ABMs against laboratory findings. Laboratory experiments are generally highly abstract and controlled in order to test specific hypotheses of particular decision making situations, as opposed to companion modelling which is context rich. Using laboratory experiments alongside other validation techniques can narrow in on a specific decision making function of agents, while leaving the surveys and interviews to gather more general information.

Janssen & Ostrom (2006) present the opportunity for experiments to empirically inform ABM, and report that use of experiments in conjunction with ABM is increasing. They argue that the increasing use of laboratory experiments in the social sciences has called into question some of the initial, simple models of human interactions in social-dilemma situations that study conflicts of decision making between benefits derived by the individual or groups. Agent-based models provide a tool to examine the consequences of more complex assumptions. Laboratory and field experiments can be performed to understand crucial components of ABMs, such as social interactions, the diffusion of knowledge and information, and the emergence of stylized facts.

Janssen (2010) argues that designing and conducting laboratory experiments enables the unpacking of complex problems and to replicate results with diverse participants. Janssen (2010) conducted a series of experiments to test the impact of communication and punishment in common-pool resource (CPR) management. The experiments test the findings of prior CPR experiments that have found that respondents are willing to engage in costly punishment, frequently generating increases in overall benefits, but at their own personal cost. Experiment results found that participants do indeed use costly punishment, however punishment without communication does not increase overall payoffs. When communication is allowed, group performance increases
significantly, but is not sustained when punishment is used and communication is no longer possible. This study highlights that experimental research can represent the spatial and temporal processes found in many social-ecological systems relevant to ecological economics.

The first comprehensive overview and use of ABM and experiments in markets is Chan et al. (1999), which constructs a simulation of a double-auction market with learning agents. Chan et al. argue that because of motives and information-processing abilities of humans, it is often difficult to assess the impact of risk aversion, learning abilities, and the degree of individual rationality on prices and quantities in experimental markets. In this study, experimental data is used to model trading agents endowed with preferences, information, and learning algorithms.

Duffy (2004) also uses ABM to understand the results of experiments in trading markets. Duffy suggests that in human experiments, a number of respondents can be replaced with artificial agents (with pre-programmed behaviours) to in turn observe the response of human participants. Secondly, data from experiments can be interpreted into empirical regularities and assigned to agents. In the associated ABM, agents have different algorithms for learning and expectation formation. Duffy and Unver (2006) examine a trading market with a modified zero-intelligence agent, used to explore patterns observed in trading laboratory experiments such as asset price bubbles and crashes.

Specifically addressing the relationship between experimental economics and ABM, Contini et al. (2006) outline the contributions that each field can make to the other. Contini et al. consider the progression of experimental economics from ‘pen-and-paper’ methodology for conducting experiments through to highly developed computer-based platforms, arguing the latter involves lower costs (per participant effort or per volume of data collected) greater accuracy of data collection and greater control of the information revealed to subjects. Perhaps most importantly, computer based experiments allows for more replications of a treatment than are possible with paper-and-pencil.
Contini et al. (2006) argue that complementarities between experimental economics and ABM have received little attention. They described a series of complementarities between the two, finding that experiments can contribute to ABM through validating representation of agent decision making by comparing experiment data and ABM results, and using experimental results for calibration of agent behaviours. Contini et al. argue that ABM can contribute to experiments through a) design of experiment, b) studying the interaction of human and artificial agents, c) investigation of cognitive processes that lead to behaviour in experiments, and d) using ABM to benchmark behaviours observed in experiments. The latter point is interesting given that results of human experiments reveal choices influence by behavioural economics, but agents in ABM can be programmed to pursue ‘extreme’ behaviours, such as true optimisation, random behaviours, or behaviours that lie outside of the expected range of variability seen in human subjects. This can set a benchmark by which to compare results in human subject experiments. Although people rarely optimise decisions, agents can be programmed to do so and the difference between perfectly rational and boundedly rational agents can be explored, for example the loss of efficiency in markets where agents express traits known in behavioural economics.

Lopez-Paradez et al. (2008) present an ABM inspired by human subject behaviour in a signalling game experiment with incomplete information, which tests the effect of communication. Experiments were performed to determine attitudes, emotion and reveal heuristics. Artificial agents are endowed with cognitive mechanisms derived from the behaviour revealed in experiments. Experiments revealed altruistic, cooperative, normative and perverse behaviours, and tracked respondent’s feelings of satisfaction, anger, or neutrality. Observed heuristics including deliberative (wait and see), reactive downing (maintaining existing strategy but deciding it is the opponents’ last chance to change behaviour), reactive tit-for-tat, and retaliation.

Evans et al. (2006) present an ABM of reforestation and agricultural land use decisions, used to test specific but highly important assumptions on agent behaviour. Evans et al. used a mixed methods approach to calibration. First remote sensing data were used to estimate agent preference parameters by regression, surveys were then used to collect social and demographic information. However, only a weak relationship between income and reforestation was found using this approach, and
other factors such as learning, information, knowledge, risk aversion, and influence of social networks were hypothesized to play a role, but not able to be captured in surveys (Manson & Evans 2007). Computer-based laboratory experiments were designed to further test hypotheses about decision making and resulting behaviours. The experiments in Evans et al. (2006) assessed how people make allocation decisions between agricultural use and reforestation. Subjects were allocated spatial areas to one of two land uses, receiving revenue according to an increasing price over time for one, and a decreasing price for the other. Experiments found considerable variance in behaviours of allocating land to each of the two uses, and where a ‘rational’ decision maker would have changed land use, the majority of experiment participants took many rounds to complete the reallocation, and some persisted in allocating to the disadvantaged option (Evans et al. 2006). The overall outcome of participant decision making was to generate overall reforestation patterns with more ‘edge’ compared to a model populated with agents who make fully rational choices.

Hartig and Drechsler (2010) present an ABM of market-based conservation instruments, examining the effect of spatial heterogeneity and the implications of different market design options. Agents represent landholders who are faced with an incentive to conserve portions of their properties for environmental services. The value of different locations is dependant on the overall configuration of habitat across properties, hence communication and coordination affect the environmental and economic payoffs. This study examines the effect of coordination (through cheap talk) and cooperation (attempting to benefit the group without increase in individual payoff). The authors argue that experimental studies as proposed in Hartig et al. (2010) could help to study which of these strategies are most likely to be realized by human agents.

Chen et al. (2010) study the significance of cognitive capacity in double auction experiments, comparing results of an ABM with results from experiments. The authors assert that cognitive capacity of traders in markets has been rarely addressed in the literature, possible due the assumption that the market mechanism is so powerful and robust that it leaves no room for participants’ intelligence and learning (Chen et al. 2010). Hence, the authors attempt to determine if cognitive capacity matters to overall market outcomes. Only weak evidence of the effect cognitive
capacity and learning was observed in human subject experiments, while in the ABM the effect was stronger. Also, human traders outperformed artificial agents, leading the authors to conclude that “finding the incarnation of human agents in terms of software agents remains a challenging task” (Chen et al 2010).

Although experiments have informed ABM and vice versa, other authors have also looked towards a future where experiments and ABM are conducted in conjunction and integrated. Chen (2007) argues that ABM matches well with experimental economics and behavioural economics, and that models of software agents and human agents should not be separate entities. A framework which can combine the study of the two will benefit economists on both sides (Chen 2007). Boscetti (2010) calls for a framework for integration, involving an ABM and a laboratory to carry out experiments in a typical experimental economics setting, and using experiments to observe and record behaviours. Barr et al. (2008) also suggest human experiments as a calibration method to draw parameters for ABMs by fitting learning algorithms to experimental data, and then reapplying these algorithms in models. ABM has increased its exposure to behavioural economics and experimental economics, the latter’s state of art is no longer a lab with only human subjects, but a lab comprising both human agents and software agents (Barr et al. 2006).
Chapter 3: Agent-based models of natural resource management

This Chapter now turns to presenting applications of ABM in ecological economics and discussing the merits of calibration techniques used. Each application is presented as a case study of using calibration techniques as discussed in the previous Chapter, namely surveys and interviews. This specifically relates to research question #1, whether techniques in social and economic science can be used to gather empirical data, and which of these offer a generalisable methodology to allow comparability between studies.

The first case study addresses cumulative effects from multiple resource users operating on the same landscape, specifically forestry and hunting. Heckbert et al. (2010a) present and describe this model, with the goal of quantifying cumulative environmental impacts (cumulative effects) caused when two resource users overlap in space and generate environmental impacts greater than the sum of their parts. Managing cumulative effects is challenging due to the complex dynamics of natural and human systems interacting. Cumulative effects in social-ecological systems are examples of emergent properties of complex systems, which arise from interactions between multiple resource users. The specific contributions of this first example are a) quantification of emergent properties in natural resource management systems, b) evaluation of different forestry road decommissioning policies and the effect on game population sustainability, c) calibration of agent behaviours from numerous empirical studies.

Preference weightings in the utility function of hunter agents are calibrated from stated and revealed preference studies of hunters. Simulations explore game population sustainability under various forestry road access management policies and with different hunter preference parameter configurations. Contrary to the intent of road access management, earlier road decommissioning is found to negatively impact overall sustainability of game populations due to cumulative effects of aggregate hunter behaviour. Altering agents’ preferences for travel cost, game populations, and
hunter congestion result in dramatically different spatial outcomes for game extirpations. Certain preference parameter settings create resonance between hunting pressure and game population growth, forming self-organized and persistent spatial resource use patterns.

The second case study addresses the issue of water quality from sedimentation caused by grazing management practices. Decisions of graziers with respect to stocking rates and managing herd grazing pressure through fencing and rotation have an effect on pasture cover and therefore soil erosion. Water quality therefore depends on a number of feedbacks between pasture growth, spatially distributed grazing pressure and herd management. A case study is presented here from the Bowen Broken catchments of North Queensland, Australia, first presented in Smajgl, Heckbert, et al. (2008). The large inland grazing region delivers annual runoff through the Burdekin River system to the waters of the Great Barrier Reef. Efforts to improve water quality have focused on incentives to producers which will result in managing grazing activities to improve sedimentation of the river system. This application of ABM involves non-mobile decision making agents who manage properties defined by GIS data. Properties are divided into paddocks and a cattle herd can be rotated throughout the property to manage grass cover. A series of interviews were performed with local graziers to help design programmed management strategies of agents. Strategies such as light and heavy stocking rates and rotation and spelling of paddocks are simulated and outcomes highlight the sensitive feedbacks that exist within the system. Depending on agent management strategies, pastures may degrade and reveal exposed surfaces susceptible to erosion. The novelty of this application is the use of state-and-transition models of pasture ecology responding to property management strategies of agents and vice versa. Modelling these systems and their feedbacks presents rangelands as a complex system, and is used to explore how the system maintains sustainability and resilience to resource use, or in turn crashes due to over-exploitation.

The third and final case study presented in this Chapter simulates patterns of urban sprawl that develop from a multitude of individual settlement choices. The selection of residential locations by numerous individual decision makers on masse creates an overall pattern which affects provision of environmental services. The geography, hydrology and topography of landscapes affect those who live there, and vice versa,
creating a complex system of feedbacks from the human-environment system. The ABM is presented in Baynes and Heckbert (2010), with agent decision making deliberately using a sparse set of rules that influence settlement decisions. The agents interact with each other and detailed spatial data on the geography and climate of a city region. Preliminary results are compared with historical data (1851 to 2001) of the urban growth of the city of Melbourne. The agents’ decision making function for settlement location are designed to be calibrated from secondary literature of preferences for site attributes.

These three examples show a progression in use of ABM using different approaches including different software packages, static and mobile agents, and the use of GIS data to generate spatial landscapes. The example addressing rangelands management is programmed using the Repast 3.1 software, and imports GIS polygons that form the property of a non-mobile decision maker. The first case study of forestry and hunting simulates mobile decision making agents in a spatially-explicit cellular landscape and uses dynamically evolving road networks which affect resource use patterns. This model is constructed in Net Logo 4.0.3 and greatly improves the representations of agents in space beyond the example from rangelands management, but lacks GIS data and hence remains in a theoretical domain. The third model described addressing urban sprawl is again modelled in Net Logo and imports detailed GIS spatial data to generate a landscape on which mobile agents function.

Calibration techniques used in these models include stated and revealed preference measurement techniques from economics, and surveys and interviews with local agriculturalists. The first and third examples of ABMs use a parameterised agent decision making function which can be calibrated using econometrically estimated values. The second example uses interviews interpreted into property management strategies. This specifically addresses research question #1, whether techniques in social and economic science can be used to gather empirical data, and which of these offer a generalisable methodology to allow comparability between studies.
3.1 An agent-based model of cumulative effects management

This first example of ABM examines the emergence of cumulative impacts which arise from multiple overlapping resource use of forested ecosystems, as presented in Heckbert et al. (2010a) and Heckbert and Bishop (in press). The example shows how forestry and hunting interact in a spatial landscape to produce combined effects greater than the sum of impacts from one resource use in isolation. This case study highlights the ability of ABM to quantitatively represent and explain cumulative environmental impacts. The modelled agents use a parameterised utility function to choose which locations to attend. The utility function takes on a functional form which allows parameterisation from studies which estimate preferences using random utility modelling. This approach can be used as a consistent method of calibrating ABMs which represent agents making selections from a set of choices, based on preferences for the choices’ attributes. This addresses research question #1 regarding the possibility of identifying techniques to gather empirical data which offer a generalisable methodology to allow comparability between studies. The use of discrete choice surveys for estimating preference functions of agents is identified as the first generalisable and comparable methodology discussed in this body of work. This technique is applied here to estimating parameters for a utility function allowing agents to choose from a set of alternative locations to attend for the purposes of hunting.

Quantifying cumulative environmental impacts (cumulative effects) as part of environmental impact assessment has been a challenge due to the inherent complexity of the systems involved. Cumulative impacts can result from individually minor but collectively significant actions (CEQ 1997), where impacts of resource developments combine with those of others, with unintended outcomes occurring over time and distance (CEAA 2004). We propose that cumulative effects are examples of emergent properties in complex systems, being systems where patterns at higher levels emerge from localized interactions and selection processes acting at lower levels (Levin 1992). Interactions between forestry and hunting provide a well-studied example of cumulative effects in natural resource management, with many examples in
The spatially-explicit ABM described here includes hunting and forestry agents, who perform behaviours within a simulated spatial environment. Decision making functions of hunter agents are calibrated from published stated and revealed preference measurement studies of hunting (Adamowicz et al. 2004; Bottan 1999; Boxall & Macnab 2000; Haener et al. 2001). Immersing these calibrated agents within a spatial landscape which represents game populations, forests and roads, and simulating the system over time, yields different spatial configurations of game extirpations (local extinctions). The goals of the study were to a) model the spatial configurations of extirpations in response to road decommissioning at 2, 5, and 10 years; b) empirically calibrate agent behaviours to improve defensibility of spatial decision making and demonstrate how this can be done using existing results from econometrically-based preference measurement studies; and c) contribute to methods of quantification of cumulative impacts in natural resource systems.

From an economic perspective, cumulative effects of multiple industrial activities can be viewed as an open access problem where the actions of several agents jointly affect a public good because of incomplete property rights (Weber & Adamowicz 2002). Legislation exists in many countries to include cumulative effects in environmental impact assessment (EIA). Australia requires cumulative impacts assessment on matters of national environmental significance (EPBC 1999), and the Canadian Environmental Assessment Act (CEAA 2004) requires EIA to account for cumulative effects, noting:

“there is no one approach or methodology for all assessments of cumulative environmental effects. Different circumstances, such as location of project and type of potential environmental effects will dictate appropriate methodologies.
Modelling, expert systems and geographic information systems are being increasingly used. However, where information is lacking, qualitative approaches and best professional judgment are used.”

The history of cumulative effects assessment in the United States dates to NEPA (CEQ 1997), and Smith (2006) reports the history of cumulative effects in legal challenges to resource developments, finding Federal agencies have a very poor track record in litigation, losing a large percentage of the cases. This is due to 1) lack of time and resources to effectively analyse multitude of individual impacts, and 2) the lack of sufficient data or methods to analyse some of the impact questions that will arise in such an analysis (Smith 2006). We argue that complex systems modelling, in this case ABM, can be used to quantitatively model cumulative effects, and contributes to the methodologies available for cumulative impact assessments under EIA. We use the example of forestry and hunting to show how cumulative effects can be thought of as emergent properties in complex systems, modelled, and their dynamics quantitatively analysed.

Interactions between forestry and hunting are well documented, with studies finding hunting pressure being related to accessibility of a hunting site. Industries which create access within forested areas may indirectly affect wildlife populations as hunters use a variety of so called ‘linear features’ to gain access to hunting sites. Access is gained to hunting sites via vehicle travel on public roads, industrial roads, pipelines, forestry haul routes, and by ATV along seismic lines, forestry cut blocks, and on trails (Schneider et al. 2003). Linear features also cause habitat loss and fragmentation, and wildlife species dependent on intact forest structures may suffer population declines, reductions in range, or even extirpation (Fleming 2001). A large number of studies have recorded the effect of increased access on hunting pressure and the effect on wildlife populations. Multiple studies have observed an increase in hunting pressure following the creation of forestry roads or other linear features, which provides hunters easier access to what was previously a more remote site, and higher harvest rates result in population declines (Courtois & Beaumont 1999; Eason et al. 1981; McMillan 1995; Rempel et al. 1997; Trombulak & Frissell 2000).
Multiple users accessing the landscape for different reasons presents a difficult management situation, and experience has shown that cumulative impacts of multiple land uses often outstrip the management ability and management intentions of any one agency (Burton et al. 2006). One policy response is to manage linear features though revegetation and road decommissioning, effectively closing a site once its industrial purpose is served. From the perspective of the industry which created the linear disturbance, decommissioning is a reversal to prior environmental condition. However, for hunters, decommissioning a road alters the relative accessibility of their combined set of possible hunting sites. How do decision makers respond to a changing choice set, and what aggregate impacts will be realized when these responses interact?

Numerous studies on hunter decision making have been conducted, providing a pool of human decision making models based on individual preferences, for example Adamowicz et al. (2004; 1997), Bottan (1999), Boxall & Macnab (2000), Haener et al. (2001) and Morton et al. (1995). In each of these studies, preferences related to attributes of the hunting experience are measured from a community of hunters. The next section describes how results from these studies were used to calibrate the decision making functions of agents.

The combined effects of forestry and hunting are modelled using a spatially explicit multi-agent system, constructed using Net Logo 4.0.4. The model code is available online (http://www.openabm.org/model-archive/huntingforestry). The model includes mobile hunter agents which reside in a ‘city’, and a cellular automata spatial landscape of forests, game populations and an evolving network of roads. During each time step representing 1 year, forestry roads are generated and decommissioned (discussed later), and hunter agents select and attend hunting sites.

Simulations reveal different spatial configurations of wildlife populations based on hunting pressure applied by the agent population over time. Behaviour of agents is influenced by access provided (or taken away) by forestry roads and their decommissioning. Different patterns are created by parameterising the hunter agent utility function from different secondary literature. In some cases the hunter agents apply an even spread of hunting pressure that does not push local game populations to
extirpation. In other cases, with the same number of agents, game populations are uniformly extirpated simply due to a relatively small difference in preferences. Emergent properties of the system are revealed during simulations, including parameter configurations that generate a self-emerging persistent spatial pattern of growing and dispersing concentric circles of game populations, termed a ‘hunting pulsar’. The emergent hunting pulsar can be considered a theoretical example of a self-regulating, persistent, and sustainable system of renewable resource use, which provides the hunter agent population with a steady stream of utility while not causing local extirpations of wildlife populations.

Hunting agents maintain an internal utility function, based on a set of preference parameters for travel cost (negative marginal utility), game availability (positive marginal utility), and encounters with other hunters (negative marginal utility). Hunter agents $i$ evaluate the expected utility, $U_i$, that would be gained by attending a given location $j$. Each location, represented in our model as a spatial cell, contains a vector of attributes $X^i_j$ for the attributes $k$ of travel cost, game availability, and hunter congestion. The utility function is a parameterized linear equation that utilizes taste weights, or preference parameters, $\beta^i_k$ which represent the marginal utility derived by hunter $i$, from attribute $k$, at hunting site $j$.

$$U_i = \sum_{k=1}^{K} \beta^i_k X^i_j$$  

Equation 1

Preference parameters $\beta^i_k$ are initialized for the agent population with a random-normal distribution $\beta^i_k \sim N(\beta', \sigma)$ where $\sigma$ is the standard deviation as a percentage of the mean $\beta'$, as defined by the model user. The $\sigma$ value introduces agent heterogeneity through assignment of individual preference parameters. The resulting initialized population of hunting agents have unique preference structures. This technique uses results from existing studies based on surveys and econometric analysis of respondent data.
In this example, parameters $\beta$ and (when available) $\sigma_\beta$ for the utility function are drawn from a number of studies that examine preferences of hunters. Simulation runs were performed with parameter weightings reported for urban recreational hunters in Ontario (Bottan 1999) and Alberta (Boxall & Macnab 2000), rural Alberta hunters (Haener et al. 2001), Alberta First Nations hunters and Alberta Metis hunters (Adamowicz et al. 2004).

Studies listed above use a variant of an econometric regression model to estimate the utility gained from a hunting experience based on a series of attributes of the site, such as abundance of game species, the travel cost to attend the site, and so forth. Each attribute contributes to, or detracts from, the utility derived by attending the hunting site. A challenge in calibrating agent decision making functions using secondary literature is whether reported utility functions are comparable. In one study ‘access by water’ may significantly influence preferences, yet is absent from other studies. The measurement of distance is continuous in some studies, and broken into discrete classes in other studies. Some measure game population by animals / km$^2$, and some by number of sightings per day. Furthermore, each study offers a snapshot of preference in time and space, and within a certain context of very diverse geography, and cultural backgrounds. As a result, comparing one study to another, and deriving complete and comparable utility functions is not possible without broad assumptions. To address this problem, a subset of parameters was selected containing only those variables common across all studies; travel cost, game population, and hunter congestion. The marginal utility weightings measured in each study and used as model parameters, sometimes requiring interpretation from the original study.

The cells of the spatial landscape contain variables corresponding to parameters in the agent utility function. Agents calculate this utility function for a limited number randomly selected landscape locations, set by the model user [default 50 known cells] and select the one which returns the highest utility calculation. Utility is a function of travel cost, game population size and hunter congestion.

Congestion is the sum number of hunters in its 8 neighbouring cells, representing the spatial interaction of agents in proximity to one another. Game population for cells is
calculated as \( N_j \) [number animals / km\(^2\)], at time \( t \) and for each cell \( j \). The population increases through a growth function representing reproduction and mortality incurred by hunting, and is a logistic growth function.

\[
N_j = N_{(t-1)} + r \left( \frac{1 - N_{(t-1)}}{K} \right) N_{(t-1)} - H_j \quad \text{Equation 2}
\]

Where \( r \) is the intrinsic population growth rate \([0.2]\) which also accounts for natural predation and mortality, and \( K \) is the population carrying capacity \([4.4 \text{ a/km}^2]\), and \( H_j \) is the number of animals harvested in time \( t \), as a function of hunting pressure, being the number of hunters present on the cell, multiplied by hunting success rate \([0.3 \text{ based on Alberta hunting data 1997-2000}].\) If the game population is reduced to 0, it will not recover and is considered a local extirpation. A further variable is included which allows adjacent cells to repopulate extirpated sites. Thus the variable controlling this effect is disabled for our study, but offers interesting future research dealing with migratory animals or umbrella species with large ranges.

The system as described to this point involves mobile hunting agents which select a hunting site from a spatial landscape of cells. The cells contain a game population which increases through reproduction and decreases hunting pressure, and cells also contain a measure of hunter congestion as a result of aggregate hunter site selection. Figure 1 shows outcomes for the simplified case where the ‘city’ is located at the centre of the map, and hunters select sites from surrounding cells. In this case with no forestry roads, distance and thus travel cost are uniform (travelling 1 cell incurs 1 unit of travel cost in all directions from the city). Each of the five circular patterns depicted is the resultant outcome of parameterising the utility function based on the studies previously discussed. The simulation is run for 250 iterations of 80 hunters, in an 80 x 80 grid. The darkest cells contain 4.4 animals per km\(^2\) (carrying capacity), and white cells have suffered extirpations from hunting.
Figure 1: Spatial configuration of game population in cells around a central origin, using parameterized hunter agent utility function from preference measurement studies. Darker cells reach carrying capacity and white cells have been extirpated through hunting.

Simulation runs depicted in Figure 1 visualize the impact the agent population has over time using different combinations of preference parameter weightings. Each scenario is identical except for the parameter weightings applied to preferences for travel cost and game population, listed in Table 2. Figure 1, panels 1-3 are parameterised from results reported in Bottan (1999), Adamowicz et al. (2004), and Haener et al. (2001), respectively. These papers report estimated preference weightings based on random utility modelling using discrete choice surveys. The reported preference parameters are inputted as the $\beta_i$ parameters in agents’ utility functions.

Table 2: Preference weightings used in parameterising agents’ utility functions, for three attributes of a hunting site.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel cost / cell</td>
<td>-0.008</td>
<td>-0.004</td>
<td>-0.0125</td>
</tr>
<tr>
<td>Wildlife Pop'n [animal / km2]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>-0.25</td>
<td>-0.49</td>
<td>-1.41</td>
</tr>
<tr>
<td>1</td>
<td>-0.20</td>
<td>0.15</td>
<td>-1.41</td>
</tr>
<tr>
<td>2</td>
<td>-0.15</td>
<td>0.15</td>
<td>0.22</td>
</tr>
<tr>
<td>3</td>
<td>0.50</td>
<td>0.85</td>
<td>0.22</td>
</tr>
<tr>
<td>4</td>
<td>0.50</td>
<td>0.85</td>
<td>0.22</td>
</tr>
</tbody>
</table>

During the model building and the process of testing performance of different utility functions, certain configurations generated emergent properties as spatial patterns over time. Figure 2 depicts a time series of a specific parameter configuration where aggregate hunter utility and game population growth ‘resonate’ resulting in the
emergence of a series of concentric circles which emanate from the central hunter city. The circles broaden and disperse, replaced by another expanding circle, ad infinitum, creating a persistent ‘hunting pulsar’. This complex pattern emerges simply from the preference of hunters to travel relatively shorter distances (which reduces game populations close to the city), and the preference for larger game populations, and thus willing to travel further afield and trade off distance for quarry. The aggregate effect is to advance a frontier of hunting pressure until game populations in cells closer to the city recover sufficiently to draw agents back. The heterogeneity of agent preferences allows the slow dispersal of the frontier. The example has interesting insights to notions of sustainability in linked human-environment systems given the parameter settings that generate this ideal sustainable system depend on natural processes such as animal population growth rates, but also and individual preference tradeoffs and the result of aggregate decision making.

Figure 2: Emergent property as persistent growing and dispersing concentric circles. Tradeoffs between these distance and density of game result in the ‘pulsar’ pattern.

Given the aim to study cumulative effects of hunting and access, we now include a road network which reproduces a choice situation analogous to that which hunters in the real world face when access is created and removed. We represent the
accessibility of a site by a travel cost function, derived from Boxall et al. (1996) and Ward (1986), which apportions cost weights to travel through forest (by ATV), via forestry roads (4WD), and highways (2WD).

\[
TC_j = \alpha^{DF} * DF_j + \alpha^{DR} * DR_j + \alpha^{DH} * DH_j \quad \text{Equation 3}
\]

Where the \( \alpha \) cost parameters are set via the model interface [default 1.2, 1.4, 2.4 respectively], and relate to the distance through the forest to the nearest road node \( DF_j \), the distance along forestry roads to the highway \( DR_j \), and the distance from the highway intersection to the city \( DH_j \). By this fashion a travel cost landscape is calculated, as depicted in Figure 3, where darker cells are more costly to access. In this way space is altered according to travel cost to access a site, and a travel cost surface is generated which changes according to road development over time.

The purpose of the road network is to produce a changing set of access alternatives to hunter agents. Static road networks can be loaded from GIS data, however questions of cumulative effects are dynamic, hence the need to offer agents a changing set of alternatives from which to choose. A dynamic road system could be hard-coded based on historical trends, drawn from forestry company management plans and instituted as a time series, or functions can be modelled to simulate the process endogenously. To better explore the complex systems nature of the resource issue, road development is modelled as an endogenously evolving network of connected nodes.
1 distance via forest
2 distance via forestry haul route
3 distance via highway

Figure 3: Travel cost surface generated from evolving road network. Darker cells in a) and b) have higher travel cost of hunters accessing the cell, via forest, along forestry haul routes, and along highways. Hunters attend a cell c) with associated congestion metric in the cell neighbourhood.

Road nodes, visible in Figure 3 c) are added to forested cells which are selected to be harvested. Selection is based on three conditions, 1) the cell’s forest age must be greater than minimum harvestable age, 2) the cell must have at least \( \chi \) number (again set by model user) of neighbouring cells which already have a road node, and 3) maximum allowable cut has not been reached.

Forestry roads evolve through a selection process, and haul routes emerge and persist based on continued use, but unused road fragments are decommissioned as they age. When a cell is selected for forestry harvest, a road node with a ‘decommissioning age’ is created and identifies a ‘parent road node’ on a neighbouring cell. Through time, the generation of a network of nodes develops in parent-child network, linking all nodes, inevitably back to the highway. On a newly created road node, a ‘route finder’ agent is created, which moves along the links from each child node to its parent, traversing a route to the highway. Along its route, it updates the age of each node to 0. The age of each node is incremented each time step, and if a route finder has not
traversed the node within the decommission age (set via interface), the road node and its upward links are deleted, representing decommissioning of the road. The linked road fragment which is deleted may be only a small segment of one or a few cells in length, or may be a linked branch which extended for a considerable distance. Various spatial patterns can be created by changing the parameter $\chi$, (number of neighbouring road nodes needed to construct a new road node), as is depicted in Figure 4, all of which have road decommissioning of 5 years.

Figure 4: Spatial patterns resultant from parameter settings for the number of neighbouring cells with existing roads required to create new roads. Darker cells contain older forest stands, and forestry road networks develop based on an endogenous selection algorithm, generating different forest age mosaics.

Combining the roads and hunting agents, simulations examine the effect of decommissioning roads at variable ages of 2, 5 and 10 years. As depicted in Figure 5a, earlier decommissioning of roads (2 years) has the effect creating extended, long tendril-like haul routes emanating from the central highway. This provides a small number of thoroughfares which attract agents. At 5 year decommissioning (see Figure 5b) a greater number of persistent haul routes increase the options for travelling further afield, and again hunters are attracted leaving a visible imprint on game
populations along these routes. Finally in Figure 5c, when roads are decommissioned at 10 years, the tendril-like road system is more spread out, offering a more homogenous travel cost surface, with the presence of more roads having the effect to spread out hunting pressure across a wider area, and not follow a specific haul route.

Figure 5: Spatial pattern of game populations (darker cells contain more game, white cells are local extinctions) resulting from decommissioning roads at 2, 5, and 10 years, with central origin of hunter agents.

Early decommissioning of roads has a concentrating effect, and hunting pressure is focused on the fewer relatively accessible areas. The total number of extirpated cells is higher with earlier decommissioning, which is contrary to the notion that road closures are good for game population numbers. This may be true for any given site, but at a landscape level our simulations describe a case where aggregately the reverse is true. Early decommissioning of roads has the effect of focusing hunting pressure on the fewer more accessible sites, resulting in more extirpations.
In conclusion, quantifying cumulative effects requires explicit representation of feedbacks and interactions within the linked human and environment system. With a perspective of modelling such phenomena as emergent properties, the goal of the study was to examine spatial configurations and patterns resulting from a) parameterising hunter agent utility functions from different stated and revealed preference studies, and b) test the effect of road decommissioning at 3, 5, and 10 years.

Noticeably different spatial configurations are created by parameterising the hunter agent utility function from different secondary literature. In some cases the hunter agents apply an even spread of hunting pressure that does not push local game populations to extirpation. In other cases with the same number of agents, the landscape is uniformly extirpated, simply due to a small difference in preferences. With respect to road decommissioning, modelling revealed a situation where early decommissioning of roads increased the total number of extirpated sites, because hunting pressure was focused onto the relatively fewer accessible cells. However, this finding is dependant on the assumption that game does not re-populate extirpated sites.

Interesting emergent properties were observed through the modelling process, including a self-emerging persistent spatial pattern of growing and dispersing concentric circles, as a ‘hunting pulsar’, and indeed formed the function of a emergent self-regulating, persistent, and sustainable system, providing the hunter agent population with a steady stream of utility while not causing local extirpations of game populations. Different forest mosaics were generated by altering a local neighbourhood parameter for the construction of road building. It is noted that these interesting findings were generated with only five simple equations, 1) cell game population growth 2) hunter agent utility calculation 3) cell travel cost calculation 4) cell eligibility for forestry harvest 5) aging, resetting the age of roads being used, and decommissioning of unused roads. Net Logo primitives (e.g. move neighbours, distance) are used as well. The model allows testing different empirical calibrations of agents, as was done here with three preference studies.
Further research steps involve addition of spatial metrics for comparison of simulation results across multiple runs, given the stochasticity of the model. For a very controlled case study, we might infer the preferences of the hunting population based on the pattern of extirpated sites in the landscape. Where multiple parameter settings in the model are able to explain macro-patterns, laboratory experiments, surveys, and/or semi-structured interviews could be used to further refine the combinations which explain the real-world hunting population. Other relevant natural resource management issues which could benefit from these techniques are access created by illegal logging, poaching in parks and reserves, spatial positioning of reserves and wetlands for migrating animals, and interactions between mining and hunting of migratory animals.

This case study presents the use of discrete choice surveys as methods to derive preference functions for decision making, and offers a generalisable methodology that is comparable across ABM applications. Estimation of preference functions is common in the environmental economics literature, is a well accepted and commonly used methodology to predict decision making. As such, this technique can be used in ABM applications where agents are faces with a set of alternatives and mush choose based on the characteristics of each alternative and the preferences for those characteristics. However, estimates of preference parameters are a snapshot in time which identify preference-based tradeoffs, but when the characteristics of the choice set change or the preferences of individuals themselves change, surveys are now well suited to capturing adaptive behaviour and identifying strategies for dealing with change. As such, the next section presents and ABM calibrated from semi-structured interviews, which allows for in-depth exploration of dynamic decision making, and what strategies do individuals employ to deal with systems as they change.

### 3.2 An agent-based model of rangelands management

The sustainable use of rangelands for grazing is a well studied topic in ecological economics. Biophysical processes such as rainfall, pasture growth, consumption by livestock and ecological succession of plant communities influence and feedback upon economic drivers such as livestock prices, management practices and
technologies, values for land, labour and capital. The integrated system is influenced by the policy setting which is directed at both economic and environmental outcomes.

In Australia’s northern savanna rangelands, the dynamics of pasture, cattle and economic drivers create a situation where overgrazing causes sedimentation into waterways. Modelling this system can help identify sustainable grazing management practices, and to identify tipping points and thresholds of pasture resilience in response to grazing. This section presents an ABM applied to grazing management in Queensland Australia, first presented in Smajgl, Heckbert et al. (2008). Rangelands can been viewed as a complex system involving property decision making, environmental conditions, and feedbacks through the presence of cattle and the dynamics of successional ecology of grass species. In this case study, an ABM is constructed to examine the process of sediment generation resulting from reduced pasture cover as a result of grazing. Pasture growth, pasture utilisation through grazing, stocking rates, and herd management combine to determine the condition of pastures and hence the level of erosion accruing from grazed landscapes. Agents use herd management strategies such as rotational grazing, cell grazing, spelling paddocks, supplementary feeding, fencing and other property improvements serve to alter and distribute the effect of grazing.

The model design and calibration process involved telephone-based interviews with graziers. Data were collected on how they use and manage their properties and why they use certain management practices. The information provided was interpreted into a typology of management strategies, which included cell and rotational grazing, as well as non-rotational grazing with varying stocking rates. Parameters for stocking rates and paddock rotation timing were programmed to agent decision making functions, and the effect of these management strategies is simulated over time.

Semi-structure interviews were selected over surveys to get detailed information on property management strategies, and also to learn under what conditions these might change according to the respondents’ perspective. Questions were based on the following categories:

- How they use and manage their properties,
- Why they use certain management practices and not others,
• Production timelines,
• What are the major constraints they are facing, and
• What are their future goals and business aspirations?

The first set of questions addressed land use and management strategies. They included a number of detailed questions regarding herd and grazing land management. The second part of the interview covered the history of the grazing property and the grazier, landscape changes and values. These questions provided insights into the relationship between the grazier and their land. In part three, the interviewees were asked about financial strategies and possible policies the State government could introduce to incentivize management practices. The last set of questions focussed on future aims and aspirations related to the property. The use of semi-structure surveys addresses research question #1, namely what techniques can be used to gather empirical data, and which of these offer a generalisable methodology to allow comparability between studies.

A small representative set of graziers were selected for an interview, sampled to represent properties from different parts of the catchment, different age groups, female and male graziers, and graziers who manage their properties using different business structures. Agricultural extension personnel with expertise in the area recommend graziers who they thought might be willing to participate. All interviews were recorded with the consent of the interviewees and transcribed verbatim. This database was supplemented with the landscape assessments and landscape photographs taken during the station visit. In 2006, 9 in-depth interviews and landscape assessments with 13 graziers were carried out at their stations. To the surprise of the field researchers, some of these stations have not been visited by agricultural extension personnel for the past 20 years. Six informal, less detailed, interviews were carried out over the phone with graziers who were not available during the two rounds of field research. The information gathered from the six informal interviews were used for validation of the in-depth interviews and landscape assessment on site.

The interview results formed the development of a typology of grazing agents based on key characteristics including grazing management practices, individual
characteristics of graziers, and attributes of the property, summarised in Table 3.

Types of agents were assigned to properties based on the configuration of paddock sizes contained in the GIS files.

Table 3: Typology of agents based on semi-structured interviews with graziers from the case study region.

<table>
<thead>
<tr>
<th>Cattle rotation strategy</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pavement</td>
<td>Cell grazing</td>
<td>Rotational grazing</td>
<td>Continuous grazing</td>
<td>Continuous grazing</td>
</tr>
<tr>
<td>Paddock size [ha]</td>
<td>311</td>
<td>536 – 2,778</td>
<td>2,125</td>
<td>2,000</td>
</tr>
<tr>
<td>Stocking rate strategy</td>
<td>12, adjusting dynamically</td>
<td>13 – 29, adjusting dynamically</td>
<td>8 - 10</td>
<td>6</td>
</tr>
<tr>
<td>Property improvements</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>None</td>
</tr>
<tr>
<td>Supplementary feeding</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Spelling</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

The model was constructed in Repast v3.1, importing GIS data on property boundaries and rivers, depicted in Figure 6. A series of sub models represent the decision making agent, the cattle herd and pasture growth which are run on each GIS-based property.

Pasture growth is modelled as a state-and-transition model of ecological succession between different species of grasses, and draws on pasture and grazing ecology literature in the definition of pasture growth and ground cover equations, specifically from Ash et al. (1994; 1995), McIvor (2002) and Scanlan et al. (1994). Cattle are modelled using live weight gain and herd dynamics functions based on MacLeod et al. (2004). Lastly, a farm-level economics model derived from MacLeod et al. (2004) is implemented to inform decision making of agents. Agents decide on stocking rate, investment in fencing, herd rotation and spelling timing.
Figure 6: Property boundaries within the Bowen Broken catchment of Queensland Australia, depicted through the user interface. GIS polygons represent properties with an associated decision making agent, and contain a simulated herd of cattle and pasture.

Vegetation growth is driven by rainfall and consumption by cattle. Biomass growth equations and rainfall data were provided by Geoff Carlin, and outlined in Carlin et al. (2007). Rainfall data was sourced from the SILO database for daily rainfall. Figure 7 depicts rainfall patterns based on historical data for a 15 year period and simulated pasture growth.

Figure 7: Daily rainfall data and pasture growth over time.

However, pasture ecology involves a composition of grass species, distributed in space, who are differentially affected and responds to herbivory. Cattle themselves are not evenly spatially distributed, either through human management such as fencing, or though geographies and access to water. Based on a body of pasture ecology
literature, pasture condition is modelled on a paddock scale where pasture condition is comprised of three possible states:

- **State 1**: Native perennial grasses, ecologically intact. Palatable and provides good feed. ‘Decreaser’ species which decline with increasing grazing pressure.
- **State 2**: Perennial grasses and/or annual grasses and forbs, beginning to be ecologically degraded. Provide excellent feed and preferred by cattle over State 1. ‘Increaser’ species which increase with increasing grazing pressure.
- **State 3**: Annual grasses and forbs, ecologically degraded, large areas of bare ground. Less palatable. Still good feed but limited quantities.

Any paddock \( k = 1...K \) on property \( i = 1...n \) will contain a mix of pasture states. A percentage of the paddock area will be in one of the three states, where \( A_s^k \) [ha] is the area of state \( s = 1,2,3 \), and the sum of the areas of each state comprising the total paddock area \( A^k = \sum A_s^k \). Each state has a unique biomass growth rate, and hence a varied total biomass level. This in turn yields a paddock-specific ground cover value. Pasture is then consumed by cattle. Each pasture has biomass which grows and cattle eat. The biomass grows in a sigmoid (logistic) shape over time (given all inputs are constant). Each pasture state 1, 2 or 3 has a unique biomass growth rate.

\[
B_{s,i}^k = \frac{A_s^k}{\sum A_s^k} \cdot B_{s,i}^k \cdot r_s
\]

Equation 4

where \( r_1 > r_2 > r_3 \) and \( A_s^k \) is the percentage of the total paddock area occupied by each state. Biomass is initialized with a mass of 1000 kg/ha for state 1, 800 kg/ha for state 2, and 400 kg/ha for state 3.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( B_{s,i}^k )</td>
<td>[kg/ha]</td>
<td>Biomass of state 1,2,3 in paddock ( k )</td>
</tr>
<tr>
<td>( r_s )</td>
<td>[0-1]</td>
<td>Growth multiplier state 1-3 calibrated</td>
</tr>
<tr>
<td>( A_s^k )</td>
<td>[ha]</td>
<td>The percentage paddock area occupied by state 1, 2, 3.</td>
</tr>
</tbody>
</table>
Once the pasture biomass has grown, it is consumed by the cattle, according to cattle preferences for pasture states. The total biomass consumed from each state is:

\[ E_{s,t}^k = SP_s \cdot 0.02 \cdot \sum_{cow} W_{cow,s}^k \]

Equation 5

This implies that each animal consumes 2% of its body weight (MacLeod et al. 2004) and distributes the consumption according to its preferences for species, which is assumed to be constant for each animal. Cattle’s preference for states is ordered such that \( SP_1 > SP_2 > SP_3 \), with \( \sum SP_s = 1 \), and are parameterised as 0.4, 0.5, and 0.1 for state 1, 2 and 3, respectively. For each time step the utilisation rate [%] is calculated for each pasture state such that

\[ U_{s,t}^k = \frac{E_{s,t}^k}{B_{s,t}^k} \]

Equation 6

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E_{s,t}^k )</td>
<td>[kg]</td>
<td>Volume eaten on each paddock</td>
</tr>
<tr>
<td>( SP_s )</td>
<td>[0-1]</td>
<td>Preference multiplier for different states 1, 2, 3.</td>
</tr>
<tr>
<td>( W_{cow,s}^k )</td>
<td>[g/day]</td>
<td>Live weight gain in paddock ( k ) in each period ( t ).</td>
</tr>
<tr>
<td>( U_{s,t}^k )</td>
<td>[%]</td>
<td>Utilisation, ratio of pasture eaten to pasture grown</td>
</tr>
</tbody>
</table>

From this point, a pasture state-and-transition model uses information from prior equations to determined the successional ecology of grass species. The relative area of each state 1, 2 and 3 changes based on grazing pressure. The higher the level of utilisation, the greater is the likelihood of long-term degradation within native pastures (Scanlan et al. 1994). To capture this, the makeup (% of area in each state) of the pasture goes through a relative transition involving natural pasture recovery and the effect of changes in utilisation rates. Figure 8 depicts the percentage of each state that would emerge over time under continued maintenance of utilisation rates. The relationships between utilisation and the percentage of the paddock in one of the 3 states, \( M_s \) [%] is based on ‘target values’ \( \bar{M}_s \) given as:

54
\[
\bar{M}^k_i = \begin{cases} 
100 & \text{if } U^k < S1T < 100 \\
100 - U^k - S1T + Sr \cdot \left(1 - \frac{U^k - 1}{100}\right) \cdot (U^k - 1) & \text{if } S1T < U^k
\end{cases}
\]

Eq. 7

\[
\bar{M}^k_2 = U^k + Sr \cdot \left(1 - \frac{U^k - 1}{100}\right) \cdot (U^k - 1) - \left(U^k - T\right)^{U^k-T} \cdot S3L \cdot (U^k - T)
\]

Eq. 8

\[
\bar{M}^k_3 = 1 - \bar{M}^k_1 - \bar{M}^k_2
\]

Eq. 9

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Parameter value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\bar{M}^k_1, \bar{M}^k_2, \bar{M}^k_3)</td>
<td>%</td>
<td>Target % of paddock k under state 1-3.</td>
<td></td>
</tr>
<tr>
<td>(U^k)</td>
<td>%</td>
<td>Utilisation rate in paddock k</td>
<td></td>
</tr>
<tr>
<td>(S1T)</td>
<td>%</td>
<td>Min utilisation rate of state 2 pasture</td>
<td></td>
</tr>
<tr>
<td>(Sr)</td>
<td>%</td>
<td>State 1-2 transition rate</td>
<td></td>
</tr>
<tr>
<td>(T)</td>
<td>%</td>
<td>Min utilisation rate state 1-3 transition</td>
<td></td>
</tr>
<tr>
<td>(S3L)</td>
<td>[0-1]</td>
<td>0.963</td>
<td>Growth rate of state 3 pastures</td>
</tr>
</tbody>
</table>

Figure 8: Pasture condition, comprised by three states of pasture type whose presence is dependant on utilisation rates.

This transition occurs over a period of 2 years \((D)\), which represents the possible recovery of grasses from root masses through the wet season. Within this time \(D\), the actual state composition of the paddock will move toward the \(\bar{M}^k_i\) values. For the purpose of simplification it is assumed that movement is linear, moving from the
The current state composition of $M_{s,t}^{k}$ towards $\overline{M}_{s,t}^{k}$, with $M_{s,t-1}^{k} = \overline{M}_{s,t}^{k}$ being the equilibrium composition converges to. In any given time,

$$M_{s,t}^{k} = \left( \frac{\overline{M}_{s,t}^{k} - M_{s,t-1}^{k}}{U_{t}^{k} - U_{t-1}^{k}} \right) \left[ U_{t-1}^{k} + \left( \frac{U_{t-1}^{k} - U_{t-1}^{k}}{D} \right) \right] + M_{s,t-1}^{k} \text{ \hspace{1cm} Equation 10}$$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_{s,t}^{k}$</td>
<td>%</td>
<td>Current % of paddock k under state 1-3</td>
</tr>
<tr>
<td>$M_{s,t-1}^{k}$</td>
<td>%</td>
<td>% paddock k under state 1-3 in period $t-1$.</td>
</tr>
<tr>
<td>$U_{t-1}^{k}$</td>
<td>%</td>
<td>Utilisation rate in period $t-1$.</td>
</tr>
<tr>
<td>$M_{s,t-1,d}^{k}$</td>
<td>%</td>
<td>Original percentage of $s$ at time $t+D$ when the utilisation rates changed.</td>
</tr>
<tr>
<td>$D$</td>
<td>Days</td>
<td>Days to transition to new utilisation rate, 2 years.</td>
</tr>
</tbody>
</table>

For example, if the pasture is currently at a composition occurring at 46% utilisation rate, it will be composed of approximately 50% state 1 and 50% state 2 (see Figure 8). If the utilisation rate increases to 54% (though adding more cattle to the paddock), the new ‘equilibrium’ composition will be approx 80% state 2 and 10% state 1 and 3. The state in any given time period will be the linear position between the original utilisation rate, $M_{s,t}^{k}$, and the new target rate, $\overline{M}_{s,t}^{k}$. If the stocking rate changes any time during the transition to this new state $\overline{M}_{s,t}^{k}$ is updated and a new transition path defined. The current $M_{s,t}^{k}$ value is the new current composition, with a new target $\overline{M}_{s,t}^{k}$ defined for the updated stocking rates.

The cover factor for the paddock can then be calculated from the relationship identified and outlined in McIvor (2002):

$$C_{i} = \kappa_{s,t} + \omega_{s,t} * R_{t}^{s,i} \text{ \hspace{1cm} Equation 11}$$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{i}$</td>
<td>%</td>
<td>The percentage of ground cover</td>
</tr>
<tr>
<td>$\kappa_{s,t}, \omega_{s,t}, R$</td>
<td>#</td>
<td>Curve parameters derived from McIvor (2002)</td>
</tr>
</tbody>
</table>
Parameter values for $\kappa_{\omega}$, $\theta_{\omega}$, $R$ are set to 100, -100 and 0.995, respectively.

Upon model initialization, the number of cattle and the age/sex composition of the herd on each property must be defined. Cattle receive attributes including age, sex, weight, adult equivalent, as well as target weight and age information. The herd is organized into 5 groups of animals by age and sex; calves, heifers, steers, cows and bulls. Weight is calculated using a logistic live weight gain function calibrated to age and sex. The herd is initialized to 35% cows, 17% heifers, 17% steers, 27% calves, and 4% bulls (McIvor, pers. comm., 2007). Therefore, the number of adult female animals at stage of model initialization equals $\overline{H}_{i,female}$ and the total herd at stage of initialization equals the sum of adult equivalents across animal types, $\overline{H}_i = \sum_{i} \overline{H}_{i,\text{female}}$.

The number of cattle on the property is based on a target size, which works as an attractor for further decision making points such as marketing of animals. This steady state herd size is defined as:

$$\overline{H}_i = \frac{\sum_{k} A^k}{SR_i}$$  \hspace{1cm} \text{Equation 12}

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\overline{H}_i$</td>
<td>#</td>
<td>Initialization number and steady state size of herd in adult equivalents on property $i$</td>
</tr>
<tr>
<td>$H_{i,t}$</td>
<td>#</td>
<td>Actual herd size in adult equivalent (AE) on property $i$ in period $t$</td>
</tr>
<tr>
<td>$SR_i$</td>
<td>ha/animal</td>
<td>The number of hectares per adult equivalents. Parameter based on typology of property owner $i$.</td>
</tr>
<tr>
<td>$A^k$</td>
<td>ha</td>
<td>Area of paddock $k$</td>
</tr>
</tbody>
</table>

Herd size in adult equivalents is based on mortality, births and sales,

$$H_{i,t} = \overline{H}_i - \delta_i^{\text{breed}} - \delta_i^{\text{dry}} + BRAND_i \cdot \overline{H}_{i,female} - N_{i,t}$$  \hspace{1cm} \text{Equation 13}
For each daily time step, every cow performs a number of functions; growth, aging (and hence advancing to other cattle groups if at a certain age), reproduction and mortality. The daily growth occurs through a live weight gain function, dependant on the utilisation rate in the as outlined in (Ash et al. 1995).

\[ LWG_t = -B_s \cdot U_t^s + LWG_{max} \]  

Equation 14

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( LWG_t )</td>
<td>[g/head/day]</td>
<td>Daily live weight gain</td>
</tr>
<tr>
<td>( B_s )</td>
<td>[#]</td>
<td>Slope parameters from Ash et al. (1995)</td>
</tr>
</tbody>
</table>

Values for \( s \) are parameterised to 4.6 for state 1 and 2.5 for state 2 and 3, taken from Ash et al. (1995).

Mortality and branding rates (ratio of calves weaned per 100 breeders mated) are a function of LWG, according to function specified in MacLeod et al. (2004) where mortality for breeding stock \( \delta_t^{\text{breed}} \) and dry stock \( \delta_t^{\text{dry}} \) are defined as:

\[ \begin{align*} 
\delta_t^{\text{breed}} &= \frac{6 + 94 \cdot e^{-0.027 \cdot (LWG_t + 50)}}{365} \\
\delta_t^{\text{dry}} &= \frac{2 + 88 \cdot e^{-0.034 \cdot (LWG_t + 50)}}{365}
\end{align*} \]  

Equations 15 and 16

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( ALWG_{\text{cow}} )</td>
<td>kg/ year</td>
<td>Annual live weight gain per animal</td>
</tr>
<tr>
<td>( \delta_t^{\text{breed}}, \delta_t^{\text{dry}} )</td>
<td>%</td>
<td>Mortality for breeder and dry stock, respectively, in time ( t )</td>
</tr>
</tbody>
</table>

We assume that mortality occurs as one event during each year. Similarly, branding occurs once and it is assumed that branding follows a linear function that depends on live-weight gain.

\[ BRAND_{\text{cow}} = 0 \leq 15.6 + 0.488 \cdot ALWG_{\text{cow}} \leq 80 \]  

Equation 17
Cattle reproduce at the branding rate, and excess animals \( N_n \) are sold on the market. From this, the herd progresses through their daily cycle, and the cattle are sold over time. The number of animals in each age/sex group that is excess to the maintenance of the steady state herd are sold.

Unlike continuous grazing strategies, rotational grazing strategies that employ wet season spelling allow the whole paddock to be rested so that all parts recover (Ash et al. 1995). Rotation strategies range from simple, large paddock rotations to highly intensive time-controlled cell grazing systems. Several rotation strategies exist. The strategy currently simulated in the model is a simple three paddock system, where one paddock is spelled for the entire wet season while two other paddocks are grazed during this time. At the end of the wet season the stock are spread evenly over all three paddocks. In the next wet season, the second paddock is rested. The cycle is completed after three years when the third paddock is rested for the wet season. In this way, paddocks receive a complete rest every third wet season.

Simulation runs depict outcomes on a daily time step, with a temporal extent of 15 years. Based on the rotation and stocking management practices used, various outcomes emerge for cattle consumption and growth, pasture state transitions, and cover. Here we describe outcomes for pastures under different rotational grazing strategies and stocking rates.

Outcomes are depicted in Figure 9 a) e) i) for pastures under a cell grazing management practice. The utilisation rate varies between 20-40\%, adjusting to changing stocking rates when cattle are frequently moved between paddocks. Under this management strategy utilisation rates are low enough to allow state 1 pastures to recover from the values set at model initialization (from 75\% state 1 to near 100\%). As such, cover levels remain near 100\%.

Under rotational grazing management practice, depicted in Figure 9 b) f) j), the stocking rate is adjusted to maintain levels of state 1 pasture. Although utilisation rates are similar to the previous example in the first few years, they are then adjusted to maintain pasture health. The result is a reversal of the loss of state 1 pastures, as
seen between year 1 and 2. The intervention occurs before an emergence of low-productivity state 3 pastures, and stocking rates are able to be increased slightly in the latter years of the simulation. This strategy of improving/maintaining pasture condition maintains cover levels near 100% for the duration of the simulation.

Properties using a non-rotation heavy stocking rate, depicted in Figure 9 c) g) k) are seen to quickly lose state 1 pastures, pasture productivity, and ground cover. Outcomes for an overstocked paddock where management practices do not intervene. High utilisation rates degrade state 1 pastures. The increase in state 3 pastures, with lower productivity, continues to fuel increasing utilisation rates and, within a few years, state 3 pastures dominate, with a subsequent plummet in cover level.

For non-rotational grazing with a mild stocking rate, depicted in Figure 9 d) h) l), the stocking rate is above the level where pasture is able to retain long-term healthy state 1 pasture. The utilisation rate is allowed to reach 40-50% in the early years of the simulation, decreasing the state 1 pasture areas. Although pasture biomass growth of state 2 areas continues to provide sufficient quality and quantity of forage, state 3 areas begin to emerge in the latter half of the simulation. By not adjusting stocking rates, the paddock then begins to produce insufficient biomass, utilisation rates increase, and a cycle of degradation is begun. At this point, cover levels plummet over a relatively few number of years.
<table>
<thead>
<tr>
<th>Cell grazing</th>
<th>Rotation</th>
<th>Heavily overstocked</th>
<th>Mild overstocking</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="cell_grazing.png" alt="Graph" /></td>
<td><img src="rotation.png" alt="Graph" /></td>
<td><img src="heavily_overstocked.png" alt="Graph" /></td>
<td><img src="mild_overstocking.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Area (%) of pasture</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="area.png" alt="Graph" /></td>
<td><img src="area.png" alt="Graph" /></td>
<td><img src="area.png" alt="Graph" /></td>
<td><img src="area.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ground cover (%)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="ground_cover.png" alt="Graph" /></td>
<td><img src="ground_cover.png" alt="Graph" /></td>
<td><img src="ground_cover.png" alt="Graph" /></td>
<td><img src="ground_cover.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

Figure 9: Outcomes for pasture use and resulting condition, under four grazing strategies.
These results highlight the fact that adaptation in decision making is critical when dealing with dynamics of complex systems. Those strategies that do not respond to signals from pasture and cattle result in degradation of the system through overuse. This in turn highlights the fact that representation of agent decision making must allow for changing strategies and conditions change. Here, this information was able to be collected through the use of semi-structures surveys which provided rich information on how graziers adapt to changing conditions, and what strategies are employed for dealing with the complex dynamics of social-ecological systems. However, addressing research question #1 of whether this technique can offer a generalisable methodology, it is determined that semi-structured interviews do not allow for comparable results. This is due to the fact that interviews are fluid in their structure, guided by the interests of the respondents, which in turn is context specific. An interview with a grazier in North Queensland, Australia might not tell us much about strategies and modes of adaptive decision making in other contexts.

3.3 An agent-based model of urban sprawl

The third example described in this Chapter uses ABM to simulate the macro-form of urban sprawl, as presented in Baynes & Heckbert (2010). The urban system can be viewed as a complex system, comprised of many acting and interacting elements with feedbacks, which inevitably determine the overall spatial form of the city within its landscape. The urban system contains human processes, such as settlement location decisions of potentially millions of individual residents, and environmental processes such as hydrology, primary productivity, and the geological form of the landscape. Understanding urban systems from this perspective requires the ability to explore the frequent non-linear and emergent phenomena that occur in space and time.

To explore the dynamics of urban form, a spatially-explicit ABM was developed and applied to the city of Melbourne, Australia. This study aims to develop, or ‘grow’ the urban form of Melbourne initially with only a few simple functions describing agent behaviour. It is hypothesized that placing agents with these simple behaviours within a spatially explicit landscape representing the Melbourne geography will be sufficient
to re-create the development pattern seen over time. The intention is to keep the
model as simple as possible and to document the outcome of any additional
complexity in the model’s specifications. It is explicitly acknowledged that the
modelling exercise is actively biased towards the goal of re-creating a historical trend,
which raises important validation issues.

The residential location decision of agents is modelled using a parameterised utility
function in precisely the same functional form as the model described in Chapter 3.1.
This specifically addresses research question #1, identifying this utility function and
its calibration process as a generalisable methodology to allow comparability between
studies. Agents in this model select a settlement location based on three attributes of
landscape cells, and preference parameters can be altered using the model user
interface. This allows the modeller to generate different urban form patterns based on
the overall outcome of a multitude of individual decisions.

The history of using ABM in urban systems modelling has shown that the use of
spatial relationships through neighbourhood interactions drives many dynamics of the
urban system. Models of urban form are based on interaction rules that correlate to the
micro-dynamics of cities and they can reproduce patterns of the same statistical
character and fractal dimension as cities (Batty 2005). ABMs of urban form often
represent heterogeneous and mobile agents. ABMs may also act in conjunction with
CA or a cellular space as in Portugali (1999). Perhaps most distinctively, with agents
we can represent qualitative choices and also adaptation: agents can react to and alter
their environment in a recursive manner.

To explore the dynamics of urban form, a spatially explicit agent-based model was
constructed. The model is described here in terms of its a) human elements of resident
agents, and b) spatially explicit landscape of distances and features such as rivers and
rainfall. The model is constructed using Net Logo 4.0.4. Population data for
Melbourne from 1851 to 2001 were sourced from the Australian Bureau of Statistics
historical censuses (ABS 2003, 2003). These data were loaded into the model, with 1
agent initiated per 2,500 population increase (set via user interface). Note that each
cell is approximately 60 hectares in area and, if filled with 2500 people, we can
consider this cell “developed” i.e. with a residential density of about 42 persons per
hectare which is at the upper end of the observed density for 70% of the city of Melbourne (DPCD 2007)

The landscape is a spatial grid of 48 000 cells representing a 27 790km2 rectangle of land that includes Melbourne Statistical Division. A cell is designated the CBD, from which agents are initialized and each cell contains a number of variables, such as rainfall, distances to other spatial elements, whether agents are present at the cell, and population density considering agents on neighbouring cells. GIS data layers were obtained for rainfall and rivers. Average rainfall data for meteorological stations was sourced from the Rainman StreamFlow Version 4.3+ Database (Clewett et al. 2003) and the locations of rivers and water courses were derived from Geoscience Australia’s Global Map Australia, River Layer (1:1million scale, 2001). All geographical data used the same GDA94 projection.

An environmental amenities function $E_j$ is created to represent the suite of environmental services (water, productive soil) from which resident agent derive utility.

$$E_j = \alpha^R R_j + \alpha^{DR} DR_j + \alpha^{DW} DC_j$$  
Equation 18

Where $R_j$ is rainfall [average mm/yr], $DR_j$ is the distance to nearest river [km] and $DC_j$ is the distance to the coastline. The weighting parameters $\alpha$ are set via the model interface, where the environmental amenity function is parameterized by the user. The resulting landscape is a gradient of values for $E_j$, as depicted in Figure 10.
Figure 10: The environmental amenity landscape based on the proximity to rivers, coastline and areas of higher rainfall, with darker areas providing greater environmental amenities.

Agents are initialized in a pre-defined location of the Melbourne CBD, and perform a search based on a weighted utility function, and a random sub-set of known grid cell from which to select from. The agents perform the decision once, and thus it is not modelling an iterated re-location decision. When selecting a cell, agents evaluate a limited set of all available cells, the size set by the model user. For known cells, agents evaluate the utility of residing in that cell based on a weighted utility function.

\[
U_j = \beta^E_j \cdot E_j + \beta^{TC}_j \cdot TC_j - (PD - S)^2
\]  

Equation 19

Where TC refers to “travel cost” measured by the (linear) distance of the agent from the CBD and PD is the population density measured as the number of agents per cell. \( \beta^E \), \( \beta^{TC} \) and \( S \) values are set by the model user interface, and are initialized to the agent population with a random normal distribution based on a standard deviation set by the model user (default of 20% of parameter value), in order to introduce heterogeneity in preference to agents, similar to Heckbert et al. (2010a).
The proposed utility function used in this model of urban form is comprised of 3 sets of terms, relating to utility derived from environmental amenities, the distance required to travel to the CBD, and population density of the cell and its neighbouring cells. The environmental amenity and travel cost are linear relationships requiring a simple preference weighting parameter. The population density term is an inverse parabola, meaning that agents do not like too few neighbours, are happier with neighbours around value of $S$ (set by model user), and again do not like overcrowding at densities above $S$.

The functional form of the utility function is consistent with the one presented in Chapter 3.1, and can thus be calibrated with stated preference studies. Secondary literature from the past on peoples’ preferences for residential location can be interpreted into parameter weightings, for example the introduction of the motor vehicle and subsequent development of road infrastructure would significantly reduce the travel cost parameter over time. Thus, the utility function offers a consistent methodology to apply across ABMs. A similar example is presented in Brown et al. (2008) where agents optimize a utility function that includes distance to service centres and aesthetic quality. The tradeoff between the two variables is represented in the commonly known Cobb-Douglas functional form.

In sequence we present indicative results from simulations of the spatial growth of residential area using agents that select a cell to live based on: i) travel cost only, ii) tolerances of population density only, iii) population density, travel cost and environmental amenity together.
Figure 11 displays results of a simulation where there is a physical limit of how many agents can fit on a cell and agents are solely interested in minimizing their travel time to the CBD. Agents simply fill up cells closer to the CBD to the allowed limit and new entrants are forced to locate further out in a roughly radial pattern.
When the preference for travel cost minimization is eliminated altogether and a measure of tolerance for population density is introduced \((S)\), we can again see a radial symmetry in the pattern of growth. Increasing the tolerance, \(S\) produces simulated distributions of agents that are more compact – see Figure 12 (a, b, c, d).

By endowing the agents with a utility function that includes a tolerance for population density, an awareness of the travel cost to Melbourne's CBD and a preference to locate closer to environmental amenity. Three very different settlement patterns result when we choose a range of values for parameters that affect these utilities, as depicted in Figure 13 (a, b, c).
a) High preference for environmental amenity, low S, and no travel costs assumed

b) High travel cost and a high preference for environmental amenity and also a high S.

c) Lower travel cost, lower preference for environmental amenity and a low S value.

Figure 13: Location of agents after 200 iterations based on a utility function that includes: population density, travel cost and environmental amenity. Background shows the environmental amenity landscape.
In Figure 13a the higher environmental amenity preference influences agents to stick close to the coast, rivers and areas of better rainfall regardless of distance to the CBD and with a low tolerance for population density, agents are spread widely over the study area.

A simulation of higher travel cost penalty and a high preference for environmental amenity in combination with a tolerance for higher population densities produces a settlement pattern that is generally closer to the CBD though still attracted to river valleys and coasts (see Figure 13 (b)). Figure 13 (c) shows a settlement pattern when the landscape of environmental amenity is less relevant, travel costs are low but higher population densities are not tolerated. The result has much in common with that shown in Figure 13 (b).

This case study identifies the possibility of representing agent decision making based on a utility function which can be parameterised through random utility modelling in the same fashion as in Chapter 3.1. The two different applications of ABM use the same functional form in agent decision making functions, and can use parameters estimated through preference modelling using discrete choice surveys. This specifically addresses research question #1, whether calibration techniques can offer a generalisable methodology to allow comparability between studies.
Chapter 4: Agent-based models of market-based instruments

Development and management of water resources are common themes in ecological economics literature. Agricultural development pursuing economic goals is limited by biophysical dynamics of rainfall, aquifers and riparian flows. In systems where agricultural water use affects the natural availability of water, functioning of ecosystems services and the values accruing from them can be affected. This tradeoff between economic and environmental benefits can be managed through policy mechanisms, one of which is the use of market-based instruments.

Market-based instruments (MBIs) for environmental management have increasingly been designed to correct market externalities which result in environmental degradation. This Chapter presents three ABMs of MBIs for environmental management dealing with water scarcity and water quality. ABM is particularly useful for modelling this style of environmental management given the ability to represent individual traders in markets who also incur environmental impacts in space. Market-based instruments are increasingly considered as regulatory options for managing public good resource problems such as cumulative impacts of natural resource use (Weber & Adamowicz 2002), and provision of environmental services (Connor et al. 2008). Determining which type of MBI and the design principles behind its implementation deserves careful consideration of property rights, risk, flexibility, equity and the evolution of the instrument over time, and the institutional setting of the MBI will influence how incentives are perceived and acted upon by traders (Reeson 2008). Water quality markets are likely to be locally to regionally administered, but the variation in emissions and land uses at this scale can be low, and the number of potential participants in the market may be small. As markets depend on heterogeneity in individual traders to realise benefits of trading, there is doubt to whether MBIs can work where there is little variation in the agriculture economy. The ABMs presented here act as test beds to explore these issues.
Two forms of MBIs for water are described in this Chapter. The first is a cap-and-trade system that limits the volume of groundwater that can be extracted for use in irrigation. The second MBI is a cap-and-trade system for the amount of fertiliser which can be applied to crops, termed a water quality market. Both forms of MBIs do not include an associated permit auction mechanism, an area identified as a future research need. As a matter semantics, the cap-and-trade system for groundwater extraction described in Chapter 4.1 is termed a ‘water market’, and the emissions trading scheme using a cap-and-trade system described in Chapters 4.2, 4.3 and 4.4 are termed ‘water quality markets’.

The first case study of applying MBIs within ABMs evaluates a cap-and-trade system for allocating groundwater extraction rights for irrigators. Simulation results are presented linking individual properties under irrigation restrictions and an aquifer from which they aggregately extract water. Results for different water market configurations are compared, revealing a number of impediments to a cap-and-trade system working successfully. Agent behaviours were calibrated using results from field experiments with actual producers from the case study region. ABM is shown to be a useful tool for testing market-based instruments, particularly in representing individual pricing and trading behaviours. Agents interact directly through water trading and indirectly through a labour market and through capped aggregate extraction. For our case study, pricing behaviours and a small population of trading agents contributed to low trading volumes, and thus reduced the water market’s ability to efficiently allocate scarce water. Some market configurations realised higher profits in wetter periods and helped buffer the effect of dry periods.

The second ABM implementing an MBI is applied to water quality management in land catchments of the Great Barrier Reef. The model is constructed using Repast 3.1, and generates a set of agents from imported GIS polygons. The agents represent agriculturalists in north Queensland with land uses of sugarcane, horticulture and grazing. Land use change occurs in the model, converting agricultural lands to rural residential areas. A cap-and-trade system is implemented on the amount of fertiliser which can be applied to crops. Simulation results examine the effect of different cap levels and report on economic indicators as land use change occurs.
The third ABM of MBIs presented here also addresses water quality impacts from agriculture and rapid land use change along Australia’s coastline. The model is constructed in Net Logo 4.0.4, and draws on the experience gained in the prior example which uses different software. The Net Logo model was constructed to implement a number of improvements on previous modelling, namely develop a GUI which allows the model to be used as a participatory modelling tool, and an experimental economics interface is integrated with the model.

This third ABM represents an emissions trading scheme to regulate water quality, examining the effect of land use change and different cap levels on the performance of a water quality market. Simulation results suggest the cap-and-trade system facilitates high input horticulture to expand while maintaining the overall cap level, and tighter cap levels have income distribution effects. Heterogeneity of farm productivity influences trading price, volume traded and gains realised from trading, also the small homogenous trading populations produces a thin market, and trading benefits might not justify creation and maintenance of the instrument and effort required to participate. Novel contributions of this section are how cap-and-trade systems function within a landscape in transition, and also how benefits of trading are distributed.

These three models identify the need for robust calibration methods. The first case study uses field experiments conducted separately from the ABM activity, but providing parameters for pricing strategies of agents. The second case study does not use an additional calibration activity beyond information available in secondary literature, and does not provide a user interface which stakeholders can interact with. The usefulness of this second case study is therefore limited, and was found to struggle with perceptions of ‘black-box’ modelling and limited stakeholder buy-in. As a result the third case study was constructed, and although the topic and location are the same as the second case study (water quality markets in catchments of the Great Barrier Reef), the modelling process was directed to building an intuitive user interface which can be used interactively with community stakeholders, agronomists, and policy makers, with significant benefits in acceptance of the model.
4.1 An agent-based model of water markets

This case study describes an ABM used to explore outcomes of implementing a market for groundwater extraction permits. Agents representing irrigators may buy and sell groundwater extraction entitlements. A case study is examined from the Tindall aquifer, Northern Territory, Australia, as described in Heckbert et al. (2006; 2007) and Heckbert (2008). The aquifer discharges into the Katherine River and is largely responsible for the flow of water occurring in the river throughout the year, particularly in the dry season (Puhalovich 2005). The river provides many environmental and cultural benefits, and as a result there is a need to understand what impact further irrigation development might have. Irrigation for use in agricultural / horticultural production in the region is done primarily through pumping groundwater from the aquifer. The dependence of the river on aquifer levels makes a link between irrigators and ecosystem services and cultural values.

The model is calibrated with data from experimental economics, and is described in Heckbert (2008), Heckbert et al. (2006), and Heckbert et al. (2007). In this ABM agents represent irrigators who trade in a water market to secure groundwater pumping entitlements. Experiments were performed externally to the ABM exercise, as described in Ward et al. (2006), and data was collected on respondents’ bid levels. This relates specifically to research question #2: examining whether experimental economics can be used with ABM to gather data for parameterising the model. The calibration process was useful for moving assumptions away from notions of rational and fully informed decision making to incorporate behavioural aspects of decision making.

Results were statistically analysed to determine the difference between an optimal trading price and the price actually selected by participants. The trends in deviation around the optimal price are interpreted as being the strategy employed by traders to secure higher payoffs. Typical in trading is the notion of a ‘markup’ on prices, where a margin is added (subtracted) from offers to sell (bids to buy).
In the water market, agents make bundled price–quantity offers. To parameterise the price and quantity function, empirical data was collected in a series of field experiments with irrigators from the case study region. These data were statistically interpreted and assigned to agents’ trading functions. The model is implemented using the RePast 3.1 simulation toolkit. The model architecture is a simple class structure with a ‘model controller’ class which schedules events and performs overall model control operations, a ‘space’ class containing system-level variables such as aggregate water extraction, current labour pool size and market prices, and finally multiple instances of an ‘agent’ class, representing the individually parameterised properties. The model operates on a fortnightly time step, and repeats an annual production cycle.

Agents represent irrigators which face water restrictions under a ‘cap’, and can enter into a water market to buy or sell permits. This hypothetical water market is then used to test scenarios with different irrigation development levels, and scenarios of different water market configurations. Simulation outcomes track relevant indicators through time, such as aquifer volumes, economic performance, and water market activity under a proposed cap-and-trade system. Within the model, agents represent irrigators who are allocated a monthly licensed volume of groundwater for agricultural production. Agents use their permitted water entitlements for crops, or sell it to other agents. The model simulates a connected system of irrigators and their crops, rainfall and the aquifer which supplies groundwater, and reports how this system changes in response to various scenarios.

Agents are allocated a monthly volume of groundwater for use in irrigated production. Spreadsheet data for monthly allocations for properties within the study area were provided by the Northern Territory Government. The model considers water allocated to horticultural/agricultural uses, and does not consider water allocated to the public water supply, industrial use, or other uses. Data for current usage and for proposed agricultural development were assigned directly to agents. Agents can then apply this water to crops or sell it to other agents.

The model simulates conditions for a number of scenarios. Baseline conditions include n=18 agents, allocated a total annual volume of 18,990 Ml to be used in irrigated production. The baseline scenario does not implement a water market.
Scenarios allow further licences to be granted (n=59 allocated a total of 35,107 ML/yr), and implements a water market to allow trading of allocations.

The Repast 3.1 simulation consists of three primary classes, WaterModel.class, Grower.class, and Space.class, with user interface depicted in Figure 14. The interface allows setting scenario specifications and initial conditions.

The model operates at a fortnightly time step, beginning with the dynamics of the aquifer, measuring water levels and recharge rates. Functions for aquifer dynamics were fitted to outcomes of hydrological modelling performed in the region (Puhalovich 2005), and based on historic rainfall patterns. Simulations were run using values of total monthly precipitation (mm) from 1975 to 2005 obtained for the study area from the Australian Bureau of Meteorology. Figure 15 a) depicts simulated aquifer volume in response to rainfall. The historical rainfall data shows an initial period of abundant rain in years 1-6, followed by a number of dry years (approx 6 to 14) where rainfall levels do not sufficiently recharge the modelled aquifer. Rainfall again becomes generally abundant from years 15 onward, and aquifer recharge levels recover. Figure 15 b) depicts (over two years) the available groundwater volume and the volume of monthly irrigation licences which draw from that aquifer, revealing a disparity between demand and supply.

The aquifer recharges each year during the wet season, and discharges throughout the year into the Katherine River, including during the dry season. A public consultation
process separate from this research exercise identified that at least 80% of annual aquifer recharge was to be allocated for ‘environmental flows’ for groundwater-dependent ecosystems. Therefore, the ‘cap’ in the water market was set no more than 20% of annual recharge. This cap sets the maximum level of aggregate groundwater extraction, and past this point extraction levels are ‘capped’, thereby maintaining sufficient recharge volume for environmental flows. Individual licence volumes are restricted under the cap.

Figure 15: Simulated hydrology dynamics a) annual rainfall and available extraction volumes and b) Groundwater volume available for extraction and monthly permitted volumes, baseline scenario (n=18, in black) and scenario 1 (n=59, in grey).

Agents proceed with production decisions based on the value of irrigating crops or selling the water. Agents’ market price for water, i.e. their willingness to accept an offer to sell or their willingness to pay to buy additional units of water, is determined by two factors, namely their value for additional units of water, and a ‘mark-up’ based on individual-specific behaviour observed in the field experiments. Agents’ average value per unit of water is the main determinant of their price for water when active in the water market.

The first element in agents’ water use decision is to compare crop watering requirements with the volume of their water licence for a given month. Agents determine their desired water use based on crop water requirement data (as provided by Northern Territory Government, Department of Primary Industry, Fisheries and Mines),
\[ N_{ti} = \frac{Q_i - R_i}{100} \times A_i \]  

Equation 20

Where \( N_{ti} \) is the total water [Ml] needed in time \( t \), \( Q_i \) is the recommended minimum watering level [mm], \( R_i \) [mm/m²] is the current rainfall, and \( A_i \) is the area [ha] under production for each crop type. The water use decision made by an agent will be the \( N_{ti} \) value, up to the constraints of their individual water licence.

Agents buy (sell) a volume of water from the water market based on the discrepancy between crop requirements and licensed water entitlements,

\[ D_{ti} = N_{ti} - E'_{ti} \]  

Equation 21

Where \( D_{ti} \) [Ml] is the discrepancy between desired water volume and licensed water volume, and \( E'_{ti} \) [Ml] is the adjusted licence volume.

Agents can buy and sell water allocations based on a specific double call market structure. In this set of market rules, potential buyers randomly access an offer to sell and compare the price on offer with their willingness-to-pay. This market structure approximates the structure proposed by Northern Territory Government departments, where once a bid to sell is posted, buyers can immediately purchase the allocation volume on a first-come, first-served basis.

A purchase would be made if the amount the buyer is willing-to-pay is higher than the selling price, and they may purchase a volume of water up to their demanded volume. If the buyer has not bought the full volume they demand from that seller, they proceed to the next seller’s offer and repeat the process. Once the full demanded volume has been purchased, or there are no offers to sell with a sufficiently low price, the next buyer agent goes through the same process until all demand is satisfied, all volume for sale has been purchased, or there are no more transactions.
The water allocations for that month for each buyer and seller are updated once the buying and selling activity is completed. Buyers incur costs based on the market price they paid and the volume they bought, and sellers receive the same in revenue. Agents then use their water allocation for that month.

Agents’ willingness to pay (accept) is determined by the changed production value from selling (buying) water, and a ‘mark-up’ based on agent-specific behaviour. These two elements determine an agent’s price \( P_{ii} \), such that:

\[
P_{ii} = AV_{ii} \times MU_{ii}
\]

Equation 22

Where \( AV_{ii} \) is the average value of units traded and \( MU_{ii} \) is the mark-up. Average value is calculated based on an optimal volume of water, as compared to an adjusted volume based on the volume bought or sold. The value of water is based on the difference between forecast profit from the crop under current water use compared with profit from the crop under an altered water use regime. These forecasts are based on the growing season’s rainfall patterns (up to the present time step), and the crop growth already realised therein, as well as forecasted prices for harvests. A more precise calculation of value would be the marginal value for units of water although it is questionable if producers would devote the attention to the increased precision over the simplicity of calculating average values. In Chapters 4.2 and 4.3 examples of marginal value calculations are given. The loss of precision is expected to reduce market efficiency by some small amount.

For buying agents, the average value of water is based on the shortfall volume of water they face and the potential profits if this volume were available,

\[
AV_{ii}^{d} = \frac{Max\pi_{i} - Current\pi_{i}}{D_{ii}}
\]

Equation 23

\[
Max\pi_{i} = TR_{\alpha^{i}} - TC_{\alpha}
\]

Equation 24

\[
Current\pi_{i} = TR_{\alpha^{i}} - TC_{\alpha}
\]

Equation 25
\[ TR_{\alpha i} = O'_{i} \times A_i \times \frac{\text{Trees}}{\text{ha}} \times \frac{\text{Price}}{\text{tray}} \]  

\[ TC_{\alpha i} = O'_{i} \times A_i \times \frac{\text{Trees}}{\text{ha}} \times \frac{\text{Cost}}{\text{tray}} \]  

Equation 26

Where \( O'_{i} \) is potential output [trays/tree] under optimal water use, and \( O_i \) is output under current water use. The calculation takes into account the existing growth of the season,

\[ O'_{i,\text{harvest}} = \sum_t O^\text{MaxW}_{i,t} \]  

Equation 27

\[ O_{i,\text{harvest}} = \sum_t O^\text{W}_{i,t} \]  

Equation 28

Where \( O^\text{W}_{i,t} \) [trays/tree] is a logistic growth function whose growth rate is dependent on the water use. In this calculation, the final output at harvest time is calculated based on the existing output volume, and either the optimal \( \text{MaxW} \), or current water use \( W \) [Ml]. In this sense, the agent calculates the value of water based on the difference between outcomes. Profit under water use which gives optimal crop growth (demand satisfied) versus the same but calculated with current water availability is compared.

Each agent is also programmed with a price mark-up variable, which represents a variety of effects on price which are not otherwise captured in the average value calculation as described above. The average values calculated as above would be appropriate for traditional neoclassical assumptions regarding agent rationality, but is limited in its ability to capture some of the more interesting processes that may affect a real producer’s behaviour towards pricing water. To elicit information on bidding behaviour, economic experiments were undertaken with producers from the region in order to observe their revealed behaviour in a realistic market setting (outlined in detail in Ward, Tisdell, Straton & Capon 2006). From this, data describing producers’ bidding behaviour shows how actual bid values deviated from the perceived average value. The deviation from the true value is termed the price ‘mark-up’.
In the experimental data, the range of average values was recorded with an associated revealed bid value. Observed bids were compared to average values, calculating the deviation from what one would expect from a perfectly ‘rational’ decision. It was found that 11 unique bidding strategies existed in the population of experiment respondents.

The results of the economic experiments yielded data about the first bid and how bidding behaviour changed over time. The bidding strategies of the participants are used to calibrate the bidding behaviour of agents in the model by superimposing the range of values observed in the experiments over the range calculated for agents in the model. Eleven bidding strategies were observed within the experiments, and were related to the value of water that experiment participants perceived, with a range of values existing within the participant population. Participant data from field experiments was provided by Dr. John Ward, and contained the optimal trading willingness-to-pay (WTP) and willingness to accept (WTA) values compared to the values actually chosen by experiment participants. The discrepancy between the two is assumed to contain behaviours aside from selecting the fully informed and rational value, and hence reflects rent seeking behaviour, ‘errors’ in calculations made by participants (which are likely heuristics to simplify the calculation), elements of behavioural economics such as loss aversion (over or under-pricing of WTA / WTP because water is perceived as a property right automatically associated with land) and other behaviour which is influenced by the context of water trading. Behaviours are depicted in Figure 16 for eleven strategies observed. Black lines are WTA (selling) values and grey lines are WTP (buying) values, which are compared to the constant optimal trading value in dashed blue lines. Grey and black lines are dashed when a trade was unsuccessful at the given WTA / WTP values, which in several cases resulted in participants adjusting their trading prices as seen in several of the strategies.

Strategy 1 corresponds to agents within the range of the lowest observed average value. Hence, it was in participants’ best interest to only make offers to sell water allocations to other bidders with potentially higher willingness to pay values. It was observed that the selling offers using this strategy were set at a constant rate of above the perceived average value.
Strategy 2 and strategy 3 again apply to only selling offers, and have an increasing value based on the success of market transactions. The difference between the two is simply the magnitude of parameters as they follow a similar trajectory. If a transaction occurs, the agent will proceed to raise the bid to the next highest level in an attempt to gain more revenue in the following potential transaction. If a transaction does not occur, they maintain their bid for a time.

Strategy 4 is the first of a number of ‘converging’ strategies observed. This strategy again only applies to selling bids. The agent begins with a large deviation from their average value (in an attempt to gain the most revenues from selling their allocation), and slowly proceeds to ‘test’ the market with an overall trend downwards, converging on the average value. In the following year, the difference between their average value and last period’s bidding price is again subject to this pattern, such that a convergence continues to occur toward the average value over time.

Strategy 5 is similar to strategy 1, in that there is a constant price value in relation to the agent’s average value, and again only applies to selling bids. The difference is that the agent will attempt to sell at a high price during the periods where demand is likely to be highest, and failing a successful transaction, will revert to a lower value.

Strategy 6 is the first strategy with both a selling and buying component. It is similar to strategy 1, in that the offers to sell or bids to buy are set at a constant value throughout the year, depending on whether the agent is buying (price lower than average value) or selling (price higher than average value).

Strategy 7 is similar to strategy 1, but applies only to buying bids. There is a constant mark-up value, and agents will maintain the bids to buy at this level below their average value.

Strategy 8 is a ‘double convergence’ strategy, in that the agent will make both offers to sell or to buy. Each strategy converges eventually towards their average value, in the same fashion described for strategy 4, above.
Strategy 9 is a buying only convergence strategy, similar to the prior convergence strategies described, except that it was shown in the experimental data that this agent overshot their ‘rational’ bidding value. Such behaviour articulates that this individual perceived a higher value than the economic average value communicated on the screen during the experiment. The strategy overshoots the average value line, but re-converges from the other side.

Strategy 10 is a buying only strategy with 2 components, the first is a convergence as described above, where bids to buy converge toward the average value, however, a very strong outlier was found in the experimental data, much lower than the converging trend seen for other data points. Hence, this strategy behaves like other converging strategies, with an addition of a stochastic ‘shock’ during one random month of the year, where the agent will offer to buy for a markedly lower price, as if testing to see how low they can go to buy water.

Strategy 11 is a ‘double stochastic shock’, in that a trend for buying and selling water, with non-rational outliers was seen. Hence, the agent will behave in a converging fashion for both buying and selling, but both have a number of stochastic shocks. On the buying side, they will buy once a year at well above their average value. On the selling side, they will sell several times during the year at ‘rock bottom’ prices.

This study utilised several innovative methodological links with agent-based modelling, experimental economics, and market-based instruments for natural resource management. The success of a cap-and-trade system exists in the heterogeneity of the actors in the market, such that the resource (in this case water) can be allocated from low-value to high-value users, while maintaining an identified maximum aggregate use. The behaviours of the individual actors therefore determine the success of the market. In our example, the heterogeneity in pricing behaviour combined with a small population, therefore less trades where willingness-to-pay and accept matched, resulting in low trading volumes. Hence, the strengths of using ABM in its ability to represent individual heterogeneity were able to identify a market configuration flaw in the case study.
Figure 16: Bidding behaviour revealed in experiments described in Ward et al. (2007), statistically interpreted for calibration to agent trading values. Black lines are WTA (selling) and grey lines are WTP (buying), compared to optimal trading value in dashed blue lines.
After agents have made their water use decisions and any purchases have been made within the water market, crop production is realised for the given time period.

\[
O'_t = A_t \times \left( O_{t-1} + \left( r^w \times \left( \frac{1 - \frac{O_{t-1}}{O_{\text{max}}}}{O_{t-1}} \right) \right) \right)
\]

Equation 29

Where \( O_t \) is the cumulative output [trays / tree] production in period \( t \), \( A_t \) is the area (ha) under production, \( O_{\text{max}} \) is the full production possibility, and \( r^w \) is the growth rate [0-1], dependant on water use.

\[
r^{w}_{t,i} = \left( \frac{r^{\text{MaxW}}_{t} - r^{W=0}_{t}}{W_t} \right) \times \left( R_i + N_{t,i} \right) + r^{W=0}
\]

Equation 30

Where \( r^{W=0} \) is the productivity associated with the minimum level of recommended water use \( W_t \), and \( r^{\text{MaxW}} \) is the productivity associated with maximum output. Hence, \( r \) is a linear function from lowest to highest productivity depending on moisture from irrigation and rainfall. Harvesting occurs once in the defined growing season, requiring a level of labour input.

\[
L_{t,i} = \frac{O_{t,i} \times \lambda}{8} - f
\]

Equation 31

Where \( L_{t,i} \) is the labour need [person days] for time \( t \), \( \lambda \) are the labour hours [0.2 hours/tray from White (2004)] required per unit of output, and \( f \) is a value of family labour [person days] that does not need to be purchased from the labour market. The labour market is represented as a pool of labour from which agents subtract a given amount of labour, at a given price. It is assumed that labour contracts run on a two week basis, and are renegotiated at that time; hence the labour pool is updated with new people (units of labour). Agents may then again approach the labour pool and hire a volume of labour for a given price again, and the process repeats for each fortnightly time period. The labour price, \( \omega_t \), or wage rate paid is calculated.
\[
\omega_i = \left( \frac{\omega_{\text{max}} - \omega_{\text{min}}}{L_{\text{max}}} \times L_i \right) + \omega_{\text{min}} \quad \text{Equation 32}
\]

Where \( \omega_{\text{max}} \) and \( \omega_{\text{min}} \) [$/hour] are respectively the maximum and minimum wage rate [$20-$8/hr], \( L_{\text{max}} \) is the maximum labour pool [number of employable persons] in time \( t \), and \( L_i \) is the current labour availability.

\[
L_i = L_{\text{max},t} - \sum_i L_{\text{it},i} \quad \text{Equation 33}
\]

Note that if the labour pool is exhausted, produce will not be able to be brought to the market. The final volume of output that is taken to market, \( O_{\text{itHarvest}} \), is then calculated.

\[
O_{\text{itHarvest}} = (O_{\text{itHarvest}} \times L_{\text{it},i}) + (f \times L_{\text{it},i}) \quad \text{Equation 34}
\]

Which is the sum of output harvested by paid labour and family labour. Agent’s profit which is realised by the volume of output brought to market. Profit, \( \pi_i \), is calculated from total revenues, \( TR_i \), and total costs, \( TC_i \).

\[
\pi_i = TR_i - TC_i \quad \text{Equation 35}
\]

\[
TR_i = (O_{\text{itHarvest}} \ast A_i \ast \rho_i) + (P_{\text{it},i} \ast W^+) \quad \text{Equation 36}
\]

\[
TC_i = (VC \ast A) + (P_{\text{it},i} \times W^+) + (\omega_i \times L_{\text{it},i}) + I_i \quad \text{Equation 37}
\]

For total revenues, \( \rho_i \) is the market price paid [$/tray], \( P^+ \) [$/] is the price paid on individual exchanges in the water market, and \( W^+ \) [ML] is the volume of water sold. For total costs, \( VC \) [$/tray] is a fixed level of variable cost of production, \( W^+ \) [ML] is the volume of water bought in the water market, and \( I_i \) [$/] are interest payments made on fixed capital. Parameters were taken directly from White (2004).

Harvesting occurs once in the defined growing season, where output can be delivered to market, requiring a given level of labour input. A labour market is represented as a pool of labour from which agents subtract a given amount of labour, at a given price.
It is assumed that labour contracts run on a fortnightly basis, updating the labour pool and resulting wage rate. Crop production will reach market unless the labour need is not fulfilled, where associated losses occur. Interviews within the region revealed minimum and maximum wage rates, and a harvest labour pool size of 4,500 workers. Revenues are calculated from output levels with projected prices for the region’s produce. Agents incur associated marketing and variable costs, and can maintain and pay interest on debt.

The baseline scenario (n=18) allows monthly allocations un-capped, and no water market exists for trading. The downward trend in profits seen in Figure 17 c) is explained partially by forecasted prices (prices are set to decrease to year 6 before levelling out). The lower profit values in the middle years of the simulation correspond to the drier years. By the time rainfall increases in the later years, lower prices serve to keep the total profit from production depressed.

Labour shortages have been identified as having a significant impact on enterprise profitability. White (2005) reports that estimated economic losses (including direct and indirect benefits) for the Northern Territory as a whole due to lack of labour range from $5.8 million to $26.1 million. The baseline simulation assumes there are 4,500 labourers available during the harvesting season. In order to determine the impact of labour availability within the study region, this is compared with the situation where labour availability is unlimited. Modelled economic losses due to shortfalls in labour availability occur in several years, with a maximum of $7.4 million in year 17, the year when rainfall patterns have improved from the previous dry years.

In scenario 1 (n=59) applications for water licences are granted, and a cap-and-trade system is implemented. Total water extraction is capped when it reaches 20% of annual aquifer recharge. Each individual license-holder must then face pumping restrictions of a certain percentage of their monthly allocation. Extraction volumes for scenario 1 compared to the baseline scenario are depicted in Figure 17 a). Note the convergence of values in these two scenarios in the drier years in the middle of the simulation, where a cap has been implemented for significant portions of the year to maintain minimum environmental flows. The implementation of the cap results in
watering at lower than recommended rates in order that minimum volumes for environmental flows during these drier years are still maintained.

Outcomes for profit under scenario 1 are compared with the baseline scenario, as depicted in Figure 17 c). The greater profits are a result of the larger amount of licensed producers in the region. The trajectory for scenario 1 follows similar dynamics to the baseline scenario, and converging closer to the baseline profit values during the drier years.

Figure 17 b) depicts the volume of water purchased on the market (Ml) and the average value of bids, either to buy or to sell. As would be expected, the volume purchased is higher when bids are lower and vice versa, generally corresponding with rainfall patterns. The lower points of volume purchased in years 10, 11 and 13 correspond to drier years, indicating that agents are trading less in these years. The volume of water purchased increases in later years of the simulation as rainfall increases, and surplus volumes are available for sale on the market.

Total profit is higher in scenario 1 compared to the baseline scenarios, although this is accounted for by the increase in the number of license-holders, rather than increased profit for each individual per se. To comply with the cap, pumping restrictions are implemented during some months during each year of the simulation. These generally correspond with months that require the highest water application. The results of this scenario indicate that capping water use and allocating pumping restrictions across all agents is impacting negatively on production. Even when extraction is not capped, however, profit is limited due to the labour constraint. Therefore, both water and labour availability impact negatively on profit.
Figure 17: a) Groundwater extraction, baseline and scenario 1 under a cap-and-trade system, b) water volume purchased and average bid, scenario 1, c) Profit, baseline and scenario 1

The cap therefore imposes risks on agents, with less certainty about licensed volumes available in future months depending on aquifer recharge rates, and hence rainfall. Conversely, the water market exists as an instrument to help agents manage their risk and to ensure an overall allocation of water to its highest value. Hence the downward influence of pumping restrictions on profit is offset to some degree by the existence of the water market.

Overall trading volumes were found to be low, with the least trading during particularly dry years. This is due to lack of surpluses, and therefore decreased volume available on the market, but also due to the relatively small population of trading agents. Because each agent has a unique price based on calibrated bidding behaviours, agents’ willingness-to-pay and accept did not always match, and therefore the number of possible trades decreased in this market configuration. The market functioned at its best, resulting in high total profit levels, when a subsequent number of wet years after a drought resulted in allocation surpluses. This configuration therefore does influence profitability and helps agents to respond after drier periods, but is not beneficial when agents are facing restrictions during a prolonged dry period.
Even when water extraction is not capped, profit is constrained due to a labour shortfall in the region. The increase in agents from n=18 to 59 results in a total profit of $61M versus $94M respectively, over 22 years. Labour shortages are a major limitation to production in the modelled system. As such, the benefits of having a water market may not be fully realised if there simply isn’t enough labour to bring the crop to market. Therefore, both water restrictions and labour shortages impact negatively on profit, and therefore should realistically be dealt with under joint policy approaches.

This case study highlights the value of using models to examine future scenarios in water development or agriculture. The agents calibrated from experimental economics provide a realistic representation of trading behaviour, notably different than if agents performed perfectly rational and fully informed decision making. This relates specifically to research question #2: examining whether experimental economics can be used with ABM to gather data for parameterising the model. The calibration process was useful for moving assumptions away from notions of rational and fully informed decision making to incorporate behavioural aspects of decision making. However, the experiments and development of the ABM were conducted separately, requiring a level of interpretation from experimental data into agent decision making functions. There is no guarantee that the decision making context faced by agents and experiment participants are consistent, and therefore risks exist in interpreting data subjectively.

### 4.2 An agent-based model of water quality markets

This cases study developed an ABM of water quality markets applied to catchments of the Great Barrier Reef, Australia. As an initial starting point for modelling the possible implementation of this MBI, the model was developed using secondary literature and does not include calibration activities such as surveys, interviews or experiments. The secondary literature involved results from interviews, but given these were done separate from the ABM activity there is again the issue of subjective interpretation of the interview results. Furthermore, agents are programmed to
function like fully informed and rational decision makers, and the model itself is limited in its ability to engender stakeholder buy-in. This highlights the importance of using participatory modelling, as even a well developed model is of limited use if the perception of the model by the target community is that of being a black-box. This relates specifically to research question #1: namely, what techniques in social and economic science can be used to gather empirical data? Given the limitations of the model, a further activity was conducted described in the next section to overcome these hurdles.

This case study applied ABM to Queensland Australia, where rapid land use change along the eastern coastline is occurring in areas historically dominated by agriculture, with conversion largely to residential use. A growing tourism industry fuels urban development, transitioning areas once used for sugarcane production. There is increasing attention on agricultural run-off of nutrients and sediments into adjacent waters of the Great Barrier Reef World Heritage Area, and a policy framework has been put forward to manage water quality from land-based pollutants entering coastal waters (AG 2003). One possibility is using MBIs to regulate agricultural run-off through a cap-and-trade system. However, this policy option must be seen within the context of land use change trends driven by urban development.

Cap-and-trade systems for environmental management have a wide variety of configurations suited to various resource and economic conditions present. This case study simulates outcomes of a cap-and-trade system where agriculturalists are allocated a licensed fertiliser application rate, based on restrictions to the catchment-scale maximum total application, as first presented in Heckbert & Smajgl (2005a; 2006). The ‘cap level’, or allowable ceiling of total application, is set to representing agronomic best-practices with respect to fertiliser application rates.

The Douglas Shire was the fastest growing Shire in the Far North Region 1991 – 1998. With two internationally-renowned tourism destinations in the Shire (Port Douglas and the Daintree National Park), and positioned between the Wet Tropics and GBR World Heritage Areas, tourism is the largest sector of the local economy (Davis 2006). Douglas Shire has experienced substantial tourism development as a result of increased domestic and international visitor numbers over the past two decades. The
Great Barrier Reef Marine Park attracted 1.6 million visitors in 2002, and there were about 730 permitted commercial tourism operators and 1500 vessels and aircraft permitted to operate in the area. Over 85% of visitors go to the offshore Cairns/Port Douglas and Whitsunday areas (Davis 2006).

The development of tourism in Port Douglas has resulted in increased land value, and demand for further residential development is creating pressure to subdivide agricultural land. Bohnet (2008) emphasises that Douglas Shire experienced the 2nd highest population growth (2.0%) in the Wet Tropics NRM Region between 1996 and 2001 (McDonald and Weston 2004). Increasing house prices accelerated the number of subdivisions. Consequentially, rents and living costs increased with particularly relevant effects for older residents and those on low or fixed incomes.

The model structure is outlined in the UML diagram depicted in Figure 18. The model operation commences with the Model.class executing a number of methods which set up, build, and populate other model classes. Model.class is also responsible for the timing and execution of events, and acts as a repository for global-level data which is called on and/or updated throughout the simulation run. Initial parameters are read into Model.class through a number of sources, most importantly through external data sets and user defined parameters. External data sets include historical meteorological data and market prices. These data are static (except when altered for scenario analysis) and read in from external .csv files as needed.
Figure 18: Model UML diagram depicting model classes, methods and attributes for an ABM of a water quality market.

The user defined parameters are available for alteration through the Repast GUI, see Figure 19, and can be altered to compare scenario runs with one set of parameters to simulation results where these parameters are altered. Further variables and parameter values are defined within the Model.class which can only be adjusted through altering the model source code through a java IDE, such as Eclipse.
The agent population is built and initialised through the execution of a number of core Repast methods, particularly buildModel(), buildDisplay(), buildSchedule(). The first operation, buildModel(), creates an arraylist for base agents and paddocks. The paddockList is further organised into another arrayList, the propertyList, based on GIS attribute data regarding which paddocks belong to which properties. The buildModel() operation populates this list from imported GIS data, which was prepared for the Douglas Shire. From this, the buildDisplay() method calls on the functionality of an imported java–based GIS visualisation software, OpenMap.
Landowners are assigned an agent type based on the conditions present on their properties upon model initialisation. The typology was derived from secondary literature, and is defined by the size, number of crops, and financial situation of properties. Bohnet (2008) identify a typology of agriculturalists in the Shire, synthesised in Table 4.

### Table 4: Typology of agriculturalists in the Douglas Shire.

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Size</th>
<th>Strategy</th>
<th>Land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Traditional specialised</td>
<td>Large</td>
<td>Acquire new land to increase production</td>
<td>Sugarcane</td>
</tr>
<tr>
<td>2</td>
<td>Traditional mixed farmers</td>
<td>Large</td>
<td>Search for alternative land use</td>
<td>Sugarcane, cattle</td>
</tr>
<tr>
<td>3</td>
<td>Early diversifiers</td>
<td>Medium</td>
<td>Diversification (crops, non-agriculture)</td>
<td>Sugarcane, flowers, fruit</td>
</tr>
<tr>
<td>4a</td>
<td>Lifestyle</td>
<td>Small</td>
<td>High value crops</td>
<td>Flowers, fruit, trees</td>
</tr>
<tr>
<td>4b</td>
<td>Hobby farmers</td>
<td>Small</td>
<td>Professional Employment</td>
<td>Trees</td>
</tr>
<tr>
<td>5</td>
<td>Graziers</td>
<td>Large</td>
<td>Develop property and off-farm income</td>
<td>Cattle</td>
</tr>
</tbody>
</table>

- Type 1 represents the traditional sugarcane farmers, with large properties and producing one crop. Historical business strategy until a few years ago has been to acquire additional land to increase production. Until now, these producers have not diversified. They generally have investments elsewhere and also off farm income. Farm-based diversification hasn’t appealed much to this group who are only slowly looking at diversification projects (Bohnet 2008).
- Type 2 summarises traditional mixed farmers, again with large properties, and are producing 2 crops, includes cattle (although it was revealed in the ground-truthing exercises there are relatively few who produce both sugarcane and cattle) farm forestry blocks, or small orchards (Bohnet 2008). This group has fewer assets outside agriculture, and diversified in recent years when sugar prices were low.
- Type 3 groups early diversifiers, with medium sized farms, producing 3 crops. These producers again were former sugarcane agents, having diversified
during the 1980s. For this group, purchasing new land to increase production was not financially possible, and diversification into higher value crops / land use was done.

- Type 4 are lifestyle farmers (4a), with small properties, producing 3 crops such as fruits, exotic flowers, orchards, or offering farms stays.
- Type 5 Hobby farmers with small properties, producing 2 crops, prefer location and environment of Mossman, earn living outside of farm, work their properties in their free time.
- Type 6 are graziers, with large properties, producing cattle. Business strategy has been to develop properties, and pursue casual off-farm income.
- The assignment of agent types occurs at model initialisation, based on property sizes and crops grown.

Sugarcane and horticulture yields are assumed to follow a production function of decreasing marginal yield with added fertiliser application rates. The functions take on the following form:

\[ O^k = \alpha^k * R^k + \beta^k * R^k + \gamma \]

Equation 38

Where \( O^k \) is output, or yield [t/ha] of crop \( k \), and \( R \) is the application rate [kg/ha]. Parameter values for \( R \) are:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sugarcane</th>
<th>Horticulture</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.0007</td>
<td>0.000045</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.37</td>
<td>0.0448</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>50</td>
<td>13.6</td>
</tr>
</tbody>
</table>

The life cycle of sugarcane operates on a fallow, plant and ratoon crops (1-4), referred to as a ‘rotation state’. Each paddock is initialised with a random rotation state, which serves to alter the yield of the paddock based on a multiplier added to the above yield equations, such that:

\[ O^{sc} = O^{sc} * m \]

Equation 39
Where the superscript \( Sc \) refers to sugarcane, and \( m = 0 \) for fallow rotation, \( m = 1 \) for the plant crop, \( m = 0.83, 0.72, \) and \( 0.66 \) respectively for ratoon crops 1 to 3 (4th is fallow) (Thorburn 2004). Once a paddock has been harvested, its rotation state is updated in the order from fallow > plant > ratoon1 > ratoon2 > ratoon3 > fallow.

Fertiliser application rates are selected based on a search function performed by the property to weight the benefits of added units of fertiliser to the expected change in yield. Hence, a marginal value of additional fertiliser units is calculated through iterating up from 1 kg/ha, up to a value where returns from additional units are uneconomical.

\[
MV_{i,R}^k = (O_{i,R} - O_{i,R-1}) \times P_i^k
\]  

Equation 40

And \( R \) is selected where \( MV_{i,R}^k > P_r^k \) and \( MV_{i,R}^k \) is the marginal value of an additional unit \( R \) [1 kg/ha] of fertiliser, \( O_{i,R}^k \) is the yield [t/ha] calculated at that application rate (calling yield equations defined earlier), with \( P_r^k \) [$/t] is the sale price of units of crop \( k \) at time \( t \), and \( P_r^c \) [$/kg] is the purchase price of additional units of fertiliser.

Simulated properties generate revenues and incur cost from production. For each of the land uses (grazing, sugarcane and horticulture production) events such as paddock harvests, cattle sales, water quality market expenses and receipts, and variable costs of production are recorded at their occurrence. The difference between the pre-and post sale day herd sizes, multiplied by 350kg (saleable weight) is the total weight sold [kg], \( W \), and cattle revenues \( RC_i \) are then calculated such that:

\[
RC_i = \sum W_c \times P_c^c \]  

Equation 41

\( W_c \) [kg] is the weight of marketable cattle \( C = 1...n \), and \( P_c^c \) is the price paid on sale cattle [$/kg]. Horticulture revenues are generated through regular monthly harvesting of an even-flow producing crop, calculating revenues \( RH_i \) such that
\[ RH_i = \frac{O^H \cdot A^H \cdot P^H}{12} \]  
Equation 42

Where \( O^H \) is the output [t/ha] of horticulture, \( A^H \) is the area of the property devoted to horticulture, and \( P^H \) is the horticulture price paid [$/t], and considering monthly harvest events over the 12 months/year.

Properties producing sugarcane receive 3 payments throughout the crushing season; an ‘over-the-bridge’ payment, second, and third payment. The over-the-bridge payment, \( OP \) is \( 1/5 \) of last year’s total sugar revenues, and the second payment, \( SP \) is \( 1/3 \) of last year’s total revenues. The third payment, \( RS \), is used to balance out the payment schedule at the end of the crushing season once the properties’ total tonnage delivered has been calculated, where

\[ RS_i = \left( P^S \cdot \sum_p O^S_p \cdot A^S_p \right) - OP_i - SP_i \]  
Equation 43

Where \( O^S_p \) is the output [t] of sugarcane on paddock \( p \), \( A^S_p \) is the area of paddocks devoted to sugarcane, and \( P^S \) is the sugar price paid [$/t]. The timing of the payments occurs based a mean date (day of year 180, 240, 280 for the three payments), assigned to properties at a date selected using a standard deviation of 10 days, normally distributed.

Properties also have a level of off-farm income, \( I_i \), which is instantiated at agent initialisation, based on the agent’s type. \( I_i \) is a normally distributed number with mean and standard deviation determined by agent type [type 1 = \( I_i \sim N(15000,10000) \), type 2, 3, 4 = \( I_i \sim N(5000,3000) \), type 5 = \( I_i \sim N(40000,3000) \), as derived from Bohnet et al. (2008)]. Finally, receipts \( RN \) [$] from sales on the water quality market are recorded for the monthly market trades. The total annual revenues \( RA \) of a property will reflect the mix of land uses present, such that:
\[ RA_i = RC_i + RH_i + RS_i + I_i + RN_i \]  
Equation 44

Property costs are for each land use \( k \) (consisting of cattle, horticulture and sugarcane) including variable costs of production, fertiliser costs (purchasing and trading costs), and financing costs (payments on debt – if any). Variable costs of grazing are calculated as:

\[ CV^k = \sum_p A^i \cdot \rho^k \]  
Equation 45

Where \( A^i \) is area of paddocks and \( \rho^k \) is the variable costs for land use \( k \). Fertiliser costs are calculated as:

\[ CN_i = \sum_k \sum_p A_{p}^k \cdot \mu^k \cdot \tau \]  
Equation 46

Where again \( A_{p}^k \) is the area of paddocks [ha] devoted to land use \( k \), and \( \mu^k \) is the land use specific fertiliser application rate, and \( \tau \) is the retail cost of fertiliser.

Each property also calculates costs associated with financing debt, and disposable income. Interest payments and total annual costs are calculated as,

\[ CI_{i,t} = \frac{D_i \cdot (\theta - 1)}{1 - \theta^{-\gamma/2}} \]  
Equation 47

\[ \theta = 1 + \frac{\alpha}{12} \]  
Equation 48

\[ CA_i = CI_{i,t} + CN_i + CV_i \]  
Equation 49

The model represents the conversion of agricultural land to urban and rural residential which is driven by population growth rates. Population change is represented by a simple growth function of 2% per annum based on an initial population size of 12,607 people. Population size and growth rate are taken from McDonald and Weston (2004).

\[ P_t = P_{t-365} + (P_{t-365} \cdot G) \]  
Equation 50
Where \( P \) is the population [\#individuals] and \( G \) is the user-defined growth rate [%].

Based on the population growth rate, demand for housing causes selected paddocks to change land use from their previous agricultural production to urban / residential use. The area converted to urban uses is updated annually, such that:

\[
A^U = \frac{AL*IM}{PD}
\]

Equation 51

where \( A^U \) is the area to be converted to urban uses. The distance of the centroid is measured using MGA94 coordinates, and using the trigonomic function a linear distance is calculated to the town centre. Because Port Douglas is located further from the sugar producing area, the intersection between Captain Cook Highway and the Port Douglas Road is taken to be the centre of the Port Douglas ring. The distances listed from the centre result form this assumption. Paddocks within each ring are randomly selected to be converted to urban areas until the area to be converted to urban is fulfilled. This urbanisation reduces the actual fertiliser demand.

The implementation of a water quality market allows producers with demand for additional fertiliser to purchase additional units from other agents. The water quality market is assumed to operate once a month. The cap level is calculated in the initial time period by taking into account the total area of cropping, considering recommended fertiliser application rates, such that

\[
C_{t=0} = \sum_i A_i^k * RR_i^k
\]

Equation 52

The model user can also alter the cap levels, with the above cap calculation used for the baseline scenario, resulting in a total allowable application of 1,138 t within the spatial extent of the case study based on agronomic recommended application rates (from Thorburn 2004).

The market configurations considered here involve the order and rules of trade. First, buyers (sellers) may place bids to buy (sell), with the agent list called randomly. The
buying agent and potential selling agent compare bid values, and a transaction will occur if the seller’s willingness to accept is below the buyer’s bid level.

The model user is asked to define a total maximum aggregate fertiliser licences [kg] to be allocated to modelled agents. This total level is then allocated back to the individual agents depending on the land uses of the property’s paddocks. In the set of policy configurations explored here, licence allocation is performed based on best practice benchmarks, where the total licensed application rate $\eta$ for individual $i$ is calculated by determining the total kg/ha from each land use $k$, here denoted as $h$ for horticulture and $sc$ for sugarcane,

\[ \eta_i = A^h_i \cdot \varphi^h + A^{sc}_i \cdot \varphi^{sc} \quad \text{Equation 53} \]

where $A^i$ are the areas of the property under either horticulture or sugarcane production.

Agents can now compare their application decision with their licensed allocation. If their desired application rate is lower than the initially aspired volume, producers calculate a demand level $D_i$, for additional kg of fertiliser:

\[ D_i = \sum \mu^i_t - \eta_{i,t} \quad \text{Equation 54} \]

It is assumed that fertiliser volumes for the two land uses can be used on either crop, and that demand is apportioned to each land use based on the ratio between $\mu^h_i, \mu^{sc}_i$ if a grower has areas of both crops.

Each agent calculates a willingness-to-pay (accept) to buy (sell) units of their licence, returning an associated price per unit. Agents’ market price for water is determined by their marginal value for additional (lesser) units of water, and a ‘mark-up’ based on agent-specific behaviour.
When \( \mu^i < \eta^i \), and hence there is demand for further units of fertiliser, the agent calculates an associated ‘buying’ marginal value, \( MVB^i \). Agents are also willing to sell units of their allocation if a posted buyer’s price is larger than their associated marginal value of selling \( MVS^i \), where

\[
MVB^i = P^i \times \frac{(O^i_{N+D_i} - O^i_N)}{D}
\]

\[
MVS^i = P^i \times \frac{(O^i_N - O^i_{N-V_j})}{V_j}
\]

\[\text{Equation 55} \]

\[\text{Equation 56} \]

Where \( P^i \) is the price paid [\$/t] for each land use \( k \), and \( V_j \) is the quantity volume of fertiliser included in any price/quantity bundle that an agent is trading on the market. Predicted output [kg/ha] is \( O_n \) under current licence volumes, \( O_{n,D} \) under current licence volumes plus unfulfilled demand, \( O_{n,n} \) under current licence volumes less volume being considered for sale to agent \( j \).

Agents calculate \( MVH^i \) and \( MVS^i \) for each crop (horticulture and sugarcane) and may enter the water quality market with bundles from either or both crops. Agents who respond to buyers’ posted bids (and are hence sellers) use the lower of \( MVS^i \), \( MVS^j \) as their marginal value, as agents would be willing to pay the lower value of the two (as well as the higher if necessary, but of course would prefer to pay less if possible). Again, agents who post supply bids to the water quality market select price/quantity bundles based on the lower of the two \( MVS^i \), \( MVS^j \) values. Conversely, buying agents who respond to posted offers to sell select the higher of the \( MVH^i \), \( MVH^j \) values, as they are willing to pay up to their higher value when making trades.

The underlying structure of the market process follows the principle of a double auction (Rasmussen 2001). Sellers and buyers undertake their valuation separately and communicate only the bid. The first postings are for bids to buy. An agent \( i \) posting a bid to buy iterates through the agent list \( 1\ldots n \) (randomised order of iteration), selecting another agent \( j \) with which to compare price/quantity bundles. A trade is made if agent \( j \) has sufficient quantity to fulfil the bid made by agent \( i \), and
the selling price of $j$ is lower than the buying price of $i$. The multiple unit market format allows for partial trades and does not require all units to be sold/bought in lumps sums.

After this first round of postings from buyers, agents who wish to sell quantities of fertiliser may post offers to sell. In a similar fashion as described above, agent $i$ posts an offer to sell, and by iterating through the agent list (this time sorted from highest to lowest buying value) agent $j$ evaluates the price/quantity bundle of $i$’s offer. Agents who were successful in buying units in the previous market step may not submit bids to sell as well (although agents who sell in the first round may buy in the second).

After exchanges have been made on the water quality market, the agent re-adjusts their licensed volumes to account for purchases made or volumes sold, resulting in a final fertiliser application rate of $\rho_i$ [kg/ha], to be used by the paddock-scale operations discussed earlier.

It is assumed that population in the Douglas Shire grows under baseline assumptions at a rate of 2%. The water quality market is simulated assuming a 40% cap and a 70% cap, relative to the agronomic recommended rates. Further simulations explore outcomes under population growth scenarios of 1.8% (low growth) and 2.2% (high growth). Population growth drives increased demand for locally produced horticulture, and as a result the increased value of horticulture production influences land use change away from sugar production towards horticulture.

Figure 20 depicts the land use change pattern for the baseline, with spatial distribution shown in Figure 21.
Population growth rates have a direct impact on the rate of urbanisation. Compared to higher population growth rates, baseline population growth results in greater area of sugar and slightly greater area under grazing, while area under horticulture remains nearly unchanged. Higher population growth shows a marked decline in the area of sugarcane, followed by grazing and a small increase in the area of horticulture. The effects on sugarcane are triggered by the proximity to growing urban areas, and the fact that sugar cane is the dominating agricultural land use close to the centre of urban development and hence has ‘more to lose’ under land use change.
Revenue as an economic indicator is depicted in Figure 22. The introduction of a water quality market impacts the most on sugarcane, with horticulture losing a relatively smaller proportion of revenues as land use change occurs.
These results suggest that although urbanisation cuts into the total area of agriculture land use, the effects are felt predominantly by the sugar industry. Given that horticulture provides a high value product from a relatively small land base, it is able to maintain and indeed increase the overall total value given the increased demand from population growth. Nevertheless, results are subject to doubt given the lack of robust calibration exercises to ensure agent behaviours match those of actual decision makers in the region. This relates specifically to research question #1, whether techniques in social and economic science can be used to gather empirical data. The secondary literature sourced to parameterise the model draws on interview results conducted externally from the modelling exercises, and hence involves a degree of interpretation that very well could affect results significantly. Given this identified limitation of the modelling exercise, a further model was developed, as described in the following section.
4.3 A participatory ABM of water quality markets and land use change

The model described in the previous section investigates possible outcomes of implementing a MBI for water quality management in catchments of the Great Barrier Reef. However, the usefulness of the model is deemed to be limited because secondary literature used for calibration is based on interviews conducted separate from the modelling exercise and therefore requires re-interpretation. Also, agents are programmed to behave as fully informed and rational agents. Lastly, the model interface is not user-friendly and merely reports aggregate outcomes without sufficient explanation of underlying dynamics. An updated version of the model in 4.2 was created using different software, and modifying model functions according to updated information through using the model with stakeholders, agronomists and policy makers.

An agent-based model of a cap-and-trade system for fertiliser permits is applied to Douglas Shire, Queensland, as described in Heckbert (in press). Farmers are represented by agents who make production decisions and determine price and quantity of trades in a water quality market. Agents are the decision making unit of the property, which is comprised of a number of GIS polygons of each paddock (agricultural plot) within the Shire. Agents face constrained fertiliser application rates through the setting of a cap-and-trade system for fertiliser permits, and may trade in a call market to buy and sell fertiliser permits. The outcomes for the water quality market are estimated for various cap levels and where land use change occurs.

Research questions address how well the MBI operates in an urbanising landscape. More specifically, how do farm profitability and the distribution of profits within the agent population respond to market configurations and land use change? What are modelled fertiliser permit trading prices, what volume is traded, and do the gains from trading justify the effort of implementing and maintaining the MBI?

One hypothesis is that the MBI will maintain limits to overall fertiliser application and will allow flexibility for those who wish to purchase additional permits from the
market. From this perspective the MBI might assist in managing production decisions in a transitioning landscape. Alternatively, the removal of agricultural lands could undermine the operation of the MBI and hinder its effectiveness, and the market might act as a barrier to producers adopting higher-input and higher-value land uses.

The ABM reports estimated permit price, trade volume, and the gains from trading and cost savings against another policy such as a uniform regulation. The model calculates income equity of the agent population through a gini coefficient to measure how the cap-and-trade system affects the distribution of income. Simulation scenarios examine the effect of various cap levels and of land use change.

Market-based instruments for water quality management are potentially useful for managing agriculture emissions to achieve environmental goals at least cost. This section presents an agent-based model of a cap-and-trade instrument for managing water quality for the Great Barrier Reef, Australia as a case study to model and report on indicators of performance of a water quality market. Simulation results reveal several expected patterns which are consistent with the emissions trading literature such as equilibrium prices and trading volume both increasing as the cap tightens. The model also finds outcomes are sensitive to the assumptions about the agent population, specifically whether the number of agents and their heterogeneity of productivity serve to create a ‘thin’ market. Two novel contributions of this research beyond these expected findings are how the cap-and-trade system functions as land use change occurs, and also how the benefits of trading are distributed amongst the population of agricultural agents.

Agent-based modelling is used in the application described here because of the ability to represent trading and the individual decision making and resource impacts of multiple individuals in space. The model was constructed using Net Logo (v4.0.4) with an interactive user interface and spatial map and figures tracking indicators over time, see Figure 23. Spatial data were collated, representing each paddock (agriculture plot) for the case study area, and was ground-truthed during field visits, and parameter values listed in Table 5 were elicited from agronomists from research and agricultural extension organisations. The model was constructed to specifically represent a real-world case study for the purposes of policy decision support to inform regional authorities about considerations in creating a cap and trade system. The model
interface allows decision makers to alter parameters and explore outcomes directly as a participatory research tool. The 3D view allows the model user to zoom, inspect and track individual properties at a paddock-level resolution.

Figure 23: Interactive model interface for setting scenarios and parameters, spatial map with paddock boundaries and properties depicted as houses, and figures tracking simulated model data over time.

Agents perform a series of scheduled operations for each time step, representing 1 year. The agent operations in each time step are presented below in sequential order, beginning with production decisions, through to trading with other agents in the water quality market. The yearly time step was chosen to reflect the annual nature of fertiliser application to crops and the annual wet / dry season cycle. Agents grow one of two crops, sugarcane or horticulture. Fertiliser application rates \( N_{ijr} \) [kg/ha] for crops \( i = \) sugar or horticulture are initialised at model setup for each agent \( j = 1...164 \) according to a normal distribution,
where \( RR_j \) is the mean recommended application rate [kg/ha] (drawn from Thorburn 2004), and \( SD_j \) is the standard deviation which determines the level of heterogeneity in fertiliser application rates across the agent population. The function takes on a temporal element \( t \) for each agent \( j \) through trading permits. Each agent has a unique production function for sugarcane or horticulture, which share the same functional form and use unique parameters summarised in Table 5. Crop yield is calculated as

\[
O_{j,ij} = \kappa_{j,i} \left( 1 - \delta_i \cdot e^{-\beta_i N_{j,ij}} \right) - \gamma_i N_{j,ij} \tag{58}
\]

where \( O_{j,i} \) is the crop yield [t/ha] realised using fertiliser application rate from equation 57, and \( \gamma_i, \delta_i, \beta_i \) are static yield parameters. The parameter \( \kappa_{j,i} \) is the property-specific yield parameter, and is the point at which production heterogeneity is introduced,

\[\kappa_{j,i} \sim N(PP_i, PSD_i) \tag{59}\]

where \( PP_i \) is mean productivity for crop \( i \), and \( PSD_i \) is the productivity standard deviation, normally distributed across the agent population. The productivity is set on a property-basis to reflect the set of management practices jointly applied over the property’s paddocks, rather than a paddock-specific productivity function. Soils in the area are relatively homogenous. Variability in production is related largely to management practices (see Roebeling & Webster 2007).

Agents derive revenues and incur costs from growing crops and from buying and/or selling fertiliser permits [kg], with total profits expressed as:

\[
\pi_{j,ij} = \left( O_{j,ij} \cdot A_{j,ij} \cdot CP_i \right) - \left( \varepsilon_i \cdot V_i + V_i \cdot A_{j,ij} + N_{j,ij} \cdot A_{j,ij} \cdot FP_i \right) + FR_{j,ij} - FC_{j,ij} \tag{60}
\]
where the first term describes production revenues with $A_{ij}$ being the area [ha] of the property under land use $i$ which is either sugarcane or horticulture and $CP_i$ is the commodity price [$/t$] paid for yield. The second term describes production costs, with variable costs for each land use being $V_i$ [$/ha$], and the parameter $\varphi_i$ [ha] represents the minimum farm size observed in our data set and used with the variable cost parameter to infer fixed costs for each land use (sugarcane being capital intensive versus labour intensive horticulture). The commercial cost of fertiliser is $FP$ [$/kg$]. The last two variables $FR_{ij}$ and $FC_{ij}$ are revenues and costs [$\$]$ respectively, incurred from selling and purchasing fertiliser permits.

In the description of profits above, all variables are exogenous and static except $FR_{ij}$ and $FC_{ij}$, which are related to trading. We might expect agents to be able to also change their application rate in search of an optimal balance between production revenues and costs, and also select a diversification to a mix of land uses in response to changes in commodity prices. However in this model, these latter two adaptive behaviours are held constant to be able to focus on trading behaviour.

Agents may buy (sell) permits for fertiliser use in a water quality market. The type of trading mechanism used in this simulation is a multiple call market, where traders submit multi-unit offers as a bundle of permits to be sold at a given price. Various market-based instruments take on designs suited to management goals and the conditions of the traded good, the environmental resource and traders’ use of the traded input to production. Cason & Friedman (1996) describe the single call market (SCM), and Cason & Friedman (1997) describe the continuous double auction (CDA) and the multiple call market (MCM) formats. For SCM, traders independently submit bids and asks that are aggregated into demand and supply curves and cleared at a uniform price once each trading period. Information feedback is non-existent during a trading period (Cason & Friedman 1996). In contrast, the CDA market structure allows traders to continuously make, accept and alter buying and selling offers in real-time during a trading period of a given length, thus including information feedbacks in multiple interactions of adjusting offers. Lastly, the MCM market is similar to SCM, in that traders submit bids and asks that are aggregated and the market is cleared at a uniform price, but the MCM market is cleared several times per period.
allowing updating of unsuccessful offers, which facilitates increased information feedback and allows unsuccessful traders to modify offers and re-submit.

One consideration in choosing an appropriate market design is the time commitment from producers in learning and participating in trading. Multiple bartering interactions with one’s neighbours and community members regarding fertiliser permits are not necessarily desirable in a small community. Consultations with government authorities and regional natural resource management bodies identified the importance of a straightforward trading format which does not require continuous attention and time commitments from farmers throughout the year. The SCM and variants was deemed suitable, but doesn’t offer flexibility for inexperienced traders, and information feedback is limited given the price signal is only revealed at the end of each period. The CDA market format allows the greatest feedback from trades and hence the best opportunity for learning and therefore efficiency in overall market performance however requires significant time commitment from traders and constant attention of current conditions in the marketplace. Because of this, CDA was not deemed well suited to the conditions of agriculturalists with limited time and many other important production decisions to attend to. This was confirmed in informal interviews with local resource managers who expressed concerns with using the CDA format for these reasons. However, a modified MCM format allows the simplicity of the call market, but can accommodate information feedbacks and adjusting of unsuccessful bids. The balance of these points suggests that MCM is a suitable market format to test using the ABM given it involves a straightforward process for traders yet allows learning through feedback.

Market designs for natural resource management issues have been tested in the laboratory setting, reviewed in Reeson & Nolles (2009) and Windle et al. (2008). Many are single-unit auctions, as opposed to our situation where multiple units of a homogenous good (fertiliser) would be traded in price-quantity bundles. Here we follow the example of Hailu & Thoyer (2007) in adjusting the MCM format to a multiple-unit design. Unlike single-unit auctions, multi-unit auctions allow traders to submit offers with quantity and price schedules rather than single quantity-price bundles Hailu & Thoyer (2007). The population of bidders has private values
reflecting different production (demand) and cost (supply) structures, indicating the amount they would be willing to supply at different prices Hailu & Thoyer (2007).

Considering these design features, the market instrument programmed here involves five steps, 1) granting of fertiliser permits to agents based on land use 2) agents determine unfilled demand 3) Agents calculate a willingness-to-pay (WTP) for demanded permits and a willingness-to-accept (WTA) payment for selling portions of their permits already granted, 4) organisation of WTP bids and WTA offers into demand and supply curves with an associated price, and 5) trading of permits and funds for successful bids / asks.

Permits $P_{jt}$ [kg/ha] are assigned to agents based on recommended rates for each land use, rather than auctioned through a bidding process,

$$P_{jt} = RR_i \times A_{j,t} \quad \text{Equation 61}$$

Because permits are distributed on a per ha basis by land use, agents receive an overall allocation depending on the size of their property. From here, demand for additional fertiliser permits $D_{jt}$ [kg] is the calculated shortfall between the agent’s fertiliser application rate and permits available.

$$D_{jt} = (N_{j,t} - P_{jt}) \times A_{j,t} \quad \text{Equation 62}$$

At this point agents calculate two price-quantity schedules; one of WTP for demanded permits and one of WTA values for permits the agent might supply to the market. The demand schedule is an array list of WTP values populated with the marginal value $MVD_{jt}$ [$/kg]$ for additional fertiliser units,

$$MVD_{jt} = (O_{j,t}^{n+1} - O_{j,t}^n) \times CP_t - FP \quad \text{Equation 63}$$

Where $O_{j,t}^n$ is yield [t/ha] at fertiliser input level $n$, which is iterated across the range of $n = P_{jt}$ to $n = D_{jt} + P_{jt}$, and $FP$ again is the price of fertiliser [$/kg$].
In a similar fashion, sellers also calculate a WTA schedule which is again stored as an array list. The WTA is calculated as the marginal cost [$/kg] of supplying additional permits to the market,

\[ MCS_{j,t} = (O^*_j - O_{j,t}^{t+1}) \times CP_j + FP \]  

Equation 64

Where \( O^*_j \) is yield across the range \( n = P_{ij} \) to \( n = 0 \). The WTA and WTP values are then added to a list a number of times equal to the quantity of the bid. The lists are sorted ascendingly for offers to sell (creating the supply curve), and sorted descendingly for bids to buy (creating the demand curve). The overall market price \( SP \) is defined at the pair-wise combination where the demand and supply curves intersect.

To represent the MCM format explored here, three trading rounds are run within each time step, all occurring prior to the start of the growing season when fertiliser is applied. The supply curve is static, and only needs to be submitted once. However, multiple buying rounds are possible, and buying agents may adjust their bid and re-submit twice more, amounting to three buyer calls per season compared to one submission from sellers. The latter point controls on-selling of bought permits, and makes the process of submitting a supply ‘function’ a simple process for traders. The selection of three iterations was made on the balance of simplicity for a real-world trader, yet mitigates the risk of not being successful in the first or second attempts at trading. In the real world, sellers could submit a price schedule (for example) of around 5 price-quantity relationships for simplicity’s sake, but this would produce a less ‘smooth’ schedule. On the other hand, it is not reasonable for producers to know with full information about the position of every point on a supply curve so some balance would be struck between simplicity and accuracy. Within the ABM simulation, the entire supply curve is calculated and submitted. Over the three buying iterations, points on the supply curve are not removed and some precision is therefore lost in the price estimate of iteration 2 and 3.

Three buying iterations have the effect of increasing the price as the demand curve shifts upwards. Successful buyers do not bid again in the next iteration and are hence
removed from the demand curve revealed in following iterations. Buyers who are not successful again decide on their WTP values as described in equation 63 and submit their bids in the next iteration, but face higher prices. Approximately 75% of trade volume occurs in the first iteration. It should be noted that the assumption of a static supply curve serves to keep prices from a further increase in iteration 2 and 3. If the supply curve was updated after iteration 1, the removal of the lowest priced offers to sell would shift the supply curve to the left. Figure 24 presents three demand schedules and one supply schedule for one instantiation of agents. All bids to buy (offers to sell) above (below) the estimated price are successful, and agents update their available permits accordingly, and lodge a cost $FC_{j,t}$ (revenue $FR_{j,t}$) for equation 60 based on the amount they each buy (sell).

![Graph](image)

Figure 24: Simulated demand and supply curves in a water quality market. Three iterations of a multiple call market allow unsuccessful buying bids to be adjusted and re-submitted, with static supply schedule for n=164 traders.

The final set of operations in each time step reflect land use change patterns occurring in many agricultural regions worldwide where high urban land values are driving conversion of agricultural land to residential use. Land use change in the case study region has been previously explored in Roebeling et al. (2007), which examines the conversion of sugarcane to grazing, horticulture and urban uses. Restrictions on urban development in the region do not allow producers to choose to sell parcels for residential development at will.
Land use change is modelled in a simplified fashion which is exogenous to agent decision making, and calculates the area converted to urban and horticultural land use based on population trends. Change to horticulture is assumed to occur for the smallest properties that have the greatest incentive to diversify, as seen in historical patterns described in Bohnet (2008).

Table 5: Parameter table for water quality market simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value (sugar / hort)</th>
<th>Eq.</th>
<th>Parameter</th>
<th>Value</th>
<th>Eq.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_{j,\alpha} )</td>
<td>130 kg/ha</td>
<td>57</td>
<td>( PSD_i )</td>
<td>20</td>
<td>59</td>
</tr>
<tr>
<td></td>
<td>300 kg/ha</td>
<td></td>
<td></td>
<td>6.6</td>
<td></td>
</tr>
<tr>
<td>( SD_i )</td>
<td>30 kg/ha</td>
<td>57</td>
<td>( CP_i )</td>
<td>30 ([$/t])</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>69 kg/ha</td>
<td></td>
<td></td>
<td>300 ([$/t])</td>
<td></td>
</tr>
<tr>
<td>( \gamma_i )</td>
<td>0.07</td>
<td>58</td>
<td>( V_i )</td>
<td>1600 ([$/ha])</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>0.015</td>
<td></td>
<td></td>
<td>3000 ([$/ha])</td>
<td></td>
</tr>
<tr>
<td>( \delta_i )</td>
<td>-0.023</td>
<td>58</td>
<td>( \epsilon_i )</td>
<td>12</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>-0.007</td>
<td></td>
<td></td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>( \beta_i )</td>
<td>0.9</td>
<td>58</td>
<td>( FP )</td>
<td>0.7 ([$/kg])</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( PP_i )</td>
<td>100</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>33</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Simulations were run for a number of scenarios which explore market and production outcomes. This section presents results from a) simulations with different cap levels for aggregate fertiliser application (and without land use change), b) simulations where land use change occurs, examining how the water quality market functions during this transition. Further results are presented on the effect of agent heterogeneity on market functioning.

Indicators tracked within the model and presented here inform the effectiveness of the MBI. The trading price \([$/kg]\) and trading volume \([t]\) inform the costs faced by traders and the market throughput. A cost savings (aka gains from trading) metric is calculated in monetary units for how much market participants have benefitted from trading. This compares a uniform regulation where fertiliser application rates are set at
(a maximum of) recommended rates and no trading is conducted. This serves to compare the scenario using a water quality market to the case where agents all face a uniform standard for application rates, but without the ability to trade, hence a ‘cost saving’ above regulation without a market. Sugarcane yield for the spatial extent of the case study [t] is impacted by the cap level and trading of fertiliser permits. The distribution of profit within the population of agents is measured by a gini coefficient, where 0 represents a completely homogenous population (exactly equal, with all agents receiving the same profits), and where values upwards of 1 occur where the distribution of profit is skewed towards only a few individuals (less equal).

Simulations were run testing 5 cap levels which constrain aggregate fertiliser application. The cap is the total number of fertiliser permits available, and is set via the model interface. Five levels were used: 1004 t (100% of recommended rates), 904 t (90%), 803 t (80%), 703 t (70%), and 603 t (60%). The term ‘recommended rates’ is the fertiliser application rate recommended by agronomists and extension officers [130kg/ha for sugarcane and 300kg/ha for horticulture], multiplied by the area under production. Figure 25 presents model outcomes for a) trading price [$/kg], b) market trade volume [t], c) cost savings comparing aggregate revenues under the water quality market with those realised under a uniform regulation with no trading [$], d) total sugarcane yield ['000 t] and e) the gini coefficient for farm profits, describing the distribution of profits across the agent population. Values in Figure 25 are mean values for 100 trading periods with re-initialised agent populations each period, and confidence intervals (α = 0.05).
Figure 25: Simulation outcomes for a) trading price, b) market trade volume, c) cost savings comparing aggregate revenues under the water quality market with those realised under a uniform regulation with no trading, d) total sugarcane yield and e) the gini coefficient for farm profits, describing the distribution of profits across the agent population. Values are mean estimates for 100 trading periods and confidence intervals.
The trading price increases super-linearly with lower (more stringent) cap levels, as might be expected. Trade volume increases linearly as less permits are available, and agents price them higher, yet demand more under stricter cap levels. Cost savings from trading versus the case where producers face a uniform regulated application rate increases nearly linearly as well. As would be expected, the total aggregate sugarcane yield decreases as the cap levels tighten, with significantly different results between 70% and 80% restrictions. The gini coefficient is higher with lower cap levels, indicating that profit distribution becomes less equitable with lower caps. Cap levels between 70% and 80% again become significantly different, indicating the distribution of profits within the agent population begins to change past this point due to concentration of profits within a smaller number of agents.

Simulations were conducted comparing a baseline scenario to the situation where land use change occurs. The baseline is set at the previously reported cap level of 803 t or 80% of recommended rates, with land use kept static over time. Against this, outcomes are reported for the same cap level of 80%, but with land use change to urban and horticulture use occurring.

Increasing urban areas occurs at the expense of sugarcane and grazing, and horticulture converts sugar areas but not grazing. During this transition over time, the water quality market is played out for the sugar and horticulture properties. Results are presented here for market performance during this land use change situation, with Figure 26 reporting mean values for 15 simulation runs of 65 time steps, and confidence intervals (α = 0.05) for a) trading price [$/kg], b) total volume traded [t], and c) the gini coefficient for profit equitability [0-1]. The grey line represents mean outcomes and confidence intervals for the baseline scenario of a water quality market operating without land use change, and the black dashed line reports mean outcomes and associated confidence intervals for the situation where land use change occurs. The temporal extent of 65 years is presented in Figure 26 given that this is an effective length to communicate statistically significant differences in the two scenarios.
Figure 26: Simulation outcomes for a static baseline (grey) and a land use change scenario (dashed black) testing the effectiveness of the cap-and-trade system as land use change occurs. Mean values are depicted for 15 simulation runs of 65 time steps, and confidence intervals (\(\alpha = 0.05\)) for a) trading price, b) total volume traded, c) the gini coefficient for equity of profit distribution.

The trading price is not significantly different for the two scenarios. Trade volumes for the baseline and land use change scenarios are not significantly different for the first half of the simulation until horticulture area has increased sufficiently to demand a larger amount of permits from sugarcane production, and at this point trade volumes pick up even though fewer permits are available as land conversion to residential use occurs. The gini coefficient for the land use change scenario decreases and is significantly different than the baseline. This indicates that profits are being distributed more evenly within the system as land use change occurs, which is perhaps counter intuitive given the fragmentation of properties that occurs with the random selection of urban plots. This can be explained by change to horticulture land use, namely that the smallest sugarcane properties are the first to transition, thereby raising the income of these properties that cannot realise economies of scale like larger properties. This has the effect of removing small, and therefore generally less profitable properties, allowing smaller properties to generate higher income on the same area of land, hence resulting a more equal distribution of income. This pattern reflects the trends reported in Bohnet (2008) that diversification to horticulture has historically been an option for small properties when sugar prices were low.
Throughout the process of testing the model, a variety of sensitivity analyses were performed. The agents’ production heterogeneity, controlled via the model interface by moving a slider for parameter $\kappa_j$, from equation 59, was found to strongly influence market outcomes. When heterogeneity is low, demand and supply curves are flat, and trade volume is accordingly low. In this case only the outliers have incentive to participate. As productivity heterogeneity increases, the supply and demand curves take on their familiar upward and downward sloping forms.

Estimates of costs savings are low from trading compared to a regulation requiring uniform standard application rates. Therefore, the benefits of a cap-and-trade instrument might be limited compared to the cost of creating and maintaining the instrument, and modest gains from trading by producers should be viewed in light of the significant time and effort that would be required to participate effectively. The transaction costs of establishing, regulating and participating in such an MBI would likely outweigh the gains. The literature on balancing the benefits and costs of creating an MBI is limited, however comparison can be made to Whitten et al. (2007) where costs (beyond transaction costs) are discussed, including the costs of designing, implementing and enforcing the policy and the ongoing administrative costs to participants under the policy. The latter study identifies that a cap-and-trade system incurs transaction costs associated with trading, as well as ‘policy’ costs which would need to average less than AUD$268,000 per annum to yield a net benefit (Whitten et al. 2007) in the case study examined therein. In the Whitten et al. study, costs of establishing and maintaining the market-based instrument include the costs of creating a registry, defining and assigning property rights and verifying trades. Results for the ABM of a water quality market involving 164 properties in the Douglas Shire achieves greater cost savings as the cap is tightened, with the highest value of AUD$110,000 realised at a cap of 60% of recommended rates. In this instance the cost of implementing the policy, if the Whitten et al. study is used as a guide, would likely not warrant the savings to producers.

The population in this case study is likely not large enough and diverse enough in their productivity to warrant the use of a market-based tool which was shown to depend strongly on the level of agent heterogeneity. Further research into crop
production functions can help to better inform this issue. However, the future landscape may look very different than the current relatively homogenous land use pattern dominated by sugarcane, and the facilitation of permits for new land uses could see the benefits of the water quality market be realised in time.

This research contributes to the emissions trading literature by examining how MBIs operate in a landscape in transition. The model represents shifts in land use from agricultural (sugarcane) to residential use, and also high-value and high fertiliser input) horticulture. The urbanisation trend effectively removes permits from the market by converting sugarcane farmland, and would thus potentially undermine the effectiveness of the market-based instrument. However, the cap-and-trade system facilitates the transition to horticulture uses by allowing areas converted to horticulture to acquire sufficient fertiliser permits from the market. The market was able to distribute permits for fertiliser application through this transition from one land use to another whereas regulation such as a uniform standard application rate without trading might hinder this transition. Land use change in the model increased trade volume because of the increased need of an expanding horticulture industry which maintains a trade volume that is significantly higher than the scenario without land use change. For these reasons, the cap-and-trade system is seen to do well at accommodating the dynamics of land use change.

This research also contributes to examining how benefits are distributed under a cap-and-trade system, with the model calculating the gini coefficient as a measure of income inequality among farmers. Income is distributed more evenly as land use change occurs, but less evenly as the cap level tightens. This finding has relevance for the broader emission trading literature, for example whether income equity of participants in a cap-and-trade scheme (for example between countries or individual polluting firms) is improved or worsened under an emissions trading system. Bosello and Roson (2000) argue that distributional effects of emission trading schemes should not be seen as separate to efficiency issues. In the emission trading literature notions of equity for bearing the burden of abatement are frequently discussed, but how the trading instrument affect income inequality within the population of trading participants appears to be little studied. The findings discussed here suggest that the internal dynamics of the regulated industry (in our case diversification patterns to
higher value and higher input crops) are critical to whether inequality is confounded or lessened by the market-based instrument.

This case study implements and ABM of water quality markets, and is an improvement on the version presented in Chapter 4.2 by developing a user interface which is interactive and intuitive for use with stakeholders, agronomists and policy makers. However, the model still assumes agent trading behaviour to be fully informed and rational and therefore does not allow testing the outcomes of simulations were assumptions based on behavioural economics. It is hypothesised that such behaviours may lead agents to make less than optimal trades, and potentially reducing market efficiency. In order to bridge this gap, an experimental economics module was constructed, described in the following section.

4.4 Calibration of agent-based models using experimental economics

This case study describes an application of using experimental economics to calibrate decision making functions in an ABM as described in Heckbert (2009) and Heckbert and Bishop (in press). The ABM described in Chapter 4.3 was constructed to explore the possibility of managing water quality using a cap-and-trade system for managing water quality. In Chapter 4.3, model results are reported for simulation using fully informed rational agents who choose optimal price-quantity bundles for trading. A method of capturing deviations from this behaviour in experiments with human participants was constructed using an experimental interface which allows participants to login to the ABM and take control of the decisions of an agent while the model runs. Participants can ‘play’ against a population of artificial rational agents, versus groups of human participants, or some combination of both. From the data revealed by participants, assumptions regarding agent behaviour can be modified in the original model. By this process, empirical data about how individuals make specific decisions can be brought into the model, supporting the defensibility of model assumptions.
The results presented in Figures 25 and 26 in Chapter 4.3 are based on model assumptions of fully informed and rational agents who optimise their production and trading behaviour, whereas agents programmed with behaviours more akin to those of real humans might result in a different set of willingness-to-pay (WTP) and willingness-to-accept (WTA) values and different production and trading decisions. This would in turn alter the price and market efficiency. Depending on market design, experience of traders, access to information and other conditions required of markets to operate efficiently, behaviour in real markets is expected to deviate from optimal behaviours.

Following from Chapter 2.2, we understand many decisions faced by humans are dealt with using strategies familiar in behavioural economics. Relevant to this application are behaviours expressed by traders in markets and agricultural decision making, namely how producers deal with uncertainty and risk, and how quickly inexperienced traders are able to learn which price-quantity trading bundles will deliver the best payoffs.

The sources of uncertainty and risk in agriculture are numerous and diverse, ranging from events related to weather conditions, changes of prices in agriculture products, the effect of fertilizer and other inputs, financial uncertainties, and policy and regulatory risks (Aimin 2010). For an individual farmer, risk management involves finding the preferred combination of activities with uncertain outcomes and varying levels of expected returns (Aimin 2010). Risk aversion therefore plays a large role in agricultural production, and has been thoroughly studied in the agricultural economics literature. Aimin (2010) and Bontems & Thomas (2000) find that when decision makers are risk averse, they are willing to give up some income to protect themselves from future events that may cause them to lose large amounts of income. Similarly, Lambert (1990) examines the effect of adoption of management practices for fertiliser applications, stating that it is well known that optimal input levels may be different for the risk averse level chosen under uncertainty compared to optimal levels predicted under certainty and risk neutrality. The conclusion for policy makers designing MBIs is therefore that pollution control mechanisms may thus over- or underestimate policy effectiveness depending on risk averse behaviour of farmers.
Isik (2003) presents a model of farmer decision making developed to determine the extent to which uncertainties about soil productivity and weather affect production input decision making. This study finds that uncertainty can lead risk averse farmers to apply more fertilizers and generate more pollution than in the certainty case. They conclude that ignoring uncertainty and risk aversion would overestimate the economic and environmental benefits of best management practices and underestimate the incentives required to induce adoption. Isik (2003) found that best management practices can reduce nitrogen pollution relative to conventional practices but in the presence of uncertainty about weather and soil conditions in the field, the incentives to over-apply nitrogen can considerably reduce environmental gains, particularly for risk averse farmers. Similarly, Mochini (2001) present an overview of decision making under risk in agriculture, identifying that many decisions an individual producer faces involve uncertainty and therefore risk. Mochini overviews models of decision making under uncertainty which mathematically represents different methods of incorporating risk aversion into economic models. This study also finds that environmental problems related to the use of agricultural inputs such as nitrogen and pesticides may increase with production uncertainty combined with risk aversion.

Agents in the model presented in Chapter 4.3 calculate optimal application rates and WTP/WTA values for trading, behaviour which is inconsistent with behavioural economics. Given this, a robust model of production and trading behaviour should incorporate key elements of risk aversion and learning. Production input decisions and the selection of price-quantity trading bundles are precise and defined decisions, well suited to study within experiments. In order to further explore how elements of behavioural economics might affect these decisions, experiments were designed and conducted. An experimental interface was built and integrated directly with the ABM presented in Chapter 4.3. Participants login as agents, making production input decisions and choosing price-quantity bundles to trade. Experiments include participants trading with artificial agents, other human participants, or some combination of both.

The calibration process for the model described in Chapter 4.3 identified a number of data items where empirical data could improve parameterisation. Specifically, agents in the model described in Chapter 4.3 do not learn through trading experience, nor do
they respond to risk. The literature from behaviour economics suggests strategies to deal with risk and learning capacity affect trading behaviour.

The experiment was designed to test two hypotheses: 1) that risk aversion will result in experiment participants over-applying fertiliser in conditions involving risk of losing fertiliser through uncertain weather events. This can be seen as a strategy under uncertainty, to possibly over apply fertiliser at a cost rather than losing production. 2) given participants’ inexperience with trading in markets, there will be a process of learning how to make profitable trades which will improve the more times they ‘play’ the integrated ABM / experiment.

The experimental interface is depicted in Figure 27. Participants see information about their property including current bank balance, productivity compared to the population average, trading prices, and a summary table that tracks outcomes over time. Participants are provided with a marginal value table (right side of interface) which informs them of optimal WTP/WTA values for different sized trading bundles. Lastly, sliders are moved by the participant to select application rates and the price-quantity bundles for trade. Respondents’ decisions are recorded, statistically analysed and re-assigned to agents within the ABM to test the effect of the revealed behaviours.
Figure 27: Experiment and spatial interface depicting experiment participants within a running agent–based model. Participants are depicted as farmer icons and artificial agents are depicted as houses. Participants use sliders for selecting fertiliser application rates and price-quantity bundles in a cap-and-trade water quality market.

Participants were given written instructions (presented in Appendix 3) and answered a simple multiple choice test to verify they understood their task before the experiments began. Participants were paid with cash based on their performance, and filled out a post-experiment survey which elicited descriptions of the strategies they used. From a pool of 20 student participants (3 Ph.D. 4 M.Sc. and 13 undergraduate), 109 replications were conducted from July 17 – 20 2009, an average replication having six participants playing simultaneously alongside a larger population of artificial agents,
and a maximum of 20 participants for treatments where only human traders were included. Wording of the instructions and interface is intentionally neutral, such that participants apply ‘inputs’ for ‘production’ rather than ‘fertiliser’ for ‘sugarcane’, in order to control for context-dependant behaviour. Participants sat at individual computers where only the interface depicted on the top panel of Figure 27 was visible, with the group of participants monitored by the researcher who was able to view participant decisions via a control panel which also includes the spatial landscape and interface presented in Figure 23 of Chapter 4.3.

The experiment consisted of three parts meant to train the participant in performing trades. The model progresses at 10 second time steps, deemed sufficient for participants to view the outcome of their decisions and adjust sliders to attempt improved outcomes. Firstly participants select input application rates over multiple time steps, and are presented with a history of outcomes as well as the results of their best outcome so far and the input application rate achieving this best outcome. When all participants have decided on ideal application rates (or the researcher at the model control board deems they will not be able to do so), the second part of the experiment begins, where a random amount of inputs is ‘lost’, akin to losing an amount of fertiliser due to uncertain rainfall events. Participants are presented with the maximum possible input loss and informed that the actual input loss will be a random number up to this level, uniformly distributed. Participants were asked to adjust application rates based on this stochastic event, again repeated over several times steps. Lastly, participants are presented with a cap on the number of inputs which can be used, and asked to select prices and quantities to trade.

All information and parameters from the interface are recorded in spreadsheets along with the participants’ selections for inputs (fertiliser application rates) and their price – quantity trading bundles. From the output data several statistics are calculated, including the difference between optimal and chosen input levels, the learning rate of participants in finding selected values, the adjustment of inputs in response to risk, and the effect of risk in trading price and quantity.

Respondent decisions were recorded and statically analysed, with results presented in Figures 28, 29 and 30. Dependant variables measured include:
• The number of time steps required for respondents to find their optimal application rate (Time to Optimal Decision)
• The standard deviation in chosen application rates until this value was found (St.Dev. Until Optimal)
• The adjusted application rate in response to risk (Risk Markup), which is measured as the difference between the expected value (½ of the maximum loss given the uniform distribution, and e( ) rather than the $ value) of input loss and the additional level of inputs chosen.
• The standard deviation of the spread of chosen application rates during risk (St.Dev. During Risk)
• The number of time steps required for respondents to make optimal trades through finding ideal price - quantity trading bundles (Time to Optimal Trade)

These were measured against dependant variables of:
• The number of times the respondent participated in the experiment (Plays)
• The productivity of their assigned properties (Productivity)
• The expected amount of fertiliser loss (Rain)

Figure 28 displays results for dependant variables in response to the number of times the respondent participated in the experiment (Plays). The number of time steps before participants find their optimal input level decreases with the number of times played. The standard deviation in their selections also decreases with the number of times played. The risk markup increases and the standard deviation in selected values decreases with the number of times played. Interestingly, the risk markup value converges to 0, meaning the more experienced the trader the closer their additional input level equals the expected value of input loss. This is contrary to hypothesis #1, that participants will select an input level higher than a risk markup of 0. The explanation for this is that participants are focussed on repeated once-off outcomes rather than the total span of temporal outcomes. Were a higher-order strategy taken across multiple time steps, participants may have found that increasing input levels greater than the expected value for input loss would have achieved higher long-term profits. This wisdom perhaps comes only when decision makers are able to consider the longer-term consequences of strategies, which is perhaps not possible under once-
off (although repeated) abstract experiments but is possible by producers who are attuned to the dynamics of their properties and production over long time scales.

Lastly for Figure 28, the time taken for participants to find an optimal trade decreases with the number of times played. The decreasing trend in four of the dependant variables and the increasing trend in the risk markup confirms hypothesis #2, that inexperienced traders learn to improve their performance with more experience playing. Although $R^2$ values in all results in Figures are low, the relationships between Time to Optimal Decision, St.Dev. until Optimal and St.Dev during Risk display among the highest $R^2$ values, which suggests these variables are ones that participants are able to ‘learn’ best.

Figure 28: Statistical interpretation of results revealed in human subject experiments integrated with an agent-based model. Curves show the rate of learning based on increased experience within experiments (number of plays).

Figure 29 displays results for dependant variables in response to productivity of their assigned properties (Productivity). Dependant variables of the time to optimal input
decision, standard deviation in input selection levels, and the standard deviation during risk slightly increase with productivity, and the risk markup value slightly decreases with increasing productivity. However very low $R^2$ values are found for all, suggesting that decisions are independent of whether the productivity of the assigned property is high or low. Interpreting this finding suggests that performance does not depend on whether the property is highly productive or not which would have presented a bias in the results, and all participants have an equal opportunity for making good (or bad) decisions.

Figure 29: Statistical interpretation of results revealed in human subject experiments integrated with an agent-based model. Scatter plot data show the relationship between participant performance and the productivity of their assigned properties.

Figure 30 displays results for dependant variables in response to the expected value of input loss (Rain). The risk markup is seen to be independent of the expected loss of input given the near horizontal trend and low $R^2$ value. However, the standard deviation of input selections during risk increases in response to greater input loss and records the highest $R^2$ value of any of the results presented. This is interpreted to mean that as the possibility of losing inputs increases, so does the range of selected values chosen to deal with this uncertainty. Or in other words, the more uncertain the system, the greater set of strategies employed to deal with this uncertainty.
Figure 30: Statistical interpretation of results revealed in human subject experiments integrated with an agent-based model. Scatter plot data reveals the relationship between strategies employed and the uncertainty related to the decision making context.

The results from Figures 28 – 30 suggest that inexperienced traders can learn to perform well with sufficient practice, that irrespective of productivity participants are able to direct decisions towards beneficial outcomes, and that participants respond to greater uncertainty with a wider range of adaptive strategies. Interpreting these results beyond hypothetical simulated markets to recommendations for implementing real markets with actual producers, the first point highlights the importance and real value of training and education. If the ‘learning curve’ can be reduced prior to real trades, overall market benefits as measured through market efficiency and gains from trading will be improved. Also, there is an equal opportunity for making beneficial decisions regardless of conditions on-farm, such as being more or less productive than other farms. Lastly, producers can deal with uncertainty through adaptive strategies and can mitigate risk.
In terms of the value of integrating ABM and experiments, it is shown here that important elements of behavioural economics can be identified in decision making and incorporated into agent behaviours. In this example, the learning rate observed in participants can help inform how much training and education might be required for producers to perform well in markets. Furthermore, unlike other applications which use experiments separate from ABM, the integrated system can find behaviours that might not have been observed using the two in separation. Specifically, this application found that risk markups converge to 0 rather than observing a longer term strategy of markups above 0 to mitigate risk across decision making events. Thus the strategy employed is a function of the decision making situation. In this case the decision making situation for participants and for agents is exactly the same given that participants login and take control of the agents within the model. Were the two methodologies used without this integration, the experimental design might have allowed for finding this risk-averse strategy, agents would be separately endowed with this behaviour, but the decision making context of artificial agents may not have called for this strategy to be employed. Thus the benefit of integrating the two methodologies is in ensuring the decision making situations are identical for participants and agents, reducing the likelihood that the researcher will embed their own subjective ideas and interpretations of revealed participant data when re-assigning the results to agents.

The fact that experiments can be designed to test specific decision making situations, such as what strategies are employed to deal with risk, and how steep is the learning curve, offers a methodology which is generalisable across studies. This specifically addresses research questions #1, whether techniques in social and economic science can be used to gather empirical data, and which of these offer a generalisable methodology to allow comparability between studies. Research question # 2 is also addressed, namely whether experimental economics can be integrated with ABM to gather data for calibrating the model, and whether there are benefits in integrating the two into a single platform. Results from this example of integrating experimental economics, the first observed in the literature, suggest that experiments are in fact a generalisable methodology for gathering empirical data, they offer the opportunity for results to be comparable across ABM applications, and there are real benefits to
integrating experiments and ABM from the reduced need for subjective interpretation of experimental results by the researcher.
Chapter 5: Discussion and Conclusions

Ecological economics addresses the interconnections between biophysical and socioeconomic processes, and simulation modelling can assist in quantitatively understanding the feedbacks within and between these complex systems. Issues such as renewable resource management, conservation, sustainable development and implementing effective environmental policies are characterised by a multitude of decision makers acting and interacting with complex feedbacks within and between human and biophysical systems. For research questions that depend on these interactions, agent-based modelling (ABM) is presented as a useful tool for representing micro-scale dynamics that lead to macro-scale outcomes.

Increasingly, researchers are using multiple methods to calibrate ABMs. Techniques to empirically calibrate representations of decision making in agent-based models are discussed in Heckbert, et al. (2010b) and Heckbert & Bishop (in press). These include surveys, semi-structured interviews, existing data sources such as GIS and census data, direct participant observation, role playing games, and experimental economics. These techniques are increasingly being used to collect empirical data upon which defensible representations of agent decision making can be represented. However, these methods are often designed within the context of the given application, and therefore do not offer generalisable techniques that are comparable across studies.

Given this, two research questions were posed:

1. What techniques in social and economic sciences can be used to gather empirical data for model calibration, and which of these offer a generalisable methodology to allow comparability between studies?

2. Can experimental economics be integrated with ABM to gather data for calibrating models, and what benefits can be realised by integrating the two into a single platform?

To address these research questions, a number of original ABMs were constructed and are presented in Chapters of this thesis, with applications to natural resource management and specifically modelling market-based instruments for environmental management. The results of these ABMs can inform environmental policy design,
however the robustness of simulation results depends on the underlying assumptions of the model, particularly how agent decision making functions are designed and parameterised.

Calibration methods presented here include surveys, interviews and experimental economics, and are presented as techniques to calibrate ABM which offer possible consistency between applications and are grounded in robust data gathering and analysis techniques commonly used in social and economic sciences. It is determined that discrete choice surveys and experimental economics are generalisable and thus allow comparability. However interviews are deemed to not be generalisable given the context dependant nature of this form of gathering data. A novel approach is described using experimental economics directly integrated with a spatially explicit agent-based model in order to reveal production and trading behaviours in a water quality market. Tight coupling of the simulation model and experiment ensures consistency in the experimental design and model algorithms, reducing the need for interpretation in subsequent use of participant data to re-calibrate artificial agents.

Combining ABM and experimental economics has begun to be identified as a useful methodology to assist development and calibration of models. Chen (2007) argues that ABM matches well with experimental economics and behavioural economics, and that models of artificial and human agents should not be separate entities. Likewise, Boscetti (2010) calls for a framework for integration of ABM and experimental economics, using experiments to observe and record behaviours. Barr et al. (2008) also suggest using human experiments as a calibration method to draw parameters for ABMs by fitting learning algorithms to experimental data, and then reapplying these algorithms in models. Nevertheless, applications using experiments with ABM are limited, namely to Chan et al. (1999), Duffy (2004), Duffy and Unver (2006), Evans et al. (2006), Lopez-Paradez et al. (2008), Janssen et al. (2009), and Chen et al. (2007; 2010). Barr et al. (2008) assert that the state of art is no longer a lab with only human subjects, but a lab comprising both human agents and software agents. Although Barr et al. (2008) and Contini et al. (2006) identify the benefits of integrating ABM and experiments, applications in the literature apply these techniques separately, using one to inform the other. There appears to be no examples in the literature of an integrated ABM and experimental economics platform.
The research questions presented here address calibration issues in ABM through a series of case studies presenting six ABMs, each involving calibration activities using surveys, interviews and/or experimental economics. The models address issues in natural resource management including cumulative impacts management, rangelands management, urban sprawl, and the use of market-based instruments in both water use and water quality markets. In each case, the design and parameterization of agent decision making functions is informed by empirical calibration exercises. The major contribution is the design of an experimental economics platform integrated with an ABM for the purpose of gathering participant data and in turn parameterisation of model functions.

Chapter 2 reviews the relevant literature, including an overview of the history of applications of ABM, ways of modelling human decision making in ABM, and presents current techniques to empirically calibrate representations of decision making in agent-based models. A variety of approaches are reviewed, including estimating agent preference functions from discrete choice surveys, as well as ways to elicit behaviours from participants through context-rich media such as visualisation and companion modelling. Increasingly, researchers are using multiple methods to calibrate ABMs. Polhill et al. (2010) use qualitative field research data to extend a pre-existing model, highlighting that data can be brought in usefully at several stages of model development and use, and that empirical data is not the only form of useful information required for building robust models. Empirical data gathering techniques are reviewed, including include surveys, semi-structured interviews, existing data sources such as GIS and census data, direct participant observation, role playing games, and laboratory experiments.

Laboratory experiments are identified as a useful tool to inform ABM and vice versa, and can be used to strip away contextual influences and test human behaviour in very controlled decision making settings. Experimental economics uses participants in laboratory settings to study economic behaviour and test theories of decision making. Using experiments in conjunction with ABM allows agent behaviours to be calibrated from the results of experiments to create a population of agents whose behaviours are
consistent with the experimental results. In this way, experiments can be used to bring empirical data into the ABM from data sets of observed behaviour.

Chapters 3 and 4 present applications of ABM using these calibration techniques. Three ABMs presented in Chapter 3 highlight how surveys and interviews can be used in designing and calibrating ABMs. The first case study addresses cumulative impacts from multiple resource users operating on the same landscape, namely forestry and hunting. This model examines cumulative environmental impacts caused when two resource users overlap in space and generate environmental impacts greater than the sum of their parts. The second case study addresses the issue of water quality from sedimentation caused by grazing management practices. The third case study uses ABM to simulate the macro-form of urban sprawl. The first and third ABMs presented use agents with a parameterised utility function to determine locations to attend. The utility function takes on a functional form which allows parameterisation from studies which estimate preferences using random utility modelling using data from discrete choice surveys (for example Adamowicz et al. 1997; 2004 and Boxall & Macnab 2000). This approach can be used as a consistent method of calibrating ABMs which represent agents making selections from a set of choices, based on preferences for the choices’ attributes. The second ABM presented uses surveys to design and parameterise grazing management strategies, using responses to calibrate timing of management actions through the production year. It is determined that interviews do not provide a comparable methodology, specifically because their content are highly context-dependant and results from one context are not likely to be representative of other contexts.

Three ABMs are also presented in Chapter 4, all modelling the use of market-based instruments for managing water issues. ABM is determined to be a particularly useful technique given the ability to represent individual traders in markets who also incur environmental impacts in space. The case study in Chapter 4.1 applies an ABM to simulate a cap-and-trade system for allocating groundwater extraction rights for irrigators, termed a water market. The second and third ABMs presented in Chapter 4.2 and 4.3 implement a cap-and-trade system to manage water quality from land catchments of the Great Barrier Reef, termed a water quality market. The third model was constructed to implement a number of improvements on previous research,
namely an interactive user interface, and an experimental economics interface integrated with the model.

Chapter 4.4 describes the integrated ABM and experiment platform. Participants in the experiment login to the ABM and take control of the fertiliser application decisions of agents and the formation of price – quantity bundles for trading. Results identify that learning to select beneficial decisions occurs with repeated ‘plays’ of the experiment. The number of time steps before participants find their optimal input level and the standard deviation in their selections decreases with the number of times played. The risk markup increases and the standard deviation in selected values under risk decreases with the number of times played. Interestingly, the risk markup value converges to 0, meaning the more experienced the trader the closer their additional input level equals the expected value of input loss. This is contrary to the hypothesis that participants will select an input level higher than a risk markup of 0 in order to buffer risk. The explanation for this is that participants are focussed on repeated once-off outcomes rather than the total span of long-term outcomes. Were the focus on achieving the best outcome across multiple time steps, participants would have found that increasing input levels greater than the expected value for input loss would have achieved higher aggregate payoff over time. This wisdom perhaps comes only when decision makers are able to consider the longer-term consequences of strategies, which is perhaps not possible under once-off (although repeated) abstract experiments but is possible by producers who are attuned to the dynamics of their properties and production outcomes over long time scales.

Experiment results suggest that inexperienced traders can learn to perform well with sufficient practice, that irrespective of productivity participants are able to direct decisions towards beneficial outcomes, and that participants respond to greater uncertainty with a wider range of adaptive strategies. Interpreting these results beyond hypothetical simulated markets to recommendations for implementing real markets with actual producers, the first point highlights the importance of training and education to reduce the learning curve prior to actual trades. By doing so individual payoff will be increased and overall market benefits as measured through market efficiency and gains from trading will be improved. Also, there is an equal opportunity for making beneficial decisions regardless of conditions on-farm, such as
being more or less productive than other farms. Lastly, producers can deal with uncertainty through adaptive strategies and can mitigate risk.

This last case study presents a novel use of integrated ABM and experimental economics to ground agent decision making in behaviours expressed by humans. Previously studies have used experiments and ABM separately to guide the design of agent behaviours, but are still reliant on subjective interpretation by the researcher in identifying and re-assigning behaviours. The example described here directly integrates the experiment with the ABM, reducing risks of misinterpretation because the experimental design and ABM offer exactly consistent decision making situations. Because the experimental interface is coupled directly with functions coded into agents, consistency in the ABM and experiment is maintained through directly linking parameters and equations programmed into the ABM into the participant interface. This allows for a very tight definition of the decision making problem, allows control over what information is available, and helps to address the issue of whether there are inconsistencies between the experimental design and interpreted behaviours. This example of an integrated experiment and agent-based model highlights ways that the outstanding challenge of calibrating models can be approached through gathering data on human behaviour. Alongside data from surveys, interviews, and participatory approaches, experimental economics can provide empirical data for designing and parameterising agent decision making functions.

Experiments can be designed to test specific decision making situations, such as identifying strategies employed to deal with risk and the rate of learning to achieve improved payoffs. This offers a methodology which is generalisable across studies which examine similar factors influencing decision making. This specifically addresses research question #1, whether techniques in social and economic sciences can be used to gather empirical data, and which of these offer a generalisable methodology to allow comparability between studies. Research question # 2 is also addressed, namely whether experimental economics can be integrated with ABM to gather data for parameterising the model, and whether there are benefits in integrating the two into a single platform.
Results from this example of integrating ABM and experimental economics, the first observed in the literature, suggest that such experiments are in fact a generalisable methodology for gathering empirical data, they offer the opportunity for results to be comparable across ABM applications, and there are benefits accruing from integrating experiments and ABM from the reduced need for subjective interpretation of experimental results by the researcher.

Results from the experiment suggest specific ranges of circumstances or model types for which calibration using experiments would be appropriate. Experimental economics is used generally to test tightly defined decision making situations in controlled settings. The omission of context is deliberate, in order to isolate specific influences on decision making. This makes experiments useful for similar situations that a decision making agent must face, with examples here of choosing inputs to production and pricing bundles of goods to trade. In essence, these are decisions where a selection from a choice set or a value on a continuum exists, each with varied tradeoffs. Experiments are particularly useful for gathering data on decision making situations where real human behaviour deviates from the notion of a fully informed and rational decision maker. The myriad of interesting behaviours revealed in behavioural economics shows where the model of homo economicus breaks down. Therefore, if the research topic addressed in the ABM is dependant on behaviours which deviate from neoclassical economic theory, experiments can be used to improve representations of decision making.

Of the many representations of human decision making used in ABM, experimental economics can support several, including the commonly used heuristic-based decision making as in Schlueter & Pahl-Wostl (2007), determining aspirational thresholds as in Gotts & Polhill (2009) and Gotts et al. (2003), moving through decision trees of sequential conditional decisions as in Deadman et al. (2004), and measuring the effect of weighted social influence and imitation of others as in Polhill et al. (2001). Janssen & Ostrom (2006) present the opportunity for experiments to empirically inform ABM, and identify that the use of experiments in conjunction with ABM is increasing. However, an extensive literature search did not reveal any applications of direct integration of experiments and ABM.
Some critical reflections and evaluation of this research process suggests that integrating ABMs and experiments can add significant improvements to models and the modelling process. A well organised modelling exercise involves several steps, including interaction with stakeholders and experts in the design phase, gathering data for calibration and validation, trialling the model at a proof of concept stage, and delivering results into a policy relevant context. All too often, modelling is not conducted in a participatory fashion and stakeholder buy-in is reduced. Experiments can assist in the model design, calibration, but also in building model acceptance. It is envisioned that experiments could be used at three stages of the research cycle 1) in calibration exercises, as described here 2) trialling models in the laboratory at the proof of concept stage, and 3) running field experiments in the policy recommendations stage with the actual people who are represented by agents in the model.

Further research and applications in this area would greatly improve applications of integrating ABM and experiments given the nascent stage of this technique. As a first step, knowledge which exists separately in each field needs to transfer over. From experimental economics, ABMs will need attention to experimental design, tightly defining the choice sets and information offered to participants and the visual structure of the experimental interface. From ABM, experiments will need to be designed which test interactions between agents and the feedbacks from aggregate outcomes back to individual decision making situations. Combined, ABM and experimental economics can grow into new areas, such as re-inserting context into the experimental setting through high-detailed visualisation media, where agents and humans as avatars can interact. This provides a setting to gather revealed preferences and behaviours, and perform interactive calibration, where agents are able to adapt, learn and develop new behaviours in response to contextual information revealed by human participants. Indeed, there are opportunities to explore artificial intelligence through integrating ABM and experiments and designing worlds where the notion of artificial versus real participants is blurred. In the meantime, this research has revealed that policy directed modelling can be improved through including empirical evidence gathered in experiments. Integrating ABM and experiments allows agent
behaviours to be based on observed data, improving the defensibility of assumptions which depart from that of rational and fully informed decision making.
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Appendix 1: Publications


Baynes, T., & Heckbert, S. (2010). Micro-scale simulation of the macro urban form: opportunities for exploring urban change and adaptation. LNAI, 5683


Appendix 2: Semi-Structured Interview Question Sheet

Semi-structured interview schedule (grazers)
Interviewee ID:
Date of interview:
Length of interview:

A. Land use and management strategies (Background information on the land/land use and management/perception of official advice)

1. What kind of grazing enterprise do you have?

2. What is the size of your grazing enterprise (in hectares)?
   2.a Is it in your ownership – are you a leaseholder?
   2.b If you are a leaseholder – what is your role in farm-decision making and how long are these leases?
   2.c Could you mark the land under your ownership and/or management control in this map, the land you lease, etc.?
   2.d Have you bought or sold, rented or let any land in the past (land can be marked on the map)?
   2.e What is the price of land per cattle/beast area (per ha)?
   2.f What is considered a viable family unit (father, mother and one married son) in the area (based on native pastures)?

3. What percentage of your property is under native pasture, improved pasture, open forest, thinned open forest, etc. (native pasture/ha, improved pasture/ha, open forest/ha, remnant vegetation/ha; etc.)?
   3.a For what purposes do you use the different land use types (eg breeding, fattening, nature conservation)

4. Could you put the different land use types on the map?

5. What is the size of your herd?
   5.a What is your herd composition (eg breeders, store cattle, fattening cattle)?
       - Why did you choose this composition?
   5.b How do you manage your herd (eg target age, target weight, stocking rate)?
       - What are your age and target weight? (weight for age)
   5.c Do you manage your different herds differently (heifers, breeders and bullocks)?
       - If yes, how?
   5.d What general stocking rates to you aim for?
       - Is there a difference in stocking rate relating to land type?

6. How do you manage your grazing land – do you follow any industry codes or guidelines?
   6.a If you are certified organic – when and why did you convert/change your farming system?
   6.b How do you manage your pastures?
       - What improved pasture species do you grow (only applicable if improved pastures are grown)?
• What proportion of your fodder is made up by legumes?
• What is the carrying capacity of these improved pastures (e.g. 3-5 times higher than native pastures)?
• How often do you replant your pastures (only applicable if improved pastures)?
• What type, if any, of fertiliser do you apply?
  How much per ha (total amount per ha per year)?
• Do you use any pesticides/herbicides?
  If yes, what type and how much (per type total amount per ha per year)?
• Do you have any ungrazed areas on your property?
  If yes, how are they used?
  Do these areas have a particular value?
• How many paddocks do you have and how many different herds graze them?
• How do you decide when to move the herd to another paddock and how do you choose the paddock where you move the herd to?
  Do you have a general rule of thumb when to move the animals?
• How many watering points do you have per paddock?
  How far are they apart?
• Do you have waterways fenced off?
  If yes, how do you manage these areas?
• Do you control regrowth?
  If yes, how often do you control regrowth and how?
  If regrowth is controlled by burning, how do you spell the area afterwards?
• Do you supplement feed your cattle?
  If yes, when, what type and how much (per head per year)?
• Do you also make hay?

(The following questions 6.c – 6.d are only asked if applicable)

6.c Orchard/s – how do you manage it/them?
• When did you plant the orchard/s?
• What is a typical yield level (tons per ha per year)?
• What varieties do you grow (traditional/modern varieties)?
• Do you use fertilisers/pesticides/herbicides/fungicides (per type total amount per ha per year)?
  If yes, what type/s, for what and how much (amount per ha per year) of each do you use and when?
• Do you have uncultivated grass strips/rough grassland margins around your orchard/s?
  If yes, how wide are they and how do you manage them?
  Why do you leave these margins?

6.d Woodlots/timber plantations/farm forests – how do you manage it/them?
• When did you plant it/them?
• What is the tree density (number of trees per ha)?
• What species have you planted?
• What type, if any, of fertiliser do you apply?
  How much per ha (total amount per ha per year)?
• Do you use any pesticides/herbicides/fungicides?
  If yes, what type and how much (per type total amount per ha per year)?
• Did you receive any grants to plant the trees?
  If yes, who were the grants from?
• Do you have a long-term management / harvesting plan?
  If yes, what for and how much (amount per ha)?

6.e Do you manage parts of your property as part of a woodland network structure?
• If yes, could you mark the area/s on the map?
• Are these areas fenced off?
• If yes, how are they managed?

6.f Have you abandoned any of your land?
• If yes, why? (fields/areas can be marked in the map)
• What are you doing on this land?
• Do you think that abandoning land has some benefit for the environment/landscape?
• If yes, in what ways?
7. How are the soils classified on your land?
   7.a Is there a relationship between soil quality and your management regime?

8. Did you carry out any changes on the land (drained marshy ground, converted native pastures, cleared native vegetation, replanted trees and/or riparian strips - orchards, changed grazing intensity, created a wetland, started a B & B, etc)?
   8.a What were the main reasons for these changes (eg to increase the area of productive land, remove a fire hazard, combat land degradation, etc)?
   8.b Did you receive advice before carrying out any of these changes?
      - If yes, was the information that you received adequate for your needs?

9. Have you used any of the agricultural extension services in the past?
   9.a If yes, which-ones?
      - For what reasons?
      - Do you find them useful?

10. Do you manage land under a voluntary conservation agreement?
    10.a If yes, who is the agreement with?
    - How long is the agreement for?
    - Is it beneficial, unsatisfactory, crucial, etc?
    - If yes, in what ways?

11. Are you managing any reserves?
    11.a If yes, are the reserves recognised by any organisation officially?
    - What sort of agreement you are having (eg management agreement) and for how long?
    - How do you manage them (if at all)?
    - Are these areas fenced-off?
    - Is it beneficial, unsatisfactory, crucial, etc?
    - If yes, in what ways?
    11.b Are there endangered plant and/or animal species on your property?

12. Do you have a whole farm plan (a map of the farmland including a list of actions to be taken over the next few years)?
    12.a If yes, why?
    - Who helped you develop it?
    - Is this plan part of an overall catchment/landscape plan?
    - Is it useful and have you managed to implement some aspects of it (eg replanting trees, fencing of bushland, soil treatments, minimum tillage, etc)?

13. Have you attended a farm-planning workshop?
    13.a If yes, why?
    - Was it useful?

14. How are your farming practices constrained by physical factors (soil quality, water, slope, climate, etc)?

15. How are your farming practices constrained by biological factors (weeds, diseases, etc)?

16. How labour intensive are your management practices throughout the year/seasons (eg mustering, sorting animals, maintenance work, feeding, fencing, etc)?
    16.a What is the division of labour between the people doing farm work?
    16.b Do you contract seasonal workers as well?
16.c Do you ever face a shortage in labour availability?
   - If so, when in the year?
16.d Did the labour intensity change over the last few years?
   - If yes, how and why?
   - Did this effect your enterprise?
   - If yes, how?

17. What farming machinery is on the farm?
   17.a What sort of activities can you carry out yourself?
   17.b Which operations (eg muster, fencing) do you contract out?

B. History (Background to grazing continuity / landscape changes and values)

1. How many years have you been living here?
   1.a Did you inherit this grazing property/business?
   1.b If yes, for how long has it been in your family?
   1.c If no, when and under which circumstances did you take over this property?
   1.d How many people live on the property?
   1.e How many are family members?
   1.f How many of them work on the property and for how many days per week?
   1.g How many of them work off-farm?
      - What do they do and for how many days per week?

2. Do you expect to have a successor who will continue to run the grazing business after you retire?

3. How old are you?
   3.a Where did you grow up (if not on this property)?

4. Do you come from a grazier’s family?
   4.a If not, how did you get into farming/grazing?
   4.b Do you have any agricultural qualifications?
   4.c Have you been in another occupation before?

5. Can you tell something about the history of this property and its surrounding (the various stages of clearing and land use/management changes)?
   5.a Time of foundation?

6. Can you describe the main changes regarding the use and management of this area?
   6.a What have been the main implications of these changes?

7. Are there any sites of historical importance on your land?
   7.a If yes, have you received any advice of how to treat these sites?

8. Are there any cultural-historical or natural elements on the farm/in the surrounding? (eg water holes)
   8.a Do they still have their ‘original’ function?
   8.b Do you integrate these elements in your farm management?
   8.c If yes, how?
   8.d If not, do you manage them – to what extent?
   8.e Do they have any value for you?
8.f If yes, which values?
8.g If not, why not?
8.h Do you think these landscape elements are threatened?
8.i If yes, do you think these threats are related to agriculture?

9. What kind of attitude is there towards nature/landscape conservation in this area – in general?
   9.a Has this attitude changed in the last few years?
   9.b If yes, what do you think this has been in response to?
   9.c Has your own perception changed?
   9.d If yes, why and how?

C. Socio-economic circumstances

1. Where do you sell your cattle (eg feed lots, life exports, local meatworks) – different products (eg breeders, store cattle, fattening cattle)?
   1.a What price do you receive for your products?
   1.b How much did the price for your different products vary over the last 5 to 10 years?
   1.c Why have there been these large changes (eg global market)?
       • How many cattle/different products do you typically sell (heads per year) and when (eg what time in the year)?
   1.d What would be a reasonable price for your products to cover your costs?

2. Does your farm satisfy any recreational/tourist needs (camping on farm, farm shop, B & B, etc)?
   2.a If yes, what and how long have these activities been operating?

3. Do you have any other (off-farm) income sources (stock market, investments, tourism, others, etc)?
   3.a If yes, what are these other sources?
   3.b What is the distribution of your income (i. on-farm income from farming and other activities, ii. off- farm employment, and iii. other off-farm income sources)?
   3.c Have these proportions changed over the last few years?

4. What are the main difficulties graziers face in this area (eg global markets, agricultural policies, climate change, scale of farm, etc)

5. Is there co-operation amongst graziers in this area?
   5.a If yes, what sort of co-operation?
   5.b Are there farmer organisations/interest groups active in your area?
   5.c If yes, what activities do they have?
   5.d Are you involved in any of these activities?
       • If yes, why?
       • If no, why not?

6. Do you think that state/federal/local government policy could or should support graziers to improve environmental conditions on farms (eg through financial incentive/agri-environmental schemes for revegetation projects/fencing on farms, schemes for the protection of native vegetation on farms, tax rebates, etc)?
   6.a In general?
   6.b In this area?
7. Do you think that state/federal/local government policy could or should stimulate land management (eg wet season spelling, fencing off different land types, off-stream watering points, adjusting stocking rates to pasture conditions, weed control) and land use change (eg crop diversification) through financial incentives and/or policy interventions (eg water restrictions)?

7.a In general?
7.b In this area?

- If yes, what kind of support/policy interventions would be useful and for what kind of activities?
- Would you respond to this kind of support (eg would you apply for funding)?

D. Future

1. What kind of future plans do you have regarding the use and management of your property?

1.a Any big changes (eg fencing off rivers and creeks, planting of riparian vegetation, fencing off different land types, use fire as a management tool, wet season spelling)?
1.b If yes, what are the reasons for these changes?
1.c Can you imagine to change your land management practices in the future (eg fencing off rivers and creeks, planting of riparian vegetation, fencing off different land types, use fire as a management tool, wet season spelling, cooperative grazing enterprises that share profit)?
1.d If yes, why and how (eg with the help of contractors, employing seasonal staff, etc)?
1.e If not, why not?
1.f What would induce you to change your land use and management practices (eg if there were opportunities for income generation, incentive schemes, other graziers who have changed)?
1.g How do you think these changes will/would affect your enterprise/the landscape of the area?
1.h With your experience and local knowledge, do you think that a certain percentage of any property in this area should be left in an uncleared state?

1.i If yes, why?
1.j If not, why not?
1.k Can you imagine converting your farming system from conventional to organic?
1.l If yes, why?
1.m If not, why not?
1.n How do you think these changes will/would affect your enterprise/the landscape of the area?

2. What are the most important aims of your work now/in the future (eg having a good lifestyle, making money out of farming, providing opportunities for children to take over farm)?

3. What are the main driving forces influencing your decision-making (eg agricultural market, succession of farm, looking after the ‘health’ of the place, creating a nice place to live, stewardship of the land)?

3.a Is the mining industry influencing the decisions you are making on your property?

4. How do you see the future of this area?

4.a In what direction do you hope this area will develop?
4.b What would be ‘the ideal prognosis’?
4.c Can you think of any circumstances under which you would consider giving up running your grazing enterprise?
Appendix 3: Experiment Instructions

Experiment Instructions

Please read the instructions carefully and answer the multiple-choice test.

Experiment Introduction

- In this experiment you can choose how many ‘inputs’ to use in ‘production’.
- Inputs cost you money to use, and using them increases output, up to a point.
- You will be paid with real money based on your profit. Decisions about inputs therefore affect how much money you make.
- You will make repeated decisions and enter your selections using a computer.
Three-Part Experiment

- There will be three parts to the experiment, within each you will select inputs within many repeated ‘rounds’.
  
  Part 1) You choose the level of inputs.
  
  Part 2) You choose the level of inputs but some may be randomly ‘lost’.
  
  Part 3) There is a limited amount of inputs for everyone in the experiment. You may keep your inputs, or trade with other participants.

Experiment Screen

- In the experiment you will use this screen to choose inputs, trade, and see the effect of your decisions.
There are four parts to the screen:

1) Current conditions
2) History of outcomes
3) Sliders to choose inputs
4) Value table

Your Information

- These boxes show current conditions.

- What you will be paid in real money
- The maximum possible loss of inputs
- Average 'Productivity' of all participants
- Your own 'Productivity'
- The number of inputs you can use (Part 3 only)
History of Outcomes

This table shows you what happened last round (1st row), in the 2nd last round (2nd row) and the best round so far (bottom).

<table>
<thead>
<tr>
<th>Input chosen</th>
<th>Inputs lost</th>
<th>Inputs traded</th>
<th>Production</th>
<th>Trading price</th>
<th>Profit from production, trading, and cost of inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Round</td>
<td>111</td>
<td>-9</td>
<td>116</td>
<td>0.76</td>
<td>930.04</td>
</tr>
<tr>
<td>Second Last Round</td>
<td>120</td>
<td>-15</td>
<td>116</td>
<td>0.71</td>
<td>920.00</td>
</tr>
<tr>
<td>Last Round</td>
<td>117</td>
<td>-2</td>
<td>121</td>
<td>0.79</td>
<td>920.04</td>
</tr>
</tbody>
</table>

Sliders to choose inputs and trading

- You can move the red button on the sliders up and down with your mouse
- The top slider is used in Part 1 and 2. The bottom sliders are used in Part 3 only (trading)
Part 1: Choosing Inputs

- **Some** items in the screen are turned off in Part 1. Part 1 is simple, you move the ‘Inputs’ slider for each round until you are happy with your decision, ending Part 1.

Part 2: Loosing Inputs

- In Part 2, a number of your inputs could be lost. *Max-Input-Loss* is the maximum number of inputs you could lose.
Part 2: Loosing Inputs

- You will lose a random number between 0 and Max-Input-Loss. Any number in that range could happen, resulting in a loss after you make your input decision with the slider. Watch the ‘history of outcomes’ to help figure out how to deal with this.

Part 3: Trading

- In Part 3 you have a limited number of inputs. You can use them for production, sell them to someone else, and/or buy more inputs to use.
- There are many other ‘traders’ who try to buy and sell, which creates a price.
- Everyone has different productivity, so the price might be good for some traders, but not good for others
Part 3: Trading

• Part 3 uses the whole screen. An equal number of inputs is available (1) to each participant, not all participants are as ‘productive’ as others (2).

How to Trade

• Inputs can be bought or sold by choosing your price and quantity
• If you have 100 units, and want 130, you can buy an extra 30, at a price determined by looking at the value table.
Choosing the quantity to trade

- If Inputs-Held (1) is higher or lower than Inputs (2) that you chose from Part 1 and 2, you may want to consider buying or selling a quantity (3).

Choosing the price to trade

- To choose the price-selling and price-buying (1), consider your quantity and Inputs-Held, and compare this to the Values Table (2).
The Value Table is used in Part 3 (trading), and shows the marginal value for each unit of input, and the range to which it applies.

For example, each 1 extra input used between 100 and 104, is worth $2.82 to you (net).

Therefore, if you currently use 104 units, by using one more, you will receive an additional $2.20.

Similarly, when using inputs in the range of 160-164, each additional one is worth $-1.42 (net). At these higher ranges, adding extra inputs costs money, but does not necessarily result in more production.

Marginal value of each input unit

<table>
<thead>
<tr>
<th>Input Range</th>
<th>Marginal Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-84</td>
<td>6.13</td>
</tr>
<tr>
<td>85-89</td>
<td>5.15</td>
</tr>
<tr>
<td>90-94</td>
<td>4.20</td>
</tr>
<tr>
<td>95-99</td>
<td>3.51</td>
</tr>
<tr>
<td>100-104</td>
<td>2.92</td>
</tr>
<tr>
<td>105-109</td>
<td>2.2</td>
</tr>
<tr>
<td>110-114</td>
<td>1.65</td>
</tr>
<tr>
<td>115-119</td>
<td>1.16</td>
</tr>
<tr>
<td>120-124</td>
<td>0.73</td>
</tr>
<tr>
<td>125-129</td>
<td>0.34</td>
</tr>
<tr>
<td>130-134</td>
<td>0.01</td>
</tr>
<tr>
<td>135-139</td>
<td>-0.32</td>
</tr>
<tr>
<td>140-144</td>
<td>-0.59</td>
</tr>
<tr>
<td>145-149</td>
<td>-0.84</td>
</tr>
<tr>
<td>150-154</td>
<td>-1.26</td>
</tr>
<tr>
<td>155-159</td>
<td>-1.25</td>
</tr>
<tr>
<td>160-164</td>
<td>-1.42</td>
</tr>
</tbody>
</table>

It is important that you understand the values in the table in order to trade effectively.

Remember the table shows the marginal value for each unit in a range.

- If you hold 124 units and you sell one unit, that unit would have been worth $0.73 at the end of the round.
- If you hold 125 inputs and you sell one unit, that input would have been worth $-0.34 at the end of the round.
- If you hold 124 inputs and you buy one unit, that input will be worth $0.34 at the end of the round.
• The price shows information about **everyone**. The Table shows information about **you**.

• If you have 100 inputs and want to buy 30, the first few will be worth more that the price \((2.82 > 0.55)\), so you would gain money from buying them

• But the last few are not worth as much as the price \((0.34 < 0.55)\), so you would lose money from buying them

• You will need to find the best combination of number to buy, and how much you

---

**Trading Rules**

• If **your** price-selling is lower than the realised price, the trade is successful

• If **your** price-buying is higher than the realised price, the trade is successful
Trading Hints

• When thinking about buying or selling units, make sure you consider the marginal values in the Value Table
• You don’t want to buy a unit for more than it is worth to you
• Nor would you want to sell one for less than it is worth
• The amount of your bid cannot influence the overall price

Finally…

• All decisions made during the experiment are confidential
• Please don’t talk or look at others’ screens during the experiment
• You will be paid in cash based on your bank balance at the end of the experiment
• You are not required to provide you name or personal information, and participation is voluntary and can be discontinued at any time. The information you provide will not be distributed for other purposes, and will not be used without your consent.
• Any questions at any time, please ask…
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Heckbert, Scott

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