A review of Multi-Agent Simulation Models in Agriculture

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Abstract

Multi-Agent Simulation (MAS) models are intended to capture emergent properties of complex systems that are not amenable to equilibrium analysis. They are beginning to see some use for analysing agricultural systems. The paper reports on work in progress to create a MAS for specific sectors in New Zealand agriculture. One part of the paper focuses on options for modelling land and other resources such as water, labour and capital in this model, as well as markets for exchanging resources and commodities. A second part considers options for modelling agent heterogeneity, especially risk preferences of farmers, and the impacts on decision-making. The final section outlines the MAS that the authors will be constructing over the next few years and the types of research questions that the model will help investigate.

Keywords: multi-agent simulation models, modelling, agent-based model, cellular automata, decision-making

Introduction

Agent-based models have become a popular method of modelling complex real world systems in the land based sector. These systems range from cattleherders' in North Cameroon (Rouchier *et al.*, 2001), to deforestation/ afforestation in Indiana (Hoffmann *et al.*, 2002) to farming in the German region of Hohenlohe (Balmann *et al.*, 2002).

This paper focuses on parts of an agent-based model for the Rural Futures FRST research programme in New Zealand, which is a 5-year FRST funded collaboration of AgReserach, Lincoln University, Otago University and others. The Rural Futures programme includes the creation of an industry level multi-agent simulation (MAS) model of New Zealand's pastoral industries. This model will describe the strategic decisions and behaviours of individual farmers in response to changes in their operating environment, and link to the production, economic and environmental impacts of their management. The MAS will need to represent the heterogeneity that exists in farmers, their systems, their responses to interventions and environmental changes, and the resultant consequences for the industry. The MAS will provide an objective tool to assist strategy and policy setters to learn about the behaviour of this complex socio-economic/biophysical system before they intervene.

MAS models allow the possibility of generating system dynamics without focussing on an equilibrium solution. MAS models provide the opportunity to assist in understanding likely emergent properties of complex systems. They are intended to capture these emergent properties, which are not amenable to equilibrium analysis. Agent Based Models are most appropriate for systems characterised by a high degree of localisation and distribution and dominated by discrete decisions.

Many MAS models have been developed for understanding and modelling land based systems, *e.g.*, AgriPoliS (Happe et al. 2006), MPMAS (Berger et al, 2007) and SYPRIA (Manson, 2005). The structures of these models are varied, but can be exemplified using an actor–institution–environment conceptual model as in SYPRIA (Manson, 2005). In such a modelling system, key actors (agent) are farmers or households. The environment defines the actors' bio-geophysical context (*e.g.*, climate and soil), and institutions (other agent types, *e.g.*, regional councils, the market, and RMA) guide actors' decision making. Three major processes are sequentially executed during each simulation time step: (1) Institutions change variables related to actor decision making (*e.g.*, policy change); (2) Environment changes according to endogenous ecological rules (*e.g.*, climate change) and the effects of actor decision making during the previous time step; and (3) each actor in the region makes land-use decisions. Information transfer among the agents constitutes an important process in decision making. It affects opinion formation, the rates of adoption of new technology, and adaption to new policy and environmental changes.

This paper focuses specifically on three parts of an agent-based model for the Rural Futures Project in New Zealand. Part one includes options for modelling land and other resources such as water, labour and capital in this model. Part two describes the incorporation of risk preferences and other personality traits into the decision making of the agents in the model. Part three discusses key drivers of the decision making process in the areas of information transfer and opinion formation. The fourth and final part examines the possibilities presented in parts one to three, discusses the

implications for modelling decision making using agent-based approaches and makes recommendations regarding a possible starting point for a model of agriculture in New Zealand. This includes discussion on how to create heterogeneous agents through modelling different risk preferences and other personality traits, which then affect the decision making of the agents in the model.

Part One: Resources and Commodities

The purpose of this part is to review the approaches to simulate resources and commodities in existing MAS models in agricultural systems.
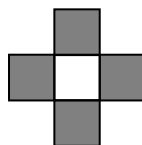
Model Structure

It is useful in any discussion of farming models to first lay out the overall structure of agent-based models. As a model of farming, perhaps the most pressing variable in question is land. Thus, a discussion of how land is represented in various models will guide the initial introduction to the various models, followed by specific discussions of how different variables such as water, labour and capital in each model are represented.

Perhaps the simplest method for modelling land was used in a model of cattleherders in North Cameroon (Rouchier, et al., 2001). In their model, the authors were interested in replicating the system by which cattleherders in North Cameroon rent access to grazing from farmers during the dry season. To model this system the authors randomly assigned a value (between certain parameters) for the number of villages in a given model run, a value for the number of farmers in each village and a value for the number of fields for each farmer. Their model did not attempt to represent land spatially because it was not of interest to model spatially oriented variables. Thus, the simple method for modelling land worked well with their model because it paralleled the way in which their cattleherder agents went about renting land.

In contrast, Balmann (1997) created a model of farming that was almost purely spatial and represented land using a cellular automata (CA) model. CA models use a grid/square structure in which each square is connected to its four neighbours (See Figure 1).

Figure 1. Visualization of a Cellular Automata Model.

Using CA to model land requires a more complex computer programme than Rouchier et al.'s (2001) non-spatial model. However, its chief advantage is that once the ground work has been done to create the CA structure, any number of different variables can easily be assigned to each cell. In addition, because each cell has a specific location, CA models can be created using GIS data or other regional, spatial data.

Recent work in modelling systems in the land based sector has developed a number of models that more explicitly combine the MAS approach that Rouchier, et al. (2001) used, with the spatial modelling CA approach that Balmann used (1997). By combining both, variables can be divided into spatial variables that are assigned to cells in a CA and personality/behavioural/decision making variables that are assigned to agents in the MAS portion of the model. A close model to our proposed model of farming in New Zealand is Berger's (2001) model of agriculture in Chile. In his model he assigned values to each of the cells in the CA matrix for soil quality, water supply, land cover/land use, ownership, internal transport costs (from the farmstead), marginal productivity or return to land. Unfortunately, Berger does not explicitly set out what variables he assigned to the agents in his model, but by implication they included at least: the amount of rented land and water rights, calculations for the highest utility for each use for each parcel of land, a variety of behavioural constraints to create heterogeneous financial and technical behaviour, and differing rates of information adoption, and the ability to exit farming if income drops below a certain level.

Manson (2000) developed a very detailed CA/MAS model of reforestation in the Yucatan peninsula of Mexico. He was interested in replicating a theoretical model in which the actors, environment and institutions were all mutually interdependent. In the CA portion of his model each cell stored values for a wide range of variables and empirical data on the real land-use and land-cover for model verification and calibration. He developed two types of agents for his CA/MAS model, smallholder and institutional agents. The institutional agents were used to communicate information to the smallholder agents about land tenure and about different markets and the smallholder agents' actions directly determined the land use/cover for each CA cell in the model. In addition, the author tested also three different decision making models – simple heuristic models, such as, use land near road for three years then leave fallow; a subsistence-oriented model whereby agents use information about each cell's agricultural suitability and distance from market to determine the location and production type necessary to feed the household; and genetic programme models, 'calibrated by matching actor land-use histories to an array of decision variables from the smallholder survey and GCA grids' (Manson, 2000). The detail that the author included in his model allowed him to incorporate a great deal of empirical data regarding soil, land use, etc.

Balmann, et al. (2002) created a model of farming in the German region of Hohenhole to address changes in European Union farming laws and subsidies. This model is similar to the model described above. The CA cells tracked values such as the distance from the farmstead, whether the area was suitable for grassland or arable farming, and the current use of the land – dairy, cattle, suckler cows, sugar beets. The farms in the model acted as the agents and thus made choices about whether to take on more loans, rent or buy land, hire addition labour, or alternatively, use labour and capital for off-farm employment (exit farming).

Modelling Resources

Among the most important commodities which could be addressed when creating a model of farming in New Zealand are land, water, labour and capital. There are a number of existing agent-based models that together encompass a variety of approaches for modelling all of these variables. In general, each of the resources can be addressed using techniques ranging from the simple to the complex. Having

provided a brief overview of a number of different models, this paper can now compare how different models have dealt with the various commodities that will be important in our model.

Land

Land is probably the most important resource in a model of farming. There are a number of ways in which land has been represented. First, Rouchier, et al. (2001) developed a purely non-spatial agent-based model, whereas, Balmann (1997) used a model that was almost purely spatial. The rest of the models that the paper examined all used a combination of a CA approach to model the spatially oriented data together with an agent approach to model differences in personality, risk behaviour and decision making approaches. Thus, for agent based modelling there are two approaches in evidence, a non-spatial approach and a CA approach with a preponderance of the modelling being done with a CA/agent-based approach.

Water

Water is also an important resource. The reviewed literature ranges from minimalist models to complex approaches to modelling water. A number of the models described above have no explicit model for water. Instead, water availability was inferred from other variables that are perhaps more proximal to farming outcomes, such as the productivity of a given piece of land, or its suitability for a certain type of land use (*e.g.* Balmann, 1997; Balmann et al., 2002). The most comprehensive model is Berger's (2001) model of farming in Chile, which used an explicit hydrological model including variables for locally available freshwater supplies, irrigation and return flows and used equations and parameters for these values derived from the Chilean Department of Public Works. He also mapped the course of water through the CA structure. Finally, this hydrological model was tied into the model for renting water rights, which further contributed to the hydrological model by establishing precedence in removing water from the system. In contrast, Rouchier, et al. (2001) modelled water simply as a value for the number of good or poor watering sites each village had access to, which they could then rent to the herdsmen. Between these two extremes, Manson (2002) used a simple model for water and assigned values for hydrology and precipitation for each of his CA cells. In the end, the modelling of water in a system only needs to be as complex as required for the issue at hand but it is useful to bear in mind that every increase in complexity entails associated additions of error and uncertainty.

Labour

Access to labour markets is another variable that distinguished the models described above. In some of the models, detailed rules were set, *e.g.*, Balmann (1997) and Balmann et al. (2002). In these models the amount of labour at each turn was based on multiple factors. First, each farm started with an initial amount of labour available. This amount of labour could then range higher as more labour was hired, or range lower as the initial labour was put to use in off-farm employment. Finally, off-farm employment could consume the entire initial on-farm labour, thus allowing the agents 'leave' farming altogether. In addition, Balmann allowed for labour units to be divisible, *e.g.*, a farmer spends some of his time in off-farm employment. The costs of labour and increases in productivity were then used in the linear model by which the farm agents made their allocation decisions. Similar to the case with water being modelled, some models did not directly take into account access to labour markets. If labour is one of the constraints on decision making, then a model that

incorporates this may lead to more realistic outcomes. That being said, there are clearly areas that could be modelled that are simple enough that there are other, more proximal constraints, than labour. In the case of these models, modelling of labour would be unnecessary and only add complexity and uncertainty to the final model.

Capital

The treatment of capital in the various models falls in line with the treatment of both water and land. In some cases capital is a detailed and important part of the decision making model for agents and in other cases capital is not included in the model. Similar to their modelling of labour, Balmann (1997) and Balmann et al. (2002) again provide more detailed and inclusive models with regard to capital. In their models, agents have access to liquid equity capital with its associated opportunity costs, short term loans and long term loans. The maximum additional long term credit a farmer has access to in the model is defined in Equation 1:

$$G \leq (L - E)(1 - v) / v \qquad (1)$$

In this equation a minimum reserve is subtracted from liquidity and the sum must be higher than the share of the acquisition costs that is financed by the equity capital. Their decision making model then also accounts for repayment of debts, assets, income, and long-term interest expenses, to fully model capital. In other, less financially oriented models, capital is not accounted for at all. Again, Rouchier, et al.'s (2001) simple model of herdsmen did not require the introduction of any form of capital market to successfully model the behaviour in which they were interested.

Markets, Trading, Trading Relationships

Markets, which can be used for exchanging resources or commodities produced with resources, are also important, as are qualifiers to these markets, such as relationships between buyers and sellers. LeBaron (2006) provides a review of four market mechanisms that modellers have used to clear their markets and this paper proposes an additional mechanism drawn from the literature reviewed thus far.

The first mechanism is a slow price adjustment mechanism, which leads to the market never arriving at equilibrium. With this type of market, agents put in orders for buying and selling, these orders are then summed and the price is increased if there is excess demand and decreased if there is excess supply. LeBaron (2006) argues that it is an advantage of the market being in disequilibrium as it might be a more accurate portrayal of the market in reality but he also criticises that the market might spend quite a deal of time far from market clearing prices, depending on the value set for the change coefficient. A specific example of this kind of market model can be found in Day and Huang (1990), who use the following equation to determine price:

$$p_t + 1 = p_t + cE(p_t) \qquad (2)$$

In this equation p_t is the price at time zero, c is the adjustment coefficient and E is the excess demand.

The second mechanism used to clear markets is a numerical solution or theoretical simplification that allows for an easy analytical solution to a temporary market clearing price. This mechanism leads to almost the exact reversal of one of the problems above. The benefit of this type of model is that the prices by design always clear the market, thus no issues arise involving a market maker, inventories or

rationing. However, this type of market model can lead to too much market clearing which could be an unrealistic divergence from the actual market in question. This mechanism most likely captures the variety of auction based methods that the farm models discussed have handled their markets. Brock and Hommes (1998) created an asset pricing model with the following equation:

$$Rp_t = Eh_t(p_t + 1 + y_t + 1) - \alpha\sigma2zs_t \qquad (3)$$

In this equation Rpt is the price in the present turn, which equals the expected price (Eht) multiplied by the sum of the future price (pt + 1) and the future increase (yt + 1), which is then subtracted from the product of risk (α) multiplied by variance ($\sigma2$) multiplied by share per person (zst). The authors then give a variation of this equation, which they argue, applies when there are zero outside shares. In this variation the risk and variance coefficients are removed from the equation:

$$Rp_t = \Sigma nh_t Eht(p_t + 1 + y_t + 1) \qquad (4)$$

The terms in this equation are the same as those above with the addition of Σnht as the sum of the number of agents of a given type at a given time.

The third mechanism for clearing a market is to borrow the idea of order books from real world markets and have the agents' orders crossed using some well defined procedure. From a microstructure perspective, this mechanism has the advantage of being the most similar to the way in which some markets operate in reality, for example, financial markets. A drawback to this mechanism is that it requires the modeller to include a great deal of institutional details into the market structure and into the agents' learning model. For example, Patelli and Zovko (2005) created a model that used the continuous double auction method, the same method widely used in modern financial markets. Just as in a true financial market, agents in the model could submit orders to buy and/or sell at any point in time. In addition, just as in financial markets in practice, both market and limit orders could be placed by agents. A market order was defined as a buy or sell order that crossed the opposite best price and a limit order was defined as a buy or sell order that did not cross the opposite best price. Just as in real financial markets, limit orders were queued and allowed to accumulate until market orders were placed, which then removed them from the queue. Finally, the author's defined the lowest selling price offered at any point as the best ask price a(t), the highest buying price as the best bid price, b(t), and the bid-ask spread as s(t) = a(t) − b(t) as the gap between the two.

LeBaron's (2006) mechanism is to allow trading only through direct contact between agents. This mechanism fits well with the model discussed already as many of them use their CA structure to determine who their 'neighbours' are and then allow trading only between neighbours. For some resources this might be the most realistic model for a market as well. For example, in models that allow the purchase or rental of water rights (*e.g.* Berger, 2001) the most accurate model could be one in which only neighbours are allowed to trade water rights. That is, if the distance between plots made trade over longer distances impossible in reality, then there would be little to gain in providing a more complex market mechanism only to support unrealistic trades. An example of this mechanism is the urban development/real estate model developed by Torrens (2001). In his model the market was based on direct contact between two agents—buyer agents first 'looked at' a neighbourhood and assessed whether that real estate market was in their price range. If the buyer agent decided that the market was in their price range they 'searched' for a home. To do this, the

agent approached locations one by one until it found one in which it and the selling agent matched on property preferences (property type, cost, etc.) In this way there was no central clearing house or market for the properties in their model.

There is also a fifth mechanism that is not discussed by LeBaron (2006), which is an auction mechanism. This mechanism could be conceived of as a direct trade between many agents to many agents and thus, perhaps, a derivation of LeBaron's (2006) fourth market mechanism of direct trades from one agent to another agent. For example both Balmann (1997) and Balmann et al. (2002) used auction based models for their markets of land purchase and rental. Specifically, each farm sequentially bid on plots of nearby land. A farm's highest bid for renting (Ry,x) was, 'the difference between the additional gross margin Δ and the transport costs TCy,x (which depend on the Euclidean distance between the farm's location and plot (y, z))'

$$Ry,x = Δ - TCy,x \qquad (5)$$

Bidding on plots continued until bids dropped below zero. Berger (2001) also used an auction-based market for his model of Chilean farmers. If a farmer's shadow price for a given plot of land was below the average for that sector they attempted to rent out the land and associated water rights. The land and water rights were then transferred to the farmer with the highest shadow price for that specific parcel.

None of the market mechanisms described above allow for any decision making beyond those guided by price. Issues like enduring relationships between a given farmer and a given supplier could be important factors in determining actual buying behaviour. Rouchier, et al. (2001) designed the only model reviewed in this paper to use relationships as a factor in the agents' decision making. In their model of herdsmen in North Cameroon, they designed one variation of their model in which the agents pursued a strategy attempting to maximize their profits. In a second design of their model, agents pursued a strategy in which they tried to maximize their relationships with the various farmers whose land they were renting. They pursued this strategy by preferentially asking the farmer with which they had most often been able to rent grazing land from in the proceeding rounds. This approach then allowed the authors to compare the outcomes for a model in which herdsmen rented based on relationships, with a model in which agents simply went to the farmer with the cheapest land to rent. Creating a model that tracked the rent versus refusal decisions between the herdsmen and the farmers also allowed the authors to examine and define 'relationships' in their model.

# Part Two: Modelling Farmer Heterogeneity

Risk

This section considers the incorporation of risk preferences and personality traits into the decision making of the agents. This does not appear to be a well developed area of agent-based models in agriculture. There are a few papers that have modelled risk in their agents, thus these equations could be used to construct agents with different levels of riskiness.

Lettau (1997) defines riskiness in his agent based model by defining risk aversion using the following equation:

$$U(w) = -e-\gamma w \qquad\qquad (6)$$

In this equation the utility of a given unit of additional wealth decreases as greater levels of wealth are attained (declining marginal utility). In this way, the baseline for riskiness in his model is somewhat risk averse. The riskiness of an agent can then be manipulated by varying the value for the coefficient $-\gamma$. In absolute terms, an empirically risk neutral agent would have a linear relationship between wealth and utility with a slope of one. Risk seeking agents then, would have a curvilinear relationship wherein higher levels of wealth would lead to even higher levels of utility (See Figure 2).

Figure 2. Riskiness as a Function of the Relationship Between Wealth and Utility
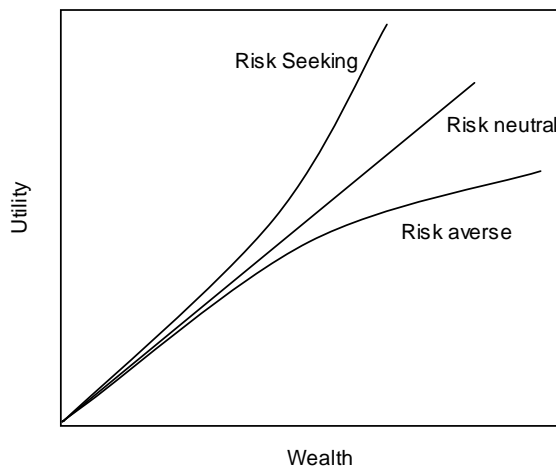
Lettau's (1997) equation can be compared to Hoffmann, Kelley, and Evans (2002) who define risk with the following equation:

$$E(u) = E^2(w) - \alpha\sigma w \qquad\qquad (7)$$

In this equation, expected utility is derived from expected wealth minus a second term representing risk aversion (α), multiplied by σw to represent undesirable random changes in wealth. Thus, this equation can account both for agents' risk aversion due to increases in wealth leading to smaller increases in utility at higher levels of wealth, and also for agents' desire to limit random variations of their wealth. That is, the second term in the equation accounts for people's preferences for more stable sources of income. A third equation for risk comes from Ishiguro and Itoh (2001), who modelled contract negotiations between pairs of agents. They describe their agents (n) as having a von Neumann and Morgenstern utility function and give the following:

$$U_n(z_n) - G_n(e_n) \qquad (8)$$

In this equation U_n, is the utility of the agent and (e_n) is the number of elements or choices that the agent has available.

Riskiness of agents can also be expressed by agents through the choice between an asset which varies in uncertainty and an asset with a fixed return. A number of financial models have modelled simple markets in which agents choose between two types of assets. For example, Grossman and Stiglitz (1980), created a hypothetical market in which one asset had a fixed dividend (R) and a second asset had a dividend (u) defined by the following equation:

$$u = \theta + \epsilon \qquad (9)$$

In this equation θ is a random variable which is observable at a cost and ϵ is a random variable which is unobservable. Thus, there are two types of hypothetical individuals in the authors' model, those that purchase information and those that rely only on the price of the risky asset. The authors also include an equation defining risk by using the utility function ($V(Wli)$) defined as:

$$V(Wl_i) = -\exp(-aWl_i), a > 0 \qquad (10)$$

In this equation a is the coefficient for risk aversion and Wli is the individual's wealth, determined by the following equation:

$$Wli = RMi + uX_i \qquad (11)$$

R, in this equation, is the return on the risk free asset, and u is the dividend of the risky asset and Mi and Xi represent the amount of risk free and risky assets held by the agent. Another example of a market in which a risky and risk free asset are modeled can be found in LeBaron's (2006) presentation of his work with the Santa Fe Artificial Stock Market (Earlier descriptions of the Santa Fe Artificial Stock Market can be found in Arthur et al. (1997) and LeBaron, Arthur & Palmer (1999)). In this hypothetical market a risk free asset is given the return (R) and a risky asset's dividend dt is:

$$dt = d + p(dt\text{-}1 - d) + \epsilon t \qquad (12)$$

Where ϵt is Gaussian, independent and identically distributed and p was set to 0.95. In addition, this model used a sophisticated learning and forecasting model. Agents use forecasting equations to try to predict the future price of a risky asset. At the end of each period, agents have a probability (p) to change their current set of forecasting

rules (p is a parameter set for each model run). Learning for an agent starts with the worst performing 15 per cent of the agent's forecasting rules being dropped. These are then replaced using a modified genetic algorithm with both crossover and mutation. During crossover, parts of rules are swapped for the different parts of an existing rule. In the course of mutation, parts of a rule are changed randomly and thus result in a rule that might not be present in the rest of the population.

Risk and other forms of 'personality' that can be imbedded into agents' behaviour highlight the benefit of an agent based model as a whole because they allow for the creation of variables which allow for more accurate modelling of real world phenomenon by mimicking the behaviour of actors in the real world. Modelling the riskiness of agents can allow for emergent properties based on different forms of riskiness to develop in the model.

Once a decision has been made as to which equation to use to define riskiness, it is a simple step to generate heterogeneous agents by either randomly or empirically assigning different values for the modifying coefficient or exponent. Defining and manipulating the riskiness of agents allows the modeller to use risk to drive different processes in a model.

Decision Making

There are a number of approaches to represent decision-making in MAS models in the land-based sector but they can be divided in two categories: behaviour heuristics and optimisation (Schreinemachers and Berger, 2006)

Behaviour Heuristics

Most agent decision making models have been represented as behaviour heuristics. Heuristics are implemented in MAS models using decision trees. They are intuitive and mostly simple rules, also called 'condition-action rules', 'stimulus-response rules', or 'if-then rules'. These rules are easy to validate by interacting with farmers and experts. Its implementation needs the modeller to identify (1) important decisions, (2) correct sequence of decisions to be made and (3) saturation level for decisions. That is, the modeller needs also to know the number of options at a decision making level, and the criteria that decision-makers use to chose one option instead of another. These criteria can be determined by sociological research, data-mining of survey data, participatory modelling and role-play games, laboratory experiment and group discussions (Schreinemachers and Berger, 2006).

Most heuristics build on the concept of bounded rationality (Simon,1991), which refers to the limited cognitive capabilities of humans in making decisions, described as a search process guided by rational principles. That is, the decision-maker is a satisficer seeking a satisfactory solution rather than the optimal one. In rural systems, farmers typically use a large number of heuristics in decision making, perhaps because of the great uncertainties of natural phenomena. The weaknesses of heuristics are its lack of information for alternatives, and the difficulty of coping with large numbers of rules, and with heterogeneity in system inputs and outputs (Schreinemachers and Berger, 2006).

Optimisation

Many MAS models in land use research use optimisation in decision-making. Optimisation can be used for a normative purpose to re-allocate resources to gain a

higher level of goal satisfaction by eliminating inefficiencies, or for a positive purpose to replicate or simulate a real-world resource allocation.

In contrast to the bounded rationality in behaviour heuristics, it is assumed that decision-makers are rational optimisers with foresight. They are able to process large amounts of information on all feasible alternatives and select the best one. Optimisation seeks to identify inefficiencies in structural factors external to the decision-makers. Optimisation models can be calibrated to the observed behaviour by carefully representing all the opportunities and constraints in the model (Schreinemachers and Berger, 2006).

Optimisation in decision making can be implemented in a MAS model using a variety of optimising algorithms, one of which is *Mathematical Programming (MP)*. This method is widely used in optimising and decision-making in MAS models in the land based sector (*e.g.*, Balmann, 1997; Berger, 2001; Becu et al 2003, Happe 2004, 2004). This approach involves constructing objective functions (*e.g.*, cash income, food, leisure time, N-leaching, GHG emission) of various activities under various constraints, and finds a best solution by solving the equations. Agent heterogeneity is represented by specifying different constraints. The advantages of MP are that heterogeneity (farmer personalities and farm conditions) can easily be represented and a large number of decisions can be incorporated. In addition, it can well capture economic trade-offs in resource allocation because it considers various decisions simultaneously and in coherence (land use options are dependent of relative resource endowment) and it is suitable for the assessment of the quantitative impact of policy interventions. Optimisation addresses inefficiencies in structural characteristics external to decision makers, so has clearer policy relevance (Schreinemachers and Berger, 2006). A critical feature of optimisation through MP is that it is often criticised as being unrealistic, not describing the way real people think (Todd and Gigerenzer, 2000), as indicated by the bounded rationality. That is, people also think of factors such as risk, uncertainty, limited information and non-profit goals. However, risk can be incorporated using chance constrained programming (Hardaker et el. 1997, 2004), and non-profit goals can be modelled either by a 'utility' type program or through Boolean or mixed integer models.

Genetic Programming (GP) is an evolutionary algorithm-based optimisation methodology inspired by biological evolution to find computer programs that perform a user-defined task. It is used in various complex optimisation and search problems. The SYPRIA (Manson 2005) model used GP in modelling decision-making for assessing effects of land use policy changes. It specifies a response variable (agricultural land use in 1992) as a function of a set of predictor variables (1987 environmental and institutional variables) chosen for their effects as hypothesised by land use theory. The weaknesses of GP are the subject of continuing research because they can be difficult to interpret and there are dangers in conflating human decision making with biologically inspired models of computer programming (Manson 2005).

Another optimisation technique is *Artificial neural networks (ANN)*, an optimisation technique which is a data modelling tool capable of capturing and representing complex input/output relationships. Development of neural network technology stemmed from the desire to originate an artificial system that could perform intelligent tasks similar to those performed by the human brain. Neural networks resemble brain function in that they acquire knowledge through learning, and store

the knowledge within inter-neuron connection strengths. The most common neural network model is the multilayer perceptron (MLP) which is used to approximate functions. MLP is also known as a supervised network. It requires inputs paired with desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data with the goal of using the model to predict future outcomes. Optimisation using ANN has potential to be used for optimisation in decision making of land use. A possible limitation of an ANN, as applied to land use decisions, is when the problem solution space changes of over time, *i.e.* the rules of the game change. The model is constructed from purely priori knowledge, and therefore may not find an appropriate solution given the contextual alterations.

Using a comprehensive approach placed at the right position on the continuum between heuristic and optimising behaviour is vital to simulate decision-making, and it is closely related with the questions that the model is designed to answer and/or the targeted model users. More behaviour heuristics should be used if the model is used by social, economic and environmental policy makers to explore the farmers' actual responses to institutional and environmental changes (*e.g.*, objective of Rural Futures project). Otherwise, if the model is to provide a tool or modelling platform to support farmers in making decisions in front of economic and environmental changes, incorporation of optimisation algorithms can be useful.

Information Transfer

The interaction of farm agents through communication networks is an integral part of decision making. Communication lowers the uncertainties for agents (Rogers 1995 in Berger et al 2006), but slows down decision-making processes (*e.g.*, adoption rate of innovations, Berger, 2001).

In a MAS model, agents are explicit entities. Inter-agent communication can either be direct (agent-to-agent) or indirect (agent-environment-agent). It can be explicitly implemented using message passing. It can also be very helpful to clarify communication among agents using the Unified Modelling Language (UML) to draw sequential activity diagram of major agents (*e.g.*, in Harpe et al 2006; Schlüter & Pahl-Wostl, 2007).

The reasoning behind modelling this information transfer and its associated network structure is to replicate information sourced from other agents in a social network which is one of the key drivers of an agent's decision making. This driver plays two key roles, firstly for creating a basis for social comparison (Festinger, 1954) and secondly as a source of information and opinion (Anderson, 1962).

The underlying network structure used for information transfer between agents, otherwise called a social network, is important (Milgram, 1967; Watts, 1998). Social networks exhibit qualities of 'connectedness' that have properties of both highly uniform networks, *e.g.* lattices, in that groups of nodes are interconnected; and of highly random networks in which the distance between any two nodes is quite short (*i.e.*, six degrees of separation, Watts, 2003)

While difficult to validate, information transfer via a social network plays an important role in agribusiness decision making and as such deserves consideration. The information passed via these types of network form the basis of social comparison as a performance metric as well as a driver for system change and/or adoption.

Opinion formation

Information transfer in an agent based model can be seen as being closely related to opinion formation (Wu, 2004). An agent must first amass information before opinions can be formed. In the context of an agent based model it is common for a proportion of the information to come via other agent in the system. For this section, opinion formation is defined as a specific process of information utilisation both by individuals and groups.

Models of opinion formation among communities of agents are among some of the earliest attempts to model complex systems (von Neumann, 1966) and are tied closely to early information/diffusion theory (Turing, 1952). The majority of these models have been continued to be based on cellular automata (one or two dimensional).

The Sznajd model (Sznajd-Weron and Sznajd, 2004) uses a dual Ising spin model to describe social influence as it applies to political attitude. In the model political attitude was viewed as a two dimensional continuous space based on 'traits' of personal and economic freedom. This model goes some way toward modelling ability of a population to reach a consensus (or not) based on the global tolerance factor. A potential weakness was identified in the model abstraction is that they may lead to complete consensus (Sznajd, 2004) which in many situations is unrealistic.

Macro level opinion formation and the underlying micro level behaviours are tied into a feedback loop whereby an individual's opinion is both driven by and forms part of the macro level opinions (or social norms). In its simplest form, the sharing of these opinions can be described as a model of knowledge diffusion.

These opinions play an important role in three key drivers of an agent's behaviour;

- Preferences *e.g.* conforming to social norms
- Perception *e.g.* to predict future performances of both self and society
- Opportunities *e.g.* to improve one's relative position in society

A number of other models can be used to describe various forms of information transfer such as epidemic spreading (unwilling transfer), rumour spreading or diffusion of innovation (willing transfer) (Boccaletti et al 2006). Game theory has also been used to simulate interactions among decision-makers (*e.g.*, Osborne 2002).

Part Three: Suggestions for a MAS Model

Previous parts of this literature review suggest that there are a wide variety of models available as starting points for a model of agriculture in New Zealand. Thus, the purpose of this section is to suggest a possible starting point for the model. First, this review indicates that a two-part model including both a multi agent (MAS) sub-model and a cellular automata (CA) sub-model is the most suitable for agricultural models. In this way, variables can be divided into those linked to specific locations and thus assigned to land in the CA sub-model, and those linked to decision making and thus assigned to agents in the MAS sub-model.

With regard to the MAS sub-model, the prior research suggests that agents should be heterogeneous in terms of risk preferences and the use of prior information (myopia). The research team should also discuss other decision rules or strategies that could be included in the model.

With regard to the CA components, it appears that land should be modelled spatially with variables for different production possibilities. That is, that each unit of land should include values for potential outputs for dairy, meat, and forestry. The research team should discuss other possible land uses that should be modelled. In addition, a discussion should be held regarding the potential need for modelling water in the model and the potential need for modelling distance in the model (distance being distance from farmstead to different fields and/or distance from the farm to market). These aspects can be treated as separate elements in the model, or simply implied by the relative productivity of CA units.

The production from various land uses can be sold based on exogenously determined prices. That is, that a sub-model for a commodities market is probably not necessary to adequately model agriculture in New Zealand, given its export focus.

With regard to modelling decision-making it can be either modelled using simple rules of behaviour heuristics, or using optimisation algorithms, or a combination of the two. Selection of the approach depends on the questions the model is designed to answer, with the targeted model users in mind. More behaviour heuristics should be incorporated if the model is used by social, economic and environmental policy makers to explore farmers' responses to institutional and environmental changes. Conversely, if the model is designed to support the decision making of farm managers, the incorporation of optimisation algorithms can be useful to help farm managers expand their bounds of rationality and make informed decisions ahead of economic and environmental changes. Information transfer among the agents can be explicitly modelled both to introduce new information and technology adoption as well as for heterogeneous goal setting/measurement of the agents as a function representation of social influence. An agent's responses to new information and opinion formation can be modelled by using appropriate network dynamic models.

By overlaying these simulated agents – constructed based on primary data on farmer behaviour – on a cellular structure that represents key features of the natural landscape of New Zealand, it should be possible to investigate the emergent properties of the country's farming sector. In particular, the response of this complex system to simulated future shocks, such as policy shifts or climate change, may provide useful information for farmers, the sector, and policy-makers.

Acknowledgements

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