Effects of land markets on competition between innovators and imitators in land use: results from FEARLUS-ELMM

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Abstract

This chapter explores the effects of a more realistic agent-based land exchange mechanism on the relative competitive success of innovative and imitative strategies for selecting land uses, using the FEARLUS-ELMM model. A key question in our investigation is whether land use decision strategies can be studied in isolation from land market exchange decision strategies. Results derived via computational experiments show that land market modelling decisions do affect outcomes, improving to an extent the relative success of innovators. We also conclude that further additions are needed to our model, and finally, we question whether a “big bang” strategy may have been more effective than our step-by-step evolution to the land market model, which was chosen to facilitate comparison to results derived from the original FEARLUS.

Keywords. Behavior Modeling, Environmental Modeling, Simulation System, Social Science

INTRODUCTION

This chapter is about spatially explicit agent-based social simulation of processes underlying land use change, in which both space and human agency are represented in rather simple and abstract ways. The work described forms part of the FEARLUS (Framework for the Evaluation and Assessment of Regional Land Use Scenarios) project. We are interested in how various aspects of human decision-making processes related to land management interact to affect the competitive advantage of some groups over others, and how these interactions shape land-use change, particularly at the regional scale and in the medium to long term. Here, we focus on decisions to change land use and to acquire land. However, some of the issues discussed are relevant in a range of contexts involving systems of interacting, territory-holding agents—see Cioffi-Revilla and Gotts (2003).

Development of FEARLUS is motivated by the limitations of models that forecast land-use change solely on the basis of biophysical properties and economic returns. Earlier approaches to rural land use change (Benson, 1995; Parry, 1996) have assumed that land managers are driven purely by profit maximisation and have unlimited computational capabilities. There is a growing current of opinion within the land use research community that to model the drivers of land use change successfully: “Simulation of decisions by and competition between multiple actors and land managers is required.” (Veldkamp and Lambin, 2001, p.2).

Those making land use decisions may be influenced in various ways by their neighbours (as well as wider social influences): the most obvious include imitation based on the success of innovative land uses or techniques (and conversely, avoidance of innovations seen to fail). The success of land managers may also be influenced by the successes and failures of neighbours, which affect managers’ ability to acquire new land and diversify production. The original FEARLUS model was designed to specifically address the first point. The ELMM (Endogenous Land Market Model) expansion to FEARLUS discussed here is designed to address the second point. This chapter begins to explore how addition of the more marketoriented land exchange mechanism in ELMM affects previously derived results on the relative competitive success of innovative and imitative land use selection strategies.

Our approach to simulation modelling makes considerable use of experiments. Simulations may be used simply to show that a model system can demonstrate a particular form of behaviour. However, if the model has any stochastic elements (including the selection of initial parameters), it is desirable to use experimental and statistical techniques to discover how the model *usually* behaves. Without such analysis, we cannot be sure an observed behaviour is robust. Moreover, comparing how a simulation model behaves under different parameter settings is central to understanding it, and this demands the ability to test whether apparent differences hold reliably.

The FEARLUS model

The key constituents of the FEARLUS model used here, and how they interrelate, are shown in Figure 1. We adopt the convention of using Capital Letters to indicate entities in FEARLUS, italicised on first use.

A FEARLUS model consists of a set of *Land Managers* (representing households, not individuals), and their *Environment*, which includes a grid of square *Land Parcels*, and a set of possible *Land Uses*. Every *Year*, Land Managers select a Land Use for each Land Parcel they own, update their *Account* according to the *Yield* from the Land Uses selected, after which Land Parcels pass from Land Managers with a negative Account to their solvent *Neighbours* or new Land Managers at a fixed *Land Parcel Price*.

The definition of Neighbour may be varied within FEARLUS, but in this chapter, two Land Managers are Neighbours if and only if they currently manage Parcels sharing a boundary or boundary point. A Land Parcel’s *Grid Neighbours* are the eight Parcels orthogonally or diagonally adjacent to it. The set of Land Parcels owned by Land Managers owning Grid Neighbouring Parcels of a Land Manager’s Parcels is the *Social Neighbourhood* of that Land Manager.

The parameters of a FEARLUS model also specify how to determine the *External Conditions*, representing a combination of economic and climatic factors, and encoded as a bitstring, the length of which is a model parameter. The bitstring can vary from Year to Year but applies across the whole grid. The initial bitstring is determined randomly, and each subsequent bitstring is produced from its predecessor as illustrated in Figure 2 (b) by applying a predetermined *Flip Probability* (f) to each bit independently: if $f = 0$ the initial bitstring will be retained throughout; if $f = ½$, each Year’s bitstring is independent of its predecessors and the External Conditions are temporally uncorrelated. If $0 < f < ½$, the External Conditions change, but are temporally correlated. Each Land Parcel has a set of *Biophysical Characteristics*, encoded as a bitstring and fixed for the direction of a simulation run (again, the length of these bitstrings is a model parameter, the same for all Land Parcels). Both parameters affect *Yield* at the parcel level as per Figure 2 (c). There are also two numerical parameters unvarying over space or time: a *Break Even Threshold* (BET), specifying how much Yield must be gained from a Land Parcel to break even, and in the original FEARLUS model prior to ELMM, the *Land Parcel Price* (LPP).

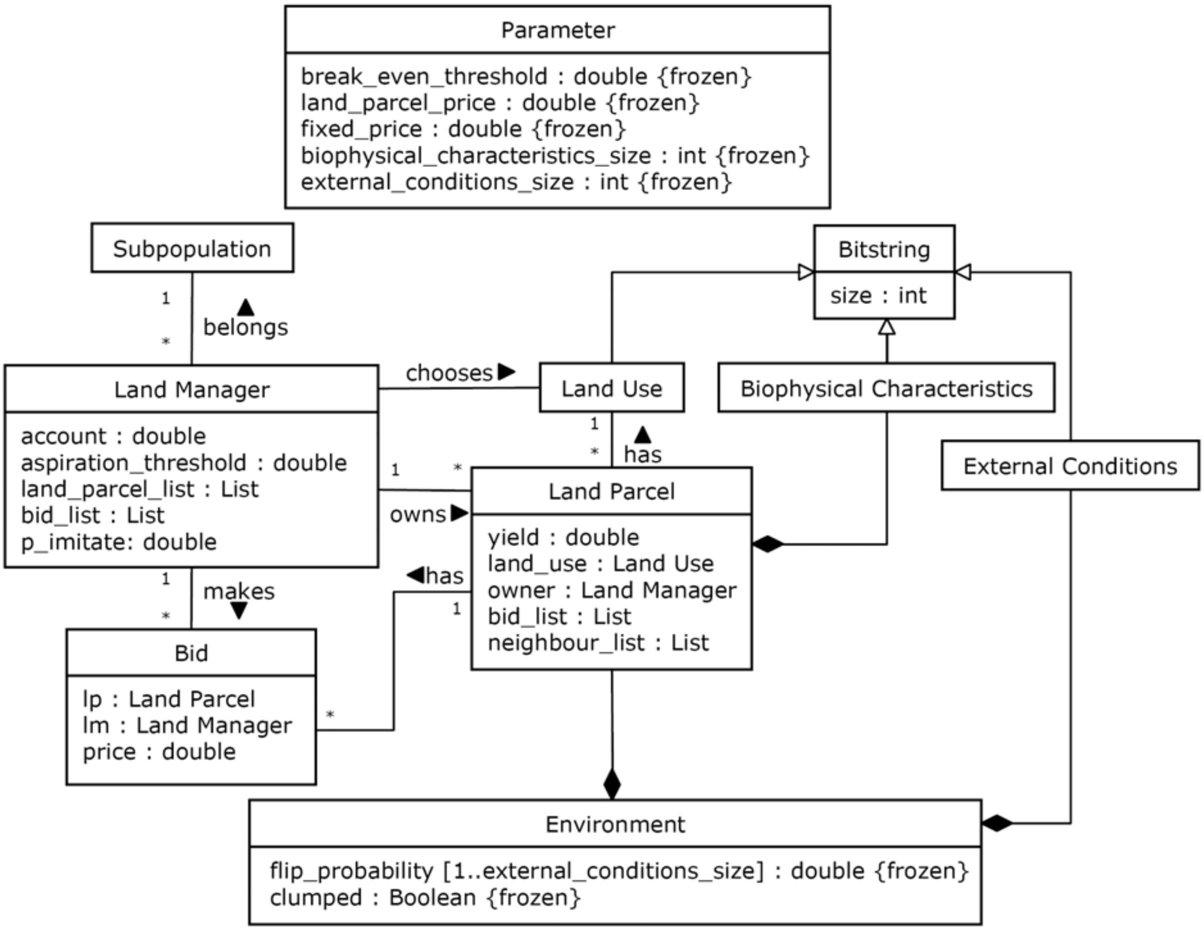


Figure 1. UML class diagram showing the main entities in the FEARLUS model used here and how they inter-relate.

The following sequence of actions occurs in the original (non-land market) FEARLUS model. In *Year Zero*, Land Parcels are assigned to Land Managers, and there is a random allocation of Land Uses to Land Parcels. (A specified number of Land Uses are created at random or loaded from a file.) Land Managers have an Account, initially set to zero (the Year Zero Yield does not affect this, but is available as information in Year 1). The rest of the run repeats the annual cycle shown in Figure 2.

A fuller description of FEARLUS models, may be found in Polhill, Gotts and Law (2001), Gotts, Polhill and Law (2003) and the FEARLUS user manual (http://www.macaulay.ac.uk/fearlus/). Typically, FEARLUS is used to investigate the relative success of Land Managers with various *Land Use Selection Algorithms* determined by the *Subpopulation* to which they belong. The proportion of *Land Parcels* collectively owned by *Land Managers* following competing approaches is used as the measure of those approaches' competitive success. (Note this is a population level, and not an individual, success measure.)

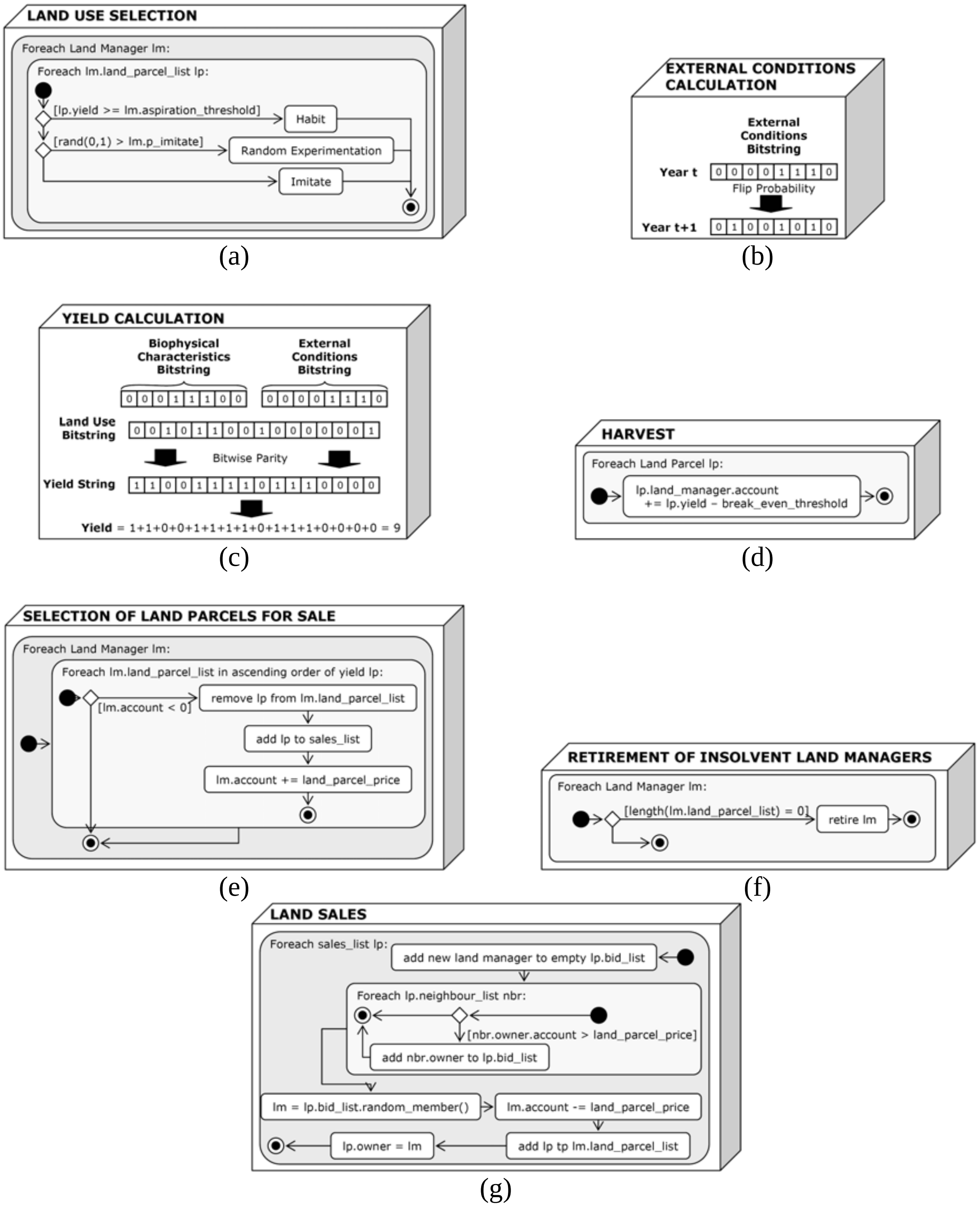


Figure 2. Depiction of the activities that take place each Year in FEARLUS, in order of occurrence: (a) Land Managers choose Land Uses; (b) External Conditions are calculated; (c) Yields are computed; (d) Land Managers update Accounts; (e) Land Parcels are put up for sale; (f) insolvent Land Managers retire; (g) Land Parcels for sale are given new owners. With the exception of (b) and (c), the activities are described using UML activity diagrams.

Improving FEARLUS's Land Market representation

The Land transfer procedure in Figure 2 is very unrealistic: the Land Parcel Price is a global constant, and Neighbouring Managers have no choice about 'buying' a Land Parcel for sale.

We hypothesize that these restrictions may affect the success of Land Managers following different Land Use Selection Algorithms, since a relatively successful Land Manager forced to invest a fixed amount of capital in a Land Parcel without assessing its value may be more vulnerable to bankruptcy, diluting the potential success of their Algorithm. Alternatively, if a Land Manager is able to decide whether and how much to bid on a parcel, that Manager's Land Market transactions can reflect their overall decision-making strategy, and may themselves contribute to differential success and failure. Note that addition of these two decisions (as well as others, outlined below) adds new dimensions to the Land Manager's strategy. These non-trivial changes to the FEARLUS framework deserve careful analysis in order to determine (a) whether the dynamics produced by the implemented changes correctly reflect the greater realism that we seek and (b) whether that greater realism leads to changes in model outcomes.

Land is usually a scarce commodity: more is demanded than is available. Institutionally, markets serve to balance competition for scarce resources among competing agents. In theory, a well-functioning market will allocate scarce resources to their highest-valued use. (In practice, true equilibria are never reached.) If a model allows land to be allocated to the bidder valuing it most highly, the land rental rate should reflect the scarcity or shadow value of that land—the amount by which it would increase the profits of the agent with the winning bid. A functioning land market model will provide information on these shadow values of land at different points in space, allowing the modeller to explore the drivers of spatially heterogeneous returns.

Further, a functioning land market model might better reflect real-world incentives faced by agents. If more successful agents can bid on land of insolvent or less successful agents, it may allow faster consolidation of wealth and land holdings. Also, if the market for land becomes saturated, due perhaps to decreasing profitability of agricultural outputs, endogenously falling land prices may lead to land fallowing and/or abandonment, an important observed empirical phenomenon. Note that (as is clear from our implementation) a functioning land market simulation need not assume that land managers are economically rational profit maximisers.

ELMM replaces steps (e) and (g) in Figure 2 with a new process that allows Managers to choose which Parcels to buy, and create their own bid for them. How this new process affects the interaction between innovators and imitators from earlier work with FEARLUS is explored in what follows. The following section briefly summarises the most relevant parts of the literature on innovation and imitation in agriculture, and results concerning the competitive performance of innovators and imitators using the pre-ELMM version of FEARLUS. We then describe ELMM and experimental work to explore its affect on these results, before a discussion and conclusion.

INNOVATE OR IMITATE?

The dynamics of imitation have been a consistent theme of work with FEARLUS (Polhill, Gotts and Law 2001, Gotts, Polhill and Adam 2003). Various forms of imitation have been both contrasted with, and used in combination with, a very simple form of innovation—*Random Experimentation*, involving a uniform random choice among all the possible Land Uses. Both Random Experimentation and imitation have generally been used in combination with an *Aspiration Threshold* as per Figure 2 (a), where 'Habit' means not changing Land Use. An Aspiration Threshold of zero will lead to no land-use change; conversely a very high

Aspiration Threshold means the Manager will always select the Land Use for that Land Parcel anew.

In the Selection Algorithms focused on here, imitation involves selecting the Land Use from those used by either the Land Manager themselves, or one of their Social Neighbours, in the preceding Year.

Several different forms of Imitation have been investigated. Those relevant here are *Selective Simple Imitation* (SSI) and *Selective Best-mean Imitation* (SBI). In both of these, a score is calculated for each Land Use employed in the previous Year within the Social Neighbourhood, and a choice is made among those scoring highest; if one scores higher than all the rest, it is selected; if two or more share the highest score, each has an equal probability of being selected. In SSI, the score is the number of Parcels assigned to the Land Use in the most recent Year; in SBI, the mean Yield from those Parcels in the Social Neighbourhood assigned to that Land Use in the most recent Year.

We have also tried combining each form of imitation with a small amount of Random Experimentation (specifically, a 1/16 probability of applying Random Experimentation rather than imitation if the threshold was not met). In general, adding this small amount of Random Experimentation made a big difference only when two Subpopulations using imitation were set in competition with each other, rather than with one using Random Experimentation: if all Land Managers are complete non-innovators (in the current context, never use Random Experimentation), there is a strong tendency towards monoculture—since once a Land Use happens to fall out of employment throughout the Environment, it will never be used again. Figure 3 demonstrates this, contrasting the Land Use pattern generated by various (combinations of) Land Use Selection Algorithms. Monoculture becomes a problem when the External Conditions change and the dominant Land Use is no longer profitable. In this sense, imitating Land Managers with no Random Experimentation depend on innovators to re-introduce Land Uses and under some conditions can exploit the risk taken by the innovators when experimenting, and are more successful.

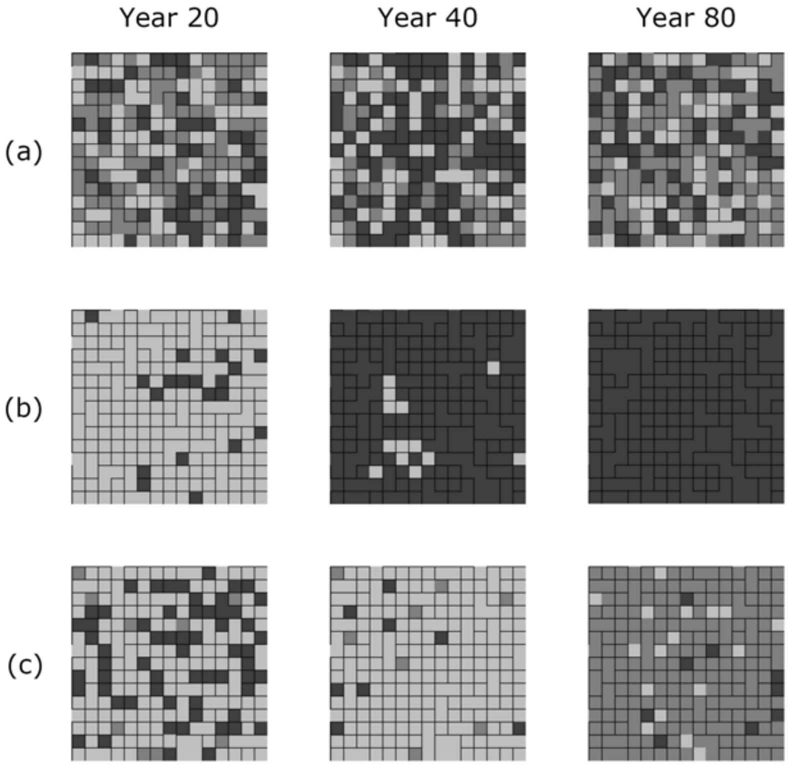


Figure 3. Illustration of the differences between innovation and pure imitation. Land Use patterns are shown from three simulation runs each using three rather than eight Land Uses as in the experiments with Land Uses represented in a shade of grey. (a) A run featuring agents with just the innovating Land Use Selection Algorithm, HR, generating a much more diverse landscape than (b) which features an imitator subpopulation (HSSI) converging to a monoculture. In (c) HR and HSBI compete, and the landscape shifts from one mostly (though not completely) dominant Land Use to another in response to changes in the External Conditions.

Extensive experimentation, both published (Polhill, Gotts and Law 2001; Gotts, Polhill and Law 2003; Gotts, Polhill and Adam 2003; Gotts, Polhill, Law and Izquierdo 2003) and unpublished, has yielded some general conclusions concerning the competitive properties of these families of Land Use Selection Algorithms across a range of FEARLUS Environments. Those relevant here are:

- The HR family of Land Use Selection Algorithms (Random Experimentation combined with an appropriate Aspiration Threshold) is remarkably robust, given its seeming crudeness.
- However, in most Environments, at least some Land Use Selection Algorithms using imitation outperform HR with any Aspiration Threshold. This is more likely with increasing spatial homogeneity of the Environment—particularly over short distances. With regard to temporal heterogeneity, intermediate degrees of autocorrelation appear to favour imitation most.
- Among the imitative strategies tried, SBI appears to be best or equal best across all Environments investigated, other than the most uncertain, where a variant which sometimes allows a lower-scoring Land Use to be selected does better (presumably

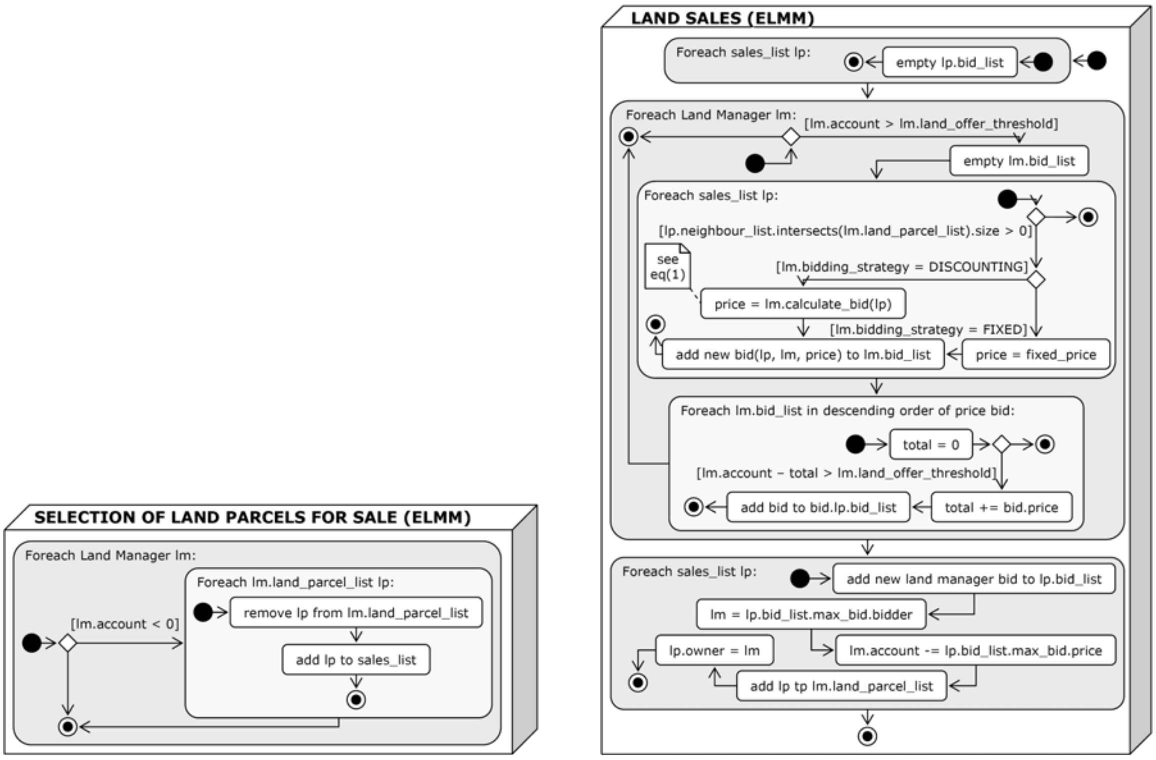
because it leads to more diversity). Land Use Selection Algorithms using SBI also beat HR in all but the most uncertain environments, where the advantages of diversity become important.

The question of the robustness of these findings naturally arises, since the competitive performance of various Land Use Selection Algorithms depends to a considerable extent on the spatio-temporal heterogeneity. A full investigation of these results' robustness as the land market model changes is beyond our scope here: our purpose is only to show that changes in land market models can affect the relative competitive advantage of Land Use Selection Algorithms.

THE EFFECT OF LAND MARKET MODELLING

Description of ELMM

Other agent-based land use models, such as Berger's (2001), already contain endogenised land rental markets. In this model, the decisions of which parcels to bid on and the bid for those parcels are simultaneously derived from farm-level mathematical programming models based on optimisation behaviour, with bid reflecting shadow prices of land. Happe's (2000) AgriPoliS model also bases pricing for land rental on the shadow price. As with Berger's model, it assumes that transportation costs and exploitation of economies of scale result in farmers bidding for land parcels nearest to the farmstead. These cost advantages are explicitly modelled in the bidding function, whereas in FEARLUS they are implicitly embedded by only allowing Neighbouring Land Managers to buy a Land Parcel for sale.



(a) (b)

Figure 4. Changes to steps (e) and (g) in Figure 2 made for ELMM, depicted using UML activity diagrams.

We take a different approach to the optimization-based approach of Berger and Happe. As much of our work has been based on the acknowledgement that ‘satisficing’ (Simon, 1957) rather than optimising is a more prevalent decision strategy among real-world actors, our land market algorithms are designed accordingly. Regardless of decision-making assumptions, various aspects of land markets require algorithms or assumptions to specify how they will work. These are discussed in greater detail in Polhill, Parker, and Gotts (2005). Here, since we are interested in comparing original FEARLUS with FEARLUS-ELMM, we minimise modifications, attempting to isolate key components that make a difference. Below, we summarise the assumptions and algorithms of this early version of ELMM. The alterations to the model in Figure 2 to create FEARLUS-ELMM are shown in Figure 4.

(a) *Decision to sell land*. Land Managers sell all Land Parcels when their Account is less than zero. See Figure 4 (a).

(b) *Which land parcels to sell*. See (a).

(c) *Selecting the reserve price*. The reserve price is the minimum a Land Manager will accept for a Land Parcel. It is not applicable in this version since Land Managers selling parcels are bankrupt.

(d) *Decision to buy land*. Land Managers will try to buy land when they reach a threshold Account, the *Land Offer Threshold*. All such Land Managers generate a bid price (see (e) below) for the Parcels for sale in their Neighbourhood using a *Land Parcel Bidding Strategy*. They then use a *Land Parcel Selection Strategy* (see (f) below) to choose which of those bids they actually make.

(e) *Deciding a bid price*. The following Land Parcel Bidding Strategies are used:

- Discounting Bidding Strategy: The bid price is given by a discounted *Weighted* sum of the average profit the Land Manager has made per Land Parcel within the *Land Purchase Profit Window* time period of the Land Manager, and the last Profit of the Parcel for sale:

  $$b = \frac{(1-w)\overline{p}_n - w(y-T)}{r} \tag{1}$$

  where *b* is the bid price, *w* is the Weight, *y* is the last Yield of the Parcel, *T* is the BET, *r* is the interest rate that the Land Manager could earn on an exogenous investment opportunity, and if *n* is the Land Purchase Profit Window, *Y* the current Year, and p_i the Profit the Land Manager made per Land Parcel in Year *i*:

  $$\overline{p}_n = \frac{1}{n} \sum_{i=(Y-n)+1,Y} p_i \tag{2}$$

  The denominator *r* in (1) reflects discounting over an infinite time horizon, on the basis that the time to bankruptcy of a Land Manager in FEARLUS is unknown and potentially unbounded. The higher the available interest rate, the lower the total expected return. The interest rate can alternatively be interpreted as a measure of the uncertainty of future returns: the higher the interest rate, the higher the perceived risk.

- Fixed Price Bidding Strategy: A constant *Fixed Price* is offered by the Land Manager for all Land Parcels, to provide a comparison with original FEARLUS.

(f) *Which land parcels to buy*. A *Buy Dearest Selection Strategy* is used, see Figure 4 (b).

(g) *Determination of the final sale price*. Wooldridge (2002) discusses various kinds of auctions. Here, ELMM uses a first price sealed-bid (highest bidder wins) auction, adding to the set of bids generated by existing Land Managers a bid from a potential incoming Land Manager sampled from a distribution termed the *In-migrant Offer Price Distribution*.

(h) *What to do with land that no-one wants to buy*. Land that no Neighbours wish to buy is automatically transferred to a new Land Manager, as per original FEARLUS.

(i) *Localisation of land sales*. Land Parcels are exchanged only between neighbouring Land Managers, as per original FEARLUS.

(j) *Handling debt*. Not applicable here.

Experiments with ELMM

In all models considered in this section, the Land Parcels are arranged in a 15 × 15 grid, with opposite sides joined to produce a toroidal topology. The bitstrings defining Land Uses' preferred conditions always contain a total of 16 bits. Environments differ in the division of these bits between Biophysical Characteristics (variable across space, but fixed over time) and External Conditions (uniform across space but variable over time). External Conditions may be either correlated or uncorrelated from Year to Year: in the former case, the Flip Probability is below 1/2 (values of 1/8, 1/4 and 3/8 have been used); in the latter, 1/2. Similarly, the Biophysical Characteristics of Land Parcels may be either clumped or unclumped. In either case, each bit is initially independently set to 0 or 1 with equal probability, for every Land Parcel. In the 'clumping' process used here, which is carried out on each bit-position in turn during initialisation, adjacent Land Parcels are selected at random to swap non-matching bit-values, for as long as there is a swap that will increase the number of Grid Neighbouring Land Parcel pairs having the same value. The Environments used are detailed in Table 1.

Env. label	**BC bits**	**BC Clumped?**	**EC bits**	**EC Correlated?**	**Type 1 HSSI**	**Type 1 HSBI**	**Type 4 HSSI**	**Type 4 HSBI**
Env-A	0	N/A	16	No	-	Yes	-	-
Env-B	0	N/A	16	Yes: 4 bits 1/8	-	Yes	-	-
Env-C	0	N/A	16	Yes: 8 bits 1/8	-	Yes	-	-
Env-D	0	N/A	16	Yes: 12 bits 1/8	-	Yes	-	-
Env-E	0	N/A	16	Yes: all 1/8	-	Yes	-	-
Env-F	0	N/A	16	Yes: all 1/4	-	Yes	-	-
Env-G	0	N/A	16	Yes: all 3/8	-	Yes	-	-
Env-H	1	No	15	No	-	-	-	-
Env-I	1	No	15	Yes: 5 bits 1/8	-	-	-	-
Env-J	1	Yes	15	Yes: 5 bits 1/8	-	-	-	-
Env-K	1	No	15	Yes: 10 bits 1/8	-	-	-	-
Env-L	1	Yes	15	Yes: 10 bits 1/8	-	-	-	-

Env-M	1	No	15	Yes: all 1/4	Yes	Yes	Yes	Yes
Env-N	1	Yes	15	Yes: all 1/4	Yes	-	Yes	-
Env-O	1	No	15	Yes: all 3/8	Yes	Yes	-	Yes
Env-P	1	Yes	15	Yes: all 3/8	-	-	-	-
Env-Q	4	No	12	Yes: all 1/4	Yes	Yes	-	Yes
Env-R	4	No	12	Yes: all 3/8	Yes	Yes	-	Yes
Env-S	8	No	8	Yes: all 1/4	Yes	Yes	Yes	Yes
Env-T	8	Yes	8	Yes: all 1/4	Yes	-	Yes	-
Env-U	8	No	8	Yes: all 3/8	Yes	Yes	-	Yes

Table 1. The Environments used in the experiments and preliminary exploration. The ‘label’ is how they are referred to in the chapter. The ‘BC bits’ column says how many bits are used to describe the Biophysical Characteristics in the run, with ‘BC Clumped?’ stating whether or not these bits are spatially correlated using the clumping algorithm described in the text. The ‘EC bits’ column is the number of bits used for the External Conditions, and their temporal correlation is described in ‘EC Correlated?’: an entry of ‘No’ indicates a Flip Probability of 1/2, an entry of ‘Yes’ is followed by a description of the number of bits given a Flip Probability of less than 1/2. The last four columns indicate which formal experiments each Environment is used in. Those not used in a formal experiment (Env-H, -I, -J, -K, -L, -P) were used in initial exploratory runs.

Aside from the parameters specifying the amount and distribution of spatial and temporal variation in conditions affecting Yield, and the Selection and Bidding Algorithms followed by Land Managers (discussed below), the only model parameter varying over the experiments reported here is the Land Parcel Price (LPP)—and this parameter only applies in the case of experiments involving the pre-ELMM version of FEARLUS. In all cases, the BET is set at 8.

The experiments have been conducted with a view to seeing what effect, if any, more realistic land market models have on the relationship between innovators and imitators as represented by HR (Habit-Random) on the one hand, and HSBI (Habit-Selective-Best-mean-Imitation) and HSSI (Habit-Selective-Simple-Imitation) on the other; all using an Aspiration Threshold of 8. When studying the relationship between such strategies for land use decision making, is it possible that consideration needs also to be given to strategies for land parcel exchange? That is, can the land use decision making part of land managers’ behaviour be studied in isolation from other strategic aspects of their business?

So far in FEARLUS, we have used three kinds of experiment to study land managers’ strategies, dubbed Type 1, Type 2 and Type 3 experiments. A Type 1 experiment tests the hypothesis that ‘Subpopulation P does better than Subpopulation Q in Environment E’, where “does better” means “owns a larger proportion of the Land Parcels at the time the simulation terminates” (see Polhill, Gotts and Law (2001) for more details on this, and on Type 2 and 3 experiments, which are not used here). In this chapter, we also present a new kind of experiment, dubbed Type 4, to compare differences in performance as various aspects of the Land Managers’ behaviour is changed. A Type 4 experiment tests the following hypothesis using paired replicate runs with a sign test:

‘Subpopulation A.X does better against Subpopulation B.X than Subpopulation A.Y does against B.Y in Environment E,’ where A and B refer to different Land Use Selection Algorithms (i.e. HR, HSBI or HSSI) and X and Y to different market strategies and models (i.e. no bidding (N), fixed price (F), or discounting (D) with rate $r = 1$, and weight $w = 1/2$.). (An interest rate of 1 implies that managers only anticipate next year’s rather than future returns. This simplification was done to facilitate comparison to fixed price bidding.) This hypothesis does not entail a complete reversal in the fate of A against B using market model X rather than Y, merely an improvement in performance.

Type 1 experiments

A series of Type 1 experiments were conducted to test whether the changes made to FEARLUS to incorporate ELMM would cause us to change the results we would report. There are three possibilities:

(A) A significant result in favour of one Subpopulation in the original FEARLUS becomes a significant result in favour of the other in FEARLUS with ELMM.
(B) A significant result in the original FEARLUS is no longer significant in FEARLUS with ELMM.
(C) A result that is not significant in the original FEARLUS is significant in FEARLUS with ELMM.

Since there are many experiments being conducted (each experiment consisting of a single contest in one Environment involving 60 or 120 runs), we set the significance level at 0.01 to avoid false positives.

The experiments were conducted in three stages:

1. A control, in which the original FEARLUS, and FEARLUS with ELMM, were configured so that existing Land Managers can never afford to buy Land Parcels, so no land transfers occur. This is achieved in the original FEARLUS by setting the LPP to a number greater than the maximum Account it is possible to accrue within the time period of the simulation, and in FEARLUS with ELMM by setting the Land Offer Threshold to such a number.
2. A comparison of results bidding at a fixed price using the LPP in the original FEARLUS, and bidding using the Fixed Price Bidding Strategy and an In-migrant Offer Price always equal to this Fixed Price (so In-migrants bid the same as established Land Managers) in FEARLUS with ELMM.
3. Finally, we used FEARLUS with ELMM to compare results using a Fixed Price Bidding Strategy with a Discounting Bidding Strategy to see if the different Land Market models would alter previous results.

For all stages, we used the Environments and HR/HSBI and HR/HSSI contests noted in table 1. For stages 2 and 3, we tried Land Parcel Price (or equivalent in ELMM where appropriate) values of 4 and 16.

In the control, we expected there to be no difference between the results reported in this case, as in each model all Land Parcels are sold to new Land Managers, which proved to be the case. In stage 2, the key difference is that in original FEARLUS, Land Managers with a negative Account can sell their Parcels one at a time and are only bankrupt when they have no more Parcels to sell, whereas in FEARLUS with ELMM, Land Managers are bankrupt as soon as their Account is negative, selling all Parcels. Here, and in stage 3, differences in the results are possible. A summary of the differences found in stages 2 and 3 is depicted in Figure 5. The stage 2 results show that there is scope for the simple modelling decision about the arrangements when the Account is below 0 to affect the results that would be reported. The stage 3 results show effects due to changes in the bankruptcy arrangements in the Fixed Price case disappearing when Discounting is used. These results in Env-U and Env-N suggest a sensitivity to differences in the Land Market Model that, in general, could not be known beforehand.

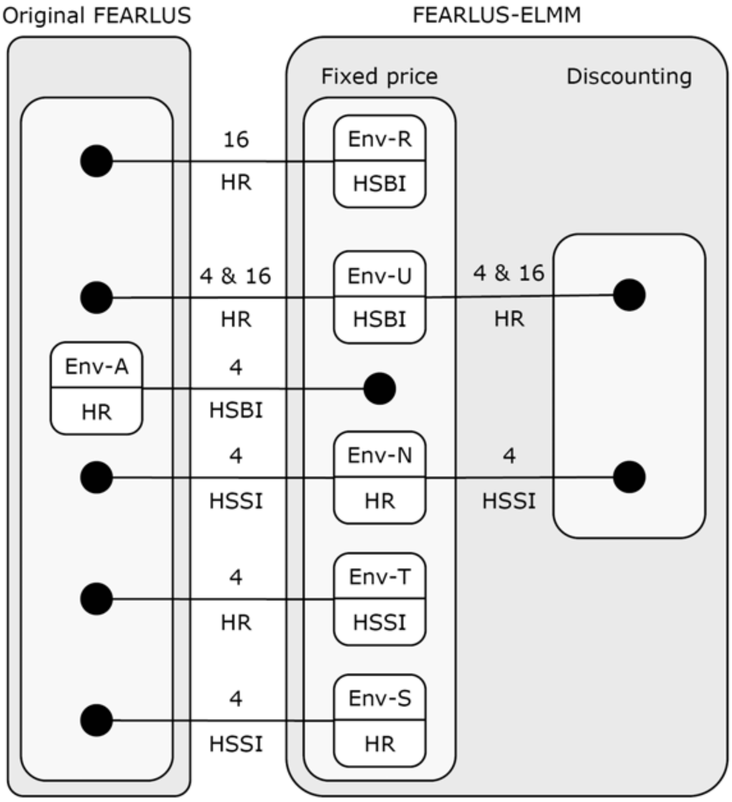


Figure 5. Summary of Type 1 significant results. The small boxes show the Environment and winning Land Use Selection Algorithm of a significant result, which are joined by a line labelled with the Fixed Price and losing Land Use Selection to a black circle representing no significant result. Stage 2 comparisons are on the left hand side, and stage 3 on the right.

Though the number of cases in which it occurred were relatively few, it is clear that changes to the mechanism by which Land is exchanged can affect the reported results of the competitiveness of strategies for choosing Land Uses.

Type 4 experiments

Although the Type 1 experiments show that there is the potential for Land Market modelling decisions to change model results, only Type 4 experiments can statistically confirm that difference. There is a further motivation for conducting Type 4 experiments: in cases where the Type 1 results seem not to have been affected, the Type 4 experiments can show where there has nevertheless been a consistent difference in the performance of a Land Use Selection Strategy attributable to the change in the Bidding Strategy. Fewer Environments were studied using Type 4 experiments: six for HR/HSBI and four for HR/HSSI (see table 1). The results are summarised in Figure 6.

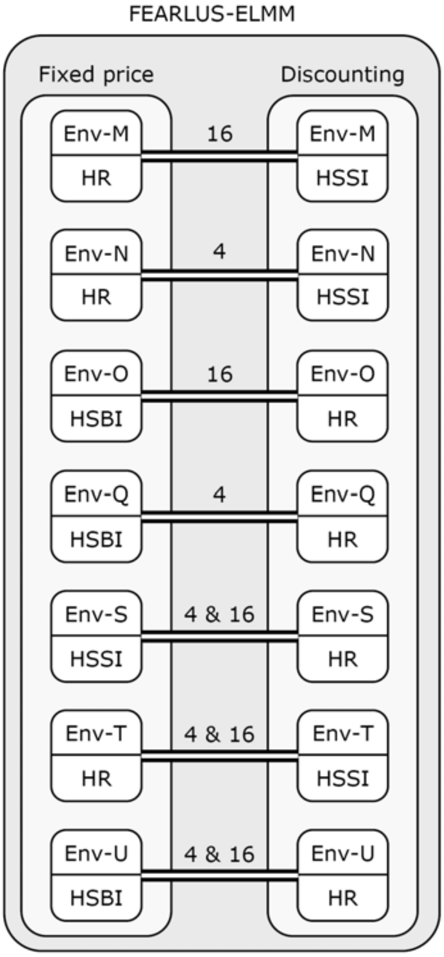


Figure 6. Summary of significant results from the Type 4 experiments, showing the Environment, Price and Land Market models under which a Land Use Selection Algorithm performed better.

Though these results show quite clearly that Land Markets have made a difference, further analysis, and visual inspection of reruns in Env-N, Env-Q, Env-S and Env-T at Price 4 indicates that an In-migrant effect is responsible for *all* differences observed between the Fixed Price and Discounting Land Market models. In-migrants affect the results in two ways. Firstly, the probability of an In-migrant belonging to either Subpopulation is exactly 1/2, whereas the population of non-In-migrant bids will be biased according to which of the Subpopulations is doing better. Secondly, In-migrant bids were set at a specific value, which, if high enough, will result in the great majority of Land Parcels being sold to In-migrants; leading in the extreme case to the same effective behaviour as when no bids are made at all. Thus, a Subpopulation using a Land Use Selection Algorithm that performs badly in the Fixed Price case can gain when Land Markets are used by increasing the likelihood of occupying Land through the In-migrant mechanism. This is a possible explanation for the result in Env-M in Table 2. HSSI loses in all Type 1 contests, and the high Price means that In-migrants often outbid others. In this case HSSI is performing more successfully in Discounting, but not because the Land Market model is better at rewarding good Land Use decision making. This may not be the only means by which In-migrants affect the results. Further experiments with different parameters are needed to explore this more thoroughly.

The important lesson here is that making Land Markets more realistic by allowing Land Managers to bid for Parcels rather than setting a Fixed Price cannot be done in isolation from consideration of other influences on Land Markets. Our efforts to maintain similarity with FEARLUS have been partly responsible for the distorting effect of In-migrants (Price 16 was that used in earlier work), and though exploring still lower values for Price than 4 may permit the desired comparison, more radical alterations to the model may be necessary to explore the effects of implementing land bidding. Our step-by-step model modification strategy may not be sufficient to test our hypotheses regarding the effects of land markets.

DISCUSSION

Imitation is one means of economising on computational resources, and/or compensating for an absence of knowledge, and is known to be one way in which land managers choose what to do (Pomp and Burger, 1995). Schmidt and Rounsevell (2006) call into question the study of imitation in agent-based models of land use change, finding that imitation leaves little noticeable trace on landscape pattern in a case study in central Belgium. Other studies (e.g. Ryan and Cross 1943; Deutschmann and Fals Borda 1962 as reported in Rogers 2003, pp.268-271, Hägerstrand 1967, pp.158-163, Lansing and Kremer 1994, Berger 2001, Letenyei 2001) do claim evidence of direct influence on the adoption of particular agricultural techniques between farmers within a locality. Though it may be significant that most of these studies have been carried out in areas where agricultural advice from non-local sources is likely to have been less readily available than in present-day Belgium, they do establish a case that the imitation of neighbours is important. Questions about imitation procedures (e.g., how imitators select their models, how far they are influenced by the simple popularity of an innovation among those models, how far they require evidence of its success) are then clearly significant. These questions have not been much investigated empirically (the usual assumption being that adoption takes place, or at least is considered, when a threshold is passed in the proportion of adopters within some population). The work by Pomp and Burger (1995) is an exception, suggesting that farmers may imitate those most similar to themselves, or those they believe to have most information. They also suggest that successful adoption by a farmer *without* a prior history of successful innovation might be particularly influential: if the innovation succeeds in their hands, it must be highly advantageous! However, their econometric models do not examine the consequences of these different types of imitation as we can with FEARLUS.

In the real world, innovators play an important and persistent role in agricultural environments. If they were not doing “better” than imitators in certain contexts, and according to certain metrics, they would not persist in the rural economy. In the real world also, in contrast to FEARLUS, land managers may choose not only land uses, but particular decision strategies, and these choices may also be based on imitation. Through innovation and intelligent imitation of decision strategies, a balance of decision makers of various types may evolve over time. These “decision ecologies” may evolve so as to ensure stability or long-run survival at the scale of the rural system. Whatever the properties of the rural system, at the scale of the land manager, the chosen strategy should have some attractiveness that motivates its selection. In short, there must be some reason to be an innovator, rather than an imitator.

Innovators as currently modelled in FEARLUS may experience too little success. Imitators seem to consistently capture a higher proportion of parcels, having, in the language of game theory, a second-mover advantage. It is possible that innovators are currently experiencing success in FEARLUS according to other individual rather than population scale metrics: from a “decision ecology” point of view, a viable landscape-scale system may in any case only need so many innovators. We have yet to examine metrics such as the number of parcels, average wealth and average longevity of innovator land managers. Such metrics may still show that innovators experience relative success in particular environments.

If such analysis still indicates that innovators do relatively poorly, options exist for increasing the chance of success for innovation. In the real world, a choice to innovate into a new land use may be based on years of experience that translates into specialized knowledge of what land outputs are likely to succeed in the marketplace. Such experience could be captured in a modelling framework by giving managers who have innovated into profitable crops in the past greater knowledge regarding the potential profitability of new land uses than other agents. Innovators would also then need the ability to choose among potential new land uses. Innovators with such characteristics may earn early profits by being first to market with a desirable good, which demands a high price when supply is relatively low. To reflect these opportunities, the model would need to implement output prices for land uses that depend (in a decreasing fashion) on their total supply.

What we have begun to show here is that the strategy for choosing land uses cannot be considered in isolation from wider aspects of farm business management. Since the way the land market works can affect the outcome of the model, it is likely that differences in land acquisition strategy will affect the relative performance of different kinds of land managers.

Discussions among the LUCC modelling community have highlighted the importance of model validation and the need for a variety of spatial and a-spatial validation techniques (Veldkamp & Lambin, 2001; Parker et al., 2002). While the model enhancements described in this chapter are designed for theoretical exploration, our conjecture that a model with a functioning land market may perform better should ultimately be subject to empirical testing.

CONCLUSION

Various aspects of the way in which Land Markets are implemented can affect the relative performance of the Land Use Selection Algorithms. Referring back to the Type 1 experiments, the comparison between original FEARLUS and FEARLUS-ELMM using Fixed Price shows that the different land market modelling decisions (a) and (b) in the list above (decision to sell and which Parcels to sell) can affect results. We also observe that In-migrant Land Managers can skew the outcome, relevant to decisions (g) and (h) (determination of final sale price and what to do with land no-one wants to buy). Since In-migrants are a feature of real-world land markets, decisions on how to handle them merit separate consideration. Results comparing the Fixed Price with the Discounting Bidding Strategy have not conclusively shown that decisions (e) and (f) (how much to bid and which Parcels to buy) affect results in isolation from In-migrant bids, though this will be the subject of future work. Thus, at least some of the decisions outlined for simulating land markets are non-neutral with respect to other aspects of a model of land use change. We hope in future to study these effects in more detail, as well as to explore the influence of other aspects of land market modelling decisions on model behaviour.

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