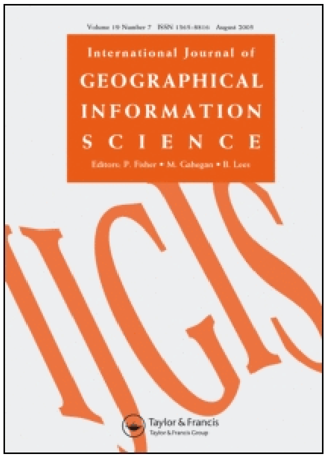

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Research Article

Spatially explicit experiments for the exploration of land-use decision-making dynamics

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We explore the special outcomes of decision-making through two laboratory-based experiments, one with a homogenous land suitability surface and another with a heterogeneous suitability surface. Subjects make resource allocation decisions on an abstract landscape and are given a monetary incentive to maximize their revenue during the experiment. These experimental results are compared with simulation output from an agent-based model run on the same abstract landscape that uses a utility-maximizing agent. The main findings are: (1) landscapes produced by subjects result in greater patchiness and more edge than the utility-maximization agent predicts; (2) there is considerable diversity in the decisions subjects make despite the relatively simple decision-making context; and (3) there is greater deviation of subject revenue from the maximum potential revenue in early rounds of the experiment compared with later rounds, demonstrating the challenge of making optimal decisions with little historical context. The findings demonstrate the value of using non-maximizing agents in agent-based models of land-cover change and the importance of acknowledging actor heterogeneity in land-change systems.

Keywords: GIS; Agent-based modelling; Experiments; Land-use change; Land cover; Model validation

1. Introduction

Various methodological approaches have been used to explore the dynamics of land-cover change, not exclusively but often with a considerable focus on spatial relationships. For example, empirical analyses of household- or community-level data have been used in coordination with land-cover data derived from remotely sensed imagery to link actor characteristics such as age, household size, and wealth with landscape outcomes (McCracken *et al*. 1999, Walsh *et al*. 1999, 2004, Munroe *et al*. 2004, Moran and Ostrom 2005). Likewise, various modelling techniques have been used to develop representations of land-cover change systems at different spatial scales of analysis. In particular, cellular automata (Clarke and Gaydos 1998, Li and Yeh 2002), spatial economic models (Mertens and Lambin 2000), and agent-based models (Parker *et al*. 2003, Evans and Kelley 2004, Brown *et al*. 2005) have

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been used to explore historical land-cover change processes and in some cases make predictions about future land-cover changes.

The actual process of spatial decision-making is often not explicitly specified in these empirical and modelling approaches, although there are certainly examples of models that do represent decision-making using utility-based or heuristic approaches (Deadman *et al*. 2004). In the case of empirical data analyses, statistical tools like logistic regression are used to correlate particular actor attributes with specific land-use decisions either reported in a survey or observed from remotely sensed imagery. This approach identifies a statistically significant relationship between actor or landscape attributes and land-cover change but does not necessarily focus insight on the explicit land-use decision-making process. For example, finding a correlation between landowner age and land-use change is useful for policy purposes but does not necessarily identify why landowners of a certain age make these decisions—this task is left to the interpretation of the researcher. Put differently, it is easier to design a survey instrument that reliably records the attributes of a household and what land uses an actor chose in a particular year than to derive the actual motivations, incentives, and preferences behind those land-use decisions from the survey instrument.

Historical land-cover data can be used to calibrate a model that uses social and biophysical data as inputs, creating a representative model of a land-change system. These tools allow researchers to consider the probability of a specific land-use change occurring. But these probability-based results do not necessarily provide clear insight into the actual decision-making process such as how an agent evaluates the benefits of a land-use change, the risks involved, and time frames considered for decision-making. Agent-based (Deadman *et al*. 2004, Brown *et al*. 2005) and statistically based (Walker *et al*. 2000) household-level models that portray individual actors have helped bridge the gap between modelling and the land-use decision-making process through the representation of agents with highly detailed specifications. However, it remains a challenge to collect the data necessary to validate the decision-making processes inherent in these models. Some recent progress has been made in the validation of agent-based models of land-cover change (e.g. Brown *et al*. 2005). Yet, most approaches to validation involve matching modelled landscapes to historical data, which does not necessarily demonstrate that the decision-making dynamics built into the model are robust. Alternative modes of validation have been encouraged in the modelling community, including an attention to structural validation (Manson 2002, Parker *et al*. 2003, Grimm *et al*. 2005), and we consider decision-making as a primary structural component in agent-based models.

The scale of analysis may also present an obstacle to linking specific land-cover change outcomes to the explicit decision-making process. Land-cover change models using counties, municipalities, or large cell sizes aggregate the decisions of hundreds or thousands of actors. These regional models may be capable of making relatively accurate predictions for particular scenarios (Veldkamp and Fresco 1996, Verburg *et al*. 1999, Kok *et al*. 2001) but do not necessarily provide explanatory power regarding the local household-level dynamics acting within each enumeration unit.

Both empirical and modelling approaches have clearly made substantial contributions to our understanding of land-change science. The objective here is to suggest that there are additional methodological tools available to land-change researchers to more explicitly explore decision-making dynamics. In particular, the use of laboratory-based spatial experiments can help test the assumptions in basic theories of spatial decision-making scenarios. Here, we use the term 'experiment' to refer to a laboratory experiment where human subjects are faced with a specific decision-making task rather than to refer to a model run or simulation. Both usages are common in various literatures, but the laboratory-based use of the term 'experiment' incorporating human subjects is standard in the field of experimental economics, and that is the usage we adopt here.

The motivation for our interest in spatial experiments is to contribute to the theoretical foundation of spatial decision-making and provide insight into the landscape patterns that emerge from heterogeneous decision-making strategies. The results presented here provide support for the modelling methods used in agent-based models and therefore add to the suite of tools available to researchers to aid in the design of models. In some ways, the use of spatial experiments can serve as one of many forms of model validation, although spatial experiments alone generally cannot inspire confidence in a model. However, we suggest that spatial experiments can be used in coordination with empirical data to help in the design and implementation of agent-based model approaches to overcome some of the challenges of designing robust agent-based models (Jager and Janssen 2002). Figure 1 represents a conceptual depiction of the complementary role we see for spatial experiments in an integrated methodology including empirical data analysis and modelling.

We believe these spatial experiments are particularly useful in exploring the theoretical basis for spatial outcomes from different decision-making settings in the same way that game theory has been used to support economic theories. Game theoretic approaches present simplified decision-making settings that are then, with caution, extrapolated to real-world contexts. Spatial experiments can inform how we study land-change systems and specifically the spatial patterns that emerge in environments affected by diverse social and biophysical conditions. For example, researchers in many disciplines have focused considerable attention on whether

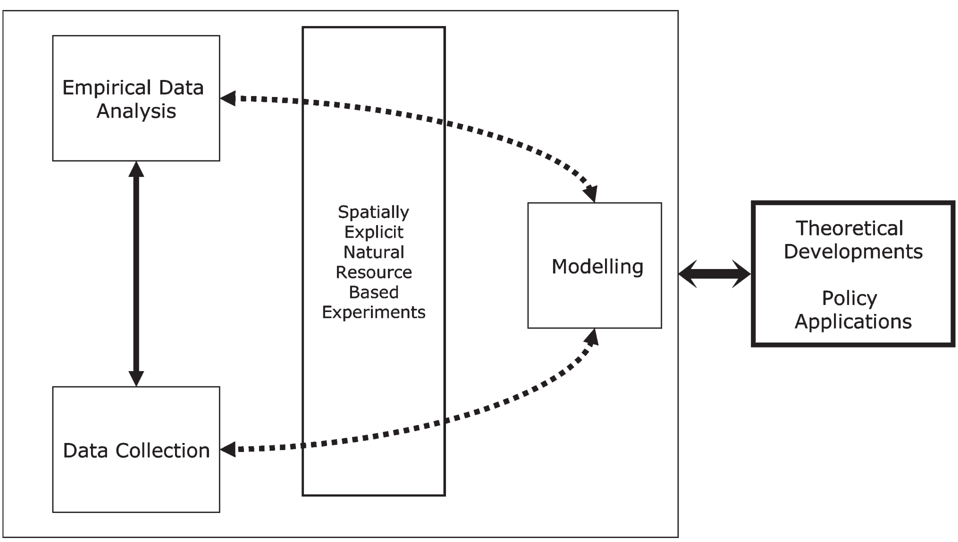

Figure 1. Role of experiments in integrated methodological framework.

actors make decisions that maximize their utility, broadly speaking (Gintis 2000, Henrich *et al*. 2001). Many land-cover change models employ utility-maximizing agents in their decision-making calculus (including Evans and Kelley 2004). However, if we find evidence that agents do not make utility-maximizing decisions, as has been debated, then what are the *spatial* implications of non-utility-maximizing behaviour? This question directly addresses the challenge of modelling the spatial pattern of land-cover change in environments that are biophysically heterogeneous and are managed by landowners with diverse attributes and decision-making strategies.

The remainder of this paper is organized as follows. In section 2, we provide a brief overview of experimental research related to decision-making and natural-resource management in various disciplines and highlight the opportunity to incorporate spatial relations in this research methodology. Section 3 describes the basic spatial experimental design we have developed. Section 4 describes our experimental results, comparing the decisions of subjects with those of a utility-maximizing agent simulated in an agent-based model. Sections 5 and 6 present a summary discussion and conclusion.

2. Experimental research and decision-making

Several disciplines have strong traditions of laboratory- or field-based experimental methods. In particular, psychology and economics have considerable literatures drawing on controlled experimental scenarios to explore key aspects of decision-making processes such as risk, cognition, bargaining, and trust. To a lesser extent experimental approaches have been applied in anthropology (Henrich *et al*. 2001, Bernard 2002), political science (e.g. Ostrom *et al*. 1994), and sociology (Kanazawa 1999). There has clearly been some reluctance to the adoption of experimental methods in disciplines such as anthropology (e.g. Chibnik 2005), but within each of these disciplines there is tacit acceptance of experimental methodologies within subdisciplinary fields. Two classic experimental designs are the Prisoner's Dilemma (e.g. Ostrom *et al*. 1994, Wedekind and Milinski 1996, Milinski and Wedekind 1998) and the Ultimatum Game (e.g. Henrich *et al*. 2001, Oosterbeek *et al*. 2004), both of which have been conducted and replicated with varying subject populations and have resulted in numerous derivative experiments.

In order to provide an example of how a particular experimental design has been applied to specific contexts, we briefly describe the Ultimatum Game. In this experiment, two players are offered a sum of money where one player proposes how to split the funds between the two players, and the other player decides whether to accept or reject the proposal. Neither player receives any money if the deal is rejected. In one widely cited laboratory-based experiment with students, the amount proposed by the first player was less when the gender of the second player was known to be female than when the gender of the second player was known to be male (Solnick 2001). The author (perhaps controversially) states that

> the results are consistent with the evidence that women are quoted higher prices for cars and that women gain smaller increases in salary when they choose to bargain. Thus, it is possible that part of the pay gap between men and women is due to bargaining differences. (Solnick 2001: 199–200)

Laboratory-based experiments with university students by Henrich *et al.* (2001) found that their behaviour was consistent with income-maximization theory. There have also been many applications of the Ultimatum Game beyond the computer laboratory-based designs. In an application of the Ultimatum Game in a series of small-scale societies by Henrich and colleagues (2001), subjects from communities that had a high degree of market integration tended to propose larger amounts than subjects from isolated communities with less market-based integration. The Ultimatum Game is just one of many experimental designs that have been used to explore various decision-making contexts, including whether decision strategies differ as a function of gender, race, or culture.

A fundamental question in experimental research is whether the subject pool is representative of the decision-making of other populations, including real-world actors. This is particularly problematic when experiments have a highly specified and applied context, such as an experiment where subjects are told they represent individuals in the fishing industry. Despite these criticisms, there has been a general acceptance of experimental research methods in many disciplines. For example, experiments exploring consumer choice have been shown to provide accurate predictions of actual consumer behaviour (Burke *et al.* 1992, Huber and Zwerina 1996). Furthermore, the Nobel Prize in Economics in 2002 was presented to Vernon Smith and Daniel Kahneman for their laboratory-based experimental research in economics and psychology. Vernon Smith's early experiments used his own students as subjects, where he saw them reach a competitive equilibrium despite the thought that subjects without perfect information could not create efficient markets (Smith 1962). Here, there is an assumption that given sufficient monetary incentives, the actions of undergraduate students in abstract experiments are capable of testing key decision-making theories applicable to real-world contexts. The suggestion is not that laboratory subjects will act exactly like real-world actors, but rather that we can gain insights through the use of laboratory research that can be valuable tools to gain new insight into real-world behaviours.

There are limited examples of spatial representation in experimental research. Spatial cognition research has employed the use of human subjects for experiments integrating principles from psychology and geography, and there is considerable research in this particular area (e.g. Golledge 1999, Klatzky *et al.* 2002). However, the objective has focused on aspects of cognition and perception rather than the spatial dynamics of economic contexts. One of the most widely cited examples of spatially explicit experimental research is Schelling's segregation model (Schelling 1971, 1978). Here, students participated in an experiment using a chessboard-like structure to explore the dynamics that lead to segregation outcomes. The experimental results are used to complement computational models, and in coordination, these two data sources have provided considerable insight into theories of how segregated cities develop.

Experimental methods have been applied to research on foraging behaviour (Wilke *et al.* 2004) because of the role of space and mobility in foraging activity. Various modelling methods, including agent-based approaches, have been used to explore foraging behaviour. Experimental methods present the opportunity to create a rich, integrated research approach combined with modelling and the analysis of field data (Goldstone and Janssen 2005). With this integrated approach, experiments can be used to provide an empirical justification for assumptions built into behavioural models because experiments can be designed to explicitly test researcher-designed scenarios. Experimental results and modelling runs can also be used to inform the design of field data collection to further provide empirical evidence for key decision-making theories.

Despite the prevalence of spatial methods (GIS, cellular automata, agent-based modelling) in land-use/land-cover change research, and the contributions of economics to land-use theory, there are relatively few examples of applications of experiments to land-use management in recent literature. In management contexts, land-use decisions have explicitly spatial outcomes, so it seems that the use of spatially explicit experiments would be a convenient method to explore decision-making dynamics in questions of natural-resource management. The participatory modelling studies of Bousquet *et al*. (2002) and Castella *et al*. (2005) are unique examples where researcher-designed scenarios have been used to inform models of land management in common-pool resource systems. In these games (referred to as 'role-playing games' rather than 'experiments'), the scenario is often highly specified and made explicitly relevant to the subjects in the game. In contrast to many experiments in economics, here stakeholders such as landowners, individuals in the fishing industry, or rangeland managers are the subjects as opposed to a pool of subjects drawn from a student population. One objective is to allow these stakeholders to develop new insight in the feedbacks present in a complex social–ecological system, similar to the application of participatory GIS approaches. Another objective is to provide greater confidence in model design (Manson 2002). This method of research contrasts that in experimental economics, where the experimental design is usually made abstract to focus attention on a key theoretical aspect of decision-making. Also, experimental approaches commonly consist of numerous replications of the same experiment while role-playing games are usually conducted in a specific field site with the explicit goal of leading stakeholders to new insights regarding resource management.

It is useful to validate a model of land-cover change not only based on the landscapes produced by the model but also by assessing what Manson (2002) refers to as the structure and 'reality' of models. One method of addressing structural validation is to develop a better understanding of the component relationships in the model, including the decision-making dynamics. For example, Jager and Janssen (2002) utilize experimental data to calibrate and validate a model of common-pool resource (CPR) dilemmas. While Jager and Janssen's CPR application is non-spatial, it demonstrates the utility of using laboratory-based experiments (Ostrom *et al*. 1994, Goldstone and Janssen 2005) to explore key decision-making dynamics built into an agent-based model.

The results presented in this paper are an attempt to bridge the methodological literature on experimental economics applications to natural-resource management and the strong theme of spatial representation in land-cover change modelling and more generally land-change science. Economists have focused substantial attention on the question of whether actors make seemingly rational decisions in different contexts, and there is considerable evidence suggesting that alternative models of actor decision-making are more appropriate, such as that of bounded rationality. If we can accept that landowners, farmers, and fishers do not make decisions in the mould of *Homo economicus*, then what are the spatial implications of the diverse behaviours that do occur in the real world? The spatial nature of this decision-making heterogeneity is a fundamental aspect of understanding the role of social complexity in land-change science.

3. Spatially explicit experimental design

3.1 *Experimental application*

The general framework of our GIS-based experimental platform is built on a client–server structure developed using Visual Basic, ArcGIS 9.0, and ArcSDE 8.3. Each experimental session consists of a group of nine subjects who make resource-allocation decisions on discrete partitions composed of a 5×5 matrix of cells. For clarification, we use the term 'treatment' to refer to a particular experimental design, and a 'session' refers to one group data collection event for that experimental design. We conducted multiple sessions of the same treatment type for replication purposes. The 5×5 cell partitions for each subject are arranged in a 3×3 pattern with the overall subject landscape composed of a 15×15 cell structure (figure 2). Subjects make decisions in a series of 40 consecutive rounds in which they can allocate any of their cells into the production of one of two abstract resources (B or G; named for colours of these resources on the computer interface, blue and green).

Subjects are seated at workstations with an interface for interacting with the abstract spatial landscape. The server coordinates the input of each subject and returns data to the clients at the end of each round. Subjects see the revenue they received on each of their cells (central grid with numbers in cells in figure 3) and what the prices for resources B and G were for the previous round (lower-left dialogue box in figure 3). Cells are graphically selected and then assigned to the B or G resource using a dialogue input box (upper left in figure 3). Cells can be selected either individually or in contiguous or non-contiguous groups. We chose a 5×5 matrix of 25 cells as a balance between a desire to have enough spatial complexity within the player partitions to see spatial patterns emerge without having so many cells that subjects could not reasonably manipulate them all in a single round.

The experiment is intentionally designed to have a simple and abstract structure. We are not seeking to elucidate perceptions or preferences for forest, or opposition to timber harvesting—issues where research subjects could potentially have strong opinions that differ from landowners in a particular geographic location. Instead, our goal was to explore the spatial implications of heterogeneous decision-making

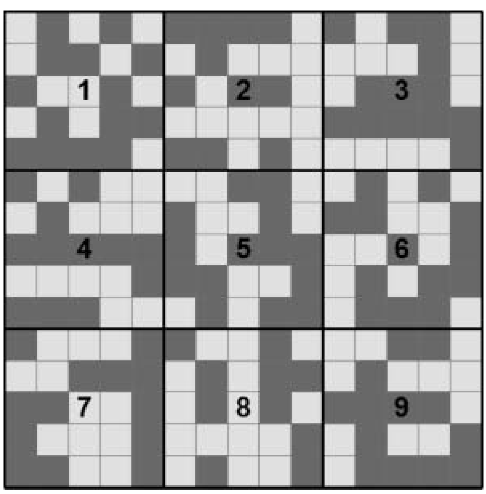

Figure 2. Experimental landscape, 5×5 matrix of cells for each of nine subjects.

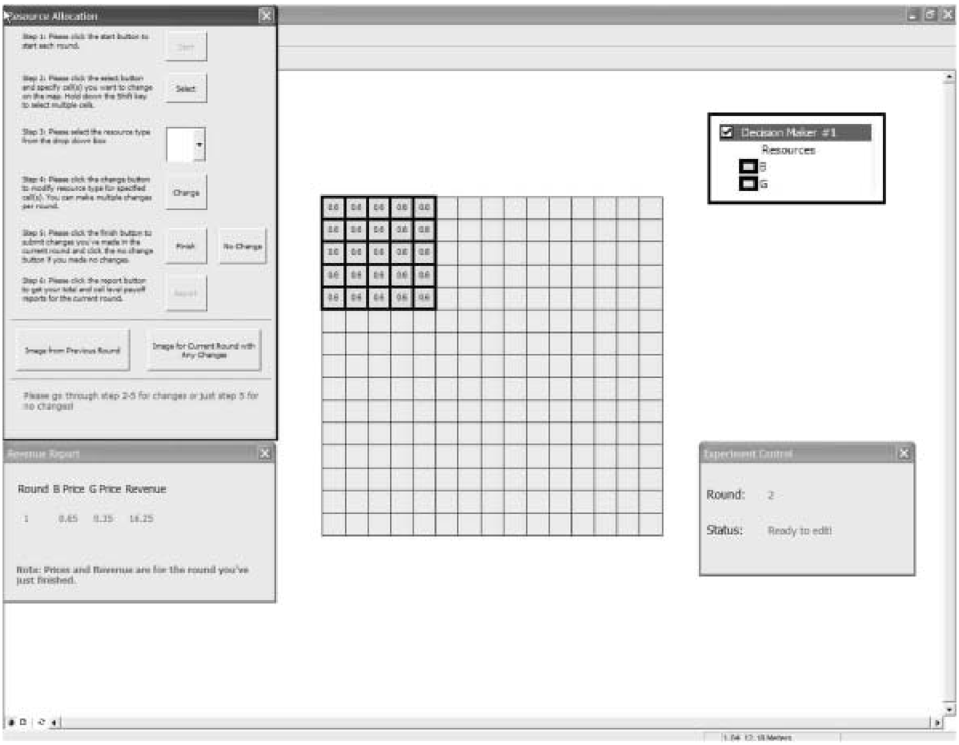

Figure 3. Experimental graphical user interface (for subject 1).

strategies. By constructing an abstract decision-making setting, we can better control the possibility for subject biases to affect our research results. This approach of designing abstract experimental scenarios is widely used in experimental economics (e.g. Henrich *et al.* 2001), from which we have adapted our approach to emphasize spatial dynamics.

Each subject is able to see the outcomes of the other subjects' decisions from the previous round at the beginning of the subsequent round. However, subjects do not see the revenue of the cells of other subjects. This level of information is analogous to a landowner who can see what land-cover changes an adjacent landowner makes on their land but may not know the revenue that landowner receives as a result of those changes. No communication is allowed between subjects during the experimental session.

At the beginning of the experiment, subjects are given an instruction sheet that describes how to use the graphical user interface and the factors that are used to calculate the cell-based revenue. The instruction sheet is read verbally to the subjects at the beginning of each session. A series of training rounds with random experimental parameters are used to allow the subjects to practice with the interface before the actual experimental session begins. During the training rounds, we also emphasize to the subjects how their decisions determine the monetary payout they receive at the end of the experiment and ensure that subjects clearly understand how to interpret the revenue reports in each round. Subjects were given up to approximately 1 min to submit their decisions for each round. Subjects are not told how many rounds the session will include but are told that the entire experiment will last 1–1.5 h, including time for the training rounds.

Many models of land-cover change are built on generalized raster environments where each cell can transition between land-cover types. In an agent-based model with non-mobile agents, each agent typically controls a set of contiguous cells. This is the structure used in an agent-based model we have developed for south-central Indiana (Evans and Kelley 2004). In spatial terms, the main departure of the spatial structure of the experimental design from our agent-based model is that the landscape employed for the experiments consists of regular-sized partitions, while the agent-based model was constructed using partitions derived from land-ownership data with irregularly sized parcels. However, the general structure of associating subjects to a defined set of cells conceptually matches the basic design of our agent-based model.

3.2 *Experimental treatments*

The basic experiments presented here are spatial resource-allocation scenarios where subjects must decide to allocate a cell to one of two resources, and they receive revenue in abstract units depending on experimental parameters. Subjects receive a monetary payoff at the end of the experiment as a function of the abstract revenue earned during the experiment. Subjects are told the range of the cash payout they can receive, but during the experiment they are not told how the revenue units in the experiment translate to dollar amounts for the payout. Undergraduate students from large enrolment introductory courses were recruited as subjects for these experiments. A brief announcement was made in these classes with instructions to send an e-mail to sign up for a particular experimental session. We recorded each student's participation in the experiment to ensure that no subject participated in multiple sessions.

We intentionally designed the decision-making scenario in the experiment to be abstract. There is no direct connection of the cell-based decisions to a land-cover change context. The two resources are referred to as 'B' and 'G' to correspond to the blue and green colours used to symbolize cells in the experimental interface. We use these abstract references rather than 'forest' or 'agriculture', because we do not want a subject's preference for a particular type of resource (i.e. an environmentalist for 'forest') to affect their fundamental decision-making in the experiment.

This paper presents the results from two treatments, one a baseline experiment using a homogenous landscape and a second experiment using a landscape with heterogeneous land suitability for one resource. The price regime for resources B and G is the same for each treatment (figure 4), so the only difference between the two treatments is the 'suitability' modifier that affects the cell revenue for resource B (figure 5). The price regime is pre-set for B and G, and subject decisions do not affect the price structure. Subjects are told that the prices that determine the revenue for B and G will change during the experiment, but they are not given any information that would allow them to initially predict the simple trend.

Cell revenue is a function of: (1) the prices of B and G, which change through the 40 rounds of the experiment; and (2) the suitability of each subject's cells for the production of B and G, pre-set at the beginning of experimental treatment. The underlying structure of subjects' revenue for resource B or G at location (*i*,*j*) of their parcel can be represented with the following equation:

$$R_{i,j} = P_{\mathrm{B,G}} + w_{\mathrm{s}} S_{i,j} \tag{1}$$

where R is the revenue received on cell i,j, P is the price (for either B or G), and w_{s} is

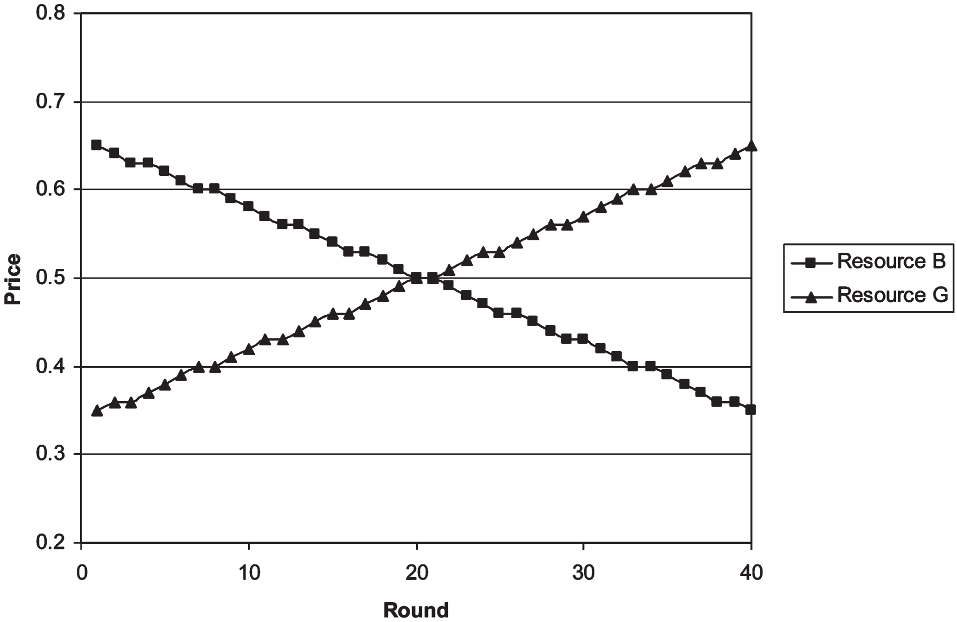

Figure 4. Time series of prices for resources B and G.

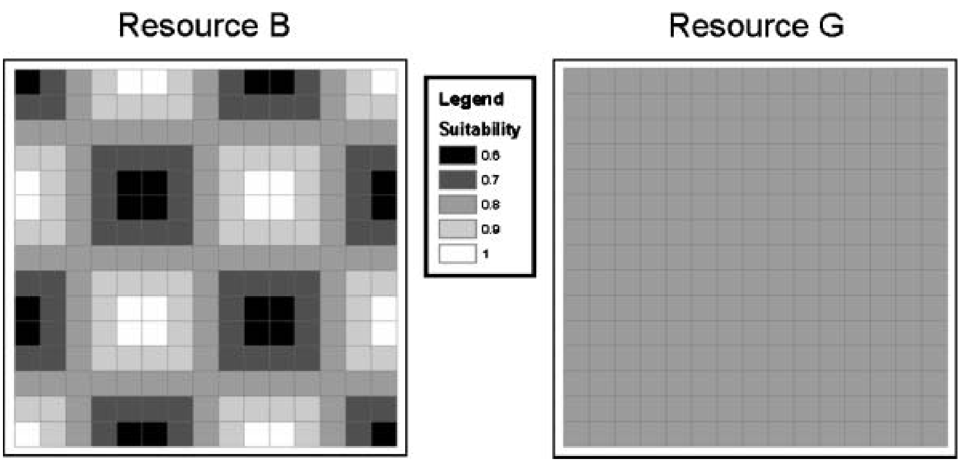

Figure 5. Cell-level landscape suitability factor for resources B and G.

a suitability weight and measure of the suitability of the cell for B or G. The suitability weight is a parameter that allows us to explore the relative influence of the suitability term on decision-making compared with a null experiment where the weights are set to zero. For the treatments presented in this paper, the suitability weight (w_s) is set to either 0 or 1. In the future, we intend to conduct additional experiments with higher suitability weights to explore how subjects respond to a higher relative influence of suitability compared with the price sequence.

The price regimes for B and G used in our experiments are relatively simple. The price for B begins high and declines linearly, while the price for G begins low and increases in direct correspondence to the B price. The prices for B and G are equal at the halfway point of the experiment such that the cell revenue will not vary depending on the subject allocation choice.

The two treatments described here are referred to as S0 and S1. The first treatment (S0) is a baseline experiment where the suitability weight is 0, and the only factor affecting cell revenue (apart from the subject choice of resource B or G) is the price sequence. The second treatment (S1) uses a suitability weight of 1. The suitability layer (figure 5) is constructed symmetrically for each player partition with suitability values ranging from 0.6 to 1. The mean suitability value for B is the same as the mean suitability value for G, which has a homogenous distribution. Thus, given equal prices for B and G, the revenue potential is the same between these two resources. As with the price trend, subjects are told that suitability can affect the cell-level revenue, but they are told neither the magnitude of that influence nor the spatial pattern of the suitability landscape. We conducted five experiment sessions each for the two treatments, resulting in a total of 10 sessions with 90 research subjects.

A critical component of the experimental design is the incentive for subjects to make effective decisions in the experiment. The use of monetary payouts has been widely adopted in experimental research. In our experiment, subjects receive between \$10 and \$35, depending on the revenue they receive in the experiment. Thus, subjects have a \$25 monetary incentive to try to maximize their revenue in each round and for the entire experiment. Subject payments are made in private at the end of the experiment so that no subject knows what the other subjects were paid.

One of the overall goals of the research is to identify the spatial outcomes of decision-making in circumstances when a subject does not have perfect information. We expected subjects to produce landscapes that have more heterogeneity and attain less than the maximum potential revenue because they do not know what the price trend is for either treatment. The baseline S0 experiment exaggerates the possibility of finding this effect because the landscape resulting from a perfect utility-maximizing agent is always a completely homogenous layer of either B or G. We designed the second treatment (S1) to specifically test whether subjects would produce a more heterogeneous landscape for a scenario where the landscape that yielded the maximum potential revenue itself had heterogeneity. For some S1 rounds, the maximum revenue is achieved from a homogenous layer of either B or G (e.g. early in the experiment where the price differential between B and G outweighs the suitability factor). But there are also rounds in the S1 experiment where the maximum revenue is achieved by choosing an allocation of a combination of B and G cells on a subject's partition. There is a clear structure to the S1 suitability surface (figure 5), but it nevertheless does present a landscape scenario with an additional layer of complexity above the S0 treatment. This design allows us to assess whether the degree of heterogeneity produced from subject decision-making matches or exceeds the heterogeneity found with utility-maximizing simulations where some degree of heterogeneity is produced.

3.3 *Comparison with utility-maximizing agent-based model*

Previous research has employed an agent-based model to simulate landowner decision-making in a study area located in south-central Indiana (Evans and Kelley 2004, Kelley and Evans submitted). To provide a foundation upon which to evaluate the results from the experimental sessions, we ran this agent-based simulation on the abstract experimental landscape using the same price-trend data, suitability landscape, and spatial structure as the experimental sessions. The simulation results produced from the agent-based model runs basically present the case of an actor with perfect information who makes perfect utility-maximizing decisions. The decision-making dynamics in the model when calibrated and fit to the real-world context of south-central Indiana are much more complex than the simple analytical scenario presented by the experimental design discussed in this paper. The optimal (i.e. utility-maximizing) land-use choice in the experiment is solely a function of the price of B vs. G in the S0 experimental treatment. In the S1 treatment the optimal land-use choice is a function of the price of B vs. G and the cell suitability for B and G (equation (1)). Thus, the agent-based model is reduced to a simple cell-based revenue calculation where no model calibration is required, differing from when the model parameters are fitted to historical data (Evans and Kelley 2004). In other words, the agent-based model is used as a simple spatial calculator to identify what landscape produces the maximum revenue for each round as a function of the price (S0 and S1 treatments) and suitability measures (S1 treatment only).

In addition to measures describing subject revenue, landscape composition and edge metrics are used to compare the landscape patterns observed from the experiments to landscapes generated by simulations with utility-maximizing agents. Specifically, we use the composition metric (percentage of landscape composed of resource B), and the total edge (amount of edge between the two resource classes) as rudimentary tools to describe the spatial pattern and composition of the experimental landscapes. Metrics were calculated using the entire 15×15 cell matrix for all subject partitions to quantify the impact of the nine subject participants on the aggregate-level landscape structure.

4. Experimental results

In the simulation of the baseline treatment (S0), the entire landscape switches from the B resource to the G resource after round 20, when the price for G exceeds the price for B (column *a* in figure 6). The S1 simulation demonstrates how the symmetrical pattern of land suitability produces more heterogeneity and more landscape edge than in the S0 simulation. The landscape pattern produced by the S1 simulation (column *a* in figure 7) directly corresponds to the pattern of landscape suitability. The prices for B and G are designed so that the S1 simulation begins with a homogenous landscape in resource B and ends with a homogenous landscape in resource G. The rounds in between vary in landscape composition as the suitability factor for selected cells supersedes the price difference between B and G.

There was considerable variance across subject partitions in both treatments. Some subjects approach the optimal revenue (as defined by the agent-based simulation), while others substantially deviate from the optimal revenue. Figures 8(*a*)–8(*d*) show the subject-level revenue for sample S0 and S1 sessions. The bold red line in figures 8(*b*) and 8(*d*) show the maximum potential revenue a subject can possibly receive in each round and the mean revenue of all nine subjects. Figures 8(*a*) and 9(*b*) demonstrate the extent to which individual subjects approach the maximum potential revenue in S0 and S1 sessions and the variance around the mean. It is apparent that some subjects are more successful than others at finding the optimal choice and thus achieving the higher potential payoff. However, no subject attained the optimum revenue in every round of the experiment.

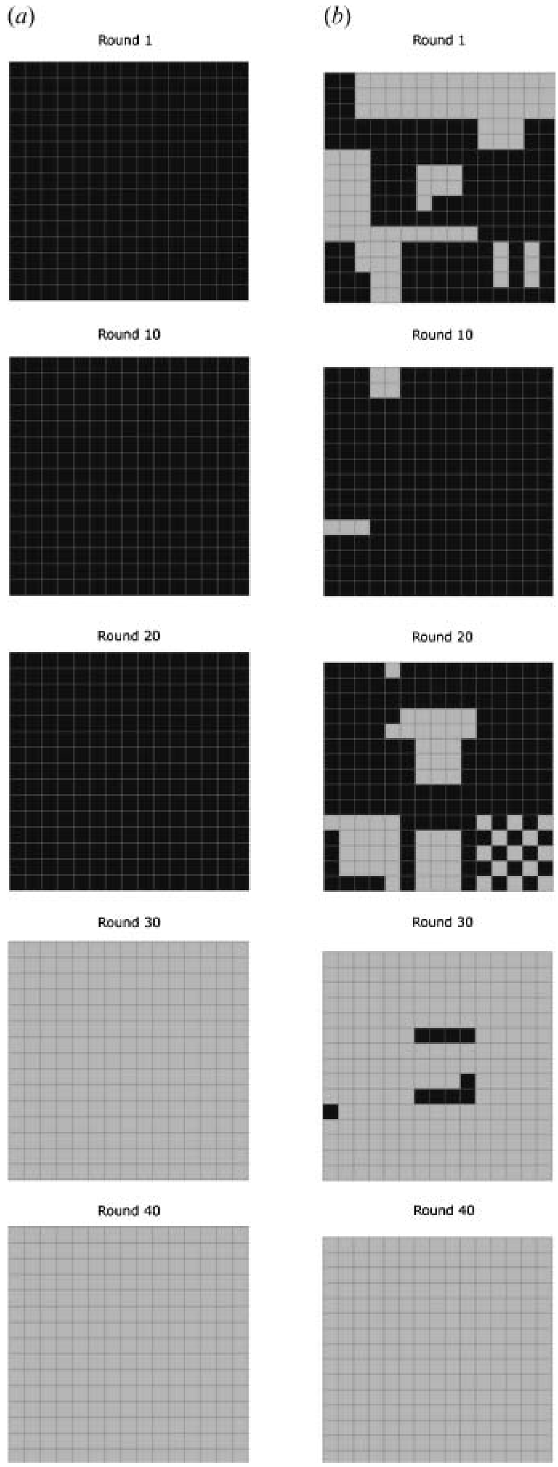

Figure 6. S0 simulation vs. sample experiment landscape, homogenous suitability for resources B (blue cells) and G (green cells). (*a*) Utility-maximizing agent simulation. (*b*) Sample laboratory session result.

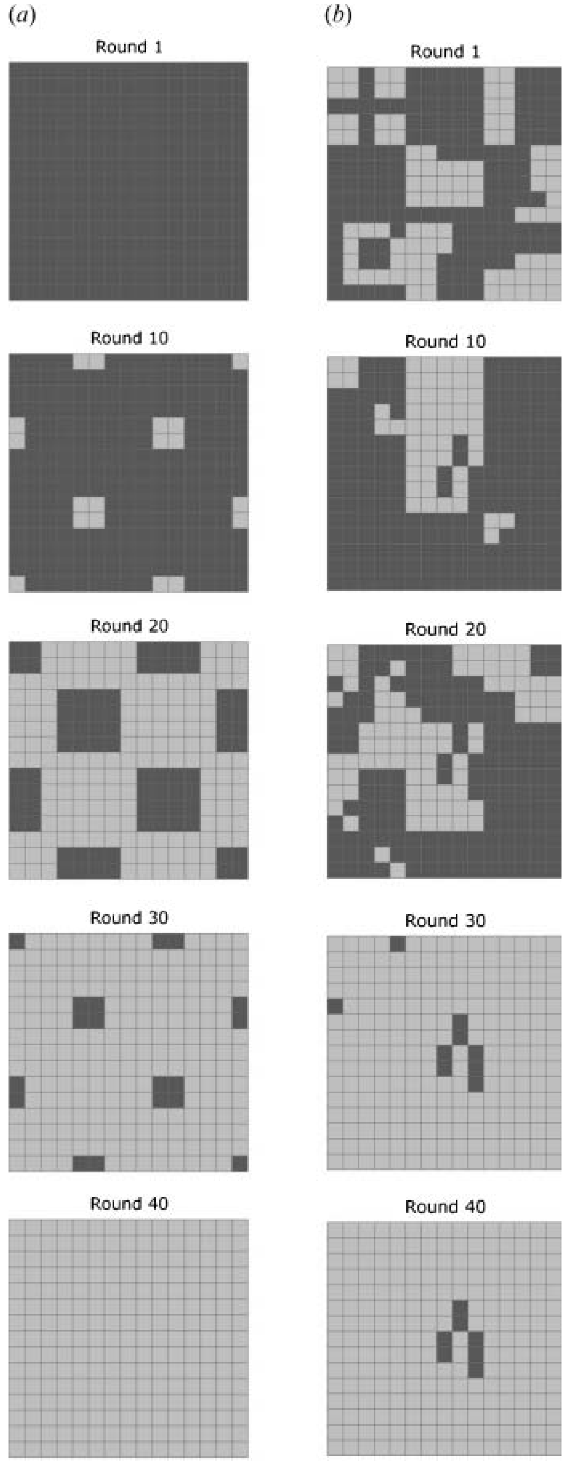

Figure 7. (*a*) S1 landscape produced from computational simulation of S1 experiment compared with (*b*) landscape produced from one sample S1 experiment session.

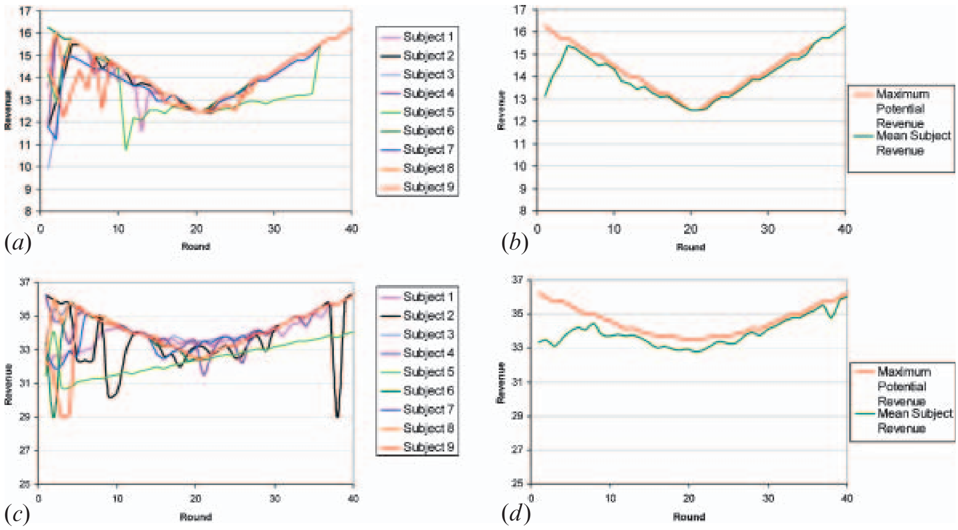

Figure 8. Subject revenue (*a*, upper left), maximum potential revenue and mean revenue (*b*, upper right) for sample session of S0 baseline experiment. Subject revenue (*c*, lower left), maximum potential revenue and mean revenue (*d*, lower right) for sample session of S1 experiment with heterogeneous suitability.

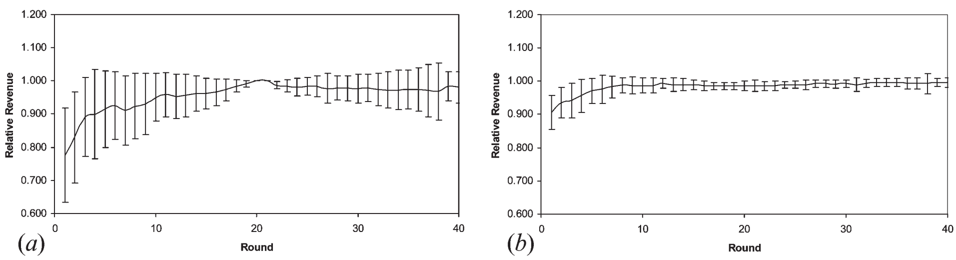

Figure 9. Mean and standard deviation of relative subject revenue for (*a*) baseline experiment (S0, n=45) and for (*b*) heterogeneous suitability experiment (S1, n=45).

Comparatively speaking, there is high variability in revenues during the initial stage of the experiment when most subjects are still learning the price trends of B and G resources. Most subjects approach the optimum point towards the end of the experiment, although some subjects still keep testing other strategies even after attaining the optimum. Note that in the S0 experiment subjects receive the maximum revenue in round 20 because the prices for B and G are identical in this round. Some subjects are consistently close to the maximum revenue through the 40 rounds, while others exhibit a surprising degree of inconsistency (e.g. Subject 4 in the S1 experiment), as demonstrated by multiple spikes of relatively low revenue.

Figures 9(*a*) and 9(*b*) present the mean relative revenue in each round with plus and minus standard deviations for S0 and S1 sessions, respectively. The relative subject revenue in each round, defined as the ratio between the revenue for a subject and the maximum potential revenue as calculated from the agent-based simulation, was quite variable in the early rounds of the experiments (figures 9(*a*) and 9(*b*)). This is in part due to the fact that subjects have little information from which to predict the linear price trend in these early rounds. Interestingly, there was still noticeable variance in revenue in the S0 experiment, which utilizes a relatively predictable price trend through the experiment. Despite over 30 rounds of monotonic price decrease for resource B and monotonic price increase for resource G, subjects still choose to 'test' choices that had a low probability of maximizing revenue given the strong and predictable previous price trend. One explanation for this 'testing' is that the marginal cost of allocating one or two cells to what would appear to be the non-optimal resource is low enough that subjects do not mind the modest lost revenue compared with the opportunity to learn more about the potential revenue of the G resource.

The results of this landscape-level analysis are qualitative, as we did not have the resources to complete over 30 sessions for each experiment. Still, some basic observations are possible by comparing the five completed sessions to the landscape composition and edge for the S0 and S1 simulations. For the S0 baseline experiment, it is evident that there is substantially more patchiness, or landscape heterogeneity, in the experiment landscapes compared with the agent-based model simulation landscape (figures 10(*a*) and 10(*b*)). This is particularly true for rounds 0–20 but is also the case for rounds 20–40. Again, this is somewhat surprising given the highly predictable price trends of the B and G resources. Even in the final round, some subjects in several sessions created more heterogeneous landscapes than the utility-maximizing scenario.

The landscape compositions for the S1 heterogeneous suitability experiments also typically exhibited a greater heterogeneity than the simulation. The landscape composition produced by the S1 agent-based model simulation shows a stair-stepping pattern as the incremental changes in the prices for B and G flip selected cells from G to B (figures 10(*c*)–10(*d*)). The spatial pattern of the suitability landscape for B is symmetrical (figure 5) where each subject partition has two corners of relatively high suitability and two corners of relatively low suitability. This symmetrical pattern propagates to the landscape composition in a stair-stepped pattern as the incremental changes in the relative prices for B and G overcome the relative influence of the suitability factor. The G resource gradually grows in from these high suitability corners until round 40, when the price of G makes this resource the most revenue producing even for the 'low' suitability cells (see column *a* in figure 7). Qualitatively, the landscape for one sample S1 session follows this general pattern but with substantial deviations from the regular pattern exhibited in the simulation landscape. Clearly, the human subjects struggle more to discern the regular pattern of the land suitability surface, which is known information for the simulation agents.

The differences in decision-making between the human subjects and simulated utility-maximizing agents are even more apparent when comparing the amount of edge in the produced landscapes. Figures 11(*a*)–11(*b*) present the edge metric measurements for the five S0 baseline experiments and the simulation. The utility-maximizing agents for this scenario actually produce no edge, as the landscape simply switches from B to G after round 20 (see column *a* in figure 6). The amount of edge produced by the experiment landscapes is dramatic. In each session, there was substantially more edge produced in the entire landscape than in the simulation landscape (figures 11(*a*) and 11(*b*)). This was even true for the final rounds of the experiment for all but one session (session 5 in figures 11(*a*) and 11(*b*)).

To a certain extent, the baseline experiment presents an extreme scenario to subjects, where any experimentation in their resource allocations will result in

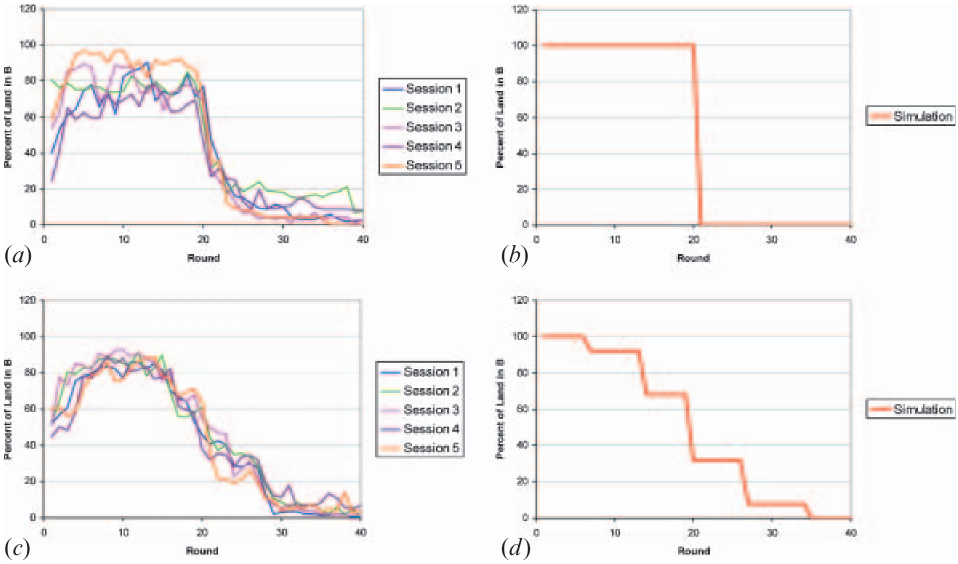

Figure 10. Landscape composition of S0 baseline experiments (*a*, upper left) and landscape composition of computational simulation of baseline experiment (*b*, upper right). Landscape composition of S1 heterogeneous suitability experiments (*c*, lower left) and landscape composition of computational simulation of heterogeneous suitability experiment (*d*, lower right).

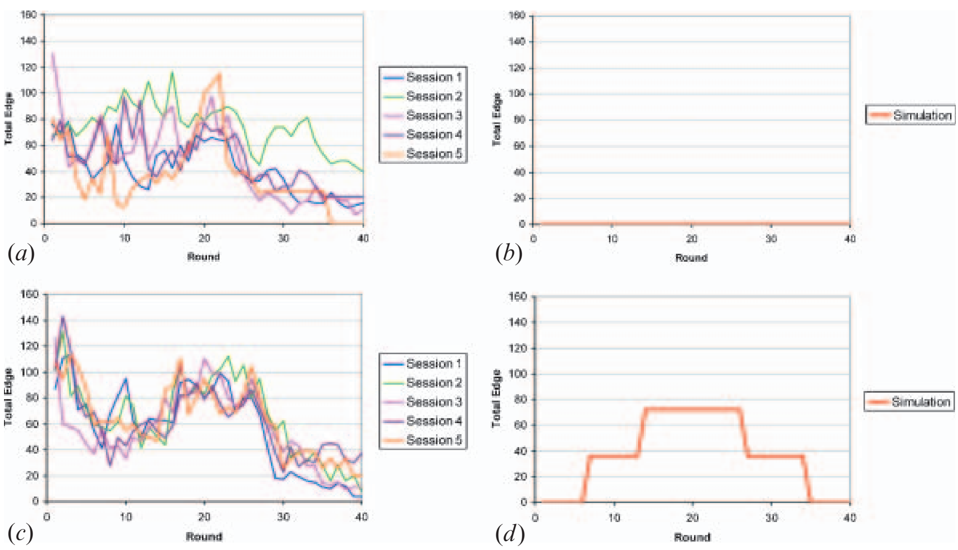

Figure 11. Landscape edge of baseline experiments (*a*, upper left) and landscape edge of computational simulation of baseline experiment (*b*, upper right). Landscape edge of S1 heterogeneous suitability experiments (*c*, lower left) and landscape edge of computational simulation of S1 heterogeneous suitability experiment (*d*, lower right).

significant departures from the edge calculation in comparison with the simulation landscape. There is again substantially more edge in the early rounds of the experiment landscapes (figures 11(*a*) and 11(*b*)). The S1 simulation produces a substantial amount of edge for the central rounds in the experiment (10–30), providing an opportunity to examine if the human subjects produce landscapes with more edge with a more complex landscape scenario (figures 11(*c*) and 11(*d*)). Here, we do see that the experimental landscapes for the five sessions still exhibit more landscape edge than the simulation landscape. It is only in rounds 30–35 that we see the simulation landscape produce more edge than some of the experiment landscapes.

These results can be summarized as follows:

- Landscapes produced by subjects result in greater patchiness and more edge than the utility-maximization agent predicts.
- There is considerable diversity in the decisions subjects make despite the fact that they are presented with a relatively simple decision-making context with a strong monetary incentive.
- Greater deviation of subject revenue from potential revenue early in the experiment demonstrates the challenge of making optimal decisions with little historical context. In later rounds, subjects get closer to maximum potential revenue but many do not reach this maximum.

The S0 and S1 treatments present subjects with the same revenue-earning potential. However, the mean revenue for the S1 subjects was significantly higher than the S0 subjects, and a difference of means test shows that this difference is statistically significant in 34 of 40 rounds (n=45, α=0.05). The decision-making strategies of subjects in both the S0 and S1 experiments produced very patchy landscapes, and the heterogeneous suitability of the B resource in the S1 experiment meant that these patchy landscapes produced higher revenues for subjects. Because the maximum revenue in the S0 experiment could be reached only if subjects created entirely homogenous landscapes, any deviation from this simple landscape structure resulted in a decrease in revenue from the potential revenue.

A fundamental question is whether the subjects were responding to information signals in the experiment at all (e.g. the changes in price by round and the spatial structure of the suitability landscape). If so we would expect to see differences in the landscapes produced by each subject between the S0 and S1 sessions (i.e. by quantifying the landscapes of the 5×5 cell subject partitions instead of the entire 15×15 cell extent for all agents). The differences between mean landscape compositions were statistically significant in nine of 40 rounds (n=45, α=0.05), and the differences in the mean edge values were also statistically significant in nine of 40 rounds (n=45, α=0.05). For the early and late rounds (1–7 and 33–40), the prices for B and G were more important to the revenue potential than the suitability factor for B, so we would expect decision-making of subjects between the S0 and S1 sessions to be similar in these rounds. Given that we would expect similar landscapes between the S0 and S1 sessions for 14 of the 40 rounds, the fact that nine of the remaining 26 rounds exhibit statistically significant differences demonstrates that subjects were reactive to the signals in the experiments. The statistical results here are limited to the subject partitions (n=45 for each treatment) because the number of sessions of each treatment type (n=5) do not provide a sufficient basis for statistical analysis of the landscapes aggregated from the nine subject partitions for each round.

5. Discussion

One challenge with experimental research is how to assess whether laboratory subjects are representative of real-world actors. To what extent do cultural or social attributes dictate decision-making? This topic has been addressed in a variety of contexts. For example, Cardenas (2003) conducted a series of field experiments in rural villages in Colombia to explore how wealth and inequality affected common-pool resource dilemmas. An exit survey was used to collect data about each experimental subject and found that wealth and inequality reduced cooperation when groups had face-to-face communication between rounds. The integration of exit surveys with experimental data provides a mechanism to further explore the basis for heterogeneity in subject decision-making. We plan to eventually conduct our own field experiments with the same abstract experimental design presented in this paper as well as more highly specified experimental treatments. The addition of an exit survey would be particularly helpful in exploring the basis for subject decision-making in these field experiments.

A fundamental question that must be explored is why subjects in the experiments are unable to reach the optimal revenue across rounds. It is quite understandable that subjects have difficulty choosing the optimal resource allocation early in the experiment when the price trend is largely unknown to them. However, even in the later rounds, there are multiple subjects in each session who do not reach the optimal revenue. We must acknowledge the possibility that some subjects simply may not have understood the computer interface or otherwise did not understand the experimental application. We tried to minimize this possibility to the extent that we could by designing the interface to be relatively simple and by conducting a series of training rounds before each session began to give subjects an opportunity to get clarification if needed. However, there appear to be different strategies or decisions made by subjects in the experiment. Some subjects may have more faith in the past price trend to continue the monotonic increase/decrease, while other subjects may be more skeptical that that trend will continue leading them to a more heterogeneous distribution of the B and G resources even later in the experiment. How subjects react to this uncertainty is likely one important factor resulting in the diverse landscapes produced by different subjects.

What we think is a more plausible explanation for the inability of subjects to reach the maximum revenues is related to the marginal cost of testing alternative resource allocations in a small number of cells. Potentially, subjects may have felt that the risk of testing decisions they believed had a low probability of yielding beneficial results was low enough that they were willing to conduct this exploration. Ultimately, this would produce more spatially heterogeneous landscapes than those produced by the utility-maximizing agent simulations. Despite the strong monetary incentive to maximize their revenue in the experiment, the penalty for making non-optimal resource allocations for a small number of cells in a small number of rounds is relatively insignificant. It would be interesting to conduct an experiment where the monetary payoff to subjects was ranked in accordance with their performance in the experiment relative to the other subjects. In this scenario, one would potentially expect less experimentation by subjects of decisions with a low probability of a benefit based on the observed price trend.

Anecdotally, we can draw a connection between the variability seen in the early rounds of both the S0 and S1 treatments and observed land-use decisions in the field. Analysis of colonists in Altamira, Brazil, in the 1970s (Moran *et al.* 2002) and south-central Indiana in the early 1800s (Evans *et al.* 2001) has suggested that early migrants with little information about the distribution of soil fertility on their landholdings have difficulty choosing the ideal locations for long-term production. As landowners learn more about the productivity of different areas within their landholdings, they are able to allocate their labor more effectively to those locations that will yield the highest return, so the effectiveness of their decision-making improves over time. The same behaviour is exhibited in the experimental results where agents have difficulty deciphering the trend in prices and pattern of suitability (in the S1 sessions) in the early rounds of the experiment but have less difficulty in later rounds. However, we do acknowledge that there are many settings where landowners have quite sophisticated spatially explicit knowledge of the heterogeneity of productivity on their landholdings, and for these contexts the learning associated with the initial rounds of the experiments presented here are not a good representation of these types of settings.

Based on the observation of the landscape dynamics from various sessions, there is some qualitative evidence that some subjects mimic what their neighbours do, especially when most of their neighbours adopt the same or similar strategies. As a reminder, subjects are able to see the resource allocation decisions of the other subjects, but they do not see the cell-level revenue received. This mimicking behaviour is an interesting finding that has implications for spatial diffusion of land-use decision-making. We do not have sufficient data to draw a statistical conclusion at this point but have developed experimental designs that will allow us to test this more concretely in the future.

Ultimately, the results presented here provide some justification for incorporating decision-making dynamics beyond utility maximization in agent-based models of land-cover change. Models that adopt this approach risk producing landscapes that have less spatial complexity (edge and heterogeneity) than what is produced in the real world. The experimental results presented here illustrate the spatial implications of this 'imperfect' decision-making in a simple abstract setting. The relevance of these results to real-world scenarios is admittedly a function of landscape complexity. There are numerous examples of locations with highly homogenous land cover (e.g. desert or plains) where there is little evidence of the behaviours exhibited in the experimental results presented here. However, in places where the land-use decision-making context is more challenging (e.g. highly variable topography, soil nutrients, water absorption), it is plausible that these experimental results present an additional empirical basis to explain the spatial complexity evident in these types of landscapes.

Given the flexibility available in the design of spatial experimental scenarios, there is an opportunity to integrate this methodological tool with more traditional methods of land-cover change modelling and land-change research. Fundamentally, the experimental results here present the first attempt in a larger design to explore the spatial outcomes of different decision-making dynamics. For example, experimental designs can be constructed to explore the spatial outcomes produced in situations with high price volatility. Experiments can also be designed to examine the spatial outcomes from 'sticky' land uses where landowners do not receive revenue for a specific type of resource until many years into the future (i.e. timber production) compared with land uses that produce an annual return (e.g. crop production). What are the implications for forest fragmentation in situations where harvest cycles increase or decrease in different biophysical settings?

Furthermore, spatial experiments offer the opportunity to explore the role of information diffusion and transfer in land-use settings. Agent-based modelling has been employed in land-change scenarios in part because of the ability to incorporate spatial interactions between actors. Yet, the data needed to empirically test the influence of these spatial interactions are elusive. We can observe locations where there are spatial clusters of different land uses, but it is more challenging to identify the specific contexts where information diffusion or transfer leads to clustering of land uses (positive spatial externalities) or heterogeneous landscapes (negative externalities), whether they be a product of information diffusion or simple spatial proximity (Parker and Munroe in press). A specific example would be a situation where a landowner chooses to contract a selective timber harvest on their property after learning that a neighbour was able to receive a significant cash payment from a private forester who harvested an adjoining parcel. The acquisition of spatially explicit field data to explore each of these research contexts can be challenging and cost-prohibitive, if not impossible to collect in some cases (i.e. where digital cadastral data do not exist). Spatially explicit experiments present one methodological option to complement existing land-use/land-cover change research methods and contribute to the development of the spatial aspects of land-use theory for these and other research questions.

Fundamentally, the results from the spatial experiments presented here provide some support for not assuming that agents in models of land-cover change are uniformly able to make perfect utility-maximizing decisions. Furthermore, models that are constructed with perfect utility-maximizing agents risk underpredicting the amount of landscape heterogeneity and edge found in the real world, depending on how the model is fit. There are various ways this finding can be considered in the design of agent-based models. First, some stochasticity can be integrated into the decision-making dynamics of agents to artificially induce heterogeneous landscape patterns. Such an approach may better mimic patterns found in the real world but does not necessarily provide a foundation for developing insight into why landscape heterogeneity exists. Alternatively, various model simulations can be run modifying the proportion of agent types based on a factor such as risk aversion. For example, a model run entirely composed of risk-averse agents can be compared with a model run of risk-loving agents which would presumably produce different types of landscape outcomes. The role of risk in producing heterogeneous landscape outcomes is one area of research to be further explored. Experimental results can provide some insight into the proportion of real-world subjects that fall into these risk-averse or risk-loving categories. Likewise experiments can help modellers explore the willingness of landowners to abandon persistent land uses, the motivations and incentives behind these changes, and the spatial outcomes that might occur. There are very substantial costs to comprehensive and frequent collection of social survey data. Ultimately, spatial experiments provide an alternative mechanism to test key decision-making theories for the purpose of land-cover change modelling and overall in land-use science.

6. Conclusion

This paper presents spatially explicit experiments as methodological tools for the exploration of spatial decision-making in land-use change systems. The results from two experimental designs are discussed: one where subjects make resource allocation decisions on a homogenous land-suitability surface and another that employs a heterogeneous suitability surface for one resource. These experimental results are compared with the landscapes produced from an agent-based model that uses a utility-maximizing agent. The main findings from this comparison are: (1) Landscapes produced by subjects result in greater patchiness and more edge than the utility-maximizing agent predicts; (2) there is considerable diversity in the decisions subjects make despite the fact that they are presented with a relatively simple decision-making context with a strong monetary incentive; and (3) there is greater deviation of subject revenue from the maximum potential revenue in the early rounds of the experiment compared with later rounds, demonstrating the challenge of making optimal decisions with little historical context. The findings demonstrate the value of using non-maximizing agents in agent-based models of land-cover change and the importance of acknowledging actor heterogeneity in modelling landowner behaviour. More generally, the results presented here demonstrate the opportunity for spatial experiments to be integrated into a broad methodological design incorporating empirical data analysis and modelling for the study of land-change science.

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