An Overview of Computational Modeling in Agricultural and Resource Economics

James Nolan,[1] Dawn Parker,[2] G. Cornelis van Kooten[3] and Thomas Berger[4]

[1]*Department of Bioresource Policy, Business and Economics, University of Saskatchewan, Saskatoon, Canada, SK S7N 5A8 (corresponding author: phone: 306-966-8412; fax: 306-966-8413; e-mail: james.nolan@usask.ca).*
[2]*School of Planning, Faculty of Environment, University of Waterloo, EV1 306, 200 University Avenue West, Waterloo, Ontario, Canada N2L 3G1 (phone: 1-519-888-4567, ext. 38888; fax: 1-519 725-2827; e-mail: dcparker@connect.uwaterloo.ca).*
[3]*Department of Economics, University of Victoria, PO Box 1700, Stn CSC, Victoria, British Columbia, Canada, BC V8W 2Y2 (phone: 250-721-8539; fax: 250-721-6214; e-mail: vkooten@uvic.ca).*
[4]*Department of Land Use Economics in the Tropics and Subtropics, Universität Hohenheim (490d), 70593 Stuttgart, Germany (phone: (49) 711-459-24116; fax: (49) 711-459-24248; e-mail: i490d@uni-hohenheim.de).*

INTRODUCTION

A major pillar of the field of agricultural and resource economics (referred to hereafter as agricultural economics) is its tradition of interdisciplinarity, especially in linking socioeconomic and biophysical processes. In contrast to economic analysis in other fields, agricultural economists are more likely to broaden their experimental perspective to include interaction or feedback between humans and the natural world. This orientation has led in large part to increased interest in studies of economic processes over both time and space, using both dynamic optimization and spatial analysis (Kennedy 1986; Miranda and Fackler 2002; Nelson 2002).

A second pillar of agricultural economics is its tradition of empirical testing of carefully derived hypotheses. However, when modeling human-environment interactions, economics in general has had difficulty linking traditional deductive theoretical models, which include just a few state variables and feedbacks for tractability, with inductive statistical models that include many independent variables but often exclude explicit representations of the underlying processes. Current analytical models are also limited in their ability to represent human learning and adaptation, a factor that is particularly important when future conditions depend heavily on the actions of other economic decision makers.

Agricultural economists recognize that individual and environmental heterogeneity are key components of dynamic human-natural systems. However, theoretical and econometric models remain somewhat limited in terms of their ability to portray heterogeneous decision-making individuals in a heterogeneous environment and in terms of modeling significant interactions between economic agents, where economic interaction can be generated by activities, such as resource transfers through local markets and imitative behavior, as well as through spatial externalities. In addition, current spatial models are often founded on the assumption that neighborhood conditions are fixed and that the supply or demand decision of a particular neighbor will not alter the spatial environment for a given individual, an assumption that rarely holds in reality. Relevant examples in agriculture include a decision to extract groundwater resources by one farmer that affects water availability for other farmers in a catchment area, or a decision by a farmer to rent out or sell land that will certainly affect the land rental options, sales, and production choices of neighboring farmers.

Concurrent with these issues, it is also the case that optimization-based farm and resource management models, often operating under short time scales with purely financial objectives, have become increasingly sophisticated over the past half century in part because of technical advances in computer hardware and software combined with improved training of students in mathematical modeling. Researchers continue to try to advance the ability of these models to capture economic and ecosystem uncertainty, irreversible thresholds (e.g., bankruptcy, destruction of shallow lakes due to excessive nutrients), as well as interpersonal (interhousehold, interfirm) and dynamic natural resource management challenges.

As the latter models have become more realistic and sophisticated, operating over longer time scales and incorporating higher degrees of human-environment feedback, they too have become more difficult to solve analytically. Ultimately, the response of the profession to all of the shortcomings described above has been the development of the field of computational economics.[1] As such, the field encompasses both numerical optimization (Glover and Laguna 1993) as well as simulation methods.

In this special issue, we examine recent advancements in two computational economics modeling approaches used within agricultural economics—stochastic dynamic programming (SDP) and agent-based modeling (ABM). SDP is used to address uncertainty in applied research, while ABM is a simulation methodology that is increasingly used increasingly in other social sciences (Berry et al 2002; Hernandez et al 2008; Waldrop 2009), particularly in cases where agents are heterogeneous and the system may be out of equilibrium. One goal of this special issue is to familiarize the wider agricultural economics profession with these powerful tools, while also providing a context with which many readers are likely familiar.

This introductory paper provides some background to these methods, albeit mostly in an informal and nontechnical fashion. In the next section, we provide a brief overview of how uncertainty is treated using SDP, as well as outline more recent advances in this field. In third section, ABM is described in more detail. Since these are computational methods, the fourth section briefly discusses software issues. Section fifth provides an overview of the applications of computational economics represented in this special issue, while sixth section concludes by listing some of the challenges facing modelers who may choose to use these computational methods.

OPTIMIZATION, UNCERTAINTY, AND STOCHASTIC DYNAMIC PROGRAMMING

Dynamic optimization, particularly the use of SDP, has a long history in agricultural and resource economics. Oscar Burt was the first to apply SDP in agricultural economics, with his first paper in agricultural economics appearing in 1963 (Burt and Allison 1963). Building upon the work of Howard (1960), who adapted Bellman's (1957) pioneering approach to include stochasticity, Burt and Allison (1963) examined the trade-off between moisture and soil conservation in a wheat-fallow crop rotation to recommend adaptive decision making based on soil moisture content that would reduce the time fields were summer fallowed (and thus reduce soil erosion).

Burt employed the Markov assumption (that all information about the past is embodied in the last observation of the state variable), developed state probability transition matrices for each control variable, and solved the problem using backward recursion based on Bellman's equation. For the policy iteration approach, Burt's method for obtaining the long-run expected return associated with each state variable was a bit awkward, with Hastings (1973) providing a much simpler approach. Subsequently, Burt and Taylor (1989) provided a means for including a two-period lag into the Markov framework. While the standard approach to SDP is relatively straightforward, it provides only an approximate solution that depends on how the state equation/variable is discretized—the fineness of the grid for the probability transition matrix.

Judd (1998) proposed a 'collocation' method for solving problems with a continuous state variable. The approach is similar to that used to linearize nonlinear functions for linear programming (see Loucks et al 1981). Compared to the 'standard' approach, collocation is much more difficult to implement (see Miranda and Fackler 2002). One of the SDP papers in this issue uses collocation, while the other employs a Monte Carlo approach, both of which extend the methods originally developed by Burt.

To put SDP in context, it is worthwhile noting that economists prefer an analytical approach based on optimal control methods (i.e., the maximum principle), but this has also made it much more difficult to address risk. To incorporate risk into optimal control theory requires increased mathematical sophistication that involves stochastic processes and the Ito calculus (Dixit and Pindyck 1994). Although originally adapted to address problems in finance, stochastic optimal control has been employed in some areas of natural resource economics, but has thus far made few inroads elsewhere in economics, including finance. In this regards, SDP still seems to be the preferred approach.

AGENT-BASED MODELING

Agent-based models are effectively micro-level simulation models that represent heterogeneous decision-making entities as well as their interactions with their social and physical environment. In contrast to mathematical or computational techniques traditionally used in agricultural economics, ABM is simulation based, not equilibrium based. Although models may reach equilibrium, it is the result of interactions among lower-level entities. Thus, they are suitable for modeling domains where the complex relationships between agent heterogeneity, interactions and cross-scale feedbacks render traditional equilibrium-based models analytically intractable (Parker et al 2003).

An elaboration of the structural differences between traditional microeconomic and agent-based models clarifies the specific ways in which ABM can address some of the limitations of traditional models, and also illustrates what is gained and lost in the move to an alternative methodological approach. The mechanisms of a traditional model are illustrated in Figure 1. On the supply side, the individual supply functions of several

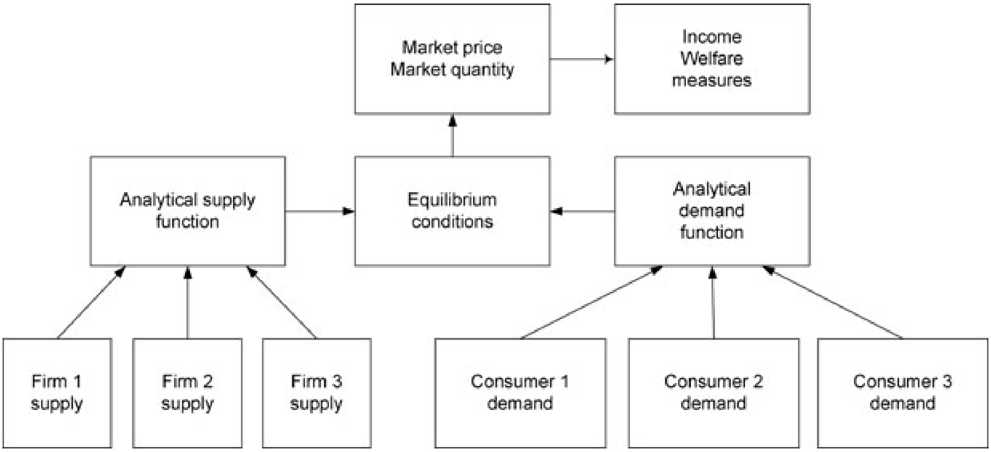

Figure 1. Traditional models

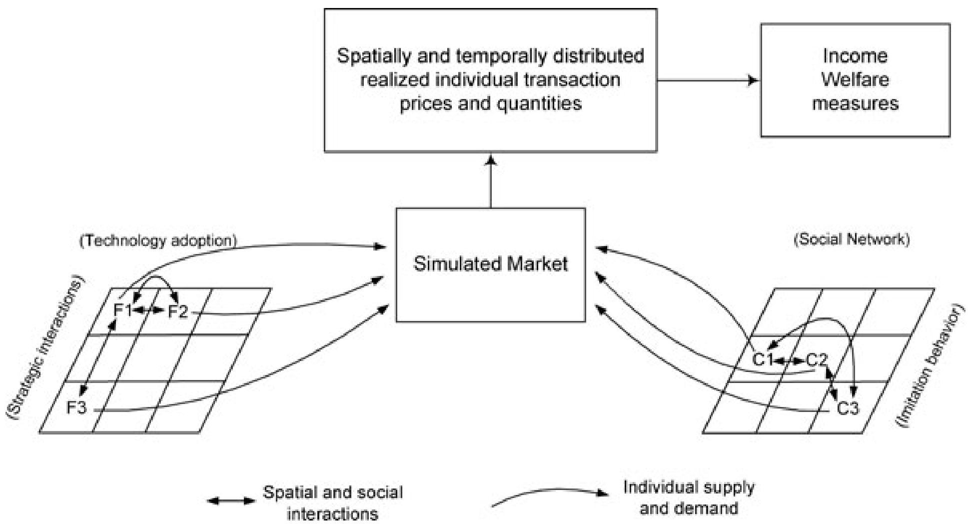

Figure 2. Agent-based spatial market

firms—potentially heterogeneous and potentially located at particular points in space in relation to markets—are aggregated to form a market supply function. Similarly, the demand functions of several potentially heterogeneous and spatially located firms are aggregated to form a market demand function. These two functions are combined with an assumed equilibrium condition that defines a market price and quantity. From these values, economic outcomes, such as income and welfare, are derived.

In the comparable agent-based framework (Figure 2), producer and consumer agents may be similarly heterogeneous and spatially situated in relation to markets. However, their spatial relationships with other consumers and producers may influence their supply and demand functions, particularly through neighborhood relationships. Interactions may also occur through social and informational networks: on the demand side, for example, through imitative behavior and social networks; on the supply side, through technology adoption and strategic interactions. Rather than aggregating individual supply and demand functions into market demand and supply functions, agents interact through a simulated market. When agents for whom gains from trade are positive connect, successful transactions occur. As these transactions take place over time, if market conditions remain stable then a market equilibrium may emerge. If market conditions are constantly evolving—for example, as price expectations or available resources change dynamically based on previous transactions—the market may not reach equilibrium. In either case, economic outcomes, such as income and welfare, can once again be derived.

As mentioned above, ABMs are generally used in situations where model complexity leads to analytical intractability, meaning that equilibrium conditions either cannot be identified or analytically solved. The corollary to this generalization is that agent-based models generally relax assumptions of full rationality inherent in traditional economic models. In contrast to full rationality, models of bounded rationality assume that economic agents have limited information, computational capabilities and resources (Simon 1996). Agents may still be modeled as goal oriented and even as optimizers, but in a complex system they cannot be modeled as fully rational optimizers. If the creator of the model herself lacks the information, resources, and computational capabilities to solve her model specification, it is simply impossible to endow her modeled agents with this capability.

The modeled actors can be endowed with adaptive mechanisms to learn about their economic environment, the behavior of other actors, and the strategies resulting in the highest payoffs. Via their interactions in a simulated market, this group of agents can act as a type of inductive search algorithm to identify an economic equilibrium, one that has the standard property that no actor has an incentive to change his behavior, given the economic environment and actions of the other actors. This behavior instantiates the story of decentralized interactions guided by an "invisible hand" that is used to motivate the existence of the equilibrium conditions imposed on analytical models. When the macro-scale properties of this equilibrium—market-clearing prices, resource allocations, paths of resource depletion over time, structural patterns of land use—depend on these path-dependent interactions between micro-level agents such that the macro-scale outcomes cannot be explained by or derived from the properties of the micro-scale elements in isolation, these macro-scale properties are often refer to as "emergent" (Holland 1998; Arthur 2006).

Whether or not the economic model is designed to attain equilibrium, without closed-form analytical solutions the modeler can no longer use traditional techniques, such as comparative static analysis to investigate the relationship between exogenous model parameters and endogenous model outcomes. Without such analytical methods, it is difficult for the modeler to completely characterize the behavior of the modeled system, especially when combinations of parameters lead to nonlinear changes. However, sensitivity analysis that sweeps parameter spaces can bring the modeler quite close to a comprehensive understanding of the behavior of her model (Judd 1998).

What is gained in return for the loss of analytical tractability, full rationality, and well-defined and explored equilibria? The gain comes in terms of a much broader range of research questions that can be explored via ABM. These questions allow exploration of the influence of agent and environmental heterogeneity; interdependencies among agents, between agents and their environment, or both; and dynamic feedbacks across levels/scale. They may also allow investigation of the effects of temporal phenomena, such as path dependence (sensitivity of the modeled system to initial conditions and/or random elements), learning, and adaptation. In short, agent-based models have the flexibility to explore research questions motivated by the characterization of economies as complex mathematical systems.

COMPUTATIONAL ECONOMICS: SOFTWARE

Computational methods in economics would not be accessible to practitioners if not for the existence of high-quality specialized software. Today, there are many numerical optimization software packages used in the profession, though among agricultural economists GAMS (www.gams.com) appears to be the most popular. While traditionally popular in mathematics and engineering, MATLAB (http://www.mathworks.com/) is also becoming a standard software tool used by economists to solve a large array of numerical optimization problems, ranging from statistical estimation to constrained optimization to approximation and ad hoc solutions. The collocation method is implemented primarily using MATLAB, for example (see Miranda and Fackler 2002). But each software package has its advantages and drawbacks. Programming is simpler in MATLAB, it is easier to input and output data, string variables can be readily identified, and there exist a very large number of extremely useful and easy to implement built-in and third-party functions (including an optimization toolbox). But MATLAB does not have the ability (whereas GAMS does) to call high-powered solvers without modifying the underlying code. Although researchers can work exclusively in one software environment, it is now possible to take advantage of the best capabilities of both software packages by calling GAMS from within MATLAB (see Ferris 2005; Wong 2009).

Agent-based models are almost universally implemented using a variety of programming languages and software libraries (Castle and Crooks 2006; Miller and Page 2007; Gilbert and Troitzsch 2005). While many of the first generation of social science researchers programmed their own agent-based environments, there are now a few good specialized open source ABM packages available to the practitioner, including the popular NetLogo (http://ccl.northwestern.edu/netlogo/; simple to program but limited to smaller applications) and RePast (http://repast.sourceforge.net/; more difficult to program but more flexible for larger applications). ABM models are now mostly programmed using third generation programming languages, the so-called object-oriented programming (OOP) languages (e.g., C++, Java) that can manipulate complex data structures in an efficient and transparent way. In the context of agricultural economics and simulation modeling, the programmed objects can represent farm-households (for convenience, they are then called "agents"), as well as other items, such as plots, machinery, cattle, or higher level entities like villages, districts, or water catchments (Berger and Ringler 2002).

COMPUTATIONAL ECONOMICS: APPLICATIONS

This issue contains several current applications of computational modeling in agricultural economics using either agent-based or SDP models. This section of the paper provides the interested reader with an overview of each of the special issue papers, classified by research topic and/or methodology.

Neighborhood Amenities and Urban Development

In recent years, there has been growing concern regarding fragmented patterns of development at the rural-urban fringe, patterns often characterized as "urban sprawl" (Torrens and Alberti 2000), as well as concurrent interest in the public value of open-space amenities (McConnell and Walls 2005). Inherent to these issues are the potential path dependence of land-use patterns and the influence of land-use decisions by a large number of neighbors. Agent heterogeneity may play an important role in the evolution of land-use patterns—city dwellers will be inherently different than rural land owners, while developers are a heterogeneous group. Ultimately, land values will be spatially interdependent, with neighboring land uses and parcel characteristics influencing parcel value.

These phenomena have been explored to an extent using econometric modeling (Bell and Irwin 2002), and cellular automaton models (Benenson and Torrens 2004; Batty 2005). In recent years, a number of authors have developed ABM approaches to meet the need for more detailed structural models capable of exploring the complex dynamics that generate these patterns, reviewed in detail in Parker and Filatova (2008). In this issue Filatova et al (2009) expand on this previous research by analyzing the effect of both positive and negative influences (coastal amenities and flood risk) on urban development and land rents. They specifically explore the effects of heterogeneous, potentially biased flood risk perceptions, demonstrating the limitations of analysis based on representative agent assumptions.

Agricultural Value Chains

There is a growing recognition that modern agricultural systems (production, distribution, marketing) are in a state of transition. Increasingly numerous and heterogeneous agents characterize evolving agricultural value chains. Little is understood about how and to what extent these varied agents interact in the value chain, which affects both system and firm performance. The Ross and Westgren (2009) and the Ameden et al (2009) papers use ABM to examine theoretical and applied issues within modern agricultural value chains. Ross and Westgren (2009) build on their previous research to reveal interactions between entrepreneurial behavior and the performance of firms in the current and future agri-food system. In the spirit of Austrian economics, they use an agent-based model to simulate a set of entrepreneurial "capabilities" within a stylized agri-food sector and report on how these capabilities affect individual firm performance.

Ameden et al (2009) focus on an important portion of an agricultural value chain that harbors the potential to inflict extensive economic damage—they simulate the interaction between border management and the infiltration of invasive species in agricultural trade. As a form of dynamic game, border agents, and importers interact on a repeated basis, gaining information about how the other agents' behavior evolves over time. By modeling the problem using ABM, Ameden et al (2009) are able to develop a set of dynamic policies that they hope will improve allocation of scarce border resources in a low probability but potentially high damage economic environment.

Structural Change in Farming

Researchers are using ABM to examine the structure of farming in various regions around the world. In this issue, Happe et al (2008) build upon their prior research to analyze farm structural change in a relatively new European Union member country

(Slovakia), Schreinemachers et al (2009) examine current policy issues in Thai greenhouse agriculture, and Freeman et al (2009) describe historical structural change in agriculture on the Canadian prairies. Each region is obviously very different, but all experience land scarcity that limits farm expansion and scale efficiencies.

Happe et al (2008) and Schreinemachers et al (2009) show that agent behavior can be created in the tradition of individual farm linear programming models, with mathematical programming methods and econometric results, respectively, used to represent decision-making processes within the agent-based simulation. While Happe et al (2008) analyze the nature of farm transition and evolution in a dramatically changing agricultural economy, Freeman et al (2009) describe the recent history of a mature agricultural region and develop a set of counterfactual simulations to examine how policy changes could have altered the path of structural change. In both papers, intergenerational transfers of land and material are extremely important to industry sustainability. Finally, Schreinemachers et al (2009) use ABM to simulate policy changes in a very exotic agricultural economy and, like the other two papers, find agricultural policies in the region lead to misallocation of resources that is incompatible with environmental sustainability.

Uncertainty and Stochastic Dynamic Programming

Bond and Loomis (2009) are interested in adaptive ecosystem management, meaning that their Bellman equation is no longer recursive. They use Monte Carlo simulation (varying the ecosystem parameters) in combination with optimization to find optimal nutrient loadings. They also compare outcomes of a stochastic learning process with a deterministic one. Bond and Loomis (2009) write their code in GAMS, which enables them to take advantage of mathematical programming within a user-written loop.

Lohano and King (2009) utilize SDP to investigate the impact of stochastic land prices and crop returns on the investment decisions over farm size for Southwestern Minnesota farms. Land values and crop returns interact and jointly determine the land investment (disinvestment) decision. The dynamic nature of the investment decision leads to increased variability in the stochastic variables, even under the assumption of risk-neutral preferences, an unusual result that would not have been obtained using static analysis. The inclusion of an outside investment option increases the variability of farm income as well as the probability of a complete exit from farming compared to the case where the outside option is absent. In policy simulations, the authors find that likely farm sizes are bimodal, clustered at either 400 or 2000 acres. Lohano and King (2009) use collocation with a program written in MATLAB (their code is available to the interested reader).

DISCUSSION AND CONCLUSIONS

There remain significant challenges for researchers interested in applying the computational techniques contained in this special issue. Although dynamic programming is relatively well established as a methodology and has been practiced in agricultural economics since the early 1960s, it is clear that better algorithms/approaches for dealing with continuous state and control variables in a nonlinear context need to be found. For example, as Bond and Loomis (2009) show, adaptive management under uncertainty is difficult to implement in an optimization framework, and learning methods need to be employed (see Eisworth and van Kooten 2007).

But due to its relative novelty, more broadly acknowledged challenges for ABM exist. While these challenges are general to social science applications, some are particularly significant for agricultural economists who wish to conduct research using agent-based methods. These include:

Model Communication
Since ABMs are written in computer code and can rely more on heuristics than on formal mathematics, concise communication of model rules and mechanisms can be challenging. Several alternative protocols for standard communication have been proposed, but no consensus has yet emerged regarding an accepted standard (Allesa et al 2006; Richiardi et al 2006; Polhill et al 2008). Development of standard and comprehensive communication protocols may be particularly important for ABM to gain acceptance in the agricultural economics community, where readers are accustomed to formal (mathematical) representations of models.

Data Needs
Applied ABMs often possess greater data requirements than mathematical programming or econometric models, simply because these models generally capture large numbers of micro-level processes. Empirical parameterization of agent decision models is a particular challenge (Robinson et al 2007). This is an area where agricultural economists can make a strong contribution to the development of ABMs, given the long tradition in agricultural economics of detailed fieldwork and surveys and the more recent contributions of agricultural economics in geographic information systems analysis and experimental economics.

Model Calibration, Verification, and Validation
Due to their complex model structure and intensive data requirements, ABMs face particular challenges for model calibration, verification (model testing to ensure conceptually and technically correct operation), and validation (comparison of model outputs to independent real-world data). Given that many statistical methods for model validation are designed for simpler systems, new methods must be developed specifically for analysis of output from complex systems (Grimm et al 2005). Again, the empirical orientation and statistical expertise of agricultural economists can be expected to contribute in this area, particularly regarding issues, such as analyzing uncertainty and error propagation, and development of methods for fitting models from data generated by complex systems (next generation econometric models).

Getting Started
Given its relative novelty in the field, there are both challenges and opportunities for a researcher or Ph.D. student wanting to construct an agent-based simulation model. Although few formal courses for economists are available, it is possible for a motivated researcher working independently to complete an ABM exercise by leveraging external resources. A current listing is provided in the appendix to this article. The challenge of mastering object-oriented computer programming is often mentioned as a significant barrier to entry to ABM. Fortunately, small scale models can be easily developed in Netlogo (see the Ameden et al (2009) and the Freeman et al (2009) papers), but we note

that the current research level ABM software of choice in the social sciences seems to be RePast.

Regarding ABM in agricultural economics, we are at a time of transition making this special issue very timely. Currently, colleagues using ABM in the social sciences (including agricultural economics) are beginning to complete the training of the next generation of graduate students in the use of appropriate models and software. It is an opportune time to get involved in this new form of computational modeling, a time not unlike the explosion of econometric work begun in the 1960s when relevant and accessible computer software became available for applied researchers. The technical skills and attention to detail of the agricultural economics community are much-needed potential assets to ABM. In addition to the applications discussed here, ABMs can and have been applied to many other related research projects, including livelihood vulnerability and degradation in developing country agricultural communities, the relationship between natural resource scarcity and civil violence, the environmental and economic effects of biofuel production, the dynamics of the housing foreclosure crisis, and the effects of regional and global carbon markets. The agricultural economics profession has a strong tradition of methodological innovation, and, building on this tradition, we invite members of this community to harness their creativity and technical expertise to develop the next generation of agent-based economic models.

NOTE

[1]This is no different than the situation in the biological and physical sciences. For example, global circulation models that project future temperatures and precipitation are nothing more than extremely large mathematical models (consisting of thousands of interlinked mathematical relations) that take many days to solve on super computers.

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APPENDIX: RESOURCES FOR ABM IN THE SOCIAL SCIENCES

Several websites provide information and resources:

- Leigh Tesfatsion's Agent-based Computational Economics (ACE) site provides start-up information and resources and current news items (http://www.econ.iastate.edu/tesfatsi/ace.htm);
- The CORMAS site provides links to software, models, and publications (http://cormas.cirad.fr/indexeng.htm);

  - The GIS and ABM blog focuses on integrating ABM and GIS (http://gisagents.blogspot.com/);
  - The Open ABM site (under development) provides a model archive library, examples of model documentation protocols, and discussion forums related generally to ABM (http://www.openabm.org/site/);

- Two earlier overviews were published as part of a 2001 ABM land use workshop (Parker et al 2002; Parker et al 2003), while updates to this literature have been made more recently (Castle and Crooks 2006). Several good overviews of ABM and related economic topics have been updated and published as part of the recent Handbook of Computational Economics (Tesfatsion and Judd 2006).
- Organized sessions and symposia at professional meetings and special journal issues provide presentation and publication opportunities. For example, ABM work has been presented as part of an ongoing set of sessions on “Geographic Perspectives on Complexity” at the American Association of Geographers since 2000, and periodically at the Geocomputation meetings, resulting in several special issues. (See Parker and Filatova 2008, for a comprehensive list.)
- Two electronic mailing lists provide opportunities for announcement posting, technical inquires, and discussion:
  - SIMSOC (http://www.jiscmail.ac.uk/lists/SIMSOC.html) focuses in general on agent-based social simulation;
  - MaSpace (https://listserv.indiana.edu/cgi-bin/wa-iub.exe?A0=MASPACE-L) focuses on landscape-based spatial models of human-environment interactions.
- In North America, a number of workshops and training programs are available (this list does not include current European programs):
  - Academic programs at the George Mason University (Graduate Certificate and PhD) and the University of Michigan (Graduate Certificate);
  - Training workshops at the Santa Fe Institute (Graduate summer schools in complex systems and in computational economics);
  - Additional special and reoccurring training workshops are regularly announced in the ACE newsletter and through the electronic mailing lists referenced above.