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Agent Based Modeling and Adaptation to Climate Change*

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Summary: Agent based modeling is a technique for simulating complex systems that allows the modeler to investigate both the potential for and the sources of emergent properties: behaviors of the system quite different from the behavior of any of the elements within it. Problems well suited to investigation by agent based models are those with many people solving a similar problem where their individual responses to the problem influence the choices that others make, where new technologies may emerge to assist them solve the problem, and where social dilemmas exist. These features are inherent in many problems of adaptation to climate change. Agent based modeling can not predict the future of a complex adaptive system – no method of modeling can – but it can offer insights into the relationship between features of current systems and the range of possible future adaptations that will be likely in response to climate change.

Zusammenfassung: Die agentenbasierte Modellierung als Methode der Simulation komplexer Systeme ermöglicht die Analyse von Potentialen und Ursprüngen emergenter Eigenschaften, die nicht allein auf Basis des Verhaltens der Elemente des Systems erklärt werden können. Für agentenbasierte Modellansätze bieten sich insbesondere solche Probleme an, bei denen eine Vielzahl von sich wechselseitig beeinflussenden Individuen in die Lösung desselben Problems einbezogen sind. Zudem kann die Entstehung neuartiger Techniken sowie bestehende Umgangsformen mit sozialen Dilemmasituationen analysiert werden. Die Probleme der Anpassung an den Klimawandel zeichnen sich durch diese Kennzeichen aus. Zwar kann die agentenbasierte Modellierung die Zukunft eines komplexen adaptiven Systems ebenso wenig vorhersagen wie andere Modelle, doch kann sie Einsichten in die Beziehungen zwischen verschiedenen Eigenschaften dieser Systeme und in die möglichen zukünftigen Anpassungsmaßnahmen an den Klimawandel und deren Kosten liefern.

1 Introduction

As it becomes inevitable that anthropogenic climate change will occur, research agendas and scientific assessments have started to focus on the process of adapting to climate impacts, namely minimizing the adverse consequences of climate change, and taking advantage of new opportunities (McCarthy et al. 2001). One response to this challenge is the concept of adaptive capacity that builds on the observation that some societies are better able to adapt, because of a combination of available resources, governance systems, and ultimately better social learning processes (Burton 1996). There are now efforts underway

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to include models of adaptive capacity into climate change assessment, both as a way of better forecasting future climate-related damages, and also as a way of suggesting immediate policies to improve adaptive capacity. Yet adaptation to climate change on local to regional scales remains a poorly understood topic for social science research. Given the complexity of these socio-economic systems, a proper assessment of adaptive capacity hinges on an appropriate understanding of the micro- and macro-behaviors of societies exposed to the impacts of climate change. The conventional economic approach to this kind of assessment assumes that entire societies can either be described and analyzed as the mere sum of individual behaviors, or as black boxes the behavior of which can be predicted based on past observation. However the complex nature of societies can only partly be captured by this approach.

In this paper, we will discuss an alternative approach towards an understanding of the behavior of complex emergent systems such as human societies, namely agent based modeling. This modeling concept has emerged from a computer based modeling approach that can be applied to any form of complex systems. It will be analyzed in this paper, where the strengths and weaknesses of this concept are with regard to climate change research. We will particularly focus on the application to adaptation behaviors of societies vulnerable to climate change that determine their adaptive capacity.

2 Problems of Conventional Modeling Approaches

Over the last twenty to thirty years, researchers from a variety of natural and social science disciplines have started to realize that the behavior of the systems they study is often quite distinct from the behavior of the individual agents within that system. In such situations, they have called these system behaviors *emergent properties* (Epstein and Axtell 1996, Lewin 1992, Waldrop 1992). Systems in which the behavior of each particle or agent depends on that of the other particles or agents – so called *complex systems* – produce emergent properties, whereas systems of relatively independent agents do not. One of the most exciting features of emergent properties, at least for scientists interested in interdisciplinary collaboration, is that one can often gain valuable insights by comparing very different kinds of complex systems. For example, in many ways the spread of the HIV virus through the population resembles the patterns by which sites on the world wide web fall victim to hackers (Barabási 2002). In both cases, the emergent property is rate of spread of a pathogen through society, something very different than the rate at which it moves from one individual to another. Even though it is impossible to predict, for a given complex system, what form it will have in the future, it is possible to gain important insights into important patterns.

The conventional approach in economics to analyze economic and social systems builds on the assumption of a largely independent rational decision maker who's behavior can either be extrapolated to the societal level, or can be placed within a system of like-minded decision makers interacting through well functioning markets; this, in turn, can lead to tractable solutions to many analytic models. This approach, however, does not account for a number of social and individual phenomena that have been found in numerous empirical studies. In particular, emergent properties of complex social systems such as societies or local communities can hardly be explained sufficiently on the basis of this model. In recent research the following concerns have been raised.

The inclusion of social norms for decision making: Whereas the rational-actor model views the individual as largely independent from social bonds in his or her decision making, uncountable experimental evidence shows the relevance of social norms, couple with communication, in people's decision making. This kind of influence can be explained to a certain extent by communication between the actors as experiments (Udéhn 1993) and field studies (Ostrom 1990, 1998) have demonstrated. As one example, a number of researchers have studied repeated games of trust, and found the results to deviate consistently from a Nash equilibrium, with the deviations dependent on features of the information flow between players, as well as the country in which the games were played (see e.g. Kahneman et al. 1986, Bolton et al. 1998, Eichenberger and Oberholzer-Gee 1998, Fehr and Fischbacher 2003, Marwell and Ames 1982).

Refinements to conventional preference theory: The theory that individuals have a clearly structured hierarchy of preferences for any kind of situations they may encounter has been challenged by research findings calling for a more refined theory of people's preferences. One of the cornerstones in this direction has been contributed by Sen (1977) and Elster (1989) who developed notions of a multiple determination of human behavior based on a two or more tier preference theory including self-interest and social norms. Thereby inconsistent choices in different situations and conflicting preferences can be grasped conceptually.

Increasing returns. A growing number of researchers are identifying places where increasing returns to scale lead an economic system to fall into unstable, or suboptimal, equilibria. For example, the attractiveness of new technologies often increases as they become more prevalent, meaning that a superior technology will often fail to diffuse because of a poor start (Arthur 1989). In such cases, it is often impossible to predict on the basis of the technology itself whether it will become widespread; rather, any model of the system must take into account agents' responses to the frequency with which the technology is already in use, i.e. the decisions of other agents.

3 Agent Based Modeling as an Approach to Grasp Emergent Properties

It is possible to study emergent phenomena in two very distinct ways. The first resonates with the conventional economic approach, and makes the system and its global properties themselves the unit of analysis (Sawyer 2003). Such an exercise is known as *equation based modeling* (EBM), with the equations describing global properties of the system. These models can simulate the system as a whole, allowing the testing of hypotheses and the making of predictions about the results of changes to the system. When external; drivers indeed act on the system as a whole, relatively uniformly, then system dynamics models are the best method of analysis. The second is to make the individual members of the system the unit of analysis, to model their interaction so as to generate the salient emergent properties. In this case, there are no equations describing the system as a whole, but rather a set of independent agents interacting with each other and with the environment through a set of interaction rules, typically logical operators. This method of analysis is known as *agent based modeling* (ABM).

ABM is the method by which one investigates and describes complex systems and their emergent properties (Bradbury 2002, Moss 2002, Sawyer 2003, Tesfatsion 2001b, Bonabeau 2002a). An agent-based model is built, not surprisingly, around a set of agents, clusters of beliefs and actions rules. Each agent observes a set of data in the surrounding program (it has percepts of its environment), exercises a set of decision rules in response to that data (it has a response function, or a utility function), and in the process generates new data (it takes actions); these actions become part of the data to which other agents react, and are incorporated into the environment for future rounds of decisions. This is most easily achieved in an object-oriented programming language, in which the language makes it easy to assign group sets of functions and variables together in different combinations. As particular styles of agent-based models have become popular, specialized languages, or at least libraries of functions, have been developed to facilitate ABM in particular. These include Ascape, SDML, and Swarm (Gilbert and Bankes 2002).

ABM has grown in importance for the social sciences only in the last 20 years. Two developments account for this recent change. First, several strands of theory have started to identify the relationship between micro- and macro-phenomena as interesting. The seminal social science study in this area was Thomas Schelling's *Micromotives and Macrobehavior*, in which he examined numerous problems, from the trivial – why do half-empty lecture halls seem to have everybody sitting in the back rows – to the important – why do people racially segregate, and does it reflect a desire to live in a completely homogenous community (Schelling 1978). At about the same time, economists started to examine economic systems in which there were increasing returns to scale, in which desirable stable equilibriums are the exception, and in which the only way to predict system outcomes is by examining them as emergent properties, in reference to the agent behavior out of which they arise (Waldrop 1992). With these theoretical insights the science of complexity studies was born (Lewin 1992). At the Santa Fe Institute and similar places, collaboration takes place between social and natural scientists in order to study common characteristics of a diversity of complex systems, from food webs to stock markets. The second development accounting for the study of emergent behavior is the advancement in computing power. Very simple models of complex systems are possible to do without the aid of a computer, such as many of the examples that Schelling himself developed (Schelling 1978). But to really understand the sensitivities of emergent properties to changing characteristics of the system as a whole, one needs the help of more sophisticated computation.

The theoretical work to support and interpret ABM depends on the degree to which the model is abstract or applied. Abstract ABMs can demonstrate classes of situations in which emergent patterns occur and the degree to which those emergent patterns differ from the behavior of the agents themselves (Epstein and Axtell 1996). For this, little additional data is required, although one often has a set of theories (such as decision theories, political theories, or social theories) that one is attempting to examine (Conte 2002, Edmonds and Moss 1997, Elliott and Kiel 2002). In their "Sugarscape" model, for example, Epstein and Axtell (1996) examined the behavior of stylized organisms on an abstract landscape, in which the organisms moved around in search of food. They were able to observe the system taking on complex properties – unpredictability in the movement of the agents, as well as emergent behavior in terms of the migration patterns of whole communities – given very little about the agents themselves that was complex. On the other hand, the researcher may want to investigate patterns emerging in real systems, either historical (Axtell et al. 2002), present (Farmer 2000, Rouchie et al. 2001, Tesfatsion 2001a), or future developments (Bonabeau 2002b, Moss and Schneider 2000, Moss 2002). For this, one needs data about the system: the agents, their relationships to each other, and the environment in which they operate. One of the best examples of this is the model of Balinese rice farmers developed by Stephen Lansing; he was able to show that a traditional set of planting rules, enforced by a hierarchy of priests, would generate greater protection against pests, and ultimately larger harvests, than a uniform planting schedule enforced by the central government (Lansing 1991). The model was especially useful, in this case, because it explained the observation that harvests declined, against all expectations, when a centralized planting system was adopted, despite the use of higher yielding varieties.

As Bradbury (2002) clearly states, no system of modeling can predict the precise future course of a complex, or complex adaptive, system. These systems are characterized by a high sensitivity to initial conditions, and are interesting precisely because they do not fall into a single stable equilibrium. What ABM can offer, given these limits, are insights into the range of future responses to inputs, and the elements of the system to which those responses may be most sensitive. In the model of rice cultivation on Bali, for example, the model showed that the degree of crop damage from pests was especially sensitive to the manner in which planting dates were coordinated, and that some mechanisms of scheduling these dates generally outperformed others (Lansing 1991).

4 Criteria for Using ABM in Adaptation Research

To check the usefulness of ABM for studying adaptation, we identify three key systems criteria. First, the system needs to be one in which agents' interactions with each other are important. Obviously, one needs to ask about the extent to which agents' actions depend on the actions of other agents, in an iterative and interdependent fashion, or are primarily determined by an outside force, the behavior of which does *not* depend on how agents are responding. Second, there often needs to be a puzzle for which traditional EBM has failed to offer useful insights. This may occur when the system is a fairly new one, and hence cannot be well predicted by reference to past systems. In these cases, it is impossible to generate the necessary systems equations, or when people have tried, the equations have generated wrong results. Third, it helps if there is sufficient data available about the agents themselves to build the agent based model. Exactly how much data is required is entirely a function of the insights that one seeks to gain.

4.1 Using ABM to Study Adaptive Capacity: Interaction Effects

Along with many other economic phenomena, the extent to which a system adapts to external changes such as climate change impacts is an emergent social phenomenon resulting from the joint decision making of many separate decision makers (Berger 2001, Tesfatsion 2002). To demonstrate why, we consider the attributes of a society that is consistently able to adapt:

Interdependent problem recognition: In order to solve an adaptation problem, society first has to recognize that the problem exists. In some cases, the recognition of risk is not a complex phenomenon, but rather one in which each person accesses a common pool of information and responds to that information, rather than to the decisions of other people. In several important ways, however, individual risk perception and choice *does* respond to the choices and actions of others, and give rise to emergent properties. A great deal of work within the fields of geography and risk communication has shown that social factors play an important part in amplifying or attenuating the perception of risk; people respond not just to the risk itself, but to other people's responses to the risk (Kasperson and Kasperson 1996).

Accessibility of appropriate new technologies: Many, if not most, of the adaptations to climate change will involve the development and implementation of new technologies. On the one hand this involves overcoming technical challenges, something that happens at the level of the single research lab or firm, the understanding of which can take place without ABM. But on the other hand, this requires that new technology, including new processes, actually be diffused and implemented widely throughout society. This is a field full of a number of interactions between large numbers of people (Berger 2001). While it may be impossible to predict which new technologies do emerge, or even which of several currently competing technologies will come to dominate, ABM can still offer interesting insights. First, it can show conditions under which the most appropriate technologies may not necessarily be expected to dominate the market (Arthur 1994). Second, it can shed light on background conditions that might accelerate or hinder the spread of new technologies (Barabási 2002).

Coordination problems: Unlike climate change mitigation, which is a response to a problem of environmental externalities, climate change adaptation can be expected to take root and be motivated by local concerns. For example, a community may be threatened by sea level rise, and needs to decide what response to take; it does not need a central authority to tell it to take action, because the action is in the community's own interest. However, these local actions can be expected to replicate themselves, fairly simultaneously, around the world. In some cases, one community's response may make the problem worse for another community, such as when a riparian community hardens the banks of the river, leading to more rapidly developing floods downstream. ABM can offer insight into when coordination problems such as these might emerge, and demonstrate the potential costliness of them.

An example of a problem that may lend itself to study by ABM is the process of adaptation to sea level rise and inundation. In this case, the risk associated with inundation is unknown, but can be inferred from the frequency of events. Several modelers have tackled the problem of belief formation by using ABM, incorporating agents who adjust their beliefs in response to their observations of events in the world, and in response to the responses of other agents in the system (Carpenter et al. 1999; Janssen and de Vries 1998). The adaptive responses in this case will depend on the range of technologies available, such as the relative cost of protecting against the water through hard measures (barriers) or soft measures (managed retreat) (Klein et al. 1998). This then implicates a problem of technological diffusion, which is a problem for which ABM has been well demonstrated. Researchers have modeled such a process, for example, as including early and late adopters of new agricultural technology, and seen how the proportions of each stimulates or retards the spread of the technology through the system as a whole (Berger 2001). Finally, the problem of responding to sea level rise and inundation, as already mentioned, involves an issue of coordination. Many of the earliest agent based models, starting with Schelling's (1978) model of racial segregation, have examined cases where decentralized decision-making can lead to outcomes contrary to what a central decision-maker would have wanted.

4.2 The Puzzle of Recurrent Failures to Adapt

Human history is full of countless stories of maladaptation: the failure to change behavior soon enough, such that the ecosystem on which a given society depended became unable to support that society, with disastrous consequences (Diamond 2004). In Mesoamerica, the Mediterranean basin, Easter Island, the Fertile Crescent, and most recently the Aral Sea, poor management decisions degraded the land on which society relied, forcing the inhabitants to move somewhere else (Erickson and Gowdy 2000, Gore 1992). The process seems to be ongoing in places as diverse as sub-Saharan Africa, the central United States, and elsewhere.

Does maladaptation occur because political leaders make wrong decisions, or do distributed problems – such as coordination problems, information asymmetries, or the combined results of individual decision-making biases – lead to outcomes contrary to the wishes of all concerned? ABM can provide the means to test whether the more mundane distributed problems could be true. Returning to the model of rice cultivation on Bali (Lansing 1991), the researchers were able to identify the problem of planting date coordination as a reason for pests damaging crops. The agent based model, then, was able to show that the coordination achieved through the traditional system of priests and temples was in fact superior to that achieved by the central government. In another landmark example, researchers showed that the population growth, and more ominously the collapse occurring among the Anasazi native American tribe was the result not of extraordinary events, but rather of mundane interactions between a heterogeneous group of people in a constrained environment (Axtell et al. 2002).

4.3 Data on Agents

The issue of data requirements is an interesting one for ABM. On the one hand, some of the most significant insights into the behavior of complex systems have been derived from models that incorporated only very stylized data (Conte 2002, Elliott and Kiel 2002). These models identify features of highly simplified systems that give rise to emergent properties, such as migration patterns resulting from the non-migratory patterns of individuals (Epstein and Axtell 1996). Other models, as we have already described, offer insights into puzzling observations of historical events. In these cases, the amount of data can vary significantly. In a model of deforestation and subsequent reforestation of agricultural lands in Indiana, for example, researchers depicted the very large area under study with a highly simplified model involving ten parcels of land, each with a single owner; even though the system was highly simplified, and the data requirements minimal, the model still provided important insights into the emergent properties observed (Hoffman et al. 2002). In other models the level of detail has been much higher, requiring significantly more specification, in some cases highly spatially defined, of agents and their environment. Rouchier et al. (2001), for example, modeled farmers and herders in Cameroon, attempting to recreate the migration patterns of the herder class. It was unclear, however, what the informal rules of interaction between farmers and herders actually were. Through the task of ABM, the researchers were able to test for these rules, identifying some as accurate representations of behavior, while ruling others out. In this case, ethnographic data did exist about the agents' individual and aggregate behavior. What the agent based model allowed the modelers to examine, which an EBM would not have been able to do, was to test hypotheses for which there was insufficient or ambiguous data.

For adaptation research, then, the question of whether sufficient data exists to engage in agent-based modeling depends entirely on the questions to be answered. If they concern abstract theoretical questions, such as the rules by which people interact, or whether the system is likely to give rise to emergent properties, then a highly stylized model will often suffice, and the data requirements will be minimal. On the other hand, if the question is about the interaction of features of the system for which reliable theory is available, then data will be needed to parameterize and later validate the model. This is more often the case when one is trying to examine the range of possible future behavior of a system. In these cases, ABM requires data on agents themselves, something EBM typically does not.

5 Conclusion

Agent based modeling is an exciting new methodology for studying the emergent properties – often surprising properties – of complex systems. It is able to identify causal pathways between characteristics of agents in a system, their networks of interaction, and the global system properties that result from these interactions. Often, in cases of new or unusual systems, but relatively familiar classes of agents, ABM can do a better job of investigating both the range of possible futures than more traditional EBM on a rational-actor basis, and the features of the system that could make one or more classes of these futures more or less likely to occur. In all cases of emergent properties, ABM ought to be able to improve our understanding of the system, and ultimately lead to better efforts to improve it, with a reduced likelihood of negative surprise.

Adaptive capacity can be thought of as an emergent property, one for which ABM is a suitable analytic tool that has not yet been developed future regional or local adaptation strategies. First, adaptive capacity arises from a complex system, in which many actions are taken in response to the actions of others. Second, adaptive capacity presents us with a puzzle – maladaptation – that conventional modeling seems unable to solve. Third, it ought to be possible to gather, often from the existing literature, the data necessary to construct valid agent based models of adaptive capacity. Fourth, given the lack of a feasible alternative, ABM may be the only way to predict the success of policy interventions.

Obviously, ABM is a challenging task. To date, the most useful ABMs in the social sciences are those that help to explain an observed surprise, a case where a social system achieves a result that none of its members would have either wanted or predicted. But models in various fields of application other than adaptive capacity are beginning to identify features of current systems that make the system more or less resilient, more or less likely to give rise to unpleasant futures (e.g. Axtell et al. 2002, Moss et al. 2001, Rouchier et al. 2001). Given the inherent unpredictability of complex adaptive systems, it is unlikely that any model – ABM or EBM – will be able to foresee long range future events with a great degree of reliability (Bradbury 2002). At the same time, ABM offers the promise of providing important insights even as society continues to cope with uncertainty.

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