Geographic Information Systems (GIS) and Spatial Agent-Based Model (ABM) Simulations for Sustainable Development

Claudio Cioffi-Revilla, George Mason University, USA

J. Daniel Roger, Smithsonian National Museum of Natural History, USA

Atesmachew Hailegiorgis, George Mason University, USA

rev. February 27, 2011

ABSTRACT

In recent years the interdisciplinary field of Computational Social Science has developed theory and methodologies for building spatial "agent-based" social simulation (ABSS) models of human societies that are situated in ecosystems with land cover and climate. This paper explains the needs and demand for Geographic Information Systems (GIS) in these types of agent-based models, with an emphasis on models applied to Eastern Africa and Inner Asia and relevance for understanding and analyzing development issues. The models are implemented with the MASON (Multi-Agent Simulator Of Networks and Neighborhoods) system, an open-source simulation environment in the Java language and suitable for developing ABSS models with GIS for representing spatial features.

Keywords: Geographic Information Systems (GIS), Spatial Agent-based Modeling (ABM), Multi-agent Systems (MAS), Computational Social Science, Inner Asia, Eastern Africa, Multi-Agent Simulator of Networks and Neighborhoods (MASON)

INTRODUCTION

Sustainable development—long-term growth with resource consumption that is trans-generationally neutral (possibly positive)—is a complex dynamic process characterized by numerous requirements, interdependencies among social, technical, and natural environments, and uncertainty concerning many relevant processes. Simple economic models like Venn diagrams (Barbier, 1987) have limited value or can be misleading, and econometric models fall short of what is required for rendering and analyzing complex socio-natural systems. Such systems are typically characterized by (1) a large number of variables (high-dimensionality), (2) non-linear relationships, and (3) evolution and adaptation endogenous to the system itself, making closed-form solutions infeasible. Advanced scientific methods and technologies from other fields are required for marking progress on multiple aspects of sustainable development, including analysis, design, decision making, implementation, and monitoring (Ostrom, 2009).

Geographic Information Systems (GIS) and Agent-Based Models (ABM) used in the interdisciplinary field of computational social science (CSS) originated just a few decades ago. They have since evolved in independent ways, including autonomous professional communities and organizations. An interesting feature of these two major methodological developments is that the intersection of GIS and ABM for social simulations now enables new scientific and policy analyses that exploit the joint, synergistic capabilities of these advanced computational technologies. Modeling and analysis for improving sustainable development represent a particularly promising area for joint use of these methodologies. In this paper we show how some current advances are providing answers to complex problems of sustainability that have resisted earlier approaches based on more traditional statistical or mathematical models. We argue that future coordinated developments in both methodologies promise even more transformative breakthroughs. This is especially so in critical areas of basic scientific research and applied policy analysis in sustainability and related topics in complex socio-techno-natural systems.

This paper consists of four sections. First, we provide some essential background on both methodologies and the specific motivation for this paper in the context of sustainable development. Second, we describe agent-based models that are geospatially referenced, with emphasis on two recent models developed with the Java-based MASON toolkit (this is the core of the paper). Third, we discuss current and future applications of GIS in social agent-based models. Finally, we present some conclusions.

Sustainable development is a complex challenge requiring use of advanced information technologies for supporting decision making. From a computational modeling perspective, a GIS is generally composed of three main classes of layers in terms of geospatially referenced data:

1. Natural features: Physical terrain, hydrology, and climate comprising an ecosystem;
2. Man-made artifactual systems: Building, roads, bridges, farms, factories, ranches, parks, and all other engineered structures or features; and
3. Human entities: People, population concentrations, land-use patterns, and cultural attributes, which are the most important data layers for purposes of this paper.

We shall refer to this last category as “social GIS” (Longley et al., 2005; Cioffi-Revilla, 2010a; ESRI, 2009), to distinguish from more traditional uses of GIS consisting of the first two categories (biophysical and technological, respectively). A defining feature of social GIS is visualization and analysis of spatial social data, including sociological, economic, political, cultural, military, or other human and social attributes and/or dynamics. Within this broad range of potential interactions, GIS is playing an increasingly leading role in understanding both scale and complexity in social landscapes.

Motivation for this paper is provided by current developments in GIS and ABM, given that these methodologies (a) originated in autonomous ways; (b) have been and will continue to rely on computational science and technology developments (for example, ABM is closely dependent on multi-agent systems, machine learning, artificial intelligence, evolutionary computation, and related areas of computer science); and (c) have an area of overlapping interest specifically engendered by spatial agent-based models that are geospatially referenced.

Geospatially-referenced agent-based models (GABM) constitute a subset of agent-based models, because not all agent-based models have a spatial domain (for example, some are purely organizational), and even among spatial ABMs, not all of them are geospatially referenced with empirical data (e.g., Schelling's [1971] segregation model). Below we describe both methodologies with a view towards illuminating their combined use through computational simulation models. We illustrate the present use of these complementary technologies with two modeling projects that are on-going and have significant potential for supporting analysis and planning of sustainable development. Additionally, we claim these technologies and modeling approaches enable analysis of sustainability in new ways that have been unavailable through earlier approaches (e.g., econometric modeling).

GEO-REFERENCED SPATIAL AGENT-BASED MODELS

Overview

Agent-based modeling (ABM) is a computational methodology for formalizing and analyzing complex social systems on many scales, ranging from small groups of individuals to organizations and larger systems, such as national, regional, or international (Axelrod, 1997; Gilbert & Conte, 1995; Cioffi-Revilla, 2002; Epstein, 2008; Gilbert, 2009; North & Macal, 2007). Complex social systems that are modeled by ABMs typically exhibit features such as: (i) many autonomous or semi-autonomous actors (called "agents") making interdependent decisions; (ii) high-dimensionality (many variables or attributes); (iii) environments (artifactual and/or natural) where agents are situated; (iv) nonlinear dynamics that govern interactions among actors and environments; and, consequently, (v) emergent ("bottom-up") macroscopic properties generated by micro-level agent-to-agent and agent-environment interactions. Such features typically defy the modeling capability of earlier formal methods, such as econometric models, dynamical systems of differential equations, or game-theoretic models. For example, econometric models are not feasible under such circumstances, due to insurmountable specification and estimation problems. ABM methodology is part of the computational simulation modeling approach in social science, which also includes other types of simulation models, such as system dynamics, queuing models, micro-simulations, and cellular automata (Gilbert & Troitzsch, 2005; Cioffi-Revilla, 2010b).

A subset of ABMs includes spatial features for modeling human or social dynamics in a given landscape (real or hypothetical); these are called “spatial ABMs” and are often applied in areas such as land-use and cover change (LUCC; Parker et al., 2003). The landscape itself may be simple or complex, depending on the purpose of the model and its level of abstraction. For example, the classical Schelling (1971) segregation model represents only a simple grid of city blocks, whereas other models, such as MASON Wetlands (Cioffi-Revilla et al., 2004), represent terrain in addition to vegetation and weather.

A subset of spatial ABMs has geospatially referenced features corresponding to a given region of the real world, based on GIS data (raster or vector; primary or secondary). It is these GIS-based spatial ABMs that we are concerned with in this paper (Castle et al., 2007), as demonstrated by simulation models of pastoralist societies in Asia and Africa.

MASON and GIS

An ABM is developed either in native code or using an existing toolkit (Nikolai & Madey, 2009), such as the MASON system (Luke et al., 2005) or other similar toolkits (Swarm, Repast, Cormas, NetLogo, and others). MASON (Multi-Agent Simulator of Networks or Neighborhoods), developed as a joint project by the Department of Computer Science and the Center for Social Complexity at George Mason University, is an academic license free multi-agent simulation toolkit flexible enough to use for a wide variety of agent-based related applications. Its applications include modeling social complexity, physical and artificial intelligence, and machine learning. MASON is fast, easily extendible, and less dependent on other external libraries.

Architecturally, MASON has two main functional components: model computation and visualization. The model computation layer is specialized for event scheduling tasks and can run in the command line independently of the visualization layer. The visualization layer is the GUI interface, which is responsible for manipulating the model object, portraying it on the screen, and inspecting its content. In addition, a utility layer is tasked for taking care of any other purpose facilities, such as the random number generator, data structures, creating movies, and snapshots. MASON includes an extensive tutorial guide and online support for users. Additionally, MASON includes specialized functionality and extensions with tutorials for Social Network Analysis (SNA; Wasserman & Faust, 1994), evolutionary computation (EC; De Jong, 2006; Luke et al., 2009), physics modeling, charting, and parameterization. Currently MASON has expanded its GIS facilities to include the import of vector data for spatial reasoning, distance calculations, determining coverage, and other functionalities.

The MASON HouseholdsWorld Model (Inner Asia)

HouseholdsWorld in MASON (Cioffi-Revilla, Rogers, & Latek, 2010) is an ABM developed to explore a wide range of social and environmental interactions, including emergence of social complexity, adaptive capacity of different types of social systems, and impacts of climate change related to pastoralism in Inner Asia (defined as northern China, Mongolia, southern Siberia, and portions of Kazakhstan). As a simulation of socio-natural systems, HouseholdsWorld uses empirical data from ethnology, archaeology, paleoclimatology, historical ecology, and experimental results from studies in rangeland and herd management (e.g., Kohler & Gummerman, 2000; van der Leeuw & Redman, 2002). It uses the relatively egalitarian social landscape of the Bronze Age, ca. 1000 B.C. in Inner Asia as the target or focal system (Askarov, Volkov, & Ser-Odjav, 1999). Beginning in 2001, archaeological teams from the Smithsonian Institution identified and excavated sites in Mongolia to strengthen the empirical data and spatio-temporal framework used in creating the HouseholdsWorld simulation.

HouseholdsWorld is part of a suite of MASON simulations developed at George Mason University in conjunction with additional research on the rise and fall of polities in Inner Asia (Cioffi-Revilla et al., 2007; Rogers, 2007; Rogers & Cioffi-Revilla, 2010). Specifically, the model is informed by multiple sources of archaeological, historical, and contemporary data. The main agent classes are Households and Camps, where Households also belong to Clans (Figure 1). Camps consist of households that decide to co-locate in the same area. Since each household belongs to a clan, such membership also affects the decision as to where to camp. However, social interactions are not deterministic, just like in the real world decision making is affected by a set of factors taken together. The step() method literally steps the state of the simulation forward, generating emergent behaviors such as camping. Additional features and interactions of the computational model are described in Cioffi-Revilla, Rogers, & Latek (2010).

HouseholdsWorld, as a dynamic model, pays close attention to both spatial and temporal resolution as these define the scale of abstraction by which phenomena can be analyzed (see Castle & Crooks, 2006). In many ways HouseholdsWorld is about how pastoralists adapt to landscape, weather, and social variability. We have analyzed the intersection of these sources of variability to study the long-term sustainability of pastoralism both from the perspectives of herd dynamics in rangeland management and in terms of policy decision making.

Households function on realistically rendered landscapes calculated at 1 km resolution, termed landscape scenarios (S1-S8). These landscapes were selected in order to sample environmental variability, and also to overlay with empirical landscape use patterns under study by archaeological teams as part of the overall project. Each landscape is either 10,000 or 40,000 sq. km. In addition to geomorphological characteristics, these landscapes use normalized difference vegetation indices (NDVI) (Hansen et al. 1998, 2000). NDVI rasters were computed for each month of the year from atmospheric corrected bands in 500 m resolution. This allows the modeling of seasonal weather as it affects vegetation. Additionally, weather events (viz., snow storms and droughts) modeled on 19th and 20th century weather data are incorporated to produce additional dynamic characteristics. The landscapes are classified into 14 land cover types and approximations are calculated for edible biomass for herd animal consumption. Coefficients for computing edible biomass are drawn from Kawamura et al. (2005).

In terms of social interaction, households in the model follow their herds, which in turn follow the distribution of biomass, which is patterned after weather. When deciding where to move, and with which other households to form camps, households undergo a decision making process that is informed by anthropological features, such as norms for association, clan membership, and past memories. Camps thus emerge from such decision processes; they are not "hard-wired" into the simulation.

Research has focused on 5 areas: north Xinjiang (S3), south Hovsgol Aimag (S5), north Hovsgol Aimag (S6), Egiin Gol (S7), and Baga Gazaryn Chuluu (S8). The S3 landscape is currently under study. It is in the Xinjiang prefecture of northwest China, between Kazakhstan and Mongolia. This is a region of moderate to low biomass density with a diversity of land cover combinations characteristic of large portions of Inner Asia. The analysis presented here is supported by a considerable quantity of rangeland management research conducted throughout northern China (Committee on Scholarly Communication, 1992; Humphrey & Sneath, 1999).

Contemporary pastoralists in many regions of northern China have experienced a decline in quality of rangelands, due to overgrazing (Figure 2). There have been various studies and management interventions proposed to improve livelihood. However, sustainability is usually considered in conjunction with improving the short-term economic conditions of herders. By running our simulation for hundreds of years we are able to show that concepts of carrying capacity based on grassland conditions at any one time are likely to be misleading (e.g., Committee on Scholarly Communication, 1992). Sustainable and resilient solutions are instead likely to depend on the use of non-equilibrium ecological models that incorporate pastoralist mobility and an understanding of local social limits.

The MASON HerdersAndFarmers Model (Eastern Africa)

Herders and other inhabitants of the Mandera Triangle region (located along the northern frontier of Kenya, bordering with Ethiopia and Somalia) have developed sustainable adaptive responses that are resilient to their changing and harsh environment. Inhabitants of these landscapes and elsewhere in arid and semi-arid regions of Eastern Africa have evolved elaborate social alliance structures and other effective and efficient governance mechanisms for coping with diverse environmental shocks, such as drought or flooding. However, the relatively recent division into states, the introduction of new actors, and the occurrence of more frequent and lengthy droughts, have created new stresses on access to resources. Such crises can have a crippling effect on otherwise successful coping mechanisms. As a result, this complex socio-natural system along the northern regions of Kenya has become highly conflict-ridden (Witsenburg & Adano, 2009).

MASON HerdersAndFarmers is an agent-based model to simulate cultural dynamics in response to herder behavior, tension caused by the introduction of new actors (farmers), and feedback from the natural environment and resulting conflicts (Rouleau et al., 2009; Kennedy et al., 2010). The model focuses on two major issues common throughout East Africa: Conflict escalation among herders and between herders and farmers; and conflict from environmental stress and ineffective land management. In turn, such conflicts can lead to deadly violence, displacement, and other consequences.

The model is developed within the MASON simulation environment and has three main components: agents, environments, and their rules of interaction. Within the model, there are two types of agents: herders and farmers. Herders are the main focus of the model. They feed and manage their herds, moving from one parcel to another in search of pasture and water. Trespassing across previously owned parcels occurs when herders are desperately in need of food due to lack of a viable parcel. Such trespassing results in the onset and escalation of conflict.

The environment, with spatial extent of 150 km by 150 km, consists of parcels and local weather. Each parcel has 1 km by 1 km spatial resolution (Figures 3a and 3b). Land parcels are spatially heterogeneous in quality, represented by the maximum amount of vegetation supported in the absence of grazing and under optimal weather conditions. Weather is represented by rainfall, which varies monthly. Droughts are simulated by decreases of 15% or more in monthly rainfall patterns.

HerdersAndFarmers uses GIS in a way that is loosely coupled with the ABM. The location of each space where agents are acting is spatially referenced. Even if initially both herders and farmers are located in the landscape randomly, they move, explore, and act on the landscape in a spatially explicit way. Agents have spatial vision and knowledge, which is expressed by proximity and experience of exploration of the surrounding environment in the search for water and pasture. These and other features are consistent with the ethnology of local societies in northern Kenya. The maximum amount of vegetation for each parcel was estimated using GIS data on land use and slope.

Our initial model demonstrates the fundamental behaviors needed to replicate conflict dynamics in the Mandera Triangle area. We find that much of the macro-patterns of conflict in

Mandera can be simulated with a set of relatively simple actors with competing agendas. This model is still being developed and will have several extensions. Future development of the model will include additional population dynamics, land use change, degradation, climate change, and deeper GIS integration to handle vector data formats.

CONCLUSIONS

There are several fields of application that currently utilize GIS and ABM. The application and abstraction of a model and integration of the two methodologies depend on the objective of a research model and field of study. Most spatially oriented fields, such as quantitative geography, ecology, or urban systems, place greater emphasis on the use of spatial information but give less weight to the use of social science within simulations. By contrast, social sciences such as economics or political science place less emphasis on geospatial dynamics.

Gimblett (2002) emphasizes the need to integrate GIS and ABM, and raises several conceptual and technical issues concerning current practice. Parker (2004) discusses the current practice of ABM based on the level of GIS integration and categorizes a range of models, from those utilizing abstract space to models with an interface that integrates both ABM and GIS into one system. Between these two extremes, the majority of models utilize GIS data for simulation initialization or visual output.

Currently there is no clear principle concerning which level of integration or coupling (loose or tight) is best and achievable (Brown et al 2005; Parker et al., 2003). For instance, Torrens and Benenson (2005) suggested building a new system or a separate framework approach that would be initially constructed with the functionality of the two systems together. They provide the architecture of Geographical Automata System (GAS) linking automata-based urban system with GIS, which can be run on different platforms. The other alternative suggested by Brown et al. (2005) is a compromise solution for bridging the gap between ABM and GIS fields by building on the existing system. Their application "builds on existing platforms and involves the development of software to handle the identity and causal relationships between the agents within an ABM environment and spatial features within a GIS environment, as well as the temporal and topological relationship issues that arise in the model." Challenges remain in both approaches. The development of object orientation and simulation and the high demand for integrating ABM and GIS in social and spatial fields offers some hope for reducing current gaps.

In terms of future developments for sustainability research, we view the following trends as significant:

1. New links are developing among sources of remote sensing data, with proxy measures for environmental variability, which will likely improve integration with modeling environments.
2. Visualization of social agents on geospatial landscapes is becoming increasingly sophisticated.
3. Agent-based dynamic analytical capabilities are being developed into GIS-based software.

Sustainable development requires analytical, implementation, and monitoring tools for handling long-term, multi-generational demographic change for assessing environmental impacts. Whether in the steppes of Central Asia or the rangelands of East Africa, sustainable development modeling through ABM and GIS enables advanced integration of social, environmental, and infrastructural modeling using simulations. This kind of interdisciplinary integration holds significant potential for discovering new insights and policy solutions in support of sustainability.

ACKNOWLEDGMENTS

Funding for this study was received from the US National Science Foundation (HSD Program, grant no. BCS–0527471) and the Office of Naval Research (MURI Program, grant no. N00014–08–1–0921), which also support the MASON Project. Thanks to all our team members of the Mason-Smithsonian Joint Project on Inner Asia and the Mason-Yale Joint Project on Eastern Africa, as well as to Lee Schwartz, Melba Crawford, Paul Bartels, and members of the US State Department Humanitarian Information Unit for providing inspiration for this paper during the international conference on "Geospatial Science and Technology for Sustainable Development in Africa: Partnerships and Applications," held at Harvard University, John F. Kennedy School of Government, May 28–29, 2009. We also thank Christina Bishop, Jai Alterman, and Justine Benanty for administrative and research assistance. The authors are solely responsible for the views expressed in this paper.

REFERENCES

Askarov, A., Volkov, V., & Ser-Odjav, N. (1999). Pastoral and nomadic tribes at the beginning of the first millennium B.C. In A. H. Dansi, & V. M. Masson, (Ed.), *History of civilizations of*

Central Asia: The dawn of civilization: earliest times to 700 B.C. vol. 1. (pp. 459–472). Delhi, India: Motilal Banarsidass Publishers.

Axelrod, R. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton, NJ: Princeton University Press.

Brown, G. D., Riolo, R., Robinson, D. T., North, M., & Rand, W. (2005). Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems, 7*, 25–47.

Castle, C. J. E. & Crooks, A. T. (2006). Principles and concepts of agent-based modeling for developing geospatial simulations. *Center for Advanced Spatial Analysis, Paper 110*. London, UK: University College.

Castle, C. J. E., Crooks, A. T., de Smith, M. J., Goodchild, M. F., & Langley, P. A. (2007). Geocomputational methods and modelling. In M. J. de Smith, M. F. Goodchild, & P. A. Langley (Ed.), *Geospatial analysis: A comprehensive guide to principles, techniques and software tools*. Winchelsea, UK: The Winchelsea Press.

Cioffi-Revilla, C. (2002). Invariance and universality in social agent-based simulations. *Proceedings of the National Academy of Science of the U.S.A.* 99 *Supp. 3* (14), 7314–7316. Article available online.

Cioffi-Revilla, C. (2010a). Computational social science. *Wiley Interdisciplinary Reviews* (*WIREs*) *Computational Statistics*, *Vol. 2*. DOI: 10.1002/wics.95

Cioffi-Revilla, C. (2010b). On the methodology of complex social simulations. *Journal of Artificial Societies and Social Simulations 13* (1). Article available from: http://jasss.soc.surrey.ac.uk/13/1/7.html

Cioffi-Revilla, C., Luke, S., Parker, D. C., Rogers, J. D., Fitzhugh, W. W., Honeychurch, W., Frohlich, B., DePriest, P., & Amartuvshin, C. (2007). Agent-based modeling simulation of social adaptation and long-term change in Inner Asia. In S. Takahashi, D. Sallach, & J. Rouchier (Eds.), *Advancing social simulation: The first world congress* (pp. 189–200). Tokyo, Japan: Springer.

Cioffi-Revilla, C., Paus, S., Luke, S., Olds, J. L., & Thomas, J. (2004). Mnemonic structure and sociality: A computational agent-based simulation model. In D. Sallach & C. Macal (Eds.), *Proceedings of the Agent 2004 Conference on Social Dynamics: Interaction, Reflexivity and Emergence*. Chicago, IL: Argonne National Laboratory and University of Chicago.

Cioffi-Revilla, C., Rogers, J. D., & Latek. M. (2010). The MASON HouseholdsWorld model of pastoral nomad societies. In K. Takadama, C. Cioffi-Revilla, & G. Deffaunt (eds.), *Simulating Interacting Agents and Social Phenomena: The Second World Congress on Social Simulation* (pp. 193–204). Tokyo, Japan: Springer.

Committee on Scholarly Communication with the Peoples' Republic of China. (1992). In Committee on Scholarly Communication with the Peoples' Republic of China, Office of International Affairs, National Research Council (Ed.), *Grasslands and grassland sciences in Northern China*. Washington, D.C.: National Academies Press.

Gimblett, R. H. (2002). *Integrating geographic information systems and agent-based modeling techniques for simulating social and ecological processes*. New York, NY: Oxford University Press.

Gilbert, N. & Conte, R. (Eds.). (1995). *Artificial societies: The computer simulation of social life*. London, UK: University College Press.

Hansen, M., DeFries, R., Townshend, J. R. G., & R. Sohlberg. (2000). Global land cover classification at 1km resolution using a decision tree classifier. *International Journal of Remote Sensing, 21*, 1331–1365.

Hansen, M., R. DeFries, R., Townshend, J. R. G., & Sohlberg, R. (1998). *UMD Global Land Cover Classification, 1 Kilometer, 1.0*. Maryland: Department of Geography, University of Maryland, College Park, MD.

Humphrey, C. & Sneath, D., (Eds.). 1999. *The end of nomadism? Society, state, and the environment in Inner Asia*. Durham, NC: Duke University Press.

De Jong, K. (2006). *Evolutionary computation*. Cambridge, MA: MIT Press.

Kennedy, W. G., Gulden, T., Hailegiorgis, A. B., Bassett, J., Coletti, M., Balan, G. C., Clark, M., & Cioffi-Revilla, C. (2010). An agent-based model of conflict in East Africa and the effect of the privatization of land. Paper presented at the 3rd World Congress in Social Simulation, September 6–9, 2010, at Kassel, Germany.

Kawamura, K., Akiyama, T., Yokota, H., Tsutsumi, M., Yasuda, T., Watanabe, O., & Wang, S. (2005). Comparing MODIS vegetation indices with AVHRR NDVI for monitoring the forage quantity and quality in Inner Mongolia grassland, China. *Japanese Society of Grassland Science, 51*, 33–40.

Kohler, T. A. and Gumerman, G. J., eds. (2000). *Dynamics in human and primate societies: Agent-based modeling of social and spatial processes*. New York, NY: Oxford University Press.

Longley, Paul A., Michael F. Goodchild, David J. Maguire, and David W. Rhind. 2005. *Geographical Information Systems and Science*. John Wiley & Sons.

Luke, S. et al. (2009) ECJ 18: A java-based evolutionary computation system, Available at http://cs.gmu.edu/~eclab/projects/ecj/

Luke, S., Cioffi-Revilla, C., Panait, L., and Sullivan, K. (2005). MASON: A Java multi-agent simulation environment. *Simulation: Transactions of the Society for Modeling and Simulation International 81* (7):517–527.

North, M. J., & Macal, C. M. (2007). *Managing business complexity: Discovering strategic solutions with agent-based modeling and simulation*. New York, NY: Oxford University Press.

Ostrom, E. (2009). A general framework for analyzing sustainability of socio-ecological systems. *Science, 325*, 419–422.

Parker, D. C. (2004). Integration of geographic information systems and agent-based models of land use: Challenges and prospects. In D. Maguire, J. M. F.,Goodchild, & M. Batty (Eds.), *GIS, spatial analysis and modelling*. Redlands, CA: ESRI Press.

Parker, D. C., Mason, S. M., Janssen, M. A., Hoffmann, M. & Deadman, P. (2003). Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers, 93*(2), 314–337.

Rogers, J. D. (2007). The contingencies of state formation in Eastern Inner Asia. *Asian Perspectives, 46*(2), 249–274.

Rogers, J. D. & Cioffi-Revilla, C. (2010). Expanding empires and a theory of change. In J.

Bemmann, H. Parzinger, E. Pohl, and D. Tseveendorj (Eds.), *Current Archaeological Research in Mongolia* (pp. 447–461). Bonn, Germany: Bonn University Press.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology, 1*,143–186.

Torrens, P. M., & Benenson, I. (2005). Geographic automata systems. *International Journal of Geographical Information Science, 19*(4), 385–412

van der Leeuw, S. & Redman, C. L. (2005). Placing archaeology at the center of socio-natural studies. *American Antiquity, 67*, 597–605.

Wasserman, S., & Faust, K. (1994). *Social network analysis*. Cambridge, UK: Cambridge University Press.

Witsenburg, K. M., & Adano, W. R. (2009). Of rain and raids: Violent livestock raiding in northern Kenya. *Civil Wars 11* (4), 514–538.

Figure Captions

Figure 1. Unified Modeling Language (UML) class diagram illustrating the relationship between major components of the HouseholdWorld model.

Figure 2. The border between Northern China and Mongolia showing extensive overgrazing (ovals) on the southern side of the border (China). (Landsat image)

Figure 3. Example of landscape visualization used in the HerdersAndFarmers model: (a) herders (small squares) dispersed throughout the landscape at initialization; (b) onset of conflicts (circled larger squares) due to some encounters among herders that compete for resources.