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Simulated experiments and their potential role in criminology and criminal justice

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The use of computational simulations in the field of criminology and criminal justice is growing rapidly (Gunderson and Brown 2000; Brantingham and Brantingham 2004; Liu et al. 2005; Wang 2005; Eck and Liu 2008). Some criminologists emphasize the importance of simulation methods for strengthening and elaborating theory (Brantingham and Brantingham 2004; Eck 2005; Groff 2007b), others focus on the use of simulation as a policy evaluation tool (Perez and Dray 2005). Groff (2007a), for example, created a society and then systematically varied specific conditions under which that society operated (e.g., average time spent away from home and the spatio-temporal constraints on routine activity spaces) to assess how varying different components of routine activity theory might variously impact on street robbery outcomes. This Special Issue of the *Journal of Experimental Criminology* takes stock of how simulation methodologies are currently used and thought about in the field of criminology and criminal justice. We have assembled a collection of seven papers that together provide a snapshot of the issues and complexities of applying computer simulation to criminology and criminal justice. Our introductory comments seek to introduce the reader to different types of simulation models, highlight the complexities encountered in building robust models, and situate the application of computer simulation within the broader spectrum of experimental criminology.

Outside of criminology, researchers have discussed the potential to conduct experiments using 'virtual' places, people or situations for some time (Dowling 1999; Berk et al. 2000). Related disciplines such as economics (Schelling 1971; Tesfatsion 2000; Wilhite 2001; Tesfatsion 2002), sociology (Epstein et al. 2001; Macy and Willer 2002; Moss and Edmonds 2005), and geography (Parker et al. 2003; Brown et al. 2004) have conducted such experiments[1].

[1] These references are but a small sample of the work that has been done in related disciplines. The natural sciences have been utilizing simulation for even longer to understand climate, ocean currents, wild fires, etc. (for a recent collection see Maguire et al. (2005) or the proceedings of the 2000 GIS & Environmental Modeling conference at http://www.ncgia.ucsb.edu/).

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Simulation is a broad field of science that encompasses a number of different approaches that share a set of characteristics. The field of simulation involves the creation of models which distill a phenomenon into its most important elements. Interactions within simulation models are extremely complex, so simplicity at the start is essential to understanding (Gilbert and Doran 1994; Gilbert and Terna 1999; Berk et al. 2000). Models are developed from theory and specified within a computer program (Gilbert and Doran 1994; Gilbert and Terna 1999) where they are able to accommodate dynamic, non-linear interactions that play out over time. A formalized computer code provides concrete documentation for the assumptions of the model and enables transparency in the research enterprise that is necessary for replication and testing of results (Chattoe 1996; Gilbert and Terna 1999). These attributes are especially important when one is trying to discover the mechanisms through which observed macro-level patterns are formed. In short, simulated experiments involve identifying and codifying a range of complex relationships and then creating a model of the world as it exists according to theory or prior to an intervention (Berk et al. 2000). Generally, parameters defining relationships between multiple variables within the prototype model are subjected to sensitivity testing using real life or synthetic data. These data are examined within the prototype model such that a researcher can observe the degree to which real-life conditions and flow outcomes can be replicated. The model is then run under the 'control' (status quo) condition first and then under one or more 'test' or experimental conditions. The results from each run are compared so that differences can be identified.

Possibly the most familiar type of simulation is dynamic systems modeling, which has been applied to criminological questions for over 25 years (Brantingham 1977; Blumstein and Graddy 1982). These models identify the inputs and outputs of a system. They the researcher systematically alters some condition in the model to examine how the outputs are changed. The models of the criminal justice system that demonstrate how increasing arrests affect the courts, jails, prisons and, ultimately, probation/parole offer a familiar example.

Agent-based modeling (ABM) is another form of computer simulation made possible through development of object-oriented programming languages and aided by advancements in data and computing power. Agent-based models rely on a bottom-up approach to computer simulation, where a few, simple, theory based rules are developed for the individual agents. The interactions of individuals in the model produce macro-level patterns that *emerge* from the simulation. The property of *emergence* refers to any unexpected consequences from the application of simple behaviors (Epstein and Axtell 1996; Gilbert and Troitzsch 1999). In addition, individuals in simulation models are able to make dynamic decisions based on changing information (Bonabeau 2002).

The employment of ABM in the social sciences has increased over the past 10 years (Gilbert and Doran 1994; Gilbert and Terna 1999; Gilbert and Troitzsch 1999; Macy and Willer 2002). This rising interest in ABM stems from its unique capabilities, which range from description, to knowledge discovery, to hypothesis testing. Criminologists have recently begun to explore how agent-based models can inform the study of crime (Xue and Brown 2003; Brantingham and Brantingham 2004; Brantingham and Groff 2004; Eck and Liu 2004, 2008). Moreover, the inherently spatial nature of human movement and interaction, as well as the role of place in influencing those elements, often requires the agent-based models to incorporate space as well as time (O'Sullivan and Haklay 2000; Gimblett 2002; Brown et al. 2005; Groff 2007a).[2]

Simulations are useful in many circumstances, particularly when opportunities to conduct field experiments are challenging at best and impossible at worst. Simulations might be considered when ethical concerns preclude random assignment of people to treatment and control conditions. For example, while police might not 'strike' for long periods of time in real life, they can do so in an artificial society. Simulations are also useful as comparatively inexpensive 'first cuts' to evaluate the potential of a program and to suggest changes that may strengthen the program before it is rolled out for proper field testing. Moreover, the cost of developing computer models and running 'virtual' experiments is a fraction of the cost involved in real-life field trials. Random assignment is consistent, the treatment is provided as specified, and there is no attrition by study subjects. While there is no substitute for field experimentation, simulation may be able to play a significant role in vetting and/or strengthening programs prior to their empirical testing.

Simulations are not inherently experimental. For a simulation to be considered 'experimental' it must include systematic manipulation of, or random allocation of, a condition. This type of simulation has been termed a computational laboratory. A computational laboratory is a set of software tools that enable the specification and execution of systematic experiments using simulation (Chen et al. 1994; Slavin 1996; Dibble 2001; Parker et al. 2001; Tesfatsion 2001). Simulations implemented in the framework of a computational laboratory offer the advantage of being able to hold the agents and/or the landscape constant and then vary one or both of them systematically. This feature provides a level of control difficult to attain using traditional social science methods (Epstein and Axtell 1996; Gilbert and Terna 1999; Dibble, unpublished article). The combination of heterogeneous agents and control enables the researcher to conduct a variety of experiments, using different conditions or applying various prevention scenarios, and then evaluate outcomes for minimal cost as compared to experiments undertaken in the real world.

The inclusion of a Special Issue on simulated experimentation is timely, given the growth of computational methodologies being applied to crime and justice issues. The papers chosen for this issue address cross-cutting, methodological issues, or they use an experimental approach to assess the relative impact of one type of intervention over another. As a bridge between criminology and computer science, however, the journal's peer review process posed a multitude of challenges. Indeed, peer review for papers that are interdisciplinary or apply a new methodology to well-known questions is always challenging, because the opinions of both a substantive expert and a methodological one are required. The search for peer reviewers for our Special Issue was no exception. Each article selected for this issue was reviewed by at least one substantive and one methodological reviewer. We thank the reviewers who participated in the review process and believe their careful comments to the authors strengthened the research presented herein.

The Special Issue begins with an article by John Eck and Lin Liu in which they take a broad look at simulation and the issues surrounding its use in criminology.

[2] For an opposite view on the importance of space, see Elffers and van Baal (2008).

The authors raise important issues about the internal and external validity of results from simulation models, and they identify the unique contributions to criminology and our criminal justice evidence base made by simulation studies.

The next group of articles applies different types of simulation models to answer a range of key policy questions and test different types of interventions within simulated laboratory environments. One of the advantages of simulation is its ability to create a counterfactual; thus, it does not have to use randomization because it can go back in time and recreate the same society upon which to apply a different treatment (Berk et al. 2000). Specifically, a society is created in which certain elements are stochastic. The society can be 'aged' forward in time under the current circumstances. Then, different treatments are applied to the same society. Put another way, the same artificial society (i.e., model) is used as a base, but the researchers systematically change one aspect of that society at a time. As such, the models presented in this Special Issue hold constant a set of conditions that underpin the functioning of an artificial society and explore the relative impact of different interventions over time. The population of all entities experiences the experimental conditions, and comparisons are made under the different experimental conditions.

The applied studies included in the Special Issue share a focus on testing innovative interventions and measuring model outcomes. In doing so, the authors clearly demonstrate the advantages of formalizing interventions and the careful measurement of outcomes into a computer program, both of which require rigorous definition. The first of three papers that present different models is by Kate Auerhahn (in this issue). She uses dynamic simulation to examine the effect of three-strikes legislation on prison populations in California. The paper by Shane Johnson (in this issue) relies on microsimulation to examine the veracity of two theories of repeated home burglary victimization. Finally, Anne Dray and her colleagues (in this issue) develop an agent-based model to test the effects of different policing strategies on a street-level drug market.

We recognize, however, that simulation modeling poses a number of core challenges. The last two papers of this Special Issue address two of these challenges. Richard Berk (in this issue) examines the complexities of model validation and asks how we know if the model's results reflect reality? Berk's central thesis is to emphasize the value of data-driven validation. Finally, Mike Townsley and Dan Birks (in this issue) put forward a framework for formalizing the evaluation of models through replication. They make the case for replication as a necessary requirement of a cumulative science and lay out a proposed methodology for conducting those replications.

The decision to develop a Special Issue on simulation might be somewhat controversial under the auspices of the *Journal of Experimental Criminology*. The journal focuses on experimental and quasi-experimental research and systematic reviews in the development of evidence-based crime and justice policy. In contrast, computational simulations test different types of interventions in abstract and virtual worlds. Research suggests that these two approaches can be complementary. We hope this issue widens the exposure of criminologists to the potential value of simulation as a vehicle for strengthening theory and conducting 'virtual' program evaluation prior to, not instead of, empirical experiments. It is in this role that simulation seems to have the most promise for leveraging our substantial investment in field trials.

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