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Forecasting Effects of Influence Operations: A Generative Social Science Methodology

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FORECASTING EFFECTS OF INFLUENCE OPERATIONS: A GENERATIVE SOCIAL SCIENCE METHODOLOGY

THESIS

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Abstract

Simulation enables analysis of social systems that would be difficult or unethical to experiment upon directly. Agent-based models have been used successfully in the field of generative social science to discover parsimonious sets of factors that generate social behavior. This methodology provides an avenue to explore the spread of anti-government sentiment in populations and to compare the effects of potential Military Information Support Operations (MISO) actions.

This research develops an agent-based model to investigate factors that affect the growth of rebel uprisings in a notional population. It adds to the civil violence model developed by Epstein (2006) by enabling communication between agents in the manner of a genetic algorithm, and by adding the ability of agents to form friendships based on shared beliefs. To identify and quantify the driving factors of rebellion and the spread of opinions, a designed experiment is performed examining the distribution of opinion and size of sub-populations of rebel and imprisoned civilians. Additionally, two counter-propaganda strategies are compared and explored. Analysis identifies several factors that have effects that can explain some real-world observations, and provides a methodology for MISO operators to compare the effectiveness of potential actions.

For my wife, whose love, patience, and support has known no bounds

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Christopher W. Weimer

Table of Contents

List of Figures

List of Tables

FORECASTING EFFECTS OF INFLUENCE OPERATIONS: A GENERATIVE SOCIAL SCIENCE METHODOLOGY

I. Introduction

Background

Ten years into what has become the US's longest war, it seems clear that the Department of Defense (DoD) must invest more effort into understanding how a *hearts and mind* campaign can be won. The most recent update of DoD Information Operations (IO) doctrine, JP 3-13 (2006, p. ix), defines the purpose of IO as "to influence, disrupt, corrupt, or usurp adversarial human and automated decision making while protecting our own." The five primary capabilities of IO are electronic warfare (EW), computer network operations (CNO), psychological operations (PSYOP), military deception (MILDEC), and operations security (OPSEC). Air Force IO doctrine, AFDD 2-5 (2005), breaks up IO differently: into electronic warfare operations (EWO), network warfare operations (NWO), and influence operations (IFO). IFO is further split into PSYOP, MILDEC, OPSEC, counterintelligence (CI), counterpropaganda, and public affairs (PA). Each area of IO can be improved upon, but this thesis will take PSYOP as its focus area.

The purpose of PSYOP is defined by the DoD in JP-13.2 (2010, p. vii) as "to influence foreign audience perceptions and subsequent behavior." In AFI 10-702 (2011, p. 2), the Air Force replaces the term PSYOP with the recently preferred term Military Information Support Operations (MISO) and defines its purpose as "to induce, influence, or reinforce the perceptions, attitudes, reasoning, and behavior of individuals, foreign leaders, groups, and organizations in a manner advantageous to US forces and objectives." This definition is important; no longer is the US focused only on decision making. Perceptions and attitudes are now recognized as critical to lasting behavioral change.

The new focus on perceptions and attitudes introduces new difficulty to a force traditionally focused on tangible effects. AFDD 2-5 (2005) discusses the challenges of effects-based planning and battle damage assessment (BDA) in the psychological domain. MISO effects are likely lagged, confounded with nuisance factors, and may include unintended consequences. Effects are therefore difficult to directly measure, and even more difficult to predict and plan for. Moreover, experimentation of MISO campaign effects at home would be infeasible, unethical, or even illegal.

AFDD 2-5 (2005, p. 28) recognizes that plans, then, “may also be based upon common sense, a rule of thumb, simplification, or an educated guess.” Relying on the common sense of personnel experienced and trained in the application of MISO, supported by expert intelligence products as noted in AFI 10-702 (2011), is the state of the art, but there may be more objective ways to forecast and plan the effects of MISO.

Simulation provides a potential alternative to experimentation. Rather than testing MISO directly on humans, it may be possible to build a virtual test bed for these operations and observe the effects on software agents programmed to react in a psychologically and culturally appropriate manner to stimuli in their environments. This thesis explores the application of agent-based modeling (ABM) to the problem area of MISO and the forecasting of its effects.

Problem Statement

There is currently a dearth of simulations appropriate for forecasting the effects of MISO operations upon the perceptions, attitudes, reasoning, and behavior of a foreign populace. To allow for realistic results, a simulation must have a firm foundation in psychological and sociological theory while being sufficiently parsimonious to be approachable to commanders who may not have a background in the social sciences. This thesis explores the use of ABM to generate sociologically valid behaviors from experimentally validated psychological theories, and uses this simulation as a test bed for MISO courses of action (COA).

Scope

The system being modeled here is not a specific real world environment or population, but a generic scenario of autonomous individuals interacting with each other. This represents a generalizable social landscape, which can be validated by comparing behaviors to established sociological phenomena. It therefore represents a realistic point of departure, or a virtual control treatment, for testing of MISO COAs. The intent is not to accurately model, in a single replication, how a specific human society or group will respond to a specific action. To accomplish this would require a level of complexity that negates the communicability of the model, relegating it to a black box. Instead, the intent is to find valid trends across replications that can inform assessment and comparison of the effectiveness of potential COAs.

For this model, the level of modeling is the individual person. As Epstein has pointed out, “individuals of any depth and interest are themselves societies” (2006, p.

346), but modeling every motivational drive as separate agents in an individual would be overly complicated for this application. From a practical perspective, this allows the use of over a century of experimentally validated psychological theories as potential rules to generate other experimentally validated sociological theories as emergent phenomena in a complex system. This also is a perspective well-suited to the bottom-up design of ABMs.

Background

Agents and ABM

A model is simply an abstraction of reality. Some common types of models include physical models, such as mockups of a construction project; conceptual models, such as an individual's perception of reality; mathematical models, such as simple linear regression models; and simulation models, which are the focus of this paper. Banks, Carson, Nelson, and Nicol (2010, p. 3) define simulation as "the imitation of a real-world process or system over time." Historically, there have been three distinct perspectives on simulation: macrosimulation, microsimulation, and ABM (Gilbert & Troitzsch, 2005).

Macrosimulation is a top-down perspective using differential equations to define variables in a system as function of other variables of interest (Macy & Willer, 2002). An example of a macrosimulation method is systems dynamics. Microsimulation builds a system bottom-up from the point-of-view of individuals, processes, and pieces of interest in a system. An example of microsimulation is discrete-event simulation. ABM grows out of microsimulation, maintaining the bottom-up perspective and adding the important ability for individual pieces, or agents, in the system to directly interact with one another.

What is an ABM?

There is much dispute about what truly constitutes an agent. Macy and Willer (2002) propose four requirements for agents; they must be autonomous, interdependent, follow simple rules, and be adaptive and backward-looking. North and Macal (2007) require that agents be adaptive, able to learn and alter behaviors, autonomous, and heterogeneous. Epstein (2006) lists common, but not required, features of agents as heterogeneity, autonomy, limited spatial range of communication, and bounded rationality. For the purposes of this thesis, an *agent* is defined as *an autonomous entity in a simulation defined by rules of movement and behavior that react to their surroundings and/or neighboring agents*. This definition is chosen over more stringent definitions because they would discount important ABMs that do not have adaptive, heterogeneous agents, such as Schelling's classic model of housing segregation (1971).

An agent-based model is defined by agents, relationships between agents, and the environment upon which they move and act (Macal & North, 2010). In modern simulations this space often takes the form of a toroid, a rectangle wrapping at both horizontal and vertical edges, but other spaces can be defined as best fits the system being modeled. Relationships, or links, formalize lasting relationships between agents and the effects thereof, and can be a source for additional analysis, such as social network analysis.

Why use ABMs?

Bonabeau (2002) lists the advantages of ABM as the abilities to capture emergent phenomena, naturally describe a system, and do so flexibly. Emergent phenomena are "stable macroscopic patterns arising from the local interaction of agents" (Epstein &

Axtell, 1996, p. 35). These are the result of ABMs typically describing complex adaptive systems (Holland, 1995).

The ability to naturally describe a system is vital for operations researchers. In operations research, models are typically built and simulations run by analysts to support a decision maker (DM). These DMs may or may not have a background in the technical bases of the model. For a DM to truly trust the results of a model, it must not be a black box; instead, the DM should be able to understand at least the basic workings of the model. It is therefore advantageous when an analyst can describe the model naturally by describing agents as people, stating what each agent perceives and why they act as they do.

The flexibility of ABM enables the intended use of this model: to act as a virtual experiment for MISO COAs. Once a model gives valid outputs, modifications are relatively simple to make. This allows an analyst to add stimuli such as leaflets or propaganda posters, change the psychological or cultural parameters for a new target audience (TA), or introduce new types of agents such as ambassadors or MISO operators.

History of ABM

The birth of ABM is regularly credited to Conway's Game of Life in 1970, which is pointed to as an example of ABM performed without the benefit of computers. Conway did actually use a PDP-7 computer to discover many aspects of the game (Gardner, 1970). This illustrates the importance of technology for ABM. ABM is a young simulation perspective that is continually growing more robust with the increased availability and power of computers.

ABM of sociological phenomena is nearly as old as ABM itself. Schelling (1971) built an ABM predicting racial segregation in housing based upon simple rules of moving when half of neighbors on a 1-dimensional space were of the other race. He found that there was a tipping point at approximately 20% minority population in a neighborhood at which the neighborhood's minority population would grow to 100%. The results have been disputed, but the methodology was intriguing.

The next 10-15 years saw very little development, but as computers became commonplace in the late 1980s, ABM began to re-emerge. Reynolds's (1987) ABM of *boids* depicting realistic bird flocking behavior seems to have ignited a renewed interest. The *boids* acted on three simple rules; collision avoidance, velocity matching, and flock centering. Even so, they exhibited the complex behavior of flocks that could not be explained from a macrosimulation perspective.

Another influential ABM development is that of the genetic algorithm (GA), as exemplified by Holland's model Echo (1995). Echo captures the behavior of complex adaptive systems by using a digital analogue to genetics. As agents replicate, "child" agents are given a mix of the two "parent" agents' characteristic string of 0s and 1s, with some rare random mutations possible. This has been used successfully to find optimal and likely solutions (Macy & Willer, 2002) and has been proposed for use in evolutionary psychology (Lickliter & Honeycutt, 2003). The general nature of the GA, like the larger field of ABM, holds the potential to be used in virtually any field.

The usefulness of ABM has been recognized perhaps more often than implemented in the social sciences. The literature contains calls for application of ABM with a robust backing in social science theory in social services (Israel & Wolf-Branigin, 2011), evacuation models (Till, 2010), and social scientists working in areas where rigorous experimentation is limited by ethical considerations (Ball, 2007).

Generative Social Science

Epstein and Axtell's (1996) Sugarscape model demonstrated a new paradigm for the study of the social sciences using ABM, which they call generative social science (GSS). In Sugarscape, agents act according to very simple rules dominated by the drive to acquire a resource, sugar, that exists in various amounts in different areas of the environment, and without which the agent will die. Emergent behaviors of Sugarscape include the emergence of differing cultures near geographically separated resource pools, inequitable distributions of wealth, and a survival of the fittest that is stifled by familial inheritance of resources.

Sugarscape demonstrates the key features of GSS. In a manifesto on generative social science, Epstein proposes a motto for GSS: "If you didn't grow it, you didn't explain its emergence" (2006, p. 8). Another key desideratum of GSS is the use of the simplest possible rules to explain an emergent behavior of interest. The canonical agent-based experiment would be to "situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules, and thereby generate – or 'grow' – the macroscopic regularity from the bottom up" (Epstein, 2006, p. 7).

GSS has gained significant popularity as a methodology, and examples of its application can be found in many of the social sciences. In economics, GSS has been used to demonstrate that diversity of suppliers leads to market stability (Zhang, Li, Xiong, & Zhang, 2010), and to generate consumer decision making processes based on culture and psychology (Roozmand, Ghasem-Aghaee, Hofstede, Nematbakhsh, Baraani, & Verwaart, 2011). In archaeology, Epstein (2006) demonstrated a realistic portrayal of the history, and sudden disappearance of, the Anasazi culture of the southwest U.S. In sociology, Mäs, Flache, and Helbing (2010) grew a cultural diversity in a population that is robust to noise. Gorman, Mezic, Mezic, and Gruenewald (2006) developed a model of drinking behavior and examined the positive and negative effects of the presence of bars at which drinkers can congregate. Epstein (2006) grew the emergence of social class hierarchy, as well as eruptions of civil violence in the face of occupying forces. In psychology, Epstein (2006) generated the behavior of thoughtlessly applying norms of behavior, which was subsequently supported in laboratory experiments by Willer, Macy, and Kuwabara (2009). This demonstrates a powerful possibility for GSS to provide theories of behavior that can be confirmed or rejected by traditional experimentation.

Social Science Primer

A basic foundation in the social sciences, and particularly social psychology, should inform the development of a GSS growing sociological behaviors. While encompassing all relevant social science is beyond the scope of this thesis, if not impossible, two specific areas emerge as particularly relevant: influence psychology and culture.

Influence Psychology

Influence psychology is a broad field of social psychology. Hogg (2009) points out that, by one popular definition, social psychology is the study of influence. For the purposes of ABM, the most relevant thrust of influence psychology research seems to be that of interpersonal persuasion. These concepts can be coded in a simplified manner as agent rules of interaction. Cialdini (2007) identifies six major concepts that define interpersonal persuasion: reciprocation, commitment and consistency, social proof, liking, authority, and scarcity.

Reciprocation is defined by the drive to repay any perceived gift or favor given by another person or group (Cialdini, 2007). This is the concept exploited by grocery stores offering free samples of a product directly next to a display full of that product with the expectation of higher sales. Furthermore, the effect of reciprocation can be compounded by the foot-in-the-door effect, whereby people are inclined to give again once they have given once, often in larger quantities or more substantial ways (Hogg, 2009).

Commitment and consistency act in concert, pushing people to commit to a decision made or action taken and act consistently with that decision (Cialdini, 2007). The state of information under which the original decision is made is irrelevant; one remains likely to stand by early decisions in the face of evidence. One possible explanation for this comes from cognitive dissonance theory (Festinger, 1957). This predicts that a basic motivation in action and belief is a negative feeling experienced by an individual whenever his or her actions and beliefs do not align with each other. People will therefore, depending on circumstance, change action, belief, or both to minimize the feeling of cognitive dissonance. Because past actions are impossible to change, beliefs are more likely to change to fit those actions, and future actions will mirror those new beliefs.

Social proof refers to the behavior colloquially known as *monkey see, monkey do*. This is the tendency to see behavior as more appropriate or acceptable when others are observed to be performing it (Cialdini, 2007). Bandura (1977) identified this effect with his social learning theory, which states that imitation of others' behavior is a genetically predisposed behavior. He also proposed that social approval is among the strongest social reinforcers for people of all ages. Indeed, laboratory experiments show that people will enforce norms of behavior, even those that they disagree with, in order to fit in (Willer, Macy, & Kuwabara, 2009). This again can act in concert with cognitive dissonance to be a very powerful factor in interpersonal persuasion.

Liking is a complex concept worthy of its own field of psychology. With regards to social influence, it is useful to recognize that people are more influenced by people they like than by people they do not like (Cialdini, 2007). Factors that influence how much a person likes another include their subjective physical attractiveness, their similarity to one another, ingratiating actions such as compliments directed toward him or her, their familiarity with one another, and their mental associations of the other person with other liked things.

Authority is an often-underestimated desire to act in accordance with the demands or desires of authority figures (Cialdini, 2007). This was made famous, or perhaps infamous, by Milgram in his classic experiments showing that most participants would shock a screaming, pleading, and even unconscious confederate participant at the instruction of a person in a lab coat (1974). Hogg (2009) points out, however, that mere compliance is a surface behavioral change that does not have lasting effects on action. Also, it appears that in cases of compliance the behavior is justified by the presence of an authority figure, and thus it activates much lower levels of cognitive dissonance thereby muting attitudinal shift.

The final concept identified by Cialdini (2007) is scarcity, which predicts that something that is rare is perceived as being more valuable than something that is more abundant. In a model where agents gather resources, this could result in agents with greater stores of resources having less motivation to continue gathering and therefore more freedom to explore other opportunities.

Audience Factors

The previous factors do not explicitly take individual differences into consideration, but naturally the audience of any message is as important as the source and content of the message. Myers (2008) identifies two important audience characteristics that lend themselves to being modeled: self-esteem and age.

Self-esteem has a non-linear effect on ease of influence; low and high self-esteem individuals are more difficult to influence than those with moderate self-esteem (Rhodes & Wood, 1992). High self-esteem yields confidence in one's opinion, while low self-esteem yields low confidence in one's correct comprehension of the message.

The effect of an audience's age has been tested against two hypotheses: that attitudes become more conservative as age increases, and that attitudes simply become more resistant to change as age increases (Myers, 2008). Experiments support the latter hypothesis; older people simply refuse to change their opinions while younger people's opinions remain more malleable. The observation of conservativism in old age merely reflects the liberalization of the popular opinion over time.

Culture

While each individual acts according to their beliefs, attitudes, and personalities, culture informs these values and may serve as a baseline in lieu of information on individuals. There are two commonly used frameworks for cultural attributes. Hofstede's cultural dimensions originally consisted of Power Distance, Individualism, Uncertainty Avoidance, and Masculinity (1980). Added to the core four are Long Term Orientation (Franke, Hofstede, & Bond, 1991) and most recently Indulgence (Hofstede, Hofstede, & Minkov, 2010). Hofstede's dimensions are focused on the roots of business behavior, being intended to inform managers of multicultural teams.

The second common framework comes from the Global Leadership and Organizational Behavior Effectiveness Research Project (GLOBE) (House, Hanges, Javidan, Dorfman, & Gupta, 2004). The GLOBE project surveyed 62 societies on a framework expanded from Hofstede. It is also primarily business focused, but its factors are both more specific and broader in scope. The nine GLOBE dimensions are Uncertainty Avoidance, Power Distance, Institutional Collectivism, In-Group Collectivism, Gender Egalitarianism, Assertiveness, Future Orientation, Performance Orientation, and Humane Orientation.

Uncertainty Avoidance is the propensity for individuals to avoid uncertainty by codifying norms of behavior (House, Hanges, Javidan, Dorfman, & Gupta, 2004). Power Distance is the level of individuals' expectations of power stratification and concentration. Institutional Collectivism is a measure of institutional encouragement of collective distribution of resources and collective action. In-Group Collectivism is a measure of the strength of identity with organizations, tribes, or families. Gender Egalitarianism is a measure of society's promotion of gender equality over strict gender roles. Assertiveness measures individuals' willingness to engage in conflict in social relationships. These first six dimensions align with Hofstede's original four dimensions, with Individualism split into the two Collectivism dimensions and Masculinity split into Gender Egalitarianism and Assertiveness.

Future Orientation is a measure of the willingness of individuals to delay gratification in favor of long-term planning; this corresponds with Hofstede's Long-Term Orientation (House, Hanges, Javidan, Dorfman, & Gupta, 2004). Performance Orientation is the cultural focus upon, and willingness to reward individuals for, performance. Humane Orientation measures the value placed upon fairness, altruism, and kindness between individuals. Performance and Humane Orientation are important factors that are not directly addressed by Hofstede's framework.

The empirically measured values of the nine GLOBE dimensions can serve as parameters to affect the application of the rules derived from influence psychology. This offers a practical methodology for accounting for differences in culture and target audience for MISO COAs.

Application to MISO

The joint MISO process, shown in Figure 1, indicates the current cycle of MISO execution. This process begins with planning the desired effect, and then examines the target audience (TA) before beginning to generate a plan. Within this framework, there is an opportunity to take the results of target audience analysis (TAA) and feed it into a simulation that allows for comparison of potential COAs and their ability to generate the desired effect without having deleterious secondary and tertiary effects. This simulation cannot and should not replace a skilled analyst with familiarity with the TA, but it can be a tool provided that it is usable and transparent to the analyst.

Figure 1. Joint MISO Process (Department of Defense, 2010)

There are models that have been developed to fill this need, but they fall into two categories that keep them from being used. First, there is the model that is too specific to be generalizable to other target audiences and too complicated to have transparency to an analyst or decision maker (DM). An example of this, and the problems associated with communicating the underlying mechanics of the model to a DM, is the Socio-Cultural Analysis Tool (S-CAT) (Murray, et al., 2011). The other case is the one that over-focuses on accuracy of forecasts and loses the ability to effectively perform what-if analysis. An example of this is the Integrated Crisis Early Warning System (ICEWS), a Defense Advanced Research Projects Agency (DARPA) funded program (O'Brien, 2010). ICEWS began with a hybrid statistical, system-dynamics, and agent-based modeling approach, but it gradually shifted during development to be dominated by statistical models to focus on forecasting performance at the cost of what-if capabilities. Models falling into either category are doomed to be of limited or no use to a MISO planner.

Improvements in MISO can have significant implications for national security. Successful implementation of MISO can prevent conflicts from requiring an armed presence or diminish the cost and duration of a military intervention. Not only is this desirable from a humanist perspective, as it limits human suffering and promotes peace, it is also desirable from a fiscal perspective as the DoD begins to face budgets more limited than seen in recent years. Clearly a more peaceful, cost-effective solution is desirable for the DoD and the international community.

Methodology

Our model represents a significant departure from Epstein's (2006) civil violence model. This research focuses on implementation of social psychology principles into rules of interaction and communication while maintaining Epstein's observed characteristics to maintain validity. It remains important, however, to adhere to the tenets of generative social science (GSS) and keep the applied rules as parsimonious as possible to generate realistic behavior, so this remains a focus.

As with Esptein's model, the scenario is a population under the influence of some government that may be perceived to be more or less legitimate or effective. Furthermore, the scope of this research is a generalized population interacting with one another without consideration of specific individuals that could be modeled, such as prominent leaders. One of the strengths of ABM is that such additional agent types can be added in future research to increase the realism of the model.

COAs under consideration may take the form of a change in the environment, or they may take the form of additional agent types that are more directly controlled than the general population. For example, a propaganda poster would take the form of an immobile agent that provides only one-directional communication about a very specific topic. It remains beyond the scope of this research to predict the perception of a specific message; instead, the specifics of modeling a given COA are left to the expert MISO analyst.

Model Construction

This model is developed from the agent level using the agent-based modeling environment Repast Simphony Beta 2.0, developed at Argonne National Laboratory (North, Howe, Collier, & Vos, 2007). This environment was selected based upon its open-source nature and the base infrastructure being amenable to social systems. Other environments were considered but discounted based upon their focus on process flow systems.

Two major changes on Epstein's (2006) model are effected. First, agents are given the ability to communicate and alter their grievance. In order to maintain heterogeneity in opinions, grievance is modeled as a gene as described by Holland (1995) rather than as a single scalar. Second, agents during this communication make friendships with like-minded others, which in turn alter patterns of movement.

The full code is presented in the appendices in six classes. Appendix A presents the Globals and Panel Factory class, which codes the global variables and user interface for the visualization. Appendix B presents the Observer class, where all methods called by buttons on the user interface reside. Appendices C-F present the agent classes: Civilians, Cops, MISO agents, and Relationship links.

Chapter 2 presents a detailed look at the development of this ABM and analytical results. Chapter 3 provides a proof of concept case study, outlining how an ABM such as this one may be used by a MISO analyst in planning a campaign. Chapter 4 concludes with significant findings and discussion of potential areas for future research. Note that Chapters 2 and 3 are structured as standalone papers, and there will be some overlap between these chapters and Chapter 1.

II. Analysis of Factors Influencing Civil Violence: An ABM Approach

Introduction

In the last decade, the United States has found herself fighting wars on a battlespace she has little expertise with: the hearts and minds of populations whose support can make or break a campaign. This sort of campaign relies heavily upon Military Information Support Operations (MISO), operations whose purpose is "to induce, influence, or reinforce the perceptions, attitudes, reasoning, and behavior of individuals, foreign leaders, groups, and organizations in a manner advantageous to US forces and objectives" (Department of the Air Force, 2011, p. 2). MISO is a difficult task. The effects are nearly impossible to measure due to confounding nuisance factors outside of the operators' control, and experimentation is not ethically viable. Therefore, forecasting of effects has traditionally relied upon subject matter experts armed with sophisticated intelligence products (Department of the Air Force, 2005).

Simulation provides an alternative method for measuring and forecasting MISO effects. Social systems tend to take the form of complex adaptive systems, which in turn are best modeled by agent-based models (ABM). ABM of sociological phenomena is not new; one of the first ABMs examined racial segregation in housing (Schelling, 1971). Epstein and Axtell's (1996) Sugarscape marked the beginning of a research paradigm known as Generative Social Science (GSS). The key desideratum of GSS is the use of the simplest possible rules to explain an emergent behavior of interest (Epstein, 2006).

GSS has gained significant popularity as a methodology, and examples of its application can be found in many of the social sciences. In economics, GSS has been used to demonstrate that diversity of suppliers leads to market stability (Zhang, Li, Xiong, & Zhang, 2010), and to generate consumer decision making processes based on culture and psychology (Roozmand, Ghasem-Aghaee, Hofstede, Nematbakhsh, Baraani, & Verwaart, 2011). In archaeology, Epstein (2006) demonstrated a realistic portrayal of the history, and sudden disappearance of, the Anasazi culture of the southwest U.S. In sociology, Mäs, Flache, and Helbing (2010) grew a cultural diversity in a population that is robust to noise. Gorman, Mezic, Mezic, and Gruenewald (2006) developed a model of drinking behavior and examined the positive and negative effects of the presence of bars at which drinkers can congregate. Epstein (2006) grew the emergence of social class hierarchy, as well as eruptions of civil violence in the face of occupying forces. In psychology, Epstein (2006) generated the behavior of thoughtless application of norms of behavior, which was subsequently supported in laboratory experiments by Willer, Macy, and Kuwabara (2009). In this way, GSS and traditional experimental social psychology can and should work hand-in-hand to advance the field.

Epstein's (2006) civil violence model serves as the basis for the present work. This model populated a 40 x 40 grid with *Agents* and *Cops*. Because the term Agents implies that the Cops are not agents, we use the term *Civilians*. On this grid, Cops and Civilians each move at random. On the basis of their perceived grievance against the government, legitimacy of the government, individual risk tolerance, and the presence of other actively rebellious Civilians and Cops in their local region, these Civilians at each step decide if they will become actively rebellious. If they do, they become potential targets for Cops to arrest and remove from the simulation for some period of time. Our model expands on this to add communication between civilians and movement that is more grounded in influence psychology, specifically the concept of liking as presented by Cialdini (2007).

In the remainder of this paper we present a more specific description of the theoretical scenario, the simulation, and a designed experiment examining the impact of some factors of interest on the behavior and opinions of individuals in a social landscape. We discuss this approach, the results, and provide some conclusions and potential avenues for advancing this research.

Scenario and Simulation Development

As in Epstein's model, the scenario is a generic population of autonomous individuals under the influence of some government with a specified degree of legitimacy. Civilians move about the landscape and interact with one another, forming friendships and sharing opinions on specific topics that aggregate to form grievance against the government. They also may choose to become actively rebellious, depending on their grievance and the perceived risk of being arrested. If they are actively rebellious, they run the risk of being arrested by Cops. Cops move randomly about the landscape arresting rebels as they find them.

This represents a generalizable social landscape, which can be validated by comparing emergent behaviors to established sociological phenomena. The intent here is not to accurately model any specific population or scenario; this has been attempted in other models such as the Socio-Cultural Analysis Tool (S-CAT) (Murray, et al., 2011). The result is an over-complicated system not generally trusted by decision-makers and therefore not used. Instead this model aims to find a parsimonious set of factors leading to realistic behaviors of interest, in the spirit of GSS.

Software and Programming Considerations

The simulation itself is built within Repast Simphony 2.0 Beta (North, Howe, Collier, & Vos, 2007). The underlying virtual space about which agents move is a 40 x 40 torus. The agents move in random order each tick of simulated time. Each patch has a holding capacity of only one un-jailed Civilian or Cop. This prevents clustering of all agents in very small geographical spaces and allows for much more effective visualization, but it adds to the computational complexity significantly. To ameliorate this issue, the software maintains a linked list of all empty patches that is polled when an agent moves rather than polling all available patches and querying the number of agents thereon. This significantly decreases processing time.

Similarly, the software maintains lists of all imprisoned Civilians, active rebels, and peaceful Civilians. The simpler alternative is to always consider every civilian in range and query their status. At the stage of development where this change was made, run speed increased from 42 to 73 ticks per minute at population density of 0.70. At population density 0.50, the change was from 58 to 76 ticks per minute, demonstrating that the change diminished the difference in processing time induced by increasing the number of agents. With any ABM, streamlining processing tasks is imperative.

Cop Logic

Cops are relatively simple agents performing two tasks directly: arresting active rebels and moving about the landscape. Each Cop has identical vision and movement range, designated *copVision*, which is set by the user. The logic is shown in Figure 2.

The cop first searches the range of *copVision* for active rebels. If it finds any, it picks one at random and arrests them. An arrest consists of setting the target Civilian's status to jailed, hiding them in the visualization, adding their occupied patch to the list of empty patches, and pulling a jail term from a uniform distribution between 0 and the user-specified maximum jail term. For all simulations in this study, the maximum jail term is 30 ticks. If an arrest is made, the Cop moves to the location of the arrested Civilian; otherwise, it moves to a randomly selected open patch within its range. If no patch is open, it simply does not move.

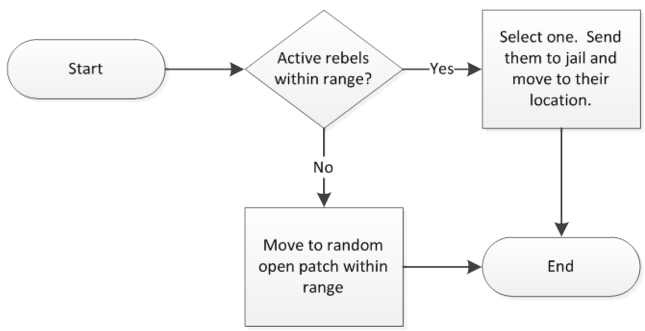


Figure 2. Cop Logic Flow

Cops also serve as a source of information for Civilians, though they do not play this role directly. Their presence in an area impacts the behavior of the Civilians that are aware of the Cop's presence. This role will be seen more in depth in the Civilian logic.

Civilian Logic

Civilians are far more complicated in their logic than Cops. The full logic is shown in Figure 3. A Civilian is aware of its surrounding to a user-specified range, designated *civVision*, and is capable of moving up to another user-specified range, designated *civRange*. At the highest level, each turn that they are not jailed, a Civilian moves about the landscape, makes a decision about whether to be actively rebellious, then communicates with another Civilian. If a Civilian is jailed, it simply checks if its jail term is complete. If so, it moves to a random open patch and makes a decision about its rebel status, and becomes visible.

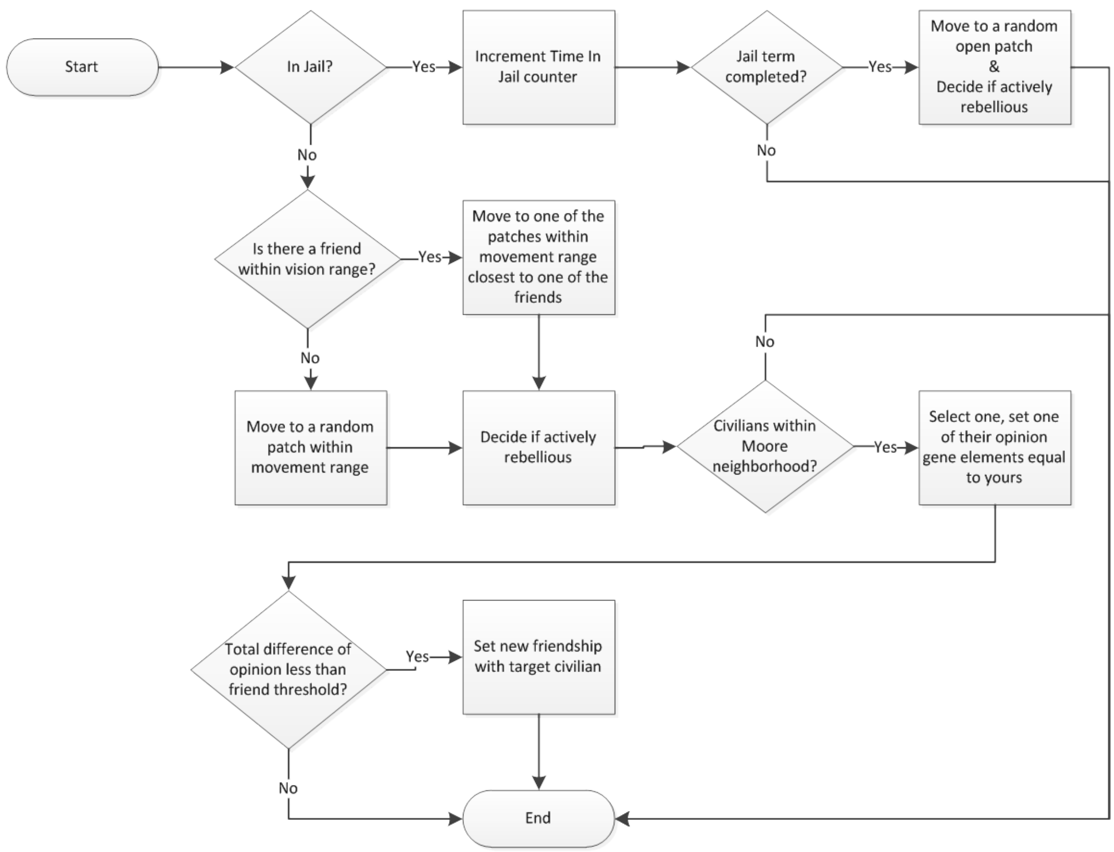


Figure 3. Civilian logic flow

If the Civilian is not jailed and one or more Civilians within *civVision* is a friend, one of those friends is chosen at random. The Civilian will then move to a random patch within *civRange* that is closest to that friend. If there are no friends within *civVision*, the Civilian moves to a random open patch within *civRange*, or stays still if there is no open patch available.

Next, the Civilian decides if it should be actively rebellious. This logic is equivalent to that in Epstein (2006). The Civilian counts both the number of Cops (*C*) and the number of active rebels (*A*) within *civVision* and computes an estimated probability of arrest (*P*),

$$P = 1 - e^{-2.3\left(\frac{C}{A}\right)_{civVision}} \tag{1}$$

It then calculates net risk (*N*) by multiplying this probability by its risk tolerance (*R*), a value between 0 and 1 which is held constant for each Civilian and drawn from a uniform distribution,

$$N = RP \tag{2}$$

If grievance is greater than net risk by at least a threshold value, designated *rebelThreshold* and set to 0.1 in all simulations in this study, the Civilian will become an active rebel. Otherwise, it will be inactive. In this way, the presence of Cops serves to force rebellious Civilians into hiding, while the presence of other rebellious Civilians serves to diminish this effect.

The value of *grievance* represents the sum of anti-government sentiment held by a Civilian. In Epstein (2006), each Civilian drew a *hardship* value of 0 to 1 from a uniform distribution and multiplied this by $(1 - legitimacy)$ to obtain *grievance*. To initialize, this simulation draws a *hardship* value between 0 and 20 from a uniform integer distribution and multiplies this by $\frac{1-\text{legitimacy}}{20}$ to obtain *grievance*. *Hardship* is thereafter characterized using a genetic algorithm (GA) as described by Holland (1995). This *opinionGene* is an array of 20 integers, each of which can take a value of 0 or 1. Each index on the gene represents a single specific opinion. These opinions amalgamate to form a concept of anti-government sentiment, which is scaled by $(1 - legitimacy)$ to maintain cohesion to Epstein's model. Thus,

$$Grievance = \left(\frac{1}{20}\sum_{i=1}^{20} OpinionGene_i\right)(1 - Legitimacy) \quad \textbf{(3)}$$

These opinions can be modified by communication or by mutation, which occurs with probability 0.01 at a random index during communication. This mutation is necessary to avoid rendering an opinion extinct. The GA is used both because it is more psychologically accurate than a single number, and because it prevents the simulation from trending toward uniform *grievance* of 0.

The final part of a Civilian's logic is communication. If there are other Civilians in its Moore neighborhood, the eight patches bordering the agent, one of them is selected at random as a target with whom to communicate. First, a topic of conversation is chosen, represented by an index on the *opinionGene*. The target's value on the *opinionGene* is replaced by the source's value. Next, the *opinionGene*s are compared. If the proportion of the opinion gene where the two disagree is less than a threshold, designated *friendThreshold* and held at 0.25 for this study, a non-directional friendship link is generated between the two Civilians. This link will remain for the next 20 turns in the absence of future communication.

Visualization

Analysis of ABMs often requires qualitative observation of trends in addition to quantitative analysis, so appropriate visualization is vital. The visualization in this simulation provides information of both the observable external state and the hidden internal state. An example for reference is shown in Figure 4. The external state is shown in the foreground. Civilians are represented by human stick figures colored red if they are active rebels and blue otherwise, jailed Civilians are not shown, and Cops are represented by gold stars. The internal state of Civilians is shown in the background and connecting arrows. Each line represents a friendship between two Civilians. The background color is scaled from black, for low *grievance* of the occupying Civilian, to red, for high *grievance*.

The screenshot in Figure 4 shows both qualitative findings from Epstein (2006) remaining present in this simulation. First, there are quite a few Civilians with very high levels of *grievance* acting deceptively in areas being patrolled by Cops, taking the role of inactive Civilians. Second, a local breakout in rebellion is occurring where random motion has left Civilians unaware of any Cops in the area. This kind of breakout is temporally punctuated, with rebellion occurring in spikes at random intervals.

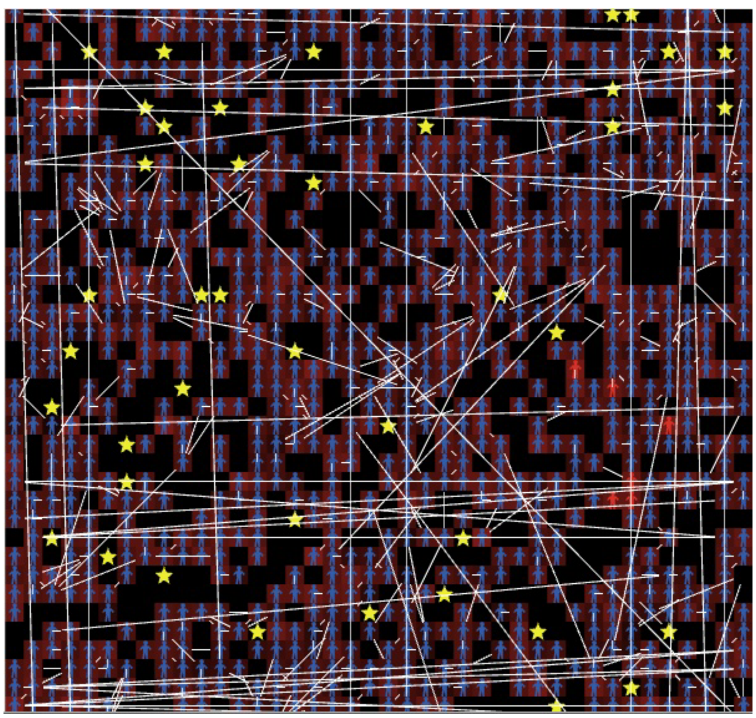


Figure 4. Screenshot of Simulation Portraying Civilians (People) Colored According to Whether They Are Active Rebels (Red) or Not (Blue) Exhibiting Grievance (Background Scaled Black to Red), Friendships (Lines), and Cops (Gold Stars)

Experimental Design

Factors of Interest

The primary purpose of this experiment is to identify the relevant structural variables that may affect the dynamics of rebellion in the simulation. Structural variables expected to possibly have an effect are civilian range of vision (*civVision*), civilian range of movement (*civRange*), cop range of vision (*copVision*), initial population density (*popDensity*), and Cop density (*copDensity*). Population density is the proportion of possible patches populated by Cops and/or Civilians at initialization, and Cop density is the proportional size of the subpopulation that are Cops. These variables in the actual system of a social landscape may be affected indirectly by geography or technology in the case of range, and may simply vary by region in the case of densities.

A secondary purpose of this experiment is to determine whether the addition of preference in movement toward friends has a discernible effect. The intent is to increase psychological realism by creating social clusters, but any observed non-qualitative effects would be useful to note.

The factors and their levels are summarized in Table 1. Other values such as threshold values remain fixed because those values were fixed in Epstein (2006). The intent is to remain aligned with the qualitative observations from Epstein's model, which are exhibited in the present model using the same values.

Table 1. Factors and Levels Used in Experiment

	Factor	Low Value	Mid Value	High Value
A	Civilian Range of Vision	1	4	7
B	Civilian Range of Movement	1	4	7
C	Cop Range of Vision	1	4	7
D	Movement Toward Friends	No	N/A	Yes
E	Population Density	0.3	0.5	0.7
F	Cop Density	0.01	0.04	0.07

Response Variables

Four response variables allow for future comparison after implementing MISO actions in the simulation. Each simulation run lasts for 300 ticks, and all observations are made after every agent has acted in random order for a given tick.

The first two response variables, *mean grievance* and *grievance variance*, relate to the distribution of *grievance* at the end of the simulation. For ease of interpretation, *grievance* is recorded here as the sum of each element of the opinion gene, before correcting for *legitimacy*. While at initialization *grievance* is distributed uniformly, it is to be expected that as each element of the opinion gene becomes its own random variable, *grievance* should tend toward a normal distribution. From prior investigation, this is observed, so only the mean and variance of the *grievance* distribution are gathered. The mean should not be affected by any factor, because there is no preference toward either 0s or 1s with the exception of arrests occurring more often to civilians with high *grievance*.

The remaining responses relate to the amount of rebellion observed under a set of conditions. Rebel activity occurs in bursts under both realistic and simulated conditions, so a point observation is not appropriate (Epstein, 2006). Rather, the mean proportion of Civilians in a given state over a period of time is appropriate. The first 100 steps are omitted to allow for initialization of the simulation. Therefore, *mean prisoner ratio* is the mean proportion of Civilians in prison over time steps 101-300, and *mean rebel ratio* is the mean proportion of Civilians that are active rebels over time steps 101-300.

Design Type

This experiment is a full factorial 2^6 design with 2 replications and 4 center points for each value of factor D, the inclusion of friendship rules, for a total of 136 replications. Fractional factorials would have allowed fewer data points, but complex adaptive systems are defined by nonlinearity and the assumption that high-order effects would be non-significant is not likely to be met.

Results

Grievance Distribution

As expected, no factors or interactions have a significant effect upon *mean grievance*. The observed *mean grievance* is 9.91, with variance 0.1813. Some factors and interactions affect variance as discussed below.

A natural logarithm transformation sufficed to normalize residuals in analysis of the *grievance variance*. The resulting ANOVA is shown in Table 2. Three factors, and every possible interaction between them, affect the variance: Civilian vision range (A), Cop vision range (C), and Cop Density (F). These are each significant with $p < 0.0001$, and jointly they are significant with $p < 0.05$. Pure quadratic curvature is also statistically significant with $p = 0.0013$, but it is not practically significant with a sum of squares less than 5% that of the next smallest effect.

Table 2. ANOVA for ln(*grievance variance*)

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	13.18662	7	1.883803	478.54	< 0.0001
A	1.469471	1	1.469471	373.29	< 0.0001
C	3.508438	1	3.508438	891.25	< 0.0001
F	2.632555	1	2.632555	668.75	< 0.0001
AC	1.474048	1	1.474048	374.45	< 0.0001
AF	1.445637	1	1.445637	367.23	< 0.0001
CF	1.443684	1	1.443684	366.74	< 0.0001
ACF	1.212792	1	1.212792	308.08	< 0.0001
Curvature	0.04288	1	0.04288	10.89	0.0013
Residual	0.499942	127	0.003937		
Lack of Fit	0.21387	57	0.003752	0.92	0.6286
Pure Error	0.286073	70	0.004087		
Total	13.72945	135			

Mean Prisoner Ratio

A power transformation with $\lambda = 0.3$ resulted in normalization of residuals for *mean prisoner ratio*. ANOVA results are shown in Table 3. Five factors and nine interactions achieve joint significance $p < 0.05$, and two interactions are included in analysis for hierarchy. Significant effects are Civilian vision range (A), Civilian movement range (B), Cop vision range (C), population density (E), Cop density (F), AC, AE, AF, CE, CF, ACF, AEF, CEF, and ACEF. Note that the factors having greatest effects are again A, C, F, and every interaction between them. Pure quadratic curvature is also significant with $p < 0.0001$, but it does not dominate.

Table 3. ANOVA for (*mean prisoner ratio*)$^{0.3}$

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	5.042679	16	0.315167	892.07	< 0.0001
A	1.426079	1	1.426079	4036.47	< 0.0001
B	0.005433	1	0.005433	15.38	0.0001
C	2.823678	1	2.823678	7992.32	< 0.0001
E	0.006652	1	0.006652	18.83	< 0.0001
F	0.301663	1	0.301663	853.85	< 0.0001
AC	0.048534	1	0.048534	137.37	< 0.0001
AE	0.010434	1	0.010434	29.53	< 0.0001
AF	0.301018	1	0.301018	852.02	< 0.0001
CE	0.008973	1	0.008973	25.40	< 0.0001
CF	0.017255	1	0.017255	48.84	< 0.0001
EF	0.000118	1	0.000118	0.33	0.5650
ACE	0.000327	1	0.000327	0.93	0.3380
ACF	0.073941	1	0.073941	209.29	< 0.0001
AEF	0.006949	1	0.006949	19.67	< 0.0001
CEF	0.003076	1	0.003076	8.71	0.0038
ACEF	0.008549	1	0.008549	24.20	< 0.0001
Curvature	0.049834	1	0.049834	141.05	< 0.0001
Residual	0.041689	118	0.000353		
Lack of Fit	0.018711	48	0.00039	1.19	0.2529
Pure Error	0.022978	70	0.000328		
Total	5.134203	135			

Mean Rebel Ratio

A natural logarithm transformation achieved normalized residuals with *mean rebel ratio*. ANOVA results are shown in Table 4. Civilian vision range (A), Cop vision range (C), population density (E), and cop density (F), and interactions AC, AE, AF, CE, CF, EF, ACF, AEF, and CEF have effects individually significant with $p < 0.0001$ and jointly significant with $p < 0.05$. Pure quadratic curvature is small but statistically significant with $p < 0.0001$.

Table 4. ANOVA for ln(*mean rebel ratio*)

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	449.6666	13	34.58974	588.56	< 0.0001
A	83.15574	1	83.15574	1414.94	< 0.0001
C	53.91509	1	53.91509	917.39	< 0.0001
E	20.22047	1	20.22047	344.06	< 0.0001
F	201.6595	1	201.6595	3431.35	< 0.0001
AC	7.098212	1	7.098212	120.78	< 0.0001
AE	10.26187	1	10.26187	174.61	< 0.0001
AF	28.39973	1	28.39973	483.24	< 0.0001
CE	1.112586	1	1.112586	18.93	< 0.0001
CF	27.58989	1	27.58989	469.46	< 0.0001
EF	7.816607	1	7.816607	133.00	< 0.0001
ACF	4.416607	1	4.416607	75.15	< 0.0001
AEF	2.138198	1	2.138198	36.38	< 0.0001
CEF	1.882091	1	1.882091	32.02	< 0.0001
Curvature	1.110018	1	1.110018	18.89	< 0.0001
Residual	7.111144	121	0.05877		
Lack of Fit	3.217693	51	0.063092	1.13	0.3095
Pure Error	3.893452	70	0.055621		
Total	457.8878	135			

Discussion

As expected, *mean grievance* was not affected by any factors, though surprisingly the expected value of the mean is slightly less than 10. The 95% confidence interval for the mean is (9.84, 9.98). This slight shift away from high *grievance* is likely a result of arrests removing civilians with highly aggrieved opinions from the communication pool.

The remaining responses each had significant curvature, both pure quadratic and interaction, including the effects of every factor except for D, the enabling of preferential movement toward friends. There is, however, an observable qualitative effect as clusters of like-minded Civilians flow into and out of existence in a replication. There may be an effect under MISO influence, but the qualitative effect (clustering) has no effect upon these quantitative responses without external influence. Removing factor D from analysis projects the design to a 2^5 full factorial design with 4 replications and 8 center points. Factor B, the movement range of civilians, was non-significant for all but *mean prisoner ratio*, and in that response it had a weak effect with no interactions. In the original Epstein model, movement and vision range of civilians were a single value, so this finding supports his formulation.

Pure quadratic curvature is modeled and found to be statistically significant, but no axial runs are made to better estimate the effect. In such a generalized model, there is no reason to estimate these effects unless they appear to have a practical effect upon interpretation. The effect of pure curvature in each response is small compared to the other factors modeled.

By the nature of this experiment, which is exploratory, there is no one set of "best results," but two outcomes seem interesting to explore: maximizing rebellion while minimizing imprisonment, and minimizing rebellion while also minimizing variance of grievance.

The former result represents the optimal conditions for successful rebellious activity. Using a desirability function with equal weight given to each response, we find that this condition occurs when all vision and range variables are low, population density is low, and Cop density is low. As seen in Figure 5, created using JMP 9.0.1, this results in *mean rebel density* of 0.2457 and *mean prisoner density* of 0.0065. Interestingly, statistical prediction of rebellion in countries has led to the finding that the presence of mountainous terrain is predictive of rebellion (O'Brien, 2010). This analysis suggests a set of possible underlying factors, as well as possible ways to counteract this seemingly unavoidable effect. By increasing range of vision for civilians and cops, perhaps by encouraging the development of internet technology or mass transit, it may be possible to decrease rebel activity in such regions without moving mountains.

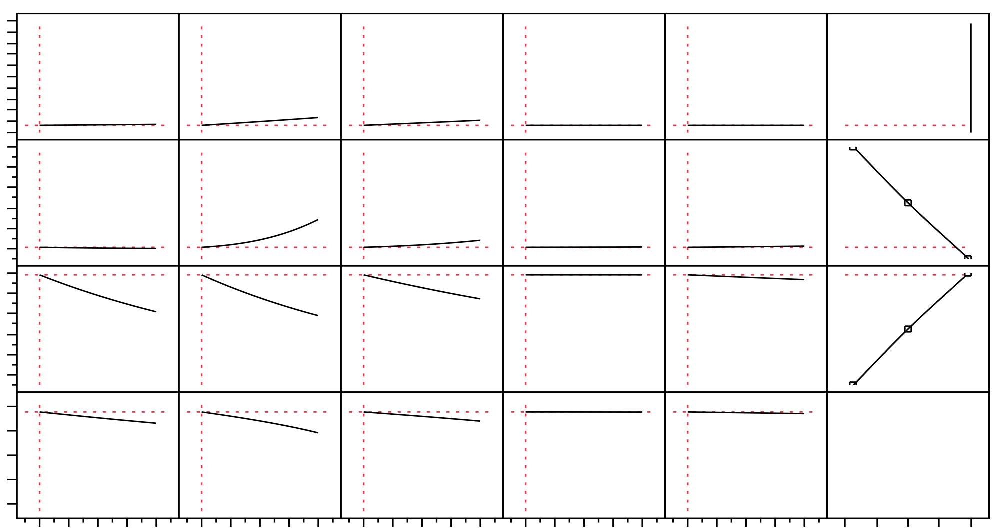


Figure 5. Prediction profile for rebel-optimal scenario

The latter result represents the optimal conditions for government: non-rebellious citizens who have a low prevalence of extremist opinions regarding the government. Using a desirability function with equal weight given to each response, we find that this condition occurs when Civilian vision is high, Cop vision is low, and Cop and population densities are high. As seen in Figure 6, created again using JMP 9.0.1, this results in *mean rebel ratio* of 0.0027 and *grievance variance* of 5.013. Low Cop vision is surprising; one might expect the ability to quickly imprison any rebels would be helpful in decreasing the presence of rebels, but that appears not to be the case. High Civilian vision is more intuitive; this increases the probability of civilians observing Cops and therefore having their rebellious tendencies counteracted by the chance of being arrested. This suggests that a highly effective police force need only have a reputation of effectiveness, be visible, and exist in large numbers.

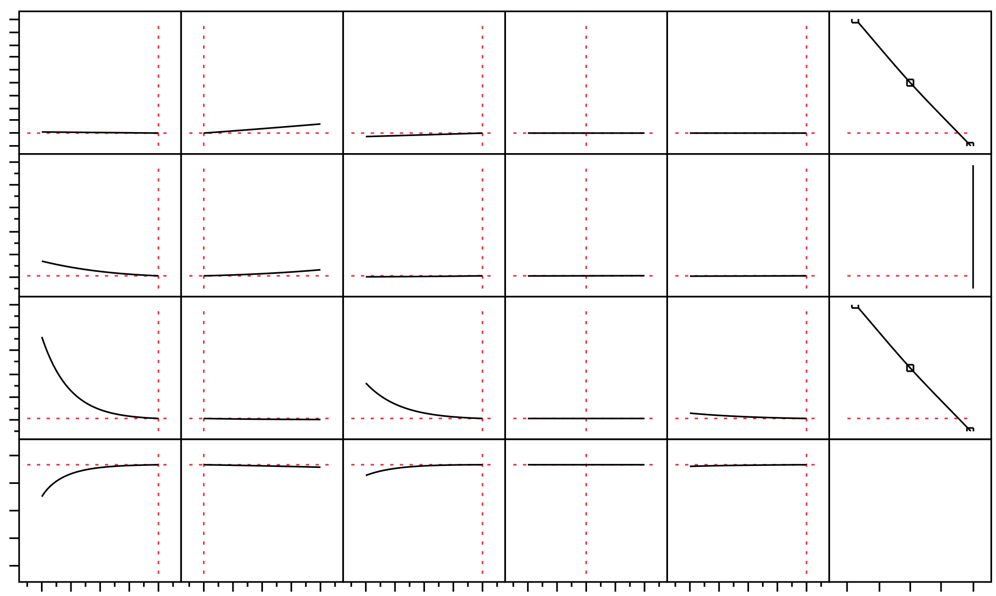


Figure 6. Prediction profile for government-optimal scenario

Future research should include analysis of changes in responses due to externally introduced factors, such as potential MISO plans in both the presence and absence of pro-rebel tactics. These can be introduced by defining and populating a new class of agent that exists outside of the original logic. Much can also be added in the form of psychological realism. Influence psychology suggests ways to increase the realism of friendships, as well as introduce new relationships that influence interactions. For examples, see Cialdini (2007).

Conclusion

Use of a designed experiment on the results of an Agent-Based Model (ABM) shows that a simplified form of communication and influence between agents is sufficient to generate realistic patterns of rebellion and suggest underlying factors that influence empirically observed but unexplained phenomena. This model represents both a proof of concept for a generative social science (GSS) approach to MISO effects analysis and a virtual test bed within which psychological experiments can be performed with complete control of external factors and no ethical restrictions. Expansion of this technique may provide MISO operators with unbiased forecasting of effects to use in operations planning.

III. Forecasting Effects of MISO Actions: An ABM Methodology

Introduction

In the last decade, the United States has found herself fighting wars on a battlespace she has little expertise with: the hearts and minds of populations whose support can make or break a campaign. This sort of campaign relies heavily upon Military Information Support Operations (MISO), operations whose purpose is "to induce, influence, or reinforce the perceptions, attitudes, reasoning, and behavior of individuals, foreign leaders, groups, and organizations in a manner advantageous to US forces and objectives" (Department of the Air Force, 2011, p. 2).

MISO is a difficult task. The effects are nearly impossible to measure due to confounding nuisance factors outside of the operators' control, and experimentation is not ethically viable. Therefore, forecasting of effects has traditionally relied upon subject matter experts armed with sophisticated intelligence products (Department of the Air Force, 2005). This research develops an agent-based model (ABM) of civil rebellion in a generalized population and allows experimentation using MISO agents to compare effects of different strategies.

This paper begins with a brief background on social simulation, with a focus on ABM, followed by an overview of the base simulation. A hypothetical application scenario is then presented, with comparison of options that may be available to the MISO planner. Results and analysis are discussed as well as a broad range of potential avenues for future research.

Background

ABM of sociological phenomena is not new; one of the first ABMs examined racial segregation in housing (Schelling, 1971). Advances in computer processing have enabled greater use of this technique in the last two decades. Epstein and Axtell's (1996) Sugarscape marked the beginning of a research paradigm termed Generative Social Science (GSS). The key desideratum of GSS is the use of the simplest possible set of rules to explain an emergent behavior of interest (Epstein, 2006).

GSS has gained popularity as a methodology, and examples of its application can be found in many of the social sciences including economics (Zhang, Li, Xiong, & Zhang, 2010; Roozmand, Ghasem-Aghaee, Hofstede, Nematbakhsh, Baraani, & Verwaart, 2011), archaeology (Epstein, 2006), and sociology (Gorman, Mezic, Mezic, & Gruenewald, 2006; Mäs, Flache, & Helbing, 2010). In psychology, Epstein (2006) generated thoughtless application of norms in an ABM and Willer, Macy, and Kuwabara (2009) supported this with laboratory experiments showing support of norms that disagree with personal beliefs. This demonstrates the potential for GSS and traditional experimentation to augment each other.

Epstein's (2006) civil violence model serves as the basis for our model. As presented in detail in Chapter 2, we expand on Epstein's work to add communication between civilians and movement that is more grounded in influence psychology, specifically the concept of liking as presented by Cialdini (2007).

Civil Rebellion Simulation

In order to be generalizable across situations, this social environment cannot be modeled after any individual nation or culture. Rather, fields are provided that can be manipulated to better reflect a given culture. Values in those fields are set here to those used by Epstein (2006), those found to be of average response in Chapter 2, or those of observed global averages. Where the deviation is not intentional, we adhere as closely as possible to Epstein's model. This serves as a form of verification and validation; we maintain every qualitative trait observed in his analysis.

Note that the strength of this abstraction is an appropriate comparison between treatments, rather than actual forecasting of specific levels of rebellion or anti-government sentiment. To accomplish the latter, every variable that affects rebellions would have to be accounted for, which would make for a very complicated and over-specified model.

All programming is done using Repast Simphony 2.0 Beta (North, Howe, Collier, & Vos, 2007). An image of the simulation is shown in Figure 7. Two types of agents are interacting in the basic social landscape: Civilians and Cops. MISO agents are later added for experimentation.

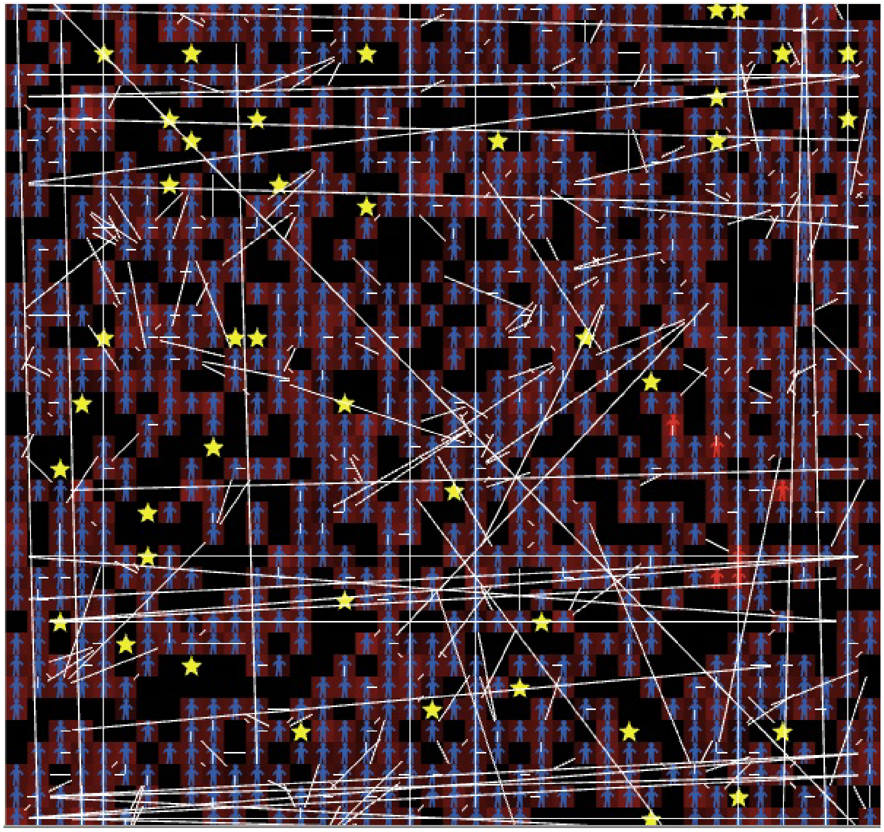


Figure 7. Screenshot of Simulation Portraying Civilians (People) Colored According to Whether They Are Active Rebels (Red) or Not (Blue) Exhibiting Grievance (Background Scaled Black to Red), Friendships (Lines), and Cops (Gold Stars)

Civilian Behavior

Civilians are represented by people in the visualization, and their logic is shown in Figure 8. The level of grievance felt toward the government is represented as *opinionGene* in the manner of a genetic algorithm as introduced by Holland (1995). Overall *grievance* is considered the mean value of 20 individual memes within the *opinionGene*, each represented by a binary digit, scaled down by the *legitimacy* of the government, which is static in this analysis at 0.82. That is,

$$Grievance = \left(\frac{1}{20}\sum_{i=1}^{20} OpinionGene_i\right)(1 - Legitimacy) \tag{4}$$

For ease of presentation, we refer instead to *grievance* as

$$Grievance' = \sum_{i=1}^{20} OpinionGene_i \qquad \textbf{(5)}$$

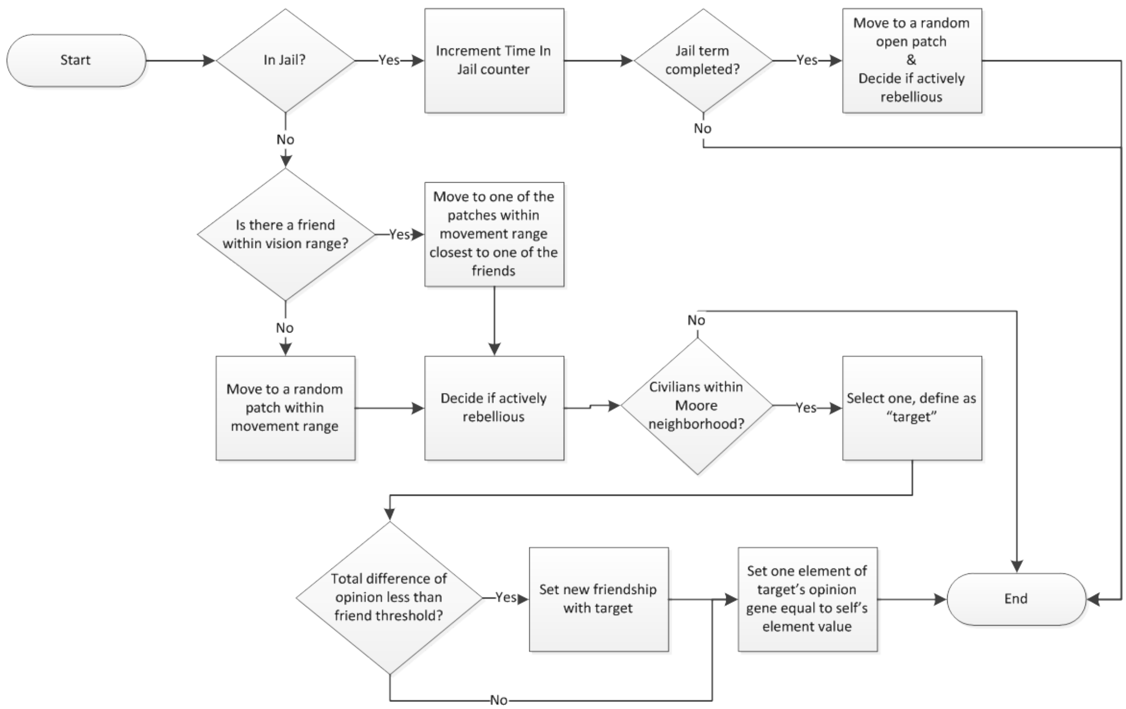


Figure 8. Civilian Logic Flow

After a civilian moves to a randomly chosen empty block within its movement range, it examines its surroundings and decides whether it should become actively rebellious. To do so, it counts both the number of cops (*C*) and the number of active rebels (*A*) in its vision range (*civVision*) and computes an estimated probability of arrest (*P*) (Epstein, 2006),

$$P = 1 - e^{-2.3\left(\frac{C}{A}\right)_{civVision}} \qquad \textbf{(6)}$$

It then calculates net risk (N) by multiplying this probability by its risk tolerance (R),

$$N = RP \tag{7}$$

If the difference between *grievance* and N exceeds a threshold (*rebelThreshold*), set here to 0.1, the Civilian will become an active rebel. Otherwise, it will remain inactive.

After choosing a state, a civilian will randomly choose a civilian from its Moore neighborhood, the eight bordering patches, with whom to communicate. A random topic, or index of the opinion gene, is chosen to discuss, and if the two civilians' opinions differ, the target civilian will change their opinion. If the 1-norm distance between the civilians' opinion genes is less than 25% of the possible difference, a friendship will be formed, and for the next 20 ticks the two civilians will prefer to move toward each other. There is also a 1% chance of a mutation, the alteration of a random opinion within the source's opinion gene. This prohibits opinions from going extinct over time.

Cop Behavior

Cops are far simpler than Civilians, as shown by their logic flow in Figure 9. Before moving, a Cop examines the blocks within its vision looking for active rebels. If it sees any, it moves to one of their locations and arrests that rebel for a random period of time between 1 and 30 steps. Arrested Civilians cannot be seen and remain static for the duration of their term. If there are no rebels within the Cop's vision, it will randomly move to an empty block within its vision.

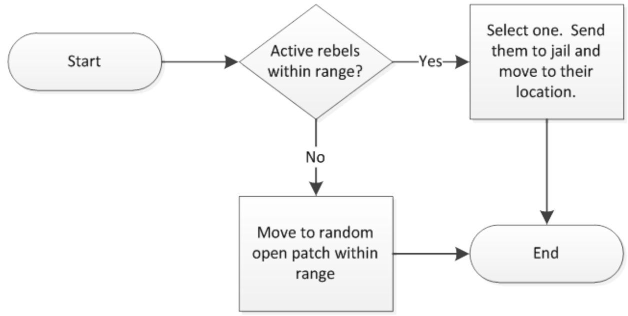


Figure 9. Cop Logic Flow

MISO Agents

MISO agents are those added into the base simulation as described above for the purpose of experimentation. Here we have coded an agent whose behavior can be modified to act in many roles by modifying variable values. These agents have limited effectiveness depending on their affiliation (government or rebel), government legitimacy, their media (written or internet), range of influence (*commRange*), the number of opinions about which they communicate (*commBreadth*), and the number of contacts that can be made in a turn (*commAttempts*). Two forms of this agent are used in this case study: a pamphlet distributor and an internet campaigner. The values associated with each are shown in Table 5.

Table 5. Variable values for two types of MISO agents

Variable	Pamphlet Distributor	Internet Campaigner
Affiliation	Government/Rebel	Government/Rebel
Susceptible Population	Literate Civilians	Web-connected Civilians
commRange	3	40
commBreadth	[1, 20]	[1, 20]
commAttempts	10	10

Every turn, this agent chooses a target list of size *commAttempts* within range $commRange$ from those susceptible to its influence. For each target on this list, one of the *commBreadth* topics to which they are assigned is chosen, and the target's opinion on that topic is set, if rebel, to 1 with probability $(1 - legitimacy)$, or if government, to 0 with probability $(legitimacy)$. Agents with written messages may only affect literate Civilians, and agents with internet messages may only affect web-connected Civilians. Generally, internet range is also unlimited, which is modeled using $commRange = 40$ rather than the pamphlet range of $commRange = 3$.

Application

In this analysis, we pose a hypothetical scenario in which an area we are interested in is being affected by a rebel pamphlet-based propaganda campaign. In this hypothetical case, the area of interest has been modeled in the past, and the values laid out in Table 6 seem to have produced appropriate responses, so they are assumed as ground truth. Note that these values correspond to those used in center runs in Chapter 2. Literacy and internet connectivity rates for the global average are used and taken from the CIA World Factbook (2012), but country-specific values could be found in the same manner. The rebel propaganda campaign is reported to have a moderate level of focus, equivalent to 25% of possible anti-government topics. Thus, *commBreadth* is set to 5 for the rebel agent.

Table 6. Values used in simulation for application scenario

Variable Name	Value
civVision	4
civRange	4
copVision	4
popDensity	0.5
copDensity	0.04
legitimacy	0.82
literacy	0.84
connectivity	0.30

Due to budget and political constraints, only one counter-rebel campaign may be implemented. Two possibilities are pamphlet campaigns and internet campaigns with pro-government information. The determination of message focus is left to the MISO planner. The goal is to minimize Civilians' mean *grievance*.

Note that the purpose of this experiment is to demonstrate how this tool could be used by a MISO campaigner. There would almost certainly be changes to the *grievance* response if *legitimacy*, *literacy*, and *connectivity* were changed, but we assume for the purposes of this experiment that these factors are fixed.

Information Medium

To determine the optimal medium for information, we performed 20 replications, each of length 500 ticks, split equally between each of four conditions: no response, pamphlet campaign, internet campaign, and both campaigns. All MISO agents for this analysis used *commBreadth* of 5, which is equivalent to the rebel pamphleteer. While the use of both campaigns has been determined not to be a choice, it may be interesting for the decision-maker to see the effect that may have. Averaging the mean grievance at each time step, we find the results in Figure 10. There is no clearly optimal medium for communicating the pro-government message. If the goal has a short-term focus, the pamphlet campaign serves as the most effective response to the rebel message; if the focus is more long-term, the internet campaign serves as the most effective. The cumulative effect of introducing both campaigns is certainly stronger than either campaign alone. As shown in Figure 11, this translates to decreased rebellious activity, though the higher noise in this variable obscures the short-term difference between pamphlet and internet responses.

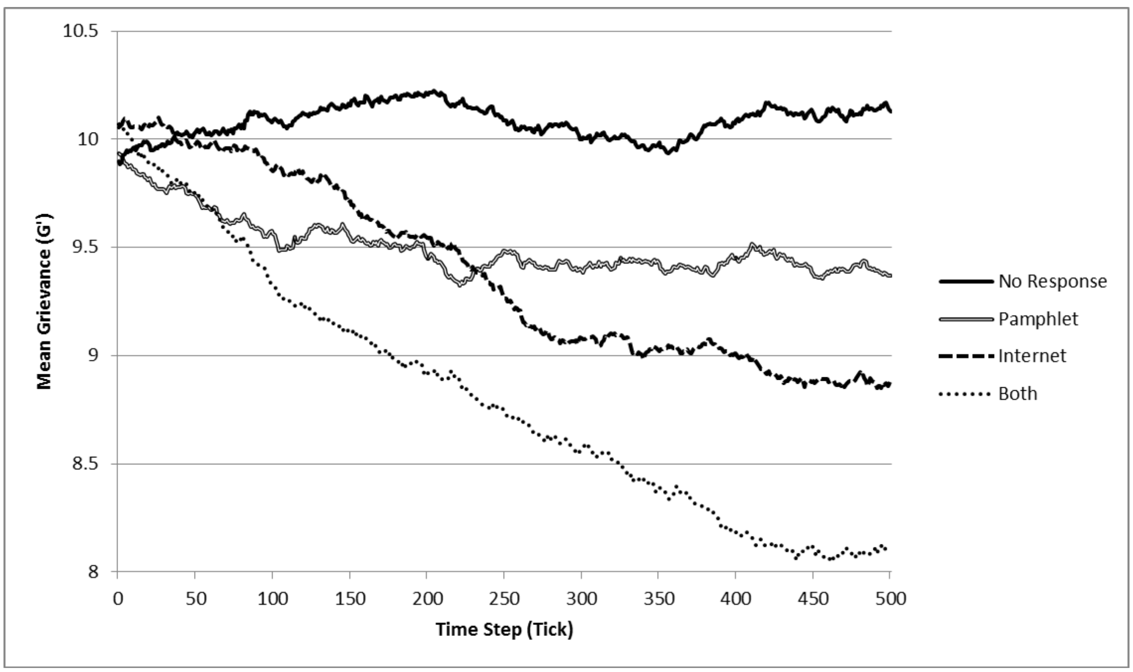


Figure 10. Civilian Grievance Response to Pro-Government Information Campagins

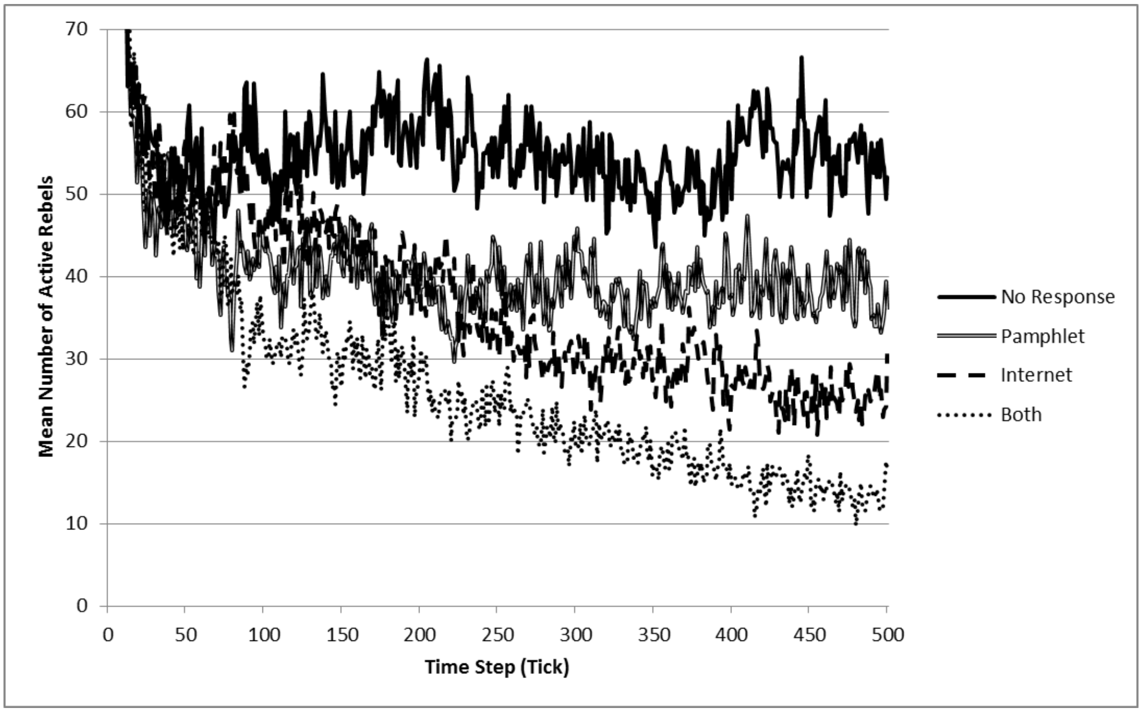


Figure 11. Civilian Rebellion Response to Pro-Government Information Campaigns

Topical Focus

Because neither medium was ruled out in the first experiment, we performed another experiment for both pamphlet and internet campaigns. We expected significant curvature in the effect of message breadth, so we performed 2 runs at each level of breadth (every integer in [1, 20]) for each medium, for a total of 80 replications. The effect is not statistically significant early in a run. At tick 100, where the difference between internet and pamphlet responses was greatest, there is no evidence of breadth affecting grievance.

At tick 500, there is strong evidence ($p < 0.0001$) of a negative linear effect of breadth upon grievance. There is insufficient evidence to show that this effect differs between treatments. Breadth and campaign type explain 44.4% of variance in grievance. The majority of observed variance, then, is attributable simply to noise, as nothing else is altered between runs. The associated ANOVA is shown in Table 7.

Table 7. ANOVA for Breadth Effect on Grievance

Source	DF	Sum of Squares	Mean Square	F Ratio	p-value
Model	2	9.031941	4.51597	30.73	<.0001
Type	1	2.616809	2.616809	7.8067	<.0001
Breadth	1	6.415132	6.415132	43.6533	<.0001
Error	77	11.31564	0.14696		
Lack Of Fit	37	6.071054	0.164083	1.2514	0.2434
Pure Error	40	5.244583	0.131115		
Total	79	20.34758			

Recommendations

Based on the analysis of our selected hypothetical scenario and parameter settings used, we would recommend to the decision-maker to use a broad-themed internet campaign for long-term effect on civilian support for the government. For a short-term effect, breadth is inconsequential, but we would recommend a pamphlet campaign.

Conclusion

The intent of this paper is not to inform a decision-maker; instead, this demonstrates the flexibility of using an agent-based model to compare MISO actions in silica. Real-world effects are more complicated and difficult or impossible to measure, so this technique offers insight into subtle effects that are otherwise hidden. Furthermore, as we begin to better understand the effects of different variables, the number of runs, and therefore analyst time, required for proper analysis may decrease. Case in point: the curvature expected in the effect of message breadth was not found. Far less data could have been collected to analyze the effect of breadth.

Much future research can be considered. As alluded to in the scenario, the results of this model currently possess only face validity. It would be interesting to attempt validating for a certain area of interest. Even altering only literacy and web-connectivity to match a particular region would be illuminating.

IV. Conclusion

Research Summary

This thesis develops an agent-based model (ABM) of a human social landscape as a technique for understanding the impact of structural factors and external factors on anti-government rebellion. The model is built in the spirit of generative social science, with a focus on rule simplicity and successful generation of realistic outcomes. It adds to the base of published work by modeling opinion with a genetic algorithm, which allows for sustainable variation in beliefs, and by examining the addition of elements from influence psychology.

In Chapter 2, a factorial experiment examined environmental effects and found that the addition of friendship behavior as modeled had no quantitative effect on Civilian opinion. This suggests that it may be an extraneous agent rule for future work, and it supports the arguments for simplicity in generative social science. Other environmental factors, such as range of vision and population density, had significant primary and interaction effects. These results agree with real-world observations. This type of analysis serves as a proof of concept for ABM in forecasting a region's proclivity to rebel.

In Chapter 3, a hypothetical application from the perspective of a MISO planner was presented, with results suggesting that while written propaganda in a limited area is effective for short-term moderation of opinions, internet-based propaganda may be more effective for a long-term effect. Furthermore, the results suggest that a broader message is more effective than a narrowly focused message, though this effect only becomes noticeable over longer periods of time. This analysis serves as a proof of concept for application of ABM to comparing MISO plans to prevent, or possibly encourage, rebellions by moderating anti-government sentiment.

Future Work

Generative social science is a young methodology, and the base of published work implementing it remains small. The subset of that work that is focused on MISO planning is sparse, so there is ample opportunity for further investigation into this field. This simulation itself could be improved upon, and its capabilities could be further examined and validated.

While the addition of friendship behavior had no significant effect, there is a plethora of additional social psychology that could be applied to Civilian agent behavior. Much of this is explored in Chapter 1. Only two of the six major concepts defining interpersonal persuasion as presented in Cialdini (2007) are implemented here. Social proof is present when a Civilian is more likely to become actively rebellious when it can see others that are active, and liking is present in the application of friendship. Commitment and consistency could be implemented by increasing or decreasing the rebel threshold depending on present state; the agent would be less likely to change states.

Reciprocation, authority, and scarcity could be added by modifying the social scenario. For example, adding states of employment that lead to borrowing and lending behavior could introduce an avenue for reciprocation. An agent may be more likely to become actively rebellious after accepting a loan from another rebel. Changing the strength of reciprocity based on agent wealth would implement the scarcity principle. Also, by adding additional familial relationships, which would necessitate agent births and deaths, social structure could be made more rigid. This would allow the simulation of authority.

Adding more social psychological principles into the model would also enable greater regional specification. The model presented in this thesis is intentionally generalized, but a user may wish for a model to be specifiable to a region. Each of the influence effects may be altered in strength depending on a culture's GLOBE values, as discussed by House et al. (2004). In this manner the effects of culture could be measured, and effects specific to a single culture could be examined with greater accuracy.

In order to truly validate the results of this model, it would probably have to be specified to a region of interest. One possible methodology for regional specification is the use of GLOBE values as discussed above, but another is to build a more descriptive response surface than that explored in Chapter 2. With a response surface examining every major input in the model, sets of input variables could be identified that would generate responses, such as rebellion and prison rates, observed in a region. Subject matter expert involvement would be necessary to identify which sets of inputs are realistic. With this "backward-validated" simulation, forecasts of MISO effects would be more directly applicable and compared to real-world observations.

Appendix A. Code for UserGlobalsAndPanelFactory.groovy

```
package civilviolence.relogo

import repast.simphony.relogo.factories.AbstractReLogoGlobalsAndPanelFactory

public class UserGlobalsAndPanelFactory extends AbstractReLogoGlobalsAndPanelFactory{
	public void addGlobalsAndPanelComponents(){

	addReLogoTickCountDisplay()

	//User Interface
	addButtonWL("setup","Setup")
		//Press to initialize a replication
	addButtonWL("go","Step")
		//Press to advance time one tick
	addToggleButtonWL("go","Go")
		//Press to advance time continually, press again to stop
	addToggleButtonWL("goDOE", "Go DOE-style")
		//Press to replicate the experiment from Chapter 2
	addToggleButtonWL("goMISOpt1", "Go MISO experiment, part 1")
		//Press to replicate experiment 1, Chapter 3
	addToggleButtonWL("goMISOpt2", "Go MISO experiment, part 2")
		//Press to replicate experiment 2, Chapter 3
	addSliderWL("civVision", "Civilian Vision", 0, 0.5, 10, 7)
	addSliderWL("civRange", "Civilian Move Range", 0, 0.5, 10, 4)
	addSliderWL("copVision", "Cop Vision and Range", 0, 0.5, 10, 7)
	addSliderWL("literacy", "Literacy", 0, 0.01, 1, 0.84)
	addSliderWL("connectivity", "Web Use", 0, 0.01, 1, 0.30)
	addSliderWL("numRebPamphlets", "Number of Rebel Pamphleters", 0, 1, 5, 0)
	addSliderWL("numGovPamphlets", "Number of Govvy Pamphleters", 0, 1, 5, 0)
	addSliderWL("numRebWebCampaigns", "Number of Rebel Web Campaigns", 0, 1, 5, 0)
	addSliderWL("numGovWebCampaigns", "Number of Govvy Web Campaigns", 0, 1, 5, 0)
	addSliderWL("rebBreadth", "Breadth of Rebel MISO Campaign", 1, 1, 20, 5)
	addSliderWL("govBreadth", "Breadth of Govvy MISO Campaign", 1, 1, 20, 5)
	addSwitchWL("unlimitedJailTerm", "Kill rather than Imprison")
		//Jailed Civilians are never released while checked
	addSwitchWL("disableComm", "Disable communication between agents")
		//Communication does not occur while checked
	addSwitchWL("disableMoveTowardFriends", "Do not move toward friends")
		//Friendships form but movement is random while checked
	addMonitorWL("totalRebs", "Active Rebels", 1)
		//Monitor to allow observation of rebel population
	addMonitorWL("prisoners", "Prisoners", 1)
		//Monitor to allow observation of jailed population
	addMonitorWL("meanGrievance", "Mean Grievance", 1)
		 //Monitor for mean grievance of all Civilians

	//Global variables
	addGlobal("legitimacy", 0.82)
		//Government legitimacy, from Epstein (2006)
	addGlobal("maxJailTerm", 30)
		//Jail terms drawn from uniform distribution between 1 and this value
	addGlobal("copDensity", 0.04)
```

```
            //Proportion of popDensity to be designated as Cops
    addGlobal("popDensity", 0.70)
            //Proportion of all patches to be populated with Cops or Civilians
    addGlobal("rebelThreshold", 0.1)
            //Threshold for going active, taken from Epstein (2006)
    addGlobal("k", 2.3)
            //Arrest constant, from Epstein (2006)
    addGlobal("emptyPatches")
            //List of empty patches to be updated
    addGlobal("inactives")
            //List of inactive civilians
    addGlobal("actives")
            //List of active civilians
    addGlobal("prisoners")
            //List of jailed rebels
    addGlobal("literates")
            //List of literate civilians
    addGlobal("webUsers")
            //List of civilians connected to the internet
    addGlobal("friendThreshold", 0.25)
            //This is later multiplied by (1-legitimacy)
    addGlobal("friendLife", 20)
            //How long a friendship lasts without interaction
    addGlobal("maxTicks", 500)
            //Ticks per replication
    }
}
```

Appendix B. Code for UserObserver.groovy

```
package civilviolence.relogo

import com.sun.jndi.ldap.Filter;
import com.sun.org.apache.xpath.internal.operations.Mod;

import static repast.simphony.relogo.Utility.*;
import static repast.simphony.relogo.UtilityG.*;
import repast.simphony.relogo.BaseObserver;
import repast.simphony.relogo.Stop;
import repast.simphony.relogo.Utility;
import repast.simphony.relogo.UtilityG;

class UserObserver extends BaseObserver{

	//methods for Panel Factory
	def relogoRun = 0
	def timestamp() {ticks()}
	def totalCops() {numCops} //number of Cops, does not change within replication
	def totalCivs() {numCivilians} //number of Civilians of all statuses, does not change within replication
	def totalRebs() {count(actives)} //number of active rebels in the model, changes with time
	def prisoners() {count(prisoners)} //number of jailed Civilians, changes with time
	def grievanceHistogram() { //Captures how many Civilians have each value of grievance
	def histogram = new ArrayList([0] * 21)
	for (i in 0..20) {
		 histogram[i] = count(civilians().with({grievance == i / 20 * (1 - legitimacy)}))
		}
		histogram
	}
	def meanGrievance() { //Captures the mean grievance of all Civilians, changes with time
		def sumGrievance = 0
		foreach({sumGrievance += it.grievance * 20 / (1 - legitimacy)}, civilians())
		sumGrievance / numCivilians
	 }

	//variables
	def totalSize //Total number of patches
	def numCivilians //Total number of Civilians
	def numCops //Total number of Cops

	//methods
	def setup() { //Run to initialize a replication

		relogoRun++
		clearAll()

```

```
		//Variable Setup
		totalSize = (maxPxcor - minPxcor + 1) * (maxPycor - minPycor + 1)
		numCivilians = round(popDensity * (1 - copDensity) * totalSize)
		numCops = round(copDensity * popDensity * totalSize)
		emptyPatches = new LinkedList(patches().toList()) //All patches are empty
		assert count(emptyPatches) == totalSize //Verification assertion
		friendThreshold = friendThreshold * (1-legitimacy) //Scale friend threshold to same scale as grievance

		populateAgents() //Initially create Civilians and Cops

		setUpLists() //Initialize inactive, active, prisoner, literate, and web-connected lists

		implementMISO() //Place MISO agents - change this method to change values

		initializeAgents() //Set Civilian and Cop attributes, place them and MISO, initial rebel decisions

		checkAssertions() //Verification assertions
	}

	def go() { //Running once corresponds to a tick
		tick()
		ask(turtles()) { //Random order step for all Civilians, Cops, and MISO Agents
			step()
		}
		ask(patches()) { //Update background color
			checkColor()
		}
		ask(relationships()) { //If a relationship reaches max age, it dies
			step()
		}
		checkAssertions() //Verification assertions
	}

	def goDOE() {
		//Note: this method replicates the experiment from Chapter 2. Random order is unnecessary but still completed.
		if(timestamp() == 0 && relogoRun == 0) {
			civVision = 7
			civRange = 7
			copVision = 7
			disableMoveTowardFriends = true
			popDensity = 0.7
			copDensity = 0.07
			setup()
			maxTicks = 300
		} else if(timestamp() == maxTicks) {
			assert relogoRun < 136

			if([2, 3, 4, 5, 6, 7,8, 9, 12, 16, 17, 27, 28, 30, 33, 36, 37, 38, 39, 41, 43,
				47, 49, 53, 54, 55, 57, 59, 60, 62, 63, 65, 68, 71, 72, 73, 78, 79,
```

```
            80, 83, 90, 93, 94, 95, 98, 102, 103, 108, 111, 112, 113, 114,
            115, 116, 118, 120, 126, 127, 128, 129, 130, 133, 134,
            136].contains(relogoRun + 1)) {
            civVision = 1
    } else if ([14,23,52,61,76,81,121,131].contains(relogoRun + 1)) {
            civVision = 4
    } else {
            civVision = 7
    }

    if([2, 3, 4, 5, 6, 9, 10, 11, 12, 19, 20, 21, 22, 24, 28, 30, 33, 36, 38, 42,
            45, 47, 49, 50, 51, 53, 58, 64, 67, 70, 72, 73, 77, 78, 80, 82, 83,
            84, 85, 90, 91, 92, 93, 94, 95, 100, 101, 102, 103, 104, 106, 107,
            108, 112, 115, 1 16, 119, 122, 123, 124, 125, 127, 132,
            134].contains(relogoRun + 1)) {
            civRange = 1
    } else if ([14,23,52,61,76,81,121,131].contains(relogoRun + 1)) {
            civRange = 4
    } else {
            civRange = 7
    }

    if([2, 6, 7, 8, 10, 11, 12, 15, 17, 21, 25, 27, 29, 30, 31, 32, 33, 35, 37, 39,
            40, 45, 46, 47, 50, 54, 57, 58, 59, 66, 67, 70, 72, 73, 75, 77, 78,
            79, 82, 83, 84, 85, 86, 87, 89, 91, 93, 95, 98, 101, 108, 109, 110,
            112, 113, 115, 118, 122, 123, 128, 130, 134, 135,
            136].contains(relogoRun + 1)) {
            copVision = 1
    } else if ([14,23,52,61,76,81,121,131].contains(relogoRun + 1)) {
            copVision = 4
    } else {
            copVision = 7
    }

    if([1, 2, 8, 9, 10, 11, 12, 16, 17, 18, 19, 20, 22, 23, 25, 26, 27, 28, 30, 31,
            35, 39, 43, 44, 45, 49, 50, 51, 53, 58, 61, 64, 65, 67, 68, 71, 72,
            73, 75, 76, 79, 80, 82, 87, 88, 89, 90, 91, 93, 95, 96, 97, 100,
            102, 106, 107, 109, 116, 117, 120, 126, 128, 130, 131, 133, 134,
            135, 136].contains(relogoRun + 1)) {
            disableMoveTowardFriends = true
    } else {
            disableMoveTowardFriends = false
    }

    if([2, 5, 10, 12, 17, 19, 21, 22, 25, 26, 27, 28, 29, 38, 39, 41, 43, 44, 46,
            47, 49, 51, 55, 57, 58, 60, 65, 66, 67, 68, 69, 70, 72, 74, 78, 86,
            88, 89, 90, 91, 92, 93, 94, 96, 98, 99, 101, 102, 105, 107, 108,
            109, 112, 113, 118, 119, 123, 124, 125, 126, 127, 129, 130,
            135].contains(relogoRun + 1)) {
            popDensity = 0.3
    } else if ([14,23,52,61,76,81,121,131].contains(relogoRun + 1)) {
            popDensity = 0.5
    } else {
            popDensity = 0.7
```

```
            }

            if([4, 9, 12, 13, 15, 17, 21, 22, 24, 29, 30, 31, 32, 33, 35, 38, 43, 44, 45,
                47, 48, 49, 51, 54, 58, 59, 60, 62, 64, 66, 67, 69, 70, 71, 72, 77,
                78, 80, 82, 83, 89, 92, 95, 96, 97, 98, 99, 102, 103, 106, 111,
                113, 117, 122, 124, 126, 127, 128, 129, 130, 132, 133, 135,
                136].contains(relogoRun + 1)) {
                copDensity = 0.01
            } else if ([14,23,52,61,76,81,121,131].contains(relogoRun + 1)) {
                copDensity = 0.04
            } else {
                copDensity = 0.07
            }

            setup()

        } else {
            go()
        }
}


def goMISOpt1() {
        //Note: This method replicates the experiment for message medium, Chapter 3
        if(timestamp() == 0 && relogoRun == 0) {
            civVision = 4
            civRange = 4
            copVision = 4
            disableMoveTowardFriends = false
            popDensity = 0.5
            copDensity = 0.04
            numRebPamphlets = 1
            numGovPamphlets = 0
            numRebWebCampaigns = 0
            numGovWebCampaigns = 0
            rebBreadth = 5
            govBreadth = 5
            maxTicks = 500
            setup()
        } else if(timestamp() == maxTicks) {

            if (relogoRun == 5) {
                numGovPamphlets = 1
            } else if (relogoRun == 10) {
                numGovPamphlets = 0
                numGovWebCampaigns = 1
            } else if (relogoRun == 15) {
                numGovPamphlets = 1
            } else if (relogoRun == 20) {
                throw new IllegalArgumentException("MISO part 1 run
                    complete.")
            }

            setup()
```

```
		} else {
			go()
		}
	}

	def goMISOpt2() {
		//Note: this method replicates the experiment for breadth, Chapter 3
		if(timestamp() == 0 && relogoRun == 0) {
			civVision = 4
			civRange = 4
			copVision = 4
			disableMoveTowardFriends = false
			popDensity = 0.5
			copDensity = 0.04
			numRebPamphlets = 1
			numGovPamphlets = 1
			numRebWebCampaigns = 0
			numGovWebCampaigns = 0
			rebBreadth = 5
			govBreadth = 1
			setup()
		} else if(timestamp() == maxTicks) {

			if (mod(relogoRun,2) == 0 & relogoRun != 40 & relogoRun < 80) {
				govBreadth ++
			} else if (relogoRun == 40) {
				numGovPamphlets = 0
				numGovWebCampaigns = 1
				govBreadth = 1
			}

			setup()

		} else {
			go()
		}
	}

	def populateAgents() { //Part of initialization, create all Civs with uniform
		opinion and Cops

		setDefaultShape(Civilian, "person")
		setDefaultShape(Cop, "star")

		createCivilians(numCivilians) {
			riskAversion = randomFloat(1)

			opinionGene = new ArrayList([0] * 20)
			int zeroPoints = random(21) // number of chromosomes to leave 0

			def posElements = new LinkedList(0..19)
			while (zeroPoints > 0) {
				posElements -= oneOf(posElements)
```

```
                zeroPoints --
            }
            for (i in posElements) {
                opinionGene[i] = 1
            }

            grievance = opinionGene.sum() / 20 * (1 - legitimacy)
        }

        createCops(numCops) {
            setColor(yellow())
        }
}

def setUpLists() { //Part of initialization, setting up all lists
        inactives = new LinkedList(civilians().toList()) //none are active yet
        actives = new LinkedList() //none are active yet
        prisoners = new LinkedList() //none are jailed yet

        def numLiterates = round(literacy * numCivilians) //set literate group
        literates = new ArrayList()
        def tempLiterates = nOf(numLiterates, civilians()) //for use here and with web users
        literates = tempLiterates.toList()

        def numWebUsers = round(connectivity * numCivilians)
        webUsers = new ArrayList()
        webUsers = nOf(numWebUsers, tempLiterates).toList() //assume illiterate cannot use web
}

def initializeAgents() { //Place all Civs, Cops, MISOs; check for rebels and set colors
        ask(turtles()) {
            targetPatch = oneOf(emptyPatches)
            emptyPatches -= targetPatch
            moveTo(targetPatch)
            assert targetPatch == patchHere()
        }

        ask(civilians()) {
            checkActive()
            checkColor()
            jailed = false
        }

        ask(patches()) {
            checkColor()
        }
}

def implementMISO() { //Adding various MISO agents, global values set in Panel
        //add a rebel pamphlet distributor
        createMISOs(numRebPamphlets) { // change this number to alter number of
```

```
such agents
		//changeable values
		commBreadth = rebBreadth
		commRange = 3
		commAttempts = 10
		susceptibles = literates
		rebel = true // set to false for government, true for rebel
		setShape("frowny")
		setColor(white())
	}

	//add a government pamphleter
	createMISOs(numGovPamphlets) { // change this number to alter number of such agents
		//changeable values
		commBreadth = govBreadth
		commRange = 3
		commAttempts = 10
		susceptibles = literates
		rebel = false // set to false for government, true for rebel
		setShape("smiley")
		setColor(white())
	}

	//add a rebel internet campaign
	createMISOs(numRebWebCampaigns) { // change this number to alter number of such agents
		//changeable values
		commBreadth = rebBreadth
		commRange = 40
		commAttempts = 10
		susceptibles = webUsers
		rebel = true // set to false for government, true for rebel
		setShape("house")
		setColor(orange())
	}

	//add a government internet campaign
	createMISOs(numGovWebCampaigns) { // change this number to alter number of such agents
		//changeable values
		commBreadth = govBreadth
		commRange = 40
		commAttempts = 10
		susceptibles = webUsers
		rebel = false // set to false for government, true for rebel
		setShape("house")
		setColor(white())
	}

	//initialization of MISO Agents
	ask(MISOs()) {
		def tempBreadth = commBreadth
		commTopics = new LinkedList(1..20)
```

```
            while (tempBreadth < 20) {
                commTopics -= oneOf(commTopics)
                 tempBreadth ++
            }
        }
    }

    def checkAssertions() { //Verification
        assert count(actives) == count(civilians().with({active & !jailed}))
        assert count(prisoners) == count(civilians().with({jailed}))
        assert totalSize == count(emptyPatches) + count(actives) + count(inactives) +
            numCops + count(MISOs())
    }


}
```

Appendix C. Code for Civilian.groovy

```
package civilviolence.relogo

import org.opengis.util.UnlimitedInteger;

import static repast.simphony.relogo.Utility.*;
import static repast.simphony.relogo.UtilityG.*;
import repast.simphony.relogo.BasePatch;
import repast.simphony.relogo.BaseTurtle;
import repast.simphony.relogo.Plural;
import repast.simphony.relogo.Stop;
import repast.simphony.relogo.Utility;
import repast.simphony.relogo.UtilityG;

class Civilian extends BaseTurtle {

	// Attributes used in checkActive
	def opinionGene //Array of size 20, used in manner of genetic algorithm
	def grievance //Mean value of opinionGene elements multiplied by (1 - legitimacy)
	def riskAversion //Drawn from Uniform(0,1)
	def C //Cops in vision
	def A //Active rebels in vision
	def probArrest //Subjective estimate of arrest probability - P in write-up
	def activePrior //True if active rebel last tick
	def active //True if active rebel
	def jailed //True if rebel jailed
	def netRisk //probArrest x risk aversion (N = RP in write-up)

	// Attributes used to track jail timing
	def jailTerm //assigned by Cop at arrest
	def timeInJail //incremented every turn while jailed, then reset at release

	// Attributes used in discrete space movement
	def sourcePatch //where Civ starts tick
	def availablePatches //patches within range that are empty
	def targetPatch //where Civ moves

	def step() { //called once every tick
		if(jailed) {
			timeInJail++
			if(timeInJail >= jailTerm & !unlimitedJailTerm) {
				releaseFromJail()
			}
		} else {
			move()
			checkActive()
			checkComm()
		}
		assert grievance >= 0 //Verification
		assert grievance <= 1 //Verification
	}

	def move() {
```

```
    assert jailed == false //Will throw error if jailed, jailed Civs cannot move

    sourcePatch = patchHere()
    availablePatches = inRadius(emptyPatches,civRange)
    if(!emptyQ(availablePatches)) {
        //First try to move near a friend
            def localCivs = inRadius(inactives,civVision) +
                inRadius(actives,civVision)
            def localFriends
            def me = self()
            if(count(localCivs) > 0 & !disableMoveTowardFriends) {
                localFriends = localCivs.with {
                    if(!relationshipNeighborQ(me)) {
                        false //no relationship, so can't be friends
                    } else {
                        relationshipWith(me).friend //checks if
                            relationship type is friend, to enable
                            other types
                    }
                }
                if(count(localFriends) > 0) {
                    def friendToMoveTo = oneOf(localFriends) // pick a
                        friend to move toward
                    targetPatch = minOneOf(availablePatches) { // pick the
                        patch closest to the friend
                        distance(friendToMoveTo)
                    }
                } else {
                    // no nearby friends, move to random patch
                    targetPatch = oneOf(availablePatches)
                }
            } else {
                // there are no local civilians, or friend movement is turned off
                targetPatch = oneOf(availablePatches)
            }
            emptyPatches -= targetPatch
            moveTo(targetPatch)
            assert targetPatch == patchHere() //Verification
            emptyPatches += sourcePatch
        }
    }

    def checkActive() {
        C = count(inRadius(cops(),civVision))
        A = count(inRadius(actives,civVision))
        if(!active) {A++} // Compare as if Civ had already gone active
        probArrest = 1 - (e()**(-k*(C/A)))
        netRisk = riskAversion * probArrest // * maxJailTerm**alpha if jail terms deter
            rebellion - see Epstein (2006)
        checkColor() // Update Civ color
    }

    def checkColor() {
        if(grievance - netRisk > rebelThreshold) {
```

```
            active = true
            setColor(red())
            if(!activePrior) {
                actives += self()
                inactives -= self()
                activePrior = true
            }
        } else {
            active = false
            setColor(blue())
            if(activePrior) {
                actives -= self()
                inactives += self()
                activePrior = false
            }
        }
    }

    def checkComm() {
        def localCivs = civiliansOn(neighbors()).with({!jailed})
        if(count(localCivs) > 0) { //if no neighbors, no communication
            communicate(oneOf(localCivs))
        }
    }

    def communicate(target) {

        def dGrievance = 0
        for (i in 0..19) {
            if (target.opinionGene[i] != opinionGene[i]) {
                dGrievance ++
            }
        }
        dGrievance = dGrievance / 20 * (1 - legitimacy)
        checkLinks(target, dGrievance)

        if(!disableComm) {
            def targetMeme = random(20)
            target.opinionGene[targetMeme] = opinionGene[targetMeme]
            target.grievance = target.opinionGene.sum() / 20 * (1 - legitimacy)

            //introduce 1% probability of random mutation
            if(randomFloat(1) < 0.01) {
                def locus = random(19)
                opinionGene[locus] = 1 - opinionGene[locus]
            }
        }
    }

    def checkLinks(target, dGrievance) { //if in friendship threshold, create or maintain friendship
        if(abs(dGrievance) <= friendThreshold) {
            if(!relationshipNeighborQ(target)) {
                createRelationshipWith(target) {
```

```
                    friend = true
                    age = 0
                }
            } else {
                def commLink = relationshipWith(target)
                commLink.age = 0
            }
        }
    }

    def releaseFromJail() {
        // Jail term is up, so release them!
        targetPatch = oneOf(emptyPatches)
         moveTo(targetPatch)
        emptyPatches -= targetPatch
        showTurtle()
        jailed = false
        prisoners -= self()
        actives += self()
        checkActive()
    }
}
```

Appendix D. Code for Cop.groovy

```
package civilviolence.relogo

import static repast.simphony.relogo.Utility.*;
import static repast.simphony.relogo.UtilityG.*;
import repast.simphony.relogo.BasePatch;
import repast.simphony.relogo.BaseTurtle;
import repast.simphony.relogo.Plural;
import repast.simphony.relogo.Stop;
import repast.simphony.relogo.Utility;
import repast.simphony.relogo.UtilityG;

class Cop extends BaseTurtle {

	// Attributes used in discrete space movement
	def sourcePatch
	def availablePatches
	def targetPatch
	def arrestedToday
	def arrestedPatch

	// Attributes used in checkArrest
	def nearbyRebels

	def step() {
		checkArrest() //look for someone to arrest
		move() //move to arrest location or randomly in range
	}

	def move() {

		sourcePatch = patchHere()

		if(arrestedToday) { // Cop moved to the arrest location
			targetPatch = arrestedPatch
			emptyPatches -= targetPatch
			moveTo(targetPatch)
			assert targetPatch == patchHere()
			emptyPatches += sourcePatch
		} else { // No arrest, so move randomly
			availablePatches = inRadius(emptyPatches,copVision)
			if(!emptyQ(availablePatches)) {
				targetPatch = oneOf(availablePatches)
				emptyPatches -= targetPatch
				moveTo(targetPatch)
				assert targetPatch == patchHere()
				emptyPatches += sourcePatch
			}
		}
		arrestedToday = false // Reset value for next turn
	}

	def checkArrest() {
```

```
        nearbyRebels = inRadius(actives,copVision)
        if(!emptyQ(nearbyRebels)) {
            // Cop sees a rebel. Book him Dano!
            def arrestee = oneOf(nearbyRebels)
            arrestedToday = true
            arrestedPatch = arrestee.patchHere()
            // Cop is going to move to the location of the poor sap.
            ask(arrestee) {
                jailed = true
                jailTerm = random(maxJailTerm)
                timeInJail = 0
                emptyPatches += patchHere()
                actives -= self()
                prisoners += self()
                hideTurtle()
            }
        }
    }
}
```

Appendix E. Code for MISO.groovy

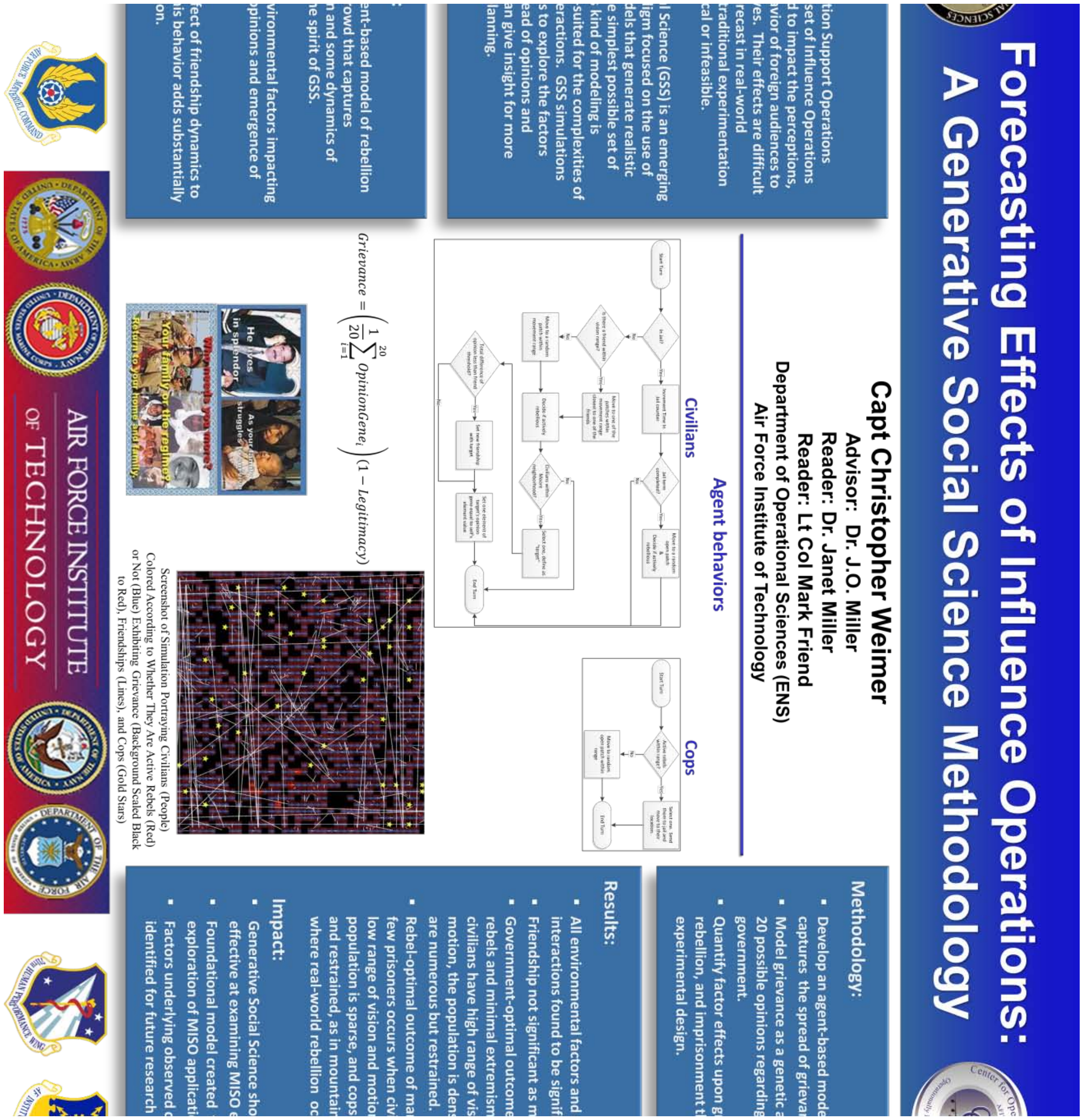
```
package civilviolence.relogo

import static repast.simphony.relogo.Utility.*;
import static repast.simphony.relogo.UtilityG.*;
import repast.simphony.relogo.BasePatch;
import repast.simphony.relogo.BaseTurtle;
import repast.simphony.relogo.Plural;
import repast.simphony.relogo.Stop;
import repast.simphony.relogo.Utility;
import repast.simphony.relogo.UtilityG;

class MISO extends BaseTurtle {

	//local variables
	def commBreadth // How many of the 20 opinions does the agent focus on?
	def commRange // How far away is communication effective?
	def commAttempts // With how many civilians can agent interact in one turn?
	def commTopics // Specific opinions this agent focuses upon
	def susceptibles // Set to either literates or webUsers, depending on type
	def rebel // Set to true if rebel, false if pro-government
	def targetPatch // Needed for initial location

	def step() {
		def targetList = defineTargets()
		//println(self().toString() + targetList) //Provides output to console for verification
		communicate(targetList)
	}

	def defineTargets() {
		def targetList = new LinkedList()
		targetList += inRadius(susceptibles, commRange).with{!jailed}
		def removals = count(targetList) - commAttempts
		while (removals > 0) {
			targetList -= oneOf(targetList)
			removals --
		}
		targetList
	}

	def communicate(targets) {
		def comm = { //set closure for use in a foreach() command (below)
			//Note: commented-out println() commands were used for verification and may be useful. They output to console.
			def topic = oneOf(commTopics)
			if(rebel) {
				if(randomFloat(1) < (1 - legitimacy)) {
					if(it.opinionGene[topic] == 1) {
						//println("Rebel " + self().toString() + " told " + it.toString() + " about topic " + topic.toString() + " and preached to the choir.")
					} else {
```

```
						it.opinionGene[topic] = 1
						//println("Rebel " + self().toString() + " told " + it.toString() + " about topic " + topic.toString() + " and was successful.")
					}
				}
			} else {
				if(randomFloat(1) < legitimacy) {
					if(it.opinionGene[topic] == 0 ){
						//println("Govvy " + self().toString() + " told " + it.toString() + " about topic " + topic.toString() + " and preached to the choir.")
					} else {
						it.opinionGene[topic] = 0
						//println("Govvy " + self().toString() + " told " + it.toString() + " about topic " + topic.toString() + " and was successful.")
					}
				}
			}
			it.grievance = it.opinionGene.sum() / 20 * (1 - legitimacy) //update target grievance
		}

		foreach(comm, targets) //communicate with each target
	}
}
```

Appendix F. Code for Relationship.groovy

```
package civilviolence.relogo

import static repast.simphony.relogo.Utility.*;
import static repast.simphony.relogo.UtilityG.*;
import repast.simphony.relogo.BaseLink;
import repast.simphony.relogo.Directed;
import repast.simphony.relogo.Plural;
import repast.simphony.relogo.Stop;
import repast.simphony.relogo.Undirected;
import repast.simphony.relogo.Utility;
import repast.simphony.relogo.UtilityG;

@Undirected
class Relationship extends BaseLink {
	def friend
	def age

	def step() {
		age++
		if (age >= friendLife) {
			die()
		}
		checkColor()
	}

	def checkColor() {
		if(friend) {
			setColor(blue())
		}
	}
}
```

Appendix G. Summary Chart



Bibliography

Ball, P. (2007). Social science goes virtual. *Nature*, *448*(9), 647-648.

Bandura, A. (1977). *Social learning theory*. Englewood Cliffs, NJ: Prentice-Hall.

Banks, J., Carson, J. S., Nelson, B. L., & Nicol, D. M. (2010). *Discrete-event system simulation* (5th ed.). Upper Saddle River, NJ: Prentice Hall.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences* (pp. 7280-7287). Irvine, CA: National Academy of Sciences.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences* (pp. 7280-7287). Irvine, CA: National Academy of Sciences.

Burris, C. T., Harmon-Jones, E., & Tarpley, W. R. (1997). "By faith alone": Religious agitation and cognitive dissonance. *Basic and Applied Social Psychology*, *19*(1), 17-31.

Central Intelligence Agency. (2012). *The World Factbook*. Retrieved January 21, 2012, from CIA.gov: https://www.cia.gov/library/publications/the-world-factbook/.

Cialdini, R. B. (2007). *Influence: The psychology of persuasion* (Revised ed.). New York City: Collins.

Department of Defense. (2006, February 13). Information operations. *JP 3-13*. Washington, D.C.: Author.

Department of Defense. (2010, January 7). Psychological operations. *JP 3-13.2*. Washington, D.C.: Author.

Department of the Air Force. (2005, January 11). Information operations. *AFDD 2-5*. Washington, D.C.: Author.

Department of the Air Force. (2011, June 7). Military information support operations (MISO). *AFI 10-702*. Washington, D.C.: Author.

Ekehammar, B., Akrami, N., & Yang-Wallentin, F. (2009). Ethnic prejudice: A combined personality and social psychology model. *Individual Differences Research*, *7*(4), 255-264.

Epstein, J. M. (2006). Agent-based computation models and generative social science. In J. M. Epstein, *Generative Social Science: Studies in Agent-Based Computation Modeling* (pp. 4-46). Princeton, New Jersey: Princeton University Press.

Epstein, J. M. (2006). *Generative social science.* Princeton, NJ: Princeton University Press.

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies.* Washington, D.C.: The Brookings Institution.

Festinger, L. (1957). *A theory of cognitive dissonance.* Stanford, California: Stanford University Press.

Fiske, S. T., Gilbert, D. T., & Lindzey, G. (Eds.). (2009). *Handbook of social psychology* (5th ed.). Hoboken: John Wiley & Sons, Inc.

Franke, R. H., Hofstede, G., & Bond, M. H. (1991). Cultural roots of economic performance: A research note. *Strategic Management Journal, 12*(S1), 165-173.

Gardner, M. (1970, October). Mathematical games: The fantastic combinations of John Conway's new solitaire game "life". *Scientific American, 223,* pp. 120-123.

Gilbert, G. N., & Troitzsch, K. G. (2005). *Simulation for the social scientist* (2nd ed.). New York, NY: Open University Press.

Gorman, D. M., Mezic, J., Mezic, I., & Gruenewald, P. J. (2006). Agent-based modeling of drinking behavior: A preliminary model and potential applications to theory and practice. *American Journal of Public Health, 96*(11), 2055-2060.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behavior, institutions, and organizations across nations* (2nd ed.). Newbury Park, CA: Sage Publications, Inc.

Hofstede, G. H. (1980). *Culture's consequences: International differences in work-related values* (1st ed.). Beverly Hills, CA: Sage Publications.

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind.* New York, NY: McGraw-Hill.

Hogg, M. A. (2009). Influence and leadership. In S. T. Fiske, D. T. Gilbert, & G. Lindzey (Eds.), *Handbook of Social Psychology* (Vol. 2, pp. 1166-1207). Hoboken, NJ: John Wiley & Sons, Inc.

Holland, J. H. (1995). *Hidden order.* New York: Basic Books.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V. (Eds.). (2004). *Culture, leadership, and organizations: The GLOBE study of 62 societies.* Thousand Oaks, CA: Sage Publications, Inc.

Israel, N., & Wolf-Branigin, M. (2011). Nonlinearity in social service evaluation: A primer on agent-based modeling. *Social Work Research, 35*(1), 20-24.

Lickliter, R., & Honeycutt, H. (2003). Developmental dynamics: Toward a biologically plausible evolutionary psychology. *Psychological Bulletin, 129*(6), 819-835.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4*, 151-162.

Macy, M. W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology, 28*(1), 143-166.

Mäs, M., Flache, A., & Helbing, D. (2010). Individualization as driving force of clustering phenomena in humans. *PLoS Computational Biology, 6*(10), 1-8.

Milgram, S. (1974). *Obedience to authority: An experimental view* (1st ed.). New York, NY: Harper & Row.

Moussaid, M., Garnier, S., Theraulaz, G., & Helbing, D. (2009). Collective information processing and pattern formation in swarms, flocks, and crowds. *Topics in Cognitive Science*, *1*(3), 469-497.

Murray, K., Lowrance, J., Sharpe, K., Williams, D., Grembam, K., Holloman, K., et al. (2011). Toward culturally informed option awareness for influence operations with S-CAT. In J. Salerno, J. Y. Schanchieh, D. Nau, & S.-K. Chai (Ed.), *Social Computing, Behavioral-Cultural Modeling and Prediction* (pp. 2-9). College Park, MD: Springer.

Myers, D. G. (2008). *Social psychology* (9th ed.). New York, NY: McGraw-Hill.

North, M. J., & Macal, C. M. (2007). *Managing Business Complexity.* New York, New York: Oxford University Press.

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.

North, M. J., Howe, N. T., Collier, N. T., & Vos, J. R. (2007). A declarative model assembly infrastructure for verification and validation. In S. Takahashi, D. L. Sallach, & J. Rouchier (Eds.), *Advancing social simulation: The first world congress* (pp. 129-140). Heidelberg: Springer.

O'Brien, S. P. (2010). Crisis early warning and decision support: Contemporary approaches and thoughts on future research. *International Studies Review, 12*, 87-104.

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *Computer Graphics, 21*(4), 25-34.

Rhodes, N., & Wood, W. (1992). Self-esteem and intelligence affect influenceability: The mediating role of message reception. *Psychological Bulletin, 111*(1), 156-171.

Roozmand, O., Ghasem-Aghaee, N., Hofstede, G. J., Nematbakhsh, M. A., Baraani, A., & Verwaart, T. (2011). Agent-based modeling of consumer decision making process based on power distance and personality. *Knowledge-Based Systems, 24*(7), 1075-1095.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology, 1*(2), 143-186.

Till, R. (2010). Improving agent based modeling of critical incidents. *Systemics, Cybernetics and Informatics, 8*(2), 79-84.

Willer, R., Macy, M. W., & Kuwabara, K. (2009). The false enforcemenet of unpopular norms. *American Journal of Sociology, 115*(2), 451-490.

Zhang, W., Li, G., Xiong, X., & Zhang, Y. J. (2010). Trader species with different decision strategies and price dynamics in financial markets: An agent-based modeling perspective. *International Journal of Information Technology & Decision Making, 9*(2), 327-344.

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14. ABSTRACT
Simulation enables analysis of social systems that would be difficult or unethical to experiment upon directly. Agent-based models have been used successfully in the field of generative social science to discover parsimonious sets of factors that generate social behavior. This methodology provides an avenue to explore the spread of anti-government sentiment in populations and to compare the effects of potential Military Information Support Operations (MISO) actions.
This research develops an agent-based model to investigate factors that affect the growth of rebel uprisings in a notional population. It adds to the civil violence model developed by Epstein (2006) by enabling communication between agents in the manner of a genetic algorithm and friendships based on shared beliefs. A designed experiment is performed. Additionally, two counter-propaganda strategies are compared and explored. Analysis identifies factors that have effects that can explain some real-world observations, and provides a methodology for MISO operators to compare the effectiveness of potential actions.

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