WHEN PEOPLE REBEL: A COMPUTATIONAL APPROACH TO VIOLENT COLLECTIVE ACTION

by

Bianica Pires
A Dissertation
Submitted to the
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Computational Social Science

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DEDICATION

To my husband, who without his unwavering support, patience, and encouragement, this would not have been possible.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

Agent-based Modeling .... ABM

Atomic Components of Thought-Rational .... ACT-R

Beliefs, Desires, and Intentions .... BDI

Central Intelligence Agency .... CIA

Computational Social Science .... CSS

Geographic Information Systems .... GIS

Global Administrative Areas .... GADM

Global Data on Events, Languages, and Tone .... GDELT

Global Terrorism Database .... GTD

Gross Domestic Product .... GDP

Graphical User Interface .... GUI

High Value Target .... HVT

Improvised Explosive Device .... IED

Internally Displaced Person .... IDP

Member of Parliament .... MP

Minorities at Risk .... MAR

Movement of April 19 .... M-19

National Intelligence Council .... NIC

National Liberation Army of Colombia .... ELN

Non-Governmental Organization .... NGO

Organization for Economic Co-operation and Development .... OECD

Peace Research Institute Oslo .... PRIO

Physical conditions, Emotional state, Cognitive capabilities, and Social status .... PECS

Popular Liberation Army .... EPL

Revolutionary Armed Forces of Colombia .... FARC

Revolutionary United Front .... RUF

Sierra Leone Selection Trust .... SLST

Social Network Analysis .... SNA

Study of Terrorism and Response to Terrorism .... START

Systems Dynamics .... SD

Unified Modeling Language .... UML

United Nations .... UN

United Self Defense Units of Colombia .... AUC

World War I .... WWI

World War II .... WWII

ABSTRACT

WHEN PEOPLE REBEL: A COMPUTATIONAL APPROACH TO VIOLENT COLLECTIVE ACTION

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Why an individual rebels, why an individual joins collective action, and how that manifests to violence are not new questions, but are questions that continue to pose a significant scientific challenge. It is the role of the conflict analyst to answer these questions by exploring the underlying dynamics, interactions, and individual behaviors of the conflict. Violent collective action, a subfield of conflict studies, is a complex system, consisting of individuals with unique attributes that interact with other individuals through interconnected networks on a heterogeneous environment. In order to represent a complex system, we must model it from the "bottom-up," as the only way to generate the macro-behaviors is by modeling the individual, micro-level components of the system. In its ability to model complex systems, a computational approach is ideal. While various computational models have explored the use of agent-based modeling (ABM), social network analysis (SNA), and geographic information systems (GIS) in the field of violent

collective action, most have explored the techniques in isolation. The models presented in this dissertation build on the value of integrating these approaches. Computational methods (i.e., ABM, SNA, and GIS) are used to develop three instantiations of more general models of violent collective action. The instantiations, or case studies, were selected for their diversity in terms of geographic location, temporal and spatial scale, and the political and cultural issues underlying the violent collective action. In addition, the case studies serve as building blocks; as I add layers to the environment, develop more sophisticated cognitive frameworks, and create agent-to-agent and agent-to-environment interactions that more closely represent reality. In addition, with the final case study I will demonstrate the value of integrating the three computational methods. Using empirical data for which to create the modeling world and inform the agents, qualitative agreement with actual events modeled are sought. The research question this dissertation addresses is: Can a bottom-up approach provide us with useful insight into the formation, spread, and strength of violent collective action? By covering a variety of different situations of violent collective action while building on the complexity of each computational technique used, the use of a computational approach to gain a better understanding violent collective action is given greater legitimacy. Through such understanding, this dissertation contributes to the existing body of knowledge on the topic of violent collective action.

1 INTRODUCTION

Why an individual rebels, why an individual joins collective action, and how that manifests to violence are not new questions, but are questions that continue to pose a scientific challenge. It is the role of the conflict analyst to answer these questions by exploring the underlying dynamics, interactions, and individual behaviors behind the conflict. Violent collective action, a subfield of conflict studies, is a complex system, consisting of individuals with unique attributes that interact with other individuals through interconnected networks on a heterogeneous environment (Demmers, 2012). In order to represent a complex system, we must model it from the "bottom-up" (Miller and Page, 2007; Schelling, 1978). In its ability to model complex systems, a computational approach is ideal.

Whereas prior computational models have explored the use of agent-based modeling (ABM), social network analysis (SNA), and geographic information systems (GIS) in the field of violent collective action, most have explored the techniques in isolation (e.g., Bhavnani, 2006; Bhavnani et al., 2008; Epstein and Axtell, 1996; Epstein, 2002; Radil et al., 2010). The models presented in this dissertation build on the value of integrating these approaches. Computational methods (i.e., ABM, SNA, and GIS) are used to develop three instantiations of more general models of violent collective action. The instantiations, or case studies, were selected for their diversity in terms of geographic location, temporal and spatial scale, and the political and cultural issues underlying the violent collective action. In addition, the case studies serve as building blocks; as layers are added to the environment, more sophisticated cognitive frameworks for modeling human behavior are developed, the sophistication of the agents' interactions are increased, and with the final case study, the value of integrating the three computational methods is demonstrated.

By defining the terms and methods most critical to this dissertation, this chapter provides the basic foundation for the remainder of the dissertation. First, Section 1.1 clearly defines the term violent collective action and Section 1.2 provides a brief background on current trends in violent collective action. Next, Section 1.3 describes computational modeling, including a general definition of a model, the advantages of computational modeling, some limitations of computational modeling, and an overview of computational methods. Finally, the chapter ends with Section 1.4, which provides the dissertation's research contribution, and Section 1.5, which gives a brief summary of how the remainder of the dissertation is organized.

The research question this dissertation addresses is: Can a bottom-up approach provide us with useful insight into the formation, spread, and strength of violent collective action? Using computational social science (CSS), an interdisciplinary science that uses computational modeling to study complex systems, this dissertation combines several disciplines to answer this research question. These disciplines include geographic information science, conflict analysis and resolution, collective action studies, social network analysis, and cognitive sciences. In addition, by covering a variety of different situations of violent collective action while building on the sophistication of each computational technique used, the use of a computational approach to gain a better understanding of violent collective action is given greater legitimacy. Through the understanding gained, this dissertation contributes to the existing body of knowledge on the topic of violent collective action.

1.1 What is Violent Collective Action?

Conflict can be defined in broad terms, as “a fight, battle, or struggle” (Webster, 1983), “a perceived divergence of interests” (Pruitt and Kim, 2004), or “the pursuit of incompatible goals by different groups” (Ramsbotham et al., 2005). The parties to the conflict can be individuals or groups. Conflict can range from a disagreement between two friends to the interstate conflicts of World War I (WWI) and World War II (WWII). On the other hand, collective action involves the pursuit of common interests by a group of individuals (Tilly, 1978). Whereas conflict relates to the *divergence* of interests, collective action concerns the *mobilization* of a group with common interests. Collective action becomes contentious when used by those without regular access to institutions, who are acting on behalf of new or unrecognized rights, and who are acting in such a way that fundamentally challenges others (Tarrow, 1994). Conflict can remain at the individual-level or can take the form of collective action, when two or more individuals choose to act jointly on a similar cause. It is often non-violent in nature, and may be very brief before conflict resolution takes place. For example, non-violent forms of contentious collective action include peaceful demonstrations, petitions, and sit-ins (Demmers, 2012).

Violent collective action is a subfield of the broader conflict and collective action descriptions above. Given the many forms of non-violent conflict, the occurrence of conflict or collective action is not a sufficient explanation for violence. When seeking to explain the turn to violence, rational choice theorists focus on the cost-benefits associating with joining violent collective action (e.g., Hobbes, 1651; Lichbach, 1995; Olson, 1971), the culturalist argument places group identity as the main source of violent collective action (e.g., Connor, 1994; Huntington, 1996; Stein, 2001), the human needs theorists hone in on the denial of collective needs (Burton, 1979; Maslow, 1954; Sites, 1973), and the opportunity-based theorists focus on opportunities for mobilization and availability of existing organizations (e.g., Cioffi-Revilla and Starr, 2003; Collier and Hoeffler, 2004; Collier et al., 2009; Fearon and Laitin, 2003; Most and Starr, 1989). Violent collective action is a complex system; it consists of individuals with "distinct identities, needs and interests" that interact with other individuals across a variety of levels (e.g., local, state, and global) (Demmers, 2012). The study of violent collective action therefore requires the analysis of the collective. In this dissertation, violence ranges from ethnic clashes in a neighborhood to civil war that spans an entire nation.

1.2 Trends in Violent Collective Action

Since 1945 a shift in the patterns of conflict occurred, from the traditional wars between states (akin to the World Wars) towards conflict within states. The end of the

Cold War actually looked to propel the number of intrastate conflicts to new levels (Goodhand and Hulme, 1999). It was during this time, in the early 1990s that we saw a peak in these types of internal conflicts (e.g., the Bosnian government versus Bosnian Serb forces following Yugoslavia's collapse between 1992 and 1995; Tutsi rebels versus Hutu government and its culmination into the Rwandan genocide in 1994; the Revolutionary United Front's rebellion against the Sierra Leone government from 1991 to 2000; and the Chechnyan war for independence following the dissolution of the Soviet Union from 1994 to 1996) (Uppsala University, 2012a). Intrastate conflict, sometimes referred to as non-interstate, internal, or civil conflict, is defined by Uppsala University (2012b) as "a conflict between a government and a non-governmental party, with no interference from other countries." Today, while the number of intrastate conflicts is fewer in number, they continue to dominate the types of conflict seen around the world. In 2012, there was only one interstate conflict: since South Sudan gained its independence from Sudan in 2011, tensions have remained high, including uncertainty over the common border (Themner and Wallensteen, 2013). Given the dominance in internal conflicts, the study of intrastate, or non-interstate, conflict has become increasingly important. This importance is only exacerbated when looking at the disturbing shift in the distribution of suffering. The proportion of total killed in conflict that were civilian was about 5 percent during WWI, 50 percent by WWII, and with the turn of century became 80 to 90 percent (Goodhand and Hulme, 1999; Ramsbotham et al., 2005). In addition to internal conflicts (as defined by Uppsala University), the organized criminality of street gangs and the emergence of deadly riots pose a significant challenge to the conflict analyst. Although smaller in scale, these conflicts are also internal in nature, and like the larger conflicts are complex systems, exhibiting similar dynamics, underlying issues, and interactions at various levels. Collective violent action ensues, and conflict may be one-sided, inflicted on individuals, or against warring parties.

The trends and characteristics of today's internal conflicts and "small wars" bring a unique set of challenges. The vast majority of these conflicts take place in the developing world, in areas already dealing with "poverty, inequities, and underdevelopment" (Lederach, 1999). Lederach (1999) compares these internal conflicts to communal and inter-communal fighting characterized by "deep rooted and longstanding animosities," psychological and cultural issues which often drive and sustain the conflict more than substantive issues, and one where people seek security within increasingly narrower and more localized identity groups. These longstanding relationships can also be described as being "protracted" or "intractable" due to their long-term nature, perception of hatred, and deep-rooted fears (Lederach, 1999). At the same time, urbanization, especially in these same parts of the world, have also played a defining role in the increase in armed violence, emergence of criminal organizations, and deadly riots. According to the Organization for Co-operation and Development (OECD, 2011), economic opportunity has provided an impetus for the migration from rural to urban areas, with most arriving in already overcrowded slums. Characteristics of urban slums that lend themselves to an increase in the potential for violence include social exclusion, lack of government support, illicit markets for firearms and drugs, and the disruption of social networks. In addition, OECD (2011) and the Global Trends 2030 report by the National Intelligence Council (NIC, 2012) reported that, for the first time almost half the world's population now live in urban areas and this number is expected only to grow. Already overpopulated slums, such as Kibera (a large slum in Kenya), most often not designed to handle increased growth, will certainly feel the pressure that increased population will put on the potential for violence (OECD, 2011). Adding to the challenge, the largest generation of youth is expected to enter adulthood soon. Almost half the world's population is under the age of 25, with the vast majority of 10 to 24 year olds living in the developing world. Youth are particularly vulnerable to being exposed and engaging in armed collective violence (OECD, 2011). According to NIC (2012), the occurrence of intrastate conflicts has increased in countries with a large population of "politically dissonant, youthful ethnic minority" (e.g., ethnic Kurds in Turkey, Shia in Lebanon). In addition, the NIC points to potential resource scarcity issues in these same countries. Environmental stressors that can lead to scarcity issues include extreme weather patterns leading to flooding and droughts, global water use, and limited land accessibility due to increased urbanization (NIC, 2012). These issues may only serve to exacerbate the number of grievances among the young population, which can contribute to mobilization as external triggers and internal opportunities present themselves (Hewitt et al., 2012). These types of challenges call for approaches that take into consideration the unique challenges and nature of these conflicts (Lederach, 1999).

1.3 Computational Modeling

In this section, the term "model" is first defined (Section 1.3.1), the advantages of computational modeling, especially over traditional approaches, are then outlined (Section 1.3.2), some limitations of computational modeling are noted (Section 1.3.3), and a brief introduction into the different computational methods is given (Section 1.3.4).

1.3.1 What is a Model?

To begin we can first distinguish between implicit (or mental) models and explicit models, which (unlike implicit models) require that assumptions be clearly laid out, can be calibrated to historical data, and allow for running multiple experiments given differing initial conditions (Epstein, 2008; Zacharias et al., 2008). An explicit model consists of structural relations (set of variables and their interrelationship), parameters (numerical constants), and an algorithm (the "computational method programmed for the computer") (Lowry, 1965). While "model" and "theory" are at times used interchangeably, they are distinct terms. The theorist is concerned with logical consistency and generality. The aim is to specify conceptually, and in general form, the variables of interest and their interrelationships. The model builder, on the other hand, is concerned with the application of theory to a particular case. Theory is most often applied to a model through the structural relations selected for input into the model (Lowry, 1965). While the role of theory in modeling has relaxed, and at times models may be developed independent of a specific theory, the process of developing good models should recognize the theories underlying the social phenomena being modeled (Crooks et al., 2008). Some reasons to model include, but are not limited to, explanation of the phenomena being modeled, policy guidance, and exploration of theory (Epstein, 2008).

In the 1960s, social scientists began using computers to perform statistical analysis (Cioffi-Revilla, 2010), whereas the use of computational methods in the social sciences is more recent. A computational model is defined simply as theory made into a computer program (Taber and Timbone, 1996). Computational modeling is different from mathematics in that it does not require a closed-form, tractable solution (Axtell, 2000; Taber and Timbone, 1996) and different from qualitative research in that it does require a degree of analytical precision (Taber and Timbone, 1996). It offers a unique way to model and understand aspects of the social world.

1.3.2 Advantages of Computational Modeling

Five distinct advantages to computational modeling over natural language and mathematics include: (1) a greater degree of realism, (2) flexibility and cost-effectiveness, (3) the ability to create "alternative" worlds, (4) a test bed for theory, and (5) the ability to represent complex systems (Taber and Timbone, 1996).

One of the major advantages to modeling computationally, especially over mathematics, is its ability to add a greater level of realism to models of the social world (Taber and Timbone, 1996). Although both represent some abstraction of the world, the degree to which we have to abstract can be greatly reduced when using computational modeling. In mathematics we are concerned with ensuring our equations are tractable (i.e., solvable), which may require oversimplification (Axtell, 2000; Gilbert and Troitzsch, 2005; Taber and Timbone, 1996).

In addition, computational models are flexible and cost-effective (Miller and Page, 2007; Taber and Timbone, 1996). A flexible model can capture a wide class of behaviors. For example, this flexibility can be applied to the scale the social phenomena is being modeled at (e.g., a building, a city, or a nation) or to the sophistication of the agents modeled (from their behavior, their rules for interaction, and their level of rationality) (Crooks and Heppenstall, 2012). Mathematical models tend to be very precise, in that they allow us to formulate an exact set of equations to represent a system which can be solved using some standard solution method (Miller and Page, 2007). However, this makes mathematical models very inflexible. If there are "holes" in our system, in that we do not have the necessary empirical data or knowledge for which to fill, the mathematical formulation can break down. On the other hand, computational models can handle such holes, either through some random variable or through sensitivity analysis. This allows us to model a wide range of systems and behaviors. Computational models are also typically low cost. The initial development of a computational model may be costly, but the incremental cost of running and modifying the model is typically low (Miller and Page, 2007).

Given the dynamic and stochastic nature of the social world, no two realizations given the same initial settings will be the same. In reality, however, we only know one outcome for a given set of initial conditions—that is, we only know the world as we see it. An advantage of computational modeling is that it offers a unique ability to rerun the world multiple times and observe the varying set of outcomes (Axtell, 2000; Gilbert and Troitzsch, 2005; Taber and Timbone, 1996). By rerunning the "artificial" world we create, we can also evaluate a multitude of "what if" scenarios (Taber and Timbone, 1996). Thus, we not only have the advantage of re-creating current conditions and observing its outcomes, we can also make changes to our world and observe those outcomes against differing sets of initial conditions. This provides constructive "proofs," in that each realization of an ABM given a set of initial conditions is a sufficiency theorem (Axtell, 2000; Miller and Page, 2007). Computational simulation also provides the ability to create "alternative" worlds for which we can explore current theory (Gilbert, 2008). They can be used to test current theory, theoretical assumptions, and empirical findings. Often, theories are based only on the social world as we see it, which is one realization of a set of initial conditions (Taber and Timbone, 1996).

Finally, the most important advantage to computational modeling is that it provides us with the ability to represent complex systems. A complex system is one in which understanding perfectly the behavior of the component parts of a system, does not imply understanding the system as the whole (Simon, 1962). Computational modeling, which provides us with the ability to model the social world from the bottom-up, has the potential to provide us with insights outside those needed to develop the original model (Batty, 2005; Heppenstall et al., 2012; Miller and Page, 2007). These insights may be in the form of emergent phenomena, or in results that might seem counterintuitive to the modeler. (Complexity theory is further discussed in Chapter 3.)

Modeling the social world, however, is no simple task. The social world is heterogeneous, both in terms of the environment and the individuals that reside and interact on this environment. Heterogeneity in the environment can be in terms of the terrain (flat versus mountainous), the distance to a country's center of power (rural versus urban), or the available transportation network (highways versus walking paths). Individuals, on the other hand, can have unique physical traits, such age and gender; socioeconomic attributes, such as income, employment status, or social status; or emotional states, such as self-esteem or frustration. In addition, the world is dynamic and uncertain; it is made-up of an immense number of decentralized, local interactions, which can emerge into stable or unstable environments. The social world is a complex system for which we can better understand if we model from the bottom-up (Crooks et al., 2008). But yet, traditional statistical models, for instance, often take an oversimplified, top-down approach. Computational modeling allows us to overcome many of the challenges faced in attempting to use traditional approaches to modeling the social world. A computational approach is more realistic and versatile, it gives us the ability to model "artificial" societies and at least begin to represent and understand the social world as a complex system (Epstein and Axtell, 1996).

1.3.3 Limitations of Computational Modeling

While there are important advantages to computational modeling, especially over traditional mathematical approaches, there are also some limitations that should be noted. These include (1) determining the most appropriate level of abstraction, (2) the challenges associated with modeling social processes such as human behavior, (3) potential limitations in computational resources and empirical data, and (4) verification and validation of models of social phenomena.

Every model is some abstraction of reality, and the degree to which we have to abstract in computational models is often less than in mathematics (Axtell, 2000; Gilbert and Troitzsch, 2005; Taber and Timbone, 1996). However, there is still a question as to the amount that we should abstract in computational models. If we abstract too much, we may build a model that is too simple, that may miss key variables, and that may be an oversimplification of the phenomena being modeled. On the other hand, too much detail can make the model unnecessarily complicated (Crooks and Heppenstall, 2012).

In building computational models of social processes, we are often (although not always) concerned with modeling humans. The accurate representation of human behavior in models of the social world is a significant challenge (Kennedy, 2012; Malleson et al., 2012). Humans do not behave randomly; behavior is a function of our individual traits, interactions, and environment (Kennedy, 2012). Attempting to quantify and calibrate such factors in a model can be very difficult (Crooks and Heppenstall, 2012). While a challenge, the flexibility computational modeling affords gives us the ability to implement the individual, localized behavior of humans into a model of the social world. (Chapter 3 provides a more detailed discussion of modeling human behavior.)

While each realization of an ABM given a set of initial conditions is a sufficiency theorem, one run of the model does not provide any information regarding the robustness of the theorem. For instance, how does the theorem hold against variations in initial conditions? The only way to answer this is to perform multiple runs while systematically varying parameter values (Axtell, 2000). Given limitations in computational resources, however, running the full parameter space may pose a challenge. When modeling large systems, the computational requirements of the model must be taken into consideration (Crooks and Heppenstall, 2012). In addition, limitations around available data to build and populate ABMs can pose a challenge (Watts, 2013; Weinberger, 2011). According to Robert Axtell (cited in Weinberger, 2011), this challenge can hinder our ability to build accurate models of human behavior and as such, "there is a large research programme to be done over the next 20 years, or even 100 years." At times, limitations around data and/or computational resources may require adjustments in the model, such as the degree to which we abstract and the scale to which we build the model.

Given potential challenges around obtaining empirical data of social phenomena and computational constraints of current resources, verification and validation of ABMs can also pose a challenge. Verification concerns ensuring the internal components of the model is working properly (i.e., that the program code is error free) (Crooks et al., 2008; Gilbert and Troitzsch, 2005). This may include code walkthroughs, testing the model at extreme parameter values, or setting up a set of test cases to run (Gilbert and Troitzsch, 2005; North and Macal, 2007). Validation, on the other hand, concerns ensuring that the model provides an accurate representation of the phenomena being modeled (Crooks et al., 2008; Gilbert and Troitzsch, 2005). The validation process involves measuring the model's goodness of fit to real world data (Crooks et al., 2008), which may be very limited. On the other hand, employing the best verification and validation strategy can help us overcome some of these limitations and ensure that we are in fact, building the "right" model for the social phenomena in question (Crooks and Castle, 2012).

Validation, for instance, may involve qualitative (versus quantitative) goodness of fit assessments, which can include visual inspection of model results to spatial-level data or distributional plots of agent properties (Axtell and Epstein, 1994; Crooks and Castle, 2012; Crooks et al., 2008). In addition, while calibration is different from validation, by calibrating parameter values to best represent the real world, we find that calibration and validation may go hand in hand. In essence, calibrating the model allows us to best fit the model to empirical results (Crooks et al., 2008). (Validation and verification strategies are discussed further in Chapter 3.)

1.3.4 Computational Methods

There exist several types of computational methods used in the study of the social sciences (which can be used in isolation or in various combinations), including: complexity modeling, geospatial analysis, social network analysis, and social simulation (e.g., ABM) (Cioffi-Revilla, 2010).

Complexity modeling refers to the use of mathematical methods to study systems in non-equilibrium. While systems in equilibrium are typically characterized as having a Gaussian ("normal" or "bell-shaped") distribution, those in non-equilibrium may take a different shape (Cioffi-Revilla, 2010; Meakin, 1998). The most common type of complexity modeling involves power law analysis, or the analysis of fat-tailed distributions (Cioffi-Revilla, 2010). Complexity modeling is largely inspired by the knowledge that many social phenomena are not in equilibrium, and thus likely follow a highly skewed distribution (Cioffi-Revilla, 2008; Clauset et al., 2009; Meakin, 1998; Newman, 2005). This is different from traditional statistical models that may assume a “normal” or Gausian distribution, an assumption often required to perform regressions on the data. Examples of social systems that have been shown to follow a power law include city sizes (Zipf, 1949), wealth distribution, known as Pareto’s law (Persky, 1992), firm sizes (Axtell, 2001), and the intensity of wars (Richardson, 1948).

GIS, a subfield of geography, is a category of information systems that tracks events, activities, and things; the time those events and activities took place; and their associated physical location (Longley et al., 2005). The use of GIS, as software or in the form of digitized data, can enable and help build on geographic problems (i.e., any problem that involves an aspect of location). GIS can be used in the study of geospatial data, an investigation of spatial patterns that can provide insight into the underlying processes being analyzed (Medina and Hepner, 2013). While GIS alone is not well suited for modeling dynamic processes, it is particularly useful for representing geospatial data in a model (Crooks and Castle, 2012). The combination of GIS with social simulation really gained traction after Epstein and Axtell (1996) showed that the modeling of individual agents can be extended to the development of entire “artificial” societies (Crooks et al., 2008).

Whereas GIS focuses on *physical location* (Longley et al., 2005), SNA studies the *relationship* between people, things, organizations, or events (called nodes). Relationships, or the edges between the nodes, can be defined in geographic terms, or in terms of kinship, interactions, affiliations, or information flows (called ties). The strength of these relationships can be attributed to the frequency of communication, the physical distance between nodes, or the number of interactions. This ability to attach values to edges gives us the ability to study relationships quantitatively (Wasserman and Faust, 2009). SNA has broad appeal to the social scientist in general, providing insights into belief systems, terrorist networks, epidemiology, and social mobility (Cioffi-Revilla, 2010; Scott, 1988). The focus here is on the “patterns of connection” between agents (individuals or collectives), instead of the geographic distance between agents (Scott, 1988). Including these networks in a social simulation requires developing agent-to-agent interaction networks that go beyond the physical location of the agents (Alam and Geller, 2012). Conversely, applying social networks over a GIS can allow for the inclusion of both social and physical distance in an analysis. An approach that has been used across various topics, including gang rivalries (e.g., Radil et al., 2010), urban planning (e.g., Comber et al., 2008), and archaeology (e.g., Mills et al., 2013).

With respect to social simulation, system dynamics (SD) models gained popularity first (Gilbert and Troitzsch, 2005), with ABM not becoming practical until the advent of sufficient computing power in the late 20th century (Epstein and Axtell, 1996). For studying complex systems, SD was seen as an improvement to the traditional statistical models as it could account for the feedback structure and nonlinearity of these systems (Ruloff, 1975). The building blocks behind any SD model are the “stocks” (cumulative) and “flows” (rate-of-change) system variables. These building blocks are incorporated into a feedback network and it’s the combination of these three elements that allows the simulation of the complex and nonlinear relationships of the social world (Radzicki and Taylor, 1997).

Treating the social world as a set of stocks and flows, SD models the world only at the aggregate-level. We cannot decompose or simplify beyond any defined subpopulations in such models (Gilbert and Troitzsch, 2005). Overcoming some of these challenges, ABM has the ability to model autonomous, heterogeneous, and interacting agents (Gilbert and Troitzsch, 2005). It allows us to model the individual, localized behavior of agents and at the same time observe the macro-behavior and spatial patterns that emerge. Within an "artificial" society, agents can interact with each other and the environment, which can range from a free (continuous) or discrete space, a static or dynamic network of connected agents, or the GIS tilings representing actual geographic locations (Macal and North, 2010). Using ABM, agent interactions over physical space (using GIS) and social space (using SNA) can be created with relative ease (Axtell, 2000). These interactions, which can be implemented at a degree of sophistication selected by the modeler, makes ABM ideal for creating models of the social world. A comprehensive review of prior models (using the computational methods discussed here) most relevant to this dissertation and the field of violent collective action are surveyed in Chapter 2.

1.4 Research Contribution

The goal of this research is to demonstrate the insights one can gain from using computational methods to model environments of violent collective action. The research question this dissertation addresses is: Can a bottom-up approach provide us with useful insight into the formation, spread, and strength of violent collective action? Through the use of ABM, SNA, and GIS, an integrative approach to modeling situations of violent collective action is taken. A distinct advantage of computational modeling is its ability to concurrently build theoretical and empirical models of social phenomena (Manson et al., 2012). While agent behavior and the creation of social networks are grounded in theory, GIS provides an empirical foundation (i.e., an actual, real world setting) for which to build the modeling world. In some instances it can also validate the macro-structures coming from micro-processes (Crooks and Castle, 2012).

Conflict is possibly "one of the messiest of all human activities to analyze" (Bohorquez et al., 2009). Thus, given the difficulties associated with empirical validation of environments in conflict, three abstract models are developed. The first two abstractions represent a country-level analysis of a government versus an insurgency (Chapters 4 and 5), while the third, and final, model represents a neighborhood-level ethnic clash (Chapter 6). An instantiation (or case study) of each model is developed. These models are then informed through empirical data of the actual region and conflict environment being modeled. The models serve as building blocks; as layers are added to the environment, more sophisticated cognitive frameworks are developed, and the sophistication of the agents' interactions are increased. In each case, individuals rebel, whether by choice or force, and collective action ensues. Agents, or actors, must decide whether to join an insurgency or a riot. The selected instantiations take place in different parts of the world and at different scales (the civil war of an entire nation to the local riots in a slum). This provides an opportunity to show the use of a computational approach across varying scales and different conflict settings.

The ability to model from the bottom-up is a key requirement for emergence to occur, yielding results that may be counterintuitive to the modeler. Emergence, which can provide insights beyond that which traditional, top-down approaches or qualitative "mental" models of social phenomena can provide, makes this approach an enhancement to current methodologies often used in the study of violent collective action. Through the insights gained, this dissertation contributes to the existing body of knowledge in the field of violent collective action.

1.5 Organization of Dissertation

The dissertation is organized into seven chapters. The first chapter has provided an introduction to the main research topic and the contribution this dissertation brings to the field of collective violent action. The second chapter provides a review of the literature around theories of violent collective action. In addition, it provides a survey of previous computational models in the field. The third chapter defines complexity theory, its relevance to the field of violent collective action, and outlines theories and frameworks for modeling human behavior. The next three chapters are the case studies used to implement three abstract models of violent collective action. Specifically, the fourth chapter uses SNA and GIS to look at the ongoing conflict in Colombia, the fifth chapter combines ABM and GIS to explore the decade-long civil war over diamonds in the western African nation of Sierra Leone, and the sixth chapter integrates ABM, SNA, and GIS to study the post-election riots that broke out in a Kenyan slum. The final, and seventh, chapter of this dissertation provides a summary of the research, further work that could build on this dissertation, and final conclusions. For the remainder of this dissertation, unless otherwise specified, the term "conflict" refers to the specific situation of violent collective action.

2. THEORIES OF VIOLENT COLLECTIVE ACTION AND HUMAN BEHAVIOR

Theorists have pointed to various explanations for the collectives turn to violence, including relative deprivation (Gurr, 1970; Morrison, 1971), rational choice approaches (Hobbes, 1651; Lichbach, 1995; Olson, 1971), group identity (Connor, 1994; Huntington, 1996; Stein, 2001), deprivation of needs (Burton, 1979; Maslow, 1954; Sites, 1973), and opportunity-based triggers (Cioffi-Revilla and Starr, 2003; Collier and Hoeffler, 2004; Collier et al., 2009; Fearon and Laitin, 2003; Most and Starr, 1989). Empirical studies (e.g., Cederman and Girardin, 2007; Gurr, 1993; King and Zeng, 2001) and earlier computational models have explored many of these theories (e.g, Bhavnani and Ross, 2003; Bhavnani, 2006; Bhavnani et al., 2009, 2008; Epstein and Axtell, 1996; Lustick, 2000; Miodownik, 2006). In this chapter, Section 2.1 provides a review of the literature on the theories of violent collective action; Section 2.2 outlines the most relevant prior models of violent collective action; and Section 2.3 provides a brief summary of those theories and models most relevant to this dissertation. The models developed for this dissertation are grounded in theory and build on earlier models of conflict. Thus, the purpose of this chapter is to review the theories and models that have provided the building blocks and core foundation for this dissertation.

2.1 Theories of Violent Collective Action

The literature pertaining to theories of the emergence of conflict, social mobilization, and collective action is vast. Some of the first influences on relative deprivation theory dates back to Marx's work in the late 1800s (Gurney and Tierney, 1982), while rational choice theory dates back even further, to Hobbes (1651) in the 1600s (as cited in Lichbach, 1995). It is beyond the scope of this dissertation to touch upon all these theories. This section therefore provides a review of the most relevant and notable theories and theorists with respect to this dissertation. The theories reviewed include relative deprivation (Section 2.1.1), rational choice theories (Section 2.1.2), theories of identity and social identity (Section 2.1.3), humanistic needs theories (Section 2.1.4), and opportunity-based theories (Section 2.1.5).

2.1.1 Relative Deprivation

Early theorists pointed to relative deprivation as the source for collective violence, defined as the difference between value expectations and value capabilities (Gurr, 1970). Deprivation depends on what one wants to have, not necessarily how little one has, and occurs in relation to some desired state (Morrison, 1971). It is said to develop during periods of economic modernization, where frustrations from the failure to reach expected benefits of modernization occur (Gurr, 1970). Beginning in the 1960s, social movement scholars used the concept of relative deprivation in theoretical and empirical work, attempting to provide a correlation between the outbreak and growth of social movements and the prevalent feelings of deprivation (Gurney and Tierney, 1982). However, explanations for the outbreak of social movement as a consequence of relative deprivation has often lacked evidence, theory, or even an assessment of the structural conditions that lead to relative deprivation (Morrison, 1971). Attempts at alleviating some of the shortcomings with the theory were made by offering some additional considerations on how it applies to social movements; including legitimate expectations (feeling that one has the right to obtain a certain goal) and blocked expectations (perception that one will not be able to receive that goal) (Morrison, 1971). The discrepancy between what one legitimately expects and what one has will cause discontent when the perceived probability of blockage is high (Morrison, 1971). While relative deprivation is an advance over previous thought, which viewed social movement as a consequence of irrational impulses, it still contains too many shortcomings to be useful in explaining the development of collective social action (Gurney and Tierney, 1982).

2.1.2 Rational Choice Theory

Rational choice theorists, on the other hand, assume that self-interest drives a person to participate in collective social movements (Gupta and Singh, 1992). Hobbes, who is said to be the first great rational choice theorist, concluded that people are motivated by self-interest and will always pursue personal profit (Lichbach, 1995). In turn, the natural state of human relations is one of constant "war and strife" as individuals seek their own personal interests. In this world, Hobbes' sought to understand what holds the collective together (Lichbach, 1995). Olson (1971) makes the hypothesis that a "rational" individual would rather be a "free rider" in a social movement to bring about public good. As the benefits of the public good is distributed evenly among all members of the group, whether or not one participated in the movement, there is an economic disadvantage (or cost) to participate. Hobbes' view was further explored by economists and other rational choice scientists who sought to explain a person's motivation to join collective action as a result of individual profit maximization (Gupta and Singh, 1992). Within this line of thought, the assumption made by theorists such as Gurr (1970) – that individual deprivation leads to collective action – was challenged by Olson and others (Lichbach, 1995). While relative deprivation might explain why someone may participate in collective action, it does not explain why a person does not participate, even in the face of extreme deprivation. On the other hand, rational choice theory places too much focus on the "free rider problem." Lichbach (1995) attempts to overcome these challenges by outlining solutions to what he calls the "Rebel's Dilemma." Dissidents have their own Hobbesion problem, how do a group of dissidents overcome the Prisoner's Dilemma and mobilize? The Prisoner's Dilemma is a two-person game whereby each person must decide whether to cooperate or defect. The payoff for defection is highest. However, if both defect, the payoff is lower than if they had both cooperated (Axelrod, 1997a). In a situation of dissent, if all cooperate (e.g., all choose to join the social movement for the public good), all are better off than if all defect (e.g., all stay home). However, the rational actor will always defect (and stay home). If this problem of collective action is not resolved, the rational actor will never rebel. This is known as the Rebel's Dilemma (Lichbach, 1995). In his theory, Lichbach (1995) provides an extension to this rational choice model by illustrating how collective dissent is an outcome of processes general to all collective action problems.

2.1.3 Identity and Social Identity Theory

While identity is the way a person is or wishes to be known by others, social identity is derived from an individual's membership in a social group. Identification with a social group can lead to a differentiation between "we" and "they" when faced with an opposing group (Stein, 2001). In addition, intergroup conflict (which arises from divergent interests between groups) may enhance intragroup cohesiveness and cooperation (Tajfel and Turner, 1979). Seeking to overcome the limitations of rational choice theory and relative deprivation, group identity was stressed as the driver of internal and ethnic conflict. This approach, known as the "culturalist" argument, gained popularity with the end of the Cold War and the increasing recognition of internal and ethnic conflicts. The argument places ethnic or religious differences at the source of conflict. With the end of the Cold War, Huntington (1996) hypothesized that "The most important distinctions among peoples are [no longer] ideological, political, or economic. They are cultural." Connor (1994) asserts that the real source of collective violence is ethnic nationalism. Culturalists stress the role of ethnic elites in generating ethnic insecurity, the importance of ethnic stereotyping in the creation of enemy images, and the culmination of these factors into a security dilemma (Brubaker and Laitin, 1998). The security dilemma occurs when the actions of one group in response to "other" are perceived by "other" to be threatening and aggressive. The fears engendered by the ambiguity of these actions culminate into a "self-fulfilling prophecy" that can lead to violence (Stein, 2001). While the culturalist argument highlights the diverse ethnic and religious identities of many of the states in conflict, it cannot explain why collective violence ensues in some places but not others, and why only some participate in the collective and others do not (Brubaker and Laitin, 1998).

Other theorists have extended the culturalist argument, attempting to differentiate between the conditions that lead to collective action and those that do not. They state that while differentiation of ethnic identity is necessary, it is not sufficient to explain the emergence of identity conflict. Gurr (2001) cites collective incentives, capacity, and opportunity in the political environment, in addition to ethnic identity, as potential precursors to collective action. Shared incentives (which build on the causes of relative deprivation) and a salient ethnic identity are preconditions for mobilization. This creates a mutually reinforcing dynamic that drives collective action in response to a new opportunity. Stein (2001) argues that images shape our interests and in turn shape our identity, a fundamental human need. This can lead to the creation of enemy images and turn into violence. She looks to describe the underlying terrain necessary for collective violence to ensue, including state weakness and resource scarcity. Escalation to violence can occur when the recognition of another group's identity is perceived to compromise their own, when granting rights to others is perceived as neglect of ones own rights, and when one fears preemptive action from the other group. In addition, manipulation of certain organization and communication channels by elites can infuse more fire. These conditions in turn can lead to a situation of the security dilemma, spiraling into a situation of violence. Brown (2001) combines ethnic identity and enemy images with several other underlying issues necessary for collective violence. He also places more emphasis on elite actions and decisions and less on individual and group behavior. Assuming the appropriate terrain is set given these factors, Brown stresses the importance of "catalytic" factors, or proximate causes, of internal conflict. Placing the focus on identity as the main source of conflict, identity theory challenges rational choice theory, which emphasizes that a groups resort to violence is a rational result of self-interests.

2.1.4 Humanistic Needs Theory

Another approach hones in on the deprivation of needs as a precondition for conflict. One of the earliest theorists on the subject, Maslow (1954, 1943) developed a hierarchy of needs. These needs were grouped into five categories: psychological, safety, belongingness/love, esteem, and self-actualization. Sites (1973), who recognized the importance of Maslow's (1954) framework, identified eight fundamental needs required to produce "normal" (non-deviant, non-violent) individual behavior. Burton (1979), although not the first to theorize on the subject, is probably most closely identified with the theory of basic human needs. Burton argued that the needs most fundamental to the human condition are identity, recognition, security, and personal development. When a state fails to provide these basic needs to its residents, conflict emerges as humans drive to satisfy their unmet needs. Similarly to other theorists, Burton emphasized identity as the most significant driver of the prevailing ethnic conflicts. Azar (1991, 1990) draws heavily on human needs theory and the culturalist paradigm, especially the process upon which enemy stereotypes are generated, in his framework for the analysis of protracted social conflict. Azar identified four preconditions for conflict: the relationship between identity groups and the state, the deprivation of needs as outlined by Burton (1979), weak states and their failure to provide basic human needs, and international linkages (Ramsbotham et al., 2005). Similarly to Stein (2001) and Brown's (2001) framework, the "terrain" predisposed to conflict must be triggered by a certain process. Azar calls these determinants and groups them into three categories: communal-level, state-level, and "self-reinforcing built-in mechanisms of conflict." These mechanisms are the mutually reinforcing dynamics of war (Gurr, 2001), also known as positive feedback, that often lead to the security dilemma.

2.1.5 Opportunity-Based Theory

Recent empirical work has posed doubt on the culturalist and needs argument, stressing the importance of opportunity in addition to motivation, willingness, or shared group identity. Fearon and Laitin (2003) argue that religious and ethnic grievances are too broad and too common to be causes of conflict. Proposing instead that conditions that favor insurgency, such as weak governments and opportunity, along with motivation (or willingness) are much stronger indicators of war (consistent with Cioffi-Revilla and Starr, 2003; Most and Starr, 1989). Utilizing a more robust dataset than in earlier works (Collier and Hoeffler, 2004), Collier et al. (2009) cite opportunity in the form of financial and military feasibility as the core driver of rebellion. On the other hand, Lujala et al. (2005) add identity, along with opportunity and motivation, as a necessary precondition for conflict in what they call a "three-factor model of rebellion," largely inspired by Gurr (1970). Additionally, Ellingsen (2000) uses the same three preconditions, labeling them frustration, opportunity, and identity. Opportunity can come in the form of financing, the availability of recruits, and the ability to garner these resources with relative ease. This ability may be due to factors such as geography, economics, and the availability of resources. The more geographically concentrated rebels and potential recruits are to each other, the easier it is to "overcome" problems in collective action and to mobilize (Lujala et al., 2005; Toft, 2002; Weidmann, 2009). It can also be economic as there is an associated cost for each recruit. For example, the lower the recruits' foregone income, the more likely they are to join the rebellion (Collier and Hoeffler, 2004; Collier, 2000a; Collier et al., 2009; Fearon and Laitin, 2003). Others have focused on the financing of war through "lootable" resources. Among some of the first to suggest that the abundance of natural resources may increase the chance for war were Collier and Hoeffler (2004, 1998) and Collier et al. (2009). Lujala et al. (2005) relates the looting of abundant natural resources to an economic opportunity for rebels. Le Billon (2001), while agreeing that lootable resources are a factor in violent conflict, argues further that the spatial dispersion of a resource is a major defining feature of a war, impacting the type of rebellion and length of the war (this theory is further explored in Chapter 5).

2.2 Earlier Models of Violent Collective Action

This section provides a review of those models most relevant to this dissertation, many of which applied some of the theories of conflict reviewed in the previous section. Empirical analysis of conflict has used statistical techniques (e.g., regression analysis and complexity modeling) (Section 2.2.1), has applied GIS to add a geospatial element to the analysis (Section 2.2.2), and has focused on SNA to study important social ties and relationships, whether over social space or geographic space (Section 2.2.3). SD models, which were seen as an improvement over traditional statistical modeling, provided the first social simulations of conflict (Section 2.2.4). With the advent of sufficient computing power, ABM, which can model at the individual-level, gained popularity as an innovative approach for simulating the social dynamics of conflict (Section 2.2.5).

2.2.1 Statistical Models

Using statistical techniques, such as regression analysis and neural networks, many of the models here looked to better define the causal elements behind violent collective action, often drawing from the theories of conflict surveyed in Section 2.1. The Minorities at Risk (MAR) Project (2009), for example, was developed in 1986 as an effort to code all ethnic groups with political significance. It was used to test the link between group- and state-level variables on the magnitude of ethno-political conflict (Gurr, 1994). Gurr's (1993) analysis of ethnic conflict in the 1980s analyzed variables associated with the "deprivation" (see Section 2.1.1) and "mobilization" (see Section 2.1.5) theories of conflict. Regressions showed that group and economic disadvantages are correlated to the grievances and demands of an ethnic group, but the most significant determinant of protest and rebellion is prior mobilization for political action. Fearon and Laitin (1999) used a modified version of the MAR dataset to further explore opportunity-based factors of conflict (see Section 2.1.5), finding empirical regularities (1) between poverty or the slow rate of growth of a country and the chance that the group is involved in large-scale armed violence, and (2) between urban or geographically dispersed groups and the likelihood to engage in large-scale violence. Cederman and Girardin (2007), drawing from identity (see Section 2.1.3) and opportunity-based theories (see Section 2.1.5), explored the link between ethnicity and conflict. Utilizing data from Eurasia and North Africa in their regressions, they argued that certain ethnic patterns are more likely to cause an outbreak of violence. Collier (2000a), on the other hand, looked at economic opportunity (see Section 2.1.5) and its link to civil war. Using empirical data over a period of 34 years (1965-1999), he argued that a rebel group's ability to raise revenue is a critical factor in that country's risk of civil war; providing evidence for his argument that the economic aspects of war is critical and something that has been largely missed by governments and the international community. Using data compiled by the State Failure Task Force (a task force set-up by Vice President Gore in 1994), King and Zeng (2001) built and improved upon the task force's earlier analysis. They developed a neural network statistical model using variables from the original analysis, such as democracy, trade openness, and infant mortality. In addition, they added military population, which allowed them to take a "resource" or opportunity (rather than grievance) approach, and population density, which provided an indicator of how "near" people may be to others with opposing views (see Section 2.1.5). Through this analysis, they described a series of empirical regularities in the data, such as the effect of democracy, infant mortality, and the size of the military on the risk of state failure.

Taking a complexity approach to the statistical analysis of violent events, studies have shown that conflict-related social phenomena can follow a highly skewed distribution. While these studies have not placed as much focus on the causal mechanisms of conflict or on hypothesizing a particular theory of conflict, they provide support to the thought that dynamic social systems of conflict are often not in equilibrium, and therefore, are a complex system. One of earliest, and most notable studies in the field is Richardson's (1948) work, which looked at the intensity of wars (defined as any "quarrel" resulting in at least one death) over a 125 year period. He found that the frequency of wars as a function of severity (number of casualties) follows a power law distribution. Extending this work, Clauset et al. (2007) used empirical data to look at terrorist events since 1968. They found that terrorist attacks show a similar property of "scale invariance" (a property of power law distributions), implying that there is qualitatively no difference between large and small events. In addition, they find that this property holds when the data is controlled for several factors, including the type of weapon used and the economic development of the target country. Similarly, Telesca and Lovallo (2006) analyzed terrorist attacks within the same time period, but focused instead on the time lapse between these events, finding that time follows a "long-range power-law correlated process." Using a power law model, they looked at the scaling exponent by the severity (in terms of number killed and injured) of events. As the severity of the included events increased, the scaling exponent, and thus the correlation between events and time, decreased. Johnson et al. (2006), on the other hand, compared the patterns of violence across three ongoing conflicts. Also looking at the severity of events using the same definition as Telesca and Lovallo (2006) in the existing conflicts in Iraq, Afghanistan, and Colombia, they found that all follow the same power law behavior. This suggests that the three insurgencies (which may be very distinct in terms of ideology, motivation, and terrain) are in fact similar from an operational perspective, characterized by the continuous process of mergers and divisions of attack units within the insurgency. Bohorquez et al. (2009) concurrently studied severity (focusing mainly on number of deaths) and timing of violent events (the number of events in a time period). They looked at almost 55,000 violent events across nine insurgent conflicts. Applying Clauset et al.'s (2007) methodology for estimating power law distributions, they found that size distributions follow power law behavior. Timing, on the other hand, follows a many (days with few events), some (days with some events), many (days with many events) distribution. Treating insurgents as an ecology of dynamically evolving groups, they developed a model that incorporates group dynamics and group decision-making. The empirical regularities found regarding size and timing are dictated by these mechanisms, providing a unified explanation of "human insurgency."

2.2.2 Geospatial Analysis

Similarly to the statistical models discussed in Section 2.2.1, geospatial analysis of conflict-related data seeks to identify the key variables underlying the emergence, spread, and strength of violent collective action. In addition, it has the unique advantage of providing a spatial perspective to the analysis, allowing us to identify any spatial patterns (Cioffi-Revilla, 2010). Many of the studies that have looked at the relationship between geography and collective violence have been empirical in nature. Using data of terrorist incidents, for instance, studies have taken a geospatial approach to exploring patterns in insurgent activity. Medina et al. (2011) looked at five years of terrorist incident data in Iraq. Analyzing the data in 6-month increments, they identified spatiotemporal patterns of attacks, including that population is correlated with the number of attacks but not the intensity of those attacks (a function of the number of victims) and that the patterns of attacks change over time, providing support to the idea that terrorist networks adapt to the environment and can be influenced by symbolic dates, cultural triggers, and political events such as holidays and elections. Other studies that have applied a spatiotemporal approach to terrorist attack data include Townsley et al. (2008), who found that attacks are clustered in space and time providing support that attack choices are not random, Siebeneck et al. (2009), who used cluster analysis to detect patterns in terrorist activity spaces, and Johnson and Braithwaite (2008), who by analyzing two types of attacks—Improvised Explosive Device (IED) and non-IED—found that spatiotemporal patterns varied by attack type, suggesting distinct insurgent strategies. Spatiotemporal patterns are consistent with choices in attack type, weapon type, and location that are not random, nor are they perfectly rational, providing support to the idea of the boundedly rational agent.

Studies have also focused on opportunity-based causes of conflict (as discussed in Section 2.1.5). Weidmann and Ward (2010) looked at the capacity for geography to add accuracy to forecasts of violent conflict. Using geocoded data and events from the Bosnian conflict in the 1990s, they found that there is a significant link between spatiotemporal factors and the outbreak of violence in Bosnia. Using regressions, other studies have looked at the impact of geography, economic variables, and rebel capacity on the spread and duration of conflict (e.g., Buhaug et al., 2009; Do and Iyer, 2010). In another study, Weidmann (2009) used GIS and conflict data at the level of the ethnic group, finding that the spatial proximity of group members provides an advantage for group coordination, and therefore, collective behavior. Using event or individual-level data of violent incidents, GIS techniques were also employed to evaluate the movement of a conflict (comparing transportation costs to land conflict mortalities) in a region of Brazil (Simmons et al., 2007); to assess the violent "hot spots" of the Chechen conflict (O'Loughlin and Witmer, 2010); and to geospatially identify the deadliest neighborhoods during the conflict of Northern Ireland (Mesev et al., 2009).

Gulden (2002), on the other hand, took a complexity approach seeking to maintain the granularity of the data. He performed a spatiotemporal analysis of the events between 1977 and 1986 during the Guatemala conflict. He found that violence in the municipalities correlated with the ethnic mix of the population. For instance, municipalities with the largest proportion of Mayans (90 to 100 percent of the population) saw a significant number of killings, but the most killings were seen in the municipalities with a large, but smaller proportion of Mayans (80 to 90 percent of the population).

2.2.3 Social Network Analysis

Social networks play an important role in collective violence, attitudes towards a certain group or leader in conflict (e.g., Friedkin and Johnsen, 1999); the flow of ethnic-centric rumors (e.g., Allport and Postman, 1947; Centola and Macy, 2007; Granovetter, 1973); and the influence of family and neighbors in rebellion (e.g., Centola and Macy, 2007; Friedkin, 2001). SNA can also provide a means for better understanding the organizational dynamics of an insurgency and how best to detect and exploit it (Petraeus and Amos, 2006). In addition, there has been focus on identifying key players in terrorist or criminal networks. For example, Krebs (2002) used media reports to map the network of the hijackers in the 9/11 terrorist attacks. Basu (2005), on the other hand, utilized data at the organizational-level to study collaboration of different terrorist groups in India, which provided insight into the organizations that were key players in the conflict. Medina (2014) used SNA techniques, such as network density and centrality measures, in his analysis of Islamist terrorist networks. He found that the network is resilient, which he tested by removing the two dominant hubs and finding that it does not severely damage the network structure. However, few studies have used both SNA techniques over a geography to study situations of conflict. Radil et al. (2010) combined the use of SNA with GIS to explore gang rivalries in a Los Angeles community. Using empirical data of the community, the analysis looked at the geographies of gang rivalry via two lenses of space, ensuring that physical distance and social relations are important. Taking a hybrid approach, Medina and Hepner (2011) used SNA and GIS to study the Islamist terrorist network, providing support to the idea that geographic proximity and social closeness are related (i.e., our social networks are strongly influenced by our physical locations).

2.2.4 System Dynamics Models

One of the earliest computational approaches to modeling violence used SD modeling. SD models can range in scale, from simulations that model the entire world population, to a nation, or a defined subpopulation, such as a group of rioters. This modeling technique was first applied to the corporate world (Forrester, 1961), but turned to the social world with the development of models of urban and socioeconomic dynamics of the world (Forrester, 1971, 1969). Stocks and flows provide the building blocks of any SD model (Radzicki and Taylor, 1997). In a model of conflict, the stocks can represent the collective (e.g., a group of dissidents or rebels) and the flows can represent the diffusion processes of a rumor, a change in available resources, or the social influences to rebel. Building upon Richardson's (1960) theory of arms race, Ruloff (1975) developed a model of difference equations to show the validity of using this type of modeling technique to gain insight into conflict systems. Similarly, Milstein and Mitchell (1969) modeled the arms race of the Vietnam War and that prior to WWI. SD models of warfare have studied a diverse range of conflicts, examples vary from the conflicts of South Sudan, Yugoslavia and Afghanistan (Stahel, 1985), to notional rival groups to demonstrate the nonlinear dynamics and interactions between aggregate-level groups (Wolfson et al., 1992). More recently, SD models were developed to better understand state stability and the propensity for state failure and collapse. For example, Choucri et al. (2007), assessed the dynamics associated with threats to stability on the resilience of the state. McDowall (2012) looked at the impact of the 2011 London riots on the prison system, a region that views punishment by jail time as the best deterrent to crime. Using a set of feedback loops to model the behavior of the prison system, McDowall assessed the impact of this theory on prison capacity and resources. Finding, for instance, that short prison sentences for rioters has long-term consequences as the overcrowding pressures on the prison system forces the early release of other prisoners.

2.2.5 Agent-Based Models

While SD models only capture the world at the aggregate-level (Gilbert and Troitzsch, 2005), ABM allows us to model the individual, localized behavior of agents from the bottom-up. The classic Schelling (1969), Sakoda (1971), and Sugarscape (Epstein and Axtell, 1996) models demonstrate the emergence of spatially explicit patterns through simple rules. For these classic models and many of the models discussed here, geography in the form of real or notional locations, terrain, and spatial proximity to agents or things (in addition to the spatially explicit macro-level outcomes) play critical roles in the analysis of the complex systems being modeled. In addition, using a regular lattice (or grid) these models create neighbor, genealogical, and friendship networks. The localized interactions that occur through simple network structures are critical to generating the dynamic processes behind the social phenomena being modeled.

One of the earliest ABMs of conflict was Axelrod's (1993) model of the emergence of new political actors. In this simple model of ten agents, each actor represents an autonomous political entity (e.g., nation or state). Inspired by theories that coercion has played an integral role in the formation of new states (Tilly, 1990, 1985), Axelrod employs agent decision rules that follow a "pay or else" strategy. Actors can demand tribute from one of the neighbors, or an actor in their alliance. That actor then has the choice to pay the tribute or fight. These dynamics see the emergence of aggregate-level new actors, thus generating higher levels of organization from local-level interactions. Epstein and Axtell's (1996) Sugarscape model, on the other hand, takes an individual-level approach to combat. In its simplest form, agents move around an environment dispersed with various amounts of sugar. Agents search within their vision for the patch with the greatest amount of sugar and then move to that location. Simple rules are later applied to create neighbor, genealogical, and friendship networks. Cultural transmission occurs through these networks, creating identity "groups" (see Section 2.1.3). Combat is then modeled as individuals of one group "fight" those in the opposing group for their resources (in this case, sugar). Using some of the same principles underlying the Sugarscape model, an ABM of the prehistoric Anasazi farming groups in northeastern Arizona is one of the first to use empirical data to create a "real world" environment (Axtell et al., 2002). The model simulates early society in the prehistoric Long House Valley region of northeastern Arizona, and is used to understand the rise and collapse of a collective. Focusing on individual-level behaviors in a setting of civil unrest, Epstein's (2002) Civil War model is probably the most notable ABM of conflict. Set in an abstract environment of discrete cells, an agent's decision to rebel or remain quite is based on a threshold calculation, which is a function of individual hardship and risk aversion. From this simple agent rule, it is found that punctuated equilibrium emerges in the system: long periods of stability are punctuated by large outbursts of violence.

Similar to Axelrod's (1993) model of political actors, more recent ABM's have used state-like agents, including Cederman's (2002, 2001, 2003) models, which explored the use of ABM at a larger-scale, looking at the processes behind democratic cooperation, interstate war, state-formation, and the transformation of geopolitical boundaries. GeoSim (Cederman, 2003), inspired by Richardson's (1948) finding that the size of wars follows a power law distribution, introduced the notion of self-organized criticality as the model generates power laws in a geopolitical context. Another model that introduced some form of social complexity includes the Iruba model, which was loosely based on the guerrilla warfare that ensued in Ireland (1919-1921) and Cuba (1956-1959) (Doran, 2005). This model extended Epstein's (2002) model, looking to create a landscape and agent population that better represented actual areas of guerrilla warfare, consisting of several autonomous regions with varying terrain and population. Model results demonstrated a situation of positive feedback. The more insurgents modeled, the greater the likelihood for success. This increased public support for the movement and subsequently increased the number of insurgents. The ISAAC (Irreducible Semi-Autonomous Adaptive Combat) model explored land combat as a complex adaptive system, modeling agents at the combat-level, from infantrymen to transport vehicles (Ilachinski, 2004). The insurgency model was further explored by Bennett (2008). He modeled civilians, insurgents, and soldiers, finding that the perception of fear and anger in the general population is a critical factor in the success of counterinsurgency tactics. Creating agents whose type, relationships, and behaviors are grounded on empirical case studies, Alam and Geller (2012) developed a hybrid ABM and SD model to concurrently simulate the power structures and the guerrilla warfare, respectively, in Afghanistan. They find that variables such as technology, public support, and social structures (i.e., the social groups and the relationships between the individuals in these groups) effect the outbreak of violence.

Some of models have focused on the emergence of organized criminal networks in a neighborhood or area of a city. Pint et al. (2010) explored how basic human needs (see Section 2.1.4), social influences, and environmental factors impact the emergence and spread of organized crime in two neighborhoods in Rio de Janeiro, Brazil. Model results found that even when the government meets the needs of one neighborhood, gang presence can "spill-over" to neighboring areas. In another model of gang networks, Hegemann et al. (2011) built an ABM of gang rivalries within a policing division in Los Angeles. The environment was created to represent the geographic area and gang networks formed through the individual interactions of agents, where movement was based on theories of human mobility. They found that the simulated gang rivalry networks were similar to observed networks.

Casilli and Tubaro's (2012) ABM of political unrest built on Epstein's (2002) model. Motivated by the recent 2011 wave of political unrest, from the Arab Spring to the UK riots, it explored the impact of social media on violence intensity. Bhavnani and Ross' (2003) model investigated recent theory on the emergence of rebellion – in that over the past couple decades popular rebellion has often emerged from the middle class. With a focus on political versus economic issues contrary to relative deprivation and scarcity theories (see Section 2.1.1), these uprisings began with pressure from below, not from the ruling elite (see Section 2.1.5). They found that polarization in the population yields model results that may be unexpected and that are hard to predict. Torrens and McDaniel (2012) built on the "socioemotional" structure of Epstein's (2002) model, in its use of hardship, legitimacy, and grievance indicators, in their ABM of riots. They added a new level of geographic sophistication, however, allowing agents to deploy more realistic spatial behavior as they interact with other agents and the environment. The model is used to explore several scenarios, which have the potential to be applied to the management of riots.

Rational choice theory tells us that the rational individual given the high cost of participation will always choose to free ride (see Section 2.1.2). In an attempt to explain collective action given the free rider problem, rational choice theorists have proposed a bottom-up solution; in the sense that informal norms emerge through the social interactions of actors (Kitts, 2006). Through these interactions, actors are influenced by others to forego their selfish interests for the good of the collective. Although not an ABM, Granovetter (1978) provided an early attempt at modeling collective behavior from the bottom-up, focusing on individual preferences and their interactions. He argued that norms, preferences, and motives are a necessary but insufficient explanation for collective action, one must also account for the social interactions of the actors in question. In his models, individuals were assumed to be rational and have unique "threshold" preferences. While his past models of cooperation took a rational choice approach to game theory (Axelrod, 1984), Axelrod (1997) adapted an earlier 2-person Prisoner's Dilemma model to explore norm formation and the free rider problem. Agents played a "norms game." In this case, however, perfect rationality is not assumed. Instead agents use a "trial-and-error" approach. For norms to emerge, however, he found that another mechanism was needed, which he called "metanorms." These were associated with the punishment around norm violation. Hammond and Axelrod (2006) further explored cooperation and built on their earlier work and the role of ethnocentrism, which they described as a predisposition for in-group favoritism. An evolutionary ABM was developed and the emergence of ethnocentric behavior was observed.

Lustick (2000) explored identity theory (see Section 2.1.3) in his ABM, whereby agents can have an activated identity as well as a repertoire of latent identities. He observed the response of an agent's identity (which are activated, deactivated, and maintained) to a set of rules built on a changing incentive structure. Bhavnani and Miodownik (2009), in an ABM, observed the impact of ethnic polarization on the onset of conflict as ethnic salience was allowed to vary or remain fixed. Bhavnani (2006) sought to understand the dynamics of mass participation by reluctant Hutu in the Rwandan genocide through the use of an ABM. In doing so, he focused on in-group dynamics of those sharing the same ethnic identity and observed how in-group interactions impacted ethnic norms and supported interethnic violence or cooperation. Similarly, Bhavnani et al. (2009) explored the dynamics of ethnic-centric rumors on the promotion of violence in a different ABM. They find that while group leaders are not required for rumor propagation, their actions influence rumor dynamics. Using GIS to build empirically grounded environments, Weidmann and Salehyan (2013) and Bhavnani et al. (2014) explored the role of ethnic segregation on the onset of violence. Weidmann and Salehyan's (2013) ABM examined the role that the 2007 U.S. led troop surge and ethnic segregation patterns in the city of Baghdad had on the reduction of violence. They find that minimal levels of policing activity can significantly reduce violence. On the other hand, a timely response is critical to success. Inspired by Weidmann and Salehyan's (2013) work, Bhavnani et al. (2014) explored the role of ethnic segregation in an urban environment, using Jerusalem as the test case. In contrast to Weidmann and Salehyan (2013), however, who focused on geographic proximity and spatial patterns, they focused particularly on intergroup relationship in social space. While reducing intergroup interactions on geographic space, through efforts such as restricting movement and agent migration or creating environments of clustered segregation, reduced conflict, the effect is greatly dependent on also maintaining social distance between members of the groups.

Other models have included opportunity (see Section 2.1.5), in the form of natural resources, economic inventive, or lootable resources, as a critical factor that drives agent behavior. Miodownik and Bhavnani (2011) examined the effects of ethnic minority rule and natural resources on the onset of civil war. Similarly, Bhavnani et al.'s (2008) model (called REsCape) studied the relationship between natural resources, ethnicity, and civil war. Users have the ability to specify a resource profile, such as purely agrarian, artisanal mining (i.e., alluvial diamonds), and industrial excavation (i.e., kimberlite diamonds), and observe the dynamics of the conflict. Miodownik (2006) examined the role of cultural differences and economic incentives on regional autonomy mobilization. He found that pronounced cultural differences and strong economic incentives contributed to the emergence of political boundaries, minority support, and minority clustering. RebeLand (Cioffi-Revilla and Rouleau, 2010) built on current computational models, including REscape and Iruba. The government and rebel organizations must compete for the population’s support. The government sought to maintain legitimacy and capacity as it looked to prevent state collapse and subsequent regime change.

2.3 Summary

By providing a broad survey of theories of conflict and a review of prior models of conflict, the purpose of this chapter was to lay the groundwork for the remainder of this dissertation. The models developed for this dissertation draw heavily from the theories of conflict discussed in Section 2.1, including identity, humanistic needs, and opportunity-based theories. As highlighted, relative deprivation and rational choice theory have too many shortcomings and are not applied in the models developed here. While relative deprivation falls short in explaining why conflict does not always emerge in situations of deprivation, rational choice theory relies too heavily on the rational agents cost-benefit of joining the collective. Identity, humanistic needs, and opportunity-based theories in combination, on the other hand, offer a solid foundation for which to explore modeling human behavior in a conflict setting.

Furthermore, prior models of conflict provided the building blocks necessary for the development of the models developed as part of this dissertation. Many of the statistical and geospatial models discussed draw from theory as they test hypothesis in an attempt to gain insight into the causes of conflict. Studies provide support to several behavioral assumptions, for which I draw from, such as the relationship between the geographic concentration of groups (e.g., Buhaug et al., 2009; Fearon and Laitin, 1999; Weidmann, 2009), ethnicity (e.g., Cederman and Girardin, 2007), and economic or resource opportunities (e.g., Collier, 2000a; Do and Iyer, 2010; King and Zeng, 2001) on the outbreak of conflict. While these studies cannot model behavior, through the spatiotemporal patterns found several studies have provided support to the idea of the boundedly rational agent (e.g., Medina et al., 2011; Siebeneck et al., 2009; Townsley et al., 2008). While early work in conflict analysis paved the way for accounting for the nonlinearities of the complex system through complexity modeling (e.g., Richardson, 1948) and SD models (e.g., Ruloff, 1975), more recent studies have provided continued support and new insights into specific conflicts (e.g., Bohorquez et al., 2009; Clauset et al., 2007; Gulden, 2002; Johnson et al., 2006; McDowall, 2012; Telesca and Lovallo, 2006).

Finding correlations between variables at the macro-level does not imply understanding of the underlying dynamics (Gordon, 2010). While many statistical models take a top-down approach, the addition of SNA allows for the study conflict of at the individual-level (Krebs, 2002; Medina, 2014). Furthermore, some took a hybrid approach, studying both the physical and social space of conflict (e.g., Medina and Hepner, 2011; Radil et al., 2010), an approach I draw upon. However, they fall short in their ability to explore theory beyond the results found in the data; you cannot simulate forward and observe the dynamics as initial conditions are varied. They also take static pictures of a conflict in time, struggling to analyze geographic and temporal dynamics concurrently except to take snapshots of the conflict across regular time periods. A limitation I seek to address in each model developed for this dissertation.

In addition, the ABMs developed in this dissertation are largely inspired by Epstein's (2002) early civil war model and build on the ideas behind many of the models discussed here, including the emergence of collective identity and ethnocentric behavior (e.g., Bhavnani and Miodownik, 2009; Lustick, 2000), the diffusion of ethnic-centric beliefs through agent interactions (e.g., Axelrod, 1997b; Bhavnani et al., 2009), the application of humanistic needs theory to drive agent behavior (Pint et al., 2010), the utilization of a terrain that resembles reality (e.g., Axtell et al., 2002; Doran, 2005), the use of SNA to track interactions (e.g., Hegemann et al., 2011) and the inclusion of opportunity, whether from natural/lootable resources or the proximity and influence of rebellious agents (e.g., Bhavnani et al., 2008; Miodownik and Bhavnani, 2011; Miodownik, 2006). While many of the models discussed here use ABM, SNA, and GIS, most do so in isolation. In addition, the application of theory to model human behavior in the ABMs is limited, the implementation of theory using an existing framework for modeling human behavior adds an additional level of realism and sophistication to the models here. With the groundwork set, the next chapter focuses on modeling violent collective action as a complex system and modeling human behavior in models of conflict.

3. MODELING VIOLENT COLLECTIVE ACTION AS A COMPLEX SYSTEM

Violent collective action, a subfield of conflict studies, is a complex system, consisting of individuals with unique attributes that interact with other individuals through interconnected networks on a heterogeneous environment (Demmers, 2012). In order to represent a complex system, we must model it from the bottom-up, as the only way to generate the macro-behaviors is by modeling the individual, micro-level components of the system (Miller and Page, 2007; Schelling, 1978). In its ability to model complex systems, a computational approach is ideal. Furthermore, the main actors in these conflicts are humans, understanding human behavior and how to model it is critical to creating realistic ABMs of complex systems. Modeling violent collective action requires an approach that takes into consideration the unique challenges and nature of these types of conflict (Lederach, 1999), such challenges must account for the fact that violent collective action is a complex system and that the main actor in the collective is human.

This chapter begins by defining complexity theory in Section 3.1. The case for modeling violent collective action as a complex system is then discussed in Section 3.2. Section 3.3 examines existing frameworks and general theories for modeling human behavior. Next, Section 3.4 discusses the need for an approach that integrates computational methods (e.g., ABM, GIS, and SNA) to models of violent collective action. Finally, the case studies used to implement three computational approaches to modeling violent collective action are outlined in Section 3.5.

3.1 What is Complexity Theory?

If you were to look up and find a flock of birds flying south for the winter, you might assume that the voyage began with the leader of the flock coordinating its followers to move in the symmetrical pattern seen. But could this collective behavior have actually emerged from the bottom-up? An ABM was developed to explore this theory. In the model by Reynolds (1987), agents (in this case birds) are provided with three simple rules: (1) move in the direction that nearby birds are moving, (2) turn to avoid another bird that is too close, and (3) move towards other nearby birds. Initially, birds are placed randomly on the grid, but once the model begins to run birds soon move into formation. What looks like the highly coordinated actions of a leader is actually the result of individual-level behavior and interactions. A complex system is one in which understanding perfectly the behavior of the component parts of a system does not imply understanding the system as the whole (Manson et al., 2012; Miller and Page, 2007; Root, 2013). Implemented in a very simple model, this example illustrates that by simply observing the aggregate (a seemingly coordinated flock of birds), we cannot always discern the underlying individual behaviors (simple rules for how the birds should move). What looks like coordinated activity from an organizer, may be collective behavior that emerged from simple bottom-up processes.

Complexity theory refers to the study of complex systems; a system where the whole is bigger and different from the "sum of the parts" (Anderson, 1972). In order to represent a complex system, we must model from the bottom-up, as the only way for which to generate the macro-behaviors is by modeling the individual, micro-level components of the system. Using Reynolds's (1987) model as an example, we find that computational models have the ability to represent complex systems, which can provide understandings of the system that were not originally known to the modeler (Miller and Page, 2007). The ability to model from the bottom-up, and therefore the local, non-linear interactions of agents, is a key requirement for emergence to occur; defined as the notion that micro-level processes aggregate into macro-processes that seems to be "disconnected from its origin" (Miller and Page, 2007). Schelling (1978) describes a variety of other situations where aggregate behavior does not necessarily explain individual behavior. Examples can range from an "awkward" seating arrangement in an auditorium, to the use (or non-use) of helmets to ride a motorcycle, to traffic jams, to neighborhood segregation. Complexity arises because the social world is made-up of many dependent and inter-related components, people do not exist in pure isolation. The decisions and actions of an individual often depends on others decisions and actions, or even just on the anticipation of others decisions or actions (Root, 2013; Schelling, 1978). Social networks exacerbate these actions as agents become closely coupled to one another. Such behavior can be reinforcing, thus creating a situation of positive feedback and instability (also known as organized complexity) (Schelling, 1978). The result of such a system is that agent interactions become highly nonlinear, the system becomes difficult to decompose, and complexity ensues (Root, 2013).

3.2 Why Model Violent Collective Action Computationally?

Conflict, in the form of violent collective action, is a complex, dynamic social construct (as discussed in Section 1.1). It is often fought between groups of heterogeneous individuals in different warring parties on an environment, which too, is heterogeneous and unique. As a complex system, exploring collective violence requires that we study many actors with dynamic and evolving interaction patterns (Axelrod, 1997b). To solve this type of problem using traditional mathematics would be very difficult and finding a tractable solution might not be possible. This makes computer simulation ideal, and the primary tool for modeling problems of complexity theory (Axelrod, 1997b). In addition, the focus placed on bottom-up processes in conflict (de Rouen and Sobek, 2004; Fearon and Laitin, 2003; Kalyvas, 2006; Lederach, 1999) has helped drive the move towards a computational approach to studying violent collective action. The simple, stylized example of flocks of birds gives evidence to the utility of computational modeling as an approach to exploring the underlying processes of collective action. For more complex models seeking to simulate real world settings, ABM may be combined with GIS, which provides a unique advantage in its ability to create a realistic spatial landscape for which agents can interact (Crooks and Castle, 2012). In addition, relationships, interactions, and communication, in the form of social networks, whether at the individual- or organizational-level, are important. Adding social networks to computational models provides an additional degree of realism to the problem being modeled. ABM, GIS, and SNA provide powerful methods for which to create our artificial world, such that we can explore the formation, spread, and strength of violent collective action.

The most important advantage to computational modeling is that it provides the ability to represent complex systems. Lederach (1999) argues that when it comes to conflict and understanding its dynamics we must study the relationship between the macro-level system and the micro-level processes. In an environment of conflict, organized complexity can lead to the security dilemma, spiraling into a mutually reinforcing situation of violence (Gurr, 2001; Stein, 2001). The intractable, or protracted, nature of many of today's conflict brings with it a "uniquely human dimension" (Lederach, 1999). This suggests that standardized formulas aimed at understanding conflict do not work (Lederach, 1999). ABM provides the ability to add a greater level of realism to models of conflict. The use of GIS allows agents to interact on an environment that represents actual geographic locations, while SNA provides realistic agent interaction over social networks.

In addition, ABM provides the ability to model heterogeneous agents and environments (Axtell, 2000). Miller and Page (2007) argue that heterogeneity of individuals and the environment is often a "key driving force" in the social world. In order to model such a world, we must have the ability to introduce agents with unique attributes who can interact with an environment, which too is unique. The decision to rebel and join collective violence is individual. Individual attributes and preferences matter, and at the same time these individual preferences are dynamic, often influenced by the changing conflict environment and the decisions of others around them. The salience of an ethnic identity highlights the fact that the individuals sharing that ethnic identity have unique attributes or characteristics. Even when a cohesive group shares a collective identity, the individuals in those identity groups maintain their heterogeneity. This makes for individual and group identities that are dynamic and changing. Regions experiencing violence are spatially heterogeneous, states are made up of heterogeneous populations with multiple ethnic identities, they may have terrain that is varied, residents may live in ethnically segregated neighborhoods, or they may be near (or far from) illicit resources. GIS, in its ability to place agents' in actual geographical locations, makes it easier to model the heterogeneous environment of the agent world. Because GIS can represent the world as a series of layers and objects of different types, it can be translated into an ABM. Traditional tools, which tend to focus on the "average" behavior of one representative agent in a homogeneous environment, would therefore be oversimplified and provide potentially misleading results (Miller and Page, 2007).

Although rational choice models of collective action assume perfect rationality, computational methods give the modeler the option to assume this is or is not the case. ABMs can model boundedly rational agents (Axtell, 2000), who have vision and knowledge limited to their geographic location and social networks. According to Simon (1996), bounded rationality is a factor of substantive and procedural rationality, whereby our ability to adjust to our outer environment (substantive rationality) is limited by our ability to find the appropriate adaptive behavior (procedural rationality). This directly refutes the idea behind the perfectly rational, utility maximizing economic actor that is so often used in our traditional tools and rational choice models of conflict, and instead, suggests that we are "satisficers," who are willing to accept "good enough" alternatives. According to Lederach (1999), the dynamics of conflict makes purely rational methods inappropriate for conflict resolution. Actors in conflict are not perfectly rational, profit optimizing agents. The decision to rebel is often more complicated than economic motivation and opportunity. An ABM that does not assume rational agents is unlikely to result in the single, most optimal solution, but experimental data shows that "satisficing" agents are more realistic (Simon, 1996).

Nations, cities, and neighborhoods are made-up of diverse components (e.g., neighborhoods, transportation routes) that are constantly changing at different rates and that reflect a system that is "far-from-equilibrium" (Batty, 2005). Although GIS is not well suited for dynamic modeling (Crooks and Castle, 2012), ABM is ideal (Axtell, 2000). Integrating the two techniques gives us the ability to model an adaptive and changing environment that is geographically realistic. The decisions of individuals are not made in complete isolation; riots, ethnic clashes, and rebellion do not emerge due to the workings of some centralized authority, collective action is often a result of many decentralized decisions and is sometimes based purely on anticipation of others' actions (Root, 2013; Schelling, 1978). People are autonomous; they are free to choose their identities. This makes ethnic identity groups dynamic and changing, their boundaries are fluid as individual intensity levels for certain identities change. But traditional approaches, with their assumption that the world operates in a state of equilibrium, fail to take any of these characteristics of the real world into account.

Implementation of local interactions into any model is a key requirement for emergence to occur. ABMs ability to produce emergent phenomena is directly related to its ability to model the localized interactions of agents. Tobler's (1970) first law of geography states that "everything is related to everything else, but near things are more related than distant things." In other words, localized interactions matter. GIS gives us the ability to model emergence through the local interactions that occur over physical space (Crooks and Castle, 2012). Geography also plays a role when it comes to the distance between warring parties, as conflicting groups typically live in close geographic proximity (Lederach, 1999). Thus "group geography" provides an opportunity for conflict (as discussed in Section 2.1.5). While GIS provides the advantage of modeling distance and actual locations, SNA gives the ability to model the relationships, flow of communication, and interactions of agents. Relationships are important (Lederach, 1999), who and how we interact with others can influence behavior. In addition, the position of individuals in a network might say something about how agents communicate, as well as the amount of influence agents may have on one another. The spread of information through social networks can impact the agent's knowledge, which can impact agent behavior (the application of social networks in theories of human behavior is discussed further in Sections 3.3.1.1 and 3.3.1.2). Additionally, SNA provides the advantage of being able to model interactions that are not necessarily physically near; social networks may be geographically concentrated or may span neighborhoods, countries, or regions (Wal and Boschma, 2009).

Violent collective action occurs on an environment that is heterogeneous, dynamic, and far from equilibrium. It emerges through the localized interactions of boundedly rational individuals, all whom have diverse identities, needs, and interests (consistent with Demmers, 2012; Lederach, 1999). ABM allows us to model this bottom-up process on an environment that can be made more realistic through the use of GIS and SNA. The recent increase in the number of ABMs used to explore topics in the field of conflict (as discussed in Section 2.2.5) gives support to the idea that using a bottom-up approach makes sense for the study of collective violence. This dissertation seeks to build on this momentum, providing further legitimacy to the use of a computational, bottom-up approach in the study of collective violence.

3.3 Modeling Human Behavior

Humans do not behave randomly; our actions and decision are based on our individual characteristics, our interactions, and our environments (Kennedy, 2012). On the other hand, our cognitive abilities are bounded and we seldom behave in ways that mimic the perfectly rational, profit-maximizing agent (Simon, 1996). Modeling human behavior is not a simple task (Kennedy, 2012); it requires a level of understanding that goes beyond these two extremes. Computational modeling allows us to model the boundedly rational agent, which interacts and makes decisions based on imperfect cognitive knowledge. In this section, we discuss several general theories of human behavior that can be applied to computational models (Section 3.3.1) and existing cognitive frameworks that can help guide the implementation of behavior in models of social phenomena (Section 3.3.2).

3.3.1 Theories of Human Behavior

This section provides background on some general theories of human behavior. It is not meant to encompass all theories of human behavior, as the literature is vast, but to highlight those most relevant to this dissertation and, although they have broader application, is often cited in situations of conflict (see Section 2.1). These theories, which include a unified theory of identity (Section 3.3.1.1), social influence theory (Section 3.3.1.2), and humanistic needs theory (Section 3.3.1.3), have been used to understand human behavior in diverse settings that may go beyond, but include, situations of violent collective action.

3.3.1.1 A Unified Theory of Identity

Identity, as it relates to the emergence of violent collective action, was discussed in Section 2.1.3. Here we take a more detailed look at the inner workings of the theory and how it relates to human behavior from a more general perspective. Identity theory focuses on the concept of identities as roles (McCall and Simmons, 1978). It is the way a person is or wishes to be known by others (Stein, 2001) and how that translates to "being and acting" in that role (McCall and Simmons, 1978). Social identity theory, on the other hand, involves the concept of social groups, where a group is a "collection of individuals" who identify with the same social category (Tajfel and Turner, 1979). Social identity is derived from an individual's membership in such a group (Hogg and Abrams, 1988; Stein, 2001). This identification can be compared to other social groups as "better" or "worse," creating a distinction between "us" and "them" (Tajfel and Turner, 1979). Hogg et al. (1995) outline the similarities and differences between the two theories and while they suggest that it may be possible to integrate certain aspects of the two theories, focus is placed on the strengths of each theory in isolation. Stets and Burke (2000), on the other hand, argue that there are sufficient similarities between social identity theory and identity theory that a unified theory can be developed.

Individuals have an array of identities that range from "me" identities to "us" identities (Oyserman et al., 2012) and by combining group-based and role-based identities into one theory, Stets and Burke (2000) integrate collective identity with the individual, heterogeneous identities of group members. This allows for the dynamic modeling of individual and group identities under one theory of identity. In this unified theory, an identity is defined as a self-categorization based on our representation of the meanings associated with a social category, such as ethnicity, gender, group membership, or a social role. It provides a way to order the social environment and define one's "place in society" (Tajfel and Turner, 1979). Together, these identities make up an individual's self-concept, which are cognitive structures that include an idea of what one believes or thinks to be oneself (Oyserman et al., 2012). These set of identities are organized in a hierarchical fashion and reflect an individual's priorities and fit in the situation (McCall and Simmons, 1978). The activated identity is one that is currently directing behavior, while identity salience is the probability that the identity will be activated in a given situation (Stets and Burke, 2000). Salience is a function of several factors, including:

- Commitment, or the embeddedness of an individual in a social structure (Stets and Burke, 2000; Stryker and Burke, 2000);
- The fit of the identity with the situation (i.e., the probability that the identity will be activated in a given situation) (Oyserman et al., 2012; Stets and Burke, 2000); and
- The characteristics of the identity, such as its accessibility (Stets and Burke, 2000).

Social networks play a critical role in identity theory in general, and identity salience in particular. According to Stryker and Burke (2000), our identities are a reflection of our social networks. An important aspect of commitment, for instance, is the number of connections (or density of ties) a person has by holding a certain identity. This is a function of (1) the number of other individuals someone is connected to that holds the same identity and (2) the strength of the relationship (e.g., number of interactions) with those individuals. In turn, the connectedness of an identity increases its salience (Stryker and Burke, 2000), which impacts the fit of the identity in the given situation. These social networks also serve as boundaries limiting the chance that a person will enter into an outside social structure (Stryker and Burke, 2000).

Once an identity is activated, an individual will compare the output behavior associated with the identity to the identity standard (or prototype), which contains the set of meanings and norms associated with the social category. This comparison process is known as the self-verification process. In identity theory, this process involves a social role, while in social identity theory this involves seeing oneself as the in-group prototype of a social group rather than a unique individual. This process (the Identity Model) is shown at a high-level in Figure 3-1.

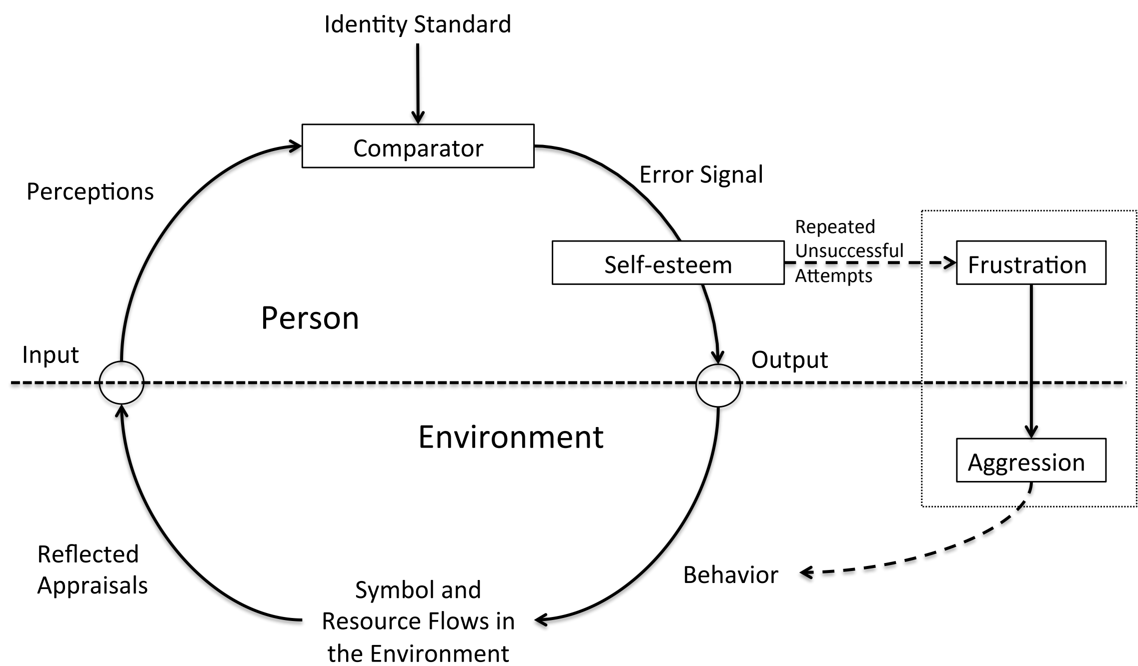

Figure 3-1. The Identity Model and the Frustration-Aggression Hypothesis (adapted from Burke and Stets, 2009; Green, 2001).

An identity has four main components organized into a control system: an Input, an Identity Standard, a Comparator, and an Output. Perceptions, which make-up what we see of the Environment, comprise the Input. The Comparator's job is to compare the Perceptions associated with the identity to the Identity Standard. The Comparator will then Output an Error Signal – the difference between the Perceptions and the Identity

Standard. The Output forms the Behavior of the Person, which occurs in the Environment and is based on the Error Signal. Thus, the relationship between the Perceptions and the Identity Standard (through use of the Comparator) predicts Behavior (Stryker and Burke, 2000).

This process forms a continuous loop; a cycle of meanings organized as a control system. Input Perceptions are continuously fed into the system and Output Behavior adjusted as the individual seeks to represent the Identity Standard. Self-verification involves making the (perceived) meanings in the situation correspond to the meanings in the Identity Standard. If successful, the result includes increased cohesion and commitment to others with the same identity, shared membership in a group, and increased Self-esteem. If unsuccessful, however, one is likely to experience negative emotional impact such as feelings of distress and hostility (Cast and Burke, 2002). These feelings increase with the degree of disparity and motivate the individual to take some form of action. Large discrepancies are a sign of some type of interruption in the identity process. An interruption could be a break in the continuous loop, which, for instance, could occur if a person is laid-off from their job abruptly breaking the individual’s “employee” identity. Another type of interruption could occur if a different identity interferes with the self-verification process of a given identity. For example, a student whose ethnic identity has been heightened due to the spread of a rumor and divisive ethnic rhetoric may select to riot along with others in the ethnic group instead of going to school (undermining the individual’s “student” identity). In addition, a lack of personal resources such as education, income, and support from family and friends, can hinder the self-verification process for certain Identity Standards. High-level Identity Standards (general principles and values) are said to guide lower-level Identity Standards (programs of behavior). A family with limited resources (e.g., single parent, low income, poor education) may struggle in the self-verification process of certain Identity Standards (Stryker and Burke, 2000). For example, a lack of resources (income) may mean that a parent cannot afford the school fees for their children, or the family may need supplemental income, requiring their children to work instead of going to school.

An important output of the identity process is Self-esteem, which is defined by how we evaluate ourselves. Individuals will seek to enhance their Self-esteem (McCall and Simmons, 1978; Tajfel and Turner, 1979), which is a function of successes (accomplishments) and goals (aspirations) and can be viewed as a reservoir of "energy" (Burke and Stets, 2009). Self-verification increases an individual's Self-esteem when successful and diminishes it when unsuccessful. The reservoir of energy, which also operates as a type of personal resource or "line of credit," allows one to continue working towards the self-verification process even after unsuccessful attempts (Burke and Stets, 2009; McCall and Simmons, 1978). This is similar to other accumulator models used to model human behavior. These models provide a quantitative means for modeling the time-lapse in human decision-making processes between receiving information and executing a response (Smith and Ratcliff, 2004). This process underlies such phenomena as group cohesiveness, ethnocentrism, cooperation, and collective action (Stets and Burke, 2000).

The Identity Model is a continuous "self-adjusting feedback loop;" as humans, out behavior is constantly adjusted in an effort to make perceptions of meanings in the situation match our internal Identity Standards (Burke and Stets, 2009). As the energy reservoir diminishes and Self-esteem lowers, distress or Frustration may increase. This Frustration could potentially lead to more severe aggressive behaviors (Green, 2001). According to the frustration-aggression hypothesis, Frustration produces the environment for which one can aggress, and Aggression cannot occur prior to Frustration. However, Aggression does not always result from prolonged Frustration (Green, 2001). Available resources, such as Self-esteem, can help individuals cope with certain levels of Frustration. The frustration-aggression hypothesis can be used as a general model of civil unrest. While Frustration can result from the dissatisfaction (or distress) of not meeting certain desires and societal expectations (e.g., unsuccessful attempts at identity verification), Aggression has been connected to riots, wars, and other forms of violence (Green, 2001). These concepts are examined further and applied to the models discussed in Chapters 5 and 6.

3.3.1.2 Social Influence Theory

In Section 2.1.5, I discussed opportunity-based theories of conflict. Opportunity can be in the form of natural resources, economic factors, or the availability of potential recruits (Collier and Hoeffler, 2004; Collier, 2000a; Collier et al., 2009; Fearon and Laitin, 2003; Le Billon, 2008; Lujala et al., 2005). Empirical studies have shown that the geographic concentration of rebels and potential recruits makes it easier to mobilize, and thus increases the likelihood for collective violence (Lujala et al., 2005; Toft, 2002;

Weidmann, 2009). But empirical analysis cannot explain how or why high concentrations of potential recruits lead to rebel behavior. Social influence theory helps provide an explanatory bridge between the physical presence of potential recruits to the rebel behavior of a collective. In identity theory and social identity theory we strive to meet the norms of a certain identity standard, which can be an in-group prototype of a social group (Stets and Burke, 2000). Social influence, on the other hand, concerns the underlying processes by which these norms emerge in social groups to create an identity standard.

Attitudes and norms, and the process by which these phenomena emerge in groups, are very similar. While attitudes are defined as a positive or negative assessment of some "object" by a person, norms are defined as a "feeling, thought, or action" of a person in a given context (Friedkin, 2001). Classic sociological theories of norm formation include Sherif (1936) and Festinger (1954, 1950). Sherif (1936) shows that the individual disparities within a group will begin to converge if disagreements are expressed, or put to light. In addition, when similar circumstances arise in future experiences, the individual's judgment on the topic will be shaped based on the final attitude resulting from the group consensus. This study shows that individual's will revise their own attitudes based on the feelings and thoughts of others in situations of uncertainty or conflict (Friedkin, 2001). Festinger (1950) proposes that Sherif's conclusions go beyond just the sampled experiments and provide the "key mechanism" for which individual's validate their opinions in situations of conflict and uncertainty. He further suggests that individuals form attitudes via a comparison process, whereby we weigh and integrate the different attitudes. This process provides validation of one's own attitude, of which prior attitudes are unstable and fluid (Friedkin, 2001). Other classic sociological theories have honed in on the process of social control, which refers to the process of producing shared agreement, and subsequently guides the collective action of the group (e.g., Janowitz, 1975). However, these theories do not provide a formal methodology that describes the underlying opinion formation process (Friedkin and Johnsen, 1999).

"Combinatorial" sociological theories of norm formation have focused on group consensus when there is an initial state of disagreement. According to Friedkin (2001), these combinatorial theories have significant implications on the emergence of norms. One of these includes Friedkin and Johnsen's (1999) Social Influence Network Theory. Based on the theory, an individual's final opinion, $y^{(\infty)}$, on an issue is a function of their initial opinion on the issue, their relative interpersonal influence, and their susceptibility to influence. A person's final opinion can thus be determined by Equation 3-1.

Equation 3-1. Final opinion (Friedkin and Johnsen, 1999).

$$y^{(\infty)} = Vy^{(1)},$$

where $y^{(1)}$ is an $N \times 1$ vector of actors' initial opinions on an issue and V is an $N \times N$ vector of total interpersonal influence. V is calculated as shown in Equation 3-2.

Equation 3-2. Total interpersonal influence (Friedkin and Johnsen, 1999).[1]
$V = (I - AW)^{-1}(I - A),$

where $W = [w_{ij}]$ is an N x N matrix of interpersonal influences $\left(0 \leq w_{ij} \leq 1, \sum_j^N w_{ij} = 1\right)$ and $A = diag(a_{11}, a_{22}, \dots, a_{NN})$ is an $N \times N$ diagonal matrix of actors' susceptibility to interpersonal influence on the issue $(0 \leq a_{ij} \leq 1, a_{ij} = 0 \; when \; i \neq j)$.

Building on this, Friedkin (2001) develops a structural approach for determining opinion formation, an approach that is particularly useful in situations where the only information available is the communication network. This approach applies methods from SNA, including structural equivalence (which looks at how identical the ties, or relationships, to and from an actor to all other actors are in a network) and centrality (a measure of the importance of actors in a social network) (Wasserman and Faust, 2009). According to Friedkin (2001), the structural equivalence of the actors in the network is a measure of their initial opinion (the more similar actors are in terms of structural equivalence, the more likely they are to share a similar opinion on the issue). In addition, an actor's susceptibility to influence can be measured by the centrality of the resident in the network. The decision to rebel is largely based on social influence. The first ABM developed for this dissertation applies a simple threshold calculation, whereby geographic concentration, which provides an opportunity to rebel (as discussed in Section

[1] $V = (I - AW)^{-1}(I - A)$ assumes $I - AW$ is nonsingular. Otherwise, V can be estimated from the following: $V^{(t-1)} = (AW)^{(t-1)} + [\sum_{t-2}^{k=0}(AW)^k(I - A)]$, where I is the identity matrix.

2.1.5), is used as a proxy measure for social influence. The more physically near agents are to one another, the more likely to be influenced. The second model, on the other hand, is more robust and through its application of SNA allows for the implementation of Friedkin's (2001) structural approach, which is a more realistic representation of human behavior and social influence. According to Granovetter (1973), the analysis of interpersonal influence networks provides "the most fruitful micro-macro bridge." It is these networks that allow localized interactions to transform into global, large-scale patterns (Granovetter, 1973).

3.3.1.3 Humanistic Needs Theory

Many of the routine activities we perform on a day-to-day basis are driven by humanistic needs theory, which were discussed in Section 2.1.4. While Sites (1973) and Burton (1979) identify the set of basic human needs, whose absence can lead to the emergence of conflict, one of the earliest theorists on the subject, Maslow (1954) developed a hierarchy of all-inclusive needs. Maslow's (1954) earlier and most cited hierarchy includes five categories: physiological, safety, love and belonging, esteem, and self-actualization (Koltko-Rivera, 2006).[2] Figure 3-2 illustrates the five-stage model of needs.

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[2] This model was later expanded to include additional motivational levels, such as self-transcendence (Koltko-Rivera, 2006). However, for the purposes of the behavior modeled as part of this dissertation, the additional levels are beyond the scope of the models, and the more widely cited five-stage model is used.

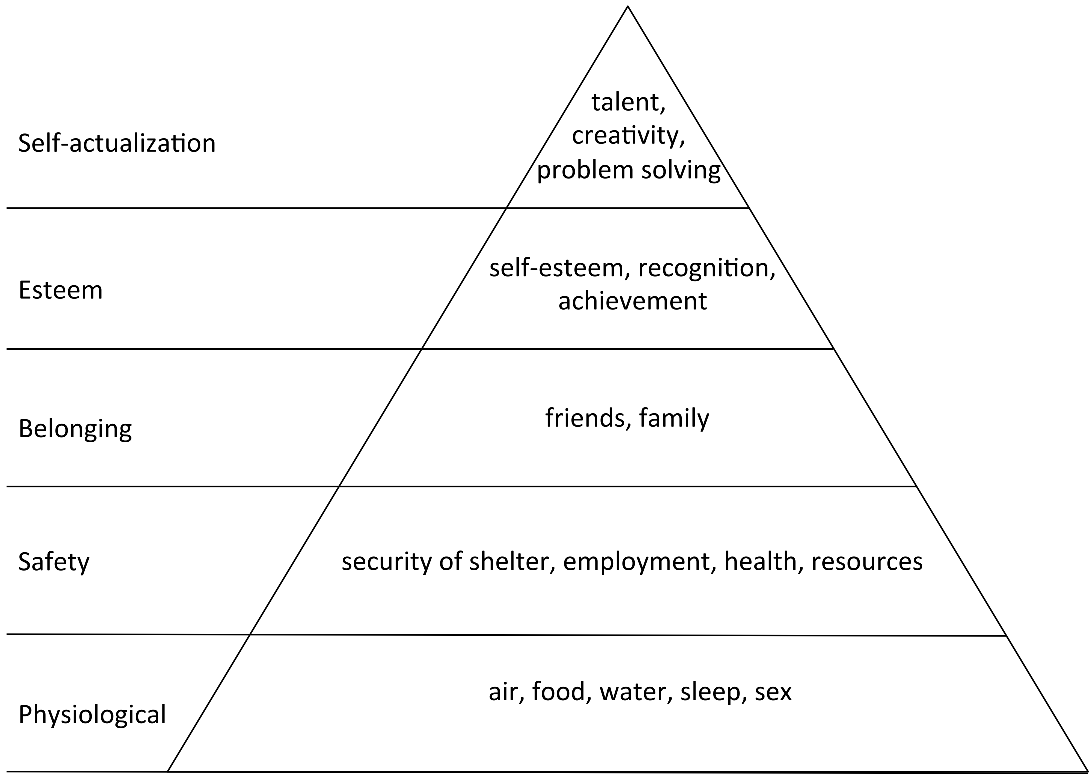

Figure 3-2. Maslow’s five-level hierarchy of needs (adapted from Maslow, 1954).

While individuals may wish to seek multiple motivations at the same time, the different levels of motivation provide an order by which the needs are met. Maslow's (1954) hierarchy of needs goes beyond the most fundamental level of needs and provides an all inclusive set of needs, which at varying motivational levels help drive the daily actions of individual behavior, in situations of conflict or peace. This theory is the primary driver of agents’ day-to-day activities in the ABMs developed here. While the first ABM models simpler behavior using Maslow's (1954) two most fundamental levels of needs (Chapters 5), the second ABM applies a more complete spectrum of human needs (Chapter 6).

3.3.2 Frameworks for Modeling Human Behavior

While theories of identity, human needs, information diffusion and social influence give us a grounded understanding of human behavior; the question remains as to how we incorporate such a diverse range of topics into a model. Creating an architecture that accurately represents human behavior is one of the biggest challenges associated with developing ABMs of the social world (Malleson et al., 2012). For this reason, the models developed for this dissertation will utilize an existing cognitive framework.

Behavior in ABMs can be represented in one of three ways. The first is using mathematical formulations (e.g., if/then statements and threshold calculations) that drive agent behavior, such as in Epstein's (2002) Civil War model. The second involves the use of cognitive architectures that focus on human cognition. The third uses conceptual frameworks that provide more abstract architectures for modeling behavior (Kennedy, 2012). While mathematical approaches may provide the simplest approach to implementing agent behavior, cognitive architectures are more complicated, but can also be very computationally expensive. Examples of cognitive architectures includes Soar (Laird, 2012; Lehman et al., 2006), an Artificial Intelligence system designed to simulate human performance on a variety of tasks, and ACT-R (Atomic Components of Thought-Rational) (Anderson and Lebiere, 1998; Anderson, 2007), which has been shown to simulate certain cognitive functions, but does not support higher-level processes, such as beliefs or desires. Conceptual frameworks include “fast and frugal,” the BDI (Beliefs, Desires, and Intentions) architecture, and the PECS (Physical conditions, Emotional state, Cognitive capabilities, and Social status) framework (Kennedy, 2012). Fast and frugal (Gigerenzer and Todd, 1999) provides a computationally inexpensive option to implementing decision-making processes in agents. However, by modeling behavior in a simple decision tree format, it does not account well for higher-level behaviors, such as emotion, acts of will, and social belonging. The BDI architecture, which is most commonly used today in models of human behavior, and the PECS framework, which provides a flexible framework for developing models of human behavior, are discussed in more detail in the sections that follow. The PECS framework is used to implement behavior in the models developed for this dissertation.

3.3.2.1 Beliefs, Desires, and Intentions

BDI (Rao and Georgeff, 1995, 1991) represents, respectively, the information, motivational, and deliberative components of the system. It is currently the most widely used architecture for modeling human behavior (Malleson et al., 2012), and has been used in a variety of applications, including air traffic management systems (Rao and Georgeff, 1995), the animation of characters in a virtual environment (Torres et al., 2003), operations in a container terminal in the shipping industry (Lokuge and Alahakoon, 2004), models of criminal analysis and prevention (Brantingham et al., 2005), and an adapted version is used to simulate geo-political conflict (Taylor et al., 2004). Beliefs are the agent's knowledge about the environment, desires contain information about the priorities and payoffs associated with the current objectives, and intentions represent the chosen course of action. BDI uses a decision tree process and deliberation function to determine the best course of action to achieve a goal. This process is transformed into an equivalent model representing the agent's beliefs, desires, and intentions. BDI agents are assumed to be perfectly rational, relying on payoff and utility maximizing functions to select goals and determine the optimal action sequence for which to achieve those goals. The strict assumption of rationality may not be ideal for modeling situations of violent collective action (Rao and Georgeff, 1995). In addition, the architecture is very general, providing only a theoretical framework for modeling human cognition (Kennedy, 2012).

3.3.2.2 The PECS Framework

The PECS framework, proposed by Schmidt (2000) and Urban (2000), states that human behavior is shaped by the individual's Physical conditions, Emotional state, Cognitive capabilities, and Social status (Malleson, 2008). PECS views agents as a psychosomatic unit with cognitive capabilities residing in a social environment. The PECS agent consists of seven main components, which can be grouped into three categories from systems theory—inputs, state variables, and outputs. The inputs are responsible for passing in and filtering the information received from the environment; the state variables process the information and develop an action plan; outputs determine the action-guiding motive with the strongest intensity, defines the action sequence, and executes the actions (Schmidt, 2002, 2000). Figure 3-3 shows the high-level structure of the PECS agent.

The two inputs are Sensor and Perception. The Sensor component takes the information from the environment and passes it on to Perception, which then filters the

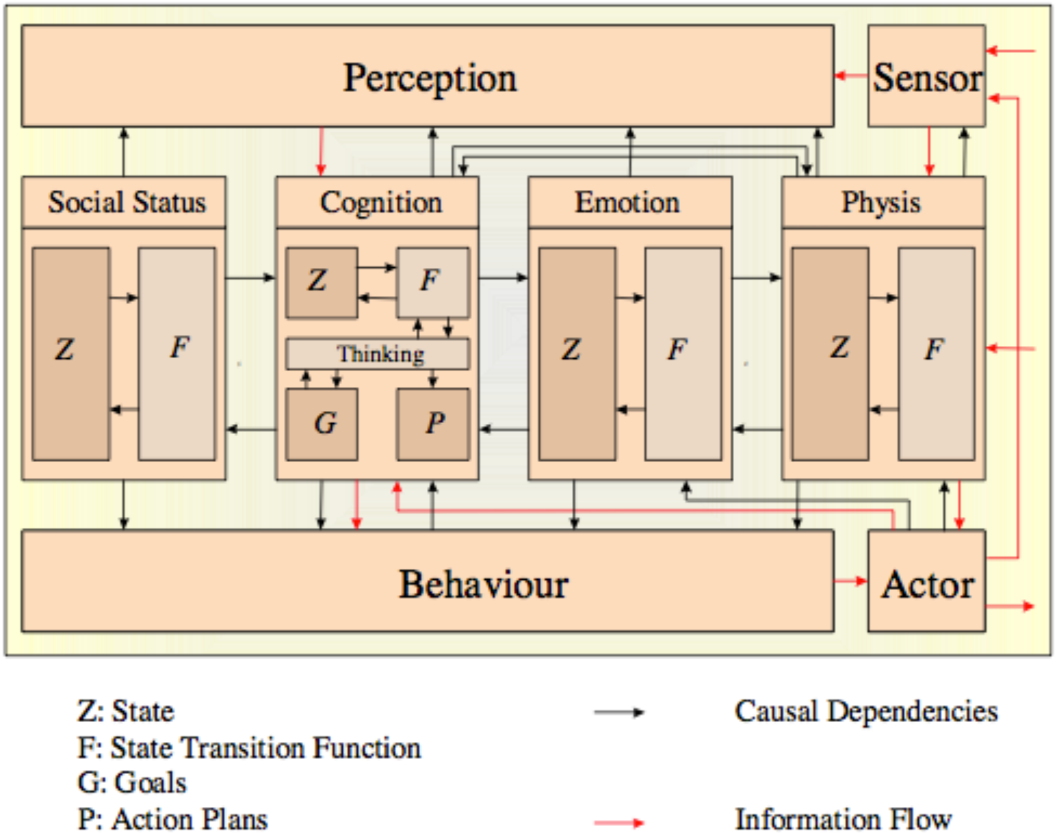

Figure 3-3. The structure of the PECS agent (source Schmidt, 2002).

information ensuring that only important information is passed on to Cognition. The PECS agent has four groups of state variables: Physis, Emotion, Cognition, and Social Status. Depending on the complexity and purpose of the model, one or more of these state variables may be used. Physis contains variables that describe the physical state of an agent, such as blood pressure, eyesight, or energy level. Emotion contains the set of emotions an agent is capable of drawing from. These may include joy, fear, and aggression. Cognition is the most intricate component and is divided further into several subcomponents, including the self model, environment model, protocol model, planning, and reflection. Each of which can contain their own set of state variables and transition functions. The self and environment models ensure agents maintain an internal model of themselves and their environment. The protocol model serves as the agent's memory, gathering and storing information on prior action plans and pursued goals. Planning is responsible for drawing up an action plan (i.e., a sequence of individual partial sub-goals) so that the agent can reach its goal. The reflection component exchanges information with the other four subcomponents in Cognition to monitor, evaluate, and improve upon current internal processes. Social Status describes the agent's social position or social satisfaction. For simple variables, the information is sent directly to Behavior. Otherwise, an action plan is developed first in Cognition and is then sent to Behavior. The two components that make up the outputs of the PECS agent are Behavior and Actor. Behavior determines the action-guiding motive from the intensities received from one or more state variables. Given the action-guiding motive and the action plan received from Cognition, Behavior is able to generate the action sequence (i.e., the execution order of the actions to be taken). Actor receives the action sequence and executes accordingly.

For simple cases, behavior can be determined directly from the state variables. For most cases, however, state variables only indirectly impact behavior, as behavior is dependent on a set of motives. The Set of possible motives (also called drives, needs, or desires) can be grouped into four general categories: Drive intensity, Emotional intensity, Will intensity, and Intensity of social desire. Agents can have multiple motives, but only one can be acted upon at any given time. Therefore, motives must compete. The intensity levels of the motives are evaluated via an "Intensity Analyzer." The motive with the highest intensity then becomes the Action guiding motive. Motives are associated with a final goal (e.g., the motive "satisfy hunger" would yield the goal "eat food"). Achieving the final goal, and any smaller sub-goals, requires that an action plan and sequence be developed and executed (Malleson, 2008; Schmidt, 2002, 2000). This process is shown in Figure 3-4, from the state variables and Set of possible motives, to the selection of the Action guiding motive (through the Intensity Analyzer) and the Set of possible actions.

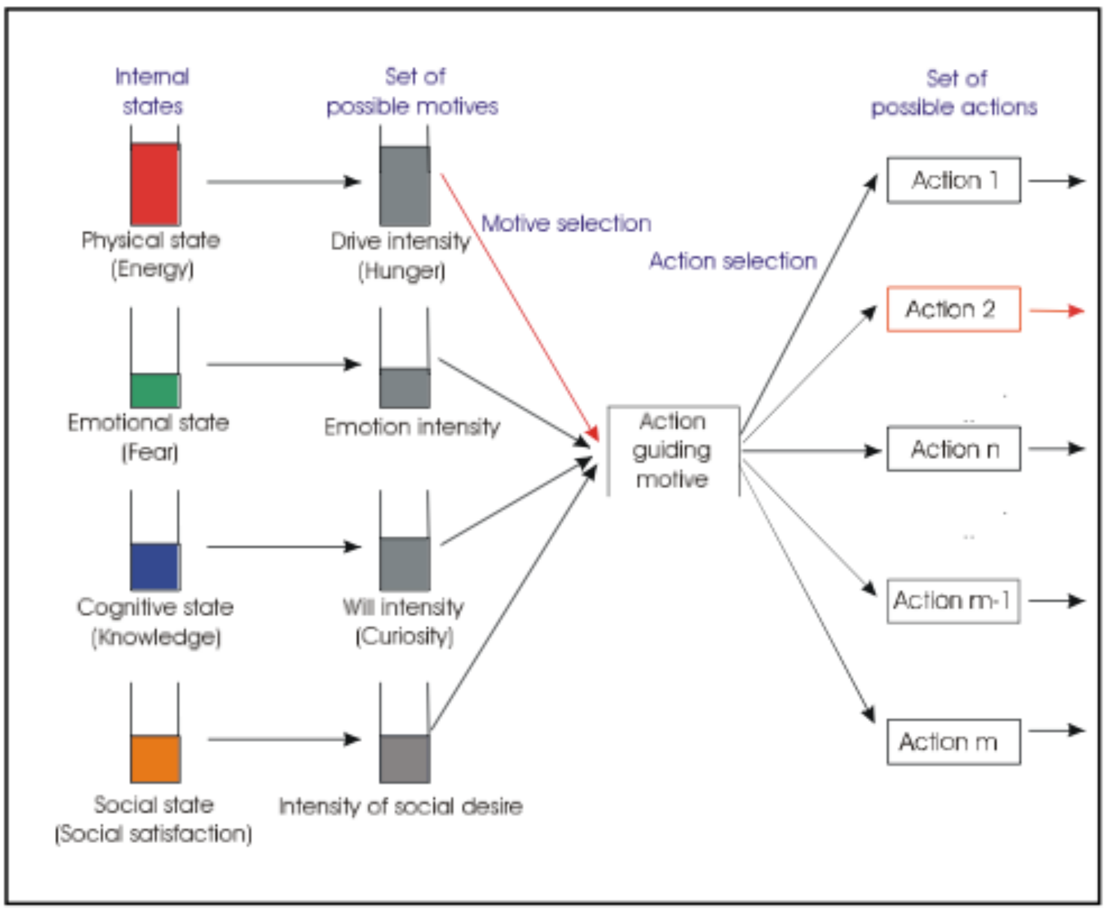

Figure 3-4. The set of motives, motive selection, and the possible set of actions (source Schmidt, 2002).

PECS groups all behavior into one of two groups: reactive and deliberative. Reactive behavior is as an unconscious or internal response to the environment (e.g., a person who is hungry may steal food). It is the simpler of two behaviors; here we assume a set of guiding rules, or actions, that can be called upon when the behavior is to be executed. The actions taken by the agent are "automatic," a function simply of the motive with the highest intensity. While the agents have goals intrinsically, they are not consciously known to the agent. Deliberative behavior, on the other hand, involves the conscious pursuit of goals (e.g., a person chooses to sell drugs for the purposes of gaining power even though other opportunities exist for which to earn adequate income). This involves an act of will, driven by the importance of the goal, distance to completion of the goal, and other influences. More intricate deliberative behavior may require the construction of self or identity, requiring that the agent be fully aware of its internal model (Malleson, 2008; Schmidt, 2002, 2000).

The PECS framework has been successfully implemented in Malleson et al.'s (2012) ABM of residential burglary. Their model simulates the occurrence of crime in a hypothetical city and tests the impact of various crime theories. Although not agent-based, the PECS framework was also used to implement patient behavior into a discrete-event simulation of disease screening (Brailsford and Schmidt, 2003). In addition, models of e-learning use the framework to add emotion into the learning environment (Ammar et al., 2006; Neji and Ammar, 2007). Although use of the framework remains limited, PECS provides certain advantages over other architectures, such as BDI, and is used to implement human behavior in the ABMs developed as part of this dissertation. The PECS framework is flexible due to its ability to model simple stimulus-response behaviors (reactive) and more elaborate reflective behaviors (deliberative). At the same time, it provides more guidance than other cognitive frameworks for implementing human behavior in ABMs (Kennedy, 2012). The PECS framework also takes into account both the internal (cognition) and external (environment, interactions) factors of human behavior. In addition, PECS is not restricted to modeling the perfectly rational, utility maximizing agent, giving us the flexibility to model the boundedly rational agent, which is a more accurate representation of human cognition (Simon, 1996).

3.4 The Need for an Integrative Approach

As noted in Section 2.2, prior models have explored a variety of topics in the field of violent collective action. Some models have taken a complexity approach to the analysis of empirical conflict data (e.g., Bohorquez et al., 2009; Clauset et al., 2007; Johnson et al., 2006; Richardson, 1948). Assuming terrorist groups make decisions around location, weapon, and attack type that are boundedly rational, other studies have looked for spatiotemporal patterns in event data (e.g., Medina et al., 2011; Siebeneck et al., 2009; Townsley et al., 2008). Analyses have combined SNA techniques with GIS to take a geographic look at criminal and terrorist networks (e.g., Medina and Hepner, 2011; Radil et al., 2010). In addition, ABMs have applied theories of conflict, including identity theory, humanistic needs theory, and opportunity-based theories, to help guide the behavior of agents in conflict settings (e.g., Bhavnani and Ross, 2003; Bhavnani et al., 2009, 2008; Miodownik and Bhavnani, 2011; Pint et al., 2010). Many previous ABMs built on some of the classic models of conflict (e.g., Axelrod, 1993; Epstein and Axtell, 1996; Epstein, 2002) provided the groundwork for further exploration through more sophisticated, realistic and theory-driven models (e.g., Casilli and Tubaro, 2012; Torrens and McDaniel, 2012). This dissertation builds on this momentum by providing further enhancements to prior models of conflict.

While the use of social networks was explored in several of these models (e.g., Bhavnani, 2006; Bhavnani et al., 2009; Cederman, 2003; Epstein and Axtell, 1996), none implemented it in an ABM using GIS. In addition, by grounding the agent's cognitive framework in theory through use of the PECS framework, we add a level of behavioral sophistication that goes beyond threshold calculations (e.g., Casilli and Tubaro, 2012; Epstein, 2002; Torrens and McDaniel, 2012). While some models explored identity theory and social influence through social networks (e.g, Bhavnani, 2006; Bhavnani et al., 2009), accounting for both social role and group-based identities in the agent's cognition, social influence that can dynamically evolve as social networks change, and the daily needs and activities of the agents provides a new level of sophistication as agents process their decision to rebel or remain peaceful. The creation of social networks is largely influenced by our physical space, as we are more likely to interact with those geographically near (consistent with Tobler, 1970). GIS facilitates the modeling of these interactions over physical space. Furthermore, using GIS to track events and activities, macro-patterns that arise from micro-processes across both time and geographic space can be observed. The implementation of social networks over a geography, in addition to the sophistication of the cognitive framework, in the models presented here adds a new level of realism to the complex systems being modeled.

While other models have explored the use of ABM, GIS, and SNA in the field of violent collective action, most have explored the techniques in isolation. This dissertation demonstrates the value of integrating the approaches. Simply put, integrating ABM, GIS, and SNA creates models that are more realistic; our interactions are affected by both our physical distance and our social networks. This allows us to model “artificial” worlds that more accurately represent reality, and subsequently, the social phenomena being modeled. In addition, the social world moves forward across time, it is not static. It is important that the temporal nature of the social world be accounted for in each model. By integrating SNA with GIS, which can track both the physical location of an event and the date it took place, a conflict can be analyzed concurrently across time and geographic space. However, we cannot simulate forward beyond the last event, a limitation that can be addressed through an ABM. While it may be difficult to create dynamic models using GIS and SNA alone, ABM is ideal. Using ABM, agent interactions over physical space (using GIS) and social space (using SNA) can be created with relative ease (Axtell, 2000). In addition, ABM allows for the creation of heterogeneous, boundedly rational agents who interact locally within their physical and social space. These interactions can be grounded in theory and implemented using a framework for human behavior. The implementation of these interactions, which are largely impacted by individual interactions via their social networks over a GIS, is a key requirement for emergence to occur. ABM, by allowing us to model complex systems from the bottom-up, provides the key requirement for emergence to occur.

Violent collective action consists of individuals with unique attributes that interact with other individuals within a connected social network over a heterogeneous environment. A bottom-up approach, first at the group-level then at the individual-level, is key to creating a model that represents a complex system. While decisions are made at the individual-level, collective outcomes can be viewed at a macro scale. Traditional top-down approaches, which require a tractable solution and possible oversimplification of these variables, would not be able to capture the emergent phenomenon of collective violence.

3.5 Intermediate Models of Violent Collective Action

Traditionally, the purpose of the model was to apply some theory, and accordingly build and validate a model so that it could be used for purposes of policy analysis (Crooks et al., 2008). As discussed in Section 1.3.1, this has been relaxed, however, and a model can range across the spectrum from theory to practice (Crooks et al., 2008). The purpose of a model and its corresponding verification and validation approach can vary depending on where the model fits in this spectrum. With the relaxation of purpose, the door is open for more types of models. ABMs specifically, can range from stylized, "toy" models that represent some caricature of reality to fully calibrated models that demonstrate quantitative agreement with micro-level processes (Axtell and Epstein, 1994; Crooks et al., 2008; Parker et al., 2003).

According to Axtell and Epstein (1994), this range can be described through four classification levels. These include Level 0 models, which represent a simple caricature of reality, Level 1 models, which seek macro-level qualitative agreement with empirical structures, Level 2 models, which seek macro-level quantitative agreement with empirical data, and Level 3 models, which seek micro-level quantitative agreement with empirical data.[3] Parker et al. (2003), on the other hand, describes this range via an explanatory (i.e., applies some abstraction of reality) to descriptive (i.e., based on empirical details of the social phenomena) continuum. Similarly, Crooks and Castle (2012) developed a matrix categorized into four areas depending on whether the agents and/or the environment are designed (i.e., explanatory) or analyzed (i.e., descriptive). This matrix is illustrated in Table 3-1. The purpose of the model, a rough placement of Axtell and Epstein's (1994) classification scheme, and the verification and validation approach is shown based on where the model fits in relation to the matrix

At the beginning of this range are Level 0 models where both the agents and environment are designed. These are simple, stylized models that seek to uncover some new relationship or test some stylized hypothesis of social phenomena (Axtell and Epstein, 1994; Crooks and Castle, 2012; Parker et al., 2003). Examples include many of the classic ABMs described in Section 2.2.5, such as Schelling's (1969) segregation model, Axelrod's (1993) tribute model, and Epstein's (2002) civil violence model. While simple, these models have provided insights into the social phenomena being modeled.

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[3] Qualitative agreement of model results can be established by comparing plots of agent properties to empirical data (Axtell and Epstein, 1994). Within this dissertation, I use the term qualitative agreement to refer to the verification and validation strategy used for the ABMs.

Table 3-1. A matrix describing modeling purpose and strategy based on its fit in the explanatory-descriptive continuum (Axtell and Epstein, 1994; Crooks and Castle, 2012; Parker et al., 2003).

		Agent	
		Designed	**Analyzed**
Environment	**Designed**	Purpose: Discovery Classification: Level 0 Verification and Validation: Theoretical comparison and replication An Example: Epstein (2002)	Purpose: Laboratory experiments Classification: Level 0 Verification and Validation: Repetition and adequacy of design An Example: Alam and Geller (2012)
	Analyzed	Purpose: Explanation Classification: Level 1 Verification and Validation: Qualitative agreement with macro-structures An Example: Bhavnani et al. (2014)	Purpose: Explanation, projection, scenario analysis Classification: Level 2 or 3 Verification and Validation: Quantitative agreement with macro- and/or micro-structures An Example: Jackson et al. (2008)

On the other hand, the level of abstraction in these models may make results difficult to evaluate in reality (Parker et al., 2003). In addition, they provided the foundation for more recent models of social phenomena, especially in the field of violent collective action (as discussed in Section 2.2.5).

Most ABMs fit somewhere in the range between a Level 1 and Level 2 classification. For instance, Alam and Geller's (2012) hybrid model creates agents that are analyzed, but that interact on a simple grid-based environment divided into four regions. On the other hand, Bhavnani et al.'s (2014) ABM used designed agents but created an environment using GIS that empirically represented the location, population, and housing settlement patterns of the real world location of interest. In addition, they empirically validated the model by comparing observed and actual macro-patterns of violence (these models and others were discussed in more detail in Section 2.2.5).

At the other extreme are Level 2 and 3 models developed with agents and an environment that are analyzed (i.e., grounded in empirical data). These models seek empirical validity, predictive ability, and scenario analysis for purposes of policy guidance (Axtell and Epstein, 1994; Crooks and Castle, 2012; Parker et al., 2003). An example is Jackson et al.'s (2008) model of residential segregation, which used GIS to build an environment that replicates an area of Boston and that showed quantitative agreement through statistical analysis of predicted versus observed land rent costs. While models at this level can replicate real world phenomena across an actual location, they represent a shift away from more general models useful for theory exploration (Parker et al., 2003). To my knowledge, no ABMs in the field of violent collective action have implemented analyzed environments and agents that offer quantitative agreement with macro- or micro-level processes.

The ABMs developed as part of this dissertation fall somewhere in between the two extremes. I refer to them as intermediate models of violent collective action. They are explanatory in their intent to explore theory and test hypothesis, but descriptive in their use of empirical data to build the environment and create the agents. Using GIS an environment that is analyzed is developed, while socioeconomic data endows agents with unique characteristics, and interactions create explicit social networks (dynamic social networks are introduced in Chapter 6). On the other hand, a normative approach to agent behavior is taken. Agents are modeled as they should behave given certain theoretical assumptions of human behavior, especially in situations of conflict (see Section 3.3.1). This application of theory is an important consideration in the field of conflict analysis (see Section 2.1), and as such, has the potential to offer further merit to this approach. On the other hand, without the ability to accurately replicate reality and use model results to perform policy research, the value of a computational approach may be met with skepticism in the field of conflict analysis, where qualitative research and quantitative, top-down approaches have largely been the methods of choice (see Section 2.2). Until this level of model development can be achieved, however, the ABMs developed here represent a significant step in that direction. That being said, the merits of a flexible model that creates a balance between the normative, theoretic and positive, empirically grounded cannot be underscored.

An advantage of creating intermediate models of social phenomena include the exploration of theory, both in model development and in model results, as through “what if” scenarios. Through the ABMs developed as part of this dissertation, I will demonstrate that such models are flexible enough to apply general theories of human behavior and to test existing theory of conflict on environments that represent actual, real world settings. When model runs yield results representative of some macro phenomena seen in reality, support is given to the theory (Parker et al., 2003). While stylized models may prove difficult to translate to a real world situation, empirically detailed, fully calibrated models move away from theory. On the other hand, these models are flexible in that they allow for a normative approach to conflicts in real world locations. We can use these models to test theory, and at the same time, see how it would fit in a real world location, potentially providing new insights into specific environments of conflict. As such, they seek a balance between abstraction and reality. This balance provides a certain level of exploratory flexibility, but at the same time, grounds the model in reality.

Given the challenges associated with empirical validation of environments in conflict, and modeling in general (as discussed in Section 1.3.3), this dissertation implements three instantiations (case studies) into three abstract models of conflict, which demonstrate the value of integrating computational methods into models of violent collective action. As intermediate models of violent collective action, the ABMs developed as part of this dissertation aim to represent a Level 1 classification and seek to show qualitative agreement with observed data. However, the final chapter of this dissertation will discuss how such models could be further developed to represent higher levels in the classification scheme.

3.6 The Case Studies

The models presented in this dissertation represent three instantiations of more general models of violent collective action. These instantiations, or case studies, build on the value of integrating the computational approaches, including ABM, SNA, and GIS. In addition, they serve as building blocks; as layers are added to the environment, more sophisticated behavior is implemented, and the sophistication of the agents' interactions are increased, exploring the use of more advanced ABM, SNA, and GIS techniques. The case studies were selected for their diversity in terms of geographic location, temporal and spatial scale of the collective violence, and the political and cultural issues underlying the violent collective action.

The next three chapters discuss the case studies in detail. Using SNA techniques and simple geographic information, the prevailing conflict in Colombia is first explored (Chapter 4). By simultaneously analyzing the conflict across both time and geographic space, this analysis provides a novel approach to the study of terrorist networks. Next, ABM is combined with GIS to model the ten-year civil war that ravaged Sierra Leone, a small country in western Africa (Chapter 5). Simple human behavior—that is grounded in theory and implemented using the PECS framework's lower levels of behavior (i.e., simple reactive behavior)—is introduced as agents interact on a simple environment that represents the actual conflict setting. Finally, ABM, SNA, and GIS are integrated to explore the emergence of riots in a Kenyan slum (Chapter 6). A level of sophistication that goes beyond the previous two models is added. Dynamic social networks are modeled, allowing us to more fully implement theories of human behavior using the PECS framework's low and high levels of behavior (i.e., reactive and deliberative). GIS is used to develop a realistic environment for agents to move and interact that includes a road network and points of interest (such as schools, religious institutions, and water points). Albeit at different scales, some form of collective violence emerges in all cases; individuals are faced with the decision to join a riot, participate in an insurgency, or rebel.

Regardless of the geographic scale of the conflict (national or local), the network of actors in all conflicts spans widely, across civilians, rebel groups, and the government. Geography (including the physical distance from rebels and spatial dispersion of resources) and social networks (impacting interactions and communication) play important roles in the cases, while ABM allows us to provide agents with human behavior grounded in theory and simulate agent-to-agent and agent-to-environment interactions on a geographically explicit environment. As I draw upon theories of collective violence, from the perspective of the model builder, I am concerned with the application of theory to specific cases of violent collection action. Each model uses empirical data to build real world environments and to inform agents. With increasing levels of sophistication, these models explore the value of using computational methods in an integrative fashion at different scales in varying conflict settings.

4. USING SOCIAL NETWORK ANALYSIS TO EXPLORE THE COLOMBIAN CONFLICT

The Revolutionary Armed Forces of Colombia (FARC) have been in existence for about 50 years, and at one point, were the largest terrorist network in the world. Since the FARC's emergence, Colombia has been in the midst of a civil war that still prevails today. The country's current president has vowed to end the FARC's role in the conflict though peace talks. Using SNA techniques with simple GIS, this chapter takes a spatiotemporal look at the evolution of the FARC. Qualitative research is then performed to gain an understanding of what might be behind the observed macro-patterns. By using SNA to analyze the FARC's evolution across both time and geographic space, this chapter provides a novel approach to the study of terrorist networks. A brief overview of Colombia's history and the FARC's role in the conflict is first discussed in Section 4.1. Next, Section 4.2 provides a detailed description of the computational methods used to analyze the FARC's evolution. The results and findings from the analysis are then summarized in Section 4.3. These findings are further examined in Section 4.4, especially as they compare to the conflict's most intense years. Finally, Section 4.5 provides a summary of the chapter.

4.1 Introduction

Colombia has been in conflict for hundreds of years, from the days of the Spanish inquisition, to the formation of Nueva Granada and Panama's cessation, to today's guerrilla warfare. Beginning in 1849, Colombia held a strong two-party system: the Liberals and the Conservatives. In Colombia, a party-based identity prevailed. The end of the War of Thousand Days (1899-1902), industrial development in the 1920s, and growth of the export-oriented coffee industry brought raised expectations and increased social disparities. It is here that the country saw a major shift; away from the party-based identity to a social class-based identity. And with this shift came a change in the network of groups in conflict: away from "Liberal" versus "Conservative" towards "Left-wing guerrilla" versus "Right-wing paramilitary" (Sanchez and Meertens, 2001).

It was in the unmet objectives of La Violencia (a war over worker's reform and land rights that left approximately 200,000 dead by 1956) (Sanchez and Meertens, 2001), increased state repression, and militaristic force, that the largest Left-wing insurgent group in Colombian history emerged (Hylton, 2006; Saab and Taylor, 2009). In 1964, the Colombian military launched "Operación Marquetalia," an operation designed to remove the rebels and its leader, Marulanda (Hylton, 2006; Ruiz, 2001). The operation forced many families to escape, but together with others in the region, they mobilized. In 1966, during a conference organized by this mobilized group, the FARC was officially born (Hylton, 2006; Rochlin, 2003). Since then, the country has endured almost 50 years of guerrilla warfare, with the FARC at its center (Saab and Taylor, 2009).

Colombia, a country about twice the size of Texas, is bordered by Venezuela to the east, Brazil to south, Ecuador and Peru to the southwest, and the Caribbean Sea and the Pacific Ocean to the west. It consists of 32 departments with the city of Bogota as its capital (CIA World Factbook, 2014). Figure 4-1 provides a map of Colombia with department borders shown, the capital represented by a yellow diamond, and other major cities, in terms of population size, represented by blue circles. With approximately 46 million residents, based on 2014 estimates from the CIA World Factbook (2014), Colombia is Latin America's third most populated country (World Food Programme, 2014) behind Brazil and Mexico. It is considered a middle-income country (U.S. Department of State, 2013) ranking 29th in the world in terms of real GDP (Gross Domestic Product), a GDP that has increased by 4 percent each year over the past three years (CIA World Factbook, 2014). In 2011, with a 43 percent increase, the country saw its highest growth in exports in 25 years. This increase was directly attributed to thriving energy and mining sectors, including gold and other minerals (Monsalve, 2012). Gold, in particular, saw a surge in prices due to increased demand. Between 2008 and 2012, the price of gold more than doubled, from approximately 700 to 1800 U.S. dollars. In addition, the government has placed more focus on gold mining, hoping to increase production as a means to bring "prosperity to all, more jobs, less poverty, and more security" (Vicente et al., 2011).

Despite the economic improvements, 48 percent of its population still lives in poverty and Colombia deals with very high levels of inequality (World Food Programme, 2014). In addition, although a coca eradication campaign has significantly reduced its production in recent years (Leon and Kraul, 2013; The Economist, 2013), Colombia continues to be a producer of illicit commodities such as coca, opium poppy, and cannabis (CIA World Factbook, 2014).

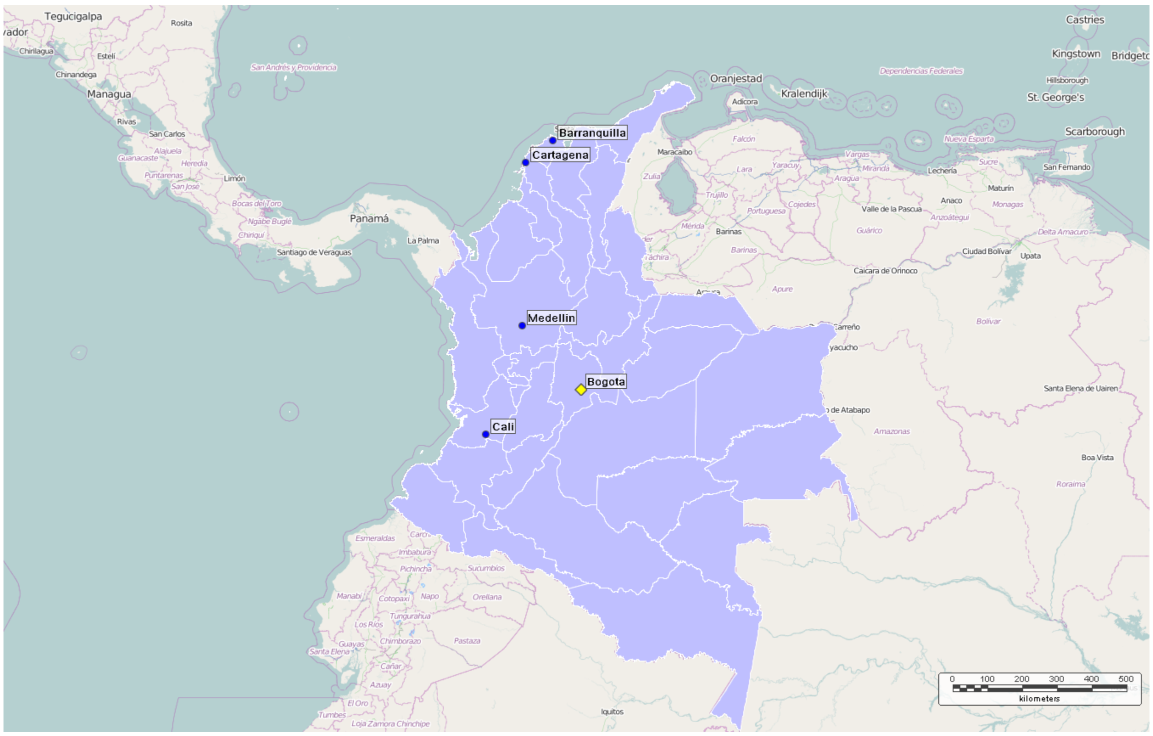


Figure 4-1. A map of Colombia. Bogota, Colombia's capital, is represented as a yellow diamond. Other major cities (in terms of population numbers) are shown as blue circles.

Since its emergence in the 1960s, the FARC has grown significantly during certain periods: state repression gave "cause" to their movement and garnered them more popularity; untimely peace negotiations were taken advantage of and used to strengthen and grow their insurgency; and the boom of the drug trade provided the financing they needed. In 1966, they consisted of 43 combatants (Saab and Taylor, 2009); between

1982 and 1984 alone, the FARC doubled the number of fronts, or subgroups, from 14 to 28 (Hylton, 2006); by 1994 the FARC had 105 fronts (Hylton, 2006); and by 2003, with 20,000 combatants, the FARC had become the largest, best-armed, best-trained insurgency in the world (Kline and Gray, 2007).

Other Left-wing groups and a stronger, more organized Right-wing paramilitary also emerged around the time of the FARC's rise. At the same time of "Operación Marquetalia's" failure in 1964, the government legalized the paramilitary, who masked themselves as civilian "self-defense" groups (Hylton, 2006). Although paramilitary groups were deemed unconstitutional in 1989, the damage had been done as the organizational structure, the support base, and members' sense of identity in the group had already been well established (Kline and Gray, 2007; Mazzei, 2009). Although no other guerrilla group grew to the strength of the FARC, they played significant roles in escalating the conflict. The National Liberation Army (ELN) emerged in 1965 as a Cuban-style Marxist rural insurgency and, behind the FARC, grew to be the second largest guerrilla group in Colombia (Kline and Gray, 2007). The Popular Liberation Army (EPL) formed in 1967 as a Maoist-inspired group (Kline and Gray, 2007; The Economist, 1995), who believed that in the rural developing world, it was the peasantry who would trigger socialist revolution. The 19th of April Movement (M-19) was the last of these Leftist insurgencies to form. Inspired by increasing urban discontent, the M-19 grew to be at one point the second largest insurgency after the FARC (Kline and Gray, 2007). Finally, drug trafficking emerged in the 1980s, after a shift away from the coffee-exporting industry gave way to a coca-driven industry. Drug cartels exploited the industry, collaborated with paramilitary groups, and added an additional level of violence onto the already precarious environment (Hylton, 2006). According to the United Nations (UN) News Service (2013), an estimated 600,000 people have died since the beginning of the insurgency. In addition, 5.2 million have been internally displaced, making it one of the world's worse cases of internally displaced persons (IDPs) (World Food Programme, 2014).

After one and a half years of preliminary discussions, the current administration under Santos began peace negotiations with the FARC in November of 2012 (BBC, 2013a; Neuman, 2012). The country has already gone through two attempts at peace negotiations with the FARC, however, both of which failed and served only to escalate the violence. In both attempts focus was placed solely on the Left-wing guerrillas, which caused the Right-wing paramilitaries to retaliate. The Left-wing then used this retaliation as support for their cause while exploiting the terms of the negotiation. In addition, there is also a matter of timing. During the time of these negotiations the paramilitaries were not considered a "political" group and thus, could not be involved in peace negotiations. Furthermore, the FARC were in an escalatory pattern in terms of their size and strength, and public support for the group was relatively high. Failed peace attempts only served to catapult the escalation dramatically further. Today, the Santos administration hopes that this third attempt at peace negotiations is successful. However, given the history between the Colombian government and the FARC, success is anything but assured.

Using SNA techniques with simple GIS to study the guerrilla warfare that still prevails today, this chapter seeks to gain insight into the Colombian conflict, specifically the FARC's role (see Section 1.3.4 for a background on SNA and GIS). SNA has been used as an approach to understanding covert networks for many years. It provides a means for better understanding the organizational dynamics of an insurgency and how best to detect and exploit it (Petraeus and Amos, 2006). Particularly, there has been focus on identifying key players in a network (e.g., Krebs, 2002; Medina, 2014). When data on individual actors is available, this may be the best to approach to gaining an in-depth understanding of a network. However, data limitations may make this type of analysis difficult, if not impossible. At times, taking an organizational-level view of conflict is required (e.g., Basu, 2005; Radil et al., 2010). While prior analysis has combined SNA techniques with GIS to take a geographic look at criminal or terrorist networks (e.g., Medina and Hepner, 2011; Radil et al., 2010), none to my knowledge have considered concurrent changes to a criminal or terrorist network over both time and geographic space (see Sections 2.2.2 and 2.2.3 for a more detailed literature review). Similarly to Medina et al., (2011), Siebeneck et al. (2009), and Townsley et al. (2008), who found spatiotemporal patterns of terrorist events consisted with bounded rationality, events are assumed not be random. The choices associated with the location, weapon, type of attack, among other incident characteristics, are made as part of a decision-making process that is boundedly rational.

This chapter takes a spatiotemporal look at the evolution of the FARC. Event data, which provides information on the perpetrator (e.g., terrorist organization), the date, the location, and the attack characteristics, is ideal for this approach. As is often the case with conflict data, however, the individual responsible may not be provided, instead some information on the perpetrator at the organizational-level may be known. A "group" in this analysis is the perpetrator responsible for the attack (i.e., the FARC), the location of the event, and the year the event took place. By creating groups with location and date information, we are able to effectively use event data to study the FARC organization across both time and geographic space.

4.2 Method of Analysis

A combination of SNA and qualitative research are used to analyze how the FARC network has evolved since 1975. As discussed in Section 1.3.4, SNA studies the relationship between people, things, organizations, or events (called nodes), while relationships, or the edges between the nodes, can be defined in terms of kinship, interactions, affiliations, or information flows (Wasserman and Faust, 2009). For the purpose of this analysis, centrality measures and hierarchical clustering are used to study changes in the FARC network across time and geographic space. Centrality measures will allow us to identity, from a spatiotemporal perspective, those events most important or representative of the conflict as a whole, giving us a better picture of the conflict and any high-level trends. Clustering, on the other hand, is used to take an in-depth look at the conflict today, particularly focusing on the years since the current administration came to power, giving us insight into how today's conflict might compare to previous years.

4.2.1 The Data

Publicly available datasets with conflict event data include (but are not limited to) the Uppsala Conflict Data Program/Peace Research Institute Oslo (UCDP/PRIO) Armed Conflict Dataset (Gleditsch et al., 2002), the Conflict and Peace Data Bank (COPDAB) (Azar, 2009), the World Event Interaction Survey (WEIS) (McClelland, 1999), the Behavior Correlates of War (BCOW) (Leng, 1995), the Global Data on Events, Languages, and Tone (GDELT) (Leetaru and Schrodt, 2013), and the National Consortium for the Study of Terrorism and Response to Terrorism's (START, 2012) Global Terrorism Database (GTD). While a few of these datasets include event data of the location and time period of interest, GTD data provides a level of detail on each event that is most appropriate for this analysis. In addition, the data is manually coded providing a greater degree of accuracy. The GTD is an open database on terrorist events around the world. It was developed and continues to be maintained START (2012) and is based out of the University of Maryland. The dataset includes over 7,500 events from 1970 to 2012. However, as there are no coded FARC-related events until 1975, the remainder of this analysis will include those events from 1975 forward.[4] Of the total events, approximately 2,100 are perpetrated by the FARC. Each event is characterized by a set of descriptors, including the event date, the location (city, department, and/or geo-coordinates), the actor (perpetrator), attack type, target, weapon used, the number killed, and the number

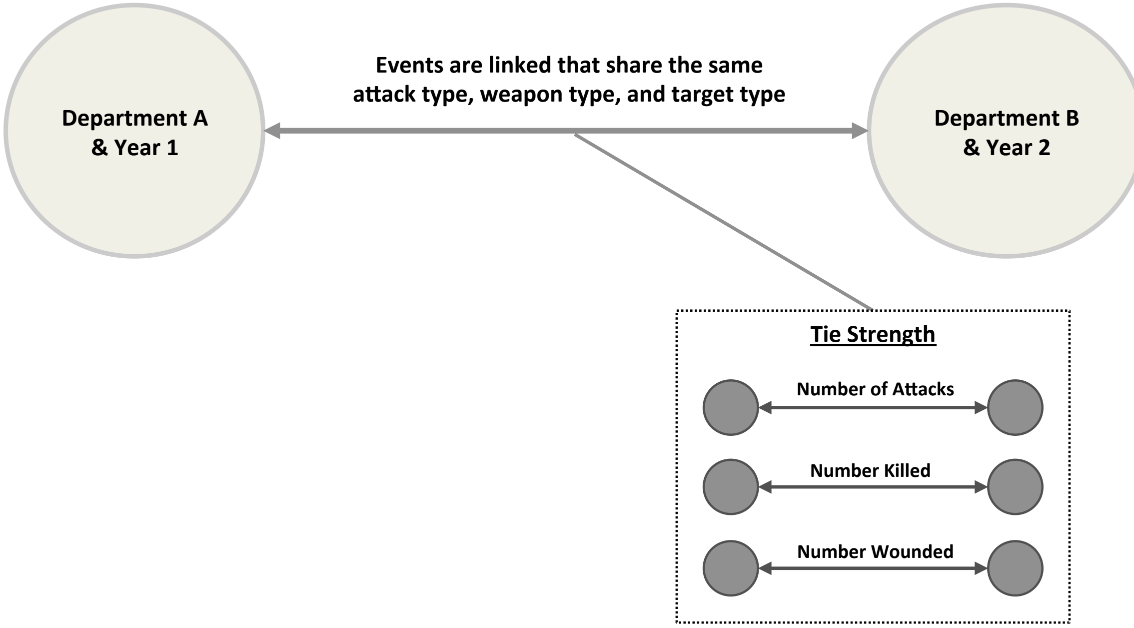
[4] There is no data for FARC until 1975. Events committed by FARC before then were likely unknown at the time. In addition, cases from 1993 were lost by START and therefore left out of the analysis. Although some events were recorded for 1993, efforts to fully recover the data have been unsuccessful. In total, Colombia saw 225 events that year (256 individuals were killed and 406 were wounded) (START, 2013).

wounded. Where geo-coordinates were not provided, location information from the event was cross-referenced against geocoded data from OpenStreetMap (2010). The actors are groups, rather than the individual(s) who actually participated in the event. These groups can include dissident organizations (e.g., guerrilla organizations), paramilitary forces, and drug traffickers. By including this level of detail for each coded event, I am able to develop a network that links events based on similar attributes, such as the type of attack, the target, and weapon used (this network is discussed next in Section 4.2.2).

4.2.2 The Network

Using only those attacks committed by the FARC, a network of events is created. Since the focus of this analysis is to study the FARC's network changes across time and geographic space, the nodes are grouped by the year when and department where the event took place (Colombia is comprised of 32 departments as seen in Figure 4-1). Because the area of study includes the entire country of Colombia over approximately 37 years of data, grouping nodes by department and year provides a level of detail that will not overburden the network but at the same time allows for the exploration of any significant year-over-year geographic trends in the conflict.

Figure 4-2A illustrates the notional network. Note that Department A may or may not equal Department B, and Year 1 may or may not equal Year 2. Figure 4-2B shows the actual network of events over a map of Colombia using number of attacks for tie strength. The links in the network are bidirectional and are defined by attack type, weapon type, and target type. Thus, two nodes are connected if they share events with the



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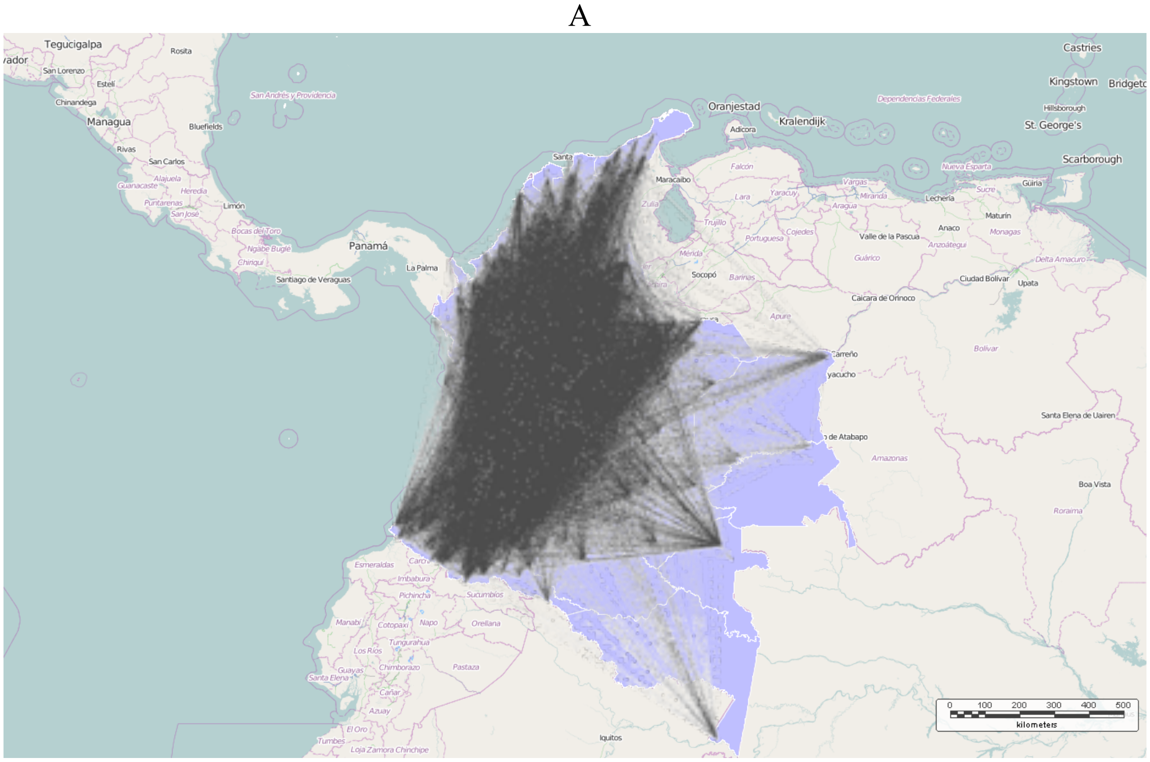


B

Figure 4-2. The network of the Colombian conflict event data. A: The notional network. B: The actual network over a map of Colombia.

same attack type, weapon type, and target type. The two connected nodes may or may not be of the same department and may or may not be in the same year. Three versions of this network are created adjusting only for tie strength. Tie strength in each network is based on the number of attacks, the number killed, and the number wounded, respectively.

4.2.3 Centrality

Centrality measures are used to determine those nodes that are central or "most important." In a non-directional network such as this one, a central actor is defined "as one involved in many ties" (Wasserman and Faust, 2009). Here, importance may be defined as those nodes (the locations and years) that best represent the conflict as a whole. Because these nodes will share similarities with many other locations and years, they may also represent the time and locations where FARC factions were the most centralized. Centrality measures are calculated for the three versions of the network. Nodes that are central will represent the subset of locations and years that are most characteristic of the conflict as a whole.

4.2.3.1 Degree Centrality

An actor is central in terms of degree if it has the most ties and/or strongest ties to other actors in the network. If the data is binary, degree is determined by counting the number of nodes directly connected to each actor. If the data is valued (e.g., a perpetrator can attack the same target using the same attack type and weapon type multiple times), degree is a measure of the sum of tie strengths (Wasserman and Faust, 2009).

The degree centrality of a specific node n_i is denoted by $C_D(n_i)$ and is defined in Equation 4-1.

Equation 4-1. Node level degree centrality (Wasserman and Faust, 2009).

$$C_D(n_i) = \sum_j x_{ij}$$

where x_{ij} is the tie strength between nodes i and j. In the FARC network, a node can be central if it is directly linked to many nodes, if it shares strong ties with some nodes, or if it shares strong ties with many nodes. When measured by degree a central actor is the "most visible" and occupies a "central location" in the network. On the other hand, actors with low degree centrality represent peripheral locations in the network (Wasserman and Faust, 2009).

4.2.3.2 Closeness Centrality

Closeness centrality is calculated by determining each nodes network distance to all other nodes. An actor is central if it has "minimum steps" in relation to other nodes. In other words, the geodesics (i.e., the shortest path between any two nodes) of a central node to all other nodes is short when compared to the geodesics of other nodes in the network (Wasserman and Faust, 2009). The closeness centrality of a specific node n_i is denoted by $C_c(n_i)$ and can be defined by Equation 4-2.

Equation 4-2. Node level closeness centrality (Wasserman and Faust, 2009).

$$C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

where $d(n_i, n_j)$ is the geodesic between nodes n_i and n_j. Unlike degree centrality, however, which only measures direct relations, because closeness takes into account all nodes on a geodesic, it also measures the indirect relationships of nodes. Thus, a central node will have the most similarities (e.g., any combination of common attack type, weapon type, and/or target type) to the most number of nodes.

4.2.3.3 Betweenness Centrality

Actors are central in terms of betweenness centrality if they lie within the geodesic of many other actors (Wasserman and Faust, 2009). The betweenness centrality of a specific node n_i is denoted by $C_B(n_i)$ and can be defined by Equation 4-3.

Equation 4-3. Node level closeness centrality (Wasserman and Faust, 2009).

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk}$$

where $g_{jk}(n_i)$ is the number of geodesics between n_j and n_k containing n_i. Because betweenness is interested in those actors that lie in between the paths of two other actors, the focus here is on the indirect relationships of the central actor. Central nodes here will share some combination of commonalities (in terms of attack type, weapon type, and target type) with many other actors.

4.2.4 Clustering

Using hierarchical clustering, positional analysis is performed on the data to determine which years and departments of the conflict are most similar. Hierarchical clustering is a method which is often used to partition actors into subsets, whereby actors within the same subset are more structurally similar than actors in different subsets (Wasserman and Faust, 2009). The first correlation matrix (a measures of structural equivalence) is used as input (Wasserman and Faust, 2009). Hierarchical clustering begins by placing each actor into a cluster. The two most similar clusters are then combined into a new cluster. This is repeated until all actors are combined into one large cluster (Hanneman and Riddle, 2005). Nodes that are clustered together will tend to share similar attack types, weapon types, and target types, in addition to similar intensity levels (e.g., many similar attacks, many similar attacks with many killed, or many similar attacks with many wounded), and similar diversity in attack characteristics (e.g., most attacks are similar in terms of the attack type, weapon type, and target type, or few attacks are similar in terms of the same descriptors). This clustering technique provides a way to determine which years and locations the FARC network was most similar.

4.3 Results and Findings

This section explores the dataset first through an initial exploration of the data and better understanding of the political landscape (Section 4.3.1). Next, centrality measures are used to identify some spatiotemporal trends in the conflict (Section 4.3.2). Finally, cluster analysis provides a more in-depth look at the network since the current administration took office (Section 4.3.3). Centrality measures and cluster results are determined using UCINET 6 (Borgatti et al., 2002), while geographic analysis is performed using Palantir 3.11 (Palantir Technologies, 2013).

4.3.1 Initial Data Exploration

Since 1975 the FARC have been responsible for 28 percent (2,127) of total attacks and 37 percent (5,400) of total deaths in the Colombian conflict. During the terms of the last two presidents (2002 to 2012), however, the FARC have been responsible for over 76 percent (769) of total attacks and 84 percent (1,146) of total deaths. Looking at these statistics it is not clear whether the FARC are strengthening, the conflict as a whole is weakening, or whether there is some other process at work. Table 4-1 provides the count of attacks, killed, and wounded by the top ten perpetrators (in terms of number of attacks), which together comprise 68 percent (5,223) of total attacks in the conflict. The FARC are at the top with the highest number of attacks, killed, and wounded.

Table 4-1. The number of attacks, killed, and wounded by the top ten perpetrators in the Colombian conflict from 1975 to 2012.

Perpetrator Name	Perpetrator Group	Number of Attacks	Number Killed	Number Wounded
Revolutionary Armed Forces of Colombia (FARC)	Left-wing group	2,127	5,400	3,812
National Liberation Army of Colombia (ELN)	Left-wing group	1,304	1,723	1,070
M-19 (Movement of April 19)	Left-wing group	552	1,396	529
Narco-Terrorists	Trafficker	349	427	797
Popular Liberation Army (EPL)	Left-wing group	262	525	154
Simon Bolivar Guerrilla Coordinating Board (CGSB)	Left-wing group	202	384	115
Death Squad	Right-wing group	171	383	82
The Extraditables	Trafficker	110	182	411
Left-Wing Guerrillas	Left-wing group	90	178	86
United Self Defense Units of Colombia (AUC)	Right-wing group	66	322	20

4.3.1.1 A Geographic Look at the Conflict

Focusing on the largest of the perpetrators, Figure 4-3 shows all FARC-related events from 1975 to 2012. This gives us a better sense of where the majority of the FARC's attacks have occurred since the early years of the conflict. We can see that the center of the country has a high concentration of attacks, spreading north and south from there. Although there are some attacks in the western regions of the country (the areas bordering Brazil to the west, Venezuela to the northwest, and Peru to the southwest), those regions have remained relatively quiet in comparison.

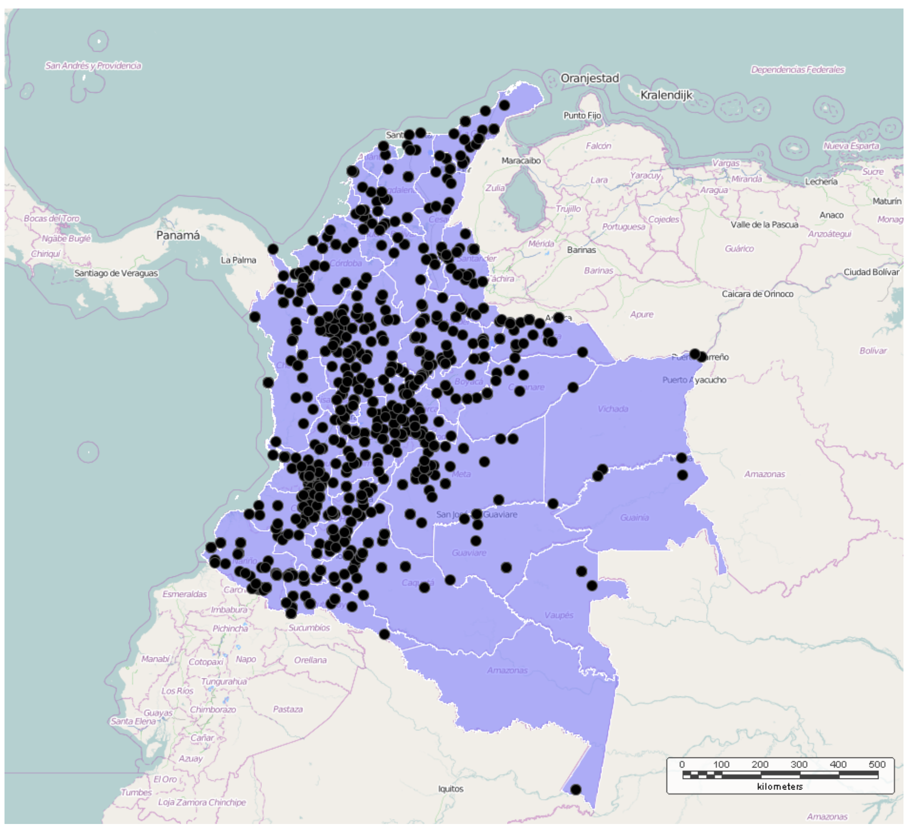
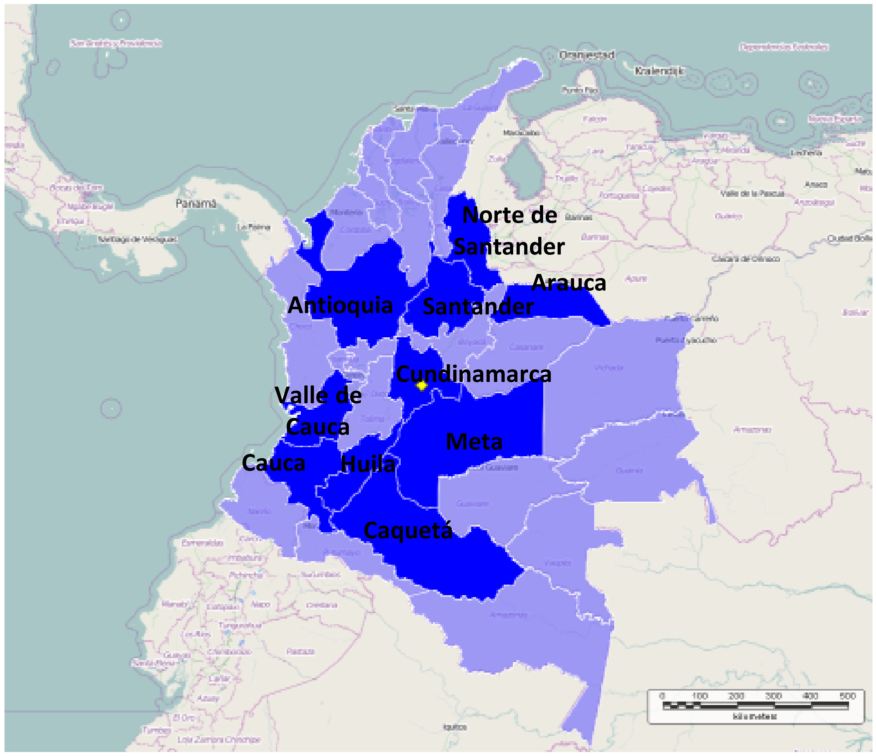


Figure 4-3. Map of Colombia showing all FARC-related attacks as black circles from 1975 to 2012.

To give a better sense of the specific departments that have seen the highest intensity of attacks, Figure 4-4 shows by department those locations with the greatest number of events involving the FARC. The departments of Antioquia and Cundinamarca (which are adjacent to one another and include the cities of Medellin and Bogota, respectively) have seen the highest number of attacks. Meanwhile, the next four departments (Cauca, Huila, Valle del Cauca, and Caquetá) are all located in southeast section of the country. With the exception of Meta, the remaining departments are all located in the north near Venezuela.

It is clear that the conflict has impacted much of the country. The top two departments in terms of number of attacks contain the two most populous cities in Colombia, Bogota in Cundinamarca and Medellin in Antioquia. However, from this analysis it is difficult to tell what this means in terms of the conflict. Are the FARC targeting urban areas? Are these same departments experiencing this level of violence today or were the majority of these attacks in the past? To begin to address the underlying issues and to better understand how the conflict has trended, the next section provides a timeline of events and the political landscape at the time.



A

Department	Number of Attacks
Antioquia	267
Cundinamarca	160
Cauca	130
Huila	116
Valle del Cauca	112
Caquetá	96
Santander	95
Arauca	71
Meta	71
Norte de Santander	66

B

Figure 4-4. The top ten departments with the highest number of attacks from 1975 to 2012. A: Top ten departments shown in dark blue. B: The number of attacks.

4.3.1.2 A Timeline of Events and the Political Landscape

Figure 4-5 displays a simple histogram with the total number of attacks and the total number killed in the conflict (shown as blue and red bars, respectively) and the total number of attacks and total number killed by the FARC (shown as blue and red dotted lines, respectively) by year. Across the top of the histogram the name of the administration is shown. Based on the histogram, the conflict as a whole (in terms of total number of attacks and total number of deaths) spiked between the late 1980s and then peaked in the late 1990s. Starting in 1998, the conflict appears to follow a de-escalatory pattern.

We can see that the FARC had a series of abrupt escalations and de-escalations, with spikes in the late 1990s and then again in the early 2000s, which is the time that the conflict as a whole looked to be declining. To give us a better sense of why we saw certain patterns, this section provides some insight into the political situation, policies, and strategies used to lessen the conflict and how they may have impacted the ongoing conflict.

From the 1970s through the early 1980s, the head of the armed forces ruled with excessive repression. With this came an increase in political violence and legitimacy for Leftist guerrilla actions (Chernick, 1988; Hylton, 2006). Without the support of his own party, the army, or the international community, Betancur (1982-1986) attempted to negotiate a cease-fire and peace agenda. Terms favorable to the Leftist guerrillas ignited counterinsurgent tactics from the army, the local elite landowners, paramilitaries, and drug

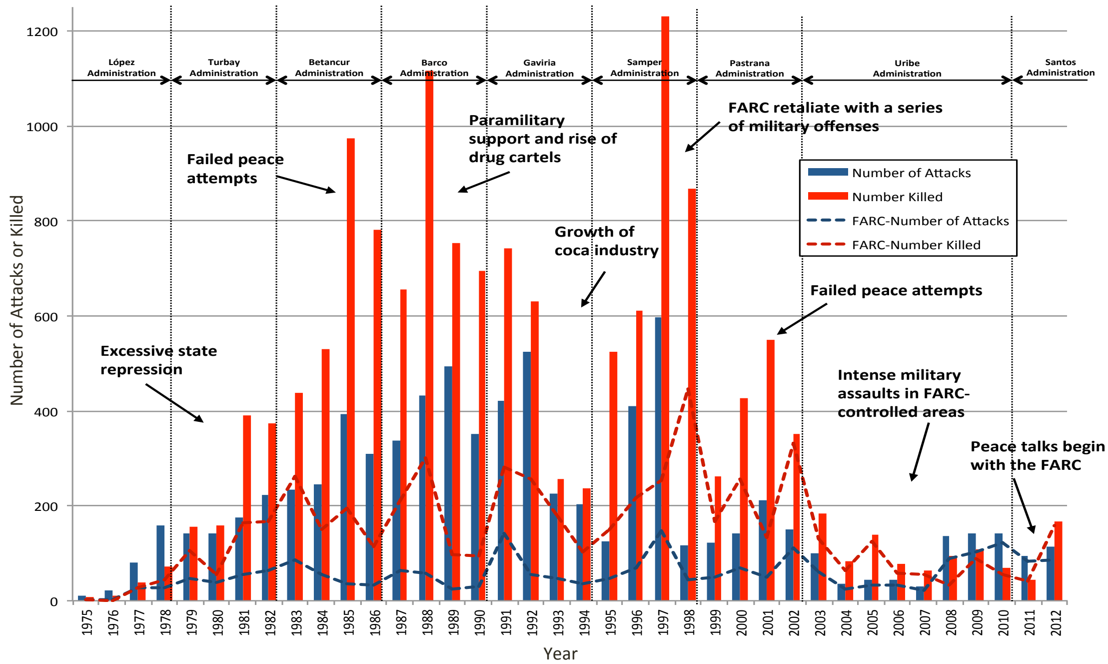


Figure 4-5. A histogram of event counts by year from 1975 to 2012 (BBC, 2013b; Bergquist et al., 2001; Chernick, 1988; Crandall, 2002; Hylton, 2006).

traffickers. The guerrillas used this uprising to their advantage by bringing attention to the atrocities being fulfilled by the army and paramilitary, and as a result the FARC were able to strengthen their own cause (Hylton, 2006). In the late 1980s, political support for the paramilitary and the rise of the drug cartels led to another spike in violence (Hylton, 2006). In the 1990s, a reduction in import tariffs placed a strain on legal crops. For many regions, coca became the only crop profitable enough to maintain. When the two major cartels (the Cali and Medellin cartels) were dismantled in the 1990s (Bergquist et al., 2001), violence went down but the new decentralized trafficking alternative was more organized than ever. The FARC played a central role in maintaining law and order within the chain between the coca-cultivator and the customer, garnering an extraordinary amount of wealth (Hylton, 2006). In the late 1990s, the increase in spending to combat the guerrillas combined with the poor management of this money provided the FARC with the fuel for which to retaliate (Bergquist et al., 2001; Hylton, 2006). The FARC launched a series of military offenses in 1997 and 1998 (Hylton, 2006).

The second attempt at peace negotiations came during the Pastrana administration (1998-2002). Pastrana began by creating a demilitarized zone in the south central region of Colombia, encompassing approximately 16,200 hectares of land and five townships with a population of over 90,000 (Almario, 2000; Hylton, 2006), and negotiating a twelve-point plan with the FARC, which revolved around socioeconomic issues, agrarian reform, and human rights (Hylton, 2006). However, Pastrana was unable to deliver on the promised reforms and FARC withdrew from negotiations due to continued abuse from the military and paramilitary. Meanwhile, the FARC used the demilitarized zone to hold kidnapped victims and to strengthen their own military operations (Gomez-Suarez and Newman, 2013; Hylton, 2006). In February of 2002, Pastrana ordered the peace talks over and the military take over the demilitarized zone (Hylton, 2006; Lansford, 2014). With the return of the demilitarized zone and the election of the right-leaning Uribe, the FARC retaliated once more.

When President Uribe (2002-2010) took office, he was determined to combat the guerrillas (Hylton, 2006). The FARC's exploitation of terms set forth during Pastrana's peace process, the events of 9/11, and the terrorist-like atrocities being committed by them provided Uribe with the support he needed. Through Plan Colombia, a U.S. backed plan to fight the "war on drugs" that provided Colombia with $1.3 billion for military and police aid, the military launched intense assaults in FARC-controlled regions (Bergquist et al., 2001; Crandall, 2002). In addition, the death of their leader, Marulanda, in 2008 (Saab and Taylor, 2009), and diminishing public support led to a decline in the number of attacks and victims killed by the FARC (Salicrup, 2008). However, Uribe's focus on high value targets (HVTs) may have backfired, as it took emphasis away from the focus on area control and allowed the FARC time to move and adapt. In addition, with the death of its leader came the appointment of Cano, who immediately put into action his plan to rebuild the insurgency.

Finally, when Santos (2010-Present) took office the perception of security had begun to diminish for the first time in eight years (Spencer, 2013). Santos vowed to change this and in November of 2011, Cano was killed (BBC, 2013a). While some offenses continue against the FARC, Santos entered into peace talks with them in November of 2012 (BBC, 2013a). Talks are focused on six key issues, including land reform, drug trafficking, political freedom, and the needs of victims' rights (BBC, 2013a). As of January 2014, the government and the Leftist group have come to agreement on two points: a plan to reduce rural inequality and a framework to allow for political participation (Neuman, 2013; Washington Office on Latin America, 2014). However, even if the two parties are able to come to agreement on all issues, there is still skepticism that it will work, including from his predecessor, Uribe (Neuman, 2013). It remains to be seen if Colombians, who have shown little support towards the FARC movement and have experienced continued security concerns, are ready to allow guerrilla members re-entry into society and politics (Neuman, 2012).

At this point, we have a sense of where the FARC fit into the conflict as a whole (as shown in Table 4-1), the departments that have seen the highest intensity of violence (as shown in Figure 4-4), and the trends of the conflict as it relates to the policies of the time (as shown in Figure 4-5). In Sections 4.3.2 and 4.3.3, I add the tactics used in the attacks (i.e., type of attack, the type of target, and the weapon used) to the analysis. At the same time, using centrality measures in Section 4.3.2 I assess the events over time and geographic space. This will give us a better sense of the trends, not just year-over-year, but also over geographic space. In addition, using cluster analysis in Section 4.3.3 today's conflict is examined and better understanding of where the trend in recent years may be heading is sought.

4.3.2 The "Most Important" Events

Using centrality measures, this section looks at the nodes (as defined in Section 4.2.2) that are the most "central" to the conflict. In the previous section, attacks were examined over time, by geographic space, against the political landscape. However, given the sheer number of attacks it is difficult to decipher what events may be most relevant or most representative of the conflict, and thus, deserving of further research. SNA combined with simple GIS allows us to look at the conflict from a spatiotemporal perspective to better understand where the conflict is today and assess what years and locations are the "most important" or representative of the conflict as whole. As discussed in Section 4.2.2, three networks were created where tie strength is measured by number of attacks, number killed, and number wounded, respectively. Nodes were ranked by the respective centrality measure and the top 20 nodes with the highest centrality in each network were analyzed further.

4.3.2.1 Degree Centrality

Nodes that are central or the “most important” in terms of degree will be linked directly to other nodes with similar attacks, where similarity is defined by the event’s attack type, weapon type, and target type. Using the top 20 nodes, Figure 4-6A displays the location of those events deemed central in terms of degree centrality in the attack network (black circles). Figure 4-6B displays the location of those events in the killed (red circles) and wounded (blue circles) networks. The timeline of these events are shown in Figure 4-6C-E. Events from the attack, killed, and wounded networks, respectively, are superimposed in yellow.

In general, the earliest central attacks begin in Antioquia (whose capital is Medellin) and Santander in the 1980s, both of which are departments in the northern part of the country. In the late 1990s and early 2000s, attacks move away of the country’s center (in terms of distance from Colombia’s capital) in departments like Vaupes (in the east bordering Brazil) and Putumayo and Nariño (in the southwest bordering Ecuador). In addition, the early 2000s brought the highest concentration of events in the killed and wounded networks into the center (the department of Cundinamarca where Bogota is located). In the attack network, events in the late 2000s are spread across the country, from the center of the country (e.g., Cundinamarca and Tolima) to the north (e.g., Antioquia) to a large concentration of attacks in the south (e.g., Huila). On the other hand, attacks in the wounded network during a similar time period have moved south, especially to the Cauca, Nariño, and Huila departments where a large number of bombings took place. By 2011, central attacks in all three networks have moved to the department of Cauca. In 2012, the wounded network shows events in Nariño and Cauca, in addition to the northern department of Norte de Santander. Overall, attacks trend south, especially to Cauca, and at times some of its bordering departments. However, a high concentration of attacks back in Antioquia (where much of the early conflict was located) is still seen and a concentration of attacks continue to spread the country. However, those with the highest impact in terms of wounded are concentrated mainly in the south and in the northern department of Norte de Santander. The attack type most commonly used in the earlier years was armed assaults. This turned into more bombings where more were wounded and less were killed as the conflict progressed and moved south.

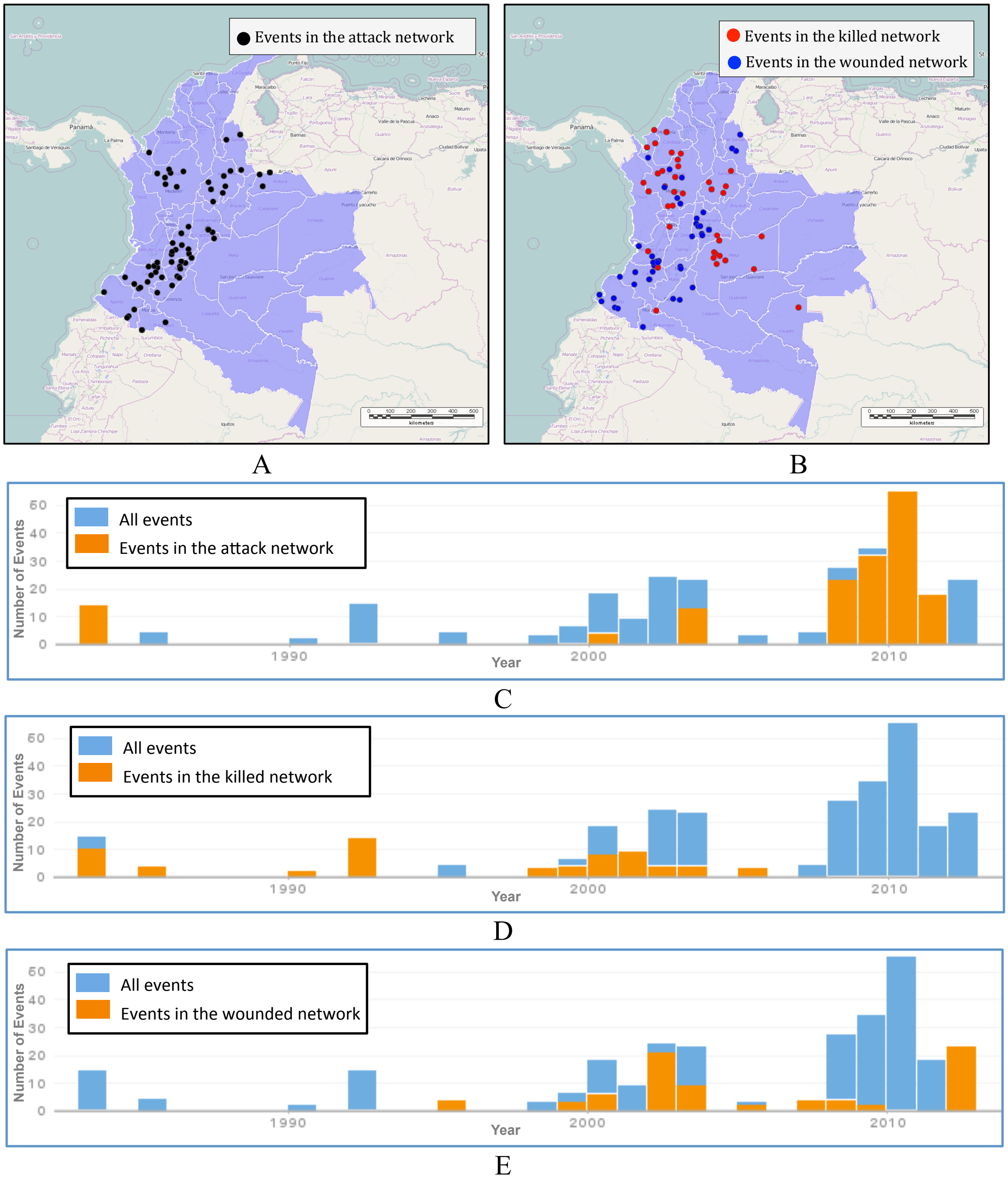
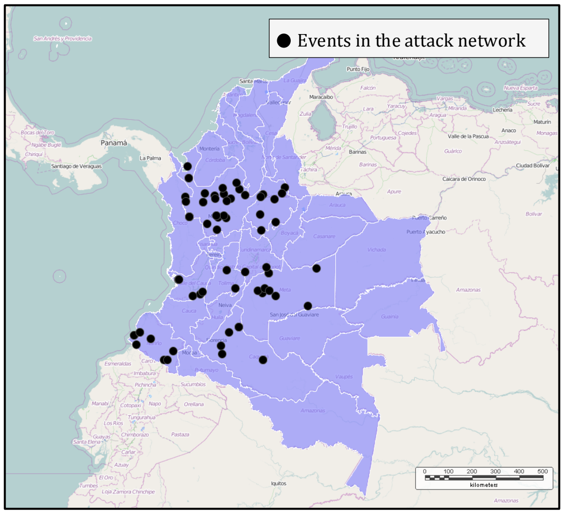


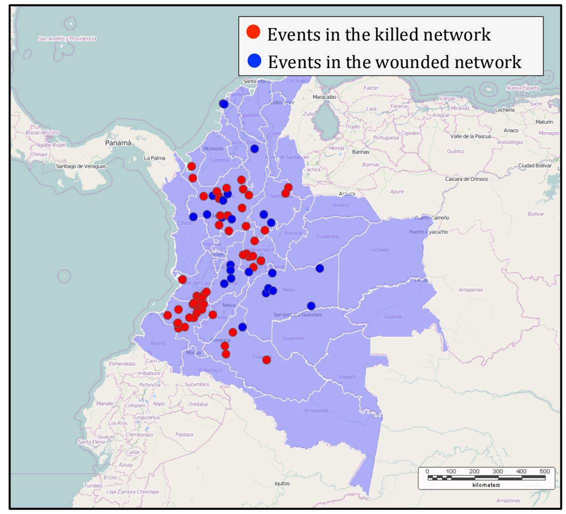
Figure 4-6. Events with the highest degree centrality from 1975 to 2012. A: Map of Colombia with the attack network. B: Map of Colombia of the killed and wounded networks. C: Timeline of the attack network. D: Timeline of the killed network. E: Timeline of the wounded network.

4.3.2.2 Closeness Centrality

Nodes that are central in terms of closeness will be linked to other nodes sharing similar attacks, in terms of attack type, weapon type, and target, and may share many commonalities with nodes that it does not have a direct relationship with. Unlike degree centrality, which measures only direct links, closeness measures both direct and indirect relationships. Figure 4-7A displays the location of the events determined to be important in terms of closeness centrality in the attack network (black circles). Figure 4-7B displays the location of those events in the killed (red circles) and wounded (blue circles) networks. The timeline of these events are shown in Figure 4-7C-E. Events from the attack, killed, and wounded networks, respectively, are superimposed in yellow.

As we saw with degree centrality, the earliest of the central attacks begin in the northern departments of Santander and Antioquia. Next, there is a shift just south to the departments of Meta, Cundinamarca, and Tolima. With the exception of new attacks in Antioquia, by 2010 attacks have shifted further south. There is a very high concentration of attacks in Cauca from 2010 to 2012 in the killed network. While degree centrality showed these more recent attacks in the southern part of country resulting in more wounded, closeness centrality results show these recent attacks in the killed network, indicating the attacks may be more severe than thought looking only at degree centrality. In addition, as with degree centrality, we see a resurgence of attacks in Antioquia in more recent years, especially in 2012. We also see the shift from armed assaults to bombings, but not as distinct as with degree centrality. The spike in killed in 2012 is largely due to a mix of armed assaults and bombings where police and military were the largest targets for these attacks.





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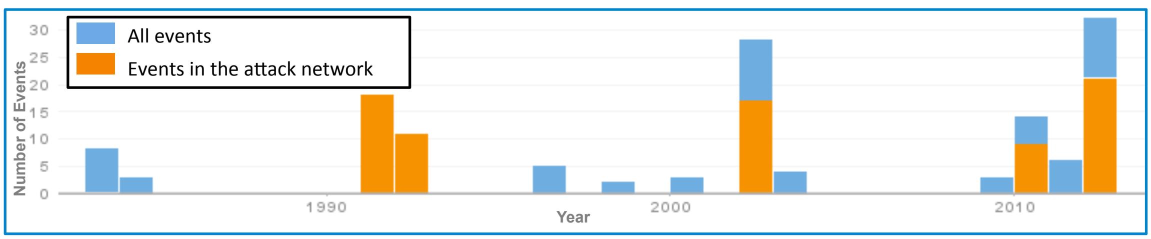

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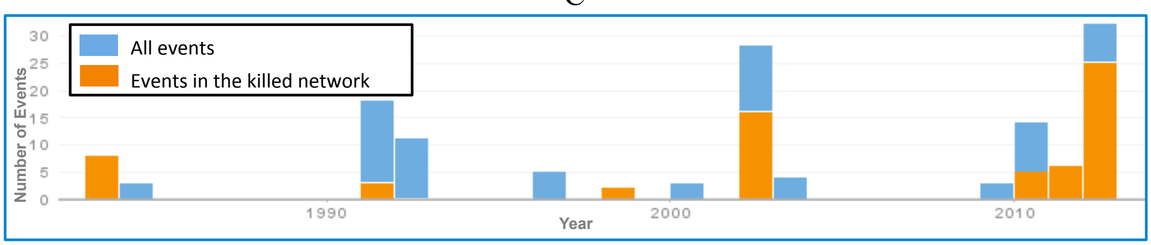

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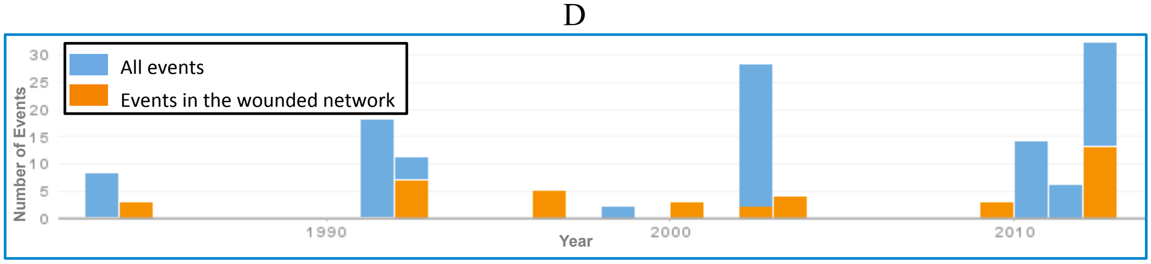


E

Figure 4-7. Events with the highest closeness centrality from 1975 to 2012. A: Map of Colombia showing the attack network. B: Map of Colombia showing the killed and wounded networks. C: Timeline of the attack network. D: Timeline of the killed network. E: Timeline of wounded network.

4.3.2.3 Betweenness Centrality

A node is central in terms of betweenness if it lies between other actors on their geodesics. The focus here is on the indirect relationships between nodes. Actors central here will most likely have some commonalities, in terms of attack type, weapon type, and target, with many other actors. Figure 4-8A displays the location of the events determined to be important in terms of betweenness centrality in the attack network (black circles). Figure 4-8B displays the location of those events in the killed (red circles) and wounded (blue circles) networks. The timeline of these events are shown in Figure 4-8C-E. Events from the attack, killed, and wounded networks, respectively, are superimposed in yellow.

Compared to results of degree and closeness centrality, the important events here are concentrated in fewer departments. Overall, with the exception of attacks in Huila in 1984, we again see the trend of attacks moving south with a resurgence of attacks in Antioquia in 2011. Attacks begin in Antioquia and Santander in the 1980s and early 1990s. By the late 1990s they have spread to nearby Choco and Cundinamarca. The early 2000s sees a move just south to Tolima and Huila. By 2009 all events, with the exception of those in Antioquia, have shifted south to the departments of Cauca, Valle del Cauca, Huila and Nariño. A spike in bombings in 2012 results from the use of explosives in Nariño.

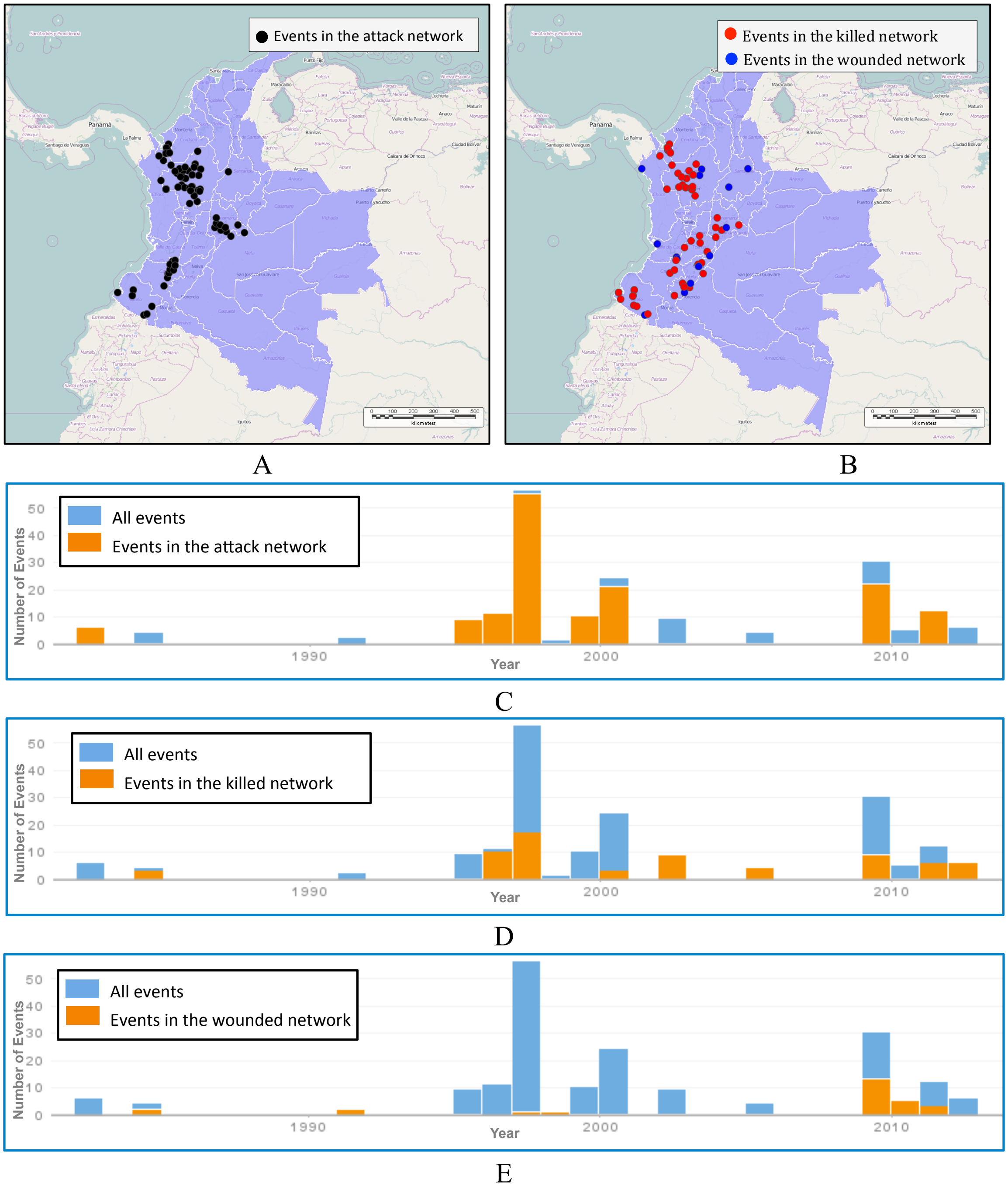


Figure 4-8. Events with the highest betweenness centrality from 1975 to 2012. A: Map of Colombia showing the attack network. B: Map of Colombia showing the killed and wounded networks. C: Timeline of the attack network. D: Timeline of the killed network. E: Timeline of the wounded network.

4.3.2.4 A Geographic Shift in the Conflict

Figure 4-9 provides a sense of how the conflict has shifted. Using only those attacks determined to be "most important" based on degree, closeness, and betweenness centrality, three heat maps are created based on the density of events.[5] The dark red areas represent the highest intensity levels (i.e., most dense) while the blue areas represent lower intensity levels (i.e., least dense). The first map shows the violence concentrated in the northern departments of Antioquia and Cundinamarca in 1990s (see Figure 4-9A); by the mid-2000s no central attacks exist in the north and there are just a few small clusters in the southwest (see Figure 4-9B); and by the time the current administration took office in late 2010 a much larger cluster in the southwest and a resurgence in the north are seen (see Figure 4-9C).

[5] The heat maps use density to determine the different intensity levels. Density in this case was calculated by counting the number of events per 50 km^2 area. The areas of highest intensity had the most number of events (Palantir Technologies, 2013).

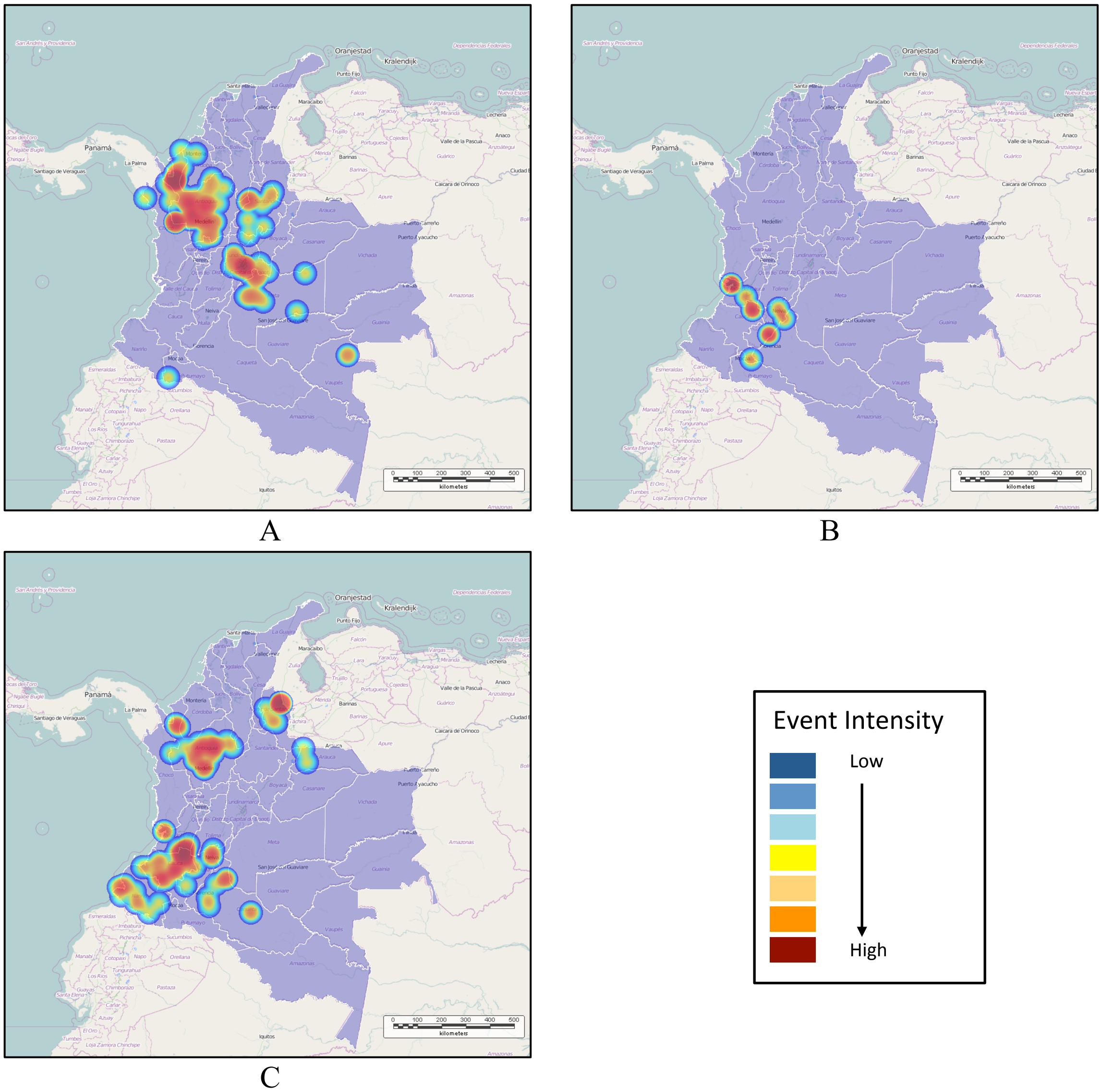


Figure 4-9. Heat maps of central attacks in the conflict. A: Attacks in 1990s. B: Attacks between 2004 and 2007. C: Attacks between 2010 and 2012.

4.3.3 Cluster Analysis and The Santos Administration (2010 – 2012)

As discussed in Section 4.1, Santos took office in late 2010, he has taken a very different approach with the FARC. Given the strategic shift from militaristic force in the prior administration to peace processes in the current administration, today's conflict under the current administration is evaluated against the conflict of earlier years. Particularly focused on the years since Santos took office, this section uses hierarchical clustering to study the structural similarities between the conflict across time and geographic space. In addition, particular attention is paid to the years 2011 and 2012 (these are the two full years since Santos took office with available event data). Clusters of nodes that are structurally similar will not only share common attack types, weapons types, and target types, but will also share a similar level of intensity by which these attacks occur. From the centrality analysis performed in Section 4.2.3, it was found that the southern part of the country has seen unprecedented levels of violence in recent years, especially in the department of Cauca, which consistently saw "important" events across all the centrality measures. On the other hand, while most of the conflict looked to move south, there was a resurgence of the violence in Antioquia. In this section, the recent conflict, particularly focused on these two departments, is explored.

4.3.3.1 The Conflict Moves South

In the previous section, a geographic shift of the conflict towards the south, particularly Cauca, was seen. The department of Cauca saw the highest level of violence in the country since Santos took office in terms of all three metrics: number of attacks, number killed, and number wounded. Table 4-2 shows the results of the cluster analysis performed, focused only on those clusters containing the department of Cauca in the years 2011 and 2012 (in bold are all departments in 2011 and 2012 that were grouped here). Note that, with the exception of Cauca, all of those in bold are departments that border Cauca.

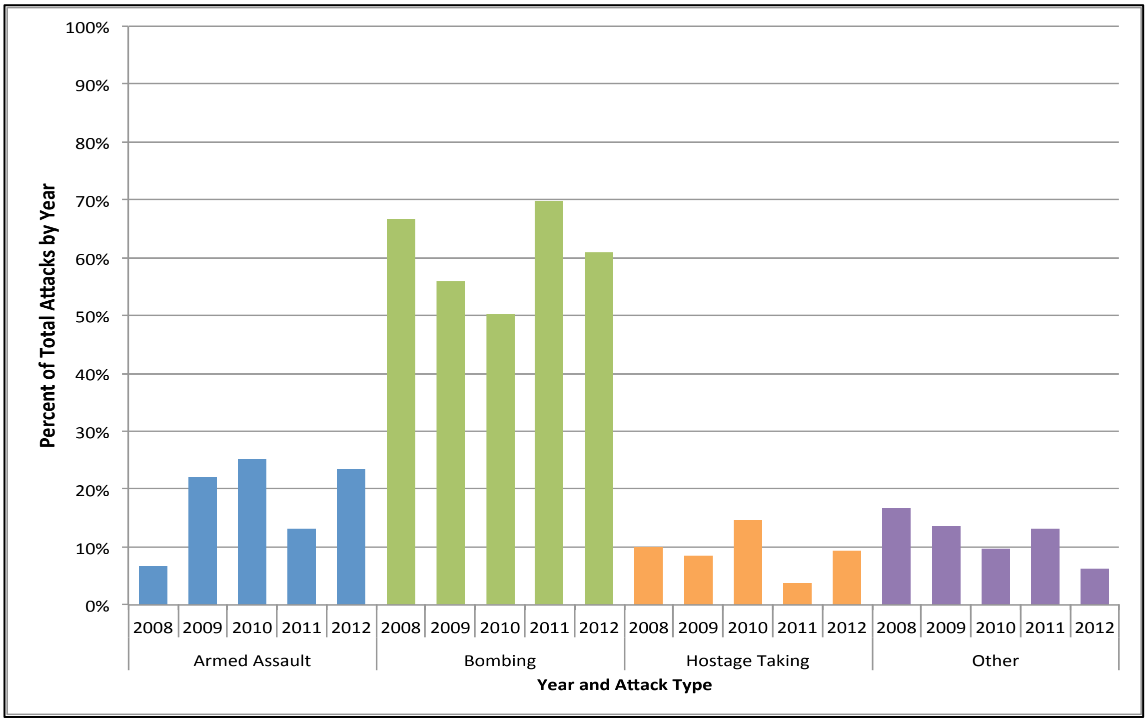
Table 4-2. Results of cluster analysis for Cauca in 2011 and 2012.

Cluster Name	Tie Strength Metric / Network Name	Cluster
Cauca 2011 attack cluster	Number of attacks / Attack network	**Cauca 2011** Cauca 2010
Cauca 2011 killed cluster	Number killed / Killed network	**Cauca 2011** Cundinamarca 1997, 2000 Antioquia 1996, 2005 Arauca 1984, 2010
Cauca 2011 wounded cluster	Number wounded / Wounded network	**Cauca 2011**, 2005 **Huila 2011** Cundinamarca 2008
Cauca 2012 attack cluster	Number of attacks / Attack network	**Cauca 2011** Cundinamarca 2002
Cauca 2012 killed cluster	Number killed / Killed Network	**Cauca 2012**, 1988 **Caquetá 2012** **Valle del Cauca 2012** Cundinamarca 1991, 1994, 1999 Putumayo 1991 Antioquia 1988 Santander 1979, 1987
Cauca 2012 wounded cluster	Number wounded / Wounded network	**Cauca 2012** **Nariño 2012** Valle del Cauca 2007 Caquetá 2003 Cundinamarca 2000, 2002

Results of the cluster analysis show two overarching trends. First, almost all clusters contain department and year combinations that border Cauca in the years 2011 and 2012. Taking a closer look at the clusters in 2011, it is found that the Cauca 2011 attack cluster is grouped only with Cauca 2010 and 2011; indicating consistency in attack intensity and tactics used over this time period within the department of Cauca. However, it does not include Cauca in 2012, indicating a potential shift in pattern that year. In addition, the cluster includes bordering Huila that same year. In 2012, specifically in the killed and wounded networks, the number of bordering departments sharing structural similarity increases. Between the two networks, Cauca 2012 is grouped with three of its bordering departments: Nariño, Valle del Cauca, and Caquetá. The grouping of these departments in 2012 could be indicative of a shift in tactics from previous years and to a shared choice of tactics amongst the entire region. From the centrality analysis, it was found that the move south started in 2009. To explore the theory that there is a potential shift in tactics, Figure 4-10A-B shows the total number of attacks by attacks type and target type in the southwest region from 2008 to 2012, respectively.[6] Percentages represent the proportion of total attacks in a given year that were of a given attack type or target type, respectively.

While bombings, followed by armed assaults, is the attack type of choice across all the years, the target type changes across the years. Overall, there is a decline in the percentage of attacks targeting businesses, government, and infrastructure and facilities across the years. There is an increase in the proportion targeting military and police (with a large spike of attacks targeting police in 2012). While private citizens and property shows a gradual increase until 2011, it drops significantly in 2012, where there is a clear move away from private citizens and property to police.

[6] Businesses include individuals or organizations involved in commercial activity. Government represents government buildings, government members, or former members. Infrastructure/ facilities can include airports and airlines, food or water supply, telecommunication, transportation, educational institutions, and religious institutions. Military include army units, patrols, and convoys. Police are police force or police installations (START, 2013).



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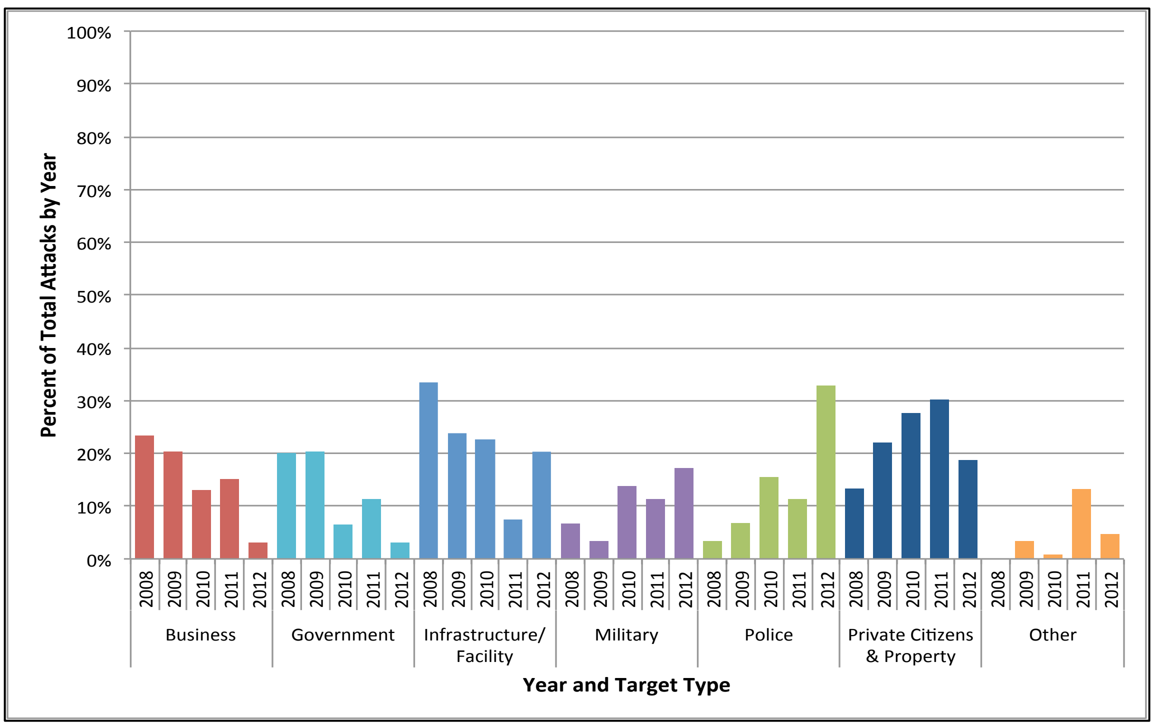


B

Figure 4-10. The distribution of attacks in the southwest region from 2008 to 2012. A: By year and attack type. B: By year and target type.

Secondly, with the exception of the Cauca 2011 attack cluster, the department of Cundinamarca appears in all the clusters, along with other nearby departments in the northern region of the country. The Cauca 2011 killed cluster contains departments at the peak of the conflict. Antioquia (home of the city of Medellin) and Cundinamarca (home of the city of Bogota) experienced some of the highest levels of violence in the late 1990s. On the other hand, the Cauca 2011 wounded cluster contains more recent years including Cundinamarca in 2008, which experienced significantly less violence than in the 1990s. As in 2011, however, the Cauca 2012 killed cluster was grouped with one of the most active departments earlier in the conflict, in this case Cundinamarca in the 1990s. The Cauca 2012 attack cluster includes Cundinamarca in 2002, which had the highest number of attacks that year. It was also a very deadly year for the conflict after Pastrana's peace attempts had failed.

The fact that in 2012 four departments in the south are clustered together shows that the similarities are both temporal and geographic. In addition, there is resemblance to the conflict of the 1990s and early 2000s in some of the most active regions, especially Cundinamarca which appears in almost all the clusters. This could indicate a resurgence of the deadly violence of the 1990s and early 2000s but one that has shifted to the south. We also see a trend in tactics, from diverse targets to a pattern of targeting the police and military, perhaps indicating that the conflict is trending from many decentralized factions or attacks to a more centralized conflict. This suggests some form of coordination between the entire southern region, which looks to begin in Cauca in 2010 and expand to Nariño, Valle del Cauca, and Caquetá in 2012.

4.3.3.2 A Resurgence in Antioquia

The Antioquia department consistently came up in all three centrality measures as having important events in recent years. In 2011 all central attacks in the wounded and killed networks were either in Antioquia or Cauca but Antioquia had the highest intensity of attacks. In 2012, however, Antioquia fell just behind Cauca and Caquetá. During the late 1990s and early 2000s, Antioquia saw some the highest level of violence in the country. With deadly drug traffickers in the mix, the city of Medellin saw much of the violence. Later, with the return of the demilitarized zone and failed peace talks, the FARC retaliated. It was the most violent department in terms of number of attacks, and to a slightly lesser extent number killed, through much of the 1990s and early 2000s. After the country (and Antioquia) saw a lull in the violence, a resurgence of attacks in 2010 and then in number killed in 2011 brought Antioquia back to the center of the conflict. Although not at the levels seen in the past, Antioquia saw the second highest number of attacks and highest number killed in 2011. In 2012, however, it drops down in ranking but had the same number killed, an indication that the violence didn't diminish in Antioquia but that the southern region (e.g., Cauca, Nariño, and Valle del Cauca) surpassed Antioquia as the center of the conflict. Table 4-3 displays the results of the cluster analysis for Antioquia. In bold are all departments in 2011 and 2012 that were clustered together.

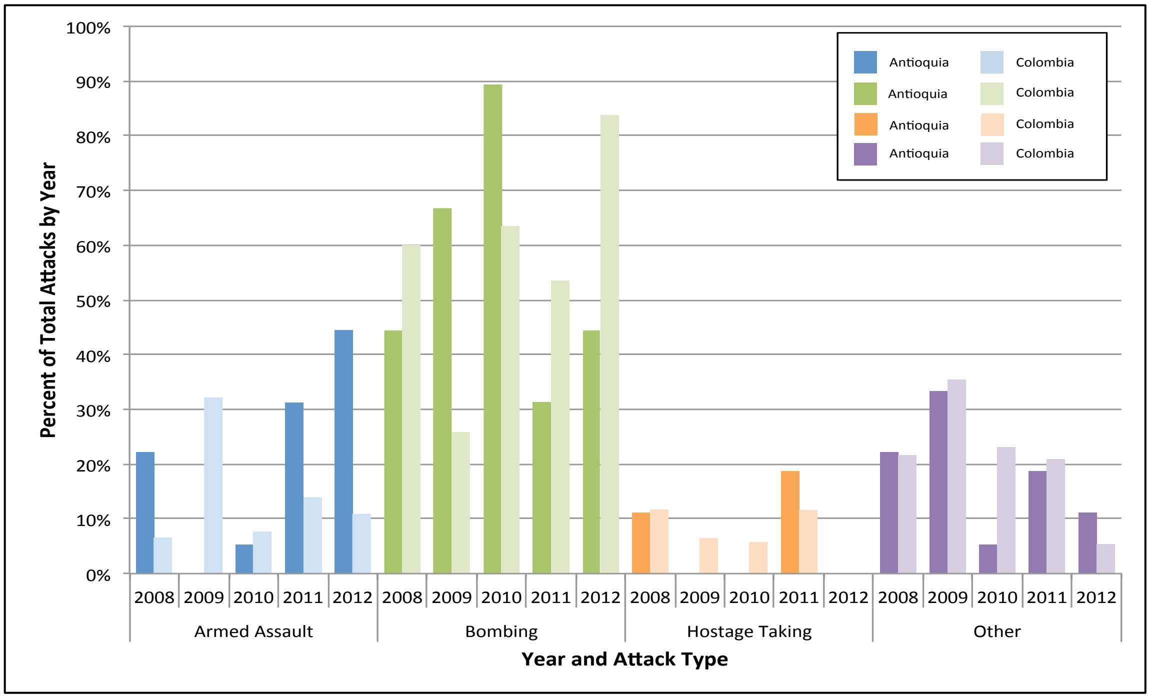
Table 4-3. Cluster analysis results for Antioquia in 2011 and 2012.

Cluster Name	Tie Strength Metric / Network	Cluster
Antioquia 2011 attack cluster	Number of attacks / Attack network	**Antioquia 2011**, 2004, 1985 Valle del Cauca 2002 Cundinamarca 1991
Antioquia 2011 killed network	Number killed / Killed network	**Antioquia 2011** Valle del Cauca 2008 Bolivar 2003 Huila 1988 Cundinamarca 1982, 1985
Antioquia 2011 wounded network	Number wounded / Wounded network	**Antioquia 2011** Choco 1996 Sucre 1996 Huila 1988
Antioquia 2012 attack cluster	Number of attacks / Attack network	**Antioquia 2012**, 1999 **Caquetá 2012**
Antioquia 2012 killed network	Number killed / Killed network	Antioquia 2012 Cauca 2010
Antioquia 2012 wounded network	Number wounded / Wounded network	**Antioquia 2012** **Caquetá 2012** **Arauca 2012** Valle del Cauca 2004 Cundinamarca 1996

Although no clear trends are seen as with the Cauca case, there are a couple things to note. While the 2011 clusters show no other departments in the same year, the 2012 clusters have grouped Caquetá 2012 and Arauca 2012 with Antioquia. One distinction between this cluster and the one in the Cauca region, however, is that Antioquia (in the northwest part of the country), Caquetá (in the southern part of the country), and Arauca (in the northeast part of the country) do not border each other. Given the geographic dispersion of the departments, this may suggest that similar tactics at similar intensity are being seen across the country, perhaps due to centralization of FARC factions beyond just a region. To investigate this further, Figure 4-11A-B illustrate the percentage of attacks since 2008 in Antioquia as compared to the rest of the country (with the southwest region removed) by attack type and target type, respectively.

Similar to the southwest, bombings is the most common attack type across the country. However, while bombings peaked in 2010 in Antioquia, it has declined and looks to be replaced by armed assaults. This is the opposite trend the rest of the country is seeing. In terms of targets, a couple things to note is that both the country and Antioquia have seen an increase in attacks against the police and decrease in attacks against private citizens and property. While Antioquia did not have any attacks against police from 2008 to 2010, the spike against police by 2012 is significantly higher than the increase seen in the rest of the country. This is because most attacks in the rest of the country are targeting infrastructure and facilities.

Antioquia consistently came up in the centrality analysis as being central in recent years. Although in 2011 Antioquia had the second highest number of attacks and highest number killed in the country, by 2012 it was no longer one of the most violent parts of the country. The fact that it continued to be central could be a potential sign of further centralization within the FARC. However, when comparing Antioquia to the rest of the country, some distinctions in the tactics used are found. Antioquia has clearly seen a shift towards targeting police, which is not as clear in the rest of the country. In addition, Antioquia has shifted away from bombings towards more armed assaults. The shift towards targeting police is especially similar to the analysis of the southwest region.



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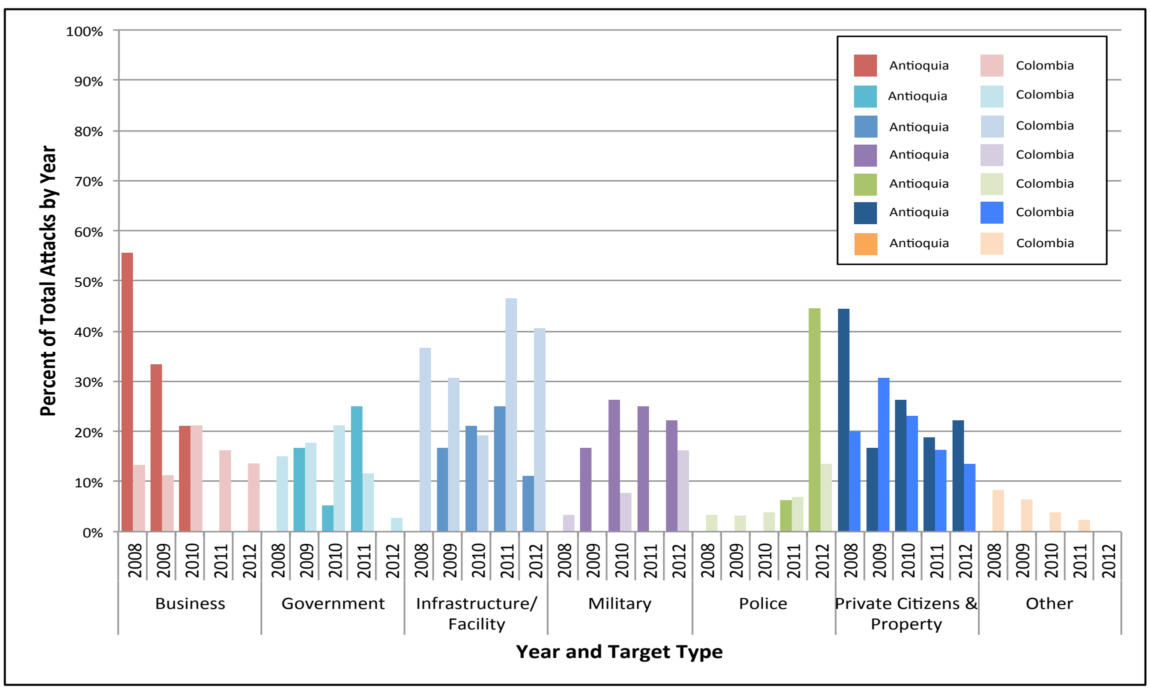

B

Figure 4-11. The distribution of attacks in the Antioquia (green) and the rest of the country, with the southwest region removed (purple) from 2008 to 2012. A: By attack type. B: By target type.

Whether these trends are indicative of further centralization in the FARC factions across the country is inconclusive.

4.3.3.3 A Centralized Network or Two Distinct Conflicts?

Using SNA, some key trends in the conflict were identified. At a high-level, the base of the conflict experienced a major geographic shift, from the northern departments of Antioquia, Santander, and Cundinamarca, to the southwest region. On the other hand, a distinct resurgence of violence could be seen back in Antioquia (after years of decreasing violence). Cluster analysis confirmed that the shift south was not isolated to just one department, but involved coordination among the entire southwest region, including the departments of Cauca, Nariño, Valle del Cauca, Huila, and Caquetá. On the other hand, the unique situation in Antioquia did not look to spread beyond the department. In addition, looking further into the attack tactics used in each region, some similarities that could potentially suggest coordination that goes beyond the southwest were found. On the other hand, some distinct differences were also noted. While both regions have effectively used explosives and both have looked to place focus on targeting police, that trend was more distinct in the southwest. After a surge of bombings in 2010 in Antioquia, the use of bombings decreased in 2011 and 2012 and was replaced with more armed assaults. Meanwhile, the Cauca region has used bombings extensively in its continued mission to combat the police in the area. Hoping to determine why the conflict has moved to these locations, and to better assess whether we are seeing some form of high-level coordination in the FARC network across the entire country, or two mostly separate and distinct conflicts, Section 4.4 delves deeper into the conflict in these two regions.

4.4 Discussion

After over a year and a half of preliminary talks, the current administration entered into peace talks with the FARC in November 2012 (BBC, 2013a). The last time the country attempted peace negotiations was during the Pastrana administration in the late 1990s; the result of which was retaliation by the FARC and a strengthened insurgency (Hylton, 2006). Although the violence is lower today than prior to the last attempt at peace, many questions remain. For instance, could the geographic shift of the violence southwest and the potential resurgence in violence in Antioquia impact the talk's success? Given the structural similarities between today and 1990s, is today's peace attempt destined for failure as well? In order to answer these questions better understanding of how today's conflict compares to the conflict during the Pastrana administration is needed. In this section, unique factors associated with today's conflict, specifically focused on the regions identified in Section 4.3, and how they may serve to help or inhibit successful negotiations at peace is discussed.

4.4.1 A Comparison of the Conflict during the Santos and Pastrana Administrations

Before delving into the unique situation in the Cauca region and in Antioquia, a comparison of the major issues in the conflict as a whole since the last attempt at peace is provided. Several key differences between the two time periods include a weakened FARC insurgency, a strengthened Colombian military, diminished public support for the guerrilla movement, a demobilized paramilitary, and a reduction in the production of coca.

Although the FARC network has shown abrupt periods of escalatory and de-escalatory patterns, Figure 4-5 illustrated that the conflict as a whole is significantly less violent than it was in the late 1990s. With the demise of the most violent drug cartels (e.g., the Medellin and Cali cartels) and other guerrilla groups (e.g., the M-19 and EPL) in the early 1990s, the FARC are the most prominent organization remaining in Colombia today (Hylton, 2006). With a decrease in overall violence, the Colombian government has been able to place their focus on the removal of the FARC. The intensity for which the Colombian military went after the FARC during the previous administration (2002-2010) was nothing like before. With an army ready for combat, improved intelligence, a focus on obliterating the guerrilla movement (with other terrorist and criminal organizations out of the way), and little to no public support for the guerrillas, intense military assaults in FARC-controlled areas was successful in weakening the organization. The size of the FARC network decreased significantly from approximately 17,000 fighters in the 1990s to 9,000 in 2012 (Neuman, 2012). In addition, the focus placed on removing HVTs during the Uribe administration put the organization into disarray, at least temporarily (Spencer, 2013). The mid to late 2000s experienced some of the conflicts lowest levels of violence, and continued success in removing top FARC leadership led the Colombian military to start thinking this may be the "end to the end"

(Spencer, 2013). But under new leadership, the FARC regrouped and demonstrated that, although they had weakened, what did remain was more organized and determined than ever (Lansford, 2014; Spencer, 2013). This is consistent with the trend seen in Figure 4-9.

Defense expenditures increased dramatically in the mid to late 1990s; however, it did nothing to strengthen the Colombian military. With minimal oversight, the money went towards administrative expenses and only 20 percent of soldiers were combat ready. In July 2000, Plan Colombia was signed in Washington (Crandall, 2002; Hylton, 2006). This time the money went towards professionalizing the U.S. backed military and police. Today, Colombia's intelligence and military are better trained, better equipped, and stronger than ever (Neuman, 2012).

State repression in the 1970s, failed peace negotiations in the 1980s, and policing and public services in rural areas provided by the FARC in the 1990s only served to increase public support for the FARC. However, as FARC atrocities reached new heights and began to increasingly impact the daily lives of Colombians everywhere, public support for the guerrilla movement had diminished significantly by the early 2000s (Hylton, 2006). For instance, in April of 2002 the FARC's tactics reached a new level when they bombed a church in the department of Choco, killing 120 and wounding 80 civilians (Hylton, 2006; START, 2012). Today, public support for the FARC and credibility in the insurgency is extremely low throughout the country (Neuman, 2012).

Masked as civilian "self-defense" groups, the paramilitary have at times been viewed as a legitimate group necessary to help in the defeat of the guerrilla insurgency (Hylton, 2006). Between 1997 and 2000, the number of paramilitaries doubled, the group improved its public image, and the organization garnered additional support from the government (Hylton, 2006; Kline and Gray, 2007). During counterinsurgency operations, the paramilitary were often used to provide a cleared path for the military into FARC-controlled regions. Even with political support, however, the paramilitary were considered unconstitutional under Colombian law and thus could not be involved in peace negotiations during the Pastrana administration (Hylton, 2006). This caused the Right-wing group to retaliate, which garnered public support for the leftist guerrilla movement and strengthened their cause. In 2006, the largest of the paramilitary groups, the United Self Defense Units of Colombia (AUC), demobilized with approximately 32,000 of its members handing over its weapons. Although violence has not reached the levels found previously under the AUC, former members are said to have formed neo-paramilitary groups who operate as drug traffickers and contribute to organized crime (InSight Crime, 2014).

In the late 1990s the coca industry was thriving. For instance, in 1998, 90 percent of cocaine imported into the U.S. originated in Colombia (Hylton, 2006). The industry exploded in the late 1990s and early 2000s, and provided the main source of financing for the FARC. By imposing a tax to maintain law and order within the chain between the coca cultivator and customer, the FARC garnered an extraordinary amount of wealth (Hylton, 2006). Since then, however, the U.S. backed coca eradication campaign has effectively reduced production in Colombia from 74 percent of the world's coca in 2000 to 42 percent in 2011, just above Peru. In 2013, it was reported to have fallen below Peru's production levels due to the eradication of approximately 327,000 acres of coca plants (Leon and Kraul, 2013; The Economist, 2013). However, the FARC have fought back by targeting coca eradicators and blocking eradication teams from entering certain areas. In addition, it is being projected that Colombia will not meet their eradication target for 2014 (Parkinson, 2013).

At the country-level, the conflict is in a very different place today than it was during the Pastrana administration. The FARC are nowhere near the size they were during their peak years, the Colombian military is stronger than ever and ready for combat, public support for the insurgency is almost non-existent across the country, the paramilitary no longer have the defining role in the conflict they once had, and coca production, the FARC's long-time main source of financing, has reduced significantly since its peak in the late 1990s. These positive trends provide support to the idea that peace talks are more likely to succeed this time around. However, looking at the specific regions identified earlier, a different story may emerge.

4.4.2 A Centralized Insurgency in the South

The southern department of Cauca is now known as a "hotbed" for the conflict between the military and the FARC (Noto, 2012). After the death of the FARC's long-time leader in 2008, Cano took over and immediately began making some key changes to renew the insurgency (Spencer, 2013). Using SNA and GIS (Sections 4.3.2 and 4.3.3), a clear geographic shift to the southwest, beginning in the Cauca department in 2010 and expanding to the surrounding departments of Huila, Nariño, Valle del Cauca, and Caquetá was discovered. This coincides with Cano's move of the FARC's main base of operation to the southwest, specifically to the Cauca, Valle del Cauca, and Nariño departments (Pettersson, 2013; Spencer, 2013). The region was ideal for setting-up the front for several reasons, including its strategic location, the coca industry, difficulty of military intervention, and public support (Spencer, 2013). Between the resources needed to finance the insurgency and exploitation of the geographic concentration of potential recruits and laborers, struggling to meet basic needs, these factors have provided the FARC with the opportunity to rebuild (see humanistic needs theory and opportunity-based theories of conflict in Sections 2.1.4 and 2.1.5). By the time Santos took office, the FARC resurgence in the south was beginning to see an impact, and for the first time in years, the country was beginning to feel insecure again (Spencer, 2013).

Bordering Ecuador to the south and the Pacific Ocean to the west, rough terrain, and poorly secured borders, make it the ideal location for hiding and transporting weapons and drugs (Spencer, 2013; Stone, 2011). Even though coca eradication has reduced production in the country, in this region coca grows freely (Neuman, 2012). The region is a large producer of coca and marijuana (Spencer, 2013; Stone, 2011). In addition, illegal mining occurs and oil drilling in Nariño provides the FARC opportunity to steal oil from pipelines. These illicit activities provide the FARC with ample sources of financing. In addition, the region is a large producer of legal crops (e.g., sugar cane and coffee) and is home to major commercial routes. Unlike attacks in remote parts of the country, events along these major routes make the news, creating the perception of national insecurity (Spencer, 2013). For the time being, the FARC in this region have ample sources for financing and it has not seen the impact the coca eradication campaign has had with other regions of the country.

Cauca is home to approximately 24 percent of Colombia's indigenous population (Wirpsa et al., 2009). According to the Colombian constitution, indigenous groups are given complete sovereignty over the land they inhabit and the right to their own legal system (Noto, 2012). As such, the Colombian government and its troops are not allowed access to their land without prior consent of indigenous leaders. The indigenous population in Cauca has been unsupportive both of the FARC and of military intervention, supporting instead non-violent means to remove the guerrilla movement (Noto, 2012; Spencer, 2013). On the other hand, the FARC spent years creating a relationship with the indigenous population (Spencer, 2013). It is believed that they have successfully infiltrated certain indigenous groups, giving them the access they need to operate while keeping the military out (Noto, 2012). While the Colombian military is stronger than that of the 1990s, without access to intervene, the strength of the military is irrelevant.

Although public support for the FARC is extremely low across the country, the Cauca region was the one area where the organization has maintained some level of a social approval (Murphy, 2014; Spencer, 2013). Minimal government presence, poverty, and lack of education make the region ideal for developing community support and finding recruits (Spencer, 2013). Through coca production, the FARC provide employment opportunities and income to a large portion of the population in the region (Murphy, 2014; Spencer, 2013). In addition, many serve in FARC militias (known as Terrorism Support Networks), who at times provide a line of defense between the Colombian military and police and the FARC's regular units (Spencer, 2013).

When Cano moved the base of the organization to the Cauca region, he also made some significant changes to its tactical operations, looking to return to traditional guerrilla warfare (Otis, 2011; Spencer, 2013), focusing on operating in smaller groups and impacting a wider geographic area (Otis, 2011). Between 2008 (when Cano took over) and 2010, attacks by the FARC had increased to levels the country had not seen since 2002 (McDermott, 2013; START, 2012). In Section 4.3.3, a shift from targeting private citizens and property towards targeting police was found. Part of Cano's strategy was to focus on increasing the use of explosives (McDermott, 2013) and focusing in on targeting police patrols and police stations (Spencer, 2013). Although Cano was killed in November 2011 and was replaced by Londono, the trend to target police increased in 2012 (BBC, 2013a). There was only a slight shift in the use of explosives, which decreased from 2011 while armed assaults increased. By 2012, the number of attacks had decreased but the number killed and wounded spiked significantly, the highest since 2003.

While the country has seen a weakened FARC, a strong military, diminished public support for the guerrilla movement, and success in the coca eradication campaign, the Cauca region has not seen these trends to nearly the same extent. In the southwest the FARC have been able to rebuild and thrive. The strategic location has garnered them ample sources of financing, support from the community, and limited military interruption. Even with the death of its leader in late 2011, the FARC remained strong in the region. On the other hand, the FARC moved here for strategic reasons. It may be the only region in the country that it can thrive to some extent. And therefore, it may be difficult, if not impossible, to spread the strong insurgency to the rest of the country.

4.4.3 A Rush for Gold in the North

With the surge in the price of gold combined with increased demand (as discussed in Section 4.1), a weakening coca industry, and pressure from the government to move away from drug trafficking, the FARC moved towards gold as a viable source of revenue (Pachico, 2012). The lootability of this new resource combined with the economic incentives, such as price and demand, has provided the FARC with new opportunity to continue to finance the guerrilla movement (see the discussion of opportunity-based theories of conflict in Section 2.1.5). This rush for gold has made Antioquia one of the most violent regions in the country (Romero, 2011).

When Cano took over FARC leadership, he sought to create a well-trained, powerful, and coordinated group of militants. In Antioquia, however, the FARC operating the gold mining areas function very differently. In Section 4.3.3, cluster analysis placed Antioquia with the Caquetá and Arauca departments in 2012. While in Cauca, this type of clustering looked to indicate coordination among multiple departments, here, given the geographic placement of these departments across the country, it is difficult to conclude that this is indicative of centralization in the network. Like the insurgency in Cauca, however, the use of IEDs was effective, especially in 2010, which saw a spike in the tactic (Pachico, 2012). By 2011 and 2012, however, the number of bombings equaled the number of armed assaults. Similar to the southwest, more police were targeted in 2012 than in the past, a small shift from targeting the military and government in 2011. While the southwest saw a surge in violence in 2012, Antioquia saw a decrease in violence. And without a strong shift in tactics between the two years, the clustering may be more a factor of the low intensity in violence than strong similarities between the locations. In addition, the FARC in Antioquia are weaker with only an estimated 60 fighters, they are poorly trained, and they have chosen not to participate in local politics. The faction in Cauca, on the other hand, have worked to develop strong relationships with local indigenous leaders. This supports the theory that this FARC may not be seeing the organizational coordination of the southwest (Pachico, 2012; Spencer, 2013).

A key difference between the conflict in Antioquia today and that of the late 1990s is that coca has been largely replaced by gold as a major source of financing (Ramsey, 2012). Even as the FARC have entered into peace talks, more resilient factions are turning to gold to continue the movement. Gold is not only profitable but, unlike cocaine, is a legal commodity and legal to transport and sell (McDermott, 2012; Romero, 2011). It is estimated that 20 percent of profits from gold mining goes to the FARC, while ELN and other criminal groups, such as neo-paramilitary groups receive smaller shares of the profits (Ramsey, 2012). In one part of Antioquia, a hotspot for illegal mining, terrorist and criminal organizations are charging exorbitant extortion fees, at times putting miners out of business (Ramsey, 2012). Similarly to coca, the FARC are taking advantage of an unregulated and decentralized industry and exploiting it by imposing taxes and charging extortion fees (Ramsey, 2012). If left unpaid, for instance, the FARC might destroy the miner’s equipment (Pachico, 2012).

After the AUC demobilized in 2006, factions of the former group are said to have formed neo-paramilitary groups known by the government as BACRIMs, or “criminal bands.” The two largest of these are the Rastrojos and the Urabeños. These organizations participate in criminal activities such as drug trafficking and money laundering (Bargent, 2013). Much like the old paramilitary group, they have also embedded themselves closely into local political alliances and security forces. On the other hand, there objective is not to combat the guerrilla movement but instead to manage the whole of the Colombia’s criminal networks (Bargent, 2013). In Antioquia, these neo-paramilitary groups, the ELN, and the FARC compete for territory. This has led to an increase in violence amongst competing groups (Romero, 2011). On the other hand, residents have reported that in places, the FARC are working side-by-side with members of the ELN and other criminal groups, such as neo-paramilitary groups, while sharing the profits (Ramsey, 2012). Signaling a potential shift in the conflict in the region, one that is based less on ideology and more on profits.

In addition, unlike the Cauca region, which sees certain levels of public support, support here for the guerrillas is very low. The FARC have driven out miners in the informal sector with extortion rates that have put them out of business (Ramsey, 2012); they have increased the level of violence and made Antioquia one of the deadliest departments again (Romero, 2011); and the unregulated mining they enforce is detrimental to the environment, making Colombia the largest polluter of mercury from mining in the world (Romero, 2011). On the other hand, while support for the FARC may be low, so is support for government intervention. Protests against government policies in the mining region add a barrier to military intervention. However, while access to the region is illegal in Cauca, it is not the case here.

The resurgence of violence in Antioquia has really been a result of the FARC's exploitation of gold mining. With the campaign to eradicate coca production, the FARC here have shifted to a new source of financing. On the other hand, the FARC in this region look to be weaker and, like most of the country, public support for them is low. While the Colombian military struggles to insert itself into the indigenously owned lands in Cauca due to legal reasons, the same barrier does not exist here. However, diminishing public support of government policies around mining has resulted in protests in the region. In addition, the mix of inter-group competition and cooperation at times supports a conflict that is more decentralized, and one that is more about profits than about ideology.

4.4.4 The Government's Response and Peace Talks

At the state-level, the Colombian conflict is at a very different place today than it was during the country's last attempt at peace. The FARC have been weakened, the military is strong, public support for the FARC is at an all time low, the paramilitary no longer play a defining role, and coca eradication campaigns have limited the FARC's source of financing. On the other hand, SNA analysis combined with GIS demonstrated some interesting regional patterns. Delving deeper into the conflict at the regional-level, we found some disturbing trends. The FARC in the Cauca region have been able to resurge, organize, and strengthen. And while they may not be as strong in Antioquia, gold mining has given the FARC, along with other criminal organizations, new life.

In the Cauca region, the FARC have been able to rebuild, the military has struggled to intervene, certain levels of community support have been achieved, and coca grows freely (see Section 4.4.2). The Santos administration has responded via a military campaign to combat the FARC. Despite resistance from indigenous groups, six new mobile task forces were created, of which three were located in the Cauca region. The new operations successfully found and killed the FARC's leader in November of 2011. Even with this success, however, the unique situation in Cauca required the government make some adjustments to its strategy. In July 2012, Santos announced that Plan Cauca would be put into place (Pettersson, 2012; Spencer, 2013). The goal being to improve transportation networks, build infrastructure, and aid in the overall development of the region through improved education, public health facilities, and poverty alleviation programs. However, implementation has been very slow and critics have been harsh. While the plan may have positive long-term effects, it is unlikely to have much of an impact on current efforts to weaken the FARC. Despite the challenges, government campaigns here seem to be making a difference and could be a major reason the FARC were willing to sit down with the administration for peace talks (Spencer, 2013).

According to Antioquia's governor, "gold is now more lucrative than coca" (McDermott, 2012). Here, the FARC have been able to move away from its reliance on coca and have found a new source of financing in gold mining, which has caused a resurgence of violence in the area and has given life, not just to the FARC but also to other old players in the conflict and new ones (see Section 4.4.3). The government has looked to regulate mining in hopes to reduce illicit mining activities. However, it does not distinguish between the small, unlicensed miners and illegal mining. In 2010, the government closed 70 mines and arrested almost 120 unregistered miners (Vicente et al., 2011). This has drawn protests from those who rely on artisanal mining for income. In July 2013, for example, unlicensed miners in Antioquia protested the government's policy of seizing and destroying their equipment (Willis and Smith, 2013).

If peace talks are to be successful, it is critical that the government address the unique social and economic dynamics of the conflict in both the Cauca region and in Antioquia. The environment in the Cauca region is very local. The indigenous population, its strategic location, and community support make Cauca unlike any other region in Colombia. These local advantages have allowed the FARC to rebuild and to create a centralized insurgency in the southwest. It seems to be the main base of operation for FARC leadership and factions here look to operate under this central authority. In addition, the government has placed much focus on counterinsurgency and development campaigns in the region in recent years. Given these characteristics, the FARC in this region are most likely to respond to successful peace talks. On the other hand, while over 90 percent of attacks in Cauca and 85 percent of attacks in the southwest region can be attributed to the FARC, the ELN still maintain some presence. The government will also need to address this organization, as a demobilized FARC may leave room for the ELN to take over. While the government has expressed an interest in opening up talks with the ELN, and while both sides could benefit from a peace agreement, formal discussions have yet to commence (BBC, 2013b; International Crisis Group, 2014).

Even with the potential challenges in the Cauca region, demobilization of a centralized organization is easier than its decentralized alternative (Medina and Hepner, 2011). In Antioquia, the FARC are weaker, but a decentralized environment may prove more difficult to dismantle (Pachico, 2012). In addition, the FARC's role in the region is smaller. Here, the ELN, neo-paramilitary, and other criminal organizations also play a large role in the violence (Ramsey, 2012; Romero, 2011). Peace talks may need to address more than just the FARC's concerns. In addition, the conflict here has shifted further from one of ideology. While this may be also true in other parts of the country, the FARC's amiability to cooperate with its former "opponents" signals that the shift may be even larger here. As such, the issues important to the FARC base in the southwest may be of less relevance to the situation here.

The road to peace in Colombia is closer than ever. Key issues that doomed the last peace talks to failure have either been addressed by the government (e.g., a demobilized paramilitary, coca production, a strengthened military) or have resolved themselves as a consequence of government programs and the long-lasting violence (e.g., a weakened FARC and diminished public support for the guerrilla movement). While government campaigns are looking to address the issues in both the Cauca region and in Antioquia, challenges remain. Even if a peace agreement is signed, it will be critical that the government address the underlying social, economic, and security issues in the Cauca region if the country hopes to sustain long-term peace (Spencer, 2013). In addition, the government's ability to develop long-lasting and working policies to combat illicit mining will be imperative in Antioquia. It is important that the government maintain the safety and legitimacy of the miners, otherwise the FARC, along with other criminal organizations, will continue to exploit the industry (Ramsey, 2012).

4.5 Summary

The use of SNA techniques with simple GIS in the study of terrorist event data is novel. The use of centrality measures allowed me to quickly hone in on the overall trends in the conflict; noting that the base of the conflict looked to have shifted southwest while a resurgence of violence seemed to have occurred back in one of the conflict's traditional territories. Cluster analysis, which grouped nodes into structurally similar subsets, confirmed that the shift southwest was most likely a coordinated effort across several departments, which began largely in Cauca in 2010 and expanded to four of its bordering departments. A clear shift in tactics to targeting police reinforced this idea. While cluster analysis of the Antioquia region did not provide as clear an insight into the regional conflict. It did provide support to the idea that the conflict in Antioquia is somewhat removed from that of the southwest region and that the factions working there are likely not as organized. Qualitative research than helped me delve further into the conflict at the state and regional-level. Current events in the Cauca region and in Antioquia re-enforced the discoveries, while also providing additional insight into key social and economic issues and the government's response.

The road to peace in Colombia is closer than ever. Key issues in the country that were either overlooked or could not be addressed prior to the last attempt at peace have largely been resolved. While the overall situation in the country looks favorable for peace negotiations, unique local and regional dynamics may still pose a challenge. The government has placed much focus on counterinsurgency and development campaigns in Cauca, while in Antioquia the administration has focused on regulating the informal and often illicit gold mining trade. However, current efforts in both regions have had its challenges, and public support of government intervention is low. Agreement to a signed peace deal would put the country in the right direction. However, long-term success and peace will result only if the country deals with the underlying social, economic, and security issues at the regional-level.

This analysis provides a generic model of conflict at the state-level that can be applied to similar event data of other conflicts. While SNA and GIS provided several leads for which to further explore in the data, it cannot tell us why we might be seeing certain trends or what the underlying issues may be in the conflict. The "why" and "what" were explored further via qualitative research. However, in the case where the available data is event data at the level of the criminal or terrorist organization, this type of analysis can quickly provide valuable insight into current trends in a conflict and may be the ideal approach.

Understanding where a conflict is trending spatiotemporally, what regions or FARC factions look to be coordinating, and what tactics are being used most prominently in these coordinated attacks, can give policy makers the understanding they need to implement policy, both in terms of the kinds of policies needed and the location(s) that policy should be implemented. This model is an improvement over traditional, top-down statistical approaches that may require aggregation and linearity assumptions that would oversimplify the social phenomena modeled. In addition, the use of SNA or GIS techniques alone would have fallen short in its ability to concurrently analyze the event data across space, time, and their unique characteristics (such as weapon type, target type, and attack type). In the next chapter, the first of two ABMs are described. Simple human behavior is introduced as agents interact over a GIS. Theory is explored by testing several "what if" scenarios and how micro-level changes in the environment impact macro-level processes are examined.

5. THE GEOGRAPHY OF CONFLICT DIAMONDS: THE CASE OF SIERRA LEONE

In this chapter, a simple ABM is combined with GIS to develop a state-level model of conflict. The previous chapter provided interesting spatiotemporal insights into the Colombian conflict, and qualitative analysis allowed us to better understand these patterns. ABM, however, provides a method for further exploring macro-level spatiotemporal patterns. By adding simple behavior that is grounded in theory into the agents modeled, we can gain a better understanding of the underlying processes responsible for the macro-level patterns. Sierra Leone, which endured nearly 10 years of civil war, provides the case study for which this model is implemented. The ease of accessibility to the country's most abundant resource (diamonds) is said to have provided the funding needed to sustain the insurgency over the years. According to Le Billon (2001), the spatial dispersion of a resource is a major defining feature of a war, impacting the type of conflict that emerges. Using GIS to create a realistic landscape and theories of conflict to ground agent behavior, this chapter explores Le Billon's (2001) theory. First, Section 5.1 further discusses the conflict in Sierra Leone and Le Billon's theory. Section 5.2 provides a detailed description of the data used, the model initialization process, and agent behavior is explained. Next, Section 5.3 discussed the simulation results and

Section 5.4 provides a discussion of experiment results. Finally, Section 5.5 provides a summary of the chapter.

5.1 Introduction

In the early 1990s, Sierra Leone, a small country on the western coast of Africa, entered into nearly 10 years of civil war. Sparked by an abusive government and fueled by an illicit diamond market, the decade-long war killed an estimated 70,000 and displaced another 2.6 million people (UN Development Programme, 2006). The war began in 1991, when the Revolutionary United Front (RUF) attacked villages on the Liberian border (Department of State, 2010). The RUF originated as a small band of students who were expelled from the country in the late 1980s. They fled to Ghana and Libya where they attended military training. Those still interested in revolution returned to the Kono District on the eastern border of Sierra Leone, where they examined diamond mines and worked to spread a revolutionary ideology (Leoa, 2010).

It is said that the primary driver of the war was the country's most abundant and valued resource, diamonds (Leoa, 2010). Although endowed with the natural resource (Goreux, 2001), Sierra Leone was ranked the poorest country in the world in 2000 by the UN (EconomyWatch, 2000), just one year before the civil war ended. More recently, it was ranked 177 out of 187 countries on the UN's Human Development Index for 2012 (UN Development Programme, 2013). In other countries the presence of rich resources has resulted in growth and the reduction of poverty. While Sierra Leone was ravaged in war, Botswana was recording growth rates similar to those of some of the richest East

Asian countries due to the abundance of diamond resources (Goreux, 2001). A key difference, however, are that Botswana's diamonds originate from kimberlite formation, while Sierra Leone's diamonds are alluvial. While diamonds extracted from kimberlite formation tend to be highly mechanized, fenced, and secure, alluvial diamonds (which are mainly found along riverbeds) are often mined by independent, small enterprises and artisans. Technology is rudimentary, mining areas cannot be easily fenced, and security of the resource is minimal. Alluvial diamonds also tend to cover widespread areas in remote parts of the country, where many of the population are poor, uneducated, and have limited employment opportunities. In effect, in such areas wages are low and workers remain poor, thus creating an attractive pool of recruits for rebel forces. Without government regulation and enforcement, this type of mining is often performed illegally, where "enforcement" is placed in the hands of criminals (Goreux, 2001).

Sierra Leone is made-up of four administrative regions: the Northern Province, the Eastern Province, the Southern Province, and the Western Area. These regions are further divided into fourteen districts (GADM, 2009). Figure 5-1 shows a simple map of the country divided into districts. The capital, Freetown, is located on the west coast and is shown as a yellow diamond. In addition, the red circles illustrate the location of the diamond mines (i.e., the sites where alluvial diamonds are extracted).

Prior to WWII, the Sierra Leone Selection Trust (SLST) dominated diamond mining. The mining environment was harsh with the majority of the alluvial deposits located in the midst of unexplored jungle. The situation raised concerns about security, as

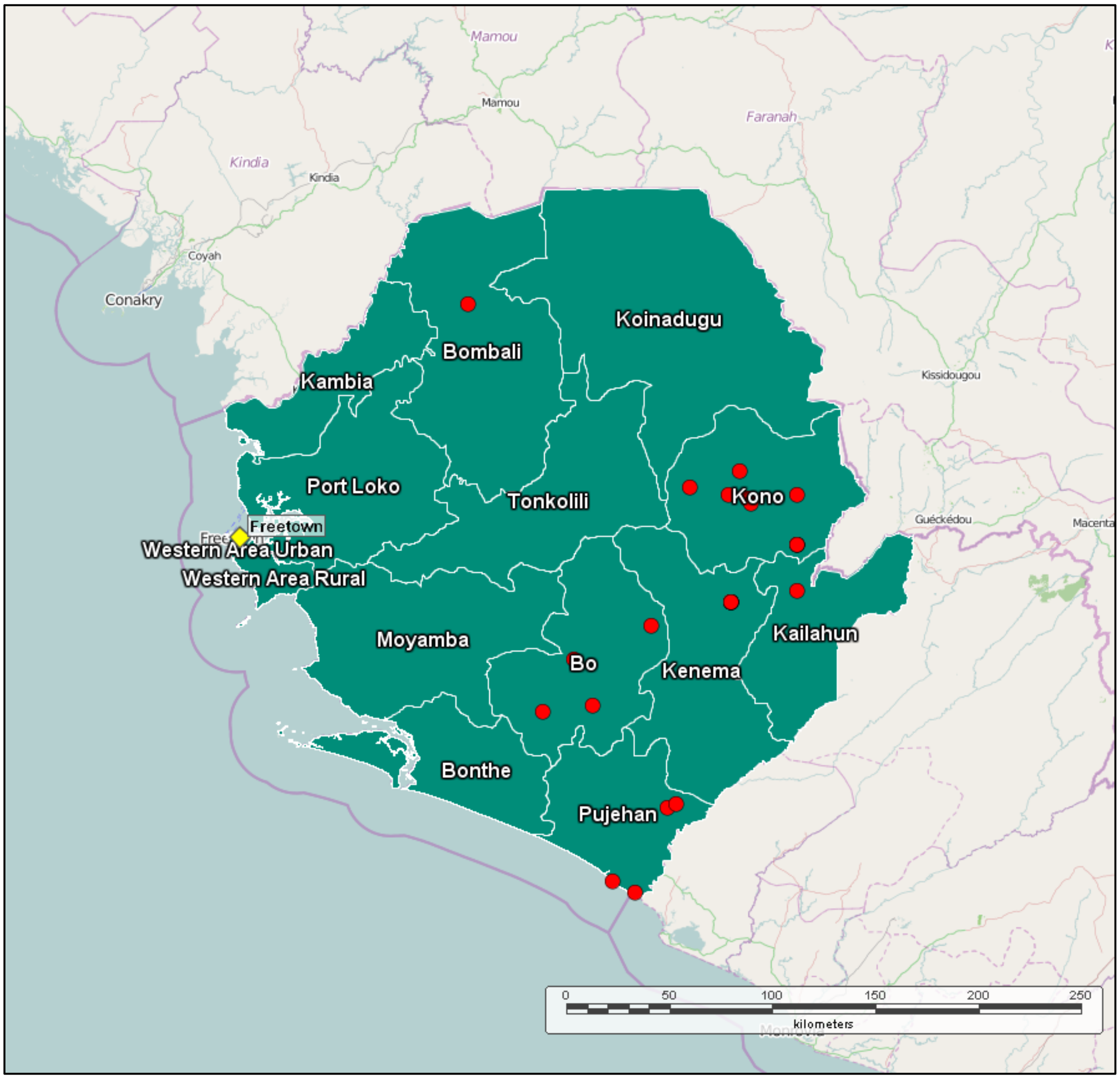

Figure 5-1. Map of Sierra Leone divided into the fourteen districts with the capital, Freetown, shown as a yellow diamond and location of diamond mines represented by red circles.

the SLST was doubtful that they would be able to control the area from theft. Their concerns came to fruition during WWII when Sierra Leoneans serving for the British army had learned of the value behind the diamonds during their time away at war. Residents abandoned their jobs and farmers ignored their crops, as thousands became independent, illegal miners. In 1954, the Sierra Leone army sent 1,300 soldiers to the Kono District to provide security for the SLST, which had formed its own militias. Violent clashes between militias and miners became regular events. This did not slow the activity of illicit diamond mining, however, as the reward far outweighed the risk. By the late-1950s, it became apparent that even with the army and militias the independent operators could not be controlled. At this point, the government introduced a licensing program allowing these independent miners to work legally. It was too late however, as the miners, working with their already established financiers, had learned to sell their diamonds to contacts outside of the country. By the time war broke out in 1991, this system was well established. With more diamonds being smuggled than legally exported, the country missed out on the export taxes and contracts that could have provided much needed funding for infrastructure, education, and healthcare (Campbell, 2004).

In the 1980s, dissatisfaction among the youth had reached new levels. A suppressive government combined with a global economic recession led to the emergence of an "army" of frustrated school dropouts and unemployed youth (Leoa, 2010), who came to be known as the RUF. The formation of the RUF came around the same time civil war in neighboring Liberia was beginning, resulting in the displacement of 80,000 to Sierra Leone. The refugees, who were often in need of medical attention, food, and shelter, and were composed largely of children, became a vital pool of potential recruits (Gberie, 2005). Children were especially vulnerable, often driven (or forced) to join due to poverty, disrupted or non-existent families, and ideology (Twum-Danso, 2003; UN CyberSchoolBus, 2014). These child soldiers, who were under the age of 18 and as young as seven (Twum-Danso, 2003; UN CyberSchoolBus, 2014) were often coerced at gunpoint, abducted from their families, and often injected with alcohol and drugs, the RUF took advantage of the situation and recruited refugees, youth, and criminals freed from prison (Gberie, 2005; UN Development Programme, 2006). After joining the rebellion, whether by choice or force, the young recruits found that the war provided a sense of strong group identity, resulting in the embracement of the rebel ideology and continued support of the movement (Gberie, 2005; UN CyberSchoolBus, 2014). This environment, combined with an ideal resource for which to finance the war, led to 10 years of conflict characterized by excessive brutality via widespread executions, amputation of limbs, decapitation, and rape (UN Development Programme, 2006).

Le Billon (2001) argued that the spatial dispersion of a resource is a major defining feature of a war, impacting the type of conflict that may emerge (see Section 2.1.5). According to the theory, conflict characteristics are affected by two geographic factors: (1) the geographic location of natural resources as they relate to the country's center (proximate versus distant) and (2) the concentration of resources (point versus diffuse). The first factor refers to the geographic distance and accessibility of a resource, which can impact a government's ability to regulate access to a resource. The more distant a resource from a countries center of control (i.e., the more remote the area) the easier for rebel forces to capture the area and take control of resource production and revenue streams (e.g., coca production, forests in remote areas, alluvial diamond mining). Proximate resources, on the hand, are easier to control and are less likely to be captured (e.g., coffee, oil near center of control). The second factor relates to the geographic concentration of a resource. Diffuse resources are widespread over large geographic areas, making the resource more difficult to secure. They are typically acquired by productive industries (e.g., agriculture, fisheries, forestry, and alluvial diamonds). Point resources, however, are concentrated in small geographic areas and typically require mechanized extraction (e.g., oil, kimberlite diamond mining). Due to the degree of mechanization and technology requirements, point resources are easier to secure and less likely to be exploited by rebel forces (Le Billon, 2001).

Assuming an environment that is ripe for conflict (see the theories of conflict outlined in Section 2.1), the geographic features of a resource can influence the type of conflict. When distant resources are diffuse, an environment of warlordism is likely to emerge (e.g., alluvial diamonds in Sierra Leone, coca production in Colombia). These types of resources, which are widespread and far from the country's center of power, give rebel leaders (or warlords) the opportunity to exploit the resource with relative ease, and through violence, they create areas of de facto sovereignty. While rebel groups may wish to overthrow the existing regime (via a coup), the availability of distant, diffuse resources provide rebels with continued funding to sustain the insurgency in case of failure. Secession attempts, on the other hand, are influenced by the presence of distant, point resources. Given the increased difficulty in accessing these resources, rebel forces will seek complete sovereignty over the area. Using the existence of these resources as justification from secession from the state, rebels seek mobilization by stressing grievances and the opportunity for future revenues. When diffuse, proximate resources are associated with large numbers of producers, rioting or mass rebellion near the country's center of power is more likely to occur. For instance, poor labor conditions, and the exclusion and displacement of laborers by large corporations may lead to mobilization. Given the challenges associated with controlling the large number of workers over a widespread area, coercive techniques (e.g., warlordism) are exchanged for a more participatory form of conflict (e.g., mass rebellion). Finally, attempts at state control or coups are most likely when point resources are proximate. These types of resources are very difficult for rebel groups to access. Given the lack of other revenue streams to finance an insurgency, the best strategy is overthrow the current regime and seek complete sovereignty over the state, and as a consequence, access to the resources (Le Billon, 2005, 2001).

Using Sierra Leone as a test case, an ABM was developed to explore Le Billon's (2001) theory. Classic ABMs of rebellion include Axelrod's (1993) model of new political actors, Epstein and Axtell's (1996) Sugarscape model, and Epstein's (2002) Civil Violence Model. More recent ABM's have explored in-group dynamic and ethnic salience (e.g., Bhavnani and Miodownik, 2009; Bhavnani, 2006; Hammond and Axelrod, 2006; Lustick, 2000). Building on this, others have studied the relationship between ethnic or group identity and resources on the emergence of conflict (e.g., Bhavnani et al., 2008; Lidow, 2009; Miodownik and Bhavnani, 2011; Miodownik, 2006) (see Section 2.2.5). While the ABM presented here shares similarities with prior ABMs that have explored income, resources, and identity as drivers of conflict, it also introduces some key differences. Utilizing GIS and socioeconomic data of the country, a landscape and population that better represent the actual setting being modeled is created. In addition, the implementation of the PECS framework (see Section 3.3.2.2) to create a more accurate abstraction of human behavior is a novel approach to ABMs of conflict. The behavior of agents in the model draws from several theories of conflict. Theorists have pointed to opportunity, along with motivation and group identity, as indicators of war (e.g., Ellingsen, 2000; Fearon and Laitin, 2003). Others extended the opportunity-based theory to focus on lootable resources, such as alluvial diamonds (e.g., Collier and Hoeffler, 2004, 1998; Collier et al., 2009; Lujala et al., 2005). The model here draws from the opportunity-based theories of conflict (see Sections 2.1.5 and 3.3.1.2). In addition, to account for motivation and group identity, it turns to humanistic needs theory (see Sections 2.1.4 and 3.3.1.3) and identity theory (see Sections 2.1.3 and 3.3.1.1) to help drive behavior.

This allows us to explore Le Billon's (2001) argument that conflict characteristics are impacted by the resource's distance from the center and the resource's dispersion. It is found that unexpected consequences can come from minimally increasing security over the diamond market when the sites are in rural regions, potentially displacing conflict rather than removing it. On the other hand, minimal security may be sufficient to prevent conflict when resources are found in the city. Different scenarios are explored as the diamond mines are made more secure (from diffuse to point) and the mining areas are moved to the capital of the country (from distant to proximate).

5.2 Model Development

An ABM was developed in MASON (Luke et al., 2005) utilizing the GeoMason (Sullivan et al., 2010) spatial extension to explore the role of geography in a resource-driven war. GIS data was utilized to create the modeling landscape, while socioeconomic data of Sierra Leone provided initial agent attributes. Due to the localized nature of social processes, including civil violence, ABM combined with GIS is ideal for modeling the unique environment of Sierra Leone and the long-lasting conflict it endured. ABM gives us the ability to endow our agents with unique attributes given their residing region and to interact locally with nearby agents and the environment. Meanwhile, GIS allows us to create a more realistic abstraction of the actual landscape of Sierra Leone, including actual population distribution, city locations, and diamond mines. Figure 5-2 displays the graphical user interface (GUI) of the model. The interface, which includes a chart showing the agent's activity by time step, helps to debug the model and to better understand model results (Grimm, 2002). For readers wanting to download the source code or executable of the model please see http://css.gmu.edu/Pires/.

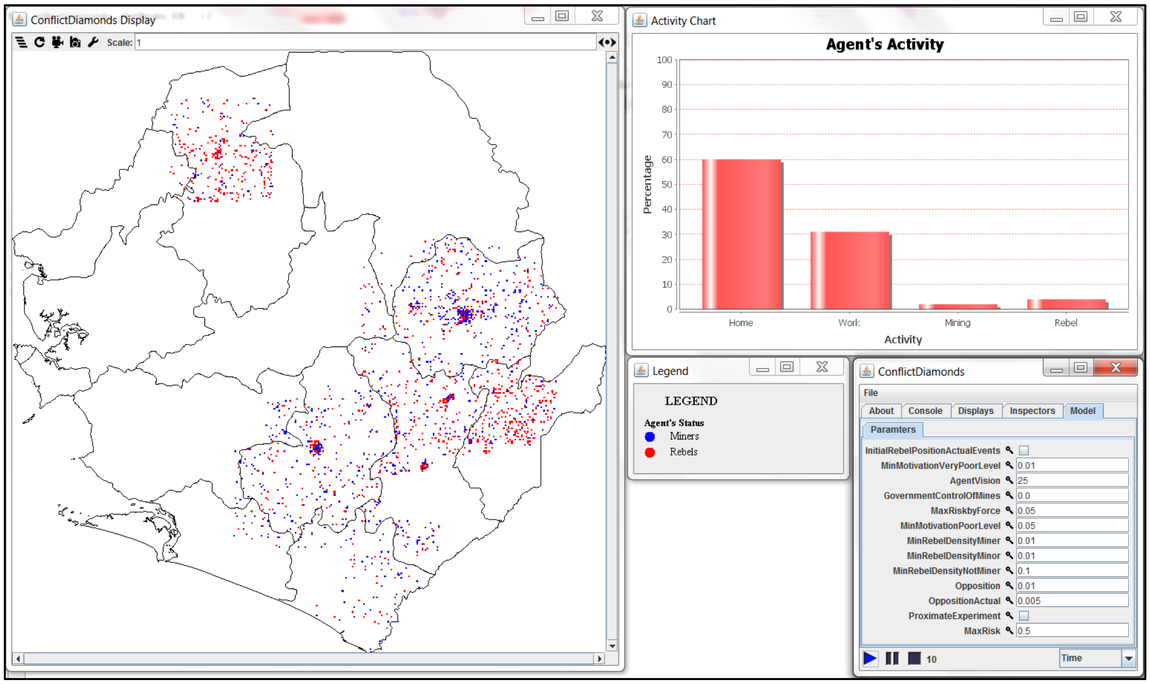

Figure 5-2. The model's GUI.

The modeling world, which is the country of Sierra Leone, is broken out into the country's 14 Districts. This is further divided into equal size Parcels, where the agents reside. The agents' (or Person) behavior is determined in the Intensity Analyzer and is executed via the Action Sequence. Depending on the results of the Intensity Analyzer, the Person will either be a Resident or a Rebel. Residents that are employed work for a Diamond Miner or Other Employers, which provides a simple way to track the employed Residents working as laborers in the diamond mines. Figure 5-3 provides the high-level Unified Modeling Language (UML) diagram of the model.

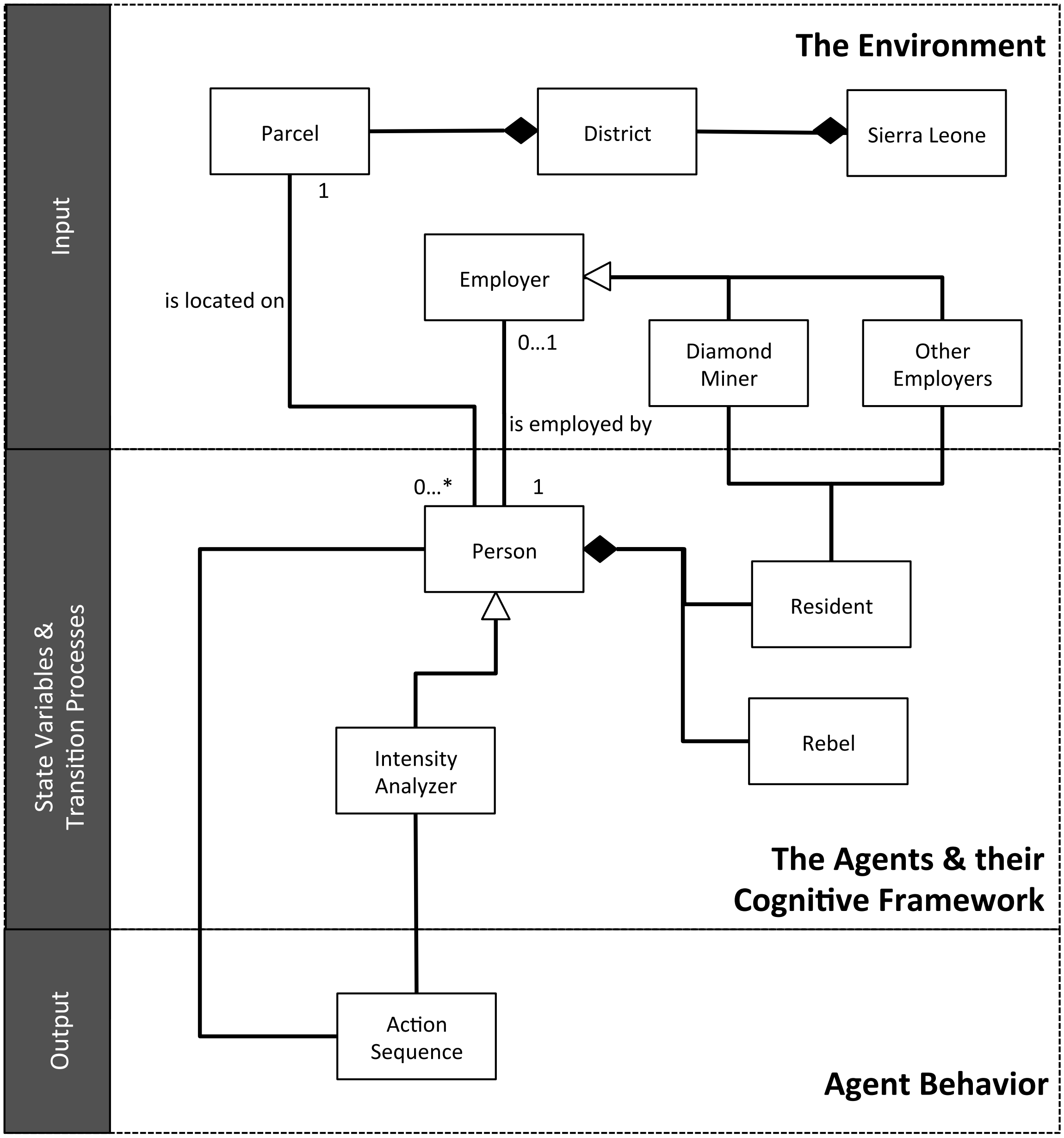

Figure 5-3. UML diagram of model.

Figure 5-4 illustrates the model's key processes, which are discussed in more detail in the sections that follow. The model's initialization process is discussed in

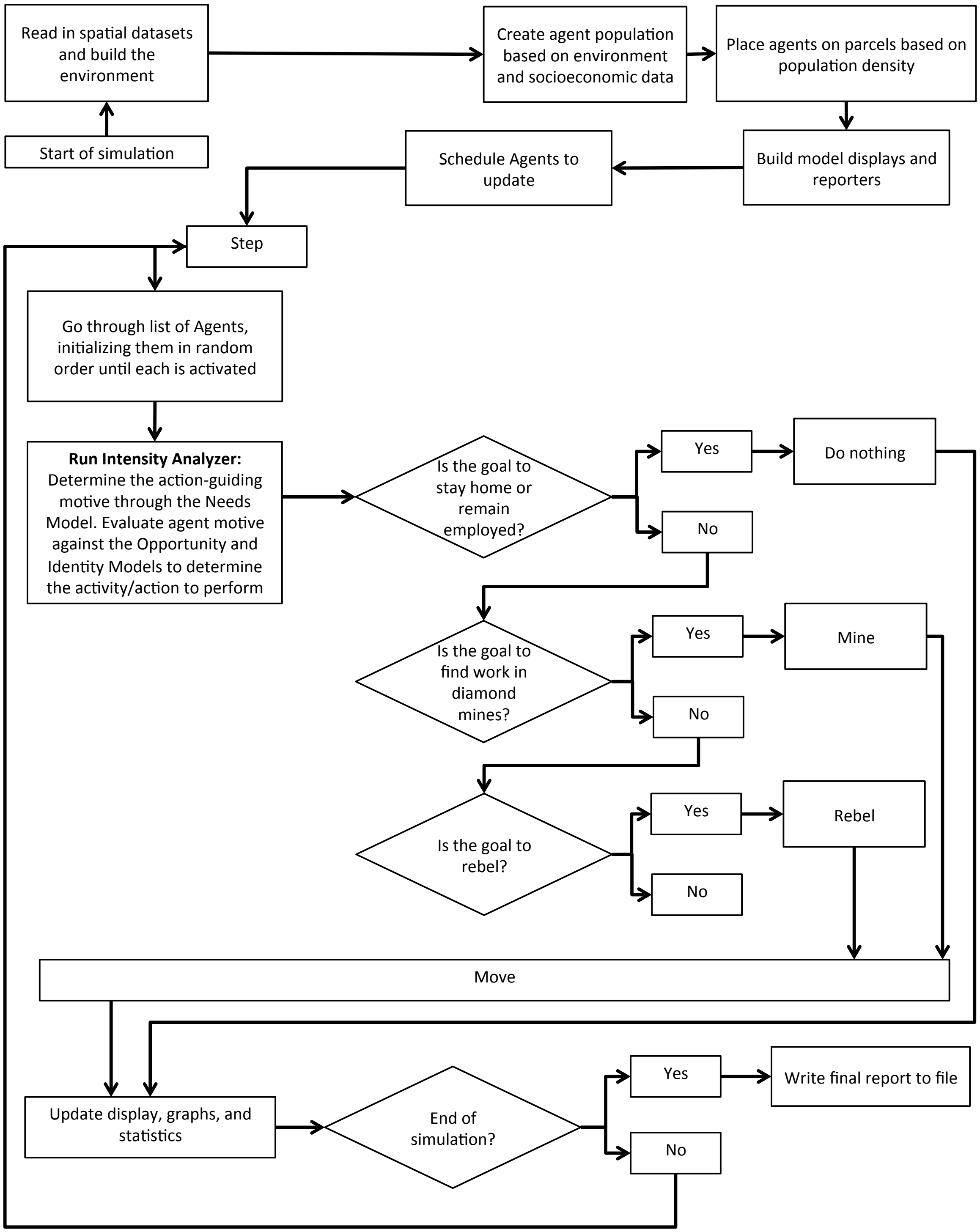

Figure 5-4. Flow diagram of the key processes in the model.

Section 5.2.1; the agents' behavior, which is determined via the Intensity Analyzer, is discussed in Section 5.2.2; and the model's outputs are reviewed in Section 5.2.3.

5.2.1 Model Initialization

This section describes the model initialization process, including creation of the environment and the population (Section 5.2.1.1) and details on the agents modeled (Section 5.2.1.2).

5.2.1.1 The Environment and the Population

Each run of the simulation begins by reading in the spatial dataset and building the environment. Data used to create the geographic landscape came from the following: the Global Administrative Areas (GADM) database (2009), which provided the political boundaries of the country and its districts; the Peace Research Institute Oslo (PRIO) Center for the Study of Civil War (Gilmore et al., 2005), which provided the geographic coordinates associated with the diamond mining areas in the country; OpenStreetMap (2010), which provided geographic coordinates of roads and cities; and the Oak Ridge National Laboratory (2007), which provided the LandScan population data.

The modeling world, which is the country of Sierra Leone, is subdivided into fourteen areas to represent the fourteen districts of Sierra Leone (as seen in Figure 5-3). In total, this landscape encompasses a 71,740 square kilometer area. Using Landscan data from the Oak Ridge National Laboratory (2007), the landscape was developed as a raster surface with cell size of 30 arc-second, or approximately 0.00833 decimal degrees. At the equator, this represents exactly one square kilometer cells (Oak Ridge National

Laboratory, 2007). In order to maintain an accurate representation of the population per cell, this cell size in decimal degrees was preserved. For Sierra Leone, which is located just north of the equator, this means each cell size is approximately 0.99 km wide and 1 km high.

Using geographic coordinates of diamond mines, cities, and roads, cost surfaces are created. The cost surface of the diamond mines provides a "cost" distance of traveling to the mines, which ranges from zero to one (the area where the mines are located have a cost distance of zero and the areas furthest from the mines have a cost distance of one). This also provides a path for the agents to move on the landscape. For example, if it is determined that an agent will work in the mines, that agent will move in the direction with the lowest cost distance until it reaches the diamond mines. This method was selected for a couple reasons: using the road network for agent movement would have been computationally intensive, and the geocoded road data includes only major highways, while locals would require use of smaller roads to reach the mining locations. The cost surface of the cities and highways is used to generate a "remoteness" value (consistent with Commonwealth Department of Health and Aged Care, 2001; Remote Footprints, 2014). Remoteness ranges from zero to one, where zero means the area is in or near a city and/or road, while one denotes the most remote areas of the country. Remoteness helps provide each cell with a "risk" level. The more remote the area, the less risky it is to mine since the ability for the government to control the area decreases as remoteness increases (consistent with Goreux, 2001; Le Billon, 2005, 2001). Figure 5-5 shows the cost surfaces (see Figure 5-5A-B) and the population raster surface (see Figure 5-5C), which were created using ArcGIS 10.0.

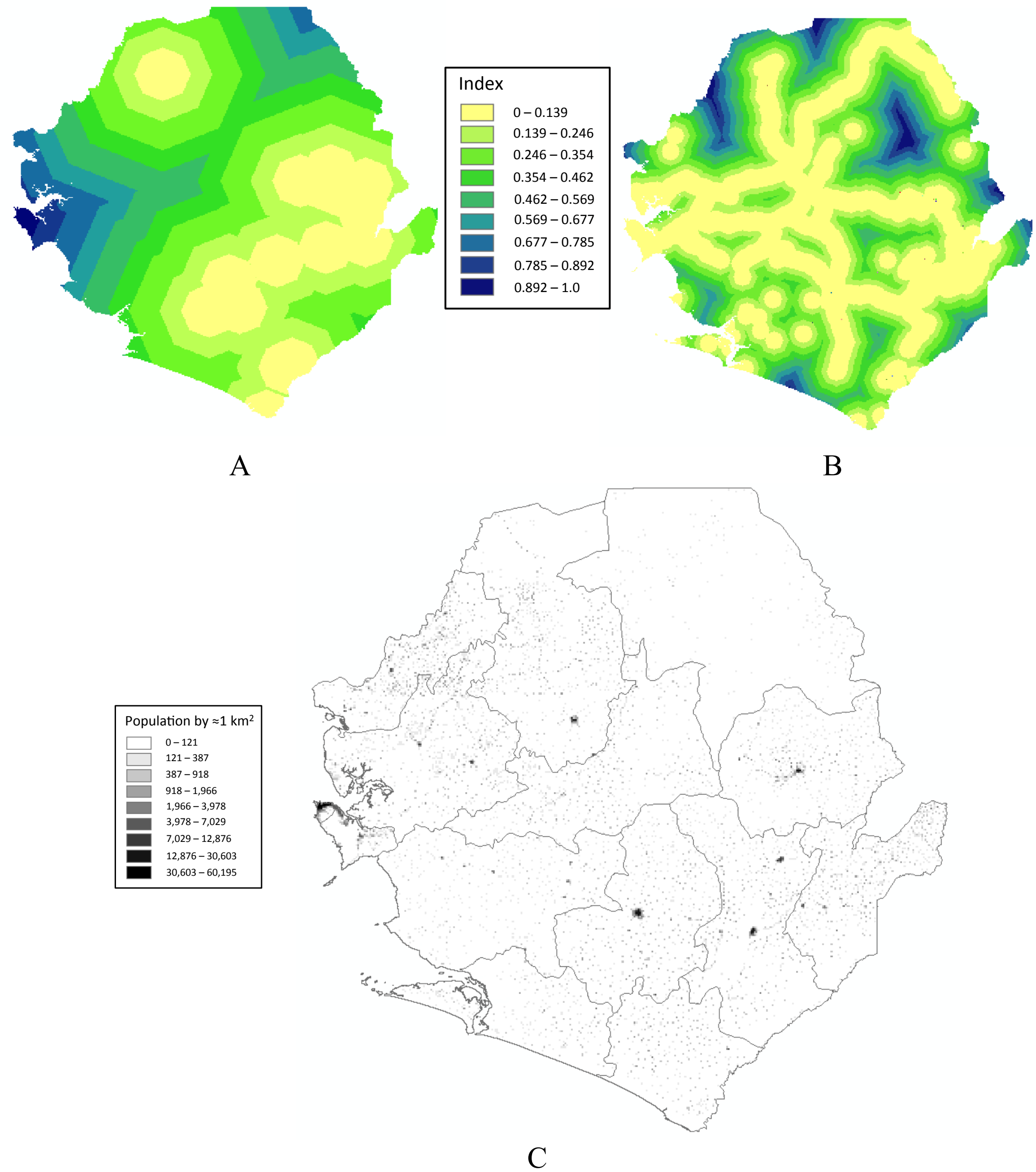

Figure 5-5. Raster cost surfaces. A: Raster cost surface of the diamond mines. B: Raster cost surface of the cities and highway network. C: Population raster surface.

Next, the agent population is created based on the environment (e.g., the population raster) and socioeconomic data. Socioeconomic data at the district-level came from the Republic of Sierra Leone 2004 Population and Housing Census (Braima et al., 2006; Thomas et al., 2006) and Statistics Sierra Leone's Annual Statistical Digest (Statistics Sierra Leone, 2006a). This data provided information on age distribution, poverty levels, and employment statistics. In Sierra Leone, the last two population and household census were performed in 2004 and 1985. The total population was approximately 4.9 million and 3.5 million, respectively (Statistics Sierra Leone, 2006b). Given the nature of the crisis, there is no census data for the years immediately preceding the conflict, during the conflict, or immediately after. In order to distribute the population across the landscape, LandScan data is used (Oak Ridge National Laboratory, 2007). Table 5-1 shows how the country's population is distributed across the districts in 1985 (based on Statistics Sierra Leone, 2006b), 2004 (based on Statistics Sierra Leone, 2006b), and 2007 (based on Oak Ridge National Laboratory, 2007). While most districts maintain the same distribution, the Kono district for instance, lost the equivalent of 4 percent of the country's total population between 1985 and 2007. Kono experienced some of the highest levels of violence during the war, and this is illustrative of the displacement of residents from the area (see Section 5.3.1). To adjust for these types of shifts in population between 1985 (the population prior to the conflict) and 2007 (the population data available by approximately one square kilometer cells), the population within each impacted cell was adjusted accordingly. For instance, the population of any cell within the Kono district was decreased by 4 percent of the country's total population. This provided a simple mechanism for backcasting the population to levels close to pre-war Sierra Leone.

Table 5-1. The population distribution of Sierra Leone across the 14 districts (Oak Ridge National Laboratory, 2007; Statistics Sierra Leone, 2006b).

District	**1985 Population Distribution (Census)**	**2004 Population Distribution (Census)**	**2007 Population Distribution (Landscan)**	**1985 to 2007 Population Distribution Change by District**
Kailahun	7%	7%	7%	0%
Kenema	10%	10%	10%	0%
Kono	11%	7%	7%	-4%
Bombali	9%	8%	9%	0%
Kambia	5%	6%	6%	+1%
Koinadugu	5%	5%	5%	0%
Port Loko	9%	9%	10%	+1%
Tonkollili	7%	7%	7%	0%
Bo	8%	10%	10%	+2%
Bonthe	3%	3%	3%	0%
Moyamba	7%	5%	5%	-2%
Pujehan	3%	5%	4%	+1%
Western Rural	2%	3%	3%	+1%
Western Urban	13%	16%	15%	+2%
TOTAL	100%	100%	100%	
TOTAL Population (in millions)	3.5	4.9	6.1	

Based on 2007 Landscan data, the total population of Sierra Leone is approximately 6.1 million (Oak Ridge National Laboratory, 2007).[7] However, due to computational constraints of modeling this number of agents, the population within each cell is reclassified. First, the population by district was adjusted to more accurately mirror the pre-war population seen in 1985. Second, the population distribution of the entire country was reclassified to equal one percent of the total population. Model runs performed at varying populations yielded similar qualitative results, so moving forward, all parameter sweeps and experiments were performed at one percent of the population.

Population attributes include age, labor attributes, and income levels. Age is based on the age distribution of the residents within each district (using Thomas et al., 2006). The active labor force is the percentage of the population between the ages of 15 and 64 that are economically active, which includes those that are employed and unemployed (Braima et al., 2006). In addition, residents are eligible to work in the illicit mining industry if they are between the ages of 7 and 64 (the age of 7 was selected because this is the youngest age minors are known to have been involved in the conflict). Finally, residents can have one of three income levels: food poor, total poor, and not poor. Food poor and total poor is defined as a household whose monthly income is less than 31,420.42 Liberian Dollars (US$7.30) and 64,223.17 Liberian Dollars (US$14.91), respectively (Statistics Sierra Leone, 2006a). Households that are not poor make a monthly income that is more than 64,223.17 Liberian Dollars (US$14.91) (Statistics

[7] As LandScan data is in approximately one square km cells, certain populations near the border may not be exact (some of the population from neighboring countries may be included). Thus, LandScan population for the country is overestimated.

Sierra Leone, 2006a). In the model this is simplified to three income levels: food poor residents have an income level of zero, total poor residents have an income level of one, and all other agents (who are not poor) have an income level of two. Table 5-2 provides the district-level distribution of the labor attributes and income levels used in the model.

Table 5-2. Sierra Leone labor and poverty data by district (Statistics Sierra Leone, 2006a).

District	Labor Market			Income		
	Percent Employed	**Percent in Active Labor Market**	**Percent Eligible to Mine**	**Percent Food Poor**	**Percent Total Poor**	**Percent Not Poor**
Kallahun	27	33	80	45	47	8
Kenema	36	38	80	38	50	12
Kono	39	41	80	22	42	36
Bombali	35	37	79	63	26	11
Kambia	30	36	79	9	62	29
Koinadugu	34	38	79	29	46	23
Port Loko	35	38	79	20	62	18
Tonkollili	29	35	79	32	52	16
Bo	38	36	78	25	39	36
Bonthe	38	36	78	35	50	15
Moyamba	38	39	78	16	52	32
Pujehan	31	35	78	14	45	41
Western Rural	46	41	84	2	13	85
Western Urban	39	35	84	15	30	55

In addition, at model instantiation, a pre-defined proportion of agents are selected to form the initial “opposition” group. This represents the initial formation of the RUF, which began as a group of frustrated youth sharing similar ideology and sought to recruit some of the most vulnerable in the population, including children, refuges, and criminals (see Section 5.1).

Table 5-3 summarizes the environment and population parameters used in the model. These input parameters create the environment and are used to distribute attributes to the agents.

Table 5-3. Environment and population parameters used in the simulation.

Parameter	Description	Reference
Initial number of agents	The population is distributed to equal one percent of the total population prior to civil war.	Oak Ridge National Laboratory (2007); Statistics Sierra Leone, (2006b)
Initial opposition group	This is the percentage of the population that strongly opposes the government and has formed the initial opposition group.	Leoa (2010)
Age distribution	Agents are assigned into one or more of the following age-related categories: young child (0-6), minor (7-17), adult (18-64), active labor force (15-64).	Thomas et al. (2006)
Income level distribution	Agents are assigned one of three income levels: 0 = food/core poor (less than 31,420.42 Le / US$7.30); 1 = total poor (less than 64,223 Le / US$14.91); 2 = not poor (greater than 64,223 Le / US$14.91).	Statistics Sierra Leone (2006a)
Labor distribution	Agents are assigned one or more of the following attributes: active labor force (between ages of 15-65 and employable); employed (part of the active labor force); inactive (not part of active labor force); eligible to work in mines (between the ages of 7-65).	Braima et al. (2006)
Vision	The distance, in terms of number parcels out, that the agent can "see."	n/a
Likelihood to mine	If an agent is poor (income is zero or one), this is the likelihood that an agent must meet to be willing to mine.	Adapted from opportunity-based theories (see Section 2.1.5)

Rebel threshold	Minimum density of rebels in neighborhood required for an agent to become a rebel (voluntarily or involuntarily). Threshold values can vary depending on whether the agent is an adult not working in the mining industry, and adult working as a miner, or a minor (between the ages of 7 and 17).	Adapted from opportunity-based theories (see Section 2.1.5)
Distance to diamond mines	Parcels are assigned a distance to diamond mines, valued between zero and one. A value of zero signifies the presence of diamond mines on the parcel. Parcels assigned a value of one are the furthest from any diamond mines.	GADM (2009); Gilmore et al. (2005)
Remoteness	Parcels are assigned a distance to roads or cities, valued from zero to one. A value of zero signifies the presence of a road or city on the parcel. A value of one is assigned to the most remove parcels, which are furthest from any roads or cities.	Adapted from Commonwealth Department of Health and Aged Care (2001); Remote Footprints (2014) OpenStreetMap (2010)
Government control over mines	This is the level of control the government has over the mining areas.	Adapted from Le Billon (2008)
Maximum parcel risk	Maximum risk associated with a parcel (a function of remoteness and government control) required for opportunity to exist to mine or rebel.	n/a

5.2.1.2 The Agents

Agents in the model represent the individual residents of Sierra Leone. They are characterized by unique attributes such as age, labor status, income level, and household employment status. Table 5-4 lists all agent parameters and provides a brief description of each. Note that households are not explicitly modeled here. The idea of a household is used only to ensure that agents can be assigned an income even if unemployed (e.g., Residents that are Inactive).

Table 5-4. Resident attributes.

Parameter	Description
Age	The Resident's age as determined by the Age distribution.
Labor status	The Resident's labor status can be employed in the formal sector, working in diamond mines, unemployed, or inactive. At initialization, this is drawn from the Labor distribution.
Income level	The Resident's level of income drawn from the Income distribution. This can be 0 (food poor), 1 (total poor), or 3 (not poor).
Household employment status	If at least one agent in the household is employed, than this set to true. Otherwise, it's false.

5.2.1.3 Assigning Agent Attributes

At model instantiation, the agents' age, labor status, income level, and household employment status are defined. Agents are first assigned an age based on the age distribution of the residents within each district (based on Thomas et al., 2006). Agents between the ages of seven and 17 are called "minors" in the model. These represent residents eligible to be recruited as child soldiers in the conflict (Twum-Danso, 2003; UN CyberSchoolBus, 2014). Next, based on age and district-level labor data, agents are evaluated for whether they will be part of the active labor force. In addition, it is determined whether they are eligible to work in the illicit mining industry. Finally, agents' are assigned an income level. There are three income levels in the model (see Table 5-2) to represent whether a Resident is food poor (income level is equal to zero), total poor (income level is equal to one), or not poor (income level is equal to two). If an agent is unemployed or inactive (e.g., a child or homemaker), their income is assumed to be generated by the head of household. Thus, an agent does not require employment to have an income. There are two types of employers modeled (Diamond Miners and Other Employers). This provides a simple way to track agents that are employed in the diamond mines and all other employed agents. At instantiation, all residents who are employed work for Other Employers (see Figure 5-3). The household employment status parameter is automatically assumed to be true for Resident's that are employed at model instantiation. On the other hand, the probability that an unemployed or inactive Resident is assigned to an employed household is determined based on the percentage of the active labor force that is employed and the assumption that each household has an average of two household members in the active labor market (based on Statistics Sierra Leone, 2006a).

5.2.1.4 Model Scheduling

At this point, the model proceeds in one-month increments. A monthly time step was selected for several reasons. First, while the decision to join the rebellion may occur in a short time period (hours or even minutes), there is a lag of weeks or even months between the time someone makes that decision (or is forced to make that decision) and the time they are actually ready for combat (BBC, 2014a; Beah, 2007). During this period, child soldiers in particular were often forced to watch violent movies, play video games, take drugs, and receive weapons and combat training (BBC, 2014b; Beah, 2007; Betancourt et al., 2010). Thus, a month includes the time to join the rebellion and then to prepare for combat. Second, similar to the Colombia case (see Chapter 4), the war lasted years. From a modeling perspective, we are interested in capturing the dynamics of the conflict over the years, not days or hours. Third, we need to consider the balance between spatial and temporal computational resources. The modeling world is the entire country of Sierra Leone and simulates the dynamics of a war as it spreads a country. Given the initial lag between the time an individual joins the movement and the time they are "combat" ready; the span of the war over years; and the computational resources need to model at this level spatially, one month increments was ideal.

5.2.2 Agent Behavior

PECS provides a framework for which to drive agent behavior (see Section 3.3.2.2). A PECS agent is made-up of three main categories - inputs, state variables, and outputs. The inputs pass in and filter the information received from the environment; the state variables process the information and develop an action plan; and outputs determine behavior and execute the actions (Schmidt, 2002). The PECS agent can have up to four types of state variables (i.e., Physis, Emotion, Cognition, and Social status). However, given the scale and purpose to model the spatial dynamics of a state-level war, individual agent activities are kept simple. In the model, focus is placed on the Physis, Cognition, and Social Status state variables. While Cognition is used to process information about the environment and to draw up an action plan, more intricate components of Cognition, such as the self model, protocol model, and reflection are not included. While agents may join or remain in conflict due to an emotional state such as aggression or fear, these factors are not explicitly modeled. Thus, the Emotion state variables is not used. Figure 5-6 illustrates at a high-level how the PECS framework is implemented in the model through three sub-models: the Needs Model (using green arrows), the Opportunity Model (using blue arrows), and the Identity Model (using red arrows).

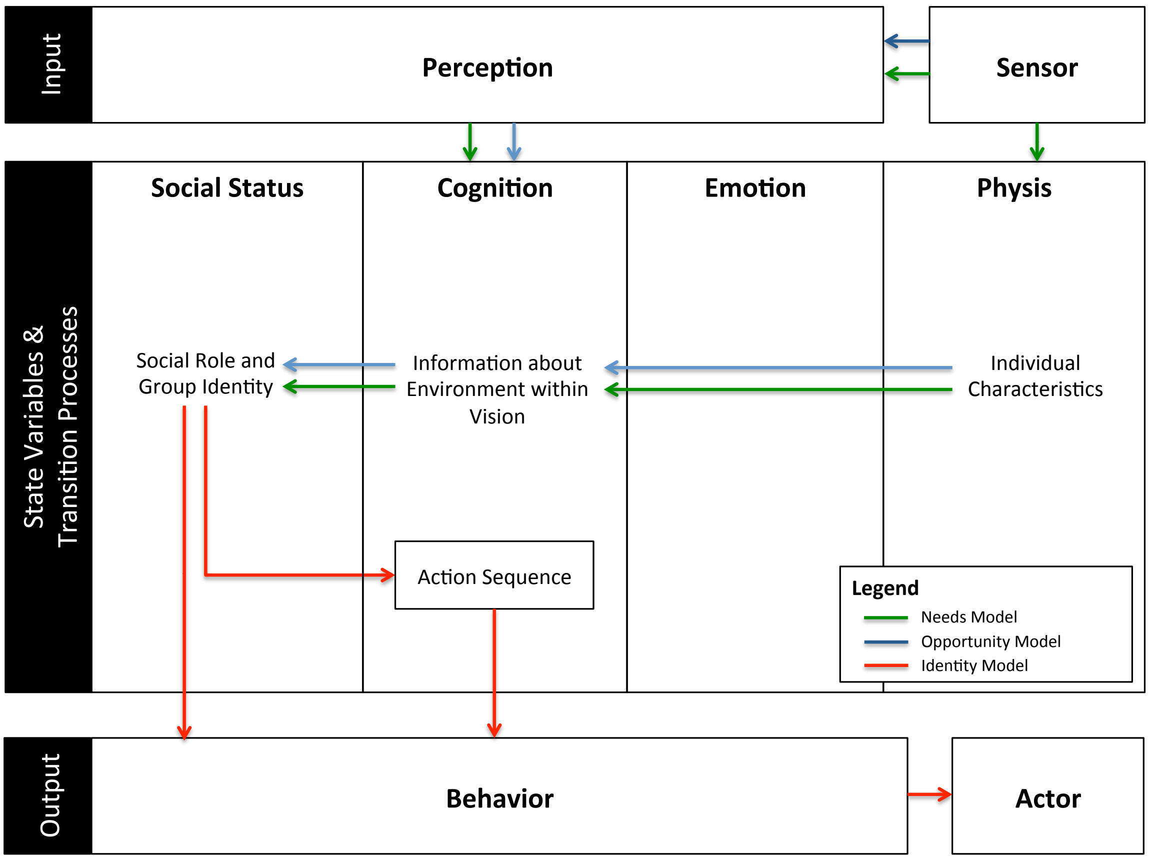

Figure 5-6. A high-level representation of agent behavior incorporated into the PECS framework (adaped from Schmidt, 2000).

Sensor (the environment) and Perceptions feed directly into Physis and Cognition. The Resident then processes any Information about the Environment within Vision, which can include environmental factors and other influences. Using the Needs Model, this information along with the Resident's Individual Characteristics determines a

Resident's need. In addition, the Opportunity Model draws from the Resident's Individual Characteristics and the Information about the Environment within Vision in Cognition to determine whether the opportunity to rebel or to become a miner exists. Using results from the Needs Model and the Opportunity Model, the agents Social Role and Group Identity are defined in the Identity Model. This identity directly impacts the action the agent will take, which is generated by Behavior and then executed by Actor. Figure 5-7 provides details on the specific motives (also known as drives, needs, or desires) and the set of potential actions available to the Resident. The process described in Figure 5-6, between receiving information from Perception and generating the Action Sequence, are implemented via the Intensity Analyzer, which is responsible for determining the action-guiding motive from the set of possible motives available to the Resident.

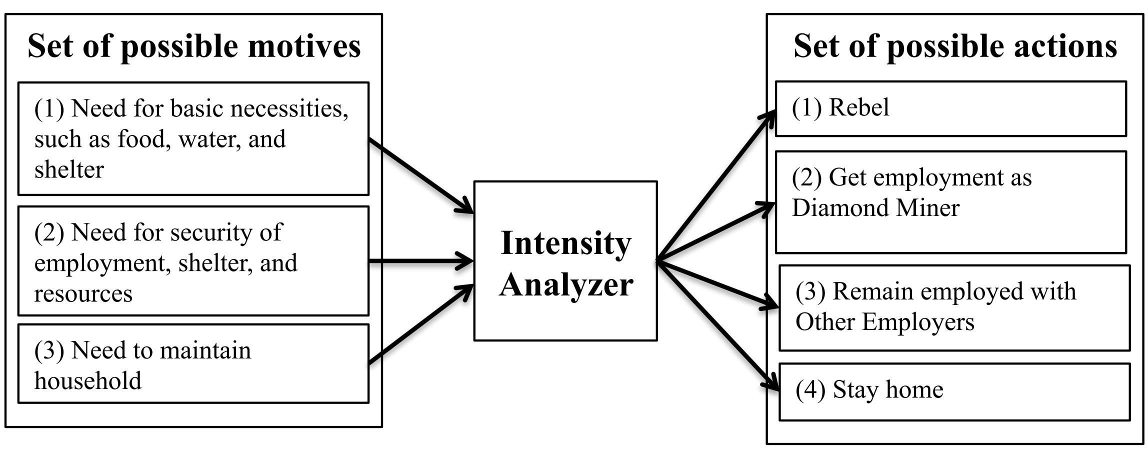

Figure 5-7. Motives and determining the action-guiding motive via the Intensity Analyzer (adapted from Schmidt, 2002).

While PECS provides the framework to model behavior, theories of violent collective action provides a means for which to drive behavior. In the ABM, three sub-models grounded in theory – the Needs Model, the Opportunity Model, and the Identity Model – are incorporated into the PECS framework to determine agent behavior.

5.2.2.1 The Needs Model

Humanistic needs theory focuses in on the deprivation of needs as a precondition for conflict (see Section 2.1.4). As illustrated in Figure 5-7, residents can have three motives: (1) the need for basic necessities such as food, water, and shelter, (2) the need for security of employment, housing, and financials, and (3) the need to maintain the household.[8] These motives represent the two most fundamental levels from Maslow's (1954) hierarchy of needs (see Section 3.3.1.3): physiological and safety. The remaining levels, including love and belonging, esteem, and self-actualization, are beyond the scope of this model.

Physiological needs such as food, water, and shelter must be purchased. In the model, Resident's may meet this need through an income, which may be due to the Resident's gainful employment or may be said to come from a "household" member. If unmet, these Residents are the most vulnerable to joining the illicit diamond mining or becoming part of the violence as they seek to meet these needs. Safety needs, on the other hand, means that the Resident is meeting its most basic of needs but is looking for a certain level of financial and personal security. This is met through an income that is

[8] While the Needs Model is responsible for determining the agents' motive, and in that sense, could be called the "Motives Model," it was instead named after the humanistic needs theory for which it draws from. This was done to highlight the application of theory in the sub-model.

sufficient to provide some level of security in addition to meeting its basic physiological needs. Residents that are food poor (income level is zero) are motivated to, at a minimum, meet their physiological needs, while Residents that are total poor (income level is one) are motivated to meet their physiological in addition to safety needs.

The Resident's labor attribute is also taken into account to determine individual motivation. Regardless of income, for example, an individual who is not part of the active labor force will be motivated to maintain the household and will not seek employment. On the other hand, Residents that are part of the active labor force will seek to either provide its household with basic necessities or security, depending on its current income level.

In addition, some Resident's will be forced to rebel. Income and labor attributes are irrelevant in this case as these Residents, by rebelling, are seeking to survive and as such, to maintain the most basic of needs. Table 5-5 provides a summary of the income levels and attributes associated with each motive.

Table 5-5. Motives and the associated income level and labor attribute.

Motive	Associated Income	Associated Attributes
Need to provide basic necessities	Food poor (income = 0) Any income level (if forced to Rebel)	Active labor force (employed or unemployed) Age is 7 or older (if forced to Rebel)
Need to provide security	Total poor (income = 1), Not poor (income = 2)	Active labor force (employed or unemployed)
Need to maintain the household	Any income level	Inactive (not part of active labor force)

While the Needs Model determines the action-guiding motive, the Opportunity Model helps determine the final goal and, subsequently, the final action the agent will take. Given the right influencing factors, for example, agents that are total poor may seek to move up to not poor. While some agents may chose (or be forced) to rebel regardless of income.

5.2.2.2 The Opportunity Model

Theorists have pointed to opportunity, along with motivation and group identity, as indicators of war (see Section 2.1.5). Pulling from opportunity-based theories—which have stressed such factors as the accessibility to lootable resources (e.g., alluvial diamond mines), the geographic concentration of rebels, and economic factors in the region—agents in the model require opportunity to join the illicit mining industry or to rebel.

The first factor of opportunity in the model is the accessibility to lootable resources. This is driven by three criteria: the presence of diamond mines, the remoteness of the area, and the level of government control (or security) surrounding the resource (consistent with Le Billon, 2005, 2001). As discussed in Section 5.1, resources can range in concentration from diffuse (e.g., the alluvial diamond mines in Sierra Leone) to point (e.g., the kimberlite diamond formation in Botswana). Diffuse resources tend to cover widespread areas of land and are the least secure (Lujala et al., 2005). The more diffuse and the more remote (or more distant an area is from a country's center of control), the costlier it is for the government to control, and therefore, the easier it may be for rebel forces to exploit it (Le Billon, 2005, 2001; Lujala et al., 2005). On the other hand, point resources that are closer to roads and population centers, are easier for the government to control, and therefore, riskier to exploit. This range in resource concentration (from the less secure diffuse resources to the more secure point resources) is simulated via a government control (or security) variable, which will be further discussed further in Section 5.3.2. All the parcels within a Resident's vision are evaluated for these three criteria and a risk-level is derived for each parcel, which is given a value between zero and one. If their exists parcels within an agent's vision whose risk-level is below the agent's threshold for risk, diamond mines are present, and the agent is likely to mine, then the first factor of overall opportunity exists.

The second factor is economic in nature. Opportunity-based theories have stressed economic incentives, including income (or need) as an impetus for conflict (see Section 2.1.5). The presence of residents in need of basic necessities can provide a pool of potential recruits and laborers (consistent with Twum-Danso, 2003; UN CyberSchoolBus, 2014). While miners, who may operate more as criminals, may not share the same ideological views as rebels in a conflict (Collier, 2000b), they nonetheless may be willing to take the risk to play a role in illicit activities. Thus, income may provide the opportunity for conflict as well as for the cheap labor needed to help fund the continued insurgency. In Collier's (2000b) model, for instance, rebel leaders recruit labor at an income that is consistent with the economy's opportunity cost of labor (Collier, 2000b). Although rebel leaders are not modeled here, there is an underlying assumption that residents in the lower income brackets are the most vulnerable to joining the conflict. For laborers, a simple likelihood to mine is applied representing the chance an agent will mine (the lower the income, the higher the likelihood to mine). Because this is a simple model, there is no explicit way to account for those residents that may need the income, but may choose nonetheless to stay away from the illicit mining industry. These may be residents that prefer to keep searching for regular employment. These may also be residents that are employed in low paying jobs (the income levels are broad, thus an income level of zero can still constitute some amount of income). For rebels, only those residents in the lowest income bracket who are also influenced due to the geographic concentration of neighboring rebels will join the violence due to economic opportunity.

The third, and final, factor in determining opportunity is the concentration of rebels within an agent's "vision." The more geographically concentrated the rebels, the easier it is to overcome challenges of collective action and to mobilize (Fearon and Laitin, 2003; Lujala et al., 2005). The proportion of agents within its vision that are rebels is calculated to determine the density of rebels within the agent's vision. This density is then compared to a pre-determined threshold. If the rebel density is higher than the agent's threshold, this second factor of opportunity is met. Since communications networks are not explicitly modeled, Friedkin and Johnsen's (1999) approach (discussed in Section 3.3.1.2) cannot be applied. However, creation of neighborhoods (i.e., the agents' vision or number of parcels out an agent can "see") allows us to implicitly model these social networks. This provides a good proxy for modeling an agent's likelihood to be influenced to mobilize and join the rebellion. This also relates to Tobler's (1970) first law which states that all things are similar, but closer things tend to be more similar. Thus, the closer (or more concentrated) agents are geographically, the likelier they are to communicate and to be influenced by one another.

In the model, if the first two factors of opportunity are met (e.g., there exists accessibility to diamond resources and the right economic incentives), then there exists the opportunity for an agent to turn to the illicit market as an independent miner. In addition to these two factors, if the third factor is also met (e.g., there exists sufficient influence from nearby rebels), then there exists the opportunity to rebel. In the case of those agents forced to rebel, however, economic factors are not considered (i.e., the agent can have any income level), as these cases were largely children abducted and violently coerced to join the conflict (Gberie, 2005; UN Development Programme, 2006).

5.2.2.3 The Identity Model

Group identity is said to lead to a differentiation between “we” and “they.” A differentiation that can spiral into violence as the actions of one group in response to the other can be perceived to be threatening or aggressive (Stein, 2001). Theorists have placed group identity at the source of conflict (see Section 2.1.3). At model instantiation it is assumed that there exists a pre-defined group of residents (selected at random) that share a common group identity, creating the initial opposition group. While group identity may be a necessary precursor to conflict (e.g., the initial opposition group), Stets and Burke (2000) argue that there are sufficient similarities between role- and group-based identities to create one Unified theory to account for both. Agents that are not part of the initial opposition can have one of four identities: Domestic, Employee, Miner, or Rebel. The model draws from the Unified theory (Stets and Burke, 2000) as agents decide which identity to pursue (see Section 3.3.1.1). In order to keep behavior simple, however, an agent is assumed to be always successful in meeting its identity standard (i.e., the "error signal" between an attempt at meeting the identity standard and the identity standard is always zero).

An activated identity is one that is currently directing behavior and is a function of (1) commitment, or the embeddedness of an individual in a social structure, (2) the fit of the identity with the situation, and (3) characteristics of the identity (Stets and Burke, 2000). While the Domestic and Employee identities are activated based only on results from the Needs Model, the Miner identity also requires that it "fit" into the situation. Fit, in this case, is measured by opportunity in the form of lootable diamond mines, which was defined in the Opportunity Model. The Rebel identity, on the other hand, requires a level of commitment in addition to fit in the situation. Commitment, or embeddedness, is a function of the number and strength of connections a person has by holding a given identity. However, since social networks are not explicitly modeled, commitment is measured as a function of the density of rebels within an agent's vision (as determined in Opportunity Model). Note that the Rebel identity may be activated not only by choice but by force, this was especially the case for children (Gberie, 2005; Goodwin, 1999; Human Rights Watch, 2000). Table 5-6 provides a summary of the requirements for activating each identity, illustrating how motive (as determined by the Needs Models) and opportunity (as determined by the Opportunity Model) feeds into the Identity Model. After running the Identity Model, the agent has determined the active identity. The agent will then perform the actions associated with the given identity.

Table 5-6. Motives and opportunity requirements for each Identity.

Identity	Action-Guiding Motive (Needs Model)	Environmental and Other Influences (Opportunity Model)
Domestic	Need to maintain household	n/a
Employee	Need for basic necessities Need for security	n/a
Miner	Need for basic necessities Need for security	Presence of diamond mines and risk is below set threshold Likelihood to mine is met
Rebel	Need for basic necessities	Presence of diamond mines and risk is below set threshold Density of rebels is above set threshold

5.2.2.4 The Action Sequence

As shown in Figure 5-7, an agent can perform one of three activities at each time step: mine, rebel, or do nothing (e.g., remain employed in the formal market or stay home). The active identity, as determined by the Identity Model (see Section 3.3.1.1), directly effects the action an agent will take. If an agent's identity is Domestic or Employee, the agent, in terms of its action sequence, will do nothing (as agents "going to work" is not explicitly modeled). If the agent's active identity changes from Employee to Miner or Rebel, that agent will leave its current employer. If the agent is now a Miner, that agent will be added to the Diamond Miner employer. In addition, if the agent's income level was zero, it is increased to one. An agent who becomes a Rebel, on the other hand, does not work for any employer, as the resident is either being forced to rebel or is seeking to take control of a mining area for purposes beyond that of the average independent miner.

Agents that are Miners or Rebels will move on the modeling landscape. As a Miner or Rebel the agent needs to be near the diamond mines, but at the same time it is assumed that the agent will want to move to a location that will minimize its potential level of risk as much as possible. Utilizing the cost surfaces developed to create the initial landscape, an agent will move to a cell within its vision that is closer to the diamond mines but more remote than its current location. The agent will continue to move until it cannot find any parcel within its vision that would be better (i.e., closer to the mines and more remote) than its current location.

5.2.3 Model Output

The model exports a set of comparative statistics. These include the number of agents by the set of labor attributes, income levels, and identities. Statistics are collected by time step and at the district-level so that changes in the conflict's dynamics can be easily assessed across time and geographic location. In addition, the spatial dynamics of the conflict as it evolves across time are observed trough the interface during model runs.

5.3 Simulation Results

This section describes the model results. First, sensitivity testing was performed to ensure the model was working as intended and to establish qualitative agreement of model results to empirical data of the conflict (Section 5.3.1). Next, two experiments are performed to explore Le Billon's (2001) theory that the spatial dispersion of a resource can influence the type of conflict (Section 5.3.2). Model runs were performed using

George Mason University's Argo Clusters, which is a high performing computer cluster. The spatial visualization of results was performed using Palantir (2013).

5.3.1 Sensitivity Testing

As discussed in Sections 1.3.3 and 3.5, verification and validation strategies vary according to the classification level of the ABM (Axtell and Epstein, 1994). In addition, distinguishing between agents and an environment that is analyzed (accurately represent real-world entities or locations based on empirical data) or designed (provided certain attributes to test specific hypothesis) (Crooks and Castle, 2012). This model seeks a Level 1 classification according to Axtell and Epstein's (1994) classification scheme, where the environment is analyzed based on empirical data (using GIS) and agents, whose behavior are kept simple, are designed based on theories of conflict. Thus, the verification and validation strategy best suited for this level of modeling is one that seeks qualitative agreement with actual results (consistent with Axtell and Epstein, 1994; Crooks and Castle, 2012). As part of this process, the model was calibrated to observed empirical data.

Verification of the model was performed through an in-depth walkthrough of the code and sensitivity testing of parameter values. To determine initial default parameter values, the model was calibrated by adjusting parameter settings and selecting values based on observed results that most closely replicated the actual conflict from a qualitative perspective. While reliable quantitative data on the number of residents that joined the illicit mining industry or that rebelled during war is not available, high-level spatial data on the intensity of conflict events is used to qualitatively compare to model results, providing validation that the model qualitatively agrees with real world results. Table 5-7 lists the model's input parameters, the initial default value, and the parameter range.

Table 5-7. The model parameters and default values.

Parameter	Unit	Description	Default Value	Range
Initial opposition density	Double	Proportion of the population that is part of the initial "opposition" group.	0.005	[0, 1]
Risk threshold	Double	Maximum risk level associated with a parcel required for opportunity to exist.	0.5	[0, 1]
Agent vision	Integer	The number of parcels out an agent can "see."	25	[0, 370]
Mine likelihood (food poor)	Double	If an agent is food poor, this is the likelihood that an agent must meet to be willing to mine.	0.01	[0, 1]
Mine likelihood (total poor)	Double	If an agent is total poor, this is the likelihood that an agent must meet to be willing to mine.	0.05	[0, 1]
Rebel threshold (adult and not a miner)	Double	Minimum density of rebels in neighborhood required for an agent to become a rebel if agent is an adult and does not work in diamond mines.	0.10	[0, 1]
Rebel threshold (adult and miner)	Double	Minimum density of rebels in neighborhood required for an agent to become a rebel if agent is an adult and works in the diamond mines.	0.01	[0, 1]
Rebel threshold (minor)	Double	Minimum density of rebels in neighborhood required for an agent to become a rebel (voluntarily or involuntarily) if agent is a minor.	0.01	[0, 1]
Government control	Double	The level of security enforced around the diamonds.	0	[0, 1]

Figure 5-8 illustrates two typical runs of the model after one year (12 ticks) using the default values (as shown in Table 5-7). Residents working in the diamond mines are blue and rebels are red. While rebellion emerged in the southern region of the country in every run (see Figure 5-8A), at times it also spread to the north (see Figure 5-8B). These results are compared to actual event intensity levels in Figure 5-8C, which is a function of the number of conflict events (e.g., battles) that occurred in each district.

While a typical run of the model shows qualitative resemblance to actual conflict results, in order to smooth run-to-run variations, a set of batch runs of the model at the default parameter values were performed. This consisted of running the model 80 times at 120 ticks (10 years) each. Using a similar color scheme as Figure 5-8C to represent intensity, Figure 5-9 shows average intensity levels of rebel activity. Because the model does not simulate events, intensity here is a function of that proportion of the total population that rebelled.[9]

All districts are within one intensity level of actual results with the exception of Kailahun and Moyamba. Kailahun, located in the southeastern part of the country (bordering Liberia and Guinea), shows very high levels of rebel activity in the model but only medium levels of conflict according to empirical data. Based on Gilmore et al.'s (2005) geocoded diamond locations, Kailahun contains one location for diamond excavation. In addition, the district has the country's highest levels of total poverty (92

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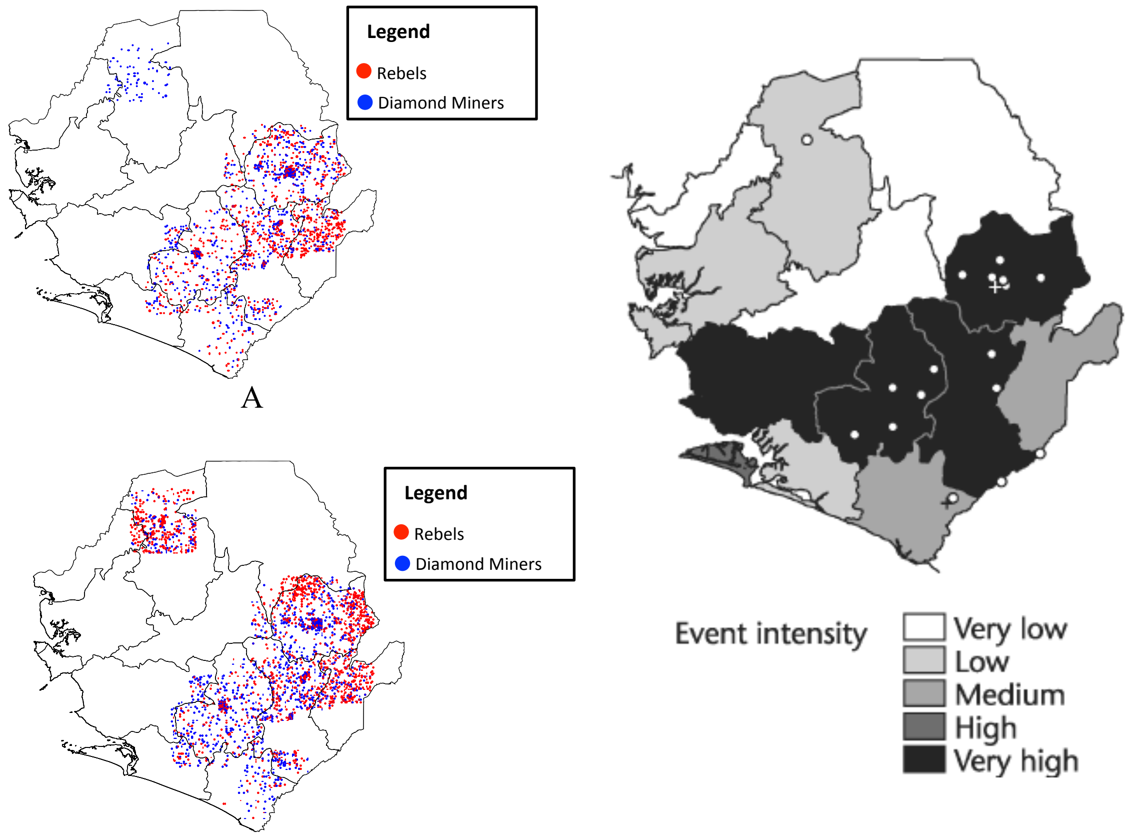
[9] Intensity was calculated by dividing the total number of rebels in a district by the total number of residents residing in that district at the end of simulation. Intensity levels were determined by creating four even intensity ranges, from low to very high (no conflict represents districts that had zero rebels).



B C

Figure 5-8. Qualitative comparison of typical runs of the model to actual event intensity levels. A: A typical run of the model where conflict spreads the southern region of the country. B: A typical run of the model where conflict is widespread across the southern region and parts of the north. C: Actual conflict events intensity based on number of reported conflict events from 1991 to 2002 (Le Billon, 2008).

percent of residents are food poor or total poor). These factors, in addition to spill over from neighboring Kono and Kenema districts (which show very high levels of violence in both the model and empirical data), have likely attributed to the potential overestimation of the rebel activity in the model. Moyamba, on the other hand, shows little activity in the

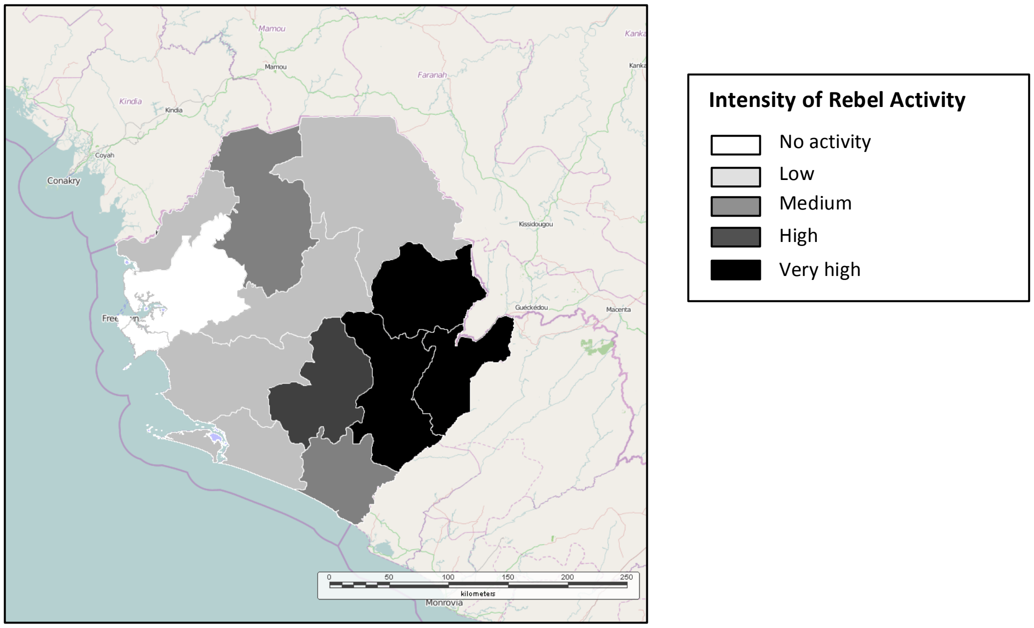


Figure 5-9. Average model results using default parameter values.

model but very high levels of conflict empirically. Unlike Kailahun, Moymaba contains no diamond mines (the closest are in neighboring Bo). Also, the percentage of population that is food poor is relatively low at 16 percent, especially when compared to neighboring Bo (25 percent) and Bonthe (35 percent). Given these factors, there must have been another process at work in both of these districts that is beyond the scope of this model.

Next, a series of sensitivity analyses were performed. Each parameter was varied systematically, while the values for all other parameters were held constant (at the default value shown in Table 5-7). For each parameter value, the model was run 10 times for 120 time ticks to represent approximately 10 years of war. Figure 5-10 provides the results of the sensitivity testing.

The first parameter evaluated was the initial proportion of the population that makes up the opposition group (i.e., the initial rebels), which was varied from 0 to 0.1. As expected, Figure 5-10A shows that when there is no opposition group (the initial proportion is set to zero), no agent's rebel. As the size of the initial opposition group increases, the number of total rebels in the population increases. The number of miners decreases slightly, however, as the opposition group increases. This is likely attributed to the increasing likelihood for some miners to become rebels.

The maximum parcel risk, which is varied 0 to 1, is the maximum level of risk associated with a parcel (as a function of remoteness and government control) for there to be the opportunity to mine or to rebel. If the risk level attached to a parcel is higher than the risk threshold, the agent will deem the area to risky and will not turn to any illicit activity. As expected, Figure 5-10B shows that the number of rebels and miners increases as parcel risk increases. However, it looks to stabilize after a maximum parcel risk level of 0.5 is reached.

Next, the Resident's likelihood to mine is varied from 0 to 0.2. The decision to mine or to rebel is based largely on income (as discussed in Section 5.2.2.1); and the presence of mines, the remoteness of the area, and the level of government control (as discussed in Section 5.2.2.2). In addition, the decision to mine includes a mining likelihood, which is the simple probability that an agent will turn to the illicit mining industry if the agent is food poor or total poor. As expected, Figure 5-10C and Figure 5-10D show that as the likelihood increases in both cases, the number of miners increases. The number of rebels, on the other hand, remains fairly constant throughout.

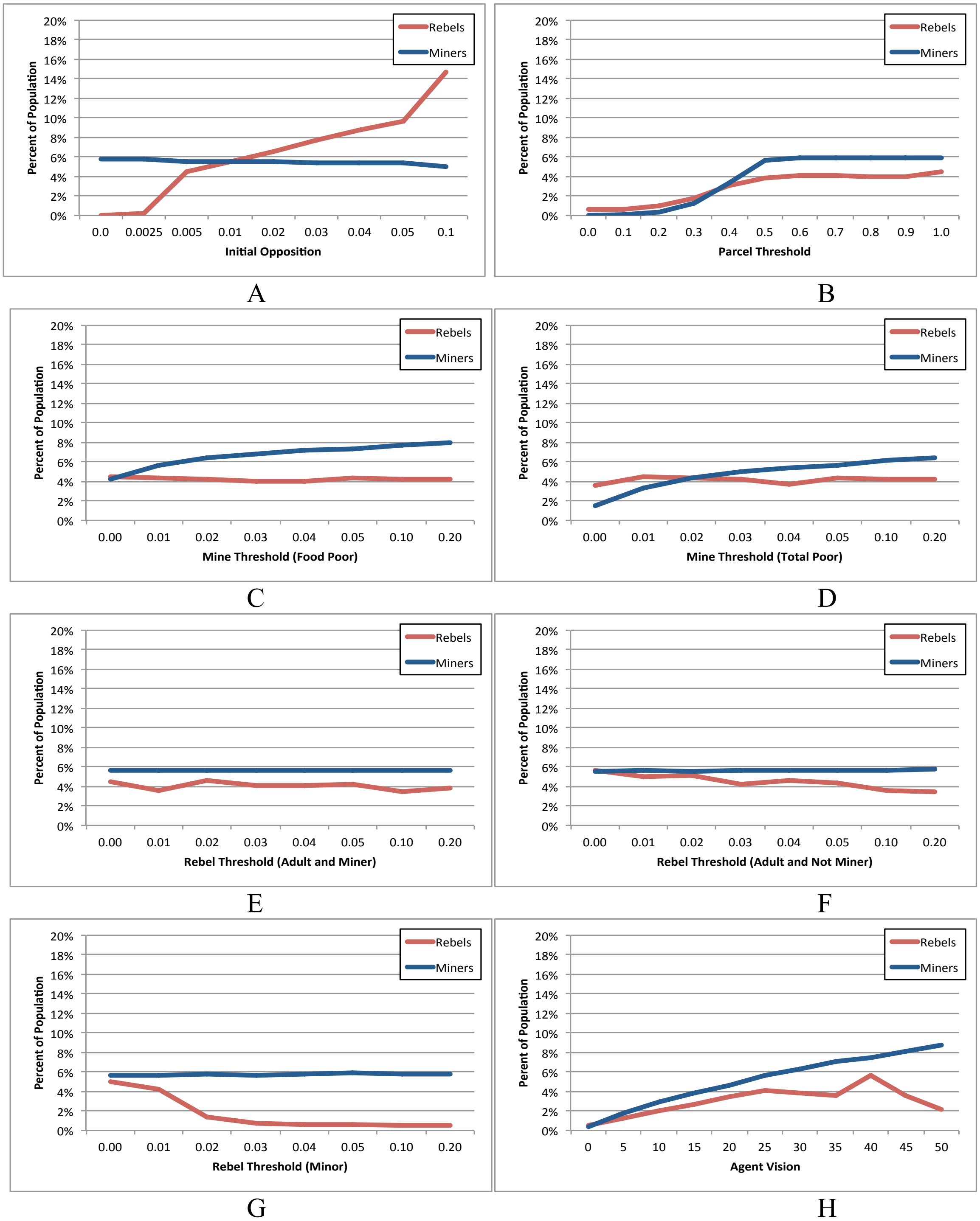


Figure 5-10. Results of sensitivity testing. A: Initial population that is in the "opposition" group. B: Maximum parcel risk level. C: Vision. D: Mining threshold if food poor. E: Mining threshold if total poor. F: Rebel threshold if adult in mining industry. G: rebel threshold if adult not in the mining industry. H: Rebel threshold if minor.

Next, the rebel threshold, which is the minimum proportion of rebels within vision required to influence (or force) an agent to rebel is evaluated as it is varied from 0 to 0.2. It is evaluated separately across three groups of agents: adults in the mining industry, adults not in the mining industry, and minors (between the ages of 7 and 17). While increasing the rebel threshold has little to no impact on the number of total miners, the number of rebels shows some interesting variations. Figure 5-10E shows that increasing the rebel threshold for miners seems to have little to no impact on the number of rebels. This could be due to the fact that the proportion of the total population that mine is fairly small (making up less than 6% of the total population) as compared to the other two groups. In addition, when agents mine, there income is set to one, thus giving them less motivation (based on need) to rebel. While we see a decrease in the number of rebels when the threshold for other adults (not in the mining industry), as shown in Figure 5-10F, and minors, as shown in Figure 5-10G, is increased, it has the most significant impact on minors. Child soldiers (minors between the ages of 7 and 17) made up much of the rebel combatants, who often joined by force. Increasing the required proportion of rebels needed for this group to rebel has the greatest impact, as "influence" from other rebels is a bigger factor for joining than need or opportunity.

Vision (the number of parcels an agent can "see" from its current position) is used to evaluate whether the opportunity exists to mine or to rebel. Interestingly, from Figure 5-10H we find that while the number of miners increases with increasing vision, the number of rebels peaks at a vision of 40. The decision to rebel, however, also includes a certain level of influence from other rebels within the agent's vision (as discussed in

Section 5.2.2.2). Influence is calculated simply as the proportion of the population within an agent's vision that are rebels. As vision increases, the population evaluated also increases. For those agents not located at the "center" of the conflict (i.e., completely surrounded by other rebels), the inclusion of a larger population makes it more likely that the proportion of agents that are rebels will not be sufficient to cause the agent to rebel.

With the simulation exhibiting results that show qualitative agreement to real-world conflict data, and relationships among outputs looking reasonable based on a series of sensitivity testing, we now turn to using the model to explore Le Billon's (2001) theory of the spatial dispersion of a resource and its impact on the type of conflict.

5.3.2 The Impact of the Spatial Dispersion of a Resource on Conflict Type

As discussed in Section 5.1, Le Billon (2001) examined four types of conflicts and the environmental factors required for each to emerge. Diffuse resources lead to rebellion and rioting when resources are proximate and "warlordism" when resources are distant. Point resources lead to state control or a coup when resources are proximate, and secession attempts when resources are remote (Le Billon, 2001). Table 5-8 illustrates this idea further as a matrix. The different types of conflicts are shown based on the resources' relation to the center of the country and the resources' concentration.

Two experiments were performed to explore the geography and intensity of conflict: (1) an experiment where resources are distant and government control is varied, and (2) an experiment where resources are moved closer to the country's center and government control is varied (all other parameter values are set to the default

Table 5-8. Matrix showing the relationship between the spatial dispersion of a resource and the resulting conflict type (adapted from Le Billon, 2001).

Concentration / Relation to Center	**Diffuse** Widely Spread with Minimal Controls	**Point** Concentrated in Small Areas
Distant Located in Remote Territories	Warlordism	Secession
Proximate Close to Center of Power	Rioting / mass rebellion	State control or coup

values shown in Table 5-7). In the first experiment, diamond mines are kept in their actual locations. For the second experiment, mines are moved to the capital (the country's "center"). In both experiments, government control is increased in increments of 0.05. This increase is similar to increasing the concentration of the resource. As discussed in Section 5.2.2.2, diffuse resources are the most difficult and costliest for a government to control, while point resources are easier to secure. Each value of government control is run 10 times for 120 ticks (i.e., 10 years). Table 5-9 provides more detail on the specifications used for each experiment.

Table 5-9. The specifications of the two experiments.

Experiment	**Parameter**	**Range**	**Diamond Mine Location**
Distant resources	Government control	[0, 1]	Actual (represents distant resources)
Proximate resources	Government control	[0, 1]	Freetown (represents proximate resources)

5.3.2.1 The Impact of the Spatial Dispersion of a Resource on Conflict Type When Resources are Distant

Le Billon (2001) argued that resource-driven conflicts are affected by the concentration of resources (point versus diffuse). Because the alluvial diamond mines in Sierra Leone are often found along widespread areas and in unexplored jungles, the mining areas cannot be easily fenced and security of the resource is low, illustrative of resources that are diffuse. On the other hand, the kimberlite mining of countries such as Botswana is fenced and secure, representing point resources. To explore the potential impact on a conflict between having distant, diffuse resources (e.g., Sierra Leone) and distant, point resources (e.g., Botswana), government control is varied and the diamond mines, whose relation to the "center" of the country is already distant, are maintained at their current locations. Government control of zero represents the minimum securities typically found with diffuse resources while government control of one represents the increased security over point resources.

Environments with distant, diffuse resources are often associated with conflicts of warlordism, while distant, point resources influence secession attempts (see Table 5-8). In the model, government control impacts a parcel's associated risk level (the higher the level of government control, the riskier the parcel). Thus, we would expect that as government control increases, the number of rebels will decrease, as the risk to exploit the mining regions may become too high in some areas. Figure 5-11 illustrates the spatial dynamics of rebel intensity as government control is increased. Results shown are the average rebel intensity during year 10 of the conflicts (ticks 108 to 120).

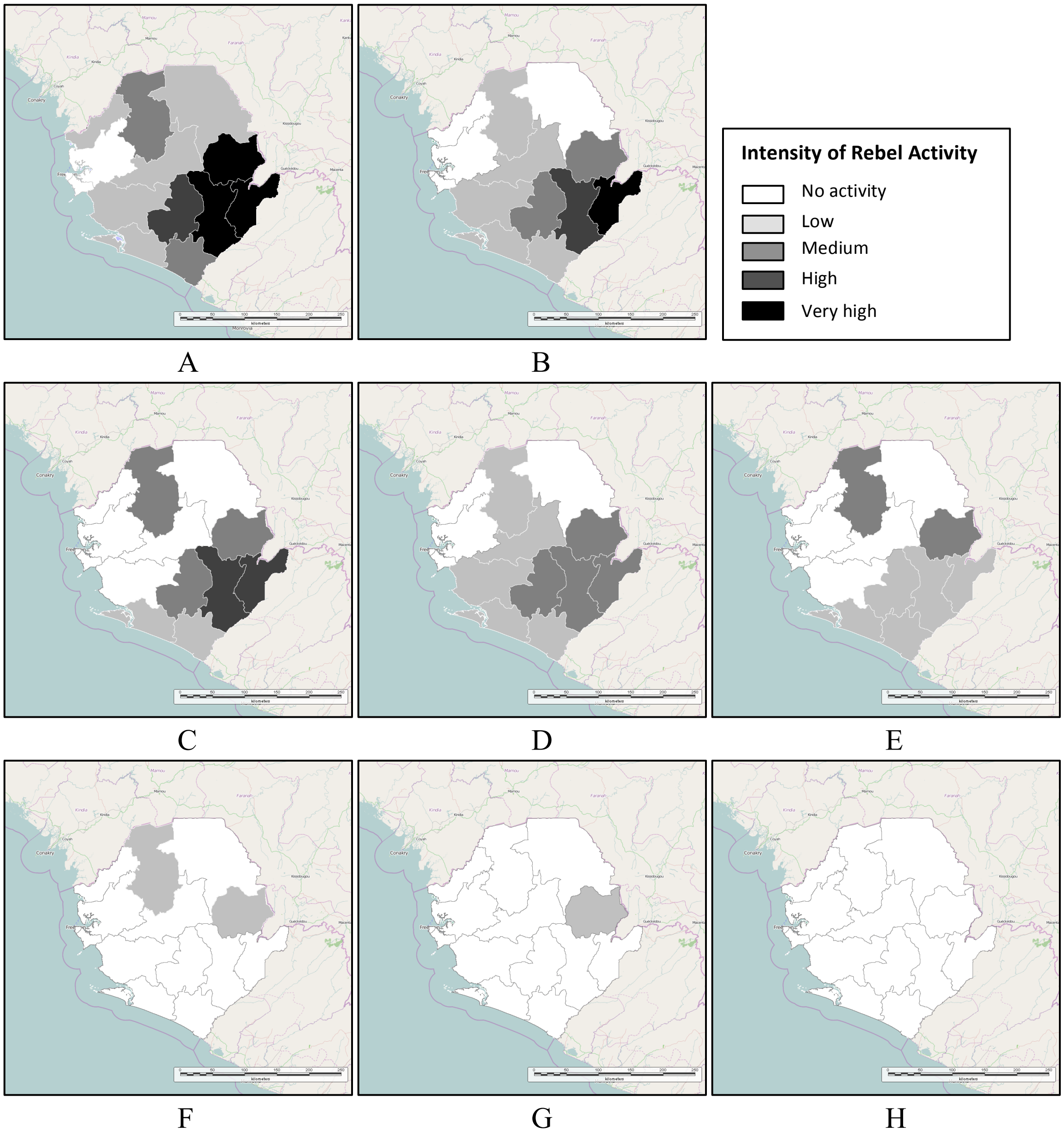


Figure 5-11. Average model results when resources are distant as government control is increased from 0.0 to 1.0. A: Rebel intensity when government control is set to 0.0. B: Rebel intensity when government control is set to 0.1. C: Rebel intensity when government control is set to 0.2. D: Rebel intensity when government control is set to 0.3. E: Rebel intensity when government control is set to 0.4. F: Rebel intensity when government control is set to 0.5. G: Rebel intensity when government control is set to 0.6 or 0.7. I: Rebel intensity when government control is set to 0.75 and above.

Figure 5-11A and Figure 5-11B show that at lower levels of government control, the resulting violence was widespread with some regions experiencing very high levels of rebel activity. In this case, the resulting spatial dynamics of the violence was similar to the actual areas where conflict was the most intense (as shown in Figure 5-8C). The civil war in Sierra Leone is often characterized as one of warlordism (Le Billon, 2001). Because of the geographic similarities between the real-world case of warlordism in Sierra Leone and model results, the model output supports the theory that distant, diffuse resources are associated with conflicts of warlordism.

As expected, Figure 5-11C-H show that with increasing government control, the intensity of rebels and the geographic spread of the violence decreased. There are a few unexpected results, however. The districts of Kenema and Kono in the south, for instance, which experienced some of the highest levels of violence empirically and in the model, quickly saw a reduction in violence as government control was minimally increased. The district of Kono, however, continued to see some level of violence, requiring higher levels of government control to stop all rebel activity. The district of Bombali in the north, however, was more unpredictable. As government control was increased, Bombali's rebel intensity actually increased at times. At government control levels of 0.1 to 0.5 (see Figure 5-11B-F), for instance, some individual runs yielded rebel activity only in the north. While minimal increases in government control were enough at times to stop rebel activity in the southern regions, the conflict looked to be displaced to the northern district of Bombali. This unpredictability could be a result of the high levels of poverty in the district. With 63 percent of its residents being food poor (the lowest income level), Bombali has the highest proportion of food poor residents in the country. As government control was increased systematically to simulate a resource situation going from diffuse to point, rebellion occurred in smaller, more contained areas, often on the boundaries of the country (especially the most northern regions of Bombali and most eastern regions of Kono). Given these spatial dynamics and the unique geographical location and size of the conflict, a situation of secession (the conflict type characterized by distant, point resources) may be feasible at higher levels of resource concentration.

5.3.2.2 The Impact of the Spatial Dispersion of a Resource on Conflict Type When Resources are Proximate

Freetown is the country's capital, most populated city, and the main financial center, including the central location for the Lebanese financiers who support the independent miners (Campbell, 2004). Freetown can thus be considered the "center" of Sierra Leone. In this second experiment, the diamond mines are moved to Freetown and results are observed as government control is varied from zero to one at increments of 0.05. Figure 5-12 shows the spatial dynamics of rebel intensity as government control is increased. Results shown are the average rebel intensity during year 10 of the conflict.

Environments with proximate, diffuse resources are associated with conflicts of mass rebellion or riots near the center of power. When government control is low, this experiment seeks to simulate this environment, as shown in Figure 5-12A. While rebel activity emerged in the model, it was largely contained to the capital and its surrounding areas. Although the resources were placed in Freetown, which is located in the district of

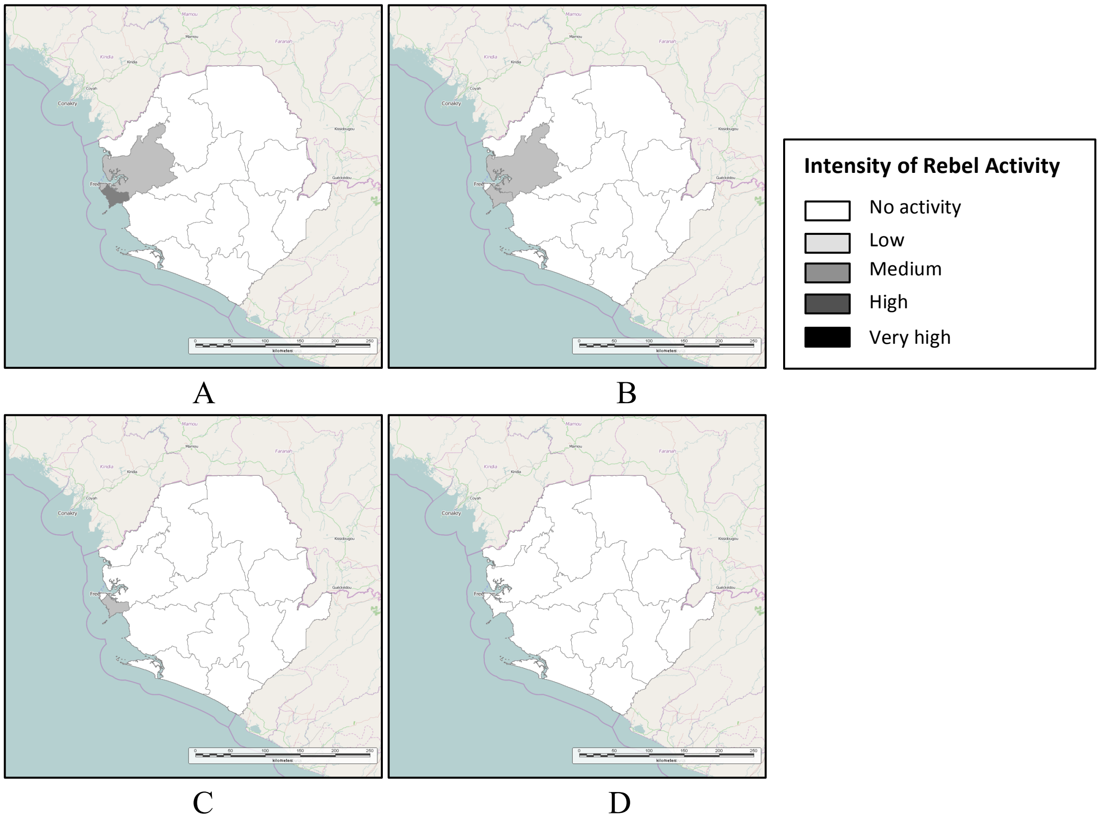


Figure 5-12. Average model results when resources are proximate as government control is increased from 0.0 to 1.0. A: Rebel intensity when government control is set to 0.0. B: Rebel intensity when government control is set to 0.25. C: Rebel intensity when government control is set to 0.35. D: Rebel intensity when government control is set to 0.45.

Western Area Urban, its neighboring district (Western Area Rural) actually experienced higher levels of rebel activity (see Figure 5-12A-C). Western Area Rural has the country's lowest levels of poverty. However, compared to Western Area Urban it is more "remote." Given the high risk (as calculated in the model) of rebelling in the capital, most rebel activity remained just outside Freetown. In addition, this proximity to a populous city and an extensive road network is likely the reason that the intensity levels never reached the ones seen in the previous experiment. Given the geographic location that rebel activity emerged and the spread of the violence in the model at low levels of government control, this provides support to the idea that diffuse, proximate resources are associated with rebellion.

From Figure 5-12, we find that only minimal increases in government control are required to rapidly drop the intensity of rebel activity. This supports the idea that proximate resources are easier for the government to control. In the model, the risk associated with attempting to capture resources located in the center of power was enough to discourage conflict from occurring. While distant resources required government control levels of 0.75 to deter all rebel activity (as shown in Figure 5-11), Figure 5-12D shows that a government control of 0.45 was enough to stop rebellion from emerging here. As government control was maximized, an environment with proximate, point resources is modeled, as shown in Figure 5-12C-D. These types of resources are associated with conflicts of state control or coups. However, in order to overthrow an existing regime, a coup would occur in the country's center of political power. At relatively low government control levels (0.25 and above), no rebel activity ensues in the capital (as shown in Figure 5-12B-D). Thus, we cannot support or reject the notion that proximate, point resources are associated with coups.

5.4 Discussion of Results

The two experiments explore conflict as government control (a proxy for resource concentration) and/or resource proximity to the "center" of the country are systematically varied. When government control was zero (simulating the diffuse concentration of a resource) and diamond mines were kept in their actual locations, widespread rebellion, much like the actual situation of Sierra Leone, emerged. However, with just small increases in control, different results emerged. For instance, small increases in government control simply displaced the conflict at times, causing it to emerge in areas that did not always experience conflict when resources were most diffuse (as seen with the situation in Bombali). Further increasing government control around resource areas leads to rebel activity that is more contained to areas in the periphery of the country. The widespread rebellion when resources are diffuse (e.g., government control is low) supports Le Billon's (2001) argument that distant, diffuse resources lead to warlordism, while the contained, border rebellion when resources are point (e.g., government control is high) supports the argument that distant, point resources lead to secession attempts.

When the resource moved to the city, so did the violence. The rebellion is more contained when compared to an environment of distant, diffuse resources. Given the geographic location of the conflict in the capital and the surrounding areas, it supports the idea that proximate, diffuse resources are associated with conflicts of mass rebellion. As government control was increased, and the resource was made less diffuse, we saw sharp decreases in rebel activity and no violence occurred in the country's center of power. Minimal levels of government control are sufficient to prevent rebel activity. While these results cannot support or reject the idea that proximate, point resources result in a coup, it can provide support to the notion that proximate resources are easier to control than distant resources.

Although model results support aspects of Le Billon's (2001) theory, they are not conclusive. The spatial dispersion of a conflict can give some insight into the type of conflict, but it is not the only factor that determines conflict type. For example, other determinants of conflict type may include the characteristics of its leaders (e.g., self-interested warlord versus a military leader with strong public support), the choice of weapon (e.g., arms, IEDs, or protest), and the main types of events that characterize a conflict (e.g., murder, mutilation, or picketing). The type of leader may effect whether the conflict will be one of warlordism or a coup, weapon choice may effect whether it is an armed conflict or a peaceful protest, and the type of events may effect whether the conflict is a secession attempt with rebels forming a cohesive group of followers (an "us" versus "them" mentality) or warlordism, where rebellion is forced via murder and mutilation.

5.5 Summary

Since diamonds were first discovered in Sierra Leone in the 1930s, the government has been unable to control the activity and provide residents with the benefits of having the valuable resource within its boundaries. Instead, the mines have been taken advantage of, first by corporations, then by illicit miners, and finally by the RUF (Campbell, 2004). The ABM presented here explores the impact the unique environmental and socioeconomic attributes of a region and its population can have on the onset of conflict. Utilizing GIS and region-specific socioeconomic data, the landscape is created. While PECS provides the framework for modeling the agents, theories of human behavior—including needs theory, identity theory, and opportunity-based theories of conflict—ground the behavior in theory. Le Billon's (2001) argues that the spatial dispersion of a resource is a defining feature of a conflict. To explore the theory, diamond mines are first kept in their actual location (distant from the country center of power) and government control is increased to simulate different levels of resource security and accessibility, from diffuse (unsecure) resources to point (secure) resources. Next, the mines are made proximate (moved to the country's capital) and government control is again varied. By performing these simple experiments, we found that we can observe the impact that increased controls has on the intensity, geographic onset, and spread of the conflict. Furthermore, we may have some indication as to the type of conflict.

The resulting intensity and spatial characteristics of conflict in the model provided support to Le Billon's (2001) theory that distant resources lead to warlordism when diffuse and secession when point, and that proximate resources lead to mass rebellion when diffuse. However, given the scale and required computational resources, social networks and the dynamics unique to an urban environment were not explicitly modeled. The density of nearby rebels was used as a simple proxy to measure social influence and thus, the likelihood that one may join the collective violence. When the diamond mines were moved to the city to simulate the proximate distribution of resources, the model did not implement the necessary detail to fully support Le Billon's (2001) claim.

As one instantiation, this model can be implemented to explore other state-level environments, especially where the lootability of natural resources may be a concern. When an environment is ripe for conflict, this type of model has the ability to give the conflict analyst valuable insight into the spatial characteristics of a conflict. This could provide some insight into geographical locations most prone to conflict as well as the characteristics of a conflict. For instance, different conflict types (e.g., warlordism, secession, riots, or a coup) may require unique strategies for conflict intervention and resolution (Le Billon, 2005), an important consideration when implementing policy.

This model demonstrated the value in integrating ABM and GIS. At the state-level, the combination of the two techniques provided interesting insights into the underlying processes of a conflict. By applying simple human behavior we were able to explore theory and test several “what if” scenarios. In the next ABM, the scale of the model shifts significantly, from a long-lasting state-level conflict to short-term riots in an urban slum. The social dynamics, social networks, and geographic detail of a neighborhood are implemented, while the sophistication of the agents’ cognitive function is increased. By integrating ABM, SNA, and GIS the next model explores how the unique social dynamics of an urban slum can lead to the emergence of riots.

6. MODELING ETHNIC CLASHES IN A KENYAN SLUM

Immediately after the 2007 Kenyan election results were announced, the country erupted into a series of riots concentrated largely around ethnic lines. Kibera, a slum[10] located in the country's capital, was the area hardest hit in the city. Kibera's unique geographic landscape (including its infrastructure and the heterogeneous ethnic distribution of its population), socioeconomic data, and the daily activities and social interactions of its residents are used to inform an ABM of the ethnic clashes that hit an urban slum. While the previous two models provided instantiations of long lasting state-level conflicts, the scale for this model (spatially and temporally) is decreased significantly. By modeling at a smaller scale, we add a greater level of detail to the environment through GIS, create social networks that are more representative of our social interactions, and implement theories of human behavior using the PECS framework to add sophistication to the agents' cognitive functions (as discussed in Chapter 3). Through the application of more advanced ABM, SNA, and GIS techniques in an integrative fashion, I build on the models developed in the previous two chapters. In the Colombian case (discussed in Chapter 4) we used SNA techniques, such as centrality

[10] The terms slum and informal settlements are often used interchangeably within the literature. However, the UN-HABITAT (2003) views an informal settlement as one type of slum, specifically where there is insecurity of tenure. Throughout this chapter we'll use the term slum for consistency.

and structural equivalence, to analyze incident data. Drawing from that model, here we utilize a structural approach to determining social influence, thus applying similar SNA measures to drive the behavior of agents. Also, by applying GIS and ABM methods, we build on the model of Sierra Leone (discussed in Chapter 5).

This ABM serves as an initial prototype for modeling riots in an urban area, with the Kibera slum serving as the case study. It explores the role humanistic needs theory, individual identity, collective social identity, and social influence (discussed in Chapters 2 and 3) play on rumor dynamics and the spread of ethnic stereotyping in the outbreak of riots. Section 6.1 begins by providing an overview of the unique social, cultural, and political landscape of Kibera. Next, Section 6.2 gives a detailed description of the model and the agents' behavior. The results of the simulation, including sensitivity testing and experimental results, are described in Section 6.3, while a discussion of experimental results are provided in Section 6.4. Finally, Section 6.5 summarizes the chapter.

6.1 Introduction

Immediately after the announcement of the results of the 2007 presidential election, Kenya broke-out in protest. Deep-rooted grievances and Kenya's long history of "political tribalism" (political and economic ethnic exclusion) led many to believe that election results were rigged. These long standing issues combined with election results quickly escalated the protests to violence, including murder, looting, rape, and arson. This violence would continue for nearly two months, resulting in 1,100 deaths and up to 350,000 internally displaced people (De Smedt, 2009).

Kenya is made-up of a number of distinct ethnic groups (Chege, 2008) of which many are aligned with specific political parties. The incumbent going into the 2007 elections was Mwai Kibaki of the Party of National Unity (PNU) and his largest support base included the Kikuyus (and closely related Meru and Embu) ethnic group. The opposition candidate, Raila Odinga of the Orange Democratic Movement (ODM), main support base included the Luo, Luyha, and Kalenjin. On December 29, 2007, it was announced that Kibaki had won by a narrow margin (under 3%) (Gibson and Long, 2009), making it the closest election since the return of a multi-party system in 1991 (International Crisis Group, 2008). A long history of anti-Kikuyu sentiment due to perceived favored status in the political system, ethnic economic and political exclusion during Kibaki's first term, and Odinga's non-Kikuyu support base, led to a backlash by Odinga supporters against the Kikuyu base (De Smedt, 2009). In Luo, Luyha, and Kalenjin dominated areas, Kikuyus, Meru, and Embu were thrown out of their homes or killed, while revenge killings soon followed in Kikuyu-dominated areas (International Crisis Group, 2008). The violence in Kenya seemed "to have tapped into an atavistic vein of trial tension that always lay beneath the surface in Kenya but until now had not produced widespread mayhem" – a view that was widely felt across Kenya (Chege, 2008). The elections simply served as a catalyst (De Smedt, 2009). Although previous multi-party elections saw similar ethnic violence, none were to the extent seen here. This was the worst crisis Kenya has had to face since independence in 1963 (De Smedt, 2009). By the second day of violence, Kenya was on the verge of civil war (International Crisis

Group, 2008) and U.S. Assistant Secretary of State for African Affairs labeled it "ethnic cleansing" (Chege, 2008).

Kibera, a slum located within the city of Nairobi and a stronghold for Odinga, who was its Member of Parliament (MP), became the "epicenter" of the violence that hit Nairobi (International Crisis Group, 2008). Similarly to so many other overcrowded urban slums, Kibera has characteristics that lends itself to an increase in the potential for violence; including social exclusion, the lack of government support, and the disruption of social networks as residents leave their homes in rural areas in the search for economic opportunity in the city (NIC, 2012; OECD, 2011) (see Section 1.2). In addition, youth are particularly vulnerable to engaging in collective violence (OECD, 2011) and almost 60 percent of Nairobi's population are under the age of 25 (Kenya National Bureau of Statistics, 2009a).

In terms of ethnic diversity, Kibera mirrors Kenya, with every Kenyan ethnicity represented. Kibera is considered a melting pot of ethnic diversity and for the most part, ethnic groups live peacefully. Kibera is divided into fourteen neighborhoods or "villages," most of which are home to a dominant ethnic group. For example, Luos make-up the majority of those living in Gatwikira while Kikuyus dominate the Laina Saba neighborhood (De Smedt, 2009). Figure 6-1 shows a map of Kibera divided into the neighborhoods. Facilities (including schools, religious institutions, and health centers) are shown as red dots and the road network is represented as black lines.

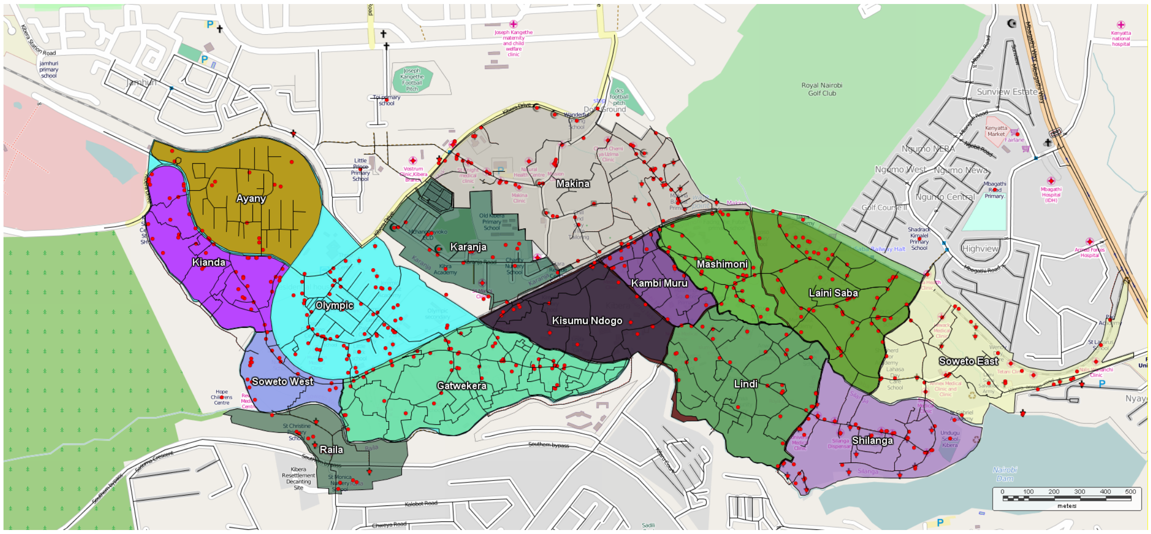


Figure 6-1. A map of Kibera divided into neighborhoods (facilities are represented by red dots and the road network is represented by black lines).

As soon as Kibaki was declared the winner, violence broke out within Kibera. Ethnic, or group, identity played a major part in the riots (see Section 2.1.3). Luo youth from Gatwikira, and those who followed, mobilized immediately and took to the streets looting homes and shops, mainly those belonging to Kikuyus and known supporters of Kibaki. In reaction, Luos in Kikuyu dominant areas were chased from their homes. In addition, the ease of which residents were able to mobilize provided the necessary opportunity (see Section 2.1.5). According to Allport and Postman (1947), a rumor is necessary to "incite, accompany, and intensify" rioting. This was no different in Kibera, where rumors, serving as the external trigger, played a significant role in the riots that hit the slum. Between cell phones, text messages and radio, rumors spread quickly (De Smedt, 2009). The dividing ethnic hate speech heard across the media often served to re-invigorate and intensify ethnic violence (Chege, 2008; De Smedt, 2009). Two months after the riots began, a power-sharing agreement was reached on February 28, 2008 – Kibaki remained President and Odinga became Prime Minister (De Smedt, 2009). Any protests scheduled for the day were canceled and violence across the country (including Kibera) ceased almost immediately. Although many hoped for things to return to normal, some things did change. In Kibera, for instance, many Kikuyus never returned. Some came back to re-open their shops but not to live. Although the violence may have stopped, deep-rooted fears and grievances did not subside so easily (De Smedt, 2009).

The emergence of such violent collective action, as witnessed in Kibera after the 2007 elections, is a complex system; it consists of individuals with distinct identities, coupled with specific needs and interests that interact with other individuals (Demmers, 2012). Riots arise from the interactions between individuals with unique attributes, all within a connected social network over a heterogeneous environment (Demmers, 2012). A bottom-up approach, one where we begin with the localized, micro-level dynamics is key in gaining a greater understanding of the macro-level patterns that emerge. Through ABM, we explore how the unique socioeconomic variables and local interactions underlying Kibera, combined with a catalyst such as that seen when election results were announced, may lead to ethnic clashes such as those seen in 2008. Given the significant role social networks play in identity theory (see Section 3.3.1.1), the flow of information (such as a rumor), and social influence (see Section 3.3.1.2), the creation and dynamic evolution of these networks is critical to any model of riots. Using GIS to create a realistic landscape for which agents can move and interact on, the creation and evolution of the dynamic social networks of the agents is modeled. The social networks are created through the many (potentially mundane) interactions agents have on a day-to-day basis, which are based on humanistic needs theory (see Section 3.3.1.3). This can include, for example, the family you live with, the friends you socialize with, your colleagues at work, or other students at school. Each new interaction creates a relationship (or tie) between two people, while each subsequent interaction strengthens these relationships.

As discussed in Section 2.2.5, there are a number of ABMs that explore the emergence of riots, including Casilli and Tubaro's (2012) ABM of political unrest, which was motivated by the 2011 wave of political unrest in the Arab Spring, and Torrens and McDaniel's (2012) model that implemented more realistic agent spatial behavior. While it added a new level of geographic sophistication, behavior was implemented via simple threshold calculations. In addition, earlier ABMs have explored a variety of topics presented in this chapter, including identity theory, rumor spread, and social influence. While the use of social networks was explored in several of these models (e.g., Bhavnani, 2006; Bhavnani et al., 2009; Cederman, 2003; Epstein and Axtell, 1996), none implemented it in an ABM over a GIS. In addition, by grounding the agent’s cognitive framework in theory through use of the PECS framework (see Section 3.3.2.2), we add a level of behavioral sophistication that goes beyond threshold calculations (e.g., Casilli and Tubaro, 2012; Epstein, 2002; Torrens and McDaniel, 2012). While some models explored identity theory and influence through social networks (e.g., Bhavnani, 2006; Bhavnani et al., 2009), accounting for both social role and group-based identities in the agent’s cognition, social influence that can dynamically evolve as social networks change, and the daily needs and activities of the agents provides a new level of sophistication as agents process their decision to riot or remain peaceful.

6.2 Model Development

An ABM was developed in MASON (Luke et al., 2005) utilizing the GeoMason (Sullivan et al., 2010) spatial extension to explore the onset of riots in a Kenyan slum. GIS was utilized to create the modeling landscape, while socioeconomic data of Kibera provided initial agent attributes. Figure 6-2 displays the GUI of the model. For readers wanting to download the source code or executable of the model please see http://css.gmu.edu/Pires.

Figure 6-3 illustrates a high-level UML diagram of the model. The modeling world is Kibera and is divided into cells, called Parcels. The localized nature of social processes such as riots makes ABM tied to a specific geographic environment an ideal method for which to model the unique environment of Kibera. ABM gives us with the ability to endow our agents with unique attributes and to interact on a local-level with other agents and the environment, while GIS allows us to create a realistic abstraction of the actual landscape of Kibera. As social networks play a critical role in both identity salience and social influence (see Section 3.3.1), including the creation and evolution of these networks allows us to more accurately reflect theory in the agent's behavior.

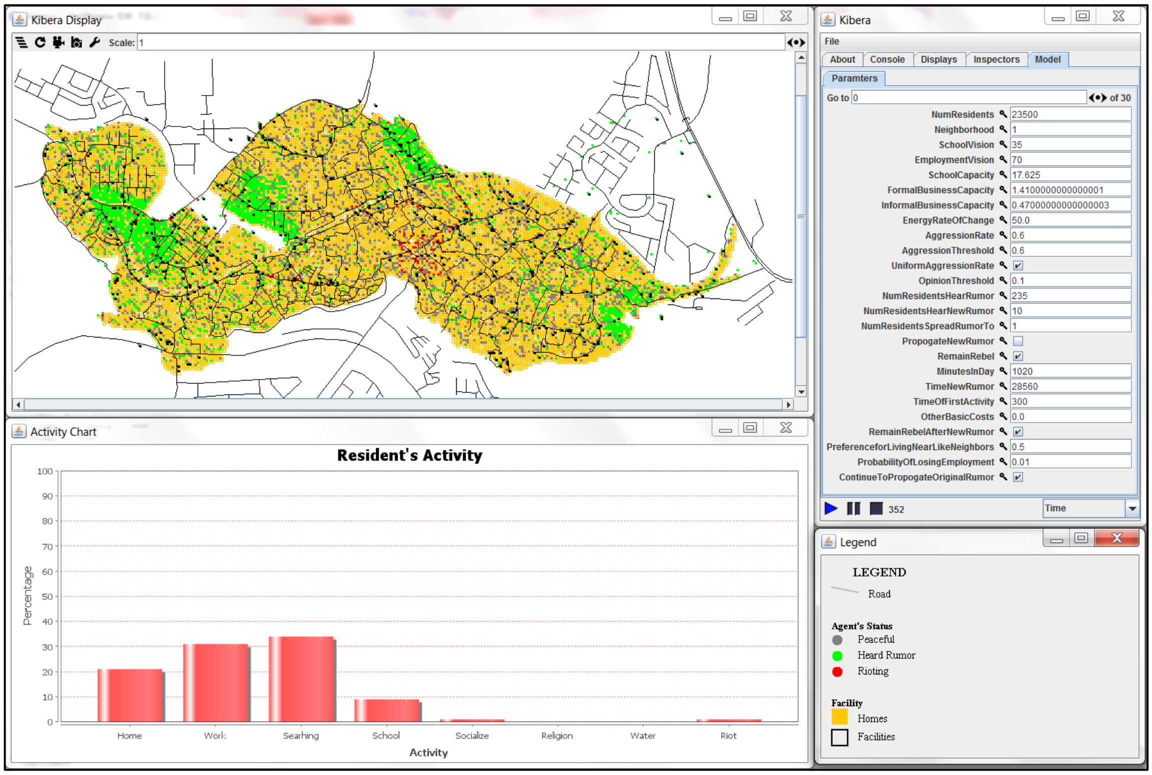


Figure 6-2. The model's GUI.

As Kibera has received considerable attention from non-governmental organizations (NGOs) and other non-profits (Hagen, 2011), an extensive amount of data has been collected, including boundary shape files, transportation shape files, and the geocoded locations of many of its facilities. The two main data sources used to create the modeling environment are Map Kibera (Hagen, 2011) and the Map Kibera Project (Marras, 2008). Map Kibera is a project to geocode the Kibera slum, which as an informal settlement was previously a blank spot on the map. Using OpenStreetMap (2013), residents of Kibera were given the tools to geocode their neighborhood, from the

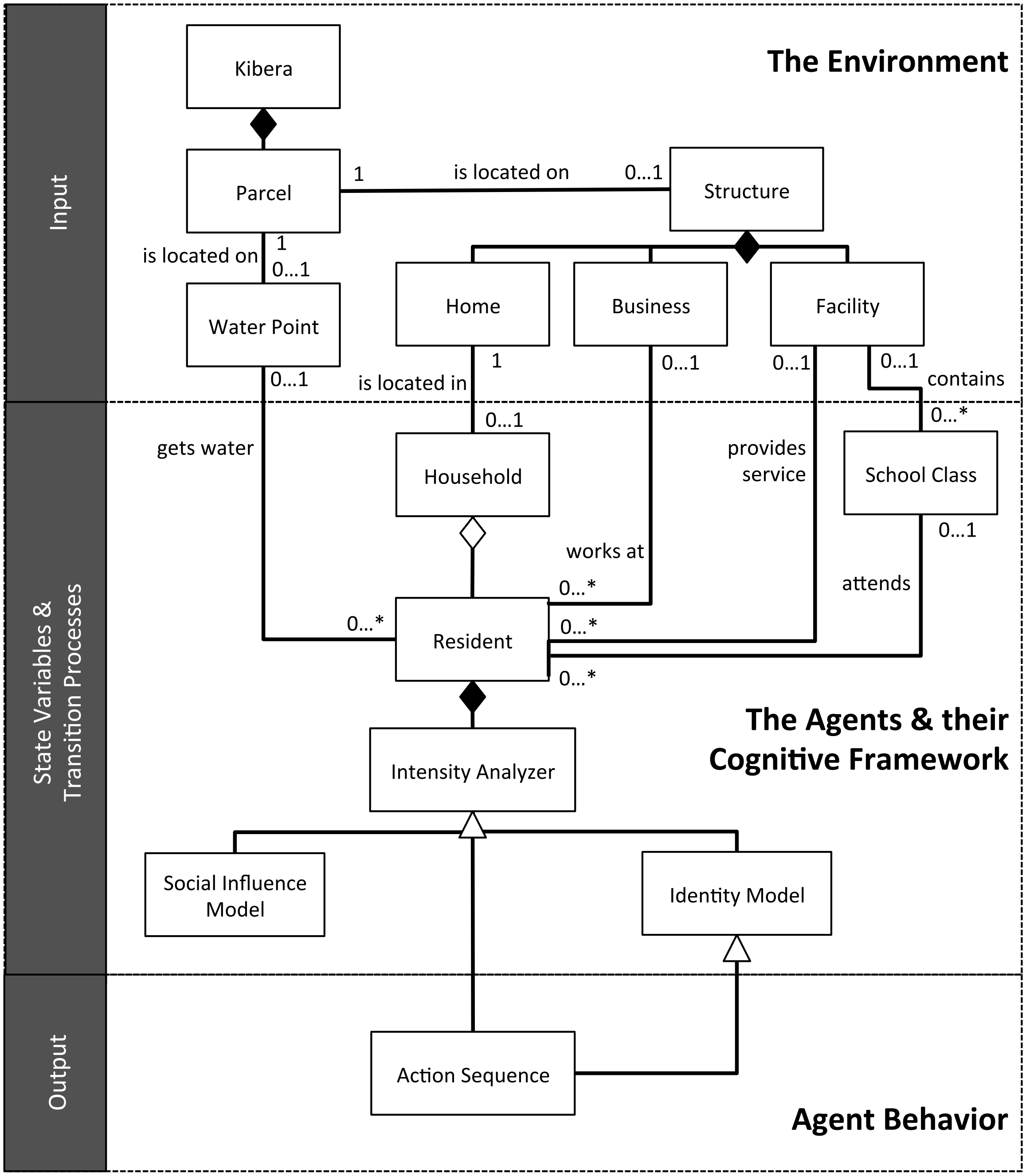


Figure 6-3. High-level UML diagram.

transportation network (including walking paths, road networks, and railway), the location of service facilities (such as heath centers, schools, and religious facilities), and water points (Hagen, 2011). While this provides the GIS data, much of the socioeconomic and demographic data comes from another project of volunteers, similarly named the Map Kibera Project (Marras, 2008). This project performed an in-depth door-to-door survey of the Kianda neighborhood in Kibera. Survey data included information on the number of households within a structure, the number of household members, and the distribution of male and female as well as child and adult household members. In addition, the amount of rent paid by room and the characteristics of each the room, such as whether it has electricity, running water, and sanitation, was included. Figure 6-4 sketches out the key model processes, which are discussed further in this section. The Intensity Analyzer is broken out into the three sub-models—the Daily Activity Scheduler, the Identity Model, and the Social Influence Model—shown within the dotted lines in the diagram. Section 6.2.1 provides details on the initialization processes, from importing spatial data to endowing agents with unique attributes. Section 6.2.2 discusses the agents' behavior. Finally, Section 6.2.3 goes over the model's output.

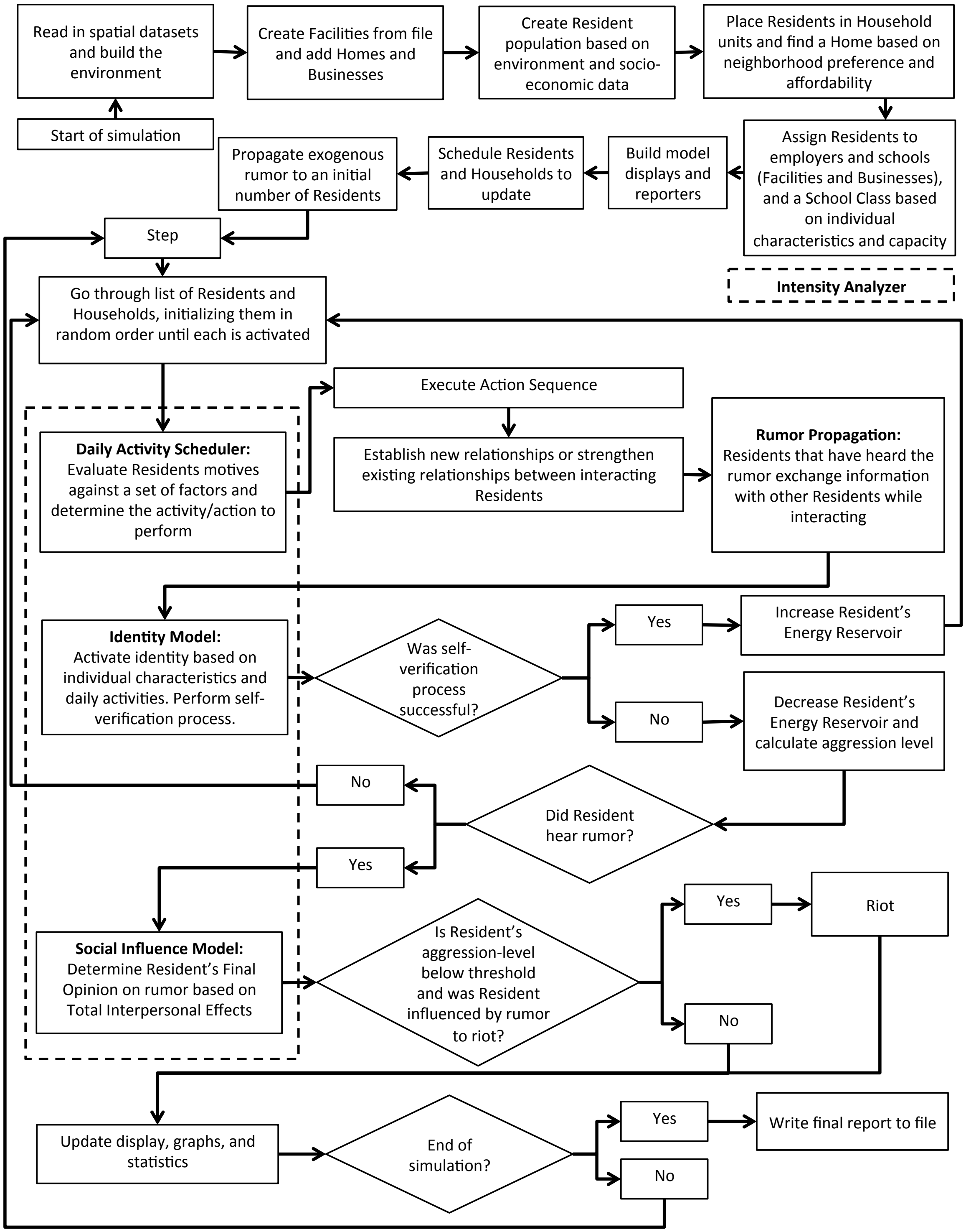


Figure 6-4. Flow diagram of the key processes in the model.

6.2.1 Model Initialization

This section describes the processes behind the initialization of the model, including creation of the environment and the population based on empirical data (Section 6.2.1.1), a description of the two types of agents modeled (Section 6.2.1.2), and the process of assigning them to a home (Section 6.2.1.3) and an employer or school (Section 6.2.1.4).

6.2.1.1 The Environment and the Population

The modeling world measures 3.9 by 1.5 kilometers (the approximate size of Kibera) with a cell (Parcel) size of 12.5 m x 12.5 m, which is based on the average size of a structure plus the average surrounding empty space (Marras, 2008). Upon model initialization, a Structure and/or Water Point is added to each Parcel. Each Structure can contain Homes, Businesses, and/or Facilities (or can remain empty). Facilities with exact GIS coordinates were added to the structure located on the same grid location.

The total population of Kibera is estimated to be between 235,000 and 270,000 (Marras, 2008), with a gender distribution of approximately 61% male and 39% female and an age distribution that is approximately 54% adult and 46% children (under the age of 18) (Marras, 2008). The population is made up of individual Residents, who are each part of a Household. Using data from the Map Kibera Project (Marras, 2008) it was determined that household size is approximately lognormally distributed with a mean of 3.55 and standard deviation of 1.61. One Resident in each Household is designated head of household. This is done to ensure each Household has at least one adult. In addition, Households are assigned an ethnicity and a religion based on the ethnic and religious distribution of Kenya (CIA World Factbook, 2013). With every ethnicity represented, Kibera characterizes Kenya's ethnic diversity (De Smedt, 2009). Given this similarity, the ethnic distribution of Kenya is used as a proxy when endowing the Residents with an ethnicity. In addition, a specified number of Residents are randomly selected to hear the exogenous rumor at initialization. Of those that heard the rumor, a proportion is selected to be influenced enough by the rumor to riot. Those initial rioters will attempt to influence other Residents as the simulation runs. Table 6-1 summarizes the population and environment input parameters used in the model. These input parameters are used to create the environment and the population.

Table 6-1. Population and environment parameters used in the simulation.

Parameter	Description	Reference
Initial number of agents	Kibera is estimated to have between 235,000 and 270,000 residents.	Marras (2008)
Preference for living near "like" neighbors	The preference for living near (within the Moore neighborhood) a household of the same ethnicity.	Adapted from De Smedt (2009); Schelling (1978)
Number of agents that heard the rumor	This is the number of agents that heard the rumor at initialization.	n/a
Proportion of initial agents that riot	Of those that heard the rumor, this is the proportion that riots at initialization.	n/a
Age distribution	If a Resident is head of household, an age between 18 and 59 is randomly selected. For all other Residents, there is a 25% chance that the Resident is an adult (age 18 to 62), and a 75% chance that the Resident is a child (under 18).	Marras (2008)

Gender distribution	Residents have a 61.3% probability of being male, and 39.7% probability of being female	Marras (2008)
Ethnic distribution	Residents are assigned one of twelve ethnicities based on the following distributions: Kikuyu (21%), Luyha (14%), Luo (12%), Kalinjin (12%), Kamba (12%), Kisii (6%), Meru (5%), Mijikenda (5%), Maasai (2%), Turkana (1%), Embu (1%), Other (9%)	CIA World Factbook (2013); De Smedt (2009)
Religion distribution	Residents can be Christian, Muslim, or Other with a distribution of 82.5%, 11.1%, and 6.4%, respectively.	CIA World Factbook (2013); Marras (2008); Pew Forum on Religion & Public Life (2010)
Employment distribution	Residents are assigned an employment status based on the following distribution: 41% of females and 60% of males are employed, 9.6% of females and 7.9% of males are searching, 43.1% of females and 27.1% of males are inactive, and 6.3% of females and 5% of males employment status are unknown.	Kenya National Bureau of Statistics, (2009); UN-HABITAT (2003)
Income distribution	The income distribution is based on average, minimum, and maximum income data for Kibera. The Lorenz (1905) curve is then used to create an income distribution.	Gulyani and Talukdar (2008); Desgroppes and Taupin (2011); Lorenz (1905)
Informality Index	The proportion of the employed population that works in the informal and formal sectors.	UN-HABITAT (2003)
Aggression threshold	The threshold a Resident's aggression must be under in order for the resident to aggress or riot.	Adapted from Green (2001)
Aggression rate	The rate of the logistic curve (between 0 and 1). The higher the rate, the slower someone is to aggress.	Adapted from Green (2001)
Energy rate	The rate of change a Resident's Energy Reservoir will increase or decrease.	Adapted from Burke and Stets (2009)
Opinion threshold	This is how similar two Residents' opinions must be on the rumor to influence one another (between 0 and 1).	Adapted from Friedkin (2001)

Employment vision	The number of Parcels out from a Resident's Home location that it can search for employment.	n/a
School vision	The number of Parcels out from a Resident's Home location that it can search for a school.	n/a
Number of household members	The number of Residents living together as part of a Household.	Marras (2008)
Household capacity	The capacity of Households that can live in one Home.	Marras (2008)
Student capacity	The maximum number of students that can be enrolled in a school.	Ministry of Education (2007)
School class capacity	The number of students in the same School Class.	OpenStreetMap (2013)
Formal employer capacity	The maximum number of employees a formal employer can hire.	Ministry of Education (2007); OpenStreetMap (2013)
Informal employer capacity	The maximum number of employees an informal employer can hire.	UN-HABITAT (2003)
Home capacity	The capacity of Homes in a Structure.	Marras (2008)
Business capacity	The capacity of Businesses in a Structure.	Marras (2008)
Home amenities	The amenities that come with a Home, such as electricity, sanitation, and running water.	Marras (2008)
Household expenditures	The average cost of Household expenditures, such as food, water, electricity, sanitation, and transportation.	Gulyani and Talukdar (2008)

6.2.1.2 The Agents

As shown in Figure 6-3, there are two types of agents modeled, the Resident and the Household. The main agent is the individual Resident, which are heterogeneous and are characterized by unique attributes such as age, gender, and ethnicity as shown in Table 6-2. In addition, a group (or unit) of residents makes up a Household.

Table 6-2. Resident attributes.

Variable	Description
Age	The Resident's age pulled from the age distribution.
Gender	The Resident's gender pulled from the gender distribution.
Ethnicity	The Resident's ethnicity, which is drawn from the ethnicity assigned to the Resident's Household.
Religion	The Resident's religion pulled from the religion distribution.
Employment status	The Residents employment status, which can be formal, informal, searching, or inactive. At initialization, this is drawn from the Employment distribution.
Income	If the Resident is not employed, income is set to zero. Otherwise, it is set based on the income distribution.
Energy	This is the Resident's current level of energy in its reservoir (valued from 0 to 100).

Households consist of a group of Residents. The size of the Household is determined as described in Section 6.2.1. Households are characterized by their ethnicity (all residents in the same Household share the same ethnicity), total income, and total Household expenditures (such as rent, food, water, and sanitation) as shown in Table 6-3.

Table 6-3. Household attributes.

Variable	Description
Household ethnicity	Each Resident in a Household shares the same ethnicity. The assigned ethnicity is pulled from the ethnic distribution of the country.
Household income	This is total monthly income of the Household. It is calculated by summing the individual income of all Residents living in the same Household.
Household expenditures	The Households' daily expenditures, including food, water, electricity, and sanitation.
Household discrepancy	The daily discrepancy between a Household's income and expenditures.

6.2.1.3 Assigning Households a Home

Within Kibera's neighborhoods, one will typically find a majority ethnicity (De Smedt, 2009). For example, Luos make-up the majority of those living in Gatwikira and Kikuyus dominate the Laina Saba neighborhood. Luos originally arrived to Kibera as early as 1948. Coming from the Nyanza province of Kenya, they typically chose to move near family already living in the slum. This aided residents paying school fees, finding a job, and taking care of them until they settled in (De Smedt, 2009). Given Kibera's ethnic make-up and resident's decision process in selecting a location to settle, the Schelling (1978) segregation model is used as inspiration as Households select an initial Home for which to reside. Schelling (1978) studied the behavior of two groups of agents on a grid. Agents were given a preference for the number of similar agents they wanted as neighbors. They then moved about the lattice until their preference for similar neighbors had been reached.

Similarly, Households in the model here are assigned a preference for living near "like" neighbors (neighbors are alike if they share the same ethnicity). If this is the first Household, the Household will randomly select an affordable Home within a Structure to reside. As new Households are added to the landscape, they survey the current landscape. If the Household prefers to live near "like" neighbors, it will randomly select an existing Household with the same ethnicity. Within the Moore neighborhood of the selected household, the new household will assess (1) its ability to afford the new place and (2) its preference for living near "like" neighbors. The new Household will determine if the area meets its preference requirement and will search for a Home it can afford. Affordability is determined by comparing the Household's total income to the costs associated with living in the Home (including the cost of rent and any amenities that may come with the Home). It is assumed that families are willing to spend a certain proportion of their total Household income on these costs (Alonso, 1964). If its preference requirement is met and the Household finds that the Home is affordable, it will move in. Otherwise, the Household will randomly select another Household with the same ethnicity and repeat the process. Figure 6-5 illustrates a typical model run after it has been initialized with 235,000 Residents and with a 50 percent preference for living near like neighbors. The different colors represent the ethnic diversity of Kibera (note that large clusters of agents with similar ethnicity have formed).

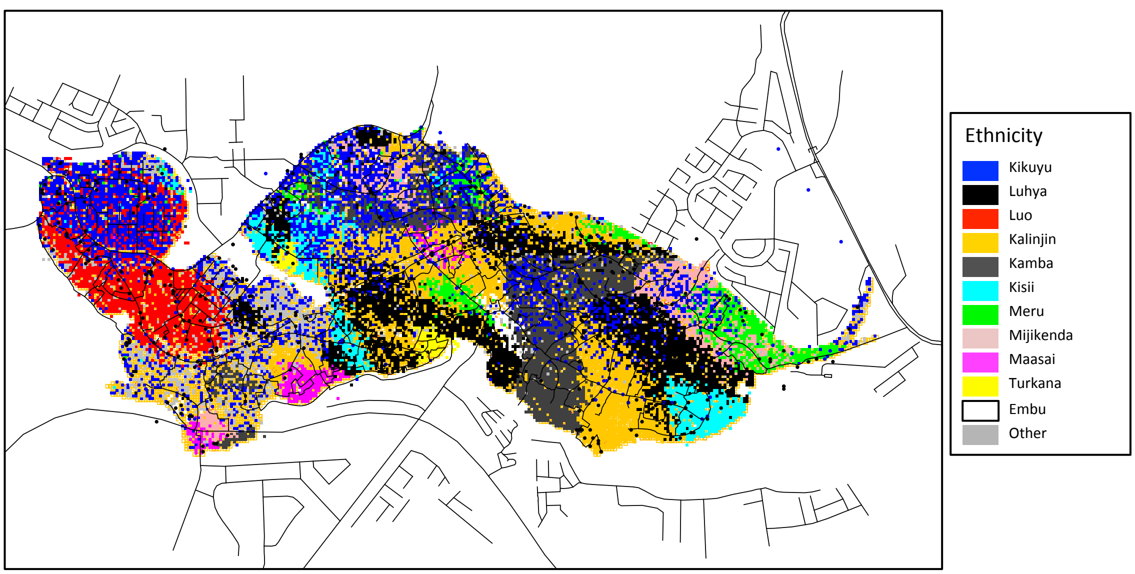


Figure 6-5. Model after it has initialized with 235,000 Residents. The different colors represent the ethnic diversity of Kibera.

6.2.1.4 Assigning Residents Employers and Schools

Once this environment is created and all Residents have been assigned a Home, they are given one of the following employment statuses: inactive (not working and not searching for work), formal (employed in the formal sector), informal (employed in the informal sector), or searching (not employed and searching for employment). At initialization, any Resident under the age of 18 is assigned the employment status of inactive. The employment status assignments for the remaining Residents (aged 18 and over) is based on empirical data for the area (Kenya National Bureau of Statistics, 2009b) and on the informality index (UN-HABITAT, 2003). Empirical data provides the percentage of Residents by gender that are employed, searching for employment, or are inactive, while the informality index provides an estimate of the percentage of employed Residents that are working in the formal sector (40 percent) or the informal sector (60 percent). Employment status is dynamic and can change throughout the course of the simulation.

Next, all Residents employed search for an employer within their employment vision that has not reached capacity. Employers in Kibera that are considered formal are the Facilities (e.g., schools, religious facilities, and health centers). If the Resident's employment status is formal, it will search for a Facility in Kibera that has not reached its formal employer capacity, which was estimated using empirical data on the number of employees at the schools in Kibera. This value was used as a proxy for all Facilities given that this type of data was not available for the religious facilities and health centers. Informal employers in Kibera are the Businesses, which can include selling goods on the street, small restaurants, and markets. According to the UN-HABITAT (2003), a business can be defined as informal if it has a maximum of 5 to 10 employees. Residents with an employment status of informal will search for a Business within the employment vision that has not reached its informal employer capacity. At initialization, if a Resident cannot find an available employer, it is assumed that the Resident is employed outside of Kibera (i.e., in other parts of Nairobi). Because employment data is empirically sound and data on the number of Kibera residents working inside versus outside the slum was not available, this ensures that the number of employed Residents more closely represents reality. Once the Resident has found an available employer, it is assigned that employer so that it goes to the same employment location each working day (e.g., Monday through Friday) moving forward.

Finally, all Residents under the age of 18 will search for an available school within their school vision to attend. Empirical data on the number of students at schools in Kibera was used to determine the student capacity at the schools (OpenStreetMap, 2013). If a Resident finds an available school, it is assigned that school so that it attends the same school each school day (e.g., Monday through Friday) moving forward. In addition, these Residents are assigned to a School Class. This ensures that students interact mostly with a smaller subset of students in a school (instead of all students in a school).

6.2.1.5 Model Scheduling

The model proceeds in minute (60 minutes / hour) time steps. A minute was selected because the spread of the rumor, the decision to riot (or not), and the mobilization of residents occurred quickly. Elections were held in Kenya on December 27, 2007, a rumor about rigged election results began to spread on December 29, by December 30 the country had broke out in protest (Chege, 2008; International Crisis Group, 2008). As quickly as a riot can start, it can end. Once a power sharing agreement was announced on February 28, 2008, rioting seized immediately (De Smedt, 2009). Details regarding the activities performed and the scheduling of specific activities will be covered in detail in Section 6.2.2.1.

6.2.2 Agent Behavior

In Section 3.3, theories of human behavior and the PECS framework were discussed in detail. Behavior in this model draws from humanistic needs theory, identity theory, and social influence theory. Maslow's (1954) hierarchy of needs grounds the Residents' daily activities and interactions in theory. In addition, both role-based (e.g., student, stay at home parent, employee) and group-based (e.g., the ethnicity one belongs to) identities are important to the daily activities and decision-making processes, making the unified theory (Stryker and Burke, 2000) of identity theory and social identity theory most appropriate for modeling agent behavior in this context. As discussed in Section 6.1, rumors played a major role in the onset and intensity of the rioting that occurred in Kibera. Rumors constitute a disruption in the self-verification process of our internal identity models. However, acting on a rumor is largely dependent on our embeddedness in our social networks and the reinforcing nature of these relationships. When effective, rumors play a role in shaping attitudes and in norm formation (Centola and Macy, 2007). Using Friedkin's (2001) structural approach (see Section 3.3.1.2), social influence theory is implemented and an agents decision to act on the rumor is determined. Rumors that effectively influence behavior provide the trigger (or opportunity) for rioting to occur.

PECS provides an ideal framework for implementing human behavior (see Section 3.3.2.2). As in Chapter 5, PECS is used to implement the behavior of the Residents here. However, the level of cognitive sophistication has increased significantly. While the previous ABM drew upon three of the state variables (Physis, Social Status, and a simple Cognition), here all four state variables are utilized, including all five subcomponents of Cognition (e.g., environment model, self model, protocol, planning, and reflection). In the ABM, three sub-models are incorporated into the PECS framework and together they drive agent behavior. Figure 6-6 illustrates how the sub-models—the Daily Activity Scheduler (flows represented by green arrows), the Identity Model (flows represented by the red arrows), and Rumor Propagation and Social Influence Model (flows represented by the blue arrows)—fit into the PECS framework at a high-level. This figure is not designed to give an exact representation of every component of agent behavior (as only those flows thought to be most significant are shown), but to give a high-level picture of how human behavioral theory works together with PECS in the model.

From Figure 6-6, Perceptions from Sensor (the environment) feed into both the self-verification (see Figure 3-1) and social influence processes (see Section 3.3.1.2). In addition, these Perceptions help guide the routine activities of the Resident. Simple behavior (such as staying home to sleep or eat) may be determined directly in Physis.

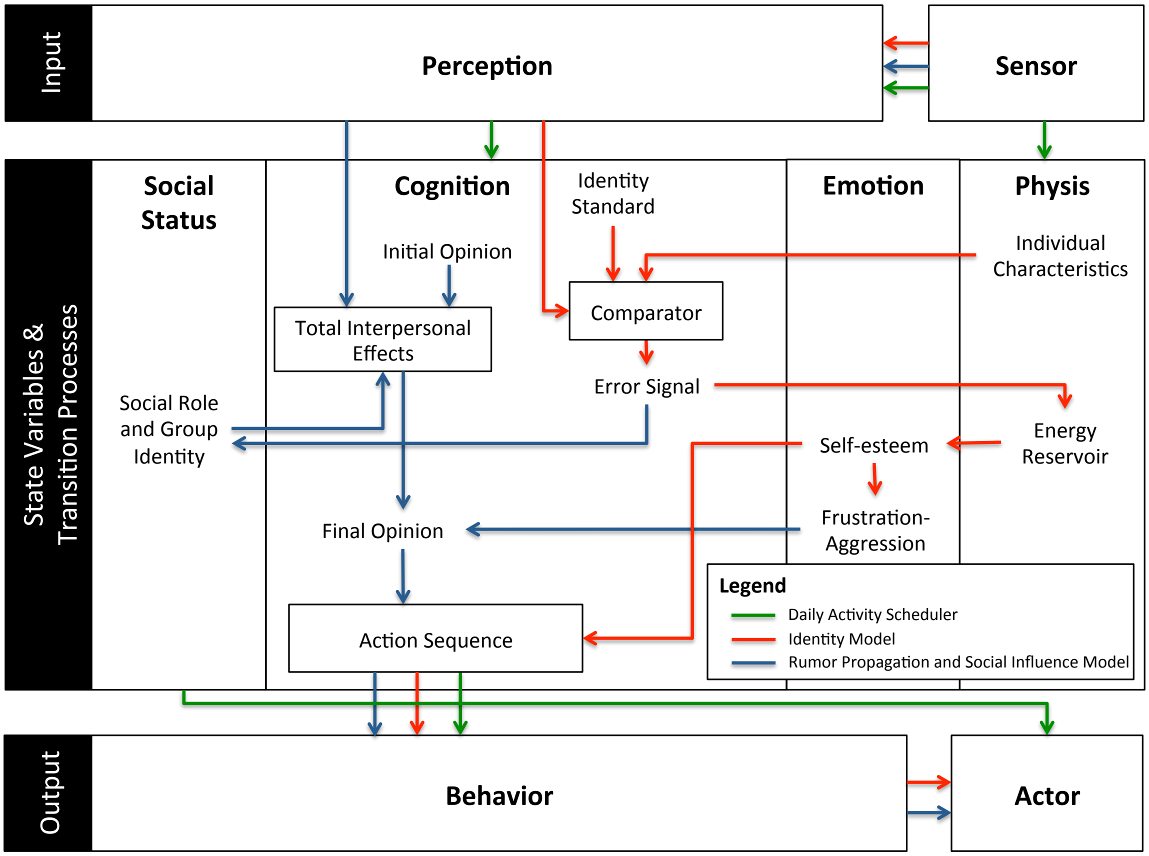


Figure 6-6. A high-level representation of the model's agent behavior incorporated into the PECS framework (adapted from Schmidt, 2000; Stets and Burke, 2000).

More intricate inputs are fed into Cognition, where the resident's Identity Standard is compared to its Perceptions. The self-verification process occurs and once complete, the Comparator outputs an Error Signal. This process is used to determine if the Resident's identity will be Domestic, Employee, Student, or Rioter. If there is no error (the resident met its Identity Standard), the Energy Reservoir is increased and Self-esteem goes up. Cognition will then generate the Action Sequence, Behavior will determine the execution order, and Actor will execute the actions associated with the Resident's identity.

If an Error Signal is produced, however, the Energy Reservoir in Physis is reduced and Self-esteem in Emotion goes down. Low Self-esteem can lead to frustration, which in turn, can cause aggressive behavior (Green, 2001; Stets and Burke, 2005). The Resident's susceptibility to influence from those in its social network is then evaluated in Total Interpersonal Effects. Its position in Social Status, both in terms of Social Role and Group Identity (outputs of the Identity Model) impact a Resident's susceptibility and Final Opinion on the rumor. If the Resident has heard the rumor, has reached a level of frustration that can lead to aggressive behavior, and has been influenced to riot by one or more Residents in its network, Cognition will generate the Action Sequence, Behavior will determine the execution order, and Actor will execute the action for one to riot. Otherwise, the Resident will remain peaceful.

Residents will continuously run their Identity Standard through the Comparator and re-evaluate their Final Opinion on the rumor being spread. This process also allows for development of the agent's Self Model (an important cognitive component to modeling human reflective behavior) as well as Emotion in the form of Self-esteem (Stryker and Burke, 2000). The Perceptions input into the Self Model are a factor of the individual's interactions with others and the environment. Internally, such interactions impact the Error Signal (difference between the input Perceptions and the Identity Standard) received by the Comparator, which directly predicts the Resident's behavior. Next, Figure 6-7 provides the complete set of motives and actions available to the Residents. The processes described in Figure 6-6, between receiving information from Perception and generating the Action Sequence, are implemented via the Intensity

Analyzer, which is responsible for determining the action-guiding motive from the set of possible motives available to the Resident.

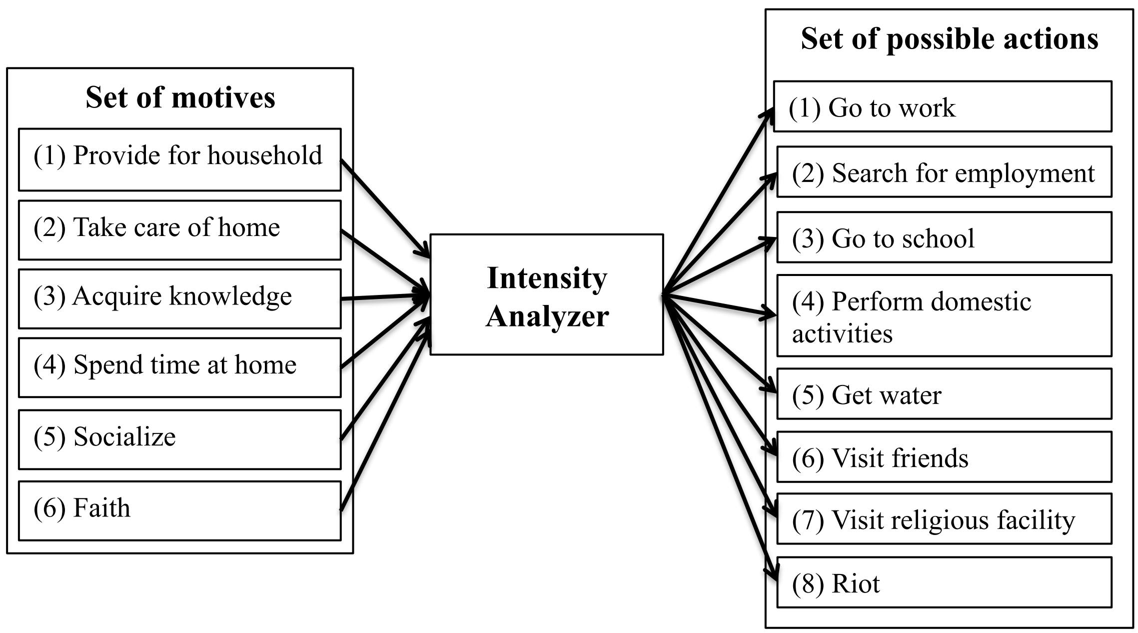


Figure 6-7. Motives and determining action-guiding motive via the Intensity Analyzer (adapted from Schmidt, 2002).

The three sub-models—the Daily Activity Scheduler (Section 6.2.2.1), the Identity Model (Section 6.2.2.2), and Rumor Propagation and the Social Influence Model (Section 6.2.2.3)—that make-up the Intensity Analyzer, and subsequently drive agent behavior, are described in detail in the following sections.

6.2.2.1 The Daily Activity Scheduler

The first step in determining agent behavior is to run the Daily Activity Scheduler, which drives the agents' daily activities. This sub-model draws from Maslow's

(1954) hierarchy of needs as agents' strive to meet their physiological, safety, love and belonging, and esteem needs (see Section 3.3.1). In a slum such as Kibera, physiological needs such as food, water, and sanitation must be purchased; this requires that one or more members of a household unit are employed and are providing sufficient income. If unmet, a Household would either increase its income (e.g., pulling a student out of school to work) or find a means to cut back on these basic necessities. Slum residents may seek safety in terms of personal security through shelter (a home) and staying indoors past a certain hour, financial security through gainful employment or knowledge acquisition in school (as a means to insure future financial security). Love and belonging includes activities such as staying home to spend time with family, going to a friend's house to socialize, or attending church or mosque to feel like part of a community. Esteem is met by continuous successful attempts at self-verification. For example, the student identity is met by regularly attending school; the employee identity is met by having regular and stable employment; and the domestic identity is met by successfully attending to the home and family. If continuous attempts at self-verification are unsuccessful, however, self-esteem will be low and may lead to frustration. The final category, self-actualization, which is met when a person feels they are at their full potential in areas such as morality, problem solving, and creativity, is beyond the scope of this model.

The Daily Activity Scheduler begins with a set of available motives that are largely attributed to human needs theory. Intensity levels of the motives are evaluated against a set of influencing factors (both environmental and internal). The motive with the highest intensity becomes the action-guiding motive, which determines the goal the

Resident will strive for. In this case, each goal is also the associated activity (e.g., if the goal is to 'Go to work', the activity would be the same). The set of motives, important influencing factors driving motive intensity, and their associated goals are listed in Table 6-4.

Table 6-4. The set of motives, important influencing factors, and the associated goals that drive agents' daily, routine activities.

Motive	Important Influencing Factors	Associated Action(s)
Provide for Household	Basic human needs (e.g., need for food and water), time-of-day and day-of-week, age, and employment status	Go to work, Search for employment
Take care of Home	Current levels water, time of day, age, and employment status	Perform domestic activities, Get water
Acquire knowledge	The need for future financial security, time-of-day and day-of-week, age, and availability of schools	Go to school
Spend time at Home	Basic human needs (e.g., need to eat and sleep), need for love and belonging, and time-of-day	Perform domestic activities
Socialize	Strength of the friendship, distance to friends house and whether friend is home	Visit friends
Faith	Importance of faith, distance to nearest religious facility	Visit religious facility

If we are to compare the set of motives in Table 6-4 to Maslow's (1954) hierarchy of needs as shown in Figure 3-2, the first three listed (provide for Household, take care of Home, acquire knowledge, and spend time at Home) would be associated with fulfilling the first two most fundamental levels of needs: physiological and safety. The two remaining motives (socialize and faith) fall under the third level of Maslow's (1954) hierarchy of needs: love and belonging. In addition, from this table (under the important influencing factors) we see that the time-of-day and the day-of-week play important roles in the evaluation process. These factors are used by the Intensity Analyzer as part of the evaluation process. The times and days associated with each activity in addition to the amount of time a Resident will stay at the activity are shown in Table 6-5.

Upon determining the activity to perform, the Resident uses the transportation network (e.g., roads and walkways) created at model initialization to move to the parcel where the activity is located. The Resident then stays at this Parcel for the activities staying period before returning Home. As an exploratory model, scheduling was kept simple. However, it can be extended to include more intricate scheduling if developed further.

At initialization Residents (nodes) are not connected to any other Residents. However, while at an activity, the Resident generally interacts with other Residents located on the same Parcel and performing the same activity. Table 6-6 shows the interactions that occur with each activity.

Table 6-5. Scheduling of activities by start time, day of week, and staying period at activity

Activity	Start Time	Day of Week	Staying Period	Activity Location
Go to work	8:00AM – 11:00AM	Monday – Friday	6 – 12 hours	Assigned work location (Business or Facility)
Search for employment	8:00AM – 11:00AM	Monday – Friday	6 – 12 hours	Home
Get water	7:00AM – 6:00PM	Everyday	10 minutes – 1 hour	Nearest Water Point
Go to school	7:00AM – 9:00AM	Monday – Friday	7 hours	Assigned school
Visit friends	7:00PM – 9:00PM (if a student or an employee and it is a school day or work day) Anytime (otherwise)	Any day	2 – 4 hours	A friend's Home
Go to church	7:00AM, 9:00AM, 11:00AM, 7:00PM	Sunday	1 – 2 hours	Nearest church to Home
Go to mosque	5:00AM – 6:00AM, 12:00PM – 2:00PM, 3:00PM – 5:00PM	Everyday	20 minutes – 3 hours	Nearest mosque to Home

Table 6-6. The interactions that occur with each activity.

Activity	Interactions
Go to work	Coworkers working with the same employer at the same time.
Search for employment	Household members.
Get water	Assumed that no interactions occur.
Go to school	Students in the same School Class.
Visit friends	The friend visited and any other of the friend's connections currently at the same location (i.e., Parcel)
Go to church or mosque	Randomly select another Resident to interact with that is also at the religious Facility.

These interactions create new Resident-to-Resident connections (ties) or strengthen existing connections. The weight of a tie between two Residents is a function of the amount of time the two Residents spend together. After a Resident has completed an activity, the weight of all the ties between any interactions is calculated. A weight of one at the end of one day would signify that two Residents spent the entire day together. Equation 6-1 shows how the weight of a tie at time t, w_t, is calculated.

Equation 6-1. Tie weight.
$$w_t = w_{(t-1)} + s/1440,$$

where $w_{(t-1)}$ is the previous weight of the tie between the two Residents, s is the amount of time the Resident stayed at the activity where both Residents were present, and 1440 is the number of minutes in one day. If a Resident were to stop interacting with another Residents (e.g., a Resident lost its job and therefore no longer interacts daily with its colleagues), the tie between the two is not removed. However, as time passes, the tie will not strengthen and will eventually become proportional insignificant compared to relationships it has with other Residents.

Figure 6-8 provides an illustration of how the social networks of ten Residents at initialization can evolve across two full days. At initialization all Residents are Home, thus they will immediately connect with any other Household members. In this example the ten Residents make-up three different Households. As these Residents begin to interact with other Residents through their daily activities, their social network grows and tie strength, which is represented by the thickness of the lines, increases as Residents continue to interact and spend more time together.

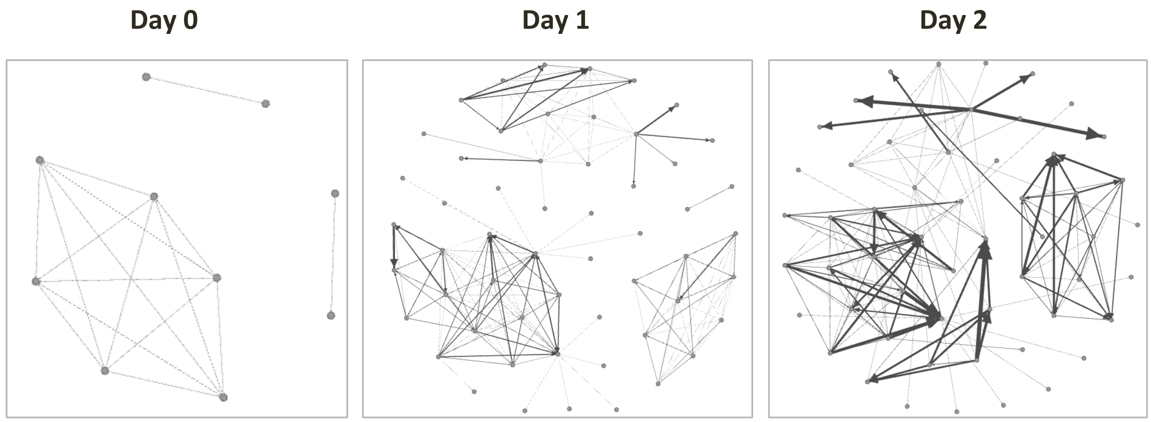


Figure 6-8. The social networks of ten Residents across the first two days of a simulation run.

Social networks play a key role in the model, both in terms of the salience, and subsequent activation, of an identity (as will be discussed in Section 6.2.2.2) and on a Resident's susceptibility to influence (as will be discussed in Section 6.2.2.3). Both of these factors are a major part of a Resident's decision to riot or to stay peaceful.

6.2.2.2 The Identity Model

As the self-verification process succeeds or fails at the micro-level, macro-level social networks and group dynamics can be observed. The unified theory allows one to consider behaviors from the "more mundane expectations for a person occupying a role," such as going to work, searching for employment, or attending church (Stryker and Burke, 2000), to meso- and macro-level formation of friendships and cohesive groups, which could potentially lead to intergroup conflict and civil unrest (see Section 3.3.1.1). Kibera is a melting pot of ethnic diversity and for the most part, ethnic groups live peacefully. The Identity Model is a critical component of human behavior and it may help us shed some light into why former friends and neighbors turned on each other during the ethnic riots.

An identity is composed of four basic components: Input Perceptions, an Identity Standard, a Comparator, and a Output Behavior (as discussed in Section 3.3.1.1). The model assumes all Residents seek to meet the Identity Standard of one of three primary, non-deviant identities (Domestic, Student, and Employee), one secondary identity (Ethnicity), and one primary, deviant identity (Rioter). Primary identities are those that (at least for purposes of this model) cannot overlap. An agent will not strive to meet both the Employee and Student identities, for example. On the other hand, the Ethnicity identity can exist along with a primary identity (a resident can be a Student and a Kikuyu at the same time). However, this identity remains latent most of the time, and is only activated should issues arise in the identity verification process of one of the primary, non-deviant identities. The final identity is the Rioter identity. This is primary because it cannot co-exist (for modeling purposes) with another primary identity, but is deviant because, like Ethnicity, is only activated should the resident have trouble with the self-verification process of a primary, non-deviant identity. In addition, a Resident must be at least five years of age for the Rioter identity to be active. Five was selected because this is the age Kenya begins to collect employment statistics on its residents. If residents are eligible to work at the age of five, it is assumed that they might participate, at some level, in a riot. Table 6-7 summarizes the identities available to Residents in the model.

The relationship between the Daily Activity Scheduler and Identity Model is a feedback loop, each informing the other. The activity an agent performed as per the Daily

Table 6-7. The set of identities available to agents.

Identity	Type	Requirements for Residents Seeking This Identity
Domestic	Primary, non-deviant	Resident is not working or attending school and is performing domestic activities.
Employee	Primary, non-deviant	Resident is employed.
Student	Primary, non-deviant	Resident is under 18 and finds a school with availability.
Ethnicity	Secondary	A disruption in the identity verification process, sufficient failed attempts at self-verification of a primary, non-deviant identity, and influence from those in the resident's social network.
Rioter	Primary, deviant	Resident is at least 5 years old and Ethnic identity is salient.

Activity Scheduler helps inform the Resident of his/her ability to match its Identity Standard (this is equivalent to the self-verification process in the Identity Model). The Residents social networks are a critical component of commitment, which is defined as their embeddedness in a network, and can effect the activation of a given identity. For instance, network ties can impact the likelihood that a Resident's ethnic identity will be activated or remain latent. In addition, the fit of an identity in a given situation is also important. For instance, if a Resident is at work, their Employee identity is likely to be active. Meanwhile, the identity a Resident is striving to meet drives the activities it may look to perform. As an exploratory model, the rules for meeting an Identity Standard were kept simple. The inputs include information such as the Resident's employment status, age, availability of employers within a Resident's vision, and availability of schools within a Resident's vision. The Comparator compares the Resident's desired Identity Standard against a set of simple rules required for meeting the Identity Standard.

Because domestic activities are not dependent on the availability of work or school and every Resident is assumed to have a Home, any Resident seeking this identity is able to achieve the Identity Standard. If a Resident is employed, the Resident has met the requirements to be happy in the Employee identity. However, if the Resident is searching for employment and has not found a job, the self-verification process for the Employee identity is said to have been unsuccessful. This is similar for the Student identity. If a Resident that is 18 or under is able to find an available school to attend, the identity verification process was successful. If, however, there are no available schools and the Resident must stay Home, the Student Identity Standard was not met. In addition, should a Resident seeking the Student identity not be able to attend school, he/she will then determine if its necessary to search for employment. If so, the employment status will change to reflect the fact that the Resident is now looking to enter the job market. If the Resident is able to find employment, his/her Employee Identity Standard is met.

The output of the identity verification process is an increase or decrease in the Resident's Energy Reservoir (this is consistent with the Identity Model described in Section 3.3.1.1). Each Resident begins the run with an energy level of 100. The amount by which the Energy Reservoir changes with each attempt at identity verification are based on the energy rate of change, a user inputted variable. The change in energy in a Resident's Energy Reservoir is calculated by using Equation 6-2, where change in time is the amount of time a Resident has been in performing the current goal divided by the number of minutes in a day.

Equation 6-2. Change in energy.
Change in energy = Energy rate of change / Change in time

If the self-verification process is successful, energy levels in the Energy Reservoir increase by the change in energy (but remain capped at 100). As Residents fail to meet their Identity Standard, their Energy Reservoir is depleted by the change in cnergy value. In addition, the model accounts for overall household "happiness." A Resident may continuously fail to meet the Employee identity. However, if its Household unit is sufficiently "happy" (i.e., household income is not an issue), the Resident may be less likely to become quickly frustrated. On the other hand, a lack of resources at Home may increase the rate at which a Resident becomes frustrated. Household happiness is a function of the discrepancy between a Household's total income and its total expenditures. Problems in self-verification reduce the Resident's ability to handle problems with identity verification. This causes increased stress, thus potentially leading to an aggressive response (Stets and Burke, 2005). In the model this takes the form of rioting.

The aggression threshold is the same for all Residents and is set at initialization of the model. A logistic curve is used to represent aggression in the model. As a Resident's Energy Reservoir gets depleted, aggression moves down the logistic curve. The initial rate of the logistic curve, called the aggression rate, is set at initialization and is specified by the user. In addition, Household happiness directly impacts the rate of the curve. If a Household's happiness level is high, the rate of the curve is increased so that it takes additional rounds of failed self-verification before the Resident becomes aggressive. On the other hand, low Household happiness decreases the rate of the curve, ensuring the opposite effect. Once a Resident's energy level dips below an aggression threshold, which is also a user inputted variable, the Resident may aggress.

Figure 6-9 illustrates the logistic curve at three different rates. Based on the figure, if the rate of the logistic curve is set at 0.6 (the red line) and the aggression threshold is set at 0.8, a Resident may aggress after its energy level has dipped below 61. When aggression goes below the aggression threshold, that agent has the potential to aggress. Whether the agent aggresses (and riots) depends on the results of the Rumor Propagation and the Social Influence Model, which is discussed next.

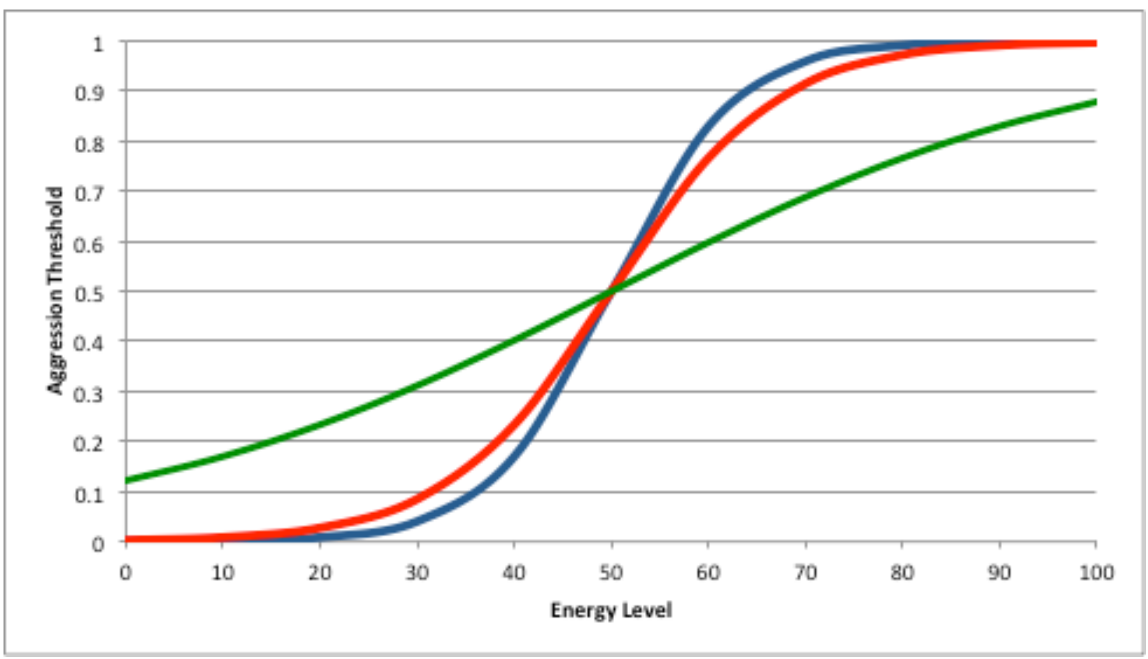


Figure 6-9. The logistic curve at three different rates (green line = 0.2, red line = 0.6, and blue line = 0.8).

6.2.2.3 Rumor Propagation and the Social Influence Model

Rumors played a major role in the riots that hit Kibera, in terms of re-igniting it, escalating the intensity, and causing displacements. The question here is therefore, how do rumors propagate or diffuse? Diffusion can be defined simply as "the spread of something within a social system," where "something" can be a rumor, some piece of information, or even a disease (Strang and Soule, 1998). In the case here, we assume "something" refers to a rumor. Rumors can serve as a disruption in an individual's routine identity verification process, potentially heightening the salience of latent identities, such as one's ethnic identity. In addition, social networks play a key role in this diffusion process, both in terms of spreading the rumor and in terms of social influence and opinion formation induced by the rumor (Granovetter, 1973). Many people will hear the rumor (especially given the prevalence of mass media and social media) but whether they act on the rumor is largely based on the diffusion of influence through their social networks. Simply hearing the rumor through mass media is not enough; the spread of the information through personal ties is key in determining whether one will act on the rumor (Granovetter, 1973). In addition, Allport and Postman (1947) stress the importance of social networks and susceptible individuals in these networks in the spread of a rumor. Similarly, Friedkin and Johnsen's (1999) Social Influence Network Theory says that a recipient's decision to act on the rumor is a function of their initial opinion on the issue, their relative interpersonal influence, and their susceptibility to influence (see Section 3.3.1).

At initialization a predefined number of residents “heard” a rumor, and of those that heard the rumor, a proportion is initially influenced by the rumor. Although these agents are rebellious, they continue to go about their daily activities as a means to spread their “message” with others in their social network. Once a Resident has heard the rumor, it will randomly spread the rumor to another Resident in its social network. If a Resident has not heard the rumor, it will continue to go about its daily activities. If the Resident is influenced by the rumor and is at an aggressive state, the identity verification process of a primary, non-deviant identity will be broken while the Ethnicity identity and Rioter identity will be activated. Studies have shown that people seldom act on a rumor unless heard through personal ties (Granovetter, 1973). For this reason, the model assumes that acting on the rumor cannot occur unless through direct interaction with others who have also heard the rumor and have been influenced to riot.

The recipient’s decision to act on the rumor is based on Friedkin and Johnsen's (1999) Social Influence Network Theory. Building on this, Friedkin (2001) developed a structural approach for determining opinion formation, an approach that is particularly useful in situations where the only information available is the communication (or interaction) network. Using this approach, the structural equivalence of the actors in the network is a measure of their initial opinion, as defined in Section 3.3.1.2 (the more similar actors are in terms of structural equivalence, the more likely they are to share a similar opinion on the issue). However, given the computational intensity of evaluating structural equivalence in an evolving social network, I modify the definition of similarity slightly. Two actors are said to be structurally equivalent if they “have identical ties to and from all other actors in the network" (Wasserman and Faust, 2009). Instead of evaluating whether two actors are connected to the exact same nodes (i.e., share identical ties), the model assesses whether two actors are connected to the same types of nodes, where node type is based on the active identity (e.g., Employee, Student, Rioter) of the node and the ethnicity of the node. This is consistent with Wasserman and Faust (2009) discussion on potential ways to relax the strict definition of structural equivalence by using a node's "role" (here role is defined as identity), for instance, as a measure of structural "similarity." The Ethnicity identity does need to be active for calculating similarity as I am measuring how embedded a Resident is in a network of Residents with similar ethnicity, an important characteristic of identity salience (Stets and Burke, 2000). The similarity between the Resident in question is compared to each agent it is directly connected to (out to one degree). An actor's susceptibility to influence, a_i, is measured by the centrality of the Resident in the network, particularly indegree centrality, and is determined by Equation 6-3.

Equation 6-3. Susceptibility to influence (Friedkin, 2001).

$$a_i = \left[1 - 1/\left(1 + e^{-(d_i - 2\bar{d})}\right)\right]^{1/2},$$

where d_i is the degree centrality of the Resident and $\bar{d}$ is the mean degree centrality of the entire network. Interpersonal influence, w_{ij}, is measured by Equation 6-4.

Equation 6-4. Interpersonal influence (Friedkin, 2001).
$w_{ij} = a_j c_{ij} / \sum_k c_{ik}$,

where c_{ij} is the probability that there is an interpersonal attachment between Resident i and Resident j. To keep the network size small and computationally feasible, influence is only evaluated against those Residents already attached. Therefore, $c_{ij} = 1$ in all instances. In Section 3.3.1.2, we defined V (see Equation 3-2) as the total interpersonal influence (both direct and indirect) of each actor. For simplification purposes, only the direct interpersonal influences, W, are evaluated here. Thus, in the model, a Resident's opinion on an issue at time t is calculated by Equation 6-5.

Equation 6-5. Opinion on issue (Friedkin, 2001)
$y^{(t)} = Wy^{(t-1)}$,

where W is the matrix of interpersonal influence. The Resident's final opinion, $y^{(t)}$, is then compared to the opinion of its direct connections. If the Resident's opinion is similar (below a user inputted opinion threshold) to any of its connections, the Resident is influenced by that connection. Those most susceptible to being influenced are those already having trouble verifying their identity and those most similar (high ethnic salience) to rebellious connections. If the Resident's aggression has fallen below the aggression threshold and the influencing connection is a Rioter, the agent is now also influenced to riot.

In addition, once a Resident decides to riot it will move to a "center" location in Kibera where it interacts with other Rioters. This is representative of real world riots where collectives have gathered in a city's main square. Recent examples include Independence Square in Kiev, Ukraine in 2014 (Arango, 2013); Tahrir Square in Cairo, Egypt in 2011 and 2013 (Kirkpatrick, 2013); and Taksim Square in Istanbul, Turkey in 2013 (Arango, 2013).

6.2.3 Model Output

The model exports a series of comparative statistics. These include the number of Residents by activated identity, the number of Residents by activity, and the number of Residents by employment status. Statistics are collected by time step so that changes in behavior or trends can be easily assessed. In addition, simple SNA statistics are gathered for the network as a whole, including mean degree centrality and total degree centrality. These statistics allow us to analyze the distribution of Residents by their identity (e.g., Rioter) and observe any interesting trends.

6.3 Simulation Results

As discussed in Sections 1.3.3 and 3.5, verification concerns ensuring that the internal components are working properly and the program code is error free (Gilbert and Troitzsch, 2005). Validation, on the other hand, concerns ensuring that the model accurately represents the phenomena being modeled (Gilbert and Troitzsch, 2005). Similar to the model discussed in Chapter 5, this model seeks a Level 1 classification according to Axtell and Epstein's (1994) classification scheme. Therefore, qualitative agreement with actual results was sought (Axtell and Epstein, 1994; Crooks and Castle, 2012). Section 6.3.1 provides an overview of the sensitivity testing performed to ensure model verification and validation. Next, Section 6.3.2 discusses several experiments that were run to explore the impact on the dynamics of the riots when education and employment opportunities are increased. George Mason University's Argo Cluster (a high performing computer cluster) was used to run the model for all parameter sweeps and experiments.

6.3.1 Sensitivity Testing

This section provides details on the model verification and validation process (see Sections 1.3.3 and 3.5 for definitions and a discussion on the different verification and validation strategies). This included an in-depth walkthrough of the code, the use of profiling tools to find potential bottlenecks in the code, and running a series of simple scenarios to ensure the model was behaving as expected (Section 6.3.1.1). In addition, calibration and validation of the model was performed by seeking model results that most closely shared qualitative agreement with the actual events that took place (Section 0). Using the parameter values determined in Section 0, a series of parameter sweeps were performed (Section 6.3.1.3). Finally, the outbreak and intensity of rioting was explored in the model results (Section 6.3.1.4).

6.3.1.1 Code Walkthrough

To begin, an in-depth walkthrough of the code was performed. At model initialization, all environment and population variables were checked to ensure accuracy, including that the number of initialized Residents by age, gender, and employment status were correct; that the average Household size corresponded to the size distribution used; that the total number of Facilities, Businesses, and Homes created were accurate; and that the distribution of income to individual Residents corresponded to the wealth distribution curve. Next, to ensure transition functions were working properly, an output file that provided individual-level and household-level data at each step in the simulation was used to perform several verification checks. Variables captured in this file include the following Resident and Household attributes:

- Resident attributes: age, employment status, activity, identity, energy level, aggression level, income, whether the agent was laid off, whether the agent heard the rumor, and whether the agent was assigned a school, formal employer, or informal employer.
- Household attributes: expenses, income, and discrepancy (income minus expenses).

The checks performed using this data included (but were not limited to) ensuring that Resident identities, employment status, and activities corresponded to one another. For instance, a Resident that is attending school should have an identity of Student and an employment status of inactive. Household attributes were also checked, such as confirming that Household income, expenses, and discrepancy were being correctly calculated. Any unexpected results were further investigated, and either determined to be correct or fixed in the code. In parallel with this process, a profiling tool was used to find bottlenecks in the code. Bottlenecks were either fixed (if a coding issue was found) or adjusted for model efficiency. This entire process was performed iteratively until all issues were satisfactorily resolved. The one exception was the Social Influence Model, which requires that the agent's susceptibility to influence be continuously checked against its social network. Because social networks are dynamic in the model, this check must be repeated each time the Intensity Analyzer is run (i.e., each time the Resident is deciding what its next activity will be). The computational resources required to repeatedly re-calculate social influence using explicit social networks is very high.

Next, to ensure that Residents were behaving as expected and that certain algorithms were functioning correctly (such as the school search, employment search, and rumor propagation algorithms), a series of simple scenarios were run. Each scenario was tested in isolation by turning "off" behaviors or algorithms not applicable to the scenario. In addition, for each scenario, the model was run 10 times for one month (28,560 time steps) with an agent population of 2,350 (equivalent to approximately one percent of Kibera's total population). At this point, the focus is not to analyze the dynamics of riots in the slum, but is instead to test that algorithms and behaviors are working as expected. Given the objective, running the model at one percent population allows for verification of the model with the use of minimal computational resources. In addition, to ensure basic functionalities were working properly, some simplifying assumptions were applied to each scenario. These included (1) setting employment and school vision to span the entire modeling world, (2) increasing employee and student capacity at employers and schools such that all Residents have employment and school opportunity, and (3) removing Household need as a factor in a Resident's decision to search for employment or leave school. Each scenario was run both with and without these simplifying assumptions and results were documented. Table 6-8 displays a high-level summary of the most relevant scenarios and the results. Any assumptions applied to a scenario are noted. For a full description of all scenarios and results see Appendix A.

Table 6-8. A series of simple scenarios run for model verification purposes.

Scenario Description	Expected Results	Actual Results
Test employment and school search algorithm	All Residents searching for employment finds employment and all Residents eligible to go to school find a school. (Applies assumptions 1, 2, and 3.)	As expected
Test that some employees are laid off (probability of being laid off is 1%)	All Residents searching for employment find employment. However, at times there are dips in the number employed and spikes in the number searching for employment due to Residents being laid off. (Applies assumptions 1, 2, and 3.)	As expected
Test that Residents (of school age) that did not find an available school search for employment	Residents that could not find a school search for employment (if they have Household need). However, since employers are at capacity, these Residents struggle to find employment. The number searching for employment increases.	As expected
Test that Residents (of school age) that are pulled from school due to Household need are searching for employment	Students in Households with inadequate income leave school to search for employment. There are dips in the Student population and an increase in the number searching for employment. (Applies assumptions 1 and 2.)	As expected
Test that inactive Residents with	Inactive Residents (that are not attending school) in Households with inadequate	As expected

Household need are searching for employment	income search for employment. The number of inactive Residents decreases and the number employed increases. (Applies assumptions 1 and 2.)	
Test that school eligible Residents that did not initially find availability, continue to search for a school	Although school eligible Residents can search for a school at any point in the simulation, due to capacity constraints and the fact that Students do leave school in this scenario, these Residents will not find an available school to attend.	As expected
Test that the rumor propagates and Residents riot	No Rioters as there are no "disgruntled" residents. More Residents have "heard" the rumor. (Applies assumptions 1, 2, and 3.)	As expected
Test all behaviors from Scenarios 1 through 6 together (without rioting)	The number employed is higher than the first scenario as inactive Residents and Students will search for employment (if there is Household need). The number of Residents searching will spike as Residents are laid off. Students with household need leave school and search for employment. (Applies assumptions 1 and 2.)	As expected
Test all behavior from Scenarios 1 through 9 together (with rioting)	Results resemble the previous scenario (in terms of number employed and number in school). However, rioting occurs.	As expected

6.3.1.2 Model Calibration

Sensitivity testing was performed by systematically varying parameter values while holding the remaining parameters at their default value. The parameters selected for adjustment were those that could not be grounded on empirical data. To determine appropriate default values of these parameters, the model was run at full scale (235,000 agents) and parameter settings were adjusted until (1) riots emerged and (2) results most closely matched qualitative knowledge on the number of potential rioters. While there is some data on the number killed and the number displaced during the 2008 riots in Kibera

(De Smedt, 2009), there is no data on the number of residents that actually joined the riot. That being said, youth are thought to be the most vulnerable group to joining violent collective action (see Section 1.2), and this was no different in Kibera (De Smedt, 2009).

According to De Smedt (2009), the majority of the violence was committed by young males from the Gatwikira neighborhood in Kibera. Other neighborhoods significantly impacted by the rioting were Kianda, Olympic, and Laini Saba. To create an "upper limit" on the number of rioters in the model, an estimate of the number of male youths living in these neighborhoods was determined. NIC (2012) defines "youth" as anyone 25 or younger. Since an agent must be at least 5 years old to join the riot in the model, a rough estimate of the number of male residents aged 5 to 25 is calculated. With the exception of Kianda, whose population was estimated by the Map Kibera Project (Marras, 2008), the total population of the four neighborhoods is calculated based on the geographic area of the neighborhood (i.e., geographic area of the neighborhood divided by the total geographic area of Kibera times the total population of Kibera). Next, using the population in Nairobi that is male and between the ages of 5 to 25, an estimate of the number of male youths in the four neighborhoods is determined. Using this method, the estimated total population of young males in these neighborhoods is approximately 18,574.

Qualitative agreement with actual results was sought first by observing the emergence of riots in the model and then by calibrating the model at full scale such that the total number of rioters was consistently at or below the total number of potential rioters calculated above. Using the determined default values, the average number of rioters at peak (across five runs of the model for two simulation weeks) was 15,404, which is below the estimated population of young males. Table 6-9 provides the set of parameters that were adjusted and their final default value.

Using George Mason University's Argo clusters, running the model at the default values and at full scale for one simulation week took approximately three full days (and up to seven days when certain parameter values were varied). While runs at full scale

Table 6-9. The model parameters and default values.

Parameter	Unit	Description	Default Value	Range
Employment vision	Integer	The number of Parcels out a Resident can search for employment.	70	[0, 343]
School vision	Integer	The number of Parcels out a Resident can search for a school.	35	[0, 343]
Probability of losing employment	Double	The probability that an Employee will lose his/her job. This provides employment openings for unemployed Residents searching for a job.	0.01	[0, 1]
Energy rate of change	Integer	The rate of change used to calculate the Resident's change in energy.	50	[0, 100]
Aggression threshold	Double	The threshold a Resident's aggression must be under in order for the Resident to aggress or riot.	0.6	[0, 1]
Aggression rate	Double	The shape of the logistic curve.	0.6	[0, 1]
Opinion threshold	Double	The maximum difference between a Resident's final opinion and other Resident's it may be influence by, for the Resident to riot.	0.1	[0, 1]

helped provide validation to the model, constraints in computational resources made it very difficult to perform all sensitivity testing and run experiments at 100 percent population. For this reason, runs were performed at different population scales to determine if similar trends emerged and to determine the feasibility of using lower population levels moving forward. These population levels included 50 percent (117,500 agents), 60 percent (141,000 agents), 80 percent (188,000 agents) and 100 percent (235,000 agents). The model was run five times for two simulation weeks (14,280 steps) at each population level. Figure 6-10 displays the results (in terms of the proportion of population that rioted) averaged across the runs by time step.

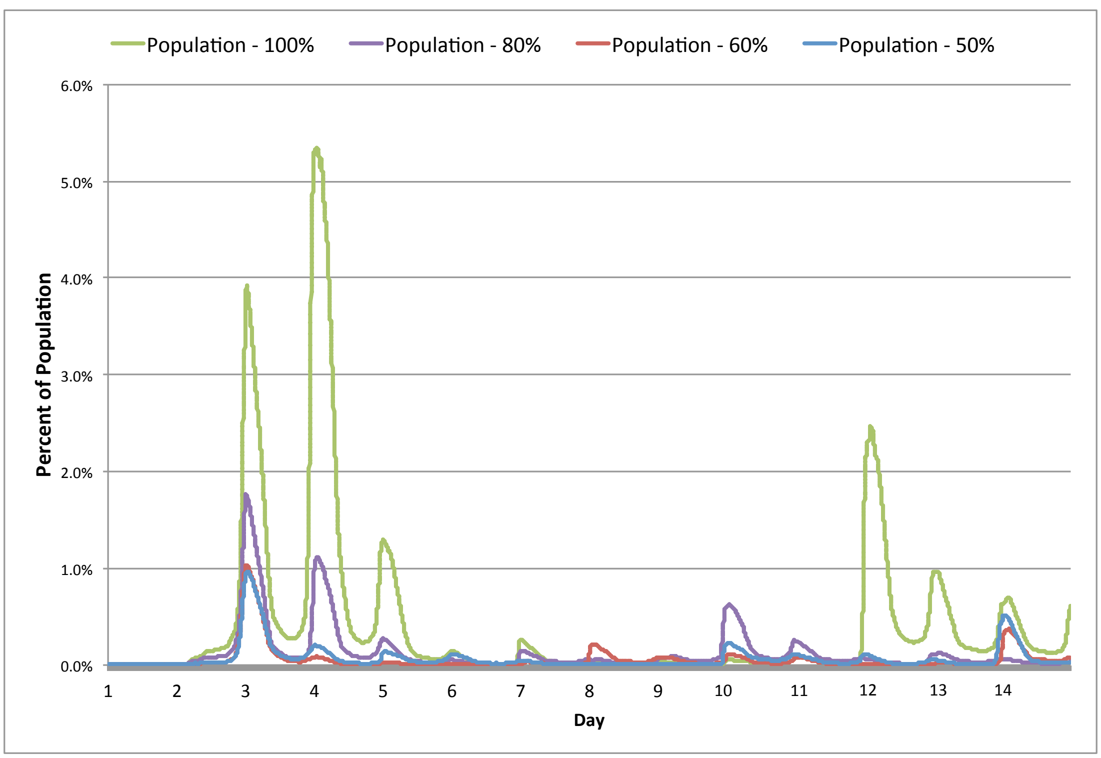


Figure 6-10. Average proportion of population that rioted by time step at varying population levels.

In general, as the overall population declines, the size of the average social networks decreases. Table 6-10 shows the mean degree centrality by each population level. Because ties are weighted, degree centrality is a measure of the sum of the weights of the ties (see Equation 4-1). Population has the potential to impact the likelihood that a Resident will be influenced to riot and relates to the idea that the geographic concentration of nearby Rioters impacts the opportunity for one to riot (see Sections 2.1.5 and 5.2.2.2). Based on Figure 6-10, we can see that this idea directly impacted the number of Rioters. As population decreased, the percentage of the population that rioted also decreased. On the other hand, the temporal trends are very similar at varying populations. Although the size of the spike varies, the occurrence of the spikes is at similar points in time. These similar patterns provide evidence that changing the population does not qualitatively change model results. Thus, given the computational constraints and qualitative similarity, the remaining runs for this model were performed at 50 percent population.

Table 6-10. The mean degree centrality by population level.

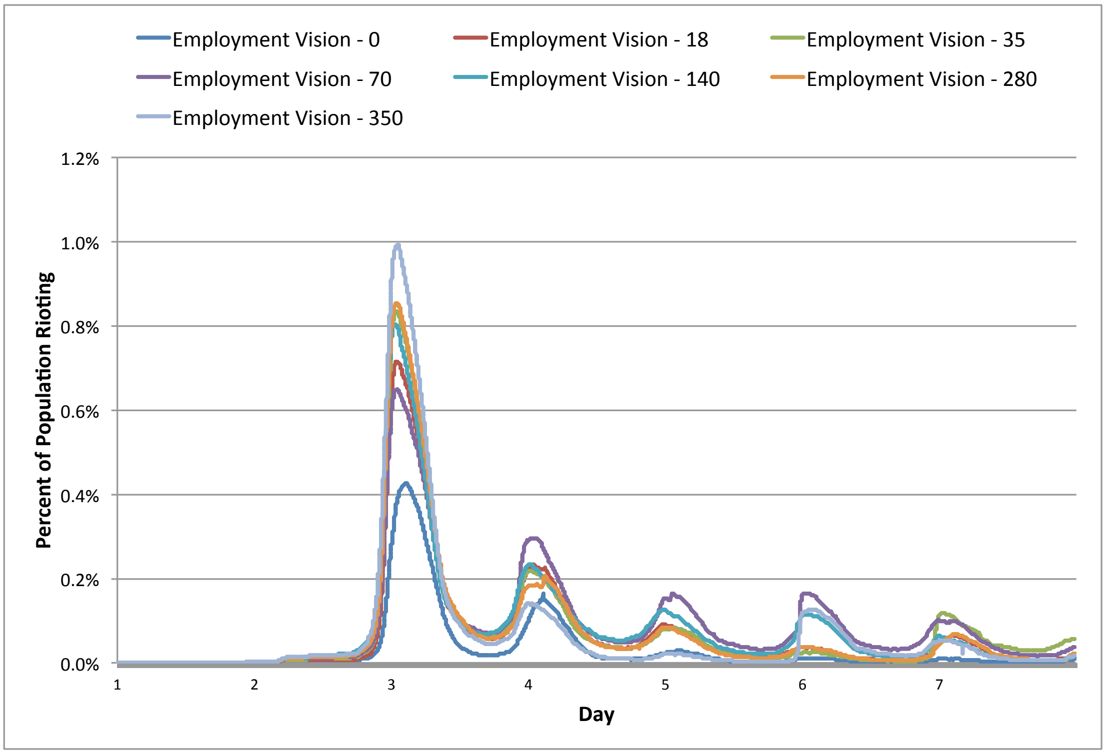
Population Level	Mean Degree Centrality
50%	11.2
60%	11.4
80%	12.7
100%	17.4

6.3.1.3 Parameter Sweeps

Additional analysis was performed to ensure the simulation was developed as intended. Using the default parameter values determined in Section 0, a series of parameter sweeps were performed. For discussion purposes, these parameters can be grouped into three different categories: employment and school-related parameters, parameters related to the self-verification process, and parameters related to the process of social influence. Each of these parameters was set at initialization and remain constant throughout the run of the simulation and across the entire agent population. Each parameter value was run 10 times for one simulation week (7,140 time steps). Model results for each parameter were averaged across the runs. Reported results include a plot of the average number of rioters across time, a table of the average number of Residents by identity and parameter value, and the correlation between increasing the parameter value and the average number of Residents by identity. Correlation is a numerical measure of the relationship between two properties and can range between -1 and +1. A correlation value at either of these two extremes indicates that the two properties are related linearly with a negative slope or a positive slope, respectively. A correlation of 0 indicates that there is no relationship between the two properties (Bhattacharyya and Johnson, 1977).

The parameters related to the Resident's employment and school opportunities include employment vision, school vision, and the probability of losing employment. Employment vision impacts how far (in terms of number of Parcels) a Resident can search for an employer within Kibera. The average size of a neighborhood in Kibera is approximately 35 by 35 parcels. Thus, the model was run at levels of employment vision that corresponded to neighborhood size: 0 parcels, 18 parcels (approximately half the size of a neighborhood), 35 parcels, 70 parcels, 140 parcels, 280 parcels, and 350 parcels (the entire modeling world). As discussed in Section 6.2.1.4, empirical data is used to determine the number employed, and if no employers are found within a Resident's employment vision, the Resident is said to be employed outside of the slum. As a consequence, with lower vision Residents will struggle to find an available employer in the slum and will therefore get jobs outside of the slum. Thus, employment vision does not impact the total number of Residents employed at initialization. However, low employment vision means more Residents are working outside of Kibera, resulting in more jobs within Kibera that are not filled (because Residents did not "see" them at initialization). Thus, even with low vision, more Residents who later decide to search for employment will find available employment.

Figure 6-11 shows model results when employment vision is systematically increased. The dynamic described along with other factors, including the subsequent impact on the potential size of a Resident's social network when more (or less) Residents are employed (or not), have potential implications on the emergence of riots. The higher the employment vision, the greater the intensity of the initial riot (as in Day 3 of the simulation) (see Figure 6-11A). At higher vision, Residents' may work geographically far from their home; this has the potential to expand the reach of their social networks and the propagation of the rumor. This has potential reinforcing effects on social influence,



A

Employment Vision	Average			
	Rioter	Domestic	Employee	Student
0	39	62,515	41,172	13,772
18	78	64,896	38,799	13,725
35	89	65,633	38,082	13,695
70	103	66,261	37,521	13,614
140	94	66,249	37,505	13,650
280	85	66,148	37,577	13,689
350	84	66,151	37,565	13,698

B

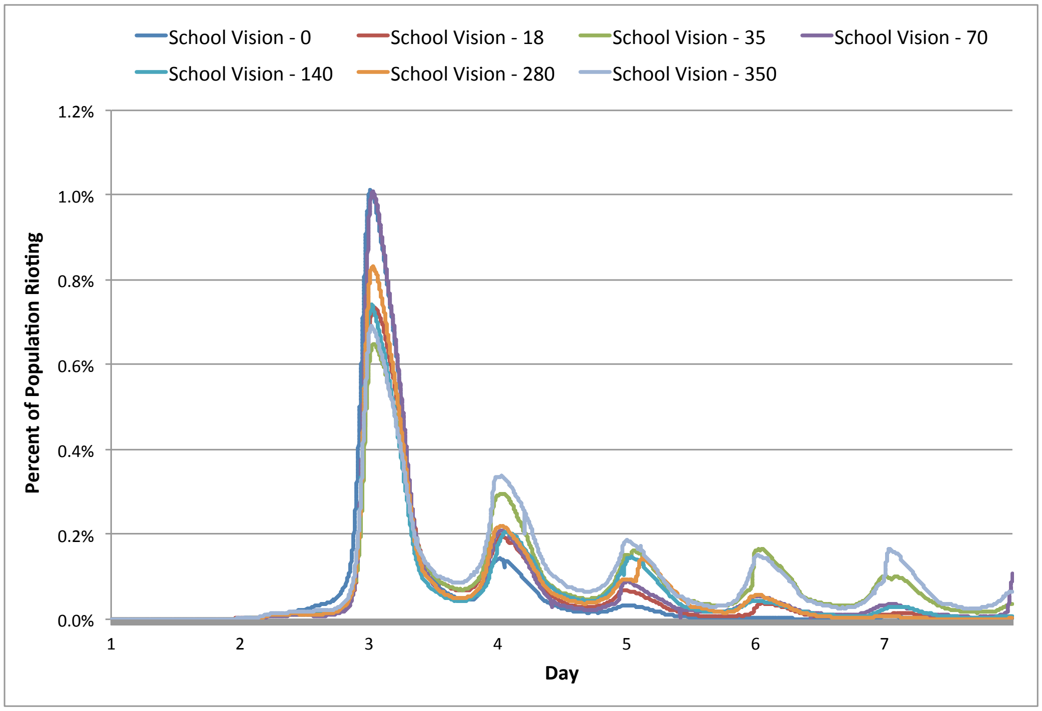
Identity	Correlation with Employment Vision
Rioter	0.31
Domestic	0.57
Employee	-0.58
Student	-0.23

C

Figure 6-11. Results of varying employment vision. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and employment vision.

and thus, the decision to act on the rumor. Due to these factors, there is no clear correlation between increasing employment vision and the number of Rioters or Employees (see Figure 6-11B-C).

Residents searching for an available school, on the other hand, will only search for a school within Kibera. Similarly to employment vision, school vision was varied based on the average neighborhood size in number of Parcels: 0, 18, 35, 70, 140, 280, and 350. Although dynamics are contained within the modeling world (i.e., Residents do not search for school outside of Kibera), the results in Figure 6-12 show similar trends to varying employment vision. Here, the highest vision did not yield the most intense riot initially, but subsequent riots (after Day 3) were consistently more intense than at lower vision levels (see Figure 6-12A). As vision increases, the number of Students increases up to a vision of 70 (see Figure 6-12B-C). Due to the model's dynamics, whereby Students may leave school to search for employment or they may riot, increasing vision beyond this point has little to no impact on the number of Students.



A

School Vision	Average			
	Rioter	**Domestic**	**Employee**	**Student**
0	77	79,543	37,612	266
18	73	66,791	37,621	13,013
35	103	66,261	37,521	13,614
70	87	65,997	37,643	13,771
140	79	66,010	37,694	13,716
280	83	65,997	37,629	13,788
350	115	65,946	37,713	13,724

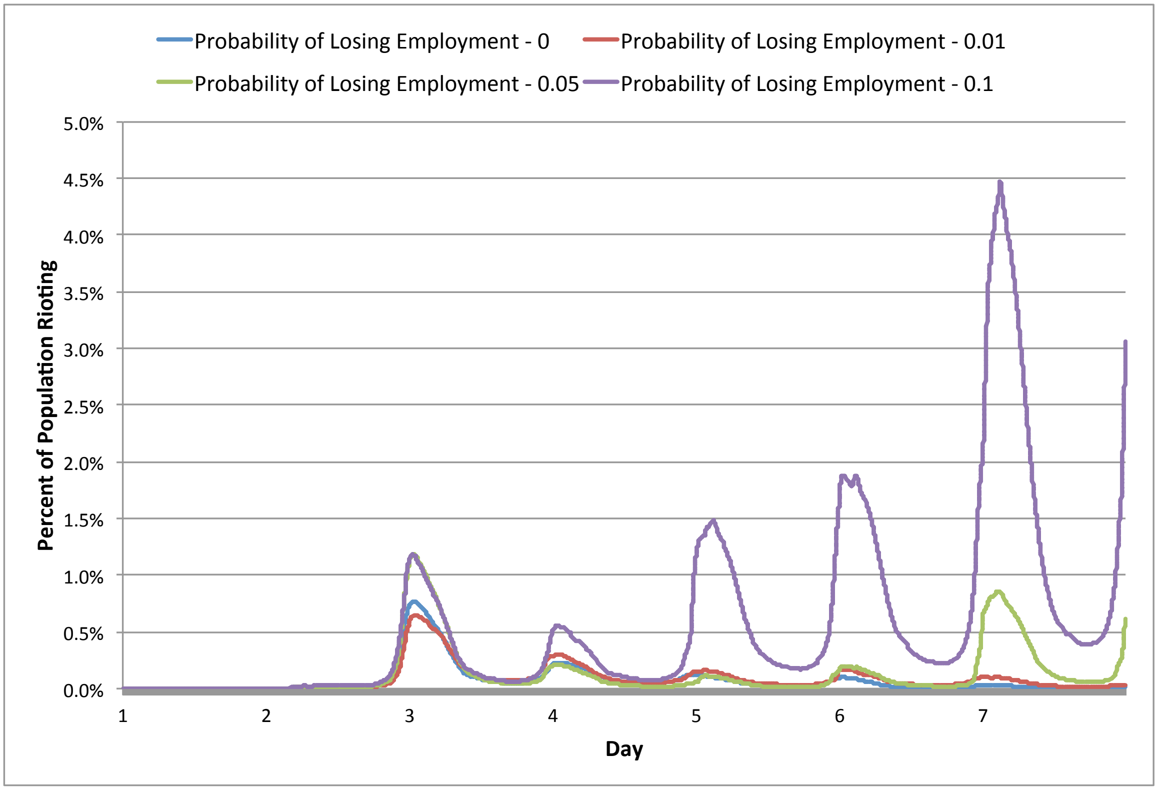
B

Identity	Correlation with School Vision
Rioter	0.55
Domestic	-0.44
Employee	0.62
Student	0.44

C

Figure 6-12. Results of varying the school vision parameter. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and school vision.

Unlike employment and school vision, which saw only small shifts in the number of Rioters as the parameter values were varied, increasing the probability that a Resident may lose its employment shows a clear trend as shown in Figure 6-13. Increasing the probability of losing employment increases the intensity of the riots, especially by Day 7 of the simulation (see Figure 6-13A). In addition, the average number of rioters and domestic residents increases while the average number of Employees and Students decrease with increasing probability (see Figure 6-13B-C). As Employees become unemployed, their identity changes to Domestic and they will search for a new job. If unable to find employment, they may become frustrated and aggress, leading to an increase in the number of Rioters. As Residents become unemployed, any Students in the same Household may be pulled from school to help bring in income.



A

Probability of Losing Employment	Average			
	Rioter	Domestic	Employee	Student
0	86	65,433	38,268	13,711
0.01	103	66,261	37,521	13,614
0.05	156	67,838	36,142	13,362
0.1	654	69,982	34,074	12,789

B

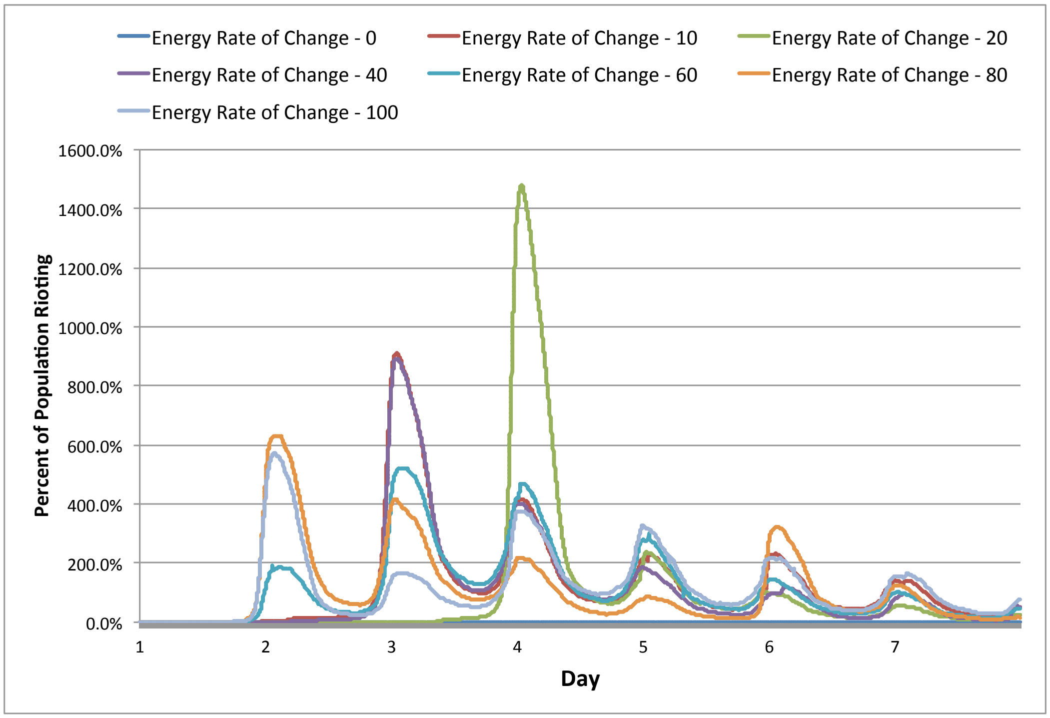
Identity	Correlation with Probability of Losing Employment
Rioter	0.93
Domestic	1.00
Employee	-1.00
Student	-0.99

C

Figure 6-13. Results of varying the probability of losing employment. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and the probability of losing employment.

There are three parameter values related to the self-verification process in a Resident's Identity Model, which plays a major part on a Resident's potential to aggress (and subsequently, riot). These are the energy rate of change, the aggression threshold, and the aggression rate. The first parameter, energy rate of change, impacts how quickly a Resident's Energy reservoir is filled or depleted upon a successful or failed attempt at the self-verification process, respectively. This parameter was varied from 0 to 100 in increments of 20 (with the exception of the default value of 50) and results are shown in Figure 6-14.

Variations in the energy rate of change impact the timing and size of the subsequent riot (see Figure 6-14A). Interestingly, while it takes four days for any rioting to emerge, a low energy rate of change of 20 yields the largest riot. On the other hand, at higher energy rates of change rioting occurs earlier in days two and three, and rioting continues to emerge at some level throughout the run of the simulation. While an increase in the energy rate of change may cause Resident's to become frustrated more quickly with fewer failed attempts at self-verification, it also causes Resident's to become happier more quickly with fewer successful attempts at self-verification. This dynamic is likely the reason we do not see a trend in the number of Rioters as the energy rate of change is increased (see Figure 6-14B-C). Note that an energy rate of change of zero results in no rioting.



A

Energy Rate of Change	Average			
	Rioter	Domestic	Employee	Student
0	0	66,111	37,719	13,669
10	103	66,261	37,521	13,614
20	82	66,142	37,656	13,617
40	90	65,997	37,690	13,722
60	98	66,230	37,522	13,649
80	93	65,983	37,735	13,688
100	100	65,999	37,644	13,755

B

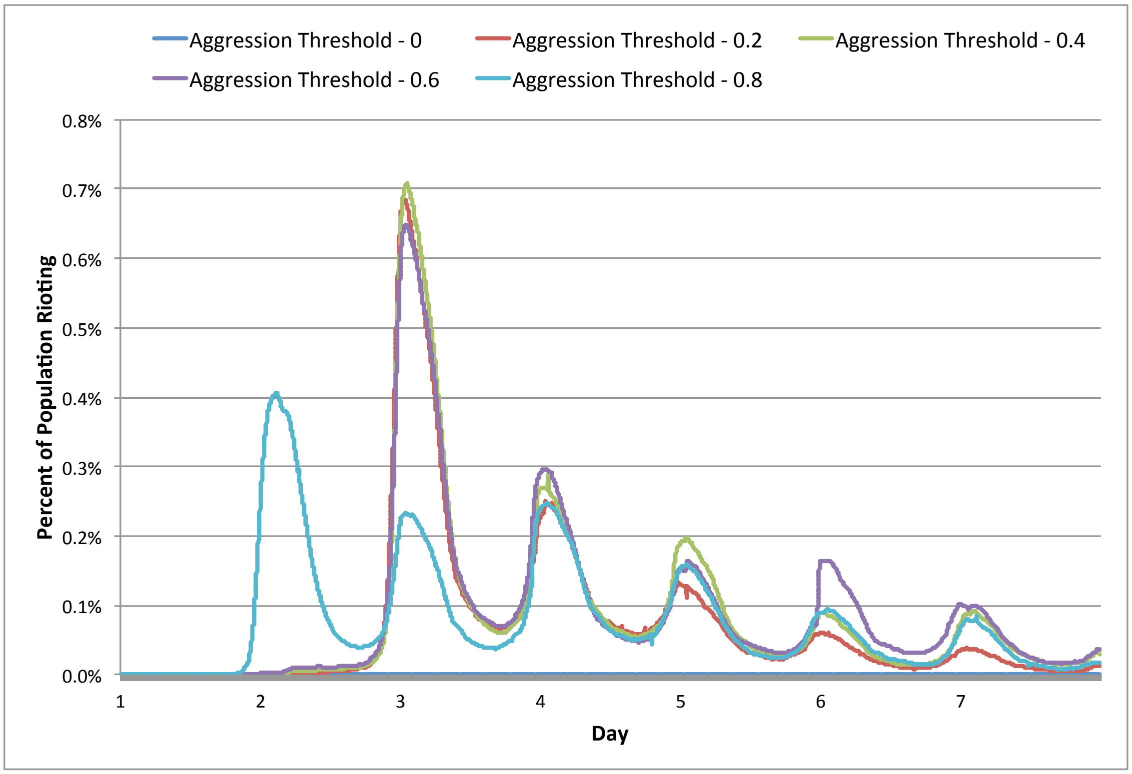
Identity	Correlation with Energy Rate of Change
Rioter	0.56
Domestic	-0.56
Employee	0.09
Student	0.69

C

Figure 6-14. Results of varying the energy rate of change parameter. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and energy rate of change.

Aggression threshold impacts the number of continuous failed attempts at self-verification a Resident is willing to endure before becoming frustrated. A Resident's energy must fall below the aggression threshold along the logistic curve (as shown in Figure 6-9) for the Resident to be eligible to aggress. Given this, it would be expected that increases in the aggression threshold would cause more Residents to riot. However, while this was often the case, it was not consistently so. Aggression threshold was varied from 0.0 to 0.8 in increments of 0.2 and results are shown in Figure 6-15. An aggression threshold of 1.0 was not run as all Residents riot in this case and such runs require large computational resources.

The largest spike in riots is caused when aggression threshold is relatively low, at 0.4 (see Figure 6-15A). However, the timing and intensity of the riots is similar for aggression thresholds between 0.2 and 0.6. As expected, the highest threshold level run (an aggression threshold of 0.8) results in rioting to occur the most quickly. However, subsequent riots were often the smallest size. Interesting, increasing the aggression threshold has the largest impact on the number of Students (see Figure 6-15B). Figure 6-15C shows the correlation between the average number of Residents at each identity and aggression threshold. The negative correlation between the number of Students and aggression threshold is higher than the positive correlation between the number of Rioters and threshold. This potentially indicates that increasing the aggression threshold causes more former Students to riot. However, the likelihood of other Residents (Domestics and Employees) to riot with increasing threshold is unstable.



A

Aggression Threshold	Average			
	Rioter	Domestic	Employee	Student
0	0	66,189	37,622	13,686
0.2	84	66,195	37,512	13,707
0.4	98	65,983	37,675	13,742
0.6	103	66,261	37,521	13,614
0.8	92	66,108	37,706	13,593

B

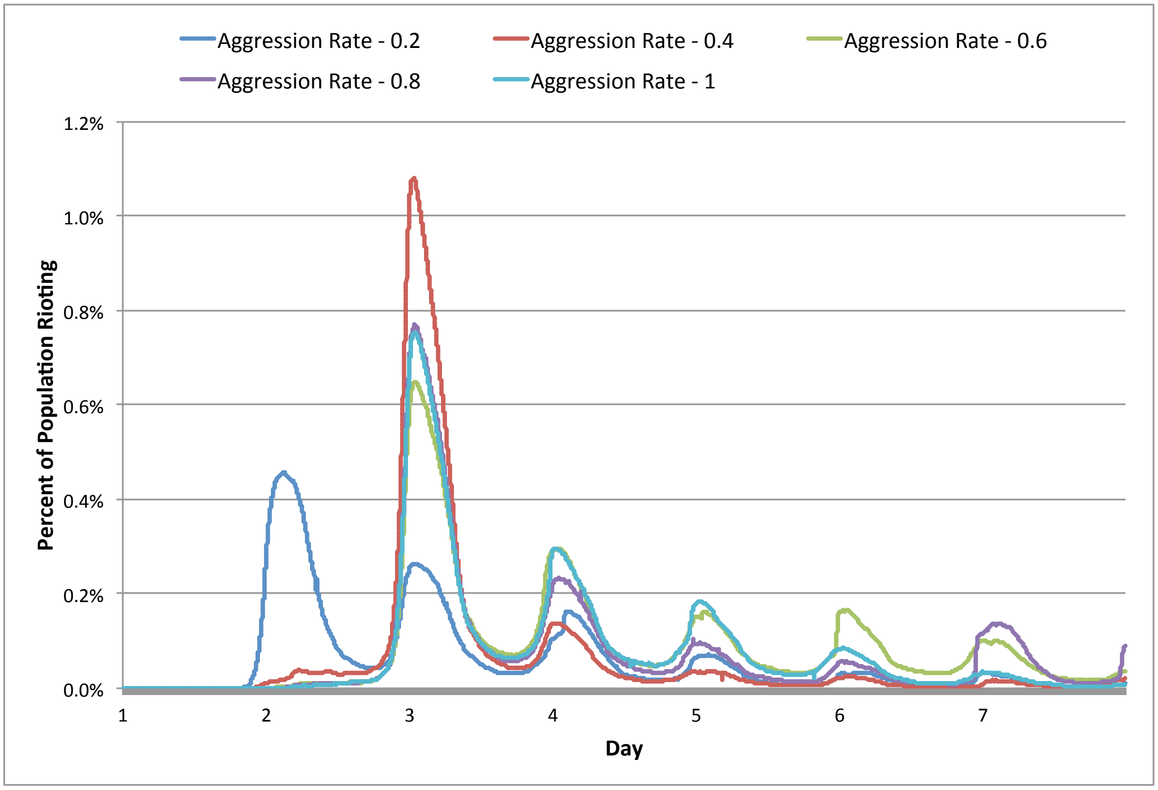
Identity	Correlation with Aggression Threshold
Rioter	0.75
Domestic	-0.14
Employee	0.32
Student	-0.70

C

Figure 6-15. Results of varying the aggression threshold parameter. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and aggression threshold.

Aggression rate affects the shape of the logistic curve (as shown in Figure 6-9). The lower the aggression rate, the quicker a Resident may dip below the aggression threshold with failed attempts at the self-verification process. Thus, it would be expected that increasing the aggression rate would result in fewer Rioters. Aggression rate was varied from 0.2 to 1.0 in increments of 0.2. These results are shown in Figure 6-16. Increasing the aggression rate has a largest impact on the size of riots that emerge (see Figure 6-16A), rather than on the average number of Rioters (see Figure 6-16B). While an aggression rate of 0.2 shows the smallest number of Rioters, riots emerged the quickest (in Day 2 of the simulation). Similarly to aggression threshold, the correlation between aggression rate and the number of former Students that riot is stronger than with any other identity (see Figure 6-16C).

Parameter sweeps of the variables associated with the Resident's internal Identity Model did not always yield results that were initially expected, however, trends in the timing and size of riots could be found, and given the dynamics these variables can induce, results concur with the intended implementation of the model.



A

Aggression Rate	Average			
	Rioter	**Domestic**	**Employee**	**Student**
0.2	73	65,987	37,818	13,620
0.4	82	65,970	37,825	13,621
0.6	103	66,261	37,521	13,614
0.8	89	65,993	37,705	13,711
1.0	93	65,978	37,710	13,717

B

Identity	Correlation with Aggression Rate
Rioter	0.67
Domestic	0.01
Employee	-0.43
Student	0.86

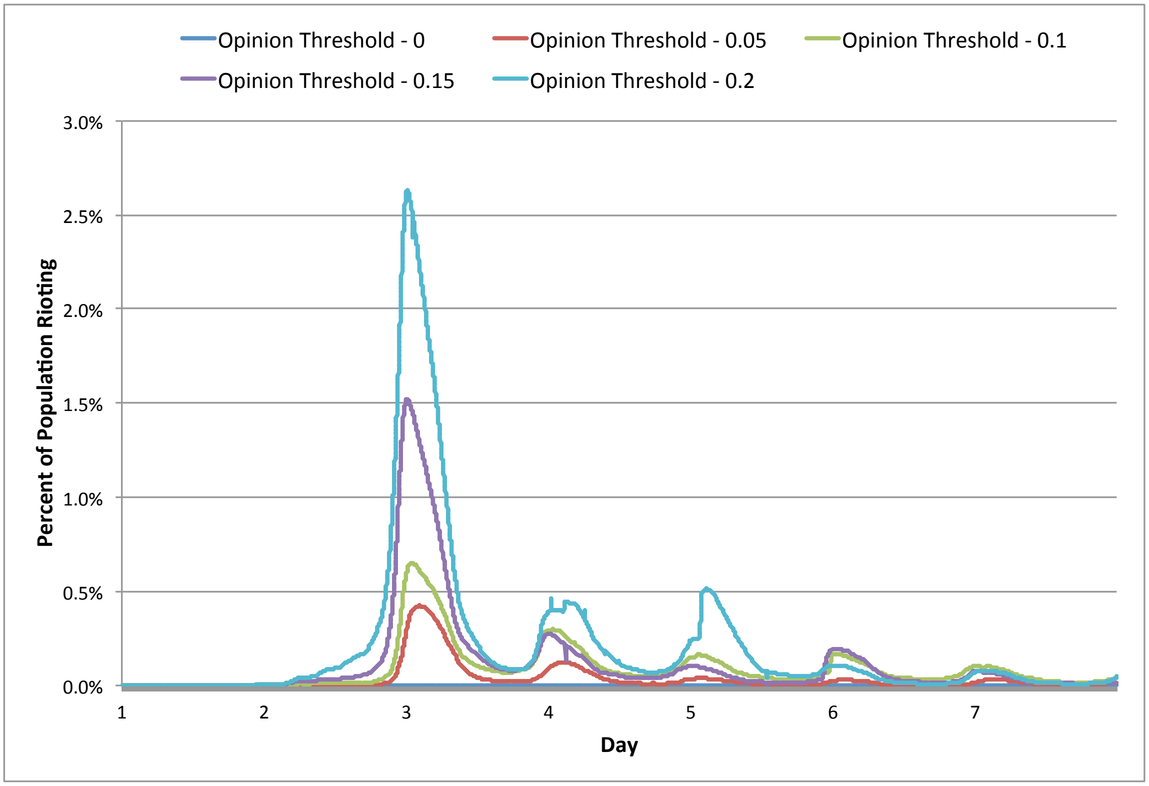
C

Figure 6-16. Results of varying the aggression rate parameter. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and aggression rate.

While the previous three parameters impact the likelihood that a Resident may aggress, whether or not the Resident does aggress is determined largely by the opinion threshold (as discussed in Section 6.2.2.3). Social influence is used to determine how close a Resident's opinion (on the rumor) is to other Residents connected in the same social network. If a Resident's opinion is close enough (within the opinion threshold) and the other Resident is a Rioter, than the Resident will riot. The smaller the opinion threshold, the more similar a Resident's opinion must be to another Resident to be influenced by that Resident. Increasing the opinion threshold relaxes how similar two Residents opinions must be in order to be influenced. Thus, it would be expected that increasing the opinion threshold, would increase the number of Rioters.

While the parameters related to the self-verification process showed results that seemed counterintuitive initially, increasing the opinion threshold showed results that would be expected as shown in Figure 6-17. In general, increasing the opinion threshold results in larger riots (see Figure 6-17A). Other than a couple exceptions, this trend continues for the seven days. As expected, the number of Rioters increases with increasing threshold, thus the high correlation between the two (see Figure 6-17B-C).

The dynamics described, its subsequent impact on the potential size of a Resident's social network, and its influence on the decision of a Resident and others in its network to riot, means that linear increases in many of the parameters do not necessarily yield linear results.



A

Opinion Threshold	Average			
	Rioter	Domestic	Employee	Student
0.2	0	66,197	37,700	13,602
0.4	41	66,082	37,671	13,704
0.6	103	66,261	37,521	13,614
0.8	144	66,095	37,662	13,598
1	255	66,017	37,660	13,568

B

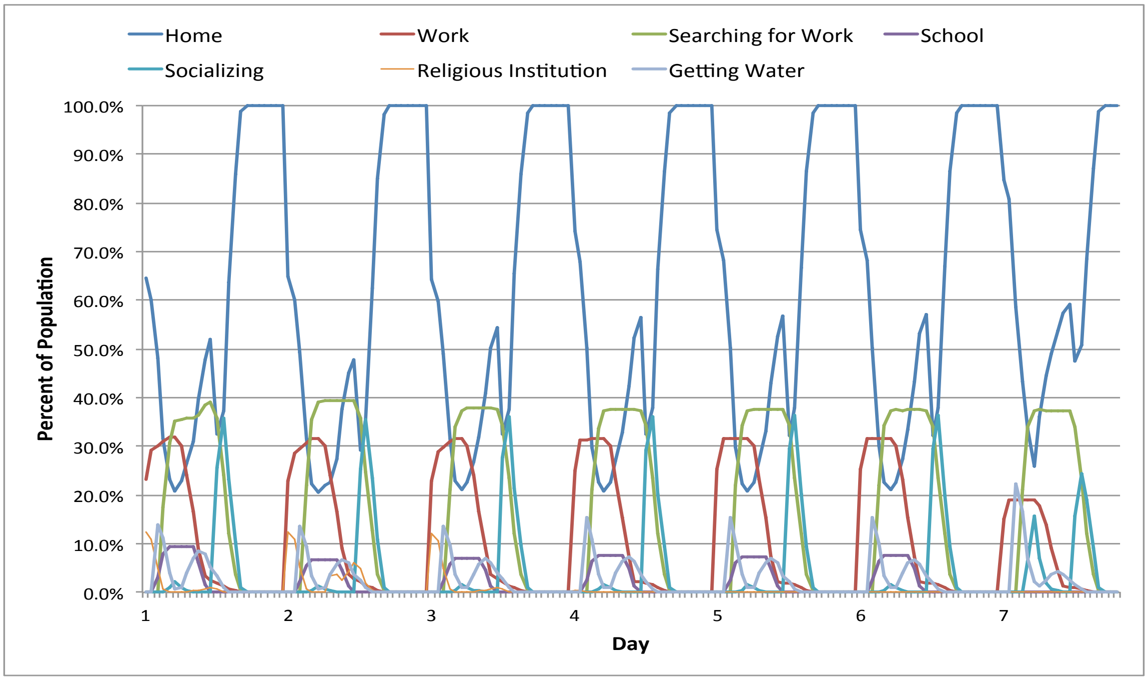
Identity	Correlation with Opinion Threshold
Rioter	0.98
Domestic	-0.56
Employee	-0.20
Student	-0.54

C

Figure 6-17. Results of varying the opinion threshold parameter. A: The average percent of population rioting by day. B: The average number of Residents by identity. C: The correlation between the average number of Residents by identity and opinion threshold.

6.3.1.4 Model Results

Taking a closer look at model results using the default values, 10 runs were performed for four simulation weeks (28,560 time steps) to ensure model behavior and trends make sense across a longer period of time. Figure 6-18A shows the number of Residents performing each activity on an hourly basis over the first week of the simulation. As expected, a cyclical pattern in the Resident's daily activities is found. All Residents begin at home. When day breaks, many Residents leave home to begin their activities for the day, including going to work, going to school, and getting water. Around 4:00 PM there is a spike in the number of Residents that have returned Home. These are mostly Students returning from school and then leaving again to socialize with friends. By 10:00 PM each night, all Residents have returned home for the day. Figure 6-18B shows the average number of Residents by identity across each day of the week. There is little to no variation in the number of residents by identity. Note that Days 6 and 7 are equivalent to Saturday and Sunday. Even though Students do not attend school on the weekends, they continue to maintain their Student identity.



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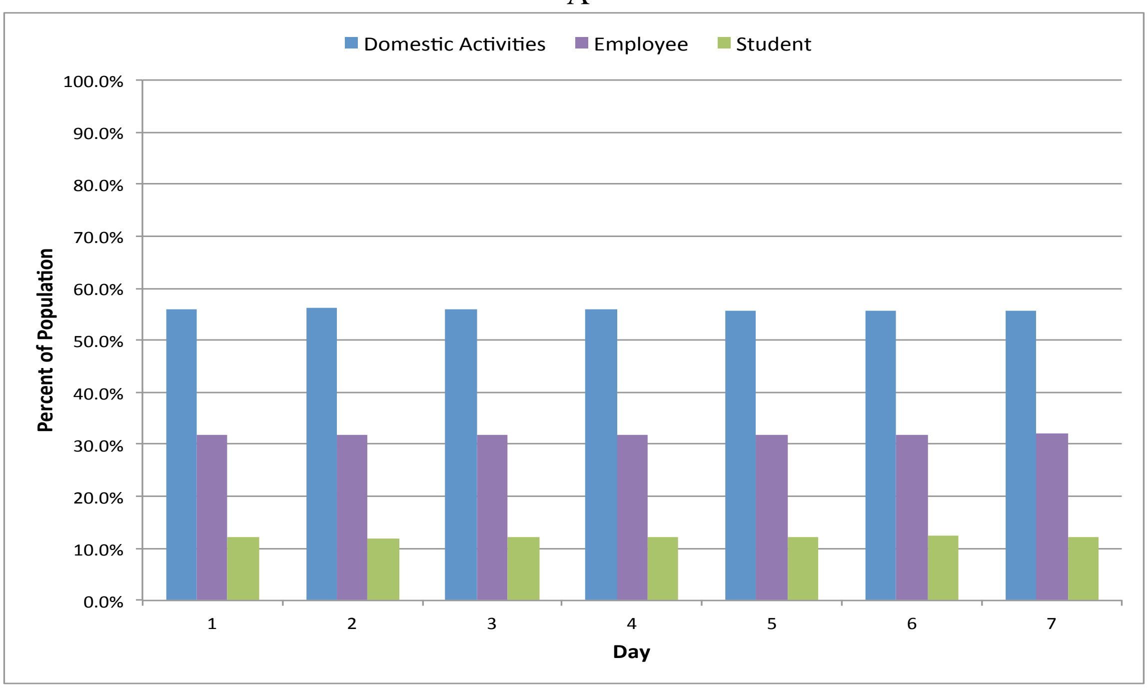


B

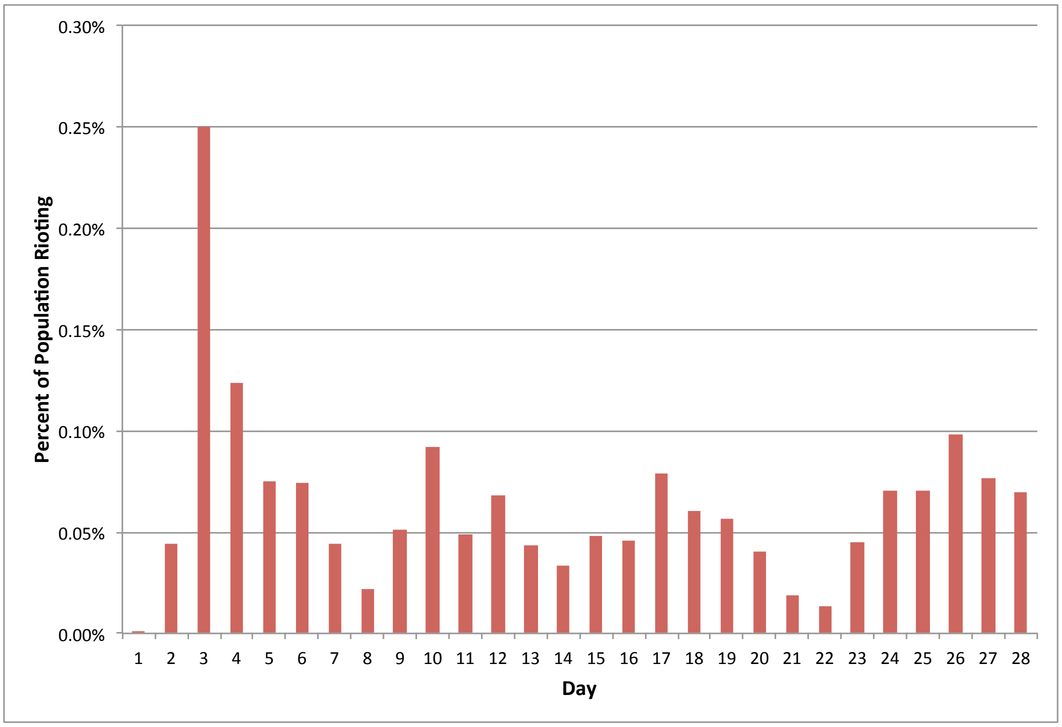
Figure 6-18. The percent of Residents by activity and identity. A: The percent of Residents performing each activity averaged on an hourly basis by day. B: The percent of Residents by identity averaged by day.

Turning to the population that rioted, Figure 6-19A shows the average percentage of the population that rioted by day. We find that the rioting peaks at Day 3, with subsequent spikes occurring approximately mid-way through each week (Days 10, 17, and 26). Using the Intensity Analyzer, Residents will constantly assess their motivation to continue rioting. Individuals that riot must still meet their fundamental needs in accordance with Maslow's (1954) hierarchy of needs. Thus, when a Resident riots, (unless there is a change in the Resident’s situation) it is constantly finding itself in a struggle between its Rioter and Domestic identities. Whether the Resident is rioting or not, it must still maintain the Home, such as ensuring the Home has adequate levels of water. The Resident may also still socialize with friends or attend a religious institution. In addition, it will need to return home at times to sleep and eat. Also, Residents do not make an income rioting, so Residents may continue to search for employment, and if a job is found, the Resident will stop rioting to go to work. Thus, a Resident that riots one day may or may not decide to riot the next day.

The reason the pattern is cyclical is likely due to positive reinforcement. The situation of one Resident can have a cascading effect across its social network. For example, a Household may consist of a working adult and a student. The working adult may lose its job, forcing it to search for employment and causing the Household’s income to reduce to zero. Due to this, the student will be pulled out of school and will also search for employment to help the Household. Struggling to find employment, one or both of these Residents may decide to riot. Given the strong connection between the two Residents, if one riots, the other is more likely to join in the riot as well. In addition, these

Residents have a broader network (former colleagues, friends, and neighbors) that may be influenced by their decision to riot. However, the adult Resident may find employment, causing it to stop rioting. Able to afford its expenses, the younger Resident may also stop rioting to return to school. No longer influencing others in its network to riot, we may see a reinforcing, cascading effect as others turn away from the riot to return to their daily lives.

To get a better sense of which Residents are rioting, a closer look is taken at the characteristics of those that became Rioters. Figure 6-19B provides information on the Rioters by four categories grouped by age and Household discrepancy. The percentages (the y-axis) relates to the proportion of total Residents in each category that rioted. It shows that the likelihood to riot is highest among Residents that are Student age (18 and under). This can indicate a lack of available schools or employment for the younger population. After an unsuccessful attempt at finding a school to attend, a Resident will either search for employment (if its Household could use the income) or will stay Home. On the other hand, a Resident who has found a school could be forced to dropout if the Household needs the income. In this case, the Resident will need to search for employment, which it may or may not find. In addition, Residents that are 18 and under are limited in their employment selection, as only jobs in the informal sector are available to them. After struggling to find employment, a Resident can became frustrated and eventually influenced to riot. Figure 6-19B also shows that Residents that are 18 and under with no Household discrepancy are more likely to riot than older Residents (over 18) in a similar situation.



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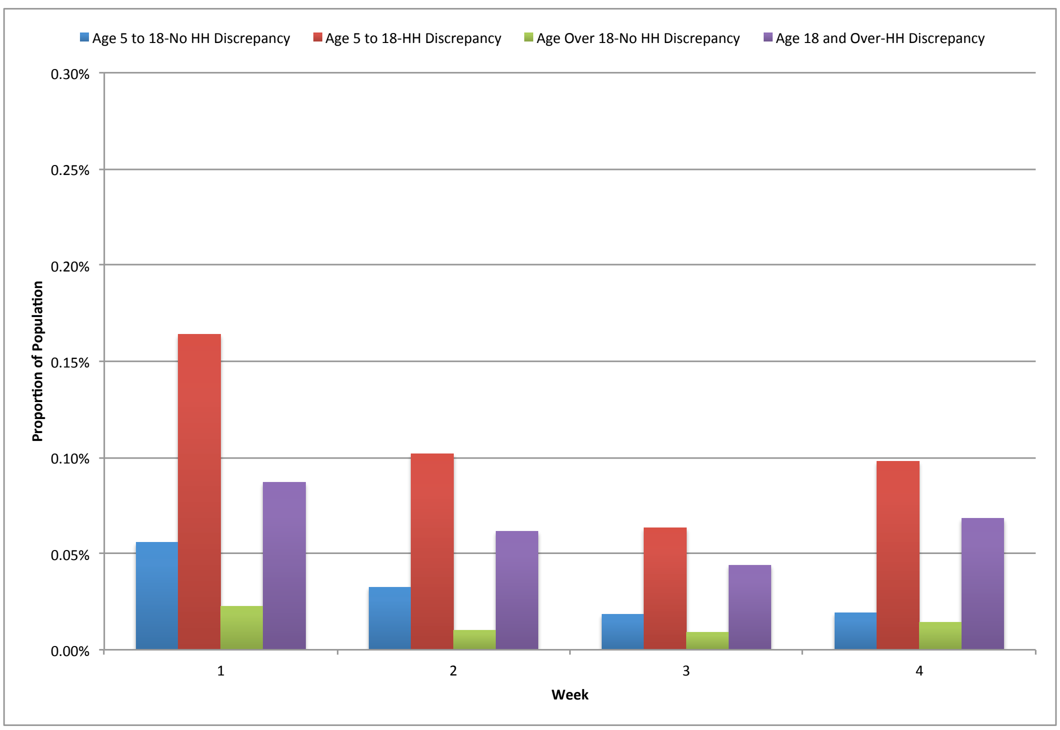


B

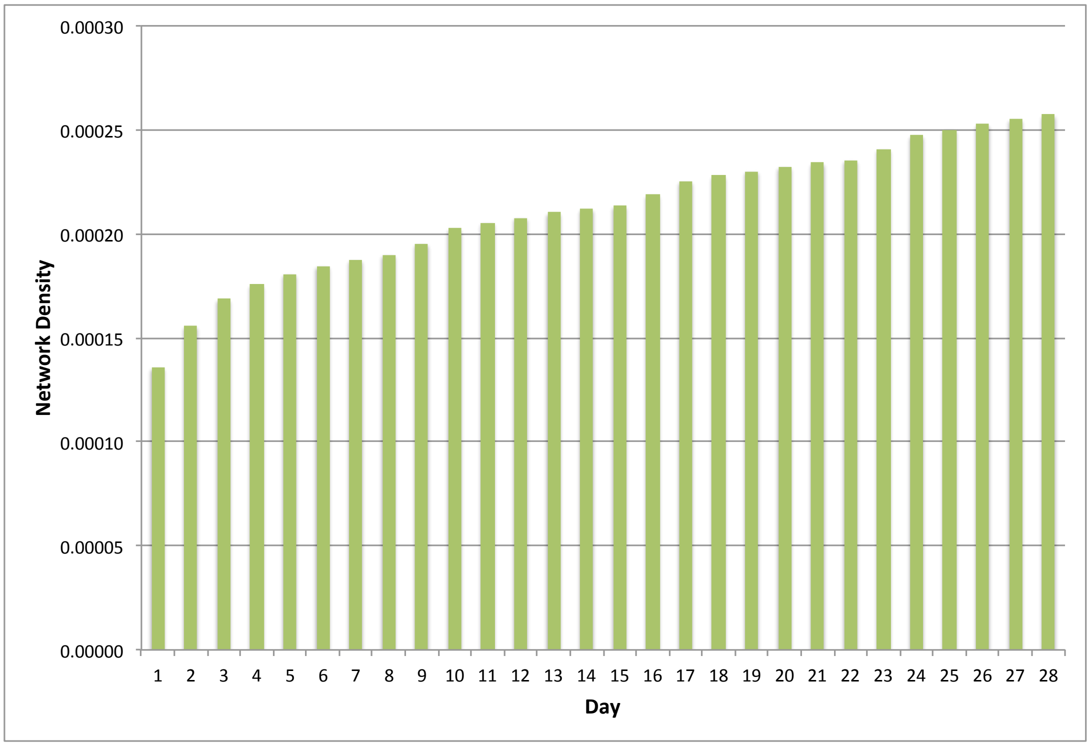
Figure 6-19. The proportion of the population that rioted. A: The total number of Rioters by day. B: The make-up of the Rioter population.

Given the importance of social networks in the dynamics of the model, the network's overall density is explored. Network density is calculated by dividing the sum of all ties by the sum of all possible ties. Note that because there is no change in the denominator across time, mean degree centrality would show the same trend as network density. Network density, Δ, of a valued graph (such as the one here) is determined by Equation 6-6.

Equation 6-6. Network density (Wasserman and Faust, 2009).

$$\Delta = \sum v_k / g(g-1)$$

where v_k is the sum of the ties over all k and g is the number of nodes in the network. To see if there is any link between rioting and changes in the network over time, Figure 6-20A shows network density averaged by day. While density increases each day, there are certain days where it looks to increase more than others. To explore this further, Figure 6-20B shows the day-over-day changes in density. It can now be clearly seen that there are distinct days where network density spikes. The first three days of the simulation show the greatest increase in network density. This makes sense as it may take a few days to "build-up" the agents' network as they begin to perform their daily activities. If we compare this to Figure 6-19A, this dynamic corresponds to the largest spike seen in rioters. In addition, the change in network density spikes on Days 10 and 17, the same days rioting also spikes. While there is a small deviation from this trend in the final week



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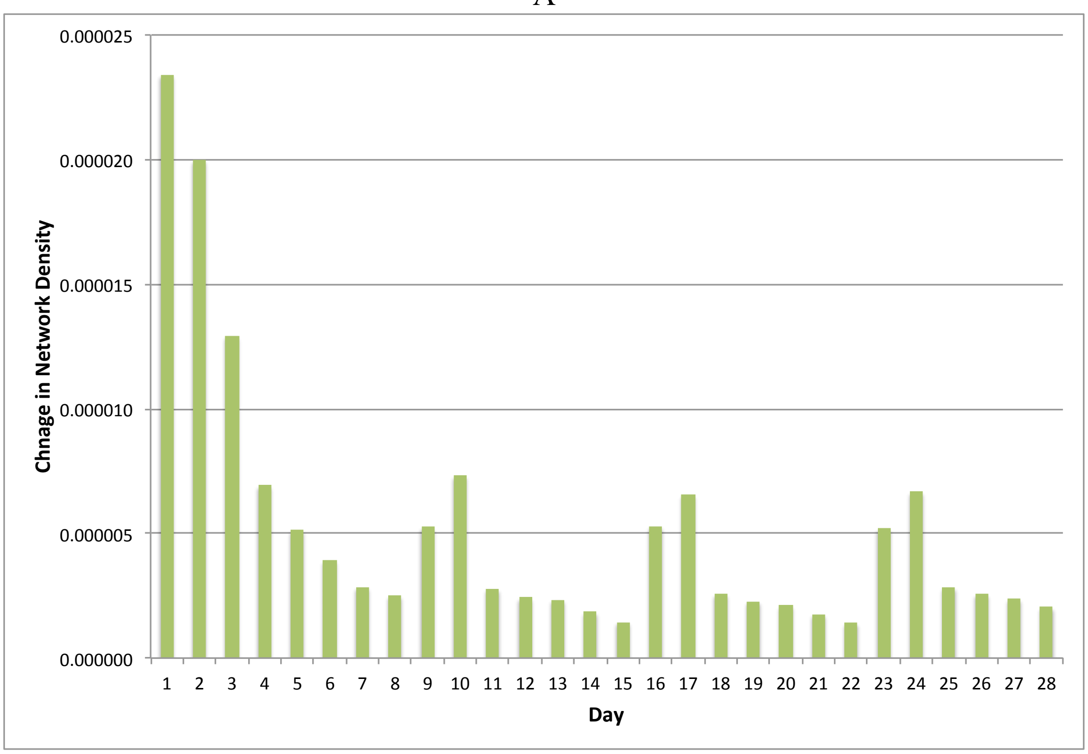


B

Figure 6-20. Average network density. A: By day. B: Day-over-day change.

of the simulation (i.e. the change in network density spikes on Day 24, while rioting that same week spikes a few days later on Day 26), the trends seen here show that there is some association between network density and the dynamics of rioting in the model. Density measures how connected actors are in a network and the strength of those connections. In turn, it also is indicative of the general size of the actors' social networks and how embedded most actors are in their networks (the more dense a network, the larger the social networks). Thus, spikes the size of most social networks are associated with similar spikes in rioting.

6.3.2 The Impact of Increased Education and Employment Opportunities on the Emergence of Riots

The likelihood to riot was shown to be highest among youth, especially in cases where the household was struggling to meet its expenditures (as shown in Section 6.3.1.4). These are Residents under the age of 18, who either did not find a school to attend or must be pulled from school to help bring-in income for the household. However, with limited employment opportunities, they may struggle to find a job. In this experiment, the effect of increasing education and employment opportunities on the outbreak and intensity of riots is explored. This was done by systematically increasing the capacity of schools, formal employers, and informal businesses by 50 percent, 100 percent, 200 percent, and 300 percent of the default value (shown in Table 6-9). School capacity was increased first in isolation (the capacity of formal and informal employers were kept at their default values), formal and informal employer capacity was increased next (the capacity of schools were kept at their default values), and finally, school and employer capacity were increased concurrently.

Note that opportunities for collective violence, such as the rumor (trigger) and the density of residents and their ethnic distribution (which can impact the ability to mobilize and ethnic salience), still exists and does not change as part of this experiment.

6.3.2.1 The Number of Students and Employees

First, the impact on the number of Employees and Students in the model as education and employment opportunities are increased is analyzed. Table 6-11 shows that increasing the capacity of schools increases the number of Students overall and Table 6-12 shows that increasing the capacity of employers increases the number of Employees. In addition, increasing education alone has no impact on the number of Employees. On the other hand, increasing employment opportunities alone, has unexpected consequences on the number of Students. Increasing employment increases the number of Students when compared to the default run. This is expected, as Residents are able to find employment, Households are better able to meet their daily expenditures, and thus, young Household members are able to stay in school (if able to find an available school). However, when comparing the increase of 100 percent to 200 and 300 percent, there is a decrease in the number of Students. As employment opportunities increase beyond 100 percent, the vast majority of Residents getting the newly available jobs are the youth. Adults that wanted employment were able to find employment when capacity was increased by only 100 percent. With most jobs taken within the Residents' employment vision in this case, youth that did not find a school at initialization, or those that dropped out of school to find employment, will struggle to find a job. However, finding that an adult Household member was able to find employment, the Household is now able to afford all expenses, and the youth will turn their focus back to searching for a school. On the other hand, when there is abundant employment for the youth (in the case where employment opportunities are 200 and 300 percent), they will find a job and go to work. Once employed (unless they are laid off in the future), the youth will continue working and will not go back to school.

Table 6-11. The number of Students as education and employment are increased.

	Number of Students		
Capacity Increase	**Increase Education**	**Increase Employment**	**Increase Employment and Education**
Default	14,329	14,329	14,329
50%	16,504	16,151	18,905
100%	18,729	16,424	21,369
200%	20,919	14,808	20,535
300%	21,305	14,942	20,825

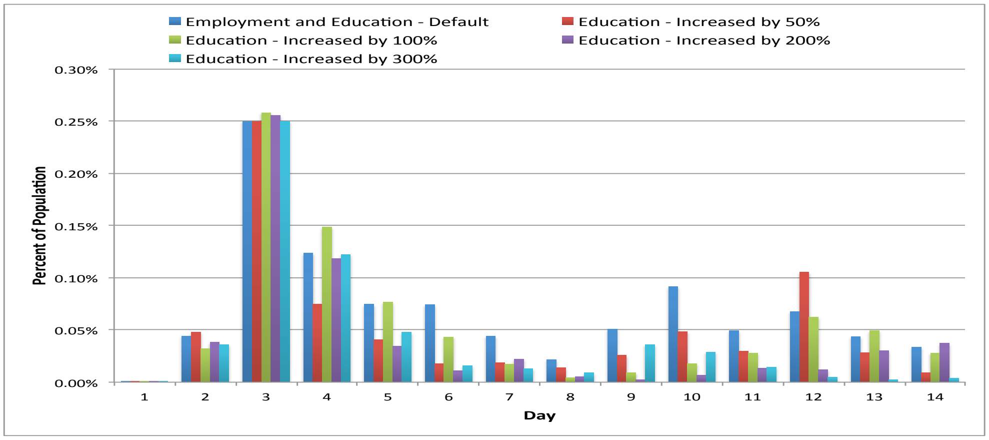
Table 6-12. The number of Employees as education and employment are increased.

	Number of Employees		
Capacity Increase	**Increase Education**	**Increase Employment**	**Increase Employment and Education**
Default	37,487	37,487	37,487
50%	37,752	54,560	54,631
100%	37,635	71,004	70,605
200%	37,619	79,354	78,925
300%	37,565	79,341	78,995

6.3.2.2 The Outbreak and Intensity of Riots

Turning to the impact these changes have on outbreak and the intensity of the riots, Figure 6-21 shows the percent of the population that riots as education (Figure 6-21A) and employment (Figure 6-21B) are increased in isolation, and as they are increased concurrently (Figure 6-21C).

While increasing employment reduced the violence, increasing education alone created an environment that is unstable. There is no clear trend here that shows that increasing education decreases the outbreak and intensity of riots. However, increasing education and employment concurrently has a more positive impact on rioting than increasing employment alone. In terms of the intensity of the riots, Residents are better off by any increase in employment or by an increase in education and employment together.



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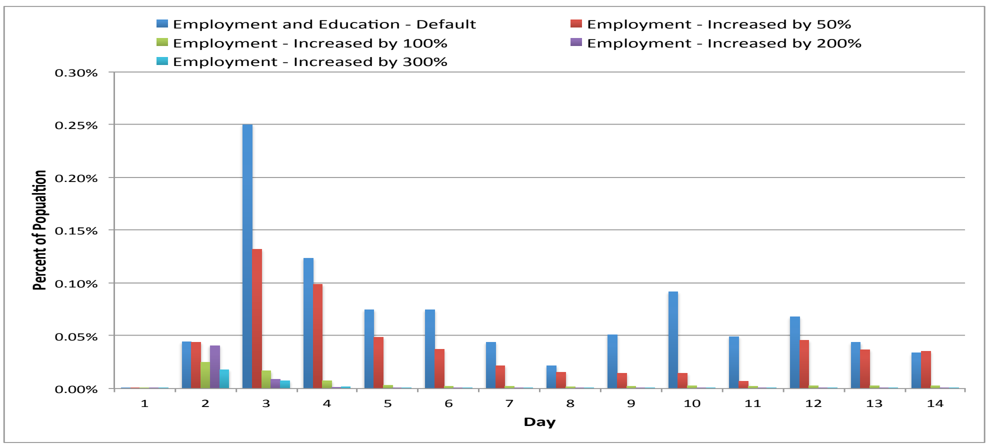

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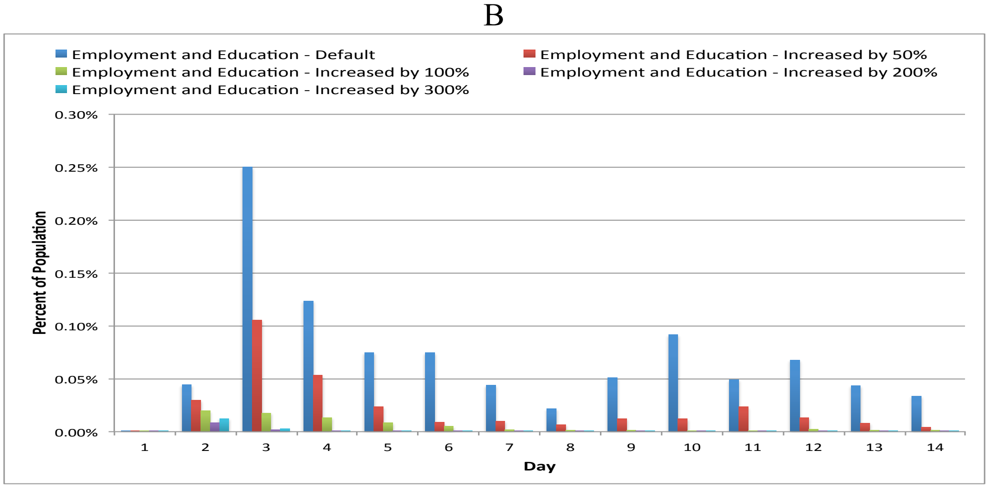


C

Figure 6-21. The number of Rioters as employment and education are increased. A: As education is increased. B: As employment is increased. C: As employment and education is increased.

In addition, based on Table 6-13, the overall impact on the number of Rioters is not linear. Increasing employment by 100 percent, for instance, decreases the average number of Rioters from 77 to 9, while a 300 percent increase only brings down the number of Rioters by two more (from 9 to 7). While increasing both education and employment by 300 percent may show the largest reduction in the average number of Rioters, this may not be a feasible solution. On the other hand, focusing on employment without regard to education may have longer-term consequences.

Table 6-13. The number of Rioters as employment and education are increased.

Capacity Increase	**Number of Rioters**		
	Increase Education	**Increase Employment**	**Increase Employment and Education**
Default	77	77	77
50%	61	49	29
100%	67	9	9
200%	52	8	4
300%	51	6	4

As an example, Figure 6-22 compares the effect of increasing education and employment by 100 percent versus increasing only employment by 200 percent. While both situations result in rioting, the dynamics of the riots vary. Increasing employment yields fewer rioters overall, however, the initial intensity of the violence (in Day 2) is significantly greater, which could be potentially more deadly. From this, however, it is not clear whether residents, in the short term at least, would be better off with all the focus placed on employment or dividing the focus between employment and education.

This idea is researched further by looking at other aspects of day-to-day life in Kibera, including the overall state of households and time spent performing other activities, such as socializing.

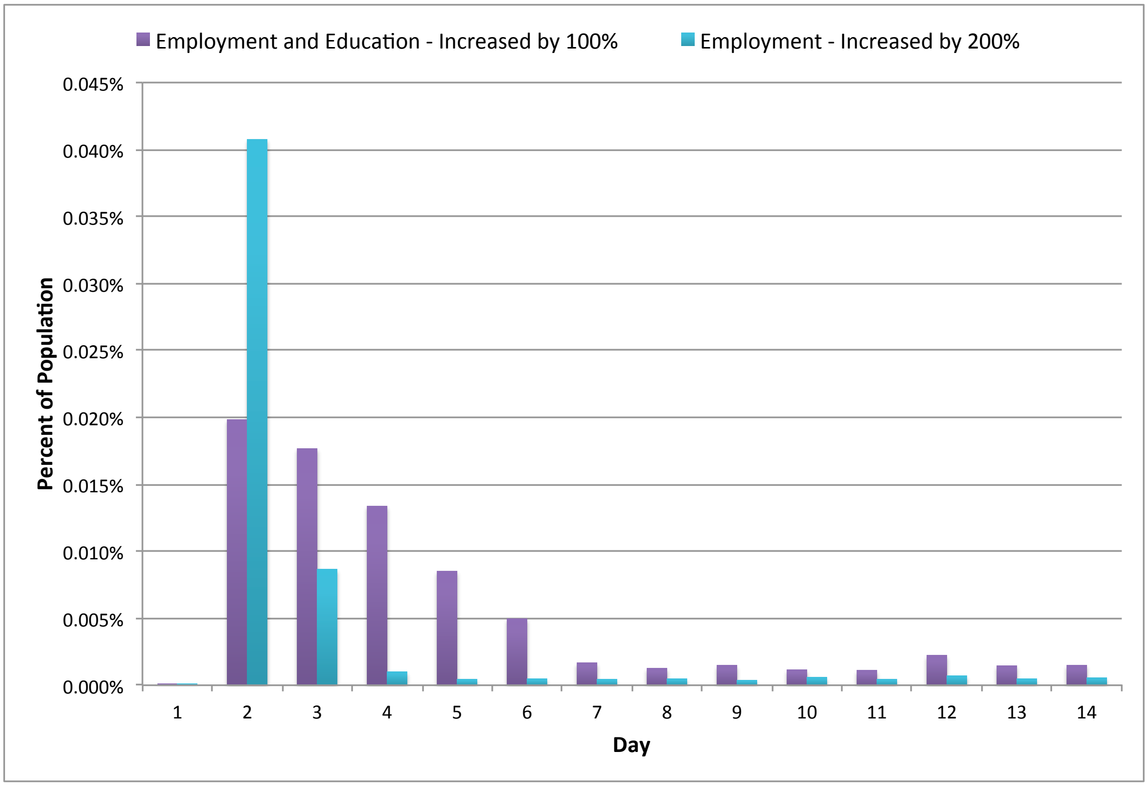


Figure 6-22. A comparison of the percent of population that riots when employment and education is increased by 100 percent and when employment is increased by 200 percent.

6.3.2.3 The Household

It is expected that increasing employment opportunities should increase overall income, and as such, should decrease the number of Households experiencing Household discrepancy. Overall, Figure 6-23 shows that this is the case. Increasing employment reduces the number of Households that are unable to afford their daily expenses. For instance, a 50 percent increase in employment, decreases the proportion of struggling Households by approximately 18 percent. This impact is further augmented when both employment and education are increased concurrently.

The largest impact, however, occurs when both education and employment are increased by 100 percent each. In this case, the number of Households experiencing a discrepancy is reduced by approximately 37 percent. While rioting continued to decrease with increasing employment and education opportunities, Households look to benefit most when education and employment is increased up to 100 percent. This is likely a result of the dynamics discussed earlier (see Table 6-11), whereby beyond this point additional employment opportunities are taken by youth who are only eligible to work in the informal market. This may shift the overall dynamics of the Household, as the Household may reduce certain expenses and an adult in the Household, that may have otherwise found employment in the better paying formal market, may now stay Home to perform domestic activities.

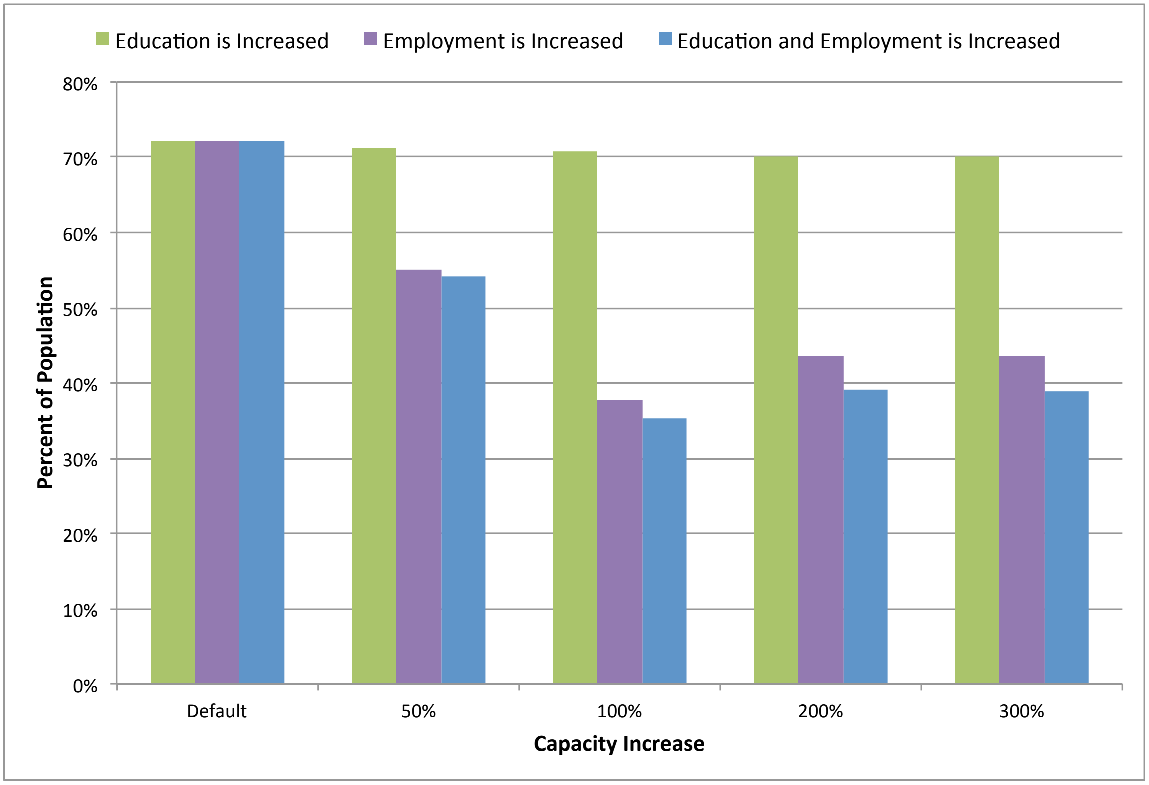
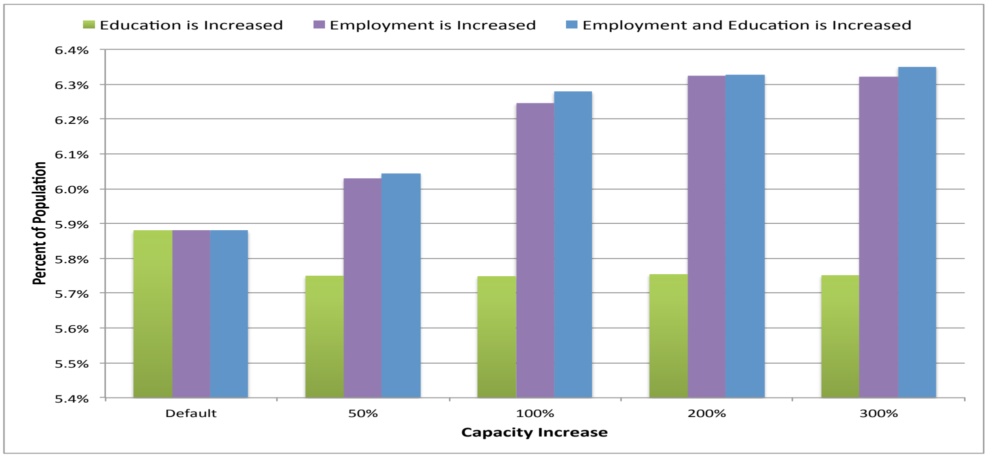


Figure 6-23. The percent of population experiencing some level of Household discrepancy.

6.3.2.4 Quality of Life

According to Maslow's (1954) hierarchy of needs, humans will seek to fulfill their most basic needs first. The need for love and belonging, for instance, would be sought after physiological and security needs have been met. In the model, love and belonging may be met through activities such as socializing, attending church or mosque, and staying home to spend time with the family (as discussed in Section 6.2.2.1). Figure 6-24 shows the average percent of the population by time step that spent time socializing (Figure 6-24A), attending a religious institution (Figure 6-24B), and staying Home



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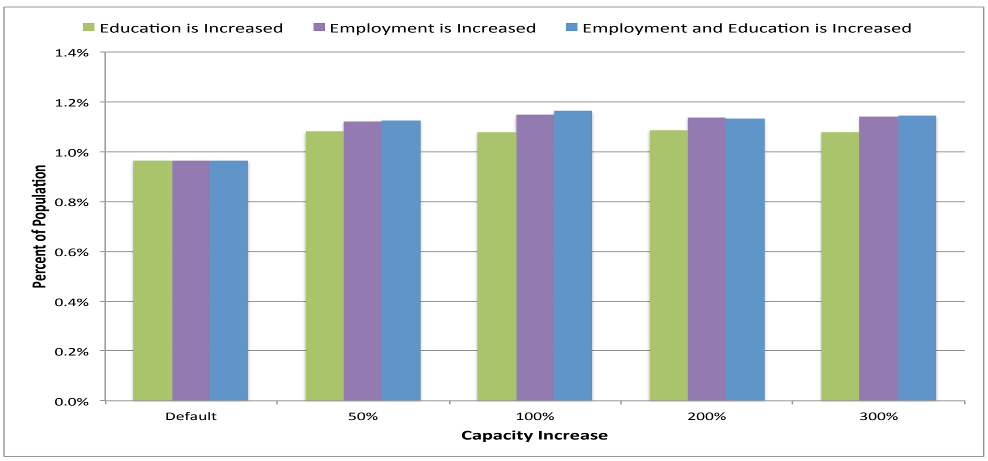

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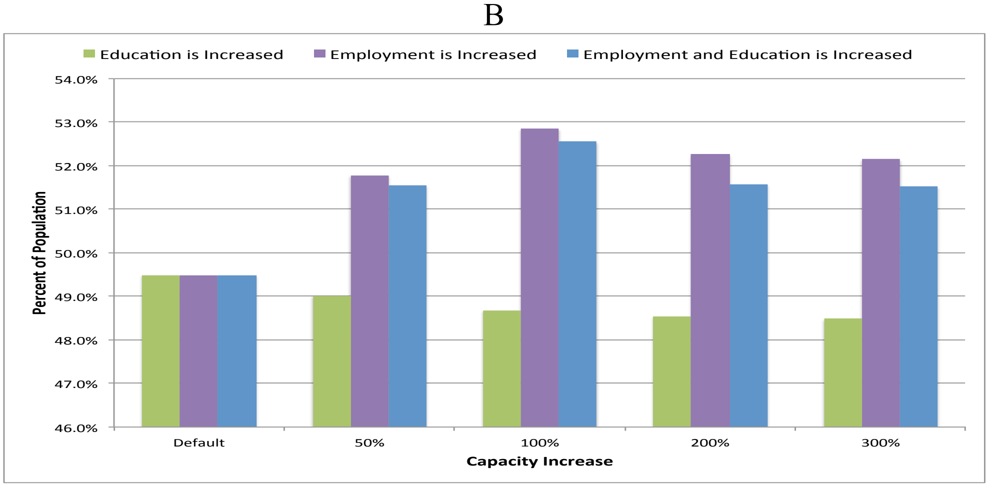

C

Figure 6-24. The average population performing an activity. A: Socializing. B: Attending a religious facility. C: At home.

(Figure 6-24C), as education and employment opportunities were increased. Note that the activity staying Home does not include time spent searching for employment.

Even though unemployed adults and youth (who are not in school) would have more time to perform these activities, their focus is on meeting their most basic of needs. In addition, frustration over meeting these needs, combined with influencing factors, may cause some to turn to violence. On the other hand, as the most fundamental needs are met, Residents can focus on higher needs such as love and belonging.

In addition to a reduction in violence, increased education and employment opportunities, increases overall quality of life, both in terms of Household income and in terms of the Residents' day-to-day activities.

6.3.2.5 The Social Networks

As discussed in Section 6.2.2.1, social networks dynamically evolve as Residents perform their daily activities. These activities include going to work if an Employee and going to school if a Student. Thus, as education and employment opportunities increase, it would be expected that Residents' social networks would expand as they interact with classmates and coworkers. Table 6-14 and Table 6-15 show the network's mean degree centrality and density, respectively, as education and/or employment opportunities are increased. As employment or employment and education are concurrently increased, the network's mean degree centrality and density increases. However, increasing education alone has no significant impact on these network variables.

Table 6-14. Mean degree centrality as education and/or employment are increased.

Capacity Increase	Mean Degree Centrality		
	Increase Education	Increase Employment	Increase Employment and Education
Default	10.96	10.96	10.96
50% Increase	10.78	12.74	12.26
100% Increase	10.53	14.28	13.85
200% Increase	10.44	18.50	17.88
300% Increase	10.30	22.69	21.78

Table 6-15. Network density as education and/or employment are increase.

Capacity Increase	Network Density		
	Increase Education	Increase Employment	Increase Employment and Education
Default	0.00019	0.00019	0.00019
50% Increase	0.00018	0.00022	0.00021
100% Increase	0.00018	0.00024	0.00024
200% Increase	0.00018	0.00031	0.00030
300% Increase	0.00018	0.00039	0.00037

Outside of work or school, Residents also interact with friends (and potentially their friends) while socializing, other church or mosque goers at a religious institution, and members of their Household and neighbors while they stay Home. In addition to going to school and work, these other activities also play a significant role in a Resident's social network. In the previous section, a significant increase in the time performing these activities was noticed when employment was increased or when employment and education were increased concurrently. Increasing education alone, on the other hand, showed a drop in time spent on these activities.

In addition, while the number of Students may be higher when education is increased, the dropout rate in Students from the beginning of the simulation to the end is also significantly increased. Increased school capacity allows more Students to enroll. However, because employment has not changed, many of these Students will be pulled out to search for employment. Thus, this dynamic does not allow for strong connections to form in between those Students going to the same school. In addition, an increase in the size of the school does not have a significant impact on the number of Students a Resident would connect with as the class size is assumed to remain the same. Table 6-16 shows the number of Students that dropped out (the number of Students at the beginning of the run minus the number of Students at the end) as education was increased.

Table 6-16. Number of Students that dropped out as education was increased.

Education Increase	Number of Students that Dropped out	Percent of Students at Initialization
Default	6,019	30%
Increased by 50%	12,770	44%
Increased by 100%	19,596	52%
Increased by 200%	25,768	56%
Increased by 300%	27,167	57%

Student dropout rates combined with less time spent performing activities such as socializing are likely the behind the reason a significant change in a Resident's social network is not seen as education opportunities are increased.

6.4 Discussion of Results

This model demonstrates that the propagation of rumors through the unique, local interactions of agents via social networks can be simulated. By grounding the agents' cognitive framework in theory and applying empirical data to create a landscape that represents a real world location, micro-level interactions resulted in macro-level phenomena in the form of rioting. Results demonstrate a level of qualitative agreement with reality; from the role of ethnic salience in collective violence, to the presence of opportunity provided by strong social ties and geographic advantage, to the characteristics of the agents that rioted. In addition, while increasing education and employment opportunities show overall results that may be expected, some surprising trends were also noted. These are discussed here in more detail.

In Kibera, residents were able to quickly mobilize in neighborhoods where they were the ethnic majority. This is a result of the strong ties and the social structures developed prior to the violence, in addition to their closeness in terms of geographic distance between "like" neighbors. Opportunity in terms of resources was in the form of the sheer number in the group. As the ethnic majority, available resources (people) was high, while mobilization was made possible through strong social ties and geographic distance. In the model, ethnicity does not play a role in terms of which agents one connects with outside of the home. However, when neighborhoods are made-up of a majority ethnicity, most of the agent-to-agent interactions are going to be with those ethnically similar. In informal settlements, where neighborhoods tend to be dominated by one ethnic majority, ethnicity becomes a source of cohesion in the community (Oxfam

GB, 2009). In the model, agents are most likely to riot if their ethnic salience is heightened; a function of their embeddedness in a communication network of similar agents. Social networks based on ethnic lines can provide a source of community and support, but on the other hand, can also create a divisive ("we" against "them" mentality) and potentially dangerous situation, as was seen in the riots of 2007. The combination of a heightened ethnic salience (mostly latent prior to violence but activated after election announcements) and the opportunity, in the form of mobilization and resources facilitated by ethnically segregated neighborhoods, provided the impetus to ignite the riots.

Results indicate that youth are more susceptible to rioting; that frustrated from staying home and being unemployed are willing to aggress. Studies have shown that unemployed youth are especially vulnerable to violence. These youth are often living in areas with little economic opportunity and large school dropout rates (OECD, 2011; Oxfam GB, 2009; UN-HABITAT, 2003). Youth in slums, in particular, have difficulty finding employment as they may be insulated from the formal job market and lack the education of their peers (UN-HABITAT, 2003). In Kibera, for instance, the main reason youth drop out of school is related to affordability (Erulkar and Matheka, 2007), as the perceived benefit of staying in school is low (UN-HABITAT, 2003). This is modeled similarly in the simulation as students dropout of school in order to work when household income is too low. The insulation from the job market is modeled by only allowing youth employment in the informal sector, which reduces the number of good paying jobs available to them. Similarly to studies that have looked at those most vulnerable to turn to collective violence, model results show that youth are most likely to turn to riot.

While the overall results may be expected, the effect of systematically increasing education and employment opportunities on overall quality of life in the model is not linear. For instance, a 200 percent increase in employment results in a 112 percent increase in the number of employees. On the other hand, increasing both education and employment by 200 percent increases the number of employees by 110 percent, which translates to approximately 430 less employed residents than when employment was increased alone. In addition, the increase in the number of employees does not directly translate to a similar increase in household income. A 112 percent increase in the number of employees, for example, resulted in a 39 percent reduction in the number of households with income discrepancy. While the same increase in education and employment reduced the number of households experiencing income discrepancy by 46 percent. While the number of employed is fewer in this case, the income being generated is higher. In addition, we see this effect in the residents overall quality of life. With an increase in the proportion of residents meeting their basic needs, there is an increase in time spent socializing and attending religious institutions. This was not an expected consequence of the model. While unemployed adults and youth may have more time to spend on these activities, time spent performing these activities actually increases when employment and education opportunities increases. This provides support to Maslow's (1954) theory that the most fundamental of needs, such as physiological and security, need to be met prior to attending to higher needs, such as love and belonging.

In addition, while it may be expected that increasing education and/or employment would reduce violence, there are reinforcing effects that are not instinctively obvious (as discussed in Section 6.3.1.4). As such, an increase in the size of Residents' social networks will have nonlinear effects on agent behavior, specifically social influence. Increasing opportunities, especially employment, will result in "happier" households. Even if a household member includes a youth unable to go to school due to school capacity constraints, for instance, the youth will be better able to cope with the situation and the rate at which it will get frustrated will decrease. Furthermore, while Residents can be influenced to riot, the opposite is also true. Social networks can exacerbate the rate at which individuals influence one another to remain peaceful. As such, households that may continue to struggle to meet their basic needs are less likely to be influenced to riot when most household nearby are "happy."

These dynamics may be indicative of a "tipping point" in the model. Tipping is described as a situation when individuals rapidly change their behavior (Miller and Page, 2007). Schelling (1978) notably described this situation in his segregation model as the point where the entrance of a few minority households resulted in a complete shift in the ethnic makeup of a neighborhood. Granovetter (1978) introduced a similar concept in his threshold models of collective behavior, whereby a critical number of rioters must exist before others are also influenced to riot. Here, we noted a significant drop in the number of rioters between an increase in employment of 50 percent (49 rioters) and 100 percent (9 rioters). By doubling employment opportunities, the number of rioters was reduced by considerably more than half, a situation likely exacerbated by social networks. Note that while employment was used as the example, increasing both employment and education saw similar results.

6.5 Summary

Shortly after the announcement of presidential election results in 2007, ethnically charged protests erupted across Kenya. Kibera, which mirrors the country in terms of ethnic diversity, saw the greatest level of violence in Nairobi. This model explored the role individual identity, collective social identity, and social influence played on rumor dynamics and the spread of ethnic stereotyping in the outbreak of riots. Using empirical data for which to build the landscape and provide agents with unique attributes, an ABM integrated SNA and GIS to simulate the outbreak of riots in Kibera. Building on the previous two models, SNA techniques were used in the development of the model, GIS grounded the landscape on empirical data, and ABM allowed for the application of theory to guide behavior.

SNA combined with GIS in Chapter 4 provided a novel approach to the analysis of event data across both time and geographic space. The spatiotemporal patterns discovered were then investigated further through qualitative research. While the technique allowed us to see significant macro-patterns in the conflict, it did not provide insight into the underlying micro-level processes. Through a simple ABM, Chapter 5 used the PECS framework to implement behavior into a simulation of conflict. The integration of ABM and GIS in the model allowed us to observe the emergent macro-patterns, and through "what if" scenarios, theory was explored and insight gained into the micro-level processes. By integrating ABM, SNA, and GIS in the model here, sophistication was added to the agents' cognitive framework, the interactions that occur over social and physical space better represented real world behavior, and the nonlinear, reinforcing nature of the system was modeled.

The development of social networks in the model was facilitated through the temporal and geographic decrease in the scale of the model. As agents interacted while performing their daily activities, social networks were dynamically created and updated. While Chapter 4 used SNA techniques to analyze event data, similar techniques such as centrality measures and structural equivalence were used to help drive behavior. On the other hand, Chapter 5 used geographic concentration as a proxy for the presence of social networks, while here the explicit modeling of social networks allowed for a more complete implementation of cognition into the agents. Social networks influenced an agent's role-based identity, the spread of the rumor, the salience of an agent's ethnic identity, and an agent's susceptibility to be influenced by the rumor. As a result, they directly impacted the dynamics of the model and any riots that emerged.

In the model, geography effected the initial placement of households on the landscape, which impacted the agent-to-agent interactions that occurred. Agents searched for employment and schools within their vision, and once found, went to work and attended the same employer or school on a daily basis until there was a change in the agents' circumstances (e.g., the agent was laid off or pulled from school). On the other hand, activities such as rioting and attending a religious facility may require going beyond this vision area, potentially leading to the creation of social networks that expanded wider geographic areas. This could directly influence the spread of the rumor to different geographic areas of Kibera; it could impact the ethnic salience of the agent since its embeddedness in a network with others sharing the same ethnicity could shift; and it could influence the agents' decision to riot or to remain peaceful.

Similarly to Chapter 5, this model applied theories of human behavior to implement behavior using the PECS framework. While behavior was kept simple in the previous model, a more complete spectrum of behavior was implemented here, from simple stimulus-response behavior to reflective behavior that required the agents' awareness of its internal model. The full development of the Cognitive component of PECS allowed for the development of the self model, which drew from identity and social influence theory. In addition, emotion, in the form of self-esteem (an output of the identity model) and frustration-aggression, added a new degree of realism to agent behavior. This internal model was regularly compared to the agents' environment (e.g., what activities is the agent performing) and social network (e.g., is the agent connected to any rioters). This provided a feedback loop between the agents' activities in physical space, the agents' interactions in social and physical space, and the agents' internal model: each informing the other and effecting behavior. As such, the sophistication of the agents' cognitive framework in this model was facilitated through the integration of SNA and GIS.

The emergence of riots as those seen in Kibera is largely due to the unique set of challenges that comes with life in urban slums. As discussed in Section 1.2, characteristics such as poverty, overpopulation, and a growing youth bulge put urban slums (such as Kibera) at greater risk for violence. Economic incentives have caused a rural to urban migration, with most moving to already overpopulated urban slums

(OECD, 2011). For the first time, almost half the world's population lives in urban areas and this number is only expected to grow (NIC, 2012). In addition, the vast majority of the growing youth population, who are particularly vulnerable to being exposed and engaging in armed violence, live in the developing world. This urbanization and growing youth population has played a defining role in the increase in riots (OECD, 2011). It would be very difficult to capture the nonlinearities of this system using traditional, top-down approaches (as discussed in Chapter 3). The cyclical nature in the emergence and dissolution of rioting is due to positive reinforcement, an effect that can be largely attributed to the agents' social networks, and thus their interactions and influences through these networks. In addition, systematically increasing education and employment opportunities did not have a similar linear impact on the number of students, employees, rioters, or even on household income. The situation is more complex. Riots arise from the interactions between individuals with unique attributes, all within a connected social network over a heterogeneous environment (Demmers, 2012). In order to gain a better understanding of the macro-level patterns that emerge, the nonlinear and reinforcing nature of this system must be modeled from the bottom-up.

7. CONCLUSIONS

The research question this dissertation addressed is: Can a bottom-up approach provide us with useful insight into the formation, spread, and strength of violent collective action? The value of using a bottom-up approach and the insights gained were demonstrated through the following overarching themes:

- An integrative approach to ABM, SNA, and GIS allows us to build more realistic models of violent collective action.
- The world we live in is complex; computational modeling allows us to build theoretical and empirical models of violent collective action that allows us to explore ideas and test theory in an "artificial society."
- Modeling human behavior that accounts for a more complete spectrum of human behavior (from reactive to deliberative) better represents human cognitive abilities.
- As violent collective action is a complex system, a bottom-up approach is an improvement over traditional, top-down approaches.

Sections 7.1 to 7.4 of this chapter summarize the main themes of this dissertation and the insights gained by using an integrative computational approach to models of violent collective action. In addition, Section 7.5 discusses the limitations of the current research and areas of future work. Lastly, Section 7.6 provides the final conclusions of this dissertation.

7.1 The Value of Integrating Computational Methods into Models of Violent Collective Action

Three abstract models of violent collective action were developed for this dissertation. Through the interdisciplinary nature of CSS, several computational methods (ABM, SNA, and GIS) were applied to the study of violent collective action. With increasing levels of sophistication, the value of each computational method was demonstrated in varying combinations, with the final case study providing a fully integrated model of violent collective action.

The first model presented in Chapter 4 used SNA techniques, including centrality measures and structural equivalence, and simple GIS to model a long-lasting, state-level conflict. The "agent" (node) in this model was at the group-level. In addition, each node included the year and location of the event, allowing for the concurrent analysis of the conflict across both time and geographic space. This provided a novel approach to exploring the spread, movement, and intensity of insurgent activity in a conflict. Using the Colombian civil war as the case study, centrality measures helped us to quickly identify the most significant spatiotemporal patterns, including a major shift of the conflict south and some resurgence of violent activity in the north. Clustering structurally similar events confirmed some form of coordination that went beyond a single department, and spanned an entire region. SNA and GIS allowed us to quickly hone in on the most prominent patterns in the conflict, and provided a direction for additional research. When time is limited, the main source of data are criminal or terrorist incidents, and understanding current patterns in a conflict is critical, this approach may be ideal.

In Chapter 5, sophistication was added to the environment and simple human behavior was introduced to a state-level ABM of conflict. Here, the long-lasting, resource-driven civil war in Sierra Leone was used as the case study. Using GIS and region-specific socioeconomic data, the landscape was created. In addition, the PECS framework was utilized to add simple behavior to the agents, which was grounded on theories of human behavior (as discussed in Chapters 2 and 3). The spatial dispersion of a resource and its impact on the geographic onset, spread, and intensity of conflict was explored. By adding simple behavior to a model of conflict, several "what if" scenarios were run and the impact that changes in the environment had on the spatiotemporal patterns of riot activity were observed. This model provided insights into the geographic locations most prone to conflict and the spatial characteristics of the conflict, which can have implications on the type of conflict that may emerge (e.g., warlordism, secession). When resources were distant, this model provided support to Le Billon's (2001) theory that the spatial dispersion of a resource is a defining feature of a conflict. Simulating a situation with proximate resources, however, requires a modeling scale that gets at the social dynamics of a more urban environment. This level of scale went beyond the scope of the model but was explored in the third, and final, model.

In the final model discussed in Chapter 6, the spatial and temporal scale was decreased and the three computational methods, ABM, SNA, and GIS, were integrated to simulate short-term, neighborhood-level rioting. This instantiation of the model was inspired by the riots that occurred in an urban slum in Kenya. GIS data that included a road network and points of interest created a landscape that more accurately reflected reality, while socioeconomic data provided agents with individual characteristics. Agent behavior that was implemented using the PECS framework accounted for both reactive and deliberative behaviors and was grounded in theories of human behavior (as discussed in Chapters 2 and 3). This behavior directed the agents' daily activities, and subsequently, the agent-to-agent interactions, which helped create dynamic social networks. In addition, geography impacted initial household settlement patterns, which had potential effects on the interactions, and subsequent networks, that were created. While agents search for employment and schools within a pre-defined vision, other activities such as rioting, attending a religious institution, and socializing, could reach beyond this pre-determined area, creating social networks that expanded a wider geographic region. When a rumor was introduced, social networks directly impacted the spread of the rumor, while SNA techniques, such as centrality and structural equivalence, provided a formal approach to implement opinion formation, which subsequently drove the agent's decision to act (or not) on the rumor. The addition of rumor diffusion processes that used explicit social networks was novel to ABMs of conflict. The integration of SNA and GIS with an ABM facilitated the development of the agent's cognitive framework, which represented a feedback loop between activities being performed in physical space, interactions in social and physical space, and the agent's internal model. This process was critical in simulating the reinforcing, nonlinear nature of this system.

The models developed as part of this dissertation were some of the first to integrate ABM, SNA, and GIS, especially in relation to collective action. Through the insights gained in each model, the value of integrating the three techniques was shown.

7.2 The Application of Theory in Empirical Models of Violent Collective Action

A unique advantage of computational modeling is its ability to concurrently build theoretical and empirical models of social phenomena (Manson et al., 2012). While agent behavior and the creation of social networks were grounded in theory, GIS and socioeconomic data provided an empirical foundation (i.e., an actual, real world setting) for which to build the modeling world.

As discussed in Section 1.3.1, the theorist is concerned with logical consistency and they aim to conceptually understand the variables of interest, whereas the modeler is concerned with the application of theory to a particular case (Lowry, 1965). While theories of conflict seek to explain why conflict emerges in certain situations based on actual observations, computational modeling allows us to apply theory and then observe the emergence (or not) of conflict given certain initial conditions. By taking a positive approach to the environment but normative approach to agent behavior, this dissertation demonstrated the advantage of building intermediate models of violent collective action (see Section 3.5). In developing the agents' cognitive functions, the ABMs presented in this dissertation drew heavily from theories of human behavior, specifically those found to be most relevant to situations of conflict, including humanistic needs theory, identity theory, and social influence theory. By grounding behavior in theory (from what daily activities an agent will perform to the decision to join a situation of collective violence), realism is added to the decision making process of agents. On the other hand, by using empirical data to develop a landscape that represents a real world setting, we can observe how behavior (that is grounded in theory) is influenced by the unique environment for which the agents use to interact.

The integration of empirical and theoretical in one computational model of conflict also has the advantage of allowing us to test certain "what if" scenarios. We can see how changes in the initial conditions (which were based on empirical data) impact the emergence of violent collective action. For instance, by moving the location of the diamond mines in Sierra Leone (from the actual locations to the country's center of power), we were able to explore Le Billon's (2001) theory and observe the spatial changes in the outbreak and intensity of rioting.

On the other hand, in the model of an urban slum, an environment that was grounded on empirical data and social networks that were created from the social interactions on geographic space impacted model dynamics: from the ability of an agent to find employment or attend school, to the diffusion of a rumor, to the spread of social influence. In this model, the effect of increasing education and employment opportunities (beyond levels seen in empirical data) on the outbreak and intensity of riots were observed. Results of this final model found that while increasing education alone created a volatile environment, increasing employment reduced the violence. However, increasing both education and employment concurrently was better than increasing only employment. In addition, an unexpected result of increasing employment and education was the increase in overall quality of life. Even though agents may be "busier" as more are in school and are employed, time spent performing "extracurricular" activities, such as socializing, attending a religious institution, and even spending time at home, increased. This provided support to Maslow's (1954) theory that people will seek to meet there most fundamental needs prior to seeking higher level needs.

7.3 Modeling Behavior in Conflict Settings that Better Represents Human Cognition

A main theme of this dissertation was to build models that more accurately represent human cognition. While prior models of conflict paved the groundwork for this dissertation, the models developed here looked to represent cognition functions that went beyond the use of simple threshold calculations, which are often used in ABMs. It sought to account for a more complete spectrum of human behavior, from simple stimulus-response behaviors to more intricate reflective behaviors, which requires a construction of self (e.g., an Identity Model) that necessitates the agent be fully aware of its internal model. However, as noted in Section 3.3, modeling behavior in an ABM is not simple (Kennedy, 2012). For this reason, this dissertation utilized an existing framework that provided the flexibility to model a diverse range of behaviors.

The models developed for this dissertation were some of the first to use the PECS framework, and at the same time implement agent behavior grounded in theory that better represents human cognition (see Section 3.3.2). The flexibility of the framework allowed for the integration of a variety of theories of human behavior, specifically humanistic needs theory, identity theory, and social influence theory. For instance, motives in PECS can easily correspond to human needs. In addition, the PECS framework and the Identity Model are divided into the same three main components: inputs, transition variables (i.e., the Comparator located within Cognition), and outputs. Furthermore, social influence processes included aspects from inputs in Perception (interpersonal effects from others in one's network) and internal processes in Cognition. Thus, the guidance provided by PECS facilitated the process of "fitting" theory into a framework of human cognition.

If careful thought is not put into the representation of human cognition in the model, however, the flexibility of the PECS framework can potentially be both an advantage and disadvantage. Every model is a simplification of the social world, designed to represent some specific aspect important to the modeler (Axtell, 2000; Crooks and Heppenstall, 2012; Gilbert and Troitzsch, 2005; Miller and Page, 2007; Taber and Timbone, 1996). In the same manner, agent cognition is a simplification of human cognition. While PECS provides a framework for modeling all aspects of human behavior, its purpose is not to utilize every component unless necessary. The modeler must bear in mind the model's purpose when determining those features of human cognition most relevant. For each of the ABMs developed here, careful consideration was put into the model's intention and theory was selected that was most applicable to the social phenomena modeled (see Sections 2.1 and 3.3.1). The next step was to create a notional design of agent behavior that integrated PECS with theory, while bearing in mind that the design must be transformed to computer code. This process was facilitated through the framework provided by PECS. On the other hand, as one of the first to use PECS, much discretion is left to the modeler. There are very few existing examples (notional or actual) on how to implement most aspects of behavior, and there are no examples that implement identity theory or social influence theory into the PECS framework. Whether I was accurately interpreting PECS and theory was a constant question throughout the process. As such, much attention had to be paid to the objective of each component of the PECS framework and to the meaning behind each aspect of theory.

Theory provided the guidance needed and PECS provided the framework for which to implement theories of human behavior into the ABMs developed here. While the modeler must bear in mind any of the potential pitfalls discussed here, the PECS framework was flexible enough to model simple reactive behavior (as in the model of Sierra Leone) to more intricate deliberative behaviors (as in the riots model of Kibera), and thus, provided a robust framework for which to model varying levels of human cognition.

7.4 Violent Collective Action as a Complex System and the Value of Modeling from the Bottom-Up

Applying theory and state of the art modeling techniques, this dissertation demonstrates the value of modeling violent collective action from the individual perspective. Violent collective action is a complex, dynamic social construct. As a complex system, it requires that we study "large numbers of actors with changing patterns of interactions" (Axelrod, 1997b). To solve this type of problem using traditional mathematics would be very difficult and finding a tractable solution might not be possible. This makes computational modeling ideal, and the primary tool for modeling problems of complexity theory (Axelrod, 1997b). In addition, the focus placed on bottom-up processes in conflict (de Rouen and Sobek, 2004; Fearon and Laitin, 2003; Kalyvas, 2006; Lederach, 1999) has helped drive the move towards a computational approach to studying violent collective action. ABM allows for the creation of heterogeneous, boundedly rational agents who interact locally within their physical and social space. In this dissertation, these interactions were grounded in theory and implemented using a framework for human behavior. The implementation of these interactions is a key requirement for emergence to occur.

Emergence, which can provide insights beyond that which traditional, top-down approaches or qualitative "mental" models of social phenomena can provide, makes a bottom-up approach an enhancement to current methodologies often used in the study of violent collective action. For instance, in the second model developed for this dissertation (see Chapter 5), I found that small increases in the control (or the security) of resources in Sierra Leone actually displaced the conflict at times. While it minimized conflict where it was originally more intense, it displaced and caused conflict to occur in areas that were relatively quiet. Through additional runs, I found that the occurrence of conflict in this region of the country was the most unpredictable. This type of insight could ensure that policy makers place focus not only in the regions battling some of the most intense violence, but also in areas at risk for conflict should nothing be done. In the final model (see Chapter 6), I found that modeling from the bottom-up was critical for simulating the nonlinear, reinforcing nature of the system. While riots broke out in all cases, the intensity and timing of the riots was attributed to micro-level interactions, social networks, and household dynamics. Due to the closely coupled situation, changes in behavior of some individuals could have a cascading effect across the population. These dynamics resulted in cyclical rioting patterns and showed that incremental changes in employment and education can have dramatic impact on reducing violence. Such dynamics could only be simulated from the bottom-up.

7.5 Limitations of the Current Research and Future Work

This research has shown the value of integrating ABM, SNA, and GIS into a model of violent collective action, and specifically, how a bottom-up approach can provide insights into the dynamics of conflict. However, the models developed also serve as a building block for future models of conflict, especially as data becomes more readily available and computational resources become cheaper.

There are some areas in each model that could benefit from further development. In the model that represented the Colombian conflict, for instance, two major spatiotemporal patterns in the violence were discovered, which helped direct the qualitative research performed. However, there were other locations, that although were less “important” based on centrality results, could still be significant. From the perspective of a conflict analyst, these locations may be important areas for further research. In the case of Sierra Leone, while the model supported theory when the resources were distant (i.e., in remote regions of the country), its limitations were observed when attempting to simulate the case of proximate resources (i.e., near the country's center of power). Modeling the proximate case requires getting at the unique dynamics of the environment in the most populous regions of the country (in this case, the country's capital). Given the models scale (at the state-level), including these types of dynamics may be a challenge. Finally, while the model of riots in an urban slum showed how the propagation of a rumor can lead to the emergence of violence, it would be beneficial to add a mechanism to stop the spread of the rumor after it starts. In Kenya, for example, as soon as a power-sharing agreement was announced in 2008, rioting ceased almost immediately (De Smedt, 2009). This type of scenario could be modeled by stopping the spread of the rumor.

A key challenge is building richer models on richer data sources. Conflict remains "one of the messiest of all human activities to analyze" (Bohorquez et al., 2009). As such, data posed a challenge in both the model development and validation processes. For example, ideally the data used to perform the SNA analysis for the Colombian conflict would be near real-time. This would allow the model to be updated regularly and any shifts in event patterns to be noted on a timely basis, in case conflict intervention is needed. A database such as GDELT, which is an open source database that updates on a daily basis by machine coding data from thousands of news sources, is a step in that direction (Leetaru and Schrodt, 2013). While the database offers a promising path for future analysis, it is still in its infancy and consideration must be taken to potential biases (e.g., a small protest receiving a lot of press may seem more intense in the data than what it really is). In the case of Sierra Leone, on the other hand, finding pre-war data for which to create the agents was difficult. While cell wise population distributions of residents prior to the war were not available, pre-war district-level figures were used to develop a simple method for backcasting the entire population. On the other hand, in lieu of available pre-war socioeconomic data, the model used more recent data that is more representative of post-war household characteristics. By seeking qualitative agreement with empirical results, both ABMs presented here would be considered a Level 1 classification. A Level 2 or 3 classifications requires quantitative agreement with empirical macro-structures and micro-structures, respectively. With an increase in the availability of data, both for model development and model validation, a higher classification can be sought. However, until this type of data becomes more readily available, this will remain a challenge. While some incident data on conflict events was available, including high-level figures on the number killed and displaced, no data on the number of people that actually rebelled or rioted in the civil war in Sierra Leone or the riots in Kibera could be found. When looking to show that the emerged conflict in a model is representative of reality, this poses a challenge.

Another challenge was around computational resources. Simulation runs were performed using George Mason University's Argo Cluster. However, even with this level of computing power, running the final model (which integrated ABM, SNA, and GIS) at full scale for one simulation week took three full days. From an agent population perspective, additional computing power would have allowed for sensitivity testing and scenario runs to be performed at full scale. In addition, there were areas where behavior had to be simplified given the computational constraints. For example, a simplified version of Friedkin's (2001) structural approach was implemented in the final model. In calculating the net effect of interpersonal influences only direct influences were accounted for. In future work, the model could include indirect relationships as well. This would involve incorporating, at a minimum, the agent's ego network (an agent's friends and their friends) into the calculation (Wasserman and Faust, 2009).

7.6 Final Conclusions

Violent collective action is a complex system. It is fought between social groups of heterogeneous individuals on an environment that is also heterogeneous. The reinforcing nature of this system can cause violence to spiral to new heights or to cease almost immediately. Attempting to understand the underlying dynamics and interactions of violent collective action requires a bottom-up approach. A computational model, which has the ability to model complex systems and dynamic processes, is ideal. Traditional top-down approaches, which would require a tractable solution and possible oversimplification of these variables, would not be able to capture the emergent phenomenon of collective violence.

While three abstract models were developed using different combinations of computational methods, the case studies (which provided the specific instantiation for these models) covered a diverse set of locations and conflicts at different scales. This diversity provided validity to the use of a computational approach in a variety of violent conflict situations. In addition, with each model, the sophistication of the environment was increased, the agent's behavior and their interactions were made more intricate, and the use and integration of more advanced agent-based modeling, geographic information systems, and social network analysis techniques were explored. By implementing three unique case studies, we were able to demonstrate the value of a bottom-up approach and to show specific areas where additional insight into the conflict was gained, specifically as it related to the onset, spread, and intensity of violent collective action. This dissertation lays the foundation for studying violent collective action from the bottom-up and sheds some light into the underlying micro-level dynamics of environments in conflict.

APPENDIX A

This appendix provides the details associated with the scenario runs performed for verifying the ABM of ethnic clashes in Kibera (discussed in Chapter 6). Each scenario was run 10 times for one simulation month. Table A-1 provides a brief description of each scenario, Table A-2 and Table A-3 provide the model specifications used to run each scenario, and Table A-4 provides a summary of the expected and actual results associated with each scenario.

Table A-1 provides a brief description of each scenario. Information on any simplifying assumptions made are shown, including (1) setting employment and school vision to span the entire modeling world; (2) increasing employee and student capacity at employers and schools such that all residents have employment and school opportunity; or (3) removing household need as a factor in a resident's decision to search for employment or leave school. The scenarios with an asterisk are those where no simplifying assumptions were made.

Table A-1. A description of each scenario.

Scenario	Description	Simplifying Assumptions
1	Test general employment and school search algorithm.	1, 2, 3
1*	Test employment and school search algorithm with realistic vision and capacity values.	
2	Test laid off function (1% probability).	1, 2, 3
2*	Test laid off function (1% probability) using realistic vision and capacity values.	
3a	Test school eligible and search for employment function.	1, 2, 3
3b	Test school eligible and search for employment function with household need.	1, 2
3b*	Test school eligible and search for employment function with household need and actual vision and capacity values.	
4a	Test students leave school to search for employment function.	1, 2, 3
4b	Test students leave school to search for employment function with household need.	1, 2
4b*	Test students leave school to search for employment function with household need and actual vision and capacity values.	
5a	Test inactive residents search for employment function.	1, 2, 3
5b	Test inactive residents search for employment function with household need.	1, 2
5b*	Test inactive residents search for employment function with household need and actual vision and capacity values.	
6a	Test if school eligible residents are searching for school function.	1, 2, 3
6b	Test if school eligible residents are searching for school function with household need.	1, 2
6b*	Test if school eligible residents are searching for school function with household need and actual vision and capacity values.	
7a	Test rumor propagation algorithm.	1, 2, 3
7b	Test riot algorithm.	1, 2, 3
7c	Test rumor propagation and riot algorithm.	1, 2, 3
8	Test all behaviors without rioting.	1, 2
8*	Test all behaviors without rioting using actual vision and capacity values.	
9	Test all behaviors with rioting.	1, 2
9*	Test all behaviors with rioting using actual vision and capacity values.	

Table A-2 and Table A-3 provide details on the specifications used to run each scenario. Information in Table A-2 includes the agent's vision, school and employment capacity levels, and whether the household's discrepancy (i.e., household income minus household expenditures) impacts the agent's decision-making process. Information in Table A-3 relates to whether certain algorithms are turned "on" or "off" in a scenario, such as school and employment search, rumor spread, and rioting algorithms.

Table A-2. The first set of specifications for each scenario.

Scenario	School Vision	Employment Vision	School Capacity	Formal Capacity	Informal Capacity	Household Need Impact
1	500	500	2350	2350	2350	No
1*	35	70	1.7625	0.141	0.047	No
2	500	500	2350	2350	2350	No
2*	35	70	1.7625	0.141	0.047	No
3a	500	500	2350	2350	2350	No
3b	500	500	2350	2350	2350	Yes
3b*	35	70	1.7625	0.141	0.047	Yes
4a	500	500	2350	2350	2350	No
4b	500	500	2350	2350	2350	Yes
4b*	35	70	1.7625	0.141	0.047	Yes
5a	500	500	2350	2350	2350	No
5b	500	500	2350	2350	2350	Yes
5b*	35	70	1.7625	0.141	0.047	Yes
6a	500	500	2350	2350	2350	No
6b	500	500	2350	2350	2350	Yes
6b*	35	70	1.7625	0.141	0.047	Yes
7a	500	500	2350	2350	2350	No
7b	500	500	2350	2350	2350	No
7c	500	500	2350	2350	2350	No
8	500	500	2350	2350	2350	Yes
8*	35	70	1.7625	0.141	0.047	Yes
9	500	500	2350	2350	2350	Yes
9*	35	70	1.7625	0.141	0.047	Yes

Table A-3. The second set of specifications for each scenario.

Scenario	Can Agents be Laid off?	Can School Eligible Agents Search for Employment?	Can Students Leave School to Search for Employment?	Can Inactive Agents Search for Employment?	Do School Eligible Agents Search for School?	Does the Rumor Spread?	Are Rioters Created at Initialization?
1	No	No	No	No	No	No	No
1*	No	No	No	No	No	No	No
2	Yes	No	No	No	No	No	No
2*	Yes	No	No	No	No	No	No
3a	No	Yes	No	No	No	No	No
3b	No	Yes	No	No	No	No	No
3b*	No	Yes	No	No	No	No	No
4a	No	No	Yes	No	No	No	No
4b	No	No	Yes	No	No	No	No
4b*	No	No	Yes	No	No	No	No
5a	No	No	No	Yes	No	No	No
5b	No	No	No	Yes	No	No	No
5b*	No	No	No	Yes	No	No	No
6a	No	No	No	No	Yes	No	No
6b	No	No	No	No	Yes	No	No
6b*	No	No	No	No	Yes	No	No
7a	No	No	No	No	No	Yes	No
7b	No	No	No	No	No	No	Yes
7c	No	No	No	No	No	Yes	Yes
8	Yes	Yes	Yes	Yes	Yes	No	No
8*	Yes	Yes	Yes	Yes	Yes	No	No
9	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9*	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A-4 provides a summary of the expected and actual results associated with each scenario.

Table A-4. A summary of the expected and actual results for each scenario.

Scenario	Summary of Expected Results	Actual Results
1	All employed and those searching for employment should be employed in the formal or informal market.	As expected.
1*	All residents who begin employed at initialization should be employed in the formal or informal market. Those searching may be employed if employers within vision have not reached capacity. The number of students will be lower than Scenario 1 due to capacity restrictions.	As expected.
2	All employed and those searching for employment should be employed in the formal or informal market, resembling Scenario 1. However, at times there will be dips in the number employed and spikes in the number searching due to residents being laid off. The number of students should resemble Scenario 1.	As expected.
2*	Results should resemble Scenario 1*. However, at times there will be dips in the number Employed and spikes in the number searching due to layoffs (number employed will be slightly lower and number searching slightly higher than Scenario 1*). The number of students should resemble Scenario 1*.	As expected.
3a	All employed and those searching for employment should be employed in the formal or informal market. In addition, school eligible residents that are not in school, will search and find employment. However, since there is plenty of school capacity, this scenario should resemble Scenario 1.	As expected.
3b	School eligible residents that are not in school and have a household need will search for employment. However, since there is plenty of schools, this should resemble Scenarios 1 and 3a.	As expected.
3b*	Residents that could not find a school will search for employment if they have the household need. However, since employers are at capacity, these residents will struggle finding employment. Thus, results for number employed and number of students should resemble Scenario 1*. The number searching will be higher than Scenario 1* as it will now include the residents that did not find an available school.	As expected.

4a	Students over the age of 5 will leave school to search for employment, regardless of household income. The number employed should be higher and the number of student should be lower than Scenario 1. The only residents that will remain students are those 5 years or younger. The number in the formal sector should resemble Scenario 1 and the number in the informal sector is higher since former students can only work in the informal sector. The number searching is higher than in Scenario 1. The number inactive is lower than Scenario 1.	As expected.
4b	Students in households with inadequate income will leave school to search for employment. We should see dips in the student population and an increase in the informal sector population. The trend should resemble Scenario 4a with slightly lower numbers of employed and slightly higher number of students (since only those students with household need will leave school).	As expected.
4b*	Due to capacity restrictions, the number employed should be lower and the number searching higher than Scenario 4b, resembling Scenario 1*. The number of students should be lower than Scenario 1* as students leave school to find employment.	As expected.
5a	Inactive residents (that are not attending school or are under 6) will search for employment. The number of inactive residents should decrease (equaling the total number of students plus the number of residents under 6). The number employed should be higher than Scenario 1 as the formally inactive residents find employment. The number of students should resemble Scenario 1.	As expected.
5b	Inactive residents (that are not attending school or are under 6) in households with inadequate income will search for employment. The number of inactive residents should be higher and the number employed should be lower than in Scenario 5a (since only those inactive residents with household need will search for employment). The number of students should resemble Scenarios 1 and 5a.	As expected.
5b*	Due to capacity restrictions, the number employed and the number of students should resemble Scenario 1*. The number Searching will be higher than previous scenarios as formally inactive residents search for employment but struggle finding available jobs.	As expected.
6a	School eligible residents that did not find a school initially or that were working but now live in a household with adequate income, can search for a school to attend. However, since there is sufficient school capacity and household need is not a factor, this scenario should resemble Scenario 1.	As expected.

6b	School eligible residents that did not find a school initially or that were working but now live in a household with adequate income, can search for a school to attend. Because there are sufficient schools, there are no school eligible resident that did not find a school initially. Additional, the function that allows school eligible students to leave to work is not turned on in this scenario, so there will be no school eligible residents at home that could go to school. Results should resemble Scenario 1.	As expected.
6b*	Although school eligible residents can search for a school at any point in the simulation, due to capacity constraints and the fact that students do leave school in this scenario, these residents will not find an available school to attend. Results should resemble Scenario 1*.	As expected.
7a	While results should resemble Scenario 1, we should see that more residents have "heard" the rumor. While only 2 hear the rumor initially, by the end of a month, almost half of the residents have heard the rumor.	As expected.
7b	No one should riot as no one heard the rumor. Results should resemble Scenario 1.	As expected.
7c	No one should riot (other than initial rioters) as there are no "disgruntled" residents. However, we should see that more residents have "heard" the rumor. Results should resemble Scenario 1.	As expected.
8	The number employed should be higher than Scenario 1 as inactive residents and students will search for employment if there is household need. The number of residents searching will spike as residents are laid off. The number of students should resemble Scenario 4b, students with household need will leave school and search for employment.	As expected.
8*	The number employed should resemble Scenario 1* due to capacity constraints. There may be some decreases in the number employed and increases in the number searching as residents are laid off. The number of students should be lower than Scenario 1* due to the number of households with need. Even as spots are made available (as students leave to find work), it is likely that most residents will not be able to attend school due to household need. The number searching will be higher than previous scenarios since students that left school and inactive residents will search for employment and struggle to find a job due to capacity constraints.	As expected.
9	Since there is adequate employment and school capacity, residents will not get disgruntled and riot (with the exception of any initial rioters). Results should resemble Scenario 8.	As expected.
9*	Results should resemble Scenario 8* with the exception that rioting will occur.	As expected.

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BIOGRAPHY

Bianica Pires graduated from Plant City High School, Plant City, Florida, in 1997. She received her Bachelor of Science in Industrial & Systems Engineering (with highest honors) from the University of Florida in 2002. She went on to get her Master of Arts in International Business from the University of Florida and graduated first in her class in 2003. She entered the PhD program in Computational Social Science at George Mason University in 2007.

Upon receiving her master's in 2003, she worked in industry for nine years. During this time, she worked as a consultant for IBM from 2003 to 2011 on projects with various clients, both domestic and abroad. Her work focused mainly around data analysis and development of optimization and simulation models. In 2008 she reduced her hours at IBM to work as a part-time Graduate Research Assistant for the Volgenau School of Engineering at George Mason University. During her time at IBM, she received numerous awards and recognition, including selection to participate in a highly competitive program that sends IBMers to work with local NGOs on projects around the world. From 2011 to 2012 she worked as a project manager for a computer software start-up. In 2012, she left industry to focus on her dissertation full-time.

Her work in industry and academia has been presented at numerous conferences. Her paper on agent-based modeling of criminal organizations was selected for publication in a conference's post-proceedings. Bianica is a candidate for the PhD degree in Computational Social Science from George Mason University in June 2014.