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Modeling the emergence of riots: A geosimulation approach

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A B S T R A C T

Immediately after the 2007 Kenyan election results were announced, the country erupted in protest. Riots were particularly severe in Kibera, an informal settlement located within the nation's capital, Nairobi. Through the lens of geosimulation, an agent-based model is integrated with social network analysis and geographic information systems to explore how the environment and local interactions underlying Kibera, combined with an external trigger, such as a rumor, led to the emergence of riots. We ground our model on empirical data of Kibera's geospatial landscape, heterogeneous population, and daily activities of its residents. In order to effectively construct a model of riots, however, we must have an understanding of human behavior, especially that related to an individual's need for identity and the role rumors play on a person's decision to riot. This provided the foundation to develop the agents' cognitive model, which created a feedback system between the agents' activities in physical space and interactions in social space. Results showed that youth are more susceptible to rioting. Systematically increasing education and employment opportunities, however, did not have simple linear effects on rioting, or even on quality of life with respect to income and activities. The situation is more complex. By linking agent-based modeling, social network analysis, and geographic information systems we were able to develop a cognitive framework for the agents, better represent human behavior by modeling the interactions that occur over both physical and social space, and capture the nonlinear, reinforcing nature of the emergence and dissolution of riots.

1. Introduction

Riots can take many different shapes and forms but can be broadly defined as a type of contentious collective action that emerges when individuals without regular access to institutions act out on behalf of new or unrecognized rights to highlight their grievances (Tarrow, 1994). They can be driven by a variety of social and political grievances, including inequality (Jackman, 2002), resource scarcity issues (Auyero & Moran, 2007), or the unfair treatment of civilians by authorities (Stark, 1972). While riots have been studied within several disciplines, including sociology (e.g., Tucker, Schweingruber, & McPhail, 1999), physics (e.g., Pabjan & Pekalski, 2007), and military operations (e.g., McKenzie, Garcia, Nguyen, Seevinck, & Petty, 2004), this has not been the case within urban studies, especially when explored through the lens of geosimulation. Furthermore, geographically explicit agent-based models have been used to study a wide variety of urban phenomena from the bottom up—including residential mobility (e.g., Jordan, Birkin, & Evans, 2014), the growth of informal settlements (e.g., Augustijn-Beckers, Flacke, & Retsios, 2011), pedestrian movement (e.g., Torrens, 2012), and crime (e.g., Malleson, Heppenstall, & See, 2010)—but little attention has been paid to the utilization of spatial data in creating agent-based models of riots. We would argue that this is an important but overlooked area especially given the rising urban population and youth bulge (NIC, 2012), which is playing a defining role in the increase in riots (OECD, 2011). For example, immediately after the results of the 2007 presidential election were announced, Kenya broke-out in protest. Deep-rooted grievances, perceptions of government illegitimacy, and Kenya's long history of political and economic ethnic exclusion led many to believe that election results were rigged, which quickly escalated the protests to violence. Rioting would continue for nearly two months, resulting in 1100 deaths and up to 350,000 internally displaced people (De Smedt, 2009).

Kibera, an informal settlement located in Nairobi, became the “epicenter” of the riots that hit the city (International Crisis Group, 2008). A map of Kibera, divided into its fourteen neighborhoods, is shown in Fig. 1. According to Allport and Postman (1947), a rumor is necessary to “incite, accompany, and intensify” rioting. This was no different in Kibera, where the rumor that election results were rigged, serving as the external trigger, played a significant role in the riots (Dercon & Gutiérrez-Romero, 2011). Between cell phones, text messages and radio, rumors spread quickly (De Smedt, 2009). Approximately two months after the riots began, a power-sharing agreement was reached and the violence ceased almost immediately (De Smedt, 2009).

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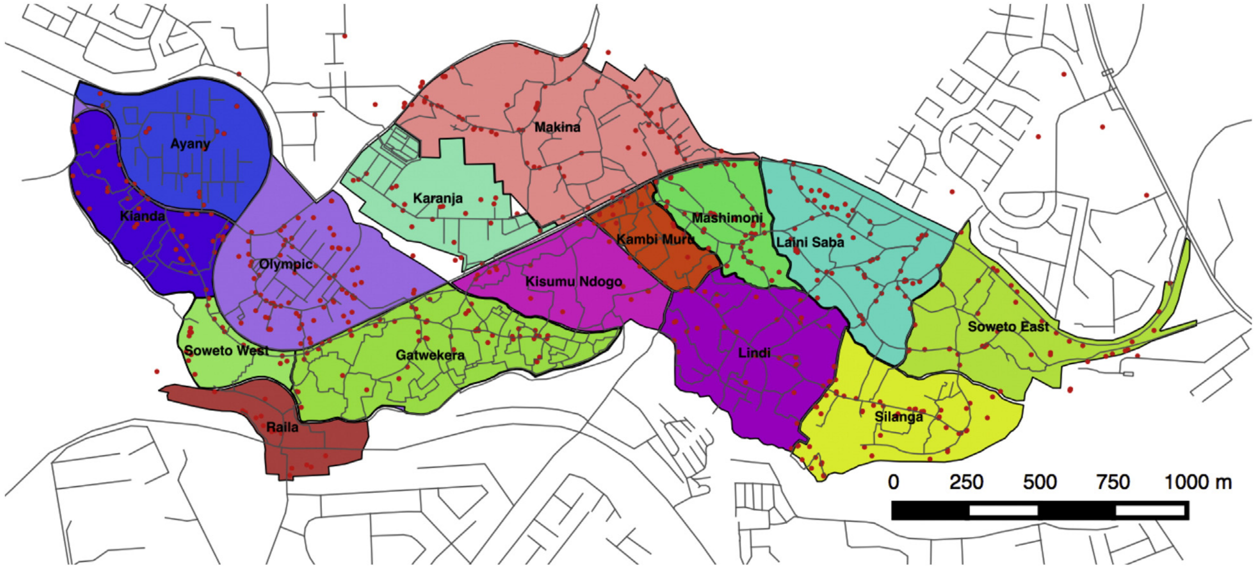


Fig. 1. A map of Kibera divided into its 14 neighborhoods. Points of interest, including schools, health facilities, and religious institutions are represented by red circles and the transportation network is represented by black lines. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The emergence of riots is a complex system; they arise from the interactions between individuals with distinct identities, interests, and needs, all within a connected social network over a physical environment (Torrens & McDaniel, 2013). In order to capture this complexity, in this paper we develop a theoretically grounded agent-based model (ABM) that integrates ABM with geographic information systems (GIS) and social network analysis (SNA) through the lens of geosimulation (Benenson & Torrens, 2004). We focus in particular on the individuals' decision to participate (or not) in collective action that may lead to riots, which incorporates the unique socioeconomic and environmental factors of Kibera, the local interactions of its residents, and an external trigger in the form of a rumor. Furthermore, as we attempt to balance complexity with parsimony, we seek to ground the model as much as possible in theory and/or empirical data (O'Sullivan et al., 2012). It should be noted that for simplification purposes, we do not incorporate additional factors introduced after the riots breakout (e.g., the role of police) as this is not the focus of the paper. While other studies have explored the use of ABM, GIS, and SNA with respect to riots, most have explored the techniques in isolation, which will be discussed in Section 2. We will argue that the integration of the techniques allows us to create models that can better capture the interconnected and nonlinear dynamics associated with the emergence of riots; allowing us to capture elements in the real world that may be missed using the techniques in isolation—our interactions are affected by both our physical distance and our social networks. The riots that took place in Kibera in 2007 are used as inspiration in the development of the simulation presented here. However, we take a "generative" approach to modeling riots, which we ground in theory, as the purpose is not to model the exact timing and outbreak of riots but to see if riots emerge through the interplay of ABM, GIS, and SNA. In the remainder of this paper, we will provide a background into theories of human behavior relevant to the riots (Section 2), discuss the details regarding development of our geosimulation model (Section 3), show the results from the model (Section 4), and summarize the paper (Section 5).

2. Background

In order to effectively construct a model of the emergence of riots, it is important to briefly review the spectrum of literature. This ranges from exploring human behavior, specifically that related to the decision to participate in collective action and riotous behavior (Section 2.1), the external triggers that influence a person's decision to riot (Section 2.2), and how researchers have attempted to incorporate such behaviors within previous models (Section 2.3).

2.1. A unified theory of identity

Modeling human behavior is not a simple task; humans neither behave randomly nor act perfectly rational (Simon, 1996). To this end, theorists have moved away from rational choice theory (e.g., Lichbach, 1995) and relative deprivation (e.g., Gurr, 1970), and have stressed group identity as the driver of internal conflict and the emergence of riots (e.g., Brubaker & Laitin, 1998). Identity theory focuses on the concept of identities as *roles* (McCall & 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 & 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 & Turner, 1979). Such identification with a social group can lead to the differentiation between "we" and "they" when faced with an opposing group (Stein, 2001), and to intragroup cohesiveness and cooperation when intergroup conflict exists (Tajfel & Turner, 1979), which can allow for group mobilization for purposes of social movements. Individuals have an array of identities (Oyserman, Elmore, & Smith, 2012) and by combining *role*-based and *group*-based identities into one theory, Stets and Burke (2000) integrate collective identity with the individual, heterogeneous identities of group members, allowing for the dynamic modeling of individual and group identities under one theory.

It has been argued that an identity has four main components: an *Input*, an *Identity Standard*, a *Comparator*, and an *Output* (Stryker & Burke, 2000). Furthermore, the identity model as shown in Fig. 2 requires aspects of both the inner and outer environments. The inner environment is the person itself (shown as the blue shaded areas) and the outer environment is the person's surrounding (shown as the green shaded area). This can be compared to Simon's (1996) view of inner and outer environments, where the inner environment is the artifact itself (in this case, the person) and the outer environment is the surroundings for which the artifact operates. The person seeks a particular goal in the outer environment, in this case, to meet the *Identity Standard*, and this in turn dictates the processes of the inner environment. The outer environment thus goes beyond geographical space to include our complete surroundings, such as meaningful feedback from others (i.e., reflected appraisals) and others perception of our

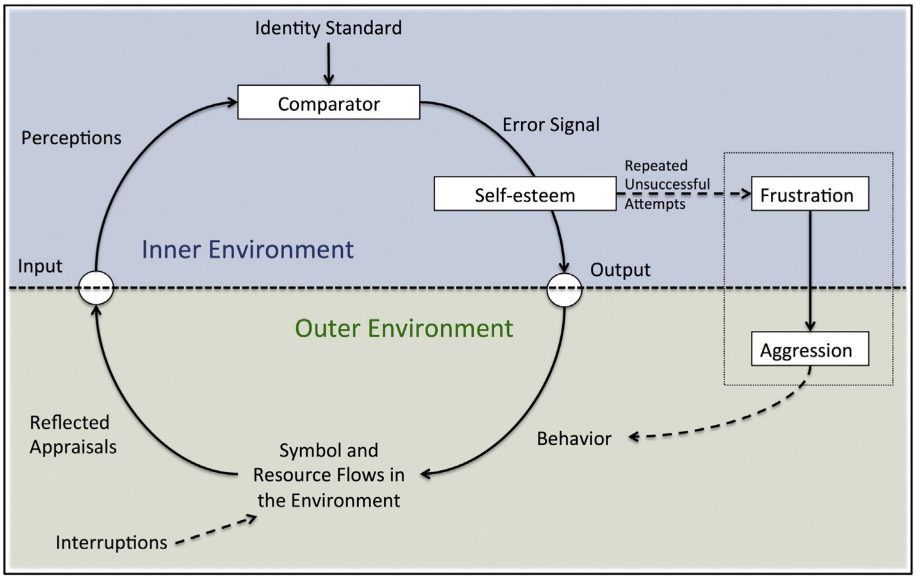


Fig. 2. The identity model and the frustration-aggression hypothesis (adapted from Burke & Stets, 2009; Green, 2001).

actions. The outer environment determines the conditions for goal attainment (the goal is to match environmental inputs to the *Identity Standard*). Perceptions, which make-up what we see of the outer environment, comprise the *Input*.[1] (Stryker & Burke, 2000). Our perceptions are driven by our surroundings (i.e., outer environment), which are effected by our routine activities. Moreover, these routine activities can be said to be driven by humanistic needs theory. Maslow (1954) developed a hierarchy of needs which include physiological, safety, love and belonging, and self-esteem. The *Comparator's* role is to compare the perceptions associated with the identity to the *Identity Standard*. The *Comparator* will then produce an error signal—the difference between the perceptions and the *Identity Standard*. A large error signal can be a sign of an interruption, such as a rumor. The *Output* forms the behavior of the person, which occurs in the outer environment and is based on the error signal. Thus, the relationship between perceptions and the *Identity Standard* predicts behavior (Stryker & Burke, 2000).

This process, known as the identity verification process, forms a continuous feedback loop. Perceptions are continuously fed into the system and behavior adjusted as the individual seeks to represent the *Identity Standard*. If successful, the result includes increased commitment to others with the same identity and increased self-esteem, which produces a reservoir of "energy" (Burke & Stets, 2009). If unsuccessful, however, the reservoir of energy diminishes and self-esteem lowers (Cast & Burke, 2002). Similarly to other accumulator models (e.g., Schurger, Sitt, & Dehaene, 2012), which provide a quantitative means for modeling the time-lapse in human decision-making processes between receiving information and executing a response (Smith & Ratcliff, 2004), the reservoir of energy allows one to continue working towards meeting one's *Identity Standard* even after unsuccessful attempts (Burke & Stets, 2009). Depletion of the reservoir of energy, however, can potentially result in increased distress or frustration (Green, 2001). According to the frustration-aggression hypothesis, frustration produces the environment for which one can aggress, such as by rioting. 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. On the other hand, a lack of personal resources such as education and support from family, can hinder the identity verification process. The unified theory allows one to consider behaviors from the "more mundane expectations for a person occupying a role," such as going to work or school (Stryker & Burke, 2000), to meso- and macro-level formation of cohesive groups, which can lead to riots.

2.2. External triggers that influence rioting behavior

Extensive studies have looked at why peaceful individuals may select to participate in contentious collective action, a step that often precedes violent behavior (e.g., Bhavnani, Findley, & Kuklinski, 2009). One thing that has been shown to influence riots is the notion of rumors (Allport & Postman, 1947), such as in the case of Kibera (Dercon & Gutiérrez-Romero, 2011). As discussed in Section 2.1, a rumor can serve as an interruption in the identity model, which can in turn, impact one's output behavior. 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" (Strang & Soule, 1998). In the case here, we assume "something" to be a rumor. In addition, social networks play a key role in this diffusion process, both in terms of spreading the rumor and in terms of being influenced by the rumor. Many people will hear the rumor but whether they will be influenced to act on the rumor is largely based on the spread of the information through personal ties and the diffusion of social influence through their networks (Granovetter, 1973), such as in social influence network theory where a recipient's final opinion on an issue, which is reflected in their perceptions (see Section 2.1), is a function of their initial opinion on the issue, their relative interpersonal influence, and their susceptibility to influence (Friedkin, 2001). 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, such as riots. In this paper, through the integration of ABM, SNA, and GIS, the opinion formation process, the identity model, and the frustration-aggression hypothesis, which together determine whether an individual will choose to participate in riotous behavior as a response to a rumor, can be studied.

2.3. Prior models of civil unrest

As one can imagine, civil unrest has been an active research area from a variety of research approaches. Some models have taken a

[1] It should be noted that the use of *input* here is not the same as input data or input parameters (Section 3.3.2). Accordingly, throughout the rest of the paper the term *input* will be followed by parameter or data. Otherwise, input refers to the agents' outer environment as outlined by identity theory. Similarly, the term *output* here refers to the agents' action (behavior) and is not the same as model output (Section 3.3).

complexity approach to the analysis of empirical conflict data (e.g., Bohorquez, Gourley, Dixon, Spagat, & Johnson, 2009), other studies have looked for spatiotemporal patterns in event data (e.g., Baudains, Johnson, & Braithwaite, 2013; Davies, Fry, Wilson, & Bishop, 2013), or have combined SNA techniques with GIS to explore criminal networks (e.g., Radil, Flint, & Tita, 2010). While such models have proven useful, they are not well suited to modeling the interactions between individuals (Epstein, 2009). Furthermore, populations are often treated at the aggregate-level with an inability to explore the heterogeneity of individuals and their behaviors. Overcoming some of these challenges, ABM has the ability to model the dynamic interactions between heterogeneous agents (Gilbert & Troitzsch, 2005). Moreover, by linking ABM to SNA and GIS we can explore complex systems, such as riots, over social and physical space. One of the earliest models of collective behavior from the bottom-up, accounting for individual preferences and their interactions, was Granovetter (1978). With respect to ABMs, researchers have studied the emergence of civil unrest from the interactions of many individuals (e.g., Durupınar, 2010; Goh, Quek, Tan, & Abbass, 2006; Jager, Popping, & Van de Sande, 2001), with Epstein's (2002) models of civil violence probably being the most notable. However, with respect to riots in urban settings, there are very few ABMs. Most that do exist (e.g., Torrens & McDaniel, 2013), can be seen as extensions of Epstein's (2002) civil violence model with respect to the use of threshold values in the decision-making process of the agents. Others are set in abstract environments (e.g., Bhat & Maciejewski, 2006; Casilli & Tubaro, 2012) and while some models are more geographically explicit and behaviorally rich with regards to human movement, no explicit mechanisms for the incorporation of social networks were implemented. For those ABMs that have explored the use of social networks with respect to conflict (e.g., Berry et al., 2004; Epstein & Axtell, 1996), only few explicitly explored identity theory (e.g., Bhavnani et al., 2009; Kim & Hanneman, 2011), and none were geographically explicit. While the model presented here builds on the ideas behind many of the prior models of civil unrest, it is the first to integrate GIS, ABM, and SNA. We believe that this is important because, as discussed above, we know that riots are triggered by influence through our social networks and our physical environment, and its only by connecting these three techniques that we can model the individual interactions of agents from the bottom up over physical space (using GIS) and social space (using SNA). Moreover, using ABM we can capture human behavior through a theoretically grounded cognitive framework.

3. Conceptual model

An ABM was developed in MASON (Luke, Cioffi-Revilla, Panait, Sullivan, & Balan, 2005) to explore the onset of riots in Kibera. The following description of the model is given using an adapted version of the Overview, Design Concepts, Details, and Human Decision-Making (ODD + D) protocol (Müller et al., 2013). A more detailed ODD + D, the source code, and data to run the model can be downloaded from https://www.openabm.org/model/4865/. This section provides an overview of the model's purpose and variables (Section 3.1), the general concepts underlying the model's design (Section 3.2), and the details of the model's implementation and output (Section 3.3).

3.1. Overview

3.1.1. Purpose

The purpose of the model is to explore how the unique socioeconomic variables underlying Kibera, local interactions, and the spread of a rumor, may trigger a riot. As discussed above, an ABM is integrated with SNA and GIS for this purpose. This integration facilitates the modeling of dynamic social networks created through the agents' daily interactions. GIS is used to develop the physical environment for agents to move and interact that includes a transportation network and points of interest. In this baseline model we focus largely on the factors that lead to the emergence of riots. However, as will be discussed in Section 4, we also observe the dynamics of the riots as they progress in the simulation. While we take a simplistic approach (e.g., the only exogenous variable we incorporate is the rumor), we were still able to gain insights into the micro-level dynamics associated with rioting (as will be discussed in Sections 4 and 5). Further work could extend this model by capturing the dynamics within the riot itself, such as violent confrontation with the police and rival ethnic groups.

3.1.2. Entities, state variables and scales

The model contains the following entities, from lowest to highest hierarchical scale: (1) *Resident* (individual), (2) *Household*, (3) *Home, Business*, and *Facility*, (4) *Structure*, (5) *Parcel*, (6) *Population*, and (7) *Environment*. Fig. 3 illustrates a high-level Unified Modeling Language (UML) diagram of the model. There are two types of agents modeled, the *Resident* and the *Household*. The main agent is the individual *Resident*, while a group (or unit) of *Residents* makes up a *Household*. Furthermore, *Residents* and *Households* are characterized by a set of attributes (i.e., state variables and parameters) such as age, gender, ethnicity, and income. The ethnicity attribute serves two purposes in the model: (1) the placement of *Residents* in *Homes* at model initialization and (2) the similarity (i.e., homophily) effect present in social influence networks (see Section 3.3.3.3). Moreover, in terms of ethnic diversity, Kibera mirrors Kenya, with every Kenyan ethnicity represented (De Smedt, 2009). Thus, in our model, each ethnicity is represented proportionally to Kenya's ethnic distribution. Note that while ethnicity is incorporated in the model, we do not model ethnic intergroup violence. For simplifications purposes, in this baseline model we chose to focus on the individual's decision to join (or not) one collective group, which we ground in theory (as discussed in Sections 2.1 and 2.2).

Households must select a *Home* for which to live based on predefined preferences (i.e., the ethnic make-up of a neighborhood) and affordability (e.g., Benenson, Omer, & Hatna, 2002). While general ethnicity maps exist (e.g., De Smedt, 2009), they are at relatively course scale and thus, precise location and exact distribution of the ethnic population is not available, therefore a simplified approach based on the notion of residential segregation (e.g., Schelling, 1978) was used to place *Households* into *Homes*. *Homes* are assigned a monthly rent and a set of amenities, including electricity, water, and sanitation (Marras, 2008). A *Facility* can be one of many, including schools, health facilities, and religious institutions (see Section 3.3). A *Parcel* represents a piece of land within the modeling area and is characterized by a unique grid location. *Structures*, *Water Points*, and the transportation network are located on *Parcels*.

While there is a wealth of literature pertaining to the role of government (e.g., King, 2013) and police in responding to riots (e.g., Wilkinson, 2006), we chose to only model government through the exogenous rumor (e.g., the disputed election results) and the police were not modeled as our focus is on the emergence of riots, not on their control. In a survey conducted by Dercon and Gutiérrez-Romero (2011), the majority of respondents believed that the election had been rigged and this is what triggered the riots, not the police.

The total population of Kibera is estimated to be between 235,000 and 270,000 (Marras, 2008). The *Environment* measures 3.9 by 1.5 km with a *Parcel* size of 12.5 m by 12.5 m (Marras, 2008). It is created by importing a set of GIS files, including the modeling boundaries, the transportation network (roads and walking paths), and the grid location of *Facilities*. Thus, space is modeled explicitly and is based on the actual landscape of Kibera. More information about the input data in the model can be found in Section 3.3.2. The model proceeds in one minute time steps and is run for three simulation weeks. In other models exploring riots, time steps are often not explicitly defined (e.g., Casilli & Tubaro, 2012; Epstein, 2002). Given the importance of social networks in our model and the impact that daily activities has on the creation of these networks, we wanted to be explicit about when and where the agents perform these activities, requiring that we define each time step. A minute was selected because the spread of the rumor, the

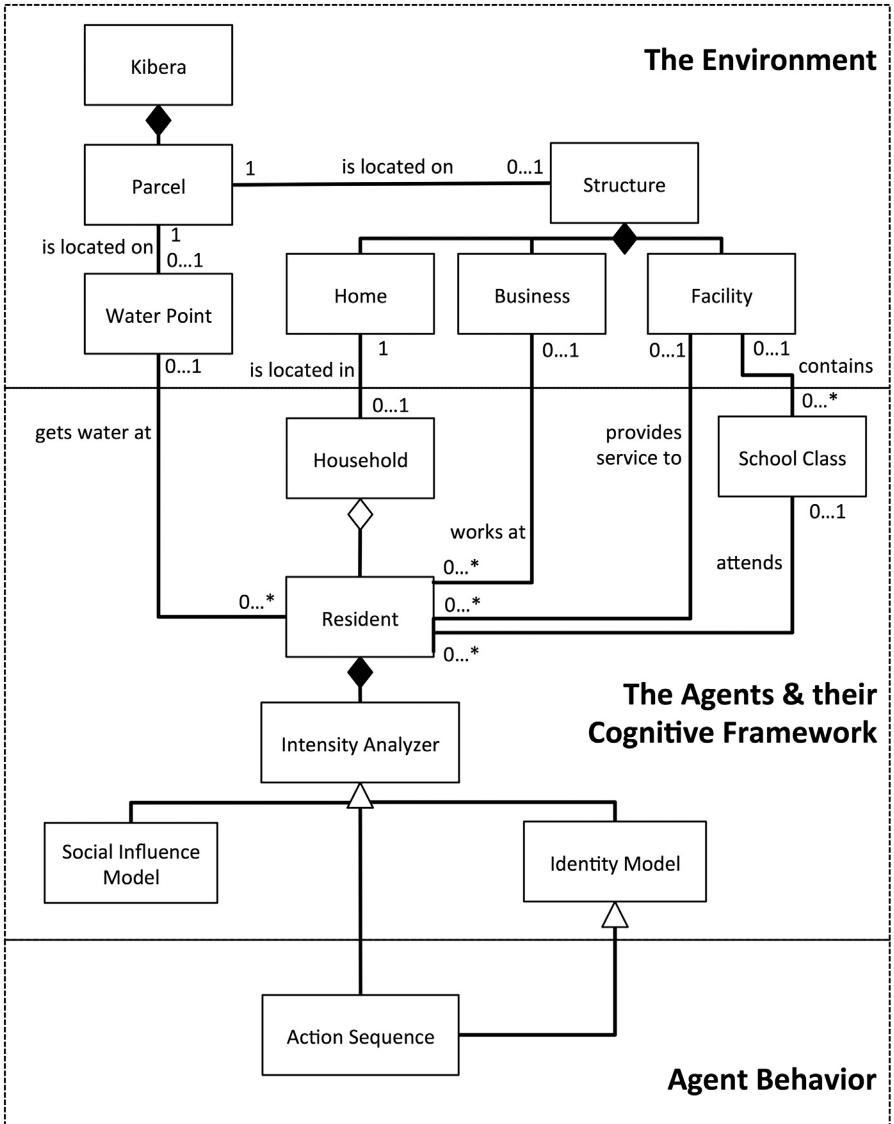


Fig. 3. The high-level UML diagram of the model.

decision to riot (or not), and the mobilization of residents occurred quickly after elections were announced (Chege, 2008). While human decision-making can occur over seconds, minutes, hours, days, or even years, a minute allows us to capture the individual interactions and activity patterns that are important to the development of social networks (Torrens, 2014).

3.1.3. Process overview and scheduling

At the beginning of the simulation, *Residents* run the Daily Activity Scheduler (see Section 3.3.3.1), which determines the activity they will perform. They will then execute the action sequence associated with performing the activity, including using the transportation network to move to the location of the activity (e.g., walking from *Home* to school). While at an activity, the *Resident* will establish new and/or strengthen any existing relationships with other *Residents*; run the Identity Model (see Section 3.3.3.2); and run the Rumor Propagation and Social Influence Model if the *Resident* has heard the rumor (see Section 3.3.3.3). Furthermore, *Residents* that have heard the rumor will randomly select another *Resident* performing the same activity at the same place and time in its social network to share the rumor with. Thus, these processes run once with each change in a *Resident's* activity. Note that while *Residents* do not seek out those with similar ethnicity in establishing relationships, *Residents* are more likely to share ties with others of the same ethnicity given the residential segregation approach used in the model's initialization (see Section 3.1.2). The output from the Identity Model and the Rumor Propagation and Social Influence Model will determine if the *Resident* will riot or remain peaceful. If the *Resident* riots, they will congregate with other rioters. At completion of each activity, including rioting, the *Resident* will return *Home* whereby *Resident* and *Household* variables such as employment status and income will update accordingly. Finally, the *Resident* will evaluate its next action by re-running the Daily Activity Scheduler, the Identity Model, and the Rumor Propagation and Social Influence Model, if appropriate.

3.2. Design concepts

The *decision-making* process is modeled at two levels: the *Resident* and the *Household*. *Residents* make decisions around what their daily activities will be for that day (e.g., going to work, getting water) and whether they will riot or remain peaceful. At the household-level, *Households* make decisions around their daily expenditures (e.g., food, rent, water). Depending on income, *Households* will dynamically adjust their expenditures to reflect a decrease or increase in income (Gulyani & Talukdar, 2008). With respect to *sensing*, *Residents* know their household income and expenditures. How much a *Household* can spend on certain household expenditures is proportional to their total income (e.g., Alonso, 1964). *Residents* will seek to make sufficient income by finding employment, which can include pulling younger *Household* members from school (Erulkar & Matheka, 2007). In addition, when a *Household's* water supply is short, a *Resident* will be required to purchase more water for the *Household* (Gulyani & Talukdar, 2008). *Residents* are also aware of who in their social network is rioting (see Sections 2 and 3.3.3). *Residents* are *heterogeneous* in terms of their demographic data, including age, ethnicity, gender, and employment status (see Section 3.3.1). Within the model at the global level, we *observe* the following statistics: the number of *Residents* that rioted, the number of *Residents* that remained peaceful, the individual demographics of the *Residents* and *Households*, and the total number of *Residents* carrying out each specific activity. Statistics are collected by time step so that changes in behavior or trends can be easily assessed. With respect to *emergence*, the outbreak and intensity of the rioting is an emergent phenomenon. The decision to riot occurs through the simple interactions of individual *Residents* with each other at the micro-level.

3.3. Details

3.3.1. Initialization

Upon model initialization, the *Environment* is created. *Parcels* and the transportation network are added; *Structures* and *Water Points* are placed on *Parcels*; and *Homes*, *Businesses*, and *Facilities* are added to *Structures*. All *Facilities* have an associated grid location based on data from OpenStreetMap (2013) and are placed within *Structures*. The number of *Homes* and *Businesses* within a *Structure* was estimated from survey data (Marras, 2008) (see Section 3.3.2). Next, individual *Residents* are created and assigned into *Households*, which are then added to *Homes* (see Section 3.1.2).

Once this *Environment* is created and all *Residents* have been assigned to a *Home*, they are given one of the following employment statuses: employed in the formal sector, employed in the informal sector, searching for employment, or inactive. At initialization, youth (any *Resident* under the age of 18) are assigned the employment status of inactive, while the employment status for the remaining *Residents* is based on empirical data (Kenya National Bureau of Statistics, 2009a) and on the informality index from the UN-HABITAT (2003).

Next, all employed *Residents* and youth search for an employer or school, respectively, which is geographically near and has not reached a maximum allowable capacity (see Table 1). Employed *Residents* that cannot find an available employer are assumed to work outside of Kibera. Once the *Resident* has found an available employer or school, it is assigned to that *Facility* or *Business* so that it goes to the same location moving forward. In addition, students are assigned to a *School Class*, ensuring that they interact mostly with a smaller subset of students in a school. We had to make these simplifying assumptions because while we had good data on the environment (see Section 3.3.2), information pertaining to individuals and their activity patterns was lacking. This is common in many less developed countries, which often lack reliable quantitative data with respect to populations and workforce (Henderson, Storeygard, & Weil, 2012). Finally, a specified number of *Residents* are randomly selected to hear the exogenous rumor at initialization. Of those that hear the rumor, a proportion will be selected to be influenced enough by the rumor to riot (see Table 1). Those initial rioters will attempt to influence other *Residents* as the simulation runs (see Section 3.3.3.3).

3.3.2. Input data

The two main data sources used to create the modeling *Environment* were Map Kibera (Hagen, 2011) and the Map Kibera Project (Marras, 2008). Via OpenStreetMap (2013), Map Kibera provided GIS files pertaining to the boundaries, the transportation network, and the geocoded locations of *Facilities* (Hagen, 2011). The estimated locations and attributes of *Structures* came from the Map Kibera Project (Marras, 2008). In order to create the *Residents* and *Households*, we synthesized data from a variety of sources, including Marras (2008), De Smedt (2009), Kenya National Bureau of Statistics (2009a), and UN-HABITAT (2003). In addition, much of the costs associated with the *Households* were from a study performed by Gulyani and Talukdar (2008) of over 1700 households in Nairobi's informal settlements. Table 1 summarizes the input parameters used within the model.

3.3.3. Submodels

While theory gives us a grounded understanding of human behavior (see Section 2.1), the question remains as to how we incorporate such a diverse range of topics into a model. There are several cognitive frameworks one could use, such as BDI (Belief-Desire-Intention) and the PECS (Physical conditions, Emotional state, Cognitive capabilities, and Social status) framework (see Kennedy, 2012 for a review). Here we chose the PECS framework (Schmidt, 2000) because it is flexible in its ability to model simple stimulus-response behaviors and more elaborate reflective behaviors but at the same time provides more guidance than other cognitive frameworks for implementing human behavior in ABMs (Malleson, 2008). Furthermore, it allows us to take into account both the *Residents'* identity (see Section 2.1) and external interactions which may cause a change in the *Residents'* activities. In addition, PECS is not constrained to the use of the three components of beliefs, desires, and intentions, which has been criticized by classical decision theorists for being overly complicated and researchers in sociology for being too restrictive (Rao & Georgeff, 1995). A high-level representation of the *Residents'* behavior within the PECS framework is shown in Fig. 4. Three submodels were created in order to capture the full spectrum of behaviors that theory suggests leads to the emergence of riots (see Section 2), specifically the Daily Activity Scheduler, the Identity Model, and the Rumor Propagation and Social Influence Model. The following sections will outline how these submodels are linked to the PECS framework using the common PECS vocabulary.

3.3.3.1. The daily activity scheduler. The first step in determining the *Residents'* behavior is to run the Daily Activity Scheduler, which drives the *Residents'* daily activities. As discussed in Section 2.1, *Residents* will strive to meet Maslow's (1954) hierarchy of needs, which can in turn, be said to drive their routine activity patterns. This association is shown in Table 2.

The Daily Activity Scheduler (illustrated as green lines in Fig. 4) begins with a set of available activities. *Perceptions* from the *Environment* (e.g., employment and school availability) are combined with individual characteristics (e.g., age, gender, and religion) in *Physis*, employment or student position in *Social Status*, and other characteristics that require memory (e.g., assigned school location) in *Cognition*, to help drive the activity the *Resident* will strive to complete. *Cognition* will generate the action (activity) sequence for more complex activities (e.g., searching for employment), simple actions will go straight to *Behavior* (e.g., staying *Home* to sleep), and the *Actor* component will execute the action.

Upon determining an activity to perform, *Residents* use the transportation network to move to the activity location (see Section 3.1.3). While at an activity, it is assumed that *Residents* interact with other *Residents* located at the same location and performing the same activity (Stets & Burke, 2000). 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 (Wasserman & Faust, 2009). Without the incorporation of GIS data, these network ties would not be geographically captured. Furthermore, as discussed in Section 2, social networks are very important with respect to social influence. In order to capture this, the weight of each tie w_{ij} between two *Residents* i and j is calculated after one of the *Residents* has completed an activity. A weight of one at the end of a day would signify that two *Residents* spent the

Table 1
Input parameters and variables.

Parameter	Range	Default values	Reference
Residents			
Preference for living near neighbors of the same ethnicity	0–1	0.5	Adapted from De Smedt (2009); Schelling (1978); Authors estimation
Probability that a *Resident* heard the rumor at initialization	0–1	0.001	Authors estimation
Probability that a *Resident* (that heard the rumor) riots at initialization	0–1	0.025	Authors estimation
Age	Age ranges	0–2, 3–5, 6–18, 19+	Marras (2008)
Gender	Male or female	M/F	Marras (2008)
Ethnicity	1–12	1–12	CIA World Factbook (2013); De Smedt (2009)
Religion	1–3	1–3	CIA World Factbook (2013); Marras (2008); Pew Forum on Religion & Public Life (2010)
Employment status	1–4	1–4	Kenya National Bureau of Statistics (2009a); UN-HABITAT (2003)
Identity	1–5	1–5	Adapted from Burke and Stets (2009); Authors estimation
Income	≥0	Empirical distribution	Gulyani and Talukdar (2008); Lorenz (1905)
Aggression	0–1	0	Adapted from Green (2001); Authors estimation
Aggression threshold	0–1	0.6	Adapted from Green (2001); Authors estimation
Aggression rate	0–10	6	Adapted from Green (2001); Authors estimation
Energy	0–100	100	Adapted from Burke and Stets (2009); Authors estimation
Energy rate of change	0–100	50	Adapted from Burke and Stets (2009); Authors estimation
Opinion threshold	0–1	0.1	Adapted from Friedkin (2001); Authors estimation
Employment vision	0–312	70	Authors estimation
School vision	0–312	35	Authors estimation
Probability of losing employment	0–1	0.01	Authors estimation
Households			
Number of *Household* members	≥1	, $\ln\mathcal{N}(3.55, 1.61)$	Marras (2008)
Maximum number of *Households* in a *Home*	≥0	Empirical distribution	Marras (2008)
Monthly cost for rent (Ksh)	>0	Empirical distribution	Marras (2008)
Per barrel cost of water (Ksh)	>0	2.5	Gulyani and Talukdar (2008)
Monthly cost of electricity (Ksh)	≥0	286	Gulyani and Talukdar (2008)
Per visit cost of using public sanitation (Ksh)	>0	5	Gulyani and Talukdar (2008)
Daily transportation cost (Ksh)	≥0	9.68	Gulyani and Talukdar (2008)
Per meal cost of food (Ksh)	>0	14	Gulyani and Talukdar (2008)
Facilities			
Probability that a *Home* has electricity	0–1	0.6	Marras (2008)
Probability that a *Home* has sanitation	0–1	0.03	Marras (2008)
Maximum number of students at a school	>1	18	Ministry of Education (2007)
Maximum number of students in a class	>1	23	OpenStreetMap (2013)
Maximum number of employees at a formal employer	>1	13	Ministry of Education (2007); OpenStreetMap (2013)
Maximum number of employees at an informal employer	>1	5	UN-HABITAT (2003)
Structures			
Probability that a *Structure* has *Homes*	0–100	0.86	Marras (2008)
Probability that a *Structure* has *Businesses*	0–100	0.13	Marras (2008)
Maximum number of *Homes* in a *Structure*	>1	Uniform (1, 5)	Marras (2008)
Maximum number of *Businesses* in a *Structure*	>1	Uniform (1, 3)	Marras (2008)

Note: The applicable exchange rate is US$1 = Ksh75.

entire day together. The weight of a tie at time t is $w_{ij}(t)$ and is calculated as shown in Eq. (1).

$$w_{ij}(t) = w_{ij}(t-x) + x/m, \tag{1}$$

where $w_{ij}(t-x)$ is the previous weight of the tie between the two *Residents* i and j, x is the amount of time the *Residents* stayed at the activity where both *Residents* were present, and m is the number of minutes in one day. Fig. 5 provides an illustration of how the social networks of ten *Residents* can evolve across two full days (the thicker the line, the greater the tie strength).

3.3.3.2. The identity model. The relationship between the Daily Activity Scheduler and the Identity Model (shown as red lines in Fig. 4) is a continuous feedback loop. The activity a *Resident* performs as per the Daily Activity Scheduler helps inform the *Resident* of their ability to match its Identity Standard (see Section 2.1). Meanwhile, the identity a *Resident* is striving to meet drives the activities it may look to perform. For example, a *Resident* under the age of 18 will strive to meet the Student identity by going to school. If the *Resident* 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. As an exploratory model, the rules for meeting an Identity Standard were kept simple.

As discussed in Section 2.1, the unified theory of identity (Stets & Burke, 2000) accounts for both role- and group-based identities, allowing us to dynamically activate a given set of identities. The model assumes all *Residents* seek to meet the Identity Standard of one of three *role*-based identities (Domestic, Student, and Employee) and two *group*-based identities (Ethnicity and Rioter). The activation of a role-based identity is directly impacted by its accessibility and fit in a specific situation, a function of the activity being performed as per the Daily Activity Scheduler. On the other hand, the Rioter identity is only activated should issues arise in the identity verification process of one of the role-based identities and should the *Resident* be influenced through its social network to riot (see Section 3.3.3.3). It is this identification with a social group (i.e., rioters) that allows for group mobilization and collective behavior (see Section 2.1). Once the identity

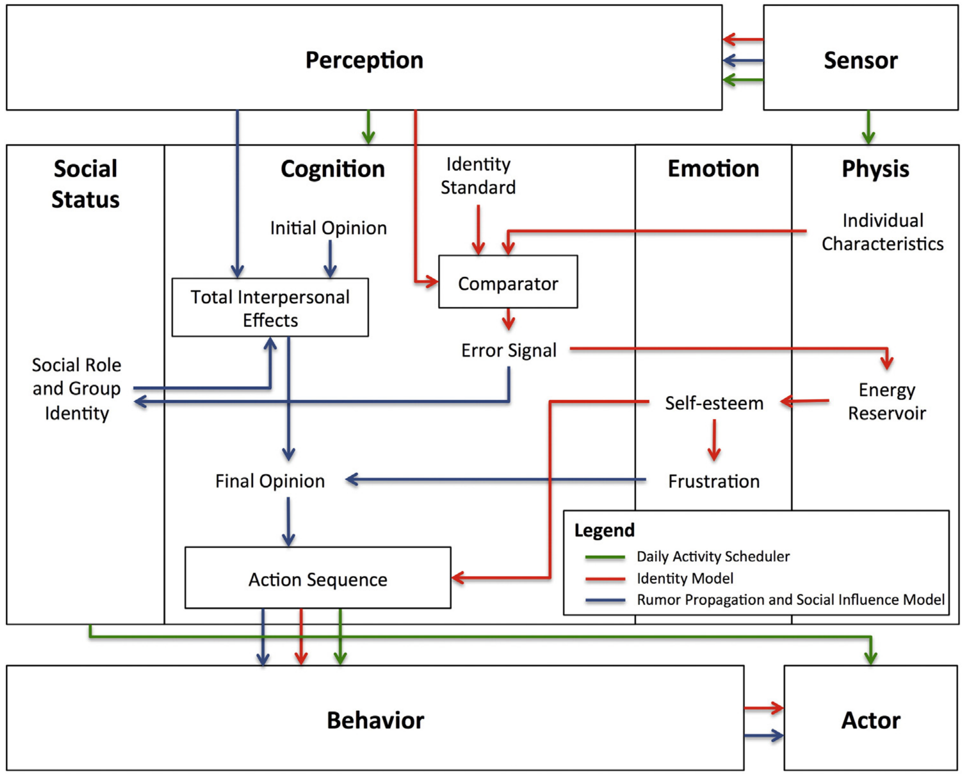


Fig. 4. A high-level representation of the *Residents'* behavior incorporated into the PECS framework (adapted from Schmidt, 2000).

verification process is complete, the individual *Resident* will compare the output behavior of the identity with the Identity Standard, producing an Error Signal (see Fig. 2). This results in an increase or decrease in the Energy Reservoir, which is calculated by using Eq. (2).

$$\Delta energy = energy\ \ rate\ \ of\ \ change * \Delta time, \tag{2}$$

where *energy rate of change* is the rate at which a *Resident's* Energy Reservoir is depleted or replenished and Δ *time* is the amount of time a *Resident* has performed the current activity divided by the number of minutes in a day. If there is no error, the Energy Reservoir is increased by the Δ *energy* and Self-Esteem goes up. *Cognition* will then generate the Action Sequence associated with that identity, *Behavior* will then determine the output behavior, and the *Actor* component will execute the actions associated with the *Resident's* identity. However, should issues begin to arise in the identity verification process (e.g., a *Resident* is unable to find employment), an Error Signal is produced, the Energy Reservoir is reduced, and Self-esteem goes down. A logistic curve is used to represent *Resident i's* level of aggression a_i in the model and is a function of the maximum aggression level a_{max}, *the Resident's* current energy level in the Energy Reservoir l_i, the midpoint of the curve l_o, and aggression rate r, which impacts the steepness of the curve (see Table 1). This is represented by Eq. (3).

$$a_i = \frac{a_{max}}{1 + e^{-r(l_i - l_o)}}. \tag{3}$$

Once a *Resident's* aggression falls below the aggression threshold, the *Resident* may riot, potentially activating the Rioter identity. As shown in Fig. 2, frustration from unsuccessful attempts at meeting one's Identity Standard can lead to aggressive behavior. Whether this aggression will emerge in the form of riotous behavior is further evaluated in the Rumor Propagation and Social Influence Model.

3.3.3.3. The Rumor propagation and the social influence model. A *Resident's* final decision on whether to riot is based on several factors, including whether or not the *Resident* has heard the rumor, the output of the Identity Model, which theory tells us can lead to collective behavior (see Sections 2.1 and 3.3.3.2), and the *Resident's* shared opinion of the rumor, which is based on Friedkin's (2001) social influence network theory for determining opinion formation (see Section 2.2) and is

Table 2
Maslow's (1954) hierarchy of needs and associated activities in the model.

Need	Influencing factors	Activity	Activity location
Physiological	Food, water, sanitation must be purchased	Go to work	Work
		Get water	Water point
Safety	Personal security (e.g., shelter), financial security (e.g., employment, knowledge acquisition)	Go to work	Work
		Go to school	School
		Search for employment	Home
Love and belonging	Spending time with family and friends, sense of community	Stay at home	Home
		Socialize	Home or friend's home
		Attend a religious institution	Religious institution
Esteem	Successful attempts at the identity verification process	n/a	n/a

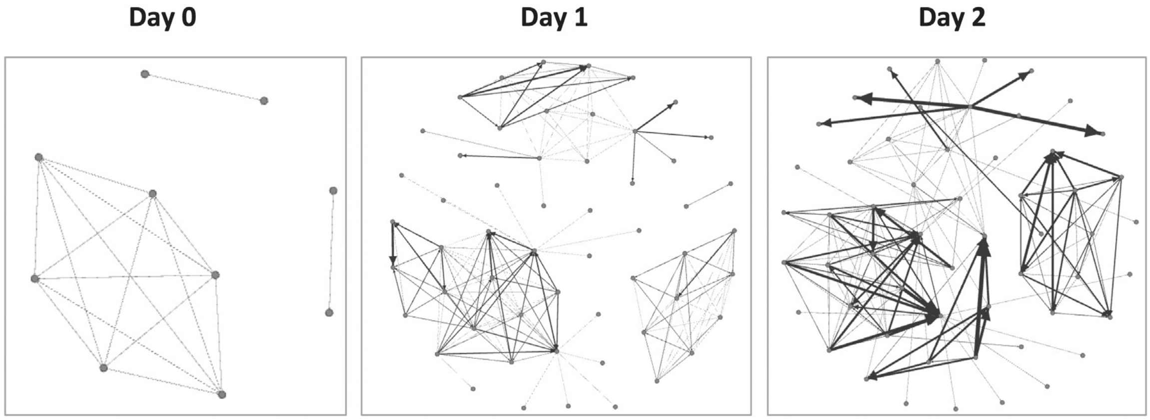


Fig. 5. The social networks of ten *Residents* across the first two days of a simulation run.

further discussed here. Thus, readers should note that this is not an opinion dynamics model as sharing the same opinion as others is not enough, *Residents* must also decide whether or not they will act (riot) on this opinion. As illustrated by the blue lines in Fig. 4, the *Residents'* Initial Opinion on rioting as a response to the rumor that election results were rigged is first evaluated. Using this approach, the structural equivalence of the *Residents* in the network is used as a measure of their Initial Opinion. However, given the computational intensity of evaluating structural equivalence in an evolving social network, we modify the definition of similarity slightly. 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 identity (e.g., Employee, Student, Rioter, Ethnicity) of the node. The similarity (i.e., homophily) effect measures the phenomenon where agents form ties with other "similar" agents. The tendency towards homophily is a central characteristic of many social networks (McPherson, Smith-Lovin, & Cook, 2001). Furthermore, this is consistent with Wasserman and Faust's (2009) discussion on potential ways to relax the strict definition of structural equivalence by using a node's "role" (e.g., identity), for instance, as a measure of structural "similarity."

The *Residents'* susceptibility to influence from those in its social network is then evaluated in Total Interpersonal Effects. *Resident i*'s susceptibility to influence s_i is determined by Eq. (4) (Friedkin, 2001).

$$s_i = \left[1 - 1/\left(1 + e^{-\left(d_i - 2\bar{d}\right)}\right)\right]^{\frac{1}{2}}, \tag{4}$$

where d_i is the degree centrality of *Resident i* and $\bar{d}$ is the mean degree centrality of the entire network. Interpersonal influence v_{ij} between *Residents i* and *j* is measured by Eq. (5) (Friedkin, 2001).

$$v_{ij} = a_i c_{ij} / \sum_k c_{ik}, \tag{5}$$

where $i \neq \{j,k\}$, c_{ij} is the probability that there is an interpersonal attachment between *Residents i* and *j*, and c_{ik} is the probability that there is an interpersonal attachment between *Residents i* and *k*, where *k* is all the agents *Resident i* is connected to. For simplification purposes and to keep the network size representative of social network structures (e.g., Friedkin, 2006), influence is only evaluated against those *Residents* already connected and it is assumed that an interpersonal attachment exists between all existing ties. Therefore, $c_{ij} = 1$ in all instances. *Resident i's* opinion y_i on an issue at time *t* is calculated by Eq. (6) (Friedkin, 2001).

$$y_i(t) = V y_i(t-1), \tag{6}$$

where *V* is an N x 1 vector of interpersonal influence, with N being the number of agents Resident *i* is connected to. *Resident i*'s Final Opinion $y_i(t)$ is then compared to the opinion of its connections. If the *Resident's* opinion is similar to any of its connections, the *Resident* is influenced by that connection.

As discussed in Section 2.2, hearing the rumor through personal ties and social influence networks are important considerations when determining whether a *Resident* will act on the rumor. Thus, if the *Resident* has heard the rumor through its social network, has reached a level of aggression that can lead to riotous 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. With each change in their activity, *Residents* will run their Identity Standard through the Comparator in the Identity Model and re-evaluate their Final Opinion on rioting as a response to the rumor (see Section 3.1.3).

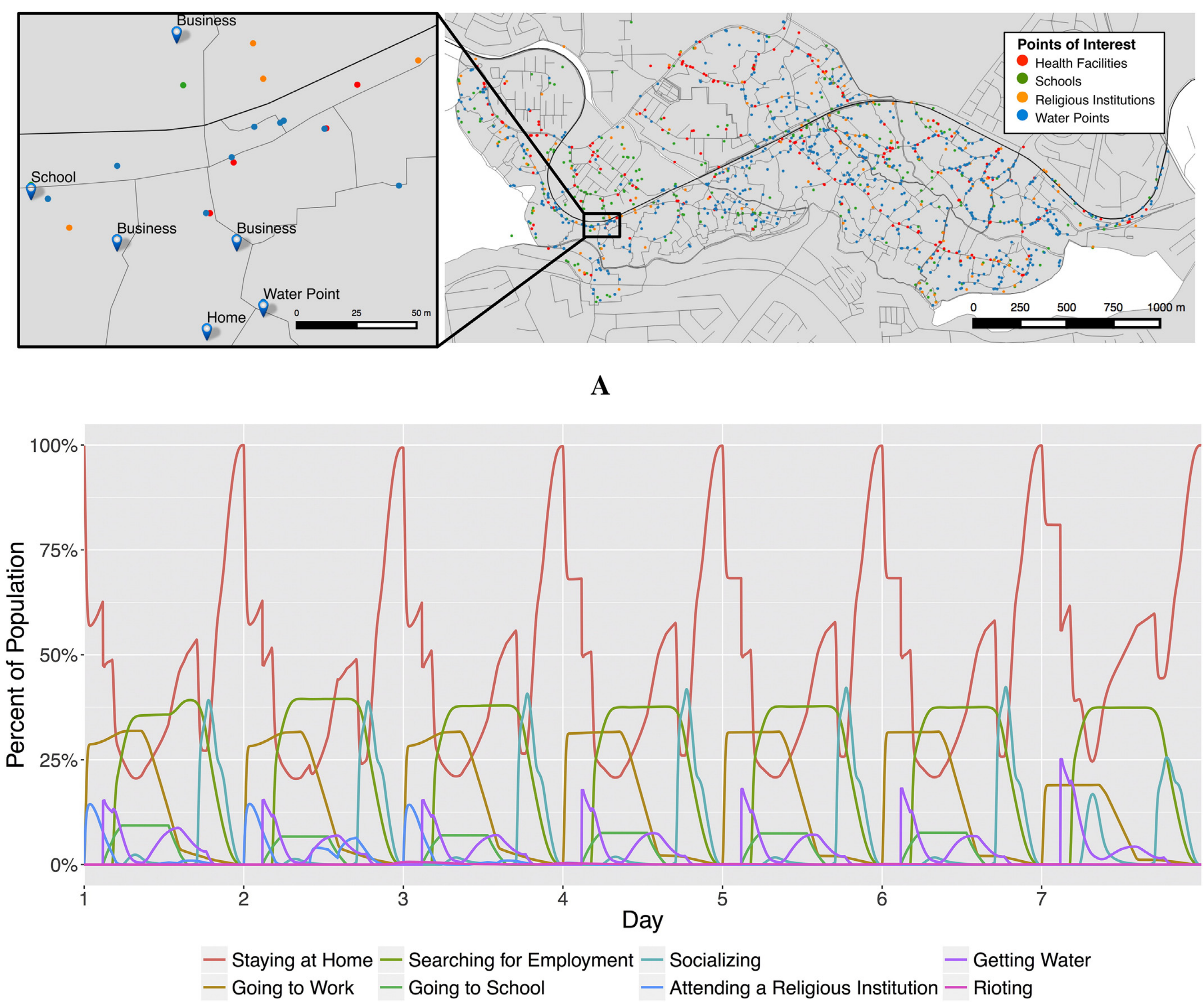
4. Simulation results

Before discussing the simulation results, it first needs to be mentioned that the code was thoroughly verified. This included completing an in-depth walkthrough of the code, performing code profiling to find bottlenecks, and running a series of simple scenarios that ensured all algorithms and submodels were working as intended and appropriate activities were selected and monitored correctly. This model seeks a Level 1 classification according to Axtell and Epstein's (1994) classification scheme. Therefore, calibration of the model was performed in parallel by seeking model results that most closely shared qualitative agreement with the peaks and troughs of the actual events that took place (see Jacobs (2011) for a discussion of the post-election violence). To determine appropriate default values of all model parameters, the model was run at full scale (235,000 agents) and a comprehensive set of parameter sweeps were performed, which included for example, systematically varying the values of the energy rate of change, employee and school vision, and probability of losing employment parameters. Linear increases in certain parameters, however, did not always yield linear results. For instance, the energy rate of change impacts how quickly a *Resident's* Energy Reservoir is filled or depleted upon successful or failed attempts at the identity verification process, respectively (see Section 3.3.3.2). As this parameter was systematically increased, the timing and size of riots were impacted. Interestingly, while it took longer for any rioting to emerge, lower energy rates of change yielded larger one-time spikes in Rioters. On the other hand, higher energy rates of change caused riots to occur earlier and to continue to emerge at some level throughout the run of the simulation. While an increase in the energy rate of change may cause *Residents* to become frustrated more quickly when the identity verification process was unsuccessful, it also causes *Residents* to become happier more quickly with successful attempts. This dynamic is one of the reasons we do not see linear trends in the number of Rioters as the energy rate of change is increased. These results are indicative of the non-linear dynamics of the model and the interplay that occurs between model variables. For brevity, results of the parameter sweeps are not reported here. However, as the source code to run the model is provided, interested readers can run the model at any combination of model settings. In this section, we provide a discussion on the average characteristics of the riots from multiple model runs using the default parameters shown in Table 1 (Section 4.1) and demonstrate that changing certain parameters lead to significantly different outcomes (Section 4.2). Note that in the following results we have chosen to focus on aggregate emergent patterns of riots and not on their precise locations as this varied from model run to model run. This allows us to focus on whether riots broke-out and on their temporal dynamics.

4.1. The outbreak of riots

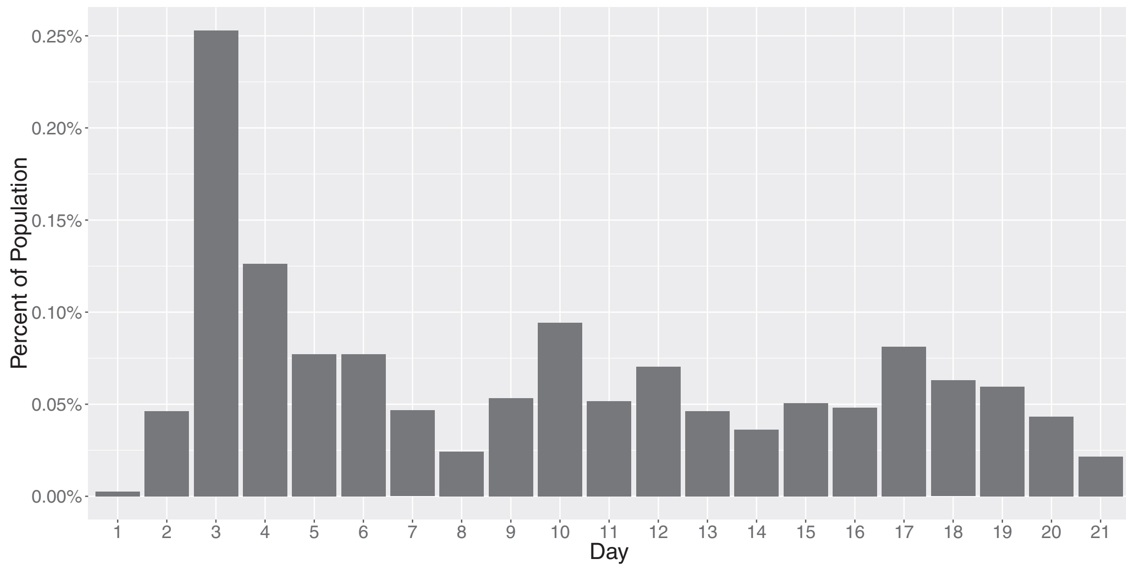
Using the default parameters, we run the model for three simulation weeks. As discussed in Section 3.3.3, *Residents* can perform one of seven activities at any one time. Fig. 6A illustrates some of the points of interest where many of the *Residents*' activities are located and the activity locations of an example *Household*. Fig. 6B shows the average percent of *Residents* performing each activity, with the exception of rioting which is illustrated in Fig. 7, over the first week of the simulation. Since many *Residents* leave *Home* in the morning to go to work, school, or perform other domestic and social activities and return in the evenings to eat and sleep, a cyclical pattern in the *Residents*' daily activities is found.

Taking a more in-depth look into rioting specifically, Fig. 7A shows the average percent of the population that rioted by day. We find that the rioting peaks at day 3, with subsequent spikes occurring approximately mid-way through the following weeks. This pattern is a result of the *Residents*' motivation to meet their needs (see Section 3.3.3), whereby *Residents* constantly assess their ability to continue rioting. This is because *Residents* that riot must still meet their fundamental needs in accordance with Maslow's (1954) hierarchy of needs. Thus, when a *Resident* riots, it is constantly finding itself in a struggle between its Rioter and other identities. For instance, each *Household* must ensure that it has adequate levels of water. If the only adult *Resident* of a *Household* is rioting, that *Resident* may be required to stop rioting in order to

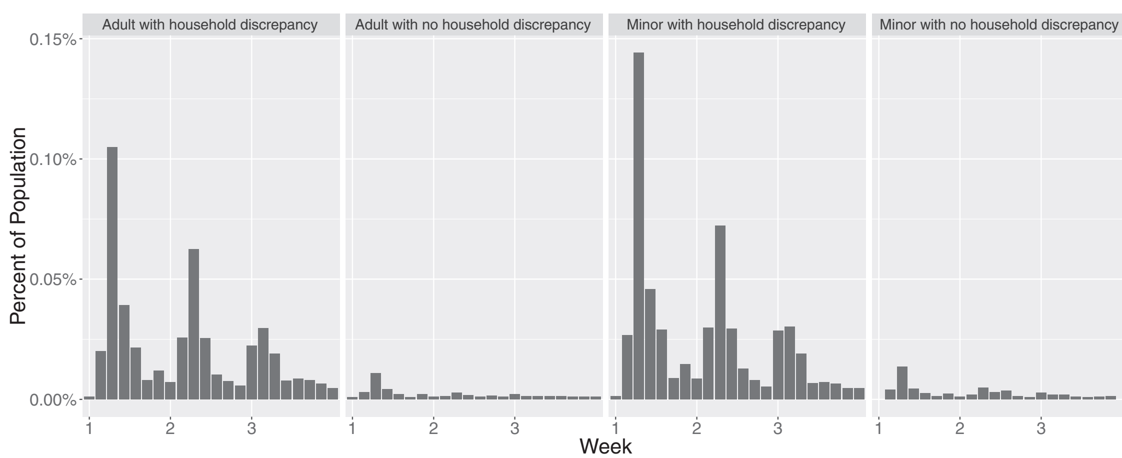


B

Fig. 6. The *Residents'* activity patterns. A: Points of interest and the activity locations of an example *Household*. B: The average percent of population performing each activity over the course of one week.



A



B

Fig. 7. The percent of the population that rioted. A: The average percent of population that rioted by day. B: The make-up of the Rioter population grouped into four categories.

get water for the *Household*. Changes in an individual's situation and subsequent decisions can have a cascading effect through its social network, creating a situation of positive reinforcement and resulting in a cyclical pattern of riots. Fig. 7B provides information on the Rioters by four categories grouped by age and household discrepancy (i.e., household expenditures are greater than household income). The likelihood to riot is highest among *Residents* that are minors (i.e., under 18) and whose household expenditures are greater than their income. This is indicative of a lack of schools and employment for the younger population (see Section 3.3.1). Youth that are unable to attend school, whether due to financial *Household* constraints or school availability, will search for employment in the informal sector. With limited employment opportunities, the *Resident* may became frustrated and influenced to riot (see Section 3.3.3).

As discussed in Section 2.3, one of the novelties of this model is the incorporation of social networks into a geographically explicit model. Network density is a widely used measure of network-level cohesion (Newman, 2010). The more cohesive a social network, the easier the spread of information (e.g., rumors). In order to calculate the network density, Δ, of a valued graph, we use Eq. (7).

$$\Delta = z_k / g(g-1), \sum \tag{7}$$

where z_k is the sum of the ties over all k and g is the number of nodes in the network. A node in this case is a *Resident*. Fig. 8 shows the day-over-day percent change in network density. The first two days of the simulation show the greatest percent increase in network density as the *Residents'* networks are beginning to form after model initialization. Consequently, this dynamic leads to the largest spike seen in Rioters (see Fig. 7A). Furthermore, this trend continues into days 10 and 17 of rioting, whereby the change in network density spikes prior to the rioting, with a 0.9 correlation between the percent of population that rioted and the lagged change in network density. This trend seems to indicate that there is some association between network density and the dynamics of rioting in the model.

4.2. The impact of increased education and employment opportunities on the emergence of riots

It is often suggested in the literature that one way of reducing civil unrest is to increase educational and/or employment opportunities (e.g., Barakat & Urdal, 2009). In order to explore this notion in our model, as an illustrative example, we systematically increase the capacity of schools and employment by 50% and 100% of their default value (see Table 1). Fig. 9 shows the average percent of the population that rioted as education and employment were increased in isolation and

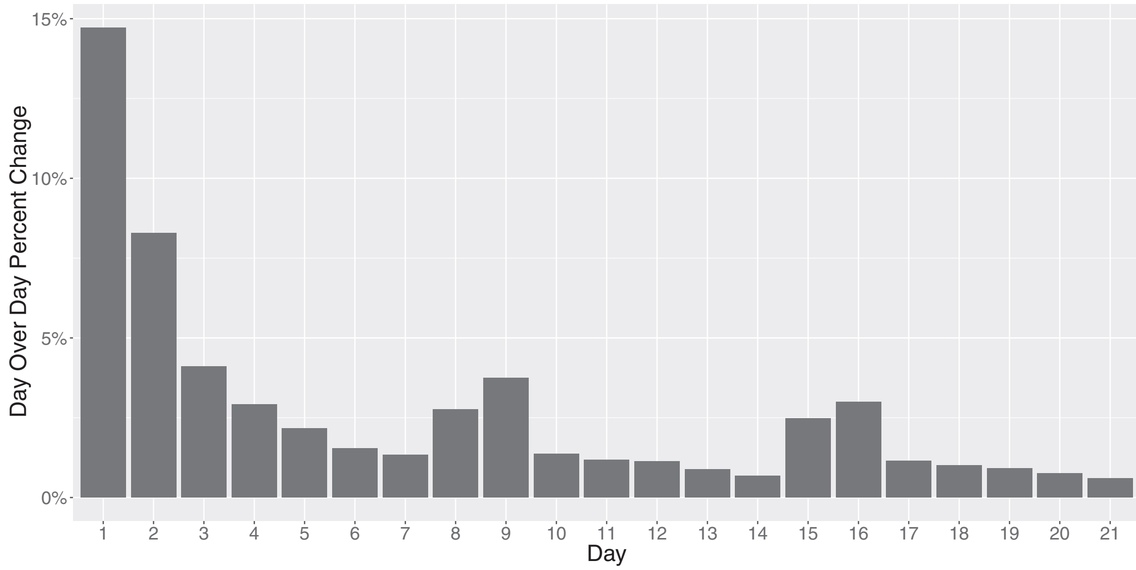


Fig. 8. The average day-over-day network density percent change.

as they were increased concurrently. While increasing employment reduced the rioting, increasing education alone created an environment that was unstable. However, increasing education and employment concurrently had a greater impact on reducing rioting than increasing employment alone.

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 a religious institution, and staying *Home* to spend time with family (see Table 2). Fig. 10 shows the overall percent change in the population that was able to spend time performing these activities as education and employment opportunities were increased. 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. Furthermore, frustration over meeting these needs, combined with influencing factors, may have caused some to turn to rioting. With increases in employment and education, we find that *Residents* are able to spend more of their time on these higher level needs.

Results show that by increasing education and employment there is a reduction in the intensity of rioting while increasing education alone yielded unstable results. Moreover, increasing employment alone or education and employment concurrently increases overall quality of life, not just in terms of household income, which would be expected, but also in terms of the *Residents'* day-to-day activities.

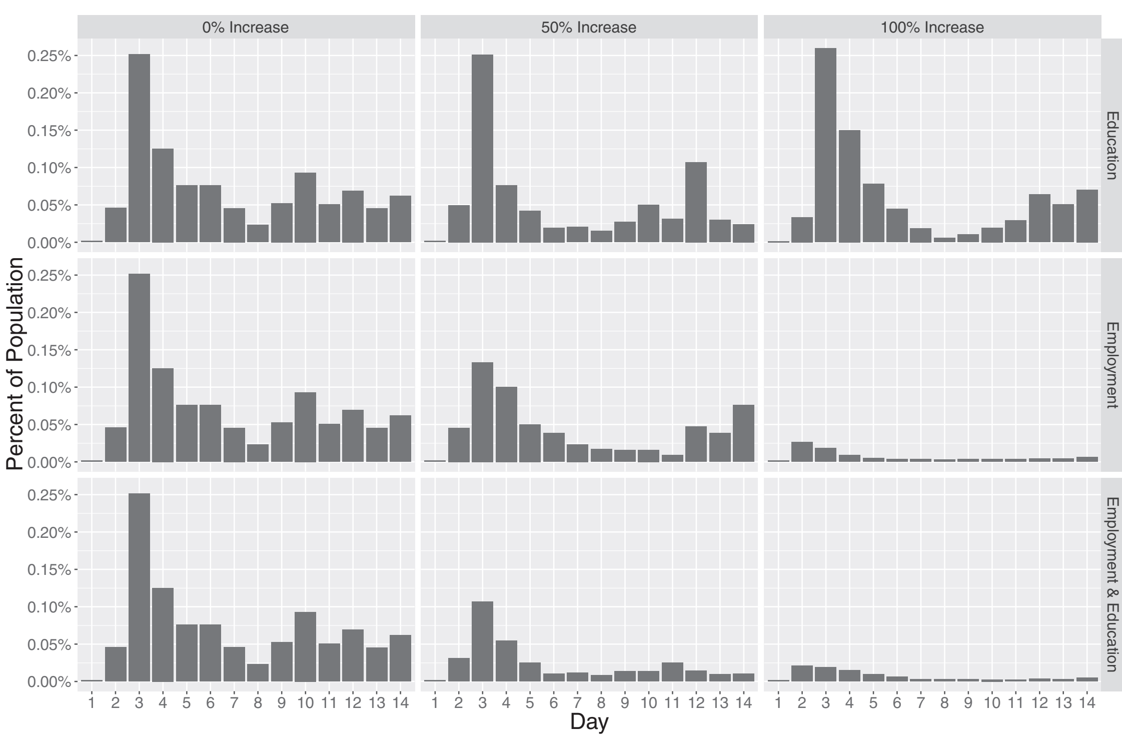


Fig. 9. The average percent of population that rioted as education and employment opportunities were increased by 50% and 100%.

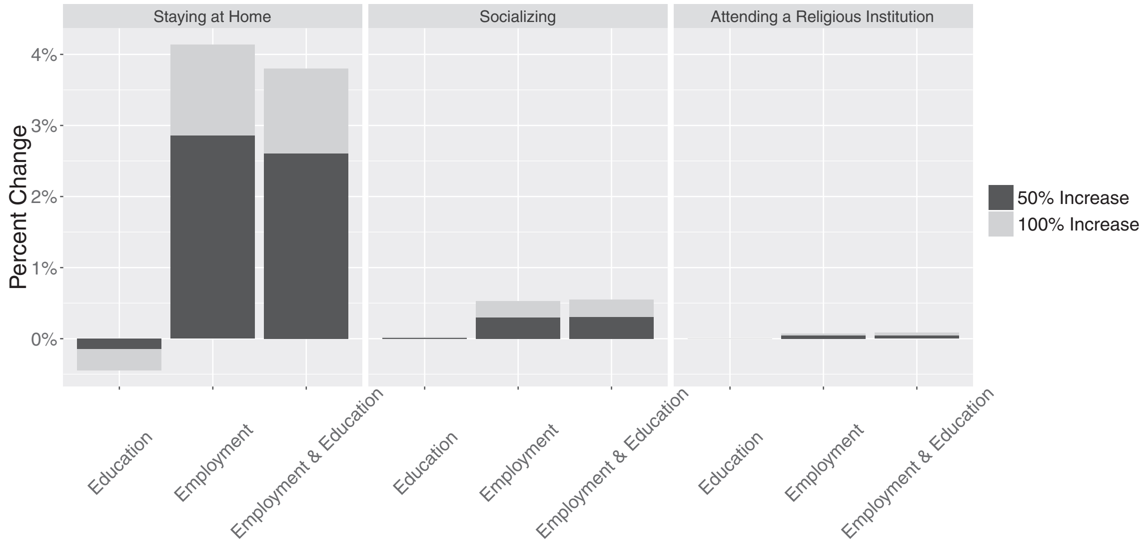


Fig. 10. The average percent change in the time spent performing the activities socializing, staying *Home*, and attending a religious institution, as education and employment opportunities were increased by 50% and 100%.

5. Discussion and conclusions

Riots are a complex system; they are composed of a connected, heterogeneous population of individuals that come together to protest for a specific cause as discussed in Section 2. Understanding the motivations behind riots is a complex task. In this paper, we have attempted to capture this complexity through the integration of ABM, GIS, and SNA. The model we developed explored the role that identity and social influence played on rumor dynamics and the outbreak of riots. It 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.

Accounting for both role and group-based identities in the agents' cognition; social influence in response to an external trigger that can dynamically evolve as social networks change; and the daily needs and activities of the agents provided a new lens to model how agents process their decision to riot or remain peaceful. Social networks influenced the spread of the rumor and an agent's identity (see Section 3.3). As a result, they directly impacted the dynamics of the model and any riots that emerged as seen in Section 4.1. Facilitated through GIS, the creation of social networks was largely influenced by physical space, as agents were more likely to interact with those geographically near (consistent with Tobler, 1970). Furthermore, the integration of SNA and GIS facilitated the development of the agents' cognitive framework, allowing for the full development of the Cognitive component of the PECS framework (see Section 3.3.3). This internal model was regularly compared to the agents' environment and social network, providing a feedback loop between the agents' activities in physical space, the agents' interactions in social and physical space, and the agents' internal model. Results indicate that youth are more susceptible to rioting; that frustrated from staying home and being unemployed are willing to aggress. While this may not be a surprising result, it does demonstrate that the model is capturing the right types of dynamics, which is a form of validation (Epstein, 2013). For instance, studies have shown that unemployed youth are especially vulnerable to violence (OECD, 2011) and almost 60% of Nairobi's population are under the age of 25 (Kenya National Bureau of Statistics, 2009b). Furthermore, increasing education, without increasing employment opportunities, created an unstable environment. This is in line with studies that show that large groups of educated youth may struggle to find employment, leading to increased frustration and civil unrest (Lia, 2005).

Social cohesion in a community can provide a sense of belonging and support within groups. Results showed that there may be a relationship between network density, a measure of social cohesion, and the outbreak of riots in the model (see Section 4.1). This increase in cohesion in the social network immediately preceding the spikes in rioting may have facilitated mobilization efforts. On the other hand, social networks can also serve to exacerbate the rate at which we are influenced to remain peaceful (see Section 4.2). The role that the structure of the social network has on the emergence of riots is an area which should be further explored in future research and linked to survey data where possible. Furthermore, with an increase in the proportion of *Residents* meeting their basic needs, there was also an increase in time spent socializing, attending religious institutions, and staying home, even though the agents would be "busier" with work and school. This was not an expected consequence of the model and provides support to Maslow's (1954) theory that the most fundamental of needs must to be met prior to attending to higher needs.

Riots are a complex phenomena and there are many types of riots with different triggers, dynamics, and outcomes (Haddock & Polsby, 1994). Likewise, there are many approaches one could take to study riots. Here we present just one approach that emphasizes the emergence of riots from the perspective of the individuals' decision to participate (or not) in such aggressive behavior, which we ground in theory and operationalize through the integration of ABM, GIS, and SNA. Moreover, we do not seek to replicate exactly the riots that occurred in Kibera but aim instead to develop a generative model of the emergence of riots. As with all modeling endeavors, however, there are some limitations with the current model that could play a role in influencing riot dynamics. This is why we have tried to be as transparent as possible by providing a detailed ODD + D, the source code, and data to run the model. For instance, while we model the individuals turn to riotous behavior, we do not account for the violent clashes that occurred between different ethnic groups and the role of police and the risk of being arrested, each of which influenced the intensity and activity space (e.g., cordoning off certain areas, residents leaving their homes and shops) of the riots in Kibera (De Smedt, 2009). These could represent important influences and should be studied as valuable extensions to this baseline model. Even with these limitations, however, this model sheds some light into the underlying micro-level dynamics that can lead to the emergence of riots. Moreover, we also observe model dynamics after the riots break-out and find that model results provide support to existing empirical evidence and theories of riots (e.g., youth are more susceptible to rioting) as discussed above. By gaining confidence in this basic model, we can test further ideas and hypothesis.

By utilizing ABM, GIS, and SNA we were able to capture the cyclical nature of the emergence and dissolution of rioting due to positive reinforcement, an effect that can be largely attributed to the agents' social networks. Furthermore, the incorporation of GIS in the model impacted the initial placement of agents, which subsequently affected their activity patterns (e.g., via routing algorithms) and the creation of their social networks. We acknowledge that the addition of the police and rival groups would provide an additional contributing factor to both positive and negative feedback, with negative feedback resulting from control of the riots by the police and positive feedback from escalation potentially by police and rival groups. Having said that, our model is nevertheless able to capture a certain level of escalation and de-escalation of riots. The addition of police agents and rival groups would just exacerbate this dynamic in the model. While our basic model captures the cyclic nature of the riots (see e.g., Jacobs, 2011), it is difficult to correlate the number of rioters with the intensity of violence as this is not recorded. If we were to take the number of rioters as the intensity of violence, the duration of the peaks in our model is less than what was witnessed on the ground. One way of overcoming this is to recalibrate the model. However, reports such as Jacobs (2011) is not necessarily capturing individuals but the average of violence as an aggregate measure. On the other hand, such things would be very difficult to capture using traditional, top-down modeling approaches. As such, our model provides a new lens to study how riots arise from the interactions between individuals with unique attributes, all within a connected social network over a physical environment. It is the first theoretically grounded ABM that integrates with GIS and SNA in the field of civil unrest. It lays the foundation for further work with respect to studying riots from the bottom-up, especially in regards to the cognitive aspect of agents, social influence, and rumor propagation, and sheds some light into the underlying micro-level dynamics that can lead to the emergence of riots.

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