Modeling Geographic Behavior in Riotous Crowds

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Under some conditions, tensions among crowd members, harbored a priori or developed on site, might catalyze a crowd to riot, with dramatic consequences. We know perhaps less than we would like to about the processes that drive rioting in crowds because they are difficult to study. In particular, we know relatively little about the influence of geographic behavior on rioting, although there exists a general sense that it is important. In lieu of pragmatic avenues for studying riots, we could use simulation as a synthetic laboratory for exploration. To be useful, simulations must be based on realistic behavioral models, but the extant science for riot modeling has not traditionally provided that support. In this article, we introduce a new approach to modeling riot-prone and riotous crowds using behavior-driven computational agents. We demonstrate a simulation architecture based on socioemotional agents, modeled at atomic levels and characteristic times for riot activity, but extended with the use of geographical functionality that endows agents with spatial perception, cognition, and action that helps to determine where, when, how, and in what contexts and company their agency should be deployed and interpreted. In essence, our agents are *polyspatial*, with the ability to adapt their behavioral geography under shifting circumstances and to differentially process geographic information from diverse sources. We illustrate the usefulness of this scheme through simulation of a varying set of scenarios for riot formation, evolution, and dissolution, as well as in exploring the interplay among different characteristics, traits, and goals of riot participants. *Key Words: agent-based model, complexity, geographic information science, riots, spatial analysis and modeling.*

在某些情况下，原先隐藏的或现场产生的群体成员之间的紧张局势，可能会催化造成具有严重后果的人群骚乱。因为这是很难研究的过程，我们对驱动人群骚乱的过程知道得也许比我们想知道的更少。特别是，我们对于地理行为对骚乱的影响知之甚少，尽管存在着的一般的感觉是它是重要的。代替研究骚乱的务实途径，我们可以使用模拟作为探索的一个合成实验室。模拟必须基于现实的行为模式才有用，但是骚乱模拟的现有科学在传统上还没有提供这种支持。在这篇文章中，我们引入一个新的方法，用行为驱动的计算机智能体来模拟容易发生暴乱和骚乱人群。我们展示了一个基于社会情感智能体的模拟架构，模拟在原子水平和特征时间的暴乱活动，但是拓展使用了地理的功能，使之赋予智能体空间感知，认知，和行动的能力，以帮助决定何处，何时，如何，并在何种情况下部署和解释智能体。从本质上讲，我们的智能体是多空间的，具有在变化的情况下适应他们的行为地理的能力，和对不同来源的地理信息的差别处理能力。我们通过模拟一套有关骚乱的形成，演化，和解散的不同情况，以及探索具有不同特点，特征，和目标的不同暴乱参与者之间的相互作用，说明这个方案的用处。*关键词：基于智能体的模型，复杂性，地理信息科学，暴动，空间分析和模拟。*

Bajo ciertas condiciones, las tensiones que se presentan entre los integrantes de una muchedumbre, en latencia o desarrolladas en el propio sitio, podrían conducir una multitud a desbocarse en asonada, con consecuencias dramáticas. Quizás conozcamos menos de lo que quisiéramos saber sobre los procesos que alientan la asonada en muchedumbres, por lo difícil que es estudiar este tipo de conducta. En particular, sabemos relativamente poco acerca de la influencia del comportamiento geográfico sobre las asonadas, así exista una sensación general sobre la importancia que esto pueda tener. A falta de aproximaciones pragmáticas para estudiar las asonadas, podríamos utilizar la simulación a título de laboratorio sintético de exploración. Para que sirvan de algo, las simulaciones deben basarse en modelos conductuales realistas, si bien la ciencia actual de modelización de asonadas todavía no ha proporcionado tal apoyo. En este artículo introducimos un nuevo enfoque de modelización de muchedumbres propensas a generar asonadas, o de turbas ya convertidas en asonada, utilizando agentes computacionales de orientación conductual. Hacemos la demostración de una arquitectura de simulación basada en agentes socioemocionales, modelados a niveles atómicos y en tiempos caracterizados para la acción de asonada, pero fortalecidos con el uso de la funcionalidad geográfica que dota a los agentes con percepción espacial, cognición y capacidad de acción que ayude a determinar dónde, cuándo, cómo y en cuáles contextos y compañía pueda desplegarse e interpretarse su agencia. Esencialmente, nuestros agentes son *poliespaciales*, con habilidad para adaptar su geografía conductual bajo circunstancias cambiantes y para procesar diferencialmente la información

Annals of the Association of American Geographers, XX(XX) XXXX, pp. 1–27 © XXXX by P. Torrens and A. W. McDaniel
Initial submission, April 2009; revised submissions, June and August 2011; final acceptance, August 2011
Published by Taylor & Francis, LLC.

geográfica proveniente de fuentes diversas. La utilidad de este esquema la demostramos a través de la simulación de un variado conjunto de escenarios para la formación de asonadas, su evolución y disolución, lo mismo que explorando interacciones entre las diferentes características, rasgos y metas de los participantes en la asonada. *Palabras clave: modelo basado en agente, complejidad, ciencia de la información geográfica, asonadas, análisis espacial y modelización*.

Up rolls a riot van and sparks excitement in the boys. But the policemen look annoyed.

—*Arctic Monkeys* (2006)

Riots are just one possible outcome of human assembly, but they are incredibly significant. They can catalyze positive social dynamics, but if riots turn seditious, the consequences can be less than desirable (McPhail 1994). Riots are difficult to study for a number of reasons. First, many types of rioting are possible, with different motivations, dynamics, and outcomes (Haddock and Polsby 1994). These include food riots due to resource shortages (Auyero and Moran 2007), social riots driven by inequality or injustice (Jackman 2002), protest riots that might begin with peaceful demonstration (McCarthy, Martin, and McPhail 2007), police riots challenging authority (R. Stark 1972), or hooliganism following antisocial behavior (Buford 1991). These distinctions are also elastic (McPhail and Wohlstein 1983), making them difficult to distinguish. Second, interpretation of rioting is almost necessarily subjective: What might be experienced as a collective assembly by participants could appear as a riot to another observer. This creates complications in characterizing riot processes. Third, rioters are unreliably available for standard qualitative inquiry such as surveys or interviews, making the collection of empirical data during riots problematic (Sampson 1999). Even analysis by pattern recognition in video footage is difficult (Wohlstein and McPhail 1979) and might provide little insight into motivations and intent of riot participants anyway (Prentice-Dunn and Rogers 1982). Fourth, secondary data can be unreliable and biased (Myers and Caniglia 2004), which hinders vicarious analysis. Fifth, rioting is often dangerous for participants and experimentation with real people—even in a controlled setting—is often infeasible (Kroon, Van Kreveld, and Rabbie 1991).

Computer simulations could provide complementary opportunities for studying rioting in a synthetic laboratory, if they can be usefully allied to theory, and this is an idea that we promote in this article. We are not the first to think of the idea, but our approach is novel. We believe that geography can offer significant insight into riot dynamics and we introduce a more authentic geographic representation of riot dynamics than existing models have considered. We argue that this significantly broadens the diagnostic ability of riot modeling.

Our approach incorporates several innovative features. First, we include a cross-disciplinary substantive foundation that accommodates traditional ideas about rioting from sociology, psychology, and criminal justice. These ideas are realized as model behaviors that determine and animate synthetic rioters' internal drivers and their interactions with the social, emotional, and physical environment developing around them. Second, our agents are endowed with rich geographic functionality that envelops their socio-psychological operability, casting it in spatiotemporal context. This is done *polyspatially*, such that agents can extensibly configure and use geographic behavior, becoming dexterous in their interaction with geographic information, across scales and contexts. Third, we built our model from the bottom up, which enables us to design, assemble, run, and control a riot—as a simulacrum (Baudrillard 1994)—in much the same way that a riot manifests in the real world. This allows us to *flexibly* experiment with different designs and characterization of synthetic rioters and varying scenarios. Fourth, we introduce a novel coupling of agent–automata models, space–time geographic information systems, spatial analysis, spatial statistics and geostatistics, and geovisualization as an integrated pipeline for designing, running, and evaluating experiments about riot dynamics.

The article is organized as follows. We discuss links between geography and rioting in the next section. We then examine existing approaches to riot modeling. Our methodological contributions beyond this foundation are presented following that. We then introduce experimental simulation scenarios and discuss results ahead of our concluding remarks.

Geographical Perspectives on Rioting

The psycho-sociological processes underpinning rioting are reasonably well covered as theory (Firestone 1972; Haddock and Polsby 1994), but *geographic processes* have received less attention. Although it is understood that geography plays a significant role in riot dynamics, this is usually only explored anecdotally in the theoretical literature.

Riots often manifest with significant *spatial patterns*. Existing investigation of this topic has emphasized the coarse patterning of rioting at the city scale (Adams 1972; Berk and Aldrich 1972; M. J. A. Stark et al. 1974; Carter 1986), but fine-resolution motifs of riotous crowds are often overlooked, despite a need to better understand interactions at this scale (McPhail 1994, 2008). Beyond the observational work of Wright (1978) over thirty years ago, little fieldwork has been done to investigate the genesis or effects of riot patterns within crowds.

Spatial interaction is a logical catalyst for rioting: people interact with each other over space and time in riotous crowds (socially, physically, verbally, and, increasingly, digitally; Marx and McAdam 1994; Rheingold 2002). Riots can also be influenced by diffusion processes: Rumor, panic, calm, and aggression can spread through riots by interaction over space and time, with individuals as vectors for their transmission (Myers 2000). The popular emphasis on the crowd—as a unit of concern—in much of the existing literature, however, sidesteps consideration of intracrowd interaction (McPhail 1994).

Scaling can also shape riot dynamics, for example, when local incidents catalyze wider response (Jacobs 1996). Spatial complexity is a related consideration. Scaling in crowd behavior is often mediated by complex phenomena such as feedback, emergence, path dependency, and self-organization, each of which rely on system scaling (Vicsek 2001, 2003). Relatively little has been done to explore the role of scaling in riot phenomena; indeed, most studies have settled on a single (usually coarse—the city) scale in analysis (Abudu et al. 1972; Adams 1972; Carter 1986; DiPasquale and Glaeser 1998).

Geographic behavior is also significant in explaining riot dynamics. Some geographic behaviors might preempt a riot: unlawful assembly, routs, collective locomotion of strangers, or loitering of groups in certain places and times, for example (McPhail and Wohlstein 1983). Police behavior amid rioting is usually geographical. This has been documented at the city scale (Yarwood 2007) but is also important *within crowds* (Prati and Pietrantoni 2009). Police can divide a crowd spatially to minimize the spread of rioting or might corral rioting crowds into spaces that can be more effectively policed or where they can minimize contact between rioters and nonrioters (Newman 1972). Spatial cognition is a crucial component in riot behavior. People's perceptions of ambient conditions in riotous crowds (Felson 1982) and shifts in their mental maps amid confusion could alter their behavior (Mawson 2005). Law enforcement could target directly rioters' spatial cognition by projecting or inflating an impression of impending force using particular collective movement strategies (Prati and Pietrantoni 2009); by disrupting rioters' spatial cognition with aerosols; by blocking line of sight; or by interfering with their spatio-aural perception (Waddington 1991). Although geographic behavior is recognized in the literature as being important, the detailed behavioral interplay between individuals and within crowds has not been investigated in sufficient detail, despite calls for focus on the topic (McPhail 1994).

Physical geography is also important to rioting. Riots might originate in places and times with significant historical geography (Haddock and Polsby 1994). Some built environments might be temporarily or permanently modified to reduce the physical substrate for rioting, using barricades and fencing, by designating sanctioned time geographies for demonstration, by charting routes for protesters to march along, or by installing surveillance equipment as a deterrent (Newman 1972). These ideas, although very relevant for understanding riot geography, have not benefited from thorough examination. Even Newman's famous work focused largely on architecture, rather than people.

Existing Riot Models

In the absence of tangible testing grounds for rioting, *computer simulation* can be used as a virtual laboratory. The theory needed to explain riot dynamics is relatively underdeveloped, however, and model builders, lacking obvious starting points for development, have tended in the past to bend models designed for other purposes to fit riot behavior.

The majority of riot modeling work has been developed for research of operations other than war (OOTW), whereby models of noncombatant crowds are infused into military simulations for the purposes of evaluating plans and strategies (Lauren and Stephen 2000, 2002; Yiu, Gill, and Shi 2002; McKenzie et al. 2004; Petty et al. 2004). Not all riots are related to military activities, however, and socio-geographic dynamics are not often a main concern.

Another thread has developed in political studies, with focus on civil violence using game-theoretic models. Game-theoretic approaches carry some limiting assumptions, however, such as rational actors, perfect information, and simple rule-of-thumb heuristics for behavior (e.g., tit-for-tat or winner-takes-all). The Brookings Model of Civil Violence (J. Epstein 2002) is a popular example of this work.

Riot-like models have also been built in physics, because of curiosity about apparent correlations between social behavior and continuum mechanics of physical particles in constrained spaces (Vicsek 2003). Continuum models are useful for representing aggregate flow and crowd turbulence in confined spaces (usually conduits like stream channels or pipes), but they do little to accommodate realistic human behavior (Treuille, Cooper, and Popović 2006). Nevertheless, many continuum models have been ported directly to riot modeling (Kirkland and Maciejewski 2003; Bhat and Maciejewski 2006; Pabjan and Pekalski 2007).

Another thread of riot models has been developed in sociology, mostly to represent psychology of social signaling in collective action, using artificial intelligence (McPhail, Powers, and Tucker 1992; McPhail 1994; Tucker, Schweingruber, and McPhail 1999). These types of models tend to emphasize individual decision making rather than intrapersonal interactions (McPhail 1994).

Generally, geography (and particularly geographic behavior) has received only cursory attention in most riot models. This is especially evident in representation of movement. Although long understood to be crucial in rioting (McPhail and Wohlstein 1986), movement is often relegated to random hopping between rounds of game-theoretic exchange (Yiu, Gill, and Shi 2002) or abstract representation using physics of particle flow. For example, the J. Epstein (2002) model treated movement by random picking up and dropping off of agents in cellular lattices. The model developed by Goh et al. (2006) actually relied on Conway's mathematical rule set for the Game of Life (Gardner 1970) for movement (this is just nonsensical; the Game of Life was built to test the computability of self-replication and has nothing to do with movement; Faith 1998).

The determination of neighborhoods of interaction is also weak in most riot models and this is another tell-tale sign of shortcutting in modeling movement. A majority of riot models use cellular automata for spatial interaction, which often limits agents' (really, cells') activity to fixed, symmetric rasters (Torrens 2009). Dibble and Feldman's (2004) graph-based agent models focused admirably on the social network space of riot participants but lacked locomotion (in fairness, their models were designed to test graph-network approaches, not movement). Considerable overhead is required to infuse mathematical models with realistic geographic behavior and so the diluted treatment of geography in existing riot models is understandable but disappointing.

A New Approach to Riot Modeling: Our Methodology

Motivated not only by a desire to build on the work we just discussed but also to broaden the range of questions that would be posed in simulation, we introduce an innovative modeling infrastructure for riot dynamics by infusing added realism. Geography is a particular focus of our efforts, but the model is flexible so that a variety of social, physical, or psychological model "engines" could be embedded within the framework that we provide. Indeed, we demonstrate how this is possible, by taking the popular J. Epstein (2002) conflict model as the engine for socioemotional agency and "wrapping" it with geographic functionality that mobilizes that agency through simulated perception, cognition, spatial interaction, way-finding, steering, and locomotion. The resulting polyspatial agents then become the building blocks for theory-driven riot simulations. Their geographic functionality also enables second-order geographic processes, such as spatial interaction, diffusion, scaling, spatial self-organization, and patterning to be derived from those primitives. Agents' dynamics in simulation are not scripted; rather, they are processed or computed from a model that determines their behavior given agent characteristics (states) and algorithms (rules) that feed on agents' endogenous attributes; the shifting social, emotional, and physical conditions that unfold around them; and the events that they choose to interact with. Any resulting riot processes or phenomena are then derived (we could say "emerged") directly from these synthetic behaviors.

Agent-Based Crowds

We use an agent–automata architecture for our model (Turing 1950), with several advantages. Agent–automata can be represented atomically and driven autonomously at individual scale and characteristic time. This helps to overcome problems of ecological fallacy and modifiable areal units (Openshaw 1983; Wrigley et al. 1996), by improving fidelity. Characteristic timing allows agents to be represented with true temporal dynamics, avoiding the need to rely on comparative snapshots as a proxy for temporal continuum (again, coarse representation is the standard approach). This is particularly valuable when dealing with dynamic crowds, where we might be keenly interested in subtle temporal differences in behavior and outcomes, small deviations from spatial and temporal regularities or norms, or serial effects in the space–time continuum of processes.

Agent–automata can be fashioned as perceptive creatures, with ability to reason about their surroundings. Agents can be given bounded rationality: Their information about the conditions unfolding around them might not necessarily be complete and they might act solely on the information they have on hand (in contrast to standard approaches in game theory, for example). This is useful for representing forces of bias and even subterfuge in riotous crowds (Prentice-Dunn and Rogers 1982).

Agents are communicative: They exchange information by passing state descriptors. This can be significant when representing information diffusion in riot phenomena (Myers 2000; Rheingold 2002). In our model, we focus on nonverbal communication, which is a topic with considerable currency in the literature (McPhail 1994).

Automata are not inherently mobile in their original design (although the information that they contain could be). Lending agents locomotive abilities enables the modeling of pursuit, avoidance, dispersal, and chasing behavior, each of which are understood to factor into rioters' behaviors (Haddock and Polsby 1994).

Using the Epstein Model to Provide Socioemotional Agency

We used J. Epstein's (2002) conflict model as the socioemotional core of our model. Although Epstein's model actually deals with civil violence, it provides a parsimonious treatment of socioemotional agency that we can (re-) use. It is important to stress that we have developed significant additional infrastructure around this foundation by wrapping it with geographic functionality and that we subsumed the algorithms for the model (not the software) in our pipeline. Coupling diverse agent-based models (Rank 2010) and spatializing nonspatial agent behaviors (Torrens and Benenson 2005) is an active topic of research in the simulation community.

Following J. Epstein (2002), we consider four classes of agent-actor in simulation; Civilian, Rebel, Jailed, and Police. Agents can transition between these roles as their agency dictates, Civilian $\leftrightarrow$ Rebel $\rightarrow$ Jailed $\rightarrow$ Civilian. Rebel agents that are apprehended become Jailed agents. (We realize that the term *rebel* has significant connotations, but we use it here to simply distinguish members of the crowd that act out an internally held grievance.) Police agents are also introduced, but Civilian and Rebel agents cannot transition to law enforcement roles and Police agents cannot be seduced to riot. These four classes provide a minimal but satisfactory set of protagonists and match standard distinctions in related models (Lauren and Stephen 2000; Ling 2001; Yiu, Gill, and Shi 2002; Kirkland and Maciejewski 2003; Petty et al. 2004; Bhat and Maciejewski 2006; Goh et al. 2006).

Socioemotional State Descriptors. Agent state-descriptors are bundled to produce a socioemotional profile for actors in simulation. States are dynamic; they can change as agents exchange information and act, react, and interact in simulation. Bundling is organized as follows.

$S_{\text{socioemotional}} = \{H, L, G, R, P, N\} \forall$ Civilian and Rebel agents,

$$\text{where} \quad \begin{cases} H = [0, 1] \\ 0 \leq L \leq 1 \\ G = H(1 - L) \\ P = 1 - \exp\left(-k \frac{C}{A} v\right) \\ N = RP \end{cases} \tag{1}$$

J. Epstein (2002) did not provide much theoretical justification for states in his original model, but we have carefully considered this in our design. (Coincidentally, the states that Epstein proposed represent the dominant theoretical arguments in riot research well.) Members of riotous crowds might act out when they reach extremes of unhappiness (Prentice-Dunn and Rogers 1982), so we lend agents an internal sense of hardship (H). $H = 1$ when agents feel suffering and $H = 0$ when they do not. Rioters usually direct their discontent at something or someone (Firestone 1972), so in simulation citizen (non-police) agents are equipped with a sense of legitimacy ($0 \leq L \leq 1$) toward authority, represented on the ground as police (Gillham and Marx 2000), ranging from an absence of respect for authority ($L = 0$) to ambivalence ($L = 0.5$) and unequivocal support ($L = 1$). Agents' feelings of legitimacy are an endogenous characteristic. As rioters might wish to keep feelings hidden from police, we represented Civilian agents' outward affect with a grievance level, $G = H(1 - L)$. Although citizen agents might feel complete dissatisfaction with their lot in life or with authority, their propensity to act on those feelings is tempered by an appreciation for the consequences of action (Milgrim 1964; McPhail and Wohlstein 1983). This is introduced as risk-taking in simulation (R) and a calculation of the net cost–benefit of acting out (N). This calculation (per agent) balances tolerance for risk, the safety in numbers of like-minded citizens in the crowd, and the local presence of authority, $N = RP$ (this is synonymous with the "gaming" calculation of relative cost introduced by Berk 1974). The state $P = 1 - \exp\left(-k\frac{C}{A}v\right)$ is the probability of capture per agent, where A is the number of Rebel agents and C is the number of Police agents. V defines how far Police agents can see; this is essentially an arrest filter per Police agent. J. Epstein (2002) originally used a Moore neighborhood (a fixed-size, nonmobile, symmetric filter) to poll states in his cellular automata model; we have extended this concept considerably. Finally, K is a scaling term used to ensure plausible values of P for values of $A = 1$ and $C = 1$. A value of $P = 0.9$ is usually reasonable (J. Epstein 2002).

Enabling Dynamically Shifting Attitudes and Emotions. Transition rules control state dynamics by allowing agents to obtain behavioral access to states (their own and those of other agents) and by providing agents with the ability to process that information for their behavior. An activation rule determines shifts in demeanor (which is a metastate) from Civilian to Rebel; that is, the decision to riot.

$$\textbf{\textit{Activation}} = \begin{cases} \textit{Civilian}_t \rightarrow \textit{Rebel}_{t+1} \textit{ if its } [H(1-L) - RP] > T \\ \textit{Civilian}_t \rightarrow \textit{Civlian}_{t+1} \textit{otherwise} \end{cases} \quad (T = 0.1) \tag{2}$$

Activation includes a user-defined parameter (T) that controls the threshold for acting out (Granovetter 1978).

Police agents' arrest behavior is described by an arrest rule:

$$\textbf{\textit{Arrest}} = \begin{cases} \textit{Rebel}_t \rightarrow \textit{Jailed}_{t \rightarrow jmax} \textit{ if Rebel}_t \in V_t \textit{ and is selected} \\ \textit{Rebel}_t \rightarrow \textit{Rebel}_{t+1} \textit{otherwise} \end{cases} \tag{3}$$

Selection was random in Epstein's model, but we added functionality to make it guided, targeted, or weighted. j_{max} is user-definable and determines the length of Jailed agents' incarceration. Jailed agents are removed from the simulated space and are essentially stripped of their agent rights while incarcerated and are not eligible for state-exchange or transition over time ($t \rightarrow j_{max}$).

Extending Epstein Agents: Introducing Geographic Behavior

The preceding characterization is sufficient for generating emotional interplay between agents. We extended this scheme by empowering agents with geographic functionality that wraps around their socioemotional agency to determine how, where, when, and in what company and contexts those agencies should be deployed or interpreted (Figure 1). We specifically bestowed agents with polyspatial behavior that allowed them to flexibly and intelligently deploy spatial cognition, vision, collision-detection heuristics, spatial targeting, way-finding abilities, locomotion, physical and affective steering, and the ability to develop and apply spatial biases, tactics, and strategies. This represents a considerably richer and more authentic geographical functionality than is usually presented in existing models. These behaviors are detailed individually as follows and the algorithmic procedure for integrating them in run time is presented in Algorithm 1.

Algorithms

Algorithm 1: pseudo-algorithm for behavioral geography update and information flow order

1 Initialize simulation scenarios
2 Assign initial (temporary) headings and directions using random values within each agent's vision
3 Check to see if weightings need to be applied (user-defined)
4 If weights are required, calculate affective targeting
5 List relevant agents within vision
6 Cull obscured agents
7 Target the closest remaining agent (if any remain)
8 Calculate vector to or away from target
9 Calculate magnitude of vector
10 Determine new position
11 If new position is occupied, return to (3)
12 Detect collisions
  a. Look toward your direction
  b. Cast a vision ray using user-defined distance
  c. Reel in the vision ray
  d. Catalog potential collisions
  e. If no collisions are within movement range, proceed to (13)
  f. If collisions are within movement range, perform brief random walk and return to (a)
13 Move
14 [For arrest, if agent is within user-defined capture threshold, arrest]

Improving Agents' Geographical Perception of Their Dynamic Surroundings. A first step in building useful geographic behavior is to provide agents with realistic spatial perception of events around them. In most

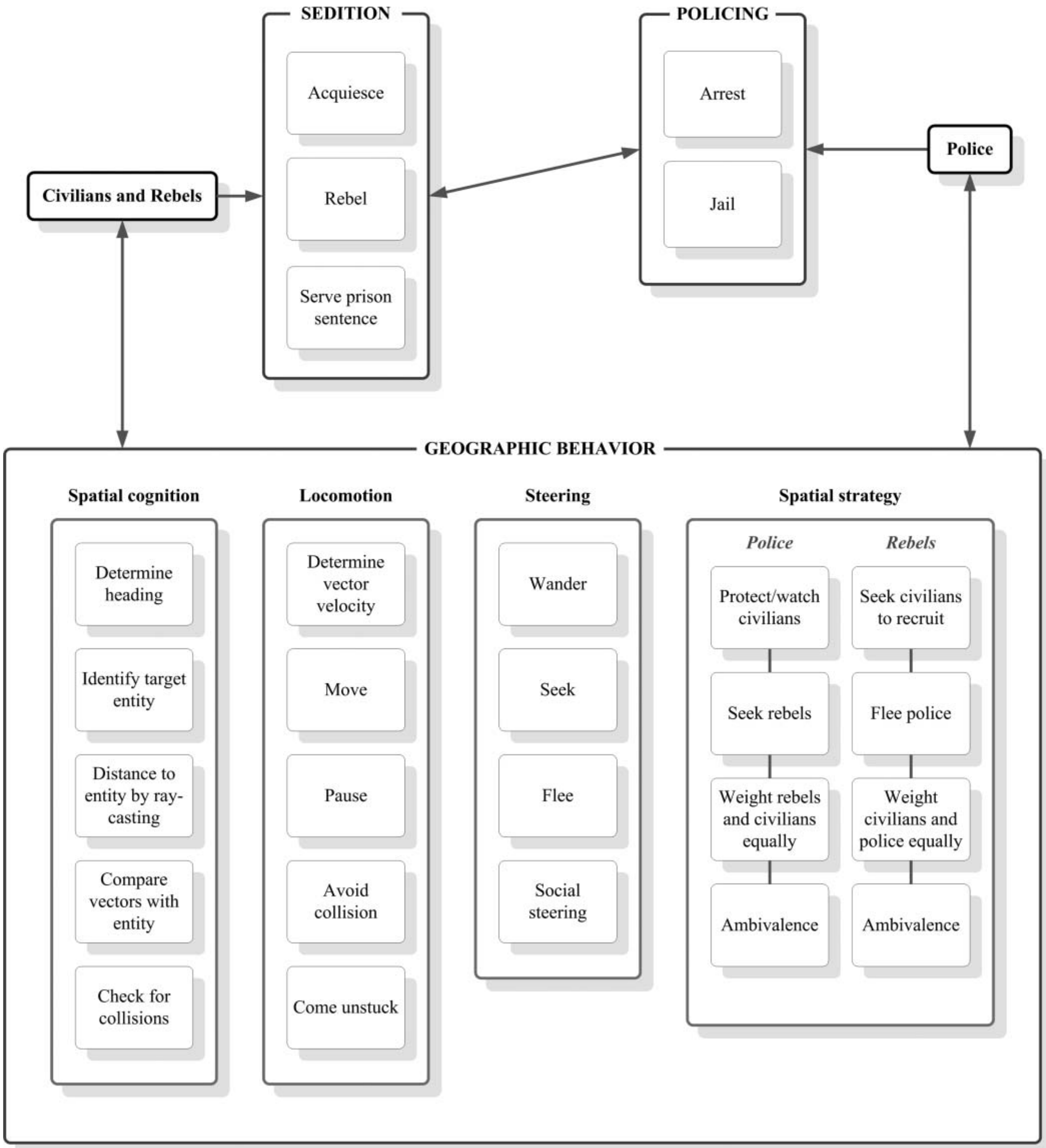

Figure 1. Schematic overview of the docking of socioemotional agency with behavioral geography.

riot models, a cellular automata (CA) neighborhood filter is used. This is a fixed and symmetrical grid that is homogeneously projected around each agent (Torrens 2009). Usually, neighborhood sizes and shapes are not differentiated. Fixed CA neighborhoods are problematic because they are unrealistic: They lack directionality and they allow people to literally have eyes in the back of their heads; they also tend to overspecify the amount of spatial interaction in a system (Torrens 2011). Instead, we use synthetic vision: Per

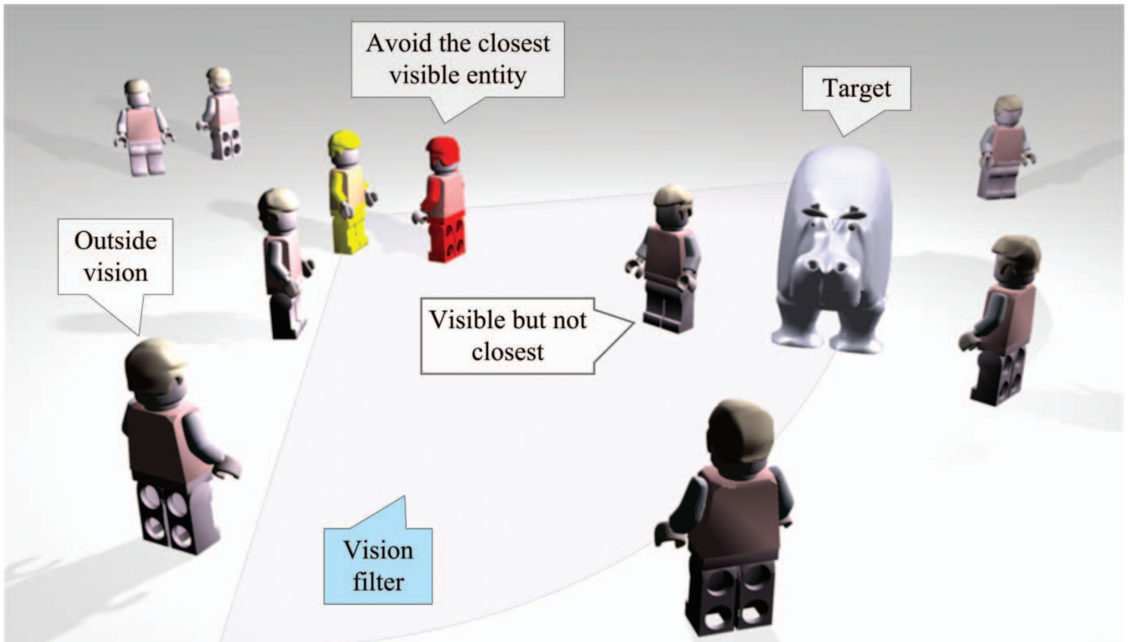

Figure 2. An agent-actor (yellow) examines its neighborhood and identifies other entities that fall within its visual filter, focusing on the entity that is closest (red). The agent-actor could also use its mental map to prioritize entities that it encounters in its environment (e.g., a wandering hippopotamus). (Color figure available online.)

agent awareness of the environment is (uniquely) projected within a visual field (Figure 2). Returned data are stored as a mental map and this provides the informational substrate for subsequent behavior.

Vision (F_t) is cast as a *sector* with origin at the centroid of an agent's footprint. Casting is projected in a forward direction along the unit vector of the agent's direction of travel ($\hat{\boldsymbol{a}}_t$), so that it is tight-coupled to agents' movement. Sizing and shaping of agents' vision is determined by user-defined parameters for radius $\boldsymbol{r}$ (line of sight) and angle θ (field of view), but these can also change dynamically or algorithmically in run time as needed ($F_t - \frac{1}{2} r_t^2 \boldsymbol{\theta}_t$). The radius of the sector is also tempered with a user-defined velocity-decay parameter $-\boldsymbol{\alpha}$ that discounts longer values of $\boldsymbol{r}$ (as $\boldsymbol{r}^{-a}$) when an agent is moving relatively quickly, enabling agents' visual appreciation of their surroundings to be elastic. Police agents can only apprehend Rebel agents when they are physically close to them. An additional test is added to the Police's vision to allow them to evaluate whether their target Rebel falls within a user-defined distance threshold. Agents also use their vision to check whether objects are obscured, by ray-casting.

Way-Finding. Before agents move, they need to decide where to go. We achieve this with synthetic way-finding by targeting. Agents use their vision to catalog their surroundings and then they prune this information by targeting specific relevant things in their vision; targets then serve as way-points for subsequent steering and locomotion behaviors.

In the absence of a specific target, agents move by *purposeful milling*. We provide them with a quasi-random feed of way-points within their vision. This produces smooth movements through incremental course correction as agents' displacement is constrained within their visual field over ($t \rightarrow t{+}1$). Note that this is not a mathematical-style random walk, where agents could perform instantaneous about-face maneuvers without having to slow down and correct their steering first. Way-finding can also be *tenacious*. For example, the locations of Rebel agents become targets for the Police, allowing them to patrol the streets literally looking for Rebel agents to apprehend. Similarly, Rebel agents might target nonrioters as recruits to their cause.

Way-finding is resolved as follows. First, an agent checks its vision for the presence of other entities, memorizing their locations. It identifies agents that it wishes to target, by checking its affect toward them. The agent then uses ray-casting to determine whether any of the candidate entities is obscured. What remains is a subset of entities that are not obscured and that are affectively relevant. The target agent that is closest to the observing agent in this set is then selected as the target (in the case of a distance tie, for example, between Rebel and

Civilian or between Police and Civilian, the Civilian is made the target). Although agents collect all of the information that they see in their surroundings, they focus their behavior and processing only on a single entity at a time. This is realistic given the small space–time geographies in our model, which run at scales of a single footstep. It is also relatively efficient computationally, avoiding unneeded querying. Moreover, this approach allows us to avoid unrealistic averaging artifacts common in many potential-based models, which might cause an agent to cancel out conflicting push–pull influences in its neighborhood and just remain in situ or float like a rudderless boat along a previous vector (Helbing and Molnár 1995; Treuille, Cooper, and Popović 2006).

Steering and Locomotion. Ready with a decision about what to do, agents actually move by steering and locomotion. Despite the significance of collective locomotion in rioting (McPhail and Wohlstein 1986), this functionality is generally not provided in existing riot models and its absence really cripples agents, depriving them of means to move relative to other things or people in simulation.

We allow agents to physically steer within crowds, and we allow them to steer emotionally, by considering their affect relative to a target. Agents' mental maps provide the vectors of visible targets, so an agent can compare its own vector to the target and it can adjust its speed and steering to adopt a trajectory that intercepts or avoids the target (Figure 3). Vectors for the pursuer ($\boldsymbol{a}$) and target ($\boldsymbol{b}$) are considered between two points in space (a_0, a_1) and (b_0, b_1), respectively. We consider only two-dimensional vectors, ($\boldsymbol{a} = [\begin{smallmatrix} a_x \\ a_y \end{smallmatrix}]$) and ($\boldsymbol{b} = [\begin{smallmatrix} b_x \\ b_y \end{smallmatrix}]$) (where a_x is the position of $\boldsymbol{a}$ in the x-axis and a_y is its position in the y-axis $\in \mathbb{R}^2$). Directions for these vectors are obtained by normalizing them such that ($\hat{\boldsymbol{a}} = \frac{a}{|a|} = 1$) and ($\hat{\boldsymbol{b}} = \frac{b}{|b|} = 1$). The velocity of the vectors is taken as the first differential of their positions (a_0, a_1) and (b_0, b_1), respectively: $\dot{\boldsymbol{a}} =^{\lim}_{\Delta t \to 0} \frac{\Delta a}{\Delta t}$ and $\dot{\boldsymbol{b}} =^{\lim}_{\Delta t \to 0} \frac{\Delta b}{\Delta t}$. When a pursuer seeks out a target, it calculates an intercept vector $\mathbf{c}$, ($\mathbf{c} = \boldsymbol{a} - \boldsymbol{b}$) by vector addition. The steering vector for pursuer $\boldsymbol{a}$ to chase and intercept $\boldsymbol{b}$ is then ($\boldsymbol{d} = \mathbf{c} - \boldsymbol{a}$) by vector subtraction.

We also introduce differential effort so that agents can move relatively quickly or slowly, as they need. The steering vector of pursuit is [$\mathbf{d} = (\mathbf{c} - \boldsymbol{a})\dot{\boldsymbol{a}}_{max}$] when $\boldsymbol{a}$ chases $\boldsymbol{b}$ with maximum effort. Here, we overload the notation $\boldsymbol{d}$ for consistency with the notation of related vectors in Figure 4; this $\mathbf{d}$ should not be confused with the distance $\boldsymbol{d}$ of the ray cast in Figure 2. Vectors for fleeing with maximum haste are taken as the inverse of seek vectors; that is, [$-\boldsymbol{d} = -((\mathbf{c} - \boldsymbol{a})\dot{\boldsymbol{a}}_{max})$]. (Note that vector calculations are computed in simulation. The notation for the equal sign therefore represents an algorithmic assignment function of variables and parenthetical statements denote the logical order in which the algorithmic methods are assessed.)

Proactively Detecting and Avoiding Collisions. To effectively actuate their behavior in busy crowds,

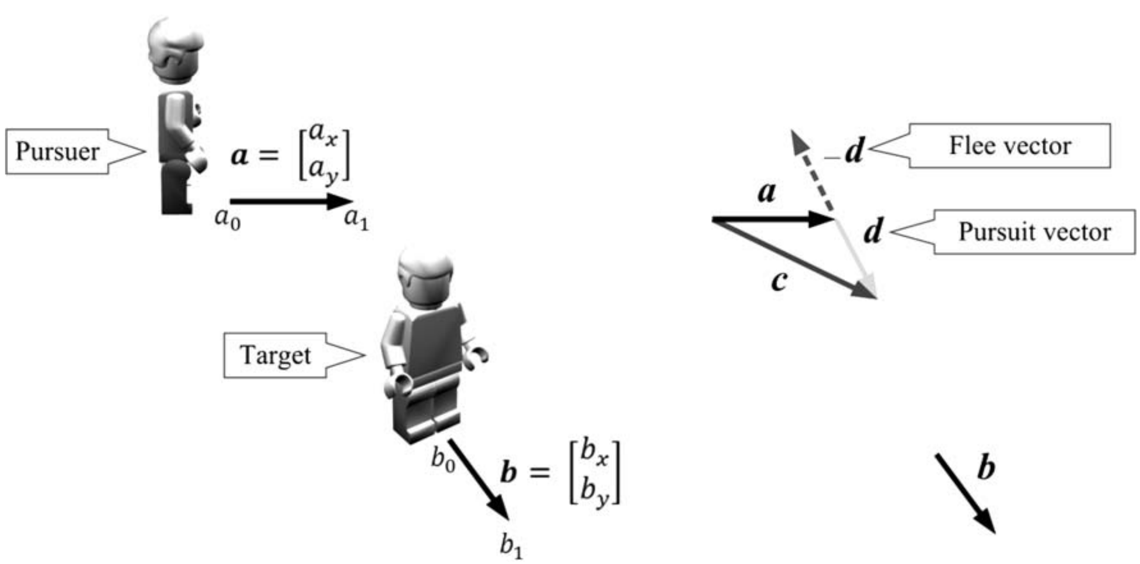

Figure 3. Steering behavior for pursuit or evasion of a target. A pursuer targets another agent and might adopt a steering vector to pursue or flee that target.

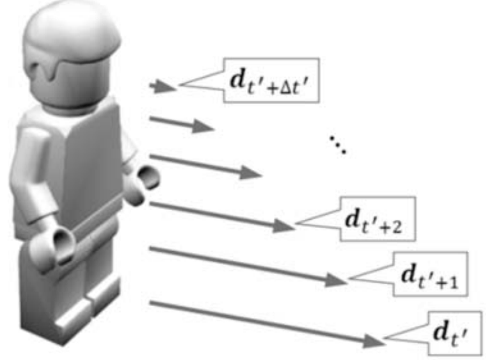

Figure 4. Ray-casting for collision detection and depth perception. A ray is cast in the direction of $\hat{\boldsymbol{a}}$ and it is successively shortened in the direction of the agent-actor until $d \approx 0$.

$$\boldsymbol{ray}\begin{cases} collision = true\ if\ \boldsymbol{d}_{t' \to \Delta t'} \cap (any\ other\ [relevant]\ object) \\ collision = false\ otherwise \end{cases}$$

agents often need to preemptively avoid or pursue things that they see or take an interest in. Existing riot models rarely treat even rudimentary geographic behavior of this kind.

We introduce collision detection using modified ray-casting (Roth 1982; see also Figure 4). This allows each agent to project its movement vector by a user-defined magnitude $|\boldsymbol{d}_{t'}|$ and to deploy the projection as a sensor. For collision detection, we take the time step ($t \to t+1$) and subdivide it into smaller subincrements nested within ($t \to t+1$), such that $[(t' \to t'+1 \to \ldots \to t'+\Delta t') \in (t \to t+1)]$. The temporal length of ($t' \to \Delta t'$) is related to the spatial length of ($|\boldsymbol{d}_{t'}|$). The cast ray is iteratively shortened at the far end of its projection ($0 \approx |\boldsymbol{d}_{t'+\Delta t'}| < \cdots < |\boldsymbol{d}_{t'+2}| < |\boldsymbol{d}_{t'+1}| < |\boldsymbol{d}_{t'}|$) until it approaches zero distance from the agent's position centroid. At each increment of t', the ray is checked for interruption by moving or fixed objects. If a collision is determined, the agent will halt movement over ($t \to t+1$), either giving the moving object time to pass by yielding or giving the other movement rules in the agent's behavior an opportunity to determine a diverted path around the obstacle. For fixed obstacles, the agent "retracts" the cast ray to a location just free of collision and uses this as a target for flee behavior.

Affective Movement. A set of weights is introduced per agent to accommodate agents' affective biases in movement (Willis, Gier, and Smith 1979). At a simple level, weighting affords agents greater interest in relevant objects than in irrelevant objects, but it also directly couples emotional perception to movement, permitting the parameterization of goal-driven strategies and tactics. We borrowed the idea of weighted interaction influence from Yiu, Gill, and Shi (2002), who used weights in their civil violence model to control information exchange in CA neighborhoods. Our approach is distinct, however, as it is specifically adapted for mobile, dynamic, sociospatial weighting of agent movement vectors. The weights are user-defined, allowing for the influence of varying strategies to be explored in simulation.

Rebel agents' affect is controlled by λ, which provides a user-defined balance of emotional affordance that might see-saw between Police and Civilian agents; Police agents are guided by μ, the relative trade-off between Rebel agents and Civilian agents. λ is calculated for Rebel agents as follows.

$$\text{For Rebel agents, } (-W_{Police} + W_{Civilian} = 1) \quad \text{and} \quad = \frac{-W_{Police}}{W_{Civilian}}, \text{ where } -1 \leq W_{Police} \leq 0 \tag{4}$$

Users can adapt Rebels' relative weighting by controlling W_{Police} (the weight that Rebel agents lend to Police agents in their local surroundings). For example, if a simulation user tips the scale to a value of $W_{Police} = -0.5$, then $W_{Civilian} = -0.5$ and λ =1, which produces an ambivalent affect for Rebels relative to Civilians and Police. If the value of $W_{Police} = -0.7$, then $W_{Civilian} = 0.3$ and $= 2.33$, which produces a strongly negative affect for Rebels, affording them a strong aversion to the Police.

Another weight (μ) is introduced for Police agents, as follows.

$$\text{For Police agents, } (W_{Rebel} + W_{Civilian} = 1) \quad \text{and}$$
$$\mu = \frac{W_{Rebel}}{W_{Civilian}}, \text{ where } 0 \leq W_{Civilian} \leq 1 \tag{5}$$

μallows Police agents to trade-off affect relative to Rebel and Civilian agents. It is controlled by adjusting the value of $W_{Civilian}$. Preference is given to Civilian agents in the event of a tie for λ and for μ.

When a pursuer identifies a target (e.g., a Police agent identifies a Rebel agent to arrest), it calculates an intercept vector in unit form and then assigns (through algorithmic update) a magnitude to that vector based on the result of its weighting calculation; that is, $|\boldsymbol{d}| = (\hat{\boldsymbol{d}} + \lambda)$ for Rebel agents and $|\boldsymbol{d}| = (\hat{\boldsymbol{d}}\mu)$ for Police. This mimics affective movement as it occurs in the real world; for example, when people steer to avoid undesirable encounters on a street or move to avail of an intervening opportunity (Dabbs and Stokes 1975).

Coming Unstuck, if Necessary. On the rare occasion that agents become stuck in situ, they divert their movement behavior:

$$\boldsymbol{a}_{t+21} = (\boldsymbol{a}_t \pm \boldsymbol{e}) \text{ , IFF the agent's position remains}$$
$$< a_{0,t} \rightarrow a_{0,t+1} \rightarrow \ldots \rightarrow a_{0,t+20} > \tag{6}$$

In Equation 6, $\boldsymbol{a}$ is an agent's original vector ($\overrightarrow{a_0 a_1}$). If an agent stays in situ for twenty time steps ($t \rightarrow t+1 \rightarrow \ldots \rightarrow t+20$), it is nudged into motion again at $t+21$ with $\boldsymbol{e}$, a random vector that sets an agent on a slightly new course with a small user-defined magnitude and random direction $\hat{\boldsymbol{e}} \neq \hat{\boldsymbol{a}}$.

A Note on Timing. Timing is handled pseudo-synchronously (Bengtsson and Yi 2004), using memory buffering to update agents' information collection and transition. One time step resolves a complete synchronization of all agents' transition processing with the information they have for that time step (Algorithm 1). The timing for this is, of course, artificial because it is simulated, but it is set to be roughly equivalent to a real-world second (based on plausible velocity for agents relative to real-world people). The simulation will often run much faster than life on a computer, but in the results that we present, the relative timing is as we have just described. (The timings and synchronization can be altered.)

Experimenting with Riots in Simulation

We devised four sets of scenarios to explore riotous crowd dynamics in simulation (the parameters for each scenario are listed in Table 1). Two scenarios were designed to establish base conditions in simulation:

- *Base*, in which 1,000 modeled agents were endowed with what will then serve as default characteristics and were placed in a plaza-type setting, as might be found in central cities or around monument infrastructure. These types of spaces are often chosen for collective assembly (Newman 1972; McPhail and Miller 1973). Fifty police agents were deployed to the crowd, to represent police units that might be called to oversee a demonstration (Earl and Soule 2006).
- *Built environment*, in which 285 agents were placed in a smaller urban setting with built infrastructure. This provided a simple test of the influence of the built environment on riot dynamics: Agents had to negotiate and move around built infrastructure and it influences their ability to acquire information about the events around them. Fifteen police were introduced, as might be found on foot patrol.

The second set of scenarios was used to explore rioting from the perspective of Civilian and Rebel agents:

- *Mass protest*, in which a larger volume of Civilian agents (5,000 instead of 1,000) was introduced. This provided ingredients for a protest riot (Earl, Soule, and Mccarthy 2003; McCarthy, Martin, and McPhail 2007).
- *Angry mob*, in which 1,000 *hyperaggrieved* Civilian agents (i.e., possessing higher initial values for grievance; see Table 1) were introduced to the simulated space. This provided opportunities to experiment with dynamics of food riots (Taylor 1996).

The third collection of scenarios portrayed crowd dynamics from the perspective of Police agents:

- *Nonengagement*, in which fifty Police agents were mobilized to supervise a crowd of Civilian and Rebel agents but were under instructions not to arrest anybody (although the Civilian and Rebel agents did not know this). This allowed us to experiment with the influence of Police on crowd perception (Prati and Pietrantoni 2009).
- *Riot police*, in which a 200-strong squad of Police agents was deployed to the riotous crowd, as a force-in-numbers (Waddington 1991), in addition to their

Table 1. Varying parameterization of the model to produce different simulation scenarios

	Simulation scenario					
Variable	Base	Built environment	Riot police	Mass protest	Angry mob	Nonengagement
Simulation run time	12 hours	12 hours	12 hours	12 hours	12 hours	12 hours
Legitimacy	0.82	0.82	0.82	0.82	0.25	0.82
Maximum jail term	24 hours	24 hours	24 hours	24 hours	24 hours	0 hours
Civilian and Rebel vision (m)	7	7	7	7	7	7
Police vision (m)	7	7	7	7	7	7
Number of Police	50	15	200	50	50	50
Number of citizen agents	1,000	285	1,000	5,000	1,000	1,000
Rebel W_{Police}	–0.5	–0.5	–0.5	–0.5	–0.1	–0.5
Rebel $W_{Civilian}$	0.5	0.5	0.5	0.5	0.9	0.5
Rebel λ	0.5	0.5	0.5	0.5	0.11	0.5
Police W_{Rebel}	0.5	0.5	0.5	0.5	0.5	0.5
Police $W_{Civilian}$	0.5	0.5	0.5	0.5	0.5	0.5
Police μ	1	1	1	1	1	1
Arrest distance (m)	2	2	2	2	2	2
Is jail a deterrent?	Yes	Yes	Yes	Yes	Yes	No
Agent field of vision	120°	120°	120°	120°	120°	120°
Patch length per agent step (m)	0.25	0.25	0.25	0.25	0.25	0.25
Distance buffer (m)	0.5	1.25	1.25	1.25	1.25	1.25
Infrastructure obstacles?	No	Yes	No	No	No	No

default behavior. This provided the seeds for a police riot (R. Stark 1972).

The fourth set of scenarios was designed to explore the interplay between varying tactics and strategies for agents (Table 2):

- *Equal treatment*, in which Rebel agents were equally disposed to pursuing Civilian agents and avoiding Police agents, and Police agents gave equal preference to chasing Rebel agents and protecting Civilian agents. This tested the balance between opposing forces of control in the crowd (this is the base scenario already described).
- *Police pursue Rebels*, in which Rebel agents balanced their preferences for fleeing from Police agents and pursuing Civilian agents to recruit, but Police agents weighted their behavior strongly in favor of pursuing Rebel agents, with a comparatively weak impulse toward Civilian agents. This created an enforcement role for police.
- *Police protect Civilians*, in which the preceding situation was reversed: Police agents weighted their behavior strongly toward protecting Civilian agents at the expense of a weakened impulse for chasing Rebel agents to arrest. This placed Police in a protective role.
- *Rebels recruit Civilians*, in which Police agents adopted equal affective propensity toward Rebel and Civilian agents, but Rebel agents weighted their behavior strongly in favor of seeking out Civilians to recruit to the cause, ceding most of their desire to evade capture by the Police. This rendered rioters relatively active in expanding further rioting.
- *Rebels avoid Police*, in which the Police adopted a balanced strategy again, but Rebel agents favored avoiding Police over recruiting Civilian agents. In essence, this characterized rioters as relatively risk-averse.
- *Battle for Civilians*, in which the Police agents strongly weighted their behavior toward protecting and recruiting Civilian agents and the Rebel agents emphasized recruitment of Civilian agents to the riot.
- *Cat and mouse*, in which Rebel agents were strongly weighted toward avoiding Police, whereas the Police were strongly weighted toward capturing them.

In all model runs, agents' bodies were represented with circular area of 0.1419 m^2, which provided a realistic physical footprint on the ground and a small buffer to account for ambulation of their limbs (Fruin 1971). We were most interested in rather small-area spatiotemporal dynamics, so agents were placed in a square field space of ~4 km^2 in area in most of the scenarios and their activity was tracked on the order of seconds.

Table 2. Varying parameterization of the model to produce varying behavioral strategies for agents in simulation

	Strategies						
Variable	Equal treatment	Police pursue rebels	Police protect civilians	Rebels recruit civilians	Rebels avoid police	Battle for civilians	Cat and mouse
Simulation run time	12 hours	12 hours	12 hours	12 hours	12 hours	12 hours	12 hours
Legitimacy	0.82	0.82	0.82	0.82	0.82	0.82	0.82
Maximum jail term	24 hours	24 hours	24 hours	24 hours	24 hours	24 hours	24 hours
Civilian and Rebel vision (m)	7	7	7	7	7	7	7
Police vision (cells/m)	7	7	7	7	7	7	7
Number of Police	50	50	50	50	50	50	50
Number of citizen agents	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Rebel W_{Police}	–0.5	–0.5	–0.5	–0.3	–0.7	–0.3	–0.7
Rebel $W_{Civilian}$	0.5	0.5	0.5	0.7	0.3	0.7	0.3
Rebel λ	1	1	1	0.43	2.33	0.43	2.33
Police W_{Rebel}	0.5	0.7	0.3	0.5	0.5	0.3	0.7
Police $W_{Civilian}$	0.5	0.3	0.7	0.5	0.5	0.7	0.3
Police μ	1	2.33	0.43	1	1	0.43	2.33
Arrest distance (m)	2	2	2	2	2	2	2
Is jail a deterrent?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agent field of vision	120°	120°	120°	120°	120°	120°	120°
Patch length per agent step (m)	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Distance buffer (m)	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Infrastructure obstacles?	No	No	No	No	No	No	No

This field space was designed as a torus for the sake of tractability in simulation, although only a small fraction of total agents interacted on the borders. (The built environment scenario was constrained to 303 m^2 in area and agents were confined within its bounds.) We should note that the model can accept larger spaces and any two-dimensional configuration of built environment.

Results

We examined the outcomes of the simulation scenarios using several vantages. First, we wanted to test whether the model could generate realistic geographic behaviors within crowds, as this is underdeveloped in existing models. The second concern was for complexity and the model's ability to produce novel behaviors through complex adaptation—what might, arguably, be termed as *emergence*—and whether it could generate qualitatively complex signatures (J. Epstein 1999). The third evaluation property relates to the usefulness of the model in supporting theoretical inquiry about rioting.

In what follows, the results of each of the scenarios mentioned in the previous section are presented in the context of the four criteria we have just described. Each simulation scenario was run ninety-nine times and we report averaged results to reduce the potential influence of artifacts from initial (random) positioning of agents at the start of a simulation run. Each individual model run generated 43.2 million data points. Running each scenario yielded a total of ~4.28 billion data points.

Base Scenarios

The base parameterization provided a mixed riot scenario, containing elements of food riots, protest riots, police riots, and hooliganism. Under this scenario the crowd phased quickly from a heterogeneous state, to collective agitation (Figure 5A), then to protest en masse with ~20 percent of the crowd joining the riot at its peak after one hour (Table 3). There was a sharp increase in rioting early in the simulation, as those individuals who were already aggrieved began to act out and this outward manifestation spread (as information) through the crowd at large. The police responded by arresting rioters, but it took some time to make much difference (~1.25 hours). After seven hours, the police gained full control, but only after widespread arrest (~40 percent of the crowd). As rioters were jailed and were removed from the crowd, there were fewer free agents to catalyze further rioting and the crowd shifted phase back to a quiescent (outward) state that locked in thereafter, although many of the citizens might still have felt (internal) hardship.

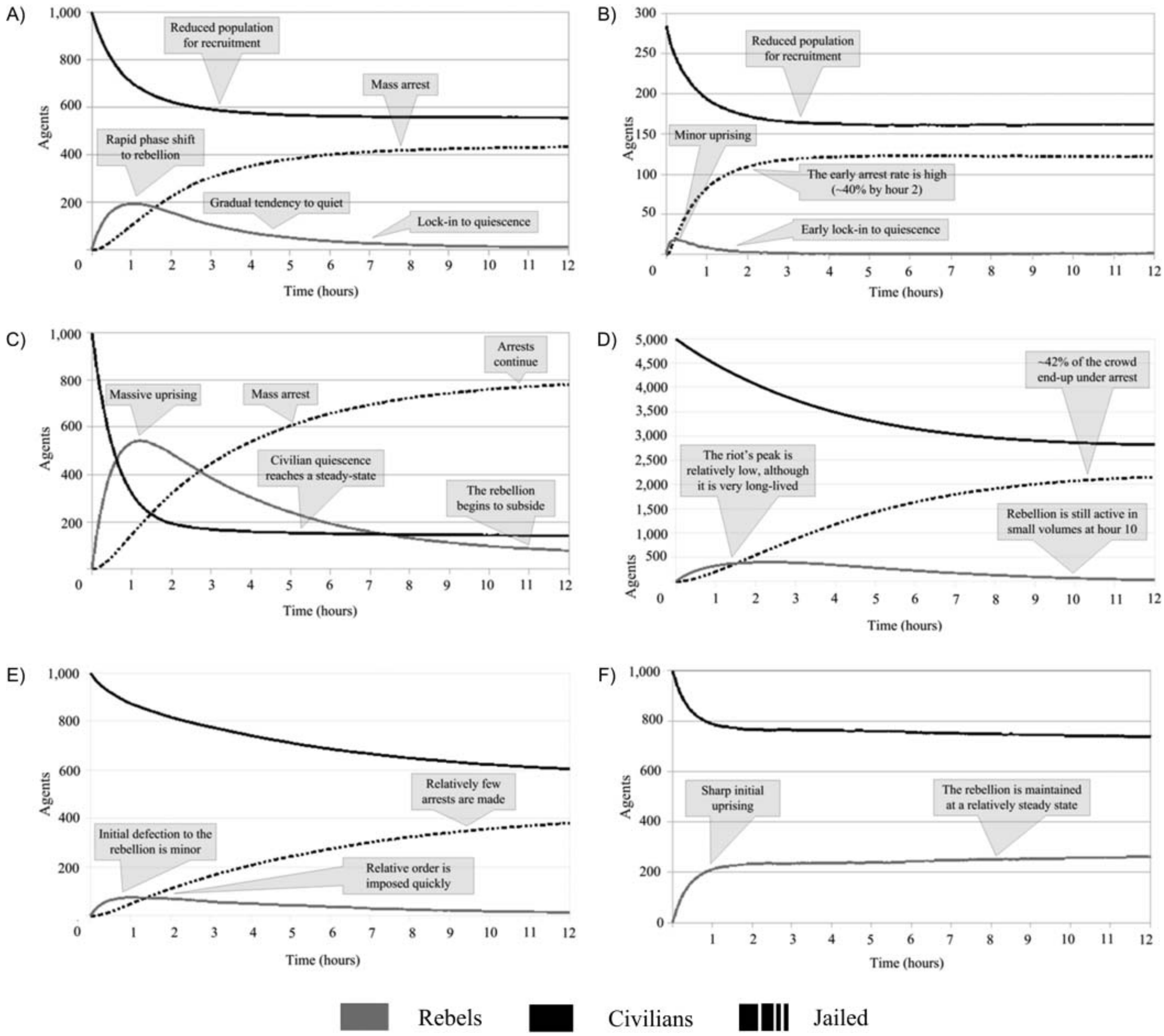

Figure 5. (A) The base scenario for the model (agents are endowed with default parameter values and seeded in a plaza-type space). In each of the line plots that follow, results are reported as averages of ninety-nine runs of the simulation with varying seed locations for agents at the initial time step. (B) Agent dynamics in the built environment scenario, in which agents are equipped with default parameter values and placed in a streetscape with urban infrastructure. (C) Agent dynamics in the angry mob scenario, in which the crowd's feeling of legitimacy toward authority is reduced to 0.25. (D) Agent dynamics in the mass protest scenario, in which the number of crowd participants is increased to 5,000. (E) Crowd dynamics under the riot police scenario. (F) Crowd dynamics under the nonengagement scenario.

We evaluated the extent to which like-minded (rioting or nonrioting) agents tended to collocate, by calculating a global (i.e., one value for the entire field space, per time step) Moran's I statistic for spatial autocorrelation ($-1 < I < +1$; Moran 1950) for every second of the simulation over the first hour (after which volatility diminished; Figure 6). Citizen agents showed a weak tendency for positive spatial autocorrelation in activity: Globally, agents tended to cluster in areas with high volumes of rioters or areas with high volumes of nonrioters. In other words, the crowd polarized through self-organization from initially heterogeneous conditions. This micro-to-macro, mass self-organization resembles end states of other complex social models (Sakoda 1971; Schelling 1971), but we can also consider its dynamics. Autocorrelation increased rapidly in the early part of the riot and fluctuated thereafter.

Table 3. Qualitative model results

	Benchmark					
Scenarios	Timing of riot peak	Crowd involvement at peak (%)	Riot duration	Peak duration	Timing of restored control	Proportion of crowd arrested (%)
Base	70 minutes	20	6 hours	70 minutes	Hour 7	45
Built environment	10 minutes	10	2 hours	25 minutes	Hour 2	42
Riot police	60 minutes	5	9 hours	3 hours	Hour 10	45
Mass protest	90 minutes	10	8 hours	4 hours	Hour 11	45
Angry mob	60 minutes	55	11 hours+	60 minutes	Never	79
Nonengagement	12 hours	27	11 hours+	11 hours+	Never	None
Strategies						
Equal treatment	70 minutes	20	6 hours	70 minutes	Hour 7	45
Police pursue Rebels	45 minutes	17	5.25 hours	60 minutes	Hour 7	42
Police protect Civilians	60 minutes	20	6 hours	90 minutes	Hour 7	42
Rebels recruit Civilians	60 minutes	20	5 hours	60 minutes	Hour 6	42
Rebels avoid Police	60 minutes	19	6.5 hours	75 minutes	Hour 8	45
Battle for Civilians	65 minutes	20	7 hours	75 minutes	Hour 8	45
Cat and mouse	50 minutes	14	3.5 hours	75 minutes	Hour 4.5	45

We can zoom in on the results to evaluate local (space–time) patterns of behavior at the scale of individual agents. This is useful in illustrating how agents use their geographic abilities and how they interact in simulation. For example, Figure 7 illustrates how rioting agents were successful in avoiding law enforcement in some areas, because they saw the police coming and were able to veer and run away. In other areas, they were less successful and resorted to deceptive behavior by dialing-down outward signs of rioting or physically

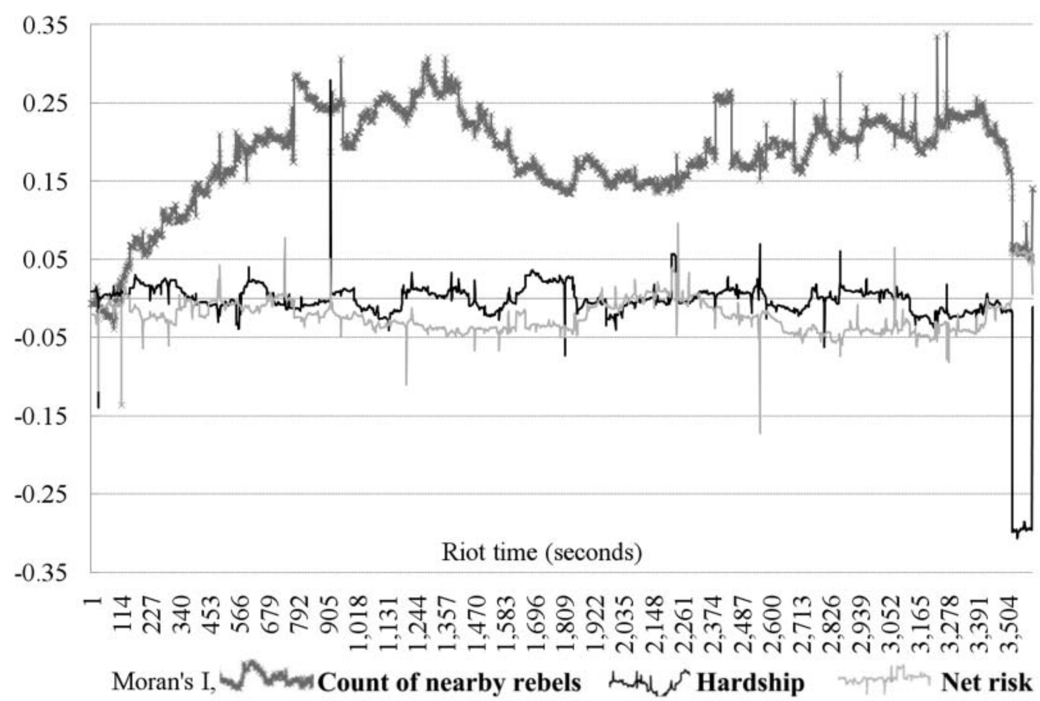

Figure 6. Global spatial clustering of agents of like state-values in the base scenario. Values of zero indicate no statistically significant clustering, positive values indicate positive spatial autocorrelation, and negative values indicate negative spatial autocorrelation. After fifteen minutes of rioting (900 seconds), citizen agents begin to cluster into areas where there are low counts of nearby rebels and areas where there are high counts of nearby rebels (I ≅ +0.25 ± 0.07) and they sustain this pattern for a further forty-five minutes. Agents show no evidence of global clustering based on hardship or net risk.

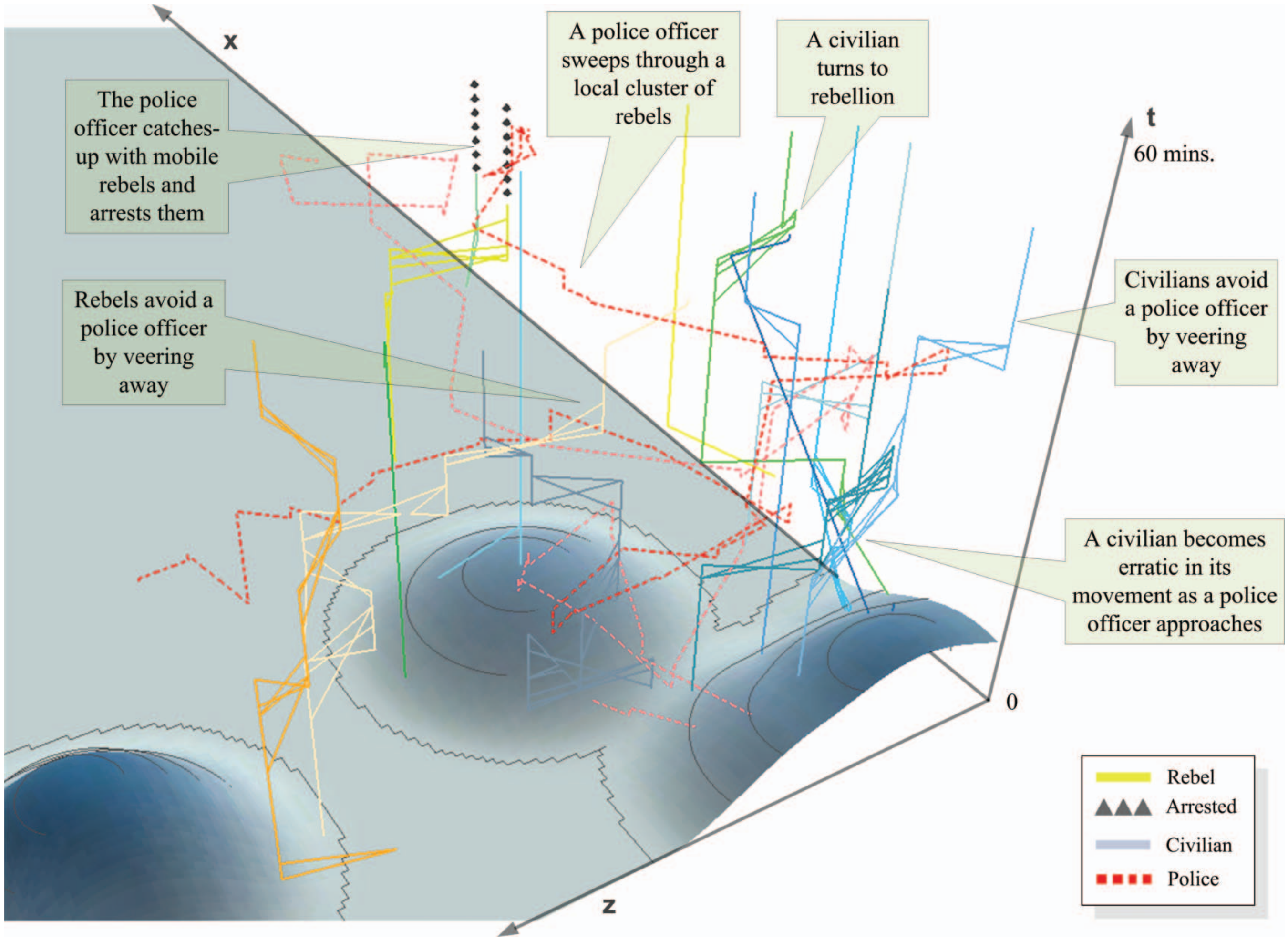

Figure 7. In this illustration, the space–time paths of a subset of the rioting crowd are shown in a portion of the simulated area. This figure corresponds with the first hour of the simulation portrayed in Figure 5A; *X* and *Z* are two dimensions of space; *t* is a temporal dimension. Local hotspots and cool spots of riotous activity are evident in the space–time movement of individuals in the crowd. Areas that Police cover well remain quiet; those that they miss are relatively active in rebellion. (Color figure available online.)

avoiding police to escape apprehension. Figure 7 also shows the police usefully employing their spatial abilities to evaluate the crowd and to identify, chase, and apprehend rioters.

Riot dynamics in the built environment scenario were dramatically different because of the reduced numbers of participants and the effect of the built environment on agent vision and movement (Figures 5B and 8). The riot was comparatively unsuccessful and short-lived; agents were relatively easily chased and apprehended when identified by the Police.

Civilian and Rebel Scenarios

The angry mob scenario was designed to examine food riots (Taylor 1996), in which individuals have been building their animosity for some time ahead of assembling in a crowd to demonstrate mass grievance. To represent this, we seeded agents with lowered feelings of legitimacy (0.25) instead of the base value (0.82). The resulting dynamics differed significantly from the base scenario (Figure 5C). The initial phase shift toward rioting was dramatic, with 55 percent of the crowd getting involved at its peak. The police responded quickly, arresting a huge portion of the rioting crowd. Compared to the base scenario, the decline in rioting and move toward quiescence was relatively sharp, largely because the arrest rate was high. The police had to arrest 80 percent of the crowd before gaining full control.

The mass protest scenario was designed to mimic the sorts of dynamics that might permit rioting to break out in a very large (5,000 agents) and otherwise law-abiding crowd, as might occur, for example, during a political rally (Gillham and Marx 2000). The results were quite close to the base scenario, despite the influx of a larger volume of participants (Figure 5D), and the reasons for this are quite interesting. The rebellion was somewhat slower to take hold, but it was longer lasting (~2.5 hours) than in the base scenario (which lasted ~1.25 hours). The civilian crowd was much larger in the protest scenario and even though there were more aggrieved agents to catalyze a riot, there were also a greater number of riot-averse agents to dampen those tendencies. In essence, this provided a natural, self-organized control mechanism within the crowd itself (Russell, Arms, and Mustonen 1999).

We analyzed the mass protest scenario for local spatial autocorrelation, using a local Moran's I statistic (Anselin 1995) on agents' arrest likelihood. The results are shown in Figure 9, against a backdrop illustrating a kernel density–smoothed (Oliver and Webster 1990) surface of citizen-agent grievance levels per time step. In the early stages of the simulation, agents were seen to form statistically significant (at a 99.9 percent confidence interval) local clusters: Agents with low arrest likelihoods clustered together in space and time (with statistically significant geography). These low–low clusters contained relatively high grievance levels and were mostly outside the attention of the small police force on the scene. This shows the model working appropriately; the Police only responded to Civilian agents' outward signs of rioting. Small clusters of agents with high arrest likelihoods were also visible, next to Police; the Police performed a relatively good job of identifying local outbreaks of rioting and moved to target them. Once a large-scale riot had taken hold, a few clusters of agents with low arrest likelihoods appeared, which the Police were able to efficiently guard. By the second hour, areas of the space that were well patrolled by Police exhibited relatively low grievance among citizens. By the eleventh hour, few riotous clusters remained, and although it still demonstrated relatively minor levels of grievance, the crowd remained under relative control. The Police still needed to patrol some previous hotspots, however, to ensure that the crowd did not revert to rioting.

Police Scenarios

The scenarios designed to test police behavior in crowd insurrection events produced significantly different dynamics, compared to the base scenario (Table 3). In the riot police scenario, 200 police were deployed to the crowd (an increase from fifty in the base scenario), providing a force-in-numbers response (Waddington 1991). As a result, the riot never really took off. The initial onset took hold with only a small minority of the crowd, ~5 percent (Figure 5E; Table 3). Just as rioting began to spread, the Police (in larger numbers and able to cover more ground) quickly imposed order, initially with a handful of arrests.

Under the nonengagement scenario, Police patrolled the simulated space, without interacting with rioters, but still influencing the actions of Civilians and Rebels that they passed. In essence, this represented preventative policing (Waddington 1991). When the Police saw rioters, they still chased them, but they did not arrest them. This had the effect of dampening overall rioting in the crowd, but the riot, once underway, was long-lasting and persistent (Figure 5F). The Police maintained relative order but never fully gained control. They did, however, avoid mass arrest.

The Influence of Strategy and Tactics

Deploying spatial weights on agents' perception, cognition, and movement allowed us to study the influence of geographical tactics and strategies. The equal treatment strategy is the same as the base scenario already discussed and Rebels and Police were balanced in their affective biases (Table 3).

Police-Oriented Strategies. Two police strategies were explored. The Police invested the majority of their effort in protecting the civilian population from rioters in the Police protect Civilians scenario. (Rebels adopted default weighting, balanced in their preference to avoid the Police and chase Civilians.) This strategy was less successful for the Police than the base scenario: The riot peaked earlier, the peak was sustained longer, and the riot lasted longer than under the equal treatment strategy (Table 3).

Under the Police pursue Rebels strategy, the Police were designed to be more aggressive in pursuing rioters than they were in protecting nonrioters. This proved to be only slightly more useful for the Police in maintaining order. The initial shift to riot occurred earlier than in the equal treatment strategy, likely because the Police were less concerned with protecting Civilians; this left the crowd freedom (and space) to riot. The Police gained the upper hand quickly, however, and they limited rioting to five hours (compared to seven hours in the base scenario). As with the equal treatment strategy, full control was achieved by hour seven and the Police had to jail a large proportion of the crowd to achieve it (Table 3).

Rebel-Oriented Strategies. Two strategies were designed to study the influence of sedition. (Weights for Police were kept at the default, balanced between

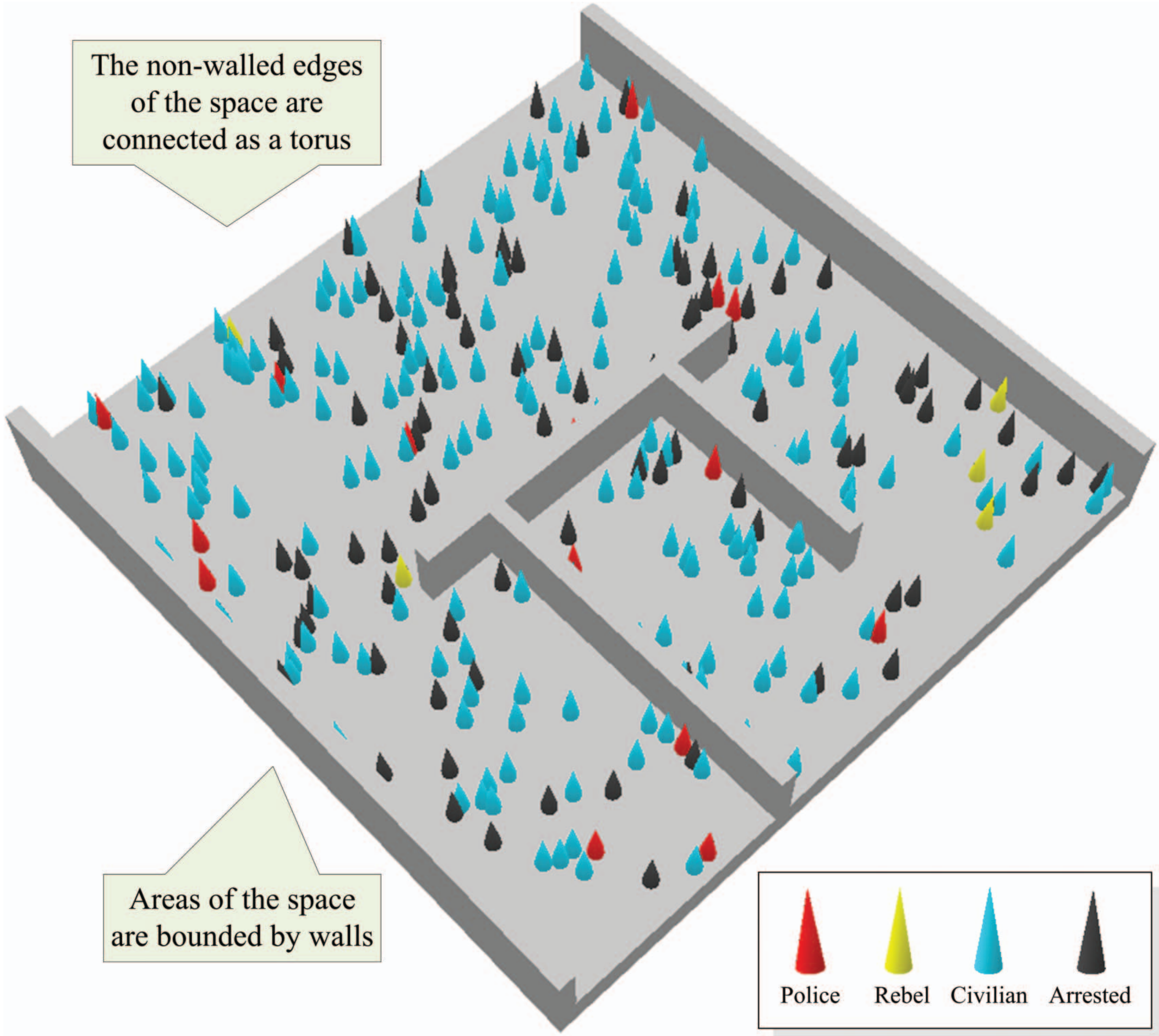

Figure 8. The position of the crowd after one hour of the built environment scenario. The crowd is reduced from fifty to fifteen Police agents and from 1,000 to 285 non-Police agents for the built environment scenario. For illustration purposes only, Jailed agents are shown at the location where they were arrested; Jailed agents are removed from the space immediately on apprehension in simulation. (Color figure available online.)

chasing rioters and protecting nonrioters.) Under the Rebels recruit Civilians strategy, Rebels were biased toward pursuing Civilians in a bid to further foment rioting (at the expense of avoiding apprehension by the Police). This strategy was not particularly effective for the Rebels: They did not recruit more Civilians than they would have under the equal treatment strategy and they did not evade capture particularly well (Table 3). The Rebels sought out new recruits, but in doing so they exposed themselves to arrest.

Under the Rebels avoid Police strategy, riotous agents adopted covert behavior, still seeking out new recruits but avoiding the Police more strongly than in the equal treatment strategy. This was slightly more effective for the Rebels, particularly in the early stages of the riot: They reached peak rioting sooner than in the base strategy and they managed to sustain the riot for an extra hour (Table 3). To some extent, the cards are always stacked against the Rebels, as the Police can remove them from the riot. The Rebels, of course, cannot

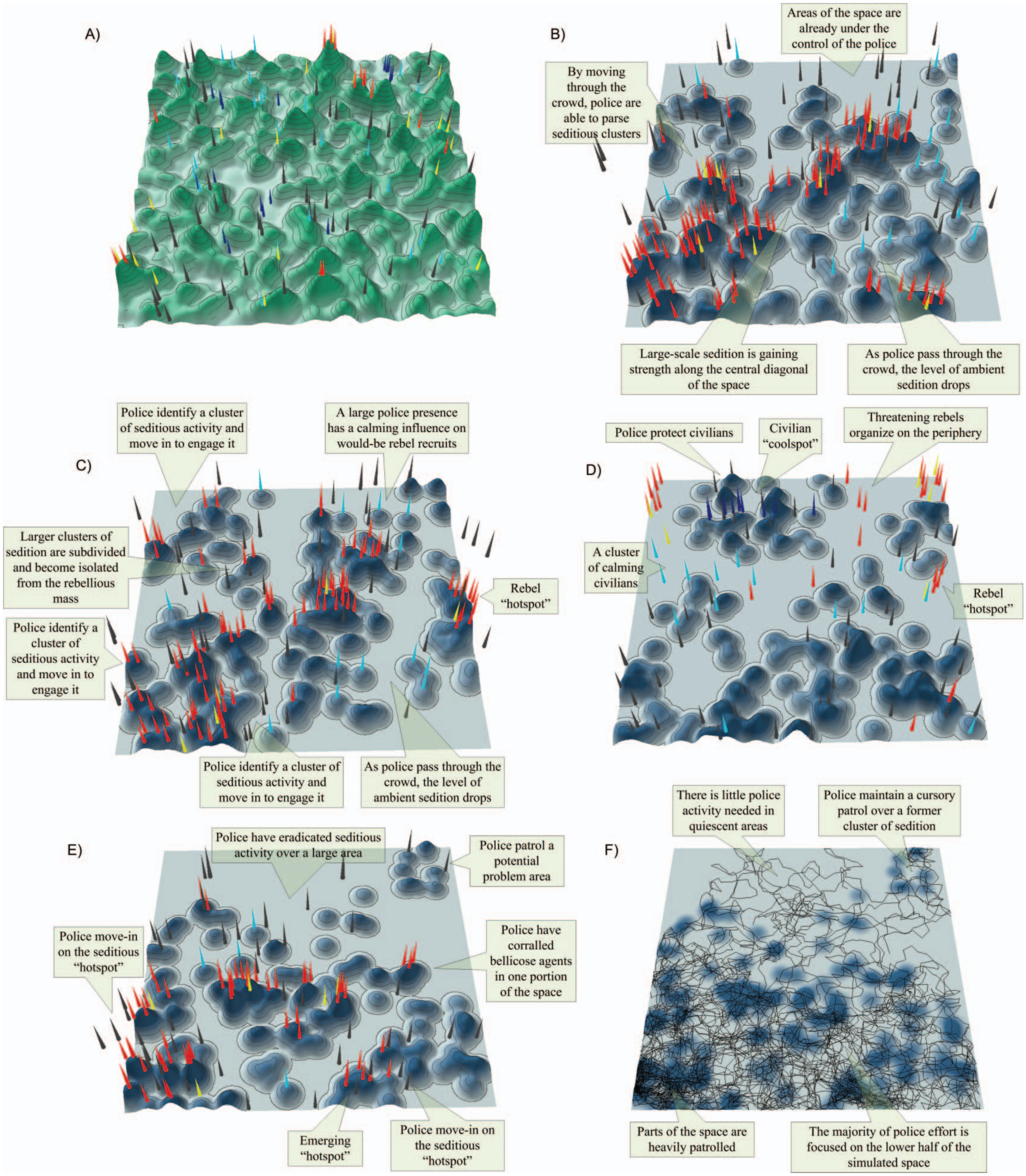

Figure 9. (A) Local surfaces of agent emotion (grievance) are calculated for the mass protest scenario. Local measures of spatial autocorrelation are used to extract statistically significant hotspots (high–high spatial autocorrelation) and cool spots (low–low spatial autocorrelation) of clustering based on likelihood of arrest for (B) hour one, (C) hour two, (D) hour four, and (E) hour eleven of the simulation. (F) Space–time paths for the first eleven hours of Police movement show the concentration of their patrols in the portion of the space with the greatest clustering of rebellion, although islands of initial outbreak must also be patrolled to keep them from reverting to riotous activity. (Color figure available online.)

oust Police. This is a realistic depiction of the relative power balance in riotous crowds.

Conflicting Strategies. The two final strategic scenarios were designed to explore crowd dynamics under conflicting strategies between Police and Rebels. Under the battle for civilians strategy, both Rebels and Police adopted strategic behavior to seek out nonrioters in the crowd. In the case of the Police, their motive was to protect Civilians, whereas the Rebels tried to recruit Civilians to riot. This strategy was only slightly less successful for the Rebels than the base strategy (Table 3).

Under the cat-and-mouse strategy, the Police and Rebels devoted the majority of their attention to each other, paying comparatively little attention to the Civilian population (except that Rebels could lose themselves in nonrioting portions of the crowd to avoid detection). The Police and Rebels essentially played a game of chase under this scenario. The Police played the game very well and the results were relatively disastrous for the Rebels. The Rebels only catalyzed a small riot, which halted quite quickly. The Police managed to restore full order within 4.5 hours (Table 3).

Conclusions

Riots are difficult to experiment with tangibly or using standard social science analyses. One alternative might be to use modeling and simulation to explore riots synthetically. Several riot models have been developed, but existing approaches have emphasized abstract representation of riot phenomena and processes that limit the range of questions that can be posed in simulation. We have presented an alternative scheme that expands the abilities of models to synthesize riots by using a polyspatial, agent-based architecture that can accommodate rich behavioral detail at process scales from the individual to the crowd. We believe that this approach is quite novel and useful.

Methodological Innovation

Our scheme introduces significant methodological innovation. Our attention to detail is much more careful than in standard approaches, so that a richer set of process dynamics can be represented, at the characteristic and atomic timing and spacing of riot phenomena. This allows us to better tailor simulations to real-world scenarios and it facilitates a wider range of inquiry with the model than is usually achieved in existing, abstract approaches. This achievement is important: Many agent-based models advertise their ability to map individuals to macro-outcomes, but coarse and abstract representation of behavioral agency is usually the norm. Many agent-based models simply use existing macro-equations on agents (Batty and Torrens 2005). This rather defeats the purpose of building individual-based models and it has led many authors to rightfully criticize the methodology quite consistently (Faith 1998; Torrens and O'Sullivan 2001; Couclelis 2002; Clifford 2008), but very little is commonly done to challenge this critique. Our approach is distinct: We embrace detailed behavior in simulation.

Another long-standing problem with agent-based models is the prevalence of anemic geographic functionality (Torrens 2010a). Geography is generally considered as an afterthought, with spatial dynamics implied from visual output, despite the fact that geography might have received only cursory treatment in the actual model (J. Epstein 2002). This is surprising, as agent-based models can support rather sophisticated geographical algorithms and processes (Benenson and Torrens 2004). Although there is a rather consistent dialogue in the theoretical literature about the significance of geography in riot dynamics, our model is among the first serious attempts to tackle geography in riot simulation. This alone is novel and, as we discuss later, it turns out to be quite valuable.

Our approach can also extend (and deepen) existing socioemotional agency with geographic wrappers that provide added geographic functionality (vision, steering, movement, neighbor inquiry, vector resolution, collision detection and avoidance, affective biasing) and second-order space–time processes (spatial interaction, diffusion, scaling, clustering, segregation, polarization, chasing, and avoidance). We achieved this in a way that retained existing social agency faithfully but enabled it spatially. This sort of model docking is a topic of avid interest in the agent-based simulation community (Torrens and Benenson 2005; Rank 2010); although this is not the central topic of this article, our example does show how such docking can be achieved for computational social science applications.

We embedded the modeling and simulation components of the work in a unified pipeline that also included spatial analysis, spatial statistics, geostatistics, and geovisualization for sweeping the parameter space and results of simulations. This goes far beyond the usual approach, which relies on simple plots of model parameters over time and descriptive multivariate statistics. Standard approaches usually lack potency anyway, because coarse, aggregate measures are commonly used to examine individually specified models. In a sense, this muddies much of the underlying detail, unless macro-outcomes are known a priori and deliberately sought out in analysis (which is difficult for riot simulation, where the whole point of modeling is to seek out such things in the first place).

Substantive Findings

We touted the potential advantages of our model as an experimental laboratory for studying rioting. So it is fair to ask what we actually learned about rioting in simulation.

The Role of Geography. A long-standing critique of agent-based modeling centers on "unwrapping" (Holland 1995, 137)—the practice of building results directly into model design only to rediscover them in simulation. We deliberately built geographic features into our model but to provide the functionality for dynamic interplay of the features in simulation. This is different than baking in outcomes. Any substantive findings that the model generates are therefore authentic (within the parameters of the simulation).

The processes that drive riotous crowds are sometimes distinct at different scales, and our model shows how they can connect, inexorably, through geography. Theory suggests—and our simulations show—that the actions of a handful of individuals can, in some conditions, shape the dynamics of an entire crowd, whereas in others the actions of the few are diluted by those of the many. Our model allows processes to jump scale barriers, because the agents that create and propagate those processes are polyspatial. In particular, they can react to information channels at diverse scales. For some situations, scaling allows individuals to be teased into rioting under the perceived protection of the group at local geographies. In the reverse direction, seditious behavior at local geography or at an individual level can be dampened by ambient quiescence in a large crowd. Temporal scaling is also important to understanding rioting. A charged crowd can shift phases from relative quiescence to sedition in just a few minutes. Our simulations show how small changes in initial conditions and behavior catalyze these shifts dynamically. The ability of agents to dip into and process information (whether real, imagined, or wrong) at different scales provides the mechanics for emergence, feedback, self-organization, and allometry. This implies that spatially nonmodifiable units on which the finest scale of the simulation is built (and their assembly into coarser process building blocks) are critical in representing riots appropriately, as is their assembly into coarser building blocks for riot processes. Ideally, atoms would represent individuals and would facilitate construction of realistic behavior that allows them to bridge scales. This seems difficult to achieve without realistic treatment of geographic behavior.

This leads us then to the role of geographic behavior in determining rioting. By representing behavior explicitly (not abstractly), our model can show how agents' use of geographic information and their spatial thinking can shape riot dynamics. We have demonstrated this specifically by playing with different configurations of characteristics and strategies. By giving agents geographic behavior, agency becomes less viscous in crowd dynamics than it might without, because agency is mobilized and interpreted in, or exposed to, different times, places, contexts, and company. Mobility also allows the conduits for information exchange between simulated entities to shift and change form, as can the inputs to individual agents' mental maps. Here, there are obvious parallels with the real world, where information exchange courses through crowds rapidly, differentially, and dynamically. Agents need to be mobile—in their activities, actions, reactions, and interactions—to be realistic in riot models. These dynamics are difficult to represent authentically in cell-based models that rely on abstract movement proxies. In CA, for example, agent cells must languish in situ and wait for information to find them and wash over them, rather than proactively seeking out (or avoiding) information in the environment (Torrens 2010a). There are other pitfalls in relying on proxies of movement, in particular, because observed effects in models could derive from artifacts of the proxy, rather than having an analog in theory or real-world phenomena. This problem has been documented for computational automata (Faith 1998) but is perhaps relevant across much of computational social science, as others have noted (J. Epstein 2007).

Physical geography is also significant. Moving a crowd from an open plaza setting to a walled (urban) space had dramatic effects, because it altered the supply of information to agents' geographic behavior. Our experiments with built environments were relatively abstract and the topic warrants further investigation, particularly into the extent to which physical and human geography codetermine riot dynamics.

Exploring Existing Riot Theory in Silico. Our main preoccupation in modeling was with geographic behavior, but we included several popular social science theories of rioting in our model, which we can hesitantly examine. For example, we considered threshold models for collective behavior. The threshold theory suggests that a domino or bandwagon effect might explain the spread of riotous activity within a crowd (Granovetter 1978), that once some target level of participation has been reached, people who would otherwise feel hesitant to act out might feel free to do so because the collective costs of their actions are reduced in aggregate. We built thresholds directly into the individual behavior of our agents by specifying legitimacy and hardship states per agent. The geographic behavior of agents then allowed thresholds to be animated locally through the activation rule and subsequently propelled at a distance by secondary geographic processes. Under certain scenarios and strategies, Rebel agents' proactive geographic behavior also allowed them to seek out nonrioters to seduce to the riot, which could catalyze or maintain some locally safe threshold for acting out. In this way, then, agents put the threshold model into proactive use. This differs considerably from Granovetter's (1978) original probabilistic/equilibrium formulation of the idea, as well as subsequent mathematical implementations (Granovetter and Soong 1983). The implications of this extension to the threshold model are significant. A much richer understanding of the genesis and formation and propagation of threshold effects can be garnered within the crowd. This understanding is distinct from the sorts of explanations usually used to account for generated macrostructures, which are commonly attributed to abstract notions of emergence (see J. Epstein 2002, or even Schelling 1971). In contrast, our formulation shows how threshold effects can generate local (or macroscale) clusters that bubble up, merge, starve for new recruits, expand, disappear and reappear in space and time, and so on. In essence, the threshold phenomenon is much more fluid because the effect is geographic.

The role of information is discussed prominently in the literature (Wright 1978; McPhail and Wohlstein 1983; Rheingold 2002), but it is rarely treated in models. Our simulations show that information is critical in determining interactions within crowds and we are able to show how information exchange can influence the larger crowd mosaic. Our scenarios demonstrate how the trade of nonverbal information can alter riot dynamics, for example, through outward expression (e.g., grievance), locomotion (police chasing bellicose rioters), or spatial interaction (clustering and colocation in space and time). These examples are important in showing how geography can foster dynamism in information. Some effects in crowds might start out as nonspatial but might become mobilized by diffusion (e.g., affect); some might be explicitly geographical (e.g., locomotion); and others might play out through dynamically malleable and scalable space–time structures (e.g., clusters). Our simulations show that the quality of information is also important. Individual agents often have incomplete access to information, particularly in densely packed crowds where their information might be limited to small-scale shifts in immediate conditions around them, and their spatial cognition might be bounded. Misinformation could be equally important. Seditious actors in a crowd might seek to deliberately manipulate the flow (a geographic process) of information to their needs (Prentice-Dunn and Rogers 1982), as when rioting agents in our simulations turned to deception near police. The police can similarly intervene in information exchange through the crowd, by falsely projecting force, for example.

The role of collective behavior in riotous crowds is also a significant subject in the theoretical literature (McPhail and Wohlstein 1983). Although our agents deployed strategies to determine their interactions relative to each other in simulation, they were not given explicit rules for collaboration; that is, each agent within a given role acted independently. Yet, collective space–time patterns did emerge in simulation, with clearly forming hotspots and cool spots of activity (and emotion), for example. There is perhaps a pedagogical lesson here: Much collective behavior can be happenstance, a product of a natural sorting and shuffling of the crowd. As other researchers have shown, this can happen even with small impulses amid a handful of local interactions (Schelling 1971).

The idea of a *crowd mentality* is a controversial hypothesis that is sometimes discussed when considering rioting: the notion that a riotous crowd might act with some sort of pack-like behavior, ceding their individuality to a collective norm. Although it has long been understood to be erroneous (Couch 1968), the idea still persists (Schweingruber and Wohlstein 2005). Our model can help to explain why the notion of crowd mentality is problematic. Interpretation is one reason: Descriptive plots of riot dynamics (Figure 5) might imply homogeneity in the crowd, but spatial analysis shows that heterogeneous geographies of clustering manifest beneath this aggregate pattern. This is what McPhail (2008) has referred to as the "crowd as patchwork." Even when agents in our scenarios were seeded with the same initial parameters and transition rules, the informational ingredients to their decision making were variable because they were polled from local surroundings, which were constantly in a state of spatiotemporal flux (because agents moved, others moved around them, or information metamorphosed as it spread). In essence, the informational currency for interaction between crowd members is always changing and so, even when given similar predispositions, behavioral response is not fixed in space or time (Granovetter 1978).

Ideas about complexity permeate all of these discussions. Because riots scale from individual action–reaction dynamics to (and within) the larger social and built substrate of the ambient environment, they often manifest as complex adaptive systems. Indeed, we identified some signature characteristics of complex systems in our simulations: emergence, self-organization, phase shifts, positive (escalation) and negative feedback (calming), and path dependency. Clearly, understanding the complex adaptive properties of riots is important in understanding the phenomenon. This is a topic that has not received much attention in the literature, even though it is actively studied for other crowd phenomena (Vicsek 2003).

To the extent that our model can be relied on as a sufficient analog for riots in the real world (and we make no warranties in this regard; we consider the model as a computational laboratory for testing phenomena in which ground truth that might "verify" the model's match to a particular riot is almost impossible to attain), the scenarios that we simulated provide some practical lessons for managing riotous crowds. The various strategic scenarios for policing show, for example, that a mass police presence might be counterproductive to calming potential sedition (Waddington 1991). Also, police can project force quite effectively without having to actually use force (Prati and Pietrantoni 2009). Also, recognizing shifting patterns in the information that a crowd exudes—particularly signatures of individual and collective behavior in space and time—and reacting appropriately and in a timely manner could be useful in managing a crowd on the brink of sedition or calming riotous crowds to more quiescent end states. Deliberately introducing, modifying, or blocking information diffusion could also be important.

Current Limitations and Future Avenues for Research

Rioting is a highly variable phenomenon, with many possible ingredients. Our model, like all models, is an abstraction of reality. We have strived to make it less abstract than existing models, but some features are missing. First, our portrayal of roles in rioting was limited to four types of protagonists. This is useful in examining some of the prevalent agencies considered in rioting, but it is perhaps stereotypical, representing as K. Epstein and Iveson (2009, 271) remarked, "a binary distinction between the 'virtuous' urban citizen (in need of protection) and the 'unruly' protester (from whom the virtuous citizens needed protection)." An extended model could add additional agents: agent-provocateurs, hooligans, instigators, riot and nonriot police, and so on. There is nothing in the architecture of the model that prevents the addition of more agents or agency, but this would be a time-consuming undertaking.

Second, our built environment scenario was quite simplistic and did not fully reference the available wisdom regarding rioters' use of urban infrastructure (Newman 1972, 1996). The relationship between behavioral geography and the built environment is the topic of a separate thread of research that we are actively engaged in, and we hope to build bridges between that work and our riot model in the future.

Third, we have not accounted for the role of social networks in rioting. The connection between social networks and space is a topic of relatively recent investigation in the literature and relatively little work has been done on this in computational social science (Butts 2009; Torrens 2010b). Dibble has made significant inroads into exploring these issues (Dibble and Feldman 2004) but at a much coarser scale than our model has considered. It is potentially a quite valuable avenue for future inquiry and, again, our modeling framework does not preclude it from being incorporated.

Fourth, we could represent information more explicitly in the model, either through vocal exchanges between rioters and police in simulation or by modeling the influence of mobile Internet and communications technologies in riot dynamics (Rheingold 2002). The role of body language and gait in crowd dynamics is something that we are examining in other models we have built, using full-body motion capture data, for example (Figure 10). This would be of clear value (Scheflen 1972) if incorporated into the scheme that we introduced in this article.

Fifth, our pipeline presents an interactive toolkit for experimenting with riot dynamics, but we are the main beneficiaries of its use. We could broaden the user base to "serious gaming" (Barnes, Encarnação, and Shaw 2009) about rioting by other researchers, police, students, or other stakeholders, for example. We are developing an immersive version of the model that allows users to control (and move) characters as avatars in

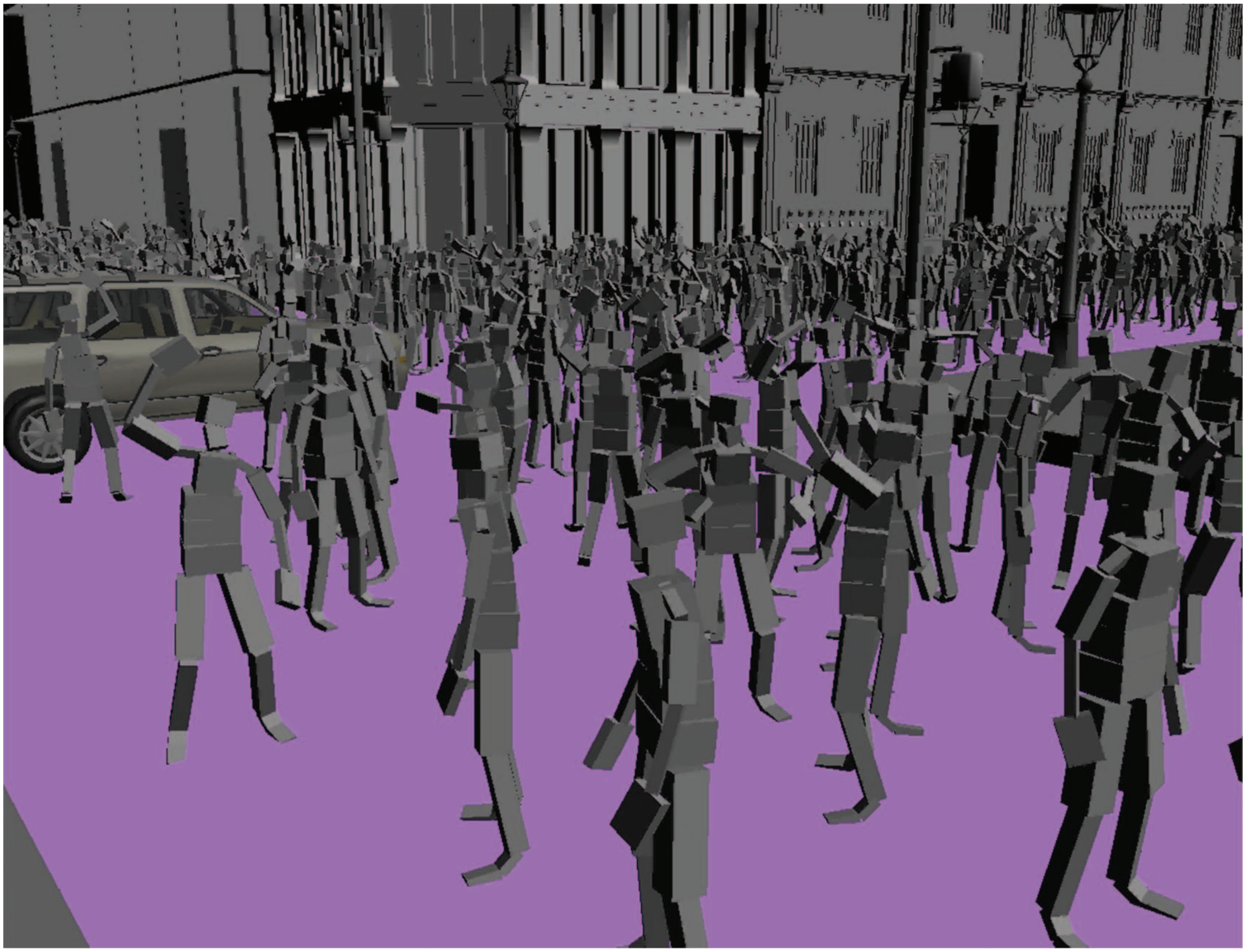

Figure 10. A screen shot from a prototyped immersive version of our riot simulation. Users can "drop into" the riot as avatars and move through the environment to experience a simulated riot vicariously. (Color figure available online.)

simulation (Figure 10), but extending this for actionable decision support will take further work.

Sixth, we did not deal with riot precursors. These could be added to our pipeline, however, in a metasimulation that would also include city-level dynamics. We have experimented with coupling agent-based models and more systems-oriented simulation architectures (input–output models, equation-free modeling, coarse projective integration, animation), but the sorts of models required to simulate city-wide, neighborhood-level, or perhaps even national target selection would likely require much more involved consideration, because of the large range of intrasystem interactions that could serve as drivers (see work by DiPasquale and Glaeser [1998] on the economics of rioting, for example).

Seventh, we have largely sidestepped the issue of calibrating or validating the model to known conditions on the ground, primarily because of the difficulties in acquiring "knowns" that we outlined earlier. Our model is informed by appropriate theory and this is actually quite innovative. Clearly, though, we need to do more to match the model and simulations to reality. Or, alternatively, the model could be used to "hindcast" about known riot events, with the view of providing opportunities for future lessons to be learned. This could be attempted with adequate data. Automata are almost infinitely extensible (Turing 1936) and our scheme does not constrain the amount of reality that can be introduced to the model. Building that know-how is difficult, although we think that our model can help.

Acknowledgments

This material is based in part on work supported by the National Science Foundation under grant numbers 1002517, 0643322, and 0624208. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Many thanks to Atsushi Nara for his help in accelerating the calculation of multiple Moran's *I* values.

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