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# Modeling Dynamic Violence: Integrating Events Data Analysis and Agent-Based Modeling<sup>1</sup>

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## Abstract

Which actions by governments stoke or pacify an insurgency? Scholarly research on the topic has often been relegated to the study of this question at the country level, comparing across large units and rarely looking inside the state. Our research focuses on the primary actors in a contest for authority within a state: the government, dissidents, and the population. In contrast to most previous work, we tackle the difficult question of how population dynamics affect the rise and fall of insurgency. We investigate the question in the context of India and its states and territories. India is particularly well suited to this research as it presently experiences terrorism, insurgency, ethnic conflict, riots and other actions that threaten the stability of the state. Using an agent-based model (ABM), geographic information systems (GIS), data on public sentiment, and events data, we address this question from a multidisciplinary approach. The agent-based model formalizes the interactions of states, dissidents, and the population, the GIS framework allows for actual demographic and geographic information to influence this interaction, and the events data and sentiment data allow us to test empirical implications from the model directly. As the NSF-Minerva grant is midstream, this paper reports initial work to couple the ABM and empirical analysis. We expect the results to have important implications for the study of political violence, order, and state-building. The approach is policy relevant, furthermore, and can be adapted to other regions and countries.

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## **Introduction**

The US and its Coalition partners invaded Afghanistan in October of 2001 thus beginning a conflict that still rages today. The first phase of the conflict for the US involved partnering with Britain, other external allies, and with the Northern Alliance, a local insurgency that challenged the ruling Taliban. After ousting the Taliban, the US and its allies helped initiate a democratic regime. The conflict then shifted into a new phase characterized by counterinsurgency against the remnants of the Taliban regime and its allies. This phase began in 2002, but the counterinsurgency campaign continues to this day. Violence levels have varied a great deal over the course of the conflict with a recent upsurge in civilian and US deaths. Since 2002, a key question permeates all military and political discussions and decisions: which actions by the US or the Afghan government encourage or discourage violence by insurgents?

This question represents one of the most enduring problems plaguing governments faced by violent opposition movements. From Vietnam to Iraq, the U.S. has grappled with this question. Numerous other governments – India, Philippines, Colombia, Algeria, Sierra Leone, Israel, Russia, for examples – face such pressure within the boundaries of their own state. As these examples suggest, modern insurgency ebbs and flows within the same state as well as across cases. We seek to understand more generally, which actions by governments stoke or pacify an insurgency.

Although much attention has been paid to these questions, in this paper we offer a unique approach. First, we place the role of the population in an insurgency central to understanding its dynamics. As Mao Zedong (2005, 93) argued in his classic treatise on guerrilla conflict that the guerrilla must move among the population as a fish swims in the

sea. In Mao's terms, most studies of insurgency have examined the fish while ignoring the sea, whereas we consider how a localized, heterogeneous population affects and is affected by insurgents and counterinsurgents.<sup>3</sup> Second, we use methodologies better suited for addressing the complexities of insurgency. In any insurgency, a wide variety of moving parts complicate the isolation of causal relationships. Randomized experiments represent the gold standard for teasing out cause and effect, but such experiments in the context of insurgency and counterinsurgency are difficult. Instead, we design and implement a computational model of the interaction among the population, insurgents, and counterinsurgents that allows a virtual laboratory in which we can incrementally change features of the model and then rerun history many different ways. Third, we test predictions from the model using original events data that incorporates actions and beliefs among the three central actors. Most notably, we match new empirical data that capture the beliefs (sentiment) and actions of the population towards insurgents and counterinsurgents with parts of the computational model.

We begin by reviewing prominent academic and military literature on insurgency, with an emphasis on work that considers the role of the population, in addition to insurgents and counterinsurgents. Drawing on substantive theory, we then develop a computational model that captures the environment, actors, and behaviors (Pepinsky 2005) of insurgency. We then identify the key concepts and outcomes in the computational model and test them using real-world data.<sup>4</sup> In particular, we discuss how we extracted data from the interaction

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<sup>3</sup> Siqueira and Sandler (2006) is a notable exception of a model that also includes the population in a study of the interaction between the state and dissidents, although even it resorts to simplifying assumptions that make the population a homogenous actor.

<sup>4</sup> It is most common for a formal algebraic model to be paired with statistical tests of the comparative statics of the model (See, for example, Drakos and Kutan (2004) and Mukherjee (2006)). Although an Empirical Implications of Theoretical Models (EITM) approach, or a

of the state, dissidents, and the population in India during the period 1998 to 2008 and present some initial empirical results. The research is currently midstream, but the initial results suggest that violent insurgent and counterinsurgent strategies make the population less likely to support the actor using violence. Thus, approaches designed to win the hearts and minds of the people appear to be more long-term strategies. We conclude with a discussion of how this approach can be applied to other countries, regions, and topical areas.

## **The Multidisciplinary Study of Insurgency**

To understand insurgency, academics and tacticians have often considered the role of insurgents, the state, or their interaction. Although insurgency, per se, is an understudied topic among academics, much academic work focuses on the causes, duration, or resolution of the most extreme form of insurgency – civil war (e.g., Collier and Hoeffler 2004, Fearon and Laitin 2003, Collier, Hoeffler, and Soderberg, 2004, DeRouen and Sobek 2004, Cunningham 2006, Walter 1997, 1999). Often civil war is conceptualized as a violent contention between the state and insurgent groups where both sides participate in killing and the death toll exceeds 1,000 battle deaths.<sup>5</sup> Inherent in this definition is the violent interaction of states and dissidents/insurgents, but few studies explicitly model this interaction (Young 2008); even more problematic, few studies consider how the population influences these outcomes.<sup>6,7</sup>

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formal model tested using quantitative analysis, has become more common in economics and political science (Granato and Scioli 2004) it has rarely been attempted using a formal computational model paired with statistical analysis.

<sup>5</sup> See Sambanis (2004) for a thorough discussion of the ways to conceptualize and operationalize civil war along with the pitfalls of different approaches.

<sup>6</sup> We use the term dissident to refer to an individual who uses non-institutional means to challenge the state and its policies. An insurgent uses violent means. All insurgents are thus dissidents but not all dissidents are insurgents.

Understanding how states resolve insurgencies requires an understanding of the populations affected by this violence. David Galula, the French military officer and counterinsurgency (COIN) theorist, suggests this is the case. Galula's (1964, 74-75) first law of COIN states that the struggle between the insurgents and the government is over the support of the population rather than territory.<sup>8</sup>

Within the academic literature, Weinstein (2007) and Kalyvas (2006) are the most prominent examples of recent attempts to understand the dynamics of insurgency while focusing on the role of the population. Each has a compelling and straightforward explanation for the use of violence in insurgent conflicts. Both rely on structural factors that explain killings in civil conflicts, which are highly correlated with the length of an insurgency. Focusing solely on rebel groups, Weinstein (2007) suggests that initial resource endowments explain why insurgents kill indiscriminately. He argues that where insurgents rely on the population for resources, they are less likely to kill. Weinstein's theory is elegant in its simplicity but does not take into account what the state is doing when explaining insurgent violence. While Weinstein can help us understand why insurgents may or may not use indiscriminate violence, it cannot tell us much about the strategic interaction between the state and insurgents. For Kalyvas (1999, 2006), the use of selective and indiscriminate violence is related to territorial control. His theory offers an explanation for where these types of violence should occur and whether the government or insurgents is more likely to commit these acts. In short, we should expect selective violence where either insurgents or the government exercises predominant authority but not complete control. Areas

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<sup>7</sup> Shellman (2006a, 2006b) and Moore (1998, 2000) are important exceptions, though they do not explicitly discuss civil war.

<sup>8</sup> Trinquier (1961), another former French military officer, argued after fighting in Indochina and Algeria that central tenet of COIN was winning the allegiance of the indigenous population.

completely controlled by one side or the other should be devoid of violence by the incumbent but should expect to see indiscriminate violence from the party that lacks control. Kalyvas' work is unique as it places control over the population at the center of the insurgent/counterinsurgent conflict and offers hypotheses about when, where, and what type of violence each side will use during the conflict. While Kalyvas strategic theory is an improvement on more static arguments, it cannot explain how heterogeneous populations influence this process. For Kalyvas, support for the insurgents or counterinsurgents relates to control rather than ideology, commitment, or belief.

## **Counterinsurgency and the Military**

Military theorists and academics who study insurgency have made complementary claims. Galula (1964), for example, argued for a strategy of dividing conflicts into three different zones depending on which side controls the territory (red-insurgents, pink-mixed, white-counterinsurgents). For Galula (1964), a successful counterinsurgency strategy attempts to hold the white areas and use them as a base to target the pink areas and turn them white. Then, the task is to make the red areas pink and so on. Galula (1964, 63) argues, quoting Mao that, "revolutionary war is 80 percent political action and only 20 percent military." This suggests an integrated approach, which includes diplomatic, informational, military, and economic means to gain the support of the population. Galula's ideas were prominently cited in the recent US Army Counterinsurgency manual authored by John Nagl and General David Petraeus, which focuses on the battle for support of members of the population (hearts and minds), rather than a war of attrition.

In contrast, in the 1970s during the height of the Vietnam conflict, Leites and Wolf (1970) suggested winning a conflict with an insurgency by raising the costs associated with

participating in violence against the state and its interests. For Leites and Wolf (1970) rational people would be dissuaded from helping or participating in violence by the extreme costs inflicted upon them by counterinsurgents.<sup>9</sup> The experiences of the US military in Vietnam seemed to discredit this approach (Bulloch 1996), but the US experience with counterinsurgency against the Native Americans seemed to support these ideas. In the current global context generating tremendous costs for populations associated with insurgencies may or may not work, but they could also have dramatic effects on the stature of the state in the international system. Emerging human rights norms and commitments to democracy are clearly at odds with this form of counterinsurgency.

In the next section, we outline how to test whether a benefit-centered (hearts and minds) or cost-centered (attrition) approach is better at reducing the strength of insurgency. We develop a computational model to approximate an experiment in which different parameters, such as the support of the population, insurgent, or counterinsurgent strategies, and many other factors, can be adjusted to explore whether they influence the number of insurgents and, thus, the strength of the insurgency.

## **Computational Model**

Computational models vary in their complexity, ranging from simple cellular automata simulations (Wolfram 1984) to complex models of single political systems (Cioffi-Revilla and Rouleau 2010) to world simulations with massive numbers of parameters (Prinn et al. 1999). No one formula is correct and complexity should be a function of the substantive problem at hand (Lustick and Miodownik 2007). Computational models of insurgent violence have

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<sup>9</sup> This approach is sometimes referred to as “attrition” (Bulloch 1996, Findley and Young 2007).

only recently begun to become more common (e.g., Bennett 2008, Bhavnani and Backer 2000, Bhavnani 2006, Cederman 2004, Epstein 2002, Findley 2008, Findley and Young 2007, Kuran 1991, Luke et al. 2005). Our computational model attempts to strike a balance between capturing realistic aspects of insurgent violence through the incorporation of GIS (Cederman and Girardin 2007) while limiting the complexity of the model to a manageable number of parameters (de Marchi 2005). The model shares much in common with Epstein (2002) and Findley and Young (2007), but extends these models in ways that allow a better understanding of the dynamics of insurgency.

## **The Environment**

Our model builds from others who model dynamics on an explicit spatial landscape (e.g., Epstein 2002; Findley and Young 2007; Schelling 1978), but we blend GIS data of country and sub-national administrative boundaries with a model comprised of artificial agents (Brown, et al 2005). Thus, a GIS representation of countries and subnational administrative districts, as opposed to an imposed landscape such as a grid or torus, represents the topography on which agents interact. The platform supports modeling insurgency and violence in 29 Southeast Asian countries; we begin in this paper with the case of India.

The boundaries of the simulation are based on the boundaries of the country of India or of various administrative districts (e.g., states and union territories) within India. GIS data on factors such as ethnicity and population density are currently built into the model, and a number of other GIS characteristics are in progress, but we do not report on them here. Instead, in this first iteration, we simply allow agents to move about within the

national boundaries of India. We discuss agent mobility below, but first turn to a specification of the agents. Table 1 (at the end of this document) lists the notation and parameters of the model along with short descriptions.

## Agents

$N$  agents are randomly assigned an initial location within the defined borders of India. Three types of agents exist in the model (Population/Civilian:  $\alpha_i^p$ ; Counterinsurgent:  $\alpha_i^c$ ; Insurgent:  $\alpha_i^i$ ) and the relative size of each group of agents is determined exogenously. Following Lichbach (1995), the population is the largest group comprised of roughly 85% of the agents; the counterinsurgents represent the next most populous group with 10% of the agents and the insurgents represent the remaining 5%. Agents are heterogenous in a set of characteristics relevant to insurgency and counterinsurgency. Each agent is comprised of the triplet:  $\alpha_i \in \{\chi_i, R_i, \beta_i\}$ .

*Commitment,  $\chi_i$* : An agent's commitment to the insurgency ranges over the unit interval,  $[0,1]$ , where the higher the value, the higher the agent's commitment to the insurgency. We begin with the assumption that the population is inclined to be neutral and support whichever side appears to be winning (Krepinevich 2004). Thus, commitment is initially distributed to each group of agents accordingly: civilian,  $\chi_i \in Norm[0.2, 0.8]$  where *Norm* represents a normal distribution; insurgent,  $\chi_i \in Unif(0.8, 1]$  where *Unif* represents a uniform distribution; or counterinsurgent  $\chi_i \in Unif[0, 0.2)$ . Each agent's commitment is updated throughout the simulation based on interactions with other agents.

*Responsiveness,  $R_i$* : Agents are heterogeneous in their propensity to change their commitment to the insurgency. Responsiveness represents something of an elasticity in which some agents might update their commitment in only very small increments while others might update in larger increments (Findley and Young 2007).  $R_i$  is drawn from a uniform distribution ranging over the unit interval, but the upper bound is parameterized to allow responsiveness to range in smaller intervals. Once assigned, responsiveness never changes for an agent.

*Beliefs,  $\beta_i$* : Given the decentralized character of insurgencies, no one agent has complete information (Clausewitz 1976; Epstein 2002; Hayek 1945). Agents are heterogeneous in their beliefs about the strength of the overall insurgency. A belief is initialized exogenously, but then an agent's belief is updated at each time step according to the commitment of agents with a local region.

After the model is initialized,<sup>10</sup> it proceeds in an iterative three-step process: agents (1) move about spatially, (2) interact with other agents, and (3) update their beliefs. Each type of agent performs at least some of these tasks, but each agent may carry them out differently. We now consider the rules governing mobility, interaction, and belief updating.

## **Mobility**

During the move phase, each civilian,  $\alpha_i^\pi$ , is randomly assigned a trajectory in degrees

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<sup>10</sup> Given the user's desired population number, percentage of insurgents, and percentage of counterinsurgents, commitment bounds for insurgents and counterinsurgents are created. These bounds are calculated so that if commitments were continuously drawn from a normal distribution with mean=0.5 and standard deviation=0.16, they would match the user specified parameters (i.e. the desired percentages for insurgents and counterinsurgents). After the user has specified the desired population size ( $N$ ), commitments are drawn from a normal distribution and compared to the predefined bounds. If the commitment is below the counterinsurgent commitment bound, a counterinsurgent is created. If the commitment is above the insurgent commitment bound, an insurgent is created. Otherwise a civilian is created.

between 0 and 360. The civilian then attempts to move in that direction.<sup>11</sup> Like Epstein (2002), vision is limited and all information is localized. Insurgents,  $\alpha_i^A$ , first find the closest neighbor within their vision,  $\phi^A$ , rather than moving randomly. If the closest neighbor is a civilian, the insurgent moves towards the civilian in an attempt to influence it. Because the government monopolizes the means of coercion, insurgents must attempt to attract supporters in the cause against the state. If the closest agent is a counterinsurgent, then the insurgent attempts to move away from the counterinsurgent. If the closest agent is an insurgent, or if there are no neighbors, the insurgent moves randomly.

Every time a counterinsurgent,  $\alpha_i^K$ , moves, it advances towards the closest insurgent or civilian within its vision,  $\phi^K$ . Counterinsurgents attempt to influence civilians to be less committed to the insurgency and target insurgents either to neutralize or kill them, which we discuss below. If no insurgents or civilians are within its vision, the counterinsurgent moves randomly.

## Interaction

In contrast to Epstein's (2002) model, in which the key dynamic is whether agents choose to rebel, in our model insurgents and counterinsurgents employ strategies to win over the population. Both insurgents and counterinsurgents exchange benefits representing basic economic improvements, security, and freedom from previous abuses (Shafer 1988; Heath, et al 2000) and costs capturing activities, such as repression, torture, intrusive searches, or abuses and crimes by the military (Leites and Wolf 1970). Beginning with civilians, we consider the different possible interactions among the agents.

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<sup>11</sup> Agents are not allowed to cross the outer boundary of the simulation. If the agent is randomly assigned a direction that will take it outside of the boundaries, it resets its position and tries again until it is successful.

*Civilians:* Civilians do not have the ability to initiate interactions with other agents; however, both insurgents and counterinsurgents provide benefits and costs to them. Intuitively, when civilians receive benefits they adjust their commitment closer to the commitment level of the agent that gave them benefits. The degree of commitment change is weighted according to the agent's responsiveness. A higher responsiveness causes agents to adjust their commitments more than agents with lower responsiveness. When agents receive costs they adjust their commitment further away from the commitment level of the agent that gave the costs, also weighted according to the receiving agents responsiveness level. Precisely, if  $\chi_i < \chi_j$ , then civilians update their commitment such that:

$$\chi_{i,t+1} = (R_i \cdot (\chi_j - \chi_i)) + \chi_{i,t}.$$

Otherwise, if  $\chi_i > \chi_j$ , the above formula can be rewritten such that agents update their commitment:

$$\chi_{i,t+1} = \chi_i - ((\chi_i - \chi_j) \cdot R_i).$$

When  $\chi_i = \chi_j$ , then civilians do not update.

If the commitment level of a civilian passes the insurgent commitment bound,  $\theta^l$ , then based on the responsiveness of the agent, there is a chance that the civilian becomes an insurgent. Otherwise a new commitment level is randomly drawn for the civilian from a normal distribution between the commitment bound of the insurgents and the counterinsurgents. The lower the responsiveness, the greater the chance the civilian will convert to the insurgency. The intuition behind this rule is that because agents with lower responsiveness change their commitment slowly, they incrementally move towards the

insurgency and are more realistically aligned with the insurgent aims. When their commitment does pass the insurgent threshold, the agent is more likely to become an insurgent. Therefore agents with lower responsiveness will be more likely to convert than agents with higher responsiveness who may simply be altering commitment under duress or political expediency.

If the commitment level of a civilian drops below the counterinsurgent bound,  $\theta^*$ , then as with insurgents, the agent's commitment is either randomly redrawn or the civilian can become a counterinsurgent.<sup>12</sup> Also similar to the shift to insurgency, agents with a high responsiveness might change commitment in large swings whereas agents with lower responsiveness will change gradually and those who change gradually are more likely to become counterinsurgents.

*Insurgents:* Once an insurgent moves within distance of a civilian, the insurgent initiates an interaction in which it gives costs or benefits. If the insurgent believes the insurgency is stronger than before, there is a higher probability that the insurgent will give the civilian benefits. Otherwise there is a higher probability that the insurgent will impose costs. Precisely, the decision to provide benefits is simply the initial probability of playing benefits plus the agent's *current* belief minus the agents' *previous* belief for insurgents. For counterinsurgents the probability of playing benefits is the initial probability plus the *previous* belief minus the *current* belief.<sup>13</sup>

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<sup>12</sup> Whether or not civilians can become counterinsurgents is determined exogenously. Like Epstein (2002), in some experiments, we do not allow civilians to convert. But in others we allow conversion to the counterinsurgency.

<sup>13</sup> Any resulting probability below zero or above 1 is simply rounded to 0 or 1. Other more complicated rules could be used, but this captures the basic intuition we are after.

As an example, if the initial probability is 0.75 and an insurgent's beliefs change from 0.75 to 0.8, then the probability of playing benefits is  $0.75 + (0.8 - 0.75) = 0.8$ , thus making the insurgent more likely to play benefits than it was before. A counterinsurgent with the same initial probability and beliefs would have a probability of  $0.75 + (0.75 - 0.8) = 0.7$ , thus making it more likely to impose costs. This provides a simple mechanism to allow benefits and costs to be given based on an overarching government or insurgency strategy, but with variation based on changing beliefs.

After costs or benefits are applied, civilians update their commitment as described above. Because insurgents attempt to flee from counterinsurgents, they typically do not initiate interactions with counterinsurgents, although the opposite can occur: counterinsurgents can initiate interactions with insurgents and provide benefits and costs. When an insurgent receives benefits from a counterinsurgent, the insurgent's commitment either decreases and shifts towards the commitment of the counterinsurgent, or the insurgent appropriates the benefit and the insurgent's commitment stays the same.

When an insurgent receives costs from a counterinsurgent either the insurgent is neutralized (becomes a civilian) with some probability or the insurgent adjusts its commitment farther away from the commitment of the counterinsurgent who gave it costs. If the insurgent's commitment level drops below its commitment bound it either becomes a civilian or it draws a new commitment level between the commitment bound and 1. The lower the insurgent's responsiveness, the greater the chance that the insurgent will become a civilian.

*Counterinsurgents:* After moving, a counterinsurgent interacts with the closest civilian or insurgent within its neighbor radius. Like insurgents, counterinsurgents choose between

playing costs and benefits. This choice is based on the counterinsurgent's belief about the strength of the insurgency. Counterinsurgents are more likely to apply costs if they believe the insurgency is stronger than it was previously and more likely to give benefits otherwise.

## **Belief Updating**

As alluded to above, the decision to provide costs and benefits to the population is based on insurgent and counterinsurgent beliefs about the strength of the insurgency. After each move, insurgents and counterinsurgents update their beliefs by taking the average commitment of all agents within their commitment subset radius. Currently the updating rule is simple: if average commitment to the insurgency at time  $t$  is greater than  $t-1$ , then the agent concludes that the insurgency has gained strength. If average commitment to the insurgency at  $t$  is less than  $t-1$ , then the agent concludes that the insurgency has weakened. If average commitment is unchanged, then the agent concludes that the strength of the insurgency is identical.

## **Initial Experimental Strategy**

In this initial exercise, we primarily varied the initial probability that counterinsurgents and insurgents would apply benefits. In other words, we change the beginning probability that counterinsurgents and insurgents are likely to play benefits. This likelihood is, of course, weighted by their repeatedly changing beliefs about the insurgency, but nonetheless allows us to gauge the likely effects of an overall “hearts and minds” strategy, that is partially mixed with a costs-based attrition strategy. The example in the “Interaction” section illustrates how this might occur.

We considered nine configurations of probabilities that counterinsurgents and insurgents play costs or benefits (summarized in Table 2). Because this is an initial modeling exercise, we set other parameters at reasonable values and do not test the effect of varying them.

Experiment	Counterinsurgent Probability	Insurgent Probability
A	0.5	0.5
B	0.75	0.5
C	0.5	0.75
D	0.25	0.75
E	0.75	0.25
F	0.25	0.5
G	0.5	0.25
H	0.25	0.25
I	0.75	0.75

Table 2: Summary of Initial Experiments; Note: Parameters that do not vary in initial runs: 1000 iterations, agents are allowed to carry out multiple interactions within their local radius, responsiveness higher bound =0.33, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, vision is set to 1 for counterinsurgents and 2 for insurgents, insurgent appropriate probability is 0.2, neighbor radius is 1, and the neutralize probability is 0.6.

## Implications of the Model

Given that we varied two parameters at a time, we first consider the effect of varying the probability of providing benefits holding constant the counterinsurgent probabilities. Thus, the first three results show insurgent probabilities at 0.25, 0.5, and 0.75 while the counterinsurgent probability is set to 0.25 for all three. Then we repeat the exercise with counterinsurgent probability at 0.5 and then 0.75. Table 3 highlights in bold the values that are changed in each experiment.

We report both the mean number of insurgents in each of these representative runs along with the corresponding plot that demonstrates the dynamics of the insurgency over time. All plots are in the Appendix and can be referenced by the appropriate plot letter.

Table 3 gives the results of varying insurgent probabilities, holding the counterinsurgent probability constant. The results of these experiments show that as insurgents provide benefits to the population, they are able to win support for their cause. The results are fairly strong in the first six conditions (plots H,F,D and G,A,C), but not as strong when counterinsurgents are also providing high benefits (conditions 7,8,9; plots E,B,I).

<b>The Effect When Insurgents Play Benefits</b>					
<i>Condition</i>	<i>Insurgent</i> Probability	<i>Counterinsurgent</i> Probability	Average number of insurgents	Plot	Trend
1	0.25	0.25	68.15	H	Insurgency grows stronger
2	<b>0.5</b>	0.25	123.57	F	
3	<b>0.75</b>	0.25	162.42	D	
4	0.25	<b>0.5</b>	33.12	G	Insurgency grows stronger
5	<b>0.5</b>	<b>0.5</b>	73.51	A	
6	<b>0.75</b>	<b>0.5</b>	96.31	C	
7	0.25	<b>0.75</b>	25.74	E	No discernible effect
8	<b>0.5</b>	<b>0.75</b>	22.03	B	
9	<b>0.75</b>	<b>0.75</b>	40.88	I	

Table 3: Results of models in which *insurgents* increasingly play benefits; Note: Parameters that do not vary in initial runs: 1000 iterations, agents are allowed to carry out multiple interactions within their local radius, responsiveness higher bound =0.33, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, vision is set to 1 for counterinsurgents and 2 for insurgents, insurgent appropriate probability is 0.2, neighbor radius is 1, and the neutralize probability is 0.6.

These initial results suggest that if insurgents can service enough of the population with various benefits, such as public goods, and the counterinsurgents are not as involved in

providing the public goods, then the insurgency will grow. This appears somewhat akin to the contention in Kalyvas (2006) about zones of control. Where insurgents are helping civilians, they are also growing stronger. Where there is a contest for control, even if in the provision of benefits, then the insurgency often struggles to compete.

Turning to changes in counterinsurgent probabilities of playing benefits while holding the insurgent probabilities constant, as counterinsurgents provide more benefits, they are also able to weaken the insurgency. As they play costs, the insurgency is strengthened. In contrast to the previous results, which were strongest in conditions 1-6, these results appear fairly strong across all nine-experiments.

<b>The Effect When Counterinsurgents Play Benefits</b>				
<i>Counterinsurgent</i> Probability	<i>Insurgent</i> Probability	Average number of insurgents	Plot	Trend
0.25	0.25	68.15	H	Insurgency grows weaker
<b>0.5</b>	0.25	33.12	G	
<b>0.75</b>	0.25	25.74	E	
0.25	<b>0.5</b>	123.57	F	Insurgency grows weaker
<b>0.5</b>	<b>0.5</b>	73.51	A	
<b>0.75</b>	<b>0.5</b>	22.03	B	
0.25	<b>0.75</b>	162.42	D	Insurgency grows weaker
<b>0.5</b>	<b>0.75</b>	96.31	C	
<b>0.75</b>	<b>0.75</b>	40.88	I	

Table 4: Results of models in which *counterinsurgents* increasingly play benefits; Note: Parameters that do not vary in initial runs: 1000 iterations, agents are allowed to carry out multiple interactions within their local radius, responsiveness higher bound =0.33, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, vision is set to 1 for counterinsurgents and 2 for insurgents, insurgent appropriate probability is 0.2, neighbor radius is 1, and the neutralize probability is 0.6.

The results of these experiments suggest the following hypotheses:

H1 (Support): When insurgents *increase benefits* imposed on the population, this leads to an *increase in insurgent strength*

(Hearts and Minds): When counterinsurgents *increase benefits* to the population, this leads to a *decrease in insurgent strength*

H2 (Attrition): When counterinsurgents *increase costs* imposed on the population, this leads to an increase *in insurgent attacks*

## **Empirical Analysis – Violence in India**

To investigate the process of violence between insurgents and counterinsurgents, we restrict our initial investigations to a single country. This allows us to make the modeling more tractable as well as establish some baseline expectations. Including other states, the influence of external actors, cross-border interactions, and other transnational processes could add more realism to the model, but at this stage, these additions would also increase the complexity of modeling exercise by adding new actors, parameters, and modes of interaction. Instead, we focus on one country, India, and its experience with political violence. India is a unique laboratory for this inquiry as it has experienced diverse forms of violence since independence from Britain, it is the world's largest democracy, and one of the most frequent receivers of domestic and transnational terrorism.<sup>14</sup> India has been plagued by separatist inspired terrorism in Kashmir since 1989, deadly ethnic riots, a Maoist insurgency that has spread across several states, and a violent campaign in the 1980s in the

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<sup>14</sup> According to the Global Terrorism Database (<http://www.start.umd.edu/gtd/>), India experienced 4,799 incidents from 1970-2008.

Punjab region (Gupta 2007, Piazza 2010). We use this country to investigate insurgent-counterinsurgent dynamics with the expectation that India will provide

## **Research Design**

To test hypotheses from the computational model, we collected events data within India from 1998 to 2010. We have data on thousands of events during this period that relate to actions perpetrated by the state against the insurgents, actions by the insurgents against the state, actions by the state against the population, and actions by insurgents against the population.<sup>15</sup> These data are unique for several reasons. Typically, studies on civil war and insurgency are cross-national and focus on highly aggregated data (at the country-level, by year). By contrast, our data include all events that can be deciphered from news reports in India each day. We aggregate them by month here, but they can be disaggregated or aggregated to the year depending on the question the researcher would like to address.

### *Data*

One way to study multi-actor conflicts unfolding over time on a day to day basis is through the collection and analysis of disaggregated event data. Event data are “day-by-day coded accounts of who did what to whom as reported in the open press,” which “offer the most detailed record of interactions between and among actors” (Goldstein 1992, 369). Most basic event datasets code the (1) actor taking the action, (2) the target receiving the action, (3) the action itself (the event), and (4) the date of the action/event (usually the day each event takes place). Some example events coded in political violence datasets include armed

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<sup>15</sup> EVENTS DATA FN1

attacks/conflict, nonviolent protests, negative statements, positive statements, low-level agreements between actors (e.g. ceasefires), and high-level agreements between actors (e.g. regional territorial autonomy).

Until recently, the collection of event data was cost prohibitive for most researchers. Historically, event data were coded manually, leading to problems such as low inter-coder reliability and a lack of coder attention to detail over time as they spend countless hours reading documents, identifying events from text, and classifying them into different categories.

In the early 1990s, the Kansas Events Data System (KEDS) demonstrated that the collection of events data could be automated (see Schrodt and Gerner 1994, Schrodt, Davis, and Weddle 1994). With automated coding, the coding rules are transparent, the data are easily and quickly reproducible, the data can be regenerated using alternative coding schemes, and the data are unaffected by individual coders' biases, as well as reducing the time required for coding from hundreds of hours of human labor to mere minutes once the input texts have been formatted and coding dictionaries prepared. KEDS and its open-source successor, the Text Analysis By Augmented Replacement Instructions (TABARI) program<sup>16</sup>, radically changed the information that is available to conflict scholars. The coded actions run the gamut from positive and negative statements to bombings to political compromises to armed raids. The result is a record of publicly recorded events, and the actors, targets, and locations associated with each event. Employing automated coding methods allows the collection of massive amounts of pertinent information on civil conflict while also eliminating inconsistencies, coder fatigue, and coding time associated with human

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<sup>16</sup> See <http://raven.cc.ukans.edu/~keds/index.html> for information on the KEDS and TABARI projects. Also see Schrodt (1996; 2006) for the respective codebooks.

coding. The result is a numeric representation of an event in the form of “someone does something to someone else” on a certain day.

Strategic Analysis Enterprises (SAE) Inc. is developing the next generation of automated natural language processing tools to code the conflictual and cooperative behavior of multiple state, sub-state, and nonstate actors. Previous coders commonly employed a “sparse-parsing” technique to extract the subject, verb, and object from a sentence and determine the appropriate codes using pattern matching on actor and verb dictionaries.<sup>17</sup> The SAE Text Analysis Suite (SAEtext) uses a part of speech tagger together with a chunk-style parser, and lemitizer to perform extractions. The key difference is that more grammatical information is available to guide all stages of the process. There are grammatical “sanity checks” (e.g., verbs must actually be verbs) as well as grammatical guidance in processes such as seeking the source and target of a verb. SAE provided the use of their coder to create the data for this analysis.

In any instance, machine coded data are only as good as the dictionaries used to code them. Given our theories about micro-level processes and our belief about the number of actors involved in civil conflicts, we attempt to make the actor dictionaries as extensive and disaggregated as possible. Human coders collect terms on any major players in society including generic terms (businessmen, religious leaders, dissidents, protestors, or anyone else without a specific name). We also made use of the SAEtext actor finder program, which identifies potential actors in texts that do not appear in dictionaries. We perused these lists

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<sup>17</sup>TABARI recognizes pronouns and dereferences them. It also recognizes conjunctions and converts passive voice to active voice (Schrodt 1998).

by ranking the number of hits each actor received in our corpus and added the ones to our dictionaries that seemed most important.

In this experiment, we analyzed a dataset compiled for India. The dataset was compiled using the SAEtext program from a Lexis Nexis corpus containing multiple news sources (BBC, AFP, the Statesman, etc.). The actor dictionary for this case was borrowed from Project Civil Strife (PCS) and is extensive.<sup>18</sup> For example, it includes actors from Prime Minister Monmohan Singh and the Indian National Congress all the way down to Tiger Memon, a Mumbai Gangster. In addition to thousands of unique individuals specified, the Indian actor dictionary captures individual political, social, religious and dissident groups and leaders. All told, the actor dictionary for India includes 4,899 terms.

The events are coded according to a verb dictionary. Our verb dictionary is a modified CAMEO verb dictionary. Verbs and verb phrases are assigned a category based on the CAMEO coding scheme. The verb dictionary is ever changing as new phrases are added and old, no longer needed phrases are removed. The dictionary used on this project is a product of a collaborative effort of KEDS phrases, SAE phrases, and Project Civil Strife Phrases.<sup>19</sup>

While the original data code individual actions, these events are often scaled on a hostility-cooperation continuum. Such scaled data are often used in studies of international

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<sup>18</sup> See Shellman (2008) for more information.

<sup>19</sup> Research Assistants from the University of Kansas, University of Georgia, Penn State, William & Mary, Lockheed Martin and SAE have all added and subtracted phrases as the verb dictionary has been used in multiple projects of late.

(e.g. Goldstein and Freeman 1991) and intranational (e.g., Shellman et al. 2010) political interactions. The scaled data were generated using the CAMEO scale.<sup>20</sup>

Although the data set is capable of functioning on a highly disaggregated level, our experiment called for a degree of aggregation. Our agent based model was parsimonious and employed only three classes of actors: insurgents, counterinsurgents, and civilians. In order to test the findings of the ABM, we mapped our actors into these three categories. All government actors, from the executive office to ministry of finance to military and police, were operationalized as counterinsurgents. Social actors including but not limited to teachers, students, refugees, workers, and businesses were placed in the civilian group. Lastly, rebels, insurgents, terrorists, and dissidents were placed in the insurgent group.

Directed-dyadic actions between these groups are then measured on a monthly basis. Measures include counts of events, Goldstein weighted totals (i.e., sum of dyadic scaled events), and Goldstein weighted averages (i.e., average of scaled events) of all positive, negative, cooperative, violent, and hostile actions.

Measures:

The dependent variables for the study are measures of insurgent violence and overall activity. While this is not a perfect predictor of insurgent strength or numbers, it is highly related. In Afghanistan, for example, attacks against US forces are at their highest level since the US-led invasion in 2001. Most observers, military and otherwise, assume that Taliban troop levels are also increasing. According to a US intelligence estimate in 2009, the Taliban increased

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<sup>20</sup> See <http://web.ku.edu/~keds/cameo.dir/CAMEO.SCALE.txt>.

their numbers fourfold from 2005-2009.<sup>21</sup> This corresponds with dramatic increases in casualties for US forces.<sup>22</sup> We use the events data to collect all violent acts by insurgents against the population and state. As robustness checks, we also use measures of all activity by insurgents against the population and state.

Based on the predictions from the model, the key independent variables need to measure costs and benefits by both insurgents and counterinsurgents applied to members of the population. These actions within actor dyads do not exist in standard conflict data. We employ measures from the data described above. First, we aggregate all negative interactions by insurgents against the population (INSURGENT HOSTILE) and all positive actions by insurgents against the population (INSURGENT COOP). Second, we aggregate all negative interactions by the state against the population (STATE HOSTILE) and all positive actions by insurgents against the population (STATE COOP). These four variables are indicators for these actions within the computational model and allow us to test hypotheses 1 and 2. We also created two measures to look at the cost/benefit ratios to try and mirror the model more precisely. We take hostile actions by the insurgents and state and divide these actions by the cooperative actions of the insurgents and the state. More formally, the measures are

$$\text{Insurgent cost/benefit ratio} = \frac{\text{totalhostileevents}}{\text{totalcooperativeevents}}$$

and

$$\text{State cost/benefit ratio} = \frac{\text{totalhostileevents}}{\text{totalcooperativeevents}}$$

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<sup>21</sup> “Taliban Growth Weighs on Obama Strategy Review,” Reuters, 9 October 2009. Found online at: <http://www.reuters.com/assets/print?aid=USN09496447>

<sup>22</sup> For a graph of this increase over the course of the war, see <http://www.icasualties.org/oef/ByYear.aspx>

These measures may be a closer fit to the expectations from the computational models. Positive numbers for each measure suggest cost-oriented approaches whereas negative numbers are more consistent with a benefits approach.

## Results/Discussion

**Table 5--Effect of STATE/INSURGENT Costs/Benefits on INSURGENT Violence and Actions, India 1998-2010.**

Variable	All Insurgent Violence	All Insurgent Actions	All Insurgent Actions
INSURGENT HOSTILE	0.006* (0.003)	0.801 0.864	
INSURGENT COOP	-0.008 (0.007)	0.767 (1.423)	
STATE HOSTILE	0.000 (0.004)	-0.577** (0.221)	
STATE COOP	0.000 (0.004)	0.207 (0.142)	
LAG		0.260 (0.092)	
INSURGENT COST/BENEFIT RATIO	--	--	0.084** (0.038)
STATE COST/BENEFIT RATIO	--	--	-16.144 (12.718)
CONSTANT	2.771*** (0.177) N=149	64.112*** (8.108) N=149	72.298*** ( 7.550) 149

Models are estimated using OLS, robust standard errors are presented in parentheses below the coefficient estimates.

\* p<0.10, \*\* p<0.05, \*\*\*p<0.01

Table 5 displays the results from our initial statistical models. These models are tentative, and care should be taken when interpreting these results. There is much more work to be done on the data, computational model, and statistical model before we would be confident in using these results as a bedrock for future work or to make policy suggestions. We present three models varying the dependent and independent variables. In the first model, we use a dependent variable of all insurgent violence towards any other actor. In the second and third models, we use a measure of all insurgent actions to all other actors. For independent variables, we use measures of hostile and cooperative actions by the state and insurgents in the first two models. In the third model, we use the cost ratio variables.

Our results are largely inconclusive. Insurgent hostile actions seem to increase future insurgent actions of all kinds. This general result is significant in the first and third model but not the second. In other words, when insurgents terrorize the population, this increases their future actions. Our computational models suggested that this had no discernible impact on the growth of insurgency. Our other results are mostly indistinguishable from zero. This is due, in part, to our small number of observations. We plan on increasing our sample by looking at subnational units in India, expanding to different countries, increasing our temporal period, and using smaller units of temporal aggregation.

## **Conclusions and Future Directions**

This paper reported on our ongoing NSF-Minerva work to couple agent-based modeling with events data analysis to understand the localized dynamics of insurgency. The research is

midstream and thus the model, data, and results represent only a first attempt to model and test the dynamics of insurgency. We contended that, despite significant attention devoted to insurgency and counterinsurgency, little attention has been given to the important role of the population. We then developed a model in which insurgents and counterinsurgents interacted with a population both heterogeneous in its commitment to the insurgency and its willingness to change its level of support. Initial results suggest that violent strategies undermine the parties that use them, whereas approaches that emphasize winning the hearts and minds through the provision of various benefits may be most constructive for insurgents and counterinsurgents alike.

Using data on India from 1998-2008, the results of our initial inquiry are inconclusive. We plan to incorporate sentiment data or data on public views of the insurgents and state to bring beliefs into the dynamic interaction between states and dissidents.

In this paper, we created an initial version of the ABM and considered only the Indian context at a national level. As the NSF-Minerva grant is only midstream, much remains to be done both to the computational model and the empirical analysis. We are actively working on these components and describe some of them below.

The ABM needs further refinement to specify the actors and environment as well as identify the most relevant, but limited set of parameters. In particular, we are now considering closely the best way to specify each parameter. For example, we currently dichotomize costs and benefits, when it might make more sense to allow some ratio of costs to benefits. Further the belief updating rule is rather simple and we are investigating whether to allow some more complicated algorithm (for multi-agent simulation), such as Bayes's rule.

The ABM also needs tighter integration with GIS data on ethnicity and other environmental factors. We expect that factors such as population density, income, the location of third-party international actors, religion, and caste could be important GIS components that should be added to the model. These different factors could condition the rules of the simulation, but may also serve as important criteria with which to seed the model.

The empirical tests need to be refined to a subnational level and then extended to other countries, which will be one of our next steps. Our event and sentiment data have the subnational precision in many cases and using a lower level of aggregation will allow us to test the computational model, once we extend it to lower levels. Furthermore, we are collecting data on a number of other Southeast Asian countries and intend to test the model cross-nationally.

Further, we plan to use more advanced statistical techniques to capture the dynamics more accurately. The model is amenable to isolating dyadic interactions and the event and sentiment data are dyadic. Furthermore, we can obtain the dyadic data at different levels of analysis. Thus, we intend to use bilinear mixed effects models to test the model with more precision.

Despite the need for greater attention to the model and empirical tests, our initial exercise in this paper suggests optimism about the prospects for integrating ABM and events data analysis.

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**Table 1: Summary of Model Parameters and Default Values**

Parameter Name	Description	Type	Default Value	Notation
Administrative Boundaries	A drop down menu that allows the user to choose the location of the simulation. The locations range from India as a whole to separate provinces within India. Future iterations will include 29 SE Asian countries	NA	India	
Move Distance	The distance that agents are able to move, in meters.	Float	5000	
Neighbor Radius	Radius of the agent's sphere of influence. Agents interact with either the closest agent or all agents within this radius. Radius is defined in degrees. A degree in India is equal to 103 km on average.	Float	1	
Counterinsurgent & Insurgent Vision	Radius of counterinsurgents' vision. Must be at least the size of neighbor radius, because an agent should not be able to directly interact with someone they cannot see. Defined in degrees. A degree in India is equal to 103 km on average.	Float	CI: 1 I: 2	$\phi^{\kappa, \lambda}$
Responsiveness	Defines the upper bound of a uniformly distributed area over the unit interval [0,1] which defines an agent's responsiveness.	Float	0.33	$R_i$
Commitment	Defines the range over which the agents' commitment levels are distributed.	Float	[0,1]	$\chi_i$
Counterinsurgent & Insurgent Commitment Bound	The upper (lower) bound of counterinsurgents' (insurgents') commitment spectrum. Calculated based on desired percentage of counterinsurgents and insurgents.	Float	CI: 0.2, I: 0.8	$\theta^{\lambda, \kappa}$
Random Belief Initialization	If true then an agent's belief is initialized randomly from a uniform distribution over the unit interval [0, 1]. If false then belief is initialized at .5 for all agents.	Boolean	TRUE	

Commitment Subset Radius		The radius of the area within which agents' commitment are used to calculate beliefs. Defined in degrees. A degree in India is equal to 103 km on average.	Float	0.4	
Insurgent Probability	Benefit	The probability that an insurgent will give benefits. This is not the true probability but is used as part of the calculation described in the paper.	Float	0.5	$P_i$
Counterinsurgent Probability	Benefit	The probability that a counterinsurgent will give benefits. This is not the true probability but is used as part of the calculation described in the paper.	Float	0.5	$P_i$
Population		Total number of agents (civilians + insurgents + counterinsurgents) to be generated in the simulation.	Int	1000	$\alpha_i^{\pi, \kappa, \lambda}$
Percentage of Insurgents		An integer value representing the percentage of the population that are desired to be insurgents. (note: since agents are created using a normal distribution this percentage will be true on average, but the actual number of insurgents will vary for individual simulations)	Int	5	$\alpha_i^\lambda$
Percentage of Counterinsurgents		An integer value representing the percentage of the population that are desired to be counterinsurgents. (see note above)	Int	10	$\alpha_i^\kappa$
Insurgent Probability	Appropriate	A float value between 0 and 1 that determines the probability that an insurgent will appropriate benefits given by a counterinsurgent. The lower the value, the more likely it is that an insurgent will become less committed when given benefits by a counterinsurgent. The higher the value, the more likely insurgents are to "appropriate" the benefits given and not change their commitment.	Float	0.6	

Neutralize Probability	A float value between 0 and 1 that represents the probability that a counterinsurgent will neutralize an insurgent with costs. The higher the value the higher the probability that an insurgent will be neutralized with costs and become a civilian.	Float	0.6	
Multiple Interactions	If set to true an agent will interact with all allowable agents within its neighbor radius. Otherwise agents will only interact with their closest neighbor.	Boolean	TRUE	

## Appendix

### Model Extensions

The GIS framework allows us to consider additional geospatial factors that might be important in the model. The ethnic identity of an agent, for example, can be based on the ethnic composition of the geographical location. When the ethnicity parameter is activated (=1), then agents in the simulation receive an ethnic identity based on where they are located. This ethnic identity conditions the behavior of every type of agent, such that members of the same ethnicity are more likely to offer benefits to co-ethnics and costs to others, regardless of whether the interaction occurs between insurgents, counterinsurgents, and the population (or any combination).

If the user selects the multiple interactions box this will set the parameter to true, and an insurgent will interact with every civilian within its neighbor radius. Otherwise, if the box is not checked, an insurgent will only interact with the closest civilian within its neighbor radius.

Appendix Table: Summary of Some Model Extensions

Benefits to same ethnicity	If set to true then when an agent encounters another agent of the same ethnicity, benefits will always be given.  (not currently implemented)	Boolean	FALSE	
Costs to different ethnicity	If set to true then when an agent encounters another agent of a different ethnicity, costs will always be charged.  (not currently implemented)	Boolean	FALSE	
Conversion to Counterinsurgents	A boolean value that, if set to true, allows civilians to convert to counterinsurgents if their commitment falls below the counterinsurgent commitment bound. If false then when a civilians commitment falls below the counterinsurgent commitment bound the civilian's commitment will be randomly redrawn in the civilian commitment range.	Boolean	False	