Modeling Armed Conflicts

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conflict and certain indicators of ethnic group distribution, one that is firmly grounded in theory. In no case did we use income-based groups or income-based measures, and in this sense our study is perfectly orthogonal to those that attempt to find a relationship between economic inequality and conflict, such as those surveyed in (*17*). Might that elusive empirical project benefit from theoretical discipline as well, just as the ethnicity exercise here appears to? It well might, and such an endeavor should be part of the research agenda. But with ethnicity and economics jointly in the picture, it is no longer a question of one or the other as far as empirical analysis is concerned. The interaction between these two themes now takes center stage. As we have already argued, there is a real possibility that the economics of conflict finds expression across groups that are demarcated on other grounds: religion, caste, geography, or language. Such markers can profitably be exploited for economic and political ends, even when the markers themselves have nothing to do with economics. A study of this requires an extension of the theory to include the economic characteristics of ethnic groups and how such characteristics influence the supply of resources to conflict. It also requires the gathering of group data at a finer level that we do not currently possess. In short, a more nuanced study of the relative importance of economic versus primordial antagonisms must await future research.

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REVIEW

MODELING ARMED CONFLICTS

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Armed conflicts have been prevalent throughout history, in some cases having very great consequences. To win, one needs to understand the characteristics of an armed conflict and be prepared with resources and capabilities for responding to its specific challenges. An important tool for understanding these characteristics and challenges is a model—an abstraction of the field of conflict. Models have evolved through the years, addressing different conflict scenarios with varying techniques.

Armed conflicts start because people disagree. They disagree on controlling territory, economic interests (such as natural resources), religion, culture, and ideology. Disagreements may lead to tense disputes, which can result in armed conflicts of various scales. History is cluttered with armed conflicts involving tribes, states, insurgencies, guerrilla groups, and terrorist organizations. Attaining victory is associated with questions regarding the use of resources, strategy, and tactics. Answering these questions is not easy; it requires a clear definition of objectives, a detailed review of capabilities and constraints, and a careful analysis of possible scenarios and courses of action. For this, military and defense analysts use models, which are abstractions of armed conflicts, their environments, and their possible realizations. These models, henceforth called armed conflict (AC) models, are used for analyzing threat situations, military operations, and force structures.

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Armed conflicts encompass hard factors such as weapons, personnel, logistics, communication systems, and sensors, as well as soft factors such as training, tactics, leadership, situational awareness, and coordination. The "art" of AC modeling is to choose those few dominant factors that make a model manageable, meaningful, and useful.

AC models have been useful for studying cause-and-effect relations on the battlefield and to help choose among alternate systems and courses of action. AC models provide insights regarding defense issues such as the relative importance of weapons and sensors, the effect of certain tactics (such as the concentration of forces), the impact of a new weapon system, etc. For this purpose, there exist reliable and complete data sets such as estimates of hit probabilities and ranges of weapons, detection rates of sensors, capabilities of command–and-control systems, and other physical characteristics of weapons and equipment. These data are collected from tests, field experiments, simulations, and, on some rare occasions, combat events. However, although some small-scale and physical (such as firing or surveillance) models can provide good predictions of specific battlefield outcomes based on the aforementioned data, in general AC models are affected by limited and unreliable operations data, rapid changes in the environment and structure of military campaigns, and the enhanced uncertainty introduced by human behavior in the stressful combat environment. Although limited in projection power, campaign models, which encompass the combined effects of large-scale joint operations, are important for comparing alternatives and improving defense planning processes by highlighting crucial aspects. In addition to supporting decision-making, AC models are also used for educating and training military officers and defense executives. In particular, recent advances in computer technologies facilitate generating virtual environments for training combatants at the tactical level (*1*).

Historical and Classical Models

Probably the earliest AC models in the modern era were Kriegsspiels—war games developed in the early 19th century for training, planning, and testing military operations in the Prussian Army. A game was played on a table with modular combinations of precast terrain formation, gaming pieces, and dice, and it progressed following rules based on actual military maneuvers and battles. These models played an important role in the military operations that led to German unification in 1871 (*2*). Up until World War II (WWII), war games were the only AC models, used primarily for relatively small-scale (for example, battalion-sized) battles. The big leap in AC modeling occurred during WWII, when more scientific approaches to military modeling set the foundation for a newly emerging scientific field—operations research (*3*).

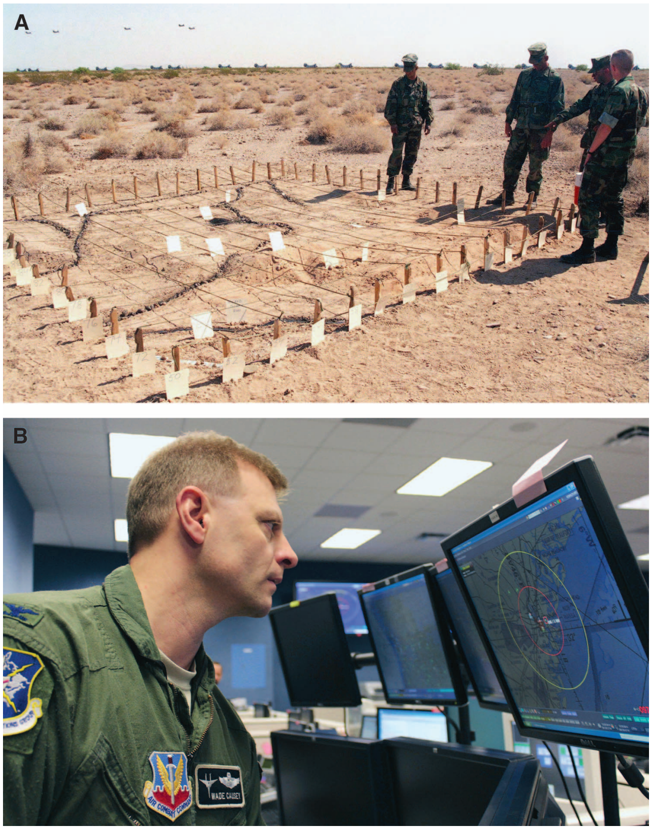

Fig. 1. (**A**) A U.S. Marine Corps physical simulation in a sand table in the desert in Yuma, Arizona. (**B**) Monitoring of airspace during a joint and binational exercise executed through the Air Force's Northern Distributed Mission Operations (DMO) system. DMO is a system of interconnected simulators that allows warfighters from across the United States and Canada to participate simultaneously in the same live scenario. [U.S. Air Force Photo by Angela Pope]

During WWII, a simple AC model changed the way supply convoys were dispatched across the Atlantic to provide the lifeblood for the Allied forces (*4*), and a back-of-the envelope calculation improved the tactics for hunting German submarines (*3*). More recent examples are mentioned below. There are many other examples of decisions supported by AC models that remain classified. With the advent of computing technologies, combat models have become more complex and detailed, requiring elaborate preparations that include parameter inputs and extensive postprocessing work and analysis. Many of these models are high-resolution large-scale simulations or agent-based models in which the conflict is modeled by a group of individual entities (*5*). Such models are used by the defense establishment to help choose weapon systems, such as air defense (*6*); select multibillion-dollar defense projects; determine operational plans (*7*); and set long-term goals, as in the Quadrennial Defense Review.

The validity of AC models is typically assessed by the defense community in a review called Verification, Validation, and Accreditation (VV&A). Verification is a technical requirement to make sure that the model has no conceptual or mathematical "bugs." Validation is "the process of determining the degree to which a model or simulation and its associated data are an accurate representation of the real world from the perspective of the intended uses of the model" (*8*). Although verification may be hard and tedious, similar to verifying a long and complex computer program, it is nonetheless a well-understood task. Validation is much more problematic for AC models because the "real world" is often inaccessible. Reliable combat data seldom exist in the quantity and variety needed for validation, and it is often not clear how to compare the model assumptions and results to the elusive "reality" (*9*). Current practice of validating AC models ranges from rigorous statistical methods for small-scale physical models (e.g., firing and detection models) and some guerrilla models that are supported with sufficient field data to reviews by subject-matter experts for large-scale campaign–level models (*10*). Accreditation is defined as an "official certification that a model or simulation and its associated data are acceptable for use for a specific purpose" (*10*).

Field exercises are designed for training and are as close as one can get to real combat. These exercises include real weapons and take place in open terrain. The only (significant!) deviation from reality is the absence of a real-life enemy. With proper control and refereeing, these models are effective for training military forces in tactics and command and control of military formations. War games are similar models that represent a higher level of abstraction. First, these models are executed on a simulated battlefield (such as a sand table, map, or computer screen) without any real weapons. Second, only selected key players take part in these models. The uncertain behavior of the enemy and the capricious effects of nature are determined by human umpires (for example, by throwing dice) or randomly generated by computers. War games may be completely manual (Fig. 1A) or be played with computerized intervention, to generate a field of combat and/or link participants (Fig. 1B). Monte Carlo or agent-based simulations are fully computerized, in which decisions, usually made by human actors, are made by some preprogrammed decision rules. The applications of Monte Carlo and agent-based simulations range from analyzing tactics and the effectiveness of weapon systems in various scenarios (*11*) to studying geopolitical competitions among states and the effect of conquest (*12*).

Although popular and sometimes useful, these simulations have a major drawback that is manifested in the gap between decision-making in a real armed conflict and decisions made in a simulation. The risk of severe damage, injury, and loss of life may dictate a different attitude toward risk in real-life combat than in simulations where, say, the loss of an aircraft carrier is manifested by simply removing an icon from the computer screen (*4*).

Unlike simulations, which can deal with a large number of parameters, analytical models capture only selected key aspects of armed conflicts. They may be deterministic [such as sets of differential equations (*13*)] or stochastic [such as Markov chains (*14*)]. Lanchester proposed a family of ordinary differential equations describing the dynamics of force-on-force engagements (*13*). These equations have been used extensively in the past 60 years in warfare models developed by the U.S. Army (*11*). Stochastic versions of Lanchester models address the inherent randomness associated with combat (*15*).

The Guerrilla Warfare model (*16*) is a variation of a Lanchester model in which one side—the guerrilla force that hides or blends into the population—engages a regular force that is fully exposed. The guerrilla force uses aimed fire (like the Taliban attacks on NATO forces in Afghanistan), while the regular force has to search for the guerrilla force. This model has given insights regarding the tradeoff between fire (attrition) and intelligence (*17*). Although providing a compelling physical description of military attrition, Lanchester models have been criticized in the literature mostly because of the difficulty of empirically validating them (*18*, *19*). There have been several attempts to fit the Lanchester models to WWII battle data (*20*–*22*), with mixed results. Lanchester equations were described as red herrings in a 1987 National Academies study (*23*); however, they are still useful as a description of attrition processes. For example, the Salvo model, proposed by Hughes (*24*), is an adaptation of the Lanchester models to modern naval warfare, which is characterized by exchanges of missile salvos.

Optimization models generate decisions that are optimal in some sense and include resource allocation to tactical defense planning (*25*), sensor deployment (*26*), and engagement tactics (*27*). A weapon assignment model (*28*) has been implemented in the U.S. Navy for real-time pairing of Tomahawk missiles with designated missions. Optimization techniques include linear and integer programming (such as defense resource allocation and weapon assignment), stochastic programming (such as sensor deployment), and dynamic programming (such as engagement tactics). Attacker-defender models, where decisions are sequential—a defender acts first, an attacker observes these actions and responds accordingly—have been treated as mathematical programming (optimization) models by Brown and others (*29*). Such models encompass a wide range of combat situations such as missile defense (*30*) and protecting national infrastructure (*29*). The basic idea in these models is that the defender acts in such a way as to minimize the effect of the attacker (or maximize its own surviving assets), whereas the attacker acts optimally in opposition. The missile defense model (*30*) has been used in recommending specific tactics to defend the United States and its allies, assess the value of improved technologies, and critically evaluate alternate defense investments.

Game theory models are, in a sense, the mathematical manifestation of war games. Instead of real (human or computerized) players who run the game, game theory prescribes policies that are "optimal" and "stable" with respect to each player, without the need to actually play the game. Game theory was originally intended to mainly explain economic behavior (*31*, *32*). The Colonel Blotto game (*33*), originated in 1921 by the French mathematician Borel, is a zero-sum game that addresses a typical dilemma of each of two adversaries: how to deploy forces among several battlefields so as to maximize their overall force effectiveness. After WWII, game theory became an important tool for analyzing strategic defense issues, in particular during the Cold War (*34*).

Current and Future AC Modeling

Armed conflicts before and after WWII and the Cold War were typically wide-ranging and involved heavily armed state actors also possessing strategic weapons such as nuclear bombs. This motivated the development of large-scale force-on-force and ballistic missile defense models. Although these types of conflicts may still be feasible and require appropriate modeling, current armed conflicts are of smaller scale and also involve nonstate actors such as rebels, guerrillas, insurgents, and terrorists. These conflicts are sometimes called asymmetric or irregular war, which has been defined by the U.S. Department of Defense as "a violent struggle among state and nonstate actors for legitimacy and influence over the relevant populations" (*35*).

Terrorism is one very prevalent aspect of armed conflicts today that has triggered several studies that range from modeling individual attacks to analyzing terror-events data to developing game-theoretic models. One of the most common forms of terror attacks is person-borne suicide bombs. Studying the effect of such attacks and analyzing response policies are of great importance to local authorities and first responders. Using some elementary geometric and probabilistic considerations, and accounting for the effect of crowd blocking, (*36*) shows that the expected number of casualties in a single suicide bomber incident is bounded by around 32—an outcome that has been observed in many such events in Israel (*36*) and Iraq (*37*). Mitigation strategies are studied in (*38*). Johnson and others (*39*) examine the patterns of violence in insurgencies and terror events and identify a common pattern regarding the size distribution of such events and their timing. Their dynamic model explaining this pattern is based on the notion of coalescence and fragmentation of insurgents or terror organizations, thus producing an ecology of groups. A more recent paper (*40*) reveals a dynamical pattern of fatal terrorist attacks. This pattern, which is manifested in a power law, identifies possible escalation scenarios of such attacks. The authors establish a new metric for understanding the momentum of these attacks and the effectiveness of counterterrorist actions—a metric that appears to be stable across multiple conflicts and at different scales.

Addressing a similar problem, Kaplan (*41*) applies queueing theory and Markov processes to predict the number of undetected terror plots and estimate the rate at which such threats can be interdicted. Game theoretic models have addressed several counterterror situations (*42*). The Israeli-Hezbollah war in 2006 motivated an optimization model for operations against entrenched guerrillas (*43*). The problem of attacks by improvised explosive devices on coalition forces in Iraq led to a model for allocating clearing devices on a network of roads in the presence of a strategic adversary (*44*). Attacker-defender mathematical programming models are well suited for homeland security problems, because defensive preparations for critical infrastructure (such as the electric grid) involve large investments, visible to any intelligent attacker who would adjust his tactics accordingly (*29*).

The two main challenges to modeling counterterror operations are detection and protection. Effective intelligence collection and analysis are crucial for timely detection and interception of terror plots. Mathematical models such as Bayesian updating, Markov random fields, exploration-exploitation schemes, and probability graphical models can improve the efficiency of intelligence collection. Advances in data mining help "connect the dots," and the application of specially tailored techniques will result in better allocation of human and equipment resources and improve the work processes during the analysis phase (*45*). Modeling the vulnerabilities of a system and the effect of mitigation actions against a terror attack by a strategic adversary is essential for developing effective protection schemes against such attacks. In particular, mathematical models should be used to provide policy recommendations in homeland security on topics such as building redundancies in national infrastructures (*29*), border screening, and biological attacks (*46*).

In one-on-one situations, the nonstate actors in an insurgency are no match for the military might of state-controlled forces, who are significantly larger and better equipped and trained. To avoid eradication, nonstate actors must hide, making themselves difficult to detect and target by state forces. This elusiveness is attained by blending in with the civilian population and using relatively simple, yet lethal, weapons such as small arms, improvised explosive devices, and even biological agents that do not require persistent exposure.

Hiding places, shelters, information, logistical support, and recruits are provided to the nonstate actors by the civilian population, either willingly or by coercion. The civilian population is also a source of information (intelligence) to the state forces, a consumer of social and economic resources, and a target of terrorist attacks. All of these characteristics make civilians a key component in irregular warfare modeling, which is absent in legacy AC models.

Following Deitchman's classic guerrilla model (*16*), more-recent work has focused on the dynamics of insurgencies, as depicted in Fig. 2. Kress and Szechtman (*47*) developed an attrition-reinforcement model representing recent wars in Iraq and Afghanistan. The model incorporates dynamic relationships among intelligence gathered, collateral casualties in the population (which can turn public opinion against the perpetrators), recruitment to the insurgency, and reinforcement to government forces. It demonstrated that, under some reasonable assumptions, an insurgency cannot be eradicated by force alone; at best, it can be contained in a stalemate, which could only be broken by nonviolent circumstances. Although reliable statistical data for validating the model is lacking, the model is consistent with available anecdotal information (*47*). Using the limited data available on the insurgencies in Malaya and Iraq, Johnson and Madin (*48*) exploit a simple population-growth logistic model to compare the dynamics of an insurgent population in these two insurgencies. They identify conditions for failure and success of an insurgency in terms of attrition and recruitment rates and the population carrying capacity (a term describing the relationship between population density and resource dependence). Berman *et al.* (*49*) model the economics of counterinsurgency, using the Empirical Studies of Conflict Project database (*50*), as a three-way contest between violent insurgents, a government seeking to minimize violence, and civilians deciding whether to share information about insurgents. The results of the model underscore the effectiveness of service provisions by the government to the population as a violence-reducing factor.

Armed revolts, such as the recent events in Libya, Yemen, and Syria, represent a somewhat different facet of irregular warfare, in which civilian demonstrations and social unrest turn into an armed conflict. A model describing this situation (*51*) suggests that, unlike classical force-on-force models, the outcome of a revolt is independent of the initial force sizes; it only depends on the fraction of the population supporting each side and on the combat effectiveness of the government forces and the rebels. This model specifies conditions for a stalemate and underscores the critical effect of foreign intervention as a game-changer, as was demonstrated in Libya.

The aforementioned papers and a few computerized simulations developed for the Department of Defense, such as COIN 1.0 and COIN 2.0 (*52*), are only initial attempts at modeling irregular warfare. COIN 2.0 is a computerized model, which includes only limited representation of violence: just casualties from improvised explosive devices and direct fire. It focuses on the social landscape in a counterinsurgency situation and models the interrelations among the coalition forces, foreign fighters, and the civilian population.

Insurgencies are combat situations in which regime forces and insurgents fight each other using a variety of weapons, such as improvised explosive devices, suicide bombs, direct fire, drone-borne missiles, and artillery. Attrition models are necessary for modeling these situations, but they are not sufficient. The big challenge is to combine attrition models; political, social, and behavioral sciences; and economic theory into a unified model.

Social and behavioral components in such a model should include social networks (*53*), which model the underlying connectivity in the population of interest, its dynamics, and its impact on the actions of state and nonstate actors (e.g., the role of Facebook in the Arab Spring that facilitated the revolution). Social network models can be used for identifying key individuals whose absence will destabilize an adversary network (*54*) in a manner analogous to the way in which advertisers target likely buyers. Models that describe the way the topology of these self-organizing networks evolves over time (*55*), and the effect of the regime's and insurgents' actions on these dynamics, are of particular interest because they can explain changes in popular behavior. Social models should also represent the spread of ideas (*56*) that affect the pace at which people change their attitudes and capture the effect of private and public preferences (*57*) that explain differences between the hidden attitude of an individual toward one side in the conflict and his exposed behavior (e.g., the effect of coercion). The effect of the mass media on public opinion, and its impact on what governments do (such as violence against civilians or foreign intervention), is also an important factor to be modeled. Economic theory models should capture the role of incentives in shaping popular behavior and buying out opponents [e.g., principal-agent models (*58*)]. Another important issue to be addressed is corruption (*59*), which is relevant for rebellious situations that stem from corrupted regimes. There is a relatively large body of important research on insurgencies

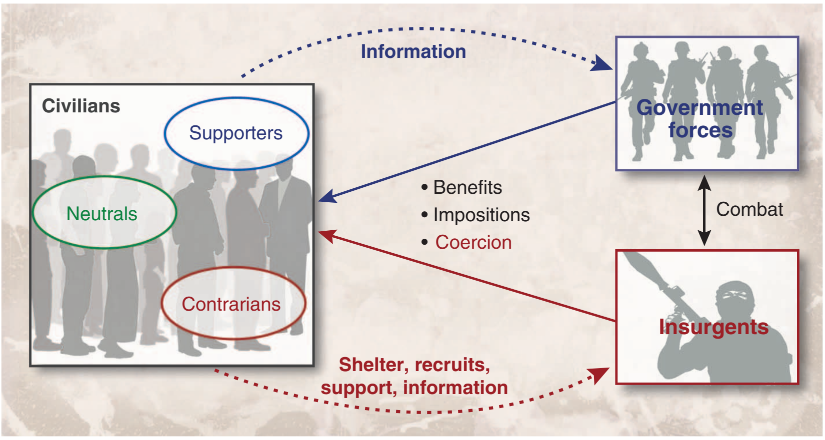

Fig. 2. Insurgency dynamics. There are three actors: the government (state) forces; the insurgency (nonstate entity); and the general population, which is divided into three sectors: supporters of the government, supporters of the insurgency (called contrarians), and neutrals. The government and the insurgents are engaged in direct combat, but both draw information from their supporters in the population. The insurgents also get other support. The size of each support group is affected by (i) social and economic incentives (such as health care and infrastructure) provided to the population (or sector(s) thereof) by each side; (ii) impositions (such as Sharia law) and coercive actions that aim to intimidate and affect the flow of information; and (iii) collateral damage caused by combat actions (such as civilians caught in crossfire) and misdirected coercion. Although in some cases the government may also execute coercive actions against civilians, in this model we assume that it does not.

in the political science literature that can be incorporated in future AC models. In particular, empirical studies of certain insurgencies shed light on the feedback effect between a regime's violence and the level of insurgency. For example, studies of the insurgency in Chechnya (*60*) and the Vietnam War (*61*) provide important insights for modeling the insurgency dynamics. In addition, data assembled in the Correlates of War project (*62*) can be used for validating future AC models, at least at the macroscopic level.

What will be needed in the future? Certainly advances in defense technology, which affect both regular and irregular warfare, will need models to assess their impact and optimize the employment of the resulting weapons and equipment. In particular, networks of sensors, which support the operation of unmanned systems, will require data fusion and machine-learning models that will facilitate an effective use of these two advanced technologies. Also, to better model and understand future armed conflicts, information technology should be implemented for systematically collecting data about the combat environment, actions, and outcomes during such events.

The emphasis in this article has been on quantitative models, but answering some broader questions may require more qualitative analysis of behavioral factors and social forces. Why does someone become a terrorist, and how can that process be stopped? How long does it take for a population to forget a multigenerational history of conflict, as in Northern Ireland or the Middle East? Insights from a range of fields, some described in this issue of *Science*, and further understanding of the complexity of human interactions during armed conflicts will need to be part of our arsenal in confronting these questions in the future.

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PERSPECTIVE

CLIMATE CHANGE AND VIOLENT CONFLICT

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Current debates over the relation between climate change and conflict originate in a lack of data, as well as the complexity of pathways connecting the two phenomena.

Since publication of the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC), the debate on the security implications of climate change has intensified. Research in this area has made progress but remains controversial [for recent reviews, see (*1*–*4*)]. Although some quantitative empirical studies support a link between climate change and violent conflict, others find no connection or only weak evidence.

A major challenge for all studies is to find adequate data. Instead of using data on the long-term average and variability of temperature, precipitation, and other climatic variables that would clearly fall under the IPCC definition of climate change (*5*), many studies have used proxies, such as short-term data on weather and extreme weather events, or on natural phenomena of climate variability like the El Niño Southern Oscillation (*6*).