Quantitative patterns in drone wars

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Attacks by drones (i.e., unmanned combat air vehicles) continue to generate heated political and ethical debates. Here we examine instead the quantitative nature of drone attacks, focusing on how their intensity and frequency compares to other forms of human conflict. In contrast to the power-law distribution found recently for insurgent and terrorist attacks, we find that the severity of attacks is well described by a lognormal distribution, indicating that the dynamics underlying drone attacks differ from these other forms of human conflict. Likewise, the pattern in the timing of attacks is consistent with one side having almost complete control. We show that these novel features can be reproduced and understood using a generative mathematical model in which resource allocation to the dominant side is regulated through a feedback loop.

INTRODUCTION

Dating back to physicist L. F. Richardson's pioneering work nearly 100 years ago [1], the quantitative analysis of human conflict has attracted research interest from across the social, biological, economic, mathematical and physical sciences [2–7]. As in other human activities [8, 9], power laws have been identified in the severity distribution of individual attacks in insurgencies and terrorism [4–6, 10], and in the temporal trend in events [5, 10, 11]. These studies found that across a wide range of insurgent wars in which a relatively small opponent such as an insurgency (Red Queen [11]) fights a larger one such as a state (Blue King [11]), the probability distribution for the severity s—the number of fatalities—of an event (i.e., clash or attack) is given by $P(s) \propto s^{-\alpha}$ where $\alpha \sim 2.5$, while the trend in the timing of attacks is given by $\tau_n = \tau_1 n^{-b}$, where τ_n is the time interval between events n and $n+1$, $n = 1, 2, \dots$ and b is the escalation parameter. When $b = 0$, the Blue King and Red Queen are evenly matched, with both effectively running on the same spot—hence the terminology surrounding the Red Queen [11]. When $b \neq 0$, there is an escalation in the frequency of attacks which can be interpreted as a relative advantage between the Blue King and the Red Queen [11]. The power-law finding for the distribution of event severities is consistent with the Red Queen (i.e., insurgent force) evolving dynamically as a self-organizing system composed of cells (i.e., clusters) that sporadically either fragment under the pressure of the Blue King (e.g., state) or coalesce to create larger cells, and taking the severity of attacks as proportional to the sizes of the resulting cells [6].

This paper examines, for the first time, event patterns in the new form of human conflict offered by unmanned combat air vehicles (drones) [12]. We focus on Pakistan and Yemen because of their association with drone strike campaigns, using data from the New America Foundation (NATSEC) and the South Asia Terrorism Portal (SATP) databases. The situation of drone wars differs from the typical situation for insurgencies and terrorism in that the attacks are now carried out by the Blue King on the Red Queen. Moreover, the sophistication of the action-at-a-distance technology means that any delay in the Blue King's next attack is likely to have come from a constraint within Blue itself (e.g., political opposition) as opposed to any direct counter-adaptation by the Red Queen. Indeed, we find that the drone attacks do not follow the universal patterns in the severity and timing for insurgencies and terrorism. Instead our analysis indicates a new regime of human conflict in which the Blue King has almost complete control over the conflict. We develop a generative model in which the severity and timing of attacks are determined solely by the resources of the Blue King, but are regulated by a positive feedback loop due to the Blue King's internal sociopolitical and economic constraints. We show that this simple model reproduces the main features of the original data and hence yields novel insight into the nature of drone warfare.

RESULTS AND DISCUSSION

Figs. 1A–D show the complementary cumulative distribution function (CCDF) of the severity and frequency of drone attacks using the NATSEC database. We fit power-law and lognormal distributions (dashed green and solid black lines respectively; see methods) for attacks in Pakistan (Figs. 1A–B) and Yemen (Figs. 1C–D). We find that the severity of the strikes is approximately described by lognormal distributions, in contrast to that expected for attacks carried out by terrorist and insurgent groups

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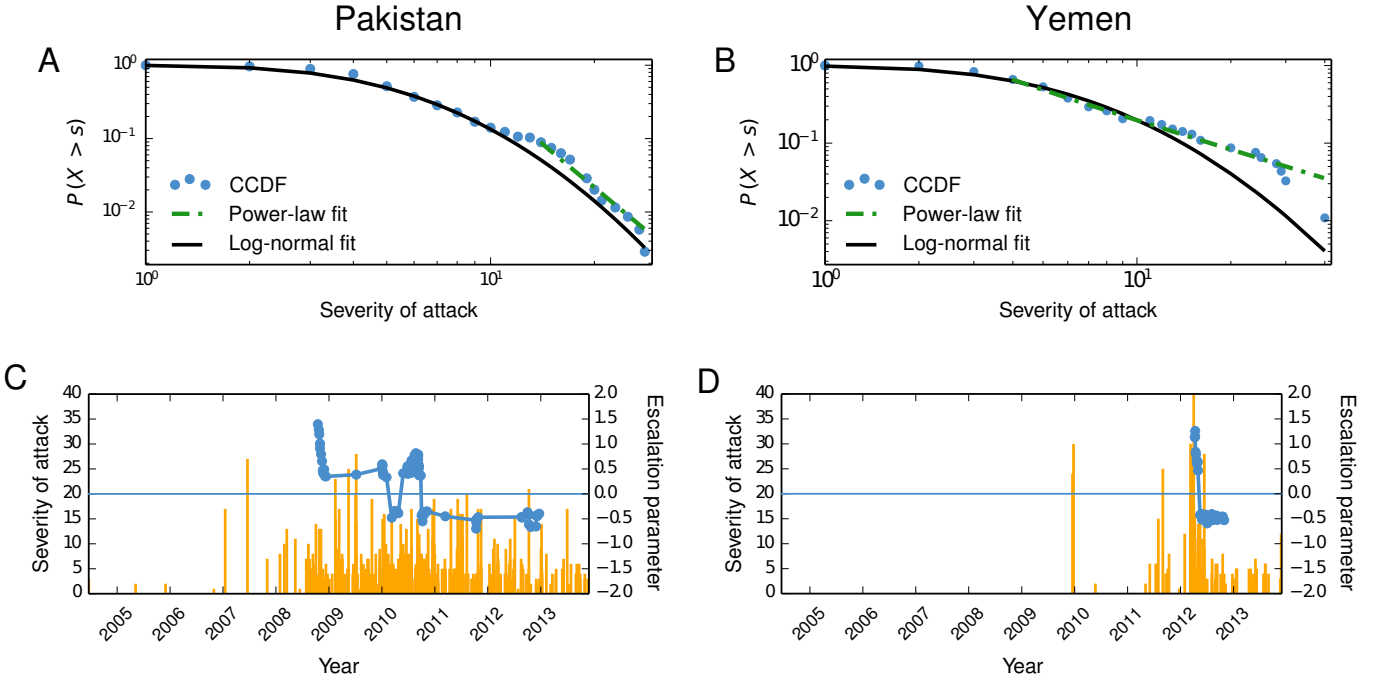‡ njohnson@physics.miami.edu

FIG. 1. **The severity of drone attacks approximately follows a lognormal distribution.** Complementary Cumulative Distribution Function (CCDF) of the severity of attacks (blue dots and solid line) and best fits (dashed line) to power-law (A, C) and lognormal (B, D) distributions for drone attacks in Pakistan (A, B) and Yemen (C, D). The optimal parameters for each distribution are (A) $\alpha = 4.82$, (B) $\mu = 1.60$, $\sigma = 0.64$, (C) $\alpha = 2.21$ and (D) $\mu = 1.65$, $\sigma = 0.77$. Bottom panels (E, F) show the severity of attack (vertical lines, left axis) and escalation parameter b (right axis) for a moving window of 50 attacks in Pakistan (E) and Yemen (F).

which follow a power-law distribution reflecting their underlying cluster sizes [13]. Our observation is most well supported for Pakistan, and tentative for Yemen for which we have far less data, and where the best fit lognormal is less sympathetic with larger events. This finding of lognormality is consistent with the notion that a drone has a specific design which tends to pre-determine the order of magnitude of its range of destruction and likely severity, in sharp contrast to attacks by a terrorist or insurgent cluster where the severity of attack can vary greatly according to the size of the cluster carrying out that attack. For drone attacks, a lognormal distribution will then arise naturally from a sum of normal distributions with variable mean and standard deviation, which in turn reflects variations away from the pre-determined impact due to differences in the terrain and the number of people in the target group.

We now turn to the timing of attacks in order to gain insight into the temporal dynamics of the Blue King-versus-Red Queen activity. Following previous work [10], we plot the time interval between consecutive attacks τ_n as a function of the cardinal number of the attack $n = 1, 2, 3, \ldots$. The escalation parameter b is the exponent of the power-law fit $\tau_n = \tau_1 n^{-b}$, which will be the slope of the best-fit line on a double logarithmic plot. In the organizational development literature in which progressive events are related to production, this is referred to as a development curve while in the psychology litera-

ture, where subsequent events correspond to completing a certain task, it is referred to as a learning curve [11]—in this sense, the 'production' or 'completion' of drone attacks has a natural connection to human activity in these wider fields.

For both Pakistan and Yemen, we find that the parameter b fails to stabilize around 0 (Figs. 1E–F). Instead, the drone attacks exhibit an initial large escalation (i.e., large positive b) which then transitions to a de-escalation (i.e., large negative b). Given the difficulty for the Red Queen to thwart drone attacks directly, Figs. 1E–F suggest that one side (Blue King) effectively holds complete control for an extended period of time, and that some internal constraints then arise within the Blue King entity that eventually de-escalate the drone attacks.

Fig. 2A shows our simple model for drone attacks. In our model, the Blue King possesses certain resources, for example experience, units, and funding. These resources degrade over time if no investment is made in the Blue King's activity, i.e., if the government does not invest in its own drone development or information research. We assume that if the investment (i.e., funding, time, etc.) is higher than the degradation rate λ, then the available resources increase due to a positive feedback loop (Fig. 2B). This feedback loop has been proposed in models of conventional terrorism [14], and can be affected by external agents, for example public opinion or by the perceived number of Red Queen cells remaining that
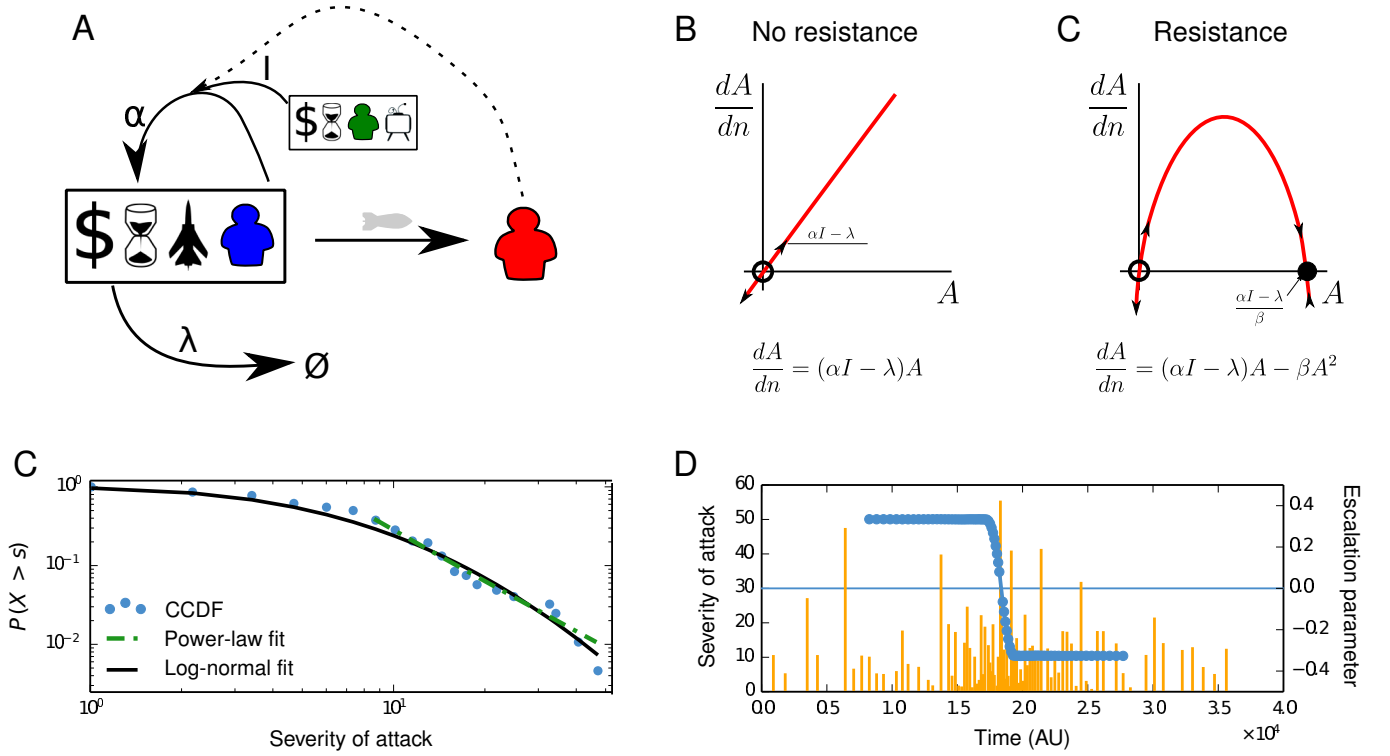
FIG. 2. **A simple model of drone wars.** (A) The Blue King's resources (funding, units, experience, etc.) influence the frequency and the magnitude of attacks. Resources are degraded continuously, with some being invested to create a positive feedback loop. The civilian population and other variables, summarized as I, influence the strength of this positive feedback. The dashed line indicates that the Red Queen (i.e., target group) is only able to affect the Blue King's attacks indirectly. The amount of resources available corresponds to A, the advantage of the Blue side. (B) Our simple model has one unstable fixed point at $A = 0$, given that $\alpha \cdot I > \lambda$. (C) A 'resistance' is added to the model due to internal Blue King constraints. The model now has a new fixed point at $A = \frac{\alpha I - \lambda}{\beta}$. (D-F) Our model is able to replicate the observed findings. Complementary Cumulative Distribution Function (CCDF) for event severity (blue dots and solid line) and the best fits (dashed line) to power-law (D, $\alpha = 2.7519$) and lognormal (E, $\mu = 1.7$, $\sigma = 0.83$) distributions for the model. (F) Severity of attack (vertical lines, left axis) and escalation parameter b for a moving window of 50 attacks (right axis) for the model. Note the resemblance to Fig. 1.

need targeting. The resources available at any particular time will affect the timing and severity of the next drone attack. For simplicity we take the frequency of attacks as directly proportional to the resource level, while the severity of the attack depends on the available resources and the characteristic of the terrorist cells (see methods). We add 'resistance' to the model to mimic constraints within the Blue King, for example due to political opposition, and hence obtain the logistic equation which has a new stable equilibrium at a non-zero value, as shown in Fig. 2C.

This simple model is able to replicate the drone strike data (Figs. 2D–F). The escalation parameter b is proportional to $(\alpha \cdot I - \lambda)$, which means that the Blue King has a positive advantage if the investment term is larger than the degradation term (Fig. 2C). A constant $b > 0$, corresponding to the frequency of attacks increasing continuously, is achieved if the resources increase exponentially—hence this is only sustainable for short periods of time. A constant $b < 0$, corresponding to the frequency of attacks decreasing continuously, is achieved

if the resources decrease exponentially, i.e., when there is little or no investment. Assuming each drone acts individually and the attack severity varies slowly with the available resources, which is consistent with increases in precision requiring significant amounts of development effort (see methods), we are able to recreate the lognormal distribution for the severity of attacks.

In summary, our analysis reveals new patterns in the severity and timing of attacks in drone wars, which themselves represent a new form of action-at-a-distance human conflict. We have purposely stepped aside from issues of ethics or technology, choosing instead to focus on the event data since they represent a quantitative measure of drone war impact. We have shown that a simple model, in which the production of drones evolves from a shared pool of resources controlled by a feedback loop, is able to recreate the original data and therefore explain the overall dynamics of the Blue King's drone campaign. Going forward, our model could be also used to explore how wars might unfold when drones are used by two or more sides in conflicts.

METHODS

We obtained all data from the NATSEC database: `http://natsec.newamerica.net/` and crosschecked with the SATP database: `http://www.satp.org/satporgtp/countries/pakistan/`.

We obtained the best fit to power-law distributions following Clauset et al. [4]. We fitted lognormal distributions using the maximum likelihood estimators. For the learning rate analysis, $\tau_n = \tau_1 n^{-b}$, we plotted the number of attack vs. the time between attacks on a log-log scale. We accepted every value of b that allowed for a correlation greater than 20%, which allows us to measure fast transitions.

We simulated 100 attacks with our model. The initial advantage was set to 10^{-3}. The time to the next attack is equal to A^{-1}. At every step (attack) the advantage of the Blue King changed by the factor $\alpha \cdot I - \lambda$. For the first 50 attacks $\lambda = \alpha \cdot I = 1.075$; for the last 50 attacks $\lambda = 1.075$ and $\alpha \cdot I = 0$. We model the attacks as individual drones strikes; each individual attack was drawn from a zero-truncated normal distribution, whose mean and standard deviation were set to be equal to the root square of the largest known Red group. The area of a self-avoiding random walk in two dimensions increases as $A \propto n^{1/2}$, where n is the number of individuals in the plane [15]; the magnitude of the attacks is fixed, hence the number of casualties scales with $n^{1/2}$. The number of known Red groups was set to $(100 + 10^4 \cdot A) = [110, 500]$ and they were assumed to be power-law distributed with $\alpha = 2.5$ [1, 6].

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