PREDICTING THE SEVERITY OF CIVIL WARS: AN ACTOR-CENTRIC APPROACH

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Abstract. We introduce an actor-centric approach to predict the severity of conflict one and six months into the future. We argue that the prediction of conflict severity needs to focus on the actors that are responsible for conducting armed violence. Hence, we predict the severity of conflict in government-rebel organization dyads. Our predictors focus especially on rebel organization characteristics, behavior, and the conflict networks actors are embedded in. Our statistical learning approach relies on random forests to predict the severity of conflict. We demonstrate that our model performs especially well distinguishing high levels of severity from very low levels.

1. Introduction

Civil wars vary greatly in the degree to which they escalate and thereby affect civilians [43], regional stability, and global order [48]. For example, the extent to which conflicts force people to seek refuge abroad is consistently a function of its severity [1, 107] and its geographic scope [76]. We put forward a novel actor-based machine learning approach to predict the severity of conflict 1-month and 6-month ahead to enable early warning facilities and contribute to the important and fast growing field of conflict prediction[26, 55].

While severity is a fundamental aspect of conflict dynamics [6], few attempts exist in the civil war literature to predict the variation in intensity of conflict [17, 4, 61]. The majority of forecasting efforts focus on the onset or occurrence of civil war [110, 60]. Severity is much more at the center of approaches focusing on one-sided violence [114, 87, 92, 51, 28] and terrorism [34]. The limited focus on civil war severity in prediction studies is quite surprising, as the field of conflict prediction is growing rapidly [e.g. 56, 83, 96, 52, 111, 95, 41, 110, 49, 60, 9, 18, 27, 59, 81, 10, 30, 82].

We provide a novel contribution to the conflict prediction literature, as we explicitly focus on the prediction of actor behavior. While prediction approaches to inter-state conflict very much capture the behavior of actors [21] and its severity [32, 18], civil war predictions mostly concentrate on geographic locations (countries, regions, or grids) [58]. A geographic unit is often necessary in context of civil war onset, as we cannot observe actors until they decide to fight the government. However, once the universe of actors is identified, there is an opportunity to make actor-based conflict predictions regarding the occurrence, duration, and severity of conflict [compare 77, 46, 47]. The advantage of actor-based predictions is that we can model the behavior of decision-making organizations and rely on a broad theoretical literature to inform predictive feature selection and creation [86, 109, 40, 38, 104, 54]. Hence, in our predictive models we include features that account...
for actors’ characteristics, their past behavior, and interdependencies between rebel organizations. Compared to a geographic prediction approach, an actor-centric approach also has the advantage of only modeling the relevant set of units, which reduces the sparsity in the observed data. Grid-based forecasting approaches can entail many cells without any conflict activity, creating highly unbalanced prediction challenges [58].

**Severity in armed conflict**

The interest in explaining the severity of armed conflicts can be traced to the very beginnings of quantitative conflict research. Richardson [90] already identified a power-law relationship between the frequency and severity of ‘deadly quarrels’. Indeed power-law based explanations of severity gained renewed attention in conflict studies [91, 25] with applications to armed inter- and intrastate conflict [2, 11, 94, 106, 45] and terrorist attacks [34, 33, 85].

The work of Richardson [90] also inspired work to link the temporal dimension of conflict with severity. Already in the early 1960s Markov process driven relationships between severity of wars their duration were found [112]. This linkage between time and severity was further explored by Klingberg [69] who puts forward a breaking point theory in the context of interstate wars, demonstrating that severity is especially high at the beginning and that conflicts end if the first derivative of the cumulative density function of casualties approaches zero. Similarly, Voevodsky [108] shows temporal patterns that indicate that early stages in interstate wars see higher levels of violence.

Research projects collecting more fine-grained information on the behavior of states [93, 75, 3] enabled a new generation of severity models that focused on the intensity of events and its actors [97, 14, 12, 13]. Concepts of reciprocity [16], conflict-cooperation scales [100], and interdependencies [63] between actors are central to the behavioral actor-centric approaches. The actor-centric perspective on predicting severity also allowed for linkages to formal modeling approaches. For example, based on an expected utility model of war Bueno de Mesquita [22] predicts that casualties rise with an increasing utility of war [see also 23].

Compared to the inter-state war literature, civil war research on the severity of conflict is relatively small [24]. An initial study by [70] shows that severe civil wars are related to duration [compare 42], ethnic homogeneity, foreign assistance, and non-democracies. A particular focus in the civil war literature has been on economic development and studies have linked lower economic development [28], food insecurity [113], and economic inequality [73] with more severe conflicts. However, on the subnational level the link between economic development remains ambiguous. In a subnational study of FARC violence, [64] relate severe violence to departments with poverty, low growth, and state repression. But in Liberia, [62] demonstrate the opposite finding that rebels tend to target ‘wealthy’ locations and therefore find a negative relationship between poverty and severity of conflict, which is in line with [74] highlighting that civil wars are most severe when they take place in areas of oil and gas production in the context of secessionist conflicts.

Lacina’s [70] finding that foreign assistance is linked to more severe conflicts has resulted in a broader agreement that third-party actors alone increase severity [101], but mediation and peace-keeping decrease battle-deaths [66, 8]. Furthermore, scholars have explored the role of economic
sanctions that increase severity, whereas arms embargoes decrease severity [67]. Conventional weapon transfers seem to be related to more severe civil wars [80].

Again following Lacina’s[70] initial insights about ethnic homogeneity, ethnicity has been linked to the severity of civil wars in several ways. While Eck[42] demonstrates that ethnic conflicts generally have a higher risk of intensification, other research proposes that ethnic polarization especially affects severity at the beginning of conflicts [36] and shows that ethnic inequality is related to more severe conflicts [65]. From a more institutional perspective, Heger and Salehyan[57] argue that government coalitions led by small ethnic groups have the highest risk of conflict severity.

Finally, it is important to distinguish between escalation and severity in this context. In the context of international relations scholars, escalation describes the process by which political conflict or contest escalates to war [50, 99, 89, 35, 71], whereas severity describes variation in armed conflict once it has escalated to this level. Theories of escalation of inter-state wars tend to focus on the path from contentious issues or low-level conflict to war, but are less interested in the variation of severity once inter-state conflicts have broken out [19, 98, 15]. Similarly, studies of repression and
dissent [72, 84], as well as non-violent to violent protests [29] are more interested in the escalation, rather than the severity of the outcome.

**Actor characteristics, behavior, and dependencies**

We present a prediction framework of severity that accounts for complex interactions between actor characteristics, behavior, and interdependencies. Actor characteristics form an important aspect of conflict dynamics. Capacity [54, 104], resources, or strength [38] have been systematically linked to the occurrence, duration, and severity of conflict. In our predictive framework, we account for actors characteristics, behavior, and interdependence by relying on data from UCDP GED (v.18.1) [103, 37] and PRIO-GRID (v.2.0) [105].

We measure actor characteristics by operationalizing variables that account for maximal observed features of severity that allows us to differentiate between stronger and weaker organizations, the time since the organization has started fighting the government, and the extent of transnational fighting events.

We capture actor behavior by focusing on short run variation in past levels of severity inflicted by rebels on government and level of severity inflicted by government on rebels (lagged dependent variables). Furthermore, we measure the days affected by violent events in a month that involve the respective rebel organization, the number of violent events per month, the geographic scope of rebel operations (number of PRIO-GRIDS affected by violent events involving a rebel organization).

Finally, we account for the argument that rebel organizations do not act in isolation. Rebel organizations are likely to condition their behavior on the behavior of the government and those of other rebel organizations, which affects the severity of conflict [24, 78]. Hence, we first include lagged measures of casualties that the government inflicts on the particular rebel organization and vice-versa. Second, the current literature demonstrates that rebel dependencies and configurations matter [e.g. 39, 38, 31]. Multi-actor setting also give rise to alliance and fragmentation dynamics [5, 7, 44, 40], which are argued to be associated with longer civil conflict duration [31]. We account for interdependencies by creating spatial lags of all character and behavioral variables. To calculate the spatial lags we first calculate a dependency matrix that connects all actors that fight the same government. This connectivity matrix is visualized in Figure 1. We then multiply the dependency matrix with each of our features to account for interdependencies. All features are temporally lagged before including them into the prediction models. The 1-month ahead prediction models include 1-6 month time lags, while the 6-month ahead model include 6-11 month time lags.

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1 An alternative data source would be ACLED [88], but compared to UCDP GED, it does not yet allow for a global prediction framework.
2 Maximum events per month/half year involving the rebel organization, maximum days per month/half year affected by events involving the rebel organization, past maximum level of severity inflicted by rebels on government, past maximum level of severity inflicted by government on rebels.
3 Duration of months a rebel organization is fighting the government.
4 Number of transnational events, which is measured as events outside of the main country of operation.
5 PRIO-GRIDS are a standardized grid structure proposed by [105]. A PRIO-GRID is at the cell resolution of 0.5 × 0.5 decimal degree. This corresponds to about 55 × 55 kilometers at the Equator.
Table 1. Test set predictive performance indicators for 1-month and 6-month ahead models for casualties inflicted on the government by rebels (Reb→Gov) and casualties inflicted by the government on the rebels (Gov→Reb).

<table>
<thead>
<tr>
<th></th>
<th>Level 0</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-month ahead rebel → government models.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.957</td>
<td>0.534</td>
<td>0.229</td>
<td>0.032</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.612</td>
<td>0.928</td>
<td>0.996</td>
<td>1.000</td>
</tr>
<tr>
<td>Precision</td>
<td>0.900</td>
<td>0.615</td>
<td>0.653</td>
<td>0.500</td>
</tr>
<tr>
<td>Balanced Accuracy</td>
<td>0.784</td>
<td>0.731</td>
<td>0.613</td>
<td>0.516</td>
</tr>
</tbody>
</table>

| 1-month ahead government → rebel models. |         |         |         |         |
| Sensitivity          | 0.959   | 0.441   | 0.292   | 0.000   |
| Specificity          | 0.554   | 0.936   | 0.981   | 1.000   |
| Precision            | 0.878   | 0.602   | 0.331   | 0.000   |
| Balanced Accuracy    | 0.757   | 0.689   | 0.636   | 0.500   |

| 6-month ahead rebel → government models. |         |         |         |         |
| Sensitivity          | 0.956   | 0.433   | 0.483   | 0.000   |
| Specificity          | 0.520   | 0.941   | 0.994   | 1.000   |
| Precision            | 0.879   | 0.614   | 0.744   | 0.000   |
| Balanced Accuracy    | 0.738   | 0.687   | 0.739   | 0.500   |

| 6-month ahead government → rebel models. |         |         |         |         |
| Sensitivity          | 0.964   | 0.414   | 0.234   | 0.000   |
| Specificity          | 0.511   | 0.941   | 0.984   | 1.000   |
| Precision            | 0.868   | 0.603   | 0.326   | 0.000   |
| Balanced Accuracy    | 0.738   | 0.677   | 0.609   | 0.500   |

Predicting Battle-related Deaths

We predict battle-deaths 1-month and 6-months ahead in a government-rebel organization dyad and distinguish between battle-deaths that rebel organizations inflict upon government forces and those that government forces inflict upon the rebels. Battle-deaths are measured at the monthly level and we distinguish between 4 levels of intensity: Level 0 (no battle-deaths), Level 1 (1-24 battle deaths), Level 2 (24-99 battle deaths), Level 3 (100+ battle deaths). Relying on the UCDP-dyadic data (v.18.1), we define the universe of government-rebel organization dyads that are included in our study (N=317). For these government-rebel dyads we extract battle-deaths information from the event data base UCDP GED (v.18.1), which provides information on the time, location, and severity of an armed conflict event. Battle-deaths are measured by using the best estimate of battle deaths in a UCDP-GED event.

We apply random forests to predict the categorial outcome variable. Random forest is a popular ensemble learning method combining bagged trees with a randomized variable selection step to reduce variance. In political science, it has shown improvement over traditional statistical approaches. We use the ranger implementation in R statistical language for its computational efficiency. Using 79 features, we grow 500 trees and conduct a grid search to identify the top performing set of hyper-parameters: the number of randomly selected variables at each split (mtry=2,5,9) and tree splitting rule (split rule) while holding the minimum node size constant at 1.

UCDP-GED differentiates between low, high, and best estimates for casualties.
We separate the data into a training (N=18330, T=1989-2009) and test sample (N=6110, T=2010-2017). The training of the random forest is done by 10-fold cross-validation without splitting observations across folds. Hence, all observations of rebel organization $i$ will be in fold $k$. We apply this cross-validation strategy, because we aim to learn about escalation dynamics across and not within rebel organizations. Model performance is assessed using the test sample. In Table 1 we provide sensitivity, specificity, precision, and balanced accuracy for each of our four models. All models perform very well in identifying the Level 0 category, but especially sensitivity decreases with higher levels of severity. However, the relatively low sensitivity at higher levels of severity obstructs the observation that a) misclassification to closer severity levels is more likely than to distant ones and b) our models tend to do well in separating high severity from low severity events. We will discuss these two observations in the next paragraphs.
Figure 3. Separation plots for test-sample predictions. Panels a) - b) pertain to 1-month and c) - d) to 6-month ahead models for casualties inflicted on the government by rebels (Reb→Gov) (a/c) and casualties inflicted by the government on the rebels (Gov→Reb) (b/d). In each panel, separation plots are provided for each level of severity. Level 0 (no battle-deaths = top), Level 1 (1-24 battle deaths = upper middle), Level 2 (25-99 battle deaths = lower middle), Level 3 (+100 battle deaths = bottom).

Figure 2 provides confusion matrices for all four models. A general trend of all models is that they underpredict higher levels of severity. At the same time, we can observe that predictions of high severity (Level 2) are associated with few false positives in regard to Level 0. This means that if the model predicts a Level 2 severity month, there is a very low probability that no casualties will be observed in this month: 1/72 (1-month ahead Reb→Gov), 2/133 (6-month ahead Reb→Gov), 4/169 (1-month ahead Gov→Reb), 1/138 (6-month ahead Gov→Reb).

Similarly, when analyzing the classification of the 205 realized Level 2 months in the test set of rebel organization inflicting 25-99 casualties on the government, we can report that the 1-month ahead models only classify 7% (16/205) of these months as Level 0 months and the 6-month ahead model does so for 14% (29/205). Realized Level 3 months (+100 casualties) are classified as Level 0 months in only 3% (1/31 for the 1-month ahead) and 19% (6/31 for the 6-month ahead model) of the cases. Looking at the 192 Level 2 months, where governments inflict 25-99 casualties on the rebels, in the 1-month ahead model 15% (28/192) are classified as Level 0 months and 22% (43/192) in the 6-month ahead model. The 121 Level 3 months (government inflicting 100+ casualties on the rebels), 4% (5/121) in the 1-month ahead and 7% (9/121) in the 6-month ahead model are predicted as Level 0 months. We can conclude that the model might not always predict the correct
level of severity, but that higher levels of intensity have a lower probability of being classified as a Level 0 month.

The general ability of the prediction models to separate months that experienced a certain level of severity from those that experienced a different level is visualized in Figure 3. For all models, we provide a separation plot at each severity level. Separation plots were initially designed for binary outcomes [53], where realized observations (red bars) and unrealized observations (white
bars) are ranked according to their predicted probability (black line). A perfect separation occurs if any realized observation has a higher probability than any unrealized observation, which would leave all white bars to the left and all red bars to the right of the separation plot. This concept can easily be generalized to a multi-categorical outcome [53], by providing separation plots for each category. For example, Figure 3 a) pertains to the 1-month ahead model predicting government casualties inflicted by the rebels and provides separation plots for Level 0 (bottom), Level 1 (lower middle), Level 2 (upper middle), Level 3 (top). For all models we can observe that Level 0, Level 2, and Level 3 months are fairly well separated and that the greatest challenge comes from Level 1 months (1-24 casualties). Going back to Figure 2, we can see that many realized Level 1 months are classified as Level 0 months, which questions the ability to correctly distinguish low severity months from no severity months in the context of an ongoing civil war.

Conclusion

In this paper, we provide an actor-centric approach to the prediction of civil war severity by focusing on the rebel-government dyad. We distinguish between severity of armed violence the government inflicts on rebel organizations and which the rebel organizations inflict on the government forces. These levels of severity are predicted at the monthly level with 1-month and 6-month ahead random forest models. Using features that relate to the rebel organization characteristics, behavior, and the interdependencies between organization, we are able to perform especially well in separating high levels of battle related deaths from months with no battle-related deaths being recorded. The main challenge that our predictive models face is to distinguish between low and no severity months, but this might not be surprising in the context of an ongoing civil war.

We believe that an actor-centric prediction approach is especially useful in the context of civil war severity, duration, and termination as it focuses on the actual perpetrators of armed violence. However, when predicting the onset of new actors/conflicts or the geographic diffusion of violence, actor-centric approaches need to be integrated and supplemented by geographic approaches.

References


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