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 month 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 in distinguishing high levels of severity from very low levels, and yields better predictions than geography-based prediction models.

1. INTRODUCTION

Civil wars vary greatly in the degree to which they escalate and thereby affect civilians [46], regional stability, and global order [50]. For example, the extent to which conflicts force people to seek refuge abroad is consistently a function of its severity [1, 113] and its geographic scope [81]. We put forward a novel actor-based machine learning approach to predict the severity of conflict one month ahead to enable early warning facilities and contribute to the important and fast growing field of conflict prediction [26, 57].

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, 63]. The majority of forecasting efforts focus on the onset or occurrence of civil war [116, 62]. Severity is much more at the center of approaches focusing on one-sided violence [120, 92, 97, 53, 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. 58, 88, 101, 54, 117, 100, 43, 116, 51, 62, 9, 18, 27, 61, 86, 10, 30, 87].

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) [60]. A geographic unit is often necessary in the 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 82, 49, 44]. The advantage of actor-based predictions is that we can model the behavior of decision-making

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organizations and rely on a broad theoretical literature to inform predictive feature selection and creation [91, 115, 39, 42, 31, 110, 56, 72]. 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 [60].

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 [95] 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 [96, 25] with applications to armed inter- and intrastate conflict [2, 11, 99, 112, 48] and terrorist attacks [34, 33, 90].

The work of Richardson [95] 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 [118]. This linkage between time and severity was further explored by Klingberg [71] 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 [114] 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 [98, 79, 3, 75] enabled a new generation of severity models that focused on the intensity of events and its actors [102, 14, 12, 13]. Concepts of reciprocity [16], conflict-cooperation scales [106], and interdependencies [65] 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 [73] shows that severe civil wars are related to duration [compare 45], 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 [119], and economic inequality [77] with more severe conflicts. However, on the subnational level the link between economic development remains ambiguous. In a subnational study of FARC violence, [66] relate severe violence to departments with poverty, low growth, and state repression. But in Liberia, [64] 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 [78] highlighting that civil wars are most severe when they take place in areas of oil and gas production in the context of secessionist conflicts.

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, 103, 15]. Similarly, studies of repression and dissent [76, 89], 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, resources, or strength have been systematically linked to the occurrence, duration, and severity of conflict [56, 110, 39, 35]. In our predictive framework, we account for actors characteristics, behavior, and interdependence by relying on data from UCDP GED (v.18.1) [109, 38] and PRIO-GRID (v.2.0) [111].¹

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,² the time since the organization has started fighting the government,³ and the extent of transnational fighting events.⁴

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-GRIDS⁵ 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, 83]. 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. 40, 39, 31]. Multi-actor setting also give rise to alliance and fragmentation dynamics [5, 7, 47, 42, 105], which are argued to be associated with longer civil conflict duration [41, 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

¹An alternative data source would be ACLED [93], but compared to UCDP GED, it does not yet allow for a global prediction framework.

²Maximum events per month involving the rebel organization, maximum days per month 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.

³Duration of months a rebel organization is fighting the government.

⁴Number of transnational events, which is measured as events outside of the main country of operation.

⁵PRIO-GRIDS are a standardized grid structure proposed by [111]. 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

temporally lagged before including them into the prediction models. Prediction models include 1-6 month time lags.

ACTOR-BASED PREDICTING OF BATTLE-RELATED DEATHS

We predict battle-deaths 1-month 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.⁶ 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.⁷

We apply random forests to predict the categorical outcome variable. Random forest is a popular ensemble learning method [20] combining bagged trees with a randomized variable selection step to reduce variance. In political science, it has shown improvement over traditional statistical approaches [108, 70, 86, 84]. We use the ranger [121] 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.

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 both 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.

GEOGRAPHY-BASED PREDICTING OF BATTLE-RELATED DEATHS

In order to test whether an actor-based approach is more effective in predicting conflict severity, we conduct an identical geography-based approach. This means that we construct the same indicators, but aggregated to the PRIO-Grid level instead of the actor level. Hence, as opposed to predicting the severity at the actor-level, we train the model to predict severity at the PRIO grid level and include lagged variables for whether actors were present in the grid in previous months.

⁶We also run all analysis for 6-months ahead predictions. The results are presented in the appendix. The findings and conclusions drawn are the same.

⁷UCDP-GED differentiates between low, high, and best estimates for casualties.

TABLE 1. Test set predictive performance indicators for casualties inflicted on the government by rebels (Reb→Gov) and casualties inflicted by the government on the rebels (Gov→Reb) for actor based models.

	Level 0	Level 1	Level 2	Level 3
1-month ahead rebel → government models.				
Sensitivity	0.956	0.534	0.239	0.000
Specificity	0.609	0.928	0.996	1.000
Precision	0.899	0.616	0.653	0.000
Balanced Accuracy	0.783	0.731	0.617	0.500
1-month ahead government → rebel models.				
Sensitivity	0.960	0.435	0.292	0.000
Specificity	0.551	0.937	0.981	1.000
Precision	0.877	0.600	0.329	0.000
Balanced Accuracy	0.756	0.686	0.636	0.500

Again, we apply random forests to predict the categorical outcome variable of conflict intensity: Level 0 (no battle-deaths), Level 1 (1-24 battle deaths), Level 2 (24-99 battle deaths), Level 3 (100+ battle deaths). We separate the data into a training (N=219519, T=1989-2009) and test sample (N=54879, T=2010-2017). As noted previously, there is greater sparsity in the data used in the geographic prediction approach because it includes all PRIO grids, many of which may not be relevant to the conflict actors. Other than the data structure, the modelling procedure is identical to that described above.

TABLE 2. Test set predictive performance indicators for casualties inflicted on the government by rebels (Reb→Gov) and casualties inflicted by the government on the rebels (Gov→Reb) for geography based models on the grid cell level.

	Level 0	Level 1	Level 2	Level 3
1-month ahead rebel → government models.				
Sensitivity	0.986	0.230	0.000	0.000
Specificity	0.244	0.982	1.000	1.000
Precision	0.906	0.604	0.000	
Balanced Accuracy	0.615	0.606	0.500	0.500
1-month ahead government → rebel models.				
Sensitivity	0.986	0.232	0.000	0.000
Specificity	0.246	0.981	1.000	1.000
Precision	0.906	0.605	0.000	
Balanced Accuracy	0.616	0.607	0.500	0.500

Table 2 reports the results for the geographic approach. Similar to the actor-based approach reported in Table 1, both models perform well in identifying Level 0 category. In fact, the geographic approach is better at predicting Level 0, which is likely due to the sparsity of the data. However, the geographic models are less effective in correctly predicting higher levels of severity compared to actor-based models. They are less effective in correctly predicting Level 1 severity (1-24 battle deaths). For example, sensitivity is just 0.230 and 0.232 compared to 0.534 and 0.435 for models predicting casualties inflicted on the government by rebel and vice-versa, respectively. Difficulties in predicting the most severe levels are more pronounced in the geographic models. Looking once more at sensitivity, it decreases to 0 for Level 2 and Level 3 in both models, considerably worse than

FIGURE 2. Confusion matrices for test-sample predictions. The first row (panels *a* and *b*) panels pertain to actor-based models for casualties inflicted on the government by rebels (Reb → Gov) and casualties inflicted by the government on the rebels (Gov → Reb). The second row (panels *c* and *d*) pertains to the geography-based models. Color shading refers to percentage of observed severity level months in the respective predicted categories. Numbers in cells refer to a count of observations that fall into this category. A perfect model would only have entries on the diagonal.

actor-based models which is 0 only in predicting Level 3 severity. Although actor-based models also struggle to predict Level 3 severity, they are more effective in distinguishing between Level 1 and Level 2 as indicated by higher sensitivity, specificity, precision, and balance accuracy. The results presented for both approaches indicate that the geographic approach under-performs in predicting the highest levels of severity, that is any level that surpasses 24 battle deaths (both levels 2 and 3). In the next section, we provide a further comparison between the actor-based and geography-based approaches.

A SYSTEMATIC COMPARISON OF BOTH APPROACHES

Figure 1 provides confusion matrices for the the actor-based (top row) and geography-based (bottom row) models. The figure once more emphasises the general trend for all models that they under-predict higher levels of severity. However, they provide important additional information

on the false positives. Looking at panel *a* for casualties inflicted on the government by rebels, we 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. Just one observation for both actor-based models has a predicted class of Level 3 when the observed class was Level 2. However, we see that the models under-predict severity, as opposed to failing to predict it altogether. For instance, in panel *a* for casualties inflicted on the government by rebels, 58% (18/31) of observed Level 3 are classified as Level 2, 39% (12/31) are classified as Level 1, and just 3% (1/31) are classified as Level 0. This pattern is similar in panel *b* for casualties inflicted on the rebels by the government, although the percentage of Level 3 observed classes classified as Level 2 is higher (78%).⁸

Similarly, when analyzing the classification of the 91 realized Level 3 months in the test set of rebel organization inflicting casualties on the government (panel *c*), we can report that the geography-based models are significantly worse at predicting higher levels of severity. For instance, only 1% (1/91) of Level 3 are classified as Level 2 and 40% (36/91) are classified at Level 1. Worryingly, the majority of realised Level 3 cases, 59% (54/91), are classified as Level 0. The trend is almost identical for the classification of the 91 realized Level 3 months in the test set of government inflicting casualties on the rebel organisations (panel *d*).⁹ This trend is clearly visible by red shading across the different levels of severity. We can conclude that the actor-based models 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 than for the geography-based models. Furthermore, geography-based models are not only less likely to predict higher levels of severity, they are also more prone to miss-classifying higher levels as expecting no observed casualties (Level 0).

The 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 the models in both approaches, we provide a separation plot for each severity level. Separation plots were initially designed for binary outcomes [55], where realized observations (red bars) and unrealized observations (grey 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 grey 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 [55], by providing separation plots for each category. For example, Figure 3 A pertains to actor-based 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 1, 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. Figure 3 shows that the

⁸78% (94/121) of observed Level 3 are classified as Level 2, 19% (23/121) are classified as Level 1 and just 3% (4/121) are classified as Level 0.

⁹1% (1/91) of observed Level 3 are classified as Level 2, 43% (39/91) are classified as Level 1, and 56% (51/91) are classified as Level 0.

FIGURE 3. Separation plots for test-sample predictions. The top row (panels *A* and *B*) pertain to actor-based predictions and the bottom row (panels *C* and *D*) pertain to geography-based predictions. The left column (panels *A* and *C*) are for casualties inflicted on the government by rebels (Reb→Gov) and the right column (Panels *B* and *D*) are the same for casualties inflicted by the government on the rebels (Gov→Reb). 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).

actor-based models are more effective in correctly predicting (i.e. separating) levels of severity, which is particularly visible for prediction of Level 1 severity (1-24 casualties).

Global fatality comparison

An interesting question is how the underprediction of the actor and geographic models translates into fatality estimates, especially because the escalation levels on the actor level are naturally higher than on the grid level. Hence, for each observed and predicted observation on the actor and grid level, we assign fatalities to escalation levels. For each observation and prediction, we draw from the underlying fatality distribution at each level for both the grid and actor level. From 1000 draws, we are then able to sum fatalities at the global monthly level for predicted and observed levels, both for the actor and grid model. Focusing on the difference between observed and predicted values, we compare the actor and geographic models in relation to fatalities inflicted on governments and the rebel organizations. The global fatality comparisons in Figure 4 shows that the actor model (red) underpredicts fatalities, but to a lesser degree than the geographic model (blue). This difference is particularly pronounced in the fatalities inflicted on government forces, shown in the top panel.

(A) Fatalities predicted-observed: Reb→Gov

(B) Fatalities predicted-observed: Reb←Gov

FIGURE 4. Panels compare fatality estimates between predicted and observed values (y-axis) for actor (red) and grid (green) level model over months (x-axis) in the test sample.

CASE ILLUSTRATION

To demonstrate the performance of actor-based models in a more accessible and applied way, we use a case illustration on the actor level. Figure 5 displays predictions from the actor-based models for Al-Qaida and the Forces of Hadi in Yemen over time. The plots show the predicted probabilities for each severity level per time and actor. At each point in time, the model predicts the intensity level that is associated with the highest predicted probability. In the figure, correct predictions that correspond with the actually observed level of violence are marked in green, while incorrect predictions are displayed in red.

Overall, the two examples underline the strengths of actor-based models in separating Level 0 predictions (no violence) from Level 1 predictions (few violent events). This is particularly clear

FIGURE 5. Test-sample severity predictions for two actors in Yemen. a) Al-Qaida in the Arabian Peninsula and b) Forces of Hadi. Green bars represent correct predictions, while red bars pertain to incorrect predictions. Panels pertain to 1-month ahead model for casualties inflicted on the government by rebels (Reb→Gov). 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).

in the case of Al-Qaida on the left side with many correct (green) predictions for Level 0 and 1. The visualization also demonstrates that with increasing intensity it becomes difficult to correctly predict levels of battle-related deaths.

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.

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APPENDIX A. RESULTS FOR 6-MONTH PREDICTIONS

The following sections present the same figures and tables presented in the manuscript for actor and geographical models for 6-month ahead predictions. We do not interpret them in detail because the interpretation is similar to the models for 1-month ahead predictions.

TABLE 3. Test set predictive performance indicators for 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) for actor based models.

	Level 0	Level 1	Level 2	Level 3
6-month ahead rebel → government models.				
Sensitivity	0.960	0.416	0.459	0.000
Specificity	0.505	0.944	0.994	1.000
Precision	0.876	0.615	0.740	
Balanced Accuracy	0.732	0.680	0.726	0.500
6-month ahead government → rebel models.				
Sensitivity	0.960	0.415	0.234	0.000
Specificity	0.514	0.938	0.983	1.000
Precision	0.868	0.593	0.310	
Balanced Accuracy	0.737	0.677	0.609	0.500

TABLE 4. Test set predictive performance indicators for 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) for geography based models on the grid cell level.

	Level 0	Level 1	Level 2	Level 3
6-month ahead rebel → government models.				
Sensitivity	0.984	0.219	0.000	0.000
Specificity	0.226	0.981	1.000	1.000
Precision	0.904	0.586	0.000	
Balanced Accuracy	0.605	0.600	0.500	0.500
6-month ahead government → rebel models.				
Sensitivity	0.984	0.219	0.000	0.000
Specificity	0.226	0.981	1.000	1.000
Precision	0.904	0.586	0.000	
Balanced Accuracy	0.605	0.600	0.500	0.500

FIGURE 6. Confusion matrices for test-sample predictions on a 6 month basis. The first row (panels *a* and *b*) panels pertain to actor-based models for casualties inflicted on the government by rebels (Reb $\rightarrow$ Gov) and casualties inflicted by the government on the rebels (Gov $\rightarrow$ Reb). The second row (panels *c* and *d*) pertains to the geography-based models. Color shading refers to percentage of observed severity level months in the respective predicted categories. Numbers in cells refer to a count of observations that fall into this category. A perfect model would only have entries on the diagonal.

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FIGURE 7. Separation plots for test-sample predictions for 6-month ahead. Panels *A* pertain to actor-based predictions and panels *B* to geography-based predictions for casualties inflicted on the government by rebels (Reb→Gov). Panels *C* and *D* are the same for casualties inflicted by the government on the rebels (Gov→Reb). 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).