Random Forest Predictions with Dyad Features*

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June 27, 2024

Abstract

We introduce a dyad-centric approach to predict the severity of conflict on the grid level. The main aim of this approach is to address heterogeneity in grid-level predictions that stem from particular armed organization dyads present in a grid and their spatial proximity. Thus, we project dyad specific distributional features to the grid level to address dyad related heterogeneity. Using dynamic-time-warping, we leverage hierarchical clustering to infer different types of severity, both spatial and temporal. Our statistical learning approach to predict the severity of conflict relies on Random Forest approaches for continuous outcomes, known to deal well with non-linearities. We train separate Random Forest models for each $t + m$ month period.

Introduction

For the 2023/2024 ViEWS Prediction Competition we propose a prediction model that takes into account both temporal and spatial variation of rebel-government dyad activity during conflict. Accounting for both temporal and spatial conflict characteristics can allow us to more accurately assess conflict areas as a whole, consider different actors, their changing behavior and its impact on conflict severity. Most previous research on rebel characteristics

*This paper documents a contribution to the VIEWS Prediction Challenge 2023/2024. Financial support for the Prediction Challenge was provided by the German Ministry for Foreign Affairs. For more information on the Prediction Challenge please see Hegre et al. (Forthcoming)) and https://viewsforecasting.org/research/prediction-challenge-2023

has focused on features that typically do not change in the short run such as ideology (e.g. Balcells, Chen and Pischedda, 2022; Gade, Hafez and Gabbay, 2019). The specific zones of rebel activity are often taken as fixed and constant attributes during conflict. However, an emerging field of literature has started to theorize and model dependencies between actors and conflict evolution across time and space (e.g. Beardsley, 2011; Beardsley, Gleditsch and Lo, 2015; Braithwaite, 2010; Buhaug and Gleditsch, 2008; Metternich et al., 2013; Salehyan, 2006, 2010).

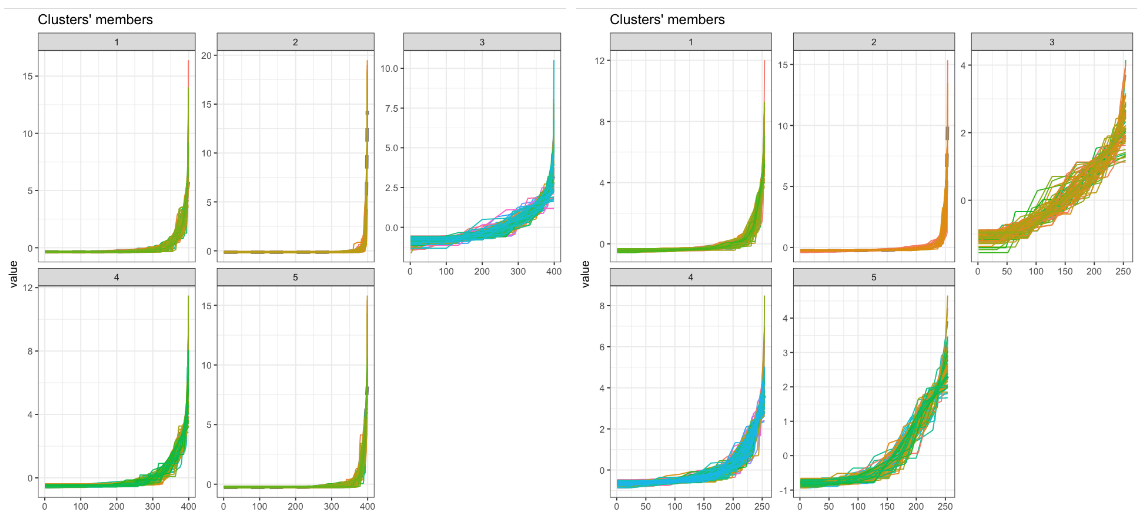
We argue that temporal and spatial dyad features have a considerable impact on conflict severity in monthly battle deaths (Metternich et al., 2019). We model temporal and spatial dependencies through the use of dynamic time warping and hierarchical clustering. This allows us to better categorise different dyads based on their temporal and spatial conflict activity. As a result, we can generate profiles of dyads based on their temporal variation in conflict severity and spatial scope and investigate which dyads engage in similar conflict behaviour at what point in time. By accounting for the different levels of conflict activity over time and space, we aim to trace group behaviours and their impact on conflict dynamics over time. To arrive at our prediction results, we train random forest machine learning prediction models with novel temporal and spatial features that stem from dynamic time warping and hierarchical clustering. We use these features for monthly-grid predictions – in addition to time-constant and lagged features provided by the ViEWS team.

In the remainder of this manuscript we first underscore the importance of temporal and spatial conflict dynamics for conflict severity, surveying the relevant literature and prior research. Subsequently, we provide further details on our operationalization of temporal and spatial dependence and random forest machine learning models that we use to predict monthly fatality numbers on a grid level basis.

Government-Rebel Dyads and Conflict Dynamics

An emerging body of research has started to theorize and model dependencies between actors and conflict evolution across time and space (e.g. Beardsley, 2011; Beardsley, Gleditsch and Lo, 2015; Braithwaite, 2010; Buhaug and Gleditsch, 2008; Metternich et al., 2013; Salehyan, 2006, 2010). In that vein, Beardsley, Gleditsch and Lo (2015) provide evidence for time-varying zones of conflict depending on whether groups are closely connected to local constituencies, receive external support, or militarily stand a chance against the government. Based on the notion of 'Roving' vs 'Stationary Bandits' proposed by Olson (1993), Beardsley, Gleditsch and Lo (2015) argue that different spatial profiles of groups will have an impact on how dyads engage in conflict. Rebel groups, fighting in government-rebel dyads, can be more mobile or less spatially confined because of direct threats posed by government forces or because they receive external support and are less dependent on a local constituency and resource mobilization. In both cases, the outcome on the battlefield can likely be seen in larger and more dispersed areas being affected by conflict, and is also likely to result in higher conflict severity on the ground compared to groups that need to rely on local support. Beardsley, Gleditsch and Lo (2015) do not explicitly consider prediction. However, we expect

Figure 1: Panels show distributions of dyads with clusters. Left panel shows dyads in temporal clusters. Right panel shows dyads in spatial clusters.



(a) Distributions in temporal clusters (b) Distributions in spatial clusters

that taking into account different spatial profiles of groups can tell us more about the groups that are active in a given conflict, and help better predict conflict severity.

We also assume that a similar point applies to taking into account temporal dynamics. Generally, conflict onsets and therefore casualties at points in time are rare events and therefore difficult to predict. However, if we take into account the conflict activity of certain dyads over a longer period of time, including their phases of activity and inactivity alike, we expect our predictive abilities to improve. Again, previous research has found that temporal dynamics of rebel groups engaging in conflict can vary considerably. For instance, Clauset and Gleditsch (2012) have shown how the frequency of terrorist attacks for groups increase with their experience and their group size. These temporal differences in behaviour can have devastating consequencies with regards to the severity of conflict, as more frequent attacks also result in high casualty counts (Clauset and Gleditsch, 2012).

Overall, severity has been a less prominent target than onset in conflict prediction (Ward et al., 2013; Hegre et al., 2013). Many theories of onset do not entail clear implications for differences in the severity of conflict. Conflict severity has received more attention in specific sub-strand of literature, namely those on one-sided violence, mass atrocities (Wood, 2010; Raleigh, 2012; Rost, 2013; Goldsmith et al., 2013; Chaudoin, Peskowitz and Stanton, 2017) as well as terrorism (Clauset, Young and Gleditsch, 2007).

Dynamic Time Warping and Hierarchical Clustering

The limited focus on civil war severity in prediction studies is quite surprising, given the rapid growth in studies with a focus on prediction (e.g. Gurr and Lichbach, 1986; O'brien, 2002;

Schrodt, 2006; Goldstone et al., 2010; Weidmann and Ward, 2010; Schneider, Gleditsch and Carey, 2011; De Mesquita, 2011; Ward et al., 2013; Gleditsch and Ward, 2013; Hegre et al., 2013; Bell et al., 2013; Brandt, Freeman and Schrodt, 2014; Chadefaux, 2014; Hegre et al., 2016; Muchlinski et al., 2016; Blair, Blattman and Hartman, 2017; Chiba and Gleditsch, 2017; Mueller and Rauh, 2018; Blair and Sambanis, 2020). Conflicts come in different sizes, and the costs of a false negative or missed conflict will be larger the more severe the conflict. Many international actors (governments, international organizations, and non-governmental organizations) are operating in areas of ongoing, often low severity, conflicts. The potential benefits of early action to prevent larger conflicts would be easier to establish with greater insights into which conflicts are more likely to escalate.

The level of severity as a cumulative feature also reflects directly changes in conflict dynamics over time. Early contributions to modeling conflict sought to link the duration of conflict with its severity (see Richardson, 1960). In the early 1960s, Weiss (1963) developed Markov process models of the relationships between severity of wars and their duration, and these were further developed by, e.g., Klingberg (1966) and Voevodsky (1969).

More recent research presents evidence indicating that conflicts have become increasingly complex and protracted, reflected in many low severity conflicts that remain active at a low level of severity over many years (Brosché, Nilsson and Sundberg, 2023). However, the events in Ukraine after 2022 powerfully underscore how even relatively low-level conflict clusters that do not figure as prominently in international news media - armed conflict had been ongoing in Ukraine since 2014, following the Russian annexation of Crimea and separatist insurgencies in the East - can see rapid escalation to intense conflict with much higher battle-related deaths. We hope to improve conflict prediction for changes in severity over time by better accounting for temporal and spatial dependencies connected to rebel groups in conflict.

In order to model temporal and spatial dependencies for our conflict prediction model, we rely on dynamic time warping from the DTW package in R (Giorgino, 2009). Dynamic time warping is an algorithm that tries to make different time series comparable over time even if they are of different lengths. This algorithm in essence examines the different 'shapes' of the time series and estimates how similar they are to each other, allowing for a comparison of a large number of time series in a computationally feasible manner. In our context, we are looking at two types of time series: a) number of fatalities connected to a given government-rebel group dyad over time (temporal), b) number of grids (and neighbouring grids) that dyads were active in and their corresponding number of fatalities (spatial). Using dynamic time warping, we can better compare dyads and their temporal and spatial activity during conflict over time.

Using hierarchical clustering after an initial sorting through dynamic time warping allows us to categorise rebel-government dyads into subgroups that show similar conflict activity temporally and spatially. Figure 1 shows clusters that were generated through dynamic time warping and hierarchical clustering. The clustering allows us to both descriptively learn more about similar conflict behaviour for different dyads and include this information into our prediction models as additional features in a computationally manageable manner. While DTW would have allowed us to include all of the time series for each dyad individually, the clustering groups together dyads that engage in similar conflict activity and we can therefore theoretically learn more about different potential conflict profiles as well. We discuss the resulting cluster conflict profiles below.

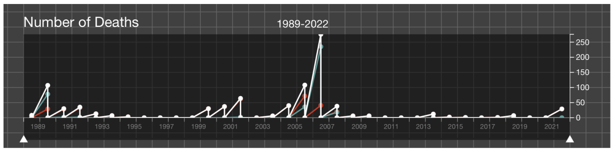
Cluster Assignment to PRIO-Grids

We restrict the clustering algorithm to $k = 5$ to arrive at a computationally manageable number of clusters. We arrive at this number after a first exploration of the data and the resulting clustering output. The results from the hierarchical clustering for both temporal and spatial clusters can be seen in Figure 3. For the prediction, we assign clusters to grids where the respective dyad was active. We furthermore engage in different approaches to cluster assignment. First, we also also assign clusters to the eight neighboring grids, which allows us to account for potential inaccuracies in the geo-coding of conflict activity as well as spillovers and diffusion of conflict that has become an increasingly important part of conflict studies (e.g. Polo (2020)). Second, we assign clusters to PRIO-grids based on historical information, thereby trying to incorporate conflict legacies into our prediction models. Third, we are trying to further tease out the interdependence between different clusters. Generally, if more than one dyad was active in a cluster at a given point in time and these dyads belong to different clusters, we would assign both of these clusters to the PRIO-grid. We can thus further tease out whether the 'multi-cluster-assignment' could mean further escalation or a dampening effect if we see low-level severity clusters active in the same grid as high-level severity clusters.

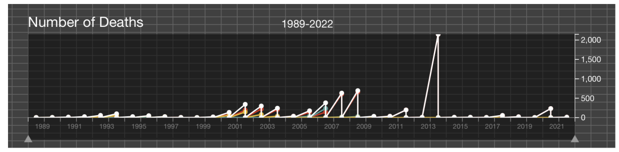
Resulting Clusters and their Descriptives

To get a better sense of the clusters, the different panels in Figure 1 visually show the distributions of conflict severity in temporal and spatial clusters. The clusters plot the different time series and provide evidence for considerable differences in conflict activity over time that we theorized above. The different panels visualize the cluster members and their individual time series in the same way. The x-axis is the 'frequency' axis, which pertains to both time periods (in temporal clusters) and prio-grids (in spatial clusters). The y-axis shows the distribution in standard deviations from the mean of a given dyad and therefore the fighting magnitude of a given cluster and their members, expressed in conflict fatalities. All of the panels feature varying length of the y-axis with some that have their distributions peaking at around 10 SD from the mean, and others going as high up as 20 SD (panel 2 in the temporal clusters). The highest peak denotes the greatest variation in fatalities for dyads in a given cluster. The visual distributions per cluster, i.e. the shape of the curve, also suggest, as expected, that many dyads feature long periods of time without any conflict activity and a fatality count of 0. In addition, the distribution per cluster shows whether the changes in fatalities temporally and spatially are rather linear (e.g. panel 3 in spatial clusters) or more exponential (e.g. panel 2 in temporal clusters). Again, these considerable differences suggest that dyads engage in armed conflict very differently, resulting in different temporal and spatial repercussions. As two illustrative examples, we can look at the dyads

Figure 2: Panels show two time series of conflict actors in the Middle East and the battle-related deaths attributed to their respective dyad with the Israeli government. Source: UCDP-GED website.



(a) Time series battle-related deaths, dyad Fatah and Israeli government



(b) Time series battle-related deaths, dyad Hamas and Israeli government

of the Israeli government and its fighting activity with the Palestinian groups of Fatah and Hamas, respectively. Figure 2 shows their respective time series 1989-2022. Right away, it becomes clear that the fighting activity differs considerably, as battle-related deaths in the Hamas-Israeli government dyad reach 8-times the number of the Fatah-Israeli government dyad. At the same time, Fatah fighting peaked in and around 2006, the Hamas fighting in 2013 (the time series ends before the October 7 attacks perpetrated by Hamas in Israel and the susequently ensuing war in Gaza). DTW estimates these differences and similarities for each of the time series of every dyad in the UCDP Dyadic dataset. For our analysis below, we take all of the UCDP dyads and their conflict profiles into account when training our prediction models with the generated clusters and the resulting temporal and spatial dependencies.

Cluster Profiles

In addition to incorporating the cluster information in our prediction models, we wanted to briefly sketch out each of the clusters, their variation in fighting behaviour and some prominent member dyads. All of the dyad information stems from the UCDP Dyadic Dataset version 23.1. We are thus looking at the type of incompatibilities, the fighting intensity, the type of conflict, the region(s) of conflict, and the years of most of the conflict activity.

Temporal Clusters

Cluster 1: Member dyads from cluster 1 show a rather stark contrast between times of no activity and fighting activity. The fighting magnitude reaches up to 15 standard deviations from the mean. Within this cluster, conflict is fought over territory and the government in a given region to a similar degree. Most of the time periods, as in all other clusters, remains below the war threshold and therefore shows between and 25 and 999 battle-related deaths. In this cluster, most dyads are engaged in intrastate conflict without any foreign involvement, where the dyads always comprise a government and a rebel side that engage in fighting. While the list of members features dyads from around the world, most of the fighting in this cluster is taking place in Asia and Africa, especially in 1992, 1993, 1994, and 2020. While in the first half of the 1990s, conflict was fought around the world, the conflict activity in this cluster concentrates almost exclusively on the African continent in 2020, including insurgencies against the governments of Sudan, Congo, Chad, Rwanda, Ethiopia, and Tanzania.

Cluster 2: Dyads from cluster 2 show an even starker contrast between periods of no fighting and fighting activity, reaching a peak of up to 20 SD from the cluster's mean. Within this cluster, conflict is predominantly fought over the leadership of a country rather than territorial claims. Most of the time periods once again remain below a war threshold with 25-999 battle-related deaths. When looking at the type of conflict, intrastate conflicts once again dominate the picture, but a non-negligible amount of dyads in that cluster is also involved in internationalized intrastate conflict, during which side A (government), side B (government or rebel group), or both receive some external support in the form of money, weapons, or personnel. Research on internationalized conflict in the past has shown that these conflicts tend to last longer and can become more severe in terms of battle-related deaths. Most conflict dyads in this cluster were engaged in conflict on the African continent between between 1990 and 2019. Most prominent governments engaged in fighting in this clusters were those of Chad, Congo, Mali, Somalia, and Sudan with 3/5 also featuring internationalized intrastate conflict.

Cluster 3: Cluster 3 shows the most linear distribution in terms of fighting activity over time. In terms of conflict characteristics and geopgraphical distribution, this cluster is similar to cluster 2. One of the main differences lies in the fact that internationalized intrastate conflict is even more prominent in this cluster, making up around 32% of all conflict dyads in this cluster compared to around 20% in cluster 2. Most of the conflict activity in this cluster is taking place around the end of the Cold War in 1989 and after 2010. Most of the internationalized conflict, as seen in UCDP trends more generally, is taking place after 2000 in this cluster, comprising for instance Islamist challengers against governments in Africa and Asia. The rise of internationalized conflict after 2000 and the more linear distribution of fighting over time in this cluster is likely a testament to increasingly protracted conflicts that often simmer below war thresholds, involve a multitude of actors and seem nigh impossible to resolve (Brosché, Nilsson and Sundberg, 2023). While most of conflict activity took place on the African and Asian continent, as mentioned before, the most prominent government actors in this cluster were the government of Afghanistan and the government of Ukraine after 2014 (both predominantly engaged in internationalized conflict).

Cluster 4: Cluster 4 shows once again a rather linear distribution of conflict fatalities over time, similar to cluster 3. It is the only cluster that primarily includes a majority of dyads that fight over territorial claims. In relative terms, as a share of dyad activity in a given cluster, it contains the largest share of conflict that surpasses the war threshold of more than 1,000 battle-related deaths in around 35% of all dyads in the cluster. The type of conflict is predominantly intrastate and conflict activity is equally prominent in Asia and Africa, with a non-negligible amount of fighting in Europe as well. Most of the fighting in this cluster took place in the late 1990s. When inspecting the conflicts in Europe (as coded by UCDP), these comprise Azerbaijan against the Republic of Artsakh, the government of Georgia against the Republic of Abkhazia and South Ossetia, as well as the government of United Kingdom against the IRA in Northern Ireland – all of these predominantly territorial conflicts. The conflicts reaching the highest threshold of fatalities, however, are predominantly on the African continent, comprising intrastate and interstate conflict in Eritrea, Ethiopia, Congo, and Rwanda.

Cluster 5: The last temporal cluster is an untypical one, as it contains only one government-rebel dyad, namely the Government of Yemen against the General People's Congress in Yemen. They have engaged in a fight over the leadership of the state, starting in 2017. While the decision to arrive at k=5 clusters was driven by preliminary exploration, the single-dyad cluster 5 still deserves further inspection with regards to its incompatibility with other clusters.

Spatial Clusters

Spatial clusters contain government-rebel dyads and model their fighting behaviour with regards to spatiality. This is to say, each dyad's activity is looked at with regards to the number of PRIO-grids they were active in during a given time period and the casualties in each PRIO-grid connected to a given dyad. We have constructed five spatial clusters. To make sense of the spatial clusters' profiles, we are once again looking at the conflict incompatibility, the type of conflict, its level of intensity, the region and time periods.

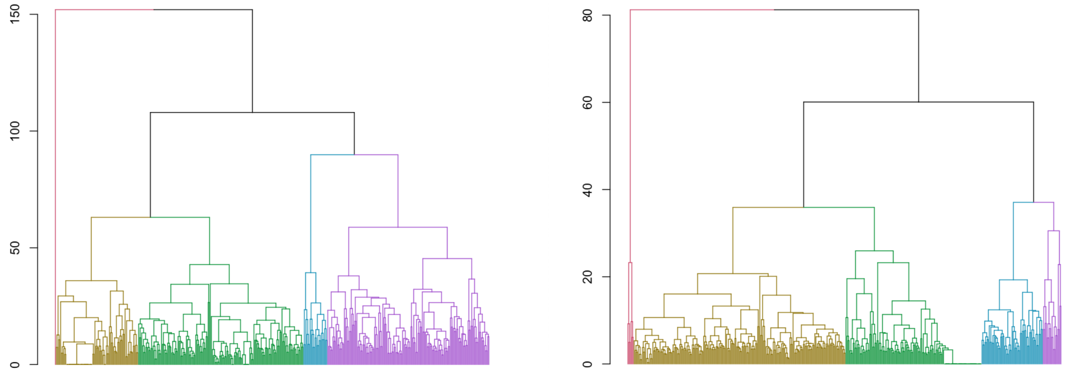
Cluster 1: The first spatial cluster and its constituent dyads were active in conflicts fought over territory and the government to roughly the same extent. Most of the conflicts were pure intrastate conflicts, with roughly 1/5 of all dyad conflicts that had an international component through support for the government, rebel group, or both. The spatiality in terms of geographical spread is rather broad, with most conflicts on the African and Asian continent, as well as in the Middle East and Europe. Most of the conflicts in this cluster took place during the first half of the 1990s and after 2010. The governments involved in most dyads in this cluster are those of DR Congo (Zaire), India, Myanmar, Pakistan and Iraq. After 2010, Islamist insurgencies lead by the so-called Islamic State (IS) and Al-Shabaab, both on the African continent are most frequently occuring in this cluster. Organizations such as IS have shown that they can engage in conflict in different countries simultaneously with a considerable geographical scope. Despite the large geographical spread, most of the conflicts in this cluster remained below the threshold of 1,000 battle-related deaths. Overall, there is a rather stark variation between no-conflict-activity and the highest peak of battle-related deaths around 12 SD away from the mean.

Cluster 2: Cluster 2 is even more exponential and the peak of the conflict activity in battle-related deaths reaches up to 15 SD from the mean of dyads within the cluster. Importantly to note, cluster 2 only contains 18 dyads, with a considerable amount of conflicts that surpasses 1,000 battle-related deaths per calendar year (around 28%). While most conflicts remain intrastate, the cluster also features some internationalized, as well as some inter-state conflicts. The geographical spread is rather similar to the first spatial cluster above, with the difference that the Americas are featured prominently in this cluster as well, namely the insurgencies led by Sendero Luminoso and the FARC in Peru and Colombia respectively. This cluster also incorporates the multi-national invasion of Iraq, led by the United States,

in 2003. Internationalized conflict is especially taking place in Africa and the Middle East. Taking into account the small number of dyads overall, the most frequent occurrence in a dyad is the government of Afghanistan, comprising both conflicts just after 1990 and in 2019. Generally, most of the conflict activity in this cluster took place around 1990 and after 2010.
Cluster 3: The conflict activity in the third cluster is distributed more linearly. This spatial cluster comprises 131 dyads and is the second-largest cluster among the spatial clusters, the largest being cluster 1 with 203 government-rebel dyads. Conflict just prior to and just after 1990 is the most frequent in this cluster, another time period of focus being the 2010s. While the geographical spread is once again broad, most of the dyads in spatial cluster 3 were active on the African continent. This is the case for around 55% of all conflicts in this cluster. The dominant type of conflict is intrastate and conflict is predominantly fought over government leadership, rather than territory (around 64% of all observations). Among the most prominent dyad members are governments on the African continent, namely those of Burundi, DR Congo (Zaire), as well as the government of Chad. In fact, the government of Chad is party to 12 different dyads in that cluster, dominating this cluster's activity more than any other government in any of the other spatial and temporal clusters. Most of the conflict activity involving the government of Chad took place in the late-1980s and the early-1990s. The peak of conflict activity is lower than in other clusters with up to four SD from the mean. [1]
Cluster 4: The fourth spatial cluster features quite an equal distribution of incompatibilities and its conflict activity is once again distributed rather linearly, albeit less than cluster 3. While the majority of conflict is still about political leadership, territorial disputes make up around 42% of all conflict activity in this cluster. The type of conflict is once again predominantly intrastate, even though around 27% of all of the conflicts internationalize through external support for the government, rebel organizations, or both. Importantly, in this cluster, in line with previous research, the higher frequency of internationalized intrastate conflict goes hand in hand with a higher occurrence of conflict that exceeds 1,000 battle-related deaths in a calendar year. 60% of all the internationalized intrastate conflicts surpass the 1,000-threshold. Overall, the highest peak of casualties reaches up to 8 SD from the mean of the dyads in the cluster. In total, around 1/5 of all conflicts in this cluster result in more than 1,000 battle-related deaths per calendar year. The geographical distribution of conflict activity in this cluster is rather broad and conflict has taken place throughout the entire period of observation, especially in the early 2010s. Most prominent dyad members in this cluster are the governments of Myanmar (Burma), the government of Afghanistan, and the government of Algeria, once again representing the geographical spread of conflict activity in the cluster.
Cluster 5: The last cluster, similarly to the temporal cluster 5, only contains 6 dyads and its distribution is similarly linear as the one in cluster 3. The descriptives for this type of cluster are thus less comparable to the other clusters. All but one of the dyads were active

[1] This counts for clusters with more than 50 members. The government of Chad in spatial cluster 3 accounts for around 9% of all dyads in that cluster. The next highest are the government of India and Myanmar in cluster 1 of the temporal cluters, amounting to around 8% of all dyads.

Figure 3: Hierarchical clustering based on DTW distances. Left panel shows clustering for the temporal distributions. Right panel shows clustering for the spatial distributions



(a) Hierarchical clustering across time (b) Hierarchical clustering across space

on the African continent, equally around the end of the Cold War in 1990 and between 2012 and 2015. The main incompatibility was once again the fight for political leadership and all but one of the conflicts (namely the dyad with the government of Central African Republic and the Popular Front for the Rebirth of Central African Republic (FPRC)) remained on a purely intrastate level. The highest peak of conflict activity, once again similarly to cluster 3, reaches four SD from the mean.

Prediction Model: Random Forest Approach in hcd_dyad

We present a prediction framework of severity that accounts for conflict dynamics connected to rebel-government dyads and their temporal and spatial conflict activity on the grid level. As alluded to in the theoretical section above, the group activity in the clusters is closely connected to actor characteristics and how conflicts are fought. Actor characteristics such as group capacity, resources or strength have been systematically linked to the occurrence, duration, and severity of conflict (Clayton, 2013; Cunningham, Gleditsch and Salehyan, 2009; Greig, 2015; Thomas, 2014). In our predictive framework, we account for the complexity of conflict dynamics by including our temporal and spatial clusters that we generated through dynamic time warping and hierarchical clustering. We use data from UCDP GED (v.23.1) (Sundberg and Melander, 2013; Croicu and Sundberg, 2017) to generate the clusters and incorporate them into our prediction models. Drawing on UCDP GED (v.23.1) and combining it with the data provided by the ViEWS team, we predict battle-related deaths on a monthly level on a grid-level basis for the years 2018, 2019, 2020, 2021, 2022, and 2024. In training our models, we noticed sensitivity to a few very large outliers in the training periods. To address this, the outcome variable in the training sets is restricted to 1000 battle-related deaths.

For our prediction models, we apply random forests. Random forests are a popular ensemble learning method (Breiman, 2001) combining bagged trees with a randomized variable selection step to reduce variance. In political science, it has shown improvement over traditional statistical approaches (Siroky et al., 2009; Jones and Linder, 2015; Muchlinski et al., 2016; Montgomery and Olivella, 2018). We use the ranger implementation in R statistical language for its computational efficiency (Wright and Ziegler, 2017). Random model classifiers have shown to be especially powerful for predicting non-linear distributions, which suits the prediction task at hand.

There are three particular aspects that we include in our model. First, we train models for each $t+m$ period that we predict. Thus, we generate 12 separate Random Forest models for the prediction challenge. The aim is to allow for heterogeneous dynamics for different future periods (t+m) and address some known weaknesses of Random Forest models to address time dynamics. Second, we confirmed existing insights of conflict prediction, that temporally aggregated models are more accurate than disaggregated ones. Thus, we initially train a Random Forest for the whole out-of-sample period (12 months) and use its predictions as a 'reference point' feature in the disaggregated monthly predictions. Third, in the training set we truncate extreme values at 1000 to gain improved prediction performance.

Using 26 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=5,10) and tree splitting rule (variance) while holding the minimum node size constant at 5. The training of the random forest is done by 10-fold cross-validation. Model performance is assessed using the test sample. We train our models on five year periods (60 months) before the test sample period. We compute standard errors using the infinitesimal jackknife approach (Wager, Hastie and Efron, 2014) and sample outcome distributions from the point predictions and the respective standard errors in each grid drawing from a truncated (min=0) random normal distribution.

Conclusion

To predict monthly battle-related deaths on a grid level, this manuscript has argued that we need to take into account both temporal and spatial dependencies that are connected to actors fighting in a conflict. Theoretically, existing work has shown that conflict actors show very different fighting patterns over time and space – with direct implications for severity levels. Following this theoretical foundation, we empirically model the temporal and spatial dependencies by generating clusters of groups who are similar in their fighting patterns through dynamic time warping and hierarchical clustering. We utilize these clusters to train random forest prediction models – in addition to the features provided by the ViEWS team. In the end, only when modelling for the temporal and spatial dependencies of conflict can we assess conflict theaters as a whole, improving existing and advancing future approaches to conflict resolution.

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