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A Tacticians Guide to Conflict, Vol. 1: Advancing Explanations & Predictions of Intrastate Conflict

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A Tacticians Guide to Conflict, Vol. 1:

Advancing Explanations & Predictions of Intrastate Conflict

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Approval of the Dissertation Committee

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Abstract

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By

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Intrastate conflict is an ever-evolving problem – causes, explanation, and predictions are increasingly murky as traditional methods of analysis focus on structural issues as precursors of conflict. Often times these theories do not consider the underlying meso and micro dynamics that can provide vital insights into the phenomena. Tactical decision-makers are left using models that rely on highly aggregated, country level data to create proper courses of actions (COAs) to address or predict conflict. The shortcoming is that conflicts morph quite rapidly and structural variables can struggle capture such dynamic changes. To address this some tacticians are using big data and advances in machine learning techniques to provide highly accuracy predictions of conflict, however these models lack explanatory power. Decision makers need a solution that can provide accurate explanations and predictions at higher frequencies and geographic granularity – essentially theory informed machine learning models. To achieve this, relational data, constructed from event data and social network analysis (SNA) is used to provide more granular and higher frequency data. Using this data and SNA, structural factors of power, parity, and satisfaction specified in Benson & Kugler (1998) and Lemke (2008) are recreated. Initial testing provides evidence that new measures capture results found in theory. Next the theoretical model was expanded using a complex adaptive systems framework to incorporate meso and micro levels of analysis. Outcomes suggest that examination conflict from all three levels of analysis provides higher explanatory power when compared to just a structural approach. Taking

insights gleaned from statistical analysis, both the theory and CAS models were used in creating a classification and regression tree as well as random forest model for prediction. Results suggest that a CAS random forest model provides highly accurate temporally frequent, geographically specific predictions of conflict. Further the parsimonious nature of the model and structure of data means that tactical decision makers can make month-to-month predictions of conflict and explain why onset occurred. Further, by leveraging data heterogeneity, predictions can be made province-by-province, extracting different drivers of onset unique to each region. Tactical decision makers can create more nuanced and specific COAs better tailored to specific areas, rather then general policy. This research provides evidence that an extended approach using social network analysis and complex adaptive systems framework can provide a more detailed explanation of conflict as well and provide highly accurate, geographically specific, month-to-month predictions. The goal is to develop a theory informed, enhanced, replicable and area agnostic framework for producing higher accuracy conflict forecasts, explanations of conflict as well as more granular temporal and geographic stability predictions – aiding the move from strategic to tactical decision making.

Dedication

This is but a humble recognition and dedication to the people who helped me achieve this.

To my loving parents Mohammad and Hanin, from the bottom of heart, thank you for providing endless support, encouragement and guidance during this journey – would not be possible without you. To my siblings Noor and Firas, thank you for having my back and providing a source of inspiration – the carajitos have come far. To my grandparents Faleh and Zahera, thank you for showing me dreams sometimes require sacrifice. To my uncles Husam, Hassan and family, Rasha, Zuzu and Fufu, and Tareq, thank you for the reassurance in my efforts.

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01

Introduction

"Strategy without Tactics is the slowest route to victory. Tactics without Strategy is the noise before defeat. " – Sun Tzu

A symbiotic relation exists between strategy and tactics, where by planning and execution mesh in the pursuit of an end goal. As we accelerate into an every changing future, fissures between strategy and tactics begin to emerge, disrupting the relation. Strategies prescribed under a set of circumstances quickly become inappropriate as conditions change under exogenous shocks. Onus then falls on the tacticians who then need to consistently modify processes to meet new targets. However without a sound strategy, tacticians would consistently respond rather than prepare.

An example of this disconnect between strategy and tactics is optimized in the 'Arab Spring'. There were obvious signs that trouble was brewing in many Arab nations. Many theories relying on structural indicators such as youth budge, high unemployment and repressive governments were suggesting instability on the horizon. Researchers provide lengthy windows as to when any disruption and mass uprising would occur. On Friday, December 17, 2011 Bouazizi a Tunisian fruit seller performed self-immolation after being confronted with increasing desperation over lack of prospects and repression.[1] This acted as the catalyst

[1] Fisher, Marc. "In Tunisia, Act of One Fruit Vendor Sparks Wave of Revolution through Arab World." The Washington Post, WP Company, 26 Mar. 2011, https://www.washingtonpost.com/world/in-tunisia-act-of-one-fruit-vendor-sparks-wave-of-revolution-through-arab-world/2011/03/16/AFjfsueB_story.html.

that sparked the Tunisian revolution and to a larger extent the Arab Spring.[2] Structural theories were not wrong, they just did not provide an actionable window in order for proper tactics to be introduced that might have been able to anticipate and address crisis sooner.

One of the main issues is not being able to perform short-term predictions as many of these models rely on structural data collected on a yearly basis and national level. This makes short-term predictions and tactical planning exceedingly difficult. The macro indicators also ignore the importance of underlying social structures and network regimes. Part of the reason why the Arab Spring spread so quickly was proliferation of information leading to sharp rises in dissent, something yearly indicators cannot pick up. However, one cannot simply look at the underlying network and make predictions without understanding the macro conditions in which they occur. Hence the value of theoretical models in explaining conflict. In order to rectify, a solution needs to merge macro, meso and micro level of analysis.

The answer lies in 'big data' and advanced machine learning algorithms. Primarily the use of event data, network analysis and machine learning. With the advent of highly sophisticated natural language processing, data mining, parsing and aggregation as well as increased sampling frequency, vast amount of event data can be collected on a global scale and used to gain insights on a highly granular level such as with the GDELT database (explained further in following sections). Critically, data collected can be constructed and analyzed through social network analysis rendering information on macro level conditions, meso level networks and micro agent attributes. Providing much more nuanced operational awareness

[2] "Mohamed Bouazizi." Wikipedia, Wikimedia Foundation, 8 July 2019, https://en.wikipedia.org/wiki/Mohamed_Bouazizi.

and the ability to keep up with ever-changing conditions. Theoretical models can leverage this more granular data and using machine-learning algorithms, provide highly accurate short-term predictions. Further these theoretical models can be extended to incorporate different levels of analysis for added fidelity.

The disconnect between strategy and tactics can be remedied by leveraging critical insights gleaned in theoretical research and combining them with more sophisticated data capture techniques, modeling and specification. This dissertation seeks to add to, as well find new evidence, of the prescribed solution – allowing strategic vision to inform tactical competence.

This dissertation seeks to replicate, extend and improve upon prevailing theories and methods in conflict studies particularly in the fields of intrastate and insurgent conflict. The study will explore the potential viability of social network analysis metrics in capturing critical measurements utilized in conflict studies theory derived from event and relational data. Existing theoretical models will then be extended using a complex adaptive system (CAS) framework – testing linkages between macro, meso and micro levels of analysis to elucidate added insights in the explanation of intrastate and insurgent conflict. Both will be tested and compared using a pooled linear model to assess ability to explain conflict. Further, both the theoretical model and CAS model specifications will compete using machine-learning techniques, classification and regression trees and random forest mehtods, to examine prediction capacity and ability to inform tactical decision making. The goal is to develop a theory informed, enhanced, replicable and area agnostic framework for producing more nuanced explanations of conflict as well as more temporally granular and geographic specific predictions – aiding the move from strategic to tactical decision making.

Over the last few decades, intrastate and insurgent conflict has been on the rise with the Middle East being hit particularly hard by this affliction, figure 1 below (Dupuy, Kendra, et al., 2017).[3] Civil wars and insurgencies have unfortunately become the norm, having engulfed Syria, Iraq and Yemen with more conflicts looming in the not to distant future. While these conflicts may have distinct precursors signaling their imminent arrival, many scholars, academics and intelligence agencies were left surprised at the speed and intensity of escalation, the spread of conflict and the longevity in fighting.

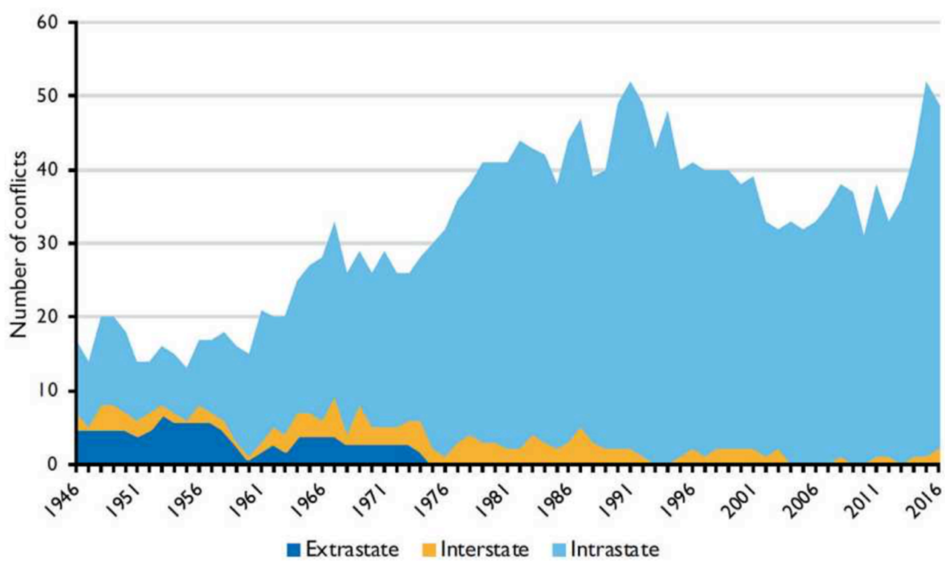

Figure 1: Number of Armed Conflicts by Type of Conflict 1946-2016, Source UCDP, CSS

Many structural models rightfully forecasted potential instability in a number of these countries – pointing at demographic pressures, power transitions, economic and political restraints and social upheavals. However, while generally accurate in those predictions,

[3] Dupuy, Kendra, et al. "Trends in Armed Conflict, 1946-2016." Center for Security Studies, 22 June 2017, www.css.ethz.ch/en/services/digital-library/articles/article.html/a7992888-34fc-44e6-8176-2fcb3aada995/pdf.

purely structural efforts lacked temporal granularity and geographic precision to aid in tactical decision-making – partly an artifact of the econometric methods and data employed in these models. Structural models are exceedingly useful in discerning longer-term trends and identifying necessary conditions of conflict, but when it comes to tactical decision-making, they are lacking. Here in lies the problem and the potential value add of this research.

The motivation behind utilizing a complex adaptive systems framework lies in addressing issues mentioned above and the desire to explain the phenomena of interest through different levels of analysis – adding greater understanding of each component and how they impact outcomes. As crises increase in complexity, straightforward structural explanations may miss key information that can aid in identifying onset in the future. Political instability, intrastate conflict, and civil wars are no different. These phenomena have structural precursors, however onset could potentially be explained by non-structural factors like interactions between different entities as well as individual agency.

Abdollahian et. al. highlight the importance of this approach in their work formalizing/agentizing human development dynamics. This came from Inglehart and Welzel's Human Development work, which took a structural approach to analyzing the change in cultural preferences and political attitudes brought on economic development. Critically, they explore the impacts of human agency and how changes in macro environments, conditions this human behavior further impacting the macro environment. Abdollahian et al. addresses this stating, *interactive political-cultural effects of macro-socio dynamics and individual agency in intra-societal transactions are key elements of a complex adaptive systems approach* – aiding in the explanation and prediction changes in agent strategies, *cultural* predispositions and revolutionary political behavior (Abdollahian et al., 2012, 2013; Inglehart 1997; Inglehart and Baker 2000; Welzel et al. 2003; Inglehart and Welzel 2005).[4 5 6 7 8 9] By taking this approach Abdollahian et al. show how human agency impacts structural changes and vice versa – highlighting nuanced insights into the influence initial conditions, agent behavior, macro incentives/ constraints and CAS approach aid in understanding Human Development.

Lempert highlights the added benefits that a CAS approach can have when examining typically structural phenomena such as climate change. Arguing most research tends analyze structural factors such as *economic activities, and in particular, the burning of fossil fuels,* concluding technological innovation will remedy it while neglecting to examine how this technological innovation is to come about. Many argue *technology incentive programs, such as tax credits [or] subsidies for low-emitting technologies* could encourage innovation, however results are mixed. Lempert asks *what should policy-makers do in the near-term to encourage such innovation?* To answer this, Lempert states a CAS approach could aid in deciding composition of policies – examining *the social and economic factors that influence how economic actors choose to adopt, or not to adopt, technologies.* Concluding this *representation is particularly useful because it conveniently represents key factors influencing technology diffusion and, thus, policy choices* as decision makers can see what

[4] Abdollahian M, Coan T, Oh H, Yesilda B: Dynamics of cultural change: the human development perspective. International Studies Quarterly 2012, 56(4): 1-17.

[5] Abdollahian et al. Complex Adaptive Systems Modeling 2013, 1:18 http://www.casmodeling.com/content/1/1/18

[6] Inglehart, Ronald. (1997) Modernization and Post modernization: Cultural, Economic and Political Change in 43 Societies. Princeton, NJ: Princeton University Press.

[7] Inglehart, Ronald, and Wayne E. Baker. (2000) Modernization, Cultural Change, and the Persistence of Traditional Values. American Sociological Review 65: 19–51.

[8] Welzel, Christian, Ronald Inglehart, and Hans-Dieter Klingemann. (2003) The Theory of Human Development: A Cross- Cultural Development. European Journal of Political Science 42: 341–380.

[9] Inglehart, Ronald, and Christian Welzel. (2005) Modernization, Cultural Change, and Democracy: The Human Development Sequence. New York: Cambridge University Press.

policies positively and negatively impact actor's adoption of pursuing innovated practices (Lempert, 2002).[10]

The use of a CAS framework clearly provides value, demonstrated by the works above. This is mainly achieved because *the whole emerges from the interaction of components and is more than the sum of its parts* (Root 2015).[11] Thus its application in extending intrastate conflict will hopefully provide the same. With the development of the framework mentioned above, can advances in data capture and modeling, utilization of CAS framework and network analysis aid in improving the forecast and explanation of intrastate conflict?

Background of Research Problem

The problems this research attempts to address are the lack of granular and frequent data collection, use of only macro indicators and the inability to forecast short-term crisis. These issues will be remedied by the utilizing event data sources, network analysis for metric operationalization and machine learning methods for added prediction quality on a short-term basis.

One of the biggest issues that arise in the pursuit of the aforementioned goal is the serve break between explanatory models and prediction models in conflict studies literature. On one side are the theory driven, structural and explanatory econometric models focusing on assessing the causal relation between a select set of independent variables, based on specified theory, as the relate to onset of intrastate. On the other hand, are machine learning methods, leveraging big data and advanced deep learning techniques, for the purposes of prediction.

[10] Lempert, Robert J. "A New Decision Sciences for Complex Systems." *RAND Corporation*, 1 Jan. 2002, www.rand.org/content/rand/pubs/external_publications/EP20020514.

[11] Root, Hilton & D Wright, James. (2015). The State as a Complex Adaptive System. Root, Hilton & D Wright, James. (2015). The State as a Complex Adaptive System.

Some of these explanatory models focus on social, economic, ethnic/ religious or political transitions or injustices as drivers of conflict, while others focus on demographic conditions, government capacity or power ratios between governments and competing groups to assess the onset of civil conflict.[12] [13] [14] [15] [16] [17] [18] [19] [20] While these models offer critical insights into explanations of civil war, their primary variables are all structural in nature and are collected on a yearly basis at the national level which makes temporally granular and geographic specific predictions exceedingly difficult. This impacts policy as it becomes difficult to pinpoint potential hotspots at a subnational level and optimize tactical responses to crisis quickly.

Machine learning models conversely do a tremendous job at parsing through and identifying patterns in large sets of data. These methods and data employed lend themselves to more granular approaches and predictions both temporally and geographically. Machine learning methods can provide researchers with good predictions but do little in the way of

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[12] Collier, Paul and Anke Hoeffler (2004). "Greed and Grievance in Civil War." Oxford Economic Papers 56(4):563-595.

[13] James Fearon and David Laitin (2003) "Ethnicity, Insurgency and Civil War", *American Political Science Review*. 97, 1, February 2003, pp. 75-90.

[14] Cederman, Lars-Erik; Nils B. Weidmann, & Kristian Skrede Gleditsch (2011) . "Horizontal Inequalities and Ethno-nationalist Civil War: A Global Comparison", *American Political Science Review* 105(2).

[15] Benson, Michelle, and Jacek Kugler. "Power Parity, Democracy, and the Severity of Internal Violence." Journal of Conflict Resolution, vol. 42, no. 2, Apr. 1998, pp. 196–209, doi:10.1177/0022002798042002004.

[16] Ted Robert Gurr (1970). *Why Men Rebel*, Princeton: Princeton University Press.

[17] Cunningham, David and Douglas Lemke. (2009). "Distinctions Without Differences: Comparing Civil and Interstate Wars." Paper Presented at APSA Annual Meeting, Toronto, Canada.

[18] Will H. Moore and Ahmer Tarar Domestic–International Conflict Linkages in McLaughlin Michell (2012) 171-188

[19] Lemke, Douglas. "Power Politics and Wars without States." American Journal of Political Science, 2008.

[20] Håvard Hegre, et al. "Toward a Democratic Civil Peace? Democracy, Political Change, and Civil War, 1816-1992." *The American Political Science Review*, vol. 95, no. 1, 2001, pp. 33–48. *JSTOR*, www.jstor.org/stable/3117627.

explanation of phenomena at hand.[21] [22] The criticism levied against pure machine learning techniques is precisely that, good prediction, murky explanation.

The problem then becomes rather obvious, one approach provides a framework for explanation, and the other provides a framework for tactical prediction. Is there a way to use proven conflict theory (namely Benson & Kugler 1998; Lemke 2008) and combine it with machine learning methods that leverages big data in order to get temporally granular, geographic specific predictions and explanations of intrastate conflict, providing insights on decision makers can use to aid in tactical decision making?

Purpose of Study

(1) Leverage high frequency and geographically specific event data through network analysis to find measures that are representative of variables found in various conflict studies literature but are captured more frequently and at a more granular geographic level

(2) Extend theoretical models using Complex Adaptive Systems framework

(3) Bridge the gap between theory informed econometric models and machine learning methods

(4) Move from structural longer-term forecasts, to shorter-term tactical predictions, with explanatory power, focused on temporally frequent and geographically specific forecasts

[21] Hammond, J., & Weidmann, N. B. (2014). Using machine-coded event data for the micro-level study of political violence. Research & Politics, 1(2), 2053168014539924. doi:10.1177/2053168014539924
[22] Mahoney, S. M., Comstock, E., deBlois, B., & Darcy, S. (2011, May 18, 2011 – May 20, 2011). Aggregating Forecasts Using a Learned Bayesian Network. Paper presented at the Twenty-Fourth International FLAIRS Conference, Palm Beach, Florida, USA.

Research Questions

The central research question focuses on examining and recreating the relationship that exists between; power ratios of government and insurgent/ opposition groups, status quo satisfaction, capacity of governments and the onset of intrastate conflict through event data and social network analysis metrics. It is further meant to examine the how the application of a CAS framework on conflict studies can further aid in conflict explanation. Figure 2 below is a visual representation of the theoretical model and CAS extension. Factors in white are from the original theory, factors in grey are extension variables and the red lines indicate that intrastate conflict impact micro attributes and meso level events thus lags of these variables will also be analyzed.

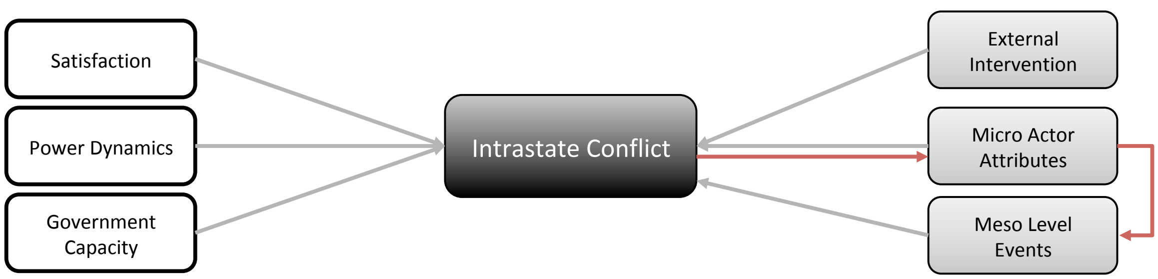

Figure 2: Visualization of Framework

The research will first test viability of new event and SNA metrics in explaining intrastate conflict using a pooled linear model. Once Benson & Kugler 1998 model is replicated, features will be examined to confirm results match theory and confirm that new measures are viable for capturing theoretical features.

This theoretical model will then be extended utilizing a complex adaptive systems framework – analyzing how meso and micro conditions impact macro conditions and the onset of violence. This will be achieved by tracking event level data such as statements, demonstrations, and demands for leadership change as well as micro level actor attributes.

This data, in addition to structural factors, will allow the extended model to track how interactions between different entities can better contextualize and provide deeper insights into how conflicts manifest. This will hopefully give more accurate predictions along with the ability of added explanation – greatly aiding tactical decision-making.

Both the theoretical and CAS model specifications will then be tested using two machine-learning methods; classification and regression trees and random forests. This will be done to determine which method and specification produce more accurate and granular predictions.

Overview of Methodology

The study will focus on the ongoing religious and ethnic civil conflict in Syria. The initial crisis began in early 2011 when protestors demanding release of political prisoners were killed sparking mass rebellion. The Syrian government responded by sending in tanks into the city of Daraa to quash the protestors. The violent methods used by the government caused more mass demonstrations eventually leading to direct confrontation between opposition and government forces manifesting into a civil conflict on going today.[23]

Data on this crisis will be drawn from public sources like GDELT who use an automated event, network and sentiment-coding algorithm to parse through news, media and articles extracting information on actors and events. Exploratory data analysis, econometric and machine learning techniques will be used to analyze the relationship between the explanatory variables mentioned above and the onset of intrastate conflict.

[23] "Syria Profile - Timeline." *BBC News*, BBC, 14 Jan. 2019, www.bbc.com/news/world-middle-east-14703995.

Significance of Study

The purpose of this work is to move from purely strategic to tactical decision-making by providing more accurate, temporally granular and geographically specific predictions and explanations of conflict. This will be achieved by accurately operationalizing necessary structural metrics from event and relational data through SNA. Confirming the causal relations between factors mentioned above and expanding upon them by using a CAS approach. Then use theory in combination with machine learning techniques and advances in data collection to boost prediction accuracy, precision and recall of conflict forecasting. This process will hopefully find replicable measurements of power and satisfaction, elucidate additional insightful meso and micro factors and aid decision-makers in optimizing tactical decision-making.

Definition of Terms

The focus of this paper is intrastate conflict and will defined as *open conflictual dissent over policy choices* (Benson & Kugler 1998) and must fall under the following criteria stemming from Correlates of War and Doyle & Sambanis 2000:

(1) Involved fighting between agents of a state and organized, non-state groups who sought either to take control of a government, to take power in a region, or to use violence to change government policies.

(2) Conflict has killed at least 1000 over its course with a yearly average of at least 100.

(3) At least 100 were killed on both sides.

As mentioned earlier, this type of conflict recently has become more rampant in the Middle East. The main belligerents are government forces pitted against some organized or semiorganized opposition who have relatively equal capacity, at least from a social structure and network perspective. The definition above applies to the case study, Syria, as conflict has reached extreme levels of severity and the ratio between dissatisfied parties, government and opposition forces, is at parity (Benson & Kugler, 1998; Lemke, 2008).

Syrian Conflict Overview

For added enrichment it is important to understand the conflict studied here from a narrative perspective. Initial tensions in Syria were on the rise due to pressures from structural factors such as; high employment, corruption and lack of political freedom under the Assad Regime.[24] The problems persisted after the transition of power to Bashar al-Assad. Largely emboldened by the Arab Spring demonstration occurring in different part of the Middle East, Syrians in the province of Daraa took to the streets demanding change. The Assad regime was not looking to compromise and attempted to quash dissent through threatening, coercive and ultimately violent actions.[25] This abuse of power triggered mass demonstrations throughout the country and eventually protesters and rebels began to arm themselves to defend against government violence.[26]

From this point, all out conflict began as armed opposition groups sought to remove the regime from power and end violence against them. Below is a plot from ACLED database showing protests, battles, violence against civilians, and riots among other key events. As seen the violence is widespread and exceedingly intense.

[24] "Why Is There a War in Syria?" BBC News, BBC, 25 Feb. 2019, https://www.bbc.com/news/world-middle-east-35806229.
[25] IBID
[26] IBID

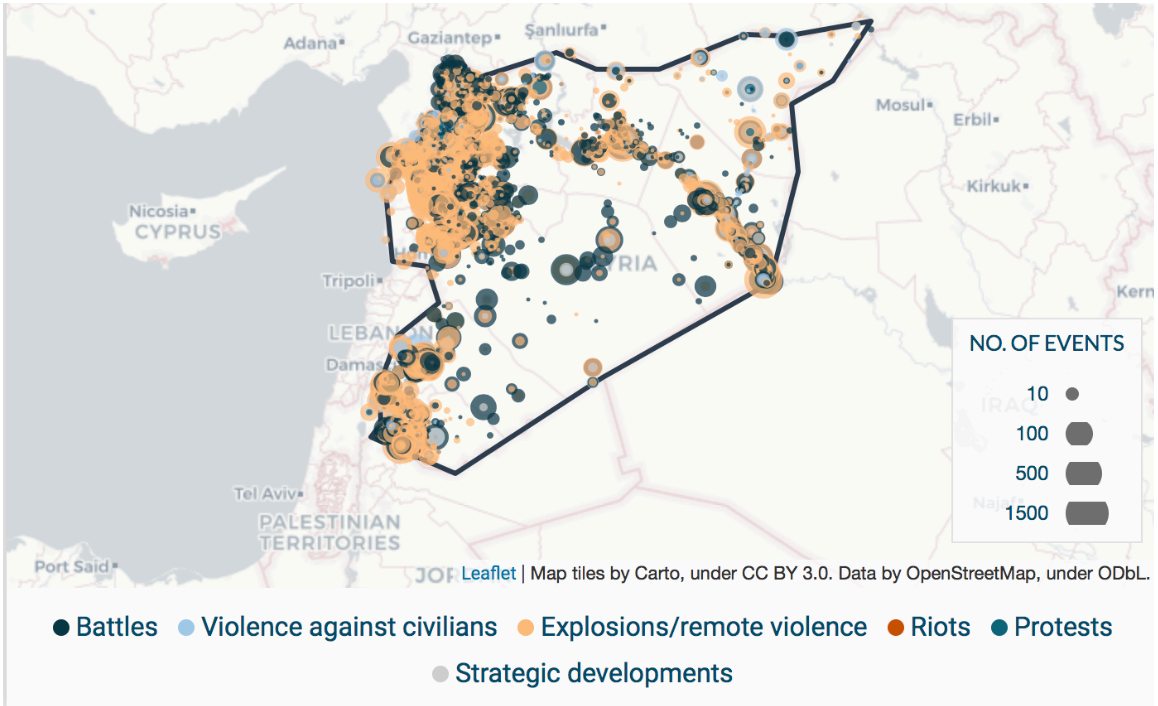

Figure 3: Syrian Civil Conflict Overview, source: ACLED

Rebel groups proved more resolute in their commitment to the conflict and government actions were more brutal then the world had expected.[27] As early as 2012, rebel groups were in control of large portions of country.[28]

The conflict can be divided into distinct phases; early protests followed by government violence against unarmed civilians, this led to formation of rebel groups like Jabhat Fatah al-Sham in 2012, with government forces in battles with rebel groups insurgency manifested between 2013-2014, at this point the US and Russia as well as other foreign actors had intervened, and in around 2017 rebel resistance began to decline.[29] As the crisis developed the conflict grew in complexity as different actors, entities and coalitions emerged and faded. Foreign intervention grew rapidly and propelled more intense conflict as sub conflicts began

[27] IBID
[28] "Uppsala Conflict Data Program." UCDP, https://ucdp.uu.se/#country/652.
[29] IBID

to emerge. Generally main combatants included Syrian government and Syrian Defense Forces, supported by Russia and Iran against Rebel groups like Free Syrian Army and Jabhat Fatah al-Sham with the US assisting 'moderate' groups as well as the PYD.[30] With the vast support the Syrian government *treated the conflict as a zero-sum game, where success for one meant a defeat for the other.*[31] The Syrian government began using chemical weapons and other archaic means to achieve their goals.[32] With this policy in place mass casualties and fatalities occurred, below is a summary of the unfortunate toll the conflict as put on the people of Syria.

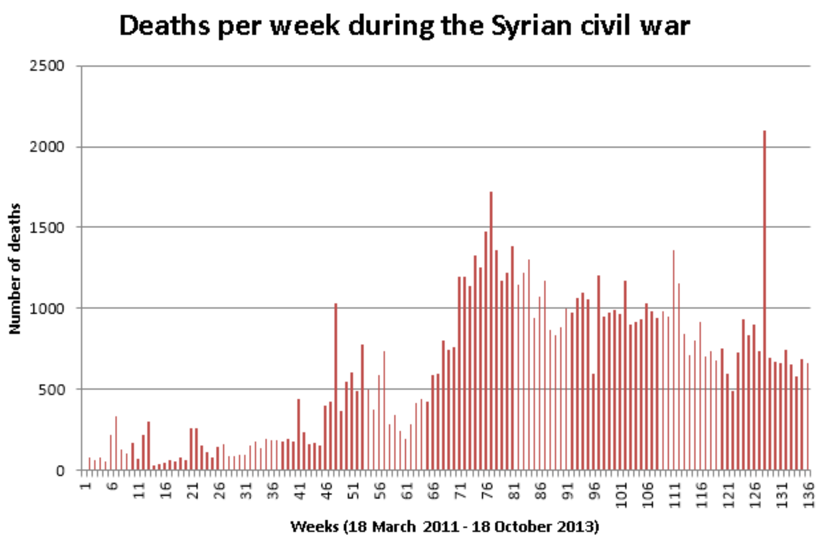

Figure 4: Deaths per Week during Syrian Civil War. Chart: GraysonWiki

The figure above shows that the loss of life was significant with approximately 165,000 civilians unfortunately taken by the conflict.[33] In total the UN found that nearly 400,000 people had perished overall by 2016.[34] By 2018 much of the territory had been eradicated of insurgent groups, while the government had a tenuous grasp on previously held rebel areas,

[30] IBID
[31] IBID
[32] IBID
[33] Stevens, Harry. "Civilians Are Still Dying in Syria, 8 Years after Start of Civil War." Axios, 15 Mar. 2019, https://www.axios.com/civil-war-syria-8-years-1351d99c-d36e-4b84-b35f-f458e0d4b0c8.html.
[34] "Syria death toll: UN envoy estimates 400,000 killed". Al Jazeera. Retrieved 23 April 2016.

and Idlib was demilitarized.[35] However, rebel groups both Syrian and Kurdish remain in open opposition and conflict is ongoing.[36] A conflict as severe as this warrants deeper examination to understand why it became so severe.

Concluding Remarks

This chapter is meant to highlight a particular issue and significance of its resolution. There is a clear need for theoretical models to utilize new data gathering techniques and be extended to look at different levels of analysis through CAS. These new specifications are meant to provide insightful explanations and better predictions aiding tactical decision-making. To reiterate, the process of the research will be; use SNA and event data to operationalize power, parity and satisfaction at a provincial, temporally frequent level. Using a pooled liner model test the viability of these new measures and confirm a match to theory. Then extend the theoretical model using CAS variables to increase explanatory power. After, the theoretical and CAS model specification will compete in two machine-learning methods to test not only what specification is better but also what method produces higher accuracy predictions. Review of literature and detailed explanation of methodology will be discussed in subsequent sections.

[35] "Syrian Civil War Fast Facts." CNN, https://www.cnn.com/2013/08/27/world/meast/syria-civil-war-fast-facts/index.html.

[36] Ibid

Chapter

02

Literature Review

The following section will briefly survey some prevailing research in intrastate conflict initiation framed in the context of a CAS framework. As this study focuses on the prediction and explanation of the onset of intrastate conflict, literature reviewed concentrates on conflict initiation and the factors that drive these events to occur. Literature examined will touch on theories addressing; macro structural conditions, meso-level event driven, and micro level interaction based research that explain the onset of intrastate conflict. Review will also cover new methods of conflict prediction that to show how leveraging different types of data in additional to traditional features can provide increase prediction fidelity.

Review of Literature

Literature reviewed gives differing explanations for the onset of conflict taken in the context of a CAS framework. Initial literature reviewed focuses on the impacts of structural factors either directly causing or setting preconditions for civil conflict. Further, literature on deriving influence from networks will be discussed. Lastly, micro level interaction driven conflict will be covered.

Macro Structural Level Theories

Scholars such as Urdal and Cincotta look to demographic compositions of nations as precursors to civil conflict. They argue that nations with higher levels of youth populations or 'youth bulges' have higher likelihoods of experiencing some level of political instability and even conflict (Urdal, 2006; Cincotta, 2015).[37] [38] Urdal in particular finds that youth bugle impacts conflict and terrorism even contributing to higher intensity instances of conflict. Stating that, increasing the active population of working/youthful age people with a decrease in dependents can lead to lower probabilities of instability. Continuing with the theme population composition, Gurr's worked focused on ethnicity and relative deprivation postulating that competing groups in a society experienced some grievance whether ethnic, religious or economic in motivation, that caused them to get into conflict with a national government. Emphasizing that disenfranchised ethnic groups have a perception of relative deprivation and seek to rectify this through conflict with the state (Gurr, 1970).[39] Horowitz (1985) also argues that there is a relationship between ethnic diversity and severe ethnic conflict, which is non-monotonic – with less violence for highly homogeneous societies and higher violence for heterogeneous societies.[40] Explaining that minority groups have little ability to influence political outcomes thus they lash out. While demographic and ethnicity-based approaches are insightful, they are more appropriate for longer-term studies due to the nature of population dynamics and how census data is collected. Further the validity of some arguments, especially Gurr and Horowitz, are found to be inconsistent.

Fearon and Laitin research departs from the theories above with findings that contradict some conclusions made in Gurr and Horowitz's work. Their research focused on finding links between ethnicity, insurgency and civil war, noting that in general ethnic diversity and board grievances were not significant in the onset of conflict. Instead they state that nations

[37] Urdal, Henrik; A Clash of Generations? Youth Bulges and Political Violence, International Studies Quarterly, Volume 50, Issue 3, 1 September 2006, Pages 607–629, https://doi.org/10.1111/j.1468-2478.2006.00416.x

[38] Cincotta, R. (2015a). Demography as Early Warning: Gauging Future Political Transitions in the Age-structural Time Domain. Journal of Intelligence and Analysis, 22(2), 129-148.

[39] Ted Robert Gurr (1970). *Why Men Rebel*, Princeton: Princeton University Press.

[40] Horowitz, Donald L. Ethnic Groups in Conflict. University of California Press, 1985.

that are poor, unstable, and populous with challenging terrain were more prone to conflict (Fearon & Laitin, 2003).[41] Their work suggests these factors are conducive to insurgencies that manifest into larger civil conflicts. Collier and Hoeffler echo the finding from Fearon and Laitin however, approach the problem from a greed versus grievance perspective. Their work finds that greed; lack of economic opportunity is more significant than grievances; religious, ethnic or political repressions in causing conflict. Arguing that lower opportunity costs, meaning lack of jobs and future, encourage insurgent and counter government activities (Collier & Hoeffler, 2004).[42] Brathwaite, Dasandi & Hudson's further emphasize the poverty notion set forth by the works above, suggesting that poverty increases the probability of internal conflict as poorer nations have greater trouble suppressing dissent (Brathwaite et al., 2016).[43] Similar to the first set of literature, the theories here also have longer-term data gathering processes.

An alternative method and one that this paper seeks to build upon focuses on key structural components of power ratios between competing dyads and satisfaction with the current status quo arrangement (benefits, or lack thereof, conferred upon each actor in the system). Stemming from the work of Organski and Kugler, the power transitions theory of major international conflict has to be proven extensible to serve on a regional and domestic level in works done by Kugler, Lemke, Tammen, Efrid, Abdollahian and Benson (Organski & Kugler, 1980, Kugler & Lemke, 1996; Tammen et al., 2000, Lemke, 2008).[44] [45] [46] [47] In

[41] James Fearon and David Laitin (2003) "Ethnicity, Insurgency and Civil War", *American Political Science Review*. 97, 1, February 2003, pp. 75-90.
[42] Collier, Paul and Anke Hoeffler (2004). "Greed and Grievance in Civil War." Oxford Economic Papers 56(4):563-595.
[43] Braithwaite, A., Dasandi, N., & Hudson, D. (2016). Does poverty cause conflict? Isolating the causal origins of the conflict trap. *Conflict Management and Peace Science*, *33*(1), 45–66. https://doi.org/10.1177/0738894214559673
[44] A.F.K. Organski and Jacek Kugler (1980). *The War Ledger*, Chicago: University of Chicago Press.

particular, the work by Lemke and Benson and Kugler focus on examining the preconditions for civil conflict. Research finds that power parity between government and opposition groups, APEs in Lemke, and dissatisfaction with the status quo leads to the preconditions for major civil conflict (Benson & Kugler, 1998).[48] Benson and Kugler also find that democratic and more capable states are more likely to stave of challenges from opposition due to increased ability to stamp out dissent and formal channels for grievance resolution.

Meso Event Driven theories & Network Analysis

Meso level theories explain phenomena by analyzing interactions between different entities or organizations leading to the onset of an event of interest, as well as discovering connections between micro and macro level analysis. Mathematicians, economists, and sociologists have leveraged the insights drawn from network analysis to assess how relations between entities impact the phenomena of study be it trade, economic growth or conflict.

Abdollahian et al. explored these interactions when examining the relations between trade and economic growth through the lens of network analysis. Extending from structural trade models like Heckscher–Ohlin or new trade theory, *network measures of degree, betweenness and eigenvector centrality* were added to capture dynamic interactions between trade dyads. Research confirmed that *degree has a strong positive impact* showing that *the more trading partners a country has*, the better economic growth is achieved where high betweenness, an indication of

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[45] Kugler, Jacek, Lemke, Douglas, eds. (1996). *Parity and War: Evaluations and Extensions of the War Ledger*, Ann Arbor: University of Michigan Press.

[46] Ronald Tammen, et al, (2000) Power Transitions: Strategies for the 21st Century, New York, CQ Press.

[47] Lemke, Douglas. "Power Politics and Wars without States." American Journal of Political Science, 2008.

[48] Michelle Benson and Jacek Kugler (1998). "Power Parity, Democracy, and the Severity of Internal Violence". Journal of Conflict Resolution. 42:2.

connection to a high proportion of trading partners, meant the state was closer to convergence. [49]

In *Trade Networks, regional agreements and growth*, Yang and Abdollahian also use a combination of structural and network level data to explore relations between trade and growth. As stated, *the social network perspective is an important empirical research tool as well as a paradigm for understanding connectivity*. Authors argue that most scholars examine trade volumes and balances while ignoring the *interactive effects of trade networks.* Network metrics of degree connectivity, closeness connectivity, eigenvector connectivity, k-core connectivity were used to study impacts of trade on growth. Their findings, like Abdollahian et al. 2013, not only confirm structural theories of growth, but also highlight other nuanced conditions such as higher closeness and eigenvector connectivity increases speed of convergence and growth (Yang, Abdollahian 2014). [50]

Work by Minhas, Hoff, and Ward built a *multilinear tensor regression framework (MLTR) that captures influence relationships* to address the topic of influence in international relations through network data. Their model studies *how the network actions of one actor may influence the future actions of another* (Minhas, Hoff & Ward, 2017).[51] The key part of note is that this study captures how actions of one impact the other, slightly different than assessing the power of a particular actor, however these methods will be used to inform network power metrics used further in this paper.

[49] Yang, Zining, Mark Abdollahian, and Patrick deWerk Neal. "Social spatial heterogeneity and system entrainment in modeling human and nature dynamics." Theory, Methodology, Tools and Applications for Modeling and Simulation of Complex Systems. Springer, Singapore, 2016. 311-318.

[50] Yang, Zining & Abdollahian, Mark. (2014). Trade networks, regional agreements and growth. 10.4337/9781781954997.00009.

[51] Minhas, Shahryar, et al. "Influence Networks In International Relations." *National Science Foundation*, 27 June 2017.

In his paper *Assessing the Political Landscape: Structure, Cognition, and Power in Organizations,* Krackhardt examines the power structures in political landscape by examining the underlying network structure. His central premise is determining whether powerful actors can be uncovered by analyzing their position in a network and their relations to other actors. His findings suggest that power accrued to those in central network positions, coalition emergence could be better understood, and audit origination or support in the network.[52] It could also be used to identify weak points in the network structures and support channels that could disrupt power distributions.

Kinsella takes the concept of social network analysis and goes a step further by using it in an application routed in power transition theory similar to the connection this research is trying to achieve. A key difference is the data used as the Kinsella relies on global arms trade data to construct the network while this research uses event-based data. Despite this difference, core concepts are relatively similar in the utilization of relational data to extract information in a power transition framework. In *Power Transition Theory and The Global Arms Trade: Exploring Constructs from Social Network Analysis,* a key point is that generally conflict has been analyzed using structural data with lesser emphasis on the underlying relations between the states in the system. The paper argues that satisfaction measures can be operationalized from the arms transfer patterns, while power and hierarchy structure could be understood by examining, which actors are interacting and how they are interacting.[53] These interactions are measured using centrality, structural equivalence, or group cohesion. Research finds initial

[52] Krackhardt, David. *Assessing the Political Landscape: Structure, Cognition, and Power in Organizations*. Cornell University, 1990, pp. 1–30, *Assessing the Political Landscape: Structure, Cognition, and Power in Organizations*.

[53] Kinsella, David Todd, "Power Transition Theory and the Global Arms Trade: Exploring Constructs from Social Network Analysis" (2013). Political Science Faculty Publications and Presentations. 15.https://pdxscholar.library.pdx.edu/polisci_fac/15

support of centrality and structural distance as measures in power transition models.[54] Further, research suggests *arms trade can serve as an indicator of the coalitional structure of the international system, one perhaps more nuanced than formal alliance patterns*.[55] This foray into SNA as a method for understanding power and satisfaction is vital for ongoing research surrounding alternative methods to operationalize power transition theory variables. The emphasis away from structural variables could allow different more nuanced approaches to the calculation of power and satisfaction. The distinction this paper makes is using event data instead of trade data, using betweenness centrality as the measure of power, and satisfaction is derived from other event variables.

Micro Interaction Theories

At this level of analysis focus is on the individual or entity, tracking, preferences on particular issues and interactions between stakeholders as they trade and bargain to achieve their goals. It can be used for conflict studies to analyze whether competing preferences on an issue will end in resolution or conflict.

An example of model can be seen in the agent-based predictive political simulation, Senturion. It is a computational model that can be used for *unbiased predictions of potential threats.* It captures metrics on entities involved, preferences on a particular outcome, ability to influence those outcomes and how important outcomes are. Using these metrics in combination with game theory, behavioral economics, spatial bargaining and micro-economics, it can forecast; *political dynamics within local, domestic, and international contexts and predict how the policy positions of competing interests will evolve over time.* It has a broad application, among which is conflict prediction and escalation. By capturing the severity in difference of

[54] IBID
[55] IBID

preferences and willingness to achieve outcomes, forecasts can be made on stability and violence in a nation. The work highlights application on the model of the Iraq war and subsequent elections. The model was able to forecast likely areas of disagreements and predict instability with the authors stating the *situation in Iraq would worsen…in terms of Iraqi attitudes toward U.S. presence as well as insurgent activity.* Also, it identified more actor specific nuances such as the expectation that the *military core was…to provide the basis for violent and persistent resistance.* By examining micro level interaction, decision makers have the ability to identify very precise pieces of information not available at the macro structural level (Abdollahian et al., 2006).[56]

Contemporary Prediction Methods

Another vital aspect of this research is how changing the data typology away from structural to macro, meso and micro event-based data will also enhance prediction capacity. Research into alternative data sources and methods for prediction of conflict and terrorist incidents has greatly increased. Analysts are leveraging event data, social media, and sentiment to augment other sources with the hopes of better forecasts. Generally, the trend has been promising and has provided valuable insights.

Leetaru, one of the main contributors to GDELT, uses event-based data for conflict prediction in his dissertation. He uses linguistic, latent-based forecasting measures derived from event data as measure for conflict analysis. Arguing that narrative discourses uncovered in natural language processing of event media can be utilized as a way to get highly granular

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[56] Abdollahian, Mark, et al. Senturion: A predictive political simulation model. NATIONAL DEFENSE UNIV WASHINGTON DC CENTER FOR TECHNOLOGY AND NATIONAL SECURITY POLICY, 2006.

predictions of conflict.[57] His results show how 'big data' is exceedingly useful in producing these highly nuanced predictions which can revolutionize how conflict analysis is approached.[58] Leetaru's work provides evidence that event based data can be used to measure variables at a highly granular and temporally frequent scale and its viability for conflict predictions.

Another interesting approach that utilizes 'bid data' employs the use of social media for conflict prediction. Overbey et. al. paper, *Correlating Twitter Sentiment and Event Data to Monitor Social and Political Unrest*, decodes twitter data by *sentiment analysis by using link-following and automated event coding*[59] that provide insight into social attitudes towards particular events and assess general sentiment of society. They argue that *monitoring changes in sentiment toward political events within these regions may reveal trends in public opinion that indicate social and political instability.*[60] While the research in this dissertation will not use social media data at this juncture, the inclusion of this article is to highlight the different approaches that are being taken to address conflict prediction. The major benefit of twitter data is that it captures information at a micro level and can be used to construct meso level network of how information permeates in a system, effectively gauging sentiment in societies at a large scale. The authors cite in their work the vital role twitter played in the spread of information during the civil unrest in the Middle East.[61]

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57 Leetaru, Kalev H. "Can we forecast conflict? A framework for forecasting global human societal behavior using latent narrative indicators." *University of Illinois at Urbana-Champaign*, Kalev Hannes Leetaru, 2016, pp. 1–184.

58 IBID

59 Overbey, Lucas, et al. *Correlating Twitter Sentiment and Event Data to Monitor Social and Political Unrest*. SPAWAR Systems Center Atlantic, 2016, *Correlating Twitter Sentiment and Event Data to Monitor Social and Political Unrest*.

60 IBID

61 IBID

The approaches described in all the above sections have contributed in some way to ICEWS. The US government through DARPA developed an integrated crisis early warning system (ICEWS) in order to predict international crisis, domestic crisis, rebellion, insurgency, and ethnic violence.[62] The system utilizes *dynamic, high-volume, heterogeneous data sources* as featured in their models.[63] The goals of the models are to *provide operators with situational awareness of past and current events in countries of interest.*[64] For example to model rebellion, the ICEWS uses variables; proximity to election, competitiveness of executive recruitment, executive constraints, GDP per capita (log), rebellions in surrounding countries.[65] While these indicators may provide situational awareness to decision makers, the ability to forecast at smaller time intervals is limited. The results of the hierarchical models generally capture the trends of the events of interest despite limitations. The ICEWS system shows the potential power when theory and practice are at the forefront of decision-making.

These articles were cited primarily because of their use of non-structural indicators for conflict, high granularity and relative success in forecasting instability and conflict on short-term basis. They provide evidence of the feasibility and larger extent useful of these approaches to decision makers. ICEWS was included to the general demand of conflict predictions and to show how systems like ICEWS could take advantage of more granular data. The research proposed in this dissertation will hope to leverage insights from these works and combine with the sound theoretical background found in structural conflict analysis.

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62 Ward, et al. "Geographical Models of Crises: Evidence from ICEWS." CRC PressI Llc, 2012, pp. 429–438.
63 IBID
64 IBID
65 IBID

Concluding Remarks

While each of the works approached the issues of civil conflict from a slightly different perspective, all highlight the importance of approaching conflict of differing levels of analysis. This paper seeks to build on this framework, explaining conflict not only tops-down but from a bottoms-up perspective – integrating and empirically testing CAS and machine learning approach to intrastate conflict.

Chapter

03

Methodology, Hypothesis & Data

This section will focus on model specifications, methods employed in this study, and data. The structure of this research is to replicate the theoretical model found in Benson and Kugler 1998 using measurements taken from network analysis metrics and event data. The theoretical model will be extended using CAS variables to assess the added explanatory of this approach compared to the theory model using pooled linear model method. After, each model specification will be tested using a classification and regression tree (CRT) and a random forest (RF) in its ability to predict. These methods will be used to see how well different more complex machine methods using theoretically informed variables perform in prediction of conflict. The following section will review the pooled linear model method that will be used for explanation as well as the two machine learning methods, CRT and RF, which will be used for prediction. Further a review of the social network analysis used to create some of the independent variables will be reviewed.

Research Questions & Hypotheses

The central premise of this paper is determining whether the relation between parity, satisfaction and conflict as specified by theory, can be recreated using alternative measures from event data and network analysis. Test an extended model using the CAS framework. Examine the relation between the features and their ability to explain conflict. Then determine whether theory informed machine models could be used to predict the onset of conflict. The research should provide evidence that alternative measures capture theory, a

CAS approach can provide added explanatory power and theoretical informed machine learning models are accurate in forecasts.

Hypotheses

H_1 Relative betweenness centrality of government and rebels impact level of violence in short term - Parity

H_2 Avg. tone of links between entities in a state impacts level of violence - Satisfaction

H_3 Event level factors impact violence – Event

H_4 Micro to meso level attributers factors impact violence – Degree in

H_5 External aid to government or opposition groups impacts level of violence – Cooperation

Hypotheses one and two are meant to test the viability of the theoretical model using structural variables of parity and satisfaction drawn from the event data and network analysis in capturing the trends set forth by original model. The remaining hypotheses are meant to examine the viability of the CAS extension in adding to explanatory power.

Models

The following equations are the specifications to be used for the pooled panel model, CRT and RF methods tested.

Theoretical Model

$$Intrastate\ Violence_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it}, Satisfaction_{it})$$

Complex Adaptive Systems Model

$$Intrastate\ Violence_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it},\\ Satisfaction_{it}, ExternalSupport_{it}, Events_{it}, Micro\ actor\ attributes_{it})$$

Equation 1: Theory and CAS Models

The theoretical model shows that intrastate conflict is explained by government power, opposition power, the power ratio between these groups and satisfaction with the status quo. The CAS extends upon this by examining the impact of meso level events such as foreign intervention, and government actions and micro level actor attributes such as degree in combined with macro level structural conditions from the theoretical model.

Research Design & Sample

The research will use cross-sectional (provincial) time-series (monthly) data drawn from GDELT for the country of Syria from 2007-2017. Due to the nature of the conflict in Syria, data from all provinces will be collected as oppositions/ insurgents groups have been present in nearly every area, even if intermittently. Provincial, monthly data used to measure intrastate conflict as well as network metrics, event data and micro actor attributes will be collected from GDELT.

Complex Adaptive Systems Approach

A key feature in the approach of this work is the utilization of a complex adaptive system.

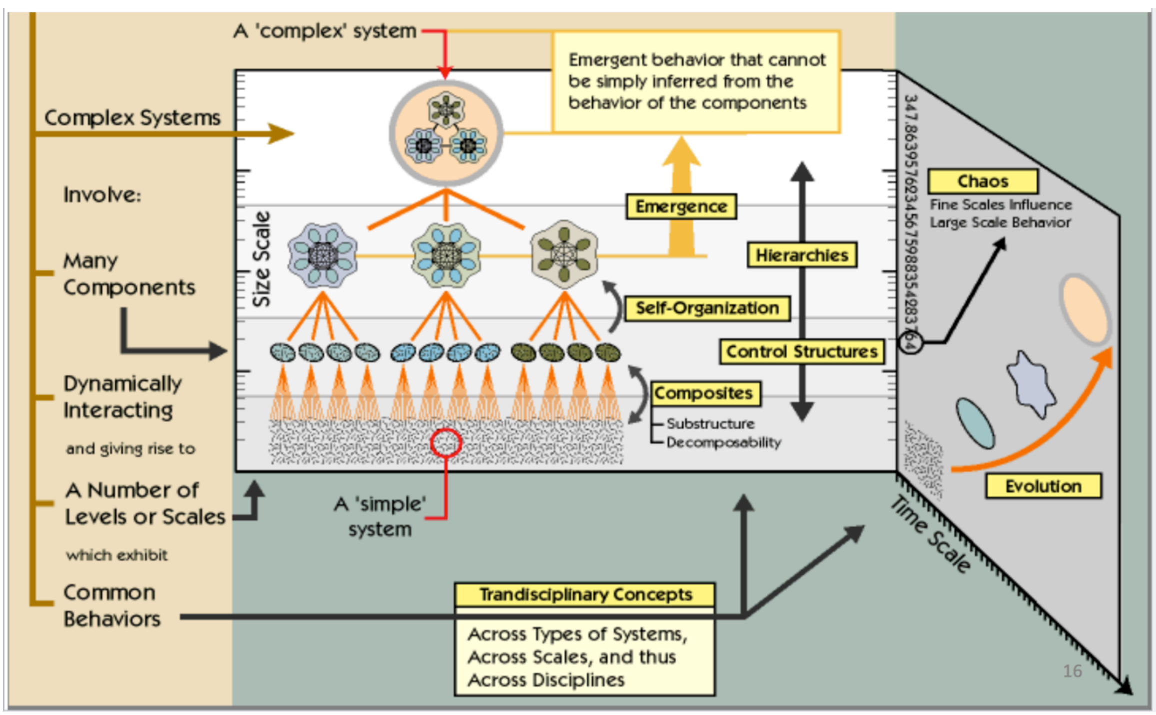

Figure 5: Complex Adaptive System Representation, source: New England Institute of Complexity 2011

While the literature review provided evidence that analysis at different levels, maco, meso, micro, can reveal an enriched understanding of the phenomena of study, it is important to understand how these levels are connected. Above is a visual representation of a complex adaptive system, the different levels, how they interact, and what they produce. Taken from the image, *complex systems involve many components dynamically interacting and giving rise to a number of levels of scale, which exhibit common behaviors*. At the bottom are the individual components and in the context of a country these can be thought of as people, entities or organizations. These components contain unique attributes that inform decisions as they interact with other components in the system. Interactions are incentivized or constrained by the macro system, which in turn change the way the components interact. Interactions between components in the system produce preferential or random networks.[66] The network formations are the output of interactions and can become more complex through time impacting the macro system in different ways. For countries, macro outcomes can consist of a wide spectrum of potential outcomes. Some interactions produce success while others, in the case of Syria, produce chaos. Macro environments can constrain or incentive individual micro level behavior as well as meso social behavior, which in turn shape the macro environment.[67] The examination of different levels of analysis allows for merger of social science theory – macro structural conditions impact component agency, which is in turn change underlying network structures, changing macro conditions. In Syria, repressive macro conditions which limited political participation constrained individual agency. Components interacted and began to demand change. The macro conditions became further constraining and thus components

[66] Miller, John Howard, and Scott E. Page. (2007) Complex Adaptive Systems: An Introduction to Computational Models of Social Life. Princeton, NJ: Princeton University Press.

[67] "Ten Principles of Complexity & Enabling Infrastructures". by Professor Eve Mitleton-Kelly, Director Complexity Research Programme, London School of Economics.

began to merge in to rebel groups that rose in power and disrupted the system. The macro conditions altered into war. By dissecting issues into its many components, greater appreciation can be gleaned as to how issues are driven by structure, network changes and component agency. For enhanced analysis, this research seeks to exploit the information in the underlying networks of Syria. The next section details how networks were generated and used for derivation of some independent variables.

Social Network Analysis (SNA)

Power and parity will be derived from relational event data organized into a social network. While there is evidence in literature suggesting that using SNA metrics such as social cohesion or betweenness as proxies for power is viable, it is important to unpack what these measures are tracking and understand why this approach may provide a different way to address power. Sociologists have understood that social structures provide insight into power dynamics between actors. Hanneman and Riddle argue that a *network approach emphasizes that power is inherently relational* and that power is closely related to the concept of centrality.[68] They find that that power in the network is both derived from *systemic (macro) and relational (micro) property.*[69] The properties are a consequence of the patterns and underlying relations found in the networks that are consistently changing over time. Due to this, the *amount of power in social structures can vary* depending on the coupling in the system, *with high-density systems…[showing] the potential for greater power* (as will be displayed in following chapter).[70] Further total power and distribution of power related yet different. Total power can refer to overall network connectivity or density while individual nodes in the network could occupy

[68] Hanneman, Robert A. and Mark Riddle. 2005. Introduction to social network methods. Riverside, CA: University of California, Riverside (published in digital form at http://faculty.ucr.edu/~hanneman/)
[69] IBID
[70] IBID

different position in the network, granting more power to actors who have an advantageous position. Hanneman and Riddle illustrate this in three sample plots.

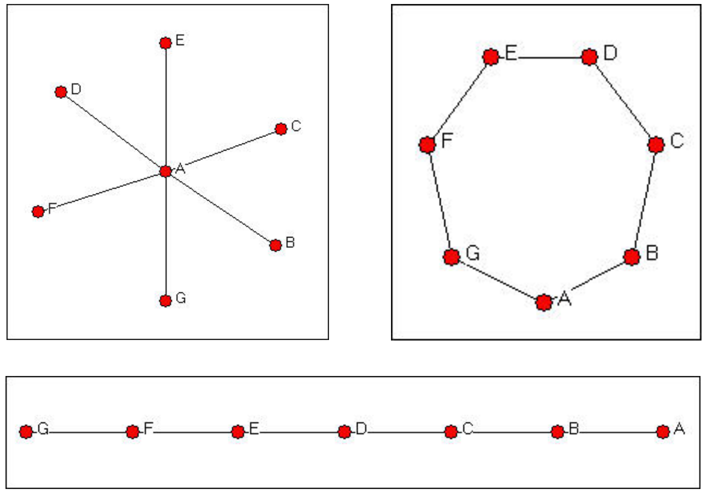

Figure 6: Example Network Plot, Star, Circle and Line, Source: Hanneman and Riddle

The plots above are example of very simple decomposed network to help give a visual reference to how power is derived. The first network represents a 'star' shape in which nodes are arranged a central vertex, a. To the right is another configuration showing a 'circle' and below a 'line' network. These three may possess the same amount of power in the over all structure the distribution are much different. Using node 'a' as an example for all three plots, it is noticed that in first plot it occupies a central position making the most powerful as it is the hub between which information or resources etc. passes. Node 'a' in the circle network has an equal connection to all other nodes. No node as a distinct advantage and 'a' is not weakest nor strongest. In the line plot node 'a' occupies the far right position only connected to node 'b' meaning it has very little power compared to node 'd' occupying a central position. Depending on the position in the network a node can *impose constraints on the actor, and [offer] the actor opportunities.*[71] These abilities are results of *favorable structural positions.*[72] As new actors are introduced they can shift the network terrain and begin to alter the

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structure and thus power dynamics. Rebel movements can have similar impacts on country structures as they disrupt the underlying hierarchy and attempt to install themselves a power brokers.

In order to ascertain the power a node has relative to others, SNA metric are used. These include; homophily, density, clustering, degree in/ out, closeness centrality, and betweenness centrality among others. Since this research is concerned with network structures and how they relate to power, closeness centrality and betweenness centrality, the eventual measure used for modeling purposes, will be examined further. Closeness centrality is defined as how central the node is relative to all other nodes in network as defined by *the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph.*[73] The calculation is as follows:

$$C(x) = \frac{1}{\sum_y d(y,x)}.$$

Equation 2: Closeness Centrality Calculation

Where *C(x)* is the closeness measure of node x as defined by *d(y,x),* the distance between the vertices x and y between all possible *x,y* combinations in the network. Betweennes centrality is also a measure of centrality based on shortest path but *quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.*[74] The calculation is as follows:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Equation 3: Betweenness Centrality Calculation

[73] Sabidussi, G (1966). "The centrality index of a graph". *Psychometrika*. 31 (4): 581–603. doi:10.1007/bf02289527. PMID 5232444.

[74] Freeman, Linton (1977). "A set of measures of centrality based on betweenness". Sociometry. 40 (1): 35–41. doi:10.2307/3033543. JSTOR 3033543.

Where σ_{st} is the total count of shortest paths from node *s* to node *t* and $\sigma_{st}(v)$ is the number of those paths that pass through *v*.[75] This is a critical measure because as Freeman states, [a node with] *higher betweenness centrality would have more control over the network.*[76] Which is what the research is more concerned with. The graphs below are an example of how nodes centrality measures change depending on the approach taken.

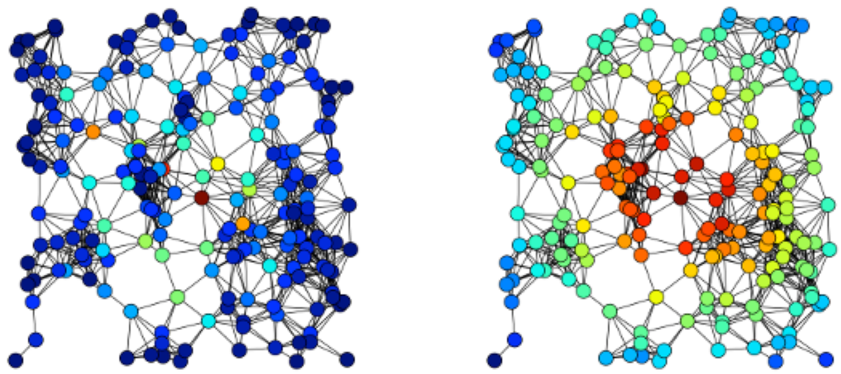

Figure 7: Betweenness (left) vs. Closeness (right) Centrality Network, Source: Tapiocozzo

Nodes that are bluer in nature have lower centrality measures when compared to those that are redder. As noticed in the right plot the closeness centrality gives a higher centrality score to more nodes as many are highly connected. However this makes its difficult to identify which node has the most power in the network, as many are equal. The plot on the left shows a much more distinct indication of which nodes are most powerful and controlling in the network. Since we are more concerned with power and who controls the system and therefore the hierarchy, betweenness centrality would be more applicable measure for the research. For the purposes of feature creation, government betweenness centrality will measure government power while rebel betweenness centrality will measure rebel power. Parity will be the ratio of rebel to government power. Below is an example network plot generated from the data used in this research.

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[76] IBID

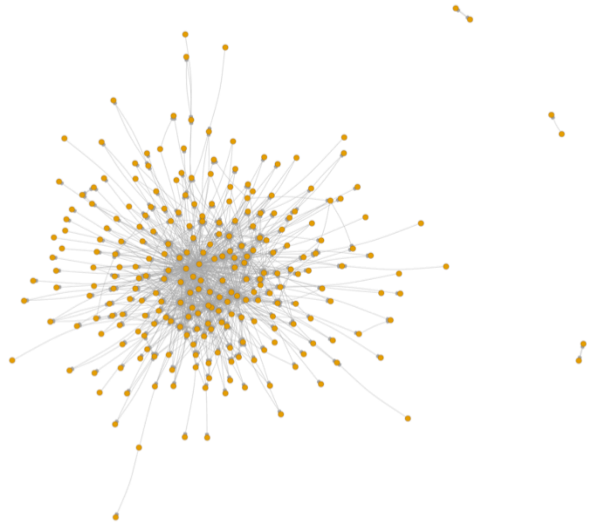

Figure 8: Sample Network, Syria 01 JAN 2006

This is a subsample of the network data used for this research reduced for visualization clarity. The network is organized reflecting the social structure of the society at the particular moment in time. The node at the center represent the most powerful as calculated by the metrics explained above. To further understand the social structure the network was paired down and labeled below.

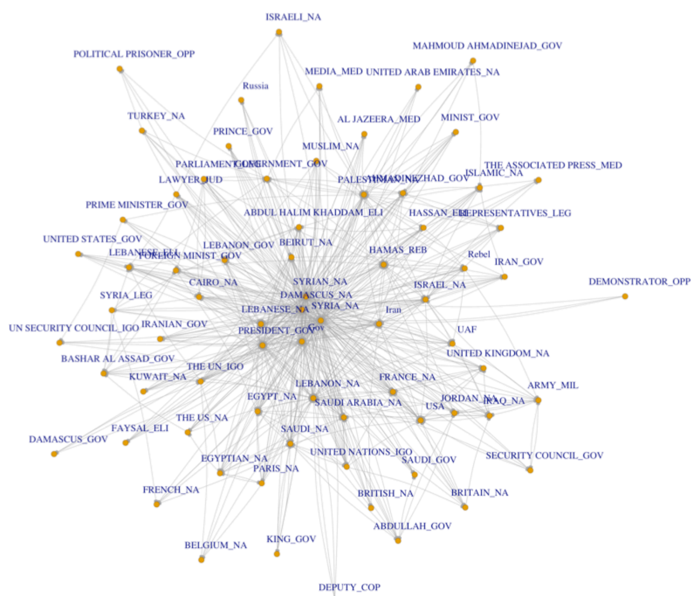

Figure 9: Sample Network, Syria 01 JAN 2006

As noticed in the very center of the network is the government and its extensions. As the center of the node they represent the most power actors in the network. The periphery shows other actors (states, entities) in which they are interacting with. This is a reflection of the social structure insights that can be gained by using relational data. These structures also vary over time. The above graph also is at a point in time when Syria was relatively peaceful. The graph below shows Syria one month before the outbreak of the conflict. The amount of edges in the network as increased significantly and critically the social structure has change. In the center of the network are new actors, rebels. They are positioned relatively close to the center of the network indication they have gained a significant amount of power.

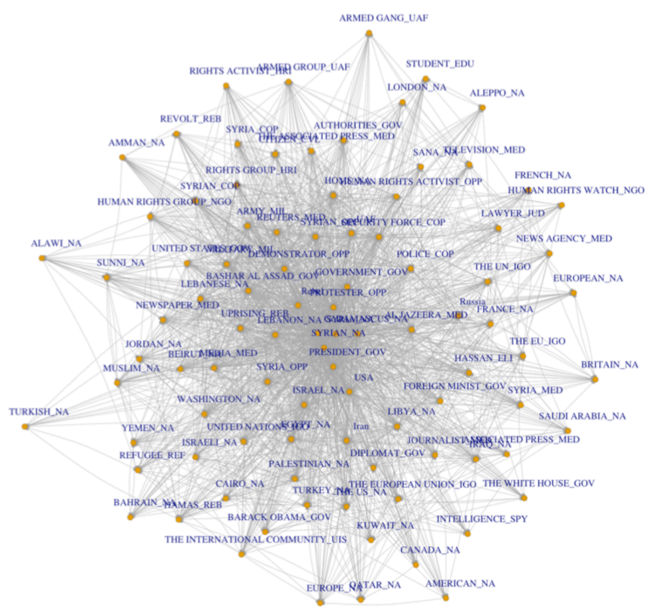

Figure 10: Sample Network, Syria 01 FEB 2011

The change in the network structure and the introduction of the rebels is exactly why this type of data structure is vital. By increasing the sampling frequency and constructing relational data, new and disruptive actors and be identified and changes to the hierarchy can be measured. The plot below shows the conflict a few years after initiation.

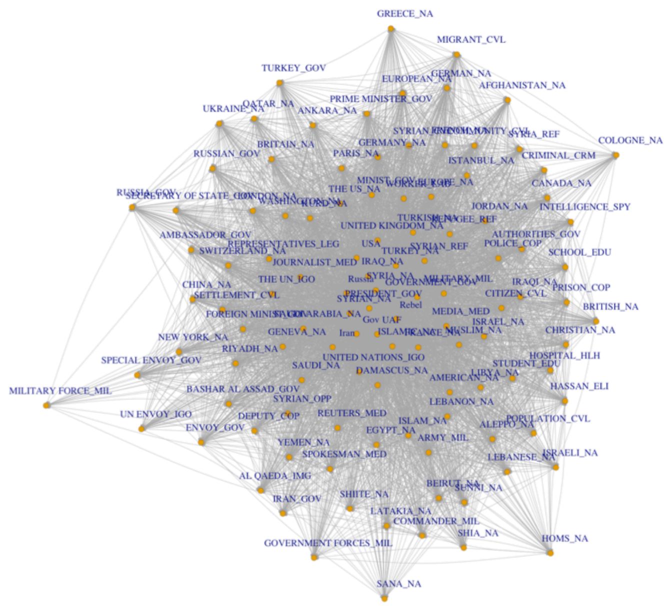

Figure 11: Sample Network, Syria 01 JAN 2016

The amount of edges has significantly increased and the structured has completely changed from a decade earlier. The government is still contesting rebels and the presence of foreign actors is high. As seen IGOs, such as the UN, are now closer to the center as mediation efforts increase. Critically though, US and Russia now occupy central roles in the structure. Over the years of the conflict their influence grew and now they are main actors in the civil war. Their presence could also be reinforcing the persistent changes in the network. The evolution of the network can be measured and tracked in order to diagnosis changes in conflict. The metrics derived will be tested to see their viability as measurements.

Dependent Variable

The dependent variable in this study will be level of intrastate violence (dichotomous occurrence variable will be for predictions). Data will be drawn from the GDELT project or Global Data on Event, Locations and tones. GDELT uses automated web scrubbing tools to collect, parse and analyze news, media and articles from around the world. It takes this data and codes it using the CAMEO ontology into structured event data.[77] Each observation indicates a unique event type, with specific actors, at a particular location. Taking this structured data the dependent variables will be measured as the number of conflict events occurring in a given province during a specific month. Specifically, it will measured using the CAMEO event 'fight' defined as *all uses of conventional force and acts of war typically by organized armed groups* (Leetaru & Schrodt, 2013). Figure 3 below shows the output of the number of 'fight' events in Syria on an aggregate level, disaggregated provincial level data will be explored in chapter 4.

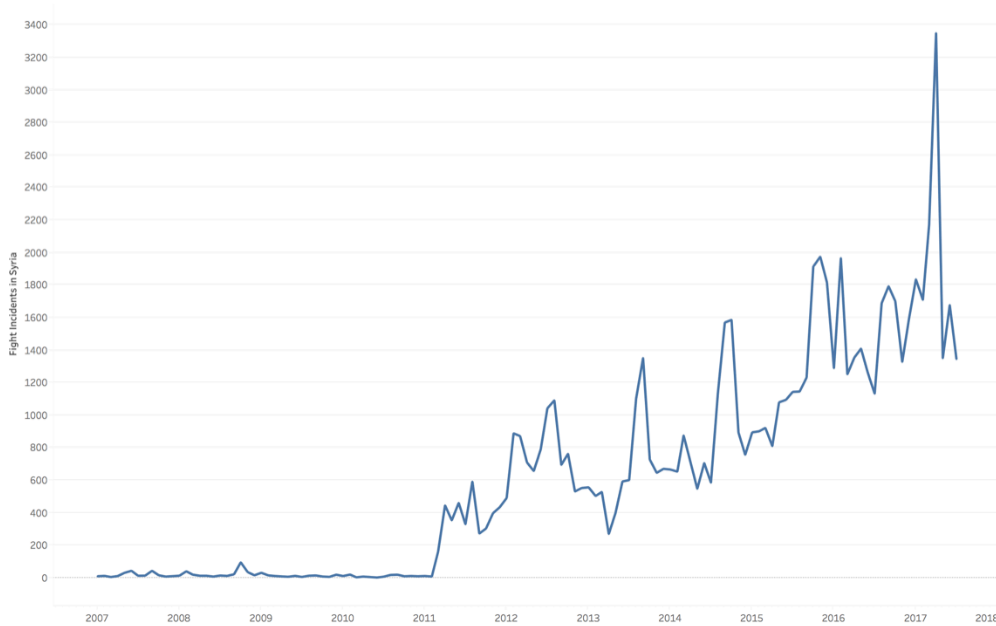

Figure 12: Number of 'Fight' Incidents in Syria

The chart shows the dramatic increase in violence starting around 2011 and the ignition the Syrian civil conflict. It was thought of to be an isolated skirmish between government and smaller bands of fighters but as the years bore on the conflict greatly intensified beyond what most has imagined. Further review of the variable will be performed in the next chapter.

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[77] Leetaru, Kalev, and Philip Schrodt. "GDELT: Global Data on Events, Location and Tone, 1979-2012." Gdeltproject.org,2013, data.gdeltproject.org/documentation/ISA.2013.GDELT.pdf.

Theoretical Model Independent Variables

IV_1: Government Power – measured Government Betweenness Centrality.

In past conflict research there has been much debate as to the different measures of power. Early on power transition specifications relied on structural measures of power. Organski initially measured power using GDP (1958, 1968) and was generally the accepted measures until it was realized that GDP was not accurately accounting for political performance. Organski and Kugler revised the measure to include population, productivity, and political performance as a better measure of the government power (Organski and Kugler, 1978, 1980, Arbetman and Kugler, 1997, Kugler and Tammen, 2011. Benson and Kugler relied on subject matter experts to get measures of power for opposition groups; this would not be feasible or useful for monthly predictions.[78] In Lemke's work on intrastate conflict, power is measured as the *APE's capabilities as its aggregate demographic endowment* due to the high correlation between population and other power measures.[79] While this is a credible measure it is not highly dynamic as would be difficult to continuously update APE census data frequently. Others, like the correlates of war project, use CINC or composite index of national capabilities including; total population of country ratio, urban population of country ratio, iron and steel production of country ratio, primary energy consumption ratio, military expenditure ratio, and military personnel ratio.[80] The point of this measure is also to move beyond just GDP. However, in all calculations noted, the main measures require structural data usually collected at a yearly frequency. This is not useful for tactical analysis, as

[78] Benson, Michelle, and Jacek Kugler. "Power Parity, Democracy, and the Severity of Internal Violence." Journal of Conflict Resolution, vol. 42, no. 2, Apr. 1998, pp. 196–209, doi:10.1177/0022002798042002004.

[79] Lemke, Douglas. "Power Politics and Wars without States." American Journal of Political Science, 2008.

[80] Garrett Heckman. "POWER CAPABILITIES AND SIMILARITY OF INTERESTS: A TEST OF THE POWER TRANSITION THEORY" (PDF). *Etd.lsu.edu*. Archived from the original (PDF) on 2010-07-18.

predictions cannot be made on a monthly basis. The alternative measure in this research uses betweenness centrality as a proxy of power as described in the network analysis section above. The measure will be constructed by identifying the proper actors, government and rebels, in the network and extracting node level attributes.

IV_2: Rebel Power – measured Rebel Betweenness Centrality.

This measure will be calculated exactly as government power above, but using betweenness centrality of rebels.

IV_3: Parity – measured as Rebel Betweenness/ Government Betweenness.

Will be measured as the betweenness centrality ratio of rebel to government groups, with a value of 1 indicating power parity between groups.

IV_4: Satisfaction – average tone of Rebel statements

In the original power transition theory, satisfaction is the alliance similarity measure Tau B (Altfeld and Bueno de Mesquita, 1979). Later was refined as S measure by Signorino and Ritter in 1999. To ascertain the level of satisfaction, the difference in alliance structures between the dominant power and that of other nations was analyzed. If the alliance structures were similar then it is thought that the nation is more satisfied with the SQ as they are aligned with similar actors in the international system.[81] [82] The draw back here is that for civil conflict it is hard to tabulate these alliances as measures are not taken and rebel groups typically do not have the longevity or diplomatic functions like states. The other issue of satisfaction measured by alliances is that alliances are not dynamic and do not have much variance. So for purposes of monthly prediction, they cannot really be used. For these

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[81] A.F.K. Organski and Jacek Kugler (1980). *The War Ledger*, Chicago: University of Chicago Press.

[82] Bueno de Mesquita, Bruce. "Measuring Systemic Polarity." Journal of Conflict Resolution, vol. 19, no. 2, June 1975, pp. 187–216, doi:10.1177/002200277501900201.

reasons an alternative measure will be explored. This is measured using 'public statement' and 'average tone' from GDELT event data. This is an event measure indicating the positive or negative sentiment of 'public statements' made from rebel groups. As seen in the literature both sentiment analysis and event data can be used to capture causes of conflict and measure satisfaction. This is not a dyadic measure but rather a general one reflecting a proxy for satisfaction with status quo.

Complex Adaptive System Model Independent Variables

In additional to the above variables, the CAS will extend upon the theoretical model using the following features.

IV_5: Satisfaction II – average tone of Civilian statements

This will be measured in similar way to satisfaction specified above however the actor isolated from the event data are 'civilian' actors while the first refers to rebels. This is used to capture additional popular dissent that maybe present in the country.

IV_6: Protests

This will be measured as event 14 or 'protest' in GDELT. This will be included as a meso level variable that captures protest events occurring in country. Protests are used a proxy of political stability and active and organized demonstration against the government or policy.

IV_7: Demands

This will be measured as event 10 or 'demands' in GDELT. This is another meso level variable meant to capture rebel demands directed at the government. This is included to account for desires of political representation, policy change, or regime change that are not being met. As they escalate this puts pressure on the government to react. The interaction between rebel and governments adds greater insight into conflict.

IV_8: Rebel Degree In

This will be measured using the total number of events from critical entities targeting rebels groups. Critical entities include government and their extensions of power, other domestic actors like civilians and religious groups and foreign entities. This is included as a approximate way to track how the rebels are being pushed in the network. The more edges coming to their vertex the more central they becomes to the network structure.

$IV_{9/10}$: Material Cooperation from USA and Russia

The will be measured as event type 6 or 'engage in material cooperation' from GDELT, and is included as a proxy measure of external support. These measure material contributions from Russia to the government and USA to rebel apart from aid. This can include arms and other assets. This is included to measure how foreign intervention, captured by material cooperation events, impact conflict.

IV_{11}: Threaten

This will be measured as event type 13 or 'Threaten' from GDELT, and it is included to capture government response to protests and demands. Literature indicates that governments with less willingness to share power and lower ability to curb dissent resort to negative and threatening actions to quell opposition. Often times this harsh response spurs more protests and increasing instability.

Variables 1-4 are to be used in the theoretical model meant to replicate theory found in literature. The remaining variables serve as features to be used in the extended CAS model.

Pooled Panel Models (PLM)

PLM will be employed as the method to test the theoretical model specification for recreation of original theory and then compare the explanatory power against that of the CAS model extension. This method was selected for this data, as there are no universal effects across time due to the ever-changing nature of the conflict. Continuous violence measures will be used as dependent variables and the main purposes is to explain conflict onset.

PLM is useful because it provides a simple straightforward way to test the relations between factors. Combining cross sectional data with times series allows for more observations, greater variation and less collinearity.[83] It also minimizes the aggregation bias and is useful for studying *dynamics of change*.[84] The method works by estimating coefficient for each feature in the model. These coefficients indicate the magnitude impact that the particular feature has on the dependent variable. Coefficients are calculated by estimating the *change in the mean response per unit increase in 'x' when all other predictors are held constant.*[85]

$$y_{it} = \alpha + \beta x_{it} + \cdots + \beta n_{it} + \varepsilon_{it}$$

Equation 4: Example Pooled Line Model

The figure above shows an example of panel model. Where y_{it} is a function of an intercept α, and features βx_{it} to βn_{it} plus error term ε_{it}. With the coefficient β indicating the impact

[83] Mishra, Madhav. "Understanding Panel Data Regression." Medium, Towards Data Science, 18 June 2018, https://towardsdatascience.com/understanding-panel-data-regression-c24cd6c5151e

[84] IBID

[85] "What Is a Regression Coefficient?" Minitab Express, https://support.minitab.com/en-us/minitab-express/1/help-and-how-to/modeling-statistics/regression/supporting-topics/regression-models/what-is-a-regression-coefficient/.

x_{it} has on y_{it} holding all other feature constant. Below are the theoretical and CAS model specifications for the pooled linear model.

Theoretical Model PLM

$$\begin{aligned} &Intrastate\ Violence_{it} \\ &\qquad = \alpha + \beta GovernemntBetwenness_{it} + \beta OppositionBetwenness_{it} + \beta Parity_{it} \\ &\qquad + \beta Satisfaction_{it} + \varepsilon_{it} \end{aligned}$$

Complex Adaptive Systems model PLM

$$\begin{aligned} &Intrastate\ Violence_{it} \\ &\qquad = \alpha + \beta GovernemntBetwenness_{it} + \beta OppositionBetwenness_{it} + \beta Parity_{it} \\ &\qquad + \beta Satisfaction_{it} + \beta Satisfaction\ II_{it} + \beta Protests_{it} + \beta Demands_{it} \\ &\qquad + \beta Rebel\ Degree\ In_{it} + \beta Russia\ Material\ Cooperation\ to\ Government_{it} \\ &\qquad + \beta USA\ Material\ Cooperation\ to\ Rebels_{it} \\ &\qquad + \beta Threathen\ Actions\ from\ Government_{it} + \varepsilon_{it} \end{aligned}$$

Equation 5: Theory and CAS PLM Specifications

The equations above are meant to represent the theoretical and CAS model specifications for the pooled panel models. A portion of this research is dedicated to operationalizing and testing the feasibility of network metrics as alternative measures to the ones originally specified. As well as test the added explanatory power of CAS features. The PLM should provide evidence to answer these initial inquires. The next portion will review prediction methods.

Classification and Regression Trees (CRTs)

The first method to test prediction fidelity of two different model specifications is classification and regression trees. This is a recursive partitioning method that can be used for both continuous dependent variables as well as categorical dependent variables, which can allow us the extensibility to test level of violence and probability of occurrence (Breiman, Friedman, Olshen, & Stone, 1984). It aids in addressing issues when attempting to predict categorical dependent variables using continuous independent variables, as is the case with the research presented here. For the purpose of prediction categorical dependent variable will be forecasted using continuous independent variables. It essentially creates if-then statements based on sophisticated parsing of the data to yield accurate predictions. It also provides distinct advantages in that trees are simple and can yield much more manageable understanding of the classifying factors. Below is a simple example to illustrate a sample CRT output and how the algorithm produces it.

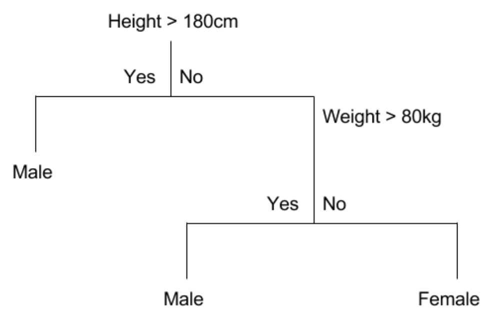

Figure 13: Example CRT

This is a tree produced from a binary dependent variable, in this case male or female, with the features being height and weight. Root nodes are the features and split points of the variable, x, while leafs are the output or y.[86] In the above example if height is greater then 180cm then the observation is classified as male. The algorithm makes these splits in the feature by *dividing the input space*.[87] The approach employs a 'greedy' technique, which uses *recursive binary splitting.*[88] To perform this, the algorithm uses a *numerical procedure where all the values are lined up and different split points are tried and tested using a cost function.*[89] The model will then optimize the splits to produce the lowest costs. The cost function is measured is

[86] Brownlee, Jason. "Classification And Regression Trees for Machine Learning." Machine Learning Mastery, 20 Sept. 2017, https://machinelearningmastery.com/classification-and-regression-trees-for-machine-learning/.
[87] IBID
[88] IBID
[89] IBID

measured by how 'pure' the classifier is, meaning how well does that split point of that feature capture the difference in the dependent variable.

$$G = \Sigma\big(pk * (1 - pk)\big)$$

Equation 6: Gini Index Function

G represent the over all gini index for all classes, and pk are *the proportion of training instances with class k in the rectangle of interest.*[90] The most 'pure' classifier has index of 0 while the worse has a value of 0.5 meaning it is no better then 50-50 at classification.[91] Two CRTs model specifications are below, one for the theory model and one for the CAS version.

Theoretical CRT Model

$$Intrastate\ Violence\ Dummy_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it}, Satisfaction_{it})$$

Complex Adaptive Systems CRT Model

$$Intrastate\ Violence\ Dummy_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it},\ Satisfaction_{it}, SatisfactionII_{it},\ Rebel\ Protests_{it}, Rebel\ Demands_{it},\ Rebel\ Degree\ in_{it}, Russian\ Material\ Cooperation\ to\ Government_{\ it}, USA\ Material\ Cooperaton\ to\ Rebels_{it},\ Threathen\ Actions\ From\ Government_{it})$$

Equation 7: Theory and CAS CRT Models

Both of the above models will be implemented in prediction trials using the CRTs method to see if the extension provides added improvement forecasting or if simply the theory driven model is more appropriate.

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[90] IBID
[91] IBID

Random Forest

The second machine learning method that will be implemented for prediction is random forest, which is an ensemble learning method for classification, and will be used to boost accuracy of predictions. It works by creating a multitude of decision trees and creating classes of mean predictions for each of the individual decision trees.[92] [93] These individual tress are trained on random subsamples of the data - greatly aiding prediction accuracy as well as ranking variable importance in a natural way.[94] Further, random forests address some flaws in singular decision trees such as over fitting to training dataset and reducing variance.[95] It may further improve upon the CRTs method by addressing issues posed with singletree methods, but at the expense of computational time. Interestingly the underlying algorithm for each tree uses the same logic as the CRT however the main difference is obviously the amount of trees and how predictions of each tree are then aggregated to produce potentially higher accuracy models. As these models are highly similar at an algorithm level it is important to emphasize where they diverge.

While the CRTs are still useful for predictions, random forest addresses some key issues. Over fitting may occur when using a single tree because, without limits, the tree will keep expanding until in perfectly classifies each observation. They issue with this is that the algorithm learns both true values as well as error.[96] To fix this, limits are set as to the depth

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[92] Ho, Tin Kam (1995). Random Decision Forests (PDF). Proceedings of the 3rd International Conference on Document Analysis and Recognition, Montreal, QC, 14–16 August 1995. pp. 278–282.

[93] Ho TK (1998). "The Random Subspace Method for Constructing Decision Forests"(PDF). *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 20 (8): 832–844. doi:10.1109/34.709601

[94] Liaw A (16 October 2012). "Documentation for R package randomForest" (PDF). Retrieved 15 March 2013.

[95] Hastie, Trevor; Tibshirani, Robert; Friedman, Jerome (2008). The Elements of Statistical Learning (2nd ed.). Springer. ISBN 0-387-95284-5.

[96] Koehrsen, Will. "An Implementation and Explanation of the Random Forest in Python." Medium, Towards Data Science, 31 Aug. 2018, https://towardsdatascience.com/an-implementation-and-explanation-of-the-random-forest-in-python-77bf308a9b76.

the tree can split however this then introduces more issues increasing the bias for reduced variance.[97] To address the issue of over fitting or high bias is to create a multitude of trees and combine the different trees into a single ensemble model or random forest. To prevent each tree from producing the same outputs bagging randomly selects each training set X = $x_1, ..., x_n$ with responses Y = $y_1, ..., y_n$, bagging repeatedly for b = 1, ..., B, that will used to train each one of the separate trees.[98] To aggregate estimates from each tree the random forest uses a bootstrap aggregating or bagging technique on tree learners following the below formula:

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b(x')$$

Equation 8: Ensemble Procedure

After all trees are trained, predictions are made on the testing set or unseen values is performed by averaging all the individual regression trees on *x'*.[99] This method results decreasing the variance in each model with not increasing the bias resolving issues from single trees. The figure below provides a visual representation of the CRT versus random forest and why potentially the accuracy is higher.

As seen in the figure below the line in the left plot demonstrates the added accuracy when leveraging more trees to partition the data. Compared with the right plot that makes one cut through the data. Being able to aggregate estimate from multiple different trees aids in better dependent variable classifications, not increasing bias.

[97] IBID
[98] Breiman, Leo (September 1994). "Bagging Predictors" (PDF). Department of Statistics, University of California Berkeley. Technical Report No. 421. Retrieved 2019-07-28.
[99] IBID

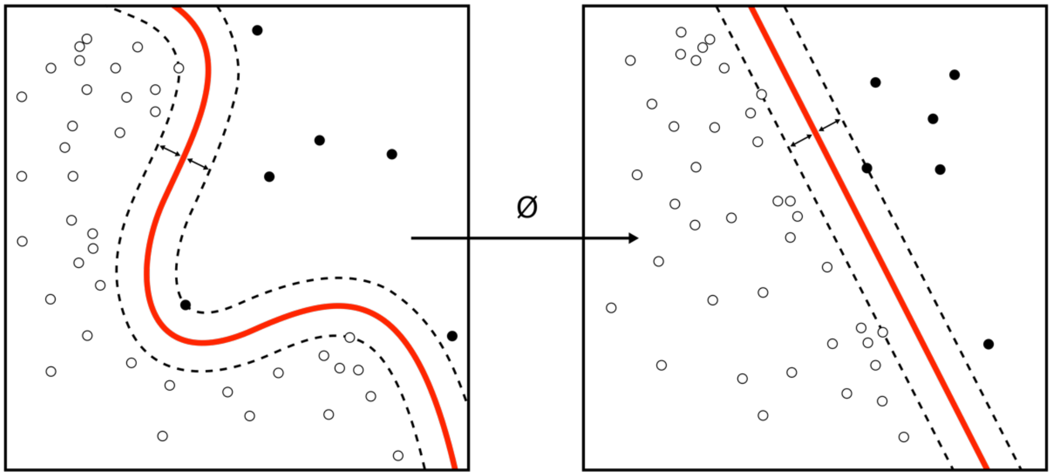

Figure 14: Separation Plots Random Forest and CRT, source: Alisneaky

Like the CRTs method, both of the below models will be implemented using the random forest method. This meant to compare not only the theory informed model with the extended CAS model but a compare the different machine learning methods as well.

Theoretical Random Forest Model

$$Intrastate\ Violence\ Dummy_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it}, Satisfaction_{it})$$

Complex Adaptive Systems Random Forest Model

$$Intrastate\ Violence\ Dummy_{it} = f(Governemnt\ Power_{it}, Opposition\ Power_{it}, Parity_{it},\ Satisfaction_{it}, SatisfactionII_{it},\ Rebel\ Protests_{it}, Rebel\ Demands_{it},\ Rebel\ Degree\ in_{it}, Russian\ Material\ Cooperation\ to\ Government_{\ it}, USA\ Material\ Cooperaton\ to\ Rebels_{it},\ Threathen\ Actions\ From\ Government_{it})$$

Equation 9: Theory and CAS Random Forest Model

Chapter 04

Exploratory Data Analysis

A vital aspect of this research centers on exploring and determining viable instruments for the critical theory variables, parity and satisfaction as well as CAS variables used to capture the different levels of analysis. In the following section, exploratory data analysis (EDA) will be performed on the dependent variable and independent variables in order to; examine balance, inspect data for completion and accuracy, extract insights before statistical analysis and refine measurements for modeling. Generally EDA is performed to understand underlying relations between data and find out key characteristics that often aid the specification of statistical models. For the purposes of this research EDA will focus on ensuring data was aggregated and parsed at a provincial level and at a monthly frequency, the dependent and independent variables were correctly extracted, decide on any transformations and begin to uncover the relations between variables. EDA will be guided by the initial model specifications, beginning by understanding each variable series individually before inspecting how they relate. Variables below will be displayed first by single province level to inspect detail and then a plot for all provinces to show variation between them, highlighting data heterogeneity.

The data used in this research is unique, as GDELT data gathering capabilities allow for highly granular data neither readily available nor viable in 1998. The benefits of such an approach allows for the decomposition of data into more distinct observations revealing heterogeneity between provinces, areas, and features. With past structural variables, data was typically collected at the nation level on a yearly basis. However, complexity tells us that each component of the aggregate has dissimilar qualities that need to be understood in order to better understand the whole. Further, not all parts of a system or state experience phenomena equally. Often it can be an isolated occurrence or possess contagion effects that cannot be captured with monolithic techniques. With the methods employed by GDELT those once hidden features of intrastate conflict are uncovered due data collected on highly granular and frequent basis. Thus Syria and conflicts in general can be scrutinized not as a whole but by province. The increased frequency will allow precise measurement of the evolution of the conflict and its determinants.

General Review

Before moving to visualization general inspection of the data is prudent. It is important to do this to avoid errors later in modeling. Below is general descriptive statistics for the dependent variable and independent variables. The independent variables are normalized in the plot below. There was large variance in values within each feature and among the different provinces so in order to compare them and model correctly, a normalization procedure we used. All IVs are scaled between 0 and 1. The DV has a range from no conflict to a high of 779. Generally the averages of most of the variables are relatively low with the exception of both satisfaction measures indicating a general presence some level of satisfaction perhaps in the prewar period.

	Intrastate Conflict	Government Power	Rebel Power	Rebel Satisfaction	Parity	Civilian Satisfaction
Min.	0	0	0	0	0	0
1st Quarter	0	0	0	0.8506	0	0.77
Median	0	0	0	0.8506	0	0.77
Mean	17.97	0.078	0.074	0.845	0.005	0.76
3rd Quarter	11	0.081	0.092	0.8512	0	0.77
Max	779	1	1	1	1	1
	Protests	Demands	Rebel Degree In	Russia Cooperation	USA Cooperation	Threaten Actions
Min.	0	0	0	0	0	0
1st Quarter	0	0	0	0	0	0
Median	0	0	0.02	0	0	0.002
Mean	0.02	0.01	0.04	0.015	0.017	0.02
3rd Quarter	0.01	0.004	0.05	0	0	0.01
Max	1	1	1	1	1	1

Figure 15: Descriptive Statistics

In terms of the data structure, the coverage is from 2007 – 2017 (11 years) for 14 provinces meaning there will be 1848 total observations in the data. Due the nature of GDELT event data there will be no missing data.

Years	Provinces	Observations	Completion
2007 – 2017, monthly	14	1848	no missing data

Figure 16: Data Structure

The correlation plot below visualizes the relationship between two variables values showing how they vary in relation one another. It is important to also check to make sure there is some relation exists between the independent variables and the dependent variable and that the independent variables are not too highly correlated amongst themselves.

The plot is encouraging from the a modeling perspective as most of the independent variables have a descent level of correlation with the dependent variable and seem to exhibit trends consistent with theory. Both satisfaction measures are negatively correlated with intrastate conflict meaning that as satisfaction goes up conflict goes down. While the power and parity measures are positively correlated, suggesting that as power and parity increase so does conflict.

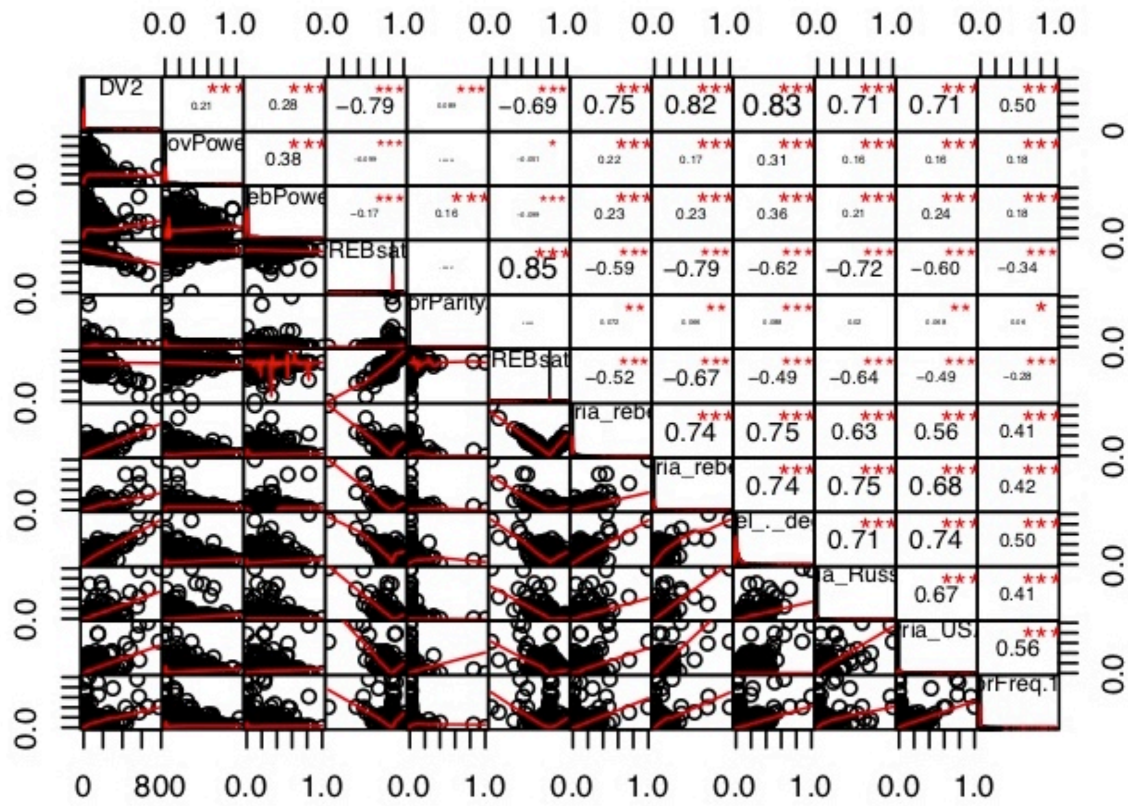

Figure 17: Correlation Matrix

Further, the independent variables are not too highly correlated amongst each other so using them in a model should pose no issues from a correlation perspective.

Dependent Variable

The phenomenon of interest, intrastate conflict, has generally been measured by frequency, severity, duration or occurrence (through use of a binary variable). For the purposes of following the original model specification from Benson & Kugler 1998, the Pooled Linear Model (PLM) will use a dependent variable measured by the number of the event 'fight' between Government and Rebel forces from the GDELT database. Fight is defined by GDELT as the *use of conventional force…by organized groups,* which accurately characterizes the Syrian conflict – representing the highest level of conflict. On one side Bashar al-Assad and his military and the on the other a disparate yet united bands of rebel fighters vying for political representation. For the purposes of the Classification and Regression Trees (CRTs) and the Random Forest (RF) methods the frequency series will be converted into a binary classification 0,1 with 0 indicating no conflict and 1 indicating conflict that will be used as the target for prediction. This transformation is necessary, as the methods employed require a dependent variable with classes.

Aleppo will be isolated and a few key points will be highlighted in order to ensure measurement validity. The plot below is intrastate conflict in Aleppo, a province hit particularly hard by the conflict.

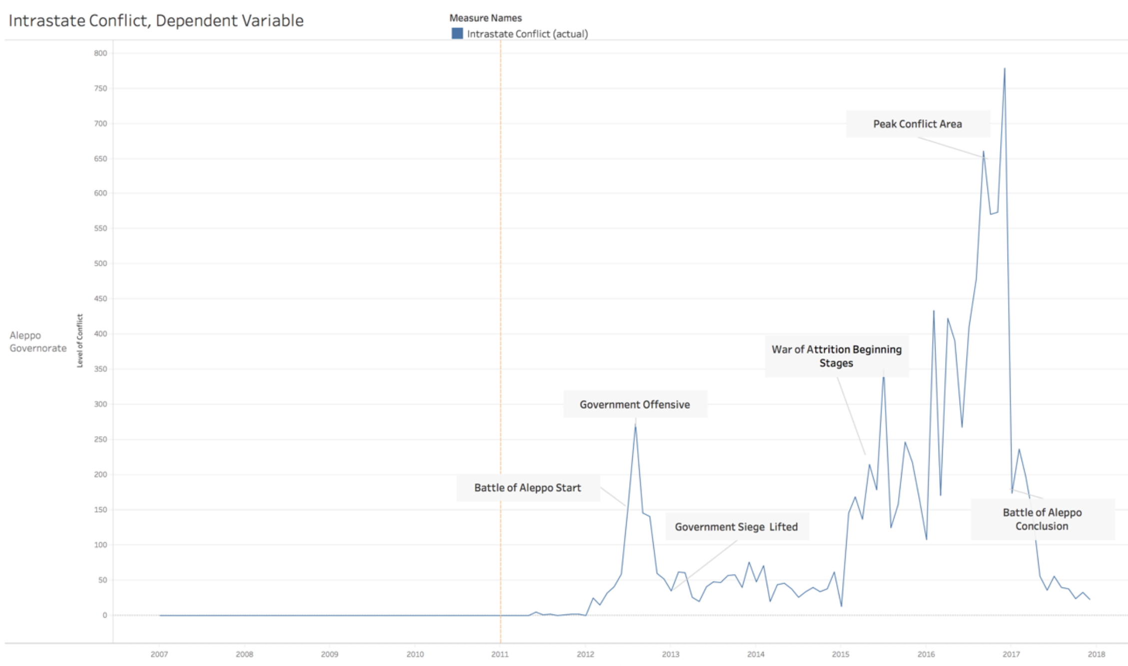

Figure 18: Time Series Plot of Intrastate Conflict in Aleppo, Monthly (conflict initiation indicated by line)

The first critical point highlighted is July 2012, which marks the initiation of the Battle of Aleppo, where government forces began attempts to quash FSA rebellion efforts.[100] Shortly after, in August 2012, rebel forces seized Anadan, a strategic checkpoint connecting Aleppo

[100] "Syria Conflict: What's Been Happening in Aleppo? - CBBC Newsround." BBC News, BBC, https://www.bbc.co.uk/newsround/38303230.

with Turkey and Al-bab, an army base.[101] The Syrian government responded by intensifying efforts in the city as seen by the spike in conflict frequency in August 2012. However, due to early success in exchanges with the government, the Rebel movement was not stopped and the initial siege ended 2013. The Government forces began to take a different approach and encircled the city through the year of 2014, keeping fighting intensity to low level skirmishes. In 2015 the 'war of attrition' began with the Syrian Government reigniting efforts to take back the city.[102] With the rebels entrenched and the government facing potential loss of the city, prolonged and intense exchanges ensued. Government forces resorted to extreme and brutal shelling, loss of life was significant. Eventually the Syrian Government achieved victory, although tenuous, in December 2016.[103] Evacuations were complete and open conflict was concluded in early 2017. The series above correctly reflects the fighting and intensity of conflict in Aleppo. Below are conflict plots for the rest of the provinces.

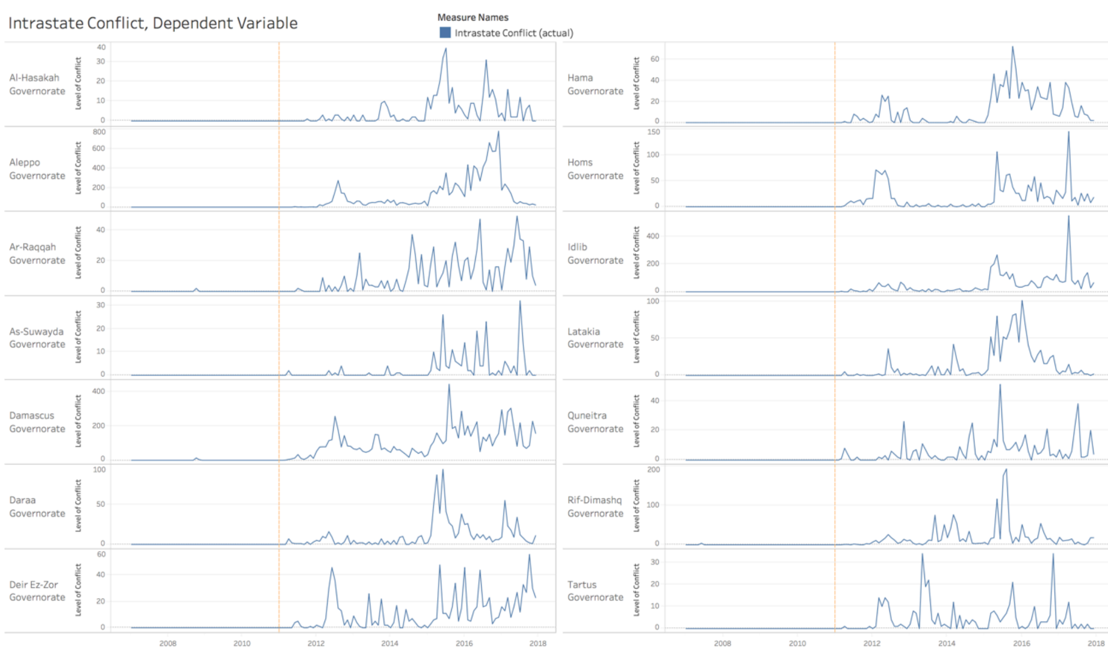

Figure 19: Time Series Plot of Intrastate Conflict by Province, Monthly (conflict initiation indicated by line)

[101] Solomon, Erika (31 July 2012). "Syrian army pounds Aleppo, rebels claim successes". Reuters. Retrieved 2 November 2012.
[102] "Syria regime forces launch new Aleppo offensive". *Mail Online*. Retrieved 18 March 2015.
[103] "Syrian army announces victory in Aleppo in boost for Assad". Reuters. 22 December 2016.

Above is a times series plot of intrastate conflict by province, monthly. Please note each sub element has an independent y-axis. As seen in the plots below, the data accurately suggests Syria was relatively peaceful and stable from 2007 to around early 2011(orange line) when the civil conflict began to take shape. Right away it can be gleaned that the conflict did not hit all parts of the country equally nor did the conflict manifest with the same trajectories in in each province. Provinces like Aleppo and Tartus have experienced much different levels of conflict, with the former having experiencing more severe fighting. Deir Ez-Zor and Daraa show how the conflict can manifest and evolve in much different ways – in Daraa it seems to cycle from skirmish to high intensity while in Deir Ez-Zor experienced a constant moderate level of conflict from initiation.

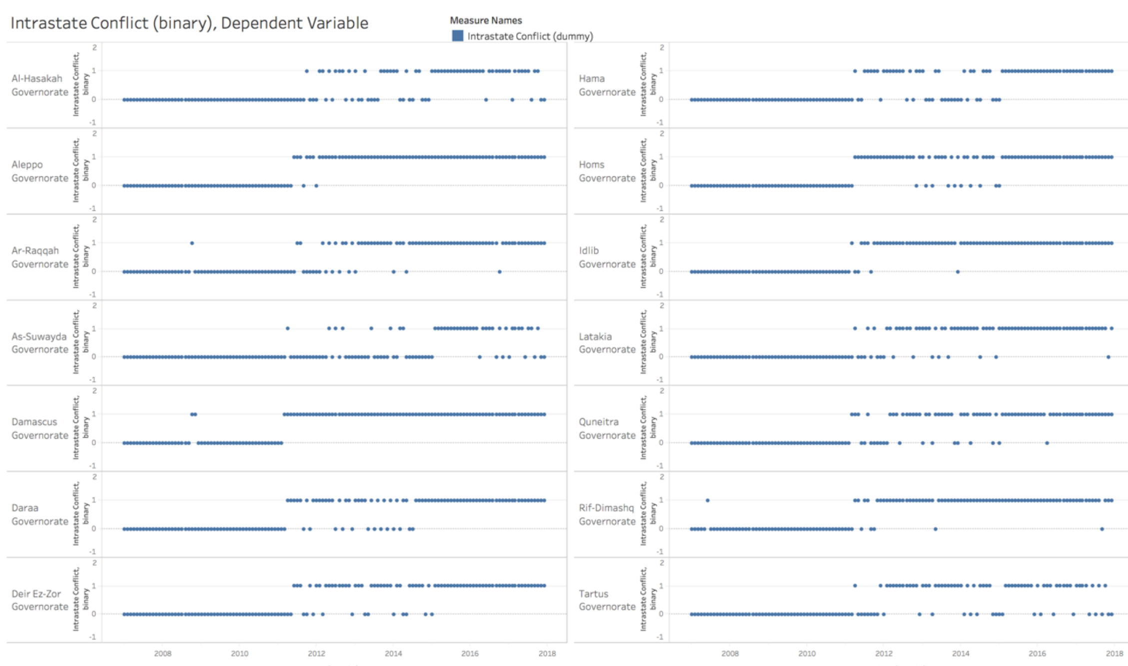

Figure 20: Time Series Plot of Intrastate Conflict in Aleppo, Monthly (binary)

For verification and visualization purposes, a plot of the binary DV is below. For reference, 0 represents no conflict and 1 represents the occurrence of conflict. The below plot can also be used to inspect the balance of the data. Balance refers to the proportion of 0 to 1. Models perform better when data is balanced and looking at the plot above the binary dependent variable exhibits a sufficient level balance to avoid problems modeling. After examination of other provinces it can be concluded that the measure derived from GDELT can serve as a measure of intrastate conflict for the purposes of this research.

Independent Variables

The independent variables are derived from raw GDELT signals as well, matching the granularity and frequency of the dependent variable. First, theoretical model independent variables will be reviewed, as they are the basis for all modeling. After which CAS extension variables will be examined. To review, theoretical model independent variables include; government power, rebel power, parity and satisfaction. The CAS model extension adds; an alternative measure of satisfaction, frequency of rebel protests, frequency of rebel demands, rebel degree in, Russian material cooperation towards Government, USA material cooperation towards Rebels, and frequency of threatening government actions. As a general note, to make measures comparable and remove variance in the different variables data ranges, measurements are normalized. Government power, rebel power and parity provide a portion of the structural variables used as explanatory variables in the theoretical model.

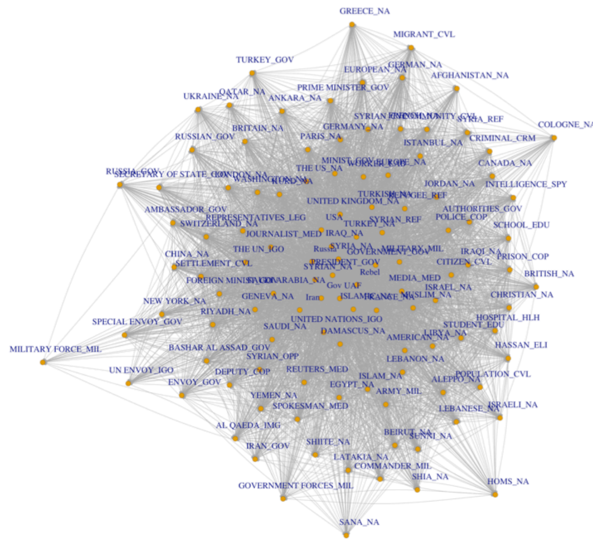

Figure 21: Sample Network, Syria 01 JAN 2016

As mentioned in the methodology section, social network analysis (SNA) was used to create the measure of government betweenness, rebel betweenness serving as the instruments of government power and rebel power. Parity is simply rebel power divided by government power. For reference, a cross–sectional network is above. The actors closer to the center of the network have more power. So in the plot above government and rebels as well as the US and Russia hold much of the power in the system. Considering the time in the conflict, this accurately reflects the hierarchy. The figure below shows plots of government and rebel power over time in Aleppo.

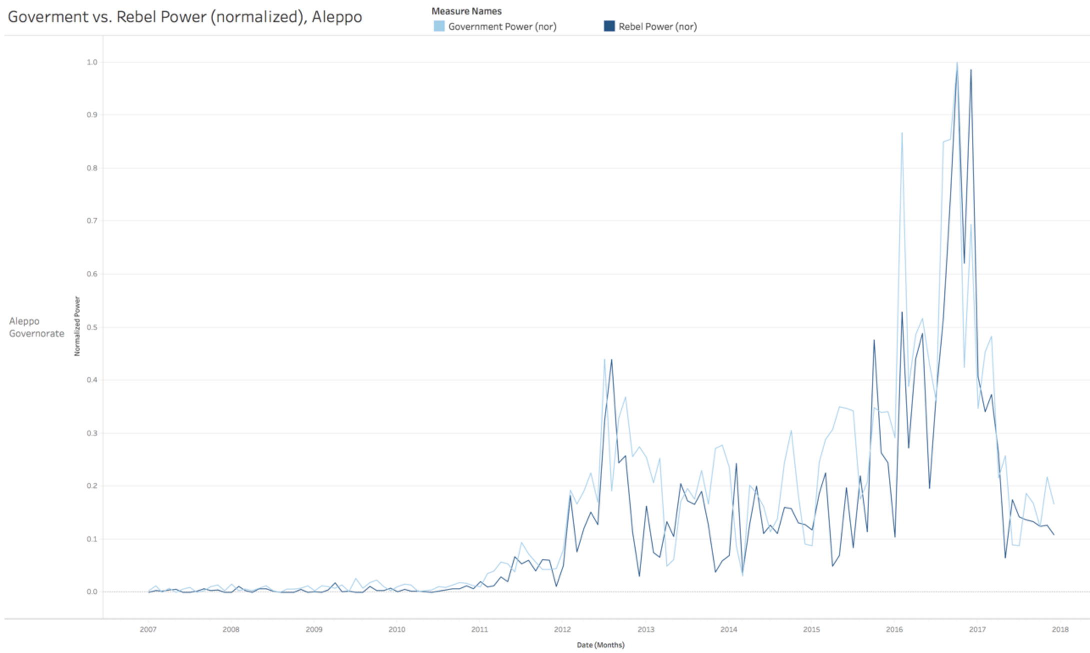

Figure 22: Time Series Plot of Government and Rebel Power in Aleppo, Monthly

The plot above shows that in general, rebel and government power were relatively equal in the months leading up kinetic exchanges. Mirroring the conflict plot about it can be noticed the 'war of attrition' occurs during the period of highest power and parity – suggesting a relation specified in theory. Below are plot for all provinces.

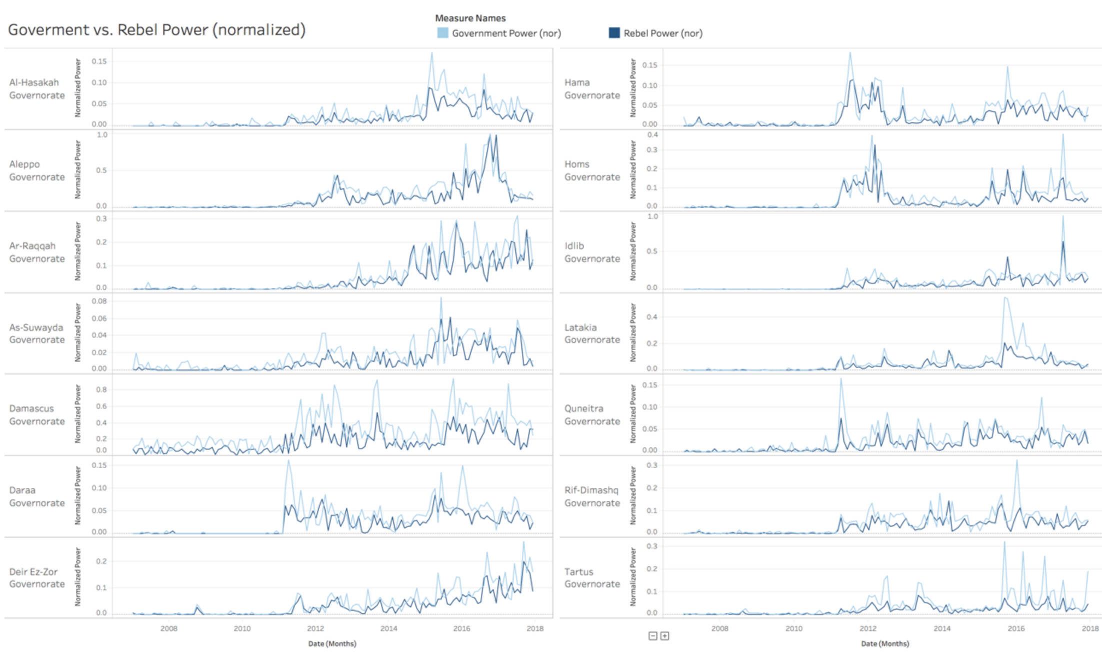

Figure 23: Time Series Plot of Government and Rebel Power, Monthly (conflict initiation indicated by line)

The benefit of deriving power from network measures is that changes in levels can be detected as combatant's increases and decrease presence in territories as the conflict progresses. As noticed some provinces have a much more prominent rebel presence like Aleppo while in Tartus, government has much more power. These measures will serve as government and rebel power in the model.

Taking the ratio of rebel to government power, parity indicates a potential for conflict as rebel groups have garnered enough power to challenge the government. It is one of the structural preconditions for conflict. Below is a figure with parity plotted for Aleppo.

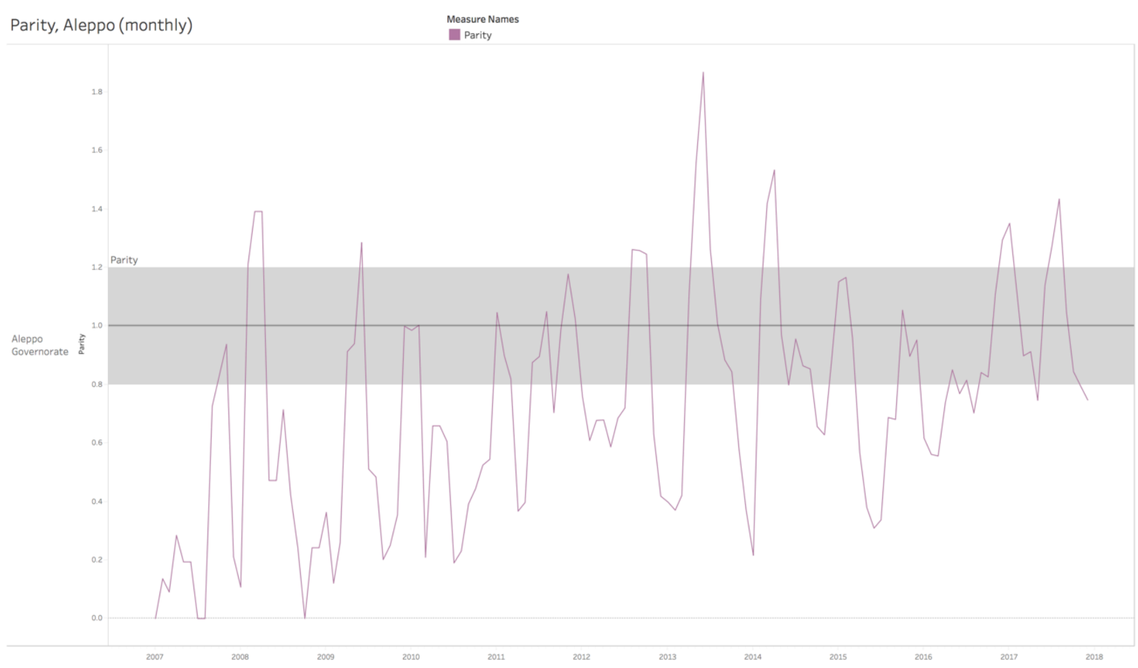

Figure 24: Time Series Plot of Government and Rebel Parity in Aleppo, Monthly

The above graphs reflect the general parity of power measures seen in the previous plot. In general in the province of Aleppo, government and rebel were generally at parity preceding conflict. Once again during the duration of the 'war of attrition' parity is present and at time

Rebels dominate. With such high levels it is reasonable to see sustained conflict during this time. Below are parity plots for all provinces.

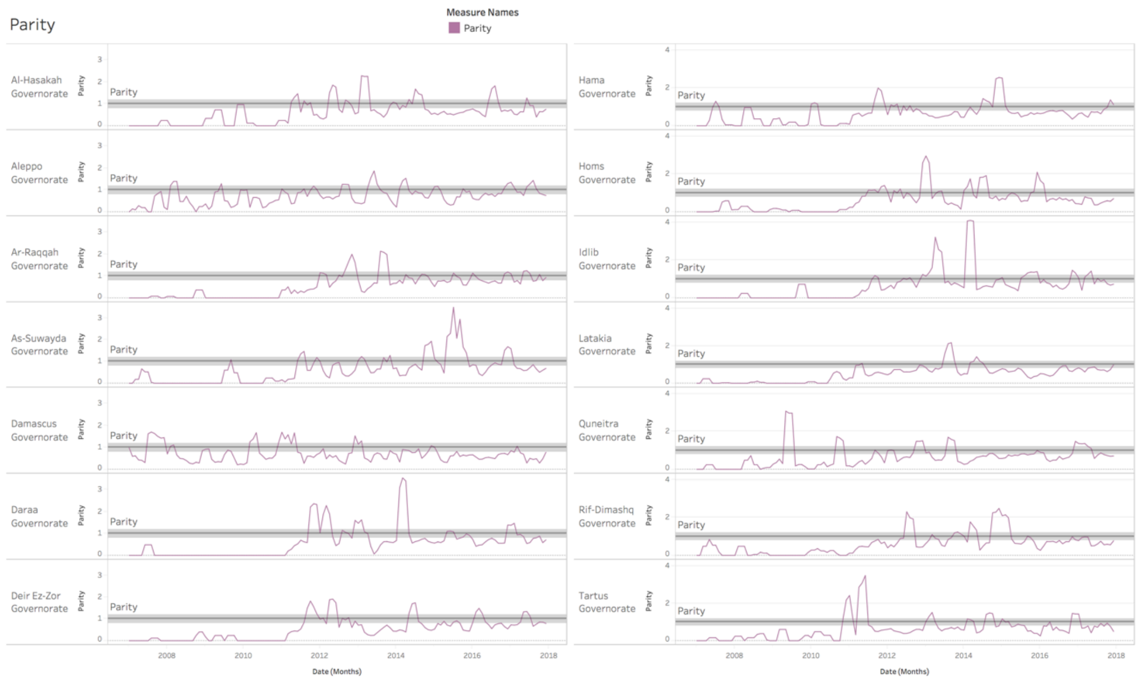

Figure 25: Time Series Plot of Parity, Monthly (parity indicated by line)

The line on the plot above is parity for reference. As noticed in many instances the rebel forces are at or above parity with government at multiple times through out the conflict. Generally however parity was achieved before the conflict began in most provinces. The parity measure is highly dynamic as it is a direct reflection of changes in the underlying network structure. So at times forces are at parity and at others, one dominates the others.

The last component of the theoretical model specification is satisfaction, taken as measure average tone of public statement made by rebel groups. The plot below is satisfaction for Aleppo monthly.

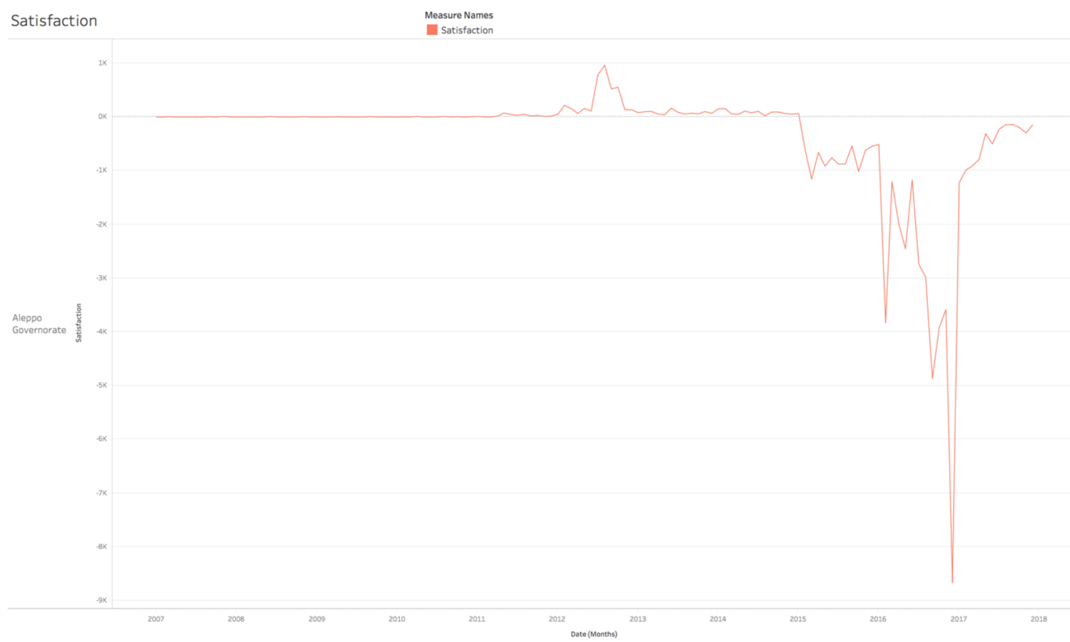

Figure 26: Time Series Plot of Rebel Satisfaction in Aleppo, Monthly

The plot above displays an obvious trend; there is a dramatic decrease in satisfaction as the conflict escalates to its highest levels. Further there was almost no discernable level of the satisfaction or dissatisfaction in the months preceding. Below are satisfaction plots for all provinces.

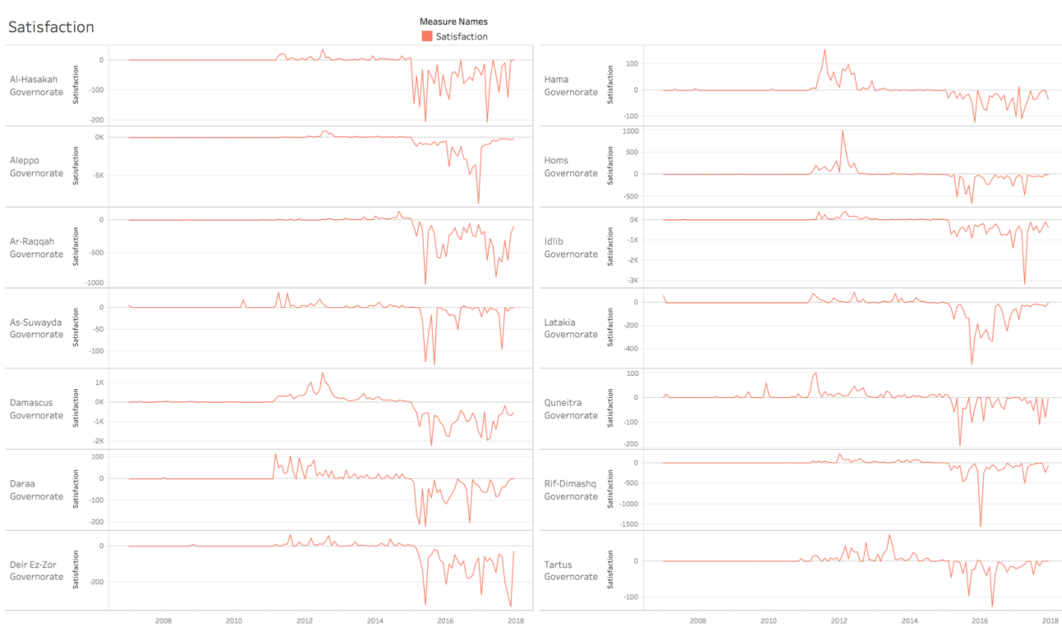

Figure 27: Time Series Plot of Satisfaction, Monthly

Generally before the conflict began some provinces showed satisfaction albeit minimally. The plot suggests that will the low level of satisfaction value before the conflict there were already seeds of discontent. As the series progresses there is a sharp down turn in dissatisfaction. This measure is designed in a way that reflects general dissatisfaction not a dyadic one so it's more reflective of satisfaction of rebel groups regarding the SQ. In the CAS extension, an alternative measure of satisfaction, focusing on civilian satisfaction, will be included. Due to the high variances in satisfaction levels between provinces, satisfaction will be normalized. Normalized plots of both measures of satisfaction are in the figure below.

After normalization stark differences between the provinces emerge. It is clear that not all parts of the country were equally dissatisfied. Some parts remained loyal to the Alowhite regime while other, were direct opposition. The provinces Aleppo and Idlib have the most drastic measures of dissatisfaction in the country, they are also the places where fighting was most intense.

Figure 28: Time Series Plot of Satisfaction (normalized, both measures), Monthly

The core measures paint quite an intriguing picture when plotted together and give preliminary understanding of the underlying relations that will be tested in subsequent sections. Below is a plot of parity, satisfaction and intrastate conflict in Aleppo.

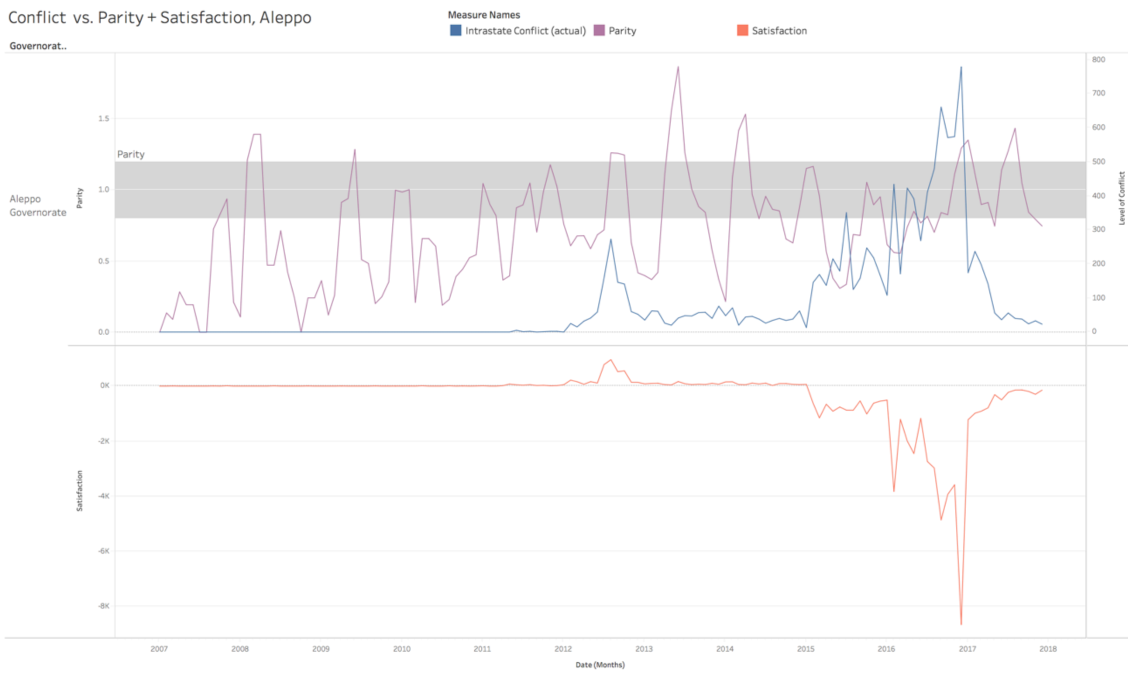

Figure 29: Time Series Plot of Conflict, Parity and Rebel Satisfaction in Aleppo, Monthly

Once the theoretical features are layered together an interesting story emerges. Rebel presence begins to emerge and fade in the years preceding the conflict while consistent mobilization occurred closer to conflict onset. The bump is satisfaction is a reflection of the initial rebel victories during earlier phases but as the government encircling begins and the 'war of attrition' starts, satisfaction plummets. This also coincides with consistent parity leading to the highest levels of conflict. As the government regains control satisfaction begins normalize as rebel are driven out, captured or perish. Below are plots of conflict parity and satisfaction in all provinces.

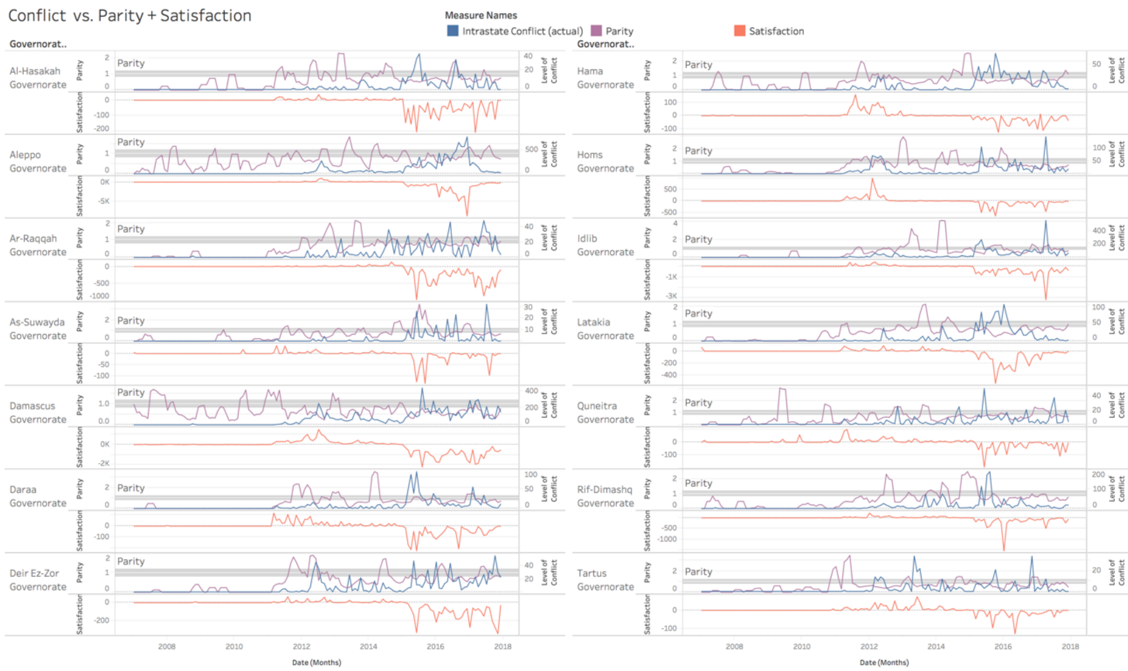

Figure 30: Time Series Plot of Parity, Satisfaction & Intrastate Conflict, Monthly

In the figure above it is important to note the increases in parity and decreases in satisfaction are directly correlated with higher levels of violence. Further focusing on parity and conflict, generally parity was achieved before conflict erupted. For example, in Aleppo parity was reached prior to conflict initiation. Further the highest bouts of conflict occur in provinces with the highest dissatisfaction. For example in Ar-Raqqah, were satisfaction is severely low preceding a portion of higher-level violence a trend prominent through the country.

The above features represent the independent variable set that will be used for the theoretical model specification using a pooled linear model, while lagged version of these values will be used for prediction the CRT and RF theory models. The CAS model will extent upon this and introduce additional variables meant to capture different levels of analysis. In the flowing section CAS variables will be explored.

Complex Adaptive System Variables (extension)

The additional CAS measures are meant to examine the remaining levels of analysis. While the theoretical models represent the macro level, the CAS model will utilize meso and micro-meso features to potentially add to both the explanatory and predictive power. Additional variables include; amount of rebel protests and demand events, rebel degree in, Russia and USA material cooperation, and threatening actions from government (civilian satisfaction reviewed above). Below is a plot rebel protests and demands in Aleppo.

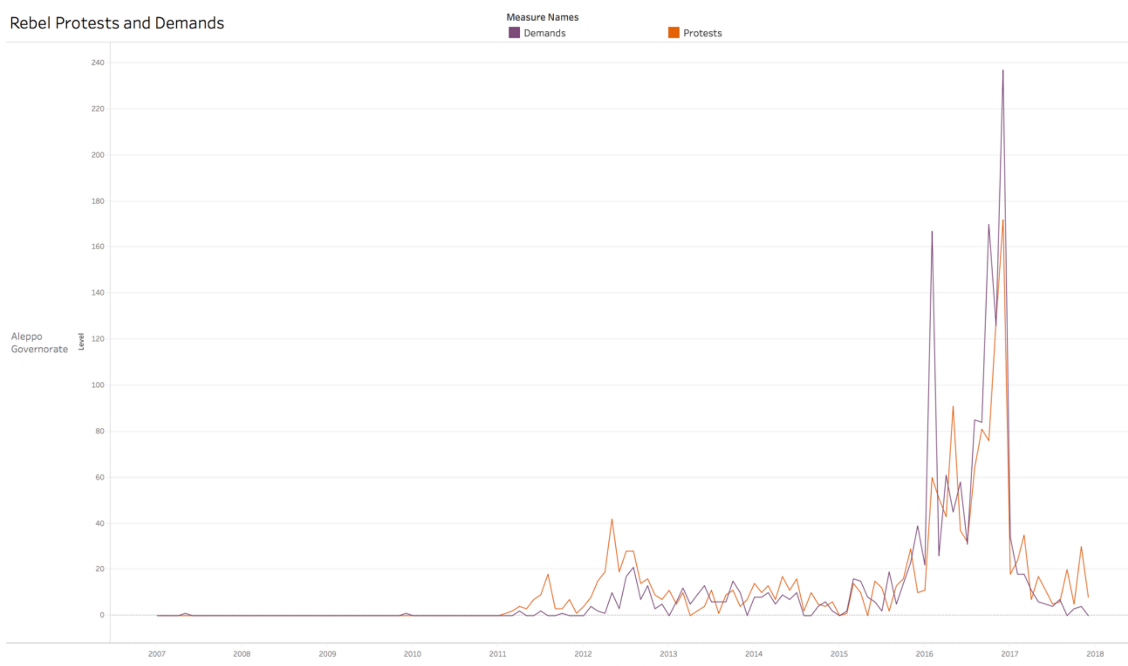

Figure 31: Time Series Plot of Rebel Protests and Demands in Aleppo, Monthly

A critical instigator of conflict in general and in Syria particularly, is rising popular dissent and lack of accommodation by government. In Aleppo it is clear that rebels were politically motivated. Their demand for political representation and protests against government oppression is prevalent. With such high levels opposition to the government present, it is no wonder Rebels had early success and why Aleppo was a target of government forces. Below are plots for protests and demands for all provinces.

For Syria, rebel and civilian groups were demanding more political representation and protesting harsh government crack downs. As described in an earlier chapter, the Syrian government was notorious for quashing dissent and demands for political representation violently. The ruling minority was keen to keep power insulated.

Figure 32: Time Series Plot of Rebel Protests and Demands, Monthly

As seen in the plot above, dissent was not prevalent in all provinces. The Alowhite regime did enjoy some support in pockets albeit minimally. Provinces with higher levels of dissent exhibited differences in duration and sustainment of protests and demand efforts. Provinces like Deir Ez-Zor shows sustained anti-government presence. Like Aleppo, this is perhaps why government and Russian forces focused on Deir Ez-Zor.

These higher-level protests and demands may be reflective of systematic targeting of rebels. To capture how the micro reaches the meso and produces events we will examine rebel degree in. This will track all events targeting rebel groups. This can give us insight as to why demands and protest may have been so high. Below is a plot of rebel degree in for Aleppo.

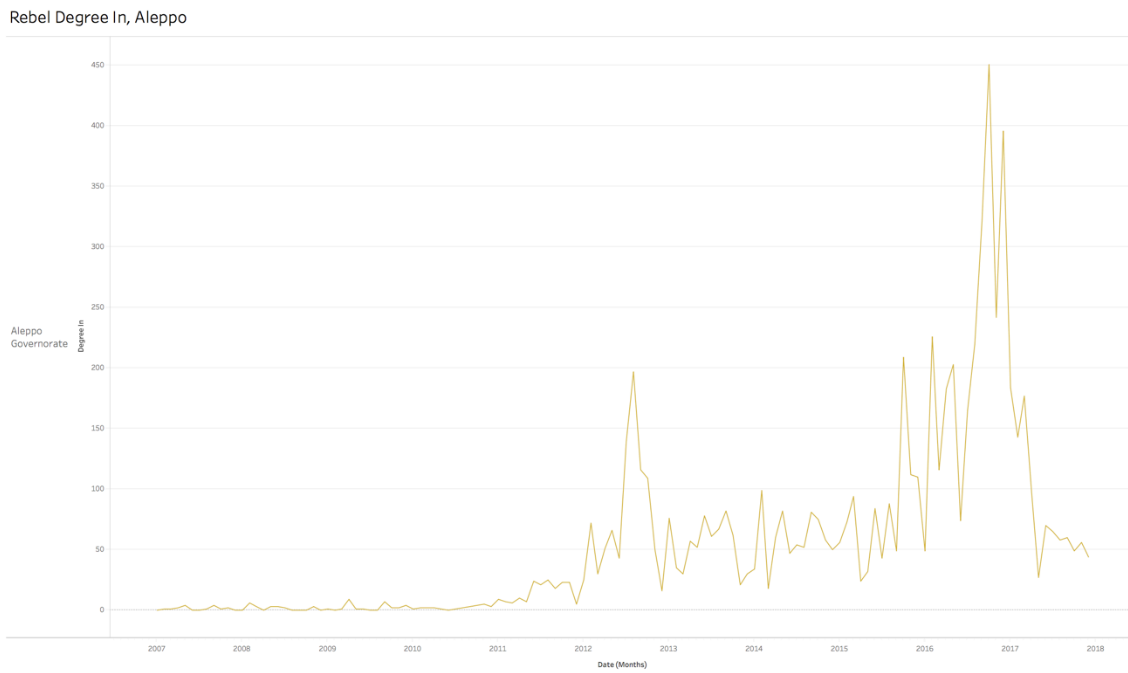

Figure 33: Time Series Plot of Rebel Degree In in Aleppo, Monthly

Preceding the conflict there is evidence that Rebel groups were targeted however initial efforts against them were relatively low level when compared to right before and during the conflict. These targeted action towards the rebel groups may have in turn spurred more demands and protests leading to more government crackdowns. It can be noted that once rebel groups effectively lost, targeted negative actions greatly diminish as rebels are disbanded. Below are plots of rebel degree in all provinces.

Figure 34: Time Series Plot of Rebel Protests and Demands, Monthly

The plot shows general provocation of rebel groups to a moderate degree preceding the conflict. Levels are higher in provinces that would eventually temporarily evade government control. Provinces also have highly disparate values between them indicating mixed tactics used against rebels. This is a key benefit of using network analysis and disaggregated data as the stark difference between provinces allowed a much different more nuanced picture to be painted. Deliberate targeting of rebel groups may eventually lead to conflict, whether it was to bolster them or destroy them. This insistent targeting may manifest to larger protests and demands – linking the micro to meso.

Intrastate conflict often brings in third parties to aid either government or opposition forces. In Syria, US and Russia were major contributors to rebel and government forces respectively. US support may have aided rebel groups in having a chance in combating the government. While Russian aid proved vital for crucial government victories. Below is a plot of such support in Aleppo.

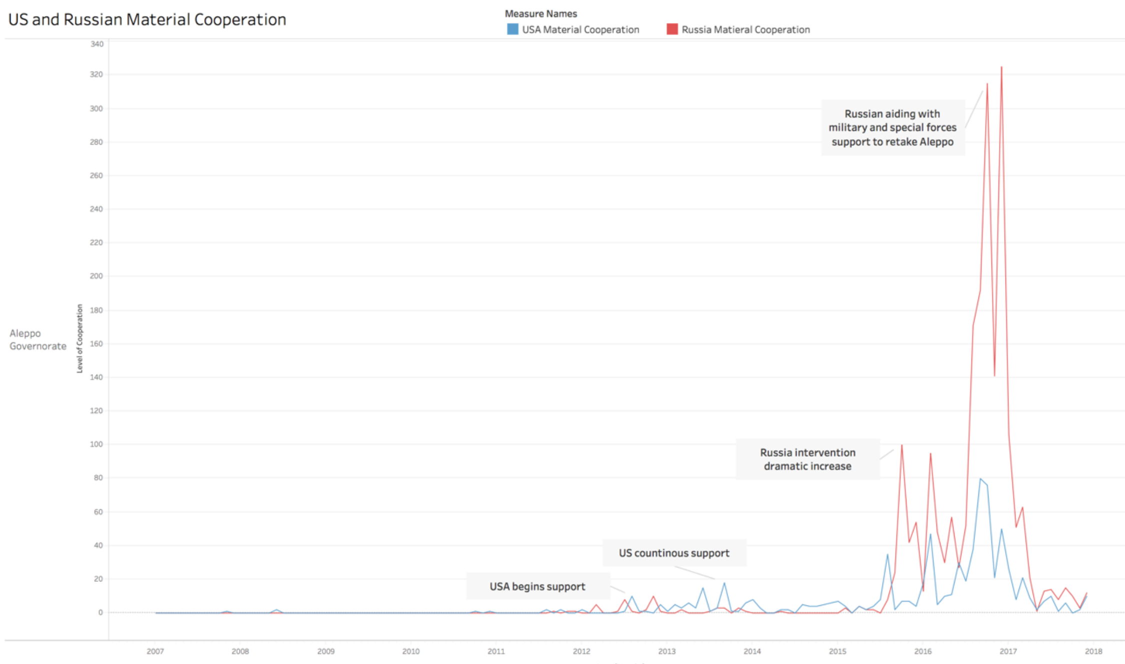

Figure 35: Time Series Plot of US and Russian Material Cooperation in Aleppo, Monthly

The plot above describes the influence of US and Russia cooperation with rebels and government forces respectively. As noticed in the plot US registers cooperation with rebels as early as 2012. It is reported that around this time US began to align themselves closer with particular rebel groups that they favored to oppose the Assad regime.[104] The US maintained this support during the early period of the engagement. This also coincided with rebel advances as seen in the conflict plot above. The initial high level of support gave rebels the upper as suggested by the data. However in 2015 Putin made it clear that the Russians were committed to the success of the Syrian government and increased supported significantly.[105] This provided the Syrian government decidedly more power. The US did not match Russian input increase and as seen Russia cooperation greatly out paced the US. With these new

[104] Schmitt, Eric (21 June 2012). "C.I.A. Said to Aid in Steering Arms to Syrian Opposition". *The New York Times*. Retrieved 4 July 2012.
[105] "Putin called the main task of the Russian military in Syria (in Russian)". Interfax. 11 October 2015.

resources the Syrian government was to go on the offensive. Russians began reinforcing Syria troops and deploying Special Forces during the siege.[106] Eventually the prolonged confrontation over Aleppo proved too much with the rebels. Without a significant injection of external aid conflict decreases. Rebels may have been able to maintain control if aid was more consistent, but the Russians and Syrian were resolute in there determination to take back the province. Below are plots for the remaining provinces.

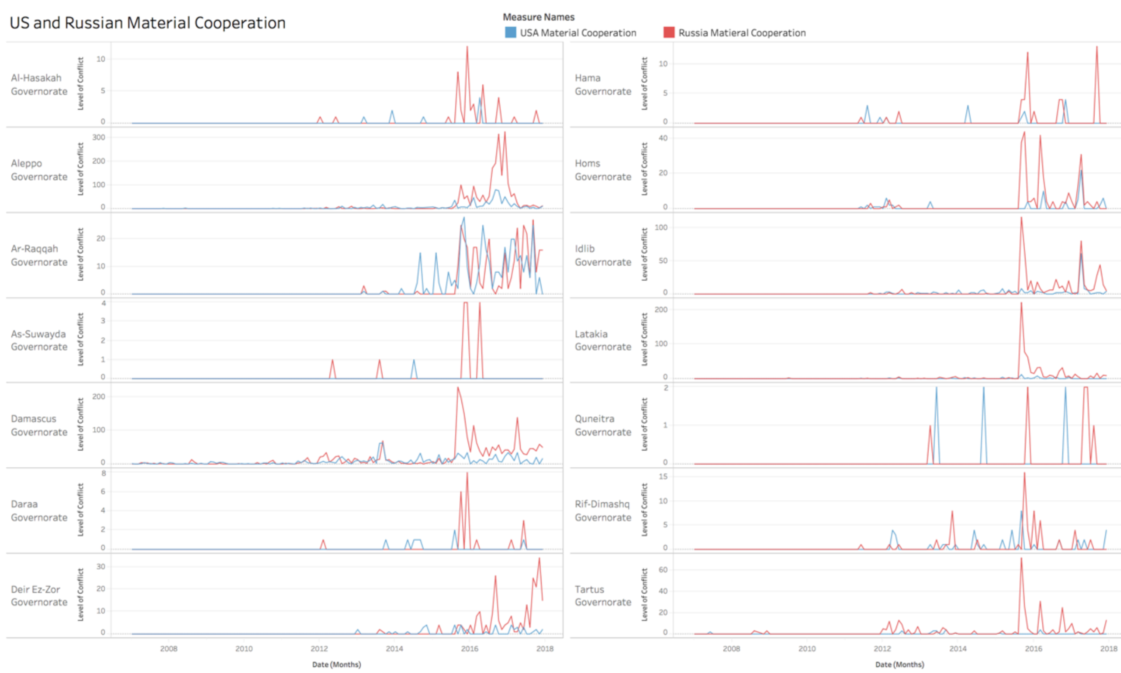

Figure 36: Time Series Plots of US and Russian Material Cooperation, Monthly

The above plots have similarities with that of Aleppo. Generally at conflict onset and even before US cooperation was at higher levels. This support dissipated and never really regained previous levels as the war waned on. This is partially a reflection of changing circumstances on the battlefield and changes in policy. While Russian material cooperation really picked up when the Syrian government decided on a new offensive strategy. Similar to Aleppo, Russia really aided in Deir Ez-Zor and Homs, areas in which rebels were entrenched. The slight

[106] "How Russian special forces are shaping the fight in Syria". Washington Post. 29 March 2016.

blimps of US and Russian cooperation in provinces like Daraa, Quneitra and Hama are potentially responses to insurgents.

Lastly another potential instigator of conflict is the response from government when facing dissent. Countries with strong arbiters and institutions can avoid the use for force or threats to prevent opposition dissent. Syria does not have many avenues to resolve power disputes. Thus the government and rebel resort to confrontational tactics in efforts to change policy. According to review of the conflict literature, one of the largest contributors to the conflict was the regime's response. More often than not threatening and coercive tactics we used. This is differs to degree in, as it is one a meso level and not restricted to just rebels. Below is a plot of threatening government actions in Aleppo.

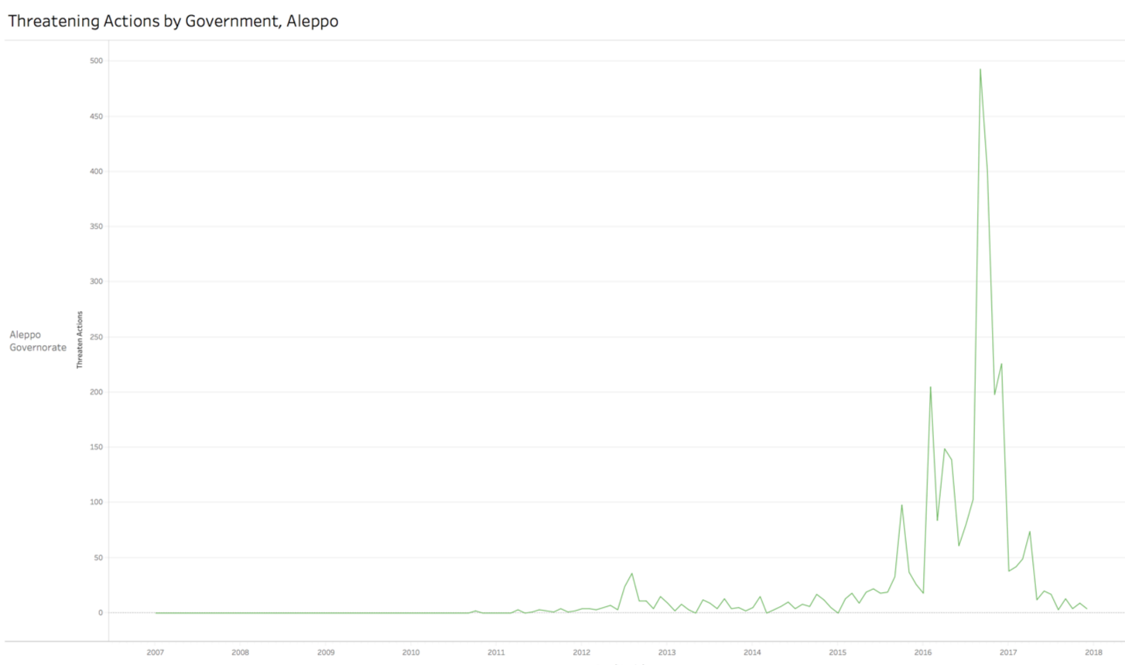

Figure 37: Time Series Plot of Threaten Actions in Aleppo, Monthly

Interestingly threatening actions picked up right before conflict began. It is a stark break point in the series from the stability epoch. The state change from a relatively low level to rapid escalation could indicate that discontent was festering and in response, more violent tactics were used. In Aleppo threaten actions were greatly used during the duration the province was under rebel control. Below is a plot of threatening action in all provinces.

Figure 38: Time Series Plot of Threaten Action, Monthly

The plot above shows that the threatening responses were used well in advance of the conflict, while at lower levels initially, and not used equally used throughout the country. Along with Aleppo, Damascus and Daraa show that this was a method frequently employed. With the exception of Damascus, rebel movements were large in other provinces. Interestingly is Idlib threatening action picked up much later in the conflict. This corresponds to movements of rebels and of the confrontation. As the rebels lost more and more ground they were forced into Idlib in the later stages of fighting, thus the sharp increase of actions in that province. This sort of resolution would have been lost if data was aggregated and at a larger sampling frequency.

General Trends

Now that each variable has been introduced alternative representation and visualizations will be produced to discuss data and trends at a higher level.

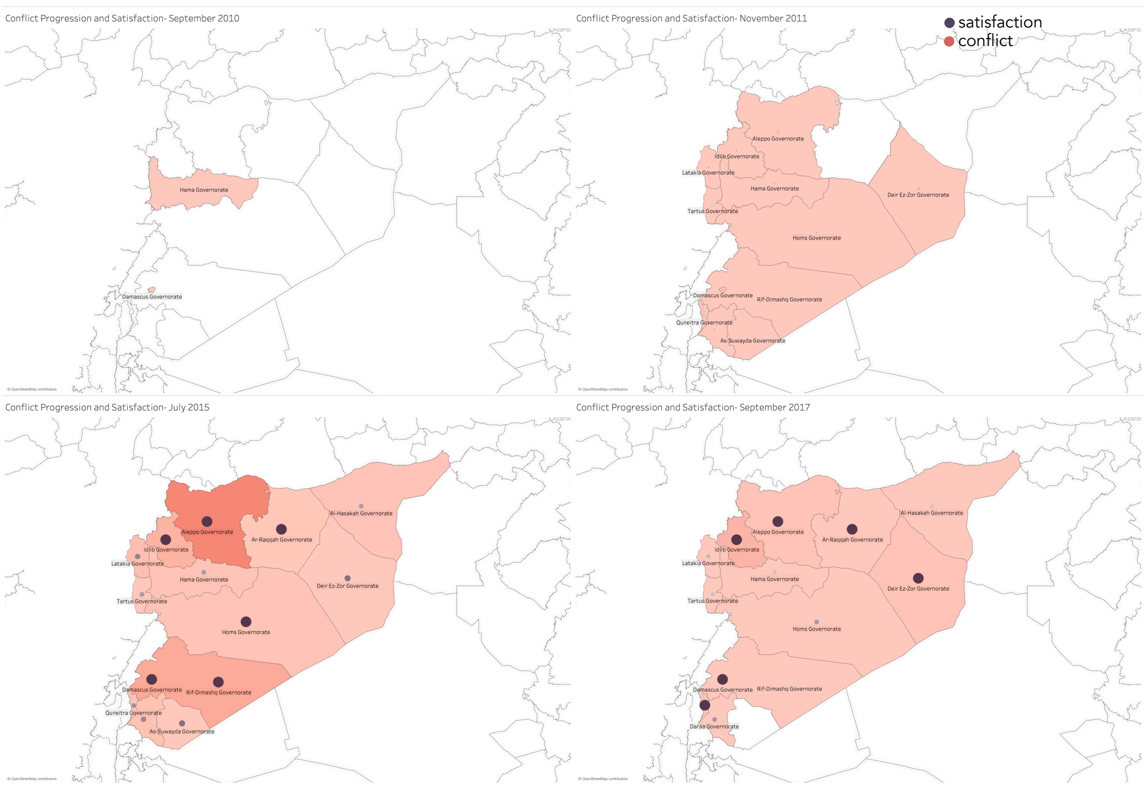

Figure 39: Conflict Progression and Satisfaction, Monthly

The plot above displays how the conflict progressed through the country with the saturation of red indicating conflict. Often times conflict are generalized and applied to country at large. This can contribute to a misunderstanding of the crisis. By tracking its evolution and progression both temporally and spatially, added meaning can be derived. As seen in plot 1 conflict is restricted to two provinces. Within about a year, in plot 2, the entire country is experiencing some level of conflict indicating fast diffusion. This rapid spread shows that perhaps much of the country was on the brink of instability and Syria quickly became engulfed. It could also signal that this could be a prolonged conflict not an isolated uprising.

In plot 3 the conflict has been raging for years, dissatisfaction is exceedingly low and conflict is widespread with severe confrontation occurring two provinces. As government began to take back land and control of provinces conflict begins to fade. Rebels power is greatly eroded. However as noticed dissatisfaction is still present indicating that re-mobilization of rebel troops may spark higher conflict again. Currently, the government has a tenuous grasp on much of the regained territory.

In deeper examination of the plots above, a scatter plot with satisfaction and conflict was constructed below.

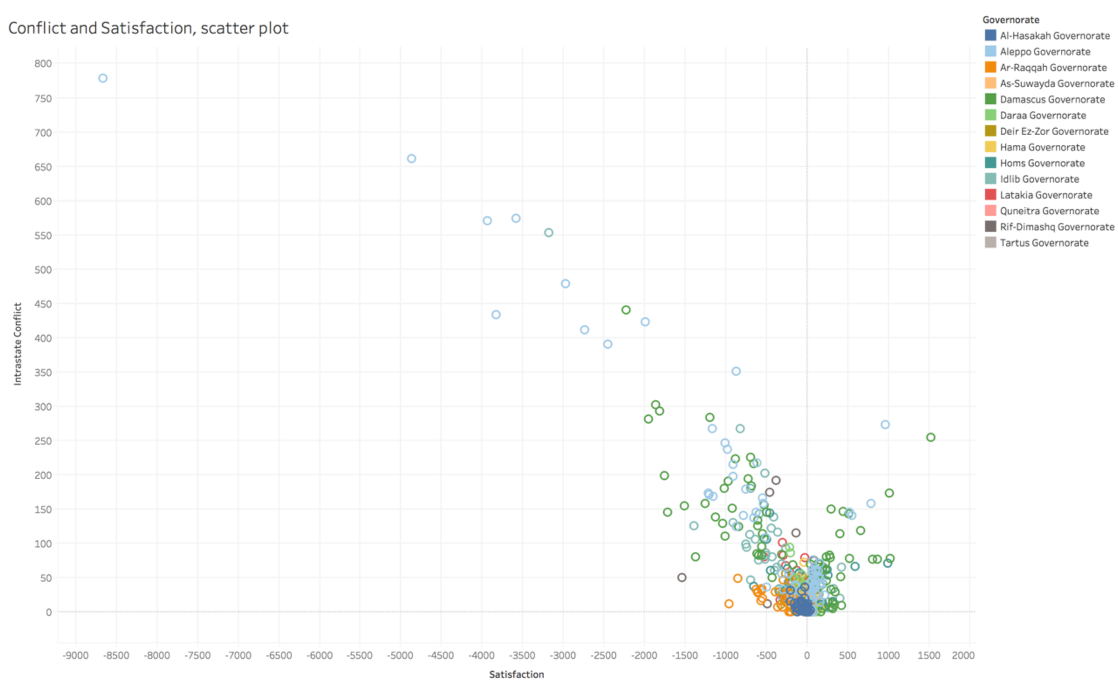

Figure 40: Conflict and Satisfaction Scatter Plot, aggregate

There is an obvious relation between satisfaction and conflict as was seen in the conflict progression graph above. The highest levels of conflict are at times with the lowest level of satisfaction while lower level encounters seem to be clustered around minimal dissatisfaction, supporting theory. Parity behaves much as theory describes as well. Below is a plot of conflict and parity.

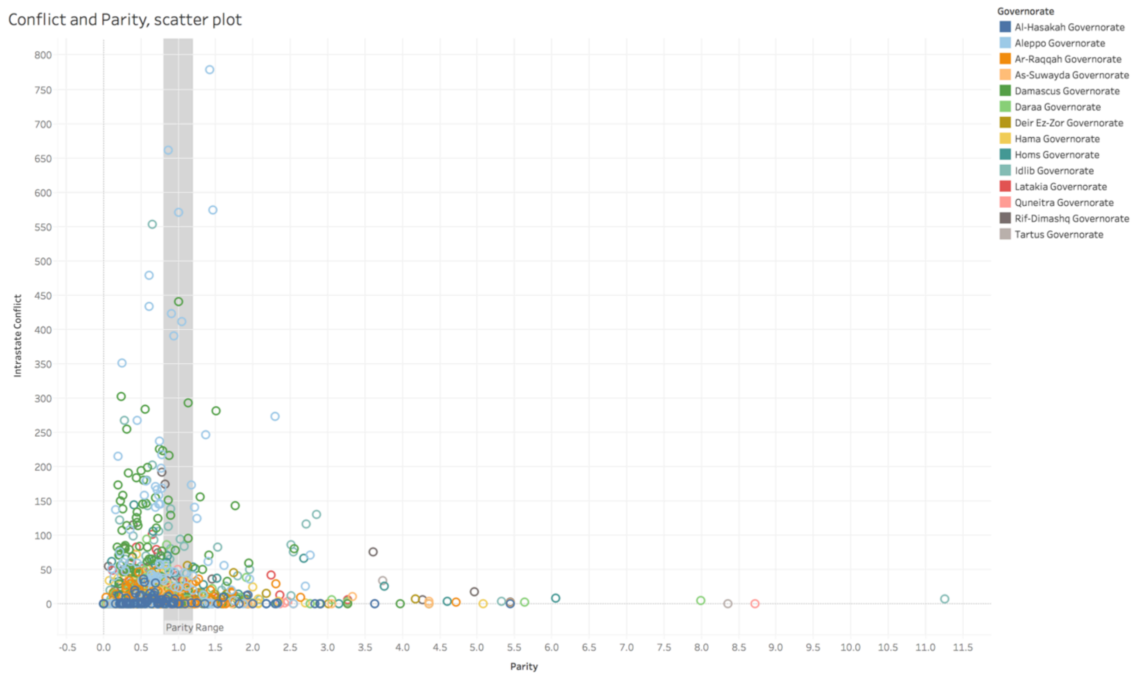

Figure 41: Conflict and Parity Scatter Plot, aggregate

In the plot above the parity zone as described in the literature is within 20% of the dominant parties power. In this case the highest levels of conflict occur in and around this zone. As the disparity in power increases and one side is clearly preponderant then conflict drops dramatically. This also reflects results of the theoretical model, however statistical testing is still needed to confirm relation.

The next below plot looks at the relation between actions targeting rebels, rebel response and eventually government action. While no granger causality was run to suggest causation, patterns will be discussed. The reason these were grouped is because much of the research tells us that micro to meso actions impact the underlying network structures and changes in relations between actors. In the case of the variables rebel degree in, protests, demands and threatening actions the relation is as follows. Positive and negative actions impacting rebels at a micro level in turn produce demand and protest events. These event may increase because rebels have more support, making them emboldened, or in response to negative government action. The more demand and protest events the more the government responds with threatening actions spurring more resentment. In the case of Syria this is one of the major contributing factors to the conflict.

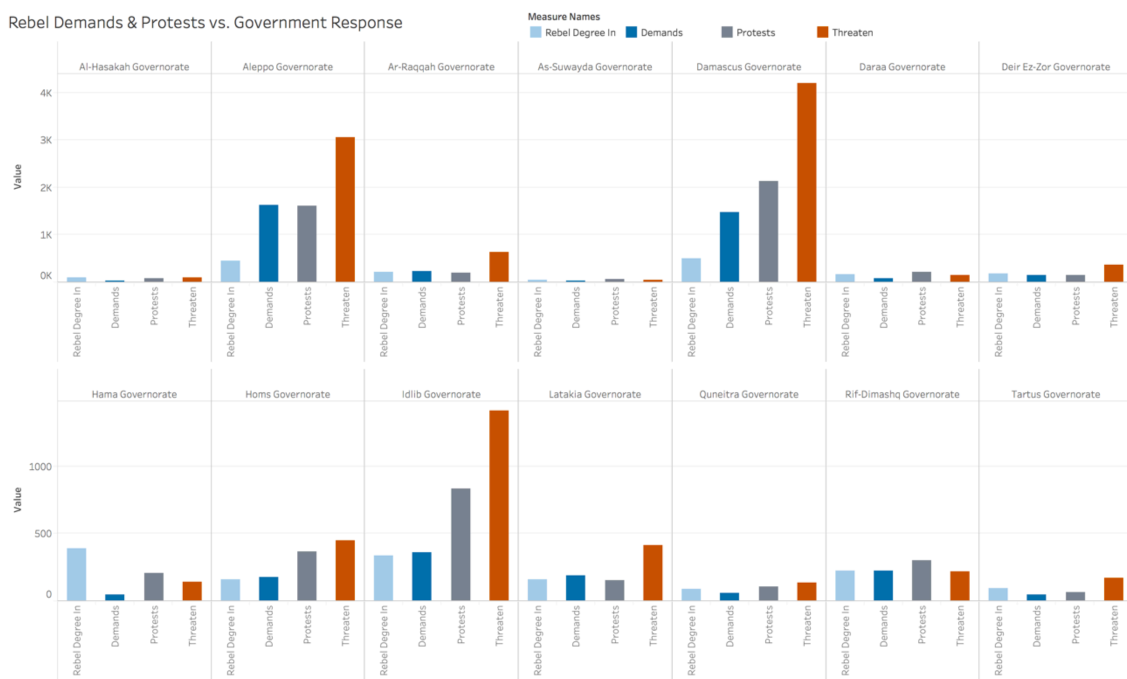

Figure 42: Rebel Degree In, Protests, Demands & Threaten Histogram

The plot above shows that in general areas in which rebel were more targeted, higher levels of protests and demands were noted, eliciting harsher responses from the government. In general, government responses were harsher in areas with significant level of protests. For example the provinces of Rif-Dimashq, Daraa, and Hama registered a decent level of protests but government response was muted. This could be a reflection of smaller rebel movements or limited government resources. However in general it is apparent that larger movements were harshly responded to.

EDA Concluding Remarks

EDA was an exercise to ensure data is usable for modeling and prediction. From initial inspection the data is complete and the dependent variable is balanced. While there are some highly correlated independent variables, none are a point of removal consideration. Generally after inspecting the data in the correlation matrix, time series plots and scatter plots there is initial evidence the measures accurately capture the values of the variables. Further, the relations also seem to support relations found in theory. This will be tested in the next chapter. Lastly, the disaggregation of the data in to higher frequency provincial level data allowed examining the heterogeneity of crisis. Not all areas, provinces and causes are equal. Traditional monolithic approaches would not be able to tease out subtle nuances that, from an exploratory perspective, are essential for a viable understanding of the crisis.

The following chapter will focus on utilizing the variables above to test the explanatory capability for conflict as well as compare the theoretical model specification against the complex adaptive system model to study possible uplift. After which prediction tests will be run to see which specification provides the most reliable predictions.

Chapter

05

Results & Predictions

Tactical analysts have the unenviable task of making actionable decisions in the face of crisis - often times relying on public or private data to make crucial calls. What is essential for them is the ability to coherently tease out underlying relations between the data available, formulating explanations, predictions and courses of action in regard to a particular phenomenon. Thus, the correct model specification and data granularity are critical for understanding and predicting conflict. The above sections described methodology and data that could potentially aid in the decision-making process. This section serves as the intersection between theory, method and data – revealing the viability of alternative measures, the significance of a complex adaptive approach, and the value of advanced forecasting techniques. The novel methodology employed is a foray into the adaptation of the structural theoretical models into tactical and actionable specifications – initial results are promising.

The section will focus on reviewing statistical evidence and model evaluation of the theoretical model recreation and the complex adaptive approach from the pooled linear model perspective – assessing the added benefits of an extended approach from an explanatory perspective as well as hypotheses confirmation. From this departure point, detailed explanation of feature impact on conflict will be performed. Fitted value and fitted value difference plots will be analyzed to visually inspect the performance and confirm the model evaluation. Followed by a brief general discussion of the two approaches. Then the theoretical and CAS model specifications will compete in predicting the onset of intrastate conflict on a provincial, monthly level using Classification and Regression Trees and a Random Forest. Underlying prediction mechanisms (model trees) will be covered as well as discussion on performance. Prediction and performance plots will be rendered in order to visualize conflict forecasts and each model specification's forecasting capability.

As a review below are the hypotheses and model specifications from the above section.

Hypotheses

H_1 Relative betweenness centrality of government and rebels impact level of violence in short term - Parity

H_2 Avg. tone of links between entities in a state impacts level of violence - Satisfaction

H_3 Event level factors impact violence – Event

H_4 Micro to meso level attributers' factors impact violence – Degree in

H_5 External aid to government or opposition groups impacts level of violence – Cooperation

Model Specifications

Theoretical Model

$$\begin{aligned}&Intrastate\ Violence_{it}\\&= f(Government\ Power_{it}, Opposition\ Power_{it}, Parity_{it}, Satisfaction_{it})\end{aligned}$$

Complex Adaptive Systems Model

$$\begin{aligned}&Intrastate\ Violence_{it} = f(Government\ Power_{it}, Opposition\ Power_{it}, Parity_{it},\\&Satisfaction_{it},\ SatisfactionII_{it},\\&Rebel\ Protests_{it}, Rebel\ Demands_{it},\ Rebel\ Degree\ in_{it},\\&Russian\ Material\ Cooperation\ to\ Government_{it},\\&USA\ Material\ Cooperaton\ to\ Rebels_{it},\ Threathen\ Actions\ From\ Government_{it})\end{aligned}$$

Equation 10: Models

In addition to these two models, two more additional models were run that are identical to the ones above however include a lagged dependent variable. This was done to address the endogeneity problem, look at ‘memory’, path dependence, and further test the explanatory power of each model specification.

Pooled Linear Model Results

Below is a result table of the PLM with both the theory (1) and CAS (3) specifications as well as the lagged dependent variable models (2)/(4) respectively. Data is normalized and coefficients are standardized so comparison within and between models is feasible.

Table 1: Theory vs. CAS Model results (with lags), Dependent Variable – Intrastate Conflict

Table 1: Theoretical Model (1) vs Complex Adaptive System Model (3) Results (with lags)

	Dependent variable:			
	Intrastate Conflict			
	(1)	(2)	(3)	(4)
Government Power	34.450***	12.842***	−0.459	−4.346
	(5.047)	(4.180)	(3.553)	(3.336)
Rebel Power	38.213***	22.069***	4.309	2.972
	(5.699)	(4.681)	(4.000)	(3.747)
Satisfaction	−1,123.832***	−716.724***	−404.088***	−404.951***
	(20.138)	(21.197)	(32.085)	(30.044)
Satisfaction II			−134.301***	−83.567***
			(21.092)	(20.000)
Parity	103.731***	58.186***	43.363***	30.576**
	(20.529)	(16.821)	(14.063)	(13.192)
Lag DV		354.264***		177.981***
		(11.649)		(11.062)
Protests			129.793***	106.728***
			(14.152)	(13.329)
Demands			149.126***	131.607***
			(23.463)	(21.997)
Rebel Degree in			264.778***	216.963***
			(13.418)	(12.911)
Russia Material Coop			−73.820***	−114.991***
			(15.130)	(14.397)
USA Material Coop			49.756***	39.574***
			(12.398)	(11.627)
Threaten			46.419***	44.591***
			(8.007)	(7.498)
Constant	961.606***	612.602***	445.365***	406.927***
	(17.113)	(18.076)	(20.081)	(18.955)
Observations	1,848	1,848	1,848	1,848
R^2	0.664	0.776	0.845	0.864
Adjusted R^2	0.663	0.776	0.844	0.863
F Statistic	909.725*** (df = 4; 1843)	1,277.618*** (df = 5; 1842)	907.374*** (df = 11; 1836)	970.165*** (df = 12; 1835)
Note:				*p<0.1; **p<0.05; ***p<0.01

The initial model (1) is the Theoretical model recreated using the alternative variables drawn from GDELT and SNA. It will serve as the baseline in which to compare all other models. Encouragingly, the model performs quite well achieving a relatively high R^2 of 66.4%. Meaning that the variables in the model explain around 66% of the variation of high-level intrastate conflict. Further upon inspection of the variables, are all highly significant at .01%, which indicates highly significant explanatory power. Government and rebel power are significant and positive replicating the original model. As both government and rebel power increase and mobilization efforts begin to take place conflict intensity and frequency heighten. Parity is also highly significant and positive. It is also a higher magnitude than that of either power measures independently. This is a good sign as parity in particular is a portion of the structural conditions for conflict. Conflict intensity and frequency are nearly doubled in instances where combatants are at parity when compared to when just one or the other is increasing in power. Parity in essence produces higher-level conflicts. The final portion of the model and the other structural condition is satisfaction. It is also highly significant and negative, which correctly replicates theoretical model conclusion in the research. This indicates that as satisfaction increases, conflict greatly diminishes and conversely as satisfaction decreases, there is punctuated increase in conflict. Of all features on the theoretical model, satisfaction is the largest in magnitude by far with nearly five times the impact on level and intensity of conflict when compared to power and parity measures combined. This is also consistent with power transition theory, which the theoretical model is based on. Satisfaction or the lack thereof is significantly more impactful on conflict than parity alone. This measure determines whether parity manifests into conflict or cooperation. In the case of Syria, extreme levels of dissatisfaction coupled with parity between government and rebel forces produced an extremely brutal and prolonged civil conflict.

Model (2) builds upon the theoretical model by introducing a lagged dependent variable as an additional regressor. This is done to, as mentioned above, check path dependence, address endogeneity and further examine the significance and viability of the other features. As noticed in the table, the addition of the lagged dependent regressor did provide nearly an 11% increase in R^2, raising it to 77.6%. While this does not diminish the results of the first model (1), it does suggest that past conflict has an impact on current conflict. This very well may be the case, or that there are some other explanatory variables that should be considered. The remaining variables maintain significance and same signs as the model (1) although diminish in magnitude as 'memory' of conflict serves as an added driver to conflict in this particular model.

Model (3) extends the theoretical model using the complex adaptive system approach. The CAS model looked at variables outside the macro/structural level of analysis, incorporating meso and micro to meso variables, attempting to achieve a more holistic understanding to conflict seeded in sound theory. The extension with the CAS variables proved exceedingly fruitful as the R^2 was increased nearly by 20% between model (1) and model (3) to 84.5%. This means that by adding the CAS variables, nearly half of the missing explanation of variance in conflict can now be better understood. For this type of social science model an R^2 of 84.5% is very high and suggests that a CAS approach can be beneficial to explaining conflict.

In terms of the CAS model features, government and rebel power lose significance, which may indicate that help from proxies Russia and USA could be accounting for some of the power these groups exercise. However, importantly, parity still remains positive and highly significant, although its magnitude is slightly diminished when compared to model (1). This still means that parity is a structural condition of conflict even in a CAS approach. Just as importantly, both satisfaction measures, satisfaction for rebels and satisfaction of civilians are also significant and negative. Maintaining the initial implication from the theoretical model that increases in the satisfaction of rebel and civilian groups decrease the level of conflict while dissatisfied parties increase it. Interestingly, civilian population satisfaction needs to be considered as well, not just that of organized rebel groups that are in direct confrontation with Government.

The next couple variables introduced in the CAS model are frequencies of protests and demands made by rebel groups and the civilians they represent. These were included to reflect part of the underlying issue that motivated the creation of the rebel groups to begin with. Rebels and civilians were consistently demanding representation and protesting government counter actions. Part of the initial reason why the conflict broke out was the extreme responses from the government towards these demonstrators. As seen in the table, increasing frequency of both demands and protests leads to higher levels of conflict. This also indicates that the less the central government appeased and responded to these demands and protests, the less rebel and civilian groups trusted the government, leading to higher levels of conflict. This is also reflected in the next variable, Rebel degree in, which represents action from critical entities towards rebel groups. It serves as a micro-meso relation. As more entity actions target rebel groups, the more conflict manifests in turn leading to added protests and demands. This captures the feedback between rebel actions, response by government, and how the rebels in turn react through added force, protests or demands. This cycle of demand, protest, government response and violence is one of the driving loops in the conflict in Syria and many intrastate conflicts.

The inclusion of Russian and American material cooperation is meant to proxy foreign intervention in the conflict. Interestingly, both are highly significant but have opposite signs indicating that foreign intervention does impact conflict. Russian material cooperation is negative, indicating that cooperating materially with the government does potentially reduce conflict due to greatly increasing the preponderance of the regime. It is not secret that Russians have been substantially aiding the government. While the rebels are at parity with the government forces one on one, once Russian cooperation is considered, the government force is powerful to fight against. US material cooperation is positive which confirms theory and reality. It is well documented that the US provided training and weapons to different rebel groups in order to compete with the Syrian government. Thus, as materials flowed in, rebels gained power and were able to challenge the government. This is not to be read as the US contributed to increases in conflict. It rather serves as a confirmation that as rebel power approaches government power, violence increases. However, the US may have contributed to prolonging the conflict. As shown in the parity measures and material cooperation plot, parity and support were not consistently maintained and thus a consistent offense against the Assad regime could not be sustained. The US needed to fully commit in order for rebels to topple the regime. With inconsistent support, rebels were unable to sustain fighting but not achieve decisive victories. While the rebels did make strides, areas where they had preponderance were not held long as Russian intervention aided the government in overcoming these challenges to power. There was a constant ebb and flow between superiority of combatants and thus a prolonged conflict. This also reflects that US and Russia were also drivers of the conflict. The elimination of significance from government and rebel power indicate that the continued conflict was aided because the combatants were receiving aid from foreign actors. This also indicates that a structural explanation may not always capture the entire meaning of a conflict. The added meso level events provided a more specific explanation in this particular instance. Indicating that in addition to structure, other levels need to be tested. Parity is still significant meaning the conditions were there but duration and severity were impacted by foreign cooperation. This creates interesting implications in the event of withdraw. If Russia leaves and weakened rebel remain dissatisfied, will wide spread conflict occur again?

Lastly, the threaten by government serves as a proxy to measure the way the government responded to rebel and civilian demands and protests. Analysts speculate that part of the reason conflict broke out was, as mentioned in earlier chapters, the threatening way in which the government responded to rebel/ civilian movements. As indicated by the high significant and positive sign, this contributed to the increase of violence in Syria.

Model (4) like model (2), adds a lagged dependent variable to the CAS model. Unlike with the theoretical model, the addition of the lagged dependent variable does not significantly change the R^2, increasing it to 86.4%. This means that much of the added explanatory power that the lagged dependent variable offered to the theoretical model was actually explained by the other CAS models. Thus, the addition of a variable to track path dependence and address endogeneity is not necessary. Further, the CAS model (3) performed better than the theoretical model (2) that included a lagged dependent variable. Meaning that the features of the CAS model provide better explanatory power than those in the theoretical model.

Results suggest another model should be run to measure material cooperation impact on the power of the government and rebels entities. The indicators for material cooperation were both significant, meaning that foreign intervention played a prominent role in this particular conflict and indeed many other intrastate conflicts. To measure how that impact changes power of belligerents, betweenness measures of both the US and Russia were added to that of rebels and government respectively. Below is the output of the CAS model in which power is measured as the sum of betweenness of the domestic entity and international partner.

Table 2: Complex Adaptive System Model, Foreign Intervention

Table 2: Complex Adaptive System Model, Foreign Intervention

	Dependent variable:
	Intrastate Conflict
Government Power (FI)	0.060***
	(0.021)
Rebel Power (FI)	0.121***
	(0.018)
Satisfaction	−396.587***
	(31.415)
Satisfaction II	−121.594***
	(20.675)
Parity	37.668***
	(13.630)
Protests	93.876***
	(14.450)
Demands	149.036***
	(23.039)
Rebel Degree In	212.579***
	(14.078)
Russia Material Coop	−83.390***
	(14.889)
USA Material Coop	17.407
	(12.711)
Threaten	40.889***
	(7.857)
Constant	428.451***
	(19.727)
Observations	1,848
R^2	0.851
Adjusted R^2	0.850
F Statistic	953.426*** (df = 11; 1836)
Note:	*p<0.1; **p<0.05; ***p<0.01

Power measures become significant again, indicating the importance of structural variables. However, the coefficients for power are very small, revealing that meso and micro factors still contribute to explanations of severity and frequency of conflict in a significant way as well. Structural indicators provide a portion the preconditions of conflict however; the meso and micro levels also provide preconditions as well as the dynamic triggers that allow preconditions to manifest into conflict. As concluded in the above models, structural conditions do provide a portion of the explanation of conflict but fusing with meso and micro data can give a more complete understanding of conflict dynamics.

These tables provide a few critical conclusions of the research. First the proxy variables for power, parity and satisfaction replicate performance and conclusions of the original theoretical model. Second, the CAS extension displays evidence that a multilevel approach to conflict may provide a better explanation to intrastate conflict than just structural based models. Third, conflicts should be examined not only as a component of the whole, but from different levels of analysis, as ignoring meso and micro level detail will inadvertently hide critical information from tactical decision makers. Fourth, the substantial benefit of these models is that they are all parsimonious in nature. Meaning they coherently and succinctly translate theory into measurement and then into explanation, without the need of a highly convoluted model.

Hypotheses Confirmation

- H_1 Relative betweenness centrality of government and rebels impact level of violence in short term – Parity

Hypothesis 1 is confirmed, as the parity is significant and positive in both the theoretical and CAS models. As combatants reach parity, higher levels of conflict are expected.

- H_2 Avg. tone of links between entities in a state impacts level of violence - Satisfaction

Hypothesis 2 is confirmed, as the satisfaction of entities impacts the level of violence. Higher levels of satisfaction lead to lower levels of conflict while dissatisfaction leads to higher conflict.

- H_3 Event level factors impact violence – Event

Hypothesis 3 is confirmed, as both protest, demand and threaten events are all statistically significant and exhibit correct signs. As higher levels of demands, protests and threaten actions occur, higher levels of conflict follow.

- H_4 Micro to meso level attributers' factors impact violence – Degree in

Hypothesis 4 is confirmed, as micro to meso interactions lead to changes in conflict levels. As rebel groups are targeted individually, they respond violently, creating a vicious feedback cycle and potentially escalating violence.

- H_5 External aid to government or opposition impacts level of violence – Cooperation

Hypothesis 5 is confirmed, as Russian and American material cooperation are significant and display correct signs. Russian cooperation aids government, making them preponderant and lowering conflict, while American cooperation aids in bringing rebels to parity, increasing conflict.

Fitted values

Fitted values were generated using both model specifications. Fitted values use the generated model coefficients and predict the dependent variable using the data provided. Essentially it is a test to see how well the models can generate values similar to observed ones. Below is a plot of the fitted values of both models along with the actual observations for the province of Daraa.

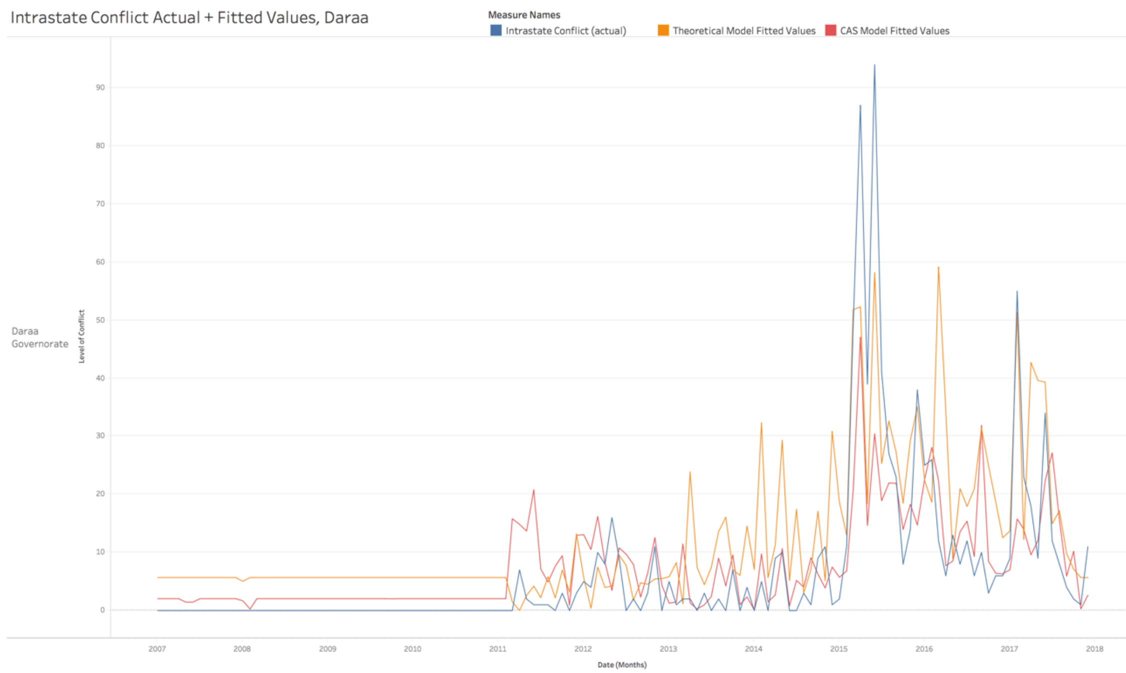

Figure 43: Theory vs. CAS Model Fitted Values in Daraa, Dependent Variable – Intrastate Conflict

The plot shows that the CAS model generally fits closer to the actual values. However, in earlier periods it did not perform as well as the theoretical model. After the initial inflated values, from 2012 forward, the CAS errors are lower in magnitude.

As seen in the plot below, the CAS model (red) generated fitted values closer to the actual values (blue) when compared to the theoretical model (orange). This is a reflection of the better R^2 and overall performance of the CAS model compared with theoretical model. Another important point to glean is that both models specified provided highly granular y-hats at provincial level and monthly frequency, which is a critical achievement. This shows that intrastate conflict can be explained on a monthly basis and can be decomposed from the aggregate.

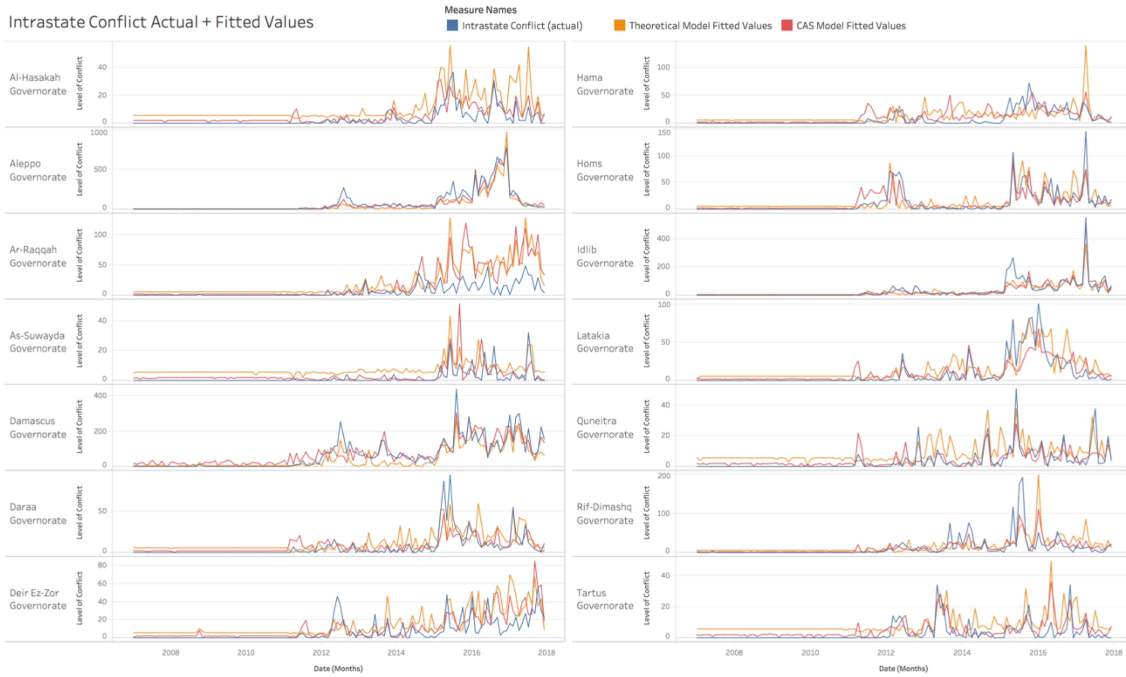

Figure 44: Theory vs. CAS Model Fitted Values, Dependent Variable – Intrastate Conflict

Theory and CAS Model Evaluation & Fitted Value difference

The table below displays the critical evaluation metrics comparing the performance of the two model specifications. The two evaluation metrics employed are RMSE and MAE. RMSE stands for root means square error examines the standard deviation of the residuals.[107] Residuals are the difference from the regression line and actual observations. Essentially, it provides a measurement on how tight the regression line fits the data[108] using a *quadratic scoring rule that also measures the average magnitude of the errors.*[109] This method squares errors thus penalizing larger errors more. RMSE is specified as:

[107] Barnston, A., (1992). "Correspondence among the Correlation [root mean square error] and Heidke Verification Measures; Refinement of the Heidke Score." Notes and Correspondence, Climate Analysis Center.

[108] IBID

[109] "MAE and RMSE - Which Metric Is Better?" Medium, Human in a Machine World, 23 Mar. 2016, medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

Equation 11: RMSE Calculation

MAE stands for mean absolute error that is the average of all absolute errors, which are calculated as the difference between the *measured value and the true value.*[110] MAE tracks the average magnitude of the errors in a set of predictions not considering the sign of the difference.[111] MAE is specified as:

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

Equation 12: MAE Calculation

While both are generally accepted best practice for model evaluation, RMSE is the harsher of the two due to the squaring of errors. Thus, models that have larger errors will have those errors amplified ensuring better evaluation of the models.

Table 3: Theory vs. CAS Model Evaluation

Table 3: Theory and CAS Model Evaluation

	ME	RMSE	MAE	MPE	MAPE
Theoretical Model	-0	31.667	14.830		Inf
CAS Model	-0	21.527	9.751		Inf

As seen in the table above, CAS model out performs the theoretical model in both RMSE and MAE indicating that predicted values generated from the CAS model are closer to the true values and further, those differences in fitted values are lower.

[110] "Absolute Error & Mean Absolute Error (MAE)." Statistics How To, 14 Oct. 2018, www.statisticshowto.datasciencecentral.com/absolute-error/

[111] "MAE and RMSE - Which Metric Is Better?" Medium, Human in a Machine World, 23 Mar. 2016, medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d.

To visualize the errors in prediction, a plot was rendered similar to the fitted values but showing the difference of the fitted values and the actual observations. This allows the visualization of the errors and insight into the RMSE and MAE measures above. Below is a plot of fitted value difference for Daraa. The plot generally shows the CAS model closer to 0, indicating no difference between y-hat and actual, when compared to the theory model.

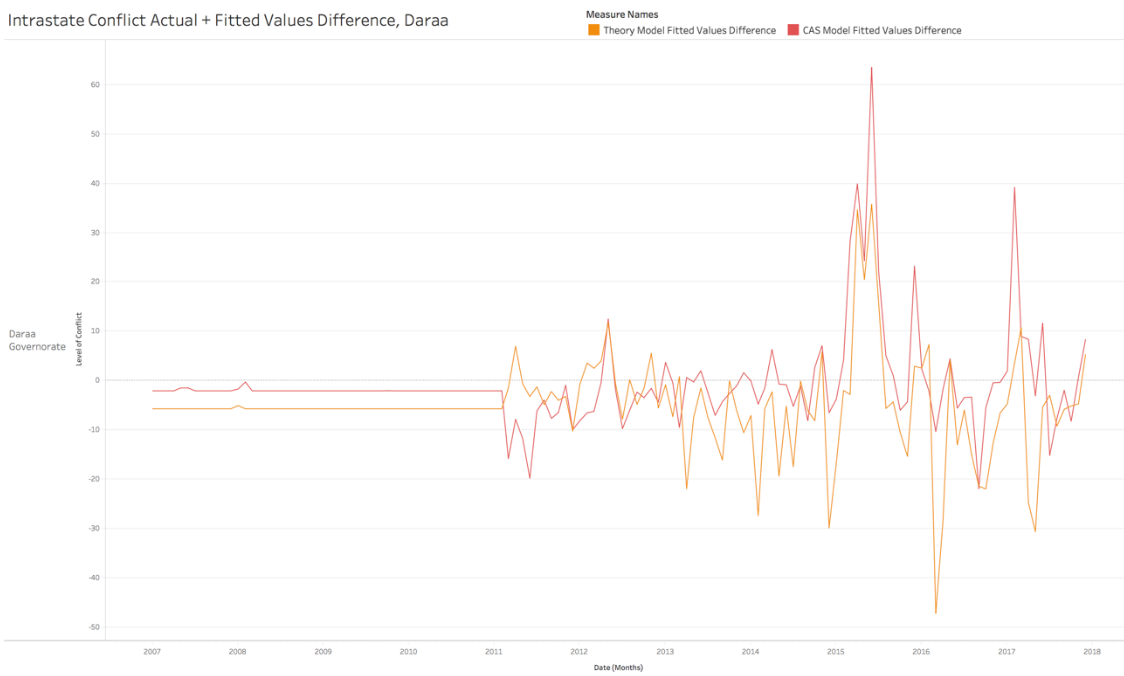

Figure 45: Theory vs. CAS Model Fitted Values Difference Daraa, Dependent Variable – Intrastate Conflict

As seen in the plots above, the CAS model (red) is consistently closer to zero than the theoretical model (orange). Being closer to zero means the difference between predicted and actual is smaller. Specifically looking at the provinces of Al-Hasakah, Deir Ez-Zor, Quneitra, the difference between the models is quite pronounced.

Figure 46: Theory vs. CAS Model Fitted Values Difference, Dependent Variable – Intrastate Conflict

To summarize the PLM method; variables were confirmed to fit original theoretical model conclusions, the CAS model was able to better explain the onset of intrastate conflict and the fitted values of the CAS model out performed those of the theoretical Model. This is a vital step in moving from strategic to tactical decision-making. Structural variables and conflict can be measured on a provincial level, monthly and a multi-level approach to analysis. Thus, using the CAS greatly expanded upon the explanatory power of the original model. For decision makers keen on understanding the shifting terrain of a conflict, results suggest this is very feasible. Instead of relying on state level, yearly understanding of conflict, crises can be decomposed and understood on a disaggregated level providing much more actionable insights.

Predictions

The PLM method gave us evidence to suggest that both theory and CAS model specifications provide sound explanation of conflict. However, explanation is not enough. Tactical decision makers need to be able to forecast conflict in order to properly allocate resources, prepare responses, evacuate civilians and position assets. The logical next step then is to see the viability of these models as predictors, not just explainers. To do this, two methods discussed in the methodology section will be employed, classification and regression tree and a random forest method. The models specification will be the same with the exception that all regressors will be lagged one period. For the model to be truly tested for predictive power, it is vital to confirm that data from a previous period is able to forecast events for the next period. After that, each model will be evaluated by accuracy, precision and recall using training and testing data sets and then compared against each other. Accuracy refers how close the measured values are to true values. Precision explains how negative values were truly negative, while recall detects how many true values were supposed to be true as summarized by the illustration below.

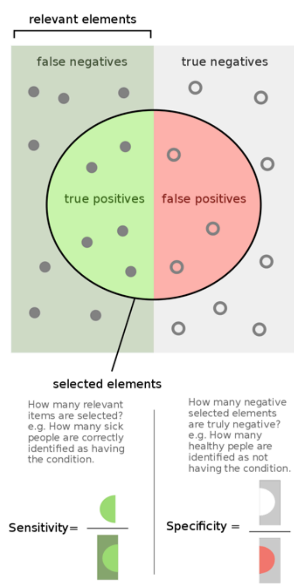

Figure 47: Precision and Recall Illustration, source: Wikipedia

Classification and Regression Trees

The first method to be tested is the classification and regression trees (CRTs). The table below displays the performance of the lagged theory CRT model in predicting the onset of conflict in the next period. Training data was used to train the prediction model and testing was then used to test its ability to predict.

Table 4: Theory CRT Model Evaluation (training vs. training), Dependent Variable – Intrastate Conflict

Theory Model Training Data CRT

87%	85%	89%
accuracy	sensitivity (recall)	specificity (precision)

reference → prediction ↓	N	Y	
N	585	66	ppv: 90%
Y	103	540	npv: 84%

training confusion matrix

Theory Model Testing Data CRT

87%	86%	87%
accuracy	sensitivity (recall)	specificity (precision)

prediction	N	Y	
N	244	35	ppv: 87%
Y	39	236	npv: 86%

testing confusion matrix

Critically the theory model performed well both in the training and testing data sets suggesting no over fitting occurred. Both sets were equal in accuracy while they exchanged higher rates for recall and precision. The testing data resulted in 39 false positive (type I error) and 35 false negatives (type II error). In the case of this analysis, it is better to exchange lower type II for a higher type I because with conflict, missing an event can be costly.

The table below displays the performance of the lagged CAS CRT model in prediction the onset of conflict in the next period. Training data was used to train the prediction model and testing was then used to test its ability to predict. The data set is the same as the one used by the theory model so results can be compared.

Table 5: CAS CRT Model Evaluation (training vs. training), Dependent Variable – Intrastate Conflict

CAS Model Training Data CRT

89%	88%	89%
accuracy	sensitivity (recall)	specificity (precision)

prediction \ reference	N	Y	
N	582	69	ppv: 90%
Y	80	563	npv: 84%

training confusion matrix

CAS Model Testing Data CRT

87%	87%	87%
accuracy	sensitivity (recall)	specificity (precision)

prediction \ reference	N	Y	
N	244	35	ppv: 87%
Y	38	237	npv: 86%

testing confusion matrix

Similar to the theory CRT model, the two data sets had similar accuracy, thus over fitting is not an issue. However, the training data did perform better overall compared to the testing set although minimally. The testing set had 38 type I errors and 35 type errors, which is only one type I error less than the theory model. The CAS CRT and theory CRT are equal in accuracy and precision with the CAS slightly edging ahead on recall. Generally, both model specifications perform relatively similarly.

While this is not enough evidence to suggest the CAS model is better at predicting than the theory model, it does suggest that theory informed models could predict conflict. This is a major breakthrough. Not only do the new measurements accurately explain conflict, their lagged values are useful in predicting conflict a period ahead. As a tactician, having this visibility in an area of responsibility is crucial in the decision-making process.

CRTs Sample Trees and Variable Importance

To get a better understanding of how the CRT algorithm predicted the values, it is vital to examine the tree produced to make the predictions, as well as how the algorithm ranked the variables in terms of importance. While the ranking may be different than what the PLM produced, it still provides insights on how the final predictions were produced. The tree below is one generated by the theory model specification. The tree makes decision at each node by partitioning the feature at a certain threshold. Depending on the value of the observation, the algorithm decides which path to take at each node. At the end node or leaf it will classify the observation as a 0 or 1.

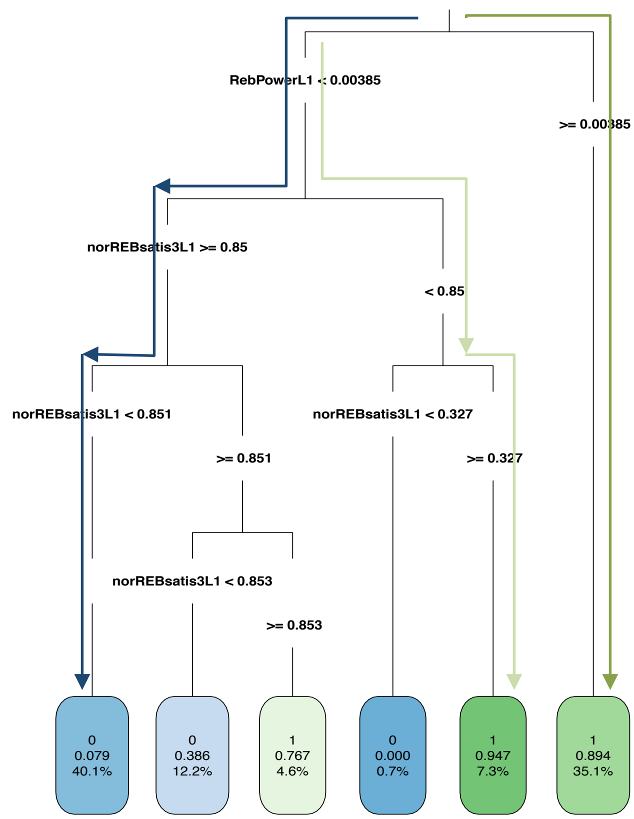

Figure 48: Theory CRT Model Tree

To interpret the above tree, each node displays the variable and cut point. Following the green line, if the lagged value of rebel power is above a normalized value of .0039 then the model predicts conflict. Following the blue line, if the lagged value of rebel power is below a normalized value of .0039, then the next feature will be satisfaction. If the lagged value of satisfaction is between .85 and .851 normalized values, then the predicted value is 0. Lastly, following the lighter green line, it takes the same path as the blue, but if the lagged value of satisfaction is below a normalized value of .85 and then again above or equal to a value of .327, the model classifies the observation as 1. The percentage at the bottom of the leaf indicates how many observations of the total observation set fall into the category.

CRTs also produce variable importance of the feature set that was the largest determinant in bifurcating the data between 0 and 1. Below is a variable importance plot of the CRT theory model.

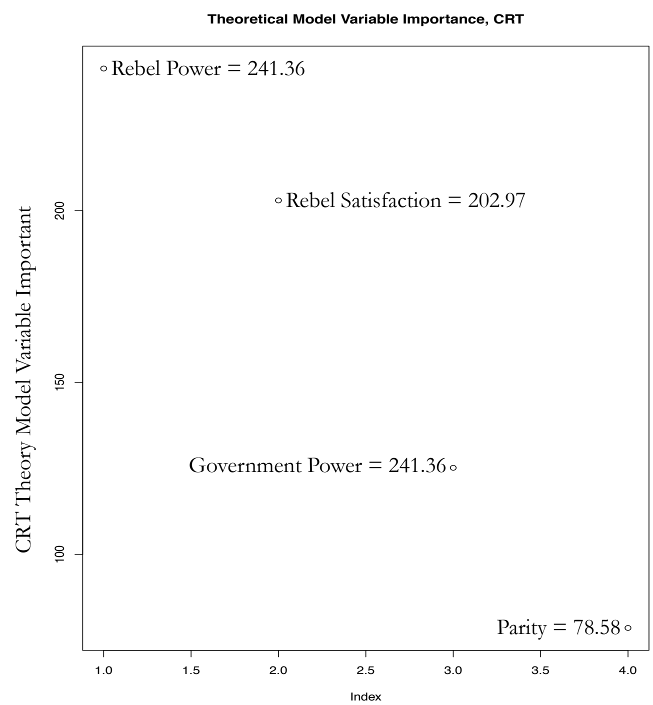

Figure 49: Theory CRT Model Variable Importance

The above plot indicates that rebel power followed by rebel satisfaction, government power and parity are the most important variables in this particular tree in terms of predicting conflict one period ahead. It is interesting to see that the CRT algorithm leaned more on rebel features rather than government-based ones in predicting conflict onset.

The next tree is generated by the CAS CRT model and will be examined below, first reviewing the tree and a couple paths, then reviewing variable importance.

Exactly like the theory CRT model, the algorithm was specified using the same variables as the CAS PLM. Below is the tree produced from the CAS CRT model.

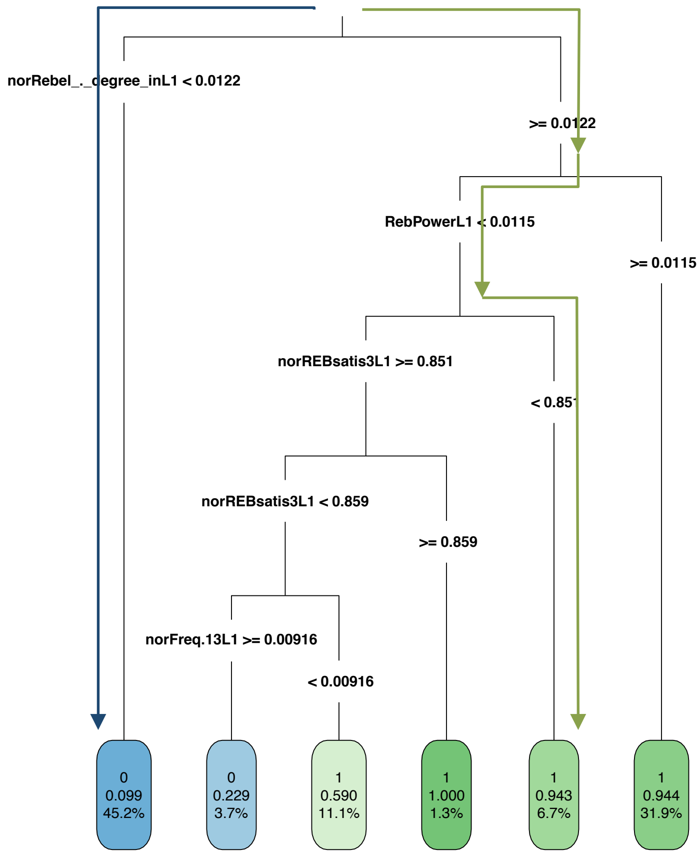

Figure 50: CAS CRT Model Tree

The blue path in this tree uses the measure of rebel degree in or the amount of action targeting rebel groups as the first classifier. If the lagged values of actions targeting rebel is below a normalized value of .012, the observation is classified to the 0. On the green path, if lagged values of actions targeting rebel are above a normalized value of .012 and if lagged rebel power is greater than a normalized value of .012 and if lagged rebel satisfaction is below a normalized value of .85 then the observation is classified as 1.

The variable importance plot below produced a different prediction explanation when compared to the theory model – falling closer in line with the CAS PLM model above in terms of what variables are most impactful.

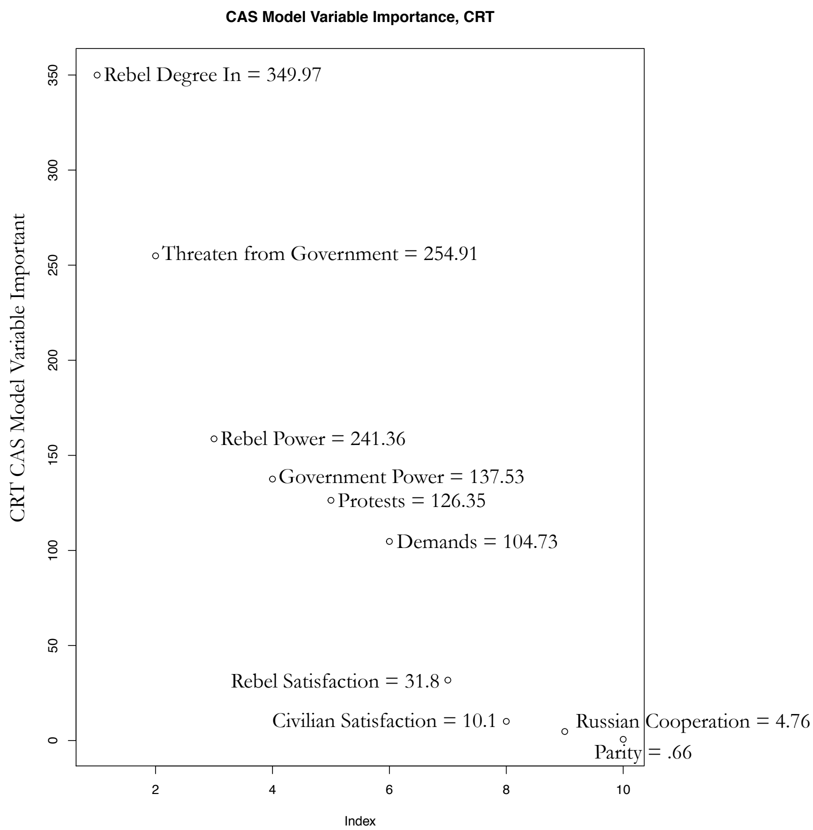

Figure 51: CAS CRT Model Variable Importance

As seen in the plot above, rebel degree and threaten from government are the most impactful suggesting that antagonizing actions by the government are highly important when predicting the onset of conflict. This is then followed by rebel and government power, protests and demands indicating that where there is high presence of combatants, protest and demands, conflict could occur. Interestingly, satisfaction, parity and Russian material cooperation are not ranked higher on the variable importance plot. Lower satisfaction importance could be caused by the addition of protests and demands. Intervention seems to be a general explainer of larger conflict more so than one that is used for prediction. This perhaps is a reflection of the nature of cooperation, where it may in general aid conflict eruption, but not viable for month-by-month prediction due to how it is delivered. Overall, it is interesting that predictions leaned heavily on micro to meso and meso level features before utilizing macro structural indicators.

CRTs Forecast Plots

Using the outputs of the CRT models, forecasts were generated and plotted to display the forecasted probabilities against the actual event occurrence. First, a province will be isolated and compared and then the rest of the provinces will be shown. Below is the forecast plot comparing the theoretical and CAS CRT models for the province of Aleppo, monthly.

Figure 52: Theory vs. CAS CRT Model Prediction, Aleppo

Generally, both models predicted quite well as shown by the performance metrics. However, both have an obvious flaw of false positives. This issue is much less severe in the CAS CRT. Both perform similarly during conflict onset and forward. Below is a plot of theory CRT model predictions for all provinces.

The predictions generally fit the actual data relatively well as was confirmed by the performance metrics above. This, however, allows a visual inspection of where the predictions were correct and incorrect. Generally, the model predicts the onset of violence and the epoch change before and after the conflict began quite well. However, in the more stable periods, some of plots like in Damascus and Aleppo exhibit higher levels of false positives in the initial phases on the observation set. Addressing this is perhaps something to take note of moving to the CAS CRT and later to the random forest method. While for conflict, false positive are not as consequential as false negatives, yet this should still be corrected.

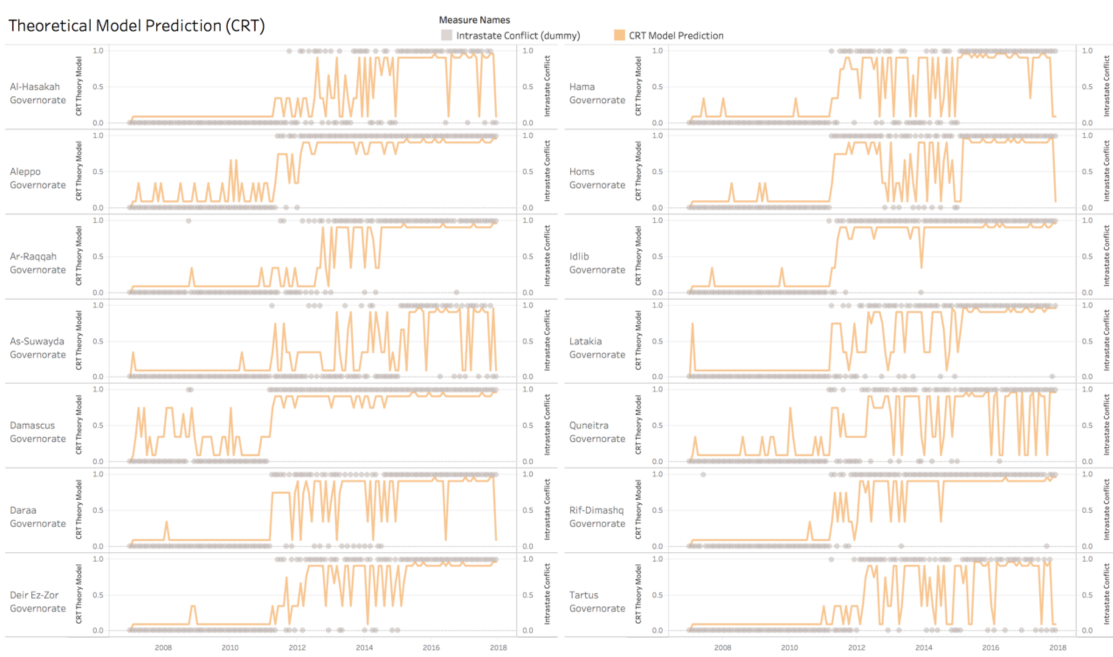

Figure 53: Theory CRT Model Prediction

Below are the forecast plots for the CAS CRT model by province, monthly. As reflected by the performance metrics and similar to the theory CRT model, the predictions are relatively decent.

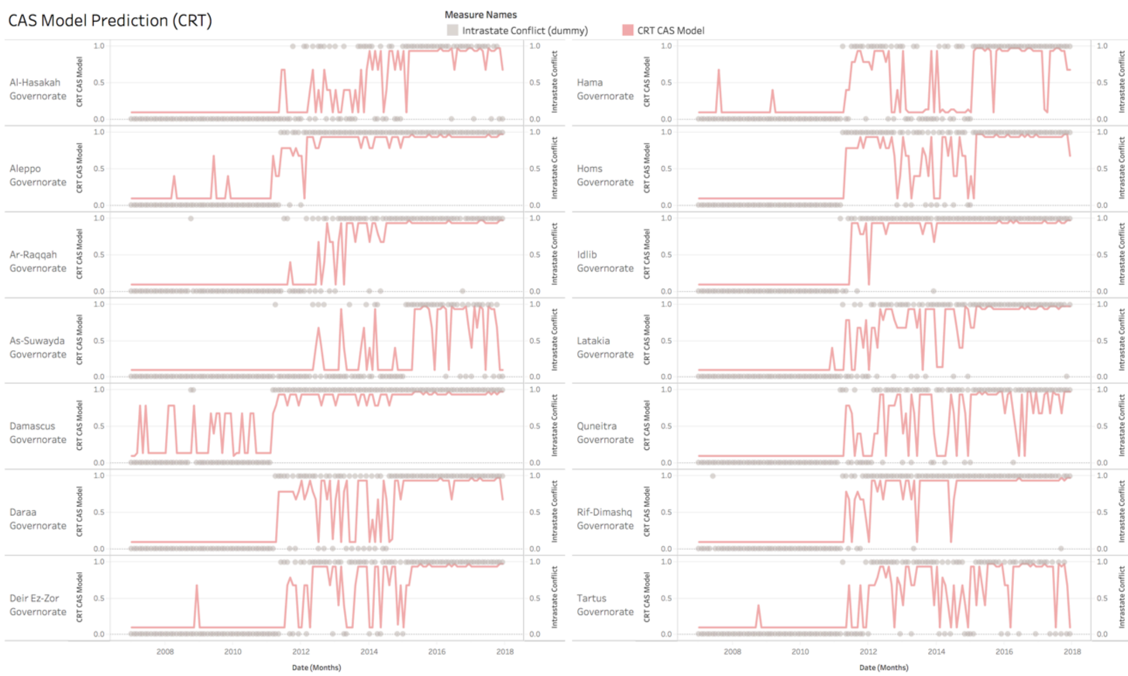

Figure 54: CAS CRT Model Prediction

What is important to note is that similar to the theory CRT model predictions, there seems to be higher levels of false positives as well, yet to a much lesser extent. When comparing the province of Aleppo in both the above plots, the number of false positives in the initial phase is greatly reduced. This suggests that the CAS model approach does reduce type 1 error, especially when in an epoch of peace or conflict.

ROC & Precision Recall Trade Off

Similar to the above plots, the following ROC curve and precision and recall plot allow for a visual representation of the performance metrics. ROC stands for receiver operating characteristic curve, *illustrating the diagnostic capability* of the model.[112] Below are ROC plots for both the theoretical and CAS CRT models.

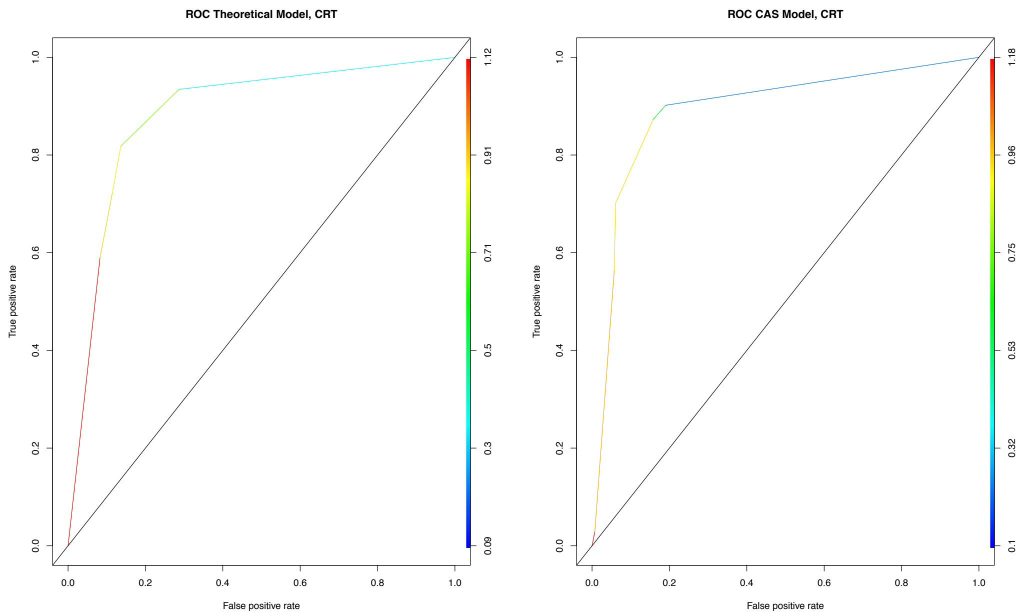

Figure 55: Theory vs. CAS CRT Model ROC Curve

Generally, both curves are similar in nature as both models have nearly the same performance. The theory model has an AUC or area under curve of .90, while the CAS model has .91. With competing models ROC and AUC can be used to make a determination between either specification, however with the results above, a conclusive decision about which specification cannot be made.

Lastly, it is important to evaluate how sensitive the models' precision and recall tradeoffs are. Below are tradeoffs plots for both models.

[112] "Detector Performance Analysis Using ROC Curves - MATLAB & Simulink." MathWorks, 2016, www.mathworks.com/help/phased/examples/detector-performance-analysis-using-roc-curves.html

Upon inspection the theoretical model seems to be more stable when trading off recall for precision. As noticed in the peak of the red portion of the CAS model plot, the line indicates that the as model is tuned to optimize for precision the recall performance gets significantly worse. The theory model has to give much less recall to gain precision. However, the CAS CRT can achieve a higher overall level of precision. Further the blue portion of line is steeper on the CAS model indicating that higher levels of precision can be achieved while maintaining good recall.

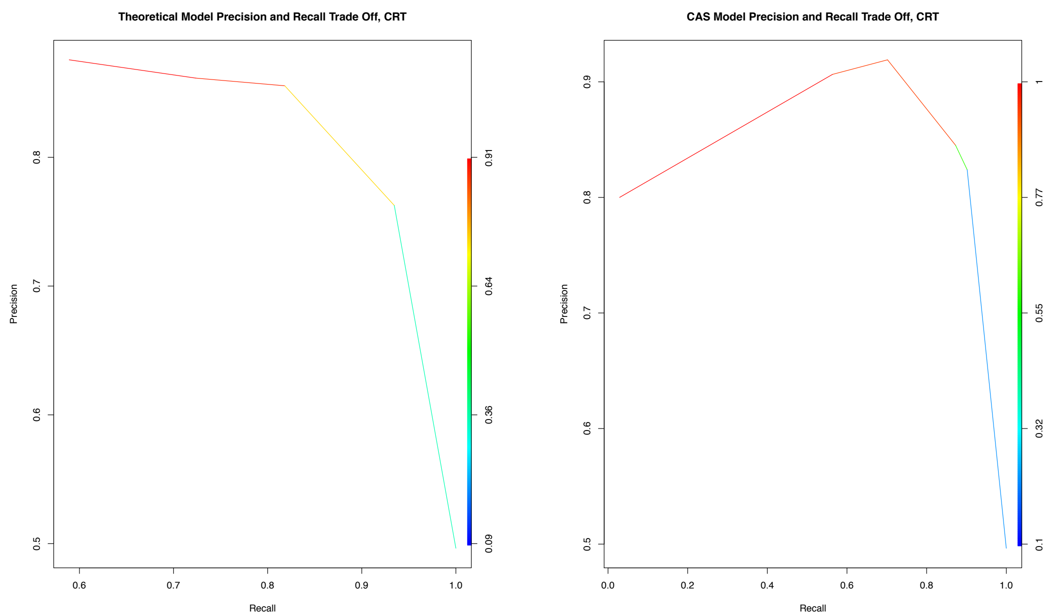

Figure 56: Theory vs. CAS CRT Model Precision and Recall Trade Off

CRT Conclusion

The initial prediction model using a CRT method provided quite intriguing outcomes. It confirmed that theory informed machine learning models can predict conflict to a decent degree. Predictions seem slightly better when using a CAS approach although not conclusively. False positives seem to be a persistent issue with both models, however CAS seems to correct this error more consistently than the theoretical model, especially in stable periods. The random forest model is slightly more advanced and will be used to address some of the shortcomings of the CRT method and improve upon prediction performance.

Random Forest

The second method to be tested is a random forest (RF) algorithm. Unlike the CRT, RFs use many more trees in its prediction formulation. Where CRT tree does one, the RF will do 400. The table below displays the performance of the lagged theory of RF model in predicting the onset of conflict in the next period. Training data was used to train the prediction model and testing was then used to test its ability to predict.

Table 6: Theory RF Model Evaluation (training vs. training), Dependent Variable – Intrastate Conflict

Theory Model Training Data RF

85%	91%	79%
accuracy	sensitivity (recall)	specificity (precision)

		reference N	reference Y	
prediction	N	591	133	ppv: 82%
prediction	Y	60	510	npv: 90%

training confusion matrix

Theory Model Testing Data RF

87%	93%	82%
accuracy	sensitivity (recall)	specificity (precision)

		N	Y	
prediction	N	258	50	ppv: 84%
prediction	Y	21	225	npv: 92%

testing confusion matrix

In assessing the theory RF model, a few distinct conclusions can be drawn, primarily the method generally performed well and there is an obvious bias towards recall. Training and testing have relatively the same performance so over fitting is not an issue. The high recall of this model greatly reduced the number of type I errors when compared to the CRT theory model, however, critically, the number of type II rose which, as mentioned before, is more costly. A potential reason for this is that the RF creates many more trees than a CRT, and with the limited feature set of the theory model, there may be a limited amount of points where the feature can be partitioned leading to lower accuracy or precision. Further, there may be information missing from the model that could aid in increasing prediction power. As seen until this point, the CAS specification has consistently improved upon the theory model. So perhaps it is necessary to introduce CAS components to potentially remedy some of the shortcomings of the theory RF model.

The table below displays the performance of the lagged CAS RF model in prediction the onset of conflict in the next period. Training data was used to train the prediction model and testing was then used to test its ability to predict. The data set is the same as the one used by the theory model so results can be compared.

Table 7: CAS RF Model Evaluation (training vs. training), Dependent Variable – Intrastate Conflict

CAS Model Training Data RF

87%	85%	89%
accuracy	sensitivity (recall)	specificity (precision)

		reference N	reference Y	
prediction	N	550	72	ppv: 88%
prediction	Y	101	571	npv: 85%

training confusion matrix

CAS Model Testing Data RF

88%	84%	92%
accuracy	sensitivity (recall)	specificity (precision)

		N	Y	
prediction	N	235	22	ppv: 91%
prediction	Y	44	253	npv: 85%

testing confusion matrix

Consistent with the previous model, both the training and testing data sets have similar performance. Critically, the CAS RF corrects the bias towards recall produced by the theory RF, while still maintaining decent recall levels. However, the major benefit is the high precision percentage. Compared to the theory RF, type II errors are reduced by more than half from 50 to 22, meaning the number of false negatives, costly events, is much lower in the CAS RF model. Further, the CAS RF also outperforms the CAS CRT model. On comparing type II errors, the CAS CRT had 35 errors in the testing set while the CAS RF has 22. In comparing all prediction model specifications, the CAS RF outperforms by achieving, on average, the best performance metrics and critically achieving the lower type II error rate of every model.

In addition to the results from the CRT method, the RF results also give evidence of the viability of theory informed machine learning models for prediction. This is very encouraging, as this novel approach can allow decision makers and tacticians a succinct, replicable way to measure and predict civil conflict. Further, with parsimonious design of the specifications, conflict probability changes can be understood in the context of theory instead of just making a decision off a probability estimate.

Random Forest Sample Trees and Variable Importance

To get a better understanding of how the RF algorithm predicted the values it is vital to examine the tree produced to make the predictions as well as how the algorithm ranked the variables in terms of importance. What is important to note is that unlike the CRT the RF produced over 400 trees in order to make the predictions, so only one sample tree will be reviewed to provide an example. The tree below is the one generated by the theory RF model specification. It makes decision at each node by partitioning the feature at a certain threshold. Depending on the value of the observation, the algorithm decides which path to take at each node. The end node or leaf indicates the proportion of values 0,1.

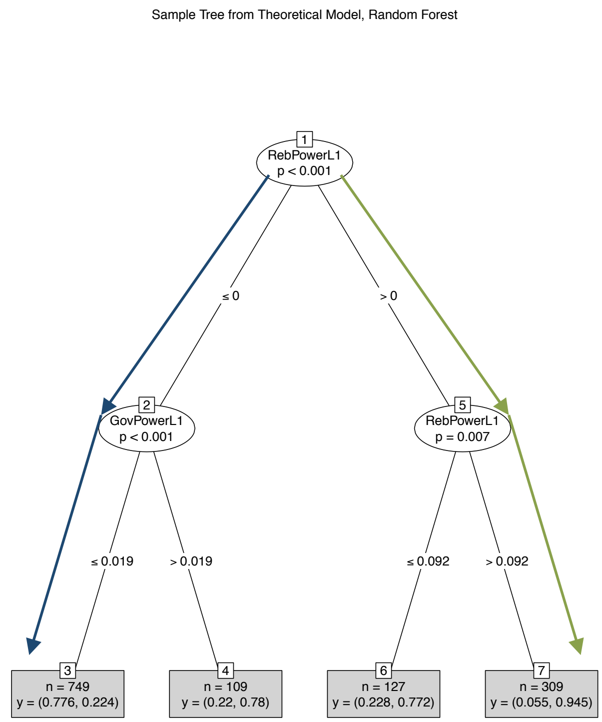

Figure 57: Theory Random Forest Model Sample Tree

To interpret the above sample RF tree, each node displays the variable and cut point. Following the blue line, if the lagged value of rebel power is less than or equal to a normalized value of 0 and the lagged value of government power is less than or equal to a normalized value of .02, the proportion of 0 to 1 is expected to be 78% to 22% respectively. Following the green line, if the lagged value of rebel power is greater than a normalized value of 0, and again if the lagged value of rebel power is greater than a normalized value of .09, the proportion of 0 to 1 is expected to be 5% to 95% respectively. The above sample plot obviously relies heavily on combatant presence to make a determination of 0 or 1, however the other 399 trees will try alternative partitioning of the feature values for such prediction which is the advantage of a RF approach.

Like the CRT, the RF also produces a variable importance plot. What is different is the fact that variable importance is calculated across all trees not just for a sample tree. Another difference is the metric for computing importance, mean decrease Gini, which is a metric of each node's Gini impurity. Gini impurity indicates the level of incorrect labels based on that particular break in the data. So those with worse prediction capabilities will have lower values. In the plot below, variable that decreased Gini the most will have lower values. Below is a variable importance plot for the theory RF model.

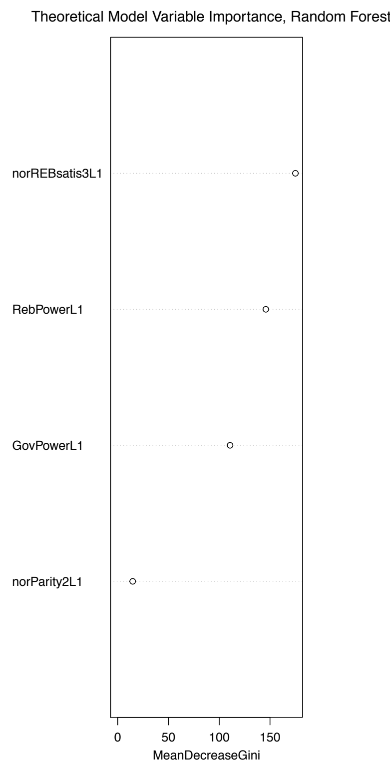

Figure 58: Theory Random Forest Model Variable Importance

In the above graph, lagged rebel satisfaction was the top variable with the lowest Gini impurity measure, meaning that using this variable as predictor of conflict resulted in the least number of misclassifications. Rebel satisfaction is followed by lagged rebel and government power, which were the measures used in the sample tree above. Lastly, lagged parity seemed to have the highest Gini impurity measure. In comparison to the CRT theory variable importance, the top two predicators are the same but in opposite positions. CRT leaned more on rebel parity with the RF preferred rebel satisfaction.

The next generated sample RF tree was produced by the CAS model specification. With more features, the sample tree is more complex with higher levels of nodes. The extra features allowed more precise division of observations and coupled with 399 different expressions. The performance was also better.

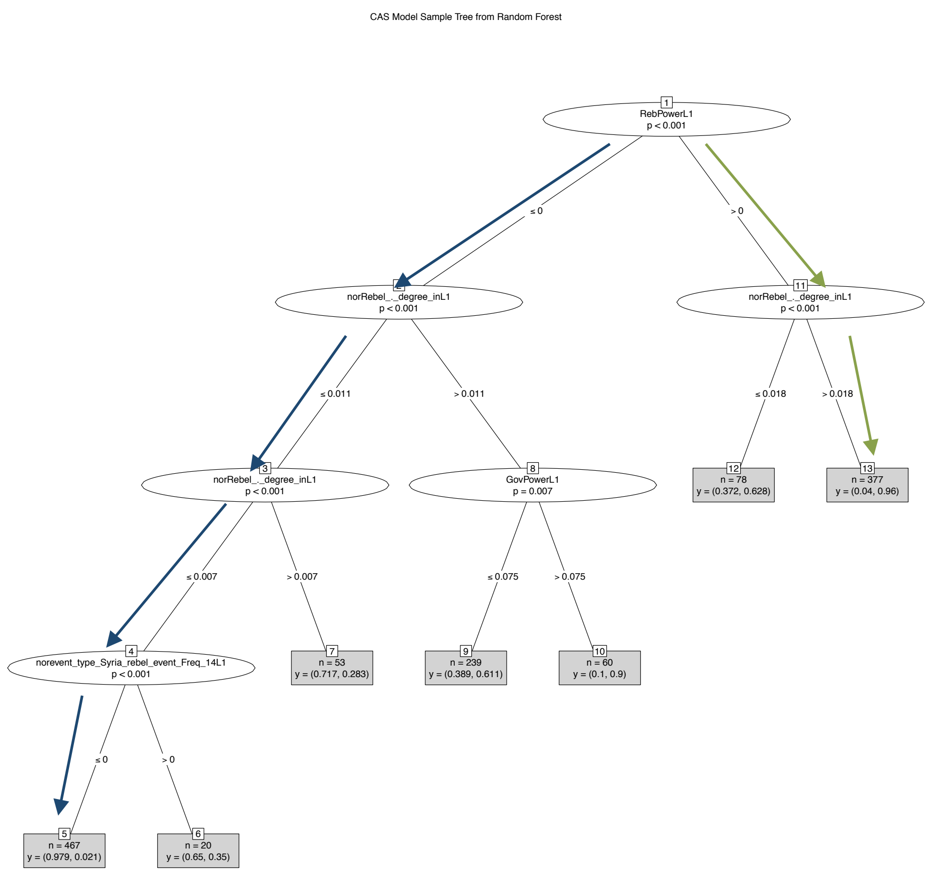

Figure 59: CAS Random Forest Model Sample Tree

Following the blue path, if the lagged value of rebel power is less than or equal to a normalized value of 0, and the lagged value of rebel degree in is less than or equal to a normalized value of .01 and .007, and the lagged value of rebel protests is less than or equal to the normalized value of 0, then the proportion of 0 to 1 is 98% to 2% respectively. Following the green line, if the lagged value of rebel power is greater than 0 and the lagged value of rebel degree in is greater than a normalized value of .02, then the proportion of 0 to 1 is 4% to 96% respectively. This sample tree provides insights echoed in the previous CAS specification in alternative models, namely the use of all different levels of analysis for explanation or prediction. This is yet further evidence that a multilevel approach built upon previous theory provides substantial benefits.

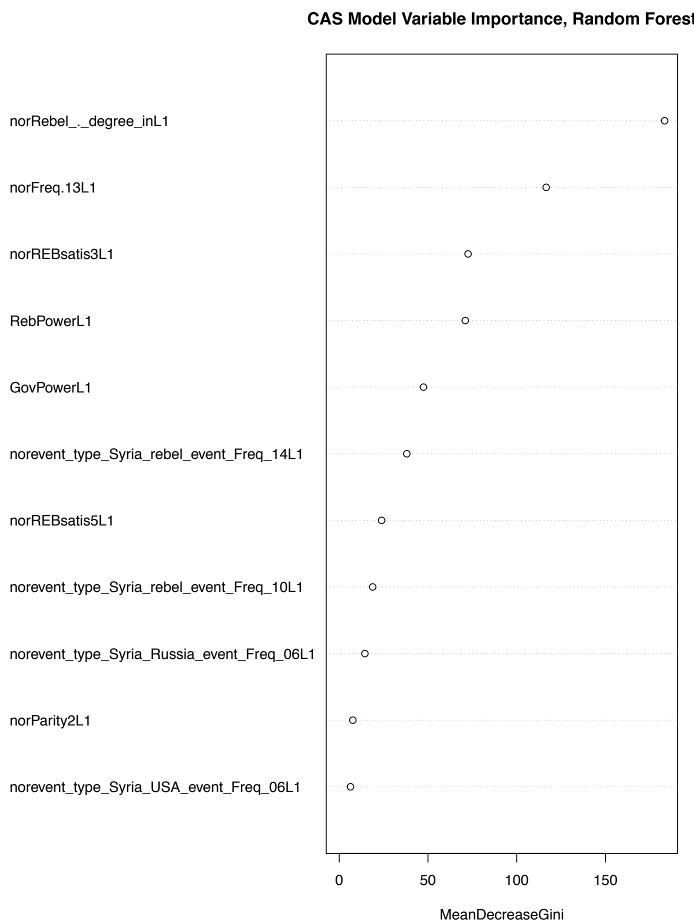

Figure 60: CAS Random Forest Model Variable Importance

Following the same logic as the theory RF variable importance, the CAS model indicated that rebel degree in has the lowest gini impurity measure, followed by threatening actions towards rebel and rebel satisfaction. The top three indicate that the interaction of three levels of analysis, as it relates to rebels, is highly critical in the determination of the onset of conflict in the next period. This is precisely why a CAS approach in vital. It can elucidate driver to conflict that was once not considered. The next set includes rebel and government power followed by protest, civilian satisfaction and demands. This is interesting as rebel attributes came before civilian ones, meaning that perhaps organized opposition was a greater challenge then larger sentiment. The last three elements, Russian cooperation, Parity (like in theory model) and USA cooperation were the worst performers. Cooperation's lack of predictive contribution has been discussed previously. As for parity, perhaps the way the power data is partitioned accounts for cases of parity there for not being needed as much.

Random Forest Forecast Plots

Using the outputs of the RF models, forecasts were generated and plotted to display the forecasted probabilities against actual event occurrence. RF forecasts produce 0 and 1 predictions as opposed to probabilities, so forecast plots will look slightly different to those in the CRT plots. Like the CRT plots, first a single province comparison of the two models will precede examination of the rest of the provinces. Below are the predictions for the theory and CAS random forest model in Homs.

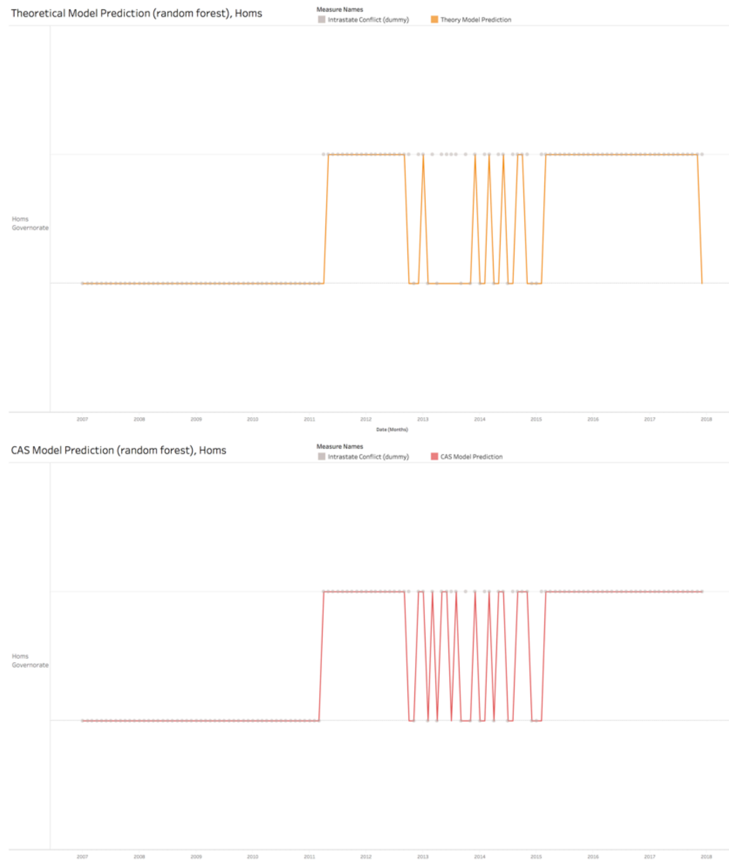

Figure 61: Theory vs. CAS Random Forest Model Prediction, Aleppo

For this province in particular, early high false positives seemed to be greatly reduced, as in early periods, the forecast is consistently zero when compared to the CRT method. However, there is a stark difference between the model specifications in the random forest. Near the beginning, the theoretical model has high number of false negatives not as prevalent in the CAS model. This trend will be examined further in the plots below.

Figure 62: Theory Random Forest Model Prediction

The prediction plot above indicates the theory model fit well, reflecting the performance measures above. What is interesting is that there is obvious correction of the false positive issue exhibited by the theory CRT model, especially when looking at the province of Aleppo that reflected the high recall score. However, upon visual inspection the problem of precision becomes obvious. The theory RF model is good at determining epochs of stability and conflict but had trouble picking up rapid escalation and de-escalation - the opposite of the theory CRT model that struggled in stable or conflict periods.

Below are the forecast plots for the CAS RF model by province, monthly. As reflected by the performance metrics this was the best performing model.

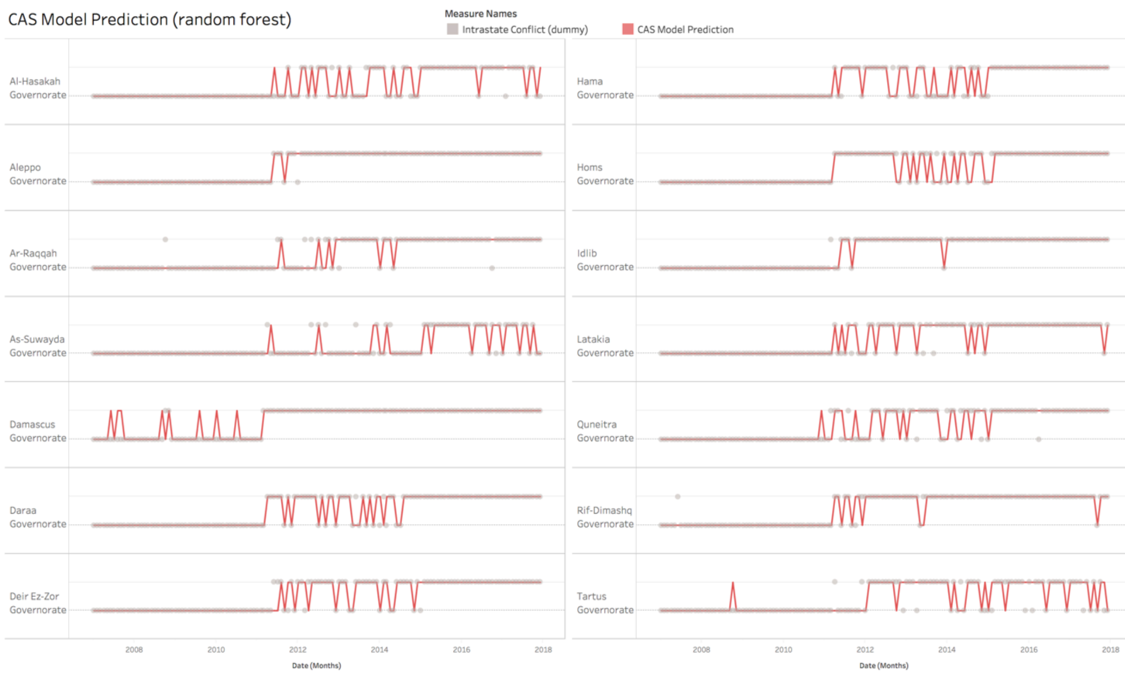

Figure 63: CAS Random Forest Model Prediction

The plot above is a reflection of those top performance metrics. Like in the theory RF model, the false positive issue is generally resolved, however, critically, the CAS RF model was also much better at picking rapid escalation and de-escalation. Looking at Aleppo once more, the false positive issue is rectified. While in the provinces of Homs, Queneitra, and Daraa, the previous issue of rapidly changing circumstances is generally corrected in the CAS RF predictions. This is a vital break through – the CAS RF model is able to correct the largest issues between the two prediction methods and model specifications. After inspection, there is clear evidence to suggest that the CAS extension provides added predictive power over a purely theoretical approach much like in explanation of intrastate conflict.

ROC & Precision Recall Trade Off

Like with the CRT models, the following ROC curve and precision and recall plot allows for a visual representation of the performance metrics for the RF models.

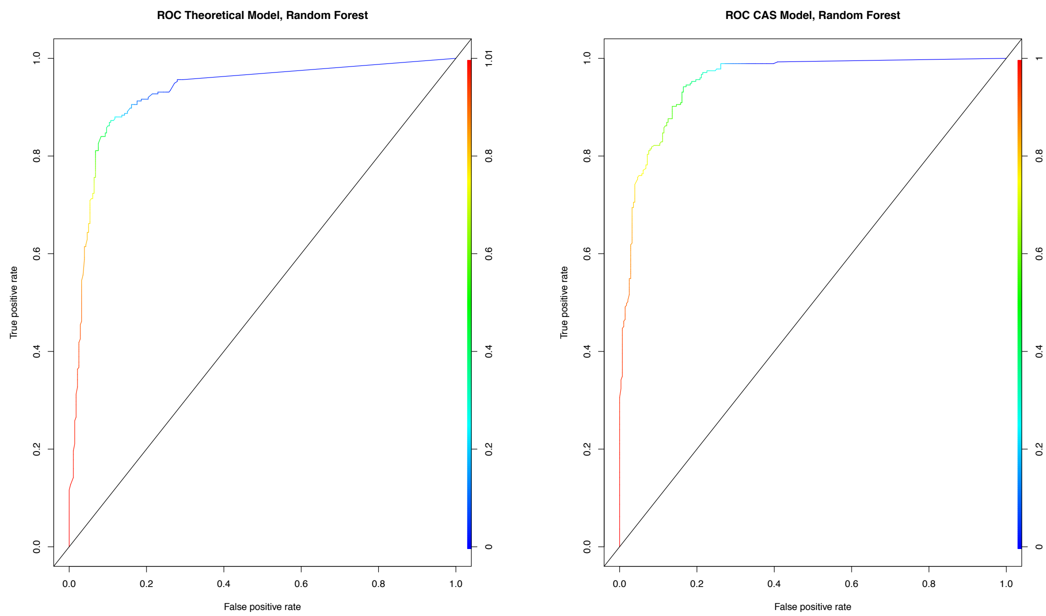

Figure 64: Theory vs. CAS RF Model ROC Curve

The theoretical model and the CAS RF models were not as similar as they were under the CRT method despite both performing relatively well as seen in the ROC plots above. The CAS RF had a better AUC and the best AUC of all models with a .94. The theory RF model had an AUC of .91 nearly the same as the theory CRT model. In this case, there is compelling evidence to choose the CAS RF model.

Lastly, like with the CRT model, it important to evaluate how sensitive the RF model's precision and recall tradeoffs are. Below are plots of the tradeoffs for both models. Upon inspection the theoretical model does not seem stable when trading off recall for precision as seen in the red portion of the theoretical model plot and as reflected by the high recall number in the evaluation. As noticed in the red portion of the CAS model plot, the tradeoff is more stable. The theory model has to give much more precision to gain recall. However, the CAS RF can achieve a higher overall level of precision and recall when compared to theory model. Further, the blue portion of line is steeper on the CAS model indicating that higher levels of precision can be achieved while maintaining good recall similar to the CAS CRT model.

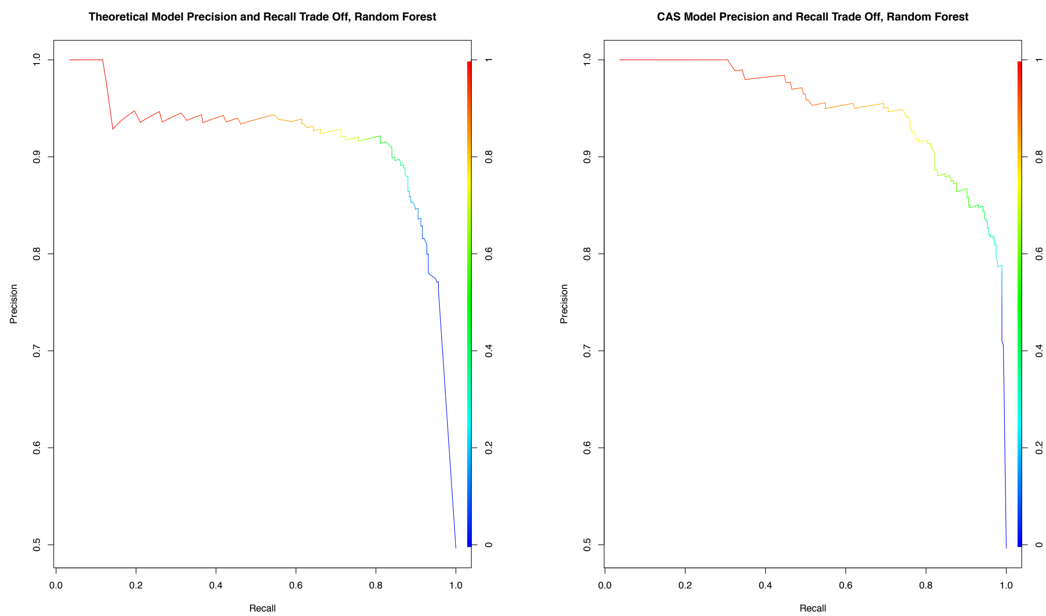

Figure 65: CAS RF Model Precision and Recall Trade Off

RF Conclusion

The prediction model using a RF method further provides evidence in supporting conclusions drawn from the CRT model prediction. Theory informed machine learning models can predict conflict to a high degree when using more advanced prediction techniques. Predictions are conclusively better when using a CAS specification with the CAS RF model having the best performance of all. The false positives issues as well as sensitivity to rapid escalation and de-escalation seems to be resolved using the CAS RF model – indicating its capacity as the best prediction model tested.

Tactical Predictions

The RF CAS model result provides evidence of the predictive power of the specification and method. The next logical step is to then see the feasibility of creating unique courses of actions (COAs) for each province. Tacticians need to be able articulate different policies and actions depending on the province and unique situation. Leveraging data heterogeneity and modeling process, data from each province with be partitioned and ran separately through the RF. The heat map plot below shows the rounded variable importance for each feature for each province.

Variable Importance by Province (Prediction)

Measure Values 0.3 – 16.0

Province	Government Power	Rebel Power	Parity	Satisfaction	Satisfaction II	Protests	Demands	Rebel Degree in	Threaten	Russia Coop	USA Coop
Al-Hasakah	2.3	7.0	1.5	6.0	2.5	2.0	0.8	10.0	9.0	0.5	1.0
Aleppo	4.0	2.0	1.0	2.0	1.0	9.0	5.0	14.0	10.0	2.0	1.5
Ar-Raqqah	3.0	7.0	0.6	2.0	1.0	4.0	2.8	13.5	8.0	1.0	2.0
As-Suwayda	2.0	3.0	0.3	6.4	1.8	1.7	2.7	10.0	4.7	1.0	0.8
Damascus	1.5	3.5	1.0	2.0	1.3	9.0	6.0	5.0	10.0	4.0	1.5
Daraa	2.0	3.0	0.8	5.0	3.0	3.0	2.0	15.0	11.5	0.5	0.7
Deir Ez-Zor	3.0	4.0	1.4	7.0	2.0	2.0	2.2	12.0	8.2	1.6	1.0
Hama	3.9	3.5	2.0	8.2	1.8	2.0	1.8	12.0	8.0	1.0	0.7
Homs	1.0	2.5	0.4	5.0	1.8	4.0	2.0	16.0	10.0	1.2	1.0
Idlib	2.0	4.0	1.0	2.0	1.8	6.0	1.5	14.0	12.0	1.0	1.2
Latakia	5.0	2.0	1.0	6.0	3.0	2.9	1.3	11.0	12.0	2.0	1.0
Quneitra	2.0	1.8	1.0	8.0	1.5	1.9	1.2	13.0	9.0	1.3	1.0
Rif-Dimashq	4.0	8.0	1.4	2.0	1.8	2.3	2.0	14.0	9.0	0.5	1.0
Tartus	1.0	1.8	0.5	4.0	1.6	1.0	1.9	11.0	16.0	4.0	1.0

Figure 66: RF Variable Importance Heat Map by Province (rounded variables)

In the figure above, darker shades indicate higher variable importance and as seen in the tessellated pattern, some critical information can be gleaned. Primarily, each province has a unique set of indicators that are of most importance in determining the onset of conflict in the next period. Due to the heterogeneity of data available in each province, unique prescriptive insights can be gained. For example in 11 of the 14 provinces above, rebel degree in, was of most importance, in the other three, threaten actions from government are of most importance. In the province of Aleppo, protests and demands are also major contributors to conflict, where in the provinces of Ar-Raqqah, Al-Hasakah, and Rif-Dimashq the substantial rebel presence was a major contributor of conflict. In articulation of policies, these factors provide critical insights on how a tactician would approach each province. Each province is unique and thus a variety of COAs are needed to manage the differing causes of instability. For example a COA for the province of Hama would be to better manage the rebel presence and decrease access to them, prevent or lessen the threaten actions from government, and work on ways to reduce dissatisfaction to attempt to mitigate conflict. Conversely, in the province of Damascus, a COA would be to address route causes of protests and demands, find ways to reduce the reliance on violence by the government with the hopes of reducing conflict. Not only does this provide insights for COAs but also due to different drivers, each province has different warning indicators for the onset of conflict. Some provinces are more responsive to rebel agitation and threats where others are more politically driven by protests and demands. By teasing out the different initiators by province, more precise evaluation can occur. As a tactician, focus can be placed on monitoring the critical factors of each province while preparation and strategies can be customized. This customization is essential because often times a single monolithic solution is proposed to remedy conflict for an entire nation and this solution may not be able to address the subtle nuances found in differing areas. For example, a policy that works in the south may not with in the north or there may be a distinction between urban and rural areas. The results above indicate that when possible, dissect the AOR and address each part as unique. As argued in the research, segmenting an area into more granular geographic spaces as well as increase the frequency of data collection elucidates critical insights that may otherwise remain hidden.

Results Concluding Remarks

The four pooled linear models, two classification and regression tree models and two random forest models provide quite a substantial test of the explanatory and predictive power of the original theoretical model versus the CAS extension. Below is a summary table displaying all results and evaluation for easier comparison.

Table 8: Summary of Pooled Linear Models with Evaluation

Model	R2	MAE	RMSE	Top Ivs
PLM Theory Model	66%	14.83	31.67	Satisfaction Parity
PLM Theory Model with Lagged DV	78%	*	*	*
PLM CAS Model	85%	9.75	21.53	Satisfaction Rebel Degree In
PLM CAS Model with Lagged DV	86%	*	*	*

Table 9: Summary of CRTs & RF Models with Evaluation

Model	Accuracy	Recall	Precision	Type I	Type II	AUC	Top Ivs
CRT Theory Model, testing	87%	86%	87%	39	35	0.90	Rebel Power Rebel Satisfaction
CRT CAS Model, testing	87%	87%	87%	38	35	0.91	Rebel Degree in Threathen from Government
Random Forest Theory Model, testing	87%	93%	82%	21	50	0.91	Rebel Satisfaction Rebel Power
Random Forest CAS Model, testing	88%	84%	92%	44	22	0.94	Rebel Degree in Threathen from Government

The main conclusion to draw is that in both explanatory power and predictive power, CAS model specification out performed that of theoretical model. In the PLM model, the CAS specification achieve a better R^2 and had lower MAE and RMSE error measures. The random forest CAS model had the highest accuracy and critically the best recall and lowest type II error. It also had the best AUC across all prediction models. For these reasons, the CAS specification out performed the theoretical model.

The top IVs also serve to tell an interesting story. PLM top IVs were variables that had the largest magnitude while prediction model variables were selected from the variable importance plots. The trend that emerges is that when only macro structural elements are available, rebel satisfaction or rebel power is generally most important. However, when the model specification was extended to use a CAS approach, the models tended to select a mix of macro, meso and micro level features. The top two performing models both use rebel degree in, the micro to meso component, while satisfaction (macro) is used in CAS PLM and threaten from government (meso) is used in the CAS RF.

This chapter provided critical evidence supporting the main goals of this research. The results suggest that the alternative variables used in the re-specification of the original theoretical model are viable in explaining conflict as original results were replicated. From an explanation standpoint, including CAS variables increased the power of the PLM model to explain conflict. Taking these insights, prediction models were tested using the same model specification but with lagged data. The impressive prediction results indicate that theory informed machine learning models do provide accurate and precise forecasting methods that still allow for diagnosis of why the phenomena was predicted to occur not just a probability estimate. These outcomes provide a sound foundation for moving away from strategic level decision making to more tactical, higher frequency actions.

Chapter

06

Conclusion, Implications & General Discussion

Science, technology and sound theory provide tools to solve most complex problems. In the field of political science and international relations, the intersection of quantitative and qualitative enhances outcomes and enriches research. This research seeks to continue in this vein. It seeks to build upon sound theory, utilize advances in data collection, algorithms and methods to provide a novel approach to conflict explanation and prediction. The research will conclude by reviewing general goals of the research, discuss key findings from data, results and predictions, provide implications, and general uses.

General Goals

The research first goal was to find suitable data to achieve three particular goals; capture theoretical variables, be high frequency and geographically specific, and display the heterogeneity of features of data. To achieve event data, GDELT, and social network analysis were used to general proxy measures of power, parity and satisfaction, on a granular and dynamic scale. Measures of betweenness centrality (power/ parity) and average tone of public statements (satisfaction) provided suitable instruments – able to accurately capture what they sought to measure and having theoretically correct relations with the dependent variable. A combination of GDELT and SNA was also used to create CAS variables for extension. Meso and mico to meso variables include; civilian satisfaction, rebel protests and demands, rebel degree in, US and Russia cooperation, and threaten actions from government. These were also found to have correct relations with the dependent variable.

Due to increased sampling frequency, difference between areas and provinces could be better understood.

Using these new metrics the next goal was to recreate the theoretical model using a PLM to confirm significance and sign of variables and extend using a CAS approach. The new variables proved to be successful in recreating the original model and the CAS model provided a significant boost in explanatory power. Providing evidence that a multilayer approach can provide added insights.

After statistical testing, the next goal was to see if theory informed machine learning models could preform accurate predictions. The CRT and RF testing showed that theory informed machine learning models can provide accurate monthly forecasts, with the CAS RF model providing the highest accuracy and lowest type two errors. This is vital in enhancing research on providing tacticians granular, short-term predictions that can be explained.

General results suggest the CAS model outperforms the theoretical model in both explanation and predictions. A multilevel approach, tracking underlying changes in network dynamics, data heterogeneity and high sample rate are vital factors in understanding and predicting conflict. Structural conditions provide the preconditions for conflict but the dynamic structure shifts in the underlying network and the interaction between meso and micro levels can explain conflict manifestation.

Data Discussion

The event data and SNA metrics alone provide a unique approach on traditional structural measures. It is well documented that sources of power are not as straightforward as population but where that population is positioned in the network structured in which it interacts. Satisfaction can be measured at much higher intervals to increase variance and shifting attitudes of populations. Further this data collection allows for operationalization of variables that have a meaning in the context of the crisis. Lastly collection methods provide a simpler way to examine heterogeneity.

Results Discussion

Results generally showed that the CAS model provided more explanatory power than the theoretical one and that meso and micro level events were relevant in the onset on intrastate conflict. This suggests that conflicts are more than the structural conditions in which they occur but rather the structural conditions incentivize or constrain actors in a system producing emergent behavior.

Predictions Discussion

High accuracy, precision and recall indicate that the models can be used for month-to-month provincial level forecasts, with the CAS RF the most successful achieving 88% and 92% precision. The forecast indicate that after preconditions are met, agitation of rebels and threaten and violent actions correspond with high probabilities of conflict the next month (retaliatory in nature) among other factors.

Tactical Discussion

The partitioning of data and running of individual prediction models for each province shows the power of this type of modeling and data usage. The ability to ascertain the unique drivers of conflict as well as being able to articulate precise COAs for each province is exceedingly valuable for tactical decision makers. Monolithic policies and strategies using country level indicators may not be extensible or successful in specific regions. From EDA to explanation to prediction, it was noticed that each province was unique and had its own set of dynamics specific to that area. By leveraging this, tactics can be better customized and hopefully more successful in mitigating the onset of conflict.

Implications

The results suggest that conflict be examined from a multilevel approach. While structural conditions provide preconditions, a better explanation of onset and manifestation can be gleaned from an extended approach. Further the results suggest phenomena do not pervade all portions of the host equally. By disaggregating parts better understandings of the whole can be achieved. Further, foreign intervention can have profound impacts on outcomes. The results suggest initial support pre-conflict can provide a boost to rebels and allow an early advantage. However if support waivers and government support is consistent then rebel movements cannot be sustained. In the context of Syria, the US bolstered rebels allowing for earlier victory. However as policies changed, support waned and rebel movements lost impotence. Russian support to the government out paced that of the US to rebels, providing a crucial edge to the Assad regime. Lastly theory and machine learning can be jointly leveraged to allow for reliable and explainable predictions.

Extensions

While this research did achieve most of what it sought to do, improvement is always necessary. From a data standpoint, GDELT has a plethora of features that can be explored as well as other sources with similar data structures. It would be interesting and worthwhile to incorporate more features and perform feature reduction techniques. Modeling could also be enhanced, volume II seeks to use nonlinear analysis and more advanced predictions methods like neural nets. As this was an initial foray, simpler methods were used. Further, forecasting at different time intervals and for different types of conflict would be valuable.

Lastly, volume II also seeks to replicate the methodology for other conflicts to validate methods and provide more evidence.

Uses

While many uses can be discussed, three will be covered. An application of this research can greatly benefit humanitarian efforts (a partial reason for endeavor initially). By providing accurate month-to-month prediction on conflict, agency like the UN can better prepare responses, mitigate human costs by moving civilians and proactively address impending issues.

For tactical decision makers enhanced explanation and prediction can provide better operational awareness and understanding of root causes of conflict can be attained. Resources and responses can be better positioned, threats to missions can be mitigated and most importantly, tactics can adapt to the ever-changing terrain of conflicts. Strategy and tactics can be better synced and long-term feature relations can be used to inform the short-term.

Lastly there is an academic use for this research. It suggests that new data collections methods can be valid in providing proxies for long-held measurements. Approaches from different disciplines provide useful tools in international studies and computation. Past findings combined with modern techniques can produce valuable tools for research.

This research hopes to be a humble contribution to the plethora of outstanding academic work before it

"Strategy requires thought, tactics require observation" – Max Euwe

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Appendix 1 - Outputs

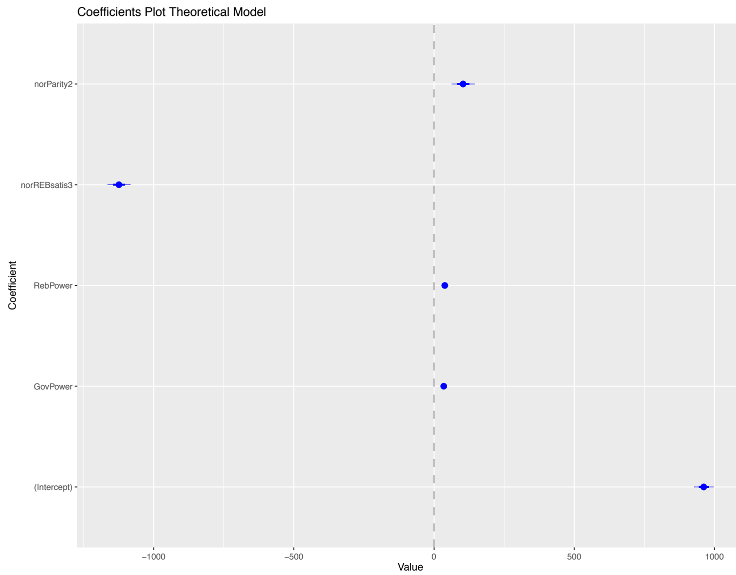

Figure x. Theory Model Coefficient Plot

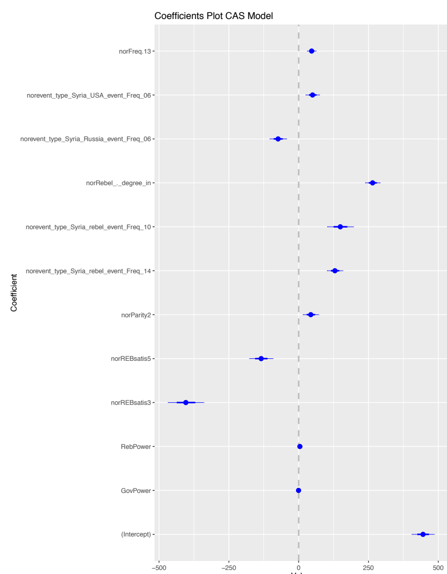

Figure x. CAS Model Coefficient Plot

```
> confusionMatrix(freq_train$DV2DUM, CRT1Train)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 585  66
         1 103 540

               Accuracy : 0.8694
                 95% CI : (0.8498, 0.8873)
    No Information Rate : 0.5317
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7387
 Mcnemar's Test P-Value : 0.005619

            Sensitivity : 0.8503
            Specificity : 0.8911
         Pos Pred Value : 0.8986
         Neg Pred Value : 0.8398
             Prevalence : 0.5317
         Detection Rate : 0.4521
   Detection Prevalence : 0.5031
      Balanced Accuracy : 0.8707

       'Positive' Class : 0
```

Figure x. Theory CRT Model Evaluation (training), Dependent Variable – Intrastate Conflict

```
> confusionMatrix(freq_test$DV2DUM, CRT1Test)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 244  35
         1  39 236

               Accuracy : 0.8664
                 95% CI : (0.8352, 0.8936)
    No Information Rate : 0.5108
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.7328
 Mcnemar's Test P-Value : 0.7273

            Sensitivity : 0.8622
            Specificity : 0.8708
         Pos Pred Value : 0.8746
         Neg Pred Value : 0.8582
             Prevalence : 0.5108
         Detection Rate : 0.4404
   Detection Prevalence : 0.5036
      Balanced Accuracy : 0.8665

       'Positive' Class : 0
```

Figure x. Theory CRT Model Evaluation (testing), Dependent Variable – Intrastate Conflict

```
> confusionMatrix(freq_train$DV2DUM, CRT1CASTrain)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 582  69
         1  80 563

               Accuracy : 0.8849
                 95% CI : (0.8662, 0.9017)
    No Information Rate : 0.5116
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.7697
 Mcnemar's Test P-Value : 0.4127

            Sensitivity : 0.8792
            Specificity : 0.8908
         Pos Pred Value : 0.8940
         Neg Pred Value : 0.8756
             Prevalence : 0.5116
         Detection Rate : 0.4498
   Detection Prevalence : 0.5031
      Balanced Accuracy : 0.8850

       'Positive' Class : 0
```

Figure x. CAS CRT Model Evaluation (training), Dependent Variable – Intrastate Conflict

```
> confusionMatrix(freq_test$DV2DUM, CRT1CASTest)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 244  35
         1  38 237

               Accuracy : 0.8682
                 95% CI : (0.8372, 0.8953)
    No Information Rate : 0.509
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.7364
 Mcnemar's Test P-Value : 0.8149

            Sensitivity : 0.8652
            Specificity : 0.8713
         Pos Pred Value : 0.8746
         Neg Pred Value : 0.8618
             Prevalence : 0.5090
         Detection Rate : 0.4404
   Detection Prevalence : 0.5036
      Balanced Accuracy : 0.8683

       'Positive' Class : 0
```

Figure x. CAS CRT Model Evaluation (testing), Dependent Variable – Intrastate Conflict

```
> CRT1$variable.importance
   RebPowerL1 norREBsatis3L1     GovPowerL1   norParity2L1
    241.35857      202.97412      125.17597       78.58404
> plot(CRT1$variable.importance, main = "Theoretical Model Variable Importance, CRT")
```

Figure x. Theory CRT Model Variable Importance

```
> CRT1CAS$variable.importance
                     norRebel_._degree_inL1                             norFreq.13L1
                                349.9697838                              254.9116176
                                 RebPowerL1                               GovPowerL1
                                158.6828902                              137.5278048
 norevent_type_Syria_rebel_event_Freq_14L1  norevent_type_Syria_rebel_event_Freq_10L1
                                126.3479341                              104.7249017
                              norREBsatis3L1                           norREBsatis5L1
                                 31.7989161                               10.1023088
norevent_type_Syria_Russia_event_Freq_06L1                             norParity2L1
                                  4.7638494                                0.6596768
> plot(CRT1CAS$variable.importance, main = "CAS Model Variable Importance, CRT")
> #install.packages("party")
> library(party)
> plot(CRT1CAS, type="simple", main = "CAS Model CRT Error Plot (Training Data)")
Error in plot.default(temp1, temp2, type = "n", axes = FALSE, xlab = "",  :
  formal argument "type" matched by multiple actual arguments
```

Figure x. CAS CRT Model Variable Importance

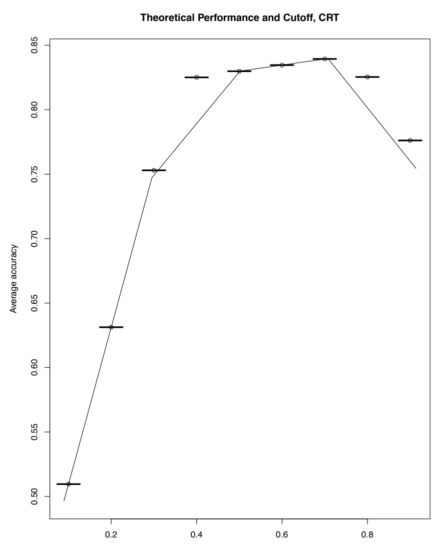

Figure x. Theory CRT Model Performance and Cutoff Plot appendix

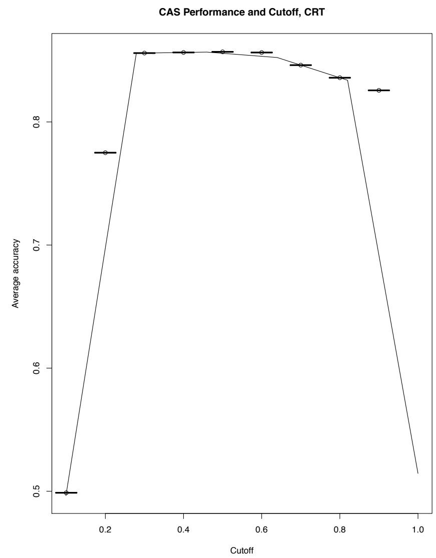

Figure x. CAS CRT Model Performance and Cutoff Plot appendix

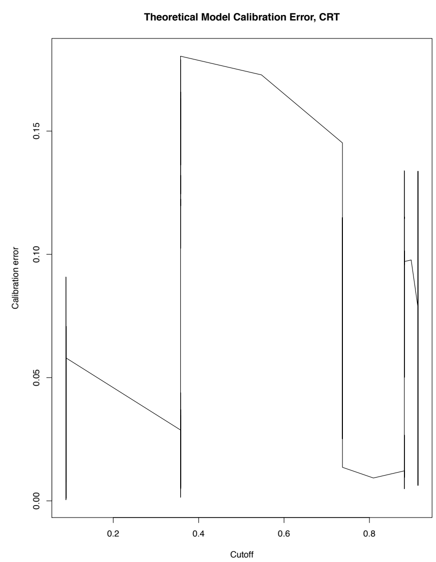

Figure x. Theory CRT Model Calibration Error Plot appendix

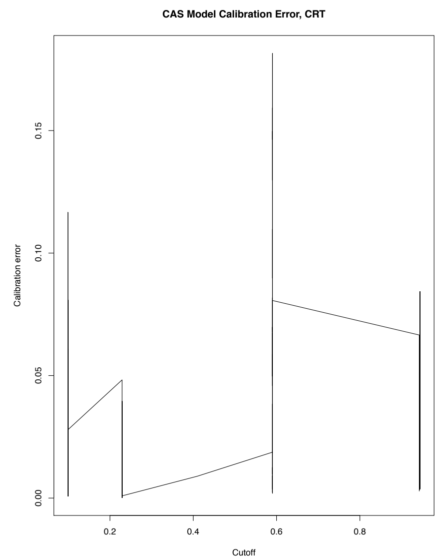

Figure x. CAS CRT Model Calibration Error Plot appendix

```
> confusionMatrix(predict(freq_train.forest), freq_train$DV2DUM)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 591 133
         1  60 510

               Accuracy : 0.8509
                 95% CI : (0.8303, 0.8698)
    No Information Rate : 0.5031
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7015
 Mcnemar's Test P-Value : 2.187e-07

            Sensitivity : 0.9078
            Specificity : 0.7932
         Pos Pred Value : 0.8163
         Neg Pred Value : 0.8947
             Prevalence : 0.5031
         Detection Rate : 0.4567
   Detection Prevalence : 0.5595
      Balanced Accuracy : 0.8505

       'Positive' Class : 0
```

Figure x. Theory Random Forest Model Evaluation (training), Dependent Variable – Intrastate Conflict

```
> #TEST
> confusionMatrix(predict(freq_train.forest, freq_test), freq_test$DV2DUM)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 258  50
         1  21 225

               Accuracy : 0.8718
                 95% CI : (0.8411, 0.8985)
    No Information Rate : 0.5036
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7435
 Mcnemar's Test P-Value : 0.0008906

            Sensitivity : 0.9247
            Specificity : 0.8182
         Pos Pred Value : 0.8377
         Neg Pred Value : 0.9146
             Prevalence : 0.5036
         Detection Rate : 0.4657
   Detection Prevalence : 0.5560
      Balanced Accuracy : 0.8715

       'Positive' Class : 0
```

Figure x. Theory Random Forest Model Evaluation (testing), Dependent Variable – Intrastate Conflict

```
> confusionMatrix(predict(freq_train.forestCAS), freq_train$DV2DUM)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 550  72
         1 101 571

               Accuracy : 0.8663
                 95% CI : (0.8465, 0.8844)
    No Information Rate : 0.5031
    P-Value [Acc > NIR] : < 2e-16

                  Kappa : 0.7327
 Mcnemar's Test P-Value : 0.03327

            Sensitivity : 0.8449
            Specificity : 0.8880
         Pos Pred Value : 0.8842
         Neg Pred Value : 0.8497
             Prevalence : 0.5031
         Detection Rate : 0.4250
   Detection Prevalence : 0.4807
      Balanced Accuracy : 0.8664

       'Positive' Class : 0
```

Figure x. CAS Random Forest Model Evaluation (training), Dependent Variable – Intrastate Conflict

```
> confusionMatrix(predict(freq_train.forestCAS, freq_test), freq_test$DV2DUM)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 235  22
         1  44 253

               Accuracy : 0.8809
                 95% CI : (0.8509, 0.9067)
    No Information Rate : 0.5036
    P-Value [Acc > NIR] : < 2e-16

                  Kappa : 0.7619
 Mcnemar's Test P-Value : 0.00974

            Sensitivity : 0.8423
            Specificity : 0.9200
         Pos Pred Value : 0.9144
         Neg Pred Value : 0.8519
             Prevalence : 0.5036
         Detection Rate : 0.4242
   Detection Prevalence : 0.4639
      Balanced Accuracy : 0.8811

       'Positive' Class : 0
```
Figure x. CAS Random Forest Model Evaluation (testing), Dependent Variable – Intrastate Conflict

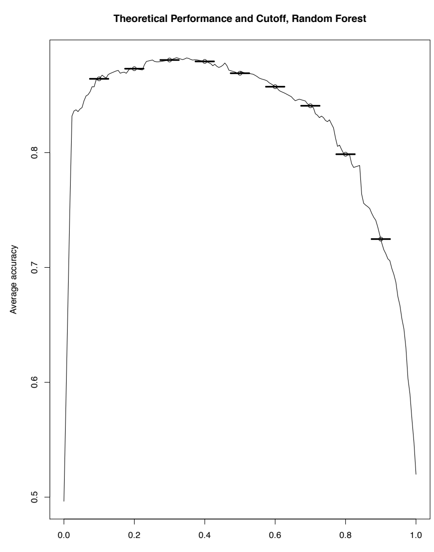

Figure x. Theory Random Forest Model Performance and Cutoff Plot appendix

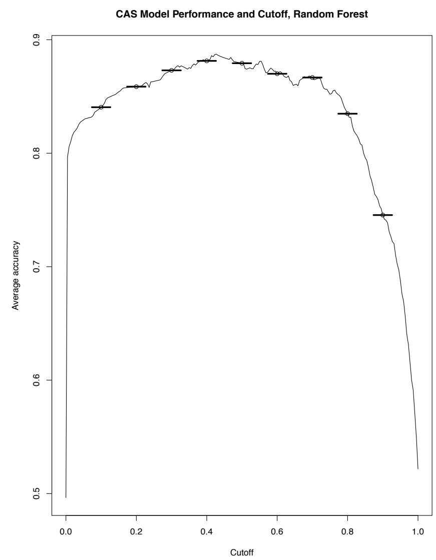

Figure x. CAS Random Forest Model Performance and Cutoff Plot appendix

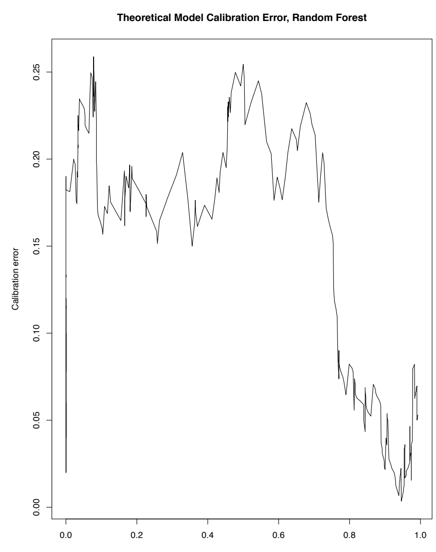

Figure x. Theory Random Forest Model Calibration Error Plot appendix

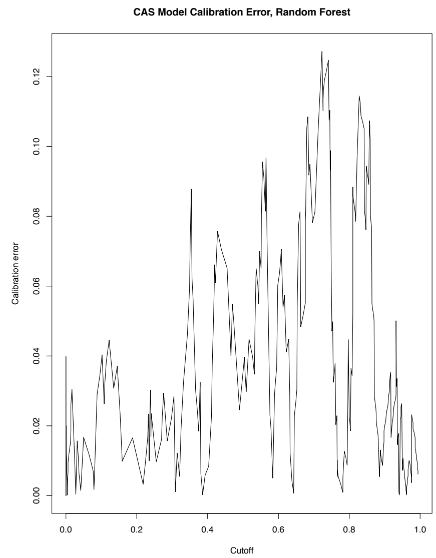

Figure x. CAS Random Forest Model Calibration Error Plot appendix

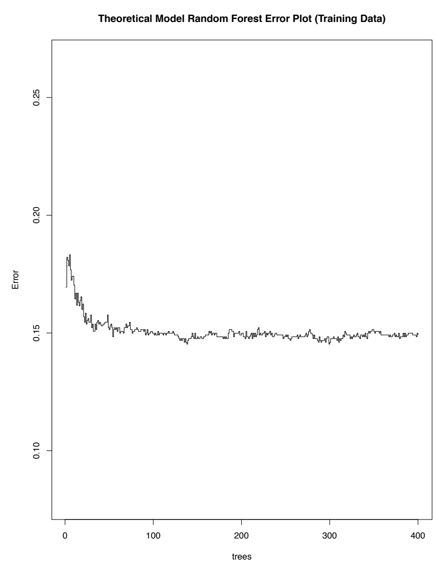

Figure x. Theory Random Forest Model Error Plot appendix

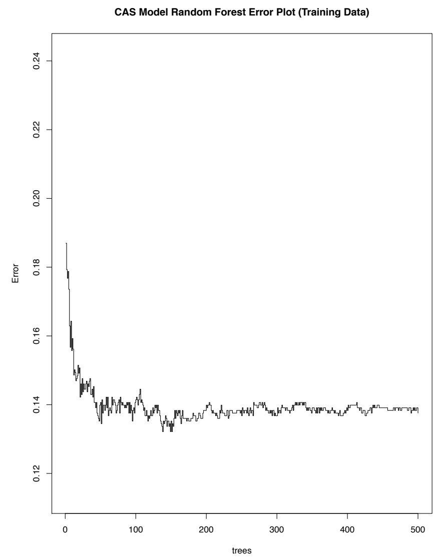

Figure x. CAS Random Forest Model Error Plot appendix