Network Analysis of Terrorist Activities

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Abstract

Terrorism remains a critical global concern, necessitating a comprehensive understanding of terrorist networks' structures and dynamics. This study employs a data-driven approach to construct a bipartite network from terrorist attack data. Through this bipartite structure, a terrorist-terrorist projection is generated, enabling the evaluation of centralities, communities, and shock propagation within the network.
The methodology involves transforming incident data into a bipartite representation, enabling the visualization and analysis of connections between terrorist groups and their target types. Utilizing established network analysis techniques, centrality measures are computed to identify pivotal nodes within the terrorist network. Furthermore, community detection algorithms uncover the underlying structures and associations among terrorist entities.
Moreover, the study investigates shock propagation within the network, exploring how disruptions or shocks in specific nodes affect the overall network dynamics. This analysis sheds light on the vulnerabilities and resilience of the terrorist network, contributing to proactive strategies for counter-terrorism efforts.

Introduction

Nowadays, terrorism stands as a grave global concern, not only due to the casualty resulting from the attacks but also due to the side effects of the insecurities they cause. The repercussions encompass various unforeseen adversities, including terrorist strikes, military interventions, and other disruptive events.Their fluidity extends to affecting financial markets, thereby posing substantial implications for stocks and bonds.(see Andrew H. Chen, Thomas F. Siems, 2004)
Many research and scholarly papers have explored the variety of aspects linked to terrorism, ranging from investigating the terrorism effects on different domains, such as its social (see G. Bruce, 2012) and financial implications(see Marc Chesney, Ganna Reshetar, Mustafa Karaman, 2011) to more direct approaches looking into the terrorist network (see Valdis E. Krebs, 2002), its evolution (see Helfstein, S., & Wright, D., 2011) and the statistical insights derived from analyzing these networks (see Fu Julei, Fan Ying, Wang Yang, Wang Shouyang, 2013). While challenging, it remains crucial to simultaneously model the relationships between terrorists and their targets, considering the complexity arising from the numerous involved subjects and intricate inter-group connections.
The primary goal is to identify the most influential actors in these scenarios. Social network methods have gained prominence in the study of terrorism activities due to their capability to explore these phenomena at a broader level, transcending individual analysis (see Matthew and Shambaugh, 2005; Husslage et al., 2015; McMillan et al., 2018; Basu and Sen, 2021). A number of contributions have focused on using centrality measures for the identification of the

key players in social networks (see Katz, 1953, Freeman, 1978, Brin and Page, 1998, Bonacich and Lloyd, 2001, Borgatti, 2006, Nasirian et al., 2020 among others), so that their removal could lead to severe disruption of network connectivity and, thus, of its potential harmfulness(see Berzinji et al., 2012).

Law enforcement agencies and police services, in their efforts to monitor criminal activities within terrorist-related networks, seek to pinpoint the most influential actors or groups, often referred to as 'key players.' Identifying these central nodes within a network is inherently intricate, especially when dealing with phenomena like terrorist attacks that can have profound societal impacts. While studies of terrorist network structures inherently focus on the evolution of these collectives, few investigations have actively considered the evolving nature of networks to detect the terrorist groups functioning as key players (or hubs) and identifying their vulnerable targets (see Lindelauf et al., 2013, Gialampoukidis et al., 2016, Husain et al., 2020, Malang et al., 2020).

In this research, we introduce a rigorously validated approach utilizing bipartite networks to collectively analyze the changing structure of relationships between terrorists and targets. This methodology is driven by the extensive use of a global terrorism database that primarily focuses on attacks. The exploration of influential nodes is facilitated by modeling terrorist-target connections as bipartite networks. In such networks, two distinct types of nodes exist, and edges connect nodes from different sets exclusively. In constructing our networks, we adopt a dual perspective, considering the number of attacks and the number of victims separately. Similarly to mainstream approaches where bipartite networks are usually compressed by one-mode projections, we obtain the terrorist interactions using terrorist-terrorist projections.

Finally, we propose an experiment, where we propagate a shock to the high ranked nodes of the network , to study how the indicators react. This exercise has the potential to increase the power of decision analysis in enhancing decision support and advice policy makers in better dealing with the ever-increasing threat imposed by terrorism.

Our observations reveal intriguing dynamics within the landscape of active terrorist groups. Notably, some of the historically most active groups exhibit a recent period of inactivity spanning the last decade,a prime example of which is Basque Fatherland and Freedom (ETA) group. Conversely, some of them are relatively new entities, such as Al-shabaab, having emerged only within the past 10 to 20 years. Furthermore, a noteworthy trend emerges as we examine recent decades' key groups, with more than half of them categorized as relatively new entities, boasting an average age of merely 13 years. This temporal variance underscores the dynamic nature of terrorism, where the prominence and activity of groups are subject to shifts and transitions over time.

Ultimately, when considering shock propagation, we demonstrate that an initial disturbance in an influential node triggers a cascade of subsequent impacts, spreading through the interconnected terrorists.

Data and methodology

Data description and pre-processing

Bipartite terrorist networks are formed by gathering data from the Global Terrorism Database (GTD). The GTD, managed by the National Consortium for the Study of Terrorism and Responses to Terrorism (START)[1], is a comprehensive dataset continuously updated. It compiles information on terrorist activities from diverse sources, including media articles, electronic news, books, journals, and legal documents. Covering the period from 1970 to 2021, the GTD contains data on terrorist attacks worldwide. Due to its extensive nature, a crucial step involves preprocessing the data to construct networks before conducting any analysis. This is because entries in the GTD often present ambiguity, making it challenging to distinguish between terrorism, criminal activities, or political violence.
The dataset we're working with has 214,666 entries, each with 135 different details like when and where an attack happened, the type and results of the attack, details about the target including nationality, the number of people affected, the group responsible for the attack, the weapons used, and more. To make the information clearer, we start by removing incidents that are uncertain, like those marked as 'Unknown Terrorist' or 'Unknown Target'. We also exclude unsuccessful attempts and incidents targeting 'multinations', along with any flagged as doubtful. Additionally, attacks by infrequent terrorist groups are removed. This cleaning process aims to preserve the connections between terrorist attacks and specific countries. After this, we are left with a dataset containing 70,616 entries.

Methodology

We create a yearly bipartite weighted directed network by consolidating data from the prepared dataset annually. In bipartite graphs, nodes are divided into two distinct sets, and connections exclusively link nodes from different groups. In our context, the main set of nodes, denoted as V, represents the terrorist groups, while the secondary set U pertains to the targets, which serve as the objectives of the attacks. In order to create the latter set of variables, we took information concerning target types which contains 21 major categories. As previously noted, the classification of terrorist groups is limited to those that have carried out a minimum of 50 attacks throughout the 52-year data span. We form a bipartite network connecting terrorists to targets, with edges E representing the total annual attacks conducted by a terrorist v on a specific target type u. To gain a more comprehensive understanding of the relationships between terrorists and targets, we also construct networks where edges denote the total annual fatalities resulting from the attacks.
The network depicting interactions between terrorists and targets, denoted as G, can be effectively illustrated using its weighted adjacency matrix $G \Leftrightarrow W(G)$, where $W(v, u)$ signifies the number of attacks carried out by a terrorist v against a target u. Given the dynamic nature of this network, it can be broken down over time into distinct sub-graphs denoted as Gt (Vt , Ut , Et), capturing the connections present at a specific period t. In our particular context, yearly aggregations form 52 sub-networks, representing terrorist actions from 1970 to 2021. Notably, data for the year 1993 is excluded due to the unreliability of more than 80% of recorded attacks.

[1] https://www.start.umd.edu/gtd/

In order to obtain terrorist-terrorist interactions, for each year, we have multiplied the matrix representing terrorist-target relationships by its transpose which is a valid technique in network analysis. This method, often referred to as a matrix multiplication or the projection of bipartite networks, allows for the transformation of the original bipartite network into a unipartite network representing interactions solely among the terrorist entities.
When multiplying the terrorist-target matrix by its transpose, the resulting matrix reflects the connections or interactions between terrorist entities. Specifically, the elements of this resultant matrix indicate the number of shared targets between pairs of terrorist groups. If there is a non-zero value in a cell of the resulting matrix, it signifies that the corresponding terrorist groups share common targets, establishing a link between them in the unipartite terrorist-terrorist network.
This technique enables the conversion of a bipartite network (with nodes in two distinct sets) into a unipartite network (with nodes in a single set), allowing for a focused analysis of interactions and relationships solely among the terrorist entities themselves. Since we built our bipartite network using two distinct approaches, we now have two representations of terrorist-terrorist networks, depicting slightly different structures.

In our quest to pinpoint influential nodes within the intricate web of a terrorist network, we first turn our attention to Degree Centrality. This metric serves as our compass in identifying the prolific actors who have left a substantial mark on the network by orchestrating many attacks. Using it as a spotlight illuminating those terrorists who, through their extensive engagement, have significantly contributed to the network's dynamics. As we analyze their degree centrality scores carefully, a clearer picture emerges of the breadth of their impact and the sheer volume of targets they have pursued. However, the landscape of a terrorist network is not solely shaped by the frequency of attacks. Here, we utilized Betweenness Centrality, a measure that transcends sheer numbers. Picture it as the architects of bridges in our network; those nodes strategically positioned to facilitate communication and interaction between distinct groups. High Betweenness Centrality implies the presence of pivotal intermediaries, individuals or groups with the unique ability to bridge divides, connecting disparate elements within the network. In the intricate flow of information, these actors emerge as orchestrators of coordination. As our exploration deepened, we encountered Eigenvector Centrality, a metric that introduces a layer of sophistication to our understanding. In this narrative, nodes with high Eigenvector Centrality are not merely prolific attackers or bridges; they are influencers adorned with a certain prestige. Think of them as nodes intricately woven into the fabric of the network, not just because of their direct connections but due to their associations with other influential actors. It's the story of strategic interconnectedness, where nodes with high Eigenvector Centrality command attention not only for their individual actions but also for their discerning company.

Furthermore, the application of community detection algorithms plays a crucial role in our work. Community detection functions as a lens through which we can identify groups of nodes that exhibit strong internal connections, revealing underlying structures and patterns within the larger network. This analysis aids in understanding how influential nodes may form clusters or communities, providing valuable insights into the cohesive forces shaping the terrorist network over time.
The analysis of shock propagation employed network projection techniques. The initial phase involved generating terrorist-terrorist projections for the two last decades period.

Following the analysis mentioned earlier, specific terrorist groups were selected for shock simulation. This involved initiating a shock within the selected groups and simulating how it spread through the network across 100 iterations.

To enhance the visualization of interactions among terrorist groups when affected and to better discern the impact of shocking these selected groups, an expanded network was formed. This was done by combining target types with their corresponding nationalities, providing a more comprehensive view of the interconnectedness among terrorist groups.

The year 2014 was chosen as a case study due to the highest frequency of attack occurrences. Subsequently, centrality and community analyses were performed on the network data for this particular year to identify the most influential terrorist group for shock simulation.

Following this analysis, the terrorist group with the highest centrality measures and the most influential community were selected for the shock simulation. Visualization of the shock propagation offered a graphical representation of how the shock disseminated among different terrorist groups over successive iterations.

Results

Preliminary analysis

An analysis of terrorist attacks spanning the period from 1970 to 2021 reveals significant shifts in the geopolitical landscape. From 1970 to 2000, several countries, including El Salvador, Spain, Chile, Sri Lanka, and the Philippines, experienced notable occurrences of terrorist incidents, with El Salvador topping the list with 2051 attacks. The subsequent period from 2000 to 2021 witnessed a shift in the affected regions, notably with Afghanistan leading the count with 9402 attacks, followed by Iraq, India, and Nigeria. In the more recent decade, between 2010 and 2021, Afghanistan maintained its prominence with 8412 attacks, accompanied by Iraq, India, and Nigeria, indicating sustained volatility in these regions. These fluctuations underscore the changing nature of terrorist activities, revealing varying levels of occurrences across different countries over the years.
Figure 1 illustrates the geographical distribution of terrorist attacks across the aggregated sample from 1970 to 2021. In this visual representation, the size of each area corresponds to the cumulative number of attacks carried out in that specific region.The findings indicate that Afghanistan experienced the highest number of recorded attacks, totaling 9404 incidents. Following closely behind, India and Iraq recorded 5363 and 5045 attacks, respectively. Colombia, Peru, Nigeria, Philippines, Yemen, United Kingdom, Pakistan, and El Salvador also ranked prominently among the top 10 countries, each witnessing a substantial number of terrorist incidents, with counts ranging from 2051 to 9404 attacks.

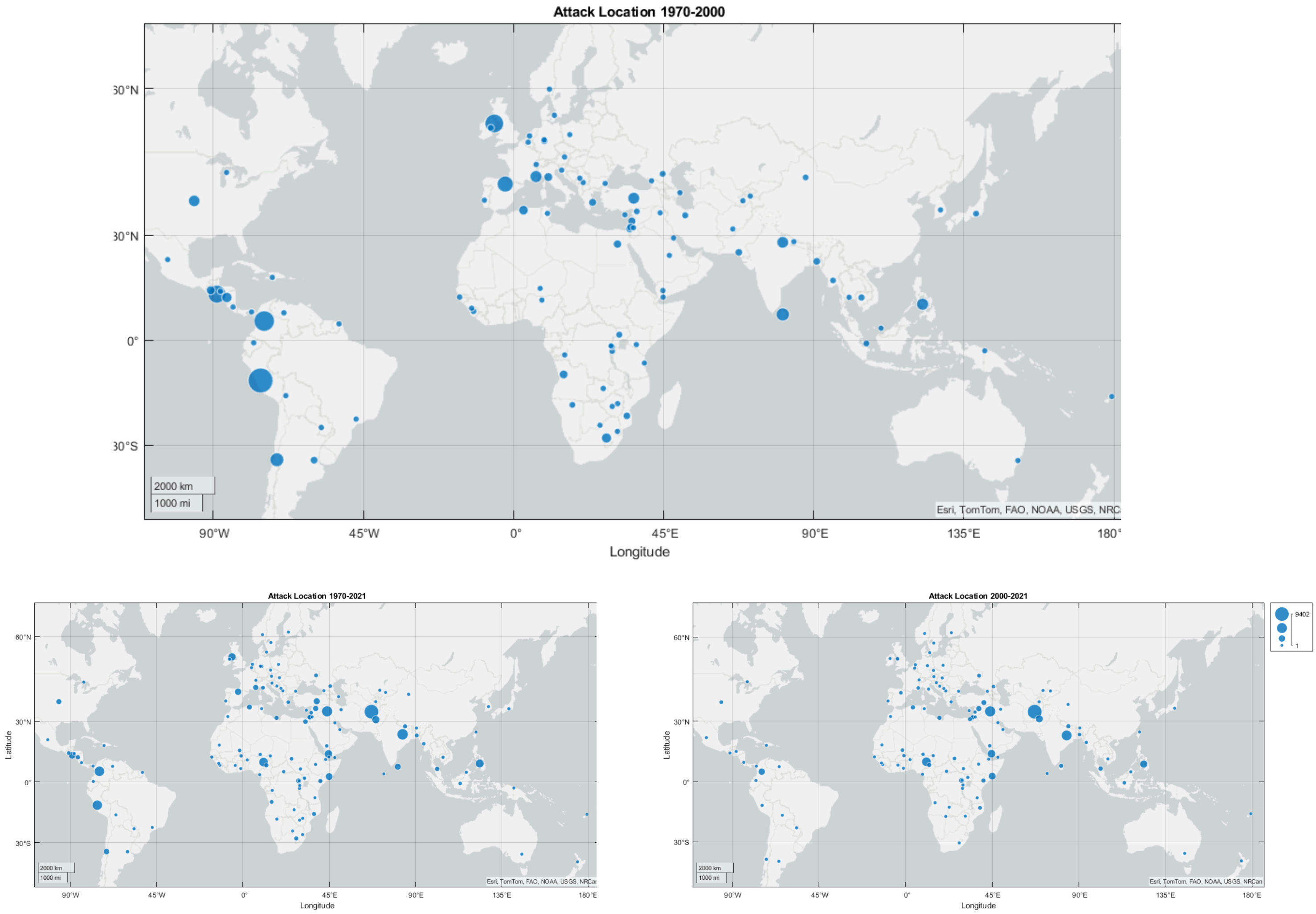


Figure 1 presents the geographical distribution of terrorist attacks across three distinct timeframes. The upper panel illustrates the global cumulative count of attacks spanning from 1970 to 2021. The lower panels depict the geographic distribution of attacks for two specific sub-periods: 1970–2000 (on the left) and 2000–2021 (on the right). In these subplots, varying sizes of regions signify the cumulative number of attacks within each area. Larger sizes indicate a higher frequency of attacks perpetrated in those particular regions.

In Figure 2, we observe the annual total of terrorist incidents grouped by continents. The data distinctly highlights a higher frequency of attacks concentrated in Asian and African nations, especially in the recent two decades. Conversely, the 1970s portray a period with comparatively fewer incidents, while a notable upsurge in attacks emerges during the 1980s and early 1990s, particularly affecting countries across the American continent.

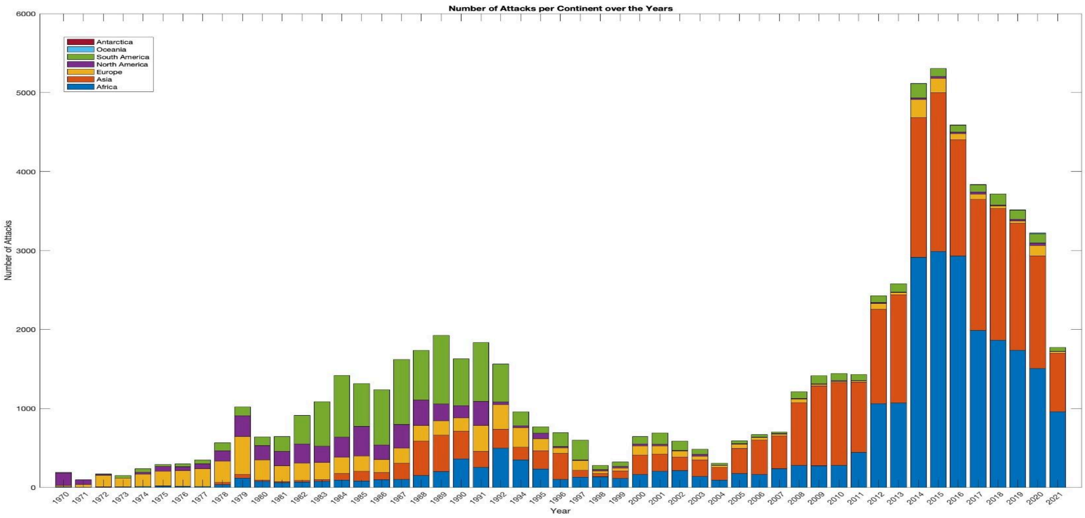
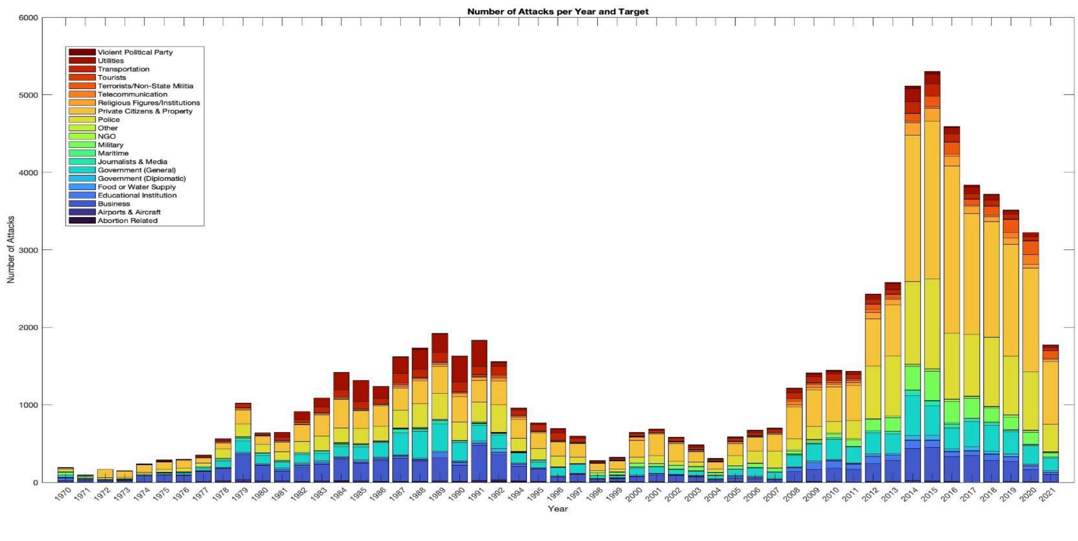


Figure 2. Barplot of the number of attacks per continent. The figure reports the yearly cumulative number of terrorist attacks perpetrated in each continent

Figure 3 offers a yearly overview, showcasing the yearly number of attacks and deaths categorized by target types. The analysis of the bar plot indicates that the majority of terrorist attacks are directed towards private citizens and property as well as police. The data reveals periods of relative calm during the seventies and late nineties, with a notable increase in attacks during the 80s. A significant surge occurs around 2015, hitting the peak of all times, followed by a decline afterwards dropping below 2000 in 2021.In summary, it can be seen that the fatality of attacks reached its peak in 2015 and has been decreasing thereafter.



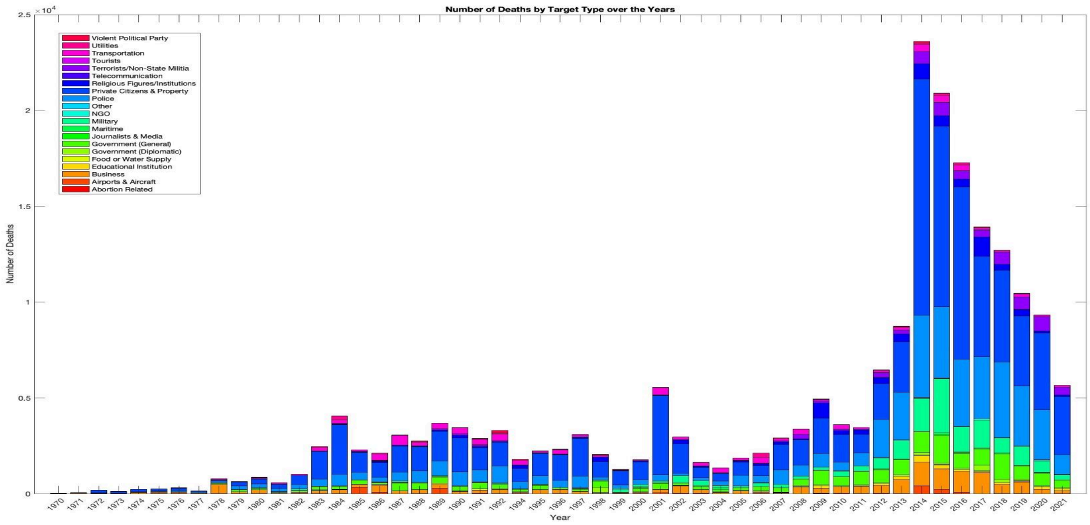


Figure 3. Barplot of the number of attacks and number of deaths categorized by the target type. Top figure reports the number of yearly attacks aimed at each target category. Bottom figure reports the yearly cumulative number of casualties of all the attacks per each target group.

Figure 4 provides insights into the mortality associated with terrorist attacks, illustrating a log-log distribution of the number of deaths, accompanied by a power-law fit (with exponent β = −1.3943), and displaying the time series depicting the number of casualties resulting from each terrorist event. The figure distinctly reveals heterogeneity in casualty numbers per terrorist attack. Indeed, the majority of attacks led to only a few casualties, underscoring the prevalent trend. However, a noteworthy observation is the occurrence of a small number of episodes that caused a disproportionate amount of deaths.

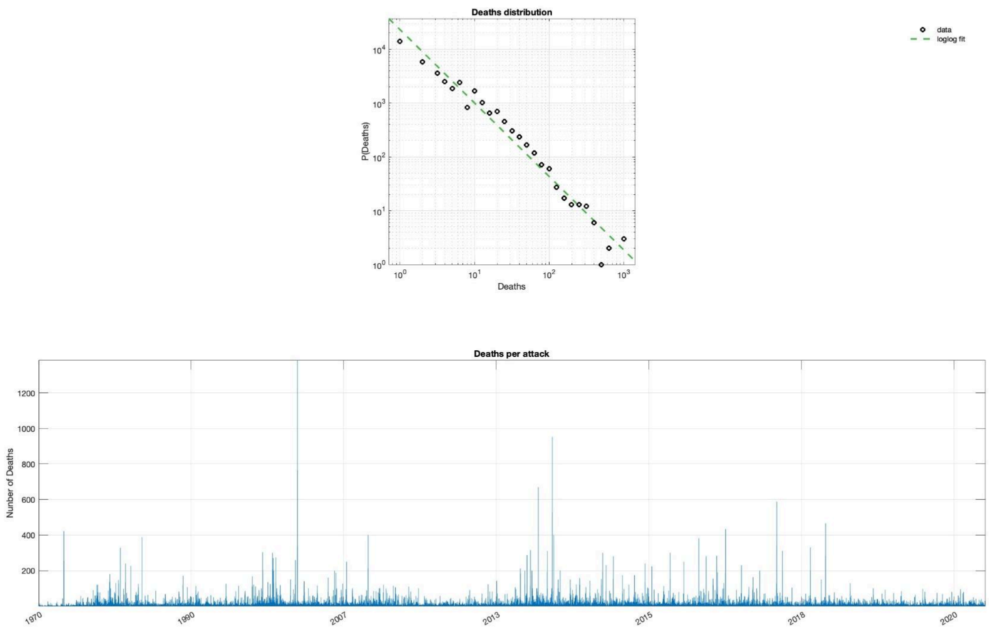


Figure 4. Insights into the mortality associated with terrorist attacks. The upper panel illustrates a log-log distribution of the number of deaths, accompanied by a power-law fit (with exponent β = −1.3943). The lower panel displays the time series depicting the number of casualties resulting from each terrorist event.

Starting from 1970, the graph exhibits distinct temporal patterns as Figure 5 suggests. A consistent upward trajectory characterizes the initial period until 1992. Subsequently, there is a downward fluctuation, leading to a prolonged descent lasting approximately 12 years until 2004. The next phase, starting around 2005, mirrors the earlier ascent in both slope and resilience. However, the denouement introduces a paradigm shift, marked by a steady decline from 2017 onwards.

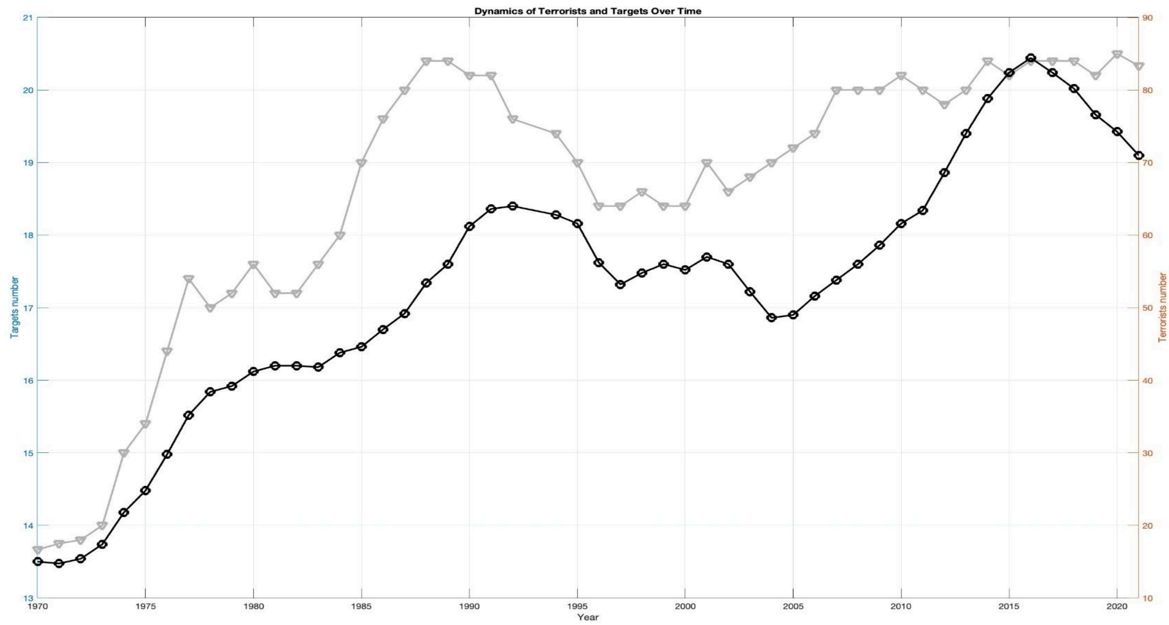


Figure 5. 5-years moving window evolution of the number of nodes. The figure reports in black the dynamics of the terrorists (right y-axis) and in gray the targets (left y-axis) nodes along time.

Centralities

Following the construction of our annual adjacency matrices, as outlined earlier, our centrality analysis unfolds through a systematic process. Initially, we compute centralities for each year, aggregating the results into a matrix. Subsequently, we identify the top 10 groups for each measure annually. To derive a conclusive outcome, we select the 10 groups that consistently appear in the yearly top 10 rankings. The ensuing step involves plotting the centrality dynamics of these chosen groups across the temporal spectrum. This approach affords us valuable insights into the pivotal roles played by specific groups within each network, elucidating their evolution over time.

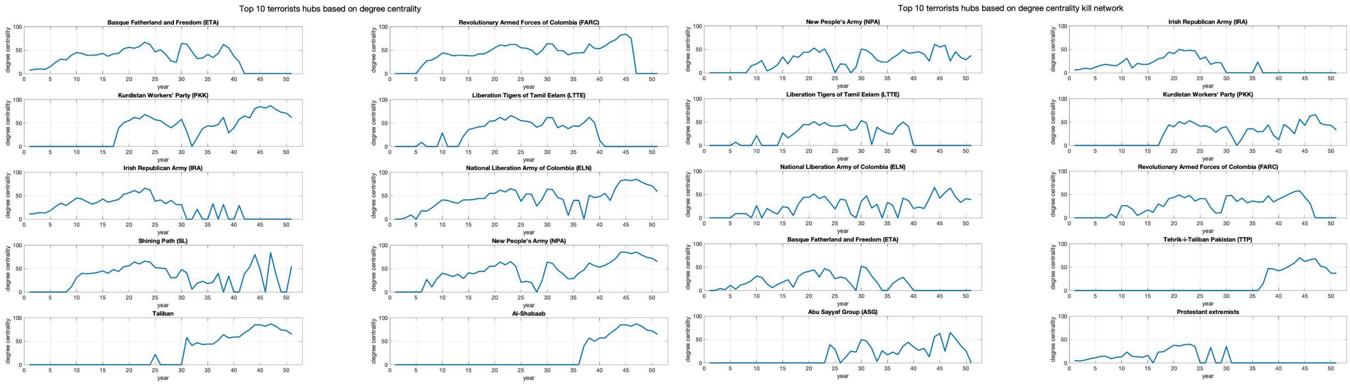


Figure 6. Degree centrality changes for the top 10 terrorists over the years 1970 to 2021, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of casualties .

In examining the results, it's evident that the degree centrality metric tends to identify a similar set of top 10 influential terrorists across both networks. As illustrated in Fig 6, approximately 70% of these groups are consistently ranked among the top 10 in both networks. However, it's crucial to note that the specific order of ranking may vary. For instance, the New People's Army (NPA) holds the highest rank in the network constructed based on the number of kills, but it occupies the 8th position in the network focusing on the number of attacks. Moreover, the analysis reveals that certain groups, deemed highly influential when considering the number of attacks, may not hold the same level of importance when the network is constructed based on casualties. Examples include the Taliban and Al-Shabab. Interestingly, these groups, despite being relatively new entities, emerge as among the most active hubs. This underscores the importance of considering different aspects, such as the nature of the attacks, when assessing the influence and significance of terrorist groups within the network.

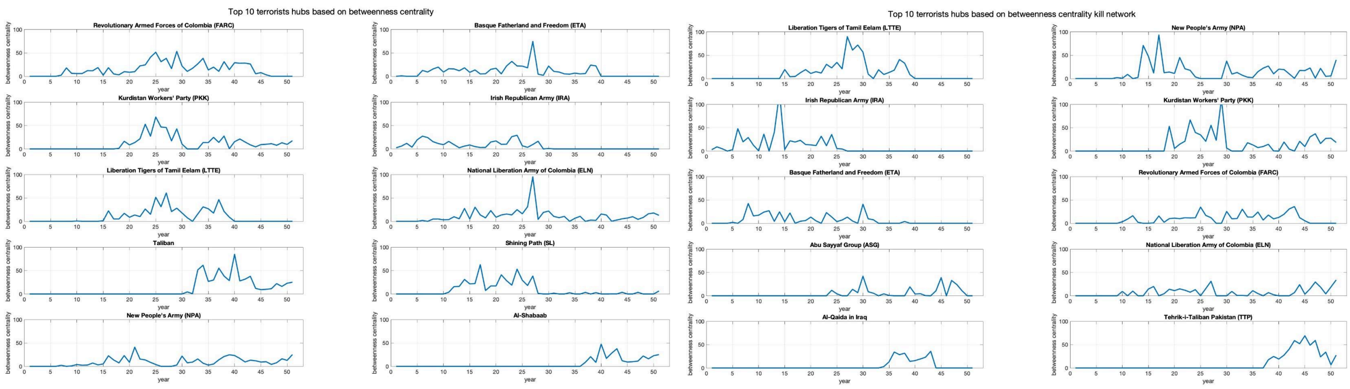


Figure 7. Betweenness centrality changes for the top 10 terrorists over the years 1970 to 2021, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of casualties .

In order to assess the significance of nodes from a different perspective using betweenness centrality, we observe a notable overlap with the results obtained from degree centrality. Figure 7 illustrates that many of the same terrorist groups emerge in a similar order. For instance, the Kurdistan Workers' Party (PKK) holds the 3rd place in both metrics, while the Revolutionary Armed Forces of Colombia (FARC) and Basque Fatherland and Freedom (ETA) have swapped positions for the first place. This consistency in rankings suggests that these nodes are not only well-connected within the network but also play a crucial role in facilitating information flow and maintaining the overall network structure. The findings in Figure 7 imply that the identified set of terrorist groups is likely to wield influence in various ways within both networks, reinforcing their significance in the broader network dynamics. However, when examining the casualties network, the distinctions become more pronounced, with new groups such as Al-Qaida emerging as noteworthy contributors.

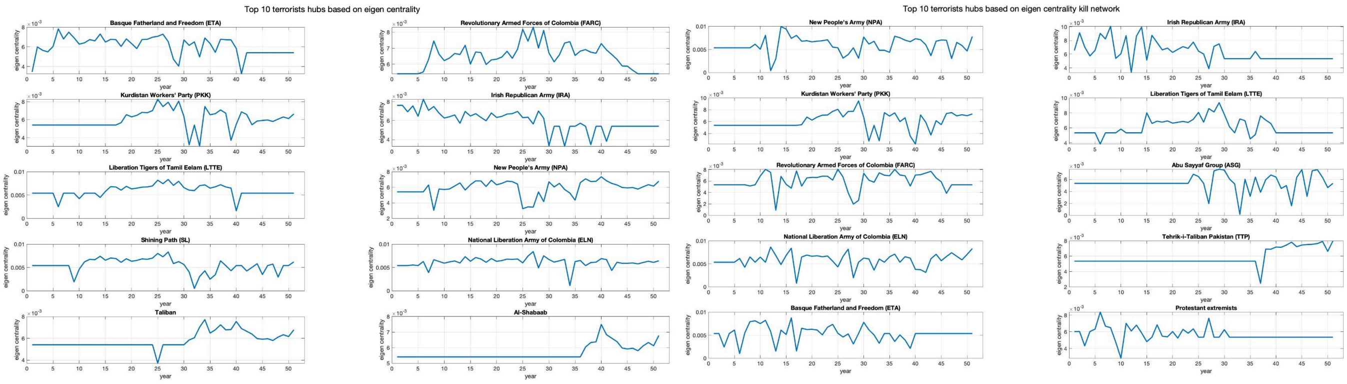


Fig 8. Eigenvector centrality changes for the top 10 terrorists over the years 1970 to 2021, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of each attack's casualties .

In our comprehensive analysis of network centrality, we extended our examination to eigenvector centrality, a more global measure shedding light on influential nodes. Notably, the same core group of terrorists surfaced prominently in both networks, maintaining consistency with our degree centrality findings. While minor variations exist in rankings, Basque Fatherland and Freedom (ETA) and New People's Army (NPA) continue to assert their significance across networks. Additionally, Abu Sayyaf Group (ASG) has ascended in the rankings, securing the 5th position. This ascent underscores its notable connections with other crucial groups, accentuating its considerable influence within the network landscape.

In conclusion, it is crucial to highlight a noteworthy discovery. Certain groups, such as the Irish Republican Army (IRA), despite their inactivity over the past decades, continue to wield a substantial impact on the network, making their inclusion in our analysis indispensable. Nonetheless, for the sake of precision, we conducted a parallel analysis focusing solely on the last two decades. The outcomes of this refined analysis are presented below.

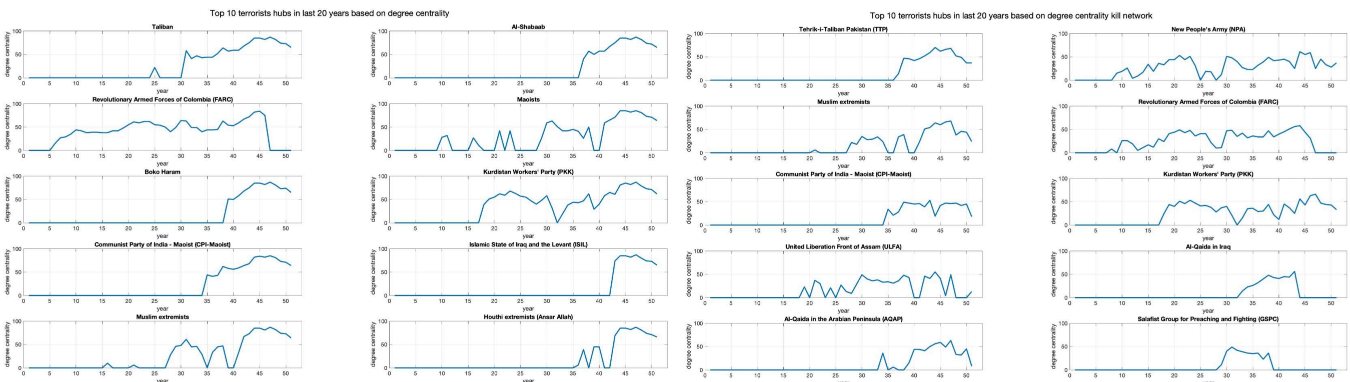


Figure 9. Degree centrality changes for the top 10 terrorists over the last 20 years, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of casualties.

As figure 9 shows, for the Degree centrality observations, the perspective of the last two decades differs significantly from the overall view. Despite the presence of groups like Al-Shabaab and the Taliban, a noteworthy observation is that, in the attacks network, most of these groups are relatively new, with an average background of around 15 years. In contrast, in the casualties network, their history extends back, on average, to 25-30 years. However, a common feature in both networks is the prominent peak observed in the last decade. Similarly to the previous analysis, we observe distinct rankings for various groups across the two networks. Notably, the key players in the attacks network do not make an appearance in the casualties network.

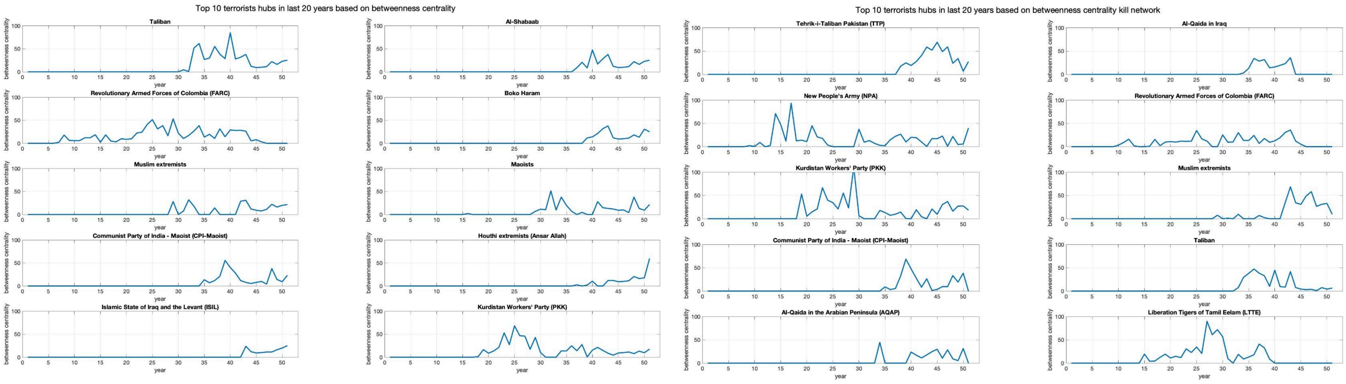


Fig 10. Betweenness centrality changes for the top 10 terrorists over the last 20 years, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of casualties .

In line with the earlier phase, we find that both betweenness and degree centrality metrics highlight the same terrorists in the attack network. However, there are some variations in the results for the casualties network. Interestingly, this time, the leading figures in the attack network are also appearing in the casualties network.

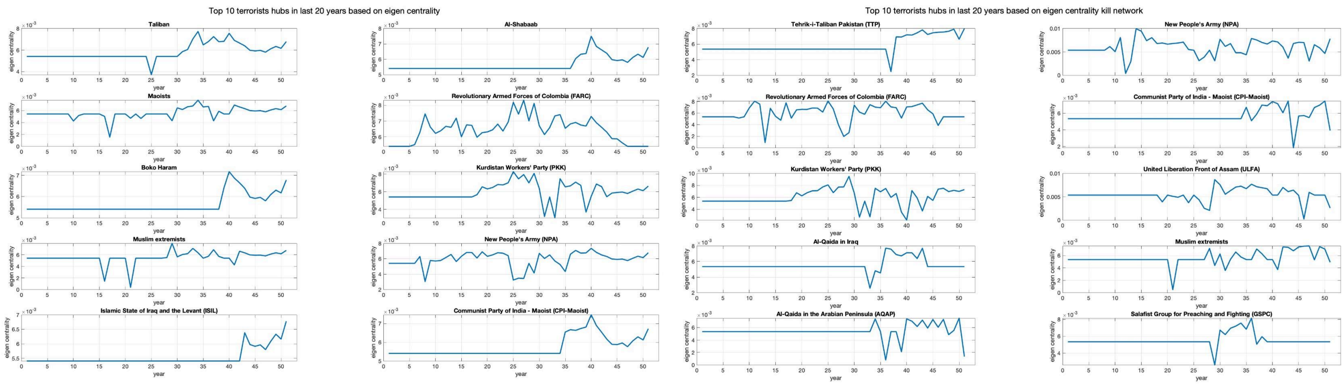


Fig 11. Eigenvector centrality changes for the top 10 terrorists over the last 20 years, the left plot shows the centrality shifts on the attacks network and the right plot illustrates the same insight over the network built on the number of each attack's casualties .

Unsurprisingly, the outcomes from the eigenvector measure highlight a comparable subset of terrorist groups. However, it is worth noting that the New People Army (NPA) is part of this subset, whereas it was absent from the results of the other two measures. Additionally, a similar pattern, observed in betweenness and degree centrality, persists here, with many of the listed groups being relatively recent in origin.

In the context of our analysis on the attacks network, the most frequently mentioned recent groups are Al-Shabaab and Boko Haram, serving as our selected groups for the latter part of the analysis. In terms of the casualties network, TTP and Muslim Extremists consistently rank at the top of all lists, making them the natural choices for further examination.

Communities

In this section, the focus revolves around the detection of influential nodes based on centralities over the past two decades and their possible impact on the network by analyzing the communities they are part of. Notably, the years 2008, 2014, and 2015 stand out as periods when these influential nodes are more prevalent as a cohesive group. The investigation delves deeper by identifying and analyzing communities within these specific years. Further exploration involves computing the densities of communities in the pivotal years of 2008, 2014, and 2015. The analysis concludes with the detection of the most densely connected community in these years and providing a list of nodes that contribute to its density. Additionally, a simulation is conducted by perturbing the nodes to observe if there are significant changes in the overall network structure, adding a dynamic dimension to the analysis.

Firstly, we employed a community detection algorithm, extracting valuable insights into the network's structural evolution. We obtained two important metrics : modularity and number of communities.
Modularity is a measure commonly used in community detection algorithms to assess the quality of the partitioning of a network into communities or modules. It quantifies how well the network is divided into distinct groups compared to a random assignment of nodes. The modularity value falls within the range [-1, 1], where a higher value indicates a better-defined community structure.
As we can see from the plot the highest modularity values are reached in the years 1970, 1974 and 1990. This phenomenon is more underlined by considering a “5 years average plot” in which it can be seen how in the 70s and 90s we have some peaks. These peaks in modularity within a terrorist attack network can be indicative of moments when certain clusters of attackers and targets exhibit stronger internal cohesion.
These values can be better visualized by plotting them.

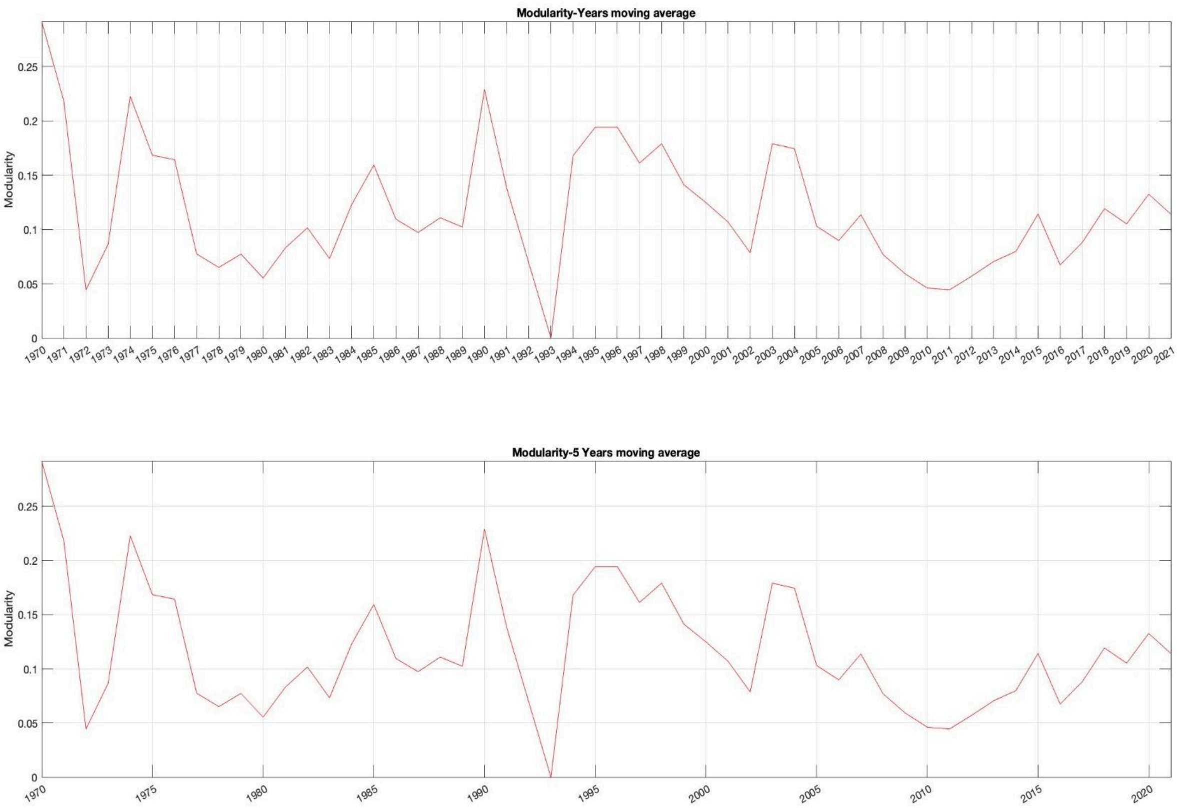


Figure 12. Modularity values for each year and modularity values every five years

The other important metric is the number of communities.
A sudden rise in the number of communities may suggest increased fragmentation within the network. This could indicate that nodes are becoming more isolated and forming smaller, more specialized groups.
We can identify a peak in 2010 and there are many years that maintain the same number of communities. The more frequent subdivision is in six communities and it is also visible from the plot that they are typical in 1979, 1986, 1987, 1996, 1997, 1999 and 2004.

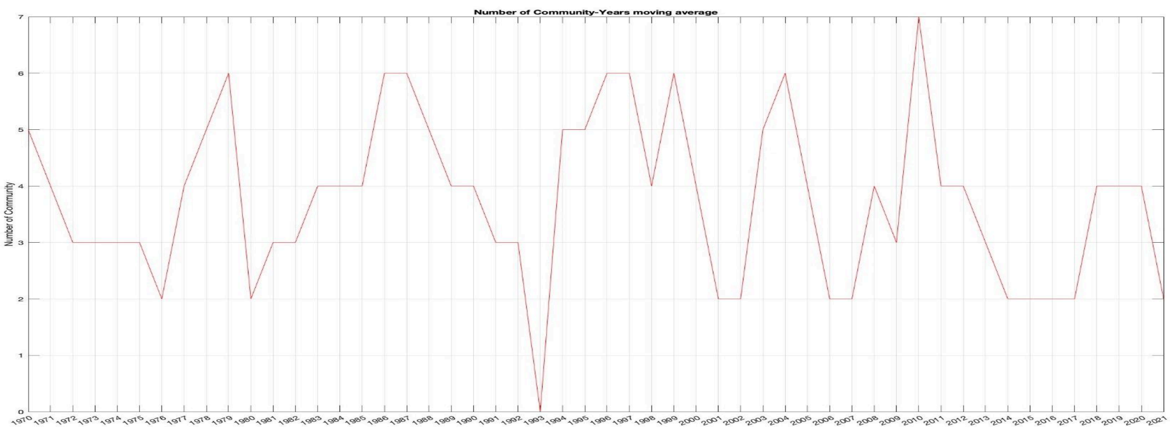


Figure 13. Plot of the number of communities from 1970 to 2021

Then ,we zoomed in on some specific years that we found interesting and from which we thought we could extract some valuable information. We started by analyzing centralities by calculating degree, betweenness, and eigenvectors for each year, providing insights into which nodes stand out in the network. Focusing specifically on the last two decades, we

identified the top 40 nodes with the highest centralities in each category during this period and unified them to pinpoint the most influential terrorists.
Furthermore, we extracted the names of these influential nodes, counted their occurrences in each year and ranked the top three years with the highest count.
As a next step we used the community detection algorithm to extract valuable insights into the network's structural evolution. Visualization is provided through network plots, specifically scrutinizing communities in pivotal years like 2008, 2014, 2015, and 2021.

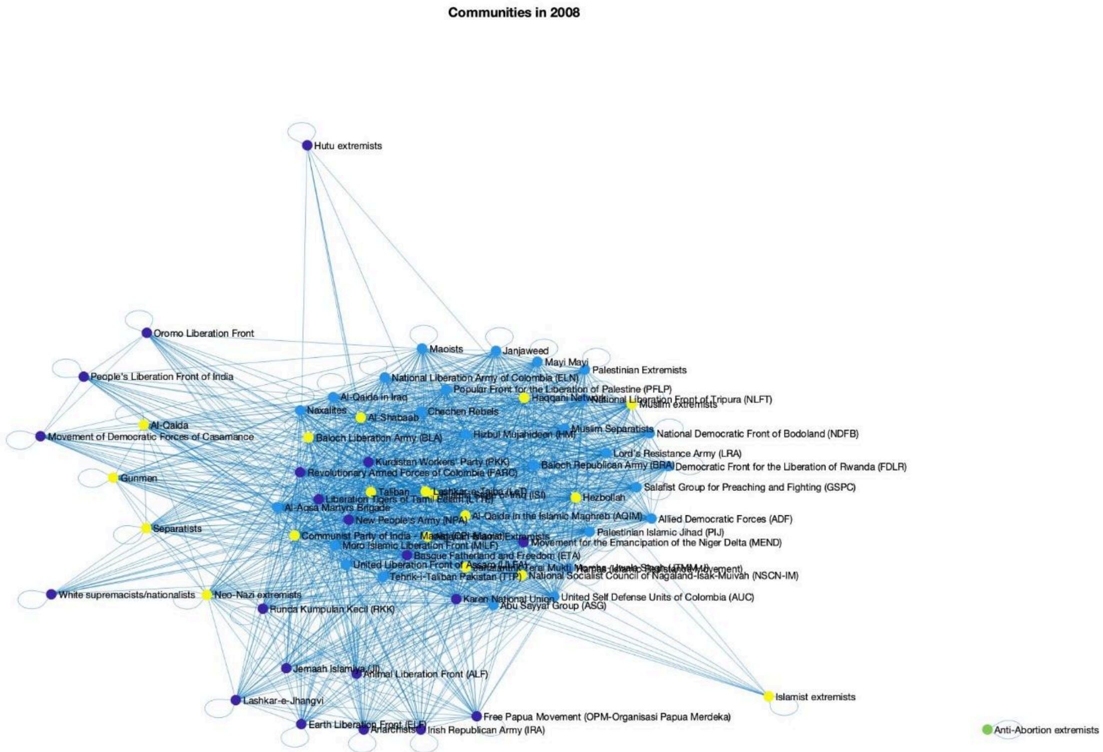


Figure 14. Plot of the communities in 2008

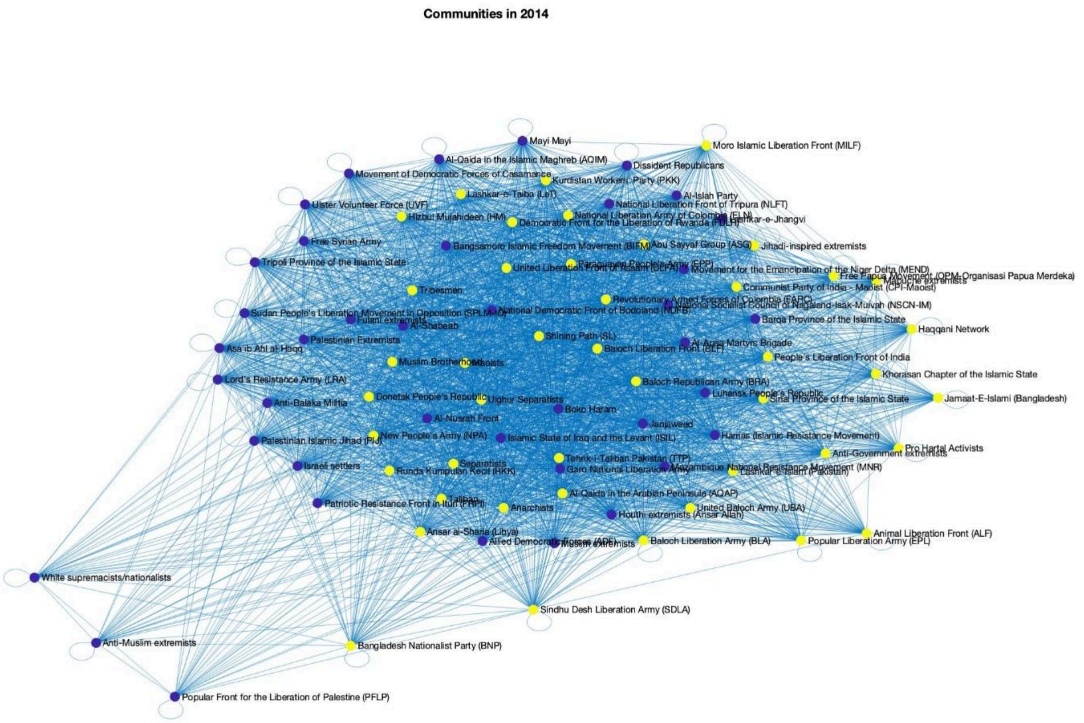


Figure 15. Plot of the communities in 2014

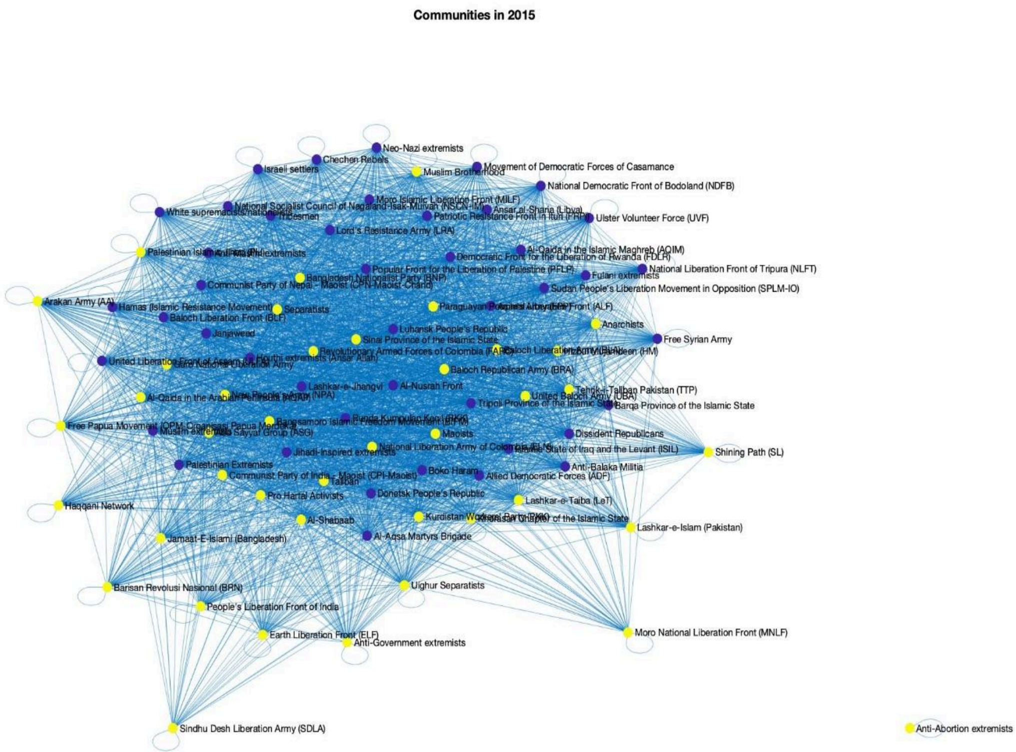


Figure 16. Plot of the communities in 2015

The highest number of communities can be observed in 2008, but as we can also see from the plots we have more dense communities in 2014 and 2015. This means that in 2008 we had terrorist groups that attacked different targets and in 2014 and 2015 there are more terrorist groups that attacked the same targets.
We decided to go further in this investigation and to calculate the density for each community in these three years. We noticed that the most dense community is in 2015. The next step was to identify the nodes that are part of that specific dense community and to shock them in order to see If they somehow influence the network's structure.

Shock Propagation in Terrorist Network

Understanding the spread and impact of shock within terrorist networks is imperative for assessing the dynamics of influence and identifying critical nodes within these networks. Leveraging network analysis tools, shock propagation studies reveal insights into how disruptions or influence within a specific terrorist group or community can cascade through the larger network over time. The following section delves into the methodology, analysis, and implications derived from the shock propagation study conducted on terrorist networks.

Centrality metrics like betweenness and degree centrality play a significant role in shock propagation. Nodes with high centrality act as bridges, facilitating the rapid spread of shocks. Targeting these pivotal nodes can disrupt communication and hinder coordination within the network.

Shock Propagation Analysis

Following the analysis using the terrorist-terrorist projection from the last two decades, the shock propagation study was conducted on this network based on the 21 target types. The shock simulation was specifically conducted on selected groups. These groups were identified through centrality analysis as having a significant influence within the network. The two identified groups for the shock simulation were Al-Shabaab and Boko Haram. The shock was initiated within these selected groups, and its impact was observed across the broader network of terrorist interactions.

The results indicated a considerable influence on various other groups within the network, with a high probability of over 0.90 affecting most groups after just 27 iterations.The most impacted groups identified were 'Arakan Rohingya Salvation Army (ARSA)', 'Palestinian Extremists' and 'Anti-Abortion extremists'.

As previously mentioned other groups worth being analyzed are “Muslim Extremists” and “TTP”. Performing the shock propagation within these groups instead presented as result reaching a high probability of 0.9661 of influencing the other groups.Among those impacted, the analysis highlighted specific groups, including White supremacists/nationalists, Anti-Balaka Militia, Arakan Rohingya Salvation Army (ARSA), and Baloch Liberation Front (BLF), which exhibited notable susceptibility to the shock.

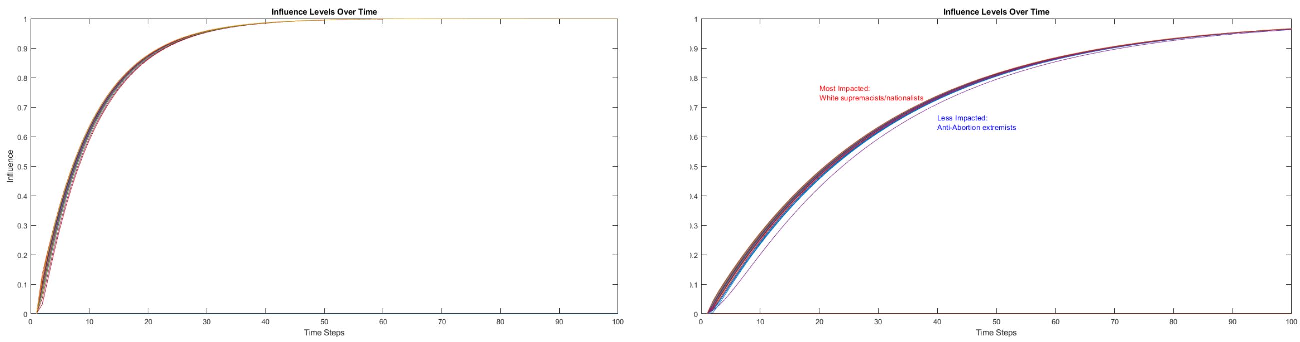


Figure 17. Influence Level of Terrorist Groups: left panel shocking Al-Shabaab and Boko Haram and right panel shocking Muslim Extremists and TTP

These findings reinforce the significance of Al-Shabaab, Boko Haram, TTP and Muslim Extremists within the network dynamics, as identified through the centrality analysis, showcasing their influence on other groups during the simulation of shock propagation.

Continuing the analysis, it became evident that the earlier results were affected by considering target types in a generalized manner. To gain a more nuanced understanding of the influential groups, a deeper exploration was conducted. This involved repeating the shock propagation analysis on an amplified network, where, instead of solely examining the 21 target types, the target types were concatenated with nationalities. This amplified network was constructed based on the latest terrorist-terrorist projection spanning the past two decades, encompassing a total of 143 distinct terrorist groups.

As anticipated, this refined analysis provided clearer distinctions among the influenced groups. Specifically, among the 143 groups assessed, three stood out, displaying involvement probabilities exceeding 0.80, when Al-Shabaab and Boko Haram are the selected groups. These three include 'Fulani extremists' , 'Indigenous People of Biafra (IPOB)' and 'Movement for the Emancipation of the Niger Delta (MEND)' with final shock values of 0.9959, 0.9951, and 0.8206 respectively. While when Muslim Extremists and TTP were the selected ones, nine groups stood up with final shock values ranging 0.8 and 0.9.

These highly affected groups include:

1. Muttahida Qami Movement (MQM)
2. Baloch Liberation Front (BLF)
3. Baloch Liberation Army (BLA)
4. Sindhu Desh Liberation Army (SDLA)
5. Baloch Republican Army (BRA)
6. United Baloch Army (UBA)
7. Ansar al-Sunna (Mozambique)
8. Lashkar-e-Jhangvi
9. Muslim Brotherhood

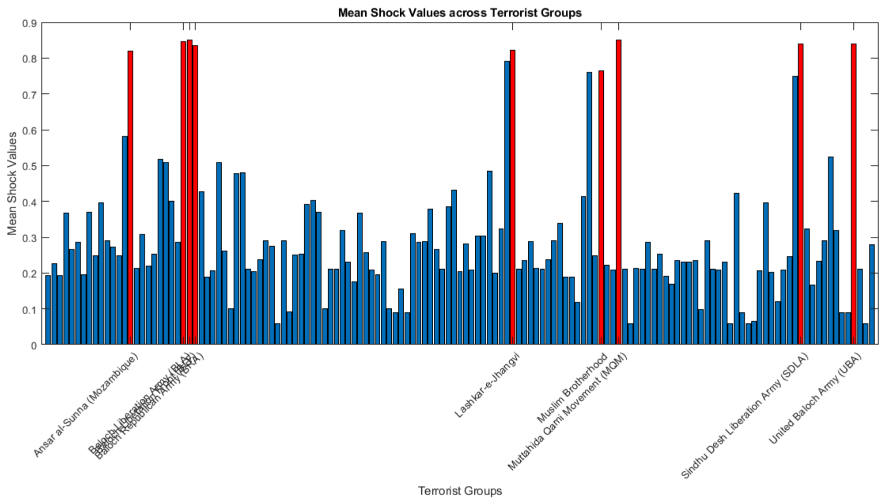


Figure 18. Mean Shock Values across the Terrorist Groups

Furthermore, the analysis identified 70% of the groups with involvement probabilities lower than 0.5 but greater than 0.1, suggesting a varying degree of engagement across all terrorist groups when selecting Muslim Extremists and TTP and 93% when selecting Al-Shabaab and Boko Haram.
This in-depth analysis, incorporating nationalities along with target types, provided a more detailed understanding of the specific groups significantly affected by the shock, demonstrating the heightened susceptibility of these nine groups compared to the larger network of terrorist interactions.

Case Study of the Terrorist Network in 2014

The selection of the year 2014 as a case study was based on the prevalence of attack occurrences during that period. For this study, the terrorist-terrorist projection was derived from the adjacency matrix, utilizing terrorist groups and the concatenation of target types with their respective nationalities for that specific year, comprising 84 terrorist groups.

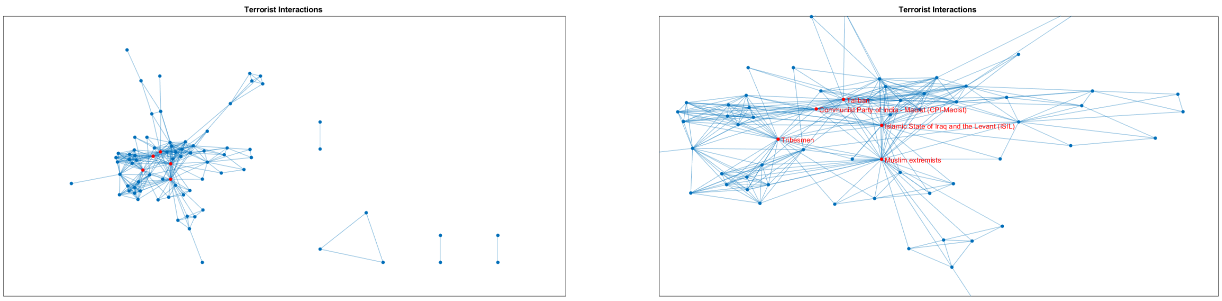


Figure 19. Terrorist Network 2014

Upon performing centrality analysis on this network, several key findings emerged. The Terrorist Group with Highest Degree Centrality was identified as "Muslim extremists" , which coincides with the group with Highest Betweenness Centrality and Highest Eigenvector Centrality. Additionally, the group with Highest Closeness Centrality was also attributed to "Muslim extremists". Remarkably, Muslim extremists emerged as the predominant group across various centrality metrics, consistent with prior identification.

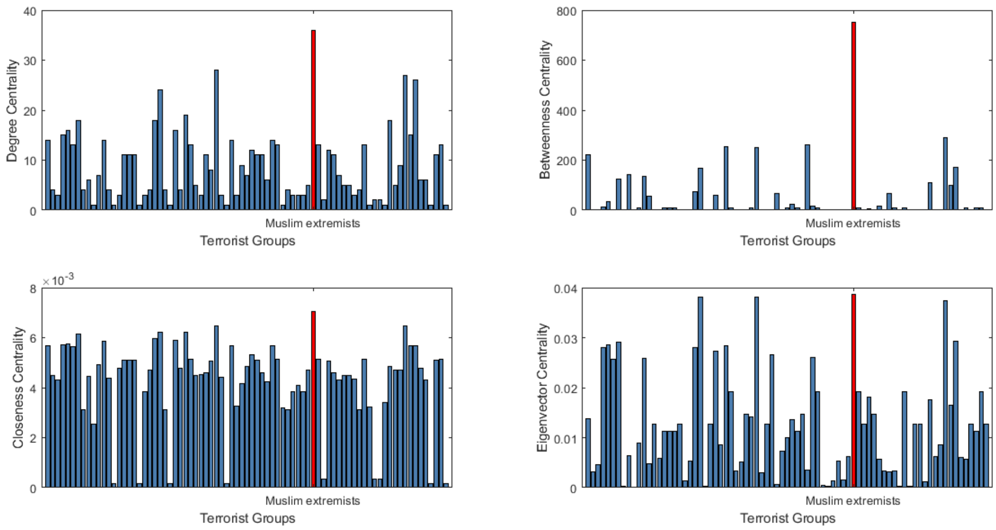


Figure 20. Centralities Terrorist Network 2014

Subsequently, a shock propagation simulation focusing on Muslim extremists was performed, revealing significant impact.

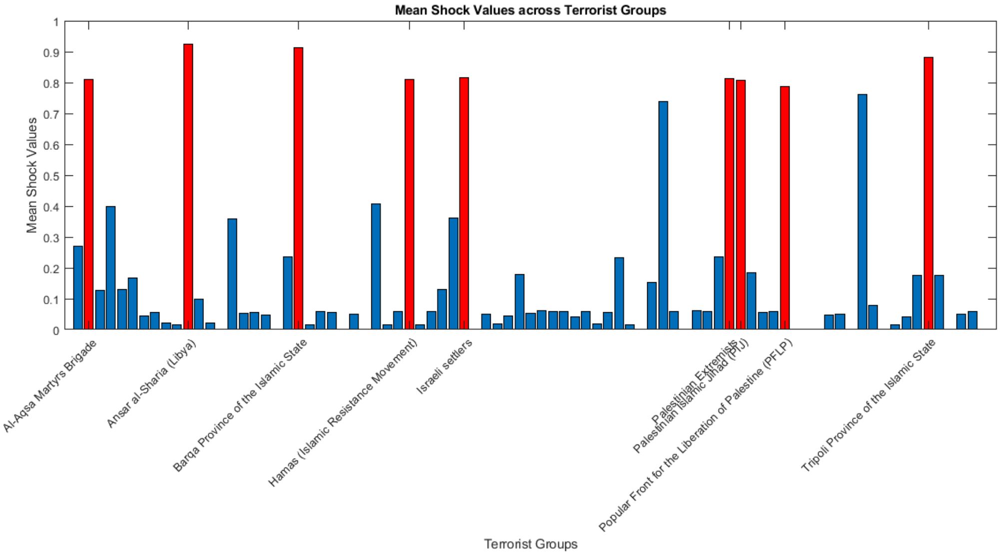


Figure 21. Mean Shock Values across Terrorist Groups with Muslim Extremists shocked

Highly Impacted Groups (with probabilities reaching over 0.90):

1. Israeli settlers
2. Palestinian Extremists
3. Al-Aqsa Martyrs Brigade
4. Hamas (Islamic Resistance Movement)
5. Palestinian Islamic Jihad (PIJ)
6. Popular Front for the Liberation of Palestine (PFLP)
7. Ansar al-Sharia (Libya)
8. Barqa Province of the Islamic State
9. Tripoli Province of the Islamic State

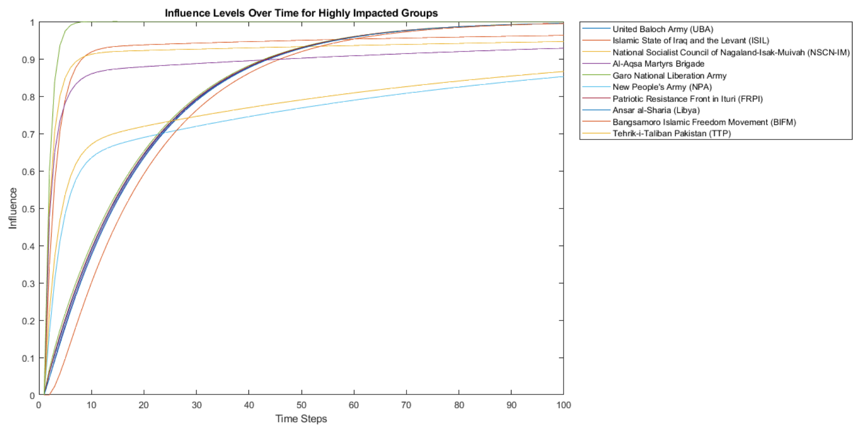


Figure 22. Influence Level of the highly impacted Terrorist Groups

The shock values associated with these impacted groups ranged from 0.9286 to 0.9954, signifying substantial influence or susceptibility to the shock initiated from the Muslim extremists' node.
The overall analysis identified 20 groups with probabilities lower than 0.05, indicating a minimal impact or influence following the shock propagation. It is noteworthy that 20% of worldwide terrorist groups exhibit a probability exceeding 0.5 of involvement when the “Muslim Extremist” group gets perturbed.

Further analysis involved community analysis, revealing other significant nodes within the network, pinpointing the Terrorist Group associated with the central node of the largest community as "Muslim extremists" and the group linked to the community with the highest density as "Communist Party of India - Maoist (CPI-Maoist)." Unsurprisingly, the two most highly central nodes, Muslim Extremists and Islamic State of Iraq and the Levant (ISIL) both emerged within the same community.

Upon conducting shock propagation analysis on the Muslim Extremists, it became evident that the most affected terrorist groups mentioned earlier belonged to the same community, which is also the largest one, reinforcing the substantial impact of this network.
Subsequently, shock propagation was performed focusing on this influential community, which comprises the aforementioned groups along with others.
Our investigation revealed two communities notably influenced by this simulation:

- Al-Islah Party
- Al-Qaeda in the Arabian Peninsula (AQAP)
- Houthi extremists (Ansar Allah)
- Tribesmen

and

- National Liberation Army of Colombia (ELN)
- Popular Liberation Army (EPL)
- Revolutionary Armed Forces of Colombia (FARC)

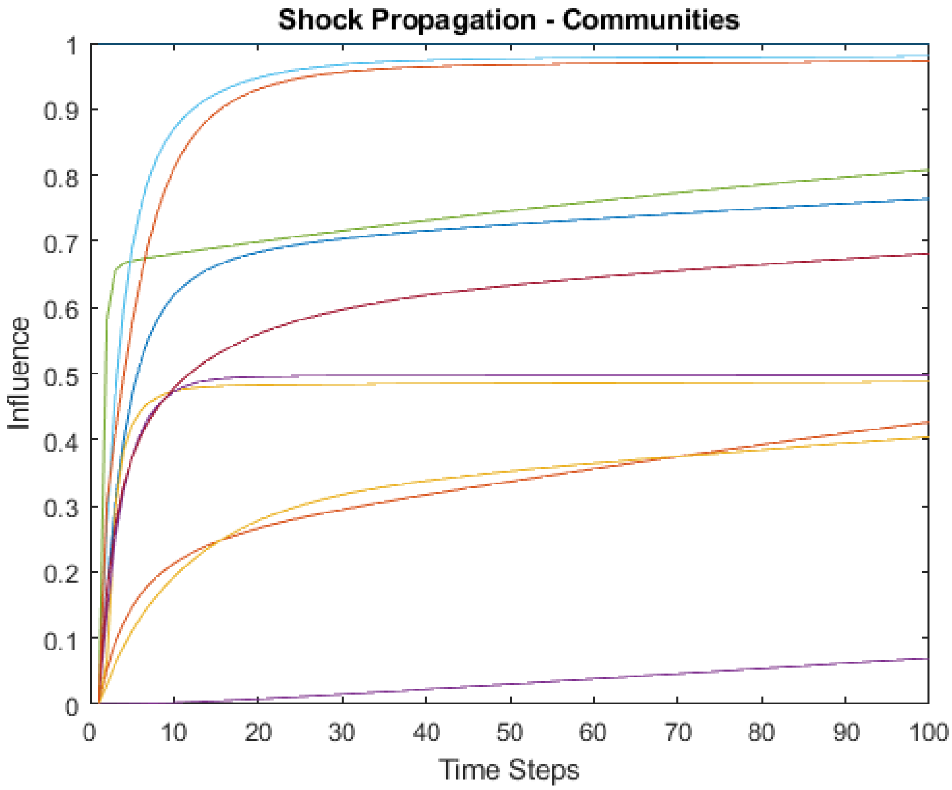


Figure 23. Influence Level across Communities

These findings shed light on the intricate connections and influence of the largest community within the network, indicating the reach and impact of certain terrorist groups on others within this broader network analysis.

This comprehensive analysis of the 2014 terrorist network, encompassing centrality, community, and shock propagation, highlights the prominence of Muslim extremists and unveils the interconnectedness and influence among various terrorist groups during that particular year.

Conclusion

In this paper we study the intricate dynamics of a terrorist network by leveraging the comprehensive data available in the Global Terrorism Database (GTD). Through a strategic blend of centrality measures and community detection methods, we successfully pinpointed influential individuals within these networks, enabling us to forecast potential repercussions of disrupting their top figures.

Centrality analysis unveiled Al-Shabaab and Boko Haram as the most frequently mentioned recent groups, prompting us to concentrate our subsequent investigations on these selected groups. Furthermore, our examination of the casualties network consistently placed TTP and Muslim Extremists at the forefront, emphasizing their substantial impact within these networks.

Notably, the community analysis revealed that the years 2008, 2014, and 2015 stood out as periods where these influential nodes cohesively operated as a group, shedding light on critical phases of concerted terrorist activities.

Moreover, the shock propagation analysis aimed to explain the extent and reach of influence within the terrorist network. By simulating shock propagation from an initial node, the study explored how disruptions or influence introduced within a single group could potentially affect the broader network dynamics. Through 100 iterations, the simulation tracked the progression of shock, illustrating its spread across different nodes within the network.

The analysis of shock propagation provided significant insights into the vulnerability and interconnectedness of terrorist groups within the network. Visualization revealed the varying degrees of influence that propagated through different nodes over successive iterations. Nodes closely connected to the initially shocked group exhibited a higher susceptibility to the propagated shock, suggesting their heightened influence within the network.

In essence, our findings underscore the intricate interplay among terrorist groups, highlighting key influencers, pivotal periods, and varying levels of engagement. Such insights could prove invaluable for devising strategic interventions and predictive models to counter and mitigate the impact of terrorist activities, thereby contributing to enhanced global security and stability.

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