TERRORISM IN COLOMBIA: THE UNTOLD CONFLICT

by

Zachary Toll
A Thesis
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Master of Science
Geoinformatics and Geospatial Intelligence

Committee:

____________________	Dr. Anthony Stefanidis, Thesis Director
____________________	Dr. Paul Delamater Committee Member
____________________	Dr. Arie Croitoru, Committee Member
____________________	Dr. Anthony Stefanidis, Department Chairman
____________________	Dr. Donna M. Fox, Associate Dean, Office of Student Affairs & Special Programs, College of Science
____________________	Dr. Peggy Agouris, Dean, College of Science
Date: ____________________	Summer Semester 2017 George Mason University Fairfax, VA

Terrorism in Colombia: The Untold Conflict

A Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at George Mason University

by

Zachary Toll
Bachelor of Arts
University of California, Santa Barbara, 2012

Director: Anthony Stefanidis, Professor
Department of Geography and Geoinformation Science

Summer Semester 2017
George Mason University
Fairfax, VA

DEDICATION

This work is dedicated to my loving family, the faculty, staff, and students of George Mason University, and the people of the Republic of Colombia who have struggled and fought so many years for peace.

ACKNOWLEDGEMENTS

I would like to first and foremost thank my committee chair Dr. Anthony Stefanidis for all of his guidance, support and encouragement throughout my time at George Mason University. An equal thank you is also given to Dr. Paul Delamater for his instruction, guidance and feedback for the entire duration of my thesis work. This work could not have been accomplished without them both. A very special thank you to Manzhu Yu, who proved to be of tremendous and invaluable support for the computer programming element of my thesis work. Thank you to John Solly and Tom Marotta both provided crucial help and support during the final hours of my Masters work at George Mason University. Last but not least, a thank you Dr. Arie Croitoru and Jacek Radzikowski for your guidance and support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

AIV .... Attack Intensity Value
ELN...................................... *Ejército de Liberación Nacional* (National Liberation Army)
FARC ......*Fuerazas Armadas Revolucionarias de Colombia - Ejército del Pueblo* (Armed Revolutionary Forces of Colombia – People's Army)
GDP.. Gross Domestic Product
ISIS ....Islamic State of Iraq and Syria
LISA... Local Cluster & Outlier Analysis
MODIS ....Moderate-Resolution Imaging Spectroradiometer
NDVI... Normalized Differential Vegetation Index
RQ .... Research Question
UTM...Universal Transverse Mercator

ABSTRACT

TERRORISM IN COLOMBIA: THE UNTOLD CONFLICT

Zachary Toll, M.S.

George Mason University, 2017

ThesisDirector: Dr. Anthony Stefanidis

Colombia has been in continuous civil turmoil since gaining independence from Spain in 1810. With the inauguration of former Colombian President Álvaro Uribe in 2002, the past 14 years have been the longest period of sustained military action against violent extremist groups in Colombia. This 52 year conflict has finally come to an abrupt end on September 26th, 2016. The goal of this thesis is to analyze variation in attack intensity values over time, identify changes in the spatial clustering of high attack intensity values in Colombia, determine locations in Colombia which are potentially more susceptible to growth in number of terrorists, analyze the spatial distribution of terrorism events in Colombia from 2000 – 2014, and comparing Department-level economic data to remotely sensed NDVI values as well as social media data.

1. Introduction

1.1 Conflict in Colombia

Modern conflict in Colombia began during the time period of *La Violencia* (“The Violence” – 1948 to 1958), in which nearly 200,000 people were killed. During this time, armed criminal groups adopted political ideologies and began using guerilla warfare tactics against the government of Colombia (Zackrison, 1989). During the mid-1960s, these guerilla groups rose to challenge the Colombian government and paramilitary groups on issues such as land ownership and political violence (Serres, 2000). The Revolutionary Armed Forces of Colombia—or *Fuerazas Armadas Revolucionarias de Colombia - Ejército del Pueblo* (FARC-EP)—and the National Liberation Army—or *Ejército de Liberación Nacional* (ELN)—were two such terrorist organizations still operating in Colombia until the Colombian Government signed a peace agreement with the FARC on September 26th, 2016 (Martinez, 2017; Casey, 2016). The ELN are still operating in Colombia today.

Data from the Global Terrorism Database show that the FARC and ELN have committed acts of terrorism in all of Colombia’s 33 Departments (provinces or districts) since 2000, with a total of 2,653 innocents killed, 4,060 wounded, and 1,495 hostages taken (Global, 2016). Circa 2015 the FARC had approximately 7,000 soldiers, compared to the ELN’s roughly 2,000 in 2014 (Kyra, 2015; McDermott, 2014).

A bifurcation point to the conflict was reached in August 2002, when then Colombian President Álvaro Uribe was inaugurate, and decided to take a more aggressive stance towards terrorism. He chose to take the fight to Colombia's most prominent terrorist organization, the FARC, by utilizing Colombia's military to its full potential to wage war on the terrorist group. This aggressive stance ended when Uribe's second presidential term ended in 2010, and he was replaced by current Colombian President Juan Manuel Santos. After a year of continuing Uribe's counter-insurgency policies, Santos abruptly changed strategy in November 2012 and returned to traditional peace negotiations as the primary method of conflict resolution with the FARC (Delgado, 2015).

This study pursues a broad, but extensive look into the long term casualties and sacrifices Colombians have made to bring forth peace, as well as spatial clusters and locations of conflict areas, the impact of natural and social barriers, and finally the potential future of terrorism in Colombia. Datasets used to examine these issues include START's Global Terrorism Database, remotely sensed MODIS imagery, Twitter, Colombian Census data, Bank of Colombia financial data, and Latinobarometro survey data.

Though this study does not use data regarding government military action, attack intensities will be used as a proxy for how successful Uribe's counter-terrorism policies were. As stated in Delgado's (2015) study, Santos's strategy was to injure the organization enough to make negotiations appear as the better avenue to resolution, rather than encountering and defeating the FARC on the battlefield.

1.2 Strategic Significance

The strategic significance of the problem addressed in this thesis is associated with its two primary parameters: narcotics and terrorism. This confluence of transnational criminal activities (associated with drug trafficking) and *terrorism*[1] is a prototypical example of today's strategic challenges faced by the US, and their study is of rather obvious importance.

Colombia has been and remains the world's top producer of cocaine ([1], Livingstone, 2003), as well as a source country of heroin and marijuana. It is estimated that approximately half of the world's cocaine coming from Colombia (Alsema, 2013), According to the State Department's annual International Narcotics Control Strategy Report, pure cocaine production in Colombia shows a notable upward trend, reaching 495 metric tons in 2015 (US StateDepartment, 2017).

From Colombia the cocaine travels by air, land, and sea to nations around the world, including North and South America, as well as Europe (Chandra et al., 2015; Campestrini et al., 2017). Kenney, M., 2007 The architecture of drug trafficking: network forms of organization in the Colombian cocaine trade. *Global crime, 8*(3), 233-259.)

Ellis RE. The Evolving Transnational Crime-Terrorism Nexus in Peru and its Strategic Relevance for the US and the Region. Prism: a Journal of the Center for Complex Operations.

[1] http://www.businessinsider.com/colombia-top-cocaine-producing-countries-record-production-2017-3

Livingstone, G. (2003). *Inside Colombia: drugs, democracy and war*. Rutgers University Press.
US State Department (2017) International Narcotics Control Strategy Report, Volume 1 – Drug and Chemical Control, March 2017, accessible at https://www.state.gov/j/inl/rls/nrcrpt/2017/

The second component if the Columbian problem nexus, namely terrorism, has been the subject of renewed focus in the years following September 11. The majority of the current research literature is focused on terrorism in the Middle East and Europe (Liu et al., 2017; Rehman et al., 2017; Drewer et al., 2016; Schomerus et al., 2017). Some recently published journal articles study terrorism in Sub-Saharan Africa (Efobi et al., 2016), as well as terrorism globally (Ezcurra et al., 2016; Procasky et al., 2016). Terrorism in these regions is relatively similar, in that non-state actors use high intensity terrorist acts to produce mass amounts of destruction and injury to national infrastructure, government capability to combat crime, and the local populace (Siebeneck et al., 2009). Colombia, however, is a special case. One motivation for the continuation of terrorism in Colombia is the drug trade, while in Europe and the Middle East, terrorism is motivated by religious and political ideologies. Limited destruction has impacted the Colombian national infrastructure or the local populace, even with approximately 7,000 FARC and 2,000 ELN soldiers (Gurney, 2015; McDermott, 2014). It is for this reason the conflict in Colombia is referred to as a low-to-medium intensity conflict (Sanín, 2006).

1.3 Terrorism and Geography in Colombia

Within the Republic of Colombia reside 33 Departments, or states. This study uses Departments due to their sub-country level resolution, while at the same time generalizing entire Departments with specific data values used later on in this study. It should be noted that the Republic of Colombia has extremely unique geography. Containing a vast rainforest, sprawling savannas, large mountain ranges, two coastlines, and connecting to two continents. Colombia is not only diverse geographically, but socially as well. Not all of Colombia is controlled by the Government, but less than half. Figure 1 displays a map of Colombia, along with the four main areas which different factions control. All areas of control are approximate, however the area of the nation of Colombia was collected from the CIA World Factbook. It should also be noted that the FARC control some area within the nations of Colombia, Brazil, Venezuela, and Ecuador, perhaps also Peru and Panama.

As mentioned previously, it is important to note that the approximate area of Government controlled territory displayed in Figure 1 may be much larger than it is in reality. This is because the 'Government controlled territory' in the southern and far eastern regions of the country are severed by a long distance of dense jungle, hills, mountains, and FARC controlled territory. The populations of these areas are very sparse, and the Colombian Government provides few to no services to these regions. These services include electricity, water, and sewage to many of the inhabitants of these Departments (Geoportal DANE, 2005). In the Departments of Amazonas, Vapues, and Guainia, 0% of inhabitants have access to natural gas. Less than half of the inhabitants within these three Departments have access to sewerage, with the Department of Guainia providing as little as 18.9% of its inhabitants with proper sewerage. Likewise, around one quarter or less of the inhabitants have access to telephone services. It is highly doubtful that the Colombian Government have solid control of the southern and far eastern regions of the South American nation. If this assumptions is correct, then the Colombian Government may control around half of the area of land that is displayed in Figure 1.

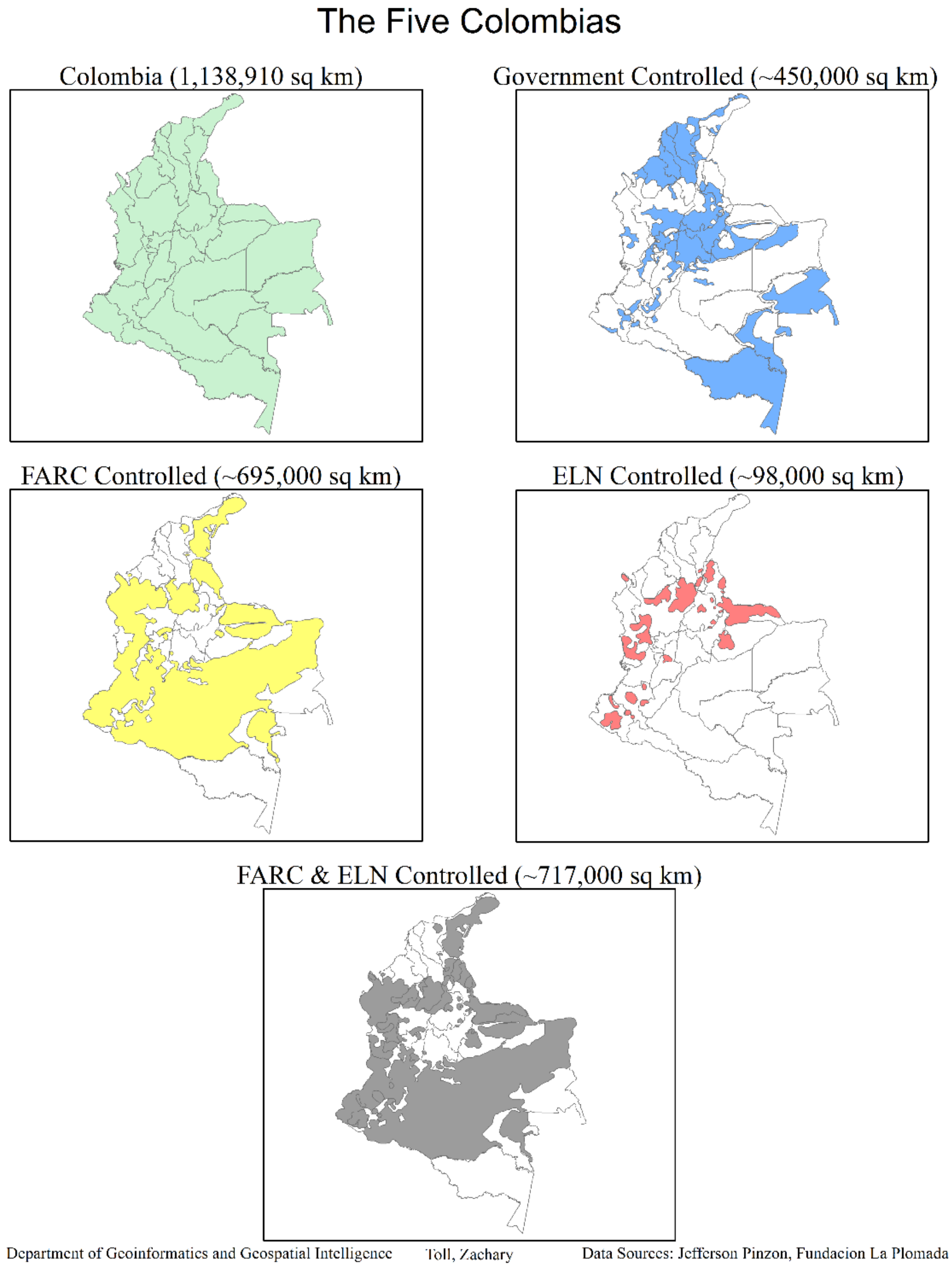

Figure 1. Map of various territory types.

Midlarsky et al.'s (1980) study of terrorism describes four patterns of geographical terrorism: randomness, heterogeneity, contagion, and reinforcement. Geographical terrorism is the notion that terrorism is dynamic and can affect and or be affected by local or international influences. Terrorism in Colombia is considered to be of the reinforcement category, which indicates "the experience of terrorism in one country increases the probability of its occurrence in the same country at a later point in time" (Midlarsky et al., 1980, p.265). Terrorist organizations in poorer nations, such as those in Latin America, develop by learning from terrorists in wealthier, more prominent nations (e.g., European countries). However, their analysis found the opposite to be true. Terror groups in Europe imitated behaviors of terrorist organizations in Latin America. Hence, terrorism in Latin America should be more of a focus in terrorism literature. A study of the tactics and activities used by the FARC and ELN might reveal patterns present in the actions taken by less prominent terrorist organizations around the globe.

Terrorism in Colombia was predominantly located in rural areas until 2003 due to financing from drug manufacturing and trafficking (Zapata, 2003). With continued income and support from other national and international terrorist groups, communist nations (namely Cuba), and the drug trade, it was a difficult decision for the FARC and ELN to come to the negotiating table and stop fighting for their cause (Zackrison, 1989). Both groups use assassinations, bombings, armed assault, and kidnapping to cause terror.

Rosenau, Espach, Ortiz, and Herrera (2014) found that, in terms of recruitment, some members joined the organizations with a false sense of hope for good wages and a better life. However, this study also revealed that some members deserted for the same reasons. Out of a sample of 15,308 former fighters, 58.7% left because they desired a happier, healthier lifestyle or to avoid mistreatment. The authors also found that 13.6% of the fighters sampled left their respective groups due to pressure from military operations, possibly the result of Uribe's aggressive counter-insurgency tactics.

Although previous studies have examined conflict in Colombia, including the number of people killed, displaced, and affected (Sanín, 2006; Serres, 2000; Zackrison, 1989; Zapata, 2003), the geographic component of violence and terrorism within the country has yet to be examined. Other studies with a spatial component lack the emphasis on a specific region or nation, and produce a less refined country-level or sub-country-level analysis of the geography of terrorism (Braithwaite & Li, 2007; Buhaug & Gleditsch, 2008; Enders & Sandler, 2006; Midlarsky, Crenshaw, & Yoshida, 1980; Nemeth, Mauslein, & Stapley, 2014; Siebeneck, Medina, Yamada, & Hepner, 2009).

1.4 Social Media and Terrorism: Influence and Recruitment

The rise of social media has made radicalization easier than ever. Before Instagram, Facebook, and other platforms, it was very risky and difficult to find like-minded individuals. Prospective members and recruiters use social media to connect through the atomicity of the internet. In addition to this, mobile devices and computers allow terrorist organizations to communicate uninhibited and with greater frequency than ever before (Berger, 2015).

Social media and terrorism were seemingly not addressed or studied in correlation to one another before the founding of ISIS. Terror networks kept a low profile and recruited locally, whether it be through a common political ideology or religious/ethnic belief. With the founding of ISIS in 2013, this changed how many viewed social media as a medium of how terror networks recruit new members and display propaganda videos and images, as well as receive funding.

Chatfield (2015) uses the tweets of the known ISIS supporter who used the twitter handle ”@shamiwitness”. It was found that up to 60% of the tweets on this account were re-tweets, with the remaining tweets being in English and written by the account owner. The content of the tweets were broken down into four major groups which are international media, regional media, ISIS sympathizers, and ISIS fighters. Using the tweets of a known ISIS supporter it is possible to target an algorithm to pick up specific categories and topics that a terrorist would be interested in.

Contents of tweets and how they influence their audience to support ISIS are investigated by Huey (2015). Some of the tweets present ISIS in a popular way, which include memes, GIFs, and anti-US propaganda. This suggests ISIS are using comedy and popular media to reach out to youths and to draw them into recruitment. One method to track terrorist recruitment is to focus on the content that is attached to the tweets, which can include images, GIFs or other attachments that can be traced.

In an interesting deviation from social norms in the Middle East, and unlike other terrorist groups such as al Qaeda, ISIS allows female supporters to run twitter accounts to recruit other females (Klausen, 2015). This allows ISIS to reach a broader audience with their content than other organizations. The information about gender may not be apparent in the account profile if the user is a female or not, but the contents of the twitter activity will suggests whether a user is male or female.

The Klausen paper identifies social media trends Western European terrorists use, analyzing their activity based on the available information on the contents of their tweets or other social media accounts. Of the tweets that were analyzed, over two-thirds of the activity on the twitter accounts were retweeting. This is done to quickly spread content over the internet without drawing attention to an individual account. It is more difficult to suppress content and to indict known terrorists if the content is spread across all of the social media outlets. With the coordinated efforts to pass along content it is also possible to find the individuals involved by working backwards and tracking which accounts are reposting the information.

One of the biggest dangers of social media is its effect on western audiences. Because of the nearly universal access to the internet in the United States, the potential for homegrown terrorism via the internet is much higher than in other countries (Thompson, 2011). For example, according to the Internet Word Stats, places such as Iraq only have 1.26% internet penetration while countries such as the US have internet penetration of 46.2% ("Asia Internet Usage Stats Facebook and Population Statistics," n.d.). Not only are western audiences well connected to the internet, they also spend a lot of time using the internet for communication. In 2013, nearly half a million twitter users tweeted about 9,100 tweets per second. Even when radicals' accounts are shut down, alternative accounts spring forth, gaining over 20,000 followers in a single day (Amble, 2012). It can be very difficult to source radical messages across the internet. Some unanswered questions include, "(1) How individuals become radicalized and (2) how do terrorists carry out coordinated attacks via the internet? (Amble, 2012).

Fortunately, several researchers have proposed models to answer some of these questions. Two commonalities between many 'Radicalization' models are the influence of social deprivation and identity crisis (King & Taylor, 2011). Two differences are the way that the models track radicalization over time. There is also evidence of an interplay between established extremist organizations and autonomous terror cells. Sageman (2008) outlines the idea that many terror groups are 'just a bunch of guys.' The role of the established organizations is to get everyone pumped up while smaller, closed knit groups carry out the organization's goals.

Although theoretical models are a great first step to understanding and combating radicalization, there are still considerable challenges. One major challenge is a lack of ground truth data to verify the models. Interviewing radical terrorists is tricky at best and much of the data on terrorists is classified. Still, there are some researchers who have done in-field research. Post et al. (2003) interviews 35 incarcerated Middle Eastern terrorists to understand the behaviors, networks, and operation of terrorists in the 21st century. If this kind of information could be supplemented with classified intelligence agency data, the whole world would be on a better course toward combating radical Islamic terrorism (King & Taylor, 2011).

During these troubling times with the rise in terrorism and terrorist propaganda, as well as a boom of social media platforms and networks; locating, identifying, and putting a stop to the growth and actions of such terror networks is critically important to maintaining global peace. While previous studies have covered terrorism in the Middle East and Europe, the nearly six decade long conflict occurring within the Republic of Colombia has been neglected. This study is different from previous studies because it includes analysis of the number of people affected over time, as well as viewing the conflict at a country level. Radicalization models, social media data, national infrastructure statistics, and economic datasets are also incorporated in an attempt to understand how individuals become radicalized, and whether/how they carry out coordinated attacks via online plans and arrangements. Above all else, this study considers two specific and prominent non-state threat actors, focusing on the temporal and spatial distribution of these groups comparatively, both in-depth and side-by-side.

1.5 Thesis Scope and Structure

Given the above, in this thesis we contribute towards improving our understanding of the Colombian conflict by pursuing a number of research questions that 1) Provide in-depth detail of the number of Colombians affected, 2) Determine how natural and social barriers prolong the conflict, 3) Gauge the spatial locations and distributions of prevalent terrorist activity, 4) Social and economic conditions that hinder Colombia from progression as a nation, and 5) Sentiment of Colombian terrorist organizations on Twitter.

This thesis is organized as follows. Chapter 2 delves into the specific research questions of this thesis as well as hypotheses. These research questions specifically target different aspects of Colombian life that influence, are influenced by, or go hand in hand with the conflict in Colombia as stated in the previous paragraph. Chapter 3 specifies the large variety of methods, as well as data sources used in answering the stated research questions. Chapter 4 discusses the results found via the methods and data sources used when applied to specific research questions. Chapter 5 discusses the major limitations that may have inhibited or prevented certain results. Chapter 6 finalizes this thesis by discussing the comprehensive outcomes of this study. Chapter 7 includes the two programming scripts used in order to create the word cloud, as well as a retweet network of tweets regarding terrorism in Colombia. Chapter 8 simply gives the list of references.

2. STATEMENT OF RESEARCH QUESTIONS AND EXPECTED FINDINGS

This thesis contributes to the greater field of Geography by pursuing eight research questions (Q1 – Q8) and associated formulated hypotheses (H1-H8), which are presented below, together with the significance of pursuing these issues. All questions are asked by the author due to their inherent necessity of understanding on order to fully assess the everlasting and untold conflict in Colombia.

Q1. How have attack intensity values varied temporally? Answering this research question will provide insight as to whether Uribe's anti-terrorism policies were effective in lowering attack intensity values during his time in office. This question will be answered by presenting statistics of terrorism data and mathematically computing attack intensity values before, during, and after Uribe's presidency.

H1. It is expected that attack intensity values lowered during Uribe's counter-insurgency campaign from 2002 to 2010. It is also expected that after Santos's change in strategy in November 2012, attack intensity values increased as less military force was used against the terrorist groups.

Q2. Are there notable spatial clusters of high attack intensity values? Computing spatial clusters of attack intensity values in Colombia is a great way to discover how the FARC and ELN operate. High attack intensity values being clustered within specific geographic areas provide insight regarding group tactics and strategies, preferred attack areas, and rough location. This question will be addressed by computing a cluster and outlier analysis for both groups for years 2012, 2013, and 2014.

H2. It is presumed that high attack intensity values have remained spatially clustered throughout Colombia due to the terrorists' familiarity with certain areas of Colombia, as well as their control over specific areas.

Q3. Have clusters of terror attacks occurred in areas with dense and healthy vegetation? Answering this research question will give great insight as to the particular geographic area and environment that the FARC live and operate in. Densely vegetated areas may be significant in terms of both operational benefits for the FARC, making it easier to hide and plot operations, as well as in terms of its link to drug production and processing. This question will be answered by comparing areas of Colombia that have both clusters of a large number of attacks, and dense vegetation.

H3. It is expected that clusters of terror attacks are more predominantly located in areas which have dense vegetation, making it easier for the terror groups to observe, plot their attacks, and hide from government forces.

Q4. Does terrorism occur in FARC and ELN controlled territories? Answering this research question will give us better insight as to how the FARC and ELN manage areas they occupy. If terrorism often occurs in their territories, it could be an indicator as to the level of control the terror groups have of their territories. More terror attacks may indicate less control of their so-called controlled land. It may also indicate that the FARC and ELN use terrorism in order to control their populace. Alternatively, the FARC and

ELN may also use terrorism as a way to intimidate the local populace to prevent them from taking up arms against them.

H4. It is anticipated that terrorism does occur in FARC and ELN controlled territories, however at a lower amount than in Government controlled territories. This would be a good indicator as to how much control the subversive terrorist organizations have over their land. It would also be a good indication as to how they deal with and control their local populace.

Q5. Does terrorism occur in regions of Colombia where economic conditions are poor, medium, or high? This research question will be answered by computing a statistical regression of number of terrorist attacks per region in Colombia against economic data. Colombia's economy is greater than that of surrounding Latin American countries, and it is likely that there will be great differences in economic conditions across the country. Answering this research question will allow a more in-depth view of whether poverty plays a role in the number of terror attacks within the nation of Colombia.

H5. It is expected that terrorism occurs in areas of Colombia where economic conditions are medium, relative to Colombian economic conditions in general. This is because high economic conditions are more likely taking place around cities, which are under high government control. Also, poor economic conditions are more likely to exist in locations of Colombia which are very rural. It is anticipated that terrorism occurs in areas where economic conditions are average, relative to the Colombian economy, because these areas are in between where the government and terrorists have control over an area.

Q6. What can we learn about terrorism in Colombia from social media, specifically Twitter? Are Twitter users that tweet about terrorism located within FARC and ELN territories? Where are tweets regarding terrorism predominantly located within Colombia? It would be interesting to see whether or not Twitter users actively tweet about the FARC and ELN while located within their controlled territories. Answering this research question will provide insight on the role social media may play as barometers of public discontent in such conditions. This could provide valuable input on how such data can be analyzed in other, comparable situations across the world.

H6. It is difficult to say whether tweets are predominantly located within FARC and ELN territories. Also, it's difficult to expect how many Colombians tweet about the two terrorist organizations. It's very possible that many Colombians don't have access to the internet, making the possibility of owning a Twitter account difficult or impossible. Of the Colombians who have internet access and a Twitter account, many Colombians may intentionally stay off social media and or don't discuss the terror groups on Twitter for fear of getting attacked by the two terrorist organizations.

Q7. What is the overall sentiment when discussing the FARC and ELN terrorist organizations on social media, specifically Twitter? Is there a small, medium or large difference in sentiment between the two organizations? Does the sentiment between the two terrorist organizations change between different locations within Colombia? Answering this research question will tell us what thoughts that the local populace of

Colombia have regarding the FARC and ELN, giving us a better and alternative insight as to the public opinion of the two organizations.

H7. It is expected that the sentiment for the FARC and ELN will be overall negative. This is because many Colombians use social media (specifically Twitter) to voice their opinions of their discontent and rejection of the FARC and ELN. It is anticipated that there will be a prominent number of tweets who have a rather positive sentiment towards the FARC and ELN. It is not uncommon for FARC and ELN guerrillas to use social media. It is only unclear as to how prominent pro-FARC and ELN voices are within in our dataset.

Q8. How well does Borum's 2003 linear radicalization model apply to terrorism in Colombia? In answering this research question we will take into account three separate factors used in the model, and apply them from 2000 to the current situation in Colombia. Answering this research question will give us insight as to why some Colombians become radicalized and end up becoming terrorists associated with the FARC and ELN subversive terrorist organizations.

H8. It is expected that because the Borum's 2003 linear radicalization model does not take into account religious or jihadist beliefs, it will be relatively simple to incorporate Colombian-related datasets into the model in order to produce significant and meaningful results. It is anticipated that Borum's model will apply quite well to the situation in Colombia.

3. METHODOLOGIES

3.1 Research Question 1

RQ 1 asks how attack intensity values (AIVs) have varied temporally. In order to answer this question, data from the Global Terrorism Database <https://www.start.umd.edu/gtd/> is used. Due to increased availability of terrorism literature since the September 11, 2001 attacks, as well as Uribe's counter-insurgency policies being put in place since 2002, data beginning from year 2000 is used until 2014, creating a 15 year study period. Using Microsoft Excel, the data was subset to Colombia only, and further subset to Colombia from year 2000 to 2014. This data was then displayed as a point layer from the latitude and longitude columns in ArcMap, and exported into a shapefile. It was then projected in the Bogota UTM Zone 18N Transverse Mercator projection. Once exported, ArcMap was used to subset only events perpetrated by the FARC and ELN.

A sub-district polygon spatial data layer was downloaded from ArcGIS Online. A simple formula was used to calculate the attack intensity ratings (A) for each quarter of every year from 2000 to 2014 (Siebeneck et al., 2009), where F = fatalities per quarter, I = injuries per quarter, H = hostages taken per quarter, and T = total terrorist attacks per quarter.

$$A = (F + I + H)/T$$

Equation 1. Formula to calculate Attack Intensity Values (AIV).

3.2 Research Question 2

Two types of analyses were used in answering Research Question 2, those being (1) Global Moran's I, and (2) a local cluster and outlier analysis (LISA). Since the Departments of Colombia were used in these two processes, spatial neighbors were defined as such, using inverse distance as the method for calculating the results. A new shapefile was created for the joins for each group from 2012-2014. To compute a Global Moran's I, as well as the cluster and outlier analysis, terrorist attacks were first separated by year, and then inserted into the Departments of Colombia shapefile via spatial join in ArcGIS. As a parameter for the spatial join tool, a one-to-one join was used, and the number of people killed, wounded, and hostages taken were summed within each column. Within the new join shapefile, a new column of data type float was created and the attack intensity formula displayed above was performed using the field calculator. The Global Moran's I is a statistical method for computing the spatial distribution of attack intensity values of attack locations throughout Colombia to determine if they are located randomly, spatially clustered, or both. The cluster and outlier analysis is similar, but used for computing which departments in Colombia have experienced high attack intensities. A Global Moran's I, as well as a cluster and outlier analysis were chosen to give better insight into the spatial distributions of attack intensity values throughout Colombia. Using these attack intensity values for the same period to determine whether attack intensity values within Departments of Colombia were spatially random or clustered. After all six shapefiles of the attack intensity values for 2012-2014 were created, a Global Moran's I was created for both groups from 2012-2014. This calculation created six different outputs; more specifically, a 2012, 2013, and 2014 output for both the FARC and ELN.

3.3 Research Question 3

Research Question 3 is answered through correlation between spatial clusters of high numbers of terror attacks within Colombia as well as areas of dense vegetation. Two methods were used in answering Research Question 3. Total numbers of FARC and ELN terror attacks from 2000 - 2014 were computed for each Department. A cluster and outlier analysis was then produced from these values. Using the Departments of Colombia shapefile, spatial neighbors were defined using these Departments. Inverse distance was used as the method of calculating the results.

A linear regression model was also computed in R to test whether a correlation could be found within the data in Table 1. The analyses in Research Question 3 use data from the Global Terrorism Database (GTD) < www.start.umd.edu/gtd/> and USGS MODIS imagery <http://earthexplorer.usgs.gov/>. MODIS NDVI data collected on January 1st 2014 was used in ArcGIS. The NDVI layer was categorized into five categories using the Jenks (Natural Breaks) method and an aggregated NDVI value was assigned to each Department. The NDVI category which had the largest amount of pixels within each Department was assigned to that respective Department. These NDVI categories per Department are also displayed in Table 1. This method was chosen, as opposed to assigning the average NDVI values within each Department to each Department, because of how the terrorists may use natural barriers to their advantage. For example if the majority of vegetation within a Department had a maximum NDVI value of 4, it is most likely that the terrorists would prefer to occupy these territories, thereby having a higher correlation between these Departments and terror attacks. If a Department contains a majority of NDVI values which are 3, 2 or 1, that Department may appear to be less desirable for terrorists to occupy. A total of five NDVI classes were used in this study, from a maximum value of 4, with a low of 1. The fifth NDVI class was 'No Data'.

Terror incidents implemented by the Revolutionary Armed Forces of Colombia (FARC) vastly outnumber those of the National Liberation Army (ELN). For the 2000 - 2014 time period, the FARC committed 1,145 terror events, and the ELN committed 228 in Colombia. Annual mean terror events perpetrated by the FARC for this time period are 76.3, having a standard deviation of 40.4 events, and a range of 23 - 163. Mean terror events perpetrated by the ELN for this same time period are 15.2, having a standard deviation of 17.9 events and a range from 0 to 56. Figure 2 displays all numbers of terror events perpetrated by the FARC and ELN from 2000 – 2014. Table 1 displays all terror events perpetrated by each group along with NDVI class per Department of Colombia.

Table 1. FARC attacks, ELN attacks, and NDVI per Department

Department	ELN Terror Attacks	FARC Terror Attacks	NDVI Class
Amazonas	1	1	NULL
Antioquia	40	137	4
Arauca	43	59	3
Atlántico	1	2	NULL
Bolívar	4	9	3
Boyaca	5	8	3
Caldas	1	6	3
Caquetá	1	62	3
Casanare	1	7	2
Cauca	6	154	4
Cesar	11	10	3
Chocó	4	27	4
Cundinamarca	10	92	4
Córdoba	1	6	4
Guainía	1	1	NULL
Guaviare	1	14	3
Huila	1	96	4

La Guajira	5	30	NULL
Magdalena	1	3	3
Meta	1	30	3
Nariño	8	73	3
Norte De Santander	54	70	3
Putumayo	1	64	4
Quindío	1	1	3
Risaralda	1	8	4
Santander	11	7	4
Sucre	1	4	3
Tolima	1	53	4
Valle Del Cauca	17	64	4
Vaupés	1	1	3
Vichada	1	3	NULL

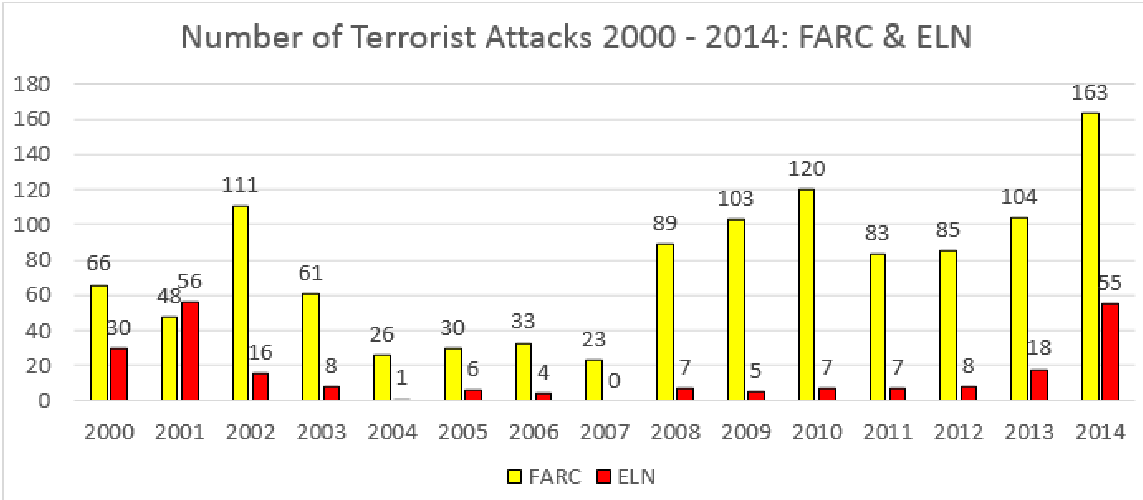

Figure 2. Annual FARC and ELN terror attacks, 2000 – 2014.

3.4 Research Question 4

The Global Terrorism Database was also used in answering Research Question 4. FARC and ELN terrorism data was subset into individual years from 2000 to 2014 within ArcMap. Government controlled, FARC controlled, ELN controlled, and FARC & ELN controlled territories were then simplified into one polygon using 'Merge Feature' in ArcMap. ArcMap's Spatial Join tool was then used to merge yearly FARC and ELN terrorism data into the Government controlled, FARC controlled, ELN controlled, and FARC & ELN controlled territories. A 'Sum' rule was applied to the number of people killed, wounded, and hostages taken, and a 'one to one' spatial join relationship was used for simplicity. After the Spatial Join, a new column titled "AIV" (Attack Intensity Value) was created in each of the 60 new layers. The AIV column calculated the attack intensity value, the formula being number of people killed, wounded, and hostages taken divided by the number of attacks. Once all attack intensities for each year, and within each territory were created, each value was exported to Excel. Charts were created and are displayed in the Results section for Research Question 4.

3.5 Research Question 5

Research question 5 asks whether terrorism occurs in regions of Colombia where economic conditions are poor, medium or high. Data used in answering this question was retrieved from Bank of the Republic: Central Bank of Colombia, or - *Banco De La República: Banco Central De Colombia* (Anuario, 2013). Specifically, the 2010 dataset was used. The dataset was translated from Spanish to English and entered desired tables within Excel. Datasets initially entered included 'GDP at current prices, according to Department' (pg 11), 'GDP per capita (mean average income in pesos)' (pg 13), 'Population' (pg 15), 'Employment and Unemployment percentage per Department' (pg 26), and 'Wages and Salaries, according to Department' (pg 44). All datasets contained data from year 2001 to 2010, with the exception of Employment and Unemployment which began year 2002.

All GDP, Population, Employment, Unemployment, and Wages data were then aggregated. GDP at current prices, GDP per capita, and Population, data were averaged per Department from 2001 to 2010, while Employment and Unemployment was averaged from 2002 to 2010. Wages and Salaries on the other hand was not averaged due to several missing values for the Casanare and San Andres Departments, therefore only the

2009 data was used to answer Research Question 5. To evaluate whether the 2009 data was representative, a Pearson's R Correlation Coefficient was used in order to ensure that using only one year of data was an appropriate method. All values from year to year have extremely high coefficients, with the max being the correlation coefficient between 2008 and 2009 being 0.99997, and the lowest between years 2001 and 2002 being 0.99908. Therefore it is fair to say that not aggregating the Wages and Salaries table is still an appropriate method to use in answering Research Question 5.

Pearson's R Correlation Coefficients were also used for all GDP, Population, and Employment data tables to ensure that no two datasets were highly correlated and likewise to ensure that aggregation of all data tables was sufficient in answering this research question, as well as finding valid results. All data tables produced extremely high correlations, with the lowest being within the GDP per capita tables between years 2001 and 2002, yielding a correlation of 0.8407. A major exception were the Employment and Unemployment tables. Employment had a low of a 0.1517 correlation between years 2002 and 2003. A correlation of 0.9388 was the max value found within the Employment table between years 2009 and 2010. Averages were nonetheless computed, and all aggregated values including the Wages and Salaries 2009 column were added into its own spreadsheet.

Once all aggregated values, along with the Wages and Salaries 2009 column were inserted into a separate spreadsheet, Pearson's R Correlation Coefficients were computed once again for each column of data. It was discovered that the GDP at current prices had a correlation of 0.973 with the Wages and Salaries and a correlation of 0.96 with

Population. Therefore, the authors decided to remove all three columns from the spreadsheet. GDP at current prices was removed due to GDP per capita being available. Wages and Salaries was also removed because of its high correlation with the Population, as well as a low correlation being found within the Wages and Salaries dataset, resulting in a rather undesirable and untrustworthy aggregated value. Therefore, the aggregated GDP per capita, Population, Employment, and Unemployment columns remained. NDVI values from Table 1 were also used. Once all datasets were consolidated, plots graphs were made to determine trends, and multiple linear regression models were computed in R.

3.6 Research Question 6

Research Question 6 used the Department-level polygon spatial data layer mentioned previously. No credible geospatial datasets were available in finding data related to FARC and ELN controlled territories. All information found was in the form of crude, low resolution raster maps which were inconsistent with one another in small scale, however consistent in large scale. Two separate maps were eventually found to be acceptable, the most consistent, and credible from a Colombian news organization (Mentiras, 2016). One map of FARC, the other of ELN controlled territories as of 2016 were then digitized as shapefiles in ArcMap. The two layers were then combined using ArcMap's 'update' tool in order to create a separate FARC & ELN controlled territories layer. Then, ArcMap's 'erase' tool was used to remove FARC & ELN controlled territories from the Colombian shapefile in order to create a Government controlled layer.

Though the maps of FARC and ELN territories which were used in the digitization process may not be completely accurate, it was the best form of available data. The limitations section of this paper will cover this topic further. It is anticipated that the FARC control the territories of the south and east. Another possible reality is that those regions are somewhat a form of 'no-man's land', in which only indigenous and very small communities of Colombians live. Other large portions of the Government controlled territories are anticipated to be fairly accurate, and have proven to be more useful and important throughout the process of this study.

In order to analyze social media networks regarding terrorism in Colombia, tweets were required to obtain and process. A short list of Twitter hashtags and handles were used in order to filter tweets associated with Terrorism in Colombia. These specific hashtags and handles were used because of the strong presence they actively carry on Twitter. The following handles and hashtags were used in order to filter for ELN-related tweets: @ELN_Paz, @MiguelAtal_ELN, @NicaraguaHoy24h, @elavisomagazine, @IFIAdvisory, @GustavoRenteria, @moreira_enzo, @PrensaToday, #ELN, #EjércitodeLiberaciónNacional.

The following hashtags and handles were used to filter for FARC-related tweets: @IvanMarquezFARC, @Timochenko_FARC, @LuciaSa79546384, @Colombia, @id_Communism, @FARC_EPeace, @risk_insights, @McnabbTeddy, @Thussman, @PeninsulaQatar, @frankgaffney, @LuisFleischman, @FARC_EPaz, @FARC_COLOMBIA, @Tanja_FARC, @BorisG_FARC, @Yadira_FARC, @PCataumbo_FARC, @ricardoansal, @FRENTEAN_FARC, @NomasFarc,

@NoMasFarcYa, @NOUribe_NOFARC, @ManuelB_FARC, #cocaine, #cocaína, #FARC, #Colombia, #Columbia, #FuerasArmadasRevolucionariasdeColombia, #FuerasArmadasRevolucionariasdeColombia-EjércitodelPueblo, #FuerasArmadasRevolucionariasdeColombia-EjércitoPueblo.

Raw tweet data was received from Twitter via a real-time streaming interface of information filtered by the handles and hashtags listed above (Croitoru et al., 2013). Tweets used in this study were published between March 24th, 2008 and February 28th, 2017. The tweets were then processed and stored in a MongoDB database. A total number of 516,203 tweets were retrieved via Twitter's streaming interface, while a total number of 283,255 tweets contained precise locational information which could then be used for geospatial processing. Tweets that contained locational information were then added into ArcMap and converted to a shapefile. The tweets were then projected to WGS 1984 since the tweets were a global dataset. A separate dataset was created by applying an intersect operation in ArcMap to the tweet dataset, along with the sub-Department spatial polygon layer which displays Colombia and its Departments. The result was a dataset of tweets located only within Colombia. A spatial join was then used to add aggregated tweet information into the shapefiles of Government, FARC, ELN, and FARC & ELN territories shapefiles. Within the ArcMap join operation, the Government, FARC, ELN, and FARC & ELN shapefiles were the 'target feature', and the point shapefile of tweets was used as the 'join feature'.

3.7 Research Question 7

Research Question 7 asks what the overall sentiment is when discussing the FARC and ELN on Twitter. Maps and shapefiles created in previous Research Questions were used. In order to determine sentiment of the ELN and FARC, 48,270 geo-tagged tweets were gathered within Colombia's Departments and sentiment was computed using a Spanish lexicon produced by the University of Southern Mississippi. Tweets were separated into two categories based on words and hashtags associated with the FARC and ELN. For each tweet, the valence and arousal was computed for each word. The mean valence and arousal for each tweet consisted of the mean of all the words contained in a tweet. Raster surfaces were generated using the kriging interpolation technique with 12 minimum neighbors, a cell size of 3,000 meters, and a spherical semivariogram model. A kriging interpolation technique was used in an effort to predict results across Departments which were missing data. 12 minimum neighbors were used to also ensure that values within Departments which were missing data could be interpolated. A 3,000 meter cell size was used in order to cover the rather large nation of Colombia while still having high spatial resolution. A spherical semivariogram model displays covariance values for pairs of locations related by the distance separating the two locations.

The data reviewed for the public opinion was survey conducted by Latinobarometro. This is a non-profit organization based out of Chile which specializes in collecting survey data from countries in South America. There are 1,200 cases collected for Colombia in each given year. The accuracy of the data that was collected has an estimated error of 3.5%. The distribution of the dataset is 75.9 urban and 24.1

rural. There were four questions pulled from the dataset. These questions are going to be used to establish a frame of mind of the public opinions of Colombians. The first two ask questions that are a bit vague to establish context. Then the next two questions ask about their attitudes towards the Federal Government of Colombia. The data will be split into Government controlled territories and FARC & ELN territories to see if there is any revealing details between the regions.

The first question selected for review is “Generally speaking, would you say you are satisfied with your life? Would you say you are....?” and the possible answers are Very and Quite satisfied or Not very and Not at all satisfied. The answers to this question are stored as 1, 2, 3 or 4 within the database. This question goes over the general outlook the responders have about their lives. It is not pointed towards politics or economics. This would be the general outlook the responder has towards life.

A word cloud was also produced in order to get an overall sentiment of terrorism in Colombia. This was done by taking all available tweets and removing all information within the tweet except for the text. Since R could not process all tweets which were available in the dataset, a sample of 15,000 tweets were used. After a sample of 15,000 tweets were subset into an alternative text file, a simple script in R was used. The script which was used is in the Appendix.

A visualization in Gephi was also created in order to further analyze social media networks regarding terrorism in Colombia on Twitter. In order to achieve this goal, a script was written in Python to create libraries of tweet ID’s, retweet ID’s, and tweet authors. Specifically, this script was intended to connect retweet ID’s with original tweet authors and tweet ID's. Once all information was connected, the script would then write these tweets and retweets to a Gephi-readable file and create a visualization within Gephi. Retweet networks were further queried in order to create a nice, legible visualization in Gephi. Below shows the script which was used to create the visualization.

3.8 Research Question 8

Why Colombians choose, or end up becoming terrorists, what role does social media have in understanding Colombian terror organizations, as well as what impact does economics in Colombia have on terrorism will be answered in Research Question 8. In order to apply Borum's model to Colombia, economic, survey, and social media data was combined. Borum states that the first stage of an ideological development is (1) 'Social and Economic Deprivation' (Borum, 2003). Borum mentions several factors for stage one including poverty, unemployment, and poor living conditions. In order to assess the status of each Department with regard to stage one, several of the factors Borum stated were collected including GDP per person, unemployment, and access to utilities such as electric, water, and gas.

Instead of setting arbitrary thresholds for each factor, an average was computed for all factors and each Department was weighted depending on how many standard deviations it was from the mean of all Departments. For example, the average unemployment for the 17 Departments was 12.3% with a standard deviation of 2.3%. A Department with 14.6% unemployment would be one standard deviation away from the mean and would be more heavily weighted for stage one alignment. Alignment is used here as a general term to describe how well Colombians living in certain Departments fall into experiencing the various stages of Borum's model. The factors used for stage one included GDP per person, and access to utilities such as gas, sewer, water, and electricity.

Stage two of Borum's model is characterized by inequality and resentment. (Borum, 2003) explains that stage two is a reaction to stage one's social and economic deprivation. The idea is that people feel "It is not right" (Borum, 2003). In order to assess each Department's alignment with stage two, survey data was gathered from Latinobarometro (2015) http://www.latinobarometro.org.mutex.gmu.edu/lat.jsp on people living in each Department. The following two questions were pulled from the survey:

1. Generally speaking, would you say you are satisfied with your life?
2. In general, would you say you are very satisfied, quite satisfied, not very satisfied or not at all satisfied with the working of the democracy in Colombia?

Answers ranged from Not Satisfied (4) to Very Satisfied (1). Similarly to stage one, means for all questions were computed and each Department was weighted depending on how far its mean deviated from the mean of all the Departments.

The Third stage of Borum's model is, 'Blame and Attribution' (Borum, 2003). In this stage, an individual is now directing the inequality and resentment felt in stage two towards an actual entity. (Borum, 2003) coins the term 'It is your fault" to describe how individuals attribute blame to an individual or group. In order to assess alignment per Department of stage three of Borum's model, thereby answering Research Question 8, Twitter data and the survey question below were used.

1. “Do you approve or not the performance of the government led by President (name)?”

The responses were aggregated per Department and a mean was generated over all Departments. Each Department was weighted depending on its deviation from the mean for all Departments. To supplement this data, Twitter data was also used to assess blame toward terrorist organizations. Tweets were gathered from within the boundaries of all Departments from March 24th 2008 to February 28th 2017. The tweets were separated into two categories, FARC and ELN depending on the hashtags and handles used in each tweet. A Spanish lexicon was used to determine the valence of each tweet. This lexicon of over 14,000 Spanish words contains information on the valence and arousal of each word (Stadthagen-Gonzalez, Imbault, Sánchez, & Brysbaert, 2016). Valence is the positivity or negativity of a word while arousal is how emotionally engaging that word is. For example, the word ‘sad’ would be a low valence (negative), low arousal (low energy) word while ‘excited’ would be a high valence (positive), high arousal (high energy) word. High valence values (<5) are indicative of a positive tone while low valence values (>5) are associated with negative tone. An average valence value for FARC and ELN was generated across all Departments. Once again, each Department was weighted depending on its distance from the Departments’ mean.

4. RESULTS

4.1 Research Question 1

In answering the first research question (How have attacks varied temporally?), the analysis showed that the average attack intensity value for the FARC and ELN decreased during Uribe's two terms in office (Table 2). The FARC's upper range of 38.67 is due to a spike during the third quarter of 2006, the FARC's highest attack intensity value of the entire 2000-2014 period. Though the standard deviation, as well as the upper range of attack intensities, has risen for the FARC during Uribe's presidency, the average intensities of the attacks dropped slightly.

Table 2. FARC and ELN AIV statistics before (2000–2001), during (2002–2010), and after (2011–2014) Uribe's Presidency.

FARC	2000-2001	2002-2010	2011-2014
Avg.	7.22	6.89	8.03
Std. Dev.	2.90	6.67	3.30
Range	4.57-12.20	0.0-38.67	3.38-12.73
ELN			
Avg.	13.49	2.96	3.53
Std. Dev.	19.71	5.78	3.88
Range	1.50-60.50	0.0-28.0	0.0-11.0

This attack intensity rating is displayed in the form of a line in Figure 3 for the FARC and Figure 4 for the ELN, along with a separate line depicting total number of attacks per quarter of every year from 2000 to 2014. This method was used to standardize results. If just comparing total number of attacks between the FARC and ELN, a great disparity would be shown. Using attack intensity values for the 2000 to 2014 study period, these groups can be compared. What the attack intensity values reveal to the reader is the average amount of violence (through those killed, injured, and hostages taken) per quarter of every year.

A drop in attack intensities is much more prevalent with the ELN. Similar to the FARC, the ELN attack intensity value spiked to 28.0 during the third quarter of 2002. The average attack intensity value for the ELN during Uribe's presidency, however, dropped dramatically from 13.49 to 2.96, then remained at 3.53 from 2011 through 2014. This decrease in attack intensity values might suggest that Uribe's counter-insurgency policies were much more effective in combating the ELN, though effects can also be seen with the FARC. There are, however, other possible explanations for the decrease in attack intensity values, including a lack of data before and after Uribe's presidency, or possibly the focus of the FARC and ELN on terrorism being redirected to protecting territory.

Figure 3 includes a comparison of attack intensity ratings with the number of attacks for FARC during the 2000-2014 study period. Figure 3 illustrates that, although the attack intensity rating has remained steadfast during Uribe's terms in office, the number of attacks committed by the FARC decreased. Attack intensity values, as well as number of attacks committed by the ELN, changed more dramatically during Uribe's time in office. Prior to Uribe's presidency, the average ELN attack intensity value was 13.49, dropping to 2.96 during his presidency. Likewise, the standard deviation of attack intensity values was at a high of 19.71 for both the FARC and ELN during the study period, but dropped to 5.78 during Uribe's presidency. According to the data, there was a combined three-year period where no attacks were committed by the ELN, resulting in no attack intensity rating.

In a similar analysis, the plot in Figure 4 compares the attack intensity ratings and the number of attacks for the ELN. The attack intensity rating for the ELN spiked to 60.5 during the second quarter of 2001, and rapidly declined to the point of no attacks from the fourth quarter of 2003 until the second quarter of 2005. It is important to note that ELN attack intensity values were higher than the number of attacks committed. Alternatively, the FARC's attack intensity values were lower than the number of attacks committed. As mentioned, Colombia is considered a low intensity conflict. Nonetheless, the ELN is a terror group which commits slightly higher attack intensities when compared to the FARC. Though there are less terrorists within the ELN organization and the ELN commit much fewer attacks, their attacks are often more violent and cause more harm to their targets. Therefore, it can be concluded that in answering Research Question 1, the FARC and ELN differed greatly in the total number of attacks for the study period, however, the attack intensity values for the ELN were higher than the total number of attacks committed for the 2000-2014 study period.

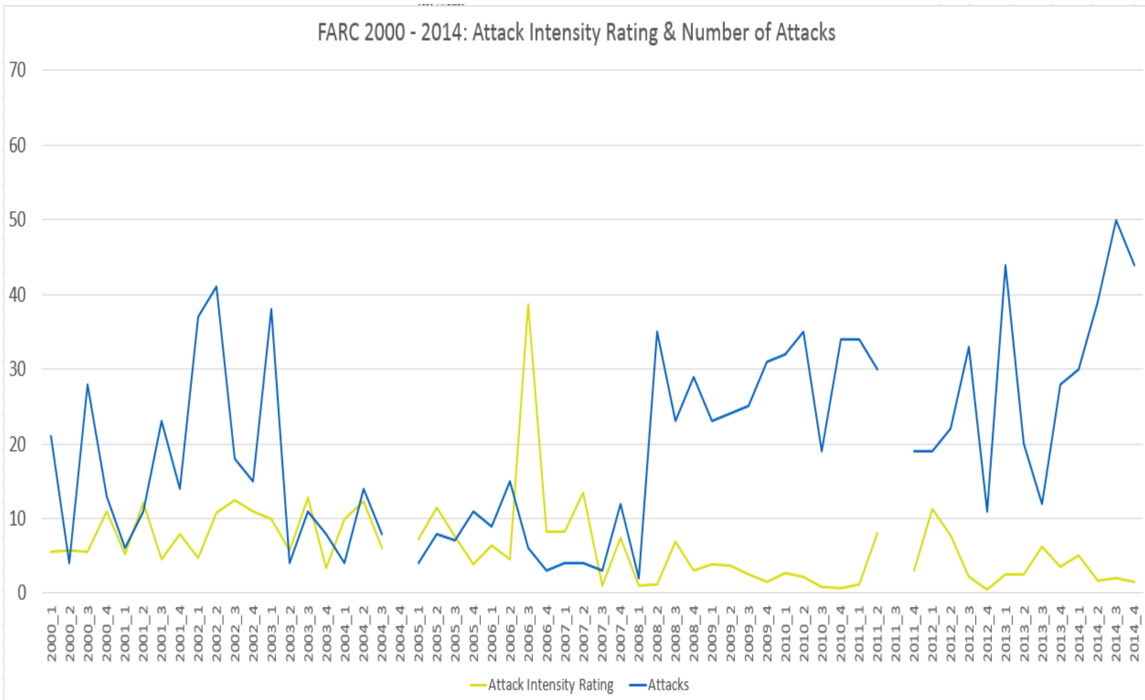

Figure 3. Attack Intensity Values and number of attacks committed by the FARC, 2000 – 2014.

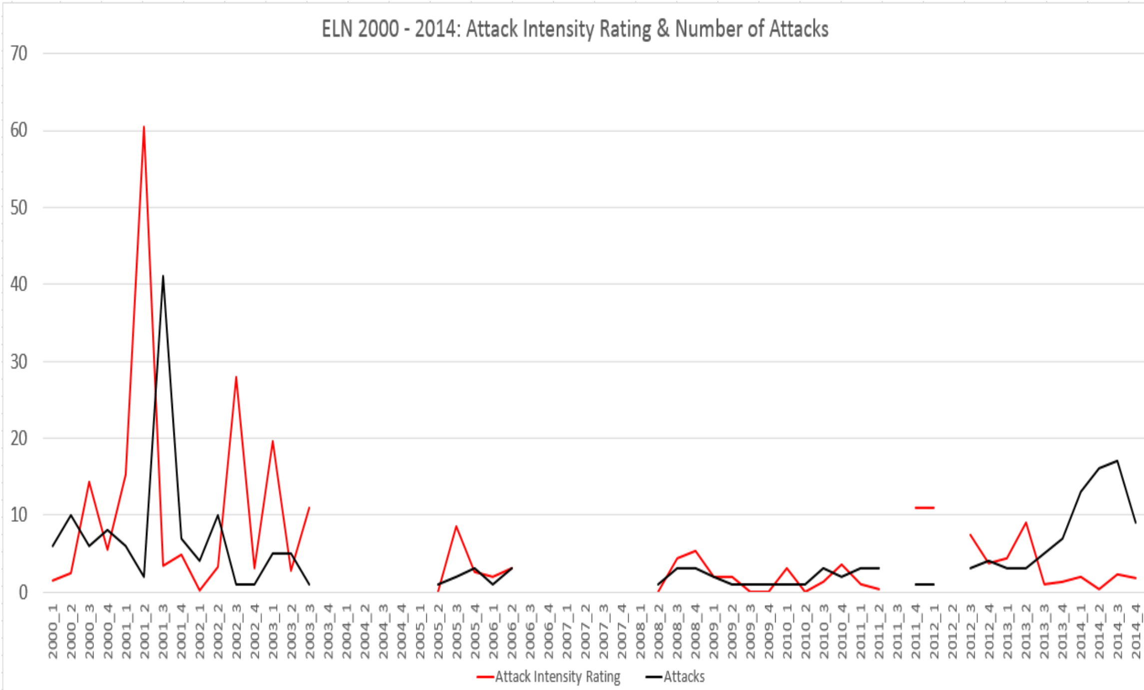

Figure 4. Attack Intensity Values and number of attacks committed by the ELN, 2000 – 2014.

4.2 Research Question 2

A Global Moran's I was used to answer Research Question 2 which asks 'Are there notable spatial clusters of attacks?' For both groups, z-scores and P-values were computed using Global Moran's I from attack intensity values for years 2012, 2013, and 2014 in Table 3. The Moran's I for the FARC between 2012 through 2014 remains between 0.227 and -0.031, and are randomly distributed for the study period. Similarly, the Moran's I for the ELN also appears to be randomly distributed. Given the results, terror attacks consistently remain randomly distributed through time and do not appear to become significantly more or less spatially clustered.

Table 3. Moran's Index and P-values if FARC and ELN AIVs, 2012 - 2014.

Years		**2012**	**2013**	**2014**
FARC	Moran's I	0.227	0.165	-0.031
FARC	p-value	0.6159	0.3445	0.9836
ELN	Moran's I	-0.008	-0.065	0.047
ELN	p-value	0.7041	0.7397	0.4843

Figure 5 displays attack locations within Colombia from 2012 through 2014 committed by the FARC (yellow) and ELN (red). Figure 6 displays attack locations from 2000 through 2014. Figure 7 depicts all high-high, high-low, low-high, low-low, and non-significant values for all Departments of Colombia. Throughout the 2012-2014 study period, a total of three Departments displayed high-high attack intensity clustering, according to the given attack intensity values. Another three departments displayed high-low outlier values, given their corresponding attack intensity values. The remaining Departments of Colombia resulted in non-significant, as there were no low-high outliers or low-low clusters found. These results also indicate that clusters of attack intensity values remained randomly distributed from 2012 through 2014.

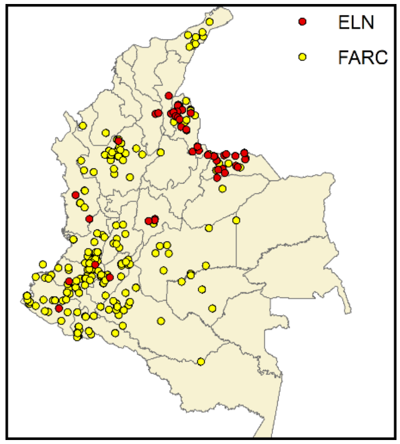

Figure 5. FARC and ELN attack locations, 2012 – 2014.

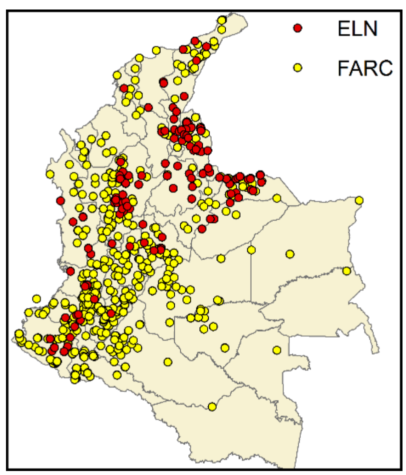

Figure 6. FARC and ELN attack locations, 2000 – 2014.

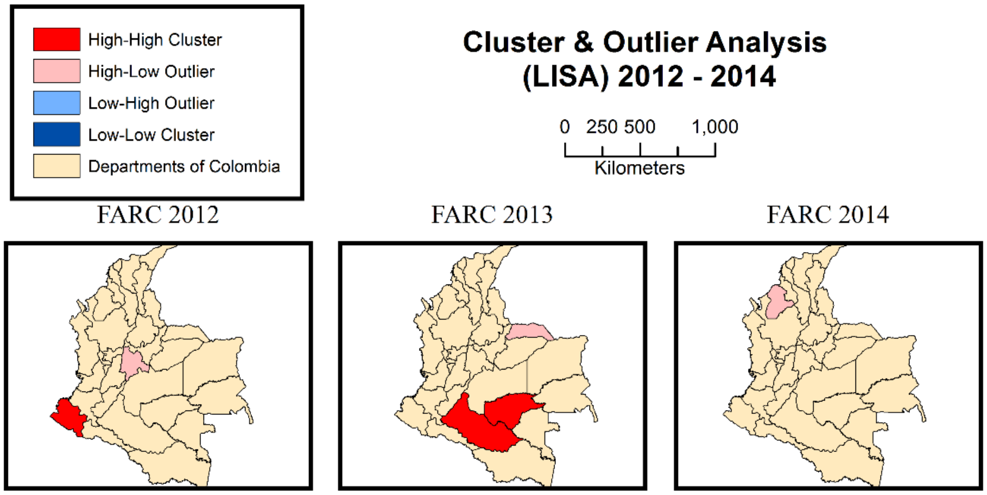

Figure 7. Cluster and outlier analysis: FARC, 2012 – 2014.

No results were found for the ELN from the cluster and outlier analysis. This is likely due to the limited number of attack intensity values corresponding to each Department of Colombia from 2012 through 2014. With limited values to input within each department, no clusters were found. These results indicate that the ELN lacked the number of attacks, and corresponding attack intensities, to be studied with a cluster and outlier analysis.

Terror attacks committed by the FARC and ELN mainly occurred in rural areas, as displayed with point locations from the START Global Terrorism Database data used in this study. Due to most terror events being located in rural areas, the difficulty for the government of Colombia to combat the terror groups is high. Areas distant from military facilities, difficult to travel to or through (mountainous/dense regions), and near international (or across) borders—not to mention the added difficulty of local support—

make the problem of fighting these groups exponentially more difficult (Buhaug & Gleditsch, 2008; Nemeth et al., 2014). Though Buhaug & Gleditsch or Nemeth et al. did not study Colombia specifically, all said factors are present within Colombia today. Buhaug and Gleditsch researched civil war, specifically the cause of violent conflict within societies. In their 2008 study, the authors found that local support, international borders, and rough terrain can impede government capabilities. Colombia was mentioned in Nemeth et al.'s (2014) study. They also found that rugged terrain, proximity to international border(s), and local population significantly impact the ability to relegate terrorist activity.

4.3 Research Question 3

Research Question 3 was answered using three different methods. Results derived from the cluster and outlier analysis determined that clusters of attacks do indeed occur in areas with dense vegetation. Figure 8 displays the NDVI classes within each Department of Colombia. It can be observed that Departments nearby the Pacific Ocean contain higher NDVI class values (3 and 4). Figure 9 displays the cluster and outlier analysis (Anselin Local Moran's I) performed from ELN terrorist attack data from 2000 - 2014. A single high-low cluster was found, that being the Department of Antioquia. Figure 10 displays the cluster and outlier analysis performed from FARC terrorist attack data from 2000 – 2014. Similar to the ELN results, a single high-low cluster was found within the Department of Antioquia, a Department with the highest NDVI classification. Four Departments were found to have high-high clustering values, those being Cauca, Huila, Nariño, and Putumayo. All Departments with the exception of Nariño contained the highest level NDVI derived from the MODIS data. These results confirm the hypothesis that clusters of terror events are located in areas covered in healthy, dense vegetation such as those in Colombia.

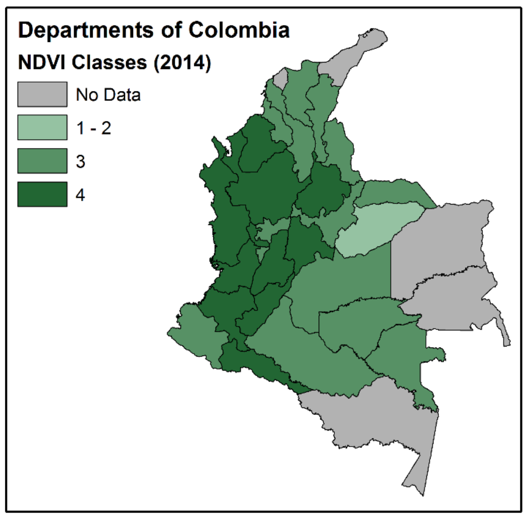

Figure 8. Departments of Colombia and corresponding NDVI class.

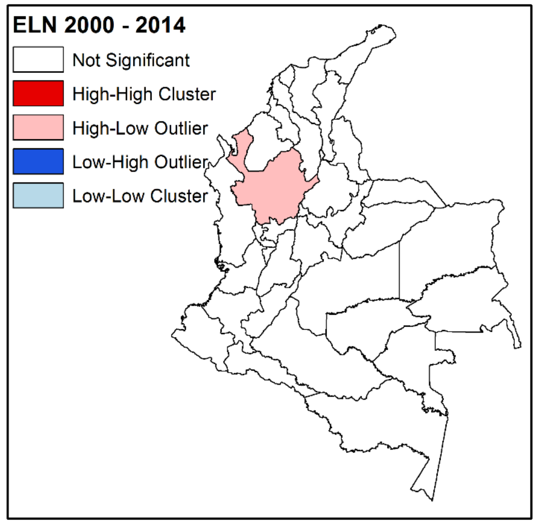

Figure 9. ELN Cluster and Outlier Analysis of terror attacks, 2000 – 2014.

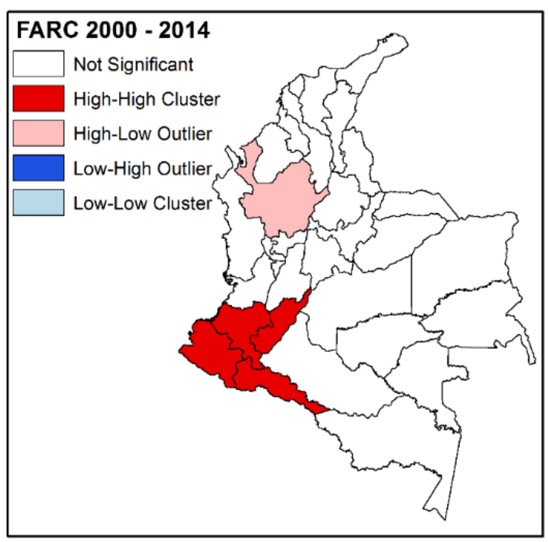

Figure 10. FARC cluster and outlier analysis of terror attacks, 2000 – 2014.

A linear regression model as well as a normal Q-Q plot were computed using the data in Table 1 with R. First, several scatter plots were produced in order to test X and Y variables. NDVI classes were used as the independent variable (X) and number of attacks committed by the FARC and ELN per Department were used as the dependent variable (Y). P-values are displayed in Table 4. Results from the linear model indicate that the P-value of ELN data (0.9001) make it not significant enough for the predictors to contribute to the model. This may be due to the fact that the number of ELN attacks within each Department are significantly fewer than those committed by the FARC. The FARC P-value (0.0235) has a 95% confidence interval within the model, and indicate that it contributes to the hypothesis.

Table 4. P-values derived from linear model computed in R.

	P-Value
ELN	0.9001
FARC	0.0235

A derived Q-Q plot (Figure 11) displays the standard residuals of the data from Table 1, specifically NDVI vs number of FARC and ELN terrorist attacks. It can be observed in Figure 11 that it is difficult to determine if the residual follows a normal distribution due to outliers in the plot. This may be the result of null values being present in the NDVI data. These null values were changed to a value of 0 in order to be handled in the regression. As mentioned before, the number of ELN attacks from 2000 – 2014 are significantly fewer than the number of FARC attacks for the same time period. This may have also affected the normal distribution Q-Q plot in Figure 11 by placing five points to have standardized residuals which are lower than -1. The derived beta value from this linear regression was 28.09, making this value extremely volatile in relationship to the computed linear regression model.

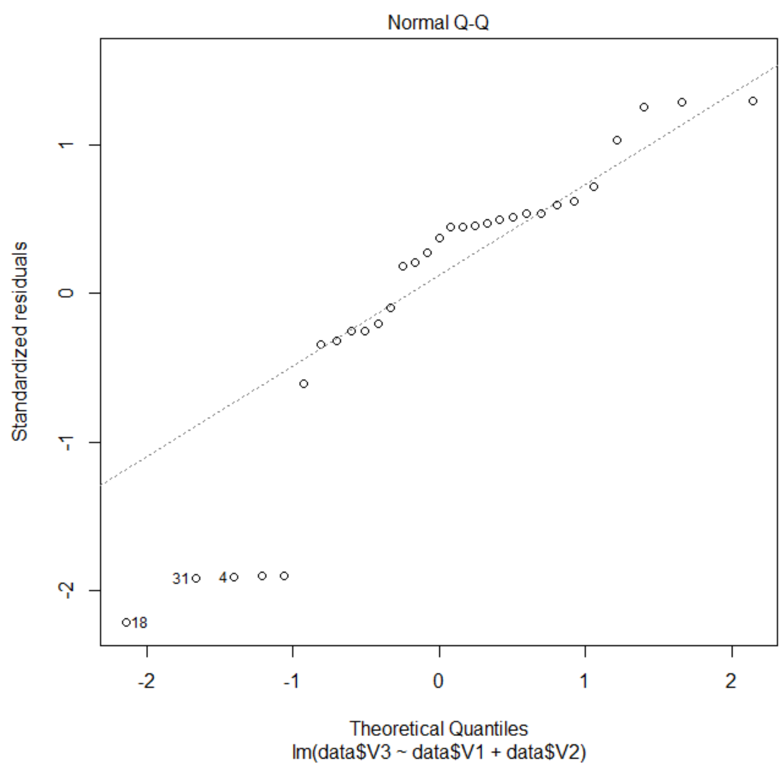

Figure 11. Normal Q-Q plot of NDVI vs terror attacks per Department, 2000 – 2014.

Several confirmatory as well as unexpected results were derived from this analysis. In answering the research question, the analysis shows that larger numbers of terror attacks do indeed occur in areas with healthy and dense vegetation. Out of the six Departments of Colombia which were found to have either high-high clusters or high-low clusters, all but one are considered to have the healthiest and densest vegetation within Colombia.

Results derived from the linear regression model display a contribution to the hypothesis that in the case of the FARC, attacks from the 2000 – 2014 period occur in areas with dense and healthy vegetation. Results pertaining to the ELN do not contribute to the hypothesis because of the limited amount of terror events perpetrated by the ELN during the 2000 – 2014 study period. Results derived from the normal Q-Q plot reveal that it is difficult to determine if the residuals follow a normal distribution. This may be because of the six Departments of Colombia which were assigned null values. Null values would in turn negatively impact the results of the regression, making NDVI and number of terrorist attacks appear to be less correlated than they actually are.

4.4 Research Question 4

Research Question 4 asks whether terrorism occurs in FARC and ELN territories. An attack intensity rating was chosen in answering this research question. Figure 12 displays an aggregated attack intensity ratings from 2000 - 2014 for terrorist attacks that occurred within Government controlled territories. Generally speaking, attack intensities are much higher for terrorist attacks that take place in Government controlled territories than in FARC and ELN controlled territories. Figure 13 displays aggregated attack intensity ratings from 2000 - 2014 for terrorist attacks that occurred within FARC & ELN controlled territories. Comparatively, it is shown that attack intensity values for terrorist attacks that occur in FARC & ELN controlled territories are much lower than those that take place in Government controlled territories. Attack intensity values for terrorist attacks that occur in Government controlled territories are generally similar or higher, with the exception of 2006, 2007, 2008, and 2012. Figure 18 displays attack intensity values within Government controlled territories compared to such values within FARC & ELN controlled territories. Attack intensity values are often times higher, or almost equivalent to attack intensity values within FARC & ELN controlled territories. The few exceptions being 2006, 2007, and 2008.

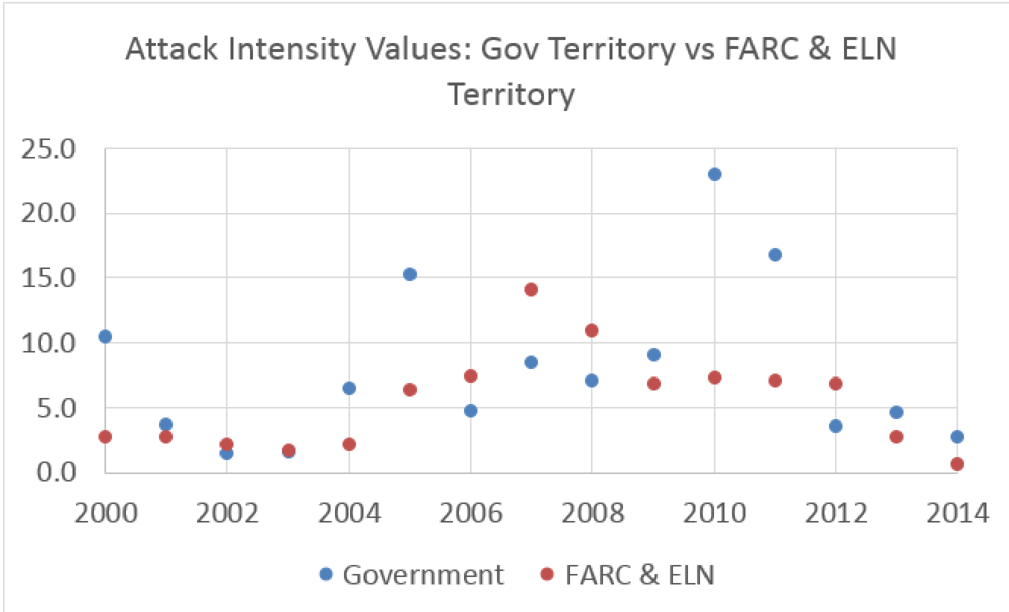

Figure 12. Comparison of annual AIVs between terrorist and Government controlled territories.

Figure 13 and figure 14 display aggregated attack intensity ratings of terrorist attacks committed within FARC, and ELN territories, respectively. Though attack intensities remain below terrorist attacks which were committed within Government controlled territories, they can still be rather high. Attack intensity values between the two territories remain somewhat similar. Between 2000 and 2014, the average attack intensity rating of terrorist attacks which occurred in FARC controlled territories is 5.53, while the average attack intensity rating of terrorist attacks which occurred in ELN controlled territories is 4.18. Essentially, on average almost one additional person is harmed during terrorist attacks that take place in FARC controlled territories than in ELN controlled territories.

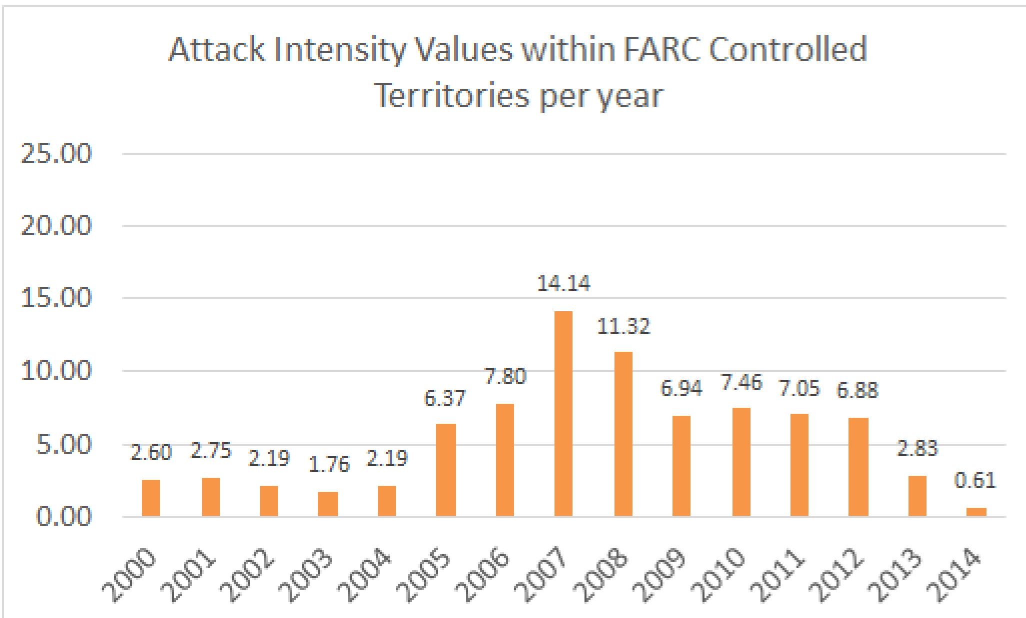

Figure 13. Annual AIVs within FARC controlled territories.

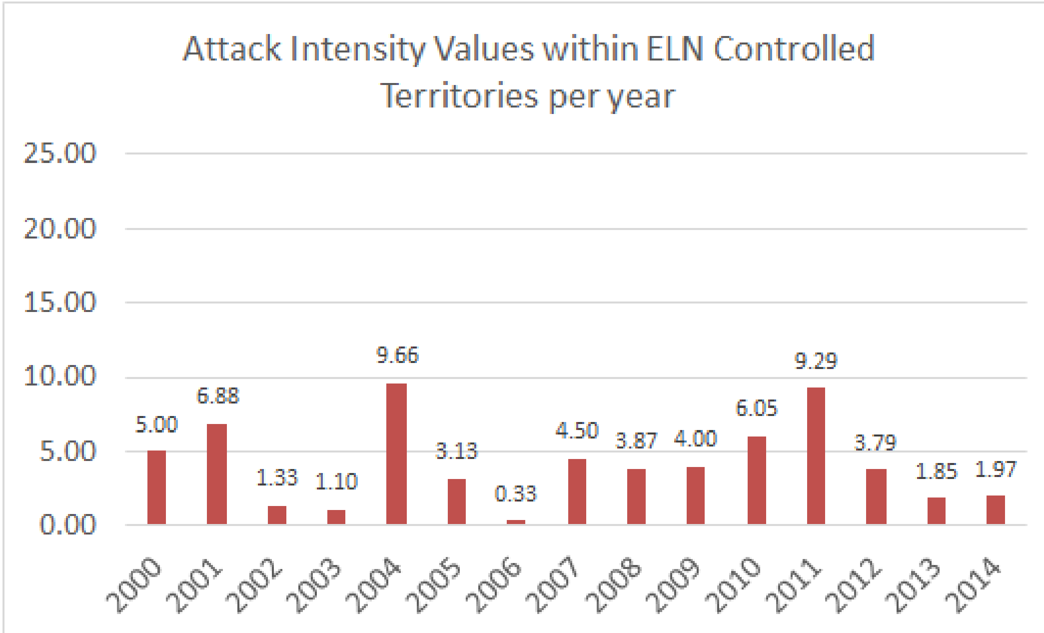

Figure 14. Annual AIVs within ELN controlled territories.

In answering Research Question 4 which asks whether or not terrorism occurs in FARC and ELN controlled territories: Terrorism absolutely does occur in terrorist controlled territories; however, it is generally less intense than terrorism in Government controlled territories. Out of the four forms of territories outlined in this study 1) Government, 2) FARC, 3) ELN, 4) FARC & ELN, Government controlled territories experience the highest aggregated values of attack intensity ratings within the Republic of Colombia. Though raw number of terrorist attacks were greater in number within terrorist controlled territories, Government controlled territories experience greater attack intensity values, and experience more dangerous and deadly terrorist attacks than the local population experience which live in terrorist controlled territories. This tells us much about the way that terrorists and guerillas in Colombia manage their territories. Perhaps the terrorists are more comfortable attacking civilians in their own territories due to a lower chance of getting killed or captured before, during, or after the attack. Also, perhaps the terrorists feel less threatened when committing terrorist attacks within their own territories, thereby lowering casualties. Committing more terrorist attacks could also be a way of intimidating and quelling resistance against the terrorist groups. Alternatively, the FARC and ELN may view committing terrorist attacks within Government controlled territories a matter of life and death. Therefore they feel more threatened, and are more likely to hurt people during their attacks.

4.5 Research Question 5

Research Question 5 ask whether terrorism occurs in regions of Colombia where economic conditions are poor, medium or high. Two methods were used in answering this research question. First, several scatter plots were produced in order to test our X variables in Table 5 again Y variables in Table 6, and then to run bivariate and multivariate linear models in R. Note that the Total Number of Tweets per Department is mainly used as a X variable, but is also used as an Y variable to further test potential correlations and experimentation.

Table 5. X variables used in linear regression models.

X Variables
Employment
Unemployment
GDP
Population
NDVI
Number of Tweets

Table 6. Y variables used in linear regression models.

Y Variables
FARC Attack Intensity Values (AIVs)
ELN Attack Intensity Values (AIVs)
Total Number of Attacks
Number of Tweets

FARC and ELN AIVs were used as the Y variable in order to create scatter plots vs the various X variables. After viewing Figures 15-20 we can see the only strong pattern that can be found for FARC AIVs is with Employment in Figure 15. FARC Attack Intensity Values tend to be higher within Departments which have high percentages of employment. There is also a pattern, however weak, between FARC AIVs vs. Unemployment (Figure 18) and FARC AIVs vs. NDVIs (Figure 20). This leads us to believe that the number of people that the FARC effect is somewhat related to percentages of Unemployment within each Department. Also vegetation, or lack thereof, is somewhat related to FARC's Attack Intensity Values. FARC AIVs vs Tweets (Figure 19) also held a small relationship. This figure tells us that Departments which tweet more about terrorism have a lower chance to experience high intensity terrorist attacks. No correlation was found between FARC AIVs vs. GDP (Figure 16) and Population (Figure 17). Essentially, FARC's Attack Intensity Values has little or nothing to do with the Gross Domestic Product of a particular Department, and likewise have little or nothing to do with the Population of a particular Department.

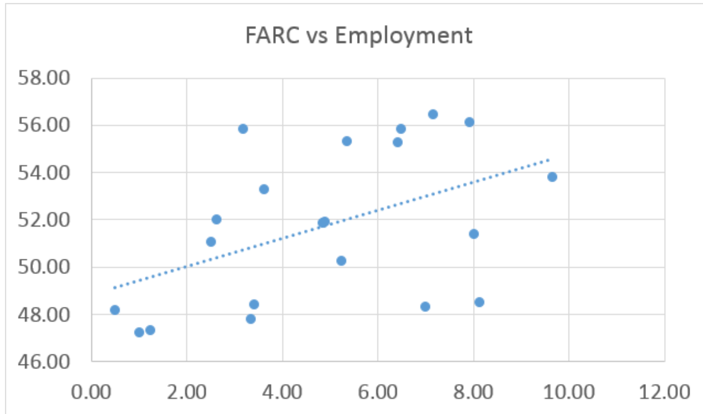

Figure 15. FARC AIVs vs Employment.

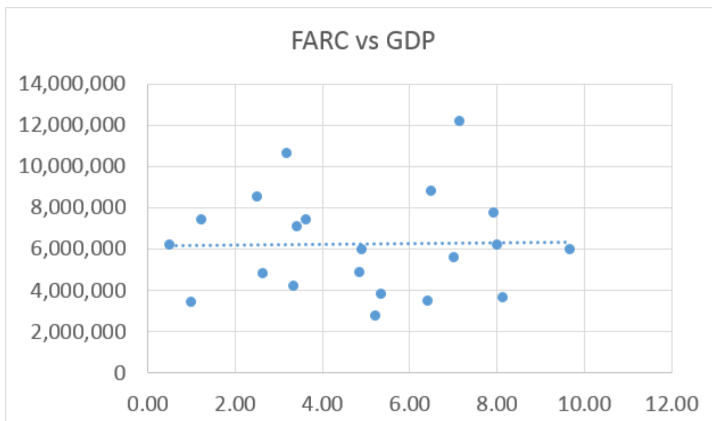

Figure 16. FARC AIVs vs GDP.

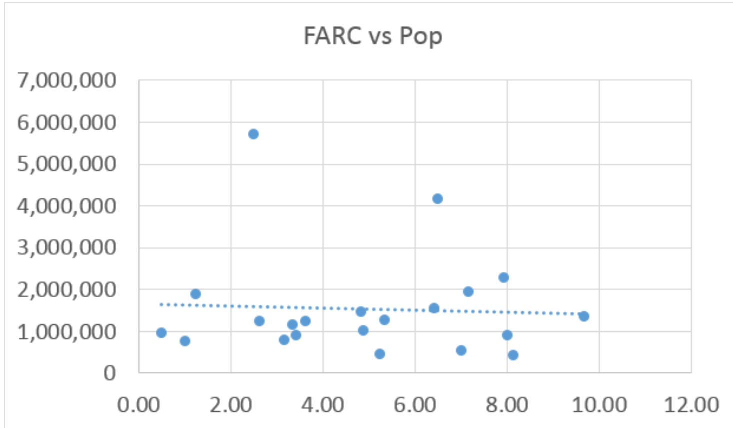

Figure 17. FARC AIVs vs Population.

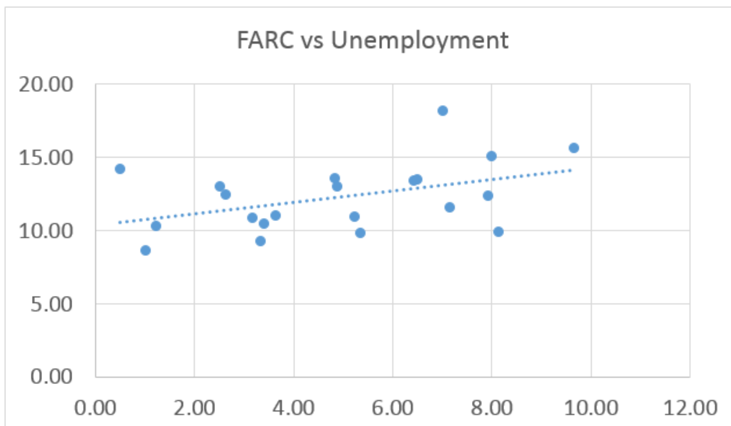

Figure 18. FARC AIVs vs Unemployment.

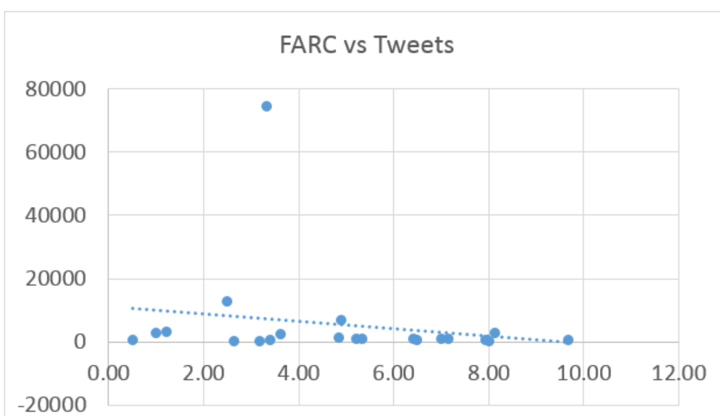

Figure 19. FARC AIVs vs Tweets.

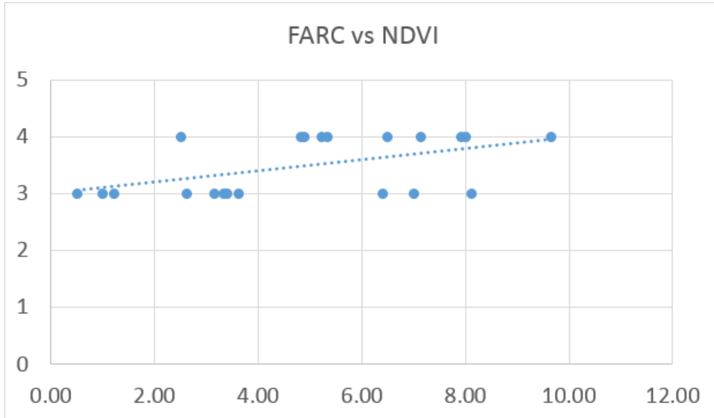

Figure 20. FARC AIVs vs NDVI.

Scatter plot results from ELN's Attack Intensity Values per Department are similar to that of the FARC's, with one main exception. ELN's AIVs vs Tweets have a strong relationship (Figure 25). Departments in which the populace produce large numbers of tweets also experience high Attack Intensity Values. A strong pattern was also found amongst ELN AIVs vs Employment (Figure 21), essentially meaning that Departments are more likely to experience high Attack Intensity Values if a Department has a high percentage of Employment. A weak accord was found between ELN AIVs vs Unemployment (Figure 24). All other scatter plots which use ELN AIVs as the Y variable showed little results. These scatter plots include ELN AIVs vs GDP (Figure 22), Population (Figure 23), and NDVI (Figure 26). Essentially, the value of ELN Attack Intensity Values has little or nothing to do with the GDP, Population, or vegetation within a Department of Colombia.

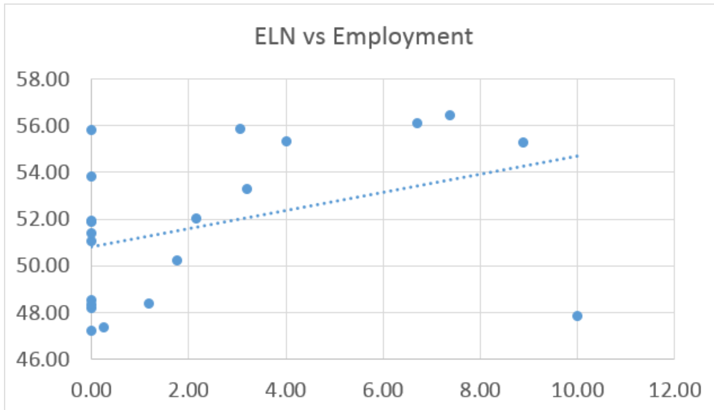

Figure 21. ELN AIVs vs Employment.

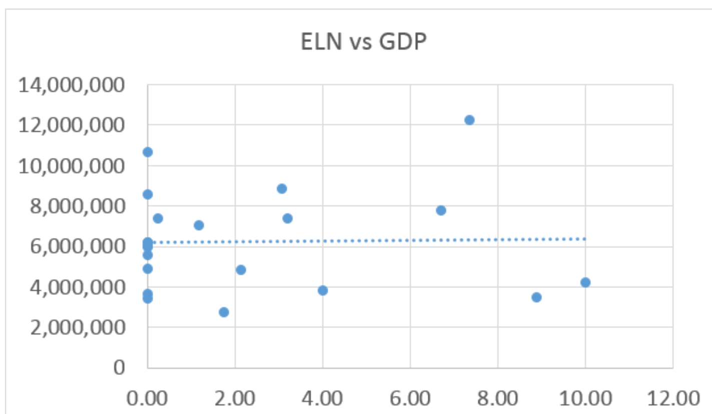

Figure 22. ELN AIVs vs GDP.

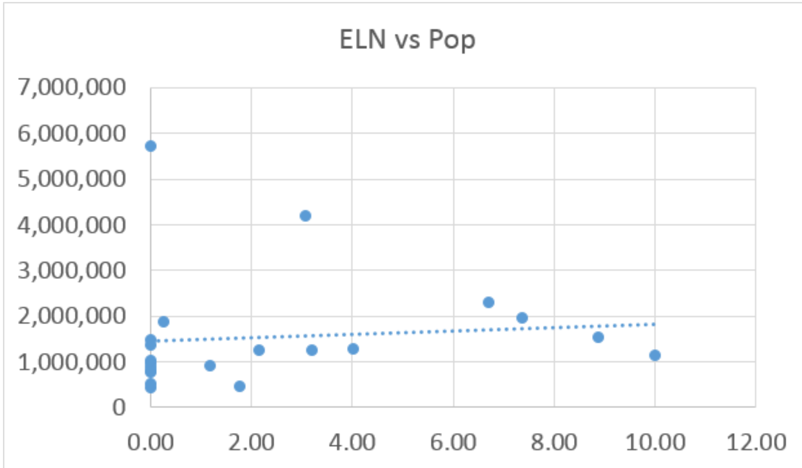

Figure 23. ELN AIVs vs Population.

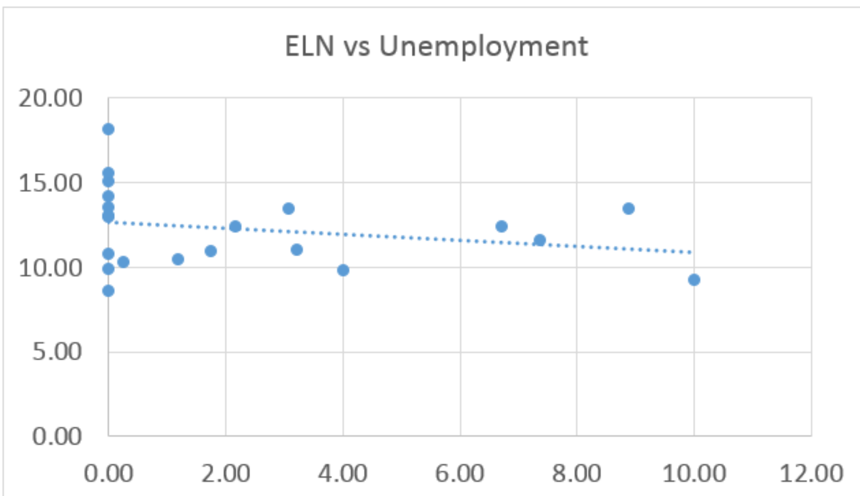

Figure 24. ELN AIVs vs Unemployment.

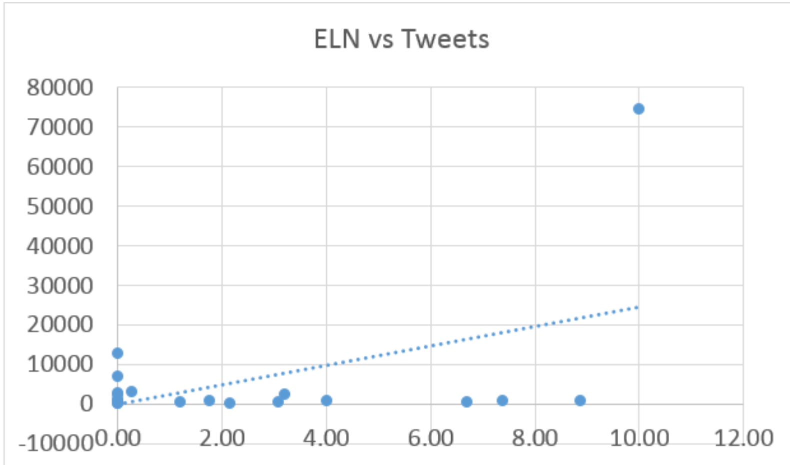

Figure 25. ELN AIVs vs Tweets.

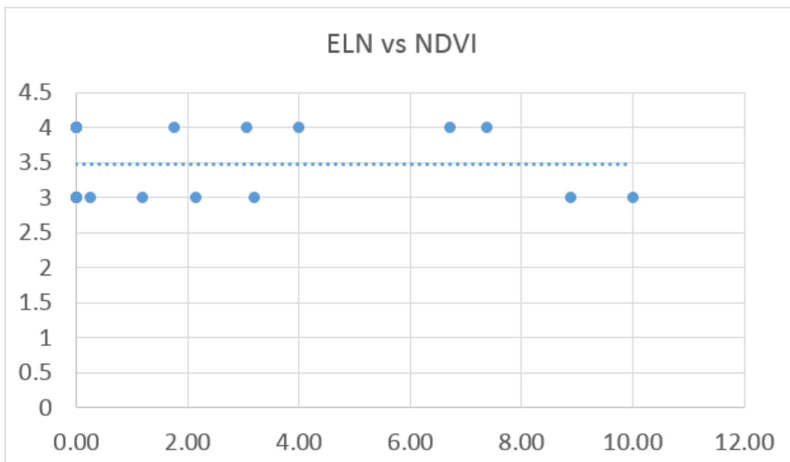

Figure 26. ELN AIVs vs NDVI.

Research Question 6 was also answered using statistical methods, specifically bivariate and multivariate linear regression models in R. In the example below the authors used FARC's AIVs or "FARC" column as the Y variable and "Employment" as the X variable in R's command line:

```
data -> read.table("H:\\Thesis\\Economic Data\\Econ+Attacks.txt",header=TRUE)
lm(data$FARC ~ data$Employment)
summary(lm(data$FARC ~ data$Employment))
```

This was repeated for all X variables and all Y variables, and inserted into the tables below. Table 7 displays several bivariate models with the Y variable being FARC AIVs per Department, and X variables being Employment, Unemployment, GDP, Population, NDVI and Tweets per Department. It can be seen that the X variables Employment, Unemployment, and NDVI all have a P-value of below 0.01, or a 95% confidence interval within the model, and indicate that it contributes to the hypothesis. Other variables such as GDP, Population, and Tweets lack a strong confidence interval, and do not contribute to the hypothesis. In Table 8 we can see that only Employment and Tweets have a 95% confidence interval, making only those two variables contribute to the hypothesis. Other X variables in the ELN AIVs model do not contribute to the hypothesis. Table 9 displays P-values associated with the Y variable being 'Attacks'. No X variables in this model have contributed to the hypothesis. Similarly, Table 10 which displays P-values associated with X variable 'Tweets' do not contribute to the hypothesis either.

Table 11 displays a multivariate linear regression model produced in R. All models (with one exception) included X variables Employment, Unemployment, GDP, Population, NDVI and Tweets. The exception being the model which used Tweets as the X variable, leaving only Employment, Unemployment, GDP, Population, and NDVI for the X variables. In the first model, FARC AIVs were used as the Y variable and produced a confidence interval of 95% with a P-value of 0.0583. Similarly, the ELN multivariate linear regression model also produced a confidence interval of 95% with a P-value of 0.0123. However, the Attacks and Tweets models produced very high P-values of 0.4430 and 0.6143, respectively.

Table 7. Bivariate Linear Regression: Y variable FARC AIVs vs individual X variables.

Y Variable: FARC	**P-Values**
Employment	0.0291
Unemployment	0.0516
GDP	0.9432
Population	0.8166
NDVI	0.0217
Tweets	0.4156

Table 8. Bivariate Linear Regression: Y variable ELN AIVs vs individual X variables.

Y Variable: ELN	**P-Values**
Employment	0.0819
Unemployment	0.2826
GDP	0.913
Population	0.6809
NDVI	0.9752
Tweets	0.0231

Table 9. Bivariate Linear Regression: Y variable number of Attacks vs individual X variables.

Y Variable: Attack	**P-Values**
Employment	0.188
Unemployment	0.8103
GDP	0.6243
Population	0.1909
NDVI	0.9732
Tweets	0.1965

Table 10. Bivariate Linear Regression: Y variable Tweets vs individual X variables.

Y Variable: Tweets	**P-Values**
Employment	0.1782
Unemployment	0.1881
GDP	0.4718
Population	0.8577
NDVI	0.4438

Table 11. Multivariate Linear Regression: Y variables FARC AIVs, ELN AIVs, number of Attacks, and tweets vs all X variables.

Y Variables:	**P-Values**
FARC	0.0583
ELN	0.0123
Attacks	0.4430
Tweets	0.6143

Bivariate and Multivariate linear regression models, as well as scatter plots, were used in answering Research Question 5. It was found that Employment, Unemployment, NDVI, and Tweets produced the lowest P-values amongst the bivariate models. GDP and Population consistently produced high P-values, and did not contribute to the model's hypothesis. Also, of the four multivariate models, the ELN AIV's model produced the lowest P-value. It was also found that of the several scatter plots displaying FARC and ELN AIVs, Employment, Unemployment and Tweets all produced either a positive or negative correlation, while GDP and Population consistently did not produce either a positive or negative correlation.

4.6 Research Question 6

Research question 6 asked whether Twitter users are located within Government held territories or terrorist controlled territories within the Republic of Colombia. Figure 27 compares the total number of tweets (per 100 tweets) to the total number of FARC and ELN terrorist attacks per territory within Colombia. We can see that there were a total number of 117,047 tweets within our dataset that originate from the Republic of Colombia, coupled with 1,374 terrorist attacks that were committed by the FARC or ELN from 2000 to 2014. Of the 117,047 tweets, 89,103 occurred within Government controlled territory while 27,944 occurred in FARC and/or ELN territory. From those 27,944 tweets, 27,603 tweets occurred in FARC territories while only 1,628 tweets occurred in ELN territories. Note that there is overlap between FARC and ELN territories, leaving only 341 tweets in ELN territory where FARC territory does not overlap.

Of the 1,374 terrorist attacks that were committed by the FARC and/or ELN from 2000 to 2014, 300 occurred in Government controlled territory while 1,053 occurred in

FARC and/or ELN territory. Of those 1,053 terrorist attacks, 1,035 attacks occurred in FARC territories while 245 terrorist attacks occurred in ELN territories. There exist only 18 terrorist attacks in ELN territories where FARC territory does not overlap.

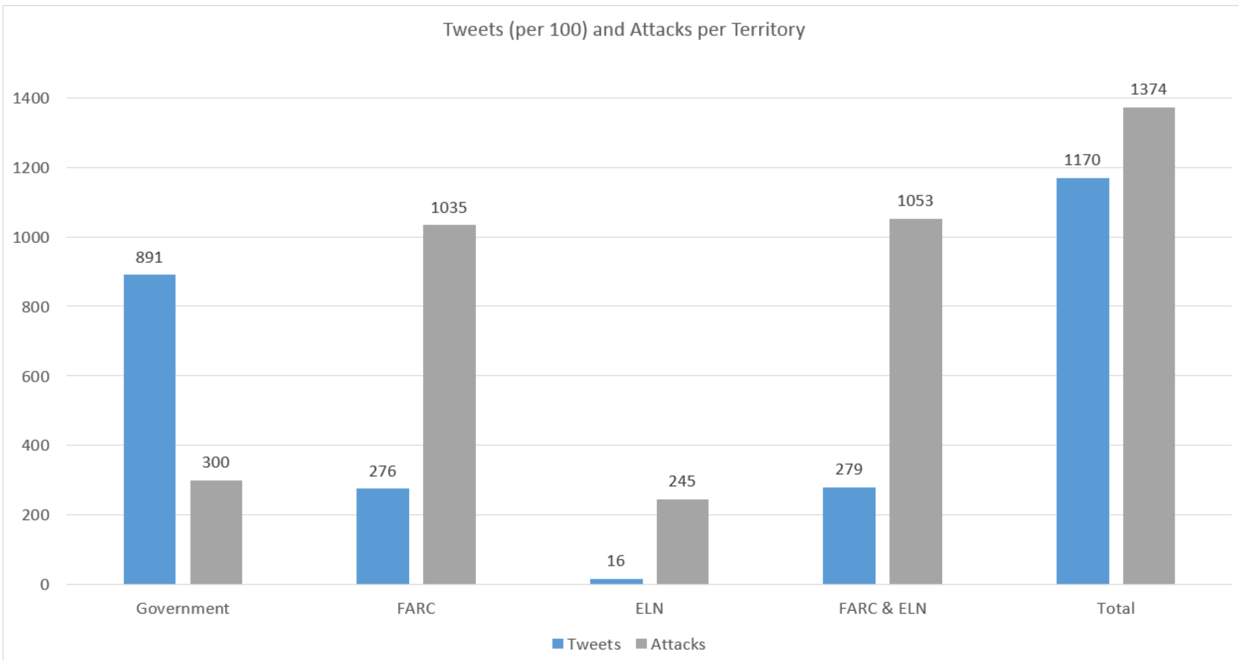

Figure 27. Tweets (per 100 tweets) compared to terror attacks by territory.

Figure 28 displays the percentages of both tweets and terrorist attacks that occurred either in Government as well as FARC & ELN territories. It is shown that 76.13% of all tweets during our study period were located within Government controlled territory while 23.87% of tweets occurred in FARC & ELN territories. Also, 22.60% of terrorist attacks occurred in Government controlled territory while 77.40% of terror attacks occurred in FARC & ELN controlled territories.

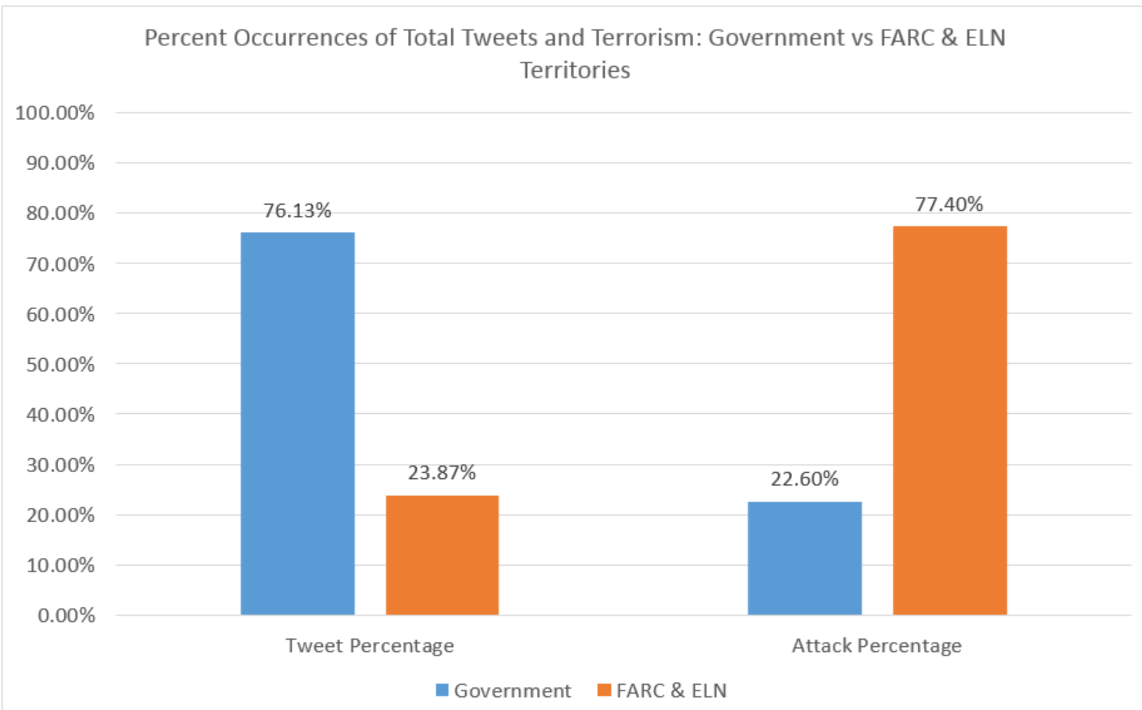

Figure 28. Percentages of tweets and terror attacks by terrorist vs Government territory.

Figure 29 displays a Department-level look into tweets and terrorist attacks within Colombia. Since the number of tweets per Department vastly outnumber the total number of terrorist attacks per Department, the tweets had to be normalized by population, and then divided by 100,000 so that they can be visually compared with number of terrorist attacks per Department. Colombians who tweet within the Department of Cundinamarca have by far the most tweets out of any other Department, with a total of 74,694 tweets which were captured within our dataset and a population of 2,298,813. This number of tweets are so disproportional that Cundinamarca was removed from Figure 29 in order to visually compare the number of tweets to terror attacks by Department. Caldas and Caquetá come in second and third place with 2,611 tweets (969,670 inhabitants), and 950 tweets (423,961 inhabitants), respectively. The Departments of Guanía and Vichada each produced 1 tweet, with Vaupés containing no tweets.

The highest number of attacks took place in the Departments of Antioquia, Cauca, and Norte De Santander with 177, 160, and 124 terrorist attacks, respectively. 12 Departments had below 10 terrorist attacks for the 2000 - 2014 study period. These Departments include Risaralda, Casanare, Caldas, Córdoba, Sucre, Magdalena, Vichada, Atlántico, Quindío, Amazonas, Guanía, and Vaupés.

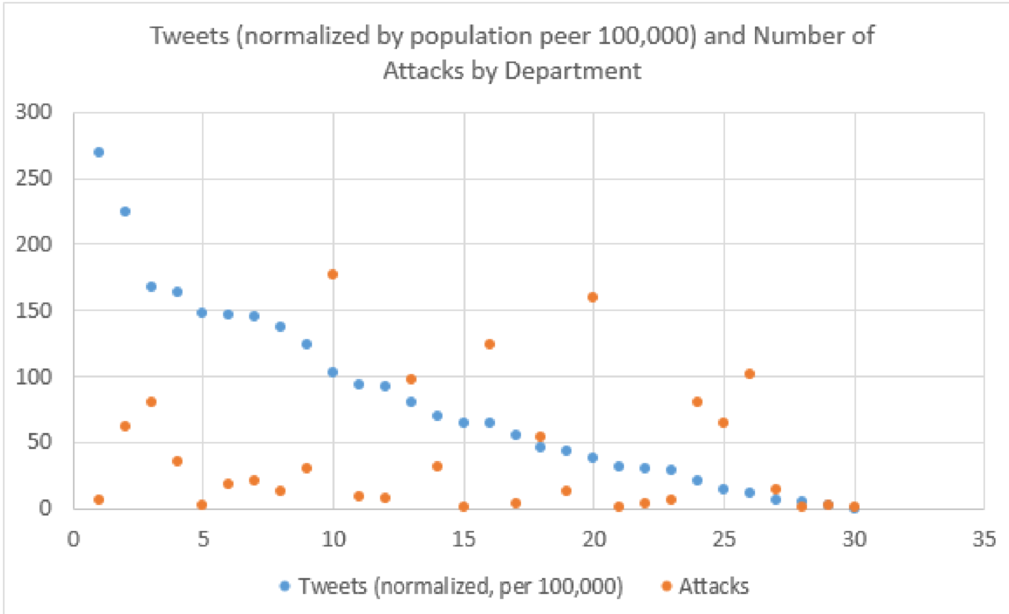

Figure 29. Tweets normalized by population (per 100,000) compared to terror attacks per Department.

Research Question 6 asked: What can we learn about terrorism in Colombia from social media, specifically Twitter? Are Twitter users that tweet about terrorism located within FARC and ELN territories? Where are tweets regarding terrorism predominantly located within Colombia? By observing the results of this research question we can say that a lot was learned about terrorism and social media via Twitter in Colombia. Twitter users within Colombia that discuss the FARC or ELN generally tweet within Government controlled territories, which was unexpected, as our hypothesis for Research Question 6 is indecisive. According to our dataset, 76.13% of tweets regarding the groups are in Government controlled territories, leaving under one fourth of tweets having been taking place in FARC and or ELN controlled territories. Figure 29 assists in answering where (which Departments) are tweets located regarding terrorism. It shows that the majority of tweets take place in the center of the country, which is also Government controlled. It was very interesting to discover that not many tweets (for or against) the rebels occur in terrorist controlled territories.

4.7 Research Question 7

FARC, ELN, and Government sentiment data was overlaid with each group's controlled territory to see if there is a relationship between perception of each organization and its controlled region. The following maps in Figure 30 depict mean valence for tweets related to the two terrorist organizations. A valence of 5 is neutral, meaning green colors indicate above neutral sentiment while red values depict below neutral sentiment.

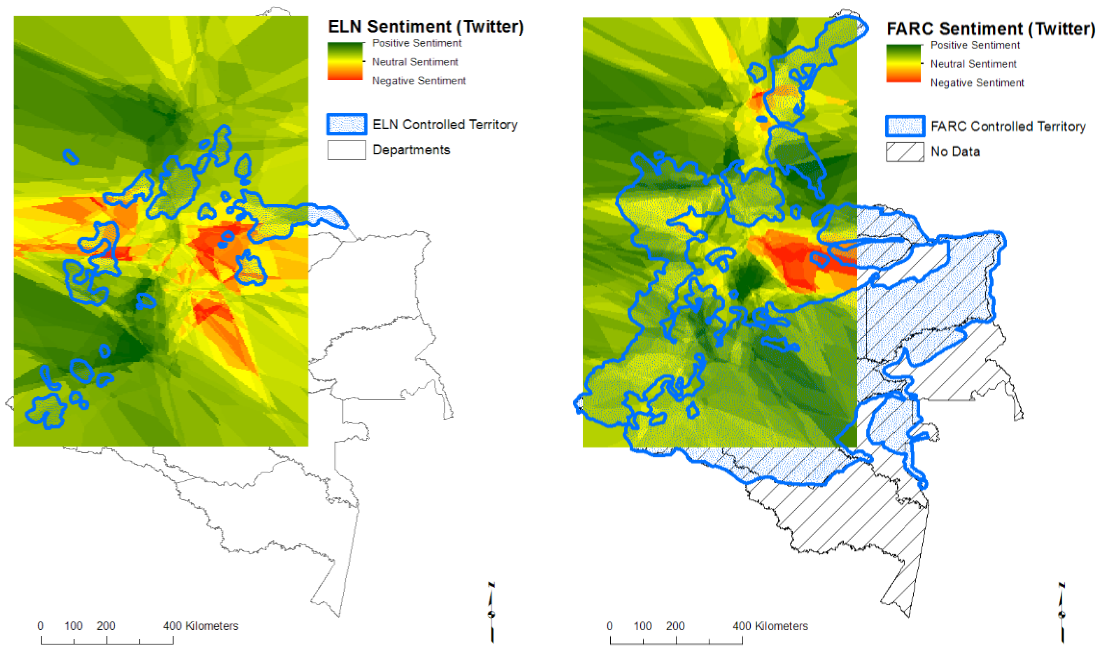

Figure 30. Twitter sentiment for FARC and ELN in Colombia. ELN (left), FARC (right).

Government sentiment was determined with survey data collected at the Department level, so no interpolation was used in Figure 31. Again, green values indicate above average sentiment for the Government in Colombia while red values indicate below average sentiment.

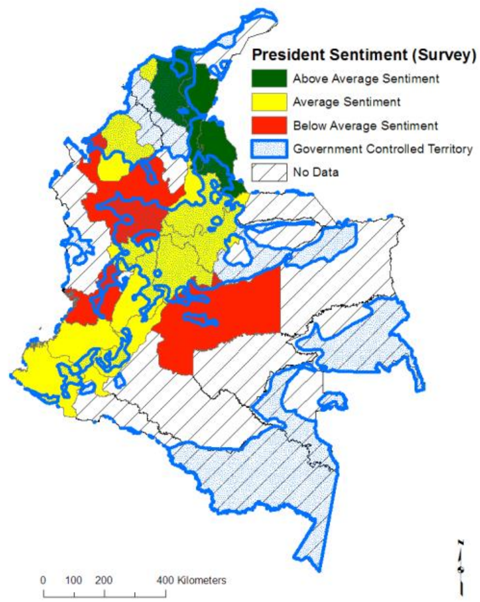

Figure 31. Sentiment of the President of Colombia, 17 displayed in 17 Departments of Colombia.

The averages of the responses were taken for the years 2005, 2010, and 2015. For the government controlled Departments the averages are 1.81, 1.72, and 1.69. The FARC-ELN controlled Departments have averages of 1.93, 1.83, 1.76, which are slightly higher than the government areas. These numbers suggest the average respondent from both groups was either 'Quite Satisfied' or 'Very Satisfied' with their lives. The question is vague on purpose to establish how the responders view their lives. The results would suggest there is something in their personal or private lives they are overall pleased with.

The second question is “In general, would you say you are very satisfied, quite satisfied, not very satisfied or not at all satisfied with the working of the democracy in Colombia?” and the answers are Very and Quite satisfied or Not very and Not at all satisfied. The answers to this question are stored as 1, 2, 3 or 4. The averages of the responses were taken for the years 2005, 2010, and 2015. The Government controlled areas are 2.51, 2.49, and 2.86. The FARC-ELN areas are 2.67, 2.52, and 2.83. The numbers suggest the responders were ‘Not Very Satisfied’ with the democracy. The responses for the Government controlled areas and the FARC-ELN areas were similar. Colombia does hold presidential elections every four years. The elections feature two main political parties which compete for votes. Politicians often have corruption accusations in Colombia which may affect the outlook citizens have of the democratic process.

The third question is “Generally speaking, would you say that Colombia is governed for a few powerful groups in their own interest? Or is it governed for the good of all?” All answers were included in the question. The responses were converted into the percentage of people who believe Colombia is governed for a few powerful groups. The percentages were taken for 2005, 2010, and 2015. For the government controlled areas the responses were 68%, 69%, and 75%. For the FARC-ELN controlled areas the responses were 70%, 71%, 76%. As seen in Figure 32 the Government controlled areas were slightly lower than the ones for the FARC-ELN controlled areas. This shows the vast majority of Colombians believe the government does not have their best interests in mind. Even though Colombia is a democracy with elected officials, the citizens do not believe the government addresses the needs of the many. Another indication of these numbers is that Colombian citizens do not trust the Government. With accusations of political leaders siphoning money and taking bribes it makes sense that respondents would distrust their elected officials. Having a stigma of stealing from the taxpayers may cause the citizens to view them as acting in their own self-interests.

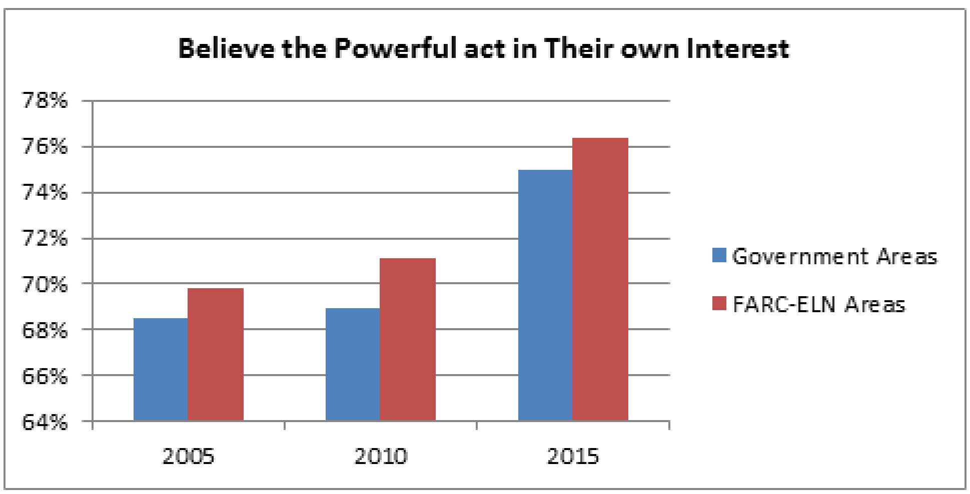

Figure 32. Percentage of Colombians who believe the Colombian Government does not act in the interest of its citizens.

The fourth question is “Do you approve or not the performance of the government led by President (name)?” Answers are included as a yes or no reply. The responses were converted into the percentage of people who replied yes to the survey. This question varies depending on who is the sitting president at the time of the survey. The president of Colombia from 2002-2010 was Álvaro Uribe. His approval rating from 2005 to 2010 ranged from 68% - 77% in the government controlled areas and 70% - 77% in FARC-ELN controlled areas. As seen in Figure 33 the Government controlled areas and the FARC-ELN areas have similar results. This is an interesting considering Uribe's policy for the guerilla factions was to fight them and push them back from the government controlled areas. Even with these policies he was viewed as highly favorable throughout his presidency. The president from 2010-Present is Juan Manuel Santos. His approval ratings in 2015 were 56% in government controlled areas and 53% in FARC-ELN controlled areas. Juan Manuel Santos is not nearly as favorable as his predecessor. This may be in part due to the negotiations he has tried to carry out with the FARC-ELN forces. He has received a Nobel Peace Prize for his attempts to end the military conflict in Colombia.

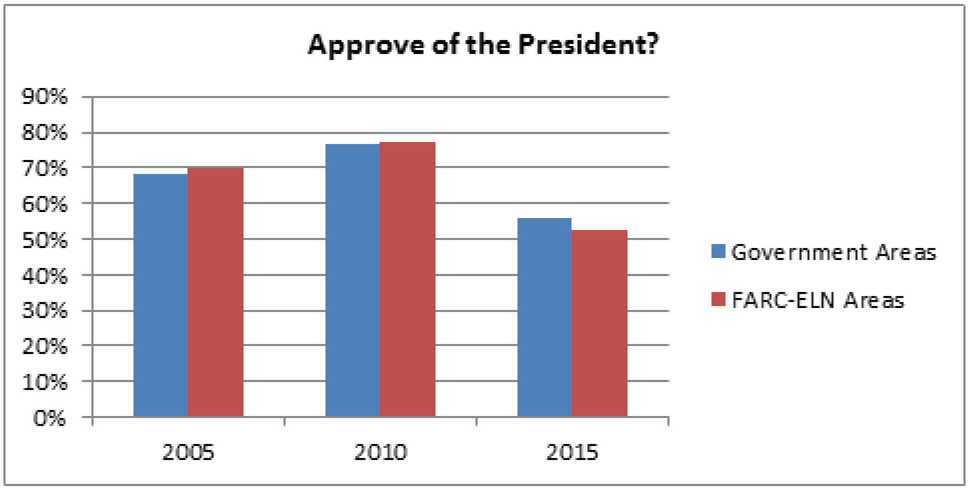

Figure 33. Percentage of people who support the Colombian President.

A word cloud was produced in answering Research Question 7 as a way to understand the overall sentiment of tweets regarding terrorism in Colombia. Figure 34 displays the most common words which were found among all tweets. ‘Colombia’ was by far the most common word found within all 15,000 sample tweets with a total of 1,700 appearances. Second was ‘Columbia’ with a total of 699 appearances. The following 7 most common words found were ‘FARC’ (611 words), ‘mía’ or ‘mine’ in Spanish (374 words) ‘cocaine’ (365 words), ‘Cocaína’ (291 words), ‘paz’ or ‘peace’ in Spanish (278 words), ‘aire’ or ‘air’ in Spanish (264 words), ‘defarc’ or ‘of the FARC’ in Spanish (254 words), and finally ‘Santos’ who is the current President of Colombia (231 words). Readers may notice several words which contain strange characters or unusual accents. This is due to R being unable to handle Latin accents or characters. Some words are still understandable, for example the words ‘cocaína’ and ‘Bogotá’ can be seen in orange. We can also see that directly below ‘colombia’ in black there is ‘Medellín’ in green, referring to the infamous Colombian cartel.

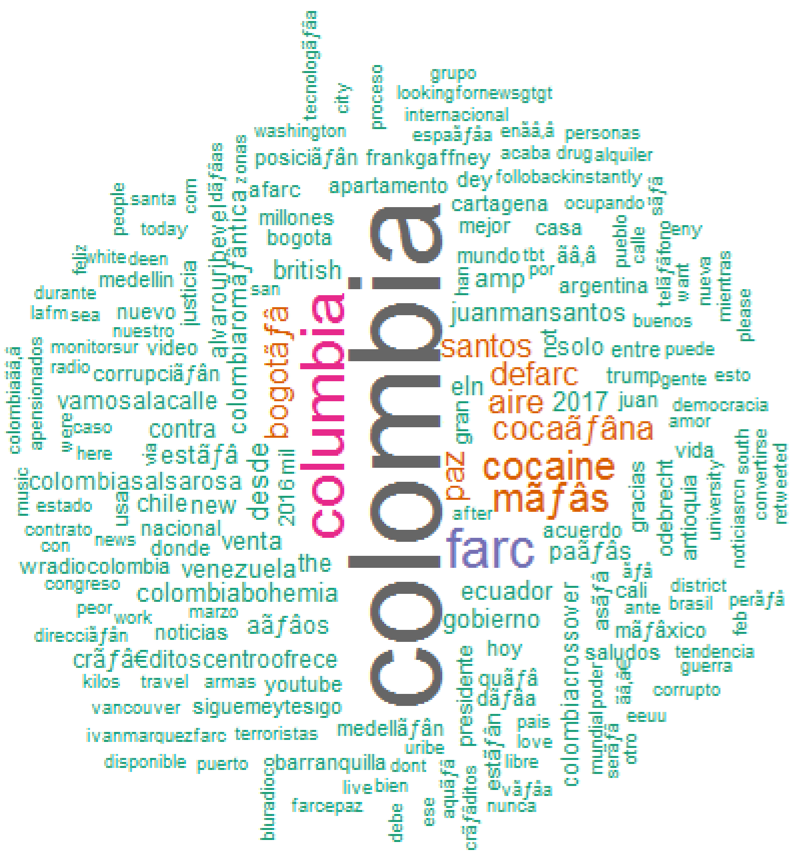

Figure 34. Word cloud displaying common words used in tweets regarding terrorism in Colombia.

A social media network visualization was also created in Gephi in order to get a more in-depth view of FARC and ELN sentiment on Twitter, as well as who is talking about the conflict in Colombia, shown in Figure 35. This visualization displays an 'Out-Degree' relationship. Tweet author labels which are large had the largest retweet networks. Some of the more well-known tweet authors included Andres Pastrana, Rafael Poleo, Frank Gaffney, Alexis Isabel, and Alvaro Uribe. Andres Pastrana was the President of the Republic of Colombia from 1998 - 2002, and is still a strong voice on Twitter regarding anything Colombian. Being the author of over 3,000 tweets and having over 174 thousand followers it is no surprise he has the strongest retweet network seen in the visualization. Frank Gaffney has the second or maybe third strongest retweet network in the visualization. Frank Gaffney is the Founder and President of the Center for Security and Policy, and host of Secure Freedom Radio in Washington DC. Frank Gaffney has produced a total of 32.7 thousand tweets and has over 30.7 thousand followers on Twitter. Rafael Poleo is a Venezuelan journalist who has created almost 29 thousand tweets and has over 594 thousand followers on Twitter. It is also important to mention Álvaro Uribe Vel who was the President of Colombia from 2002 - 2010. With over 55,000 tweets and 4.69 million followers, it is surprising his retweet network is not larger than it is in our Gephi visualization. President Uribe has been a strong voice of counter-terrorism throughout his years as a politician in Colombia, and it is no surprise he has a top spot amongst the major retweet networks we found using this visualization.

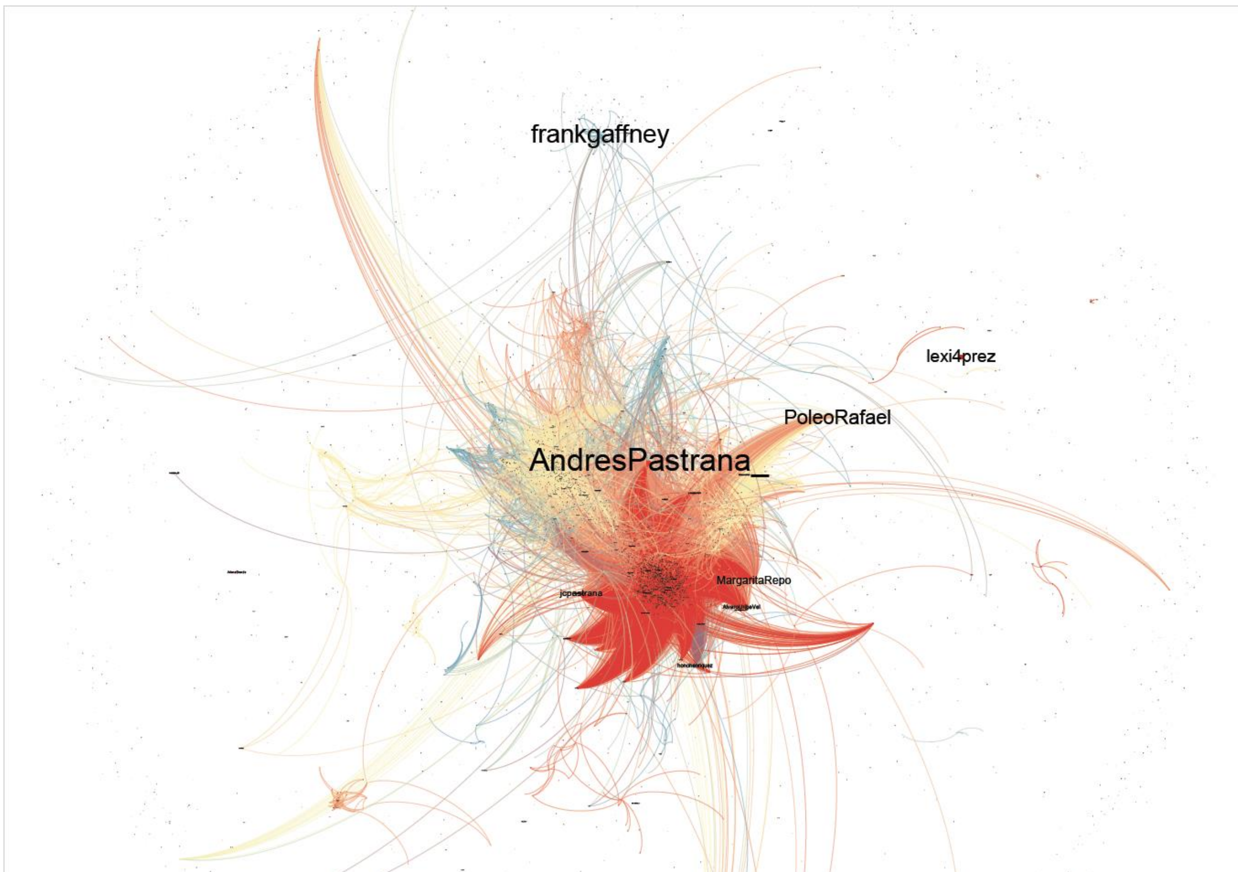

Figure 35. Gephi Visualization of terrorist-related retweet networks.

4.8 Research Question 8

Research Question 8 asks how well Borum's 2003 linear radicalization model applies to terrorism in Colombia. Table 12 is comprised of each Department and how far that Department's stage one value deviated from the group mean of all Departments. Lower values indicate more deprivation. For example, the Department of Cauca was approximately one standard deviation below the mean of all Departments for the factors of GPD per person, access to utilities, and employment rate.

Table 12. Stage one alignment (Borum, 2003) for 17 Departments of Colombia.

Department	STAGE_ONE_ALIGNMENT	STAGE_ONE_RANK
Cauca	-1.0032	1
Nariño	-0.8069	2
Córdoba	-0.7836	3
Boyacá	-0.2627	4
Cundinamarca	-0.2001	5
Cesar	-0.1300	6

Huila	-0.0647	7
Antioquia	0.0721	8
Tolima	0.0864	9
Magdalena	0.1451	10
Norte de Santander	0.1987	11
Santander	0.2359	12
Meta	0.2431	13
Caldas	0.3144	14
Atlántico	0.7942	15
Risaralda	0.7953	16
Valle del Cauca	0.8072	17

For stage two, Departments were weighted depending on their deviation from the group mean for the survey questions selected to assess the part of Borum's model dubbed, “It is not fair” (Borum, 2003). Lower values indicate less satisfaction, and is displayed in Table 13.

Table 13. Stage two alignment (Borom, 2003) for 17 Departments of Colombia.

Department	STAGE TWO ALIGNMENT	STAGE TWO RANK
Valle del Cauca	-1.0867	1
Cauca	-1.0304	2
Huila	-0.7637	3
Meta	-0.5788	4
Nariño	-0.4868	5
Antioquia	-0.3956	6
Cundinamarca	-0.3399	7
Tolima	-0.3231	8
Risaralda	-0.2055	9

Boyacá	-0.0876	10
Santander	0.1695	11
Córdoba	0.1933	12
Caldas	0.3021	13
Norte de Santander	0.4372	14
Atlántico	0.5937	15
Cesar	1.6990	16
Magdalena	1.9035	17

Stages one and two were averaged to rank Departments depending on the combination of their stage one and two values in Table 14. This represents Departments that are both deprived and unsatisfied.

Table 14. Stage one and two alignment for 17 Departments of Colombia.

Department	STAGE ONE AND TWO VALUE	STAGE ONE AND TWO RANK
Cauca	-1.0168	1
Nariño	-0.6469	2
Huila	-0.4142	3
Córdoba	-0.2951	4
Cundinamarca	-0.2700	5
Boyacá	-0.1752	6
Meta	-0.1678	7
Antioquia	-0.1617	8
Valle del Cauca	-0.1397	9
Tolima	-0.1183	10
Santander	0.2027	11
Risaralda	0.2949	12
Caldas	0.3082	13
Norte de Santander	0.3179	14
Atlántico	0.6939	15

Cesar	0.7844	16
Magdalena	1.0243	17

Figure 36 is a visual depiction of stage one and stage two alignment for each Department. The large unhappy faces represent Department's with a satisfaction value that is lower than average for Colombia. The underlying color represents how deprived a Department is compared to other Departments in Colombia.

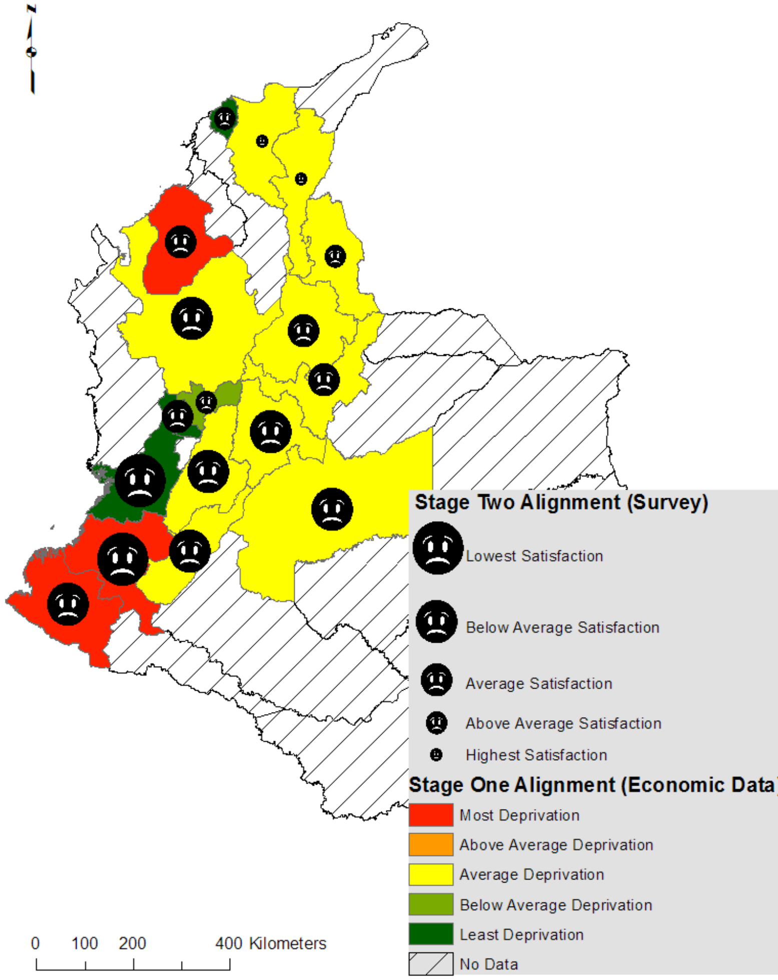

Figure 36. Depiction of Tables 5 and 6. Satisfaction and deprivation in 17 Departments of Colombia.

.

Figure 37 is a combination of the two factors in the previous map into a single color scheme. Green values have above average satisfaction and the lowest deprivation while red values have below average sentiment and the highest deprivation.

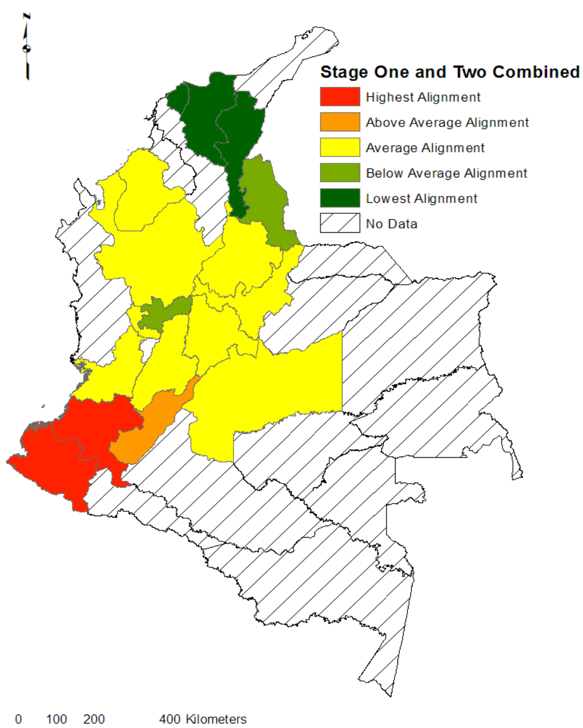

Figure 37. Stage one and two alignment combined (Borum, 2003) for 17 Departments of Colombia.

The assessment of stage three alignment was determined through survey and Twitter data. Alignment with regards to the ELN (Table 15) and FARC (Table 16) were established through sentiment of geotagged Twitter sentiment with each Department using a Spanish lexicon. Alignment of stage three for the Government (Table 17) was determined through survey data. Lower values indicate a more negative outlook on either the ELN, FARC, or Government.

Table 15. Stage three alignment for the ELN terror organization (Twitter).

Department	STAGE THREE VALUE, ELN	STAGE THREE RANK, ELN
Meta	-1.6017	1
Caldas	-1.4047	2
Atlántico	-1.3013	3
Magdalena	-1.2038	4
Huila	-0.7115	5
Norte de Santander	-0.4915	6

Córdoba	0.1491	7
Valle del Cauca	0.1585	8
Boyacá	0.2840	9
Antioquia	0.2902	10
Cundinamarca	0.3184	11
Cesar	0.7031	12
Risaralda	0.7441	13
Nariño	0.8775	14
Santander	1.3089	15
Tolima	1.4487	16
Cauca	1.9752	17

Table 16. Stage three alignment for FARC terror organization (Twitter).

Department	STAGE THREE VALUE, FARC	STAGE THREE RANK, FARC
Huila	-1.4946	1
Boyacá	-1.4533	2

Caldas	-0.7936	3
Cauca	-0.4981	4
Santander	-0.4887	5
Cesar	-0.3487	6
Atlántico	-0.2505	7
Tolima	-0.2220	8
Risaralda	-0.1268	9
Antioquia	-0.0989	10
Cundinamarca	-0.0970	11
Norte de Santander	0.3256	12
Valle del Cauca	0.3368	13
Magdalena	0.3515	14
Córdoba	0.5084	15
Nariño	1.8012	16
Meta	1.9446	17

Table 17. Stage three alignment for the Government of Colombia (Survey).

Department	STAGE_THREE_PRESIDENT_ALIGNMENT	STAGE_THREE_PRESIDENT_RANK
Magdalena	-0.1506	1
Cesar	-0.1227	2
Norte de Santander	-0.1018	3
Tolima	-0.0601	4
Atlántico	-0.049	5
Córdoba	-0.0253	6
Cauca	-0.0253	6
Santander	-0.0192	8
Risaralda	-0.0078	9
Boyacá	0.0070	10
Nariño	0.0200	11
Caldas	0.0244	12
Huila	0.0700	13
Cundinamarca	0.0855	14

Valle del Cauca	0.1021	15
Antioquia	0.1216	16
Meta	0.1319	17

Next, all three stages were combined and the Departments were ranked according to Borum's three stages. This represents a combination of social and economic deprivation, dissatisfaction, and negative sentiment for an entity. Lower values indicate better alignment. All stages for the ELN are displayed in Table 18, FARC in Table 19, and Government in Table 20. Figure 38 displays visual representations of these tables.

Table 18. All stages of alignment for ELN.

Department	All STAGES VALUE, ELN	ALL STAGES ELN RANK
Meta	-0.8848	1
Huila	-0.5629	2

Caldas	-0.5482	3
Atlántico	-0.3036	4
Magdalena	-0.0897	5
Norte de Santander	-0.0868	6
Córdoba	-0.0729	7
Valle del Cauca	0.0093	8
Cundinamarca	0.0241	9
Boyacá	0.0544	10
Antioquia	0.0642	11
Nariño	0.1153	12
Cauca	0.4792	13
Risaralda	0.5195	14
Tolima	0.6651	15
Cesar	0.7438	16
Santander	0.7558	17

Table 19. All stages of alignment for the FARC.

Department	All STAGES VALUE, FARC	All STAGES RANK, FARC
Huila	-0.9544	1
Boyacá	-0.8142	2
Cauca	-0.7574	3
Caldas	-0.2426	4
Cundinamarca	-0.1835	5
Tolima	-0.1701	6
Santander	-0.1430	7
Antioquia	-0.1303	8
Risaralda	0.0840	9
Valle del Cauca	0.0985	10
Córdoba	0.1066	11
Cesar	0.2178	12
Atlántico	0.2217	13

Norte de Santander	0.3218	14
Nariño	0.5771	15
Magdalena	0.6879	16
Meta	0.8884	17

Table 20. All stages of alignment for the President of Colombia.

Department	ALL STAGES VALUE, PRESIDENT	ALL STAGES RANK, PRESIDENT
Cauca	-0.5210	1
Nariño	-0.3134	2
Huila	-0.1720	3
Córdoba	-0.1602	4
Cundinamarca	-0.0922	5
Tolima	-0.0892	6
Boyacá	-0.0840	7
Antioquia	-0.0200	8
Valle del Cauca	-0.0187	9

Meta	-0.0179	10
Santander	0.0917	11
Norte de Santander	0.1080	12
Risaralda	0.1435	13
Caldas	0.1663	14
Atlántico	0.3221	15
Cesar	0.3308	16
Magdalena	0.4368	17

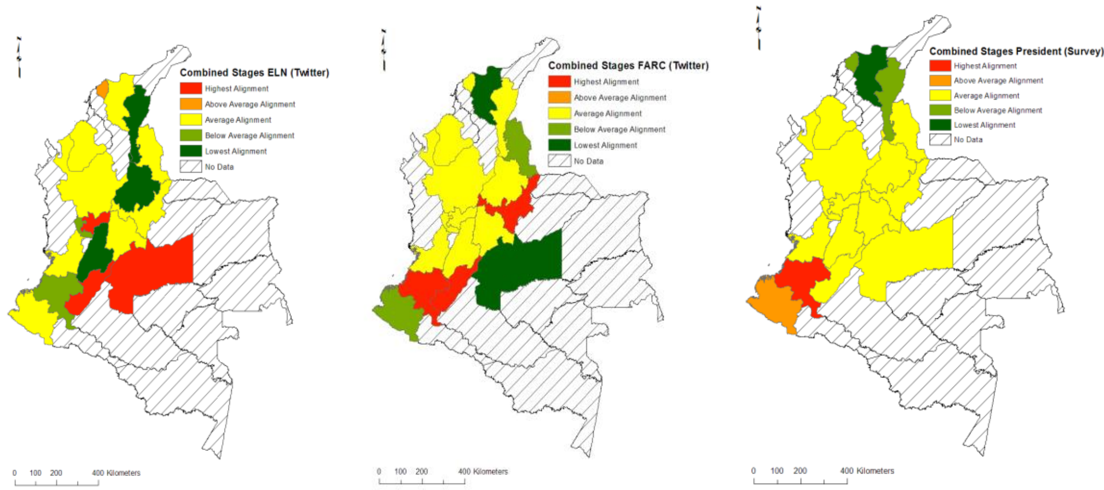

Figure 38. Alignment for all stages of 17 Departments of Colombia. ELN (left), FARC (center), Government (right).

In answering Research Question 8, it was found that Borum’s 2003 linear radicalization model applies quite well to the Departments of Colombia. Compiling and applying several datasets provided for excellent visual representations of the potential for radicalization of terrorism. Such datasets include Colombia’s DANE (Census) data, Bank of Colombia data, and social media (Twitter) data. The Departments of Cauca and Nariño are highlighted within Research Question 8 due to their strong alignment with stages one, two and three of Borum’s radicalization model. Coincidentally, these two Departments are also highlighted in Research Questions 2 and 3, having also exhibited correlations between spatial clusters of terrorism as well as dense vegetation, which contribute to the presence of terrorism within the Republic of Colombia.

5. LIMITATIONS

The University of Maryland START's Global Terrorism Database contained some limitations worth mentioning. During the 2000-2014 period, 231 out of 1,739 terror events were committed by unknown perpetrators within Colombia, and 134 terror events were identified as having been committed by groups other than the FARC or ELN. The analysis for this study simply compares known terror events committed by the FARC and ELN. If terror events committed by all known terror groups were known, this study may have yielded different results. Likewise, if the 231 terror events perpetrated by an unknown group were known, the results may have also been different.

Results for the ELN cluster and outlier analysis were limited by the number of attack intensity values perpetrated by the ELN during the study period. Only four Departments of Colombia had attack intensity values for 2012, five for 2013, and 10 for 2014. This is in comparison to the FARC's 15 for 2012, 16 for 2013, and 18 for 2014. If more attack intensity values were available to compute a cluster and outlier analysis for the ELN, actual results would have been computed. Additionally, both the Global Moran's I and the cluster and outlier analysis methods used Euclidean distances as a parameter to measure distances between the departments of Colombia within the computation and not a road network. By using a road network, thereby increasing the distances between the attack intensity values, the values derived for the Global Moran's I would most likely be increased, and perhaps fewer or no clusters of high attack intensity values would have been found.

Results of the NDVI classifications could have also produced significantly different results depending on the number of classes used, and the quantitative method used to determine the class for each Department of Colombia. This study is also limited by the relatively small number of terrorist attacks perpetrated by the ELN during the 2000 – 2014 study period. As mentioned in the materials section, the ELN committed only 228 terrorist attacks compared to the FARC's 1,145. Additionally, the cluster and outlier analysis methods used Euclidean distances as a parameter to measure distances between the Departments of Colombia within the computation and not a road network.

Maps of FARC and ELN territories which were used in the digitization process may not have been completely accurate, however it was the best form of data at the author's disposal. Throughout hours of searching for maps displaying FARC and ELN territories, few were found. Maps which were found did not have consistent boundaries of FARC and ELN borders, making the process more difficult. The final map which was found and used was a raster image with spatial resolution which was small enough to digitize. This map also was quite consistent with previous maps found.

It is also important to note that within the Colombian GDP, Population, Employment and Unemployment datasets that there were several Departments missing. Specifically, a total of 10 Departments: Amazonas, Arauca, Casanare, Chocó, Guainia, Guaviare, La Guajira, Putumayo, Vaupés, and Vichada. Results could have been quite different, depending if these Departments were available. Another important issue to note is that many of these 10 Departments which were not available also had few numbers of terrorist attacks which occurred during our 2000 - 2014 dataset. It is the author's hope that due to a low number of terrorist attacks occurring in these missing Departments, the results would not have changed very much.

The survey data is available for the country of Colombia and there are regions which are either underrepresented or are left out entirely. The dataset breaks the country into the 32 Departments and the capital Bogota. The Departments without data are Arauca, Caqueta, Casanare, Choco, Guainia, Guaviare, Putumayo, San Andres y Providencia, Vaupes, and Vichada. This accounts for 10 of the 33 areas within the county. Of the Departments with no information San Andres y Providencia is an island off the coast of Colombia and six of the nine mainland Departments are FARC-ELN controlled territories. Even though these places do not have data there is enough information available to complete the analysis.

Borum's model was intended to be interpreted at the individual level, but many of the factors Borum used were available at the Department level, lending to its applicability at a different scale. For stage three of the model, Blame and Attribution, positive/negative sentiment was used in place of measuring explicit blame. These decisions are justified in that Borum never tested his own model and only proposed it to the US government as a way to simplify the radicalization process. With more refinement and factors, a better radicalization model might be created to be able to assess the progress of radicalization at the population level.

Different results for Research Question 8 could have been yielded if all tweets could have been used. Due to R being able to read only up to roughly 15,000 tweets, either different popular words could have been found, or less popular words that were found could have been more popular. Though this does not severely limit our results, the authors nonetheless feel that this aspect of the study is still worth mentioning.

6. CONCLUSION

Though the conflict in Colombia has recently come to an end, there is still a wealth of undiscovered information regarding the conflict and the both local and global impacts of the leading terrorist organizations within the Republic of Colombia. According to previous research findings and the results of this analysis, the situation was a low-intensity conflict. Low-intensity conflicts are preferred to high-intensity conflicts (e.g., conflicts in the Middle East) due to fewer casualties being inflicted on the local populace. In answering the first research question, this study suggests that attack intensity values varied dramatically throughout the 2000-2014 study period, especially for the ELN. The average attack intensity value for both groups dropped during Uribe's presidency from 2002-2010; however, the range and standard deviation for the FARC increased due to a spike in attack intensity values during the third quarter of 2006. The results for the second research question suggest that attack intensities remained randomly distributed throughout Colombia. It was also discovered that local clusters could not be found for the ELN due to a lower number of attacks and corresponding attack intensities. Overall, these results indicate that during the time period of former President Uribe's counter-insurgency policies, average attack intensities dropped, but attack intensity values remained randomly distributed throughout Colombia.

Results in answering the research question indicated that spatial clusters of terrorism events are located in the Departments of Colombia which were classified as having high NDVI values. Results provided in this paper should indicate to a general audience that spatial clusters of terrorist attacks in Colombia generally occur in areas with healthy, dense vegetation. This statement was proven using MODIS NDVI data compared with a cluster and outlier analysis tool. It was also proven in a linear regression model using R that classified NDVI values correlate with the number of FARC terrorist attacks up to a 95% confidence interval.

It was discovered that the majority of tweets regarding terrorism in Colombia are tweeted within areas of Government control, specifically 76.13%. Inversely, the majority of terrorist attacks that occur within Colombia take place in terrorist controlled regions of the nation. Though there are fewer, the terrorist attacks which take place in Government controlled territories also harm the civilian population the most. This study also produced statistical evidence that FARC and ELN Attack Intensity Values coincide best with Employment, Unemployment, NDVI and number of Tweets per Department. Unfortunately, no strong relationship was found between FARC and ELN AIVs vs. GDP and Population statistics.

Stage one and two of Borum’s model describe areas that have a large amount of social and economic deprivation along with a large amount of dissatisfaction of one’s life and the direction of the country in general. The top Departments in Table 12 (above) can be thought to be fertile grounds for an ideological movement towards terrorist organizations. The third stage which depicts blame and attribution is the final stage of

Borum's model. At this point, people pick an organization or entity to blame for the deprivation and dissatisfaction that is felt. In Colombia's case, there are three major powers. The ELN, FARC, and the government. Although the FARC and ELN are rival organizations, they share a common enemy, the Colombian government. Therefore, the most dangerous stage three would be a Department that has high values for the first two stages and a strong alignment with an entity for stage three. Table 21 depicts the top ten Departments with respect to stages one and two along with the targeted stage three entity.

Table 21. Top 10 Departments according two stage one and two alignment, and negative sentiment (Borum, 2003).

Department	ALL STAGES ALIGNMENT	ALL STAGES RANK	ENTITY
Huila	-0.9544	1	FARC
Meta	-0.8848	2	ELN
Boyacá	-0.8142	3	FARC
Cauca	-0.7574	4	FARC
Huila	-0.5629	5	ELN

Caldas	-0.5482	6	ELN
Cauca	-0.5210	7	GOVERNMENT
Nariño	-0.3134	8	GOVERNMENT
Atlántico	-0.3036	9	ELN
Caldas	-0.2426	10	FARC

The two most dangerous Departments with respect to susceptibility to terrorist ideologies would be the Department of Nariño and Cauca, shown in Figure 39. They are the top two Departments in terms of stages one and two and they disapprove of the government more than any other Department (STD -0.3) and (STD - 0.5). Nariño also has above average sentiment for both major terror organizations, ELN (STD +0.88) and FARC (STD +1.8) while Cauca has positive sentiment for ELN (STD + 1.98) and negative sentiment for FARC (-0.50).

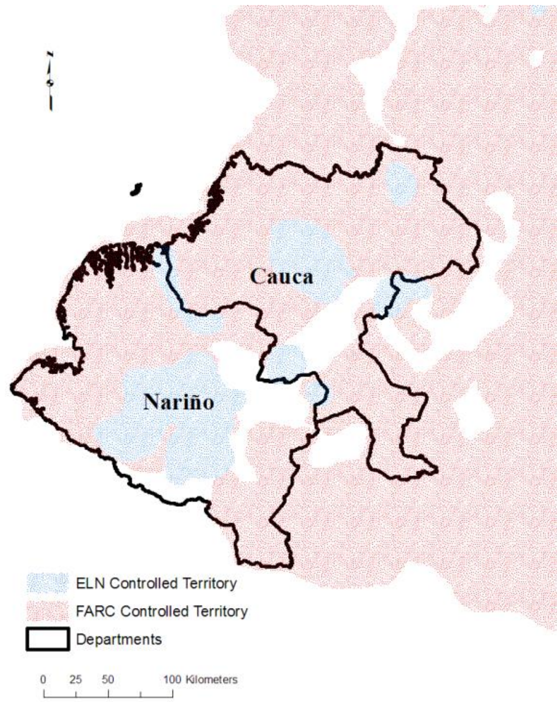

Figure 39. The two Departments found to most likely succumb to radicalization.

It was also found that ‘Colombia’, ‘FARC’, ‘cocaine’, and current Colombian President ‘Santos’ were found within the word cloud which was created from tweets regarding terrorism in Colombia. As far as the Gephi visualization which was produced displaying social media retweet networks on Twitter; Andres Pastrana, Rafael Poleo, Frank Gaffney, Alexis Isabel, and Alvaro Uribe were the largest retweet networks which were found. These authors have very prominent roles within the Colombian, as well as freedom and democracy communities on Twitter.

The results from the survey data reveal there is not much differentiation between Government controlled areas and the FARC-ELN controlled areas. According to the polling there may be a few percentage points in one direction or the other but were overall similar. The answers were also consistent throughout the different Departments in Colombia. While people seem to be satisfied with the outlook of their own lives, they do not have the same confidence with the Colombian government. More than two-thirds of people believe the government acts in their own interests and with the election of Juan Manuel Santos these numbers have grown. To start his presidency Juan Manuel Santos was not viewed favorably and his numbers have declined dramatically since. Each question that was reviewed for analysis also has a negative trend since the election of Santos. This includes the first question which does not ask about their views of the government. His elections appears to have influenced political opinions as well as impacted their outlook on life. As of 2017 Santos' approval ratings have dropped below 30%. The peace talks between the president and the FARC-ELN groups seem to be driving public trust against the government. Instead of viewing the talks as an end to violence it instead appears to be taken as negotiating with the enemy. The resentment towards the government comes from a place of distrust and disapproval.

7. APPENDIX

7.1 Word Cloud Script

```
library(tm)
library(SnowballC)
library(wordcloud)
library(RColorBrewer)

text=readLines(file.choose())
docs=Corpus(VectorSource(text))

toSpace=content_transformer(function (x , pattern ) gsub(pattern, " ", x))
docs=tm_map(docs, toSpace, "/")
docs=tm_map(docs, toSpace, "@")
docs=tm_map(docs, toSpace, ")

        # Convert the text to lower case
docs <- tm_map(docs, content_transformer(tolower))
        # Remove numbers
docs <- tm_map(docs, removeNumbers)
        # Remove english common stopwords
docs <- tm_map(docs, removeWords, stopwords(""))
        # Remove your own stop word and specify your stopwords as a character vector
docs <- tm_map(docs, removePunctuation)
        # Eliminate extra white spaces
docs <- tm_map(docs, stripWhitespace)
        # Text stemming
        # docs <- tm_map(docs, stemDocument)

dtm <- TermDocumentMatrix(docs)
m <- as.matrix(dtm)
v <- sort(rowSums(m),decreasing=TRUE)
d <- data.frame(word = names(v),freq=v)
head(d, 10)
set.seed(1234)
wordcloud(words = d$word, freq = d$freq, min.freq = 1,
max.words=200, random.order=FALSE, rot.per=0.35,
colors=brewer.pal(8, "Dark2"))
```

7.2 Gephi Visualization Script

```
import math
from numpy import *
import fileinput
import glob
import datetime
print datetime.datetime.now() #print current date and time

def getColumns(inFile, delim='\t', header=True): #get columns from 3-column text document
	ID={} #create Tweet ID library
	ID2={} #create Tweet Author library
	cols={} #create retweet library
	indexToName={} #create
	for lineNum, line in enumerate(inFile):
	if lineNum==0: #if this is first line of text file:
	headings=line.split(delim) #split lines by delimeter (Tab)
	i=0
	for heading in headings:
	heading=heading.strip()#strip columns
	if header:
		cols[heading]=[] #create a list of columns by heading
		indexToName[i]=heading #make the heading be an element in the indexToName list
	else:
		cols[i]=[heading] #define the heading as an element in the cols list
		indexToName[i]=i #define i as an element in the indexToName list
	i+=1 #increment i by 1
	else:
	cells=line.split(delim) #split the lines by delimeter (Tab)
	cell3=cells[11].strip() #make variable 'cell3' equal to the third column of .txt file
	if cell3!='': #if a row is empty:
	if bool(ID)==False: #if ID is empty:
		ID[cell3]=[cells[0]] #in ID library make cell3 the first element of cells list
		ID2[cell3]=[cells[8]] #in ID2 library make cell3 the second element of cells list
	else:
		if cell3 in ID.keys(): #if cell3 is in the keys list of ID library:
		ID[cell3].append(cells[0]) #append the first element of cells list to cell3 in the ID library
		ID2[cell3].append(cells[8]) #append the second element of cells list to cell3 in the ID2
library
		else:
		ID[cell3]=[cells[0]] #make the first element in cells list to be cell3 in ID library
		ID2[cell3]=[cells[8]] #make the second element in cells list to be cell3 in ID2 library

	return ID, ID2 #return ID and ID2 libraries

	#-#######################-DATASET-#######################-#
lists=file('H:\GGS 685 Capstone Course in Geoinformatics\Project\Data\colombia_class_feb2017.tsv','r')
#make lists variable to read the 3columns.txt file
	#-#######################-DATASET-#######################-#
```

```
ID,ID2=getColumns(lists) #store results of getColumns function into ID and ID2 libraries

id_name=[] #makes id_name an empty list
	#-########################-WRITE-########################-#
w=open('H:\GGS 685 Capstone Course in Geoinformatics\Project\gexf\Colombia.txt','w') #open file to
write
	#-########################-WRITE-########################-#
w.write('<?xml version="1.0" encoding="UTF-8"?>'+'\r'+'<gexf
xmlns:viz="http:///www.gexf.net/1.1draft/viz" version="1.1"
xmlns="http://www.gexf.net/1.1draft">'+'\r'+'<meta
lastmodifieddate='+'"'+str(datetime.datetime.now())+'">'+'\r'+'<creator>Gephi
0.7</creator>'+'\r'+'</meta>'+'\r'+'<graph mode="dynamic" defaultedgetype="directed" idtype="string"
timeformat="dateTime" type="static">'+'\r'+'<nodes count ="">'+'\r') #write to file to declare it a proper
XML file
node = 1
for key in ID2.keys(): #for each key in ID2 library:
	index=0
	retweet=[] #create empty list of retweets
	#-########################-DATASET-########################-#
	f=open('H:\GGS 685 Capstone Course in
Geoinformatics\Project\Data\colombia_class_feb2017.tsv','r') #open file to read
	#-########################-DATASET-########################-#

	originalName='' #create empty string to store tweet author name
	for line in f: #for line in file:
	index+=1
	if index!=1: #if index is not 1:
	cells=line.split('\t') #split cells by 'tab'
	if key == cells[0]: #if the key is the first element of cells list:
	originalName=cells[8] #make the second element of cells list to originalName
	for i in range(len(ID[key])): #for each element in the range and length of ID library and key list:
		retweet.append(ID[key][i]) #append each element of ID library to retweet list
		retweet.append(ID2[key][i]) #append each element of ID2 library to retweet list
	f.close() #close document from reading
	resultstr1='<node id="'+key+'" label="'+originalName+'"/>'+'\r' #define result string which will
later be written to file
	if len(retweet) < 8: #if the retweet has less than 8 elements (2 or less retweets)
	pass #do nothing
	else:
	if originalName == '': #if there is no author name in resultstr1:
	pass #do nothing
	else:
	w.write(resultstr1) #write resultstr1 to file
	print 'node #'+ str(++node) #print which number node this is to let user know how far along the
scipt is
	node+=1 #increment node by 1


w.write('</nodes>'+'\r'+'<edges count="">'+'\r') #write to file
node=1
edge=1
for key in ID2.keys(): #the follow lines are the same as above, only printing a different result string to file
to separate nodes from edges (for GEXF file format)
```

```
            index=0
            retweet=[]
            #-#######################-DATASET-######################-#
            f=open('H:\GGS 685 Capstone Course in
Geoinformatics\Project\Data\colombia_class_feb2017.tsv','r')
            #-#######################-DATASET-######################-#
            originalName=''
            for line in f:
            index+=1
            if index!=1:
            cells=line.split('\t')
            if key == cells[0]:
            originalName=cells[8]
            for i in range(len(ID[key])):
                        retweet.append(ID[key][i])
                        retweet.append(ID2[key][i])
            f.close()
            resultstr2='' #define empty result string
            if len(retweet) < 8: #if the length of the reweet has less than 8 elements (less than 2 retweets)
            pass #do nothing
            else:
            if len(retweet) > 2: #if the length of the retweet has nmore than 2 elements:
            a = retweet #make variable 'a' the retweet list
            value=(len(retweet)/2) #value is the length of the retweet list divided by 2
            for i in range(value): #for each element in the range of the number of variable 'value'
            resultstr2='<edge id="'+str(++edge)+'" source="'+str(retweet[(2*i)+1])+'" target="'+key+'"
weight="'+str(1)+'"/>'+'\r' #define resultstr2, which will later be written to file
            #resultstr2='<edge id="'+str(++edge)+'" source="'+str(key)+'" target="'+str(retweet[(2*i)+1])+'"
weight="'+str(1)+'"/>'+'\r' #define resultstr2, which will later be written to file
            node+=1
            if resultstr2 == '': #if resultstr2 is empty (an element such as an element of retweet) is missing:
            pass #do nothing
            else:
            w.write(resultstr2) #write resultstr2 to file
            edge+=1 #increment edge by 1
            print 'edge #'+ str(++edge) #print which number edge this is to let user know how far along the
script is


w.write('</edges>'+'\r'+'</graph>'+'\r'+'</gexf>') #write this to file to end the XML document
w.close() #close file
lists.close() #close lists
print datetime.datetime.now() #print current date and time
```

8. REFERENCES

(PRIO), P. P. I. O. (n.d.). Contagion or Confusion? Why Conflicts Cluster in Space. Retrieved September 30, 2016, from https://www.prio.org/Templates/Publication.aspx?id=331&epslanguage=en&x=4018

"EarthExplorer." Accessed April 1, 2016. http://earthexplorer.usgs.gov/.

"Global Terrorism Database." Accessed February 14, 2016. http://www.start.umd.edu/gtd/.

Braithwaite, A., & Li, Q. (2007). Transnational terrorism hot spots: Identification and impact evaluation. *Conflict Management and Peace Science*, *24*, 281-296. http://doi.org/10.1080/07388940701643623

Alsema, A. (2015, August 2). Fact sheets: Colombia drug trafficking. *Columbia Reports.* Retrieved from http://colombiareports.com/drug-trafficking-in-colombia/

Amble, J. C. (2012). Combating Terrorism in the New Media Environment. *Studies in Conflict & Terrorism*, *35*(5), 339–353. https://doi.org/10.1080/1057610X.2012.666819

Anuario Colombia regional en cifras. (n.d.). Retrieved April 19, 2017, from http://www.banrep.gov.co/es/temas-filtro-fecha/6607

Asia Internet Usage Stats Facebook and Population Statistics. (n.d.). Retrieved February 20, 2017, from http://www.internetworldstats.com/stats3.htm#asia

Berger, J. M. (2015). The metronome of apocalyptic time: Social media as carrier wave for millenarian contagion. *Perspectives on Terrorism*, *9*(4). Retrieved from http://terrorismanalysts.com/pt/index.php/pot/article/view/444

Borum, R. (2003). Understanding the terrorist mindset. *FBI Law Enforcement Bulletin*, *72*(7), 7–10.

Campestrini, I., & Jardim, W. F. (2017). Occurrence of cocaine and benzoylecgonine in drinking and source water in the São Paulo State region, Brazil. *Science of The Total Environment*, *576*, 374–380. https://doi.org/10.1016/j.scitotenv.2016.10.089

Casey, N. (2016, September 26). Colombia Signs Peace Agreement With FARC After 5 Decades of War. *The New York Times*. Retrieved from https://www.nytimes.com/2016/09/27/world/americas/colombia-farc-peace-agreement.html

Chandra, S., & Joba, J. (2015). Transnational cocaine and heroin flow networks in western Europe: A comparison. *International Journal of Drug Policy*, *26*(8), 772–780. https://doi.org/10.1016/j.drugpo.2015.04.016

Chatfield, Akemi Takeoka, Christopher G. Reddick, and Uuf Brajawidagda. "Tweeting propaganda, radicalization and recruitment: Islamic state supporters multi-sided twitter networks." *Proceedings of the 16th Annual International Conference on Digital Government Research*. ACM, 2015.

Colombia drug trafficking | Fact sheet. (n.d.). Retrieved July 30, 2017, from https://colombiareports.com/drug-trafficking-in-colombia/

Croitoru, A., Crooks, A., Radzikowski, J., & Stefanidis, A. (2013). Geosocial gauge: a system prototype for knowledge discovery from social media. *International Journal of Geographical Information Science*, *27*(12), 2483–2508. https://doi.org/10.1080/13658816.2013.825724

Delgado, J. E. (2015). Colombian military thinking and the fight against the FARC-EP insurgency, 2002–2014. *Journal of Strategic Studies*, *38*, 826–851. http://doi.org/10.1080/01402390.2015.1005610

Drewer, D., & Ellermann, J. (2016). May the (well-balanced) force be with us! The launch of the European Counter Terrorism Centre (ECTC). *Computer Law & Security Review*, *32*(2), 195–204. https://doi.org/10.1016/j.clsr.2016.02.003

Efobi, U., & Asongu, S. (2016). Terrorism and capital flight from Africa. *International Economics*, *148*, 81–94. https://doi.org/10.1016/j.inteco.2016.06.004

Ellis RE. The Evolving Transnational Crime-Terrorism Nexus in Peru and its Strategic Relevance for the US and the Region. Prism: a Journal of the Center for Complex Operations.

Enders, W., & Sandler, T. (2006). Distribution of transnational terrorism among countries by income class and geography after 9/11. *International Studies Quarterly*, *50*, 367–393. http://doi.org/10.1111/j.1468-2478.2006.00406.x

Enders, Walter; Sachsida, Adolfo; and Sandler, Todd (2006). The Impact of Transnational Terrorism on U .S. Foreign Direct Investment" (2006). Published Articles & Papers. Paper 55. http://research.create.usc.edu/puplished_papers/55

Ezcurra, R., & Palacios, D. (2016). Terrorism and spatial disparities: Does interregional inequality matter? *European Journal of Political Economy*, *42*, 60–74. https://doi.org/10.1016/j.ejpoleco.2016.01.004

Fuhriman, C., Medina, R. M., and Brewer, S. (In Review) A Point Process Analysis of Terror Attacks in Afghanistan, 2002-2013. Abstract accepted for *Military Geography*, Special Issue – Operating in Extreme Environments: Arctic and Urban Military Challenges. Submitted, 02/22/2016

Geoportal DANE - Estadísticas Georeferenciadas. (n.d.). Retrieved April 19, 2017, from https://geoportal.dane.gov.co/v2/index.php

Global Terrorism Database. Accessed February 14, 2016. Retrieved from http://www.start.umd .edu/gtd/

Gurney, K. (2014, June 11). Colombia announces peace talks with ELN guerrillas. *InSight Crime*. Retrieved from http://www.insightcrime.org/news-briefs/colombia-announces-peace-talks-with-eln-guerrillas

Huey, Laura. "This is not your mother's terrorism: social media, online radicalization and the practice of political jamming." *Journal of Terrorism Research* 6.2 (2015).

King, M., & Taylor, D. M. (2011). The Radicalization of Homegrown Jihadists: A Review of Theoretical Models and Social Psychological Evidence. *Terrorism and Political Violence*, *23*(4), 602–622. https://doi.org/10.1080/09546553.2011.587064

Klausen, Jytte. "Tweeting the Jihad: Social media networks of Western foreign fighters in Syria and Iraq." *Studies in Conflict & Terrorism* 38.1 (2015): 1-22.

Latinobarometro Corporation. 1995-2016 Data Bank. Retrieved March 18, 2017, from http://www.latinobarometro.org.mutex.gmu.edu/latContents.jsp.

Laura K. Siebeneck , Richard M. Medina , Ikuho Yamada & George F. Hepner (2009) Spatial and Temporal Analyses of Terrorist Incidents in Iraq, 2004–2006, Studies in Conflict & Terrorism, 32:7, 591-610, DOI: 10.1080/10576100902961789

Leaderless Jihad | Marc Sageman. (n.d.). Retrieved July 30, 2017, from http://www.upenn.edu/pennpress/book/14390.html

Liu, A., & Pratt, S. (2017). Tourism's vulnerability and resilience to terrorism. *Tourism Management*, *60*, 404–417. https://doi.org/10.1016/j.tourman.2017.01.001

Magdy, Walid, Kareem Darwish, and Norah Abokhodair. "Quantifying Public Response towards Islam on Twitter after Paris Attacks." *arXiv preprint arXiv:1512.04570* (2015).

Martínez, L. R. (2017). Transnational insurgents: Evidence from Colombia's FARC at the border with Chávez's Venezuela. *Journal of Development Economics*, *126*, 138–153. https://doi.org/10.1016/j.jdeveco.2017.01.003

McDermott, J. (2014, May 26). The reality of the FARC peace talks in Havana. *InSight Crime.* Retrieved from http://www.insightcrime.org/investigations/reality-farc-peace-talks-havana

Mentiras y verdades de la paz en Colombia (infografías). (2016). Retrieved March 11, 2017, from http://fundacionlaplomada.blogspot.com/2016/10/mentiras-y-verdades-de-la-paz-en.html

Midlarsky, M. I., Crenshaw, M., & F. Yoshida (1980). Why violence spreads: The contagion of international Terrorism. *International Studies Quarterly*, *24*, 262 -298. http://doi.org/10.2307/2600202

Nemeth, Stephen C., Jacob A. Mauslein, and Craig Stapley (April 1, 2014). The Primacy of the Local: Identifying Terrorist Hot Spots Using Geographic Information Systems. *The Journal of Politics* 76, no. 2 304–17. doi:10.1017/S0022381613001333.

Post, J., Sprinzak, E., & Denny, L. (2003). The terrorists in their own words: Interviews with 35 incarcerated Middle Eastern terrorists∗∗This research was conducted with the support of the Smith Richardson Foundation. *Terrorism and Political Violence*, *15*(1), 171–184. https://doi.org/10.1080/09546550312331293007

Procasky, W. J., & Ujah, N. U. (2016). Terrorism and its impact on the cost of debt. *Journal of International Money and Finance*, *60*, 253–266. https://doi.org/10.1016/j.jimonfin.2015.04.007

Rehman, F. U., & Vanin, P. (2017). Terrorism risk and democratic preferences in Pakistan. *Journal of Development Economics*, *124*, 95–106. https://doi.org/10.1016/j.jdeveco.2016.09.003

Rosenau, W., Espach, R., Ortiz, R. D., & Herrera, N. (2014). Why they join, why they fight, and why they leave: Learning from Colombia's Database of Demobilized

Militants. *Terrorism and Political Violence*, *26*, 277–285. http://doi.org/10.1080/09546553.2012.700658

Sanín, F. G. (2006). Internal conflict, terrorism and crime in Colombia. *Journal of International Development*, *18*, 137–150. http://doi.org/10.1002/jid.1267

Schomerus, G., Stolzenburg, S., Bauch, A., Speerforck, S., Janowitz, D., & Angermeyer, M. C. (2017). Shifting blame? Impact of reports of violence and mental illness in the context of terrorism on population attitudes towards persons with mental illness in Germany. *Psychiatry Research*, *252*, 164–168. https://doi.org/10.1016/j.psychres.2017.02.053

Serres, P. (2000). The FARC and democracy in Colombia in the 1990s. *Democratization*, *7*(4), 191–218. http://doi.org/10.1080/13510340008403689

Stadthagen-Gonzalez, Hans, et al. "Norms of valence and arousal for 14,031 Spanish words." *Behavior research methods* (2016): 1-13.

The World Factbook — Central Intelligence Agency. (n.d.). Retrieved March 28, 2017, from https://www.cia.gov/library/publications/the-world-factbook/geos/co.html

Thompson, R. (2011). Radicalization and the Use of Social Media. *Journal of Strategic Security*, *4*(4), 167–190. https://doi.org/10.5038/1944-0472.4.4.8

Witmer, Eric W. "Terror on Twitter: A Comparative Analysis of Gender and the Involvement in Pro-Jihadist Communities on Twitter." (2016).

Zackrison, J. L. (1989). La Violencia in Colombia: An anomaly in terrorism. *Journal of Conflict Studies*, *9*(4), 5-18. Retrieved from https://journals.lib.unb.ca/index.php/JCS

Zapata, G. D. P. (2003). Terrorism in Colombia. *Prehospital and Disaster Medicine*, *18*, 80–87. http://doi.org/10.1017/S1049023X00000807

BIOGRAPHY

Zachary Toll graduated from University High School in Los Angeles, CA in 2008. He received her Bachelor of Arts from the University of California, Santa Barbara in 2012. He was employed as a researcher, graduate teaching assistant, consultant, and Marine Corps Heavy Infantryman/Demolitions Expert and received his Master of Science in Geoinformatics and Geospatial Intelligence from George Mason University in 2017.