A SPATIAL ANALYSIS OF TERRORIST KIDNAPPING INCIDENTS IN AFGHANISTAN

by

Alison Marie Regan
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DEDICATION

This thesis is dedicated to my parents who have always believed in me, and showed me the value of faith and hard work.
I would like to thank my academic advisors, friends, and family who have helped me achieve this goal. First, I would like to express my deepest appreciation and gratitude to my advisor, Dr. Rice, for his expert guidance and help in the completion of this thesis and in my academic career. I would like to acknowledge the members of my thesis committee, Drs. Stefanidis and Curtin, for their guidance and assistance in this endeavor, and Mr. Matthew Tabler for creating the wonderful map of the insurgency in Afghanistan that appears in this document. I would also like to thank my colleagues, especially FTC and PGA, for their constant support, encouragement, and advice over the last two years. Finally, I must express my profound gratitude to my parents and my sister for their unfailing support, for understanding the demands of graduate school, and for the invaluable time spent reviewing this thesis. This would not have been possible without them.
TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>List of Tables</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>viii</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>List of Figures</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ix</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>List of Abbreviations</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>x</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Abstract</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>xi</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter One: Introduction</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.0 Chapter Overview</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.1 Region of Study and Topic Background</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.2 Thesis Objectives and Research Questions</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.3 Limitations</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.4 Hypothesis and Anticipated Results</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.5 Thesis Organization</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter Two: Conceptual Framework and Review of Related Literature</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2.0 Chapter Overview</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2.1 Foundations of Geography and Geospatial Intelligence in Terrorism Research</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1.1 The geographic nature of terrorism and violence</td>
<td>11</td>
</tr>
<tr>
<td>2.1.2 A spatially-centric definition of terrorism</td>
<td>12</td>
</tr>
<tr>
<td>2.1.3 Evaluating terrorism using cluster analysis</td>
<td>14</td>
</tr>
<tr>
<td>2.2 Historical Context of Conflict and Control in Afghanistan</td>
<td>17</td>
</tr>
<tr>
<td>2.2.1 History of conflict and the struggle for control in Afghanistan</td>
<td>17</td>
</tr>
<tr>
<td>2.3 Factors contributing to continued instability in Afghanistan</td>
<td>21</td>
</tr>
<tr>
<td>2.3.1 Cultural</td>
<td>21</td>
</tr>
<tr>
<td>2.3.2 Physical</td>
<td>22</td>
</tr>
<tr>
<td>2.3.3 Political</td>
<td>23</td>
</tr>
<tr>
<td>2.3.4 Terrorist Tactics</td>
<td>25</td>
</tr>
<tr>
<td>2.4 Building Law Enforcement Capacity and Capability</td>
<td>27</td>
</tr>
<tr>
<td>2.5 Terrorist Kidnapping</td>
<td>28</td>
</tr>
</tbody>
</table>
4.3.1 Have kidnapping events clustered in space over time? .............................. 81
4.3.2 Are there any clusters of kidnapping incidents, events given the population? 81
4.3.3 Have the districts or provinces experiencing these events changed over time?
Are any patterns consistent? ........................................................................ 82
4.3.4 Are there any districts that are outliers? ................................................. 83
4.3.5 Informing Strategic prioritization ................................................................ 84

Chapter Five: Conclusions And Future Research ........................................ 85
5.1 Chapter Overview ....................................................................................... 85
5.2 Summary .................................................................................................... 85
5.3 Conclusions ............................................................................................... 86
5.4 Improvements and Recommendations for Future Research .................... 87
  5.4.1 Potential Improvements ....................................................................... 87
  5.4.2 Further Analysis of Ethno linguistic trends and other social-spatial factors that
may influence kidnapping ............................................................................... 90
  5.4.3 Creation of an Intensity Statistic ............................................................. 90
  5.4.4 Space Time Interaction Analysis ............................................................. 91
  5.4.5 Interactive Visualization Tools ............................................................. 91
References .................................................................................................... 93
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 1 Number of Kidnapping Incidents and Victims per Period</td>
<td>42</td>
</tr>
<tr>
<td>Table 2 Interpreting Moran's I Results</td>
<td>48</td>
</tr>
<tr>
<td>Table 3 Districts included in Hot spots or as outliers in analysis of incident count data</td>
<td>77</td>
</tr>
<tr>
<td>Table 4 Districts included in Hot spots or as outliers in analysis of incident per capita data</td>
<td>79</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1 Map of Afghanistan</td>
<td>3</td>
</tr>
<tr>
<td>Figure 2 The Spread of the Insurgency from 2002-2006</td>
<td>20</td>
</tr>
<tr>
<td>Figure 3 The calculation for Moran's I</td>
<td>46</td>
</tr>
<tr>
<td>Figure 4 The mathematic formula for Getis-Ord Gi*</td>
<td>51</td>
</tr>
<tr>
<td>Figure 5 Calculation of Local Moran's I</td>
<td>54</td>
</tr>
<tr>
<td>Figure 6 Incremental Spatial Autocorrelation: Z scores per distance (2009-2010 Per Capita Data)</td>
<td>58</td>
</tr>
<tr>
<td>Figure 7 2005-2006 Hot Spot Analysis Results</td>
<td>60</td>
</tr>
<tr>
<td>Figure 8 2005-2006 Cluster And Outlier Analysis Results</td>
<td>61</td>
</tr>
<tr>
<td>Figure 9 2007-2008 Hot Spot Analysis Results</td>
<td>64</td>
</tr>
<tr>
<td>Figure 10 2007-2008 Cluster and Outlier Analysis Results</td>
<td>66</td>
</tr>
<tr>
<td>Figure 11 2009-2010 Hot Spot Analysis Results</td>
<td>67</td>
</tr>
<tr>
<td>Figure 12 2009-2010 Cluster and Outlier Analysis Results</td>
<td>69</td>
</tr>
<tr>
<td>Figure 13 2011-2012 Hot Spot Analysis Results</td>
<td>70</td>
</tr>
<tr>
<td>Figure 14 2011-2012 Cluster and Outlier Analysis Results</td>
<td>72</td>
</tr>
<tr>
<td>Figure 15 2013-2014 Hot Spot Analysis Results</td>
<td>73</td>
</tr>
<tr>
<td>Figure 16 2013-2014 Cluster and Outlier Analysis Results</td>
<td>75</td>
</tr>
</tbody>
</table>
LIST OF ABBREVIATIONS

Armed Conflict Location & Event Data ................................................................. ACLED
Afghan National Police ....................................................................................... ANP
Afghan National Security and Defense Forces ................................................... ANSDF
Afghan National Security Forces ......................................................................... ANSF
Center for Terrorism and Intelligence Studies ................................................... CEITS
Central Intelligence Agency ................................................................................... CIA
Complete Spatial Randomness .............................................................................. CSR
Federally Administered Tribal Areas ..................................................................... FATA
False Discovery Rate .............................................................................................. FDR
Geographic Information Systems .......................................................................... GIS
Geographic Information Science .......................................................................... GISc
Global Terrorism Database ................................................................................... GTD
Global War on Terror ......................................................................................... GWOT
International Security Assistance Force ............................................................. ISAF
Inter-Services Intelligence Directorate ................................................................. ISI
Islamic State of Iraq and the Levant ....................................................................... ISIL
Islamic State of Iraq and Syria .............................................................................. ISIS
Institute for the Study of Violent Groups ............................................................... ISVG
Local Indicators of Spatial Autocorrelation ........................................................... LISA
Local Moran’s I ....................................................................................................... LMI
North Atlantic Treaty Organization .................................................................... NATO
Non-Governmental Organization .......................................................................... NGO
Natural Language Processing ............................................................................... NLP
Pinkerton Global Intelligence Service ................................................................. PGIS
Study of Terrorism and Responses to Terrorism .................................................. START
University of Maryland .......................................................................................... UMD
World Geodetic System ......................................................................................... WGS
ABSTRACT

A SPATIAL ANALYSIS OF TERRORIST KIDNAPPING INCIDENTS IN AFGHANISTAN

Alison Marie Regan, M.S.

George Mason University, 2016

Thesis Director: Dr. Matthew T. Rice

Since October 2001, United States forces have been engaged in Afghanistan. A primary objective has been to eliminate the threat of Taliban and of Al Qaeda in the country. The U.S.-backed-post-Taliban government has struggled to exercise full control over the country, particularly in the rural tribal regions. A Taliban insurgency, supported by Al Qaeda, continues in the east and south near the country’s border with Pakistan. Insurgents maintain these footholds through terror and intimidation. This thesis uses geospatial intelligence methods to identify districts of Afghanistan that featured clusters of kidnapping attacks in the period from 2005 to 2014. The information presented in this paper can be used to strategically prioritize outreach and training, and to improve critical governance structures, particularly the Afghan National Police (ANP) and supporting Afghan National Security and Defense Forces (ANSDF). Improvement of the ANP and ANSDF in these locations may strengthen rule of law, the judicial process, and the public’s confidence in law enforcement. This would in turn improve overall governance.
and state security. This study uses data from the University of Maryland’s Global Terrorism Database, which houses information on terrorist events around the world from 1970-2014. The database includes a total of 551 kidnapping incidents in Afghanistan from 2005-2014. Geostatistical methods, including hot-spot analysis and spatial autocorrelation, are used to identify clusters of kidnapping incidents in two year aggregate periods. Districts and regions consistently included in clusters, or identified as outliers, could be prioritized as high risk areas that could benefit from the strengthening of ANSDF structures.
CHAPTER ONE: INTRODUCTION

“In the midst of chaos, there is also opportunity”
— Sun Tzu, The Art of War

1.0 Chapter Overview

Following the events of September 11, 2001, the United States and the international community have been engaged in what has been referred to as a Global War on Terrorism (GWoT). This effort aims to eradicate terrorist groups and networks and the governments that shelter them (Bush 2001). A large part of this mission is focused on Al Qaeda and the Taliban regime that sheltered them in Afghanistan. Although the Taliban government was ousted in the winter of 2001, installing a sovereign administration and establishing successful governance in Afghanistan has been difficult. A Taliban insurgency persists. The group relies on terror tactics in its attempt to regain and retain control in Afghanistan.

This thesis applies geospatial intelligence methods to identify clusters of kidnapping events, both by incident count and incidents per capita, from 2005 to 2014. This information can be used to recommend strategic prioritization of outreach and training in order to improve critical governance structures, particularly the Afghan National Police (ANP), and supporting Afghan National Security and Defense Forces (ANSDF). Improvement of the ANP and ANSDF may strengthen rule of law, the judicial
process, and confidence in law enforcement. Weaknesses in these areas have been identified by scholars as factors contributing to the Taliban insurgency (Johnson and Mason 2007; Jones 2008; Giustozzi 2008; Hughes 2014). There is a unique opportunity for law enforcement entities to prevent and disrupt kidnapping, and for law enforcement to prosecute the perpetrators. Prosecution paints the Taliban and Al Qaeda as criminals and terrorists rather than warriors. Strengthening ANSDF to carry out this critical task would improve overall governance, and the security of the state.

Data from the Global Terrorism Database (GTD) from the University of Maryland’s National Consortium for the Study of Terrorism and Responses to Terrorism (START) is used in this study. Terrorist kidnapping incidents from 2003-2014 are evaluated using spatial statistics, including Moran’s I and Getis-Ord Gi*, to evaluate distribution of incident clusters and patterns in clustering over time.

This chapter provides a basic overview and background on the topic of interest. Specific thesis objectives, research questions, and limitations of the study are addressed, followed by a brief discussion of the hypothesis and anticipated results. The chapter concludes with a short description of the remainder of the thesis organization.
1.1 Region of Study and Topic Background

The region selected for this study is the country of Afghanistan. Located in South Asia, the nation is bordered by Tajikistan, Turkmenistan, and Uzbekistan in the north, Iran in the west, Pakistan in the east and south, and China in the northwest (see Figure 1). Conflict and war have torn Afghanistan for the last three decades and have decimated the power- and institutional- structures in the country (Johnson and Mason 2007).

![Map of Afghanistan](image)

Figure 1 Map of Afghanistan (CIA 2015)
Security and judicial structures in Afghanistan have had to be rebuilt, almost from the ground up. This has been a challenge due to weaknesses of the central government, corruption, and an operational environment that forces a focus on counterinsurgency and security efforts over community policing (Johnson and Mason 2007; Hughes 2014). Significant resources have been devoted to improving judicial and policing structures, and major strides have been made (Defense 2015). The International Security Assistance Force (ISAF) has helped to provide and structure training. Still, the critical link between policing and prosecuting via the judicial system is underdeveloped (Hughes 2014). District policing efforts and capabilities vary throughout the country. Public confidence in ANSDF has consistently hovered at about 70 percent in 2015 (Defense 2015).

Kidnapping remains a major security problem in the country. Afghanistan has one of the highest percentages of terrorist kidnappings globally (Forest 2012a). Of the events captured in the GTD from 2001-2014, Afghanistan accounts for 12% of all terrorist kidnapping events, ranking third highest worldwide. Kidnapping is one of the many tools used by terrorists and insurgents to force political change, incite terror, and gain funding. Although the kidnapping of foreigners in the country has received significant international attention, the overwhelming majority of kidnap victims are Afghans (Forest 2012a).

The Afghan people prioritize security and justice (Jones 2008). ANP and ANSDF are in a unique position to facilitate both, particularly in regards to kidnappings which are easily identified as crimes rather than acts of war. Targeted training and outreach to
enhance the rule of law, and the people’s confidence in the judicial process is needed. Counterinsurgency operations alone are not enough (Hughes 2014).

1.2 Thesis Objectives and Research Questions

This thesis has two major objectives:

1. Evaluate whether kidnapping incidents have clustered at the district level in Afghanistan and if outliers exist; and,
2. Identify districts or regions where kidnapping events have focused over time, both by incident count and by incidents per capita, to better inform strategic prioritization of training and outreach.

To meet these objectives, the following scientific research questions are explored:

- Have kidnapping events clustered in space over time?
- Are there any districts that are outliers?
- Are there any clusters of kidnapping events given the population?
- Have the districts that are included in any clusters changed over time? Do patterns or trends exist?

1.3 Limitations

There are limitations of this study. This analysis relies on terrorist kidnapping event data to identify clusters and outliers. It is important to recognize that kidnapping is one of the most underreported crimes (Forest 2012a). It is very possible that there are kidnapping events that were not included in the data. This impacts the accuracy of the
results. Underreporting underscores the need to improve citizen confidence in the police force.

The open source database used is derived primarily from media reporting; thus, the data is subject to biases of overreporting and underreporting. Unclassified studies and reports could include mistakes or omissions, for instance, in locations and other event data, which would also introduce error. Limitations of the data and methods used are discussed in depth in section 3.2.2

This study does not attempt to recommend how training and outreach in districts should be implemented or conducted. Nor does this study discuss the content and details of potential training or advisory programs. Instead, the focus is on providing guidance on the strategic selection of geographic areas that could benefit from some sort of outreach or assistance in order to aid prioritization and resource allocation efforts.

It is also important to acknowledge some of the general limitations of the methodology and analysis of this study. The analysis centers on the concept of statistical significance; it is critical to recognize that this idea does not address what areas are more “important” than others. Rather, statistically significant results suggest that it is much less probable that distribution of events is associated with random chance or variation. Identification of areas of statistical significance would indicate that distribution is instead the result of underlying factors. This could be valuable in understanding kidnapping, and is a valuable consideration in strategic resource allocation, to which this study aims to contribute. Identification of statistically significant clusters, and their overall impact and value are discussed in depth in section 2.1.3.
1.4 Hypothesis and Anticipated Results

It is anticipated that kidnapping incidents will cluster at the district level in Afghanistan, in analysis of incident count data, and incidents per capita. It is also anticipated that some districts will consistently be included in either the significant incident count or significant incident per capita clusters across the period of study. These districts or regions could then be prioritized to receive assistance and training to support ANSF and critical judicial and law enforcement structures.

1.5 Thesis Organization

This thesis is divided into five chapters. The first chapter is this introduction. The second chapter addresses the conceptual framework of the study, and provides a review of related literature. The third chapter details the data and methodology used to conduct this examination. The fourth chapter analyzes and discusses the results. The final chapter provides conclusions, recommended improvements, and ideas for future research.
CHAPTER TWO: CONCEPTUAL FRAMEWORK AND REVIEW OF RELATED LITERATURE

2.0 Chapter Overview

This thesis addresses how geographic principles can be applied to identify districts consistently included in clusters of kidnapping events in Afghanistan. This analysis can be used to strategically prioritize training and outreach for security and law enforcement structures in the country.

This chapter provides a conceptual framework and reviews the relevant literature. It first addresses the contributions of geospatial intelligence in the study of terrorism and the methods used in such studies. An overview of the theory regarding spatial distribution of conflict and violence and the relationship to the control of space follows. Historical background on conflict, violence, and terrorism in Afghanistan is then discussed, as are factors that may contribute to the lack of control and instability in the state. Assessments of ANSDF and lingering areas for improvement are included. The chapter culminates with a summary of terrorist kidnapping in general and in the region.

2.1 Foundations of Geography and Geospatial Intelligence in Terrorism Research

Much of the research conducted on terrorism focuses on understanding qualitative aspects of terrorist organizations and terrorist attacks. Others have thoroughly investigated the group leadership, organization, and chronologies of major attacks and
events (Siebeneck, Medina et al. 2009). Core geographic concepts are often excluded from these studies, limiting their versatility, and omitting how geography contributes to terrorism, as several studies have.

A 2009 analysis by Siebeneck, Medina, Yamada, and Hepner addresses the spatial and temporal distribution of terrorist incidents in Iraq using geographic methods. The analysis provides justification for the application of geographic analysis to terrorism, and discusses how it can contribute knowledge of terrorism and how it can provide additional information to inform counterterrorism efforts. The study notes that theoretically, patterns in terrorist activities can be attributed to the manifestation of underlying social, political, and cultural influences across the physical landscape (Siebeneck, Medina et al. 2009). The authors hypothesize that terrorism and terrorist events are inherently both geographic and non-random. They further hypothesize that terrorist events in Iraq will cluster in both space and time. They use geographically referenced data on terrorist events to conduct their analysis, and employ Geographic Information Science (GISc) methods, including hot spot analysis, to identify patterns in the data. Their results confirm the theory. The Siebeneck et al. study highlights the strengths of including geographic methods in analysis of terrorism and conflict. Further, it demonstrates how such information can then be analyzed and interpreted to communicate additional information on underlying factors of terrorism, and it shows how this knowledge can be used to influence counterterrorism strategy.
Contribution and communication of knowledge via spatial data and products, as exemplified in Siebeneck et al. is the core of geospatial intelligence. Geospatial intelligence is specifically defined in 10 U.S.C. § 467 as:

[T]he exploitation and analysis of imagery and geospatial information to describe, assess, and visually depict physical features and geographically referenced activities on the earth. Geospatial intelligence consists of imagery, imagery intelligence, and geospatial information.

A 2013 study by Bahgat and Medina overviews geographic methods in the study of terrorism and further highlights strengths of incorporating “imagery, imagery intelligence, and geospatial information” (Bahgat and Medina 2013). Terrorism, violence, and conflict are complicated. Bahgat and Medina reiterate the idea, proposed in Siebeneck et al., that terrorism and its underlying factors can be better examined in a multidisciplinary way. As the authors note, geography is a science of convergence, where disciplines can intersect in the study of events, influences, and processes in a spatial context. The examination of approaches stresses that the geographical perspective is not intended to substitute for other theoretical approaches, but instead provides an opportunity to test and strengthen those theories (Bahgat and Medina 2013).

The idea that information generated by analysis of geographic information can contribute to knowledge of a problem is critical to this study. This research relies on the results of geospatial and geostatistical analysis of spatial data to generate recommendations. Geography as a science of convergence is equally important in this study, as it approaches how strategic and political recommendations can be influenced by, and can benefit from, the use of geographic information.
2.1.1 The geographic nature of terrorism and violence

As detailed by Bahgat and Medina, the geographic approach provides opportunities to test and validate theories. The idea that geography is an optimal convergence of disciplines is also echoed in geographic research on the distribution of violence. At the core of this thesis is the “control-collaboration” model developed by Stathis Kalyvas in his well-known work, *The Logic of Violence in Civil War*, which merges political science and the idea of space (Kalyvas 2006).

Kalyvas’ proposed “control and collaboration” model suggests that the spatial variation of violence can be attributed to the control of space. Kalyvas conceptualizes space as a five zone model, with control ranging from areas “fully controlled by the incumbents in one end to areas fully controlled by insurgents in the other end.” Three intermediate zones separate these two poles. The model centers on the idea that indiscriminate violence is inversely related to the level of governmental control. He proposes that selective violence is most likely in zones where control by an armed group is predominant, but not absolute (Kalyvas 2006).

He further refines his model in a review of corresponding micro-studies. In those studies, he suggests that selective violence may also be found in areas where the incumbents and insurgents are close to parity. He also proposes that the model should potentially expand beyond its reliance on homicides, as a microstudy indicated that non-lethal attacks, such as kidnapping and expropriation, were also used tactically by insurgents in areas of incomplete control (Kalyvas 2012).
A 2014 thesis by Crawford focuses on Kalyvas’s theory and proposes an expansion based on criminological and social science tenets. Specifically, Crawford discusses the least effort principle, the optimum foraging principle, the sequential relationship between rivals, and the strategic goals of an organization. Crawford addresses how the terrorist decision-making process and causal logic can explain rational decision-making behind target selection, and how, when combined with Kayvalas’s ideas on contested zones of control, could explain how and why terrorists carry out attacks in each zone. He proposes that this synthesis be used to evaluate factors contributing to the spatial and temporal patterns of insurgent attacks (Crawford 2014).

These works highlight the importance of geography as a science of convergence, and provide the specific lens to interpret how spatial distribution of terrorist attacks can help explain interactions between conflict and space in Afghanistan. Further, they reinforce the idea that attacks are deliberate, and non-random in space.

2.1.2 A spatially-centric definition of terrorism

An evaluation of the geographic nature of terrorism by John Rock continues the idea that terrorism and place are inherently linked. As noted by Rock, this desire to gain and control geographic space can be considered a “driving force” behind terrorism. Although terrorist groups may attribute their actions to political or religious motives, Rock states that their actions are inherently attempts to dictate how and by whom space is used. Rock advocates for a geocentric focus on interpreting terrorist activity and motivations, as opposed to ideology alone. He proposes that space is the missing link in almost all definition and studies of terrorism, and that all terrorism it is rooted in the
desire to acquire, control, and benefit from land. He summarizes the importance of this consideration, stating:

We do not need an in-depth understanding of a certain terrorist groups’ dogma, we need only to examine what geography is vital to them—we must determine what land they use as a base of operations, what land(s) they seek to control, and what country currently stands in their way.

(Rock 2006,3)

Rock also links terrorism and the contestation of space to a desire for legitimacy at the global level, similar to that of legitimate nation states, as a main motivation for terrorist groups worldwide. His alternate definition of terrorism highlights the interwoven nature of terrorism and geography (Rock 2006).

Several studies have focused on the geographic nature of terrorism. A 2011 study by Medina and Hepner addresses the impact of hybrid space on Islamist terrorist operations. The study maps sociospatial dependencies to determine the impact of distance on terrorist networks. Medina and Hepner created a database with representations of 358 terrorist entities and the connections between them. Each entity was given a single geographic location, representative of planning and attack locations or capture location. The bulk of the data related to the Al Qaeda-led larger Islamic terror network. Geographic measurements between dyads were then used to evaluate the connectivity of the network. Both first and second degree distances were examined. The results of the study indicate that a majority of interactions occur at 1,000 km or less (Medina and Hepner 2011). Over one third of the nodes examined are 100 km or less, meaning that a majority of interactions are occur face-to-face and regionally, rather than over the internet
(Medina and Hepner 2011). The authors conclude that it is therefore more likely for a network’s neighborhood to be “geographically close.”

The results of the study on sociospatial connections are critical in this thesis. As noted by Medina and Hepner, social connections are representative of operational communication and coordination. This thesis examines clustering of terrorist kidnapping events with a focus on identifying regional, localized trends. Medina and Hepner’s conclusions—that a majority of islamist terrorist sociospatial connections are under 1,000 km, with over one third falling under 100 km—bound the conceptualization of neighborhoods and space in this study (Medina and Hepner 2011).

2.1.3 Evaluating terrorism using cluster analysis

Several studies have focused on the idea that clustering of events and incidents may generate additional knowledge on terrorism. Authors have defended the inclusion of cluster analyses in these studies and have explained their rationale in depth. Braithwaite and Li’s 2007 study of Transnational Terrorism Hot Spot Identification uses Getis-Ord Gi* to evaluate terrorism events and pinpoints countries that fall within terrorist hotspots using three year aggregates of terrorist incidents per country (Braithwaite and Li 2007). The authors strongly advocate for use of Local Indicators of Spatial Autocorrelation (LISA) statistics, specifically the analysis of clusters, in understanding terrorism. They argue that understanding whether an individual country falls within a terrorist hotspot provides a more refined understanding of the distribution of terrorism than traditional regional mapping alone. They also argue that the empirical knowledge that can be gained through cluster analysis helps to enable consistency in analysis over time, and that it
helps to refine policies and ensure countermeasures have an appropriate social/scientific rationale. Braithwaite and Li specifically identify that their results can be used to focus efforts and allocate resources appropriately in the fight against terrorism (Braithwaite and Li 2007).

The Braithwaite and Li study provides excellent precedent for application of LISA statistics to analyze terrorism. The specific implications and value of cluster analyses in the field are addressed in depth. As this thesis has similar objectives and employs similar methods, the empirical information produced in this study carries similar benefits. As informing strategic resource allocation is a primary objective of this thesis, the fact that Braithwaite and Li specifically point to this as an implication reinforces the idea that this objective may be achieved.

A 2010 study by O’Loughlin et. al also exemplifies an application of cluster analysis in the study of terrorism. The authors use Getis Ord Gi* on point data on terrorist attacks and ISAF offensives from WikiLeaks to generate information on terrorist violence, and counterinsurgency activities from 2004-2009 (O'Loughlin, Witmer et al. 2010b). The results of the analysis show the progression of violence and activity in the Global War on Terror (GWOT). The authors also point out how hotspots, and the movement of hotspots, can provide additional evidence in the identification of patterns and trends. They specifically identify movements of the Taliban insurgency following the beginning of the Obama administration, and continuous concentration of violent events along the Afghanistan/Pakistan border, through analysis of cluster locations. The idea that empirical knowledge generated by hotspot analysis can also be informative is
affirmed in the O’Loughlin study. The authors are able to definitively identify differences in the congregation of violence over time by looking at the dispersal and land area included in hotspots. The O’Loughlin study is additional evidence that these tools and clustering analyses are effective when applied to the study of terrorism generally, and particularly when applied to the study of terrorism in Afghanistan (O'Loughlin, Witmer et al. 2010b).

A similar analysis by Siebeneck, Medina, and Hepner examined terrorist activities in Iraq from 2004-2006. The authors use Getis Ord Gi* to identify clusters of cities with similar concentrations of terrorist incidents, and similar attack intensities. They defend their rationale by stating that cluster analysis is specifically necessary to determine the “spatial foci of terrorist activity spaces” (Siebeneck, Medina et al. 2009, 594). They stress that spatial patterns in the locations of hotspots are also indicative of patterns in terrorist behaviors. This may in turn assist decision makers in designing policies and plans that are reflective of these patterns.

The identification of patterns and trends in terrorist kidnapping events is a major objective of this thesis. As Siebeneck et. al discuss, cluster analysis is a preferred method to understand how incidents and events may cluster in space. Like this thesis, the Siebeneck study authors also tie into the idea that cluster identification can influence strategic decision making, and influence policy to target the spatial areas where terrorist behaviors are focused.

All three of the studies discussed in this section employed LISA statistics to generate additional knowledge on terrorism. As this thesis intersects several of the main
ideas presented in these three studies, they also provide additional, peer-reviewed precedent for the employment of the methods discussed in chapter three.

2.2 Historical Context of Conflict and Control in Afghanistan

Conflict, war, and violence are not new phenomena in Afghanistan. Since the 1970s Soviet intervention in the country, there has been a persistent struggle for control of space. Significant research highlights the struggle for security, the progression of conflict in the country, and the conflicts between individual actors in Afghanistan. Afghanistan’s history of conflict and instability play a significant role in the fight for control that the country is experiencing today. This section is included to provide the necessary context for the discussion and analysis presented in this thesis.

2.2.1 History of conflict and the struggle for control in Afghanistan

After the withdrawal of the Soviets in 1989, civil war dominated Afghanistan. Rival warlords and mujahedeen groups fought for power (Johnson and Mason 2007). The country was divided into several factions, operating almost as “mini-states” (Soherwordi, Ashraf et al. 2012). Thousands were killed, infrastructure that remained after the Soviet conflict was destroyed, and bombings and mortar attacks were rampant (Johnson and Mason 2007). All remnants of the pre-Soviet invasion traditional power structure were destroyed. The leadership and power void that resulted from the civil war contributed to a state of anarchy, especially in the more rural areas. In the countryside war lords, drug lords, and bandits reigned supreme (Johnson and Mason 2007).
As all of this occurred religious schools, known as madrassas, were constructed in the border area of Afghanistan and Pakistan (Soherwordi, Ashraf et al. 2012). These schools, which were heavily financed by Saudi Arabia and the Gulf States, were intended to spread the conservative view of Islam as practiced in the Gulf States (Johnson and Mason 2007). An organization whose members were dissatisfied with the warlordism and deterioration of Afghan society emerged from these schools. The name, Taliban, comes literally from the Arabic term for “students” of Islam (Soherwordi, Ashraf et al. 2012). Backed by the Pakistani Inter-Services Intelligence Directorate (ISI), the Taliban emerged to recruit and instill their vision of government (Johnson and Mason 2007). The Taliban took control of the capital in 1996 (Johnson and Mason 2007). Following their takeover, they worked to destroy the warlords that they perceived had promoted civil war and the destruction of the country. The group simultaneously instituted a strict and ultraconservative interpretation of Sharia Law (Johnson and Mason 2007).

The rise of the Taliban in Afghanistan made the country an attractive location for Al Qaeda to operate and train. (Soherwordi, Ashraf et al. 2012). More of a “network of networks” than a traditional hierarchical group, Al Qaeda focuses on the promotion of radical anti-Western, anti-Semitic, and anti-Zionist ideology (Burke 2004). A primary focus of the movement is to destroy those the group believes are guilty of dividing or humiliating Islam (Burke 2004). This militant terrorist group was led in part by Osama bin Laden. The group was responsible for several attacks around the world, including the 1993 World Trade Center bombing, the attack on the USS Cole, and the September 11, 2001 (9/11) attacks on the United States.
It was the 9/11 attacks that prompted the United States and the International Community to invade Afghanistan in October of 2001. By December of the same year, the Taliban regime was ousted, and Al Qaeda fighters were on the run. An interim government was put into place. In August 2003, The North Atlantic Treaty Organization (NATO) took the lead in Afghanistan with the establishment of the International Security Assistance Force (ISAF). Despite these initial successes, the influence of the Taliban and Al Qaeda was not completely eradicated. In 2002, an organized effort to reestablish the Taliban began in Pakistan, and later in the border villages of Afghanistan. Although displaced and widely regarded as defeated, the “neo-Taliban” began to gain momentum. By 2003 and 2004, the movement had obtained strongholds in parts of the Afghan countryside (see Figure 2). By 2006 a full blown insurgency was underway, with escalating attacks, improved methods of operation, and organized offensives. The Taliban had regained its footing in the country, and it had re-initiated its fight for control of the state (Giustozzi 2008).
Since then, Afghan forces, with support from the international community, have pushed back against the Taliban in an attempt to regain full control. The primary objective of ISAF, according to the NATO main webpage, was to provide security and develop Afghan security forces. The ISAF mission ended in 2014, with the international community transitioning to “Operation Resolute Support.” The current mission focuses on training, advising, assisting Afghan forces.

As of October 2015, an analysis by Roggio and Weiss, published by The Long War Journal, suggests that government control remains tenuous in areas of the country.
Out of the country’s 398 districts, Roggio and Weiss assess that at least 29 of the districts are under Taliban control, with another 36 contested. They classify districts under Taliban control as those being openly administered by the Taliban, with the group providing services and security. Contested districts may have government control of the district center, but the Taliban controls large areas outside of the center. The assessment is based on unclassified reporting, as well as Taliban claims (Roggio and Weiss 2015).

Roggio and Weiss make an additional interesting point, explaining that the Taliban does not always constantly hold a district, instead choosing to occupy it briefly, leave, and return at a later date. This pattern may be visible or evident in any trends in kidnapping events.

2.3 Factors contributing to continued instability in Afghanistan

There are a number of cultural, physical, and political factors contributing to problems with control in Afghanistan. There is a substantial amount of literature attributing terrorism and the continuation of the Taliban insurgency to some combination of these factors. Although it is impossible to associate or attribute every detail of operations and contested districts using these factors, they are inherently connected to the space and place of the country. The factors provide context for analysis and discussion of any results and recommendations made in this study.

2.3.1 Cultural

The tribal composition of Afghanistan can be interpreted as a factor influencing the struggle for control of the region. Tribalism is one of Afghanistan’s primary methods
of organization (Johnson and Mason 77). The distribution of tribes in the country is a
direct result of ethno-linguistic ties, dating back centuries. One ethnic group may be
divided into many major tribes, which can then be subdivided into confederations.
Johnson and Mason’s 2007 work attributes some elements of the rise of the neo-Taliban
insurgency to the tribal systems.

The authors note that the neo-Taliban insurgency’s major area of influence
includes land inhabited primarily by Pashtuns from the Ghilzai confederation, and the
Kakar tribe from the Gurhjusht confederation. Taliban leadership has historically been
primarily from the Hotaki Ghilzai tribe (Johnson and Mason 2007). Johnson and Mason
suggest that this tribal composition has influenced the direction and priorities of the
Taliban insurgency since the 2006 resurgence. Rather than driving towards Kabul in the
Northeast, and attempting to seize power from the newly established Karzai government,
the Taliban instead focused efforts on dominating areas occupied by the Durrani tribes in
the Southern part of the country, specifically the Kandahar and Helmand areas. The
Durrani tribes are hated by the Hotaki tribes (Johnson and Mason 2007). Johnson and
Mason cite this rationale as clear evidence that the movements of the Taliban and the
insurgency are influenced by factors beyond a desire for power alone (Johnson and
Mason 2007).

2.3.2 Physical

Several authors attribute the rise of the insurgency and continued difficulties in
Afghanistan to physical aspects of the country, particularly in the Taliban safe havens
along the Afghanistan/Pakistan border. Johnson and Mason claim that “insurgency in
Afghanistan has always sprung from the hills . . . and the Taliban is no exception.”(Johnson and Mason 2007, 60) Following the initial defeat of the Taliban in 2001, the Hindu Kush and mountainous rural region along the country’s border with Pakistan became the group’s safe haven. This can be attributed to some of the same cultural influences discussed above, as well as the mountainous terrain. Difficult to traverse and poorly mapped prior to the U.S. invasion, the Kush is an ideal landscape for evasion and to regroup (Johnson and Mason 2007).

Guntarana and Nielsen argue that the center of gravity for terrorism in the region shifted to the mountainous border region following the initial defeat of the Taliban. The especially difficult, rugged mountainous terrain provided good cover. Guntarana and Nielsen also state that the wooded terrain made it difficult to obtain any useful overhead imagery of the area. This allowed the Taliban to reconstitute, regroup, recruit, and train, despite ISAF’s overwhelming technological superiority (Gunaratna and Nielsen 2008).

Guntarana and Nielsen reiterate the tribal and cultural appeal of the region as well; the border region is incredibly porous, and inhabited by the same Pashtun tribes found in Afghanistan, providing a familiar haven in another country. The rugged terrain of the Hindu Kush, its relative inaccessibility, and opportunity for cover, provided significant safe haven for the Taliban (Gunaratna and Nielsen 2008).

2.3.3 Political

Political factors also contribute to difficulties of controlling Afghanistan. A 2008 examination by Jones focuses on structural weakness of governance in Afghanistan following the overthrow of the Taliban regime. Effective state building did not occur.
The Afghan government proved unable to provide basic services to the population, and proved incapable of establishing law and order. Jones also assesses that there were not enough international forces or resources available to fill the void left in either category. This failure led to both a lack of confidence in the central government by the Afghan people and provided a significant opportunity for the Taliban (Jones 2008).

Jones terms Afghanistan, following the initial defeat of the Taliban and installation of the new government, as a “weak state”; it lacked adequate bureaucratic and institutional structures to ensure that it could function properly. Jones assesses that these weaknesses included a lack of trained civil servants, corruption, weak courts, and almost no social systems or services. In addition, the Afghan government was faced with a major challenge: attempting to unify a fragmented society with almost no sense of national identity (Jones 2008).

Jones further states that traditions of local and tribal governance, rather than central control, also created a reluctance to embrace any governance from the central state, particularly one which was unable to prove or provide any benefits to the country as a whole. Jones asserts that this mindset posed a challenge to the establishment of the new state from the start, as there was no clear indication to the tribal population that, as individuals of the state, they would be better off (Jones 2008).

The Jones study concludes that the new government was unable to overcome these weaknesses, and prove its use and benefits to the people. Assistance from the new government was primarily diverted to urban centers, leading to frustration, additional mistrust, and resentment from the rest of the population. Jones cites a 2005 World Bank
Study as a good example of this failure and the increasing disenfranchisement of the populace. The World Bank Study, as Jones notes, indicated that only 6% of the population had access to power from the country’s electrical grid in 2004, three years after the ousting of the Taliban. Jones cites additional mistrust stemming from the national lack of security. Afghan police forces were poorly trained and corrupt, and the improvement of the police force was not a priority in the initial establishment of the state. With limited and ineffective training, police corruption remained a major problem. The resulting gaps in service and security left a void that ISAF alone was unable to fill. The assistance force was spread too thin to address each area where the central government continued to fail (Jones 2008).

The line of reasoning that follows is simple: the Afghan government was unable to provide, and failed to provide, essential services and security. This contributed to distrust and lack of confidence in the government by Afghanis, and provided a target of opportunity for the Taliban, especially in the rural areas of the country.

2.3.4 Terrorist Tactics

The Taliban have capitalized and continue to capitalize on the physical, cultural, and political factors identified above, and the group has adopted tactics, techniques, procedures that prey on gaps that still exist in the Afghan state. Giustozzi’s *Koran, Kalashnikov, and Laptop* specifically addresses how the Taliban exploited and manipulated these problems to their advantage.

Giustozzi states that one of the core tenets in the insurgent strategy is the focus on the rural regions, and obtaining rural support. The initial focus of the Taliban was
obtaining support of the rural Pashtuns in order to regain a foothold in country. Focus on other more removed villages in the country followed. Gizustozzi assesses that these areas, primarily close to the border with Pakistan, were some of the first to fall under control of the insurgency. These areas are also those where the government has displayed the most weakness and the greatest inability to provide services. There, Gizustozzi writes, the Taliban has been able to capitalize on mistrust and mistreatment from the government, and it has been able to offer services to bridge the gap, specifically by offering protection and security. Some administrative structures, including a judiciary system, have also been established by the Taliban in these areas. Gizustozzi states that this simple strategy—infiltrating the exterior of the country—is one of the strongest causes of the insurgency’s success (Giustozzi 2008).

Giustozzi also reviews how intimidation has been used by the Taliban to obtain control of people and areas. As the insurgency has pushed its way back into the country, the group has attempted to root out communities and leaders that support the central government. The author addresses how those found to be “pro-Kabul” or “collaborationists” have been driven out, or coerced, often through violent means. “Night Letters” are also often used to threaten consequences should specific individuals or villages be found to have close ties to the official state. Giustozzi asserts that the use of fear has been an effective tactic for the Taliban (Giustozzi 2008).

These carrot and stick methods have had significant impact on the development of the insurgency, and the efforts of the Taliban to regain control in Afghanistan. Weaknesses of the central state helped the Taliban gain ground across the country. By
providing basic administrative services, and by using fear, the Taliban has been able to establish a foothold for an effective insurgency in the country. Because an objective of this study is to identify areas to prioritize strategic training and advisory efforts to improve ANSDF structures, understanding how the Taliban has previously exploited institutional weaknesses is critical.

2.4 Building Law Enforcement Capacity and Capability

As mentioned in section 2.2, coalition troops have been providing support in both combat roles and state-building roles. Since the beginning of US and NATO involvement in Afghanistan, there has been recognition that state building and establishment of effective governance is critical. One of the major roles of the coalition forces in the country is to support the building of an improved state. Particular attention and funding has been devoted to improving national and local police forces. Establishing security and the rule of law is key to successful governance. Although progress has been made since 2002, substantial effort is still needed to institute mature law enforcement in Afghanistan.

Several reviews by the Department of Defense and non-governmental organizations assess the Afghan National Security and Defense Forces, highlight their importance to the future success of the Afghan state, and provide updates on the current status of the ANSDF’s effectiveness. A December 2015 report by the Department of Defense (DoD) *Enhancing Security and Stability in Afghanistan* addresses the overall progress of Afghan police forces. The report focuses on the growth of the Afghan National Police in force strength, logistics, and supporting ministerial structures. Most of the issues are at the ministerial level, and the report identifies how structural and
organizational improvements may have a positive impact at the operational, local level. The report notes that 70% of Afghans are confident that ANP can provide local security. The report also mentions, in passing, how adherence to the rule of law and accountability remain important to the NATO advisory role to the ANP. (Defense 2015)

A review of the ANP by Michelle Hughes of the US Institute for Peace approaches the current status of law enforcement in the country differently. While Hughes acknowledges the major improvements made by the ANP and Afghan law enforcement, she highlights a remaining weakness not mentioned in the DoD report; the country lacks a plan to transition its police force from a counterinsurgency group to a civilian law enforcement organization. The focus is still very much on counterinsurgency and security efforts, rather than rule of law. Hughes cites the separate paths of development of the police and the judicial system, and she notes that much of the police force sees the two systems as separate and distinct. Hughes states that in order to have long term success as an institution, the link between the policing and governance must be clarified and strengthened. Development of these coequal structures will, in the long term, influence and mature the ANP to a true law enforcement organization, capable of conducting policing-generated investigations from initiation to adjudication. (Hughes 2014)

2.5 Terrorist Kidnapping

Kidnapping by terrorist groups has long been a global phenomenon (Forest 2012a). It is one of the many tools used by terrorists and insurgents to attempt political change and incite terror. The global geographic distribution of kidnappings by terrorist
groups has shifted in recent years from South and Central America to the Middle East and South Asia (Forest 2012b). Islamic terror groups have emerged as chief culprits worldwide in terror in general and kidnappings in particular.

Afghanistan has one of the highest percentages of kidnappings globally (Forest 2012a). Of the events captured in the GTD from 2001-2014, Afghanistan accounts for 12% of all terrorist kidnapping events, the third highest total worldwide. Locals are the primary targets in kidnapping events, although NGOs, coalition forces, and Westerners remain attractive options (Shay 2007). For terrorists, kidnapping has become an attack method of choice.

Terrorist kidnapping, in this study, is defined as an act in which groups take control of hostages, move the hostages, and hold them in another location. In doing so, the groups attempt to achieve a political objective through concessions or through the disruption of normal operations. This definition is driven by the event data captured in the Global Terrorism database, and the inclusion criteria used therein.

2.5.1 Global Trends and Kidnapping in Afghanistan Currently

Kidnapping has been a tactic used by terrorist groups for decades (Forest 2012b). In recent years, additional international attention has been drawn to the issue (Yun 2007). A 2012 global examination of terrorist kidnapping trends by Forest reveals that kidnappings by terrorist groups make up a small proportion of terrorist attacks worldwide. Other attack types, including bombings and shootings are more prevalent. Forest also notes an increase in the number of terrorist attacks in the last several decades. He notes that the highest concentration of kidnappings has recently shifted from Latin
America to the Middle East and South Asia. Marxist and Leftist organizations are no longer the chief perpetrators of terrorist kidnappings; instead, Muslim extremist groups are now the major culprits. Forest states: “The epicenter of terrorism has shifted from Latin America to South Asia, so too has the epicenter of terrorist-related kidnappings” (Forest 2012, 139).

A 2009 study examination of crime and insurgency in Iraq by Williams attributes this shift to disorder due to the extended conflict in the region, and a weak central government. Williams states:

Although there is a long tradition of kidnapping in Iraq and elsewhere in the Middle East, the phenomenon expanded enormously amid the chaos and disorder following the U.S. invasion in March 2003. The lack of a legitimate central government; the weakness, corruption, and sectarian infiltration of the police; the general sense of lawlessness; the spread of anomie; and ruthless opportunism, as well as the availability of a large and highly vulnerable target population or victim pool, contributed to the massive upsurge of kidnappings from mid-2003 onwards. (Williams 2009, 106). This statement reflects the conditions in Afghanistan addressed in section 2.3. The governance problems experienced in the country, and state of lawlessness can be directly attributed to the increased potential for kidnapping.

A 2004 study by Voss on negotiations and ransoms in terrorist kidnapping further elaborates on this idea. Voss notes the difficulty in preventing and addressing kidnappings in areas where law enforcement and prosecution are impossible. There, kidnapping for ransom can flourish. He analogizes kidnapping by terrorist groups to piracy in the 1700s; it is a plague, a weapon of influence, and a source of funding (Voss 2004).
This rationale translates well to understanding kidnapping in Afghanistan. The lawlessness of the rural and tribal areas, and the struggles faced by the fledgling central government following the fall of the Taliban match the chaos described by Williams and Voss. This provides additional evidence for prioritizing areas for additional law enforcement education and instruction in order to potentially disrupt and resolve kidnapping plots conducted in the country.

2.5.2 Terrorist Kidnapping Motivations

Why do terrorist groups kidnap? The review conducted by Forest in 2012 addressed trends and motivations in this regard. Globally, motivations fall into two major categories: political and financial (Forest 2012b). Other objectives may include vengeance, protection of group secrets, or to instill fear in local population. Fear as a method to keep the local populace in check was, and remains, especially popular with Al Qaeda in Iraq and the Taliban in Afghanistan (Forest 2012a). Forest asserts that terrorist groups appear to be more interested in using kidnapping as a policy tool than for profit, as only a low proportion of terrorist kidnapping events are associated with a ransom worldwide (Forest 2012a). Kidnapping as a form of coercion, he states, appears to be more apparent, and is used to give what otherwise may be small, obscure groups a platform to pressure governments and advocate for the terrorists’ cause. Forest uses the Munich 1972 Olympics as an early example of this coercion. There, Israeli athletes were taken hostage by a Palestinian terrorist group known as Black September, who demanded the release of Palestinians in Israel as well as safe passage home. The incident ended in tragedy; all the athletes were murdered. For the first time, the modern Olympics were
suspended. This episode exemplifies the pressure that can be asserted by terrorists, and
the international attention that they can demand (Forest 2012a).

In his study, Williams similarly states that kidnappings can incite fear, highlight
the instability and vulnerability of a government, and affirm the perceived importance of
terrorist groups. A terrorist group’s ability to level the psychological playing field
between can be summarized with the statement “I kidnap, therefore I exist and you need
to acknowledge me” (Williams 2009, 111).

The 2007 kidnapping of twenty three Korean missionaries by Taliban insurgents
highlights kidnapping for political motivations. The group was able to successfully force
the Korean government to withdraw all Korean troops, remove all Korean NGO workers,
and institute a ban on Christian missionaries. The Taliban was able to extract these
concessions even though it had already killed hostages (Kim 2008).

Financially motivated kidnappings have long been a source of revenue for
terrorist groups (Forest 2012a). Globally, groups have made millions, and kidnappings
serve as a central source of profit. Terrorist groups in the Middle East and North Africa
have modeled some operations off the success of kidnap–for-ransom schemes in Latin
America. They have effectively used kidnapping as a source of income (especially the
kidnapping of Westerners). Upon evaluation, Forest assesses that only a small number of
kidnappings have a are associated with a public ransom. He attributes this to the political
nature of negotiations, and the reluctance of governments and groups to admit
concessions made to terrorists (Forest 2012a).
Kidnapping by terrorists presents an opportunity for both political and financial gain, as in the case of the Korean hostages. Kidnappings garner attention and can be attempts to gain equal footing on the international stage and project an image of power and control. There is also an opportunity to coerce and ransom money from individual victims and families.

### 2.5.3 Previous Geospatial Intelligence Work Evaluating Kidnapping

Spatial statistics and geospatial intelligence methods have been used to analyze kidnapping previously. A 2014 study conducted by Larsen used global and local Moran’s I to test kidnapping events in Nigeria for spatial association (Larsen 2014). The study employed data from the Armed Conflict and Location Event Data (ACLED) program, another open source database derived from media and research publications. ArcGIS was used to run Global Moran’s I and Local Moran’s I to determine whether spatial patterns existed in the data, and evaluate where clustering occurred. The study also examined the ACLED data for patterns in three key kidnapping characteristics in the country: whether a ransom was associated with the events, whether the victims were foreigners, and whether fatalities occurred. Using these tools, Larsen was able to successfully identify kidnapping clusters in Southern Nigeria, which she attributes to the prominent multinational oil industry in the region (Larsen 2014).

Although this study examines a different country and region of the world, the Larsen study highlights a successful use of geographic methods in the analysis of kidnapping event clusters.
CHAPTER THREE: DATA AND METHODOLOGY

3.1 Chapter Overview

This chapter discusses the data and methods used in this study. The strengths and limitations of the primary data set used, the START Global Terrorism Database, are discussed in depth. Preprocessing steps are outlined. The spatial statistics used in this study are then addressed. An overview of Global Moran’s I, Getis Ord Gi*, and Anselin Local Moran’s I is provided, along with their respective applications in the analysis of kidnapping data.

3.2 Data Overview

This study uses data from the University of Maryland’s (UMD) Global Terrorism Database, which houses information on terrorist events and incidents around the world from 1970-2014. The GTD is compiled from publicly available, unclassified materials, including media reporting, news archives, legal documents, and prior data sets. Prior to 2011, the data currently housed in the GTD was collected by the Center for Terrorism and Intelligence Studies (CEITS), Pinkerton Global Intelligence Service (PGIS), and the Institute for the Study of Violent Groups (ISVG). In the current 2015 edition of the GTD, all data from these collection institutions has been synthesized and adjusted to match the definitions and data structure used by START. This collection included retroactively coding some of the incidents recorded by the external institutions. All data from 2011
onward is collected and coded by START personnel. More than 100 field codes provide information on event characteristics, including locations, dates, attacks types, and responsible group(s) (START 2015).

The database includes a total of 552 kidnapping incidents in Afghanistan from 2001-2014, and provides details on the target, outcome, and whether there was an associated ransom for each event. The GTD is one of the largest and most comprehensive open source databases available. It provides detailed information on terrorist perpetrated kidnapping events in Afghanistan from 2001-2014, including location information. This makes the database ideal for the statistical and categorical analysis of this study.

This study also uses the Afghanistan Administrative Boundaries shapefile, obtained from the Princeton Empirical Studies of Conflict Center. The file can be downloaded online. (https://esoc.princeton.edu/files/administrative-boundaries-398-districts.) This file is used to aggregate kidnapping events to the district administrative level and provide the boundaries to calculate the incident per capita values.

Landscan global population databases, developed by Oak Ridge National Laboratory is used to calculate the population of each district (Bright, Coleman et al. 2012). The Landscan population distribution data is one of the most comprehensive population databases with global coverage; this data is used in lieu of traditional census data due to the inconsistencies and gaps in Afghanistan’s census records. Landscan provides a better population estimate at the district level for the 2000s than Afghan records.
3.2.1 Variables and Attributes of Interest

The GTD provides detailed information on each event captured in the database. This information includes country, event type, target type, outcome information, and whether a ransom was associated with the event. Location information is also captured, and the latitude and longitude of the event is included at the city level where possible. Where no city is listed, the event is coded to the province or state where it occurred (START 2015).

Event type, location, and incident date are the most critical attributes in this study. Kidnapping events in Afghanistan are aggregated for two-year periods based the administrative district in which they occur. This aggregation is used to count the number of incidents per district, which is used in the incident count analysis. This incident count data is also used to calculate the number of events per 100,000 people per administrative district using the event count and Landscan population data (hereafter referred to as the per capita statistic). This per capita statistic is also used to evaluate the spatial distribution of kidnapping events in Afghanistan for the study period. Both the count data and per capita statistic are used in analysis.
3.2.2 Data Limitations

The GTD is widely used in studies of terrorism (Forest 2012a). There are however some weaknesses with the database that should be acknowledged. The database relies on open source reporting, including news sources, books, and legal articles. This reporting may be imprecise, as information provided via these outlets may lack details or be produced by individuals without appropriate training or background knowledge. The GTD also uses automated translation and filtering to collect data from news articles and reports in languages other than English (START 2015). Automated translation is an imperfect science and can also introduce error. Natural Language Processing (NLP) and machine learning techniques are used to further refine the results, and to remove duplicate entries included in the GTD along with manual review (START 2015). Still, incidents may be included or excluded from the database improperly.

In terms of the data on kidnapping, there are additional weaknesses. Kidnapping remains one of the most underreported crimes worldwide. It is estimated that worldwide 80% of kidnap-for-ransom incidents are not reported (Forest 2012a). Afghanistan should also be considered a developing state. Data collection and reporting is substandard and inconsistent across that country compared to other countries regionally and globally. This introduces error by omission in this study. Despite these challenges, analysis of the limited information available may provide insight that can be used in strategic positioning of ANP and ANSDF outreach.

The location information captured in the GTD is also limited. There are several levels of geocoding specificity included in the database, from the country level down to
the specific latitude and longitude of an event. A majority of the kidnapping events in Afghanistan included in the GTD are geocoded to the district level. This level of accuracy restricts analysis to those boundaries, or a more coarse aggregation scheme, which is why the district polygons are used as the method of aggregation in this study. This level of spatial accuracy does impact the results. Incident data at a better spatial resolution (i.e. the city, town, or incident location) would provide more impactful analysis. Section 5.4.1 includes additional detail on this potential improvement.

Even with these biases and weaknesses, the GTD remains one of the largest and widely used open source databases available in the study of terrorism. No other unclassified dataset was identified that included Afghan kidnapping events and critical location information at the same level of detail as the GTD.

3.2.3 Data Acquisition

Data selected for inclusion in this study was extracted from the GTD based on the event code criteria. To obtain this, the entire GTD was downloaded in MS Excel format from UMD START (http://www.start.umd.edu/gtd/contact/). The June 2015 version was used, which includes all GTD incidents from 1970 to 2014. There are a total number of 141,966 recorded incidents worldwide.

The relevant Landscan data was downloaded via the EastView Geospatial Landscan Portal, with the licensing provided by George Mason University (http://www.eastview.com/online/landscan). The Afghanistan data from 2005-2014 was downloaded for each year in zipflie format.
3.3 Pre Processing

3.3.1 In MS Excel

First, using MS Excel, all Afghanistan incidents were selected. The data was sorted to display only events from 2001-2014 with the “Attack Type” code as “Hostage Taking (Kidnapping).” A manual review of the event description column, which provides a summary of the attack, ensured that were no events included that were improperly coded, or duplicates.

Events without the necessary level of location data were also removed in pre-processing. This included events with no location data associated, or with a level of geocoding specificity that was inappropriate for this study. This includes all events in the GTD with a “Geocoding Specificity” rating of four or five. This variable identifies the resolution of the latitude and longitude. As this study is focused on the district level, anything at a lower geocoding resolution (i.e., at the provincial level, country level) were not included. Only 67 events total from 2005-2014 do not meet this criteria. The provincial information available for the events removed showed a relatively even distribution across Afghanistan; lack of specificity in reporting was not limited to a single geographic area, but occurred throughout the country. After these events were removed, a total of 478 events remained for 2005-2014.

3.3.2 Importing Data

The incident data was then imported into ArcGIS using the XY data import feature. The XY data imported from excel was exported from ArcGIS to a shapefile to facilitate the statistical analysis, as XY information alone is not compatible with the
spatial statistics toolbox found in ArcGIS. The Landscan population data was also imported into ArcGIS. Each of the .lyr population raster files were added to the workspace.

3.3.3 Projecting Data

The default coordinate system for all XY points imported from excel sheets is World Geodetic System (WGS) 1984. This coordinate system had to be changed in order to allow for additional, accurate spatial analysis. The WGS 1984 projection is not compatible for the spatial statistics analyses that were conducted. Data was projected using the ArcGIS re-project tool into the equidistant conic projection. This is a preferred projection for spatial statistics and analysis it maintains the integrity of distance between points and features along meridians and two selected standard parallels. This is useful in countries elongated from East to West, such as Afghanistan.

The standard parallels selected were 30.92 and 37.00. A central meridian of 66.23 and latitude of origin of 34 were used. Having the standard parallels inside of the region of interest helps to minimize distortion throughout the entire region of interest. In this case, it ensures that the distance calculations made in the analysis of kidnapping at the district level will be consistent.

3.3.4 Defining the Study Boundaries

The Afghanistan districts shapefile was clipped to eliminate all districts that did not experience any kidnapping events for the entire study period (2005-2014). This was done in order to limit the geographic area of the study and improve the results of the
spatial statistical analysis, by removing additional, empty areas with consistent zero values. This is a best practice in cluster analysis (Esri 2015d). This also limits the total area of study and any clustering results to districts that have been impacted by kidnapping in the 10-year timeframe examined in this analysis.

### 3.3.5 Aggregating Event Data

The kidnapping point data was then aggregated into two-year groupings: 2005-2006, 2007-2008, 2009-2010, 2011-2012, and 2013-2014. This was done in order to conduct a basic temporal analysis, and the grouping allows the event data to be examined across the entire frame of study to facilitate the question posed in the introduction of this thesis: Do patterns exist and have they changed over time? Similar aggregation schemes have been used in analysis of terrorism and insurgency (O'Loughlin, Witmer et al. 2010a). Using 2005-2014 also restricts the analysis to kidnapping events after the initial establishment of the Afghan government (2003), and the beginnings of the Taliban insurgency offensive (2005-2006), as referenced in chapter two of this thesis. Table 1 summarizes the total number of kidnapping incidents per aggregate period, and estimated number of victims per period. Victim estimates are derived from the GTD’s “nkidhost” event attribute, which includes the number of victims per kidnapping incident. Although number of victims per incident is not a focus of this thesis, the table helps to exemplify the scope of kidnapping incidents in the country; a majority of events involve multiple victims.
Table 1 Number of Kidnapping Incidents and Victims per Period

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Kidnapping Incidents</th>
<th>Total Estimated Number of Kidnapping Victims</th>
</tr>
</thead>
<tbody>
<tr>
<td>05-06</td>
<td>19</td>
<td>61</td>
</tr>
<tr>
<td>07-08</td>
<td>64</td>
<td>344</td>
</tr>
<tr>
<td>09-10</td>
<td>111</td>
<td>490</td>
</tr>
<tr>
<td>11-12</td>
<td>92</td>
<td>492</td>
</tr>
<tr>
<td>13-14</td>
<td>191</td>
<td>925</td>
</tr>
</tbody>
</table>

Each of these 5 subsets of point data were then spatially joined with the clipped district boundaries, with the events aggregated by total count of kidnapping events per district. This figure was also used to calculate the per capita values for each district. Both this number and the per capita statistic are used in the statistical analysis of kidnapping events.

The aggregation scheme selected is, as with all aggregation schemes, a limitation to this analysis overall as it imposes artificial temporal and physical bounds on the data. The district level polygon scheme was chosen for use in this study due to the limited level of geocoding specificity in the GTD data, as addressed in section 3.2.2.

3.3.6 Calculation of Population per District

Following the aggregation of kidnapping events by year and by district, the population per district was then calculated for each of the subsets. Using the Landscan population data and the zonal statistics as table tool in ArcGIS, the sum of all raster tiles was computed for each of the two years in the data subset to obtain a population estimate for each year. The tables produced by the zonal statistics tool were then joined to each of
the two year aggregates. An additional field was created and field math was used to
compute the average population per district for that two year period.

3.3.7 Calculation of the Per Capita Values

The final step in pre-processing was to calculate the event per capita values. This
is done in ArcGIS with an additional field for each of the data aggregates. Field math was
then used to divide the count of events per district by the average district population, and
multiply that number by 100,000. This created a per capita statistic addressing the
number of events per 100,000 people. This statistic is used in the core methodology and
computation of spatial statistics that follows. For the sake of transparency, replication,
and potential future research, the per capita feature class and raw point data are available
online for download¹.

3.4 Methodology

Global Moran’s I and Local Indicators of Spatial Association (LISA) statistics
(specifically Getis-Ord Gi* and Anselin Local Moran’s I) are used to determine the level
of spatial association between events, determine where any clustering occurs, and
determine where outliers occur respectively. These statistics are generated using ArcGIS.
Corresponding cartographic products are also produced in ArcGIS to display statistical
outcomes. Results are analyzed to determine what clustering and patterns, if any, occur
and where.

¹ The feature classes used in this analysis can be downloaded at
geo.gmu.edu/archive/aregan3/ARegan_Kidnapping_AfghanistanFiles2016.zip
As referenced in section 2.1.3 Evaluating terrorism using cluster analysis, understanding spatial clustering of terrorist events can contribute to the overall understanding of terrorism. Cluster analysis can provide empirical evidence consistently, can identify areas where terrorist efforts are focused, and can provide another method to verify social-spatial information to refine policy and plans. These methods are applied to answer the scientific questions identified in the introduction of this study.

3.4.1 Incremental Spatial Autocorrelation Testing: Global Moran’s I

Moran’s I is a global measure of spatial autocorrelation that considers locations and feature values simultaneously (Esri 2015c). This spatial statistic can be applied to determine whether data is clustered, random, or dispersed (Esri 2015c). Global Moran’s I is one of the most commonly used measures of spatial distribution (O’Loughlin 2002). The global measure examines the data set as a whole, and does not provide any detail on the exact locations of the spatially significant segments of the data (Braithwaite and Li 2007).

Moran’s I output includes a z-score and p-value. If the output Moran’s index is positive, combined with statistically significant p-value and z-score, the data is considered clustered. A negative Moran’s index with the same significant z-score and p-value, data is dispersed (Esri 2015c).

Global Moran’s I’s can be used to evaluate clustering across a series of distances, to determine the distance value where clustering peaks. This “brute force” method can be used to evaluate the clustering of data over multiple distances, sometimes in order to determine an appropriate scale of analysis and conceptualization of distance. Because
clustering and the distribution of events over a landscape are really the result of underlying spatial-social processes, incremental spatial autocorrelation and peak clustering distances obtained can be informative and appropriate for study. Incremental spatial autocorrelation will be used investigate potential distances for the conceptualization of the neighborhood used in this study. Although an appropriate distance that specifically addresses kidnapping was not identified in the literature review conducted, the analysis by Medina and Hepner on social spatial connections in Islamist terrorist networks addressed in the literature review is used to help bound the overall conceptualization of spatial relationships in the incremental spatial autocorrelation testing. As discussed, their study revealed that a majority of social interactions between elements of terrorist networks occur at under 1,000 km, and one third of those under 100 km (Medina and Hepner 2011). 150 km is therefore considered as the maximum distance examined by incremental spatial autocorrelation. This is intended to limit the space examined to localized, operationally coordinated elements of terrorist networks.

The math behind the calculation of Moran’s I is included in Figure 3.
The Moran’s I statistic for spatial autocorrelation is given as:

\[
I = \frac{n}{S_0} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j
\]

(1)

where \( z_i \) is the deviation of an attribute for feature \( i \) from its mean \((x_i - \bar{X})\), \( w_{i,j} \) is the spatial weight between feature \( i \) and \( j \), \( n \) is equal to the total number of features, and \( S_0 \) is the aggregate of all the spatial weights:

\[
S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}
\]

(2)

The z-score for the statistic is computed as:

\[
z_I = \frac{I - E[I]}{\sqrt{V[I]}}
\]

(3)

where:

\[
E[I] = -1/(n - 1)
\]

(4)

\[
V[I] = E[I^2] - E[I]^2
\]

(5)

Figure 3 The calculation for Moran’s I (Esri 2015c)

The mean and variance for the attribute that is being examined are calculated first. Then, the mean is subtracted from each feature value to create a deviation from the mean. Those values are then multiplied together for neighboring features to form a “cross-product.” When one value is smaller than the mean, and the other greater than the mean, “the cross-product will be negative.” When neighboring feature values are either “both larger than the mean or both smaller than the mean,” the cross-product is positive. The
larger the standard deviation from the mean, the larger the resulting cross-product will be (Esri 2015c).

After the index value is calculated, the expected index value is calculated. The two values are then compared. ArcGIS uses the total number of features and variance for all data to compute the z-score and the p-score values to indicate whether the difference is statistically significant (Esri 2015c).

The interpretation of Global Moran’s I is reliant on p-value and z-score returned. If the p-value is statistically significant, the null hypothesis can be rejected. That is, with a significantly significant p-value, the data can be considered more clustered than random. The z-score is then used to determine whether the data is more clustered or dispersed compared to random distribution. Positive z-scores indicate clustered data. Negative z-scores indicate dispersed data. The table below from Esri details possible interpretations of the p score and z-score (Esri 2015c).
### Table 2 Interpreting Moran's I Results (Esri 2015c)

<table>
<thead>
<tr>
<th>p-value Status</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not statistically</td>
<td>You cannot reject the null hypothesis. It is quite possible that the spatial distribution of feature values is the result of random spatial processes. The observed spatial pattern of feature values could very well be one of many, many possible versions of complete spatial randomness (CSR).</td>
</tr>
<tr>
<td>Significant</td>
<td>You may reject the null hypothesis. The spatial distribution of high values and/or low values in the dataset is more spatially clustered than would be expected if underlying spatial processes were random.</td>
</tr>
<tr>
<td>Significant, Z-score</td>
<td>You may reject the null hypothesis. The spatial distribution of high values and low values in the dataset is more spatially dispersed than would be expected if underlying spatial processes were random. A dispersed spatial pattern often reflects some type of competitive process—a feature with a high value repels other features with high values; similarly, a feature with a low value repels other features with low values.</td>
</tr>
</tbody>
</table>

The calculation of Moran’s I can be iterated in ArcGIS using the Incremental Spatial Autocorrelation (Global Moran’s I) tool in ArcGIS. This is found in ArcToolbox under spatial statistics. Given a shapefile of features and associated attributes, the tool repeatedly calculates global Moran’s I Index value, expected index value, Z score, and P score across a series of distances defined by the user. These results are output to an HTML file with a summary of the results, including a graph of the resulting Z scores by distance (Esri 2015e). The results at each distance can be compared to identify distances where clustering peaks.

In this study, Moran’s I is calculated for each data set 30 times. The calculation of Moran’s I is iterated from 84144m to 150000m (150km). 84144m was selected as the starting distance because it is the distance at which all features have a minimum of one
neighbor. 150km was selected as the maximum distance for exploration as it is slightly over the 100km threshold for social-spatial Islamic terror network connections as identified by Medina and Hepner and discussed in section 2.1.2 of this study. This limits the conceptualization of the neighborhood to localized elements of the terror network.

The re-projected Afghanistan shapefile with the joined kidnapping count and per capita data are used as the main feature input in this tool. Both count data and per capita data are analyzed. Euclidian distance is used as the distance method. Row standardization is applied in order to mitigate some of the aggregation scheme bias imposed by the polygon features. Esri recommends that this standardization be applied whenever polygons are used in analysis (Esri 2015e). The incremental spatial autocorrelation tool is run against both count and per capita data for each data subset.

Statistical output (Moran’s Index, Expected Index, Variance, P-value, and Z-score) is calculated for each aggregate period for both per capita and count data. The results are compared across each subset. A distance that is a statistically significant peak across several data sets is selected. That distance is applied in the LISA calculations to conceptualize the spatial relationships and the neighborhood in this study.
3.4.2 Hot Spot Analysis: Getis Ord Gi*

Getis-Ord Gi* is a Local Indicator of Spatial Autocorrelation (LISA) statistic (O'Loughlin 2002). LISA statistics should be used to identify the location of spatial clusters, hotspots, and cold spots over global statistics (see Anselin 1995, Braithwaite 2007, O’Loughlin 2002, Seibneck et. Al). Getis-Ord Gi* is used to answer the following scientific questions posed in the introduction:

- Have kidnapping events clustered in space over time?
- Are there any clusters of kidnapping events given the population?
- Have the districts that are included in any clusters changed over time? Do patterns or trends exist?

As addressed in section 2.2.4, Getis-Ord Gi* has been widely applied in the detection of local clusters. This statistic examines each event or feature within the context of its neighbors, and calculates z-scores and p-values for each. The measure provides an indication of whether values are clustered around a single observation (i) (O'Loughlin 2002).

The calculation for Getis-Ord Gi* is captured in Figure 4.
The Getis-Ord local statistic is given as:

$$G^*_i = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{\sqrt{n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2}}$$

(1)

where $x_j$ is the attribute value for feature $j$, $w_{i,j}$ is the spatial weight between feature $i$ and $j$, $n$ is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

(2)

$$S = \sqrt{n \sum_{j=1}^{n} \frac{x_j^2}{n} - (\bar{X})^2}$$

(3)

The $G^*_i$ statistic is a z-score so no further calculations are required.

Figure 4 The mathematic formula for Getis-Ord Gi* (Esri 2015d)

It is also important to note the significance of the False Discovery Rate (FDR) correction method here. This is an optional parameter that can be applied in the computation of Getis-Ord Gi* to reduce p-value thresholds. This helps to account for spatial dependency (i.e., features near to each other tend to be similar). This similarity can inflate spatial significance. The FDR correction estimates the number of false positives per confidence level, and adjusts the p-value accordingly. Statistically significant p-values are then ranked, and the largest (weakest) false positives are removed from the data output. (Esri 2015d)
ArcGIS gives the option to ignore this dependency, but this introduces some additional error. Including the FDR correction as a part of methodology improves output and results as opposed to approaching data as if all events occur in isolation (Esri 2015d). FDR correction is included in this study in order to help mitigate both false positives and spatial dependencies.

The calculation of Getis-Ord Gi* results in a Z-score for each feature. To be considered a statistically significant hot spot, the feature must have a high value, and be surrounded by other high value features. The sum for the feature and all of its neighbors is compared against the sum of all features. When local sums are different than the expected local sum, and when that cannot be due to random chance, the output Z-score value is considered statistically significant. (Esri 2015d)

For positive scores, the larger the value, the clustering of high values is more intense and the area is considered a hot spot. For negative scores, the smaller the score, the clustering of low values is more intense and the area is considered a cold spot (Esri 2015d).

Getis-Ord Gi* can be computed in ArcGIS using the Hot Spot Analysis tool. This tool outputs a Z score, p-value, and a confidence level for each input feature. Hot Spot Analysis is available in ArcToolbox under the spatial analyst toolbox (Esri 2015d).

The Hot Spot analysis tool is run twice in ArcGIS for each data subset; once using the count value as the input field, and again using the per capita value. This study uses the fixed distance band method, with the distance calculated using incremental spatial autocorrelation for the overall conceptualization of spatial relationships. FDR correction
is selected to reduce multiple testing errors as discussed in 3.5.3. Euclidian distance is used.

ArcGIS computes Getis-Ord Gi* for each feature and correct statistical results using FDR correction. Data output includes z-scores, p-values, and Gi bin results (which indicate confidence level) for each event (Esri 2015d).

All results at a 90% confidence level or higher are included in hotspots due to the exploratory nature of this topic. Very little literature exists on kidnapping in Afghanistan, and no literature cited in this thesis specifically addressed distribution of kidnapping in the country. A more liberal confidence interval is included as a result (Hurlbert and Lombardi 2009).

The Hot Spot Analysis tool outputs a new layer in ArcGIS with the Gi* index, the Z score, and the P value. Results for each aggregated data period are mapped, and the output values are included in a table. This is used to evaluate patterns and trends in hotspots over time.

**3.4.3 Cluster and Outlier Analysis: Anselin Local Moran’s I**

Anselin Local Moran’s I is another LISA statistic. Like Getis Ord Gi*, the statistic is used to identify clusters of high or low values. Local Moran’s I also identifies outliers (areas where high values may be surrounded by low values, and vice versa). This statistic is used in this study to specifically answer the following scientific question:

- Are there any districts that are outliers?

The calculation for Anselin Local Moran’s I is included in Figure 5
When the I value returned is positive, neighbor features have similar low or high measured values and the feature is located in a cluster. A negative I value means that the feature is surrounded by dissimilar values, and is either a high or low outlier. The P value must be statistically significant in both cases to be considered a cluster or an outlier (Esri 2015b)
Anselin Local Moran’s I can be calculated in ArcGIS using the Cluster and Outlier Analysis tool, which can be found in the spatial statistics toolbox. The tool calculates a Local Moran’s Index, Z-score, P-value, and cluster or outlier type ID for each feature in the input data set (Esri 2015b).

This tool is used to calculate Local Moran’s I attributes for each aggregated period, using both the count and the kidnapping per capita field as the input. Like in the Getis-Ord Gi* calculation, the tool uses the distance measure produced by the incremental spatial autocorrelation Global Moran’s I testing as the distance band. For conceptualization of distances, a fixed distance band is used. Both row standardization and FDR correction are applied. FDR correction is used for the same reasoning discussed in the Getis-Ord Gi* calculation. Row standardization is applied to correct some of the biases of the aggregation scheme, as discussed in 3.3.5. Euclidian distance is used as the distance method.

The cluster and outlier analysis tool outputs a new feature class with the Anselin Local Moran’s I attributes calculated for each feature (Esri 2015b). This layer is used to create a map of the results for each aggregate period for both the count analysis, and the incident per capita analysis.

It is anticipated that the results of this study will indicate some clustering and statistically significant hotspots of kidnapping events for both incident count, and the number of incidents per capita, due to the numerous socio-spatial phenomena that have impacted the war in Afghanistan, as detailed in chapter two of this thesis. This would allow the null hypothesis that events are randomly distributed to be rejected.
It is also likely that some districts will consistently be included in both the count and incident per capita analysis. Objectives of the terror networks and operations are driven by social-spatial connectivity, which supports the idea of regional clustering (Medina and Hepner 2011). It is likely that kidnapping operations have consistently focused on select districts of Afghanistan as a result.
CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Chapter Overview

This chapter presents the results obtained following the implementation of the methods addressed in chapter three. The results of incremental spatial autocorrelation testing are discussed, followed by the results of Getis Ord Gi* (Hot Spot Analysis) testing and Anselin Local Moran’s I (Cluster and Outlier Analysis) for each two-year-aggregate period. Following the review of the research results, an analysis of the outcomes is discussed. The discussion centers on the scientific questions and hypothesis identified in the introduction of this thesis, as well as identification of patterns and trends in the results.

4.2. Results

4.2.1 Global Moran’s I

Incremental spatial autocorrelation testing was conducted for each of the two-year aggregates to identify a distance band appropriate for analysis. As addressed in section 3.4, the distance window examined began with the distance at which districts had at least one feature, and capped at 150km. This distance window helped to facilitate identification of clusters that may be influenced by the same localized elements of Islamic terrorist networks.
Incremental spatial autocorrelation testing across each two year aggregate, for both the count and per capita statistic, indicated a statistically significant peak measure at 90729.6 m with a Z score greater than 2.58. The exception to this was the 2013-2014 dataset, and the 2009-2010 count data, in which the Z score was not statistically significant. The distance value of 90729.6 m was maintained in all calculations of Getis Ord Gi* and Anselin Local Moran’s I for each of the two-year aggregates.
4.2.2 2005-2006

The 2005-2006 subset included 19 kidnapping incidents total. This is the lowest number of incidents of any of the aggregate periods examined. Getis Ord Gi* and Anselin Local Moran’s I were used to analyze these events at the 90729.6 km distance measure identified using Global Moran’s I testing. These tests were run on both the raw count data, and the events per capita statistic.

The Hot Spot Analysis tool computed Getis Ord Gi* on each of the 185 districts included in the area of study. For the analysis of the count data, a total of 16 districts were identified as statistically significant hotspots (Ghorak, Ajristan, Nad Ali, Maywand, Qarabagh, Arghistan, Mizan, Atghar, Qalat, Daychopan, Gelan, Muqur, Ab Band, Shahjoy, Shinkay, and Naw Bahar). These 16 districts fall within just four of Afghanistan’s 34 provinces; Hillmand, Ghazni, Kandahar, and Zabul.

For analysis of the per capita data, only two districts were identified as hotspots, Registan and Shorabak, both located in the Southern end of Kandahar province. The clusters identified by the Getis Ord Gi* analyses are included in Figure 7.
Anselin Local Moran’s I was also used to analyze 2005-2006 events. The cluster and outlier analysis tool was run against the aggregated count and per capita data. A total of 13 districts were identified as High-High (HH) clusters (Nahri Sarraj, Lashkar Gah, Sangin, Miya Nishin, Mizan, Atghar, Qalat, Muqur, Andar, Ghazni, Qarabagh, Shahjoy, and Shinkay). Like the Hot Spot Analysis, these districts are from just four of Afghanistan’s provinces, Hillmand, Ghazni, Kandahar, and Zabul. Three districts were also identified as High- Low (HL) outliers in the count analysis; Kabul, Gurbuz, and Kandahar.
The per capita cluster and outlier analysis identifies only one district as being a HH cluster, Atghar, located in Zabul province (see Figure 8).

Combining the results of the Gi* and local Moran’s I analysis for both incident count and incident per capita statistics, the incident count hotspots detected are the result of local concentration of events to districts located in Zabul, Kandahar, and Ghazni.
provinces, with other neighboring districts having a relatively smaller number of events. Kabul, Gurbuz, and Atghar all similarly experience negative spatial autocorrelation, and are identified as HL outliers as those districts experience a higher number of kidnapping events, but are surrounded by districts with few or no kidnapping events.

Similarly, the incident per capita hotspots detected are due to high per capita rates localized to in and around Registan and Atghar. The results between the Gi* and local Moran’s calculation vary slightly due to how the two statistics approach the concept of neighborhoods differently; Gi* is inclusive of the district being analyzed in the calculation, where local Moran’s looks only at the values of the districts surrounding the location being analyzed, as noted in section 3.4.

Consideration should be given to how few incidents were included in this subset. The number of incidents may be low for several reasons. First, as identified in the literature review, the early 2000s were extremely difficult for Afghanistan. Governance and basic structures were in the process of being rebuilt and reestablished after the removal of the Taliban government. Because much of the GTD is derived from media reporting and other open source materials, it is possible that kidnapping was not a major topic during that period. Another reason may be that the Taliban insurgency did not completely emerge in Afghanistan until 2006. Less activity in 2005 could have impacted the total number of incidents for this period.

The clusters identified are all relatively close to the initial Taliban strongholds of early 2006. The Eastern and Southern districts of the country that are close to the border,
identified by several authors in the literature review as especially vulnerable in 2006, are included in clusters in this period (reference Figure 2).

4.2.3 2007-2008

The 2007-2008 data subset included a total of 64 incidents. As with the 2005-2006 data, both Getis Ord Gi* and Anselin Local Moran’s I were used to evaluate local clusters in the dataset.

For the count data, Getis Ord Gi* identified 23 districts as statistically significant hotspots (Ahmad Abad, Mata Khan, Gelan, Andar, Chaharikar, Surkhi Parsa, Surobi, Mohammad Agha, Charkh, Muqur, Dih Yak, Kabul, Musayi, Puli Alam, Baraki Barak, Ab Band, Ghazni, Qarabagh, Maydan Shahr, Jalrez, Nirkh, Chaki Wardad, and Saydabad). These districts fall within seven provinces (Paktya, Paktika, Ghazni, Parwan, Kabul, Logar, and Maydan Wardak).

When run against the incidents per capita statistic, only two districts are identified as hotspots, Anar Dara and Nili, located in Farah and Daykundi provinces, respectively. The results of the Gi* analysis are mapped for both count and per capita incidents in Figure 9.
Like the Getis Ord Gi* analysis, several districts were identified as hotspots in the Anselin Local Moran’s I analysis of count data (Mohammad Agha, Puli Alam, Charkh, Gelan, Dih Yak, Ghazni, Qarabagh, Kabul, Jalrez, Nirkh, Chaki Wardak, and Saydabad). These districts all fall within Logar, Ghazni, Kabul, or Maydan Wardak provinces. Hirat was identified as an HL outlier.

The per capita statistic evaluation identified several other districts as HH clusters. Anar Dara, Khaki Safed, Bala Buluk, Bakwa, Nili, Ghazni, and Nirkh were all identified as HH clusters. These districts all fall within the provinces of Farah, Daykundi, Ghazni,
or Maydan Wardak. No outliers were identified from the evaluation of per capita data (see Figure 10).

Combining the results of the $\text{Gi}^*$ and local Moran’s I analysis for the incident count indicates that the incident count hotspots detected are the result of a high number of events localized to the districts of Zabul, Ghanzi, and Kandahar, with other neighboring districts having a relatively smaller number of events. Hirat is the only district that experiences negative spatial autocorrelation, and is identified as an HL outlier. From 2007-2008 the district experiences a significantly higher number of kidnapping events than surrounding districts.

The incident per capita hotspots detected are due to high per capita rates in and around Anar Dara and Nili. No outliers were detected in the per capita analysis for this time period.

The shift towards the interior and Western portion of the country in hotspots, compared to the 2005-2006 analysis is noteworthy here. This, as addressed in the literature, supports the geographic spread of terrorism following the 2006 resurgence of the Taliban. There is a clear expansion to the north and west compared to both the incident count and per capita analysis of the 2005-2006 period. Some of the same districts are identified as statistically significant hotspots across the 2007-2008 and the 2005-2006 count analyses, meaning that there is some consistency in where kidnappings have been focused in this period. The per capita analysis however shows that, relative to population, there has been a significant shift from 2005-2006. Western and interior districts are statistically significant hotspots in the 2007-2008 analysis, as opposed to
2005-2006 where Southern districts only were experiencing unusually high focus of kidnappings given population.

![Figure 10 2007-2008 Cluster and Outlier Analysis Results](image)

4.2.4 2009-2010

The 2009-2010 subset included 111 incidents. Hot Spot Analysis and Cluster and Outlier Analysis were again run on both the count and per capita data for this time period.
Hot Spot analysis of the count data for 2009-2010 identified one district as a statistically significant hot spot: Zurmat, located in Paktya province.

Hot spot analysis of the per capita data identified 14 districts as statistically significant hotspots (Anar Dara, Andar, Zurmat, Zadran, Shamal, Ziruk, Urgun, Sar Hawza, Mata Khan, Sharan, Sarobi, Yahya Khel, Waza Khwa, and Dih Yak). These districts all fall within Farah, Ghazni, Paktya, Khost, or Patika provinces. The results of both the incident count and incident per capita analyses are mapped in Figure 11.

Figure 11 2009-2010 Hot Spot Analysis Results
Cluster and outlier analysis of the 2009-2010 count data identifies five districts as HH clusters (Mata Khan, Sharan, Sarobi, Andar, and Saydabed). These all fall within Paktika, Ghazni, and Maydan Wardak province. One district is identified as an HL outlier (Arghandab, Kandahar province).

Per Capita data identifies 9 districts as HH clusters (Anar Dara, Zadran, Shamal, Sar Hawza, Mata Khan, Sharan, Sarobi, Yahya Khel, and Waza Khwa). These clusters fall only within Farah, Paktya, Patika, and Khost (see Figure 12). No outliers are identified.

When combined, these analyses support that the hotspots detected are the result of a high number of events localized to the districts of Paktika and Paktya, with other neighboring districts having a relatively smaller number of events. Arghandab is the only district that experiences negative spatial autocorrelation, and is identified as an HL outlier, meaning that that district experienced a higher number of events than surrounding neighbors.

The per capita analysis indicates that a similar region in the east, including some of the districts identified in the count analysis, experienced unusually high numbers of kidnapping events given their population. Unlike the count analysis, per capita analysis reveals that Western districts, particularly Anar Dara, are again experiencing unusually high numbers of events given their population.

Both the hot spot analysis results, and cluster and outlier analysis results support the continued struggle for control of the border area and more remote regions of the
country. The inclusion of Anar Dara and Western districts as hotspots for a second aggregate period, in terms of incidents per capita, is also of interest.

4.2.5.2011-2012

92 incidents were included in the 2011-2012 subset. Hot spot analysis and cluster and outlier analysis were conducted on both incident counts and incidents per capita for
2011-2012. Hot spot analysis of count data for this period identified four districts as statistically significant hotspots (Khaki Safed, Shindand, Pusht Rod, and Bala Buluk). All fall inside Hirat or Farah province.

The per capita hot spot analysis identified 14 districts as statistically significant hotspots (Shindand, Nurgal, Chawkay, Chapa Dara, Sarkani, Marawara, Dara-I-Pech, Wata Pur, Nurgaram, Shaygal wa shital, Dangam, Nari, Kamdesh, and Parun). These districts are located in three provinces: Hirat, Kunar, and Nuristan (see Figure 13).
Cluster and Outlier Analysis of count data identifies only five districts as HH clusters (Khaki Safed, Shindand, Pusht Rod, Bala Buluk, and Wata Pur), all located in Farah, Hirat, or Kunar province.

The per capita evaluation of the 2011-2012 data includes nine districts as HH clusters (Khaki Safed, Pusht Rod, Chapa Dara, Marawara, Dara-I-Pech, Wata Pur, Dangam, Nari, and Parun). These are all located within Kunar, Nuristan, or Farah province. One HL outlier is identified, Maydan Shahr, located in Maydan Wardak (see Figure 14).

The 2011-2012 data and districts identified as hotspots are similar to those identified in the 2009-2010 period. The provinces in which hotspots occur have some overlap. There is also some movement north in the per capita hotspots identified.

When combined, these analyses support that the hotspots detected on analysis of count data are the result of a high number of events localized to the districts of Farah and Hirat, with other neighboring districts having a relatively smaller number of events.

The per capita analysis indicates that the same Eastern region, including some of the districts identified in the count analysis, experienced unusually high numbers of kidnapping events given their population. This is indicative of the fact that kidnappings were focused in that region. Unlike the count analysis, per capita analysis also reveals that districts in the Northeastern part of the country experienced unusually high numbers of kidnapping events given their population. This is particularly true of districts of Kunar province. Maydan Shahr is also marked as an HL outlier in this analysis and experienced
negative spatial autocorrelation, meaning that the district experienced an unusually high number of incidents per capita, and was surrounded by comparably low values.

Figure 14 2011-2012 Cluster and Outlier Analysis Results

4.2.6 2013-2014

191 events were included in the 2013-2014 subset. This is the final data subset included in the study. Hot spot analysis and cluster and outlier analysis were performed
on both count and per capita data. Hot spot analysis identifies no statistically significant clusters for either the incident count data, or number of incidents per capita (see Figure 15). It is very likely that this was a result of the aggregation scheme used in the analysis. With almost every district experiencing kidnapping events for this aggregate period, Gi* was unable to identify any statistically significant clustering of either count or per capita values. The district level may be too coarse of a unit to use with such a high number of events.

Figure 15 2013-2014 Hot Spot Analysis Results
Cluster and Outlier Analysis of count data identifies four districts as HH clusters (Pusht Rod, Farah, Bala Buluk, and Ajristan) Zurmat, and Marawara and Kabul are identified as HL outliers. These are all located within Farah, Ghazni, Paktya, and Kunar province.

This analysis indicates that a high number of kidnapping incidents were focused in the Western districts and the interior of the country. High values were also found in the three districts identified as HL outliers, but those districts were surrounded by comparatively lower values.

Cluster and outlier analysis, when performed on the 2013-2014 data, identifies only Ziruk as a HL outlier. This district is located in Paktika. This indicates that an unusually high number of events occurred in that district, given its population, compared to similarly low values in neighboring districts. The results of the cluster and outlier analysis are mapped in Figure 16.
4.2.7 Summary of Results

The spatial cluster and outlier analyses indicate that there are several districts where terrorist kidnapping incidents have clustered from 2005-2014, both by incident count and incidents per capita. Outliers were also identified in both analyses. Five two year aggregates were examined using both Getis Ord Gi* hot spot analysis, and Anselin Local Moran’s I cluster and outlier analysis techniques. The following tables (tables 2 and 3) are beneficial in visualizing the results of both the incident count and incident per capita examination over time. These outline what districts were designated as statistically significant hotspots (indicated by a filled circle) or as statistically significant outliers.
(indicated by an open circle). In both tables, Getis Ord Gi* is abbreviated as Gi*, and Anselin Local Moran’s I is abbreviated as “LMI”.
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Table 4 Districts included in Hot spots or as outliers in analysis of incident per capita data

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In both the per capita and the count analysis, it is evident that both kidnapping incident count and kidnappings per capita do cluster by district. For example, in the per capita analysis, several districts in Paktika are included as hotspots in 2009-2010. The same is true in the count analysis; several districts located in both Ghazni and Logar provinces are included in hotspots in 2005-2006 and 2007-2008. Similarly, locations near those hotspots exhibit similar traits for each of the aggregate periods.

Some of the same districts are also included in clusters over time. In the incident count analysis, several districts from Ghazni province are included in hotspots from the 2005-2006 period to the 2007-2008 period. Districts from Paktika and Paktya are consistent between the 2007-2008 analysis and the 2009-2010 analysis. Districts from Farah province are identified as hotspots in the 2011-2012 and 2013-2014 period. Districts of Kabul, Kunar, and Kandahar province also fluctuate between hotspot and outlier status across the five year period of study. Although identified as hotspots, districts from Hillmand, Logar, Maydan Wardak, and Zabul provinces are identified as hotspots in single aggregate periods only.

Incident per capita analysis similarly reveals some patterns in clustering. Most districts were included in hotspots in single aggregate periods only. Of the districts examined in this analysis, only districts from Ghazni and Farah were identified as hotspots over multiple aggregate periods. Maydan Shahar and Ziruk were the only two districts that were included in hotspots for one aggregate period and were identified as outliers in another.
4.3 Discussion

This discussion section examines the results outlined in 4.2.7, and provides additional observations in the context of the scientific questions posed in the introduction of this thesis.

4.3.1 Have kidnapping events clustered in space over time?

For the time aggregates examined, with the exception of the 2013-2014 Gi* results, all analyses of incident count and incident per capita distribution indicated that some statistically significant clustering exists. The lack of results for the 2013-2014 Gi* analysis may be due to the coarse nature of the district aggregation scheme, as addressed in the methodology section of this thesis. It can be interpreted that clustering in this dataset indicates that kidnapping events in Afghanistan are non-random, and are influenced by elements of a terrorist network. Both the results of the incident count analysis and the per capita analysis show a progression and shift in kidnapping clusters to the interior and Western districts of the country from the border regions with consistently high incident counts along the border region. This is similar to the path of the Taliban insurgency, and the strongholds maintained by the group described by several authors referenced in the literature review of this thesis.

4.3.2 Are there any clusters of kidnapping incidents, events given the population?

Analyzing the distribution of the number of incidents per capita from 2005-2014 also indicates clustering of events per capita for several districts. The districts identified in this analysis have similarly high values of kidnapping incidents, given their population.
These results may be the most beneficial in understanding locations in Afghanistan that have felt the most significant impact of kidnapping by terrorist groups. Visibility of kidnapping incidents and the impact of kidnapping events on the average person would be much higher in these areas. Like the incident count analyses, the analyses of per capita data indicate a shift in the employment of this tactic from the southeast of Afghanistan to the north and west over time. Specific cluster abnormalities identified by the per capita analysis, when compared to the count analysis alone, indicate that several districts in Western Afghanistan, and North of Kabul are included in clusters.

4.3.3 Have the districts or provinces experiencing these events changed over time? Are any patterns consistent?

The results of this study suggest that the districts where kidnapping attacks are focused, both per capita and by incident count, fluctuate over time. No districts were included in hotspots across all 5 data aggregate periods. Still, at the district level, kidnapping incident count and per capita data does appear to cluster in an organized pattern. General trends include shifts in hotspot locations from the Southeastern part of the country to the north and west, as well towards the country’s interior.

In the count analysis, there are districts that are included as hotspots in consecutive aggregate periods (e.g., Qarabagh, Pusht Rod). Although inconsistent across the total 10 year period, there is some consistency regarding where incident counts cluster. Similarly in the per capita analysis no district is included in a hotspot in more than two of the five total aggregates. Still, like the count analysis, there were districts that
were identified as hotspots twice, consecutively. This is indicative of an abnormal number of kidnapping incidents given the population.

Although no districts were consistently included as hotspots in more than two time periods, further examination of hot spot locations on a more regional level indicates something noteworthy; even though the same districts are not included in hotspots every aggregate period, other districts from the same provinces are. For example, in the per capita analysis, several districts of Farah province are included in three of the five total aggregates. The same is true of Ghazni in the incident count analysis. This suggests that the progression of kidnapping in Afghanistan is regionalized. In Afghanistan, kidnapping is a localized and focused tactic, but the geographic locus shifts over time.

4.3.4 Are there any districts that are outliers?

Outliers were identified in both the analysis of incident count data and incidents per capita. For the count analyses from 2005-2014, the outliers identified are generally major cities or population centers of Afghanistan (Kabul, Zurmat, etc.). This is generally less informative in terms of aiding strategic prioritization; population centers and urban areas will always have relatively inflated numbers of most things, compared to neighbors, and compared to the country as a whole.

Outliers from the per capita analysis are much more informative. The districts identified in that analysis are locations where the number of kidnappings are abnormally high given the district population and the number of incidents experienced by neighboring districts. Only two districts were identified as outliers in the per capita analysis: Maydan Shahr in 2011-2012, and Ziruk in 2013-2014. Both districts were also
included in per capita hotspots in earlier aggregate periods, prior to when they were identified as outliers. This suggests that although the focus of kidnapping may have shifted from that district and its immediate neighbors, the tactic remained heavily employed in that area.

4.3.5 Informing Strategic prioritization

Possibly of highest interest for strategically informing prioritization of resources, are the districts and provinces that are included as hotspots in both the per capita and count analyses multiple times over the five aggregate periods. Inclusion as hotspots in both analyses is indicative of a district located in an area with a high number of incidents overall, and a high number given the population. Those areas then generally experience a higher number of kidnapping events on average compared to the rest of the country. Out of all the districts analyzed, those in Farah province are included in hotspots across both analyses the most, followed by districts in Ghazni province and Paktika. Districts of Paktika and Maydan Wardak are also included in hotspots and as per capita outliers. These areas are also a focal point for kidnapping events. Although no single district within these provinces was consistently included in kidnapping clusters across all five aggregates, the local, repetitive, regional inclusion in clusters suggests that these regions should be prioritized to receive support to counter kidnapping.
CHAPTER FIVE: CONCLUSIONS AND FUTURE RESEARCH

5.1 Chapter Overview

This chapter summarizes the outcomes and implications of this study. The conclusions made are addressed in terms of the objectives and hypothesis posed in the introduction and methodology section of this thesis. Recommended improvements, and ideas for future research are also included.

5.2 Summary

This thesis examined the spatial nature of kidnapping events in Afghanistan from 2005-2014, with the objectives of identifying clusters of incidents by count alone, and of identifying clusters given the population to identify areas consistently experiencing kidnapping events, and to strategically prioritize outreach to those regions. Information on kidnapping in Afghanistan was obtained from the UMD START Global Terrorism Database. A methodology using Getis Ord Gi* and Anselin Local Moran’s I was introduced to evaluate clustering of kidnapping incidents in the country from 2005-2014.

The hypothesis proposed in chapter two of this thesis was twofold: that spatially significant clusters and outliers would exist across the data aggregates, and that the hotspots would be somewhat consistent across the districts (meaning the same districts would be included in hotspots across aggregate periods).
5.3 Conclusions

Getis Ord Gi* and Anselin Local Moran’s I analysis of kidnapping incident and per capita data show clustering in 18 out of the 20 total analyses conducted. The 2013-2015 Gi* analysis was the only instance where no clustering was recorded. This supports the first part of the proposed hypothesis, namely that kidnapping events would cluster both by incident count and by incidents per capita.

The second part of the hypothesis focused on the idea that the same districts would be included in these hotspots over time. This was not true. In both the count analysis, and the per capita incident analysis, more districts were identified as hotspots only once than were included over all time periods. This suggests that the location of kidnappings has shifted over the period from 2005-2014, and that the spatial focus of these events have changed over time. This appears to be indicative of the movement of the Taliban insurgency.

When examined at amore regional level however, some consistencies are evident. District from the same provinces are included in hotspots identified over time. This suggests that kidnapping is a more regional phenomenon. Both the count and per capita analysis reveal that the district clusters often occurred in the same provinces or in neighboring provinces.

When all analyses are compared, two regions have districts identified as hotspots by incident count and by incidents per capita across aggregate periods: Farah province in Western Afghanistan and districts in Ghazni province and Paktika, located in Eastern Afghanistan near the border with Pakistan. Districts of Paktika and Maydan Wardak, also
in Eastern Afghanistan, are also included in hotspots, and as per capita outliers. These areas are also a focal point for kidnapping events. Some limited regional strategic guidance on prioritization of training and outreach can therefore be suggested as a result of this analysis.

The inclusion of districts in Eastern Afghanistan in both count and per capita clustering over time is not entirely surprising. As noted by several authors, the portion of Eastern Afghanistan along the border has long served as a haven for the Taliban and Al Qaeda. However, the repeated inclusion of Western districts in both incident count and per capita results was unexpected. It is possible that this may be linked to Iran, which closely borders the western districts that were consistently included in clusters of kidnapping incidents. Additional analysis would have to be conducted to generate more definitive information on why that region is included in hotspots repeatedly.

These results suggest that outreach and prioritized training for ANP and ANSDF could be strategically prioritized to the western and eastern districts and provinces consistently included in statistically significant hotspots. Potential additional research and other possible improvements are included in section 5.4 of this thesis.

5.4 Improvements and Recommendations for Future Research

5.4.1 Potential Improvements

Several improvements could be made to refine the review of kidnapping incidents in Afghanistan in order to improve the strategic recommendations that can be made. These improvements are based both in the data used in the study and in the methodology applied.
This study was limited by the relatively small number of kidnapping incidents included in the GTD from 2005-2014, and the geocoding specificity constraints of the GTD. The total sample size of 478 incidents total is relatively small. The limited location information and geocoding specificity at the district level reduced the robustness of the possible analysis. With more than half of the points included in the GTD geocoded to the district level, options were limited in terms of accurate aggregation schemes. Including additional data, beyond what is available in the GTD alone would be an improvement.

Still, the GTD is one of the only open source databases that includes information on terrorist kidnapping events for Afghanistan. Manual collection of information, or transition of a similar study to a classified forum may provide opportunities to include additional kidnapping incidents.

Widening the spatial aperture to include parts of Pakistan, and specifically the Federally Administered Tribal Area (FATA), would also be an interesting improvement to this study. With the porous border and so much tribal crossover, including that region may provide additional information on activities occurring in Eastern and Southern Afghanistan. Kidnapping data for Pakistan is also available in the GTD.

Additional aggregation methods should also be considered to improve this study. As with all aggregation schemes, the use of the districts experiencing kidnapping events from 2005-2014 imposes artificial physical and temporal bounds on the data. This selection was made for this study due to the geocoding specificity of the GTD data on kidnapping events available. An overwhelming majority of the kidnapping incidents in the GTD were geocoded at the district level. If a future study was able to obtain data
coded at the city level, or even more specifically to the actual latitude and longitude, additional methods of aggregation could be considered, and more accurate distances could be calculated. These accuracy improvements would provide additional options for analysis. An ideal solution would involve analysis using grid cells, or count per city or location. This would provide more specific and robust results on the spatial distribution of kidnapping incidents and clusters than the analysis conducted in this study at the district level.

Analysis at a more granular level, such as at by city or a fishnet grid, would help to mitigate some of the limitations and constraints imposed by using the larger district polygon boundaries. Still, implementation of these techniques would necessitate data geocoded to the city level at minimum. This also supports inclusion of additional data, an additional improvement previously addressed.

A similar improvement could be to adjust the conceptualization of neighborhoods used in this study. This could be done through the selection of user defined neighborhoods with a more “natural” geographic unit than the fixed distance that was implemented in this study. For instance, tribal boundaries and ethnic group patterns may be more appropriate in the determination of geographic areas that are “neighbors” than a fixed distance between district or provincial boundaries. Clusters of kidnapping incidents using attribute based selection of neighbors would be more informative than a more general fixed distance, as applied in this study (reference section 3.4.1).

Another potential improvement would be to obtain 2015 data. Very few of the kidnapping events and incidents captured in the GTD from 2005-2014 mention the
Islamic State, often referred to as ISIS, ISIL, or DAESH. Only 3 out of the 484 kidnapping events used in this study mention ISIS/ISIL, and none attribute any events to the group. There are no references to Daesh. Given the status of current events and the group’s presence in the region in 2016, it would be prudent to see whether more recent data would indicate other clusters in Afghanistan.

5.4.2 Further Analysis of Ethno linguistic trends and other social-spatial factors that may influence kidnapping

Given the results of this study and the regional nature of kidnapping clusters, a similar analysis conducted using ethnic or ethnolinguistic areas of Afghanistan might also reveal information regarding the patterns and focuses of kidnapping. As ethnic and tribal divisions have a significant influence on the distribution of people and activities in Afghanistan, it would be interesting to examine kidnapping incidents at that level. The argument could be made that this information and understanding of social-cultural influences could strategically position training and outreach for increased impact. Other social factors that may influence the distribution of kidnapping events (e.g., the economy, education, etc.) could also be combined with this analysis to improve the understanding of other influences. These attributes could also be used in the creation of user selected neighborhoods, as referenced in section 5.4.1.

5.4.3 Creation of an Intensity Statistic

Evaluation of clustering using an intensity statistic as opposed to the count or per capita data alone is another method that could be applied to study clusters of kidnapping. As exemplified in the Seibneck and Medina study referenced in 2.1.3, understanding
clustering of event intensity can generate additional information on event patterns and data trends, and provide indicators of terrorist network strength. A similar measure for kidnapping intensity may involve the number of individuals kidnapped, fatalities, duration, and other attributes. This would help to identify if terrorist kidnappings are especially successful or have increased impact in similar areas.

5.4.4 Space Time Interaction Analysis

A more sophisticated temporal analysis would also be useful in understanding terrorist kidnappings. This study used simple two-year aggregates to evaluate clustering of events over time. Additional statistical and geographic methods exist that can provide a more granular, detailed approach. The Knox and Mantel indices and Space-Time Scan Statistic examine variations on space-time interaction by comparing distance and time between points. All three methods are used frequently in crime analysis. Use of these statistics may identify temporal aspects of clustering. These have previously been used in evaluation of terrorist incidents to determine whether clustering occurs in space around key holidays and celebrations. (Siebeneck, Medina et al. 2009). This analysis would have the greatest impact in the evaluation of kidnapping with data geocoded to the city level (or more accurately), and might provide additional justification for identification of additional data on kidnapping as outlined in 5.4.1

5.4.5 Interactive Visualization Tools

The results of this study could also be presented in an interactive visualization tool. This would be an effective method to visualize the results of the analysis over time.
The user would be able to utilize their own perception in the detection of patterns and trend. This would be an effective supplement to the descriptions and two dimensional maps presented in the results section of this study.
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BIOGRAPHY

Alison Marie Regan graduated from Robinson Secondary School, Fairfax, Virginia, in 2011. She received her Bachelor of Arts from Virginia Polytechnic Institute and State University (Virginia Tech) in 2013. She received her Master of Science in Geoinformatics and Geospatial Intelligence from George Mason University in 2016.