

ESTIMATING POPULATIONS AT RISK IN DATA-POOR ENVIRONMENTS:
A GEOGRAPHICALLY DISAGGREGATED ANALYSIS OF BOKO HARAM TERRORISM
2009-2014

by

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DEDICATION

This study is dedicated to the countless refugees and IDPs that wish to live free of war, oppression, and persecution.

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TABLE OF CONTENTS

DEDICATION	ii
ACKNOWLEDGMENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF EQUATIONS	ix
LIST OF ABBREVIATIONS	x
ABSTRACT	xii
CHAPTER 1: INTRODUCTION	1
1.1 Motivation	1
1.2 Case Study: Estimating Population at risk in Borno State, Nigeria	4
1.3 Research Framework	6
CHAPTER 2: BACKGROUND AND LITERATURE REVIEW	8
2.1 The Boko Haram Insurgency	8
2.2 Breeding Ground for Terrorism	10
2.2.1 Ethno-Political and Religious Tensions	11
2.2.2 Topography and Economic Development	12
2.3 Counter-Insurgency Operations and Issues	15
2.4 The Strategic Importance of Nigeria	16
2.5 Understanding Terrorism through GIS	17
2.6 Estimating Population at Risk	20
2.6.1 Population at Risk for Disaster Response	20
2.6.2 Population as Indicators of Risk for Terrorism	21
2.6.3 Defining the Spatial Extent of Terrorism Effect	22
	iv

2.7 Challenges within Data poor environments and Uncertainty in Variables	22
CHAPTER 3: METHODOLOGY	24
3.1 Methodology Framework	24
3.1.1 Research Hypotheses and Variable Summary	26
3.2 Study Area and Unit of Analysis	27
3.3 Data Sources and Variables	30
3.3.1 Data Prep with ArcGIS	30
3.3.2 Dependent Variable – Boko Haram Attacks	31
3.3.3 Independent Variables – Sources and Preparation	33
3.3.3.1 Population Data	34
3.3.3.2 Populated Places	35
3.3.3.3 Road Data	36
3.3.3.4 International Borders	36
3.3.4 Strengths, Assumptions and Limitations	36
3.4 Exploratory Methods	38
3.4.1 Identifying Boko Haram Attack Patterns over Space and Time	38
3.4.2 Dasymetric Mapping	42
3.4.3 Exploring Independent Variables	45
3.4.3.1 Cost Surface	46
3.4.3.2 Population Variables	46
3.4.3.3 Populated Places	46
3.4.3.4 Roads	47
3.4.3.5 International Borders	48

3.4.3.6 Distance from Prior Attacks	48
3.5 Identifying Terrorism Risk through Cox Regression	48
3.5.1 Testing the Risk Terrain Validity	50
3.6 Estimating Population at Risk	51
CHAPTER 4: RESULTS	52
4.1 Risk of Boko Haram Conflict Analysis Using Cox Regression	52
4.1.1 Hypotheses Results	55
4.1.2 Visualizing Risk	57
4.1.3 Classifying Risk	60
4.2 Testing the Risk Terrain Validity	63
4.3 Estimating Population at Risk	67
4.3.1 Population and Risk Overlays	68
CHAPTER 5: DISCUSSION AND CONCLUSIONS	72
5.1 Key Observations and Value	72
5.2 Contrast with Previous Studies	76
5.3 Recommendations for Future Research	77
REFERENCES	80
APPENDIX A: Attribute Fields and Descriptions for ACLED Dataset	85
APPENDIX B: ACLED Data Spatial Autocorrelation Report	86
APPENDIX C: Cox Regression Outputs from SPSS	87

LIST OF TABLES

Table 1: Independent Variable Summary	27
Table 2: LGA Area, Population and Density Estimates	29
Table 3: LGA Area, Population, and Density: Mean, Max, and Min	29
Table 4: Attacks by Year	39
Table 5: Time Periods for Risk Terrain Validity Testing	51
Table 6: Cox Regression Results: Estimating Risk of Boko Haram Conflicts	53
Table 7: Estimated Relative Risk Classes and Definitions	60
Table 8: Attacks by Year Represented in Each Risk Class	67
Table 9: Population at Risk to Boko Haram Attacks by Risk Class	68
Table 10: Case Processing Summary	87
Table 11: Omnibus Tests of Model Coefficients	87
Table 12: Cox Regression Variable Results	88
Table 13: Correlation Matrix of Regression Coefficients	89

LIST OF FIGURES

Figure 1: Overview of Study Area – Borno State, Nigeria	5
Figure 2: The Boko Haram Crisis Overlaid on the Ethno-religious Landscape in Nigeria	14
Figure 3: High Level Methodology Framework	24
Figure 4: Map representing LGA administrative divisions of Borno State in Nigeria	28
Figure 5: Boko Haram Attacks from July 1, 2009 – June 30, 2014	33
Figure 6: 2014 Borno State Population Density by LGA	34
Figure 7: Attack and Attack Intensity Average per Quarter from July 2009 – June 2014	39
Figure 8: Spatiotemporal depiction of Boko Haram attacks by year July 2009 – June 2014	41
Figure 9: Mean Center Cluster of Boko Haram Attacks by Year: July 2009 – June 2014	42
Figure 10: Dasymetric Map of Population by Cell	45
Figure 11: Estimated Risk Terrain of Boko Haram Terrorism in Borno State 2009 – 2014	59
Figure 12: Classified Estimated Relative Risk Values for Boko Haram Terrorism	61
Figure 13: Overlay of Variables and Risk Class Terrain	62
Figure 14: Attack and Distinct Location Counts (Raw) by Year	63
Figure 15: Comparison of Year 3 Risk Terrain to Year 4 Attacks	64
Figure 16: Year 4 Risk Terrain Compared to Year 5 Attacks	65
Figure 17: Year 5 Risk Terrain Compared to Year 6 Attacks	66
Figure 18: Comparison of Risk and Population	69
Figure 19: High Risk/ High Populated Areas in Relation to Attacks, Roads, Major Towns	70
Figure 20: Hazard Function at Mean of Covariates	90

LIST OF EQUATIONS

Equation 1: Population Growth..	35
Equation 2: Streeth Weighting (SW) Method.....	43
Equation 3: Address Weighting (AW) Method	43
Equation 4: Areal Interpolation (AI) Method.	43
Equation 5: Combining SW, AW, AI Methods.	44
Equation 6: Cox Regression.....	49

LIST OF ABBREVIATIONS

ACLED	Armed Conflict Location and Event Data Project
AI	Areal Interpolation
AQIM	Al Qaeda in the Islamic Maghreb
AW	Address Weighting
CFR	Council of Foreign Relations
DSG	Feature Designation
FAO	Food and Agriculture Organization of the United Nations
GADM	Global Administrative Areas
GIS	Geographic Information Systems
GDP	Gross Domestic Product
IDMC	Internal Displacement Monitoring Centre
IDP	Internally Displaced Person
JTF	Joint Task Force
KM	Kilometers
LGA	Local Government Area
MAUP	Modifiable Areal Unit Problem
NCFR	National Commission for Refugees
NGA	National Geospatial Intelligence Agency
NGO	Non-Governmental Organization
NEMA	National Emergency Management Agency
OCHA	Office for the Coordination of Humanitarian Affairs
PPL	Populated Places
SPSS	Statistical Package for the Social Sciences

SRTM	Shuttle Radar Topography Mission
SW	Street Weighting
UNFPA	United Nations Population Fund
UNHCR	United Nations High Commissioner for Refugees
USD	United States Dollars
VBIEDS	Vehicle-Borne Improvised Explosive Device
VMAP	Vector Map

ABSTRACT

The increasing threat and globalization of terrorism has heightened the need for estimating the geographical extent of population at risk to terrorist attacks. These estimations provide effective and efficient analyses to support various organizations for estimating necessary aid resources as well as identifying areas that require military and governmental involvement. With no consistent framework available for studying terrorism risk or handling data gaps, the goal of this study is to provide a baseline methodology for spatially estimating population at risk within a data-poor environment (Willis et al. 2005). This thesis examines the Islamic insurgent group, Boko Haram, and their historical attacks within Borno State, Nigeria over a five year period from July 2009 to June 2014. Data is disaggregated using a dasymetric mapping method designed to increase spatial quality to provide a more intimate look at risk throughout the state. Cox Regression, a statistical method to analyze time between events in accordance with covariates' relationships, estimates risk through hazard ratios which are applied to spatial cells. Classified risk cells are used to estimate population at risk in areas through this model. Results depict detailed areas and population at risk to Boko Haram terrorism, the spread of Boko Haram from Borno State to nearby areas over time, and geographic variables which increase odds of Boko Haram attacks to occur. These results are useful to understand the areas and amount of people affected by Boko Haram terrorism and aim to improve methods and techniques using geographic information systems (GIS) and statistical methods for risk analysis. Geographically disaggregating data in data-poor countries provides previously unknown insights to analytical problems potentially facilitating solutions for various subjects such as medical and environmental crises, terrorism, and urban development.

CHAPTER 1: INTRODUCTION

Soon after the September 11, 2001 terrorist attacks, President George W. Bush declared a War on Terror and rallied the nation to “pursue nations that provide aid or safe haven to terrorism” (Bush 2001, 1). Over a decade later, the number of groups utilizing terrorism has more than doubled and uncertainly in the global socio-political and economic atmosphere has increased to staggering proportions. Nation-states are failing and the economic turmoil created through instability and corruption creates an ideal environment for the establishment of terrorist groups (Medina and Hepner 2014). Nigeria in particular is struggling to confront these challenges as instability has spread throughout the region of West Africa due to issues of poverty, ethno-religious tensions, corruption, and economic downfall, an ideal breeding ground for terrorism (Onapajo and Uzodike 2012; Siegle 2013). The most significant threat to the region is Boko Haram, an Islamic insurgency rampant in Nigeria. The group is currently active in more than half of the country and spreading to neighboring countries displacing hundreds of thousands of people, and murdering thousands more (Onapajo and Uzodike 2012; Spindler 2014).

1.1 Motivation

In northeastern Nigeria, internally displaced persons (IDPs) and refugees are products of Boko Haram terrorism. Those that do not want to join Boko Haram’s cause or live outside Boko Haram’s strict lifestyle guidelines are forced to flee or face murder, kidnapping, living amongst violence, or sold as wives and slaves (Spindler 2014; Beyani and Izsak 2014).

Violence is intensifying creating more IDPs with little to nothing left. Many villages, such as Doron Baga have been burnt and residents shot or drowned. A resident described, “They burnt the whole village including fishing and farming tools. People are leaving the area in droves because of fear that their village could be targeted next” (IRIN 2014, 1).

The number of displaced persons in Nigeria is one of the highest in the world. In 2014, 3.3 million people are estimated to be displaced since 2010 not only due to Boko Haram violence, but extreme cycles of droughts, floods, and land conflicts between ethno-religious crises (Datti 2014). There are significant limitations, however, for estimating the displaced population across Nigeria, especially in the northeast, and official numbers sway drastically.

First, population counts of the area are outdated and aggregated to large administrative boundaries. The last census was conducted in 2006 and was surrounded by controversy, corruption, and conspiracy (Odunfa 2006). Growth rates are estimated between 2.7 – 3.0 percent with Borno State at an estimated 3.4 growth rate (UNFPA 2009; World Bank 2014). Population estimates are an imperative first step to determining population at risk for displacement due to manmade and natural crises (Dobson 2003). Understanding where population resides as well as potential threats aid mission planners in governments and humanitarian organizations to determine amounts of resources necessary to help displaced people from natural to man-made disasters. Over and under-estimating population has consequences of improper allocation of resources to lives lost. Most current estimations are concentrated on regional effects and less on state-level estimations.

Second, due to the continuous insecurity and remoteness of the northeast, many IDPs and refugees fleeing Boko Haram violence have severely limited access to national and international humanitarian support. Without this support, Nigerians stay with host families or in schools but resources attempting to support this influx of people to new areas and surrounding countries are severely strained (Spindler 2014).

Third, without enough national and international humanitarian support, it is impossible to understand how many people are actually displaced, or address the IDP situation. When entering

humanitarian camps, displaced people are registered and counts are reported for planning and to collect resources and supplies. As of late 2014, there are several varying estimates of people displaced, but these numbers usually portray newly displaced and not continuously displaced.

For example, it is estimated roughly 470,500 newly displaced people were fleeing violence from Boko Haram in Borno, Yobe, and Adamawa States as of the end of 2013 (IDMC 2014). Humanitarian organizations are skeptical of these figures as neither the National Emergency Management Agency (NEMA) nor the National Commission for Refugees (NCFR) supply methodologies accounting for people displaced. In addition, with the limited access to the northeast, there are poor communications to address the situation and there are not consistent avenues for monitoring displaced persons: the actual number of IDPs impacted remains unclear (IDMC 2014; Spindler 2014).

Lastly, a need for understanding how many people are displaced or where they are from is necessary as this leads to secondary consequences such as food insecurity and without a counter-insurgency resolution. NEMA has estimated that roughly 60 percent of farmers have left their fertile crops which supply a vast majority of food to the region (Beyani and Izsak 2014). Also, planners and decision makers do not have a specific enough analysis to understand the overwhelming reach of Boko Haram into various parts of the country and where or why Boko Haram would attack a location (Onapajo 2013).

As addressed by Willis et al. (2005) there is no consistent methodology for modeling terrorism risk. Risk to terrorism is defined many ways; however, this study concentrates on Willis et al.'s definition of risk using threat. Threat is defined as the probability that an attack will occur against an area at specified time interval. Spatially and temporally identifying

terrorism risk at high resolutions is a unique but paramount first step to truly understanding the depth of humanitarian crises.

1.2 Case Study: Estimating Population at risk in Borno State, Nigeria

The goal of this study is to provide a methodology for handling low resolution data to spatially estimate population at risk to Boko Haram attacks from July 2009 – June 2014. Figure 1 depicts the study area of Borno State, Nigeria and emphasizes the administrative divisions within the state. Borno State is the birthplace to the Boko Haram insurgency with most of the group's activity occurring here during the study period. Borno State is divided by 27 Local Government Areas (LGAs) with a total estimated population of 5.4 million (2014) in 69,435 sq. km (UNFPA 2009). Each LGA incurred at least one attack from Boko Haram between July 2009 – June 2014 except for the LGAs Bayo and Monguno.

For public use, population figures are only attainable at the aggregated LGA level. For a useful estimation of population at risk to Boko Haram terrorism, a more specific population count is necessary. A dasymetric mapping method utilizing areal interpolation and feature weighting is used to estimate population across a finer spatial resolution.

Historical Boko Haram attacks are geo-located by city throughout Borno State and provide a high resolution of spatial understanding to where events are occurring. These events are used to perform a spatial analysis to identify areas that have correlating factors to potential terrorist attacks. Terrorism does not occur randomly but has specific spatial implications of cause and effect factors which can be predicted through spatial analysis (Medina, Siebeneck, and Hepner 2011). Not all villages or locations are at equal risk to a terrorist attack, so understanding where violence has occurred can help determine the why.

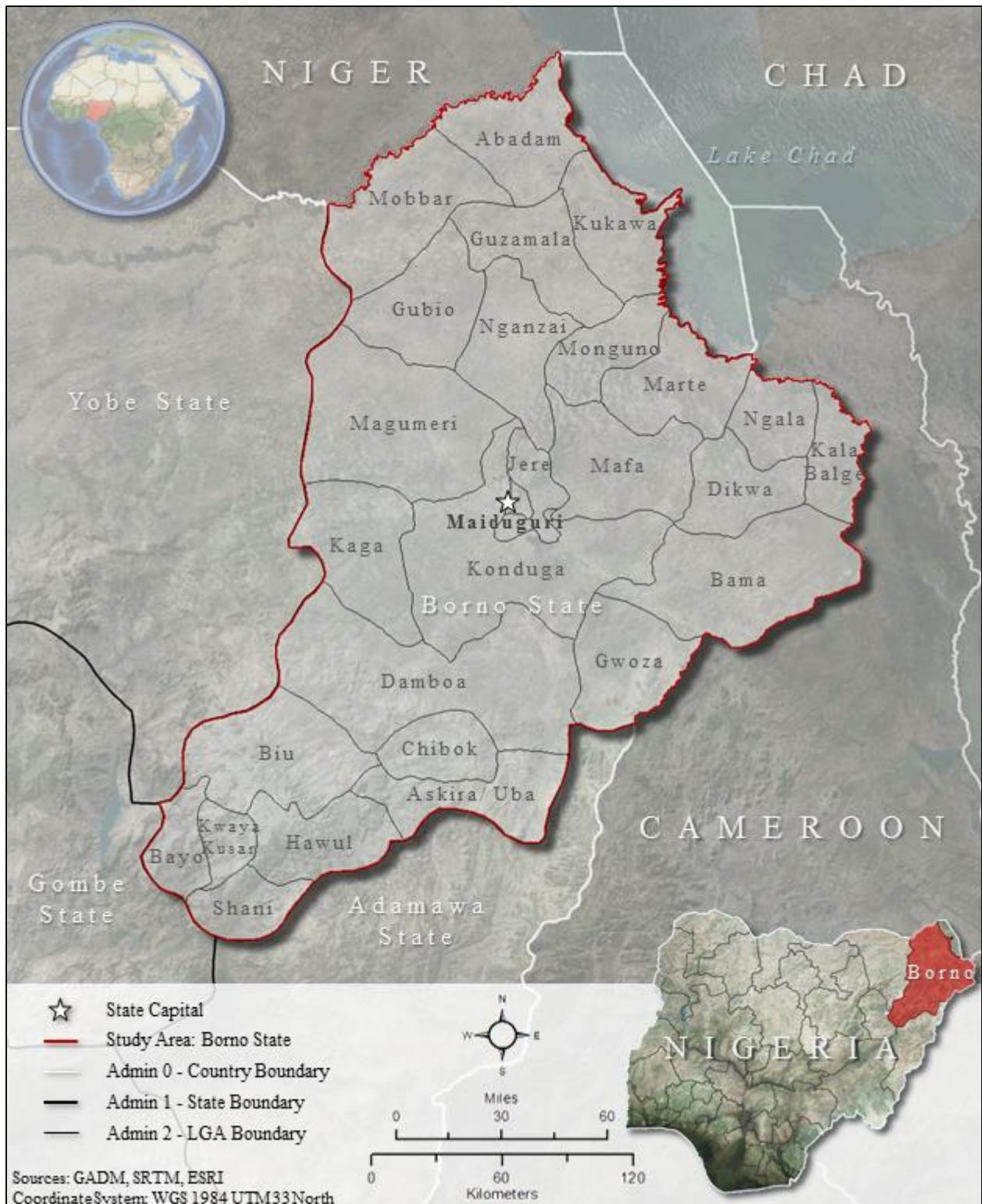


Figure 1: Overview of Study Area - Borno State, Nigeria

Many factors can contribute to why a location appeals to terrorists. Locations are targeted due to symbolic value, psychological impacts, potential human and physical damages and accessibility (Medina and Hepner 2013; Sidhu 2014). Accessibility pertains not only to the ability to reach a location but the possibility of using it to blend in with the local population (Sidhu 2014).

Factors used in this particular study to identify statistically significant correlations to terrorism events are concentrated around estimated population, and accessibility to population through road networks. By utilizing these factors and understanding the amount of impact they have on historical terrorist attacks, areas can be identified which have a higher risk of future terrorist activity and potential for population displacement. Cox Regression, a type of survival analysis, is used to study the interactions of factors to historical attack data over space and time. Multivariate layers provide a visualization of areas at risk and estimated population at risk through very low to very high classifications.

1.3 Research Framework

This study follows previous work by Raleigh and Hegre (2009), Medina, Siebeneck, and Hepner (2011), and Riebel and Buffalino (Tapp 2010) to answer the following questions:

- a) What areas are at risk to Boko Haram attacks?
- b) Approximately how many people are at risk to Boko Haram attacks?
- c) What variables have a statistically significant correlation to Boko Haram attacks?
- d) What are the spatial and temporal trends to Boko Haram attacks?

The research and methods outlined in the following chapters answer these questions to spatially understand and visualize the extent of Boko Haram terrorist activity to better identify and estimate populations at risk for more accurate humanitarian mission planning.

The remainder of this thesis is divided into four chapters. Chapter Two provides a background on Boko Haram and the political and socioeconomic factors which contribute to persistent violence in northeastern Nigeria. This chapter will also review complications with uncertainties in estimation in data-poor environments such as Nigeria. Chapter Three describes the study area, data sources, and framework methodologies for employing the population at risk model. This chapter also highlights the methods used to answer the research questions and identify hypotheses used for a more advance statistical analysis.

Chapter Four presents the analysis and results of the study's methods along with visualizations of the results. Chapter Five reviews the importance and difficulties of the study along with discussing further opportunities for research and development.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW

Boko Haram has increased in strength in Nigeria despite counter-insurgency measures. This has occurred primarily due to the lack of understanding of the group, its allies, and severe lack of data. This chapter presents an overview of the origin of the Boko Haram insurgency and the gaps in research which prevent the containment of the movement. Previous research is discussed to obtain a further understanding of this situation through a spatial analysis of terrorism studies. Understanding where terrorism is occurring reveals patterns and trends which depict high risk areas vulnerable to Boko Haram attacks and thereby population at risk. Population at risk is imperative for national and international humanitarian organizations to plan for providing innocent, displaced civilians with basic necessities such as shelter, water, and food.

2.1 The Boko Haram Insurgency

Boko Haram, as it is known today, is a terrorist organization¹ founded around 2002 by Mohammad Yusuf in Maiduguri, Nigeria. Boko Haram is generally classified as a Salafist² organization, strictly forbidding Western culture and anything that strays from their strict ideals (Nance 2014). The formal name is *Jama'atu Ahlis Sunna Lidda'awati Wal-Jihad* which roughly translates to “People for the Tradition of the Prophet for Jihad” (Onapajo and Uzodike 2012). The more common name, Boko Haram, translates to “Western Education is a Sin (or Forbidden)” but the group prefers “Western Civilization is Forbidden” (Onuoha 2012). The group is motivated by the political corruption by the Western-educated government officials contaminating the country and exacerbating poverty and economic inequality (Onapajo and

¹A terrorist organization uses terrorism is used to promote change through violence, force, and fear based on nationalist/separatist, cultural/religious, and/or ideological notions (Medina and Hepner 2013).

²Salafi Islam is a belief that to be a good Muslim, one must follow the examples of the first three generations of Islam- those closest to the era of Muhammad (Nance 2014).

Uzodike 2012). The main purpose of the group is to overrun Western-influenced Nigeria and establish an Islamic state based on their strict interpretation of the Quran and Sharia Law.

Boko Haram uses Islamic fundamentalism as a tool to justify their actions and condemn their enemies. They believe Nigeria is corrupted by Western influence and social vices, therefore devout Muslims should rid Nigeria of the Westernized and educated leaders that failed to care for the state, their immoral practices, and establish the ideal Islamic society without political corruption or lack of morality (Onuoha 2012). Typical targets of Boko Haram attacks include police, military, churches and Christians, schools, Western-owned facilities, the media, government officials, and moderate Muslims (Medina and Hepner 2013).

There is a general consensus throughout the community that the group violently radicalized as of July 2009, after a crackdown from the Nigerian State led to over 700 members' deaths to include their leader, Mohammad Yusuf. After multiple days of fighting, thousands of citizens were displaced and many members were detained. The surviving members vowed to retaliate against the State and in 2010 led a successful attack against the Bauchi central prison, freeing their surviving members awaiting trial (Onuoha 2012).

As the Bauchi prison attack in 2010 showed, Boko Haram's armament and strategies had not only significantly developed, but vulnerabilities in Nigerian intelligence and security capabilities were realized (U.S. State Department 2012; Onuoha 2012). Terrorist events, membership, and presence increased and spread from northeastern Nigeria to greater Nigeria, Cameroon, Niger, Chad, and Mali (U.S. State Department 2014). Boko Haram became more ruthless and incorporated mass kidnappings, murders, targeted attacks, and even developed more technical attacks utilizing Vehicle Borne Improvised Explosive Devices (VBIEDs) (U.S. State Department 2012).

The most recognizable attack of 2014 included a mass kidnapping of over 250 girls from a school dormitory in Chibok, Borno State. The kidnapping brought international attention to the group inspiring a social media frenzy to *#BringBackOurGirls*. Celebrities and the First Lady of the United States, Michelle Obama, posed with pictures to spread the hashtag and awareness in hopes to pressure the Nigerian government to do something about Boko Haram. It is reported the girls' fate were to be auctioned as wives of the terrorists (Kristof 2014). Other major school attacks have also occurred at both male and female, Muslim and Christian schools but have mainly ended in mass murder and the burning down of facilities.

Although Boko Haram violence has increased dramatically since 2009, the government of Nigeria does not know how to effectively rid the area of Boko Haram, how to curtail its spread to the region, or anticipate subsequent attacks (Maiangwa and Uzodike 2012).

2.2 Breeding Ground for Terrorism

Boko Haram has flourished in Nigeria due to many factors relating to political, economic, and ethno-religious conflicts (Okpaga, Chijioke, and Eme 2012). Boko Haram takes advantage of the lack of governance and infrastructure, mass poverty, ethnic tensions and inequality, and official corruption to gain a foothold in northeastern Nigeria. In 2010 roughly 100 million Nigerians were making less than \$1.00 USD a day. In addition, less than 30 percent of people living in the north had access to safe drinking water (CFR 2010).

With the extreme rates of persisting poverty in the north, many youths and graduates are easy targets for radicalization as they are disillusioned with the government to provide basic resources, employment, and security to the north (Onuoha 2012; Adesoji 2010). Also a factor is the bitterness against the south and central government with its wealth and vast resources. Many see a misappropriation of resources for the rural north to fatten the political elite's wallets instead

of improving the livelihood of its citizens from mass poverty (Adesoji 2010). Poverty in the north is at an average of 70.1 percent with the south at an average of 34.9 percent (Onuoha 2012).

2.2.1 Ethno-Political and Religious Tensions

Ethno-religious issues in Nigeria consistently revive violence. Not only does Nigeria have the largest population in Africa, it is also one of the most ethnically diverse with over 350 ethnic groups and 400 languages (Solomon 2013). Three main ethnicities which also represent a majority of the government include the Hausa and Fulani (29 percent) in the north, Yoruba (21 percent) in the southwest, and Igbo (18 percent) in the southeast (Forest 2012). Other ethnic minorities are often marginalized, not represented politically, and roughly two thirds of these groups are found in the northern states (Forest 2012).

Ethno-religious conflicts are largely motivated over land and scarce resources, power, chieftaincy, market control, religious interpretations such as the use of Sharia Law, and a caste system (Okpaga, Chijioke, and Eme 2012). Issues are made worse by injustice and inequality towards different ethnic groups. State and local governments exclude certain ethnicities from having rights depending on which jurisdiction one resides in. With so many ethnicities in the area, choosing who has rights and who does not is entirely discretionary and creates discord with politics and trust in the system. In addition, many ethnic groups have conflict over land due to migration and their ethno-religious differences. Distribution of wealth and power between groups has historically driven the region to violence, culminating in the tragic reality that breeds terrorism and radicalized sentiment.

A majority of the members of Boko Haram come from the Kanuri tribe which represents approximately 4 percent of the population and reside in the northeast (Forest 2012). Hausa and

Fulani members have also joined the cause due to the persisting concerns of the north such as poverty, lack of opportunities and resources, and marginalization of the central government.

Another factor driving ethnic tensions aligns with a strong religious polarization in Nigeria. Fifty percent of the population is Muslim and located in the north with the south roughly at forty percent Christian and ten percent indigenous beliefs. With the multitude of ethnicities and polarizing religious beliefs, imagining a one Nigerian nationality and uniting under a single government is practically impossible (Maiangwa and Uzodike 2012).

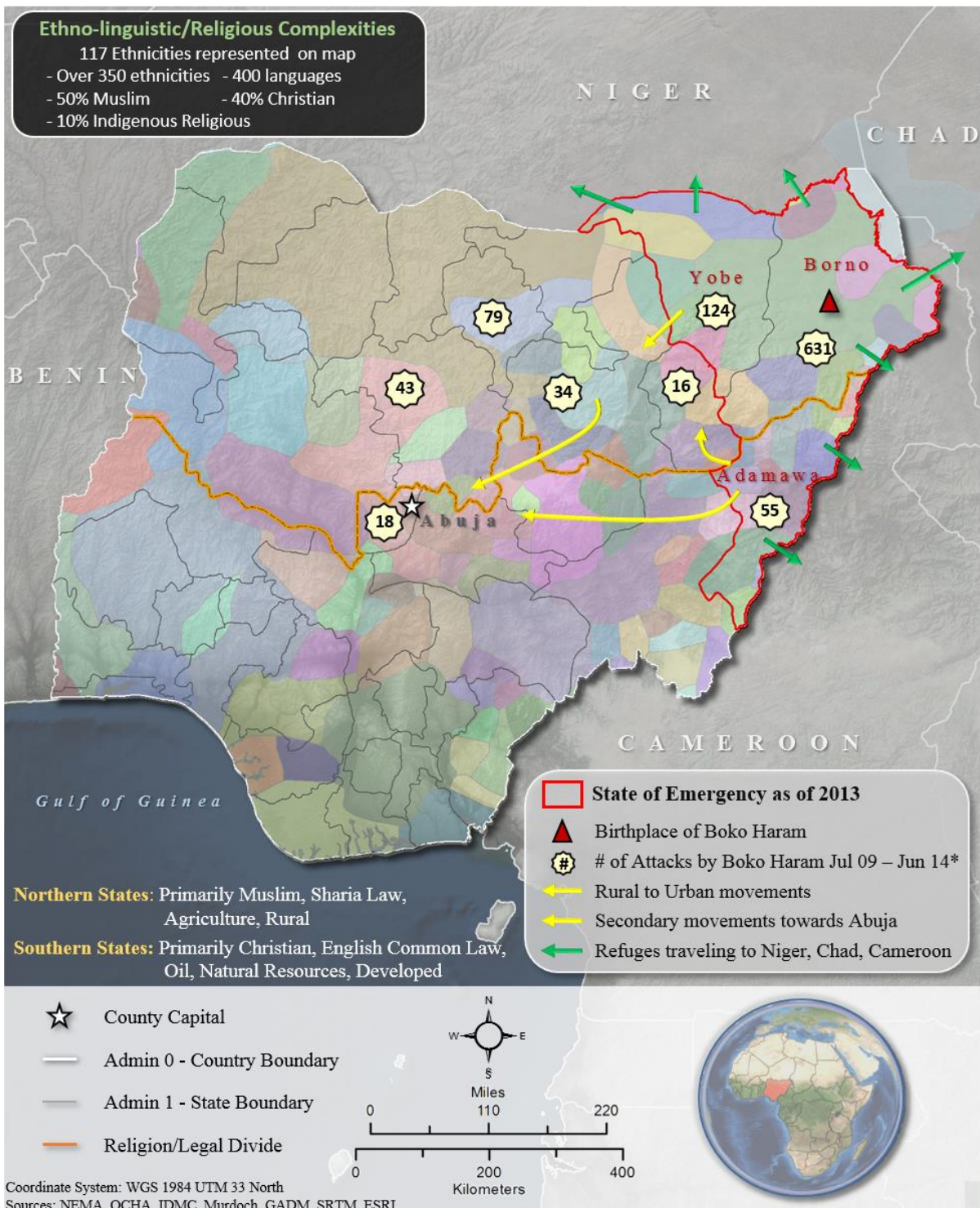
2.2.2 Topography and Economic Development

Nigeria has the largest economy in Africa with an estimated GDP of USD 510 billion mostly involving oil and agricultural sectors (U.S. State Department 2012; Barungi 2014). Although the GDP has climbed an approximated 7.4%, many inhabitants of the north question why such high levels of persistent poverty and lack of infrastructure and development are occurring (Okpaga, Chijioke, and Eme 2012; Barungi 2014). In addition, cyclical issues of drought and flood as well as desertification, puts much strain on an impressionable environment both economically and ethnically through land control. Without a trustworthy political system to aid in land disputes or resources and infrastructure to support those in need, violence tends to increase and originate during these conflicts (Okpaga, Chijioke, and Eme 2012).

According to the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) and United Nations Refugee Agency (UNHCR), insecurity and violence in the north, especially the northeast, have prevented humanitarian and development organizations from investing in and providing aid to the area (Campbell 2014; UNHCR 2014). In addition, the harsh and rural environment makes it difficult to traverse the terrain and reach those in need. Food insecurity in the region is rampant due to continuous failed crops and difficulty identifying where

resources are needed most. Hundreds of thousands of people displaced also puts an incredible amount of economic strain on nearby communities attempting to host those in need (Campbell 2014).

Figure 2 summarizes the ethno-political, religious, and economic issues contributing to persistent conflicts in Nigeria. This figure depicts the demarcation of north and south, Sharia versus English Common Law, respectively. Also shown are major ethnic groups (117 displayed out over 350) which exist in Nigeria. The Boko Haram crisis is overlaid on this landscape depicting the states which have declared a state of emergency, states with Boko Haram attacks, and the movement of IDPs and refugees.



*Represents states which incurred 16 or more attacks during the study period

Figure 2: The Boko Haram Crisis Overlaid on the Ethno-religious Landscape in Nigeria

2.3 Counter-Insurgency Operations and Issues

The counter-insurgent operation to northeastern Nigeria is deemed ineffective and has received numerous criticisms from international organizations, governments, and humanitarian groups (Onapajo 2013). Onapajo (2013) contends that Boko Haram persists due to a major lack of intelligence on the insurgency and its members. There are the numerous contradictions and conflicting information of Boko Haram's origin, purpose, radicalization, external support, and even name (Adibe 2013). The background described in the previous sections follow some of the more well-known and accepted variations, speculations, hypotheses, and data about Boko Haram, but a significant issue remains: there is an urgent need for more research into the understanding of what Boko Haram is, what they stand for, what they intend, and what they are capable of. What is undeniable is that Boko Haram is a significant problem.

The prevalent question is who are the Boko Haram? March 2013, President Goodluck Jonathan made an official visit to the stronghold area of Boko Haram, Borno State, and labeled the group as 'faceless' and as a 'ghost (Onapajo 2013).' This is intriguing considering the past five years Nigeria has been combating the issue. Also, in 2011, Nigeria created a Joint Task Force (JTF) to specifically combat Boko Haram. Since the JTFs creation, they have boasted numerous successes of arresting and killing a large amount of members. Contrary to their reports, not only have Boko Haram attacks increased, become more sophisticated, but a vicious splinter group has evolved³. Also, humanitarian organizations have complained that the JTF has not been killing Boko Haram, but innocent civilians leading to more migration issues and a significant spatial shift of property ownership and ethnic control (Onapajo 2013).

³ The splinter group is known as *Jama'atu Ansarul Muslimina fi Biladis Sudan* or *Ansaru* which is translated roughly as "Vanguards for the Protection of Muslims in Black Africa (Land of Sudan)." They have a larger regional focus for the establishment of an Islamic Caliphate and have ties to AQIM. This group is outside the scope of this study.

While we do know Borno State is a stronghold for Boko Haram, their exact locations for their camps and training areas are classified in nature and misunderstood as well as their capabilities and strategies. Also, while the Boko Haram continues on for its fifth violent year, troops from the JTF are becoming disillusioned of the ability to successfully combat the insurgency. There are reports of soldiers deserting and fleeing combat as low morale is spreading throughout the ranks (Nigeria Security Network 2014). There is also inadequate equipment being supplied to the JTF to traverse the terrain as well as insufficient ammunition available.

2.4 The Strategic Importance of Nigeria

Africa is home to some of the most heinous crimes against humanity in the world due to ethno-religious and political conflicts. This issue involving Boko Haram and the security of Nigeria, however, has dire consequences which can affect the stability throughout Africa. The U.S. State Department (2014) describes Nigeria as unique and significant in Africa as it has the largest population and economy on the continent. With these attributes, Nigeria plays a significant role in the stability of the region of West Africa through their deployment of troops for peacekeeping missions and significant supply of trade and resources (U.S. State Department 2014; Siegle 2013). For example, annual trading in Kano was worth roughly \$15 billion, but has since dropped dramatically. Without this economic hub, prices have reached astronomical levels and production has dramatically decreased, creating a catastrophic lack of resources for nearby countries which are dependent on trade.

In addition to the economy, lack of security and violence, insights fear and migration to the wider region consequently bringing more ethno-religious tensions and drain on resources. (Okpaga, Chijioke, and Eme 2012). Since 2009, hundreds of thousands of people have been displaced with violence escalating which discourages economic investment and humanitarian

groups from going into the region and providing aid and development (Crowley and Wilkinson 2013).

Boko Haram is also gaining international acclaim from other Islamic militant groups, to include al-Qaeda in the Islamic Maghreb (AQIM). Since 2011, Boko Haram announced an alignment with al-Qaeda and fighters from Benin, Chad, Mauritania, Niger, Somalia, and Sudan have joined their cause. Capabilities, armament, and tactics have drastically improved with the influx of membership from experienced militants, monetary support, and training (Siegle 2013).

2.5 Understanding Terrorism through GIS

Terrorism is an ideal subject for GIS analysis as terrorists have goals that affect targets in specific spaces (Medina and Hepner 2013). These spaces are connected through social, economic, or infrastructural means that GIS analysis can understand as networks (Medina and Hepner 2013). Typical targets center on places of a symbolic nature, connected by these networks, and which incite fear within the civilian population (Medina, Siebeneck, and Hepner 2011). Medina, Siebeneck, and Hepner (2011) argue that analyzing these trends in a GIS can lead to the prediction of future events, locate safe-havens and recruitment centers, and identify vulnerable populations. Other benefits of the analysis is to provide valuable information to aid in securing future target populations as well as help to prioritize resources designated to curtail Boko Haram violence and influence.

Terrorism analysis is often limited, mainly concentrating on event data rather than driving factors (Medina and Hepner 2013). Medina and Hepner (2013) argue that ethnic, religious, physical landscape, and access to resources should be incorporated in the study of terrorism as these factors heavily influence terrorist behavior and are considered the main causes of terrorism in Africa. Issues arise, however, when studying terrorism in data-poor countries,

such as Nigeria. Often, data does not have the required spatial resolution to understand the specific dynamics of terrorism and events. In this case, performing a spatiotemporal analysis provides benefits, especially through highlighting areas that are of more concern due to number of terrorist events to population (Medina, Hepner, and Siebeneck 2011). By highlighting these areas, such as administrative boundaries, recommendations can be made to collect more data in these areas for further research into why terrorism is occurring

Spatiotemporal analysis allows a user to analyze patterns across multiple dimensions (Guo, Liao, Morgan 2007). This is particularly useful for terrorism analysis as terrorists shift their spatial extent over time. Targets, weapons used, and tactics also change over time as resources, training, and recruitment increase or diminish. Analyzing these attributes in a spatiotemporal environment will aid in discovering patterns and assessing counterterrorism measures.

Temporal data is easily visualized through time lines and histograms, and animated maps are used to visualize spatial trends over time (Guo, Liao, and Morgan 2007). These techniques employ a univariate visualization, while Guo, Liao, and Morgan (2007) desire representing event and time data as multivariate data. To do so, they use a reordered matrix to show spatio-multivariate, spatiotemporal, temporal-multivariate, and spatiotemporal-multivariate visualizations.

More related to the Boko Haram study is Medina, Hepner, and Siebeneck's work with their spatiotemporal analysis of Iraq (2011). The authors contend that terrorists are not random in their behavior but respond in a cause and effect manner from their environment. By understanding this and taking account the environment, attacks may be prevented and vulnerable populations can be protected (Medina, Hepner, Siebeneck (2007).

Perlmutter (2004) explains that social, political, and economic data is useful to understand drivers of terrorist behavior for the cause and effect of terrorist events. Since data is lacking for these drivers, a spatiotemporal analysis will be useful to understand patterns, frequency, and intensity of attacks, the spatial extent of attacks, vulnerable populations and targets of attacks, weapons used, and actor types (Medina, Hepner, Siebeneck 2011). The authors utilized a GIS to display various choropleth maps accompanied with tables, matrixes, and a tiled time series to present a clear understanding of administrative districts with issues of terrorist behavior.

An advanced companion to spatiotemporal analysis is survival analysis. In survival analysis, specifically Cox Regression, an attack occurring marks the change from peace to conflict in an area over time (Raleigh and Hegre 2009). The model then calculates a hazard function describing the risk of change for an area to have an attack occur using supplied variables. Raleigh and Hegre (2009) used this method to identify the importance of variables to attacks over time to provide a risk layer of their sample study area. They were able to identify the importance population and population concentrations had on terrorism as well as distances from capitals and the significance of international borders.

The goal of this project is to utilize GIS to demonstrate an approach to understanding terrorist attacks over time conducted by Boko Haram in a data-poor environment. Nigeria and many African countries have poor data quality and many data gaps. This should not deter analysts or academics from study, but instead inspire them to devise ways to mitigate unknowns in datasets. Insecurity and instability in Africa has led to a breeding ground for terrorism, therefore, we must find a way to curb radicalization and protect vulnerable populations and states (U.S. State Department 2012). This analysis will identify these areas and relationships most

vulnerable to terrorism to better understand targets and strategies of Boko Haram. The consequences of this study produces graphics and methodologies for identifying populations and locations at risk to further attack in the hopes that planning for humanitarian missions and counterterrorism efforts can be effective and efficient.

2.6 Estimating Population at Risk

There are two main reasons why estimating population at risk is important: 1) estimating population at risk aids disaster response teams to effectively supply those in need with resources and 2) population is a usual factor associated with attracting terrorist activity (Willis et al. 2005; Garb et al. 2007, Raleigh and Hegre 2009). This section discusses both motives in addition to discussing defining the spatial extent of terrorism effects on population.

2.6.1 Population at Risk for Disaster Response

A significant challenge in preparing for crises is determining the location and the amount of population at risk to terrorist events. To properly aid those in need, an organization first must prepare for the estimated amount of people at risk to future attacks and then execute the response to those that are actually affected (Garb et al. 2007). The issue arises when population counts are aggregated to larger geographic units such as states or counties. With data attributed to these scales, disaster preparation and response cannot properly define a specific enough area for estimating affected population. Instead, using applicable geographic units such as the area affected by terrorism or water drainage basins for flood disasters are much more useful and accurate to describe population affected by the crisis (Garb et al. 2007).

2.6.2 Population as Indicators of Risk for Terrorism

In terrorism studies, population is often used as an exploratory factor to understand motivation for terrorist attacks to a certain area (Willis et al. 2005). This exploration is typically used in simplistic models for initial terrorism studies or for areas with poor data quality. Willis et al. (2005) argue that there are correlations between population and terrorism, but that there is a clear difference between population, population density, or population concentration (Raleigh and Hegre 2009).

Using simple indicators of terrorism risk is useful and most of the time necessary in areas with poor data. While using simple indicators of terrorism risk to describe an area is severely limited, there is very little consensus or validated methods for creating a simple risk estimator using multiple indicators (Willis et al. 2005). For example, other factors which could be considered indicators for terrorism for Boko Haram would include areas where a large amount of Christians reside or areas with many government buildings (Onuoha 2012). By incorporating these other factors, the result of estimating the area at risk would be more accurate.

Population as a single indicator is not without its uses, however. Exploring correlation coefficients or regression analyses are two simple methods which can explore the statistical significance of the relationships between population and historical terrorism events (Medina, Siebeneck, and Hepner 2011; Zammit-Mangion et al. 2013). Exploring these methods depict how well population, population density, or population concentrations explains Boko Haram terrorist attacks. If the relationships are positive, this indicates that the population metric is a good indicator for terrorism risk.

2.6.3 Defining the Spatial Extent of Terrorism Effect

Spatially defining the area of extent for terrorism is incredibly difficult and lacking in study. Most studies involve aggregating population to large cities or counties and display their results in tables or graphs (Willis et al. 2005; Zammit-Mangion et al. 2013). In addition, research for disasters such as chemical attacks or flooding is much more common in estimating population at risk as the events have definable areal consequences. Chemical attacks, for example have a particular range of effectiveness depending on the element used (Garb et al. 2007).

More sophisticated models with better data incorporate such factors as weapons used, historical targets, landmarks, and loss frequency estimates (Zolkos 2005). Such factors would be more useful in a specific city analysis of risk and is much more difficult to accurately use in areas such as Nigeria with poor data quality and the rural nature of the north. More useful factors in the case of Nigeria would be targets of ethno-religious and political nature: data which does not exist in a complete enough capacity at a sub-LGA administrative level as open-source information (Forest 2012; Adibe 2013).

2.7 Challenges within Data poor environments and Uncertainty in Variables

Uncertainties in estimation produce numerous discussions of how to properly model terrorism events (Willis et al. 2005). Uncertainties in analysis not only arise through data quality, but through estimating values of factors associated with terrorism analysis. Such factors which are important to a terrorism analysis include the goals, motives, and capabilities of terrorists. Representing these factors spatially, however, can be difficult as often these factors are not as clear and concise or agreed upon from the experts. For example, if a group had the goal to destroy every Christian Church in New York using VBIEDs, this would be an easier risk study to

formulate with clear goals and capabilities. Groups like Boko Haram, however, have multiple goals and capabilities which change weight constantly and thrive on opportunistic targets as well as strategic targets (Adibe 2013). In addition, providing values towards factors and weights are often subjective and based on historical accounts and expert advice when available (Willis et al. 2005). This also means that no one model can fit each terrorist group, but an individual analysis must be conducted to best represent the group's goals, capabilities, and motives.

CHAPTER 3: METHODOLOGY

This chapter examines the study area of Borno State, Nigeria, Boko Haram terrorism data, and provides a methodology for achieving the research objective of spatially analyzing and estimating the population at risk to terrorist attacks over time.

3.1 Methodology Framework

The following sections outlined by Figure 3 describe the criteria and methods used to analyze data to answer the following questions:

- a) What are the spatial and temporal trends to Boko Haram attacks?
- b) What variables have a statistically significant correlation with Boko Haram attacks?
- c) What areas are at risk to Boko Haram attacks?
- d) Approximately how many people are at risk to Boko Haram attacks?

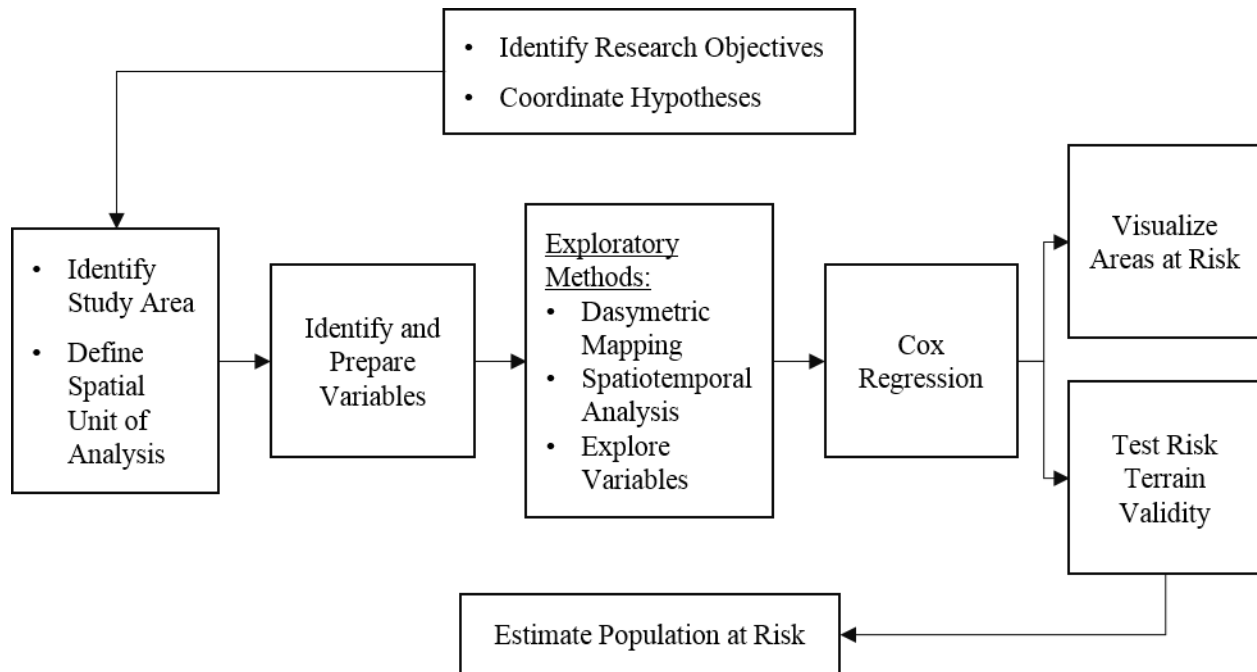


Figure 3: High Level Methodology Framework

As mentioned above, Figure 3 depicts a high-level workflow to answer these proposed questions. Section 3.2 provides an overview of the study area and defines the spatial unit of analysis. All data was downloaded and prepared for use in ArcGIS as outlined in Section 3.3. Exploratory methods outlined in section 3.4 further prepare the variables for use in SPSS and disaggregate variables to a high spatial resolute cell.

Dasymetric mapping is used to disaggregate population variables from the LGAs to the smaller unit of analysis. As described in questions ‘C’ and ‘D’ above, the main objective of the thesis is to spatially identify populations at risk to Boko Haram attacks; therefore, providing a more precise areal unit depicting population numbers are necessary.

Section 3.5 describes the Cox Regression methodology which implements a proportional hazards model to assess the relative risk of Boko Haram attacks to areas through independent variables, otherwise known as covariates. This model was used as the dependent variable, Boko Haram attacks, have a specific time stamp which can be used to analyze time between events in relation to the covariates. This model not answers the questions pertaining to which areas are at risk, but ascertains which covariates are attractors or detractors of attacks and how strongly they are correlated. The validity of this analysis is then tested by year to investigate how well the model performed and to identify spatial and temporal trends.

Estimating population at risk is described in Section 3.6 where risk classes are defined and counts are provided to understand how many people are at risk to Boko Haram attacks. These numbers and risk classes are useful for many purposes but most importantly, is the first step to understanding the IDP and refugee crisis in Nigeria.

3.1.1 Research Hypotheses and Variable Summary

The following hypotheses were developed from previous research literature and Boko Haram historical patterns to answer the research objectives. These hypotheses are tested through the Cox Regression model with the goal to identify locations that are at risk to Boko Haram attacks as well as identify the correlating variables and their impact on the attacks over time. The hypotheses are as follows:

The risk of terrorism events occurring at a location:

- 1) Increases with the size of population in the geographical neighborhood
- 2) Is higher near international border areas
- 3) Increases near major routes
- 4) Increases near major cities
- 5) Increases near Boko Haram headquarter locations
- 6) Increases near prior attack locations

The variables constructed to test these hypotheses are summarized in Table 1. These variables are identified to provide a fundamental analysis of statistical correlations with Boko Haram attacks. As this analysis is taking place in a data-poor environment, the variables expressed are used to identify more prominent factors which could attract or detract Boko Haram activity. For example, the Major Towns variable is used to express locations which have typical targets of attacks such as government figures and buildings as well as schools.

Table 1: Independent Variable Summary

Variable	Explanation
Population	Number of population disaggregated by cell
Population in Neighboring Cells 1st, 2nd, 3rd Order	Testing the statistical significance of population concentration in 1 st , 2 nd , and 3 rd order
Distance from Capital	Importance of capital: 1)BH founded here, 2) Most attacks, 3) Most population, 4) Most targets
Distance from Rebel Group Headquarters	The two most significant headquarters in Borno State where training, resources, and camps are located
Distance from Major Town	Include top targets (government, police, large populated areas, moderate ideals, schools, places of worship). Used to express concentration of targets are
Roads	Provides access to localities, used often to move across the rough terrain of the state. Expressed by type
International Borders	Used to bypass opposing forces that do not have jurisdiction to cross border. Access to other cities and resources
Distance to Prior Attack	Attacks are coded by distance to an attack that occurred within a week of one another

3.2 Study Area and Unit of Analysis

The study area for this thesis encompasses Borno State in northeastern Nigeria. Boko Haram not only began their terror campaign within this state, but the majority of terrorist events from July 1, 2009 to June 30, 2014 occur here as well. Borno State has an estimated population of 5.4 million (adjusted for 2014) and like many states in the northeast of Nigeria, is sparse with nucleated hamlets and rural with occupations predominately agricultural in nature.

Twenty-seven local government areas (LGAs) administratively divide Borno State. The capital, Maiduguri, lies roughly in the center of the state and has the highest population estimated over 500,000. The northern LGAs have a lower population due to the harsh climate conditions and lack of infrastructure. Although freedom of religion is proclaimed, the states' legal system is dictated by Sharia Law and the residents are primarily Muslim.

Administrative boundaries were downloaded from the Global Administrative Database at www.gadm.org. This dataset provided country, state, and LGA - administrative levels zero, one, and two respectively. The map in Figure 4 displays an overview of the study area of Borno State within Nigeria and the states' 27 LGA administrative divisions.

Official population data is aggregated to the LGA level and extracted from Nigeria's census which was last conducted in 2006. Borno State was estimated to have an annual growth rate of 3.4 percent which was applied to the 2006 population numbers equally across the LGAs.

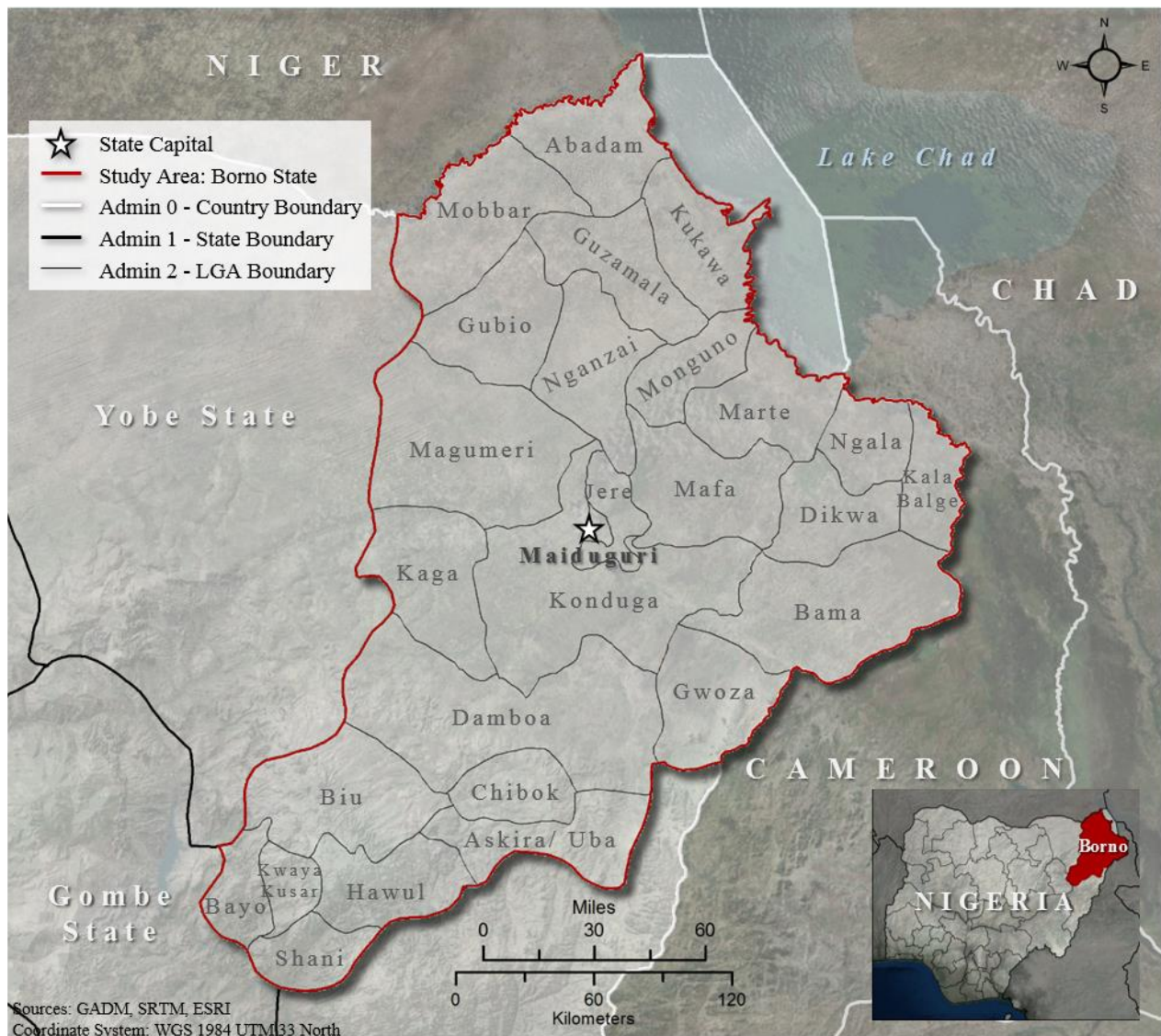


Figure 4: Map representing LGA administrative divisions of Borno State in Nigeria

Using the LGAs as the unit of analysis provides very low resolution analysis and issues with the Modifiable Areal Unit Problem (MAUP). MAUP is an issue that arises from using artificial units such as administrative divisions. By creating areas, even at a similarly spatial scale, misrepresentation of data is possible through the ability to group data by different units or scale. The official census aggregates the population data to the LGA administrative level as depicted in Table 2. Areal variances in LGA (Table 3) impact analysis on terrorism point data and population counts through the dividing of data to these units. By having these boundaries, it may highlight one area more without actual significance.

Table 2: LGA Area, Population and Density Estimates

LGA	Area (km ²)	Pop2014	Pop Density	LGA	Area (km ²)	Pop2014	Pop Density
Abadam	2,422	130,751	53.98	Kala/Balge	1,236	79,490	64.31
Askira/Uba	2,191	187,262	85.47	Konduga	5,868	205,567	35.03
Bama	4,466	352,955	79.03	Kukawa	2,078	265,701	127.86
Bayo	1,064	103,328	97.11	KwayaKusar	734	74,093	100.94
Biu	3,319	229,659	69.20	Mafa	2,922	135,371	46.33
Chibok	1,394	86,675	62.18	Magumeri	5,118	183,269	35.81
Damboa	6,464	304,714	47.14	Maiduguri	131	705,620	5,386.41
Dikwa	1,783	137,255	76.98	Marte	2,274	169,094	74.36
Gubio	2,496	197,680	79.20	Mobbar	3,235	152,400	47.11
Guzamala	2,304	125,428	54.44	Monguno	1,509	143,516	95.11
Gwoza	2,422	361,382	149.21	Ngala	1,323	309,024	233.58
Hawul	2,073	157,758	76.10	Nganzai	2,493	129,457	51.93
Jere	871	273,233	313.70	Shani	1,195	131,959	110.43
Kaga	2,765	117,595	42.53	TOTAL	66,150	5,450,236	82.39

Table 3: LGA Area, Population, and Density: Mean, Max, and Min

	Area (km ²)	Population	Population Density
Mean	2,593	201,861	285.02
Max	6,464	705,620	5,386.41
Min	131	74,093	35.03

To provide a higher resolution study than large LGA boundaries, the unit of analysis is disaggregated to a ‘locality’ (here on out called cells) in Borno State which is defined by the average distance from one populated place (city/town) point to another which is rounded to 3km. These cells represent more populated towns and their nearby hamlets which depend on the towns resources.

3.3 Data Sources and Variables

The data sources below are used to create the variables used for the Cox Regression as summarized in section 3.1.1. There are five main datasets used to develop the variables for the study. The datasets discussed include: Armed Conflict Data (ACLED), population, road, populated places, and borders.

3.3.1 Data Prep with ArcGIS

ArcCatalog was used to organize and prepare data for this study. Data was projected to WGS 1984 UTM zone 33N (SRID 32633) and imported into a single file geodatabase. Two feature datasets were created to house data for Nigeria and the extracted study area dataset of Borno State.

ACLED data was downloaded in table form and for the entirety of Africa. An expression was created to select data for Nigeria which involved Boko Haram between July 1, 2009 and June 30, 2014. In addition, extracted incidents were included if Boko Haram was mentioned in fields ACTOR1, ACTOR2, ALLY_ACTOR1, OR ALLY_ACTOR2. The table was converted into a feature class using the latitude and longitude fields that were included in the dataset.

Population data was manually extracted from Nigeria’s census of 2006. After creating a table, the population data was joined with the LGA feature class to calculate and visualize

population numbers across each LGA. The annual growth rate of 3.4 percent was applied to the population numbers for a current representation of population.

A grid was created to represent 3 km cells over the extent of Borno State. These cells are used to distributed population numbers from LGAs. 3 km cells were used to define a ‘locality’ and are from here on out notated as cells.

A cost distance raster was created combining the classes of roads, Landcover, and Elevation data. This cost raster was used to calculated variables using distance as a factor. These variables include: Distance to Major City, Niger Border, Cameroon Border, Lake Chad, Capital, and Boko Haram Headquarters.

3.3.2 Dependent Variable – Boko Haram Attacks

Boko Haram attack data are provided by the Armed Conflict Location and Event Data Project (ACLED). This database houses over 80,000 individual events from 1997 in Africa. The project collects real-time data, is updated monthly, and has been considered the most comprehensive dataset that is publically available.

ACLED data is collected through three means: 1) information from local, regional, national, and continental media; 2) Non-government organization (NGO) reports; and 3) News reports which are focused on African events to add extra information. Appendix A provides the type of attributes and descriptions associated with this particular dataset.

Each event has coordinates to identify their location and are available through an excel spreadsheet. The Nigerian dataset and time frame of July 1, 2009 – June 30, 2014 was extracted from the original spreadsheet using Microsoft Excel and converted to shapefile format through ArcCatalog. Boko Haram events were then further extracted through a query on fields ACTOR1,

ACTOR2, ALLY_ACTOR, and ALLY_ACT1. If Boko Haram was mentioned in any of these fields, they were deemed a viable point for the study.

For the 5 year period, there were 1025 events in Nigeria involving Boko Haram. Borno State had 58.6 percent of all Boko Haram events, therefore it was chosen as the state for study. ACLED data was then further extracted using ArcGIS to include only Borno State events, of which there were 601.

All events have a field GEO_PRECISION indicating their spatial accuracy. Of the 601 events, 492 have a geo precision of 1 indicating coordinates for the town. 95 events took place near a town, in a small region and were classified as a 2. Due to the rural nature of the study area, these events were kept for the study. 14 points were classified as a 3 which indicated a provincial capital. These were evaluated as having too large a spatial resolution and were deleted from the database. The total event points totaled 587.

The event points were aggregated to the unit of analysis which is the 3 x 3km cell defined as a locality. The map in Figure 5 displays the location of all 587 ACLED event points within their respective cells involving Boko Haram from July 1, 2009 to June 30, 2014.

In addition to location and geoprecision, the events have a day time stamp. With a high geoprecision and time precision, patterns across time and space are available for study to predict possible areas at risk in the future. A Cox Regression Survival Analysis will be used for this purpose.

To prepare the dataset for use in the Cox Regression model, each of the 587 attacks in a cell at their given date equals a dependent variable. A Moran's I test for spatial autocorrelation is conducted which shows that this variable is clustered, indicating a less than 5 percent chance the data is a result of random chance (See Appendix B). To handle the dependence between attacks,

the model uses the precise date and geographic location to concentrate on the relationships between the preceding attacks in the same and nearby cells. This variable (Distance from Prior Attack) is further explained in the independent variables section.

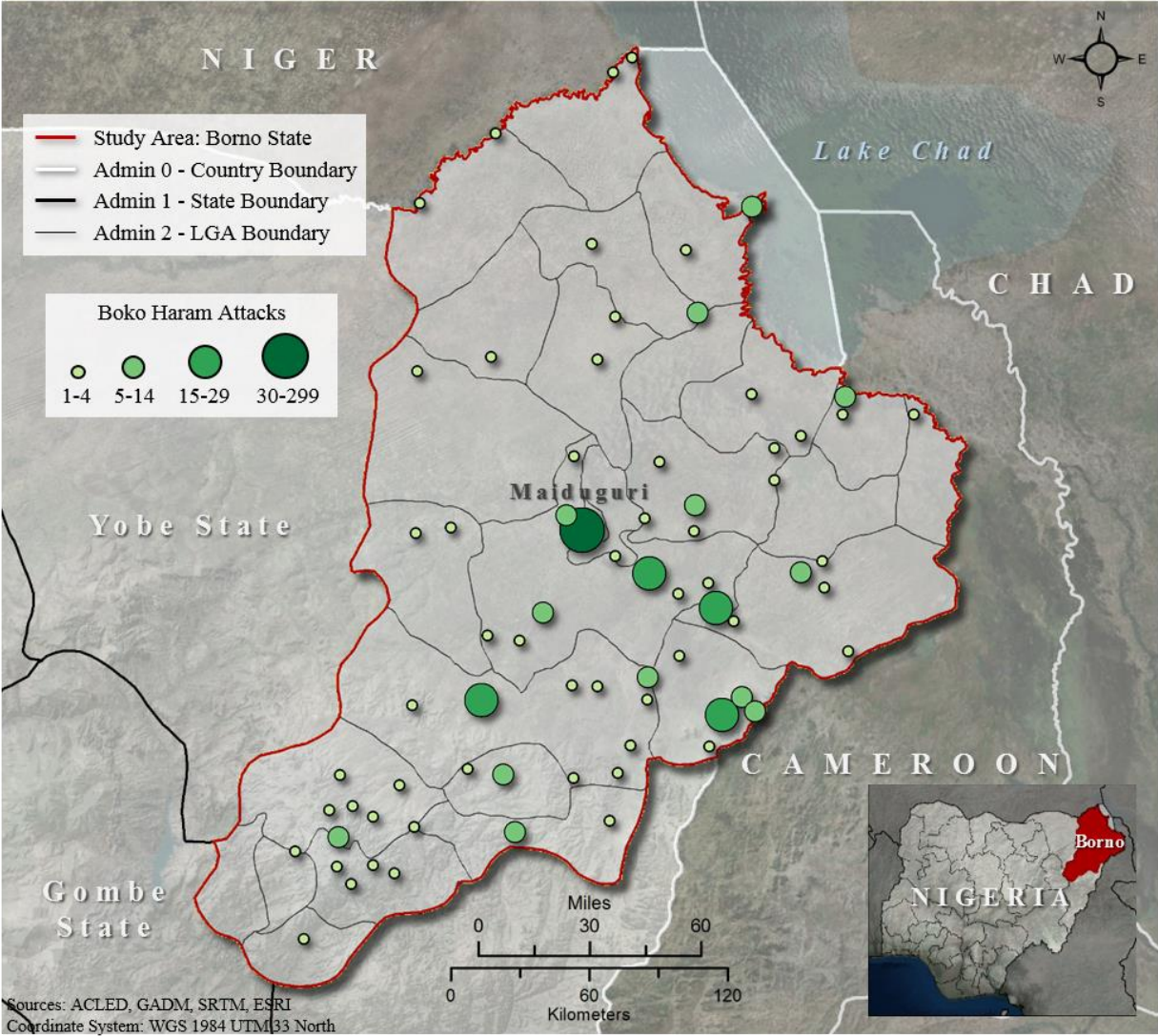


Figure 5: Boko Haram Attacks from July 1, 2009 – June 30, 2014

3.3.3 Independent Variables – Sources and Preparation

These variables include data that is hypothesized to correlate with Boko Haram attacks. The exploration of the data below describes the variables’ use in the study to identify the statistically significant variables to be used in a risk analysis.

3.3.3.1 Population Data

The main objective of this thesis is to spatially identify populations at risk from Boko Haram terrorism. Population data was extracted from the National Population Commission of Nigeria which provides data from Nigeria's official census. The last census was conducted in 2006 and is aggregated to the LGA.

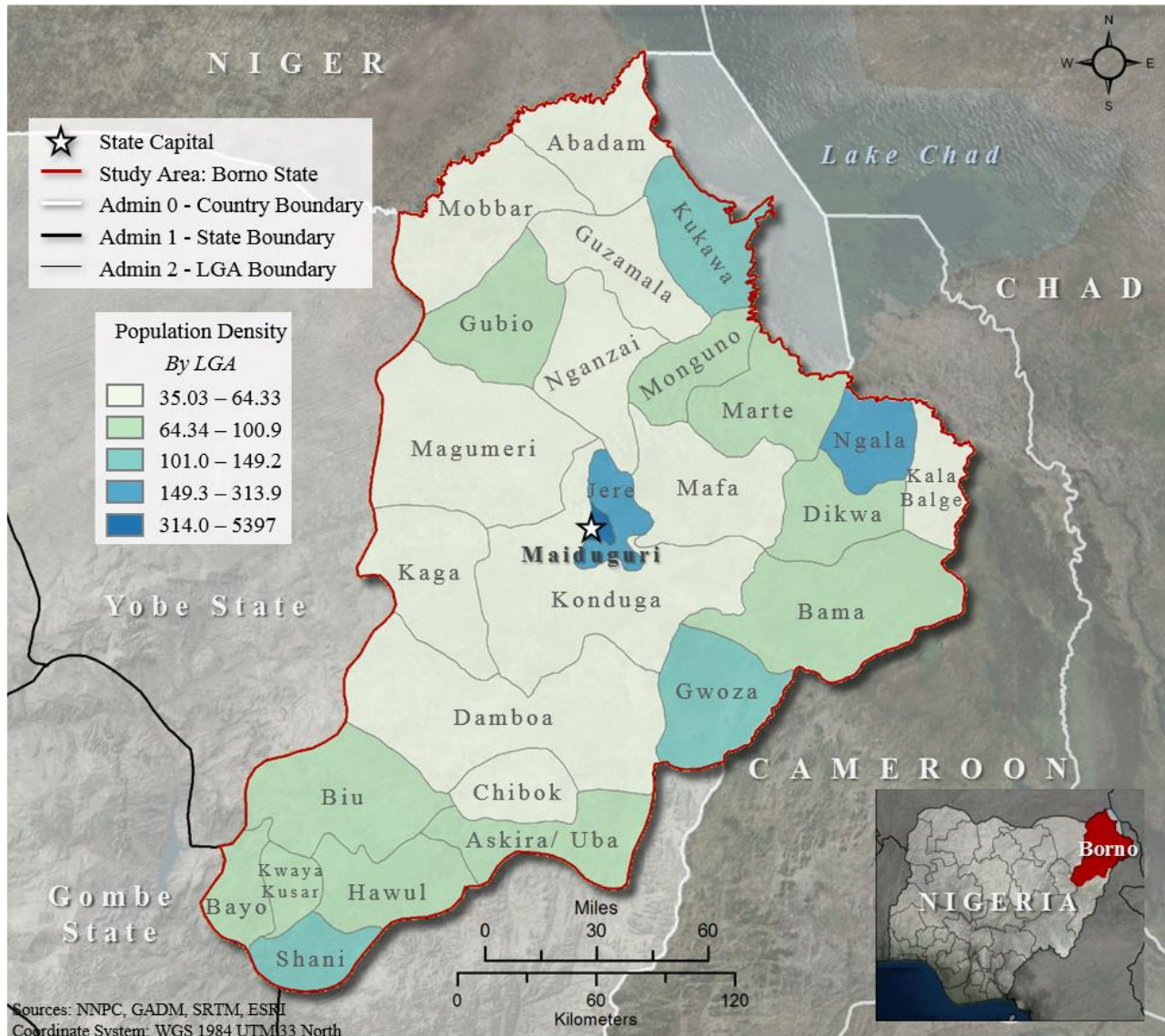


Figure 6: 2014 Borno State Population Density by LGA

Figure 6 displays the population density per LGA. As seen in these figures, the LGAs vary in size, are large, and do not do a sufficient job in visualizing the dispersion of population throughout the LGA. To provide an effective analysis of population at risk to terrorism events, a dasymetric model (section 3.4.1) will disperse the population numbers to the spatially similar unit of analysis (locality) throughout the LGAs instead of assuming a homogenous distribution across an LGA.

The population per LGA was downloaded in PDF format and entered into an excel spreadsheet. The LGA names were then used to join both the shapefile of LGA boundaries and the table containing population numbers. In addition, the annual growth rate of Borno State is estimated at 3.4 percent and used to provide a more current estimation of population through Equation 1. To calculate the growth rate, the population from year 2006 is multiplied by the growth rate (i) of 3.4 percent, with n describing the number of periods, in this case years, to find the population for year 2014.

$$Pop_{Future} = Pop_{Present} * (1 + i)^n$$

3.3.3.2 Populated Places

The populated places dataset is obtained from the National Geospatial-Intelligence Agency (NGA) GEOnet Names Server (GNS). This dataset is updated weekly and provides an official repository of places with standard and variant spellings. Location, quality, administrative level, and type of place are types of attributes that are included within this dataset. The Feature Designation Code (DSG) attribute designates the type of feature. For this study, all DSG attributes coded as populated places (PPL) were extracted to create a populated places shapefile to express where people reside.

3.3.3.3 Road Data

Road data is extracted from the Vector Map (VMap) level 0 and include primary and secondary roads. This dataset is best at a 1:1,000,000 scale therefore Open Street Map and Google Earth Imagery were used to update and digitize routes for a more robust and spatially accurate variable. VMap was used as the primary road dataset as it was more representative of major routes Borno State. Road Data is important to use within this study as it helps to identify possible populated areas. Borno State is very rural and tiny hamlets are regularly dispersed off of roads and trails. The populated places dataset is robust, although many of the smaller hamlets and towns are not accounted for. To help in the dasymetric process of distributing population throughout an LGA, roads are used to account for the unidentified populated places.

3.3.3.4 International Borders

International borders are extracted from the GADM dataset which represents administrative borders. Borno State borders Niger to the north, Chad to the northeast, and Cameroon to the east and south east. These borders are explored as possible key variables as they are porous and provide Boko Haram some coverage from opposing forces on either side of the border.

3.3.4 Strengths, Assumptions and Limitations

All data collected for this study are acquired from differing sources and have different spatial accuracies and confidence levels. Population data is expressed through the administrative level LGA and is adjusted from the official census of 2006 to reflect a 3.4 percent growth rate. Not only is this census eight years old, but the census process was mired in controversy and inaccuracies. Insecurity within Nigeria and arguments of whether or not to include ethnic and religious questions motivated traditional and political leaders to dissuade their constituents to partake in the census. In the end, the sensitive questions were not included in the census process

but it is believed that much of the numbers were inflated for political reasons. Additionally, methods are unknown to determine the 3.4 percent growth rate for Borno State.

IDPs, refugees, and nomadic groups are also not represented within the official population count and may present inaccuracies for estimating vulnerable populations. Despite the controversy and the estimated numbers, population for the LGA will be assumed as sufficient for the study of estimating population distribution.

The populated places feature class includes 2,432 locations and is current as of September 3, 2014. These points represent the majority large towns throughout Borno State. Although this is a robust dataset, it does not include many of the smaller populated areas throughout rural regions. Populated Places was used to weight major towns in the area for a dasymetric population map. Roads were also used to weight population as people live along these routes. Although both road and populated places datasets are incomplete, together they are assumed to be sufficient and a complete representation of population and distribution for this study.

ACLED data is updated monthly and is deemed as one of the most comprehensive, publically available datasets. As ACLED data is derived from various methods of reporting firsthand accounts, challenges arise through recording the details and locations of events. Many times, events are reported near a known town or landmark rather than a specific hamlet, or locations are recorded incorrectly. Some discrepancies were found within the dataset where some points were geo-located within a different LGA than reported. In this case, the point was cross-referenced with the populated places database to resolve discrepancies.

Events from the ACLED database are also subject to over-exaggeration of deaths or injuries during the event as it is difficult to verify. In addition, some attacks may not be

represented. In the ACLED dataset, many of the actors are listed as ‘unknown.’ These could also be Boko Haram events, but there is currently not enough information to identify it as such. These ‘unknown’ actors were not included within the study as they could potentially misrepresent Boko Haram patterns.

3.4 Exploratory Methods

The following sections describe the criteria and methods used to analyze the data to answer the following questions:

- a) What are the spatial and temporal trends to Boko Haram attacks?
- b) What variables have a statistically significant correlation with Boko Haram attacks?
- c) What areas are at risk to Boko Haram attacks?
- d) Approximately how many people are at risk to Boko Haram attacks?

A spatiotemporal analysis is conducted to visualize trends within the dataset. The spatiotemporal analysis at the aggregated level helps to validate trends depicted at the theorized locality spatial level. Section 3.4.2 outlines methods used to conduct a dasymetric model for disaggregating population data to each cell. Last, variables are explored and prepped for the Cox Regression to visually validate the constructed hypotheses as outlined in section 3.1.1.

3.4.1 Identifying Boko Haram Attack Patterns over Space and Time

Since the beginning of Boko Haram’s violent campaign in 2009, attacks their intensity have increased as depicted by Figure 7. Five years later, attacks are more frequent and more deadly motivating Nigeria and the international community to declare a state of emergency in the northeast of Nigeria. Table 4 shows the amount of attacks per year in the study depicting the raw increase of attacks by year with the mean number of attacks per LGA also increasing.

Over the study period, Boko Haram has increased their capabilities through training and funding from other terrorist organizations. Attack intensity is used to show this increased capability and calculated by summing the amount of fatalities, injuries, and hostages and dividing by the total number of attacks. Injuries and hostages are equally summed with fatalities as they are explained as possible fatalities. This increase is also shown in Figure 7.

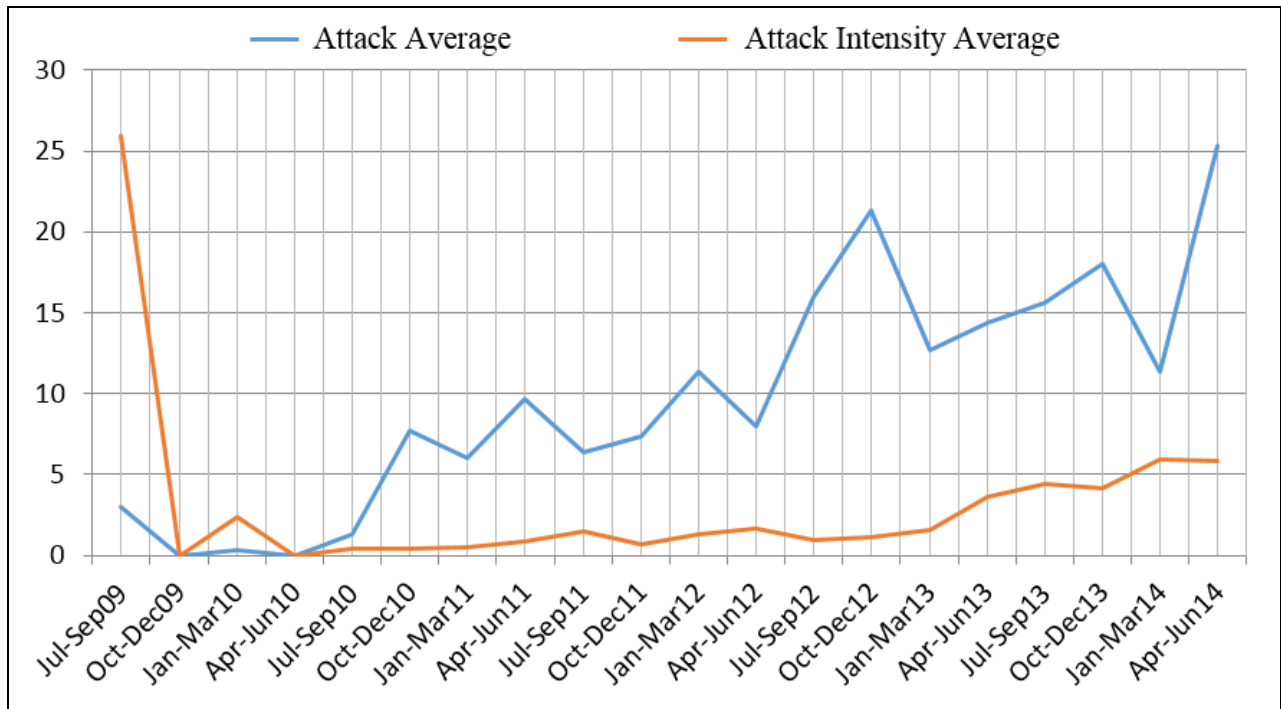


Figure 7: Attack and Attack Intensity Average per Quarter from July 2009 – June 2014

Table 4: Attacks by Year

Date	# of Attacks	Mean # of Attacks by LGA
July 09 – June 10	10	0.37
July 10 – June 11	74	1.79
July 11 – June 12	99	3.88
July 12 – June 13	193	5.16
July 13 – June 14	211	15.3

As the Boko Haram insurgency gained momentum, attacks have spread from the capital of Maiduguri to other areas within the state as expressed by Figure 8. Figure 8 is a spatiotemporal depiction of attacks per LGA over a one year period. The number of attacks per LGA are expressed by Quartiles which contain an equal number of features per quantile. This method was used to compare and highlight areas which had the highest (top 25 percent) amount of attacks occur by year to identify trends.

The spatiotemporal trend shifts from the capital outwards with a higher amount of attacks in the southern region of the state. Figure 9 supplements the spatiotemporal figure by expressing the spatial shift of the mean center of events by year. It is likely more attacks are occurring the south of Borno State where there is more infrastructure and resources and provide access to other states as well as Cameroon.

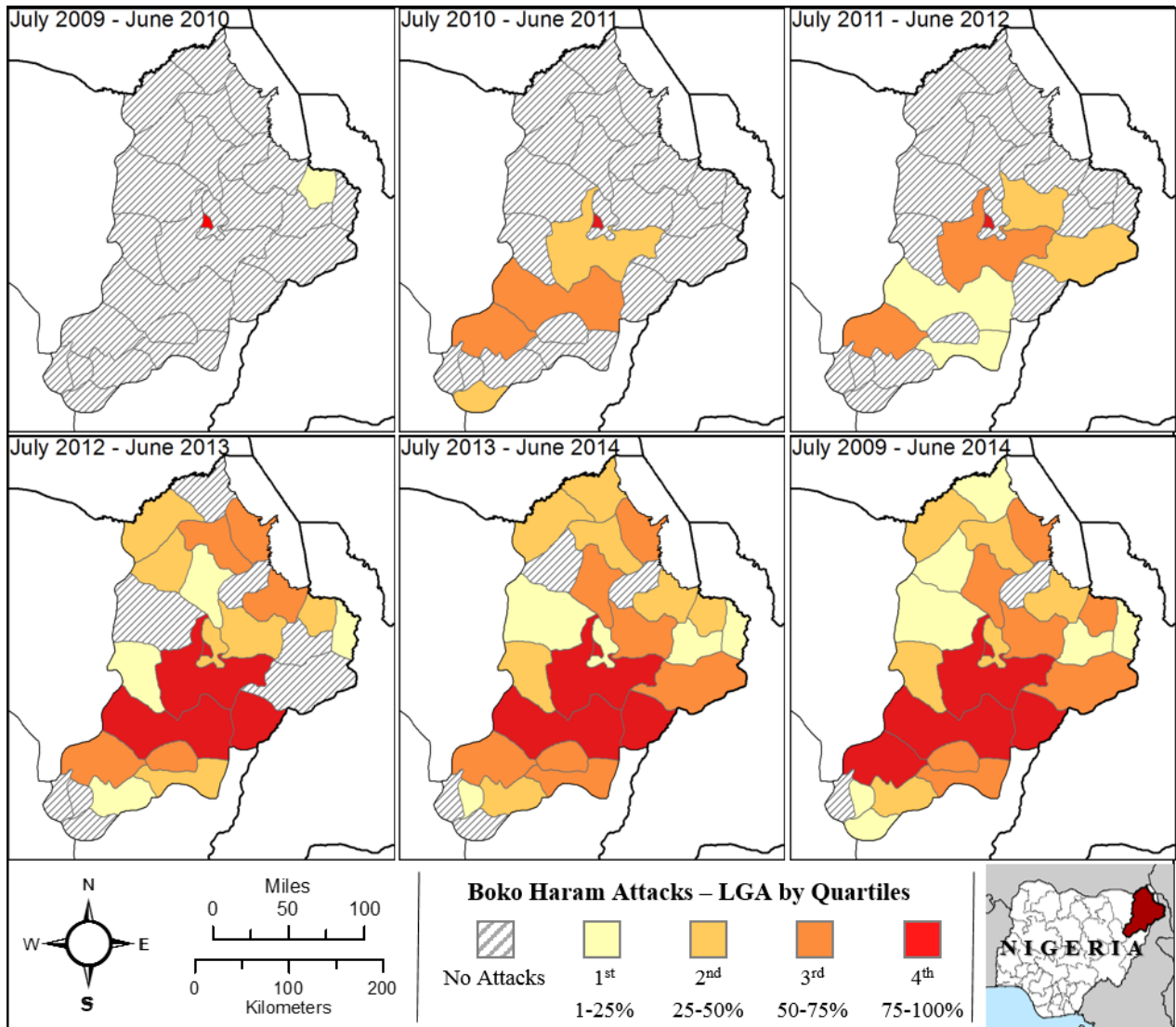


Figure 8: Spatiotemporal depiction of Boko Haram attacks by year July 2009 – June 2014

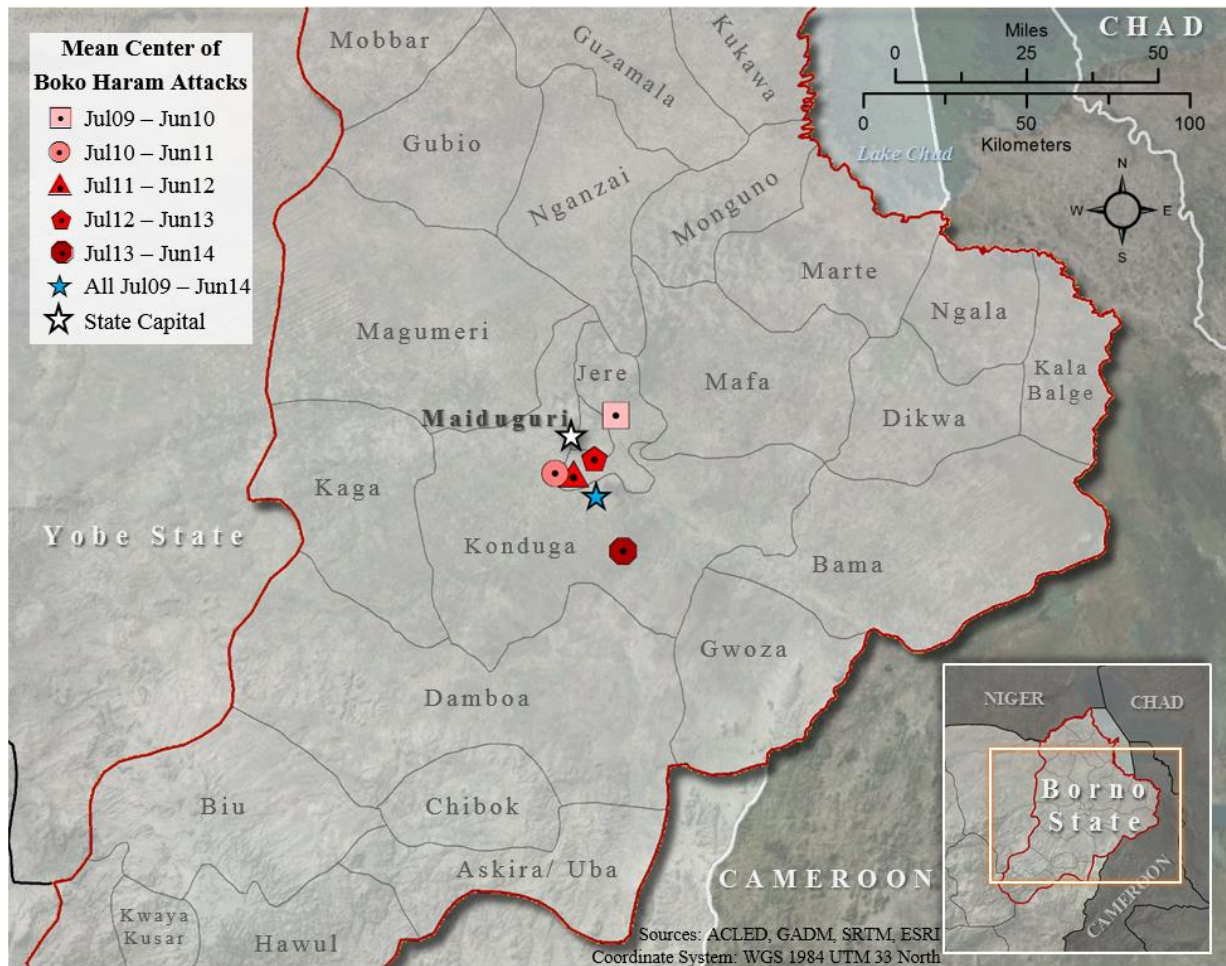


Figure 9: Mean Center Cluster of Boko Haram Attacks by Year: July 2009 – June 2014

3.4.2 Dasymetric Mapping

Dasymetric mapping methods were explored to disaggregate population data from larger administrative levels (LGA) that differ in size to smaller, spatially-similar units. Using the lower resolution LGA units significantly affects the spatial analysis of the study as well as assumes homogeneity of population distribution throughout the entire area. Using a dasymetric method against these units allows for a more precise measurement of population in a cell and produces a higher resolution of results for analyzing terrorism effects on population.

The cell sized used is equal to the average distance between populated points, 2,612 meters. This was rounded to 3 kilometers and used as the unit of analysis for the study.

The dasymetric method used for this study combines Riebel and Buffalino's (2005) Street Weighting (SW) and Address Weighting (AW) Methods, and Areal Interpolation (AI). In the SW method, total population is taken from each LGA and distributed to smaller cells by calculating the length of street segments throughout each cell. Equation 2 outlines the steps taken to assign weights per cell by street length:

$$W_i = \frac{L_i}{L_t} \quad P_i = W_i \times P_t \quad P_{cs} = \sum P_i$$

The first calculation weights each street segment (represented as W_i) by dividing the length of street segments in a cell (L_i) by the total length of all street segments in the LGA (L_t). The population of the street segment (P_i) is calculated by multiplying the weight of a street segment (W_i) to the total population of the LGA (P_t). Population per cell (P_{cs}) is then calculated by summing all street segment populations (P_i) that are contained within that cell.

Equation 3 represents the AW method which is applied in a similar manner where the weight of populated places within a cell (W_p) is equal to one divided by the total number of populated places within the LGA (N_a). The average population per populated place (P_a) is the product of the populated place weight (W_p) and total population of the LGA (P_t). Population per cell (P_{cp}) is then calculated by multiplying the number of populated places in a cell (N_{ab}) to the average population at each populated place (P_a). The equations are expressed as follows:

$$W_p = 1/N_a \quad P_a = W_p \times P_t \quad P_{cp} = N_{ab} \times P_a$$

AI is conducted through Equation 4 where the area for the new grid ($Area_n$) is divided by the area of the LGA ($Area_o$). The weight is then multiplied by the population per LGA to distribute population throughout the grids within the LGA (P_{ai}).

$$P_{ai} = (Area_n / Area_o) * Pop_{LGA}$$

These three methods, SW, AW, and AI each represent 100 percent of the population distribution. To combine all assessments, weights are assigned to streets (W_s), populated places (W_{pp}), and AI (W_{ai}) to recalculate population distribution. For this study, these variables were deemed equally important in assessing where population resides. By combining the methods equally, populated places weight the distribution higher within the cells. This is ideal as the larger populated places (such as cities and towns) are the majority features represented within the populated places shapefile.

Equation 5 combines all methods through first assigning weights to streets (P_{cs}), then Populated Places (P_{cp}), and lastly the Areal Interpolation (P_{ai}). The ending values are summed together for the updated and disaggregated population layer.

$$P_s = P_{cs} \times W_s \quad P_p = P_{cp} \times W_{pp} \quad P_a = P_{ai} \times W_{ai} \quad P_{spa} = P_s + P_p + P_a$$

The new population distribution by street (P_s) per cell is calculated by multiplying population designated by the street method (P_{cs}) to a weight (34 percent). The new population distribution by populated place (P_p) is calculated by multiplying the population by the populated place method (P_{cp}) to its weight (34 percent). Lastly, AI method is weighted with a 32 percent. The final population count per cell (P_{spa}) is the sum of the new populations of street, populated place, and areal interpolation methods. This method observes the pycnophylactic principle,

ensuring the total population count per LGA is realized by summing each cell within the LGA.

Figure 10 represents the final dasymetric output for population in Borno State.

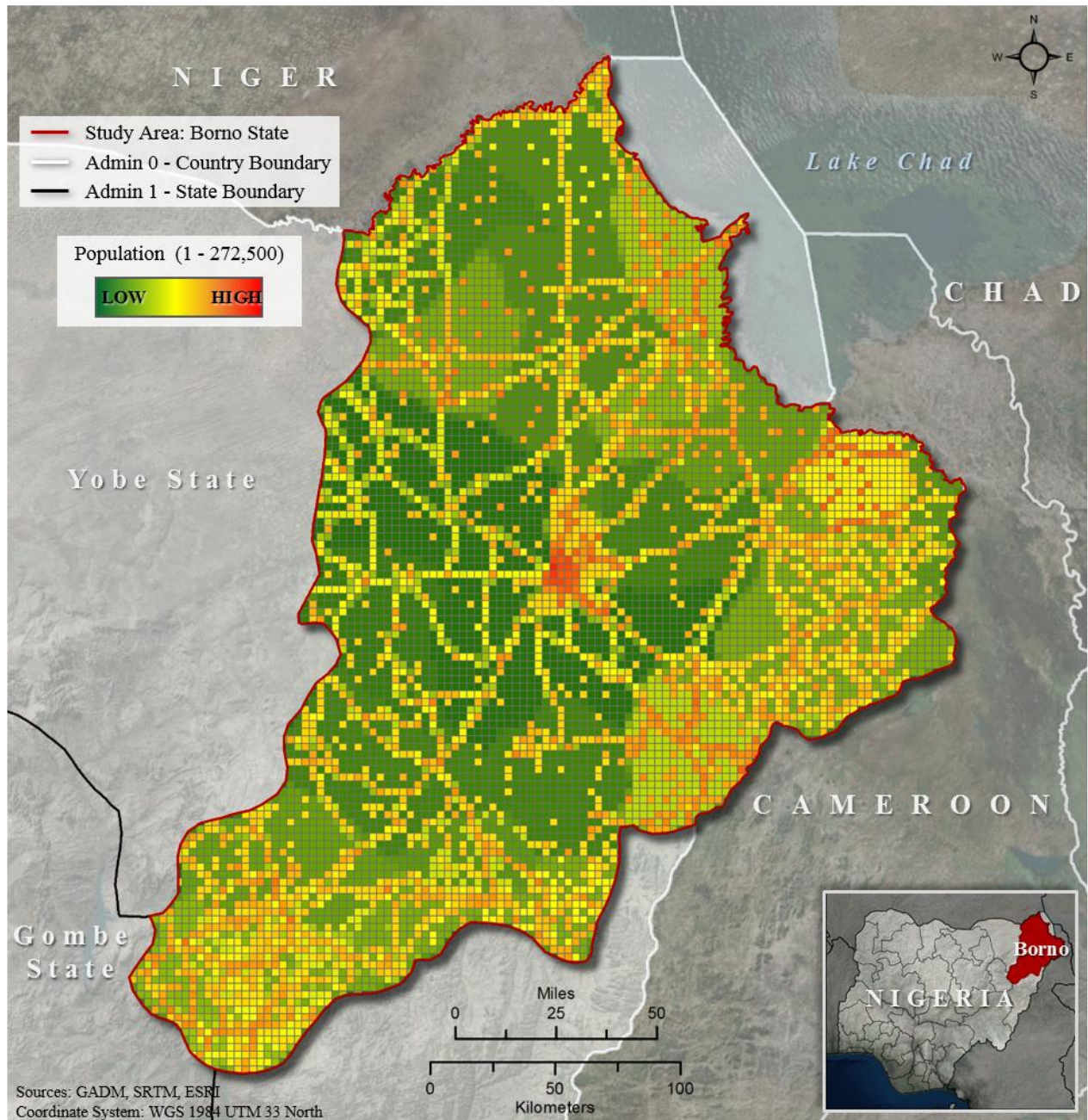


Figure 10: Dasymetric Map of Population by Cell

3.4.3 Exploring Independent Variables

This section describes the additional exploration and preparation of variables used in the Cox Regression for validating the constructed hypotheses as outlined in section 3.1.1.

3.4.3.1 Cost Surface

A cost surface is created to give the distance variables a cost to travel across cells. The three variables used to create the cost surface include roads, Landcover, and elevation. All three variables are resampled to the 3 km cell size and reclassified from 0-4, having 0 indicate no impedance and 4 as not navigable.

3.4.3.2 Population Variables

Population per cell is expressed through dasymetric mapping as described above (3.4.2). To reduce the influence of extreme observations, this variable is log-transformed.

3.4.3.2.1 Log Population in Neighboring Cells

This variable is used to test the concentration of population in neighboring cells. This is split into three variables. The first is equal to population per neighborhood, 1st order- the immediate eight contiguous cells summed. Second, is equal to the 2nd order neighborhoods summing the immediate 16 cells. Third, is the 3rd order neighborhood summing the 24 contiguous cells. These different variables are used to see if any of them present statistical significance to attacks.

ArcGIS's Focal Statistics is used to create these variables.

3.4.3.3 Populated Places

The populated places data layer is used to depict the following variables: the capital of Borno State, Boko Haram Headquarters, and Major Towns. The following sections outline the importance of the variable and the additional preparation for use in the Cox Regression.

3.4.3.3.1 Distance from Capital

Within the capital, Maiduguri, is the primary seat of government for Borno State as well as many of the other targets Boko Haram enjoys exploiting to include schools, Christians, and police.

Boko Haram members can easily hide among the population, retrieving resources and attacking vulnerable targets. Boko Haram was also founded in Maiduguri and is of strategic importance to the group. This variable estimates the distance per cell to the capital using the cost raster and is log-transformed.

3.4.3.3.2 Distance from Boko Haram Headquarters

The headquarters variable depicts the top two locations that were active for Boko Haram headquarters through the period of 2009 – mid 2014. As with the variable of Distance from Capital, the distances are attributed to each cell by using ArcGIS's Cost Distance tool and a cost raster. The distances are then log-transformed. This variable is expected to increase likelihood of attack with decreasing distance to Boko Haram's headquarters. 73 percent of Boko Haram attacks occur within 50 km of their headquarters.

3.4.3.3.3 Distance from Major Town

As most of Borno State is rural and lacking infrastructure, the variable Major Town is used to represent locations where government, police, schools, and resources are. Major towns are defined as LGA capitals and other towns that are above 40,000 people. The distances from major towns are attributed to cells using ArcGIS's Cost Distance tool with the cost raster and log-transformed. It is expected that the closer a square is to a Major Town, there will be a higher likelihood of an attack. 74 percent of the Boko Haram attacks in Borno State occurred within 1 km of a Major Town and 81 percent are within 10 km.

3.4.3.4 Roads

Roads present accessibility to towns throughout Borno State. There is a severe lack of infrastructure with many of the roads being dirt and more like well-worn trails. The roads in this

database are split into primary and secondary roads which depict the main routes used in the state. A cell with a road occurring is coded as a one with no road as a zero. 95 percent of attacks have occurred within 5km of a road, therefore it is expected that roads will be an attractor for Boko Haram activity and increase risk.

3.4.3.5 International Borders

The border variable is split into Niger, Cameroon, and Lake Chad border areas which each cell having a value of distance to a border. These areas are designated as a zone of question for Boko Haram members to cross. As depicted in the spatiotemporal maps in section 3.4.1, the Cameroon border is more likely to have attacks occur than the Niger border.

3.4.3.6 Distance from Prior Attacks

Each attack is given a distance value from a prior attack occurring. This variable handles the dependence between the attack data by connecting them through a function of time and space. It is hypothesized that attacks are likely to occur in nearby locations, and this variable tests the significance of these nearby locales. Distances were calculated from a single attack to the previous week of attacks occurring. This method was chosen due to static variables used such as Headquarter locations. While analyzing the attacks temporally, it was noticed that as Boko Haram grew with recruits and funding, they would be in multiple locations. Therefore, prior attack distances were calculated against other attacks which occurred in the same time period as well as near prior attacks.

3.5 Identifying Terrorism Risk through Cox Regression

Cox Regression is used to measure a hazard ratio from predictor variables (as described above) and whether these variables increase or decrease the odds of an event occurring as time

continues. Use of these variables helps to identify locations that incur a higher (or lower) relative risk to an attack.

This methodology mirrors Raleigh and Hegre's study (2009) using Cox Regression and ACLED data within data-poor environments. Their study chose Cox Regression to utilize ACLED data's time stamp to explore the relationships of variables over time and identify relative risk to areas. Using this statistical model also deals with the dependence between attacks (as attacks are related or lead to subsequent attacks) through creating a variable handling distances to prior attacks. This variable is possible through this model to use with the specific time stamp as well as location of each attack. In addition, Cox Regression is a semi-parametric model which allows the analysis to occur without having to specify a baseline hazard ratio or firm data assumptions.

The model can be described by Equation 6:

$$\ln h(t) = \ln h_0(t) + b_1x_1 + \dots + b_px_p$$

Where $h(t)$ is the hazard at time t ; x_1, x_2, \dots, x_p are the explanatory variables; and $h_0(t)$ is the baseline hazard when all the explanatory variables are zero. The coefficients b_1, b_2, \dots, b_p are estimated from the data using SPSS.

As explained previously, the following hypotheses were highlighted to test the model.

They are as follows:

The risk of terrorism events occurring at a location:

- 1) Increases with the size of population in the geographical neighborhood
- 2) Is higher near international border areas
- 3) Increases near major routes
- 4) Increases near major cities

- 5) Increase near Boko Haram headquarter locations
- 6) Increases near prior attack locations

These hypotheses help to guide the analysis of the results from the SPSS outputs which include regression coefficients (β) and hazard ratios ($\exp(\beta)$) for this study. These two outputs help describe the relationship and impact the variable has on the dependent variable over time.

Positive regression coefficients indicate an increase in risk (hazard) while negative coefficients indicate a decrease in risk. The hazard ratio expresses the probability of increasing or lowering the odds of an attack occurring. With 1.0 indicating no effect, the further below 1.0 indicates lowering the odds of an attack (or increasing survival time), while the further above 1.0 increases the odds of an attack.

Each cell is also given a number expressing relative risk which is joined in ArcGIS to visualize a risk layer. Risk is then classified to present results.

3.5.1 Testing the Risk Terrain Validity

Creating the risk layer identifies areas of high concentration of ‘aggravating factors’ for Boko Haram attacks. The final risk layer was then split into three time groups (Table 5) to test the predictive ability of the classified risk cells to historical events. For example, a risk map depicts risk from Period 1-3. Boko Haram attacks from the following time period, Period 4, are spatially joined with the Period 1 risk map giving the final raster two values: 1) the risk value (from 1-5) and 2) the number of attacks from the consecutive time period. The values are used to identify the predictive validity of the risk model per time period in a statistical analysis.

Table 5: Time Periods for Risk Terrain Validity Testing

Time Period	Begin Date	End Date
Period 1-3	1-July-09	30-June-12
Period 4	1-July-12	30-June-13
Period 5	1-July-13	30-June-14
Period 6*	1-July-14	31-January-15

* Period 6 occurs after the study period but is used to test the overall risk terrain

3.6 Estimating Population at Risk

There is a logical link between areas at risk and population at risk to terrorism. Risk cells are classified through ArcGIS and defined by the probability of attacks based on historical data.

These risk classes are overlaid with the disaggregated population data to provide the estimated amount of people at risk per class.

Estimates completed at the local level highlight areas within LGAs that can be used for further research and study for terrorism impacts on the areas. These highlighted areas can also later be used to effectively collect and create higher resolution data from remote sensing and GIS to identify areas which need humanitarian, military, or government aid in accordance to actual affected population numbers.

The expected outcome of this analysis will provide a high resolution model to identify the number of estimated populations and areas within Borno State that are at-risk to Boko Haram attacks. By identifying numbers of people affected and areas that need the most attention, this will help with prioritizing resources to effectively combat Boko Haram as well as bring aid to those that need help and support. Boko Haram is an increasing, powerful threat and is affecting the stability of not only Nigeria, but Western Africa. Effective prioritization of areas is necessary to combat Boko Haram and bring stability back to Western Africa.

CHAPTER 4: RESULTS

This study's main objective is to identify areas at risk and estimate population at risk to Boko Haram attacks. Cox Regression, a type of survival analysis, is used to explore the relative importance of variables over time to Boko Haram attacks. The outcome presents a proportional hazards model expressing the relative risk of time to an attack occurring through estimating the hazard ratio ($\exp(\beta)$) of the variables. Each cell receives a calculated value expressing relative risk which is used to visualize an estimated relative risk layer for locations and population that is at risk to attacks from Boko Haram. To assess the validity and predictability of the model, the outputs are generated yearly to compare to subsequent attacks. Finally, population and relative risk classes are explored to estimate population at risk and identify concentrated areas at risk to Boko Haram attacks.

4.1 Risk of Boko Haram Conflict Analysis Using Cox Regression

As mentioned in Chapter 3, Cox Regression is used to measure a hazard ratio from independent variables (here on out called covariates) and whether these covariates increase or decrease the odds of an event occurring as time continues. Table 6 documents the results for the covariates' impact for the analysis from different models labeled 1, 2, and 3. These models vary with the addition of population variables from local-level, LGA-level, and population concentration in 1st and 2nd order neighborhoods.

Full model tables and outputs from SPSS are included within the appendices. For the purposes of this study and to validate the hypotheses and satisfy the research objectives, the β (regression coefficients) and $\exp(\beta)$ (hazard ratio) are mainly concentrated on to analyze the effect of variables to Boko Haram attacks.

Table 6: Cox Regression Results: Estimating Risk of Boko Haram Conflicts

COVARIATE	MODEL 1	MODEL 2	MODEL 3
	β (exp(β))	β (exp(β))	β (exp(β))
Log Distance from Prior Attack	-0.16*** (0.852)	-0.166*** (0.847)	-0.177*** (0.838)
Log Distance from BH Headquarters	-0.772*** (0.462)	-0.764*** (0.466)	-0.752*** (0.471)
Log Distance from Major City	-0.762*** (0.467)	-0.722*** 0.486	-0.735*** (0.479)
Log Distance from Capital	0.436*** (1.547)	0.748*** (2.113)	0.804*** (2.234)
Log Distance from Niger Border	-0.059 (0.942)	-0.072 (0.411)	-0.101 (0.904)
Log Distance from Cameroon Border	-0.335*** (0.715)	-0.292*** (0.747)	-0.311*** (0.732)
Log Distance from Lake Chad	-0.397*** (0.672)	-0.385*** (0.681)	-0.396*** (0.673)
Road Type 1: Primary Route	2.294*** (9.915)	2.205*** (9.071)	2.423*** (11.284)
Road Type 2: Secondary Route	1.333*** (3.791)	1.042*** (2.834)	1.12*** (3.066)
Log Population per Cell		-0.085 (0.918)	-0.025 (0.975)
Log Population in Neighborhood 1st Order		1.157*** (3.182)	-0.076 (0.927)
Log Population in Neighborhood 2nd Order			1.743*** (5.715)
Log Population in LGA			-0.356 (0.7)
No. of Events	587	587	587
If Null Model	-10,528.84	-10,528.84	-10,528.84
If Full Model	-7,356.57	-7,332.49	-7,312.56

*p<0.10, **p<0.05, ***p<0.01

These results satisfy the research objective to identify statistically significant variables which correlate with Boko Haram attacks. Aiding in this objective are the hypotheses which guide the models' analyses. The hypotheses are reiterated below:

The risk of terrorism events occurring at a location:

- 1) Increases with the size of population in the geographical neighborhood
- 2) Is higher near international border areas
- 3) Increases near major routes
- 4) Increases near major cities
- 5) Increase near Boko Haram headquarter locations
- 6) Increases near prior attack locations

Model 1 tests the covariates without the addition of population. Models 2 and 3 add the local-level population and population concentration with LGA-level numbers respectively to test their effect on the model. Model 3 had the highest performance therefore it is here on out concentrated on to answer the hypotheses with Models 1 and 2 present for reference and comparison. This was an expected outcome as it was hypothesized that population concentrations would increase risk of terrorism attacks.

The Null Model, a model run without the covariates, establishes a baseline for model performance. The Full Model indicates model performance with the introduction of covariates and in this case, the model was improved and found to be statistically significant. This reveals that at least one of the covariates contributed significantly to explain attacks or survival from attacks.

Values represented in Table 6 represent the positive or negative β (regression coefficients), indicating an increased or reduced hazard of attacks occurring respectively. The

$\exp(\beta)$ is the hazard ratio which is associated with either increasing or decreasing the odds of attacks occurring. A value at 1.0 indicates no effect on time to an attack occurring. Values below 1.0 represent lowering the odds (increasing survival times), while the more values are above 1.0, the more the covariates increase the odds (decrease survival time). These two values were chosen to identify whether the covariates increased or decreased the likelihood of an attack as well as their strength of their predictive power against attacks. In addition, p values are used to identify variables which influence attacks. If the covariate is found to be significant, the null hypothesis is rejected.

4.1.1 Hypotheses Results

Hypothesis 1 is supported by the covariate Population in Neighborhood 2nd Order. As seen in Model 3, the covariates Population per Cell, Population in Neighborhood 1st Order, and Population in LGA are not found to be statistically significant. While population concentrations were hypothesized to be a more significant variable over straight population counts, it was expected that the Population per Cell variable would still be considered a significant factor.

In addition, when running the model with 1st and 2nd Order Neighborhood Concentrations individually, both are statistically significant and increase risk. 1st order Neighborhoods changes when the 2nd Order is added. The same occurred with Population per Cell and the addition of Population Neighborhoods 1st Order. While the population covariates changed in their significance, it is clear that the increase of population concentration does have an impact on increasing risk for Boko Haram terrorism. Adding these population covariates help to control the variables, further improving model performance and identifying Population in Neighborhood 2nd Order as being the spatial extent as significant. With the average distance to any event location

as ten kilometers, it is not surprising that the 2nd Order Neighborhood is significant as it covers a fifteen square kilometer area.

Hypothesis 2 uses three covariates: Distance to Niger Border, Distance to Cameroon Border, and Distance to Lake Chad. All three variables have a negative β indicating as distance from these variables increases, risk of Boko Haram attack decreases. These covariates have a moderate association of increasing odds of Boko Haram attacks as expressed by the $\exp(\beta)$ as they all are within .32 of 1.00. The closer to 1.00 the $\exp(\beta)$ is, the less effect a covariate has on time to an event occurring.

Distance to Cameroon Border and Lake Chad are found to be statistically significant while Distance to Niger Border is not. This is to be expected as more attacks have occurred around these areas than near the Niger Border. The Niger Border is the furthest area away from Boko Haram headquarters and resources necessary to traverse the harsh, rural areas in the North. The Cameroon Border, provides Boko Haram easy targets for kidnapping, destroying towns, and evading Nigerian military and is much closer to their headquarters.

Hypothesis 3 is clearly supported with the covariates Road Type 1 and Road Type 2. Both road types strongly indicate an increase in likelihood for attacks to occur. Routes provide access to resources and the ability to efficiently move from one area to another with troops and equipment. Boko Haram uses these routes to move across Borno State and when they come across a town, they will take what they need. It was expected that roads would be the highest correlated factor to Boko Haram attacks as 95 percent of the attacks occur within 5km of a road.

Hypothesis 4 uses both covariates Distance from Capital and Distance from Major Cities. Major cities (as well as the capital) will always be important for Boko Haram activity. These places have more resources than most towns throughout Borno State as well as have symbolic

and political targets for them to attack. While the capital of Maiduguri will always be prone to attack and of symbolic nature for Boko Haram to control, over time, Boko Haram has spread their attention from the capital and their military defenses to other places in Borno State and beyond. This explains why the model has a positive β for Distance from Capital and a negative β for Distance from Major City: over time, Boko Haram has spread to other areas. This was not initially expected, but after reviewing the subsequent section of testing the risk terrain validity as well as reviewing the Mean Center Statistics per year, this result became evident.

Hypothesis 5 is supported and performed as expected with the negative β and statistically significant covariate, Distance to Boko Haram Headquarters. As distance increases from the headquarters, the likelihood of attacks decrease. With the difficult terrain and lack of resources in Borno State, Boko Haram depends on their camps to replenish resources such as food and ammo and to regroup.

Hypothesis 6 is supported as it was found that with increasing distance from a prior attack, the associated risk decreases. This verifies the hypothesis that locations closer to previous attacks are more likely to experience an attack. Looking at the data over the study period of five years, there were 104 separate locations corresponding to 587 different attacks. Also, the average distance between attack locations was 10.2 kilometers with the maximum as 44.8 kilometers, supporting the hypothesis that attacks occur close to one another.

4.1.2 Visualizing Risk

X*Beta is an output for Cox Regression analysis in SPSS which depicts the linear predictor score calculated from summing the product of mean-centered covariates with each cell's related parameter estimate (β). This variable provides a relative risk for each cell to have a Boko Haram attack occur given the cells interaction with the covariates. This output is then

joined to a layer in ArcGIS using each cell's spatial ID code as seen in Figure 11. The estimated relative risk of Boko Haram attacks increase with the values as seen in the figure.

The visualization provides an excellent depiction of risk throughout the state. Highlighted are main population concentrations, with the largest concentration focused around the Capital's area. Also highlighted are specific roads which connect attacks and major cities to one another. The low values (indicated in green) represent some of the most rural and inaccessible areas in Borno State. Altogether, the model performed as expected and was crucial to specify the areas at risk and areas which are connected to one another as the Boko Haram crisis continues.

Especially exciting is the highlighting of the southeastern border of Borno State which borders Cameroon. This area has grown in significance over time with an increasing of attacks and cross-border operations conducted by Boko Haram. Areas within the northeast bordering Lake Chad were not expected to be found with a high risk level but more moderate. More research should be conducted to identify causes of this significance.

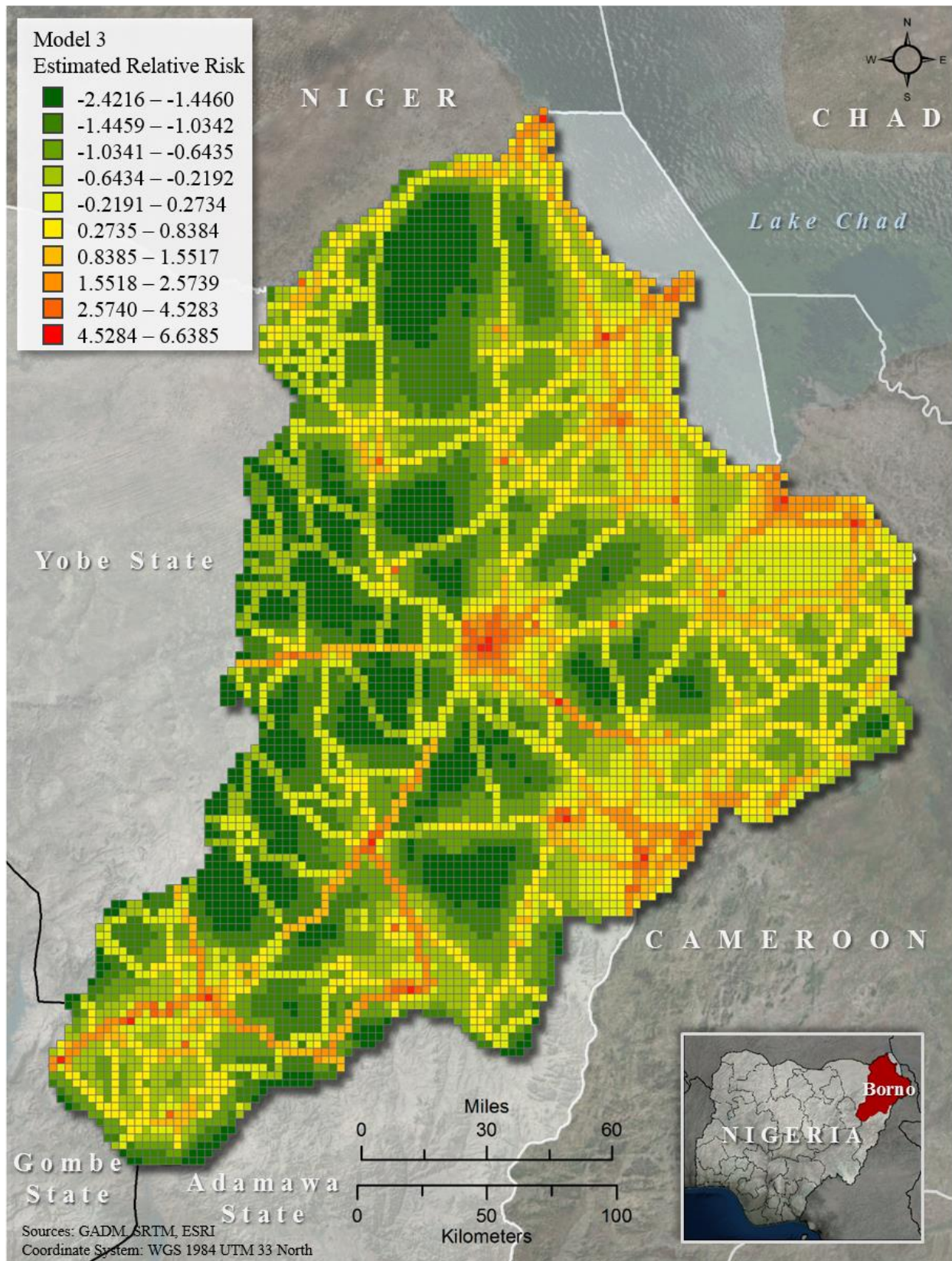


Figure 11: Estimated Risk Terrain of Boko Haram Terrorism in Borno State 2009-2014

4.1.3 Classifying Risk

Risk is classified using Natural Jenks in ArcGIS to visualize and compare clusters of the X*Beta output. To define risk, the probability of an attack occurring per year in a cell within a risk level category was calculated by year and then averaged. The descriptions within Table 7 display the five classes of risk and their definitions.

Table 7: Estimated Relative Risk Classes and Definitions

Risk Level	X*Beta Output	Probability of Attack
Very Low	-2.422 – -0.902	4% chance of attack
Low	-0.901 – 0.047	6% more likely for attacks
Medium	0.048 – 1.257	12% more likely for attacks
High	1.258 – 3.979	25% more likely for attacks
Very High	3.980 – 6.639	53% more likely for attacks

To visualize the output spatially, cells with multiple attacks are dissolved to keep the attack which occurred last to display their current relevant risk. Figure 12 displays the classed estimated relative risk layer for the study period July 1, 2009 – June 31, 2014. As the figure shows, the higher the value, the more risk is associated to that cell for Boko Haram attacks.

Most notable is the impact the roads have on risk. As described above, roads had a high predictor value to increase the chance of attacks occurring (11.284 times more likely to have an attack than a cell without a road). Roads provide accessibility to towns and resources and are a crucial asset for movement. The roads most associated with attacks and connecting between attacks are highlighted with higher risk values.

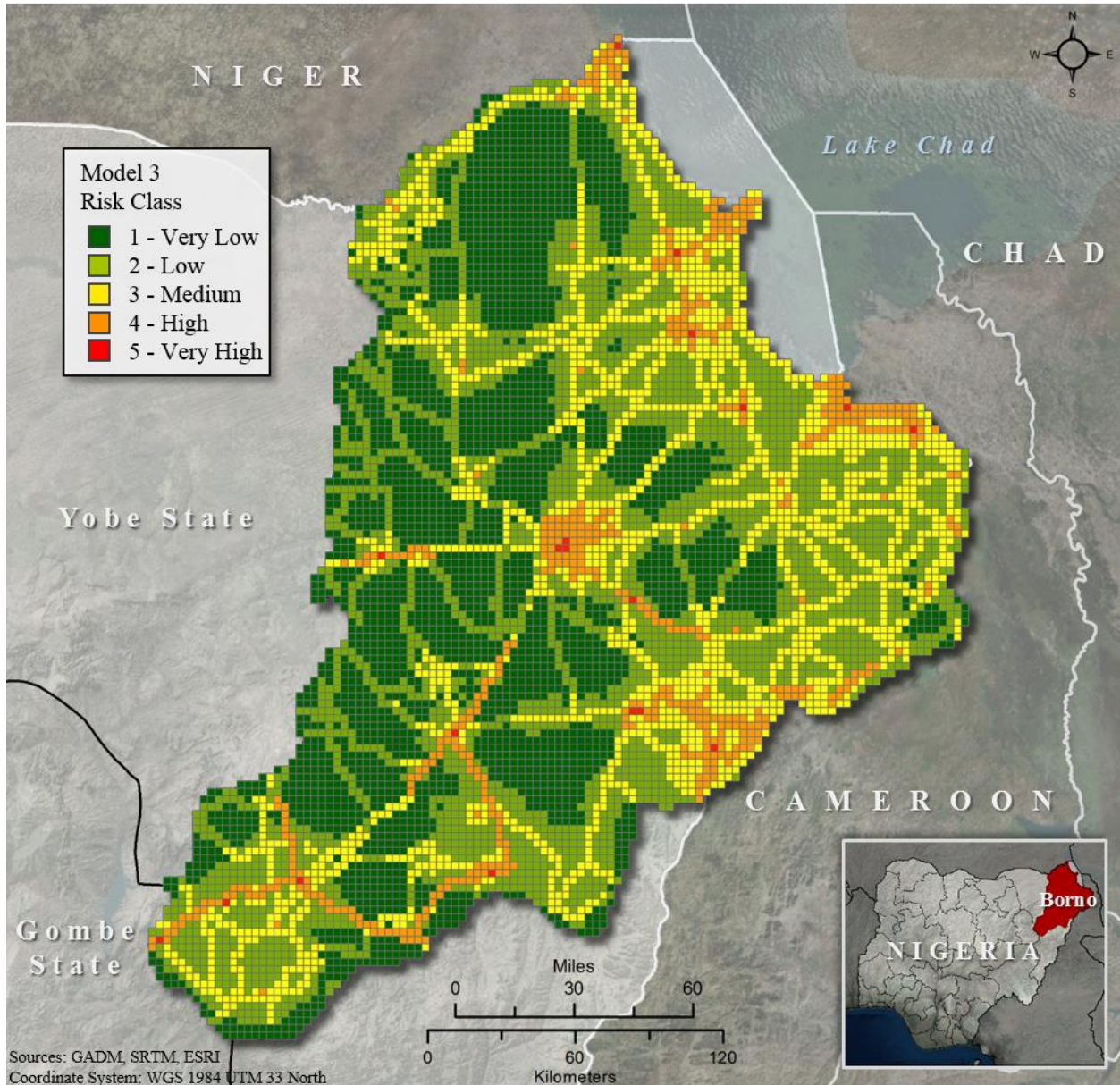


Figure 12: Classified Estimated Relative Risk Values for Boko Haram Terrorism

Roads clearly also play into the impact of previous attacks occurring near other attacks. Figure 13 shows the risk layer compared to Boko Haram attacks to visualize how well the model predicted risk to actual events. Also a strong predictor for this model was Major Cities (also seen in Figure 13). The closer to a Major City, the more risk is associated with Boko Haram attacks.

As time progressed during the study period, the Boko Haram insurgency spread to other locations such as major cities for new targets, resources, new headquarters, and recruitment.

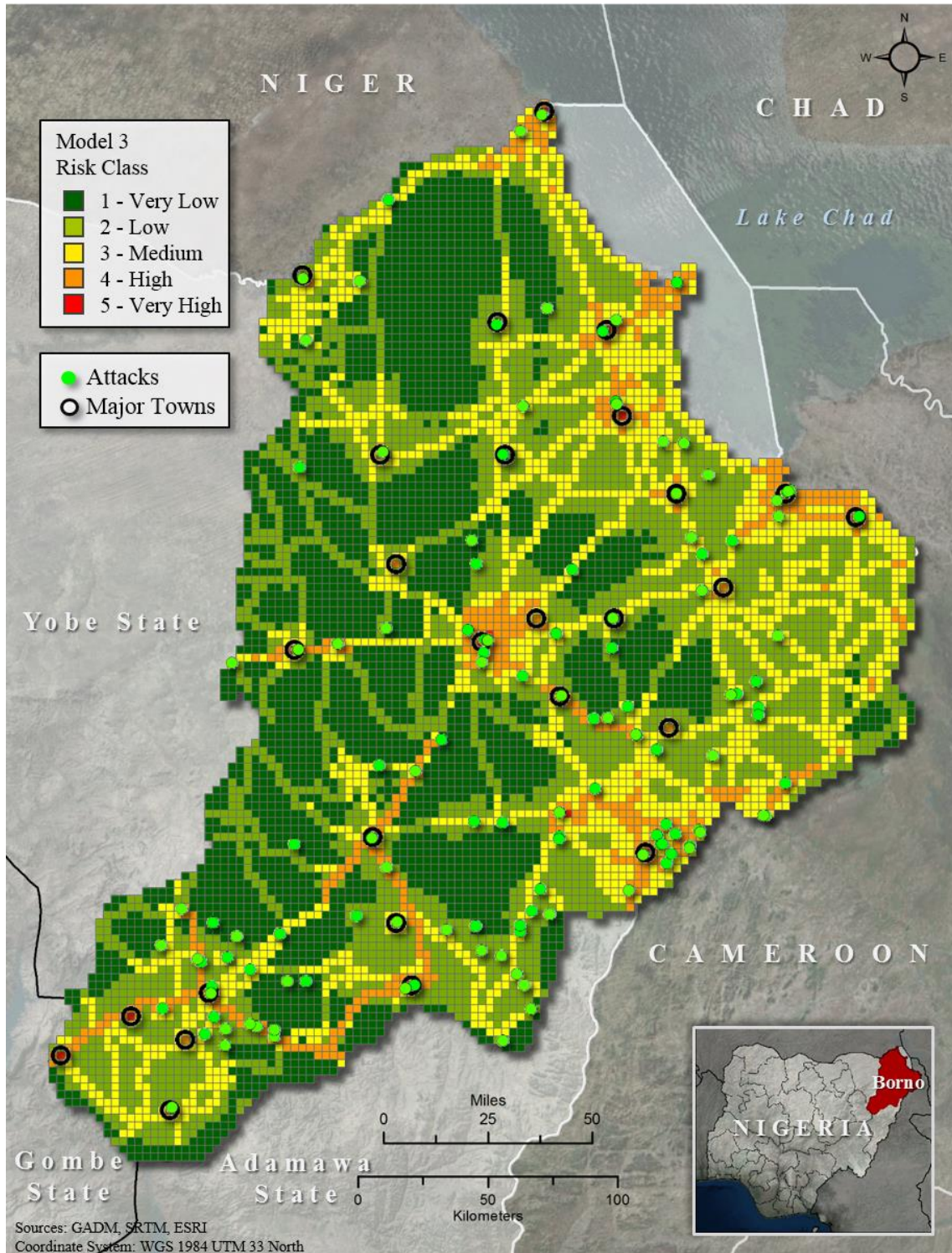
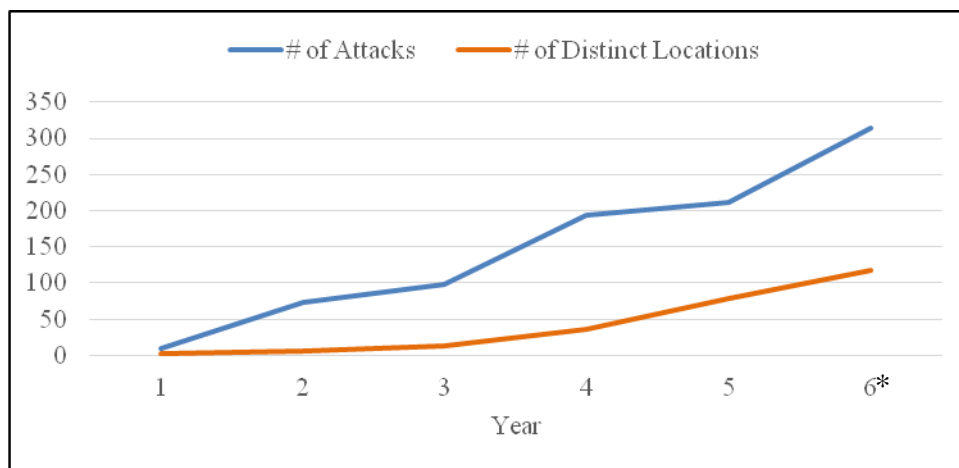


Figure 13: Overlay of Variables and Risk Class Terrain

4.2 Testing the Risk Terrain Validity

To test the validity of the risk layer and the cox regression model, the output was split by year and compared to subsequent year of attacks. Figure 14 depicts the increasing number of attacks per year as well as the increasing number of distinct locations where attacks occurred. The number of attacks and lack of disparity between attacked locations during years one, two, and three exclude them from the yearly test. Instead, they are incorporated together with the other years to establish more substantial pattern over time. To test year five and the overall model, attacks that occurred after the study period are included and feature the time period of July 1, 2014 – January 31, 2015.



*Year 6 reflect projected counts.

Figure 14: Attack and Distinct Location Counts (Raw) by Year

The following figures test the risk terrain layers of years three, four, and five to their respective, subsequent attack points. Each risk terrain incorporates the previous years of attacks to provide a risk layer for future attacks. Each figure also provides a table which gives percentages of attacks that were found in each risk class cell to show how well the model performed. Attacks that were found in locations that had not been previously attacked are also noted to display the predictive value of the model.

Figure 15 compares the risk terrain incorporating years one through three to the attacks that occurred during year four. Highlighted are the attacks that occurred in new locations that have not yet before been attacked. The Year 3 Risk Terrain model performed very well, finding 74.1 percent of attacks within cells designated as a Risk level 5 and 93.8 percent of attacks within cells with a risk level of 4 to 5. Twenty-two new locations of attacks occurred during Year Four with 72 percent of these attacks falling within risk level 4 cells.

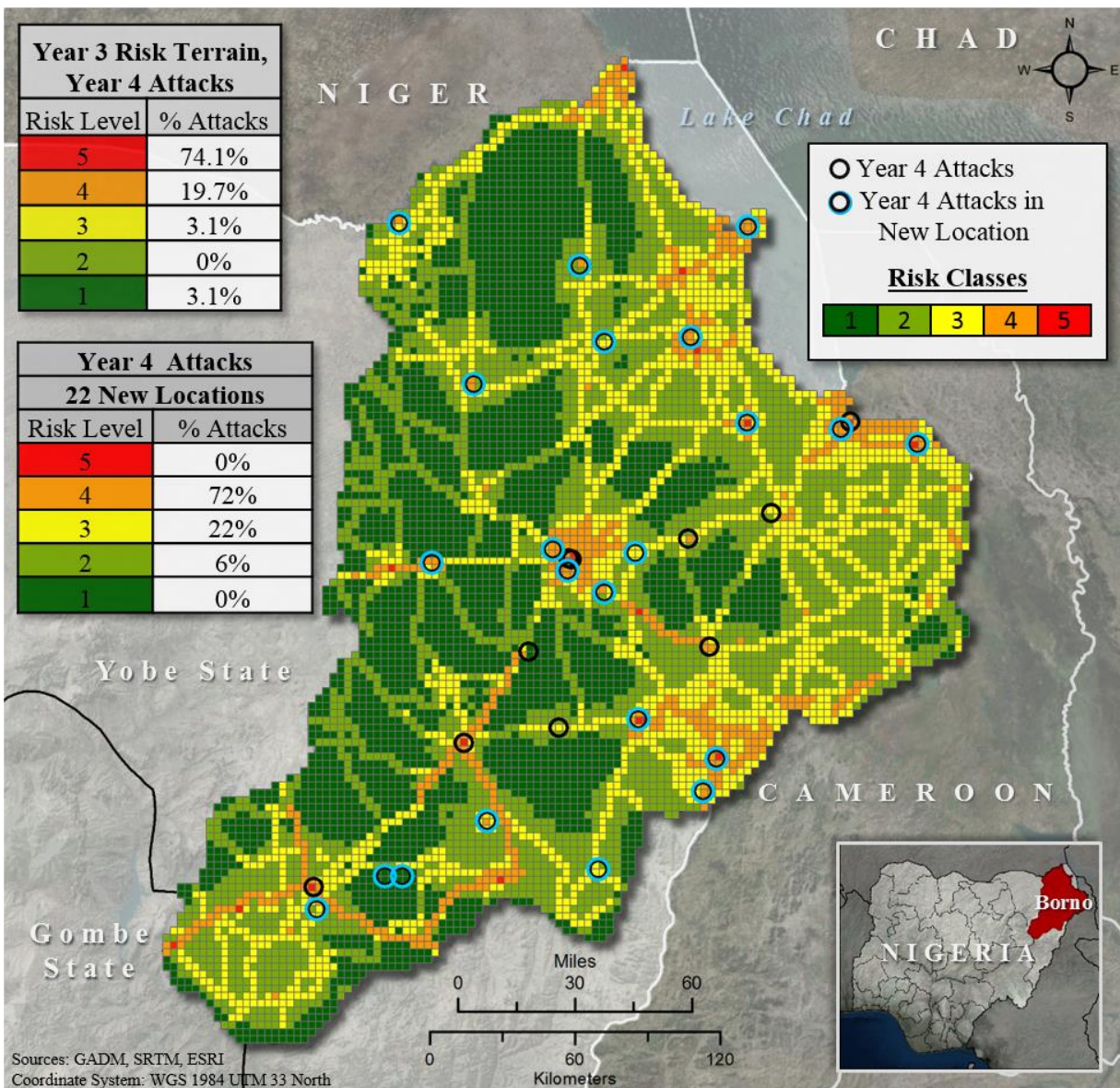


Figure 15: Comparison of Year 3 Risk Terrain to Year 4 Attacks

Figure 16 compares the risk terrain of year four to attacks that occurred during year 5. The model performed very well, forecasting 73 percent of attacks within risk class four and five. In addition, year five saw an increase to 51 new locations of attacks with 42.5 percent occurring within the top two risk classes.

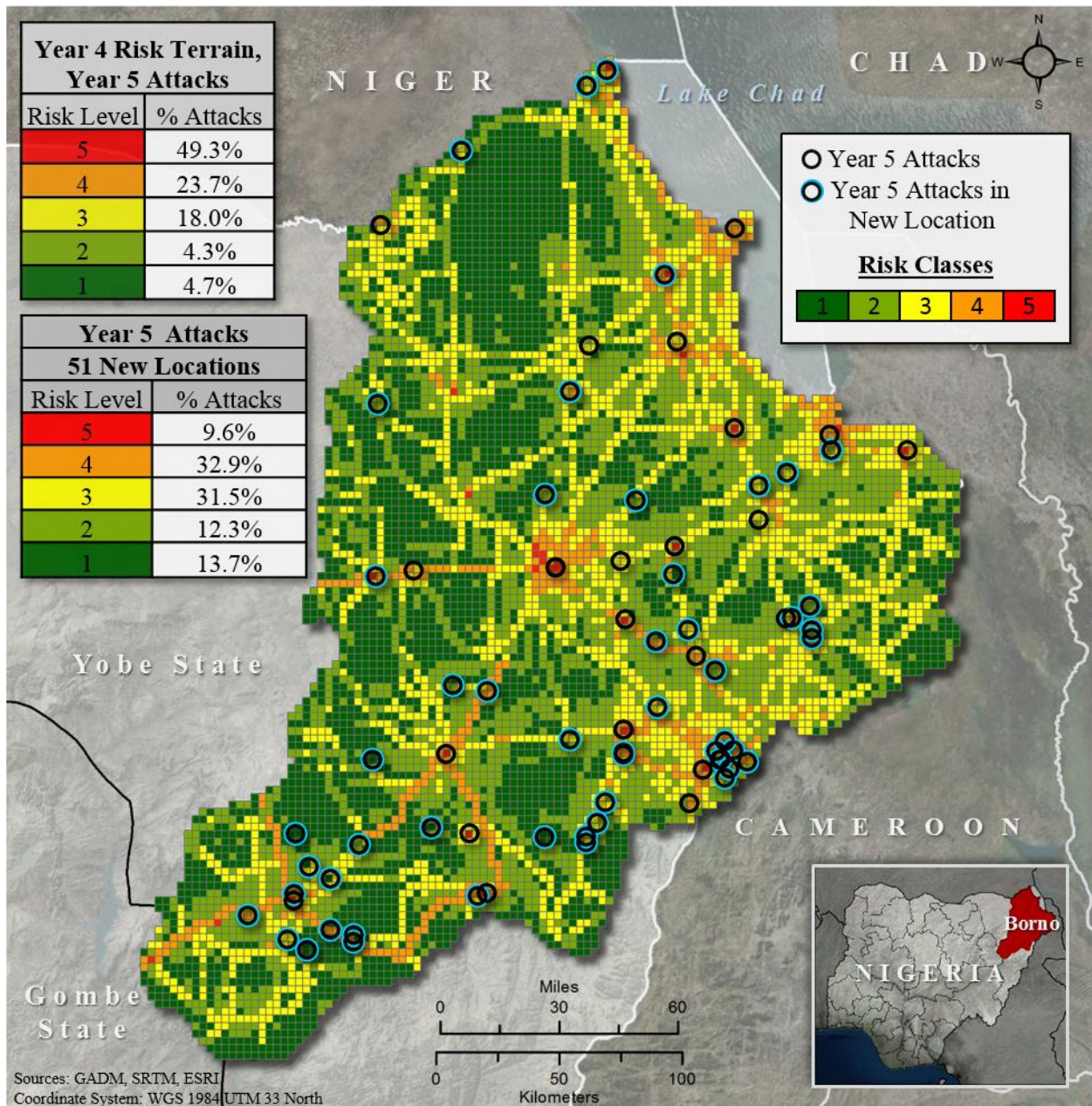


Figure 16: Year 4 Risk Terrain Compared to Year 5 Attacks

Figure 17 depicts year six attacks, although the data is not representative of the full year—only July 1, 2014 – January 31, 2015. 58.4 percent of attacks fall within risk cells four to five. 35 new locations were attacked so far with 27.2 percent of these attacks within risk four level cells. Although the model performed well, it was less accurate than the previous year models. This is most likely due to the growing presence of the military as well as new headquarter stations for Boko Haram. In 2013 (year 5), a state of emergency was declared in the region and a larger presence of the military and international support affected Boko Haram’s movement and targets.

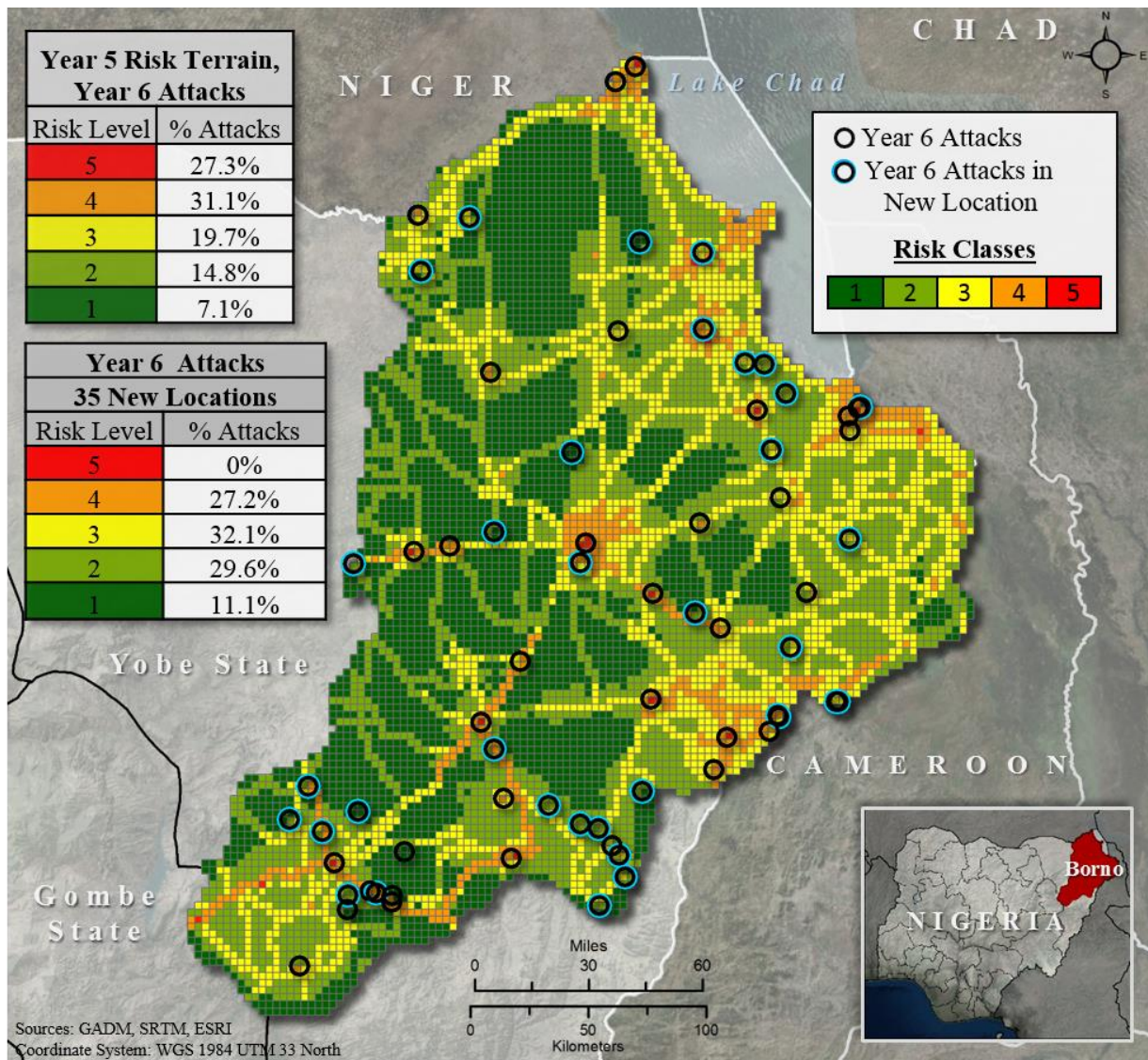


Figure 17: Year 5 Risk Terrain Compared to Year 6 Attacks

Table 8 compares the attack years and their risk associations from their risk terrain layers. As discussed previously, the models performed very well indicating the covariates did a sufficient job modeling risk. Model performance declines as the years increase, however, due to other factors in the environment affecting Boko Haram movement.

Table 8: Attacks by Year Represented in Each Risk Class

	Attacks		
Risk Level	Year 4	Year 5	Year 6*
5	74.1%	49.3%	27.3%
4	19.7%	23.7%	31.1%
3	3.1%	18.0%	19.7%
2	0.0%	4.3%	14.8%
1	3.1%	4.7%	7.1%
Total Events	193	211	183
New Locations	22	51	35
Total Locations	37	78	69

4.3 Estimating Population at Risk

Estimating population at risk to Boko Haram attacks is accomplished through calculating the dasymetric values of the population per risk category. Table 9 describes the amount of population by risk class for the study period and adjusted for population growth to year 2014. These numbers are slightly higher than specific population figures for Borno State (seen in Table 1) due to incorporating full cells along the border areas which diminish edge effects.

The amount of population with an elevated level of risk to Boko Haram attacks (risk levels three through five) is estimated at 3.58 million: 63.1 percent of the population of Borno State. To be more precise, the amount of population at a severe risk (risk levels four-five) is estimated at 1.69 million, which is 29.8 percent of the population.

Table 9: Population at Risk to Boko Haram Attacks by Risk Class

Risk Class	1	2	3	4	5	%
Population	683,492	1,413,799	1,890,997	1,283,115	406,372	
High Risk				1,689,487		29.8%
Medium to High Risk			3,580,484			63.1%
Low to High Risk		4,994,283				88.0%
Total Population	5,677,775*					

*2014 projected population including study area cross-border population figures

4.3.1 Population and Risk Overlays

Identifying locations that were estimated to have high risk and high population value were found by creating a bivariate map as seen in Figure 18. Risk level one includes Very Low to Low Risk cells. These cells not only highlight the very sparse areas such as in the north of Borno State where accessibility is difficult, but they also highlight routes that are less likely to be used by Boko Haram.

Risk level two, as expressed by the blue cells includes the Medium level risk classification. The darker the blue, the more population is within the cell. These areas typically highlight opportunistic areas to attack along a route. Red cells, which indicate Risk levels high to very high are typically main routes that are used by Boko Haram and areas which could indicate a more significant presence or possible new camp location for the group. This is expected as Boko Haram is attempting to control the northeast of Nigeria; controlling towns and setting up new posts is integral to this mission.

Identifying the areas with the most risk and high population has many values. These values give humanitarian agencies the ability to more accurately place aid centers as well as prepare for the amount of people that may need help. There is also a military and government potential to identifying high risk/ high populated areas. Reducing the area for military to patrol

and concentrate their resources helps to more effectively protect the people and possibly curtail Boko Haram activity. The darker red cells (3x2 and 3x3) identify these high priority areas for humanitarian and military organizations to 4,230 square kilometers, roughly a mere six percent of Borno State.

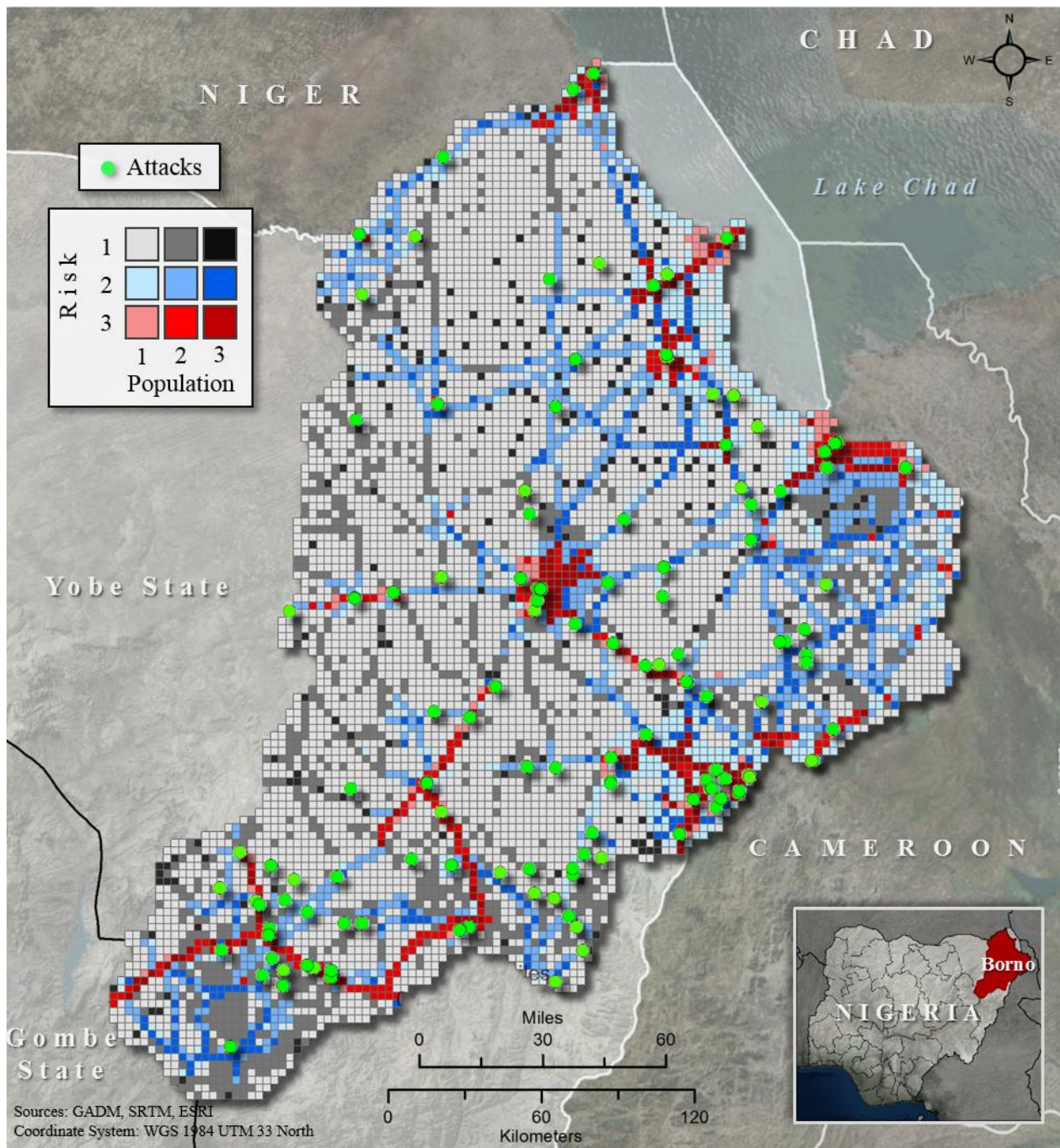


Figure 18: Comparison of Risk and Population

As expected, the capital of Maiduguri falls within the high risk/ high populated area as well as the southeastern border between Borno State and Cameroon. Corresponding with the bivariate map is Figure 19 which portrays the high risk/high populated areas in accordance to their position with routes, major towns, and roads.

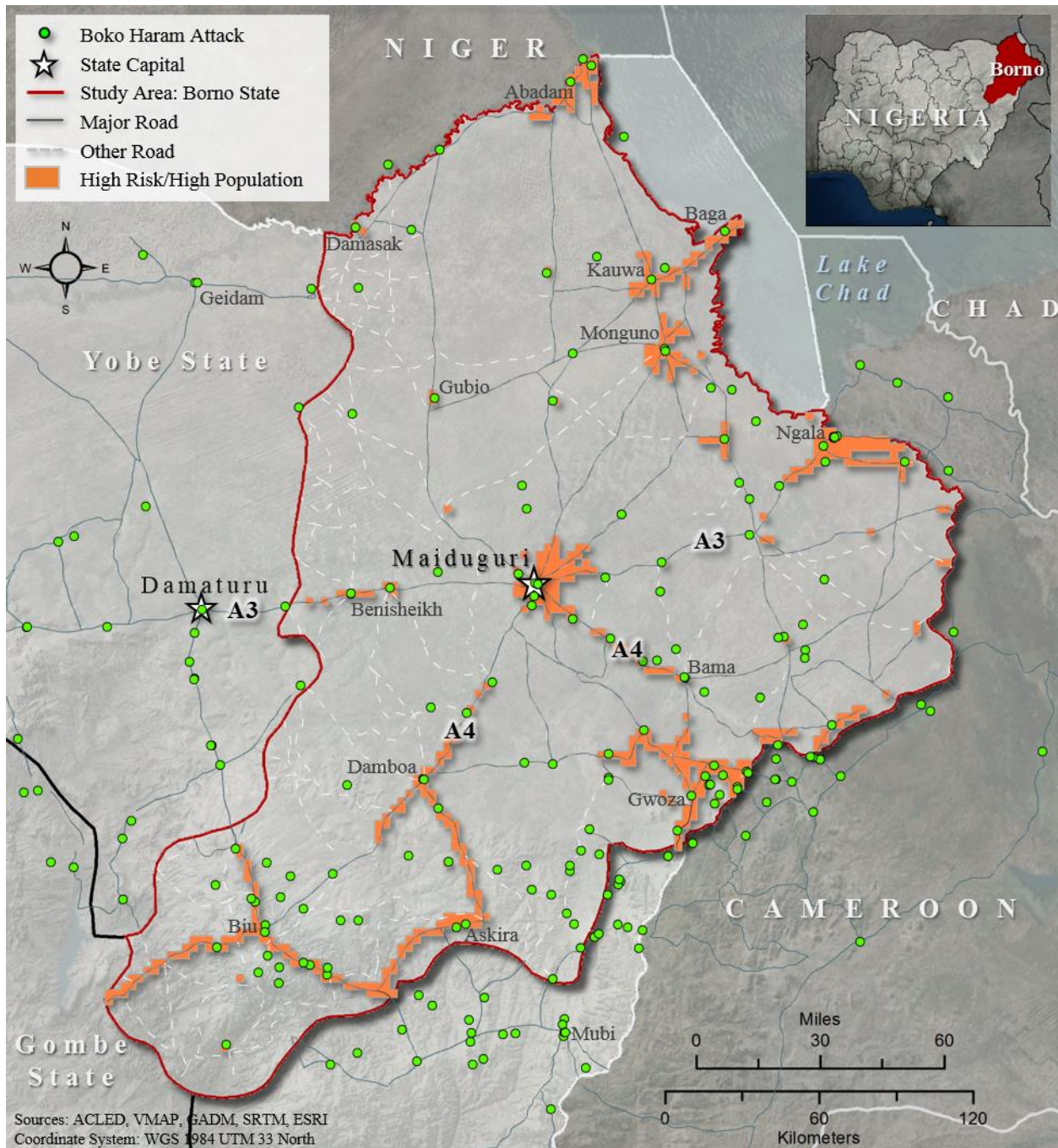


Figure 19: High Risk/ High Populated Areas in Relation to Attacks, Roads, Major Towns

Figure 19 was created to substantiate the areas that were not expected to be identified as high risk. This figure portrays attacks, routes, and major towns outside of Borno State which help to ascertain their significance. The areas around Ngala and Gwoza, for example, show routes connecting Nigeria and Cameroon along with many cross-border activity by Boko Haram.

Routes A3 and A4 are highlighted as they are the main routes in Borno State as well as along paths that have incurred multiple attacks. Also not surprising are the highlighted routes towards Yobe, Gombe, and Adamawa States as Boko Haram is spreading their movement across these states. The routes connecting Biu and Maiduguri to the Yobe State capital, Damaturu, will continue to be significant for not only movement but opportunistic attacks by Boko Haram.

CHAPTER 5: DISCUSSION AND CONCLUSIONS

The goal of this study was to present a methodology for estimating population at risk within data-poor environments. A combination of exploring variables through a spatiotemporal analysis and a subsequent survival analysis model led the study to identify specific areas at risk to Boko Haram terrorism as well as identify significant variables correlating with attacks. By testing the output's validity, this study has revealed potential benefits for conducting this methodology despite low data quality. This chapter discusses the value of the study, key observations contributing to model performance, benefits to existing research, and future possible applications.

5.1 Key Observations and Value

The results from this study proved to be highly effective answering the research objectives which were aimed at understanding Boko Haram's spatiotemporal trends, correlating variables with historical attacks, and estimating areas and population at risk. The spatiotemporal trends indicated the movement of Boko Haram southward spreading the insurgency through other areas in Nigeria as well as into neighboring Cameroon. The visualizations presented by the spatiotemporal analysis aided in creating hypotheses used to test a Cox Regression model with the goal of identifying locations that are at risk to Boko Haram attacks. The hypotheses tested were as follows:

The risk of terrorism events occurring at a location:

- 1) Increases with the size of population in the geographical neighborhood
- 2) Is higher near international border areas
- 3) Increases near major routes
- 4) Increases near major cities

- 5) Increases near Boko Haram headquarter locations
- 6) Increases near prior attack locations

Most notable and expected was the correlation between roads and Boko Haram attacks. 95 percent of attacks occurred within 5km of a road. With the harsh terrain in northeastern Nigeria, roads bring accessibility to some of the most remote locations. Some terrorist organizations use trails or less traveled routes while maneuvering across their areas, however, this analysis indicates that Boko Haram is comfortable moving along main routes to include the primary A3 and A4 roads. 19.2 percent of attacks occurred along route A4 while 8.7 percent occurred through A3 (excluding through the capital and LGA, Maiduguri)

Population was also expected to have a high correlation with Boko Haram attacks, however, only Population in Neighborhood 2nd Order was consistently statistically significant. While it was thought all population levels would have a significant relationship, the analysis expressed that concentrations of populations were more attractive for attacks than dispersed populations.

Also interesting was the positive regression coefficient for Distance to Capital indicating that as distance increases from the capital, attacks are more likely to occur as the Boko Haram crisis evolves. As a large portion of attacks occur within the capital, this variable was expected to be an attractor for activity. Further analysis, as well as the spatiotemporal analysis, demonstrated that as the crisis evolved, more attacks were occurring away from the capital and spreading towards other areas in Nigeria as well as to Cameroon.

Supplementing the analysis that Boko Haram is spreading and growing is the variable expressing Distance to Prior Attacks. This variable was found to be statistically significant and indicated that as distance increased from prior attacks, the odds decreased. Surprisingly, the

hazard ratio ($\exp(B)$) indicated that while the odds are lowered as distance increases, it has only a slight effect. This can be described by Boko Haram spreading throughout the region and gathering more sympathizers and troops for their cause.

Other key observations express the amount and locations of population at risk to Boko Haram attacks. This model identified an average of 88.7 percent of attacks found within a cell with an elevated risk level of three and above. This greatly improves prior knowledge of Boko Haram spatial patterns by reducing the coverage area of the entirety of Borno State to roughly 30.9 percent of the state.

Interestingly, performance of risk layers over time declined from 91 percent to 78.1 percent. The model is still successful at this percentage and was still able to identify 35 new locations of attacks. The decline in performance is likely due to the changing mission of Boko Haram and the increasing international pressure on Nigeria to curtail their activities. Over time, Boko Haram gained substantial funding and training making them an increasingly dangerous insurgency infecting the area. A state of emergency was declared during this time period in the northeast of Nigeria and troops were deployed to affect the insurgency. While the military involvement has not been entirely successful, Boko Haram's spatial pattern did change as noted by the analysis.

The benefits of this analysis include identifying that the population at an elevated risk level in Borno State was estimated at 3.58 million. This includes risk levels three through five with each level increasing the probability of attack by 12, 25, and 53 percent respectively. A more severe account of population at risk is estimated at 1.69 million, defined by risk layers four through five (25 and 53 percent increase in attack probability). This is a reflection of estimated physical risk rather than emotional. Many people have fled Borno State in fear of Boko Haram,

which is not accounted for within the model. These ranges of population at risk are within the ranges dictated by various organizations. Previously, official population risk estimates were between 250,000 and 3.3 million for Borno State.

This study's results are useful for many purposes dealing with Boko Haram and terrorism within Nigeria. By identifying locations and population at risk to attacks, this helps organizations and government to effectively plan for humanitarian missions and counting population that is displaced. By overlaying the high risk areas with the high populated areas, 4,230 square miles were found to be highly significant for Boko Haram attacks. This reduces the previous risk area by 93.9 percent. Identifying these specific areas reveals potential benefits to humanitarian organizations for efficient planning of displaced populations. By understanding where and how many people may be affected to an impending attack, organizations may better prepare for the amount of resources necessary to effectively assist those in need.

There are many long term effects of displaced populations, to include food scarcity. The region near Nigeria is mostly a desert, therefore Borno State as well as other northern states provide the region with much of their food supplies. With the population in these states leaving in droves, leaving their crops, and Boko Haram burning crops, food scarcity will be inevitable for the region in the coming year. This study helps identify the potential areas which are most vulnerable to contributing to a food shortage.

In addition, identifying locations at risk, trends, and correlating variables provides the military and government an advantage for effective counter-insurgency planning to affect the growth of Boko Haram. Specified locations at risk prepare new target areas as well as routes for the interdiction of insurgent operations.

5.2 Contrast with Previous Studies

Many scholars suggest that the Borno State is rampant with Boko Haram's members. In addition, previous studies lump Borno State with Yobe, Gombe, and Adamawa States for a more generalized analysis. In contrast, my study presents specific locations that identify the areas where the covariates converge increasing the odds of attacks occurring. In addition, this study presents its methodology to establish a baseline to estimate population at risk. Previous studies conducted by humanitarian organizations and the Nigerian government all have conflicting numbers ranging from 250,000 to 3.3 million. Effective planning cannot be conducted with such a wide range of estimation.

As mentioned by Willis et al. (2005) there is no consistent methodology for analyzing terrorism risk. This study not only presents an effective method for handling terrorism risk, but it also and perhaps more importantly, does it within a data-poor environment. Terrorism often occurs or begins in areas which are not privy to high resolution data. These groups should be studied early in their development before they grow and affect more urban populations.

There are many dilemmas facing analysis of Boko Haram. Many of these dilemmas are social in nature and not represented within this spatial study. Some of the factors which are represented in texts discuss ethno-political issues and bribery. Ethnic ties diminish certain ethnicities impact in the area as well as make them targets for attacks. Bribery allows Boko Haram to flourish and evade counter-insurgency operations. Further spatial analysis should be conducted using ethnic and tribal data to further refine the model.

One dilemma that was specifically expressed in this study includes borders. The results identified the importance of the border areas which fell into medium to very high risk classifications. As expressed by Oarhe (2013), the borders are porous which Boko Haram

exploits for recruiting immigrants, bringing in weapons, and evading security forces. This study highlights certain border areas which have consistently seen Boko Haram activity which have a possibility of leading to trafficking routes.

The benefit of this study provides specific locations and correlating variables to identify and predict locations that are at risk to Boko Haram activity as the crisis evolves. Previous studies mention likely attractors for attacks. In contrast, this study presents a method for quantifying the likelihood of increasing the odds of an attack.

5.3 Recommendations for Future Research

There are many possible avenues for future research with the foundation of this study. Specifically for continuing crisis of Boko Haram and Nigeria, the interaction between variables and Boko Haram change. This study did not deal with time-dependent variables, but instead held the variables static through the five year time period. The Boko Haram headquarters is a variable which would benefit from being a time-dependent variable. Over time, Boko Haram has captured towns to set up new camps in northeastern Nigeria. Updating their new camp locations would improve the predictability and performance of the model. Also important over time is the increase of military and civilian militias fighting against Boko Haram. As presented in the analysis, the pattern of attacks over time changed and spread to other locations and away from heavily guarded areas such as Maiduguri. This would be increasingly helpful when conducting a larger study focusing on Nigeria.

Further improvements to the model can be made with the inclusion of ethnicity and social factors. Ethnicity plays a significant role in Nigeria and to Boko Haram; therefore mapping the locations of tribes and ethnicities would be useful and prove to be effective.

Social media would also be a useful inclusion to modeling risk and estimating population at risk. To name a few, the National Emergency Management Agency (NEMA) for Nigeria, the National Commission for Refugees, Migrants, and Internally Displaced Persons, and the Borno State Government use Facebook, twitter, YouTube, and Flickr. Social Media provides information that also has the capability of being geo-located at a high resolution. These sites aim to track issues within their region of interest to include attacks and IDP movements.

Outside of the specificity of Boko Haram analysis, one of the most significant benefits to identifying population at risk is to then use this information to help identify numbers of people displaced from their towns. IDPs and refugees need aid and support as they flee violence. Identifying population at risk helps to find the locations that are in need so organizations can be better prepared for an influx of IDPs and refugees or set up new camps accessible to these people. Tracking social media applications also plays into identifying IDPs and refugees as many regional and state organizations track the movement of the displaced through their camps.

One of the most crucial benefits this study presents is conducting research in data-poor environments, which has an abundance of uses. Some of the world's worst atrocities occur within places that have little to no data making planning for crises exceptionally difficult. Emergency management, terrorism research, drug and human trafficking could all benefit by employing the methods presented in this study by disaggregating data and setting up a statistical model analyzing variables in a spatiotemporal design. Possible applications include identifying locations at risk, identifying routes or hubs used by traffickers, or identifying camps or bed down locations. For emergency management, this methodology may be used to plan for hurricanes for example, identifying which areas are most susceptible to flood and how many people are potentially affected.

The medical profession may also employ this methodology by tracking diseases or patients. Cox Regression is often used for studying events within the medical world; applying a spatial attribute to the study could prove to be highly beneficial for understanding the patterns and trends with disease control, planning for medical emergencies, or identifying areas at risk to medical exposure.

In a more positive outlook, working within data-poor environments has many encouraging uses as well. The methodology presented here can be used to identify areas for urban development for example, such as needing schools, identifying possible business locations, or even identifying traffic patterns for new road development. The most significant benefits presented by this study is through converging spatiotemporal analysis with statistics, analyzing relationships, and identifying possibilities.

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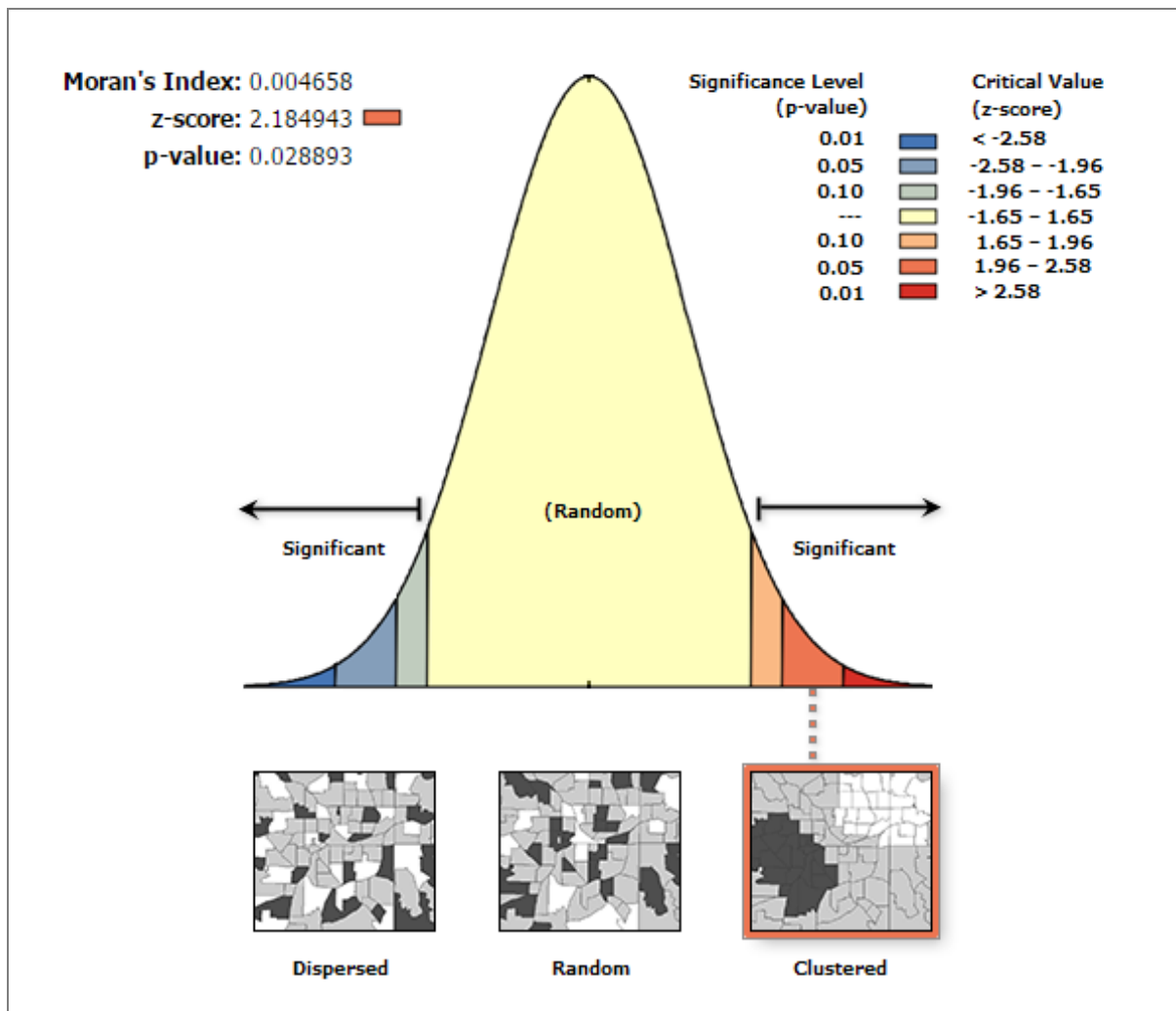
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APPENDIX A: Attribute Fields and Descriptions for ACLED Dataset

FIELD NAME	DESCRIPTION
GWNO	Code for each country
EVENT_ID_CNTY	Individual identifier by number and country acronym
EVENT_ID_NO_CNTY	Individual numeric identifier
EVENT_DATE	Day, month, year an event took place
EVENT_YEAR	Year event took place
TIME_PRECISION	Numeric code indicating level of certainty of the date used for the event
EVENT_TYPE	Type of conflict event
ACTOR1	Named actor in the event
ALLY_ACTOR_1	Named actor allied with ACTOR1
INTER1	Numeric code indicating type of ACTOR1
ACTOR2	Named actor in the event
ALLY_ACTOR2	Named actor allied with ACTOR2
INTER2	Numeric code indicating type of ACTOR2
INTERACTION	Numeric code indicating the interaction between types ACTOR1 and
COUNTRY	Country where event took place
ADMIN1	Sub-national administrative region where event took place
ADMIN2	2 nd largest sub-national administrative region where event took place
ADMIN3	3rd largest sub-national administrative region where event took place
LOCATION	Location of event
LATITUDE	Latitude of event
LONGITUDE	Longitude of event
GEO_PRECIS	Numeric code indicating level of certainty for location of event
SOURCE	Source(s) of event report
NOTES	Description of event
FATALITIES	Number of reported fatalities which occurred during event

APPENDIX B: ACLED Data Spatial Autocorrelation Report



Given the z-score of 2.18494285189, there is a less than 5% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.004658
Expected Index:	-0.000131
Variance:	0.000005
z-score:	2.184943
p-value:	0.028893

APPENDIX C: Cox Regression Outputs from SPSS

Table 10: Case Processing Summary

		N	Percent
Cases available in analysis	Event ^a	587	7.2%
	Censored	7558	92.8%
	Total	8145	100.0%
Cases dropped	Cases with missing values	0	0.0%
	Cases with negative time	0	0.0%
	Censored cases before the earliest event in a stratum	0	0.0%
	Total	0	0.0%
Total		8145	100.0%

a. Dependent Variable: Time

Table 11: Omnibus Tests of Model Coefficients

-2 Log Likelihood Null Model	-2 Log Likelihood Full Model	Overall (score)			Change From Previous Step and Change from Previous Block		
		Chi-square	df	Significance	Chi-square	df	Significance
10528.84	7312.561	13989.635	13	0	3216.278	13	0

Table 12: Cox Regression Variable Results

	B	SE	Wald	df	Sig.	Exp(B)	95.0% CI for Exp(B)	
							Lower	Upper
Distance from Prior Attack	-.177	.030	34.837	1	.000	.838	.790	.888
Distance from BH Headquarters	-.752	.081	86.586	1	.000	.471	.402	.552
Distance from Major City	-.735	.040	334.179	1	.000	.479	.443	.519
Distance from Capital	.804	.106	57.611	1	.000	2.234	1.815	2.749
Distance from Niger Border	-.101	.087	1.332	1	.249	.904	.762	1.073
Distance from Cameroon Border	-.311	.055	32.070	1	.000	.732	.658	.816
Distance from Lake Chad	-.396	.076	27.427	1	.000	.673	.580	.780
Road Type 1: Primary Route	2.423	.228	113.374	1	.000	11.284	7.223	17.628
Road Type 2: Secondary Route	1.120	.196	32.580	1	.000	3.066	2.087	4.504
Population per Cell	-.025	.175	.020	1	.886	.975	.692	1.374
Population in Neighborhood 1 st Order	-.076	.341	.049	1	.825	.927	.475	1.809
Population in Neighborhood 2 nd Order	1.743	.352	24.501	1	.000	5.715	2.866	11.397
Population in LGA	-.356	.363	.965	1	.326	.700	.344	1.425

Table 13: Correlation Matrix of Regression Coefficients

	Prior Event	Headquarters	Major City	Capital	Niger Border	Cameroon Border	Lake Chad	Road Type 2	Road Type 2	Pop. Per Cell	Pop. 1 st Order	Pop. 2 nd Order
Headquarters	-.252											
Major City	-.298	.174										
Capital	.083	-.682	-.058									
Niger Border	.046	.041	.011	-.041								
Cameroon Border	.002	.079	.014	.164	.188							
Lake Chad Border	.071	.086	.083	-.021	-.260	-.039						
Road Type 1	.067	-.041	.170	-.164	-.126	-.261	-.223					
Road Type 2	-.005	.100	-.044	-.295	.015	-.067	-.163	.688				
Pop. per Cell	.091	-.059	.351	.250	.062	.039	.097	-.300	-.382			
Pop. 1 st Order	-.051	-.051	.074	.207	.048	.076	.013	-.148	-.153	-.310		
Pop. 2 nd Order	-.065	.037	-.090	.162	-.104	-.033	-.032	.218	.072	.053	-.710	
Pop. Per LGA	.151	.193	-.076	-.128	-.113	.171	-.009	.156	.138	-.329	-.078	-.010

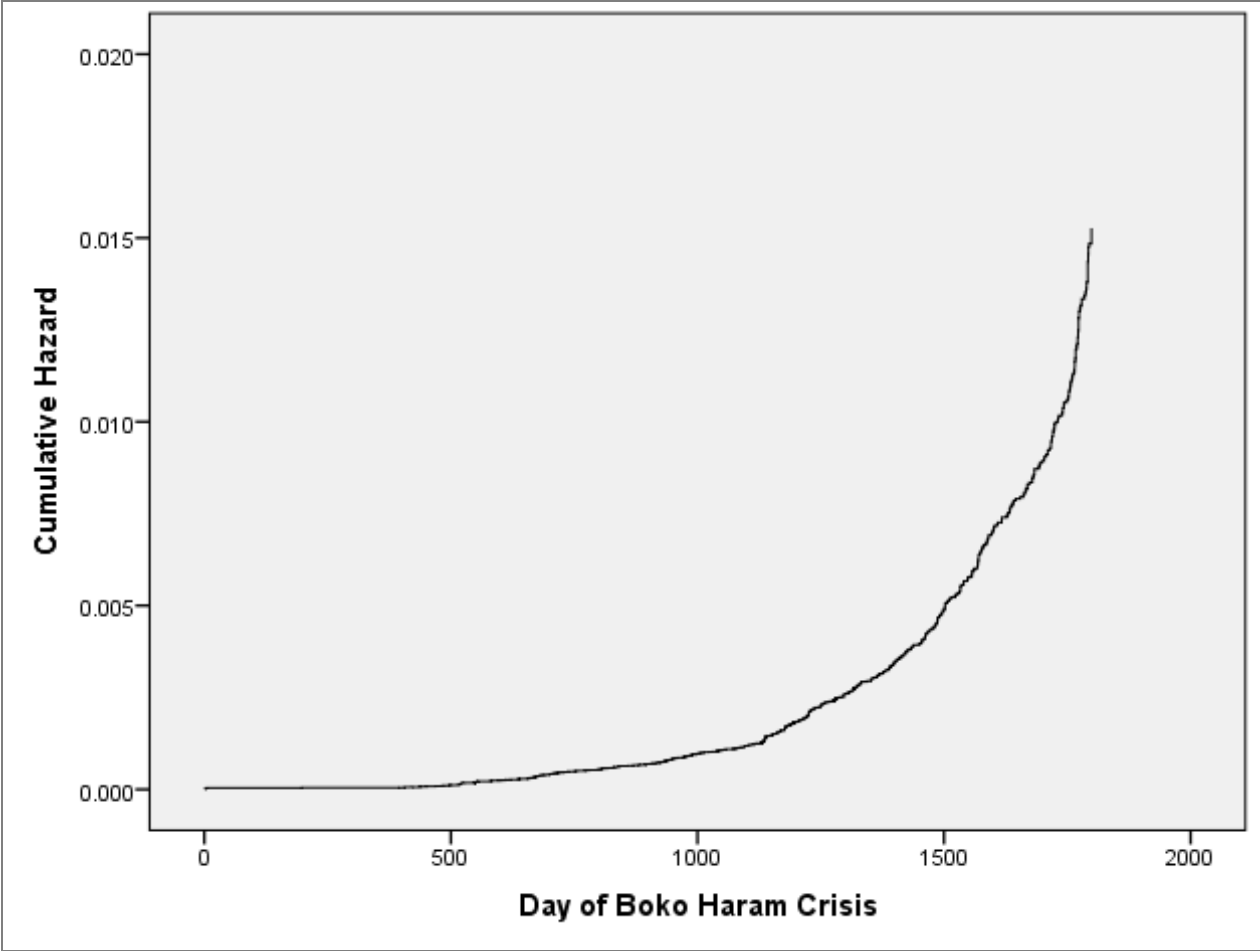


Figure 20: Hazard Function at Mean of Covariates