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Women and Stability: A Topological View of the Relationship between Women and Armed Conflict in West Africa

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THESIS

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WOMEN AND STABILITY: A TOPOLOGICAL VIEW OF THE RELATIONSHIP BETWEEN WOMEN AND ARMED CONFLICT IN WEST AFRICA

THESIS

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Abstract

The relationship between women and stability, if any, is a topic of much debate and research. Several large and influential organizations have all researched women's effect on stability. Furthermore, several of these world organizations, the United Nations, in particular, have declared gender equality to be a driving force in promoting stability and conflict prevention. Due to the United States active involvement in conflict prevention in such regions as West Africa, research concerning the relationship between women and stability is of particular interest to the United States Africa Command.

As such, this research applied Topological Data Analysis, combined with other machine learning algorithms, to Demographic and Health Survey Program data combined with Armed Conflict Location and Event Data so as to observe the relationship between women's status and armed conflicts in the West African region. While this team did not observe any direct correlation between women's well-being and stability - defined as a lack of armed conflict events - the chosen methodologies and data usage have potential implications for future research concerning stability and conflict.

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I dedicate this thesis to my loving family. A special feeling of gratitude to my parents whose constant and unwavering love, faith, and sacrifice made me the person who I am today. My siblings, whose love, friendship and and encouragement have continually pushed me to try and succeed in that which I may not have otherwise. They, along with my faith, are the foundation on which I stand and without, would be lost.

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Finally, I must express my gratitude to my family for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This accomplishment would not have been possible without them.

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WOMEN AND STABILITY: A TOPOLOGICAL VIEW OF THE RELATIONSHIP BETWEEN WOMEN AND ARMED CONFLICT IN WEST AFRICA

I. Introduction

To what extent do women affect their community's, nation's, or region's stability, particularly with respect to armed conflict and violent extremism? The relationship between women and stability is a particularly complex one in which copious amounts of research and inquiry have attempted to answer in some form or the other. Researchers in such fields as Economics and Women Studies attempt to answer this question within the confines of the assumptions and doctrines of their respective fields. However, as the ever growing, and ambiguously defined, field of Data Science continues to grow, along with the availability of sizable data samples, the assumptions supporting several of these field's traditional methodologies have become less necessary and more of a formality of the field itself.

For the purposes of this research, which is sponsored by the United States Africa Command (US AFRICOM), this team will examining women and stability in the West African region, as defined by the Table 1. The goal of this research is to attempt to answer questions about the connection between women and stability in West Africa, obtain a better understanding of the women in that region, and to pinpoint specific areas for future research.

In order to answer these questions with as little bias and as few assumptions as possible, a new unsupervised machine learning technique called Topological Data Analysis will be implemented on data collected through survey and violence databases. Geospatial Analysis will then be implemented on interesting groupings found in the data. Through these techniques, a more thorough understanding behind the relationship between women and stability, and the specific geospatial significance influencing theses relationship(s), will be gained.

Table 1. West African States

Number	Member State	Capital	Flag
1	Benin	Porto-Novo	
2	Burkina Faso	Ouagadougou	
3	Cabo Verde	Praia	
4	Cote d'Ivoire	Yamoussoukro	
5	Gambia	Banjul	
6	Ghana	Accra	
7	Guinea-Bissau	Bissau	
8	Guinea	Conakry	
9	Liberia	Monrovia	
10	Mali	Bamako	
11	Niger	Niamey	
12	Nigeria	Abuja	
13	Sengal	Dakar	
14	Sierra Leone	Freetown	
15	Togo	Lomé	

Understanding the historical development of any culture is imperative to address the societal problems it may face today. West Africa's history will assist this research in understanding the affect women have on their community's security and stability. As such, a general background of the West African region, as defined by the US AFRICOM, will be provided in Section 1.1. In the Background, the effects of the Slave Trade, Colonialism, and the Cold War will be examined and the conflicts that erupted as a result along with a general overview of the theories surrounding these events. Additionally, the struggles and conflicts facing these countries today will also be examined.

1.1 Background

The Continent of Africa is almost three times the size of the United States and holds more than 1,000 different ethnic groups - each with their own unique identities and backgrounds [14]. West Africa itself contains some of the most ethnically diverse countries Africa has to offer, as demonstrated by Harvard University's Ethnic Diversity Map in Figure 1. While the official language for most nations in West Africa are the respective languages of the western nations that colonized them (France, Portugal and Britain (See Figure 3) each country can have multiple different spoken languages and dialects [13]. For example, Nigeria, Africa's most populous nation, has an estimated 250 different ethnic groups [13] with potentially twice that many languages and dialects [14]. Depending on which country one is looking at, the religions tend to be split between Christianity and Islam (with a majority leaning one way or the other) and the rest being made up of various other faiths including tribal and non-religious [13, 14].

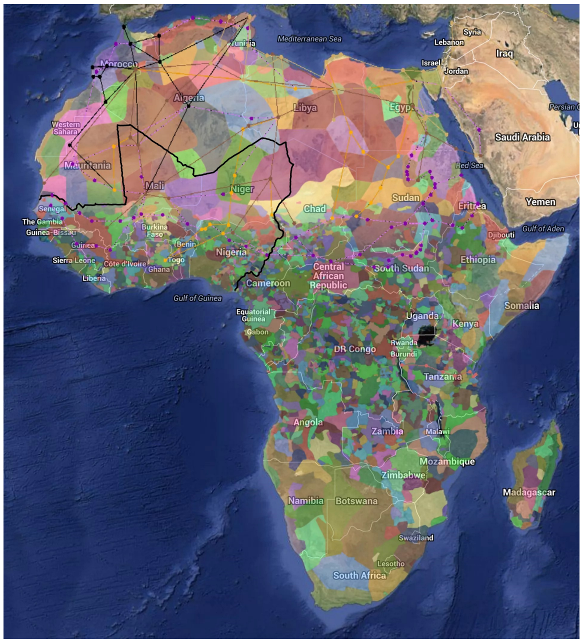


Figure 1. Hardvard University's Map of Ethnic Diversity in Africa [1]

On top of the cultural richness that is provided by West Africa's diversity, the region is also extremely wealthy in it's abundance of natural resources such as diamonds, gold, and petroleum to name just a few [13] (See Table 2 for detailed summary). However, despite the vast wealth of natural resources, mismanagement and corruption in political systems, in addition to a series of devastating conflicts from the late 1980's to early 2000's, the region (with the exception of Cabo Verde) has lacked economic stability since gaining independence starting in the 1950's [13,15–18]. In fact, it could be argued that the state's strict reliance on its natural resources has been perpetuated political corruption, originally created by the colonial powers that previously governed the West African States [15–17]. Whatever the reasons may be, it cannot be denied that West Africa, though technically growing, holds some of the world's poorest nations. Eleven out of the fifteen nations (Benin, Burkina Faso, The Gambia, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Senegal, Sierra Leone, and Togo) are currently labeled as low-income economies by The World Bank while the rest (Cabo Verde, Cote d'Ivoire, Ghana, and Nigeria) are described and Lower-Middle-Income economies [19].

Table 2. West Africa’s Natural Resources [13]

Country	Natural Resources
Benin	Small offshore oil deposits, limestone, marble, timber
Burka-Fasso	Manganese, limestone, marble, small deposits of gold, phosphates, pumics, salt
Cabo Verde	Salt, Basalt rock, limestone, kaolin, fish, clay, gypsum
Cote d’Ivoire	Petroleum, natural gas, diamonds, manganese, iron ore, cobalt, bauxite, copper, gold, mickel, tantalum, silica sand, clay, cocoa beans, coffee, palm oil, hydropower
The Gambia	Fish, clay, silica sand, titanium (rutile and ilmenite), tin, zicron
Ghana	Gold, timber, industrail diamonds, baxite, manganese, fish, rubber, hydropower, petroleum, silver, salt, limestone
Guinea	Bauxite, iron ore, diamonds, gold, uranium, hydropower, fish, salt
Guinea-Bissau	fish, timber, phosphates, bauxite, clay, granite, limestone, unexploited deposits of petroleum
Liberia	iron ore, timber, diamonds, gold, hydropower
Mali	gold, phosphates, kaolin, salt, limestone, uranium, gypsum, granite, hydropower, note: bauxite, iron ore, manganese, tin, and copper deposits are known but not exploited
Niger	uranium, coal, iron ore, tin, phosphates, gold, molybdenum, gypsum, salt, petroleum
Nigeria	natural gas, petroleum, tin, iron ore, coal, limestone, niobium, lead, zinc, arable land
Sengal	fish, phosphates, iron ore
Sierra Leone	diamonds, titanium ore, bauxite, iron ore, gold, chromite
Togo	phosphates, limestone, marble, arable land

The obstacles facing West African nations in their economic development and protection of their citizens’ human rights are numerous and complicated. While several countries in this region (mainly Nigeria and Ghana) are starting to grow their economies, most of their development is being halted by conflicts and political corruption within their respective nations [15]. Additionally, women in particular are facing obstacles and injustices in their communities from Female Genital Mutilations and Cuttings (FGM/C), Rape, child/forced marriages, and general restricted access to resources and liberties [13, 20, 21]. The introduction for this thesis will examine West Africa's history and the factors that pushed this arguably wealthy region into the crises that its nations find themselves in today.

1.1.1 West African History.

West Africa's history is both complicated and fascinating. The West African region held some of the wealthiest kingdoms of their times, was the most affected by the Transatlantic Slave Trade, and has survived civil wars, coup d'etats, and wide-ranging disease outbreaks that have ravaged their respective countries and made economic and social development difficult in the following years [13, 22–24].

1.1.1.1 West Africa's Wealth.

Before the intrusion of western powers, West Africa had several major kingdoms, all of which were extremely wealthy and heavily involved in trade with the rest of Africa and even Europe [14, 16, 25]. For the purposes of this research, this research team will briefly cover the first two kingdoms - the Ghana Empire and the Mali Empire. The Ghana Empire lasted from about AD 300 - 1076 [25]. Due to the Trans-Saharan trade and iron work, the Ghana Empire went from a village and grew in a kingdom so large so as to warrant a political system that required the ruling of several kings - and their respective governors - all providing loyalty and taxes to their central government [16, 25]. The wealth of the Ghana empire was its gold, something of great value to both Northern Africa and Europe [25]. All the gold that Europeans possessed at that time was either mined in Europe or West Africa [25]. The Ghana empire was able to obtain their gold mines and expand its kingdom due to their skill as iron workers, providing them the significant advantage of iron weapons against their neighbors [25]. The kingdom following the Ghana Empire was the Mali Empire which lasted from roughly 1234-1468 AD [16].

Mali's economy was agricultural based but "supported by the profits of the flourishing gold trade" [16:1-22]. The Mali Empire spread its influence to the Sudan through the power of its "chain-mailed cavalry" [16:1-22]. The Mali Empire was then spread west to the coastline through the militant king Sabakura, a freed slave who seized the throne in 1285 and eventually developed the kingdom depicted in Figure 2 [16].

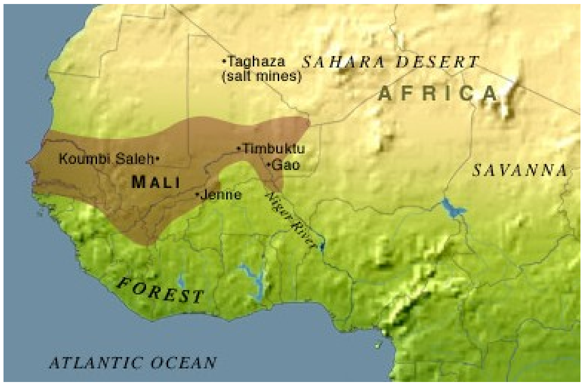


Figure 2. Mali Empire in 1300 AD [2]

The Mali Empire's wealth is best illustrated in the story of its most famous king - Mansa Munsa (1312 - 1337). Mansa Munsa gave fame to the Mali Empire on his extravagant pilgrimage to Mecca where he was said to be accompanied by a force of 60,000 men and 500 slaves, each of whom carried a golden rod [16].It was Mansa Munsa's excessive consumption and spending that earned him and his empire's fame throughout Northern Africa and Arabia.

The wealth and success of the Ghana and Mali empires demonstrates the wealth and sophistication in West Africa before Europe and other Western powers became involved. This helps to dispel the common western myth of a poor continent in need to aid and western intervention - a myth that helped perpetuate the ideas supporting colonialism.Long before the west was involved with Africa, the continent had several kingdoms, each wealthy and governed by a relatively complex political system for its time.

1.1.1.2 The Slave Trade and Colonialism.

Europe's knowledge of West Africa was through the Muslim traders that transported West Africa's gold through the Trans-Saharan routes. However, Portugal in the early 15^{th} century sent out sailing explorations along the western coast of Africa in hopes of circumventing the economic middle man inorder to trade directly with West Africa for its gold and recruit them in their fight against Islam [16]. Eventually, Portugal would go around the African continent to India and only continue trade with West Africa in gold, and later on, slaves [16].

Slavery was an established institution in Africa well before Europeans started trading with West Africans [16]. However, slaves in West African society similar to a domestic servant than a slave, who's value was determined by the "prestige that he awarded his master" rather than the economic value that he represented in Europe and the Americas [16:197-199]. Though a slave never belonged to a kinship group, he was awarded status within society [16]. However, once West Africans drained the supply of their own slaves in trade with Europe, they started to obtain slaves through warfare [16]. While relatively few people were sold into slavery as a yearly percent of the population, it was mostly the young, fit and healthy - predominately men - who were captured and sold [16]. The general historical and economic consensus that the loss of able body labor hindered the regions of Africa affected by the slave trade [16]. One study in the *American Economic Review* observed that there was a positive correlation between areas in Africa that were most affect by the slave trade and their ability to trust today [26]. The importance of this finding, as it relates to the West

African economy today, is that a willingness to trust is necessary for most economic activities. This indicates that the slave trade is affecting West Africa's economic development today.

However, in the 18^{th} century, European (specifically British) attitudes towards the Trans-Atlantic slave trade started to change. Due to the influence of Enlightenment ideas and evangelical Christianity in addition with an increased interest in "legitimate" trade and exploration, abolitionist ideas started to spread across Europe [16:220-225]. This eventually lead to England's criminalization of the slave trade in 1807. By 1833, the practice of slavery had been abolished throughout the entire British Empire [16]. England, through diplomacy, convinced several powerful European and American nations to abolish the slave trade by 1817 [16]. However, despite naval action taken by Britain, slavers continued to evade British ships and transport slaves from West Africa to the Americas [16]. Due to this, there was a growing idea in Britain and Europe that the way to stop the slave trade was to go further inland and set up legitimate trade and spread Christianity [16]. This lead to the slogan of "Christianity, Commerce, Colonization" which was the ultimate start to the colonization of the African Continent [16:220-225].

As depicted in Figure 3, the West African region was colonized by France, England and Portugal with the exception of Liberia; a somewhat peculiar incident of Colonialism. Despite its lack of accuracy, Liberia is often considered the United States only Colony in Africa [27]. An organization called the American Colonization Society (ACS), founded in 1812, made up of Quakers and slave holders, wanted freeborn Blacks and former slaves to colonize Africa [27]. The Quakers believed that freeborn Blacks and former slaves would face better chances for freedom in Africa, while also spreading Christianity. The slave owners, however, wanted to avoid a potential slave uprising like the one in Haiti [27]. Despite significant disagreement from several prominent African American figures and other white abolitionists, with the help of a few legislators, the ACS was able to start their first colony in 1821 with 86 African American volunteers in modern day Liberia [27]. Upon arrival, the white ACS members governed the colony of Liberia for several years [27]. The Americo-Liberians grew in number over the years due to further immigration and would eventually become pseudo colonists over the indigenous Africans there before them [17, 27]. Yet, despite several problems that the country would later on develop, Liberia would eventually become a model for several other African Colonies wanting independence as Liberia was one of the few free republics in Africa while colonialism in Africa was at its height [27].

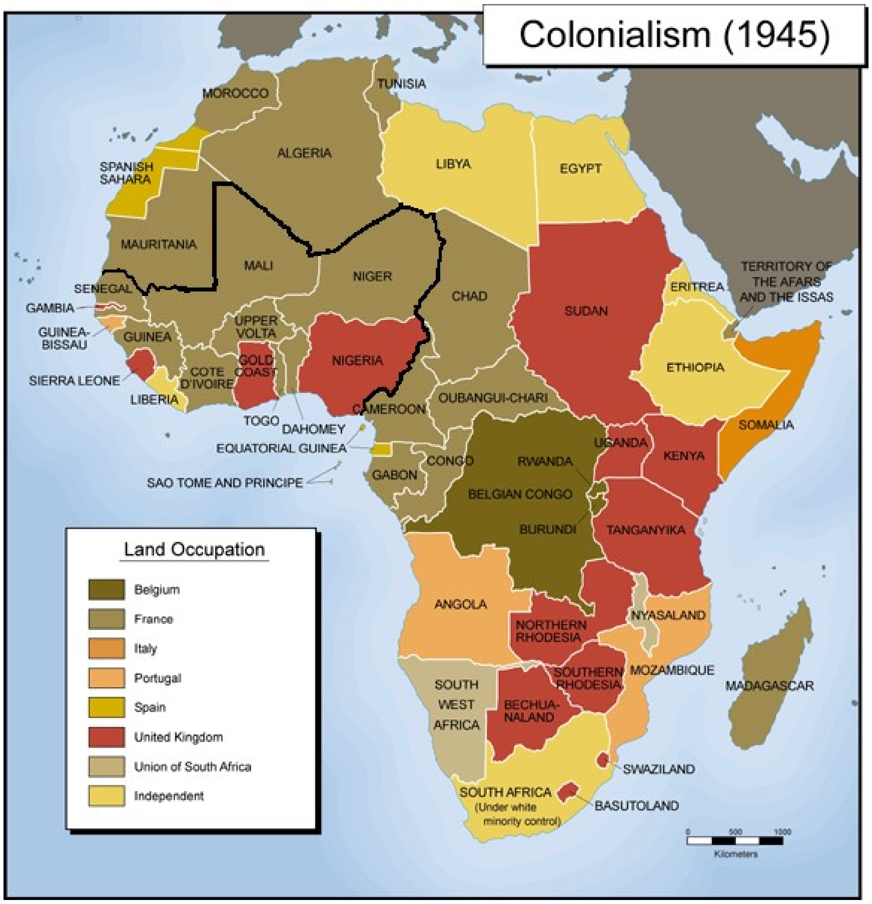


Figure 3. Africa with Colonial Powers [3]: West Africa Outlined in Black

France was the primary colonial power in West Africa, as evident by Figure 3. France significantly benefited from its colonial standpoint in West Africa. In fact, during World War I and II, France had enlisted several of its African citizens in their armed forces to fight on the front lines in Europe [16]. The general consensus in French colonialism was to build up the African colonies and encourage a certain level of self-governance while still maintaining a level of Western/French superiority [16]. France's view of colonialism was the general consensus in most of the Western world, as evident in the famous poem "The White Man's Burden", written by Rudyard Kipling in 1899:

> "Take up the White Man's burden —
> Send forth the best ye breed —
> Go bind your sons to exile
> To serve your captives' need;
> To wait in heavy harness,
> On fluttered folk and wild —
> Your new-caught, sullen peoples,
> Half-devil and half-child." (1-7)

The West viewed their colonialism as a mutually beneficial arrangement - they profited and the poor people of inferior cultures were civilized. There still exists a debate between those in related fields concerning the extent to which colonialism affects Africa today [16] However, most experts agree that colonialism did negatively affect colonized nations. All but two countries - the former Portuguese colonies of Guinea Biassau and Cabo Verde - gained independence in a relatively peaceful manner. However, the colonial powers that colonized West African nations did little to prepare them for Independence [17]. Additionally, some contribute colonialism to the corruption of Africa's governing bodies, which eventually lead to the region's conflict and economic instability [16,17,28]

1.1.1.3 Civil Unrest.

The end of the Cold War has been "characterized by a wave of violent civil wars that produced unprecedented humanitarian catastrophe and suffering" [17:1-9]. These violent conflicts, starting with the first civil war in Liberia in 1991 to the coup d'etat in Cote d'Ivoire in 2002, West Africa has been plagued with catastrophic violence in Liberia, Sierra Leone, Mali, Niger and Cote d'Ivoire [17]. From the documented cases of force amputations in Sierra Leon's civil war to the cannibalistic war lords in Liberia's civil wars, it is not hyperbolic to claim that these wars were hell on earth [29,30].

The reasons for these conflicts vary, though the underlining ethnic tensions and political corruption are persistent underlining themes. The arbitrary boarders drawn up by France, Great Britain and Portugal has magnified ethnic tensions within the region. The arbitrary boarders continually cause social and political unrest in several African nations [17]. Indeed, it was the arbitrary boarders drawn by France and Great Britain concerning Gambia that caused serious problems in the secessionist war in the Casamance region of Sengal [17]. Since these boarders were drawn with no thought towards the existing tribes and their communal ancestry, intrastate conflicts have spread across boarders as members of the same ancestry will often come to the aid of their kin [17].

While ethnic tensions have and continue to influence several conflicts in West Africa, a significant force behind these conflicts are widely attributed to general mismanagement of economic funds and political corruption [15,18,24]. Unlike most colonial states in Asia, Africa's road to Independence was relatively fast and surprising to most of their colonial powers [17]. Additionally, all three colonial powers restricted their African subjects' ability to self-govern [17]. As a result, most African were illiterate and lacked the necessary skills to govern a nation [17]. Furthermore, Africans became accustomed to a centralized, authoritarian form of governance from their colonial rulers. As a result, most freed African nations placed a significant amount of power in the hands of a few, most of whom lacked the skills necessary to succeed [17]. As most of Africa's wealth came from its natural resources, the mismanagement of such resources, along with the significant debt brought on by rampant borrowing, eventually lead to conflict within the region [13, 17]. The resulting conflicts have sabotaged the economic growth several West African nations, spreading poverty, crime and disease.

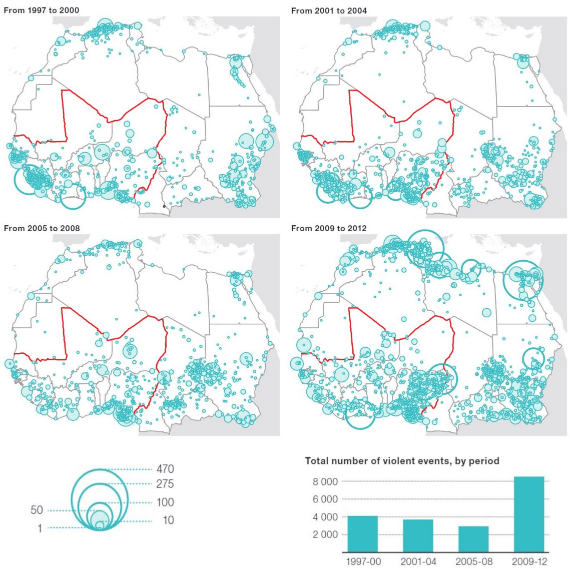


Figure 4. Violent Events in West Africa (1997-2012) [4]

1.1.1.4 Ebola Crisis.

The Ebola Crisis, which lasted from 2013-2016, incapacitated the countries of Guinea, Liberia, and Sierra Leone. According to the Center for Disease Control

(CDC), the disease started in a small village in Guinea in December 2013 where an 18-month old boy was believed to be infected by bats [31]. Over a span of two and a half years, the disease spread to two other nations, infecting 28,600 people and killing 11,325 [31–33]. Figure 5 provides a geographical representation of where the virus was most effective.

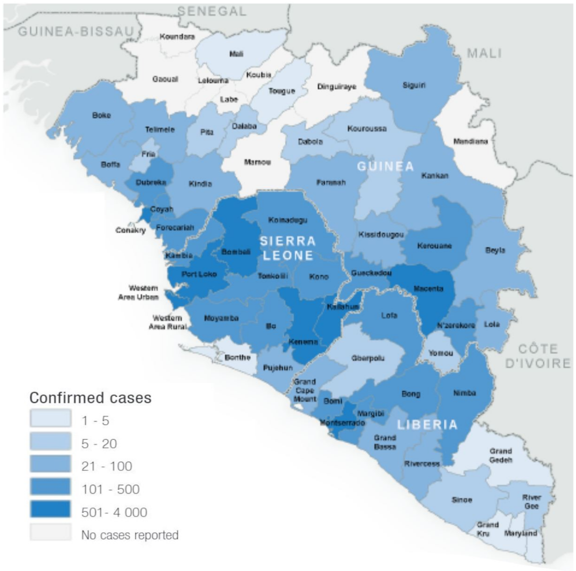


Figure 5. 2016 Map of the Ebola Outbreak in West Africa [5]

Though large, the death toll is not adequately represented by those whose death was solely caused by Ebola. Due to fear of hospitals and medical workers, created by the rampant spread of Ebola, others who required medical attention unrelated to Ebola failed to obtain it [22, 32, 33]. In addition to lives lost, these three nations had recently experienced serious conflicts and were starting to rebuild their economies. The loss of production, human capital, and costs associated with trade restrictions impeded the economic and social growth of recently war-torn nations [22, 31–33]. The unbridled spread of the Ebola virus eventually lead to a global health crises that forced the international community to intervene [31].

The rampant spread of the Ebola has several causal factors including a lack of communal knowledge and training concerning disease control and prevention, insufficient reaction speed - both communally and from the international community - and failure to recognize the importance of a “safe and dignified burial” from multiple West African communities [32:2]. However, experts place primary blame on inadequate health services [22, 31–33]. In a report titled, “A Wake Up Call: Lessons from Ebola for the world’s health systems”, Save the Children organization reported that in 2012 Guinea spent an average of $9 per person on health care, compared to a recommended minimum expenature of $86 per person [32:4]. Lack of funding was further exacerbated by an insufficient supply of doctors, nurses and hospitals required to contain the virus [22,31–33]. Due to the absence of necessary health care resources, the international community was forced to get involved, costing the rest of the world $4.3 billion [32:9].

1.1.2 Current State.

The West African region is currently home to some of the Continent’s more stable countries (Ghana and Sengal) and also houses several countries (Ivory Coast, Liberia, Sierra Leone) who have successfully transitioned from war to relative peace [15]. The region, overall, has transitioned from the post Cold War conflicts to a state where the political institutions are relatively stable. However, this transition is more or less a transition from one type of conflict to another.

Currently, the region is under tremendous stress due to the transition from “conventional and large-scale conflict events” [15:24] to instability driven by election related violence, drug trafficking, violent extremism, piracy, and overall criminality [15].

1.2 Women

In West Africa, Women face significant obstacles such as early marriages, FGM/C, a lack of education, and significantly high maternal mortality rates [13]. As you can see from Table 3, several of West Africa's countries lack what most developed countries would view as basic necessities for women. The inadequate maternal care and female education oppresses women living in these nations. Without an education and basic maternal heath care, women will face substantially greater obstacles in their lives compared to most men in similar economic living standards. Two of the nations in West Africa, Niger and Seirra Leone, are leading the world in fraternity rates and maternal mortality rates respectively [13].

Table 3. West African Women Statistics [13]

	West African Countries															**Reference Countries**	
Metrics	*Binin*	*Burkina Faso*	*Cabo Verde*	*Cote d'Ivoire*	*Gambia*	*Ghana*	*Guinea-Bissau*	*Guinea*	*Liberia*	*Mali*	*Niger*	*Nigeria*	*Sengal*	*Sierra Leone*	*Togo*	*South Africa*	*USA*
Mothers Mean Age at First Birth	20.3	19.4	N/A	19.8	20.9	22.6	N/A	18.9	19.2	18.8	18.1	20.3	21.5	19.2	21	N/A	26.4
Maternal Mortality Ratio (dealths/100,000 live births)	405	371	42	645	706	319	549	679	725	587	553	814	315	1,360	368	138	14
Infant Mortality Rate (deaths /1,000 live births)	52.8	72.2	21.9	55.8	60.2	35.2	85.7	50	52.2	69.5	81.1	69.8	49.1	68.4	42.2	31	5.8
Total Fertility Rate (children born per woman)	4.77	5.71	2.24	3.38	3.52	4	4.09	4.77	5.06	6.01	6.49	5.07	4.28	4.73	4.38	2.29	1.87
Contraceptive Prevalence Rate	17.9%	25.4%	N/A	15.5%	9.0%	33.0%	16.0%	8.7%	31.0%	15.6%	18.9%	13.4%	25.1%	16.6%	19.9%	54.6%	72.7%
Physician Density (physician/1,000 population)	0.15	0.05	0.79	0.14	0.11	0.1	0.08	0.08	0.02	0.09	0.02	0.38	0.07	0.02	0.06	0.82	2.57
Female Literacy	27.3%	29.3%	82.0%	32.5%	47.6%	71.4%	48.3%	22.8%	32.8%	22.2%	11.0%	49.7%	46.6%	37.7%	51.2%	93.4%	N/A
Male Literacy	49.9%	43.0%	91.7%	53.1%	63.9%	82.0%	71.8%	38.1%	62.4%	45.1%	27.3%	69.2%	69.7%	58.7%	77.3%	95.4%	N/A
Female School life Expectancy	11	7	13	8	9	12	N/A	8	N/A	7	5	8	9	N/A	N/A	13	16
Male School Life Expectancy	14	8	13	10	9	12	N/A	10	N/A	9	6	9	9	N/A	N/A	12	17

Figure 6 provides a geographical representation of some of the problems women in West Africa face today. The Organization for Economic Cooperation and Development's (OECD's) Development Center Published a paper by Gaelle Ferrant and Alexandre Kolev titled "Does gender discrimination in social institutions matter for long-term growth?". Ferrant and Kolev's research concluded that gender discrimination is estimated to collectively cost nations over 12 trillion USD, or roughly 16% of 2016's global GDP [34]. Gender discrimination can be observed through forced child marriages, FGM/C, the lack of legal standing or the loss of life and human capital found in high maternal mortality rates [20]. For example, Despite laws providing widows with equal legal rights as widowers towards their inheritance, accusations of witchcraft can be used to prevent widows and daughters' right to claim their inheritance [20]. Additionally, only in Liberia and Mali do laws exist to guarantee men and women equal access to financial services [20]. Gender discrimination actively hinders half of any given population from contributing to the potential economic growth of a nation. Furthermore, child marriages prevent young girls from finishing their education by prematurely burdening them with children of their own, thereby diminishing female labor force participation.

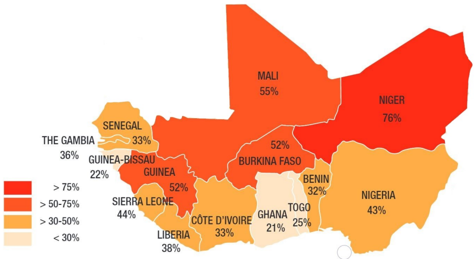


Figure 6. Percentage of Young Women (20-24 years) Married before the Age of 18 [6]

1.2.1 Conflict and Stability.

Women are both contributors and victims of conflict. For example, during the post Cold War conflicts in West Africa systematic rape was rampant [17]. Women and the young were often targets of such violence [17]. However, women have also been contributors to conflict. Such examples are women being used as a recruitment tool through rearranged marriages between members of extremist groups and young women [35]. Women and children, whether through coercion or their own convictions, have committed suicide bombings and other acts of violent extremism [35]. Boko Haram, earlier in its development, managed to appeal to and recruit women followers [21]. Initially, Boko Haram educated their female members in Islam [21]. However, such practices have diminished and women are now taught only in the house [21]. Today, Boko Haram uses women as incentives (willing or forced) for their male members as wives, providing status and other favors [14]. As such, Boko Haram started kidnapping girls and women, mainly in christian dominated sections of Nigeria [21]. In April, 2014, Boko Haram kidnapped over 200 schoolgirls in the town of Chibok, causing international outrage and activist groups to join the “Bring back our girls” campeign [21]. Nigeria’s President at the time, Goodluck Jonathan, took three weeks before making a statement while his wife, Patience, supposedly speculated that the girls’ abductions occurred [21]. Boko Haram continues to kidnap women and use them as bargaining chips for recruitment and terrorist activities [21].

1.3 Department of Defense Presence in West Africa

The United State’s involvement in Africa has been relatively insignificant when compared to other nations such as France, Portugal or Britain. However, as religious extremism and terrorist activities increase in Africa, the United States has increased their militaristic presence on the continent mainly through the United States Africa Command (AFRICOM) [36]. Department of Defense (DoD) activity and expenditures in West Africa have been on the rise, as seen in Figure 7. Back in 2003, President George W. Bush sent several hundred troops to Liberia as a humanitarian peace keeping attempt near the end of Liberia's second civil war [37]. However, before U.S. troops were able to reach Liberia, Nigerian troops, under the Economic Community of West African States (ECOWAS) authority, were sent to stop the fighting and help restore peace [30]. In more recent news, according to a npr report in 2018, the DoD had over 1,000 personnel in the Nigeria, Niger and Mali region alone [38]. U.S. activities in Africa go beyond that of simple expenditures and man hours. In October of 2018, four Americans were killed during an ambush in northern Niger [38].

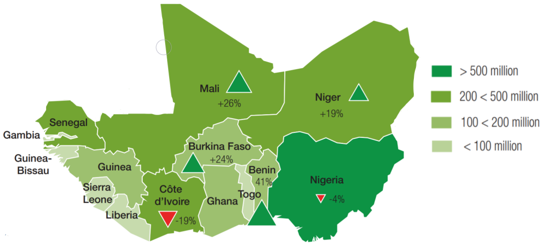


Figure 7. Military Expenditures in West Africa [7]

According to AFRICOM's website, their mission is to "strengthen security forces, counter transnational threats, and conduct crisis response in order to advance U.S. interests and promote security, stability and safety" with local partners [39]. According to an article published in the Orbis Journal titled, "Assessing a Decade of U.S. Military Strategy in Africa", the U.S. presence in Africa, through AFRICOM, differs from U.S. DoD presence in other continents in that AFRICOM "prioritizes a light footprint and the priorities of African partner nations" [36:657]. AFRICOM implements their priorities of cooperation and stability by "attempting to reduce the sources of insecurity and helping to strengthen African security capabilities" [36:657]. AFRICOM's, and by extension the U.S. Military's, mission in Africa is to promote stability within the continent while also promoting the U.S's interests - particularly against terrorist activities and extremism.

Africa's "security, stability and safety" are primary concerns for AFRICOM [39]. Additionally, several respectable organizations, such as the UN, have declared gender equality to be a key determinant in stability and maintaining peace [40]. Given AFRICOM's mission statement, researching the relationship between women and stability could potentially determine whether DoD investment in gender equality in Africa could assist in the promotion of AFRICOM's mission statement.

1.4 Problem Statement

West Africa is a region with a complex history filled with various Western interventions, slavery, Colonialism and is continually dealing with ethnic, religious and politically charged conflicts, human rights violations, and overall criminality. Several global organizations, like the United Nations, have already started to seek out ways to increase gender equality in West Africa and similar regions so as to encourage stability and peace in war torn nations. However, there is little research done to better observe and summarize the complex relationship between women and armed conflict and the specific regions in which it may take place. Due to the absence of quantitative research pertaining to women and conflict, this research will endeavor to capture the relationship between conflict and women and its geographic significance, if any exists.

1.5 Assumptions

As with all research, necessary and preferably valid assumptions were implemented in order to continue with the project. Below is a comprehensive list of the assumptions utilized in this research.

- Surveys of women in West Africa, collected over a 16 year period (1998-2014) depicts an appropriate singular picture of women in West Africa today. In other words, the various samples that vary over time, without any determinable pattern, are collectively an appropriate snap shot of the region today. Provided the format of the data set used, disparate survey samples that vary over years and countries with no discernible pattern in location and time collection, this is a very necessary assumption. Furthermore, after some initial analysis, utilizing the chosen methodology, this team saw no obvious differences between women over the collected time period, thereby validating the assumption.

- As discussed previously, the boarders separating the nations may not be the best representation of a separation between people, culture or even national identities. As such, the boarders separating the survey samples will be considered arbitrary. This assumption draws its argument from colonial history. The Western nations who drew the borders were more concerned with its natural resources than the native people's culture and history. As such, these boarders should be considered arbitrary when considering soci-economic factors such as gender equality and women's well-being.

- Niger 1998 will have to be a sufficient data sample size as it is the only survey sample with GPS locations that were provided. This assumption is necessary due to Demographic and Heath Survey (DHS) samples from Niger either did not collect GPS data, or did, but later found them to be corrupted. Due to the chosen methodology, this assumption does not significantly affect the analysis, however, Niger will be under represented in the analysis due to the lack of data.

- The data has some shape in $\mathbb{R}^n$ and the shape of the data matters. This is the most significant assumption behind the primary chosen methodology, Topological Data Analysis, and will be discussed further in the following chapters. Researchers in Applied Topology and Data Science found this assumption to be necessary, valid, and even additive in data analysis.

- Missing values in the data have meaning and are therefore significant to the shape of the data. This is a common assumption in Social Science fields [41] and provided the data set, is both necessary and valid. For example, if a women has a NaN value for a variable describing the "Age at First Birth" for each women. In this variable's instance, the NaN value implies that the woman simply has not had a child yet, implying that the NaN value protrays meaning and therefore holds significance in the analysis. For the purposes of this paper, this team added a binary indicator variable for NaN or missing values when believed to indicate meaning.

- Niger, for the year 2008, had missing values for all conflict data. However, only Nigerien women with DHS survey answers from 1998 also had accompanying sample GPS locations. Therefore, due to the length of time between survey sample and missing conflict data, the missing conflict event data from 2008 should not significantly affect analysis. As such, all 2008 conflict events for Niger were made to be zero.

- The answers to the DHS survey sample questions collected, seen in Appendix A, are a good proxy for measuring a woman's well being. Most of the variables collected were concerning a woman's socio-economic status. Most of the literature concerning women's well-being in relation towards stability, the women's socio-economic status were primary variables. As such, DHS survey questions concerning socio-economic status was collected. However, other indicators could be more appropriate and further research is necessary to evaluate the validate this assumption.

- A key assumption in the analysis is that a woman's proximity, as measured by a 10 kilometer radius from survey sample GPS location, during a five year window of time, is an adequate measure of the stability/instability in her immediate surroundings. While other measures of stability and/or instability could potentially better capture stability, in relation to women; due to time constraints, this assumption was used instead. Further analysis and study would be required to validate this assumption or implement research with a better assumption.

1.6 Overview

The primary research question is concerning the relationship between treatment of women and a region's, nation's, or community's stability. This paper defines women's station or well-being in life through the use of the Demographic and Health Survey (DHS) Program data and stability through conflict data gathered from The Armed Conflict Location & Event Data Project (ACLED) database. For the purposes of this research, "stability" is defined from a Department of Defense (DoD) view point by observing conflict that involves the use of arms and threatens potential military intervention. Additionally, Geospatial analysis will be implimented on important socio-economic indicators alongside a few supervised and unsupervised machine learning algorithms. The data and the definition of conflict and stability/instability will be discussed in more detail in later chapters.

The following chapter (Chapter 2) will cover an adequate overview of research concerning women and their affect on stability. Chapter 2 will also cover the chosen methodologies. The third chapter will give a comprehensive overview of any methodologies that where explored. This will leave Chapter 4 for the analysis of any findings and chapter 5 for a conclusion of the findings and potential future work that could be applied to this dataset or research question.

II. Literature Review

2.1 Overview

As discussed in the Introduction, West Africa is a large region filled with diverse groups of peoples, cultures, communities, and histories. Provided that women are roughly half of any given population, the theory that women and how they interact within their communities will impact those communities. However, as it relates to the relationship between women and stability, researchers struggle with three primary aspects of researching this topic:

- How do is “stability” defined?
- Given the definition of stability, how do women affect stability (if at all)?
- To what extent do women affect the decided definition of stability (significant or not)?

Provided that this research is currently being sponsored by the United States Africa Command (AFRICOM), a military organization, this research team will be defining stability as the lack or minimization of occurrences of armed conflict events. Armed conflict events could be described through battles between nation states or local militia, violent extremist attacks against unarmed civilians, or riots. The precise definitions of stability will be revisited and more thoroughly explained in the following chapter.

This chapter will examine previous research that attempted to examine the relationship between women and stability/instability. This chapter will also provide a general explanation concerning this research’s chosen methodology.

2.2 Women and Stability Research

Little quantitative research has been implemented when observing the relationship between women and the definition of stability that this research will be focusing on. The lack in research is in large part due to the structure/format of the data. How does one numerically capture, in a structured manner, the intricate role women may play in a terrorist organization, or how many women were involved in a particular battle or riot and their socio-economic status? Despite the shortage of data, there is plenty of qualitative research implemented on the subject.

Several prominent organizations are trying to better understand the role women may play in terrorist organizations [42].There are reported cases of men joining terrorist organization in order to help pay a bride price [35]. Furthermore, in West Africa, there are documented cases of Boko Haram forcing the kidnapped girls into arranged marriages as a recruitment tool [35].

Research articles looking at a more direct link between women and stability, to the extent that is normally desired in quantitative research and public policy decision making, are scarce at best. However, a recent research article titled "Women's Participation in Peace Negotiations and the Durability of Peace", and published in *International Interactions*, found a positive correlation between the number of female signatures on peace agreements and the durability of the peace agreement [43]. Moreover, peace agreements with female signatures had a "significantly higher number of peace agreement provisions aimed at political reform, and higher implementation rates for provisions" [43:985]. This suggests that women may impact stability as defined by this research team.

2.2.1 Women and General Stability.

While there has been little to no quantitative research applied towards women and stability, as defined earlier, there are copious amount of research on women's affect towards a more general sense of stability - such as economic and/or social. The relationship between women and stability is most researched when it comes to girls' and women's education and economic growth.

In economics, there has always been a positive correlation (and arguably causation) between education and economic growth [44]. In fact, education is believed to be a leading "determinant of economic growth, employment, and earnings in modern knowledge-based economies" [44:3]. Women's education, specifically, has been consistently documented to have higher rates of return then men's education [45]. Furthermore, women facing discrimination are costly to nations. According to The Organisation for Economic Co-operation and Development (OECD), gender-based discrimination in social institutions results in an estimated loss of USD 120 billion in income for the West African region alone [20].

2.2.2 Hypothesis.

Given that women are roughly half of any given population, and have been documented to have significant impacts on a nation's socio-economic stability, women will affect the stability of a nation when it comes to armed conflict. The relationship between women and the definition of stability, as defined in this research, will most likely be multifaceted, complicated, and buried amongst several other cultural, historical and soci-economic layers of the West African region. As such, the relationship between women and stability, as defined in this research, is not likely to be completely captured in a single research paper.

However, this research team will attempt to investigate the relationship between women and stability through the *shape* of the data. It is this research teams hypothesis that if the relationship between women and stability exist, it will be best observed and researched by investigating the *shape* of the data rather than through traditional statistical practices.

2.3 Topology

Topology, though not a established field of mathematics until the late 19^{th} to early 20^{th} century, is often considered to have its origin with none other than Leonhard Euler [8, 46]. Euler published his paper *The solution of a problem relating to the geometry of position* in 1738 with his solution to the *Königsberg bridge problem* depicted in Figure 8 below.

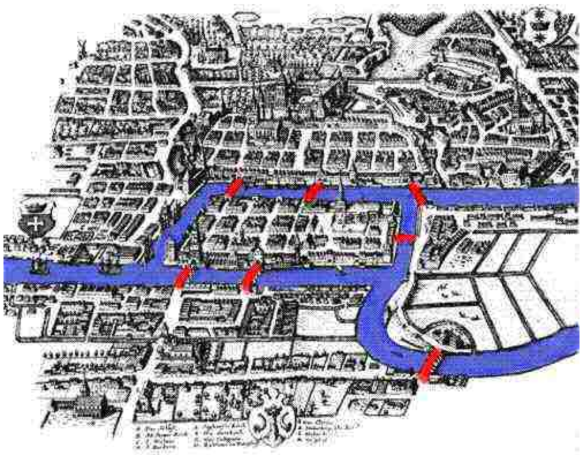


Figure 8. Diagram of the Königsberg bridges [8]

The Königsberg bridge problem, depicted in Figure 8 was as follows: is it possible to start at one point and cross Königsberg's seven bridges only once in a single journey [8]. Euler solved the Königsberg bridge problem not through strict geometric analysis, but rather by drawing up a crude diagram of only the relevant information;

the bridges' relative position to one another and the blocks of land mass [46]. Euler proved that it was in fact impossible to make the desired journey [8]. Even though it would be a couple hundred years after Euler published his paper that the precise formulation of Topology as a sub-field of mathematics would be defined, Euler and the Königsberg bridge problem are most often attributed with the birth of Topology [8]. The Königsberg bridge problem is considered to be the birth of Topology because Euler took a problem concerning shape and geometry and deformed it to its core components, ignoring irrelevant information concerning shape that often defines Geometry's notion of shape.

Instead of Geometry's rigid definitions concerning shape and congruence, Topology, "deals with qualitative geometric information" [47:256]. In fact, Topology ignores most quantitative information describing shape, such as distance and angle, and instead "replaces them with the notion of infinite nearness of a point to a subset in the underlying space." [47:256]. Topology's definition of shape has influenced the spread of a joke that does a decent job of describing how Topology's defintion of shape: A Topologist can't tell the difference between a coffee mug and a donut [9]. As one can see from Figure 9 below, both the coffee mug and the donut have a hole or loop; the coffee mugs handle and the hole in the donut. Assuming that the donut was made of a material that could be bent, molded and transformed at will - so long as this material was never torn - the donut could be continuously transformed into a coffee mug with a handle [9].

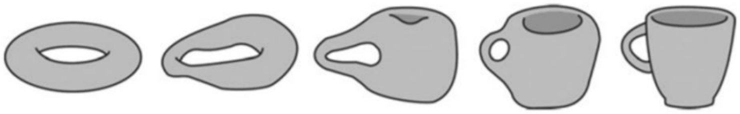


Figure 9. A transformation from donut to coffee cup [9]

Though Topology has been studied for a few centuries, it has not been until recent decades that mathematicians and data scientists have started to apply Topology's looser notions of shape to the world of data [46]. There are three key properties in Topology that make the mathematics' field potentially superior to others when dealing with data:

- *Coordinate invariance*: According to this property, Topology's study of shape does no depend on the set of coordinates chosen [10]. according to the coordinate invariance property, which is depicted in Figure 10, all three ellipses are considered equivalent [10]. This is value added in data analysis because data often undergoes several different transformations in the data matrix [10]. These transformations are equivalent to simple changes in the vectors' coordinates [10].

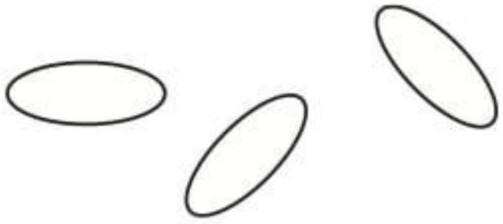


Figure 10. Example of Coordinate Invariance Property [10]

- *Deformation invariance*: According to this property, a geometric shape can be squashed, stretched, and deformed (provided that is is not torn) without changing it's topology [9]. A good example of this is humans' natural ability to determine equivalency between two slightly different shapes. For example, when looking at each shape in Figure 11, a human can easily tell that each shape is the letter "A" in different font styles [10]. The change in font style does not change the shape or the meaning behind the shape itself; all three are the letter "A".

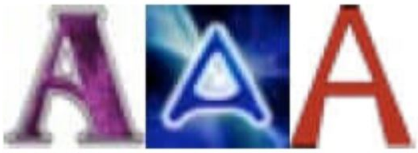


Figure 11. Example of Deformation Invariance Property [10]

A stricter geometric approach to this property can be seen in Figure 12. According to the deformation invariance property in Topology, all three shapes are considered to be essentially the same [11]. The edges of the square can be rounded off and the shape molded into the circle, and since the points on the edge of the shape that were "near" each other before the deformation are still "close" to each other after, the shapes are considered to be essentially the same [11].

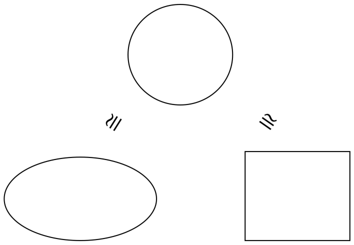


Figure 12. Geometric example of Deformation Invariance [11]

- *Compressed representation*: This property is one of the most useful tools when applied to data [10].Instead of trying to describe the infinite number points and pairwise points in the circle depicted in Figure 13, one can compress the circle into the hexagon next to it [10]. Both capture a critical quality of the circle (the loop) but the hexagon is infinitely easier to examine and describe [10]. This property is beneficial when visualizing data and relationships within the data that is currently in $\mathbb{R}^n$ space [10].

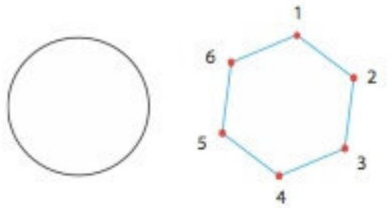


Figure 13. Compressed Representation Property Example [10]

For more information on Topology as a field of mathematics please see Munkres [48].

2.3.1 Topological Data Analysis.

Mathematicians and data scientists recently started to apply Topology to the world of data [46]. Topological Data Analysis (TDA) is a growing field of applied mathematics that involves applying certain concepts and definitions derived from Topology to data [9]. There are two major methodologies in TDA, Persistent Homology and MAPPER [9]. For the purposes of this research, this team will be focusing on the MAPPER Algorithm and its applications.

2.3.1.1 MAPPER.

The MAPPER algorithm was first introduced at the Eurographics Symposium on Point-Based Graphics by Gurjeet Singh, Facundo Mémoli, and Gunnar Carlsson in their papper *Topological Methods for the Analysis of High Dimensional Data Sets and 3D object Recognition* back in 2007 [49]. Since then, Singh and Carlsson and Harlan Bennet Sexton founded the Ayasdi Company that built software that implements the MAPPER algorithm along with providing TDA to clients. This research utilized the Ayasdi software in its analysis and as such will use terminology created and coined by Ayasdi.

The MAPPER algorithm is a statistical implementation of applying a simplicial complex onto a topological space [49]. For more information on simplicial complexes and how they relate to the field of Topology, please see Hatcher [50]. The MAPPER algorithm is provided in detail by Singh et al [49:3-4], Chazal and Michel [12:7-9], Carlsson [47:284-287], Kraft [9:12-14], and Brown et al [51:2-3]. First, define X and Z be two separate metric spaces, and $f : X \longrightarrow Z$ be a continuous map between them. In application, X is the original data space in $\mathbb{R}^n$, where $n > 0$ and has no upper limit, Z is in $\mathbb{R}^2$ or $\mathbb{R}^3$, and f is any real function that represents an array of data into a single point. Once in Z, an open covering $\mathcal{U} = \{U_i\}_{i \in I}$ will be applied. Let $f^*(\mathcal{U})$ denote the *pullback cover* $\mathcal{V}$ in X which is obtained by cutting the connected components in $f^{-1}(U_i)$ and then collecting them so as to obtain an open cover in X space. The Mapper construction $\mathcal{M}(X, Z, f, \mathcal{U})$ is the simplicial complex that is created by taking the nerve of the pullback cover.

$$\mathcal{M}(X, Z, f, \mathcal{U}) = \mathcal{N}(f^*(\mathcal{U})) \tag{1}$$

For a more visual representation of the MAPPER algorithm described in mathematical terminology above, see Figure 14, provided by Frédéc Chazal and Bertrand Michel in their paper titled: “An introduction to Topological Data Analysis: fundamental and practical aspects for data scientists”.

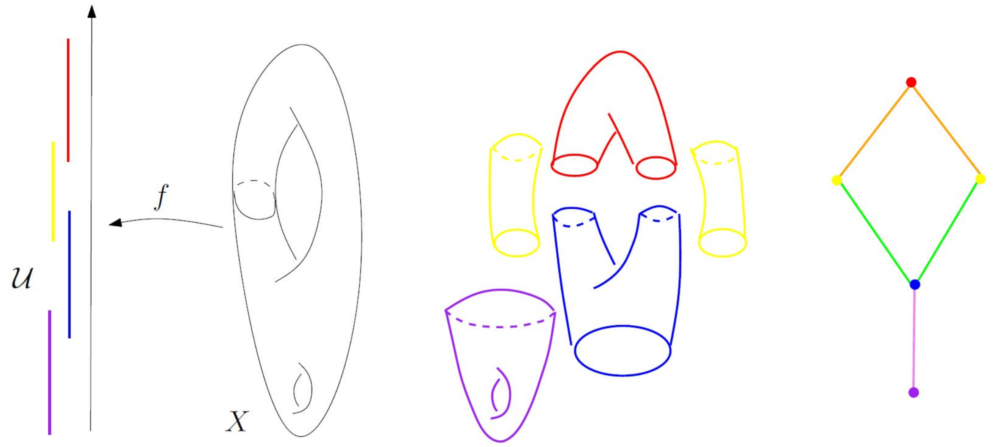


Figure 14. MAPPER example [12]

In simpler terminology, the MAPPER algorithm creates a simplicial complex in the original data space X by first mapping the data into another space Z through a continuous function f, or as Ayasdi has termed it, a *lens* along with some define notion of similarity (or distance) that Ayasdi as termed as a *metric* [52]. A lens, in practice, can be any method that produces a single number for a point or array in n dimensional space [52]. A metric, is just some notion of similarity or distance between rows, such as Correlation or Euclidean distance and is often dependant on the data format [52]. It is through this lens and metric combination that the data in X is then mapped to Z. As such, it is the lens and metric that defines what points in X space are "close" to each other and which are "far away", thereby making the lens and metric choice critical to any analysis.

Once in Z space, an "open cover" is then applied to the data. This open cover "bins" the data points into a predetermined number of open sets that overlap by some predetermined amount [52]. The number of open sets and the overlap between them are parameters set by the analyst and are called the *resolution* and *gain* respectively in the Ayasdi software [52]. Once the "neighborhoods" are defined, these neighborhoods are then mapped back into the original X space where some clustering algorithm is applied to create *nodes* of similar observations [52]. Nodes that share observations, due to the overlapping of "neighborhoods", are connected by an *edges* [52]. This results in a simplicial complex that summarizes the shape of the data as defined by a lens, a notion of similarity (or metric), the resolution and the gain.

It is within the open covers in X that some clustering algorithm will be applied, and clusters that share points will be connected by *edges* and a nerve, or simplicial complex, will be applied to the data. The number of neighborhoods that the "filtered" data is binned into and the amount by which these neighborhoods overlap are parameters set by the analyst and are referred to as the *resolution* and *gain*, respectively, in the Ayasdi software. A depiction of such a simplicial complex can be seen in Figure 15 below.

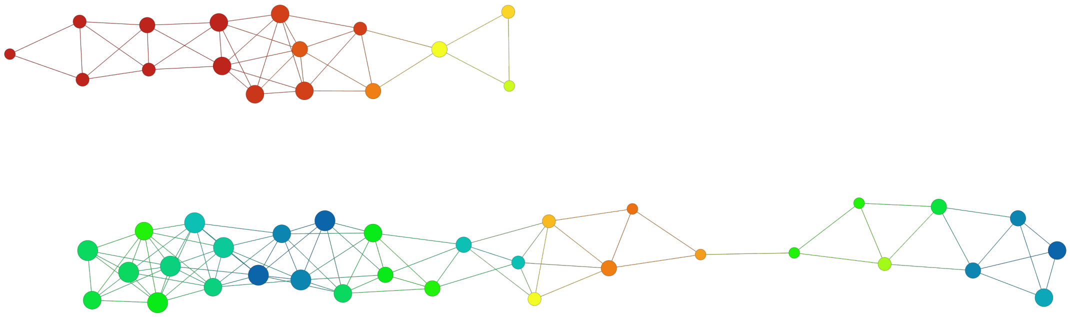


Figure 15. Mapper Simplicial Complex with Fisher's Iris Data Set

The figure above was created in Ayasdi's Workbench using Fisher's Iris data set [53], pulled from UCI's Machine Learning Repository [54]. Fisher's Iris data set is made up of sepal length and width measurements of 150 flowers belonging to three different iris flower species: setosa, versicolor, virginica. The simplicial complexes above were created using Multidimensional Scaling (MDS) lenses, Correlation as the metric, and a *resolution* of 30 with a *gain* of 3 ($\approx$ 67% overlap). The percentage overlap between the open sets is calculated by $1/(1 - gain)$. Figure 15 is currently being colored by a density estimate of the variable sepal width; with red nodes indicating the containment of rows with wide sepals and blue nodes indicating the opposite. After some initial analysis, it can be observed that the iris flower species setosa is all collected within the top connected component. The other two iris flower species, versicolor and viginica, exist within the connected component at the bottom of Figure 15. While there is some overlap, the two species - versicolor and virginica - are decently separated within the bottom connected component. By coloring the simplicial complexes with a petal width density estimate, one can observe that the overlap between the two iris flower species - versicolor and virginica - occur where petal widths are suddenly wider, and then branch off to being skinnier for either flower species. This provides the analyst with the information that, for some reason, the versicolor and virginica flowers that are most likely to be confused with each other have wider petal widths then the rest of the flowers in their species. More analysis would be necessary to know why, perhaps coloring by petal length density estimate.

2.3.1.2 Applications of MAPPER.

MAPPER, due to its unique capabilities with complex and high dimensional data sets, has been implemented with relative success in the medical fields. In one paper, researchers were able to identify a unique subsets of breast cancer tumors that *(i)* "exhibit clear and coherent clinical characteristics" and *(ii)* have a 100% survival rate [55:7265-6]. These researches were able to define these sub-groupings of cancers patients through MAPPER by using a continuous function/lens specific to the medical field called *Disease-Specific Genomic Analysis (DSGA)* [55]. They also created a Web tool that applies their methodology - which is an implementation of MAPPER specific to genomic data dealing with diseases [55].

Another implementation of MAPPER in the medical field is a paper published in *Science Translational Medicine* that was able to identify three distinct subgroups of Type 2 Diabetes (T2D) [56]. In addition to identifying three distinct sub-types of T2D, the researchers were also able to test for specific diseases that T2D patients are often considered high risk [56]. The study found, from it's implementation of the Mapper algorithm on the medical records and genotype data from 11,210 T2D patients that each subgroup had significant correlation with defined groupings of diseases that T2D is often characterized as being high risk [56]. Subtype 1 of T2D was "characterized by T2D complications diabetic nephropathy and diabetic retinopathy"; Subtype 2 of T2D was "enriched for cancer malignancy and cardiovascular diseases"; and subtype 3 of T2D was "associated most strongly with cardiovascular diseases, neurological diseases, allergies, and HIV infections" [56:1]. They concluded that there is a need for a more nuanced definition of T2D that might impact important clinical decisions and doctor/patient interactions [56].

MAPPER was also implemented in fraud detection. Ayasdi analyzed highly complex transaction data for one of the top 5 consumer credit card issuers - dubbed "The Company" in Ayasdi's report to protect client information [57]. According to Ayasdi's report, by looking at the shape of the data, they were able to increase the company's fraud detection rate from 28% to 99% for a newly identified type of fraud [57]. Ayasdi was able to create new parameters for The Comapny's fraud detection algorithm. By adding the new parameters, The Company was able to maintain their original false positive rate at 1% while also decreasing their false negative rate from 75% to 0% [57].

2.3.1.3 Topological Hierarchical Decomposition.

Topological Hierarchical Decomposition (THD) is a new application of MAPPER that was recently developed and is currently undergoing testing and validation by the Air Force Research Laboratories (AFRL) at Wright-Patterson Air Force Base (WPAFB) in Dayton, Ohio. AFRL recently published a paper titled "HELOC Applicant Risk Performance Evaluation by Topological Hierarchical Decomposition" in which they describe the process in detail [51:3-4]. THD is an algorithm that "decomposes" a dataset into smaller groupings based on an iterative application of MAPPER [51:3]. The algorithm starts by applying MAPPER on the entire dataset X at an initial resolution N_0, which is typically small (≈ 1). This starting *topological model* is typically a single node with no connected components or *singletons* (single nodes with very few observations that have no edges). Keeping the gain parameter g fixed throughout the entire process, iteratively apply Mapper on X, increasing the resolution by set value δN to create a *topological network* K. A topological network is a topological structure, created by running MAPPER on a data set, consisting of nodes that are connected through edges and can be seen in Figure 15. For each K_i, if the number of data points $|X_i|$ in this connected component is above some threshold $t > 0$, a *split* in the original topological network has occurred. A split will result in a *branch* in the THD structure starting from the current network K. If there are no splits after applying MAPPER on a topological network, MAPPER will be implemented again, increasing the resolution by δN until another split occurs [51]. This will continue to run until there are no topological networks that meet the threshold limit $t > 0$. The result will be a tree like structure with branches of different decomposed connected components, with the smallest connected components at the end of the structure, which will be refereed to as *leaves* in this paper.

Algorithm 1 Topological Hierarchical Decomposition (THD) Algorithm Summary [51]

```
1. Choose lens combination $f$, gain $g$, metric $m$, observation threshold $t > 0$ and resolution start $N_0 \approx 1$
2. Apply Mapper to dataset $X$ to creat topological network $K$
3. Increase resolution for by $\delta N$ until split occurs
    (a) For each $K_i$ increase resolution by $\delta N$ until the number of observations in $K_i$ is less than threshold $t$
```

THD decomposes the topology of the data into its core components while recording the decomposition process. While AFRL has researched using this methodology as a predictive model of sorts, this team will be implementing THD as an unsupervised learning technique that aims to observe the decomposition of women's well-being relative to conflict. Assuming women and stability have some kind of relationship, the theory is that as the data decomposes itself based on the topology of a women's well being, conflict indicators will be statistically higher in certain groups of women then others. Hopefully, if the correlation between women's well-being and how this research team defined conflict is prominent enough, as the topology decomposes, conflict data will follow certain women who are prone to be near conflict down a branch earlier in the THD process.

2.4 Important Machine Algorithms Utilized

2.4.1 Random Forest.

Random Forest is a predictive algorithm that utilizes bootstrap sampling to build a large collection of "de-correlated trees" and then averages them [58:587]. Random Forest is what most refer to as a black box predictive model. Few assumptions are needed to build a Random Forest. Random Forests are robust to variance in the data as it is a simple average over several different trees which reduces bias in the predictions [58].

Algorithm 2 Random Forest for Regression and Classification [58:588]

```
1. For $b = 1$ to $\mathcal{B}$:
    (a) Draw a bootstrap sample $\mathcal{Z}^*$ of size $N$ from the training data.
    (b) Grow a random-forest tree $T_b$ to the bootstrapped data, by recursively
        repeating the following steps for each terminal node of the tree, until the
        minimum node size $n_{min}$ is reached.
        i. Select $m$ variables at random from the $p$ variables.
        ii. Pick the best variable/split-point among the $m$.
        iii. Split the node into two daughter nodes.
2. Output the ensemble of the trees $T_{b1}^{B}$.

To make a prediction at a new point $x$:

Regression: $\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$.

Classification: Let $\hat{C}_b(x)$ be the class prediction of the $b$th random-forest tree. Then
$\hat{C}_{rf}^{B}(x) = \textit{majority vote}\left\{\hat{C}_b(x)\right\}_1^B$.
```

2.4.2 Isolation Forest.

Isolation Forest is built similarly to a Random Forest in that both build a “forest” of decision trees using bootstrap sampling [59]. However, instead of trying to predict new observations, Isolation Forests calculates the average path length necessary to isolate an observation from the data set [59]. The primary concept being that anomalous observations will have a shorter path compared to normal observations and as such will be easier to isolate from the rest of the data set [59]. This methodology is relatively new, and has yet to be thoroughly tested outside of academic research.

2.4.3 t-Distributed Stochastic Neighbor Embedding (t-SNE).

One of the lenses that was utilized for this research is a lens provided by Ayasdi called Neighborhood Lenses 1 and 2. Though these lenses are proprietary in nature, according to an answer provided on Ayasdi's Support Blog [60], the lenses were developed from Hinton's and Van der Maarten's data visualization technique t-Distributed Stochastic Neighbor Embedding (t-SNE) [61]. Therefore, even though the precise methodology in Ayasid's Neighborhood Lenses are proprietary, the t-SNE algorithm is close to the one used for this paper's models and as such will be presented as a decent example for methodology used. The goal of all dimensionality reduction techniques is to convert a high dimensional data set $X = \{x_1, x_2, ...x_n\}$ into two or three-dimensional data set $Y = \{y_1, y_2, ...y_n\}$ that can be easily observed in a scatter plot [61]. The aim of dimensionality reduction is to preserve as much of the significant structure of the high-dimension data while mapping the data matrix X into a lower-dimension Y [61]. Other traditional techniques, such as Principal Component Analysis (PCA) or Multidimensional Scaling (MDS) aim to preserve some global structure of the original data matrix X. In contrast, t-SNE aims to preserve the local structure in the original data matrix X when mapping onto Y [61]. As such, t-SNE is better at capturing natural clusters and groupings that could be found in the original high-dimension data structure X [61]. This makes t-SNE a particularly useful as a lens in MAPPER as a defining function of "nearness" in the binning process, described in Section 2.3.1.1 and seen in Figure 14.

The t-SNE algorithm chooses two similarity measures between pairs of points - one for the high-dimensional structure X and one for the low-dimensional structre Y [62]. It then attempts to create a lower-dimensional embedding that minimizes the Kulback-Leibler (KL) divergence between the "vector of similarities between pairs points in the original dataset and the similarities of points between pairs of points in the embedding" [62:2]. The algorithm accomplishes this through non-convex optimization with a randomized starting point [62]. For a closer look at the math please see Van der Maaten's and Hinton's original paper [61] or a more condensed version out of Princeton University, originally written for learning purposes [62].

2.5 Geospatial Analysis

Geospatial analysis is said to date as far back as 15,000 years ago to the Lascaux cave in southwestern France [63]. Though crudely drawn by early man, these maps depicts man's earliest attempts at mapping different aspects of the world as they saw it.

It was not until 1854, during a particularly bad cholera outbreak in London, that geospatial analysis was seen as a valid and useful scientific method [63]. Dr. John Snow, an English physician, decided to map out reported cholera deaths around London while noting the locations of water pumps [63]. With this map, Dr. Snow was able to pinpoint the location of the outbreak to a certain water pump in the city [63]. Due to his analysis, Dr. Snow was able to help halt the spread of the disease [63]. Since then, geospatial analysis has been utilized for mapping the spread of diseases, social norms, natural disasters and even human war far [63]. Geospatial analysis was recently utlized in the West African region during the 2013-2016 Ebola epidemic [33].

III. Methodology

3.1 Overview

The chosen methodology for this research project is to observe the shape of womens' survey data in the West African region through use of Ayasdi's Topological Data Analysis MAPPER algorithm, Geospatial analysis, and other unsupervised and supervised machine learning algorithms.

3.2 Topological Data Analysis (TDA) Models

All applications of MAPPER were conducted in Ayasdi's TDA platform named the *Workbench*. The lenses utilized were Neighborhood lenses 1 and 2 (see t-SNE in Chapter 2). The only metric used was IQR Normalized Euclidean. IQR Normalized Euclidean distance is also known as the *interquartile range metric* [64]. IQR Normalized Euclidean normalized the distance between two columns of data based on the interquartile range of said column [64]. See equation below:

$$IQR(X,Y) = \sqrt{\sum_{i=1}^{N} \left(\frac{X_i - Y_i}{R_i} \right)^2} \tag{2}$$

Where:

- $X, Y =$ data points
- $N =$ dimensionality of $X, \mathbb{R}^N$ (i.e., the number of columns chosen for analysis)
- R_i is the interquartile range associated with each column i

3.2.1 Toplogical Hierarchical Decomposition (THD).

Two Topological Heirarchical Decompositions (THDs) were created through AFRL's platform tool built to interact with Ayasdi's Workbench, both of which require Python 2.7 [65]. The first THD was built only looking at the DHS Program's women survey data, meaning that no variables related to conflict were included while applying MAPPER. The second THD was created using both DHS Survey Data and the conflict matrices described further in Chapter 4. The lenses used were Neighborhood lenses 1 and 2, with a gain of 1.5 ($\approx 33\%$ overlap), IQR Normalized Euclidean metric, and a starting resolution of 1 with an iterative increase of 15. Additionally, to establish the difference between the separate groups/connected components of interest, statistical comparisons were implimented using Kolmogorov–Smirnov tests for continuous variables and hypergeometric tests for categorical variables.

3.3 Geospatial Analysis

All maps were created using Python 3.7 [66] libraries GeoPandas [67] and GeoPlot [68]. The shape files that located each DHS survey cite was downloaded directly from the DHS Program website and merged with the dataset used for analysis on the variable *DHSID* - see Appendix A. DHSID was the identification number that linked each woman with her respective DHS survey cluster location.

Two additional shape datafiles were downloaded and utilized in the geospatial analysis. The first is the World Borders shape file from thematicmapping.org [69] so as to outline the countries being observed in the Geospatial Analysis maps. The second is the World Cities shape file from ArcGIS Hub website [70] which were used to show the location of large cities in any mape that was created.

The primary analysis tool utilized was spatial kernel density estimate plots using a function provided in the geoplot library. According to documentation, kernel density estimation is a unsupervised learning technique that helps to estimate the distribution of underlining data [68]. When applied in a spatial representation, it can be used as a way to estimate the density of points on a map and quite random noise [68]. This is a helpful tool as it allows us to have a clearer visual understanding of where women in certain groupings, with statistically defined qualities, are densest in their respective regions. Provided below in Figure 16 is a map of the methodology used.

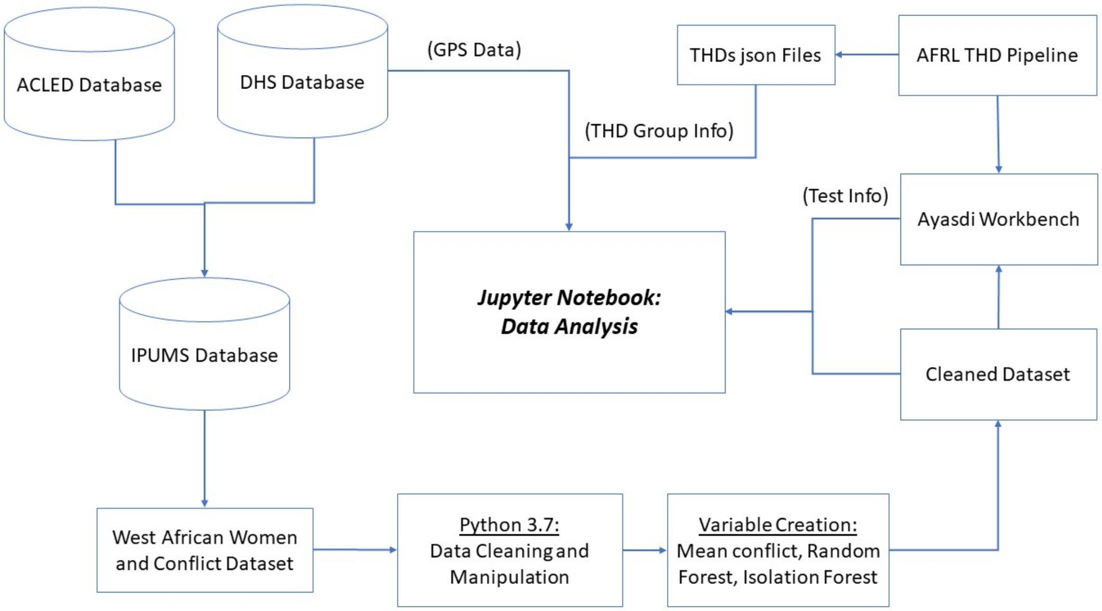


Figure 16. Methodology Map

IV. Analysis

4.1 Overview

This team utilized several techniques on the obtained dataset: initial statistical analysis, Topological Data Analysis through MAPPER, Topological Hierarchical Decomposition, supervised and unsupervised machine learning algorithms and Geospatial Analysis.

4.2 Data

This research team pulled data from the Integrated Public Use Microdata Series (IPUMS) database which is part of the Institute of Social Research and Data Innovation at the University of Minnesota and is directed by Regents Professor Steven Ruggles [71]. The data that IPUMS housed and merged together was originally pulled from the Demographic and Health Survey (DHS) Program [72], funded by USAID, and from the The Armed Conflict Location & Event Data Project (ACLED) [73]. The DHS Program collects answers to questionnaires, or "samples", that are supposed to be representative of the nation at large [72]. Only surveys that were conducted on women with attached cluster longitude and latitude location information were used for this research. A cluster, in the DHS survey context, is a randomly selected number of households, which are "selected with Probability Proportional to Size (PPS)" for any given selected region within a country [74]. It should be noted, however, that in order to secure the anonymity of the survey subjects, each cluster GPS location is provided a random dislocation buffer of a minimum of 0 kilometers to 10 kilometers, depending on rural or urban status [72].

Using IPUMS as the sole data source had both its advantages and disadvantages.

Due to IPUMS being relatively new, the database does not have all DHS collected country surveys; resulting in a possible data set loosing five of the countries listed in Table 1: Gambia, Liberia, Sengal, Sierra Leone and Togo. IPUMS had eight of the fifteen listed countries: Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Mali, Niger, and Nigeria; the DHS Program did not collected any surveys from Guinea-Bissau and Cabo Verde. Additionally, in order to increase country samples and to better capture Nigeria's boarder, Cameroon, a country of stated interest that lies along Nigeria's eastern boarder, was added to data pulled from IPUMS. All data samples were collected in the time range of 1998 to 2014.

Table 4. Dataset Country and Sample Years

Country	Sample Years
Benin	2001, 2011
Burkina-Fasso	2003, 2010
Cameroon	2004, 2011
Cote d'Ivore	1998, 2011
Ghana	1998, 2003, 2008, 2014
Guinea	1999, 2005, 2012
Mali	2001, 2006
Niger	1998
Nigeria	2003, 2008, 2013

Despite the lost in survey samples, IPUMS was chosen as the data source due to its obvious advantages. IPUMS was able to attach conflict variables pulled from ACLED and then attach them by the location of the DHS clusters and merge them with the DHS survey data set. The three conflict variables provided by the IPUMS database are riots, battles and civilian violence. According to ACLED, "A politically violent event is a single altercation where often force is used by one or more groups for a political end, although some instances - including protests and non-violent activity - are included in the dataset to capture the potential pre-cursors or critical junctures of a conflict" [75:7]. According the the ACLED 2017 Code book [75], the three events used in this research are defined as such:

- ***Battles***: A battle between two or more violent armed groups, both official (national military) and unofficial (rebel militia).
- ***Riots***: A violent form of demonstration
- ***Civilian Violence***: Violence against an unarmed group of civilians at the hands of a violent and armed group (militia, terrorist organization, or even military).

Each of the three conflict event indicators listed above are a set of twenty variables, ranging from 1997 to 2016, capturing the number of events that occurred within a 10 kilometer buffer around the survey cluster of each women for each given year [71]. Each set of conflict variables is a data matrix $C^{m \times 20}$ where C is any one of the three conflict variable set described above, m are the number of observations in the data set and 20 is the number of years ranging from 1998-2016 that the conflict variables range over. The conflict variables added to the data set provided this team with a way to view womens' "well-being" as described by their answers to the DHS survey and conflict around them.

Currently, the DHS Program provides their datasets in either SaS, SPSS, or STATA data file formats. The data format in which the DHS Program provided their data files impeded this research as this research team is unfamiliar with theses programming languages. IPUMS, however, provided their data in CSV format which could be loaded into a Python interface as a DataFrame using the Pandas library in Python 3.7 [76]. This helped to decrease any uncertainty surrounding data quality going forward.

Figure 17 is a map plotting the DHS sample points and is colored by country. Figure 17 presents the spatial distribution and density of the samples gathered. For instance, both Niger and Mali are relatively sparse in terms of samples, while Nigeria and Ghana are both relatively dense. This disparity between number of representative samples of women for each country is partially due to a difference in demographics. For instance, both Nigeria and Ghana have significantly higher population densities compared to other countries in the data sample [13]. Furthermore, each country does not have the same number of DHS Surveys, as indicated in Table 4.

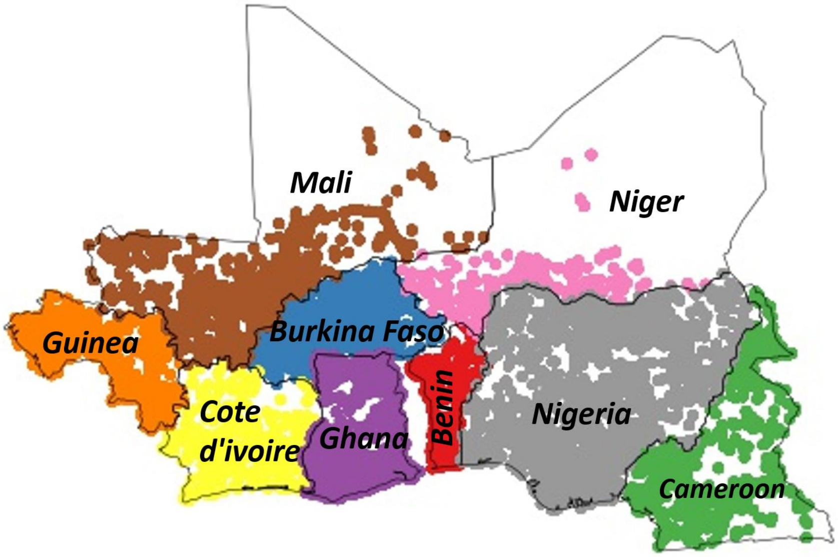


Figure 17. DHS Samples Map

4.2.1 Data Manipulation and Imputation.

4.2.1.1 Manipulation.

Due to the nature of survey data, data manipulation was required for the provided data set. Several of the variables used, which are listed in Appendix A, were categorical or nominal. According to common data manipulation practices, all nominal and categorical variables were coded into binary indicator variables through the use

Python 3.7 [66] lists and dictionaries, which are provided in Appendix B. Due to differences in country surveys, or certain questions not pertaining to all women interviewed, there were several missing values in the data set. In contrast to most machine learning assumptions, the missing values in this data set had intrinsic meaning. For instance, a missing value in the variable pertaining to a woman's age at their first marriage indicates that the woman is not married. As such, instead of imputing missing values - or other common practices in machine learning - missing values were captured in their own binary indicator variables. In the social sciences, where missing values often times hold meaning beyond data impurities, codeing missing values to be binary indicator variables is considered common practice [41]. Additionally, all of the continuous variables were normalized using the Min-Max method depicted below:

$$y_i = \frac{x_i - Min(\vec{X})}{Max(\vec{X}) - Min(\vec{X})}, \forall i \in \vec{X} \tag{3}$$

Later in the data manipulation process, there was an error found in the conflict event indicator variables. For some reason, unknown to this research team, Niger's riots variable for 2008 were all missing. However, since Niger only had one sample in 1998, the potential affect that the lost conflict event data could have on the analysis is believed to be negligible at worst. As such, all the missing values for riots in Niger's 2008 sample were simply imputed as 0 under the assumption that there were few riots that year. Though this assumption is hardly justified, due to time constraints, it was necessary. At the end of the data manipulation process, the data set was left with $255,221$ Observations.

4.2.2 Variable Creation.

A single variable for the mean number of riots, battles and civilian violence events surrounding a woman's sample cluster were computed. These computed conflict variables were continuous indicators of the number of riots, battles, or civilian conflicts that had occurred around a DHS cluster within a certain time frame window. The equation used to compute these continuous conflict variables is provided below where the riots data matrix $R^{255221\times 20}$ is being used as an example:

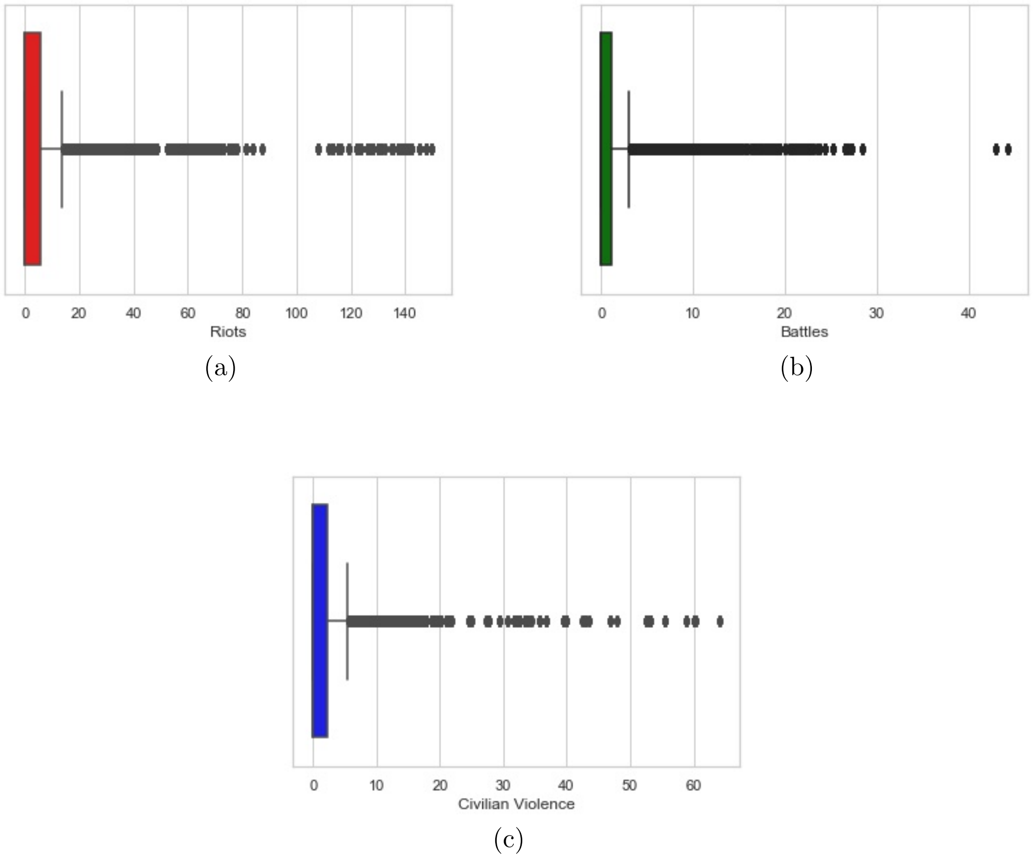
$$y_i(R|h) = \left(\frac{1}{2h+1}\right) \sum_{\forall j \in J} \big(R_{i,j}\lambda_j(w_i)\big) \ \forall\ i \in I \tag{4}$$

Where:

- $I = \{1, 2, ..., 255221\}$, indexed by i is the set of women surveyed in DHS sample cluster.
- $J = \{1997, 1998, ..., 2016\}$, indexed by j, is the set that corresponds to the conflict year range.
- w_i is a vector of length i that corresponds to the year in which woman i was interviewed for the DHS survey.
- h is the half-width parameter, set somewhat arbitrarily by the analyst, that is the number of years before and after the year in which any given woman was interviewed for the DHS Program survey.
- $y_i(R|h)$ is the mean number of riots for women i over the years surrounding the woman when she was surveyed, given the half-width length h.
- $\lambda_j(w_i) = \begin{cases} 1 & \text{if } w_i - h \leq j \leq w_i + h \ \forall i \in I \\ 0 & \text{otherwise} \end{cases}$

For this research, $h = 2$ years. This h value means that for each woman in the data set, there is a pseudo-confidence interval of length 5 around each woman's correlated conflict events - 2 years before and 2 years after plus the year in which she was interviewed. The reasoning behind setting the length of this interval to 5 years was that if there is some kind of correlation behind a woman's well-being and stability/conflict, that a 5 year window would be a sufficient time length to capture the conditions of each woman's surrounding. Again, this is a parameter set by the analyst and can be changed and further tested in later research.

Figure 18 below are box plots of the continuous variables created with $h = 2$. As one can observe, the mean for each of these variables (Figure 18a $= y_i(R|h)$, Figure 18b $= y_i(B|h)$, and Figure 18c $= y_i(C|h)$) are close to zero. However, each mean conflict variable has a significant number of extreme outliers with some women experiencing an average of over 140 riots per year near them within a five year period.



(a)

(b)

(c)

Figure 18. Continuous Conflict Variables Boxplots

A continuous mean conflict variable was created for each set of conflict variables - riots (R), battles (B) and civilian violence (C) - with an additional continuous conflict variable that was the mean of the continuous conflict variables:

$$y_i(All|h) = \frac{1}{3}\Big(y_i(R|h) + y_i(B|h) + y_i(C|h)\Big), \forall i \in I \tag{5}$$

Binary indicator variables were also added onto the data set for each of the mean conflict variables described above. Each indicator variable was one if the mean conflict variable was greater than 0, and 0 otherwise:

$$b_i(R|h) = \begin{cases} 1 & \text{if } y_i(R|h) > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

The conflict binary indicator variables, depicted above for riots, was utilized for Analysis purposes while examining TDA models.

4.2.3 Machine Learning Variable Creation.

Three different sets of conflict variables were created using the random forest and isolation forest algorithms.

4.2.3.1 Regression Random Forest Predictions.

A Regression Random Forest algorithm was trained to predict the number of mean conflict events for each conflict type ($y_i(R|h)$, $y_i(B|h)$, $y_i(C|h)$, $y_i(All|h)$) using the Sklearn Python library [77]. The algorithm was trained on 75% of a randomly selected subset of the data set, and then tested on the remaining 25% of the data set. The predictor variables used to predict the Random Forest models were only variables that represented a woman's well-being; i.e. answers to the DHS Program's survey questions. Table 5 below is the Mean Squared Error (MSE) and adjusted R^2 for each trained model when applied to the testing dataset.

Table 5. Regression Random Forest Model Scores

Dependant Variable	MSE	R^2_{adj}
$y_i(R\|h)$	151.947	0.173
$y_i(B\|h)$	5.961	0.167
$y_i(C\|h)$	11.206	0.176
$y_i(All\|h)$	250.247	0.207

The women's survey data, by itself, were not good predictors of conflict. The highest R^2_{adj} value was 0.207 with a Mean squared error (MSE) equal to 250.247 conflict events. However, though slight at best, the predictive values for the continuous conflict variables - which will be defined as $\widehat{y_i(R|h)}$, $\widehat{y_i(B|h)}$, $\widehat{y_i(C|h)}$, and $\widehat{y_i(All|h)}$ - are useful when trying to see how women and conflict interact in TDA models built using MAPPER.

In addition to the four predicted continuous conflict variables, the absolute difference between the true conflict events and the predicted conflict events were calculated for each woman. See equation 7 for reference:

$$riots_i^{abs} = |y_i(R|h) - \widehat{y_i(R|h)}|, \forall i \in I \tag{7}$$

The absolute difference between the ground truth and predicted values will be useful when observing which observations were harder to predict than others and where they exist in the topology of the data. Additional statistical tests can be administered to determine any particular traits between hard to predict observations and others within the Ayasdi workbench.

4.2.3.2 Isolation Forest Anomaly Scores.

As mentioned in the previous chapter, isolation forests are used to find anomalous observations. Using the Sklearn Python library [77], two different isolation forests, utilizing bootstrap sampling, were built. One was built on a subset containing only the DHS Program woman survey answers, $X^{i\times 363}_{women}$ where i is the number of observations in the data set (255,221). The other isolation forest was built using the augmented matrix of the DHS Program women survey answers and all three separate conflict variable matrices (*riots*, *battles*, and *civilian violence*).

$$X_{conflict}^{i \times 423} = (X_{women}^{i \times 363} | R^{i \times 20} | C^{i \times 20} | B^{i \times 20}) \tag{8}$$

Figure 19 below shows the distribution of the anomaly scores between the two different datasets. The lower the score, the more anomalous the observation where any score being less than 0 is to be considered anomalous. According to the histograms in Figure 19, the dataset containing only DHS women survey answers ($X_{women}^{i \times 363}$) has more anomalous observations than when the DHS women survey answers are merged with the conflict variable sets/matrices.

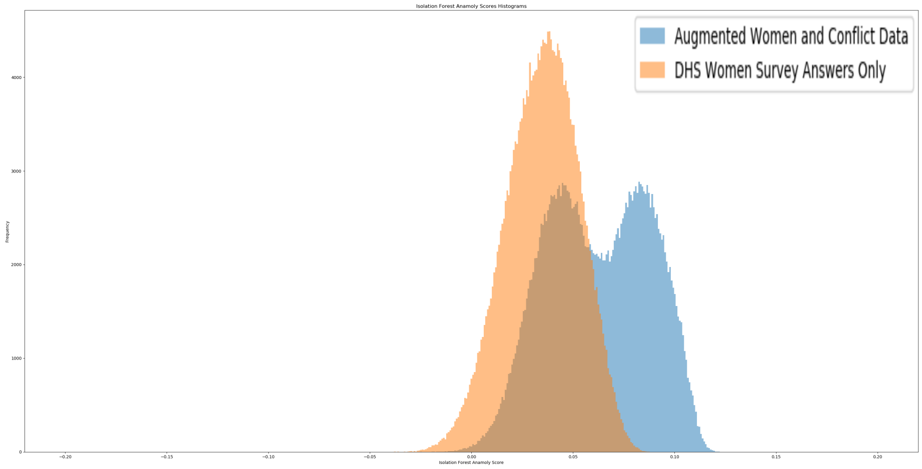


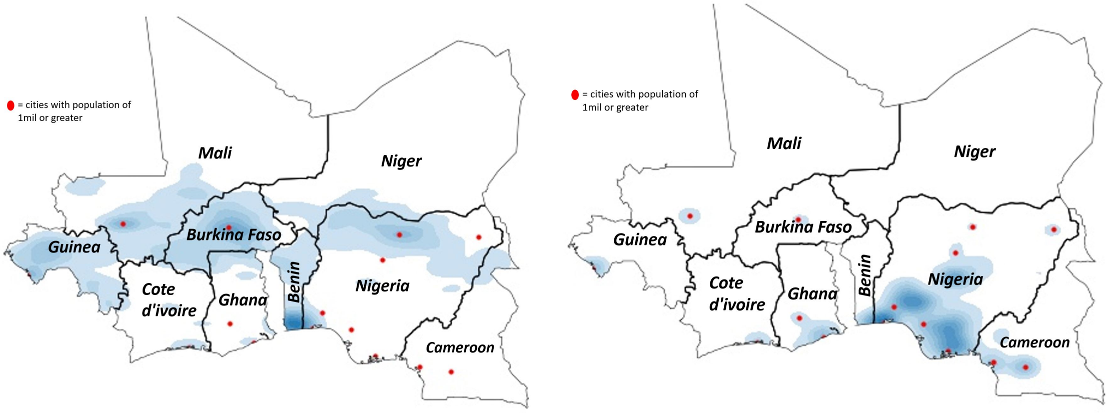
Figure 19. Anomaly Scores Distributions by Dataset

4.3 Initial Findings

4.3.1 Initial Geospatial Analysis.

4.3.1.1 Education.

Initial analysis of the data consisted of spatial kernel density estimate plots of women in pre-defined groupings of interest. A kernel density estimate is an unsupervised learning technique which, when applied to geospatial data, can be used to smooth out random noise and find the true distribution/density of points in a given space [68]. As indicated in Chapter 2, the research investigating women's impact on "stability" is generally focused on a nation's economic stability - typically presenting itself in education attainment by women. Given that this definition of stability is most researched, this research team believes it beneficial to look at the distribution of women who are defined by a certain binary indicator. Figure 20 contains two heat maps consisting of women who indicated as having received no formal education (20a) or as having received an education level higher than a completed secondary education (20b).



(a) No Formal Education

(b) Higher Education

Figure 20. Heat Maps of Women by Education Level Attained

Upon observing from the maps above, women with no education level (131,572 women) are most densely distributed away from the cost line in Burkina Faso, Guinea, Mali, Niger, Benin and upper Nigeria. In contrast, the women who have obtained a "higher" level of education - meaning some level of education higher than a completed secondary education degree - are most dense in Nigeria's coast line. Women with a higher level of education (10,137 women) are also concentrated in large cities throughout the region with a slightly higher density around Ghana's coast and Cameroon. This is in line with Nigeria, Ghana and Cameroon being some of the more economically stable countries in the region (and even the African Continent) [13].

4.3.1.2 Female Genital Mutilation/Cutting.

Another area of interest is that of Female Genital Mutilation/Cutting (FGM/C). This practice can be damaging to young girls well-being and health. Additionally, several large organizations are interested in the public health problem including the United Nations and the Economic Community of West African States (ECOWAS). Figure 21 is a heat map of the women who answered positively when asked if they had been circumcised.

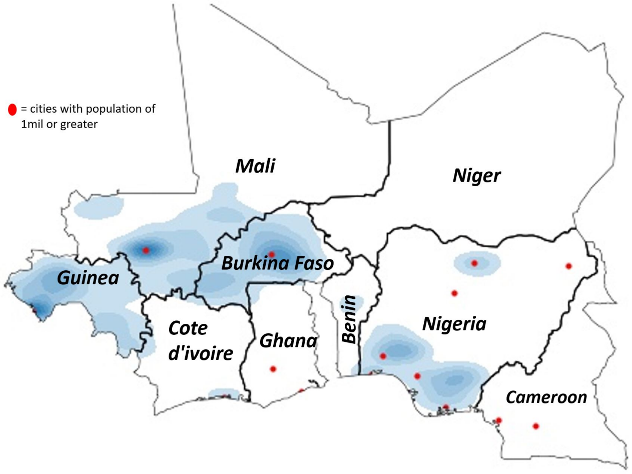


Figure 21. Heat Map of Women Who Have Been Circumcised

In Figure 21, the concentration of FGM/C is in Mali, Burkina Faso, Guinea and Coastal Nigeria.

4.3.1.3 Anomalous Women.

An additional research question of interest was observing women who would be considered as "anomalous" through the isolation forest algorithm, their spatial density estimate maps, and what dimensions in the data set might account for their "anomalous" classification. Figure 22 below is the heat map showing the density distribution of the 7,786 women who had anomaly scores less than 0 (which according to Sklean's isolation forest documentation would be considered strictly anomalous) [77].

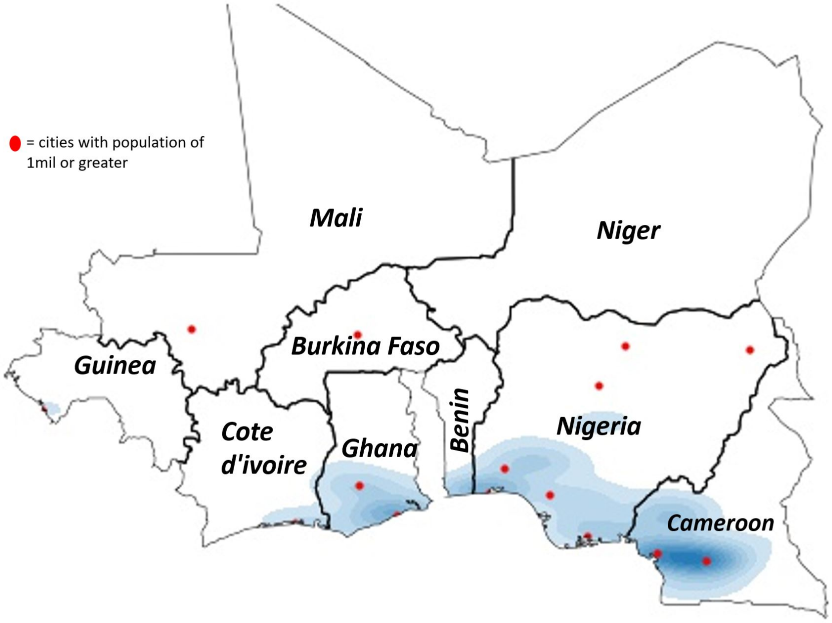


Figure 22. Heat Map of Women with Anomaly Scores < 0

Statistical comparisons in Ayasdi Workbench indicated that the anomalous women not only experienced more instances of violence then the rest of the dataset, but also had higher values associated with the mean number of conflict events described Section 4.2.2 above. Additionally, the anomalous women were better educated overall, were wealthier and had a relatively high percentage of catholic believers and relatively fewer Muslims. For the statistical comparisons, see Table 6. It should be noted that the KS score refers to a Kolmogorov-Smirnov Statistic which lies between 0-1, where the higher the statistic the more different the distributions of the continuous variables. The P-value column refers to either the KS statistic's correlating P-value for continuous variables, or the p-value of a Hypergeometric test for the binary variables.

Table 6. Statistical Test Results on Anomalous Women and Rest of Data Set

Variable	Anomalous Women (mean & %)	Rest of Data Set (mean & %)	P-value	KS Score (continuous)
$y_i(R\|h)$	3.00	0.00	5.37e-13	0.260
$b_i(R\|h)$	74.2%	48.2%	0.00	
$y_i(B\|h)$	0.600	0.00	5.37e-13	0.238
$b_i(B\|h)$	68.7%	44.9%	0.00	
$y_i(C\|h)$	1.20	0.00	5.37e-13	0.257
$b_i(C\|h)$	73.5%	47.8%	0.00	
Wealth Index	1.29	-0.281	5.37e-13	0.471
Education Achieved None	3.3%	53.1%	0.00	
Education Achieved Incomplete Secondary	40.1%	18.5%	0.00	
Education Achieved Higher	23.5%	3.4%	0.00	
Current Contraceptive Method is Modern	56.5%	9.0%	0.00	
Catholic	32.9%	14.9%	0.00	
Age at First Marriage	17.18 years	14.88 years	5.37e-13	0.163
Muslim/Islam	13.6%	51.4%	0.00	

4.4 Topological Hierarchical Decomposition

Two different THD's were created using AFRL's TDA Pipeline. Both models were made with Neighborhood lenses and IQR Normalized Euclidean Metric. The first model was created only using women's answers to their respective DHS survey. In the Ayasdi Workbench, analysis could be implemented utilizing variables not used to build the model. Therefore, even though no conflict variables were used to build the first THD model, the research team was able to track conflict variables throughout the topology's decomposition. The second THD model was created using the DHS survey data augmented with the conflict data (see Equation 8).

4.4.1 DHS Data.

Figure 23 is a summary of the of the THD model created using only DHS survey data. The blocks represent connected components that broke off from the main data structure and the number in circles are naming the different splits for reference.

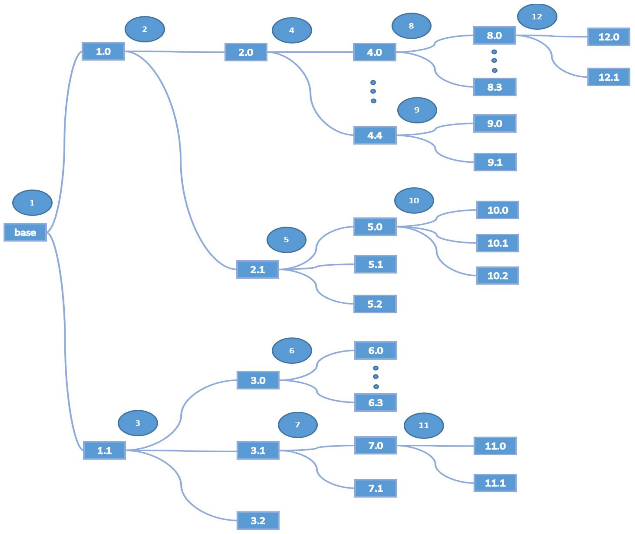


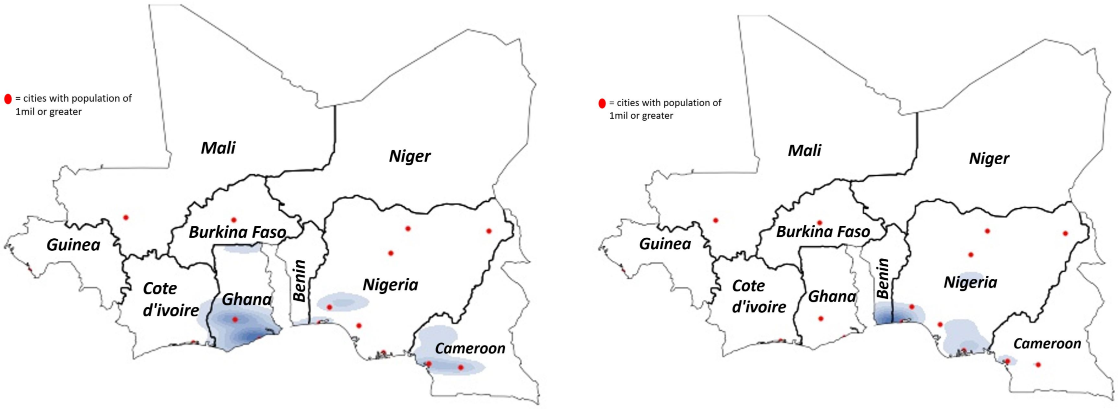
Figure 23. Summary of THD Model with Only DHS Data

The data is first split into two primary groups (and therefore most prominent dimensions) of women, with 1.0 being married women and 1.1 being single women with no children. The connected component made up of only single women with no children was further split into three primary groups. The first group (3.0) contains women who are poorer, uneducated and currently working with a mean age of 19. The next two groups (3.1 and 3.2) consists of what seems to be mainly full-time students (primarily college) and seem to be divided mainly by geographic location;

3.1 is mainly Nigerian while 3.2 has mainly Ghanaian and Cameroonian women. Each grouping then splits further based mainly on variables describing FGM/C.

Split 2 in Figure 23 splits married women into women with children and women without children. Following married women with children (which was a majority of the dataset), this connected component is split further at split 4 into five separate connected components. These connected components differ mainly in the number of children over a 5 year period who have died and the age at which they died. These women are then split further based on Education levels, wealth, Urban status, and FGM/C.

Throughout the decomposition of the data set there was no single branch or connected component with an obvious concentration of conflict events. However, at the very end of the decomposition, two connected components had slightly higher concentration of conflict events (as a proportion) compared to others (8.0 and 8.1). After applying statistical test on both of these groups, both groups had higher levels of education attainments, higher wealth indices, lower number of women who had been circumcised, greater access to birth control, and higher mean ages at first marriage and first birth. Essentially, most western women would want to be in these connected components, however, each had higher instances of conflict events and therefore instability. Figure 24 below depicts the spatial density maps for the women in the different connected components.



(a) 8.0

(b) 8.1

Figure 24. Spatial Density Maps of Women in THD_1 Connected Components

4.4.2 DHS and ACLED Data.

The second THD model created used the data set made up of the DHS survey data merged with the conflict events data matrices (see Equation 8). With the added 60 dimensions in the data matrix the shape/topology of the data was affected. As such, the women in the second THD model decomposed differently compared to the first THD model. Figure 25 is the summary of the DHS Survey and ACLED data THD model that was created using Neighborhood lenses, IQR Normalized Euclidean metric and a gain of 1.5 ($\approx 33\%$ overlap).

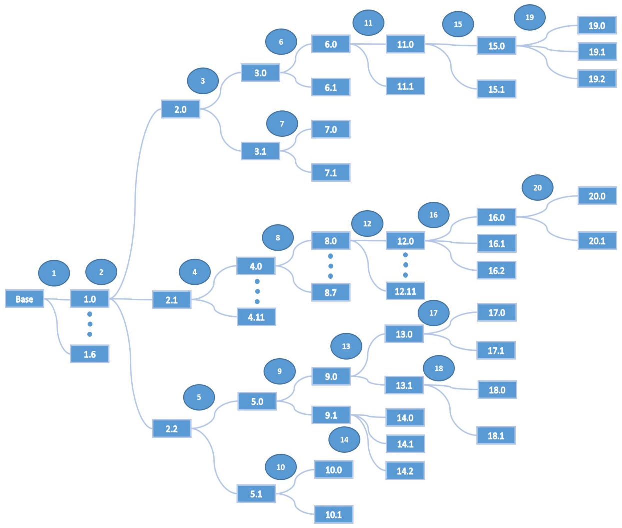


Figure 25. Summary of THD Model with DHS and ACLED Data

The first split at 1 was separating connected components that held extreme mean conflict variable values. Additionally, it seems that it split these extreme components (1.1 - 1.6) into specific time and spatially spread out events. The second split (labeled 2 in Figure 25) splits the women in a similar manner to the first THD model - married women in 2.0 and single women in 2.2 - except that this split created a third connected component (2.1). In this connected component (2.1) 99% of the remaining conflict events ended up residing in connected component 2.1 (96,459 women). The splits in the branch started by 2.1 seem to be broken up mainly by specific conflict events, driven by the conflict matrices (see equation 8). The heat map that represents the spatial location and density of these women in connected component 2.1 can be observed in Figure 26 below.

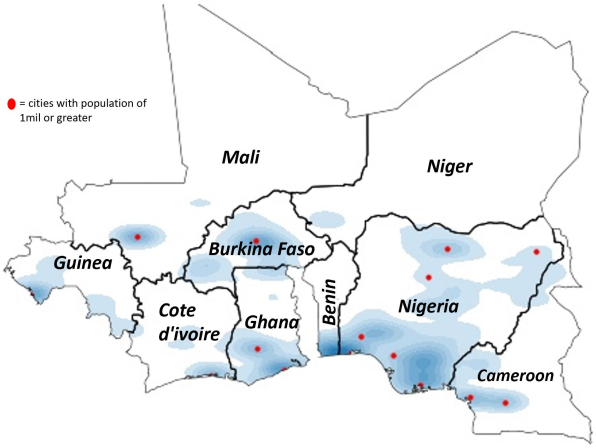
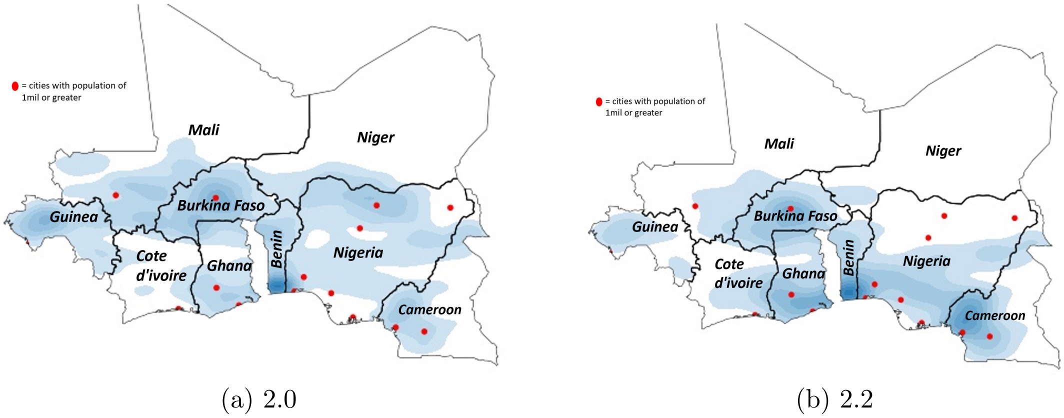


Figure 26. Heat Map for Women in 2.1 Node of THD model with DHS and ALCED Data

Figure 26 displays women, in connected component 2.1, that appear to be centered around larger more densely populated areas. The women in this connected component tended to be wealthier, younger and better educated.

Furthermore, when observing the other two connected components (2.0 and 2.2) that were brought out from connected component 1.0 (see Figure 25), one can observe that each connected component contains women who are slightly poorer and live in rural areas. Figure 27 shows each connected component, connected component 2.0 being Figure 27a and connected component 2.2 being Figure 27b.



(a) 2.0

(b) 2.2

Figure 27. Heat Maps of Women in Connected Components Lower Conflict Events

As one can observe from both Figure 27a and 27b, especially when compared to Figure 26, the women in connected components 2.0 and 2.2 are considerably more spread out compared to connected component 2.1, which contains 99.9% of the remaining violence. The women in connected component 2.1 appear to be more concentrated around cities.

V. Conclusions and Future Research

5.1 Discussion

After implementing a Topological Hierarchical Decomposition on two slightly different sets of data, each a representative random sample of women from their respective country, it would appear that there is no significant correlation between women and stability as defined in this paper. The first THD decomposed the women based solely on their answers to the DHS survey while disregarding time, location or conflict data. Ideally, if there is a correlation between women and stability, or rather instability, women who had seen higher instances of conflict events would gather together. While this did occur in select connected components of different branches, there did not seem to be an obvious reason driving the decomposition with respect to conflict. The nodes with slightly higher instances of violence seemed to contain women that, according to western standards, are more fortunate compared to other women in the data sample. Upon closer examination, most of these women resided in urban areas and were concentrated around larger cities. From these findings, there are two plausible conclusions.

One plausible conclusion is that conflict, in developing or under developed nations, is correlated with women who are more economically and socially secure. It could be hypothesised that as people are less encumbered by the simple desire to survive day to day and are provided more free or leisure time due to technological and economic advances spend more time and resources on education and other self-development activities. However, as education and leisure time rises, especially in a region where lingering effects of colonialism exists and extremist views are rampant, discontent and the ability to communicate and desire change also increases. It is possible that as a nation develops in a politically unstable environment that there is a inverse relationship between economic and social stability and conflict events. As people are provided with the ability to voice their discontent through violent actions - in that their not just living day to day - people will do so until a more politically stable environment is created. This “conclusion”, however, is simply a hypothesis and far from being substantiated solely on this research. Further investigation would be necessary to substantiate this hypothesis.

However, it is true that these women appeared to be concentrated around cities and urban areas and that cities, on average, have more economic opportunities, educational institutions, and jobs requiring higher levels of educations. Cities are also where conflict events tend to occur. The second plausible conclusion, and what is arguably the more likely conclusion, is that women have no direct correlation with conflict and any correlation that was observed had more to do with the their location then the woman’s well-being. The probability of observing women with more economic and social freedom tend to be higher in urban areas. Perhaps the correlation that can by hypothesised between a woman’s well-being and instability argued before is happenstance and is rather proximity to a more populous area. Both conclusions, however, would need to be investigated further.

5.2 Future Research

The primary utility that this paper provided was the structuring of a way to observe the relationship between women and stability. Most research trying to capture this relationship has defined stability through economic terminology: economic growth, Gross Domestic Product (GDP), GPD per capita, and so on. However, from a DoD perspective, little to no research has been implemented when defining stability through conflict that may require military intervention. A significant reason for this is data quality, structure and availability. However, even as data becomes more available, the complexity of the data creates problems when trying to apply a methodology. Topological Data Analysis, particularly MAPPER, can handle data with high complexity better then traditional methods. Furthermore, the primary assumption driving the MAPPER algorithm is that the shape of the data should drive the analysis of the data; an assumption that analysts implicitly execute anyways. By utilizing a TDA methodology, analysts can look at women in relation to conflict in such a way that traditional statistical analysis would never permit provided the complexity of the current available data.

As the IPUMS database grows to include more countries, the methodology applied in this research will become easier and faster to apply. While the data cleaning process implemented in this paper was long and exhaustive, through writing several variable specific dictionaries and lists, this process could potentially be automated. A Python GUI could be built to make the data pulling and cleaning process more user friendly. Furthermore, depending on the coding and database management abilities of the team, the methods utilized by this research team could be drastically expanded.

Due to time constraints, that this team only looked at specific economic and social indicators of women's well being. Though it would cut down on sample size and also increase time spent on data cleaning, the DHS Program also collects biomarker information such as weight, height and even blood samples. DHS Program also collects survey information from men and children. The data sample could be expanded by adding these new dimensions and drastically different results could be observed. Furthermore, this research team looked at the relationship between women and conflict through a women's proximity to conflict as defined through the IPUMS database. However, this definition could be expanded. Other teams could bypass the IPUMS database and combine the ACLED, DHS and any other database that have geospatial locations differently. Other teams could try to define “proximity” to conflict more strictly instead of this teams forced definition due to time and data availability constraints. Also, this team did not control for population density differences, which, later on, proved to be potentially detrimental to the analysis. If this team had controlled for population density differences in the conflict indicators, such as conflict events per capita, perhaps the topology of the data would have decomposed differently. For future studies, a control for population densities in conflict event numbers should be first to be implemented.

Furthermore, this team only observed the data collected through one lens and metric combination - Neighborhood lenses and IQR Normalized Euclidean metric. Other lens and metric combinations could define “nearness” of observations completely differently compared to this paper’s chosen combination, which could potentially better capture the relationship between women and stability. A more thorough comparison and validation of lens and metric combinations would be needed to either confirm or deny this paper’s conclusions.

Appendix A. Variables

Name	Description
DHSID	Key to link DHS clusters to context data (string)
COUNTRY	Country
INTYEAR	Year of interview
WEALTHS	Wealth index factor score (5 decimals)
RELIGION	Religion
PREGTERMIN	Ever had pregnancy terminate via abortion, miscarriage or stillbirth
FLOOR	Main material of floor
COOKFUEL	Type of fuel household uses for cooking
TOILETTYPE	Type of toilet facility
DRINKWTR	Major source of drinking water
WKCURRJOB	Woman's occupation
WKEMPLOYWHEN	Respondent works all year, seasonally, or occasionally
WKEARNTYPE	Type of earnings for respondent's work
HUSJOB	Partner's Occupation
LITBRIG	Literacy bridging variable
EDACHIEVER	Summary educational achievement
HUSEDACHIEVER	Husband's summary educational achievement)
NEWSBRIG	Reads newspaper: Bridging variable
RADIOBRIG	Listens to radio: Bridging variable
TVBRIG	Watches television: Bridging variable
DECBIGHH	Final say on making large household purchases
DECFEMEARN	Final say on spending woman's earnings

FERTPREF	Fertility preferences
UNMETNEED2	Unmet need for Family Planning (2nd def)
IDEALGIRLS	Ideal number of boy children
IDEALBOYS	Ideal number of girl children
HUSFERTPREF	Husband's desire for children
FPKNOTYP	Know any type of family planning method
FPMETHNOW	Current method of family planning
FPRADIOHR	Heard family planning message on radio
FPPOSTHR	Seen family planning message on poster or pamphlet
FPLASTSRCS	Last source for family planning ofr current users, standardized
AIDSHEARD	Heard of AIDS
STIHEARD	Heard of AIDS or other sexually transmitted infections
FCINTENDDAU	Intends to have daughter(s) circumcised in future
FCCONTINU	FGM/C should continue or stop
FCINFIB	Vaginal area sewn closed for FGM/C
FCNICK	Genital area nicked without removing flesh
FCFLESH	Flesh removed from genital area for own FGM/C
FCCIRC	Ever circumcised
UNION1MORE	Woman had one or more than one union
DURMARGRP	Marital or cohabitation duration (grouped)
MARSTAT	Woman's current marital or union status
URBAN	Urban-rural status
HUSBINHOME	Husban/partner lives in woman's household
AGE	Age
HHMEMTOTAL	Total number of household members

HHELIGWOMEN	Number of eligible women in household
HHKIDLT5	number of children under 5 in household
AGEFRSTMAR	Age at first marriage
CHEB	Total children ever born
SONSATHOME	Number of own sons living at home
DAUSATHOME	Number of own daughters living at home
SONSAWAYHOME	Number of own sons living away from home
DAUSAWAYHOME	Number of own Daughters living away from home
SONDIED	Numbr of own sons who have died
DAUDIED	Number of own daughters who have died
CHEBALIVE	Total number of living children born to respondent
AGEAT1STBIRTH	Age at first birth
HHEADAGE	Age of household head
KIDAGEDIEDIMP	Child's age at death in months (including imputed) - up to 20
DELDOC	Doctor gave delivery care (in last 5 years for up to 6 children)
DELTBA	Traditional birth attendant gave deliery care (in last 5 years for up to 6 children)
DELOTH	Other person gave delivery care (in last 5 years for up to 6 children)
DELNONE	No one gave delivery care (in last 5 years for up to 6 children)
DELCESR	Delivery by caesarian section (in last 5 years for up to 6 children)
ANCARE	Received prenatal care (in last 5 years for up to 6 children)

ANCAREDOC	Doctor gave prenatal care (in last 5 years for up to 6 children)
RIOTS	Riots annual time-series (20 variables: 1997 - 2016)
BATTLES	Battles annual time-series (20 variables: 1997-2016)
CIVILIAN_VIOLENCE	Violencce against civilians annual time-series (20 variables: 1997-2016)

Appendix B. Variable Dictionaries and Lists

The following code describes the dictionaries and lists utilized to manipulate the data used for the Topological Data Analysis.

The following Python packages were used:

- numpy >= 1.15.2 [78]

```
# −*− coding: utf−8 −*−
”””
Created on Thu Oct 11 15:10:46 2018

@author: Michaela
”””

import numpy as np

#Dict for country code and country name
country_dict = {
        120: ’Cameroon’,
        148: ’Chad’,
        204: ’Benin’,
        288: ’Ghana’,
        324: ’Guinea’,
        384: ’Ivory Coast’,
        466: ’Mali’,
        562: ’Niger’,
        566: ’Nigeria’,
        686: ’Sengal’,
        854: ’Burkina Faso’}

#indicator variable for if husband is in home or not
husbinhome_dict = {
        0: ’husband_home’,
        1: ’hus&wif_live_apart’,
        9: ’not_married’}

#indicator variables for woman’s declared religion
religion_dict = {
        100: ’Muslim/Islam’,
        200: ’Christian’,
        210: ’Catholic’,
        220: ’Protestant’,
        221: ’Anglican’,
        222: ’Methodist’,
        223: ’Presbyterian’,
        224: ’Lutheran’,
        225: ’Baptist’,
        226: ’Salvation Army’,
        230: ’Pentacostal/Charismatic/Evangelical’,
        231: ’Apostolic Sect’,
        232: ’Seventh Day Adventist/Baptist’,
        233: ’Jehovah Witnesses’,
        234: 'Universal',
        240: 'Other Chirstian, unspecified/general',
        241: 'Other Protestant, unspecified',
        250: 'Other Chirstianm specified',
        251: 'Ethiopian Orthodox',
        252: ' Celestial  Church of Christ',
        253: 'African Zionist',
        254: 'Munu Mwama (African Pentocostal)',
        255: 'United Faith Church',
        256: 'African Orthodox Church',
        257: 'Evangelical Luteran Church in Namibia',
        258: 'Lesotho Evangelical Church',
        259: 'Kimbanguist',
        260: 'Orthadox',
        261: 'Mammon',
        300: 'Other, not Christian or Islam',
        301: 'Hindu',
        302: 'Sikh',
        303: 'Buddhist/Neo-Buddhist',
        305: 'Jewish',
        306: 'Parsi/Zoroastrian',
        307: 'Doni-Polo',
        308: 'Sanamahi',
        309: 'Bahai',
        310: 'Bisaka group/Faith of Unity',
        311: 'Kirat',
          400: 'Traditional/Spritual/Animist',
          401: 'Traditional',
          402: 'Spiritual',
          403: 'Animist',
          404: 'Voodoo',
          500: 'No Religion',
          600: 'Other',
          601: 'Religion 1',
          602: 'Religion 2',
          603: 'Religion 3',
          604: 'Religion 4'}

#Dict for if a woman had more than 1 union
union1more_dict = {
          1: 'union1more_yes', #if its zero is also no
          8: 'union1more_missing',
          9: 'union1more_niu'}

#Dict for indicator variable for woman's marital status
currmarr_dict = {#currently married dictionary
          0: 'never_married',
          1: 'currently_married',
          2: 'previously_married',
          8: 'currmarr_missing'
          }
```

```
#Dict for highest education acheived by woman
edachiever_dict = {
        0: ’no_education’,
        1: ’incomplete_primary’,
        2: ’complete_primary’,
        3: ’incomplete_secondary’,
        4: ’complete_secondary’,
        5: ’higher’ ,
        8: ’NaN’}

#Indicator variable for whether or not woman terminated a pregnancy
pregtermin_dict = {
        0: ’Preg_not_term’,
        1: ’Preg_term’,
        8: ’missing’,
        np.NaN: ’preg_term_NaN’}

#Dict for indicator variable on wether woman has electricity
electrc_dict = {
        0: ’ no_electricity ’,
        1: ’ yes_electricity ’,
        8: ’missing/non_resident’,
        np.NaN: ’electicity_NaN’}

#Dict on woman’s cooking fuel type
cookfuel_dict = dict(
        [(100, 'electricity')] +
        [(i, 'pretroleum_based') for i in range(200, 250)] +
        [(300, 'bio_gas')] +
        [(i, 'coal_based') for i in range(400, 450)] +
        [(i, 'wood_or_grass_based') for i in range(500, 550)]+
        [(600, 'dung')]+
        [(i, 'agricultural/crop_based') for i in range(700, 750)] +
        [(i, 'other/jelly/solar') for i in range(800, 810)] +
        [(995, 'no_food_cood_in_house')]+
        [(997, 'missing')] +
        [(np.NaN, 'cook_NaN')]
        )

#Dict for floor type that woman lives in
floor_dict = dict(
        [(i, 'earth_based') for i in range(100, 119)] +
        [(i, 'dung_based') for i in range(120, 140)] +
        [(i, 'wood') for i in range(200, 219)] +
        [(i, 'palm/bamboo') for i in range(220, 225)] +
        [(i, 'bricks/adobe/unfinished_stone') for i in range(230, 235)]+
        [(i, 'polished_wood/vinyl') for i in range(300, 329)] +
        [(i, 'tiles_mosaic') for i in range(330, 336)] +
        [(340, 'cement/concrete')] +
        [(350, 'carpet')] +
        [(360, 'terrazzo')] +
        [(370, 'stone')] +
        [(380, 'bricks')] +
        [(i, 'plaster/other') for i in range(390,401)]+
        [(i, 'non_resident/missing/unknown') for i in range(900,1000)] +
        [(np.NaN, 'floor_NaN')]
        )

#Dict describing
toilettype_dict = dict(
        [(0, ' no_facility ')]+
        [(i, ' flush_toilet_unspecified ') for i in range(1000,1130)]+
        [(i, 'modern_flush_toilet') for i in range(1200, 1215)]+
        [(1300, ' traditional_tank_flush ')]+
        [(i, ' bucket_flush_toilet ') for i in range(1400,1440,10)]+
        [(i, ' non_flushing_toilet ') for i in range(2000,2400,100)]+
        [(i, ' pit_toilet_latrine ') for i in range(3000, 3460)] +
        [(i, 'unimproved_toilet') for i in range(4000,4400,100)] +
        [(5000, ' toilet_other ')]+
        [(i, 'non_resident/missing/NIU') for i in range(9996,9999)]+
        [(np.NaN, 'toilet_NaN')]
        )

drinkwtr_dict = dict(
        [(i, 'piped_water') for i in range(1000, 1220)]+
        [(i, 'well_water') for i in range(2000, 2350)] +
        [(i, 'spring_water') for i in range(3000,3300)] +
        [(i, 'rain_water') for i in range(4000,4100,100)] +
        [(i, 'purchased') for i in range(5000,5500)] +
        [(6000, 'other_water_source')] +
        [(i, 'water_missing/non_resident/NIU')
         for i in range(9996,9999)]+
        [(np.NaN, 'water_NaN')]
        )

hhphone_dict = {
        0: 'no_phone',
        1: 'phone_yes',
        6: 'non_resident_phone',
        8: 'phone_missing',
        np.NaN: 'phone_NaN'}

currwork_dict = {
        0: 'currwork_no',
        10: 'currwork_yes',
        11: 'currwork_yes',
        12:'currwork_yes',
        98: 'currwork_missing'}

wkcurrjob_dict =dict(
        [(00, 'wwork_notcurr_working')]+
        [(10, 'wwork_prof_tech_mgmt')]+
        [(i, 'wwork_clerical/sales') for i in range(20,23)]+
        [(i, 'wwork_Agricultural') for i in range(30,33)]+
        [( i , 'wwork_household/domestic_worker') for i in range(30,33)]+
        [( i , 'wwork_skilled/unskilled_manual') for i in range(50,53)]+
        [(60, 'wwork_armed_forces')]+
        [(96, 'wwork_other')] +
        [(98, 'wworkwork_missing')]+ #didn't want to answer
        #universe = women 15-59 who have worked in past 12 months
        [(99, 'wwork_NIU')]
        )

wkemploywhen_dict = {
        10: 'wworkwhen_all_year',
        21: 'wworkwhen_most_year',
        22: 'wworkwhen_part_year',
        23: 'wworkwen_seasonally',
        24: 'wworkwhen_temporary',
        29: 'wworkwhen_other',
        98: 'wworkwhen_missing',
        #universe = women 15-59 who have worked in past 12 months
        99: 'wworkwhen_NIU',
        np.NaN: 'wworkwhen_NaN'} #not asked

wkearntype_dict = {
        0: 'wearn_not_paid',
        1: 'wearn_cash_only',
        2: 'wearn_cash&kind',
        3: 'wearn_kind_only',
          4: ’wearn_other’,
          8: ’wearn_missing’,
          #universe = women 15−59 who have worked in past 12 months
          9: ’wearn_NIU’,
          np.NaN: ’wearn_NaN’} #not asked

husjob_dict = dict(
          [(10, ’husjob_did_not_work’)] +
          [(12, ’husjob_unemployed’)] +
          [(13, ’husjob_student’)]+
          [(20, ’husjob_prof/tech/mgmt’)]+
          [( i , ’ husjob_clerical_or_sales ’) for i in range(30,33)]+
          [( i , ’husjob_agriculture’) for i in range(40,43)] +
          [( i , ’husjob_domestic’) for i in range(50,53)] +
          [( i , ’husjob_s&us_labor’) for i in range(60,63)] +
          [(70, ’husjob_other’)]+
          [(71, ’husjob_army’)] +
          [(97, ’husjob_dont_know’)]+
          [(98, ’husjob_missing’)]+
          [(99, ’husjob_NIU’)]+
          [( np.NaN, ’husjob_NaN’)]
          )

 litbrig_dict  = dict(
          [( i , ’wlit_can_read’) for i in range(10,13)]+
          [(20, ’wlit_cannot_read’)] +
          [(30, 'wlit_uncertain')]+
          #no card with person's language on it to read
          [(31, 'wlit_no_language')]+
          [(32, 'wlit_blind_impaired')]+
          [(98, 'wlit_missing')] +
          [(99, 'wlit_NIU')] +
          [(np.NaN, 'wlit_NaN')]
          )

edachiever_dict = {
          0: 'edachiever_none',
          1: 'edachiever_inc_primary',
          2: 'edachiever_com_primary',
          3: 'edachiever_inc_seconday',
          4: 'edachiever_com_secondary',
          5: 'edachiever_higher',
          7: 'edachiever_unknown',
          8: 'edachiever_missing',
          np.NaN: 'edachiever_NaN'}

'''
 educlvl_dict = {
          0: 'wedu_none',
          1: 'wedu_inc_primary',
          2: 'wedu_com_primary',
          3: 'wedu_inc_seconday',
          4: 'weud_com_secondary',
          5: 'wedu_higher',
          7: 'wedu_unknown',
          8: 'wedu_missing',
          np.NaN: 'wedu_NaN'}
 '''

 edyrtotal_dict = dict(
          [(i, 'weduyrs_' +str(i) + '_years') for i in range(1,27)] +
          [(96, 'weduyrs_inconsistent')]+
          [(97, 'weduyrs_unknown')] + #didn't know
          [(98, 'weduyrs_missing')]+
          [(np.NaN, 'weduyrs_NaN')]
          )

 husedachiever_dict = {
          0: 'husedu_none',
          1: 'husedu_inc_primary',
          2: 'husedu_com_primary',
          3: 'husedu_inc_seconday',
          4: 'husedu_com_secondary',
          5: 'husedu_higher',
          7: 'husedu_unknown',
          8: 'husedu_missing',
          np.NaN: 'husedu_NaN'}
```

```
newsbrig_dict = dict(
        [(i, ’read_news_none’) for i in range(0,2)]+
        [(i, ’read_news_yes’) for i in range(10,12)]+
        [(97, ’read_news_unknown’)]+
        [(98, ’read_news_missing’)]+
        [(99, ’read_news_NIU’)]
        )

tvbrig_dict = dict(
        [(i, ’watch_tv_none’) for i in range(0,2)]+
        [(i, ’watch_tv_yes’) for i in range(10,12)]+
        [(97, ’watch_tv_unknown’)]+
        [(98, ’watch_tv_missing’)]+
        [(99, ’watch_tv_NIU’)]
        )

radiobrig_dict = dict(
    #negative answers - not really
        [(i, ’radio_none’) for i in range(0,2)]+
        #positve answers - at least some
        [(i, ’radio_yes’) for i in range(10,12)]+
        [(97, ’radio_unknown’)]+
        [(98, ’radio_missing’)]+
        [(99, ’radio_NIU’)]
        )
```

```
decbighh_dict = dict(
        [(10, ’decbighh_women’)]+
        [(20, ’decbighh_woman&hus’)]+
        [(30, ’decbighh_woman&someone_else’)]+
        [(40, ’decbighh_hus’)] +
        [( i , ’decbighh_other’) for i in range(50,54)]+
        [(98, ’decbighh_missing’)]+
        [(99, ’decbighh_NIU’)]
        )

decfemearn_dict = dict(
        [(99, ’decfemearn_NIU’)]+
        [(98, ’decfemearn_missing’)] +
        [(60, ’decfemearn_other’)]+
        [( i , ’decfemearn_family_mem’) for i in range(50, 54)]+
        [(40, ’decfemearn_hus’)]+
        [(30, ’decfemearn_woman&other’)]+
        [(20, ’decfemearn_woman&hus’)]+
        [(10, ’decfemearn_woman’)]
        )



 fertpref_dict  = {
        10: ’fp_have_another’,
        20: ’fp_undecided’,
        30: 'fp_no_more',
        40: 'fp_up_to_god',
        50: ' fp_not_at_risk_of_preg ',
        52: ' fp_declare_infecund ',
        51: ' fp_sterilized ',
        53: ' fp_virgin ',
        98: 'fp_missing',
        99: 'fp_NIU'}

 husfertpref_dict  = {
        1: 'husfertpref_want_same',
        2: 'husfertpref_wants_more',
        3: ' husfertpref_wants_fewer ',
        4: 'husfertpref_both_numeric', #no #
        7: 'husfertpref_unknown',
        8: ' husfertpref_missing ',
        9: 'husfertpref_NIU'}

fpknotyp_dict = {
        0: 'fp_knowlege_none',
        11: ' fp_knowlege_folkloric ',
        12: 'fp_knowlege_trad',
        20: 'fp_knowlege_modern',
        99: 'fp_knowlege_NIU'}

fpmethnow_dict = dict(
        [(0, 'fp_current_none')]+
        [(i, 'fp_current_modern') for i in range(100,150)]+
        [(i, 'fp_current_traditional') for i in range(200, 240)]+
        [(i, 'fp_current_other') for i in range(300,304)]+
        [(997, 'fp_current_unknown')]+
        [(998, 'fp_current_missing')]+
        [(999, 'fp_current_NIU')]+
        [(np.NAN, 'fp_current_NaN')]
        )

fpradiohr_dict = dict(#Ever hear about fp on the radio?
        [(0, 'fp_radio_no')]+
        [(i, 'fp_radio_yes') for i in range(10,13)] +
        [(98, 'fp_radio_missing')]+
        [(97, 'fp_radio_unknown')]+
        [(99, 'fp_radio_NIU')]+
        [(np.NaN, 'fp_radio_NaN')]
        )

fptvhr_dict = dict(#Ever hear about fp on the TV?
        [(0, 'fp_tv_no')]+
        [(i, 'fp_tv_yes') for i in range(1,2)] +
        [(8, 'fp_tv_missing')]+
        [(7, 'fp_tv_unknown')]+
        [(9, 'fp_tv_NIU')]+
        [(np.NaN, 'fp_tv_NaN')]
        )

fpposthr_dict = dict(#Ever seen poster about fp?
        [(0, 'fp_poster_no')]+
        [(i, 'fp_poster_yes') for i in range(1,2)] +
        [(8, 'fp_poster_missing')]+
        [(7, 'fp_poster_unknown')]+
        [(9, 'fp_poster_NIU')]+
        [(np.NaN, 'fp_poster_NaN')]
        )

fplastsrcs_dict = {
        1: ' fp_source_gvt_clin /pharm',
        2: 'fp_source_gvt_home/comm_deliv',
        3: 'fp_source_NGO',
        4: ' fp_source_priv_clin /deliv',
        5: 'fp_source_priv_pharm',
        6: 'fp_source_misc', #church, shop, friends, books
        7: 'fp_source_other',
        97: 'fp_source_unknown',
        98: 'fp_source_missing',
        99: 'fp_source_NIU'}

fpsterilage_dict = {
        1: ' ster_age_less25 ',
        2: 'ster_age_25_29',
        3: 'ster_age_30_34 ',
        4: 'ster_age_35_39 ',
        5: 'ster_age_40_44 ',
        6: 'ster_age_45_49 ',
        7: 'ster_age_50_54 ',
        9: 'ster_age_NIU'}

aidsheard_dict = {
        1: 'aidsheard_yes',
        0: 'aidsheard_no',
        8: 'aidsheard_missing',
        9: 'aidsheard_NIU'}

stiheard_dict = {
        1: 'stiheard_yes ',
        0: 'stihead_no',
        7: 'stiheard_unknown',
        8: ' sti_missing ',
        9: 'sti_NIU'}

fcage_dict = {}



fccirc_dict = {#ever cirumcised?
        0: ' fccirc_no ',
        1: ' fccirc_yes ',
        7: 'fccirc_unknown',
        8: ' fccirc_missing ',
        9: 'fccirc_NIU',
        np.NaN: 'fccirc_NaN' #not asked
        }

fcflesh_dict = { #flesh removed from genital area for own fc
        0: ' fcflesh_no ',
        1: ' fcflesh_yes ',
        7: 'fcflesh_unknown',
        8: ' fcflesh_missing ',
        9: 'fcflesh_NIU',
        np.NaN: 'fcflesh_NaN' #not asked
        }

fcnick_dict = {#genital area nicked w/out removing flesh
        0: 'fcnick_no',
        1: ' fcnick_yes',
        7: 'fcnick_unknown',
        8: 'fcnick_missing',
        9: 'fcnick_NIU',
        np.NaN: 'fcnick_NaN' #not asked
        }

fcinfib_dict = {#vaginal area swen closed for FC
        0: ' fcinfib_no ',
        1: ’ fcinfib_yes ’,
        7: ’fcinfib_unknown’,
        8: ’ fcinfib_missing ’,
        9: ’fcinfib_NIU’,
        np.NaN: ’fcinfib_NaN’ #not asked
        }

fccontinu_dict = {#fc continue or stop?
        1: ’fccontinu_yes’,
        2:’fccontinu_no’,
        3: ’fccontinu_depends’,
        4: ’fccontinu_other’,
        7: ’fccontinu_unknown’,
        8: ’fccontinu_missing’,
        9: ’fccontinu_NIU’,
        np.NaN: ’fccontinu_NaN’
        }

fcintenddau_dict = {#intends to have daughter circumcised
        0: ’fcintenddau_no’,
        1: ’fcintenddau_yes’,
        2: ’ fcintenddau_all ’, #all daughers already circumcised
        7: ’fcintenddau_unknown’,
        8: ’fcintenddau_missing’,
        9: ’fcintenddau_NIU’, #universe depends on country and year
        np.NAN: ’fcintenddau_NaN’}
```

```
idealboys_dict  = dict(#ideal number of sons
        [( i ,  'idealboys_'  + str(i))  for  i  in range(0,40)]+
        [(60,  'idealboys_non_numeric')]+
        [(61,  'idealboys_god')]+
        [(62,  'idealboys_any_num')]+
        [(63,  'idealboys_never_thought')]  + #never thought about it
        [(64,  'idealboys_as_many_as_possible' )]+
        [(65,  'idealboys_depends_hus')]+
        [(66,  'idealboys_current' )]+
        [(67,  'idealboys_no_sex_pref' )]  +
        [(99,  'idealboys_NIU')]+
        [(98,  'idealboys_missing' )]+
        [(97,  'idealboys_unknown')]
        )


idealgirls_dict   = dict(#ideal number of sons
        [( i ,  ' idealgirls_ '  + str(i))  for  i  in range(0,40)]+
        [(60,  'idealgirls_non_numeric ' )]+
        [(61,  ' idealgirls_god ' )]+
        [(62,  'idealgirls_any_num' )]+
        [(63,  ' idealgirls_never_thought ' )]  + #never thought about it
        [(64,  ' idealgirls_as_many_as_possible ' )]+
        [(65,  ' idealgirls_depends_hus ' )]+
        [(66,  ' idealgirls_current  ' )]+
        [(67,  '  idealgirls_no_sex_pref  ' )]  +
        [(99, 'idealgirls_NIU')]+
        [(98, ' idealgirls_missing ')]+
        [(97, 'idealgirls_unknown')]
        )

unmetneed2_dict = dict(
        [(99, 'unmetneed2_NIU')]+
        [(98, 'unmetneed2_unknown')]+
        #position to not get pregnant
        [(i, 'unmetneed2_unnecessary') for i in range(50,54)]+
        #don't want fp
        [(i, 'unmetneed2_no_unmetneed') for i in range(40,43)] +
        #already had fp failure
        [(i, 'unmetnee2)_failure') for i in range(30,33)] +
        #currently using fp for some reason
        [(i, 'unmetneed2_current_fp') for i in range(20, 23)] +
        #has an unmet need
        [(i, 'unmetneed2_unmet') for i in range(10, 13)]
        )
durmargrp_dict = {
        0: 'durmargrp_not_marr',
        1: 'durmargrp_1to4_yrs',
        2: 'durmargrp_5to9_yrs',
        3: 'durmargrp_10to14_yrs',
        4: 'durmargrp_15to19_yrs',
        5: 'durmargrp_20to24_yrs',
        6: 'durmargrp_25to29_yrs',
        7: 'durmargrp_30+_yrs',
        96: 'durmargrp_marr_not_cons',
        98: 'durmargrp_missing'
        }
resident_dict = {
        1: ' resident_yes ', #zero being no
        8: ' resident_missing '
        }


marstat_dict = {
        10: 'marstat_never_marr',
        11: 'marstat_uncons',
        20: 'marstat_marr_or_liv_tog ',
        21: 'marstat_marr',
        22: 'marstat_cohabit',
        30: 'marstat_formerly_marr',
        31: 'marstat_widowed',
        32: 'marstat_divorced',
        33: 'marstat_separated',
        34: 'marstat_deserted',
        98: 'marstat_missing'
        }
urban_dict = {
        1: 'urban'}
```

```
husbinhome_dict = {
        0: ’husbinhome_yes’, #zero being no
        9: ’husbinhome_NIU’
        }

 binary_variables_dict  = {
        ’RELIGION’: religion_dict,
        ’PREGTERMIN’: pregtermin_dict,
        ’FLOOR’: floor_dict,
        ’COOKFUEL’: cookfuel_dict,
        ’TOILETTYPE’: toilettype_dict,
        ’DRINKWTR’: drinkwtr_dict,
        ’HHPHONE’: hhphone_dict,
        ’CURRWORK’: currwork_dict,
        ’WKCURRJOB’: wkcurrjob_dict,
        ’WKEMPLOYWHEN’: wkemploywhen_dict,
        ’WKEARNTYPE’: wkearntype_dict,
        ’HUSJOB’: husjob_dict,
        ’LITBRIG’: litbrig_dict,
        ’EDACHIEVER’: edachiever_dict,
        ’HUSEDACHIEVER’: husedachiever_dict,
        ’NEWSBRIG’: newsbrig_dict,
        ’RADIOBRIG’: radiobrig_dict,
        ’TVBRIG’: tvbrig_dict,
        ’DECBIGHH’: decbighh_dict,
        ’DECFEMEARN’: decfemearn_dict,
        ’FERTPREF’: fertpref_dict,
        ’UNMETNEED2’: unmetneed2_dict,
        ’IDEALGIRLS’: idealgirls_dict,
        ’IDEALBOYS’: idealboys_dict,
        ’HUSFERTPREF’: husfertpref_dict,
        ’FPKNOTYP’: fpknotyp_dict,
        ’FPMETHNOW’: fpmethnow_dict,
        ’FPRADIOHR’: fpradiohr_dict,
        ’FPTVHR’: fptvhr_dict,
        ’FPPOSTHR’: fpposthr_dict,
        ’FPLASTSRCS’: fplastsrcs_dict,
        ’FPSTERILAGE’: fpsterilage_dict,
        ’AIDSHEARD’: aidsheard_dict,
        ’STIHEARD’: stiheard_dict,
        ’FCINTENDDAU’: fcintenddau_dict,
        ’FCCONTINU’: fccontinu_dict,
        ’FCINFIB’: fcinfib_dict ,
        ’FCNICK’: fcnick_dict,
        ’FCFLESH’: fcflesh_dict,
        ’FCCIRC’: fccirc_dict,
        ’UNION1MORE’: union1more_dict,
        ’DURMARGRP’: durmargrp_dict,
        ’RESIDENT’: resident_dict,
        ’MARSTAT’: marstat_dict,
        ’URBAN’: urban_dict,
        ’HUSBINHOME’: husbinhome_dict
```

```
        }


#cont + bin variables list and dictionaries!

deldoc_lst = []
for i in range(1,7):
    deldoc_lst .append(’DELDOC_0’ + str(i))

deltba_lst = []
for i in range(1, 7):
    deltba_lst .append(’DELTBA_0’ + str(i))

deloth_lst = []
for i in range(1, 7):
    deloth_lst .append(’DELOTH_0’ + str(i))

delnone_lst = []
for i in range(1, 7):
    delnone_lst .append(’DELNONE_0’ + str(i))

delcesr_lst = []
for i in range(1, 7):
    delcesr_lst .append(’DELCESR_0’ + str(i))

ancare_lst = []
```

```
for i in range(1, 7):
    ancare_lst.append('ANCARE_0' + str(i))

ancaredoc_lst = []
for i in range(1, 7):
    ancaredoc_lst.append('ANCAREDOC_0' + str(i))



bin_cont_dict = {
        1: deldoc_lst,
        2: deltba_lst,
        3: deloth_lst,
        4: delnone_lst,
        5: delcesr_lst,
        6: ancare_lst,
        7: ancaredoc_lst
        }

kidagediedimp_lst = []
for i in range(1, 10):
    kidagediedimp_lst.append('KIDAGEDIEDIMP_0' + str(i))

for i in range(10, 21):
    kidagediedimp_lst.append('KIDAGEDIEDIMP_' + str(i))

#list of variables to normalize:
```

```
norm_lst = [
        ’AGE’, #age of woman
        ’HHMEMTOTAL’, #total number of pple in house
        ’HHELIGWOMEN’, #num of eligable women in house
        ’HHKIDLT5’, #num of kids under 5 years in house
        ’AGEFRSTMAR’, #age at first marriage
        ’CHEB’, #number of children born to respondant
        ’SONSATHOME’, #number of sons living at home
        ’DAUSATHOME’, #number of daughters living at home
        ’SONSAWAYHOME’, #number of sons living away from home
        ’DAUSAWAYHOME’, #number of daughter living away from home
        ’SONSDIED’, #number of sons who have died
        ’DAUSDIED’, #number of daughters who have died
        ’CHEBALIVE’, #number of children born alive now
        ’AGEAT1STBIRTH’]#age at first birth

 as_is_lst  = [
        ’DHSID’,
        ’CLUSTERNO’,
        ’COUNTRY’,
        ’INTYEAR’,
        ’WEALTHS’]


#conflict data dictionary and lists
```

```
riots_lst = []
for i in range(1997, 2017):
    riots_lst.append(’RIOTS_’ + str(i))

civ_violence_lst = []
for i in range(1997, 2017):
    civ_violence_lst.append(’CIV_VIOLENCE_’ + str(i))

battles_lst = []
for i in range(1997, 2017):
    battles_lst.append(’BATTLES_’ + str(i))

violence_cols = riots_lst + civ_violence_lst + battles_lst

violence_yr_lst = []
#could be any of the violence variables = all have the same years
for i in riots_lst:
    violence_yr_lst.append(int(i.rsplit(’_’)[1]))

violence_lsts = [
        riots_lst,
        civ_violence_lst,
        battles_lst]

violence_lst = list(riots_lst + civ_violence_lst + battles_lst)
```

```
shp_lst  = [
          ’BJGE42FL.shp’,
          ’BJGE61FL.shp’,
          ’BFGE43FL.shp’,
          ’BFGE61FL.shp’,
          ’CMGE42FL.shp’,
          ’CMGE61FL.shp’,
          ’CIGE3BFL.shp’,
          ’CIGE61FL.shp’,
          ’GHGE42FL.shp’,
          ’GHGE4BFL.shp’,
          ’GHGE5AFL.shp’,
          ’GHGE71FL.shp’,
          ’GNGE42FL.shp’,
          ’GNGE52FL.shp’,
          ’GNGE61FL.shp’,
          ’MLGE42FL.shp’,
          ’MLGE52FL.shp’,
          ’MLGE6BFL.shp’,
          ’NIGE32FL.shp’,
          ’NGGE4BFL.shp’,
          ’NGGE52FL.shp’,
          ’NGGE6AFL.shp’
          ]
```

Appendix C. Python Functions for Data Manipulation

The following code describes the functions created to manipulate the data used for the Topological Data Analysis.

The following Python packages were used:

- numpy >= 1.15.2 [78]
- os [66]
- json [66]
- glob [66]
- pandas >= 0.23.4 [76]
- numpy >= 1.15.2 [78]
- geopandas >= 0.4.0 [67]
- sklearn >= 0.0 [77]
- matplotlib >= 3.0.2 [79]
- shapely >= 1.6.4.*post*1 [80]

```
# −∗− coding: utf−8 −∗−
”””
Created on Thu Oct 11 12:29:26 2018


@author: Michaela
”””
import os
import json
import pandas as pd
import numpy as np
import glob
import geopandas as gpd
from sklearn import preprocessing
from shapely.geometry import Point



'''
function to get a list of binary indicator variabeles from a dictionary
 listing column name full of categorical variables and lists of potential
binary indicator values
'''

def ind_dict_all (df, col_dict , new_df):
    for k, vs in col_dict .items():
        new_df = pd.concat([new_df,
                            pd.get_dummies(df[k].map(vs))],
                            axis=1)
    return new_df

'''
use previous function and dictionary of dictionary to impute list of like
 like variables
```

```
'''
def  indicator_variables_dict_all  (database, dictionary,new_database):
    for key in dictionary:
        new_database = (pd.concat([new_database,
                                    pd.get_dummies(database[key].map(
                                        dictionary[key]))],  axis  = 1))
    return new_database


#Not really used
def single_binary(database,
                  column_name,
                  one_value,
                  zero_value,
                  new_name,
                  new_database):
    lst  = []
    for i  in database[column_name]:
        if  i  == one_value:
            lst.append(1)
        else:
            lst.append(0)
    bin_col  = pd.DataFrame({new_name:lst})
    new_database = pd.concat([new_database, bin_col], axis = 1)
    return new_database

'''
```

```
Reduces a list of colums relating to multiple variables dealing with the same
subject matter into two variables - one coninuous and the other binary.
Used for variables like DELDOC (number of kids delivered by a doctor in past
3-5 years) which allows for up to 6 kids to indicate as either yes (1) or
no (0) or not related (8, 9, or NaN)
'''
def mult_bin_cont(df, col_lst, new_df):
    cond_num = [] #numeric col for # of whatever variable measuring
    nan_obs = [8, 9]
    sub_df = df[col_lst].replace(nan_obs,np.NaN) #NIU & missing = nan
    for col in col_lst: # if true for one child
        cond_num.append(sub_df[col] ==1)
    #num of kids who were delivered by doctor
    col_num = pd.Series((np.where(cond_num, 1, 0)).transpose().sum(axis=1))
    #doesn't have kids, answered or questions not asked
    col_nan = pd.Series((np.where(
        sub_df.isnull().all(axis=1), 1, 0)).transpose())
    col_num.index = sub_df.index #making indes the same for concat
    col_nan.index = sub_df.index
    sub_df_new = pd.concat([col_num.rename(col_lst[0].lower().split('_')[0]
                                           +'_num'),
                            col_nan.rename(col_lst[0].lower().split('_')[0]
                                           + '_na')],
                            axis = 1)

    #normalize based on wether not you had a kid delivered
    #in the past 3-5 years
    cond_norm = sub_df_new.iloc[:, 1] == 0 #condition for which rows to norm
    s_norm = col_num[cond_norm] #series of observations to normalize
    d_min = s_norm.min().astype(float) #series min
    d_max = s_norm.max().astype(float) #series max
    sub_df_new.iloc [:, 0] = (np.where(cond_norm, sub_df_new.iloc[:, 0].apply(
            lambda x: (x-d_min)/(d_max-d_min)), 0))
    new_df = pd.concat([new_df, sub_df_new], axis = 1)

    return new_df

'''
same as up top, except it takes a dictionary ( list of list ) and does all the
varialbes that are like that all at once
'''
def mult_bin_cont_all(df, col_dict , new_df):
   for key in col_dict :
      new_df = mult_bin_cont(df, col_dict [key], new_df)
   return new_df

#months of child at death variable and such:
def mult_cont(df, col_lst , new_df):
    sum_cond = []
    sub_df = df[ col_lst ]. replace(999, np.NaN)
    sum_cond = sub_df.notnull()
    col_num = pd.Series(sub_df[sum_cond].count(axis=1)) #num of kids who died
```

```
#its ignoring NaN values and finding mean number of months at dealth
month_num = sub_df.mean(axis=1)
col_nan = pd.Series((np.where(sub_df.isnull().all(axis=1),
                              1, 0)).transpose()) #no kids died
col_nan.index = col_num.index

sub_df_new = pd.concat([col_num.rename(col_lst[0].lower().split('_')[0]
                                   + '_num'),
                       col_nan.rename(col_lst[0].lower().split('_')[0]
                                   + '_nan'),
                       month_num.rename(col_lst[0].lower().split('_')[0]
                                     + '_mean_month')],
                       axis = 1)
#normalize
cond_norm = sub_df_new.iloc[:, 1] == 0
#series of number of children to normalize
s_norm_num = col_num[cond_norm]
#series of mean age (months) to normalize
s_norm_month = month_num[cond_norm]
#getting appropriate min and max for nomralization
num_max = s_norm_num.max()
num_min = s_norm_num.min()
month_max = s_norm_month.max()
month_min = s_norm_month.min()

sub_df_new.iloc[:, 0] = (np.where(cond_norm, sub_df_new.iloc[:, 0].apply(
            lambda x: (x-num_min)/(num_max-num_min)), 0))
    sub_df_new.iloc [:,  2] = (np.where(cond_norm, sub_df_new.iloc[:, 2].apply(
            lambda x: (x-month_min)/(month_max-month_min)), 0))
    new_df = pd.concat([new_df, sub_df_new], axis=1)

    return new_df



'''
normalizing function for varaibles with mainly continuous values but
does contain some categorical values
'''
def min_max_normalize(df, col):
    col_norm = (df[col] - df[col].min())/ (df[col].max() - df[col].min())
    return col_norm


def min_max_normalize_lst(df, col_lst , new_df):
    nan_lst = [95, 96, 97, 98, 99]
    sub_df = df[ col_lst ].replace(nan_lst, np.NaN)
    for col in sub_df:
        if sub_df[col].isnull().any():
            #indicator variable for missing values as this dataset's
            #null values carry meaning -
            #ex.) age1stbirth == NaN means that women hasn't had child yet.
        col_nan = pd.Series((np.where(
            sub_df[col].isnull(), 1, 0)).transpose())
        col_num = min_max_normalize(sub_df, col)
        #adding one to every obs-shift continuous spread
        col_num = col_num.apply(lambda x: x+1)
        col_num = col_num.fillna(0)#replacing NaN's with 0
        col_nan.index = sub_df.index
        col_num.index = sub_df.index
        new_df = pd.concat([new_df,
                           col_nan.rename(col.lower() + '_nan'),
                           col_num.rename(col.lower() + '_norm')],
                           axis = 1)

    else:
        col_num = min_max_normalize(df, col)
        #making normal scale equal for every cont. variable
        col_num = col_num.apply(lambda x: x+1)
        col_num.index = sub_df.index
        new_df = pd.concat([new_df,
                           col_num.rename(col.lower() + '_norm')],
                           axis = 1)

return new_df
```

```
'''
normalizing functions for  strictly  continuous varaibles
'''


def normalize_cont(df,
                   col_lst ,
                   new_df):
    sub_array = df[ col_lst ]. fillna (0). values
    min_max_scaler = preprocessing.MinMaxScaler()
    array_scaled  = min_max_scaler.fit_transform(sub_array)

    norm_lst = []
    for  i  in  col_lst :
        norm_lst.append(i.lower()  + '_norm')
    sub_df = pd.DataFrame(data = array_scaled,
                          index = new_df.index,
                          columns = norm_lst)
    new_df = pd.concat([new_df, sub_df],  axis  = 1)

    return new_df



'''
Load and combine geodataframes
'''
```

```
def gis_df(path, geo_df_name):
    filenames = glob.glob(path + ”/∗.shp”)

    gdfs = []
    for filename in filenames:
        gdfs.append(gpd.read_file(filename))

    # Concatenate all data into one DataFrame
    geo_df_name = pd.concat(gdfs, ignore_index=True, sort = True)

    return geo_df_name

’’’
Create y variables for random forest algorithms. Consists of mean number of
conflicts surrounding each women given a certain year range
’’’

def y_var(df,
          col_lst ,
          years_lst ,
          k):
    sub_df = df[ col_lst ]

    #get starting and ending date based on k half−width range
    start = []
    end = []
```

```
for i in df['INTYEAR']:
    start.append(int(i - k))
    end.append(int(i + k))

#convert to pd.series and make sure every one has the same indicies
start = pd.Series(start)
start.index = df.index
end = pd.Series(end)
end.index = df.index

violence_bool = []
for i in years_lst:
    violence_bool.append((i >= start) & (i <= end))

violence_bool = pd.DataFrame(violence_bool).transpose()
violence_mean = pd.DataFrame(np.where(violence_bool,
                                      sub_df.values,
                                      np.NaN)).mean(axis = 1)
#violence_mean = np.array(violence_mean)

return violence_mean
```

```
#
    #####################################################


#Make dataframe into GeoDataFrame with geometry point 'clust_coord'
def df_to_gdf(df):
    df['clust_coord'] = list(zip(df.LONGNUM, df.LATNUM))
    df['clust_coord'] = df['clust_coord'].apply(Point)
    gdf = gpd.GeoDataFrame(df, geometry = 'clust_coord')

    return gdf



#Function that returns a geodataframe for a group in the THD based on the
#json files from the Segmentations Folder

def group_gdf(gdf, #GeoPandas Dataframe already loaded
              thd_path, #Path to THD
              json_file_name #String indicating file name
              ):



    #The json file
    json_file = THD_PATH + json_file_name

    #Empty Dictionary to hold json file
    CONFIG_PROPERTIES = {}

    try:
        with open(json_file) as data_file :
            CONFIG_PROPERTIES = json.load(data_file)
    except IOError as e:
        print(e)
        exit ()

    #list of rows in the THD group − will be used to create a subset of
    #the larger whole dataset attributed
    row_indices = CONFIG_PROPERTIES['rows']

    #Geo Dataframe of data in Subgroup
    sub_gdf = gdf. iloc [row_indices, :]

    return sub_gdf


#
    ######################################################

'''
a function to grab a bunch of nodes from a list that I will define
based on anlysis from some simplicial complex created through TDA
that that statistical analysis can be implimented on it later on
```

```
UPDATE: Switched to Ayasdi from kmapper − thses functions are no longer
relavant but potentially useful if you want to use kmapper.
Just add kmapper and respective libraries to run

'''


'''
def grab_cluster_group(lst, array, scomplex):
    cluster_grouping = np.empty((0,array.shape[1]), float)
    for i in lst:
        cluster_grouping = np.append(cluster_grouping,
                                     mapper.data_from_cluster_id(i,
                                                                 scomplex,
                                                                 array),
                                                                 axis = 0)
    cluster_grouping_unique = np.unique(cluster_grouping, axis = 0)

    return cluster_grouping_unique


def grab_clusters_id(lst, array_index, scomplex):
    clusters_id = []
    for i in lst:
        clusters_id = np.append(clusters_id,
                                mapper.data_from_cluster_id(i,
                                                            scomplex,
                                                          array_index),
                                                          axis = 0)
    unique_id = np.unique(clusters_id, axis = 0)

    return unique_id

,,,
```

Appendix D. Data Cleaning and Manipulation Code

The following code was used to clean and manipulate the data before implimenting Topological Data Analysis through Ayasdi Software and Geospatial Analysis in Python Jupyter Notebooks.

The following Python packages were utilized in the code below.

- numpy >= 1.15.2 [78]
- sys [66]
- glob [66]
- pandas >= 0.23.4 [76]
- numpy >= 1.15.2 [78]
- geopandas >= 0.4.0 [67]
- sklearn >= 0.0 [77]
- matplotlib >= 3.0.2 [79]

```
# −∗− coding: utf−8 −∗−
”””
Created on Wed Oct 10 14:42:34 2018

@author: Michaela
”””
#
    ####################################################
```

```
#Libraries imported
import sys
import pandas as pd
import numpy as np
import geopandas as gpd
import glob
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.ensemble import RandomForestRegressor
from sklearn import ensemble
from sklearn.metrics import mean_squared_error
import thesis_functions as func #importing functions for data manipulation
import thesis_dictionaries as dic #import dictionaries and lists for data manip


#Path to datafile - change depending on whoes using script
path = ('C:\\Users\\Michaela\\Documents\\Thesis' +
          '\\Data-Code\\Data_final\\Manipulation\\')
#^^ had to put on two lines due to length and fitting in appendix

#Load csv datafile as pandas DataFrame
df= pd.read_csv(path+'women_conflict.csv')

'''
Drop all observation before the year 1997 due to conflict data restrictions ,
And replace -998 (DHS survey doesn't have GPS locations) with NaN so that
I can drop them
'''


df = df.drop(df[df.YEAR < 1997].index)
df = df.replace(-998, np.NaN)
conflict_cond = (df['CIV_VIOLENCE_1997'].notnull())
df = df[conflict_cond] #getting rid of observations are Nan
#Country abreviation (first two letters) + year (YYYY) - 33 samples
#helps with data cleaning process, but not really used after
df['ID'] = df.DHSID.str[:6]
df.ID.astype('category')
df['COUNTRY'] = df['COUNTRY'].map(dic.country_dict)



'''
Create the DataFrame that will be exported out for Analysis and add variables
that can be transported as is - see dictionaries.py for list
'''
df_tda = []
for col in dic.as_is_lst:
    df_tda.append(list(df[col]))

df_tda = pd.DataFrame(df_tda).transpose()
df_tda.columns = dic.as_is_lst
df_tda.index = df.index #have to make sure indicies match up for later
```

```
'''
Taking all of the desired catogorical variables and turning them into binary
indicator variables - necessary for TDA Mapper - see dictionaries.py for
 list of variables
 '''

df_tda = func. ind_dict_all (df,
                             dic. binary_variables_dict ,
                             df_tda)



 '''
Month at child's death variable imputation
This is a unique variable and therefore needs special function
 '''
df_tda = func.mult_cont(df,
                        dic.kidagediedimp_lst,
                        df_tda)

 '''
Continuous variables that need to be normalized using min-max formula
 '''
```

```
df_tda = func.min_max_normalize_lst(df,
                                    dic.norm_lst,
                                    df_tda)



’’’
HHEADAGE has different missing values so it has to be normalized by itself
’’’
hheadage_norm = func.min_max_normalize(df, ’HHEADAGE’)
hheadage_norm = hheadage_norm.apply(lambda x: x+1) #same as other cont.
    vars.
df_tda = pd.concat([df_tda, hheadage_norm], axis=1)

’’’
Variables like DELDOC that make up several variables that relate to each
potential mothers multiple children that could have been in the past 3-5 years
will be composed of two variables, one with a normalized number relateding to
the number and another indicator variable indicating if the women belongs in
universe (meaning the women can provide a meaning fule answer, i.e. I had
a baby in the past five years therefore I can answer a question pertaining
to my prenatal care and so on).
’’’

df_tda = func.mult_bin_cont_all(df,
                                dic.bin_cont_dict,
                                        df_tda)


’’’
Add on riots, battles and civ_violence variables
’’’



#get predictor values - based of off 2 year half width
y_riots = func.y_var(df, dic.riots_lst, dic.violence_yr_lst, 2)
y_civ = func.y_var(df, dic.civ_violence_lst, dic.violence_yr_lst, 2)
y_battles = func.y_var(df, dic.battles_lst, dic.violence_yr_lst, 2)
list_of_lists = [y_riots, y_battles, y_civ]
y_all = [sum(x) for x in zip(*list_of_lists)]

y_riots.index = df_tda.index
y_civ.index = df_tda.index
y_battles.index = df_tda.index
y_all = pd.Series(y_all, index = df_tda.index)

bin_riots = y_riots.apply(lambda x: 1 if x > 0 else 0)
bin_civ = y_civ.apply(lambda x: 1 if x > 0 else 0)
bin_battles = y_battles.apply(lambda x: 1 if x > 0 else 0)
bin_all = y_all.apply(lambda x: 1 if x > 0 else 0)

’’’
Add to dataframe for latter csv extractions
```

```
'''


'''
Add on riots, battles and civ_vi0lence variables normalized (lower case)
'''

df = df.fillna (0) #just for the Riots_2008 (Niger 1998 sample data mix-up)
df_tda = func.normalize_cont(df,
                             dic.violence_cols ,
                             df_tda)

'''
Anomaly Detection using Isolation Forest and data with both Violence data and
no violence data - i.e. only women survey data
'''
var_names = list(df_tda) #get list to determine X_violence and X_women
X_violence = df_tda.iloc [:,  4:427].values #Take away DHSID, country, ect.
X_women = df_tda.iloc[:,  4:367].values #Take away violence data

#Isolation Forest using Bootstrap sampling
model = ensemble.IsolationForest(bootstrap = True,
                                 random_state=123,
                                 max_samples = 25)
model.fit (X_violence)#Fiting model to data
 lens_violence  = model.decision_function(X_violence) #Getting anomaly scores
```

```
model.fit(X_women)#Fiting model to data
lens_women = model.decision_function(X_women)#Getting anomaly scores

#Convert numpy arrays to series so that they can be added to dataframe
anomaly_violence = pd.Series(lens_violence, index = df_tda.index)
anomaly_women = pd.Series(lens_women, index = df_tda.index)

#Add everything to data frame
df_tda = pd.concat([df_tda,
                    y_riots.rename('y_riots'),
                    bin_riots.rename('bin_riots'),
                    y_civ.rename('y_civ'),
                    bin_civ.rename('bin_civ'),
                    y_battles.rename('y_battles'),
                    bin_battles.rename('bin_battles'),
                    y_all.rename('y_all'),
                    bin_all.rename('bin_all'),
                    anomaly_violence.rename('anomaly_violence'),
                    anomaly_women.rename('anomaly_women')],
                    axis = 1)

#Anomaly scores distributions plot
bins = np.linspace(−0.2, 0.2, 500)

plt.hist(lens_violence, bins, alpha=0.5,
         label='Augmented Women and Conflict Data')
plt.hist(lens_women, bins, alpha=0.5,
         label='DHS Women Survey Answers Only')
plt.legend(loc='upper right')
plt.ylabel('Frequency')
plt.xlabel('Isolation Forest Anamoly Score')
plt.title('Isolation Forest Anamoly Scores Histograms')
plt.show()



#get list to determine X
var_names = list(df_tda)
'''
get Random Forest predicted values for violence using sklearn and convert
data to numpy arrays (or just use origional numpy arrays)
'''


X = df_tda.iloc[:, 4:367].values
X_t, X_v, y_r_t, y_r_v, y_b_t, y_b_v, y_c_t, y_c_v, y_a_t, y_a_v =
    train_test_split(
    X, y_riots, y_battles, y_civ, y_all, test_size=0.25, random_state=123)

'''
Build Regression Radom Forest Tree for lenses for each Y variable with
bootstrap sampling
'''
```

```
reg = RandomForestRegressor(bootstrap = True,
                            random_state=123,
                            n_estimators = 75)
#riots lens
reg.fit(X_t, y_r_t)

riots_pred_test = reg.predict(X_v)
riots_mse = mean_squared_error(y_r_v, riots_pred_test)
riots_score = reg.score(X_v, y_r_v)

lens_pred_riots = reg.predict(X)

#battles random forest regression lens
reg.fit(X_t, y_b_t)
battles_pred_test = reg.predict(X_v)
battles_mse = mean_squared_error(y_b_v, battles_pred_test)
battles_score = reg.score(X_v, y_b_v)

lens_pred_battles = reg.predict(X)

#civ violence random forest regression lens
reg.fit(X_t, y_c_t)
civ_pred_test = reg.predict(X_v)
civ_mse = mean_squared_error(y_c_v, civ_pred_test)
civ_score = reg.score(X_v, y_c_v)
```

```
lens_pred_civ = reg.predict(X)

#all violence acts random forest regression lens
reg. fit (X_t, y_a_t)
all_pred_test = reg.predict(X_v)
all_mse = mean_squared_error(y_a_v, all_pred_test)
all_score = reg.score(X_v, y_a_v)

lens_pred_all = reg.predict(X)

lens_pred_riots = pd.Series( lens_pred_riots )
lens_pred_battles = pd.Series( lens_pred_battles )
lens_pred_civ = pd.Series(lens_pred_civ )
lens_pred_all = pd.Series( lens_pred_all )



#Add new lenses onto the dataframe to be loaded up into Ayasdi

df_lens = pd.concat([lens_pred_riots .rename('riot_lens'),
                     lens_pred_battles .rename('battles_lens'),
                     lens_pred_civ .rename('civ_violence_lens'),
                     lens_pred_all .rename(' violence_all_lens ')],
                    axis = 1)
df_lens .index = df_tda.index
```

```
df_tda = pd.concat([df_tda, df_lens], axis = 1)



#Load in absolute difference between predicted and actual
 riots_diff = pd.Series((y_riots − lens_pred_riots).abs(), index = df_tda.index)
 battles_diff = pd.Series((y_battles − lens_pred_battles).abs(), index = df_tda.
    index)
 civ_diff = pd.Series((y_civ − lens_pred_civ).abs(), index = df_tda.index)
 violence_all_diff = pd.Series((y_all − lens_pred_civ).abs(), index = df_tda.index
    )

 df_diff = pd.concat([riots_diff.rename('riots_diff'),
                      battles_diff.rename('battles_diff'),
                      civ_diff.rename('civ_diff'),
                      violence_all_diff.rename('violence_all_diff')], axis = 1)

 df_diff.index = df_tda.index
df_tda = pd.concat([df_tda, df_diff], axis = 1)



'''
Geopandas GIS data
'''
#Reading in all shape files loaded from DHS Program website and concat together
gdf = func.gis_df(path + 'shps\\', 'gdf')
```

```
gdf_sub = gdf[['LATNUM', 'LONGNUM', 'geometry']]

df_tda = pd.merge(df_tda, gdf[['DHSID', 'LATNUM', 'LONGNUM']], on = '
    DHSID')


path_analysis = ('C:\\Users\\Michaela\\Documents\\Thesis\\Data-Code' +
                 '\\Data_final\\Analysis\\') #Too long and went of page

df_tda.to_csv(path_analysis + 'analysis_data.csv')
```

Appendix E. Jupyter Notebook Analysis

The following Jupyter Notebook output summarizes all geospatial analysis implimented.

The following Python packages were utilized in the code below.

- numpy >= 1.15.2 [78]
- sys [66]
- os [66]
- glob [66]
- pandas >= 0.23.4 [76]
- numpy >= 1.15.2 [78]
- geopandas >= 0.4.0 [67]
- geoplot >= 0.2.1 [68]
- seaborn >= 0.9.0 [81]
- sklearn >= 0.0 [77]
- matplotlib >= 3.0.2 [79]

In [2]:

```
import os
import sys
import glob
import numpy as np
import json
import pandas as pd
import geopandas as gpd
import geoplot as gplt
import thesis_functions as func
import thesis_dictionaries as dic
from shapely.geometry import Point
import matplotlib.pyplot as plt
import geoplot.crs as gcrs
```

In [3]:

```
#Segmentation Folder path
THD1_path = ('C:\\Users\\Michaela\\Desktop\\AFRL\\Segmentations\\' +
            'N1N2_IQR_WomenData(2)_IQR Normalized Euclidean_analysis_data_6.cs
v 2_2018.12.14 16.20.58\\')

THD2_path = ('C:\\Users\\Michaela\\Desktop\\AFRL\\Segmentations\\' +
            'ALL_N1N2_IQR_IQR Normalized Euclidean_analysis_data_6.csv 2_2019.
01.10 17.53.40\\')

#Data File path
path = 'C:\\Users\\Michaela\\Documents\\Thesis\\Data-Code\\Data_final\\Analysi
s\\'
```

In [4]:

```
#Grab the list of json files that will be used to index data from segmentation
 folder
files = [i for i in os.listdir(THD1_path) if os.path.isfile(os.path.join(THD1_
path,i)) and \
         'GROUPDATA_' in i]

print(len(files)) #if correctly done, should only be 137
```

```
137
```

In [5]:

```python
#read Pandas DataFrame used for the Analysis
df = pd.read_csv(path + 'analysis_data_6.csv')
print(df.shape)
df.head()
```

```
(255221, 448)
```

Out[5]:

	Unnamed: 0	DHSID	CLUSTERNO	COUNTRY	INTYEAR	WEALTHS	Anglican	Animist
0	0	BJ200100000001	1	Benin	2001	-0.22614	0	0
1	1	BJ200100000001	1	Benin	2001	-0.22614	0	0
2	2	BJ200100000001	1	Benin	2001	-0.40480	0	0
3	3	BJ200100000001	1	Benin	2001	-0.40480	0	0
4	4	BJ200100000001	1	Benin	2001	-0.46920	0	0

5 rows × 448 columns

In [6]:

```python
#Unnamed columns was column added when reading out dataframe to csv after manipulation, so I'm going to get rid of it
df = df.drop(['Unnamed: 0'], axis = 1)
df.head()
```

Out[6]:

	DHSID	CLUSTERNO	COUNTRY	INTYEAR	WEALTHS	Anglican	Animist	Catholic
0	BJ200100000001	1	Benin	2001	-0.22614	0	0	0
1	BJ200100000001	1	Benin	2001	-0.22614	0	0	0
2	BJ200100000001	1	Benin	2001	-0.40480	0	0	0
3	BJ200100000001	1	Benin	2001	-0.40480	0	0	0
4	BJ200100000001	1	Benin	2001	-0.46920	0	0	0

5 rows × 447 columns

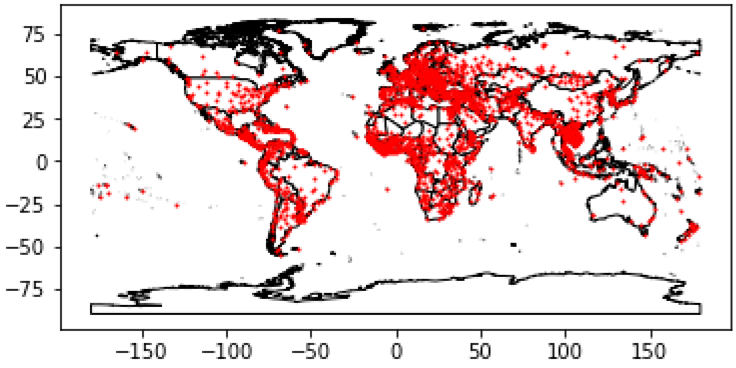
In [7]:

```python
#read in shape files and merge with DataFrame on the DHS Cluster ID number to
 make a geodataframe
path_shps = 'C:\\Users\\Michaela\\Documents\\Thesis\\Data-Code\\Data_final\\Manipulation\\shps\\'
gdf_survey = func.gis_df(path_shps, 'gdf')
df = pd.merge(df, gdf_survey[['DHSID', 'geometry']], on = 'DHSID')
gdf_full = gpd.GeoDataFrame(df, geometry = 'geometry')
```

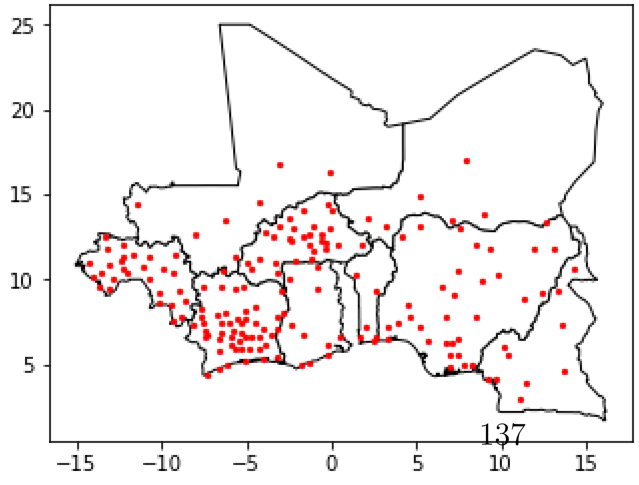
```
In [8]:  #So that I can graph later on
         gdf_full.crs = {'init' :'epsg:4326'}
```

Load borders and cities geodataframes for graphing purposes

```
In [9]:  #Load borders shape file from thematicmapping.org
         borders = gpd.read_file(path + 'TM_WORLD_BORDERS-0.3.shp')
         #Uploading world cities shape file - downloaded from ARCGIS Hub website
         cities = gpd.read_file(path + 'World_Cities.shp')
         #plot
         base = borders.plot(color = 'white', edgecolor = 'black')
         cities.plot(ax=base, marker='o', color='red', markersize=1)

Out[9]:  <matplotlib.axes._subplots.AxesSubplot at 0x1c607943780>
```

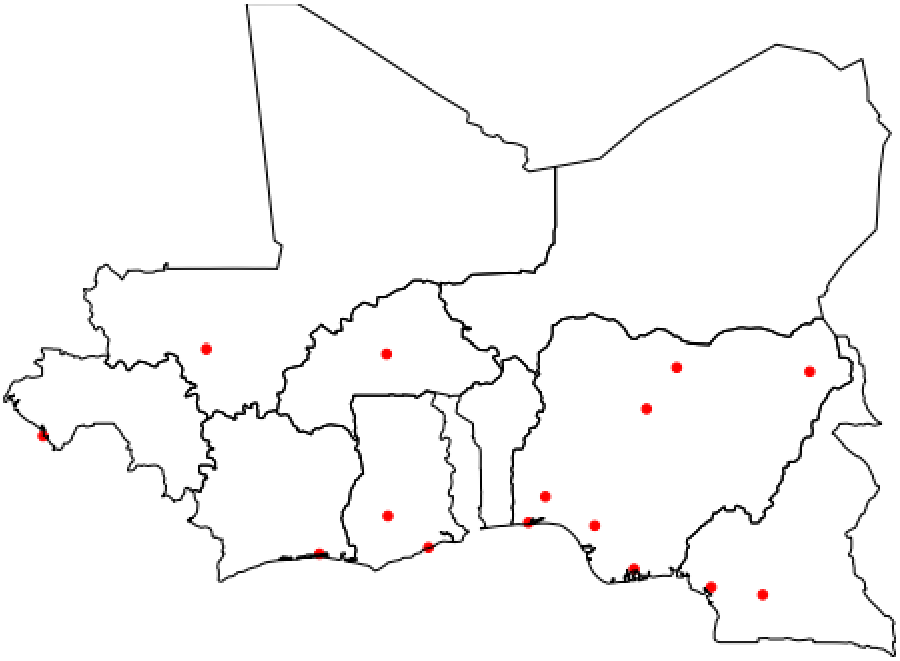


```
In [10]: #reduce the borders and cities geodataframe to hold the 9 countries of interes
         t with cities
         country_list = ['Benin', 'Ghana', 'Nigeria', 'Niger', 'Guinea', 'Burkina Faso'
         , 'Cameroon', 'Mali', 'Cote d\'Ivoire']
         borders = borders[borders['NAME'].isin(country_list)]
         cities = cities[cities['CNTRY_NAME'].isin(country_list)]
         #plot
         base = borders.plot(color = 'white', edgecolor = 'black')
         cities.plot(ax=base, marker='o', color='red', markersize=5)

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1c607122828>
```



In [11]:

```
#only look at realy large cities so as to lessen the information on the map
large_cities_lst = [ '1,000,000 to 4,999,999', '5,000,000 and greater'] #cities with 1million or more population
cities_large = cities[cities['POP_CLASS'].isin(large_cities_lst)]
#plot
base = gplt.polyplot(borders)
gplt.pointplot(cities_large,ax=base, color='red')
plt.savefig("bage.jpg", bbox_inches='tight', pad_inches=0.1)
```



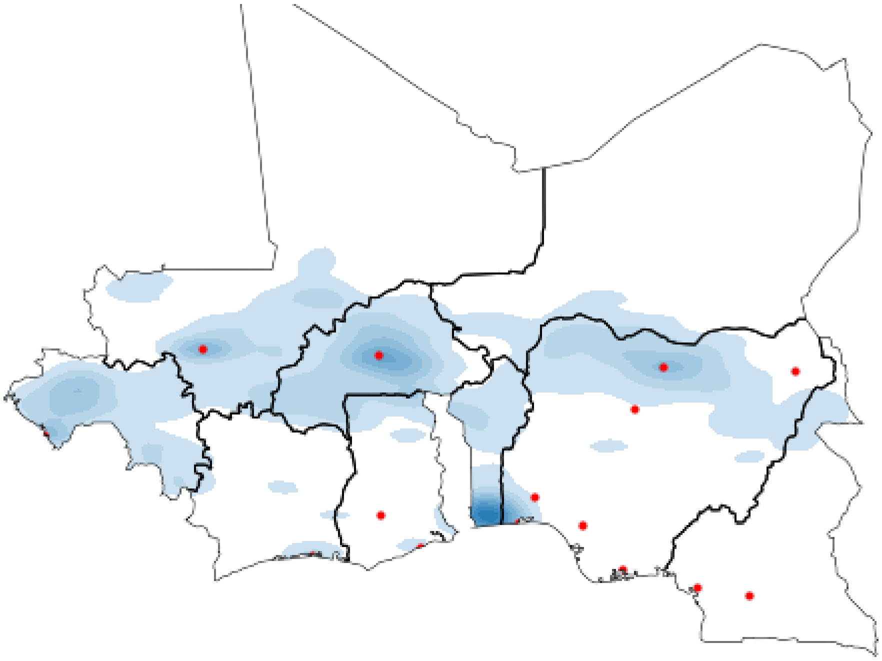
Initial Geospatial Analysis

Looking at certain indicators that are believed to be determinants of well-being, particularly: *education*Literacy *FGM*Conflict

```
In [12]: #Education = none:
         points = gdf_full[gdf_full['edachiever_none'] == 1] #only have points that rep
         resent women with no education
         #Kernal density map showing where the women with no education are densest
         print(points.shape)

         ax = gplt.kdeplot(points,
                       shade=True, shade_lowest=False,
                       clip=borders.geometry)
         base_borders = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("edu_none_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

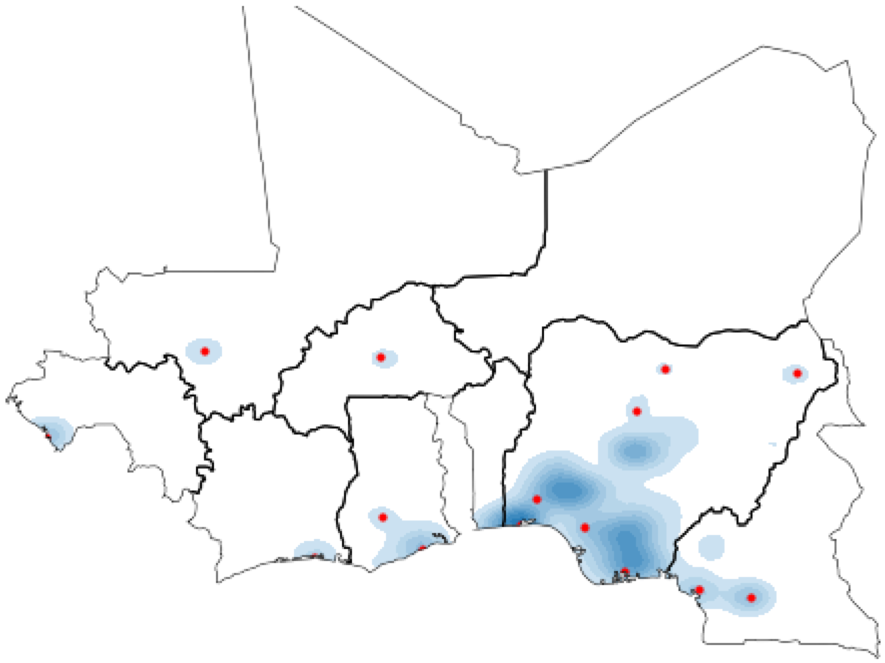
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
(131572, 448)
```



```
In [13]: #education = higher:
         points = gdf_full[gdf_full['edachiever_higher'] == 1] #only have points that r
         epresent women with some form of higher edu
         #Kernal density map showing where the women with higher education are densest
         print(points.shape)

         ax = gplt.kdeplot(points,
                      shade=True, shade_lowest=False,
                      clip=borders.geometry)
         base_borders = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("edu_higher_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

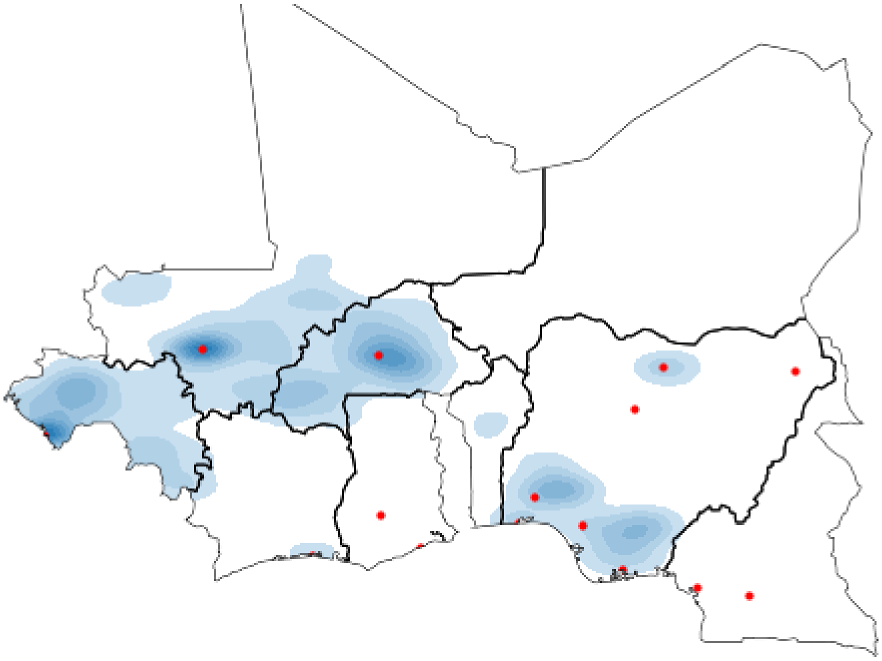
```
(10137, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



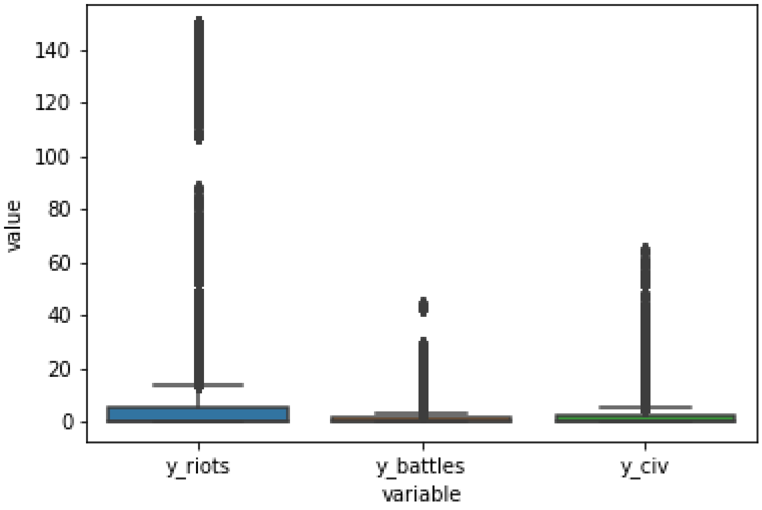
In [13]:

```
#FGM = yes:
points = gdf_full[gdf_full['fccirc_yes'] == 1]
#Kernal density map showing where women are circumcised are densest
print(points.shape)

ax = gplt.kdeplot(points,
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("fgm_yes_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

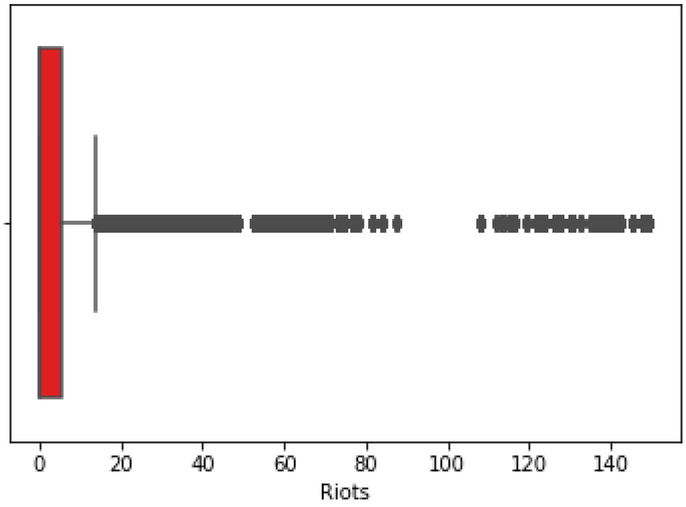
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [15]: #Conflict variables box plots
         import seaborn as sns
         conflict = pd.DataFrame(gdf_full[['y_riots', 'y_battles', 'y_civ']])
         ax = sns.boxplot(x = "variable", y="value", data=pd.melt(conflict))
         plt.savefig("conflict_boxplots.jpg")
```



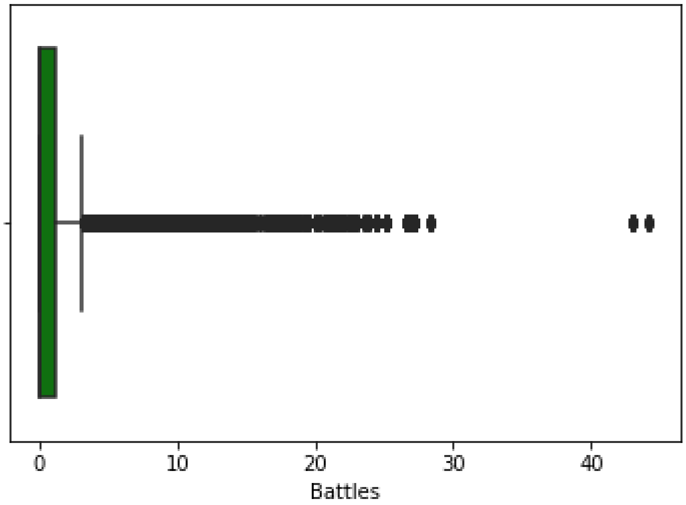
```
In [16]: ax = sns.boxplot(conflict.y_riots, color = 'red')
         ax.set(xlabel='Riots')
         plt.savefig("riots_boxplot.jpg")
         plt.show()
         print(conflict.y_riots.describe())
```



```
count    255221.000000
mean          5.511230
std          13.678973
min           0.000000
25%           0.000000
50%           0.000000
75%           5.600000
max         149.400000
Name: y_riots, dtype: float64
```

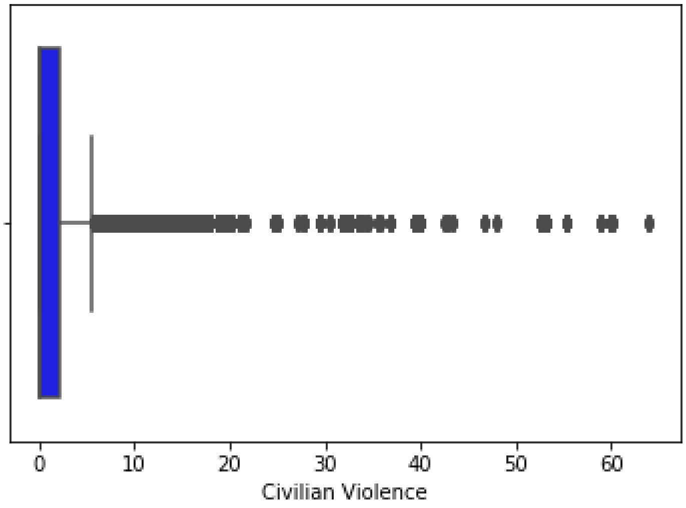
In [17]:

```
ax = sns.boxplot(conflict.y_battles, color = 'green')
ax.set(xlabel='Battles')
plt.savefig("battles_boxplot.jpg")
plt.show()
print(conflict.y_battles.describe())
```



```
count    255221.000000
mean          1.101642
std           2.662744
min           0.000000
25%           0.000000
50%           0.000000
75%           1.200000
max          44.200000
Name: y_battles, dtype: float64
```

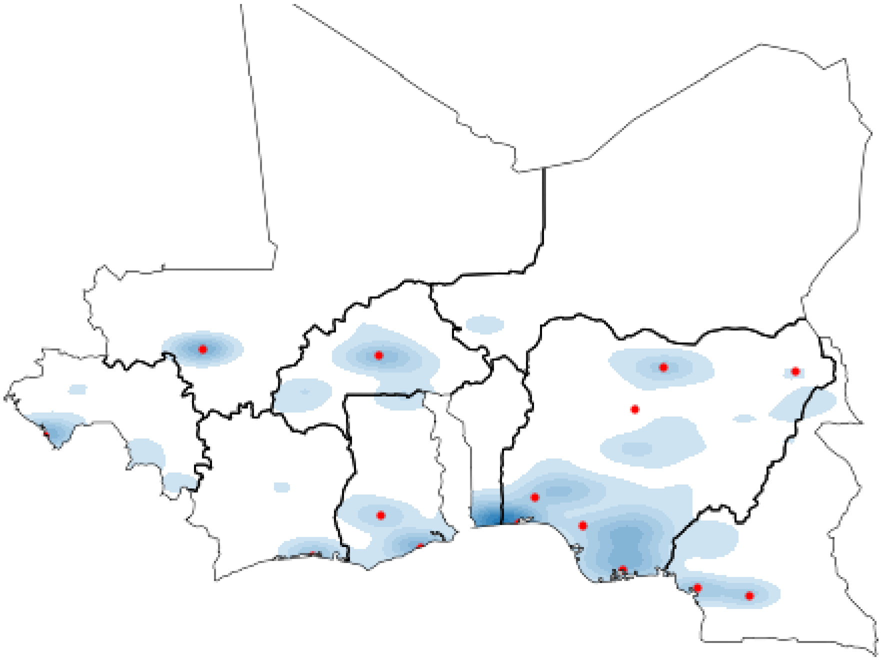
```
In [18]: ax = sns.boxplot(conflict.y_civ, color = 'blue')
         ax.set(xlabel='Civilian Violence')
         plt.savefig("civ_boxplot.jpg")
         plt.show()
         print(conflict.y_civ.describe())
```



```
count    255221.000000
mean          1.729243
std           3.740114
min           0.000000
25%           0.000000
50%           0.000000
75%           2.200000
max          64.000000
Name: y_civ, dtype: float64
```

```
In [19]: #Riots _bin_all:
         points = gdf_full[gdf_full['bin_riots'] == 1]
         print(points.shape)
         ax = gplt.kdeplot(points,
                       shade=True, shade_lowest=False,
                       clip=borders.geometry)
         base_borders = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)


         plt.savefig("bin_riots_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

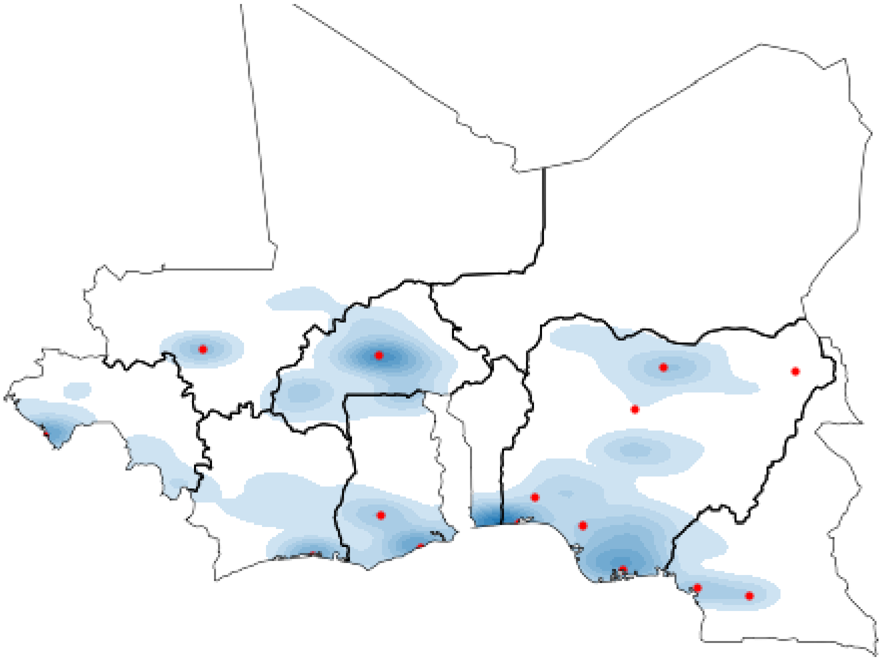


In [20]:

```
#Riots_bin_greater than 5.6 - only looking at extreme conflict in riots (5.6 =
 75% in riots)
points = gdf_full[gdf_full['y_riots'] > 5.6]
print(points.shape)

ax = gplt.kdeplot(points,
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)


plt.savefig("extreme_riots_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
(63720, 448)
```

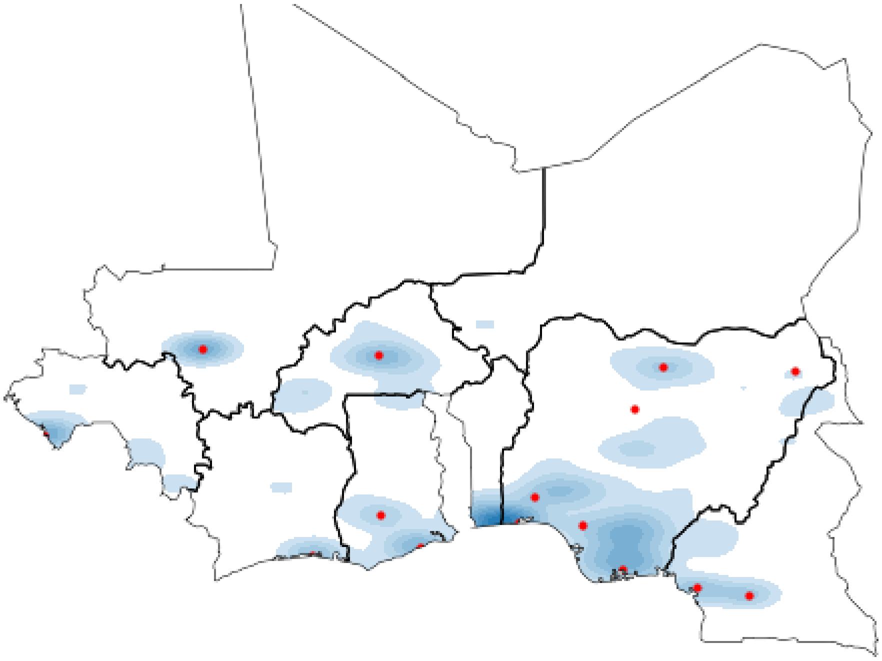
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [21]:

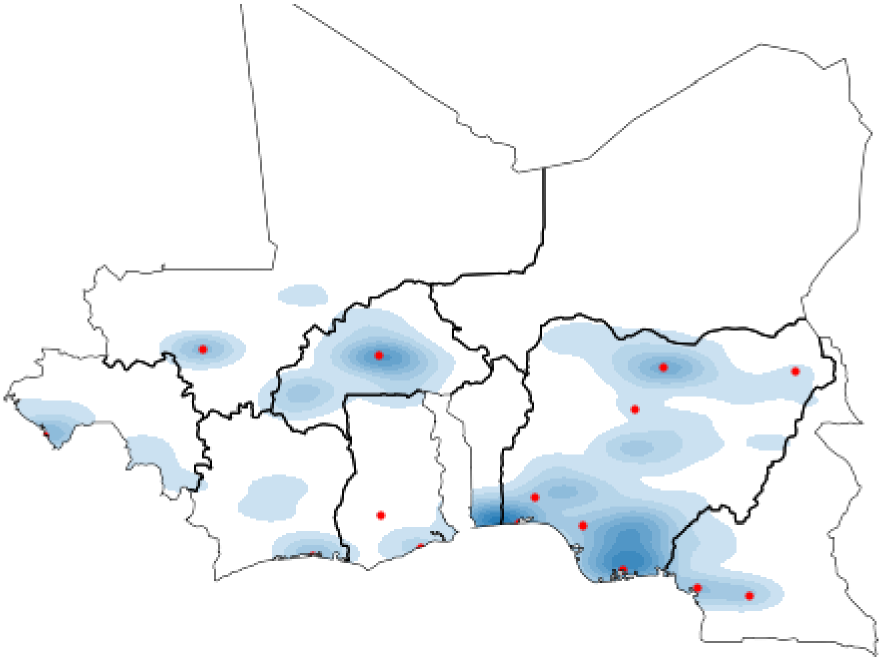
```
#battles:
points = gdf_full[gdf_full['bin_battles'] == 1]


ax = gplt.kdeplot(points,
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("bin_battles_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [22]: #battles_greater than 1.2 - only looking at extreme conflict in battles (1.2 =
          75% in battles)
         points = gdf_full[gdf_full['y_battles'] > 1.2]
         print(points.shape)

         ax = gplt.kdeplot(points,
                      shade=True, shade_lowest=False,
                      clip=borders.geometry)
         base_borders = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("extreme_battles_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1
         )
```

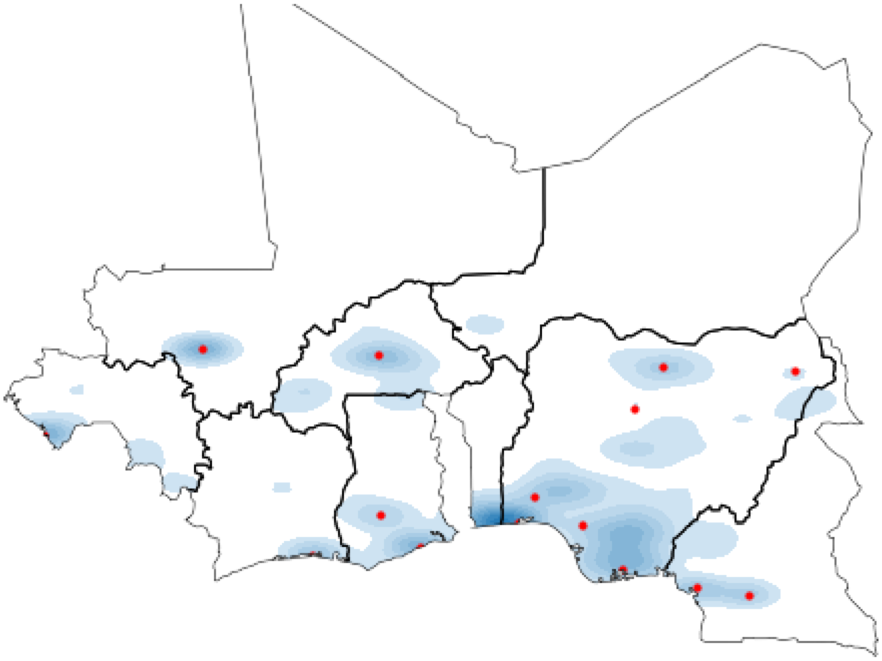
```
(56637, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [23]:

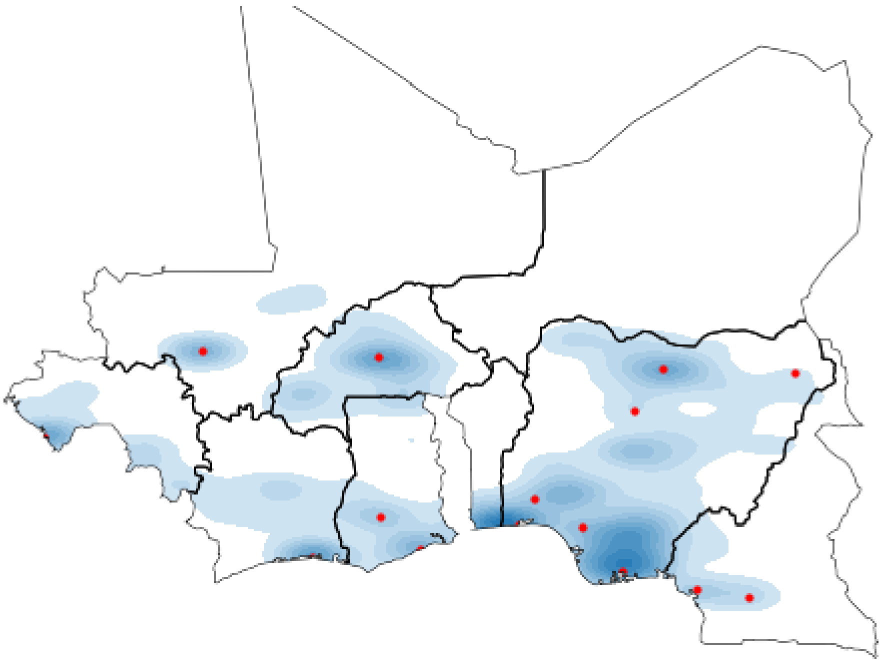
```
#civ_violence:
points = gdf_full[gdf_full['bin_civ'] == 1]

ax = gplt.kdeplot(points,
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("bin_civ_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [24]: #civ_greater than 2.2 - only looking at extreme conflict in civilian violence
          (2.2 = 75%)
         points = gdf_full[gdf_full['y_civ'] > 2.2]
         print(points.shape)

         ax = gplt.kdeplot(points,
                       shade=True, shade_lowest=False,
                       clip=borders.geometry)
         base_borders = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("extreme_civ_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1)
```

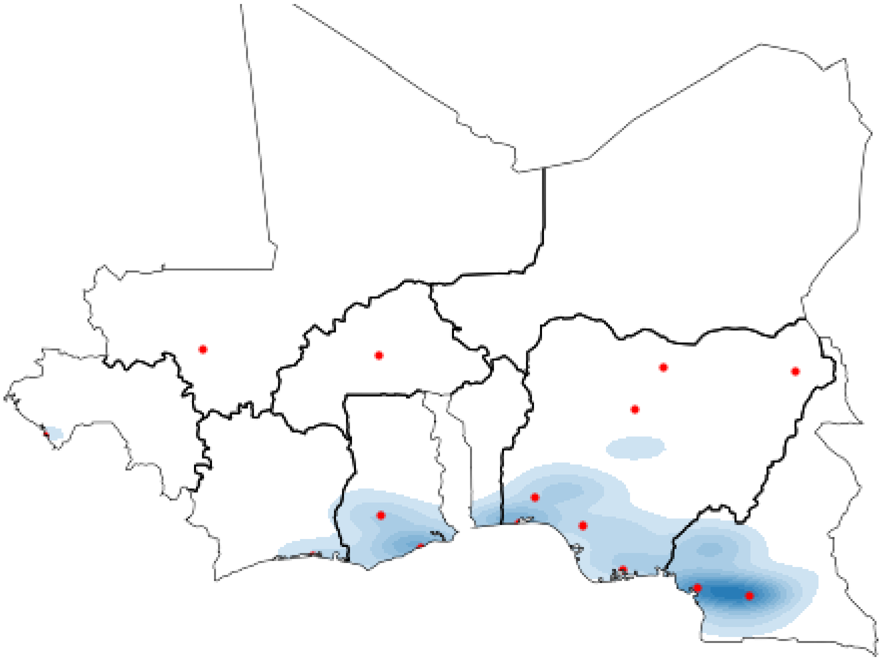
```
(59695, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [25]:

```
#Anomalous Women
points = gdf_full[gdf_full['anomaly_women'] < 0]
print(points.shape)
ax = gplt.kdeplot(points,
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("anomalous_women_KLD_map.jpg", bbox_inches='tight', pad_inches=0.1
)
```

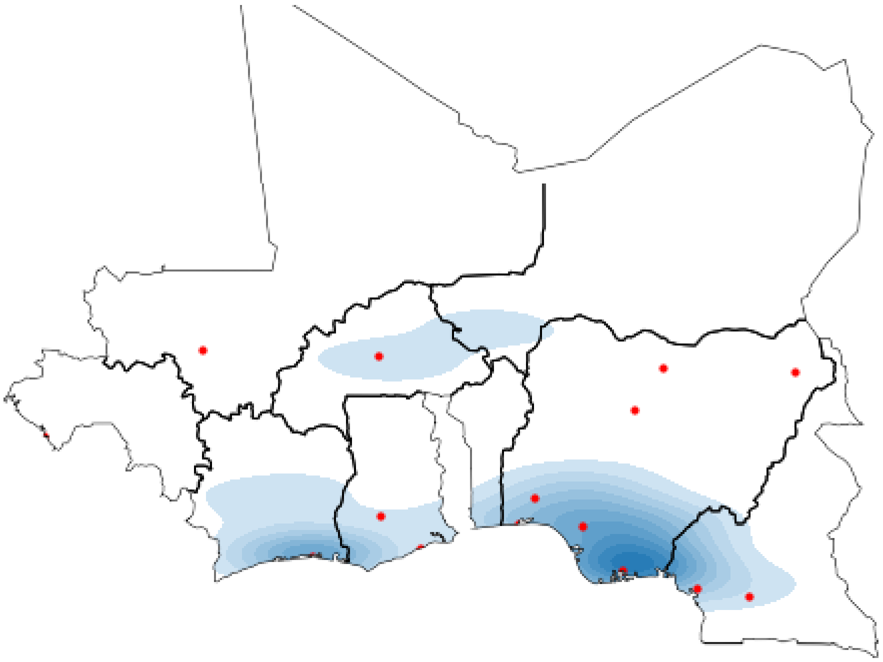
```
(7786, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [27]:
```
#Anomalous_violence Graph
points = gdf_full[gdf_full['anomaly_violence'] < 0]
ax = gplt.kdeplot(points,
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base_borders = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("anomalous_violence_KLD_map.jpg", bbox_inches='tight', pad_inches=
0.1)
print(points.shape)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
(424, 448)
```



THD Geospatial Analysis

Obtaining sub-dataframes from the main dataframe based on the THD and then holding them in a dictionary that can be called by THD name

In [30]:

```
#Grab the list of json files that will be used to index data from segmentation
 folder
files = [i for i in os.listdir(THD1_path) if os.path.isfile(os.path.join(THD1_
path,i)) and \
         'GROUPDATA_' in i]

print(len(files)) #if correctly done, should only be 137

#Dictionary holding all of THD1's GeoDataFrames groups
gdfs1 = {} #Starting empty dictionary

# Got this code from this youtube video: https://www.youtube.com/watch?v=hZNeK
PZRPdM
for file in files:
    group_name = file.split(' ')[1][:-5].replace('.', '_') #get group number i
n format of #_#_#
    dataframe_name = 'gdf' + '_' + group_name #example = gdf_25_1_0
    json_file = THD1_path + file

    #Empty Dictionary to hold json file
    CONFIG_PROPERTIES = {}
    try:
        with open(json_file) as data_file:
            CONFIG_PROPERTIES = json.load(data_file)
    except IOError as e:
        print(e)
        exit(1)

    #list of rows in the THD group - will be used to create a subset of
    #the larger whole dataset attributed
    row_indices = CONFIG_PROPERTIES['rows']

    #Geo Dataframe of data in Subgroup
    gdfs1[dataframe_name] = gdf_full.iloc[row_indices, :]


#checking
for gdf in gdfs1:
    print(gdf), print(gdfs1[gdf].shape)
```

```
137
gdf_0_0_0
(255221, 448)
gdf_1_0_0
(255221, 448)
gdf_10_0_0
(177558, 448)
gdf_10_1_1
(201, 448)
gdf_10_7_2
(8633, 448)
gdf_10_7_3
(6264, 448)
gdf_10_7_4
(4225, 448)
gdf_10_7_5
(1913, 448)
gdf_10_7_6
(288, 448)
gdf_10_7_7
(259, 448)
gdf_10_8_10
(127, 448)
gdf_10_8_8
(11761, 448)
gdf_10_8_9
(4301, 448)
gdf_10_9_11
(264, 448)
gdf_10_9_12
(204, 448)
gdf_10_9_13
(168, 448)
gdf_10_9_14
(151, 448)
gdf_11_0_0
(176065, 448)
gdf_11_2_1
(835, 448)
gdf_11_2_10
(183, 448)
gdf_11_2_2
(545, 448)
gdf_11_2_3
(485, 448)
gdf_11_2_4
(396, 448)
gdf_11_2_5
(330, 448)
gdf_11_2_6
(324, 448)
gdf_11_2_7
(200, 448)
gdf_11_2_8
(185, 448)
gdf_11_2_9
(185, 448)
```

```
gdf_11_3_11
(776, 448)
gdf_11_3_12
(482, 448)
gdf_11_3_13
(159, 448)
gdf_11_3_14
(106, 448)
gdf_11_3_15
(100, 448)
gdf_11_4_16
(103, 448)
gdf_11_8_17
(3460, 448)
gdf_11_8_18
(2576, 448)
gdf_11_8_19
(890, 448)
gdf_11_8_20
(834, 448)
gdf_11_8_21
(195, 448)
gdf_11_8_22
(181, 448)
gdf_11_8_23
(119, 448)
gdf_11_9_24
(176, 448)
gdf_12_0_0
(173792, 448)
gdf_13_0_0
(171695, 448)
gdf_14_0_0
(168693, 448)
gdf_14_0_1
(235, 448)
gdf_14_0_2
(202, 448)
gdf_15_0_0
(163016, 448)
gdf_15_0_1
(199, 448)
gdf_15_0_2
(104, 448)
gdf_16_0_0
(157204, 448)
gdf_16_0_1
(176, 448)
gdf_17_0_0
(151749, 448)
gdf_17_0_1
(411, 448)
gdf_17_0_2
(252, 448)
gdf_17_0_3
(120, 448)
gdf_18_0_0
```

```
(147444, 448)
gdf_19_0_0
(141533, 448)
gdf_19_0_1
(565, 448)
gdf_19_0_2
(506, 448)
gdf_19_0_3
(235, 448)
gdf_2_0_0
(197763, 448)
gdf_2_0_1
(57458, 448)
gdf_20_0_0
(106845, 448)
gdf_20_0_1
(25348, 448)
gdf_20_0_2
(2386, 448)
gdf_20_0_3
(1256, 448)
gdf_20_0_4
(1070, 448)
gdf_20_0_5
(578, 448)
gdf_21_0_0
(91627, 448)
gdf_21_0_1
(376, 448)
gdf_21_0_2
(166, 448)
gdf_21_0_3
(159, 448)
gdf_21_0_4
(122, 448)
gdf_21_0_5
(110, 448)
gdf_21_1_10
(219, 448)
gdf_21_1_11
(188, 448)
gdf_21_1_12
(185, 448)
gdf_21_1_13
(102, 448)
gdf_21_1_6
(4100, 448)
gdf_21_1_7
(3302, 448)
gdf_21_1_8
(853, 448)
gdf_21_1_9
(408, 448)
gdf_22_0_0
(79438, 448)
gdf_23_0_0
(65054, 448)
```

```
gdf_23_0_1
(173, 448)
gdf_23_0_2
(128, 448)
gdf_23_0_3
(120, 448)
gdf_23_0_4
(104, 448)
gdf_24_0_0
(12457, 448)
gdf_24_0_1
(12414, 448)
gdf_24_0_2
(10163, 448)
gdf_24_0_3
(8468, 448)
gdf_24_0_4
(1141, 448)
gdf_24_0_5
(412, 448)
gdf_24_0_6
(305, 448)
gdf_24_0_7
(197, 448)
gdf_24_0_8
(116, 448)
gdf_24_0_9
(113, 448)
gdf_25_0_0
(139, 448)
gdf_25_0_1
(122, 448)
gdf_25_0_2
(118, 448)
gdf_25_0_3
(107, 448)
gdf_25_1_4
(5915, 448)
gdf_25_1_5
(3099, 448)
gdf_3_0_0
(181408, 448)
gdf_3_0_1
(16353, 448)
gdf_3_1_2
(57404, 448)
gdf_4_0_0
(181407, 448)
gdf_4_1_1
(16345, 448)
gdf_4_2_2
(57314, 448)
gdf_5_0_0
(181361, 448)
gdf_5_1_1
(16163, 448)
gdf_5_2_2
```

```
(57055, 448)
gdf_6_0_0
(181241, 448)
gdf_6_1_1
(15864, 448)
gdf_6_2_2
(56433, 448)
gdf_7_0_0
(180925, 448)
gdf_7_1_1
(14748, 448)
gdf_7_2_2
(54941, 448)
gdf_8_0_0
(180193, 448)
gdf_8_1_1
(7956, 448)
gdf_8_1_2
(2703, 448)
gdf_8_1_3
(1392, 448)
gdf_8_1_4
(575, 448)
gdf_8_1_5
(150, 448)
gdf_8_2_6
(53056, 448)
gdf_9_0_0
(179247, 448)
gdf_9_1_1
(2303, 448)
gdf_9_1_2
(1504, 448)
gdf_9_1_3
(1097, 448)
gdf_9_1_4
(888, 448)
gdf_9_2_5
(166, 448)
gdf_9_2_6
(124, 448)
gdf_9_6_7
(24524, 448)
gdf_9_6_8
(19993, 448)
gdf_9_6_9
(5204, 448)
```

```
In [15]: #Grab the list of json files that will be used to index data from segmentation
          folder
         files = [i for i in os.listdir(THD2_path) if os.path.isfile(os.path.join(THD2_
         path,i)) and \
                  'GROUPDATA_' in i]

         #Dictionary holding all of THD2's GeoDataFrames groups
         gdfs2 = {} #Starting empty dictionary

         # Got this code from this youtube video: https://www.youtube.com/watch?v=hZNeK
         PZRPdM
         for file in files:
             group_name = file.split(' ')[1][:-5].replace('.', '_') #get group number i
         n format of #_#_#
             dataframe_name = 'gdf' + '_' + group_name #example = gdf_25_1_0
             json_file = THD2_path + file

             #Empty Dictionary to hold json file
             CONFIG_PROPERTIES = {}
             try:
                 with open(json_file) as data_file:
                     CONFIG_PROPERTIES = json.load(data_file)
             except IOError as e:
                 print(e)
                 exit(1)

             #list of rows in the THD group - will be used to create a subset of
             #the larger whole dataset attributed
             row_indices = CONFIG_PROPERTIES['rows']

             #Geo Dataframe of data in Subgroup
             gdfs2[dataframe_name] = gdf_full.iloc[row_indices, :]

         #Checking
         for gdf in gdfs2:
             print(gdf), print(gdfs2[gdf].shape)
```

```
gdf_0_0_0
(255221, 448)
gdf_1_0_0
(255221, 448)
gdf_10_0_0
(95617, 448)
gdf_10_0_1
(652, 448)
gdf_10_0_2
(344, 448)
gdf_10_1_10
(191, 448)
gdf_10_1_11
(152, 448)
gdf_10_1_12
(141, 448)
gdf_10_1_13
(141, 448)
gdf_10_1_14
(140, 448)
gdf_10_1_15
(115, 448)
gdf_10_1_16
(109, 448)
gdf_10_1_17
(106, 448)
gdf_10_1_18
(105, 448)
gdf_10_1_19
(105, 448)
gdf_10_1_3
(1198, 448)
gdf_10_1_4
(794, 448)
gdf_10_1_5
(354, 448)
gdf_10_1_6
(316, 448)
gdf_10_1_7
(303, 448)
gdf_10_1_8
(272, 448)
gdf_10_1_9
(210, 448)
gdf_11_0_0
(92953, 448)
gdf_11_0_1
(118, 448)
gdf_12_0_0
(90427, 448)
gdf_13_0_0
(85520, 448)
gdf_13_0_1
(279, 448)
gdf_14_0_0
(77533, 448)
gdf_14_0_1
```

```
(631, 448)
gdf_15_0_0
(66514, 448)
gdf_15_0_1
(1433, 448)
gdf_15_0_2
(351, 448)
gdf_15_0_3
(298, 448)
gdf_15_0_4
(185, 448)
gdf_15_0_5
(104, 448)
gdf_15_0_6
(100, 448)
gdf_16_0_0
(32627, 448)
gdf_16_0_1
(21668, 448)
gdf_16_0_2
(202, 448)
gdf_16_0_3
(189, 448)
gdf_16_0_4
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gdf_16_0_6
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gdf_17_0_3
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gdf_17_0_4
(821, 448)
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gdf_17_0_6
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gdf_17_1_10
(106, 448)
gdf_17_1_7
(7839, 448)
gdf_17_1_8
(598, 448)
gdf_17_1_9
(408, 448)
gdf_18_0_0
(106, 448)
gdf_2_0_0
(235782, 448)
```

```
gdf_2_0_1
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gdf_2_0_10
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gdf_2_0_11
(507, 448)
gdf_2_0_12
(261, 448)
gdf_2_0_13
(128, 448)
gdf_2_0_2
(3043, 448)
gdf_2_0_3
(2982, 448)
gdf_2_0_4
(2442, 448)
gdf_2_0_5
(1563, 448)
gdf_2_0_6
(1418, 448)
gdf_2_0_7
(946, 448)
gdf_2_0_8
(806, 448)
gdf_2_0_9
(648, 448)
gdf_3_0_0
(235552, 448)
gdf_3_2_1
(234, 448)
gdf_3_2_2
(148, 448)
gdf_3_2_3
(107, 448)
gdf_3_4_4
(112, 448)
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gdf_4_0_1
(96459, 448)
gdf_4_0_10
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gdf_4_0_2
(21008, 448)
gdf_4_0_3
(971, 448)
gdf_4_0_4
(879, 448)
gdf_4_0_5
(674, 448)
gdf_4_0_6
(569, 448)
gdf_4_0_7
(488, 448)
gdf_4_0_8
(180, 448)
gdf_4_0_9
```

```
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(8629, 448)
gdf_5_1_10
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(1010, 448)
gdf_5_1_12
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(1005, 448)
gdf_5_1_14
(800, 448)
gdf_5_1_15
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gdf_5_1_17
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gdf_5_1_18
(684, 448)
gdf_5_1_19
(680, 448)
gdf_5_1_2
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(606, 448)
gdf_5_1_21
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gdf_5_1_23
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gdf_5_1_24
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gdf_5_1_25
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gdf_5_1_26
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gdf_5_1_4
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gdf_5_1_5
(2011, 448)
gdf_5_1_6
(1923, 448)
gdf_5_1_7
(1867, 448)
gdf_5_1_8
(1771, 448)
gdf_5_1_9
(1650, 448)
```

```
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gdf_5_2_29
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gdf_6_2_12
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gdf_6_2_13
(537, 448)
gdf_6_2_14
(509, 448)
gdf_6_2_15
(474, 448)
gdf_6_2_16
(440, 448)
gdf_6_2_17
(360, 448)
gdf_6_2_18
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gdf_6_2_19
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gdf_6_2_2
(42788, 448)
gdf_6_2_20
(284, 448)
gdf_6_2_21
(259, 448)
gdf_6_2_22
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gdf_6_2_23
(152, 448)
gdf_6_2_3
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gdf_6_2_4
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gdf_6_2_7
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gdf_6_2_8
(1224, 448)
gdf_6_2_9
(1149, 448)
gdf_6_28_28
(9816, 448)
gdf_6_28_29
(5100, 448)
gdf_6_29_30
```

```
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gdf_6_29_31
(2459, 448)
gdf_6_3_24
(143, 448)
gdf_6_5_25
(143, 448)
gdf_6_6_26
(175, 448)
gdf_6_7_27
(109, 448)
gdf_7_0_0
(102526, 448)
gdf_7_1_1
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gdf_7_1_2
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gdf_7_1_3
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gdf_7_2_11
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gdf_7_2_12
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gdf_7_2_13
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gdf_7_2_7
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gdf_7_2_9
(684, 448)
gdf_7_28_17
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gdf_7_28_18
(4566, 448)
gdf_7_29_19
(1857, 448)
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(1242, 448)
gdf_7_30_22
(2062, 448)
gdf_7_30_23
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gdf_7_31_24
(1580, 448)
```

```
gdf_7_31_25
(587, 448)
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(383, 448)
gdf_7_4_16
(176, 448)
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(2042, 448)
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(4231, 448)
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(555, 448)
gdf_8_19_32
(354, 448)
gdf_8_19_33
(290, 448)
gdf_8_19_34
(136, 448)
gdf_8_2_10
(127, 448)
gdf_8_2_11
(110, 448)
gdf_8_2_7
(190, 448)
gdf_8_2_8
(170, 448)
gdf_8_2_9
(159, 448)
gdf_8_20_35
(470, 448)
gdf_8_20_36
(150, 448)
gdf_8_21_37
(315, 448)
gdf_8_22_38
(139, 448)
gdf_8_22_39
(132, 448)
gdf_8_4_12
(17843, 448)
gdf_8_4_13
```

```
(1221, 448)
gdf_8_4_14
(1187, 448)
gdf_8_4_15
(617, 448)
gdf_8_4_16
(584, 448)
gdf_8_4_17
(534, 448)
gdf_8_4_18
(437, 448)
gdf_8_4_19
(436, 448)
gdf_8_4_20
(278, 448)
gdf_8_4_21
(273, 448)
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gdf_8_4_23
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gdf_8_4_24
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gdf_8_4_25
(181, 448)
gdf_8_4_26
(176, 448)
gdf_8_4_27
(163, 448)
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gdf_9_12_10
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gdf_9_12_11
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(205, 448)
gdf_9_12_13
(165, 448)
gdf_9_12_14
(143, 448)
gdf_9_12_15
(121, 448)
gdf_9_12_2
(1250, 448)
gdf_9_12_3
(701, 448)
gdf_9_12_4
(698, 448)
gdf_9_12_5
(535, 448)
gdf_9_12_6
(525, 448)
gdf_9_12_7
(336, 448)
```
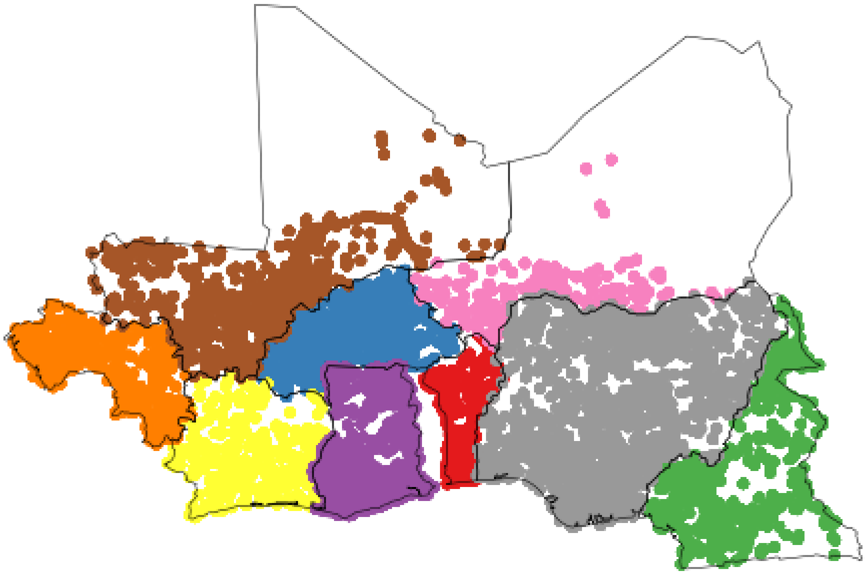

```
gdf_9_12_8
(329, 448)
gdf_9_12_9
(295, 448)
gdf_9_28_16
(876, 448)
gdf_9_28_17
(322, 448)
gdf_9_28_18
(101, 448)
gdf_9_29_19
(891, 448)
gdf_9_29_20
(171, 448)
gdf_9_30_21
(1466, 448)
gdf_9_30_22
(1006, 448)
gdf_9_30_23
(348, 448)
gdf_9_30_24
(176, 448)
```

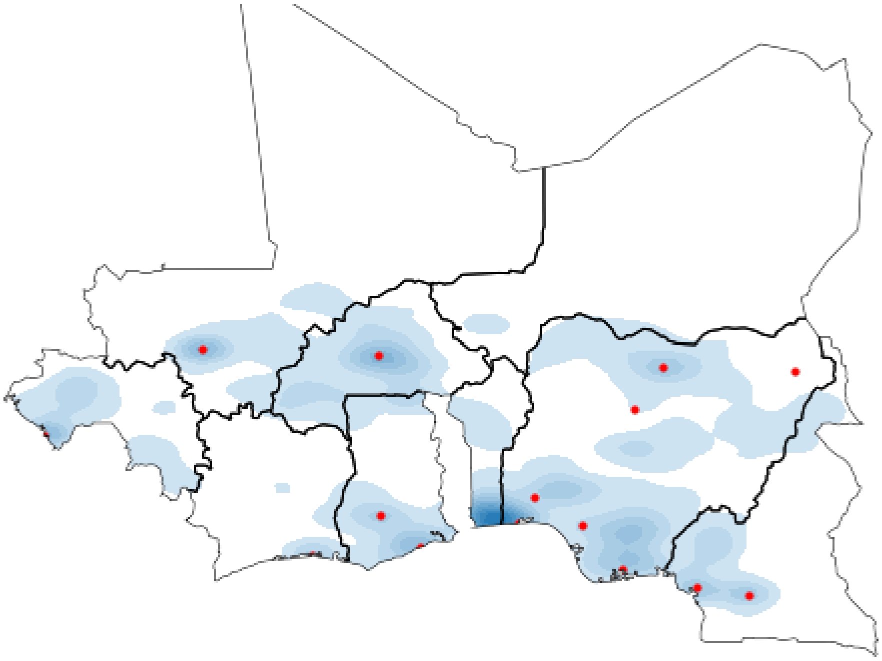
In [32]:

```
#Plot out entire database
#plot sample points colored by year
base = gplt.polyplot(borders, linewidth=0.5, projection=gcrs.AlbersEqualArea
())
gplt.pointplot(gdf_full,
               hue = 'COUNTRY', legend=False, categorical=True,
               projection=gcrs.AlbersEqualArea(), ax=base)
plt.savefig("full_data_point.jpg")
```



```
In [33]: #plot heat graph
         ax = gplt.kdeplot(gdf_full,
                          shade=True, shade_lowest=False,
                          clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)
         plt.savefig("full_data_KD.jpg")
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

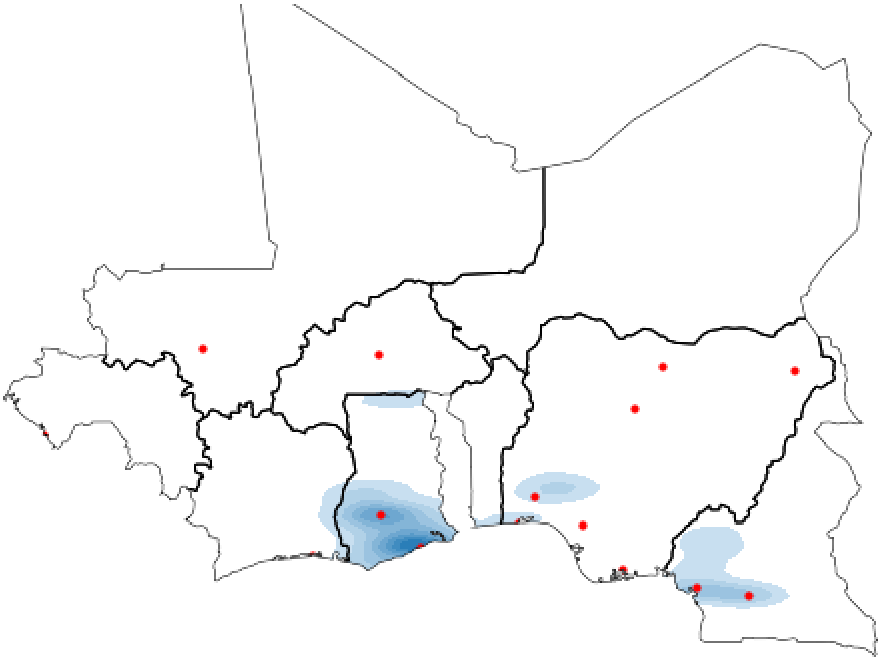


As we can see from the heat map of the entire dataset, there are certain areas where the DHS survey sampled more women. This is to be expected as the DHS samples a representative random sample from randomly selected areas. Areas that have a larger population will need a large sample size to be a decent representative of the population (STAT 101).

THD with only DHS survey data

```
In [34]: #THD2_24.0.1 - Higher instances of violence:
         points = gdfs1['gdf_24_0_1']
         ax = gplt.kdeplot(points,
                           shade=True, shade_lowest=False,
                           clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax=ax, marker='o', color='red', markersize=10)

         print(points.shape)
         plt.savefig("THD_women_24_0_1.jpeg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

(12414, 448)
```

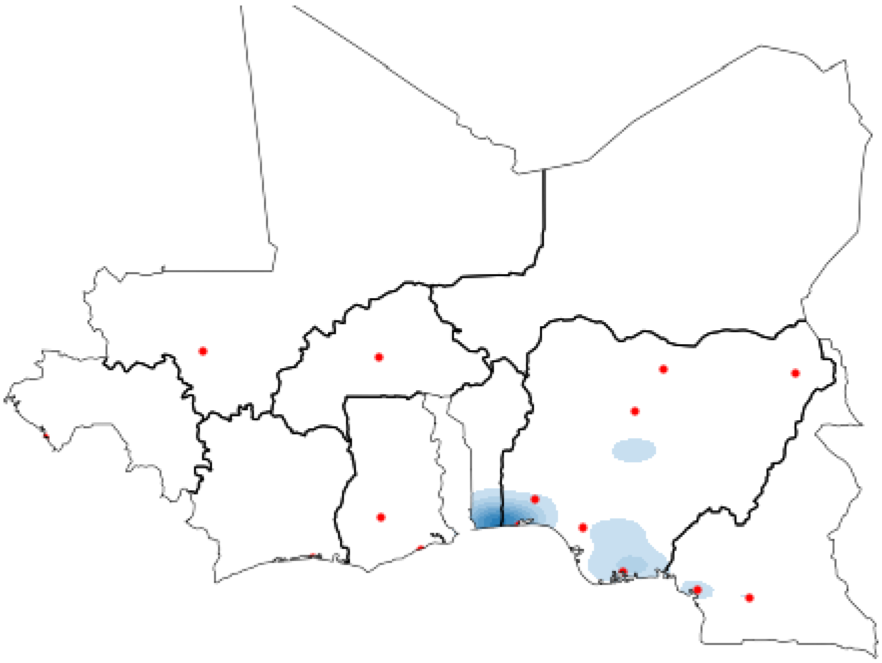


In [35]:

```
#THD2_24.0.3 - Higher instances of violence:
points = gdfs1['gdf_24_0_3']
ax = gplt.kdeplot(points,
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax=ax, marker='o', color='red', markersize=10)

print(points.shape)
plt.savefig("THD_women_24_0_3.jpeg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

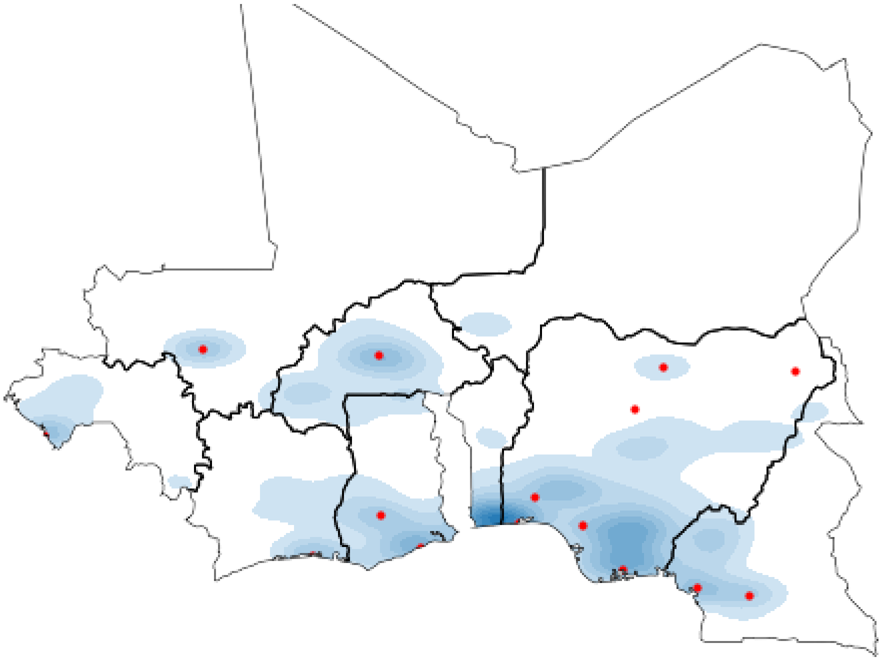
```
(8468, 448)
```



In [36]:

```
#2.0.1 - Mainly young and unmarried women - higher instances of violence
ax = gplt.kdeplot(gdfs1['gdf_2_0_1'],
             shade=True, shade_lowest=False,
             #n_levels = 50,
             clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_women_2_0_1.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

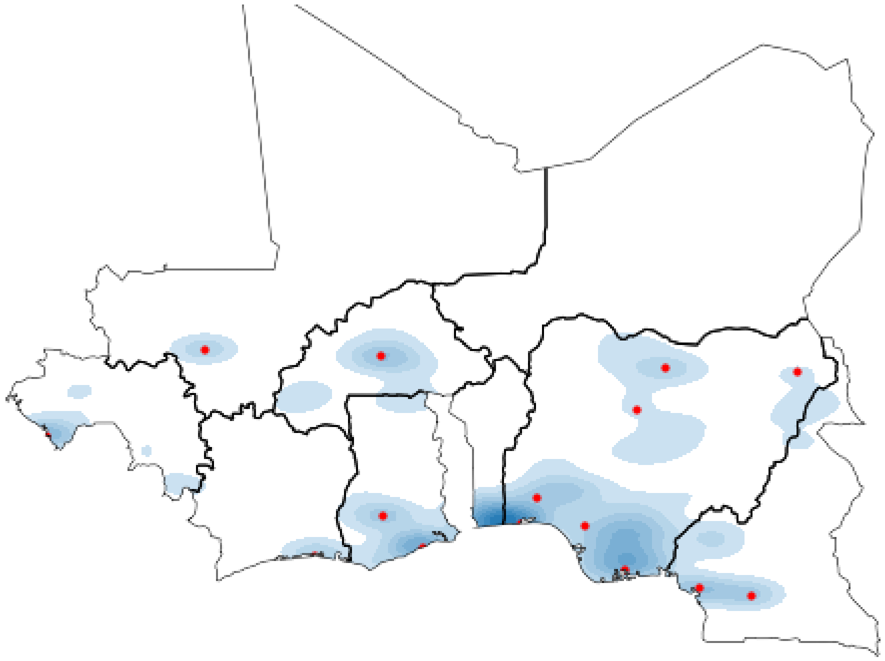


THD with DHS and ACLED Data

5.1.2 - 5.1.13 come out of the connected component who held 99% of remaining conflict instances after the major split where data with 99% of the conflict went into one connected component and the rest was split between singl and married women. I want to see what might be causing the split because it's hard to tell using the comparisions in Ayasdi.

```
In [38]: #THD2_5.1.2 - Frist break from 4.0.1 and only one to continue to decompose
         ax = gplt.kdeplot(gdfs2['gdf_5_1_2'],
                      shade=True, shade_lowest=False,
                      clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_2.jpg", bbox_inches='tight', pad_inches=0.1)
```

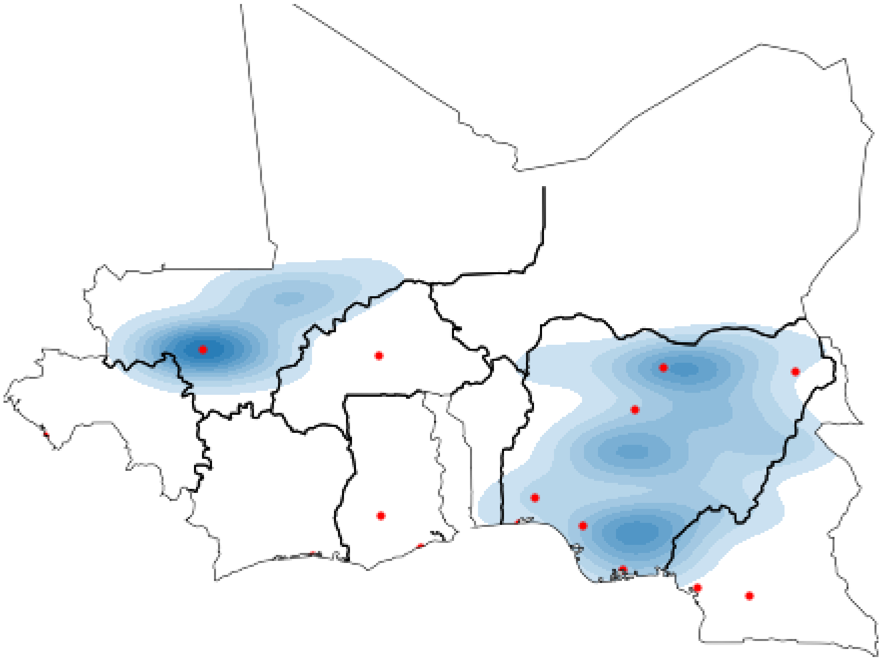
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [39]:

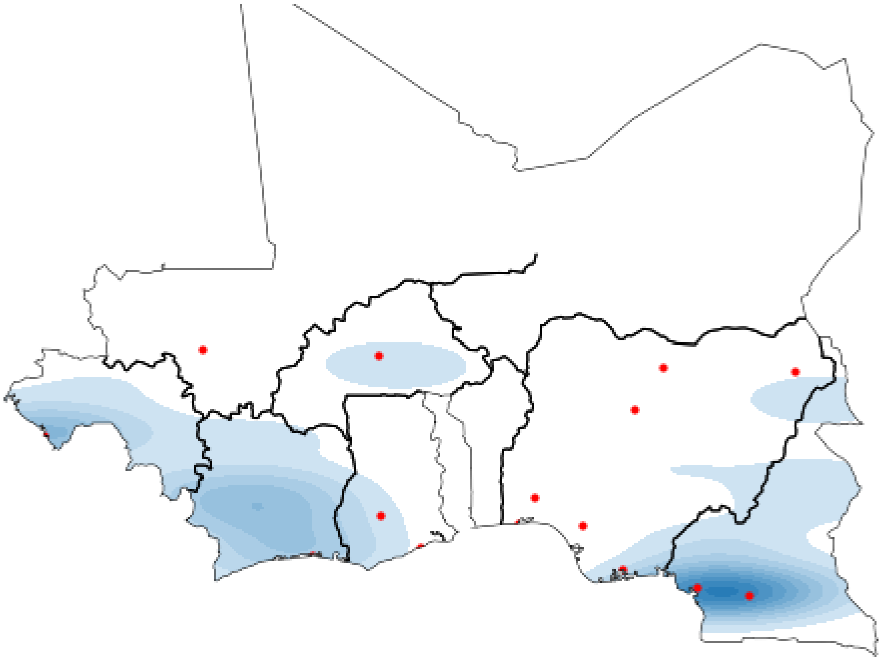
```
#THD2_5.1.3
ax = gplt.kdeplot(gdfs2['gdf_5_1_3'],
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_all_5_1_3.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



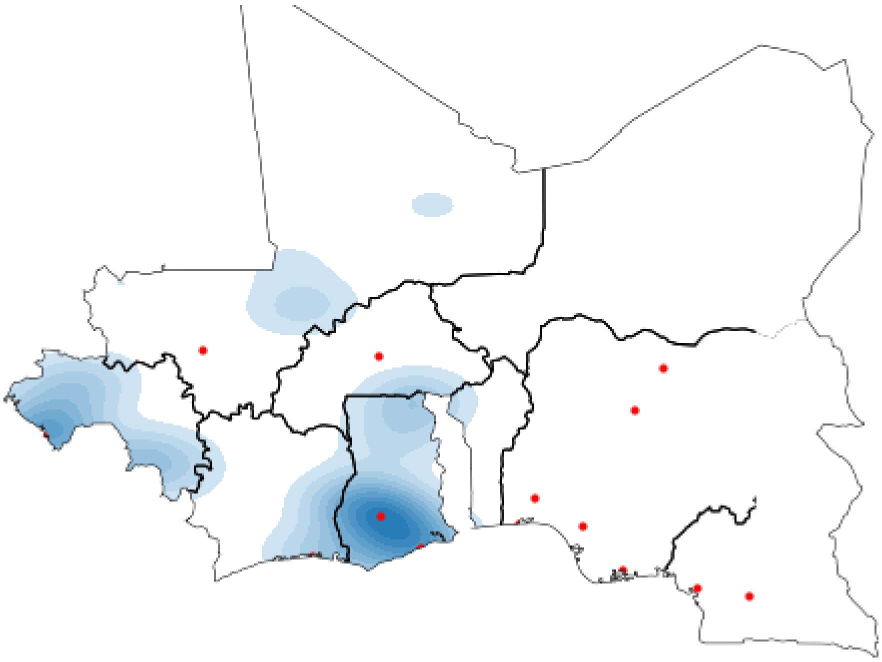
```
In [40]: #THD2_5.1.4
         ax = gplt.kdeplot(gdfs2['gdf_5_1_4'],
                      shade=True, shade_lowest=False,
                      clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_4.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [41]: #THD2_5.1.5
         ax = gplt.kdeplot(gdfs2['gdf_5_1_5'],
                          shade=True, shade_lowest=False,
                          clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_5.jpg", bbox_inches='tight', pad_inches=0.1)
```

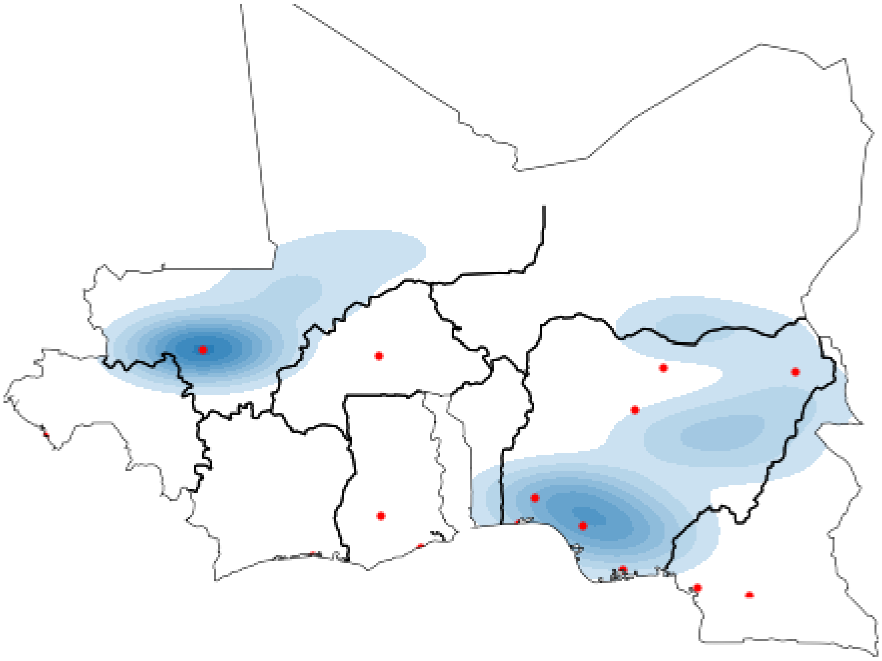
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [42]:

```
#THD2_5.1.6
ax = gplt.kdeplot(gdfs2['gdf_5_1_6'],
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_all_5_1_6.jpg", bbox_inches='tight', pad_inches=0.1)
```

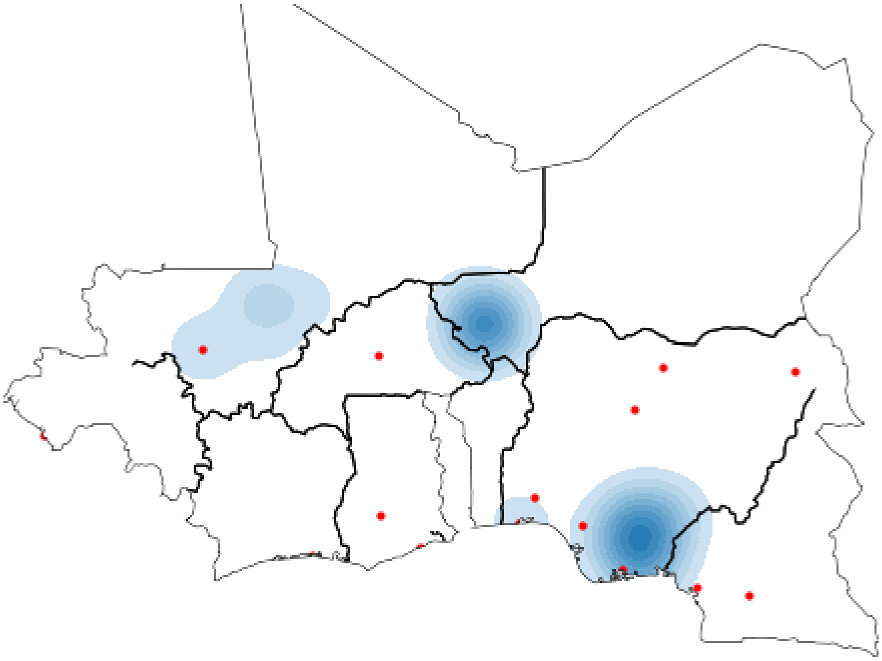
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [43]:

```
#THD2_5.1.7
ax = gplt.kdeplot(gdfs2['gdf_5_1_7'],
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_all_5_1_7.jpg", bbox_inches='tight', pad_inches=0.1)
```

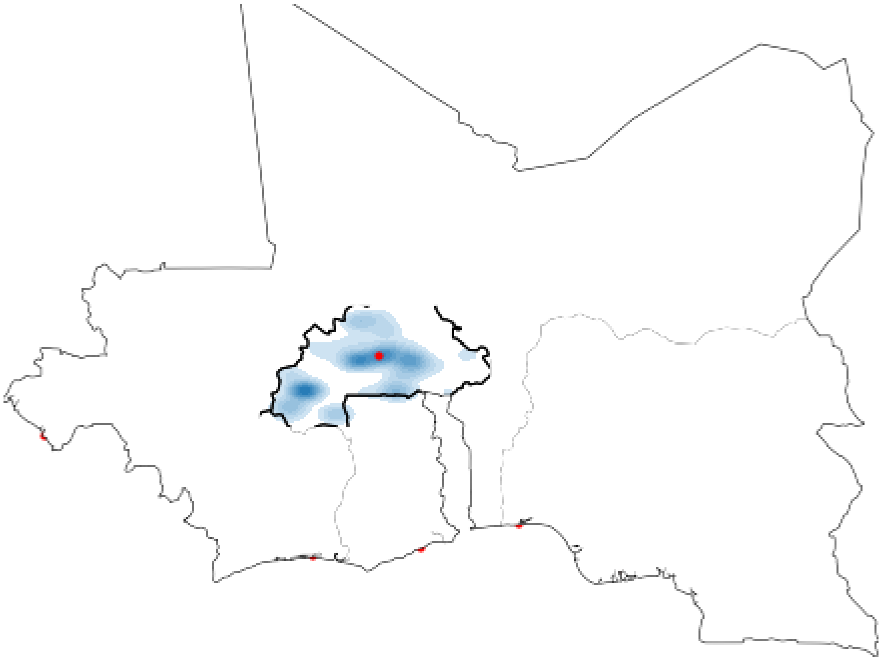
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [44]:

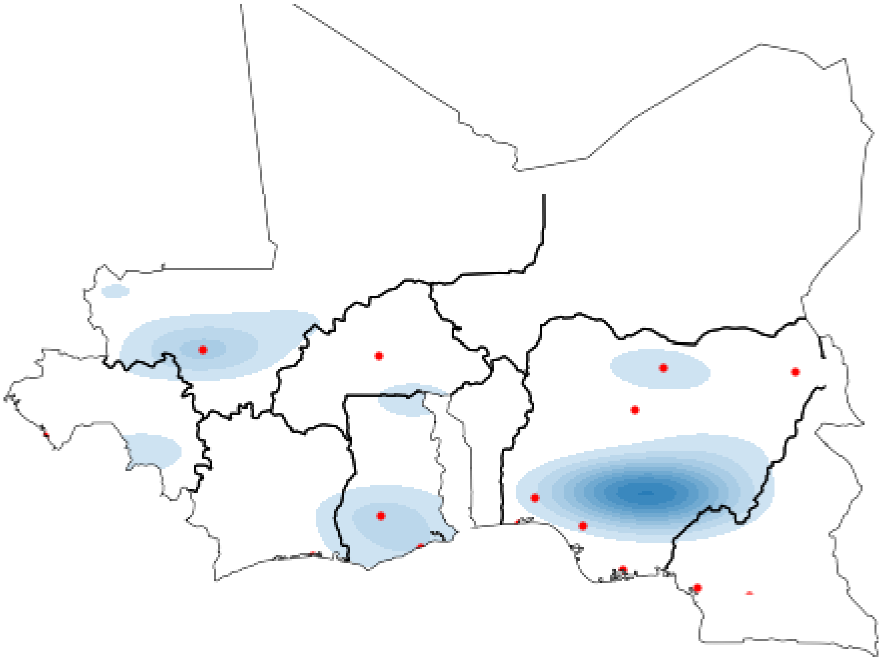
```
#THD2_5.1.8
ax = gplt.kdeplot(gdfs2['gdf_5_1_8'],
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_all_5_1_8.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [45]: #THD2_5.1.9
         ax = gplt.kdeplot(gdfs2['gdf_5_1_9'],
                           shade=True, shade_lowest=False,
                           clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_9.jpg", bbox_inches='tight', pad_inches=0.1)
```

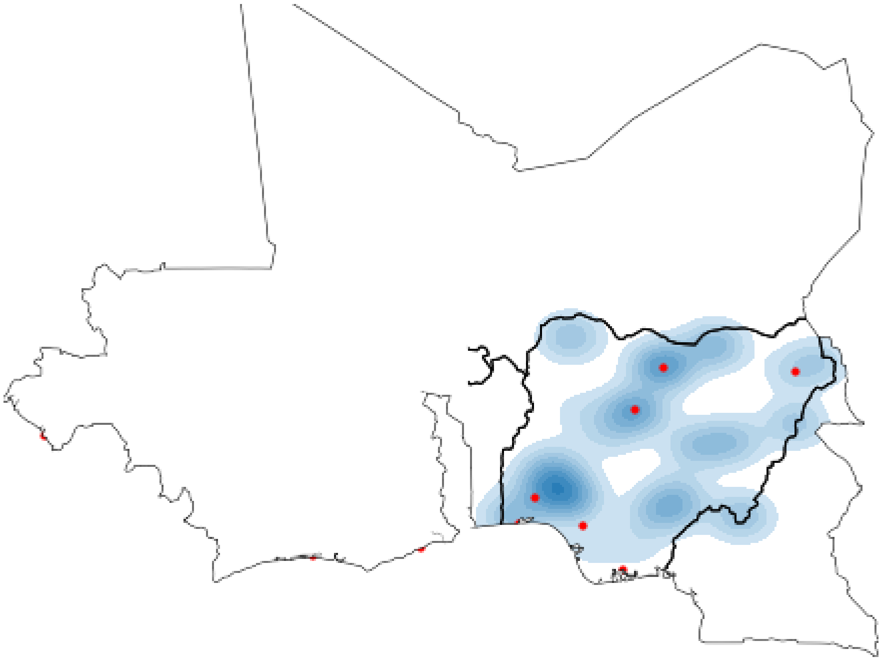
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [46]:

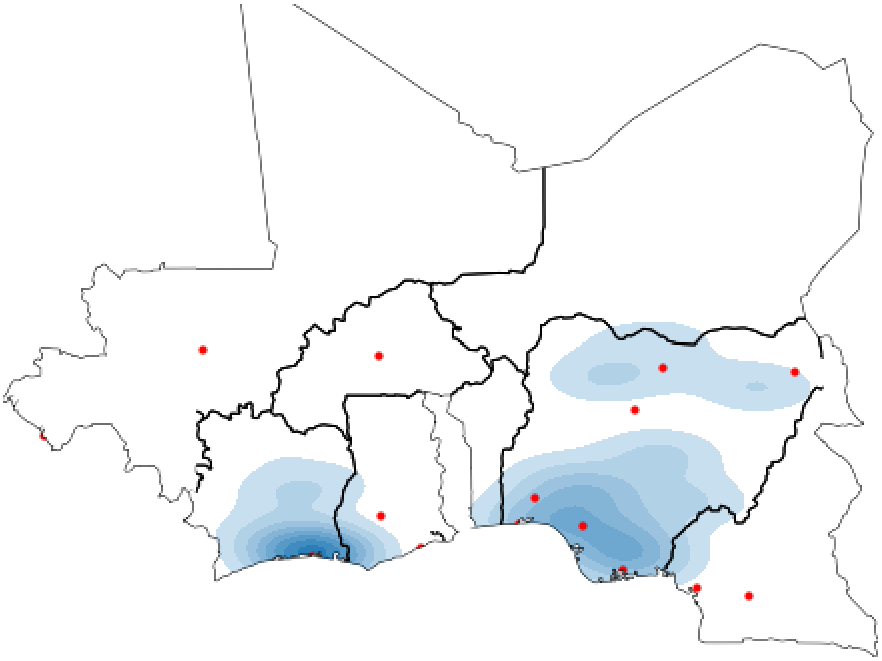
```
#THD2_5.1.10
ax = gplt.kdeplot(gdfs2['gdf_5_1_10'],
             shade=True, shade_lowest=False,
             clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

plt.savefig("THD_all_5_1_10.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



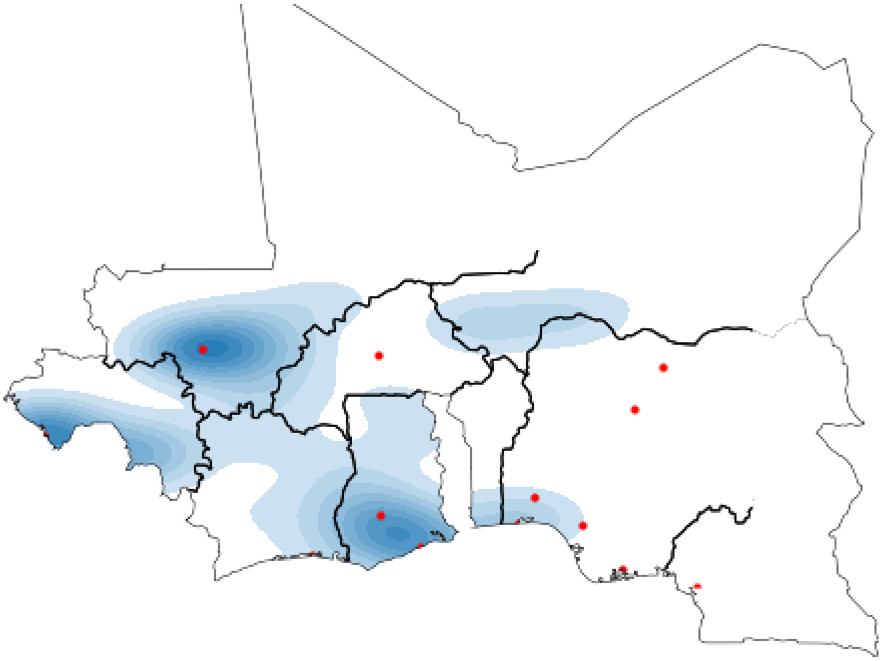
```
In [47]: #THD2_5.1.11
         ax = gplt.kdeplot(gdfs2['gdf_5_1_11'],
                          shade=True, shade_lowest=False,
                          clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_11.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [48]: #THD2_5.1.13
         ax = gplt.kdeplot(gdfs2['gdf_5_1_13'],
                          shade=True, shade_lowest=False,
                          clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
         0)

         plt.savefig("THD_all_5_1_13.jpg", bbox_inches='tight', pad_inches=0.1)
```

```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



^^ They seem to be more specific events.

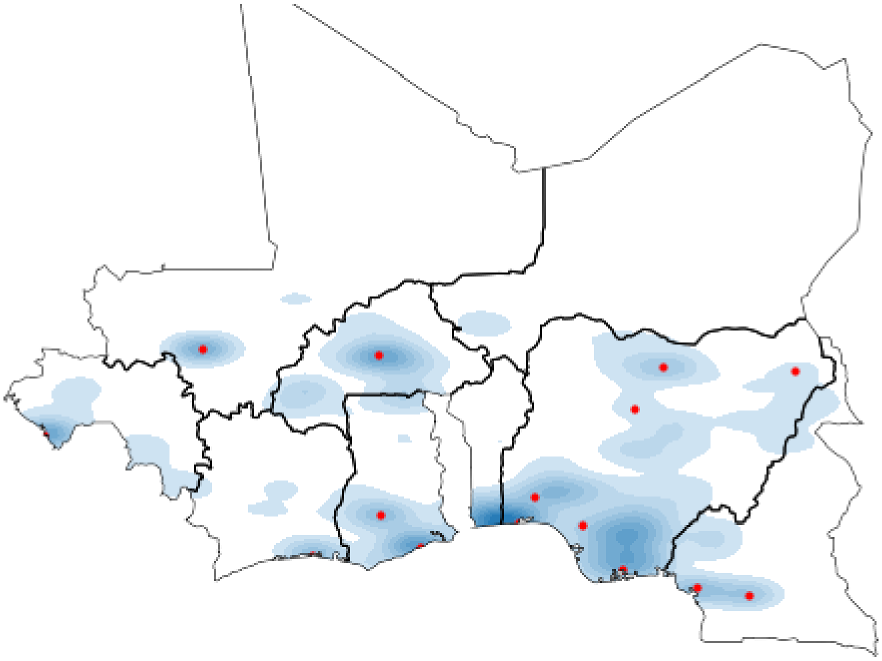
These are the nodes after the major split

In [21]:

```
#THD2_4.0.1 - Almost all instances of violence
ax = gplt.kdeplot(gdfs2['gdf_4_0_1'],
                  shade=True, shade_lowest=False,
                  clip=borders.geometry)
base = gplt.polyplot(borders, ax=ax)
base_cities = cities_large.plot(ax = ax, marker='o', color='red', markersize=1
0)

#print(gdfs['gdf_4_0_1'].shape)
print(gdfs2['gdf_4_0_1'].shape)
plt.savefig("THD_all_4_0_1.jpg", bbox_inches='tight', pad_inches=0.1)
```

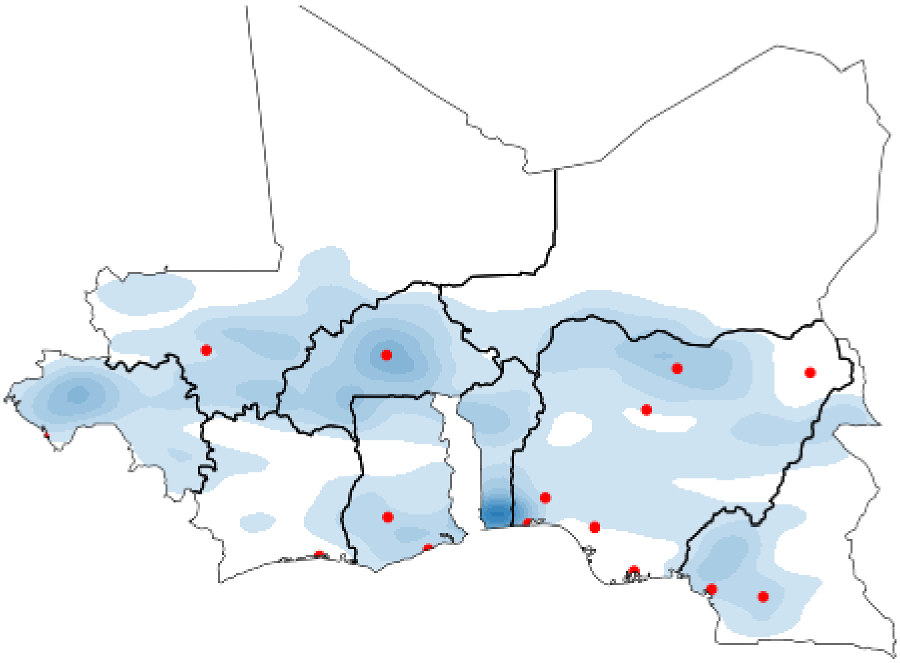
```
C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
(96459, 448)
```



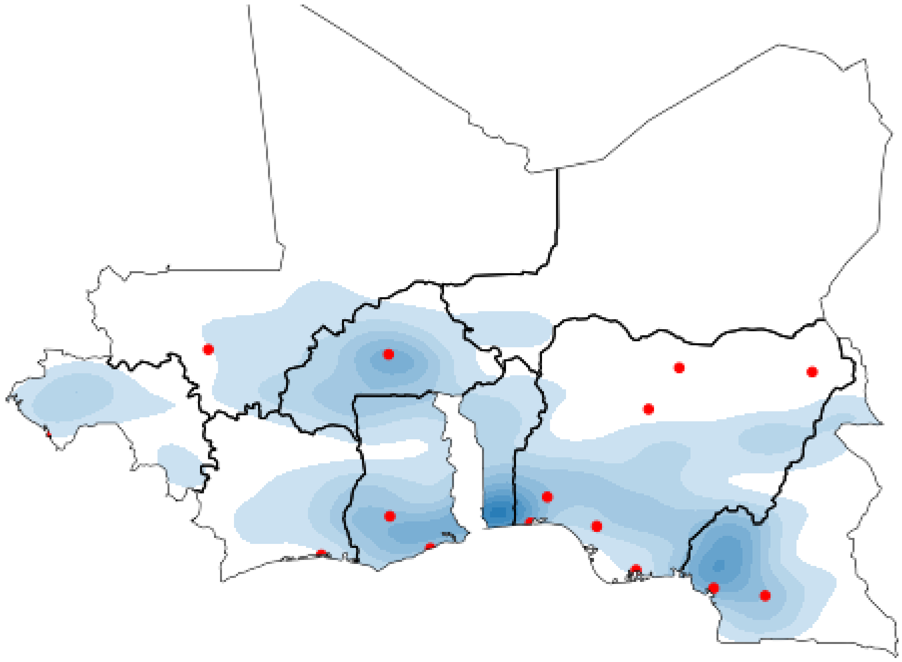
```
In [20]: #THD1_4.0.0 - married women with little conflict
         points = gdfs2['gdf_4_0_0']
         print(points.shape)
         ax = gplt.kdeplot(points,
                           shade=True, shade_lowest=False,
                           clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = gplt.pointplot(cities_large,ax=ax, color='red')

         plt.savefig("THD_all_4_0_0.jpeg", bbox_inches='tight', pad_inches=0.1)
```

```
(111773, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [19]: #THD1_4.0.2 - married women with little conflict
         points = gdfs2['gdf_4_0_2']
         print(points.shape)
         ax = gplt.kdeplot(points,
                          shade=True, shade_lowest=False,
                          clip=borders.geometry)
         base = gplt.polyplot(borders, ax=ax)
         base_cities = gplt.pointplot(cities_large,ax=ax, color='red')
         plt.savefig("THD_all_4_0_2.jpeg", bbox_inches='tight', pad_inches=0.1)
```

```
(21008, 448)

C:\Users\Michaela\AppData\Roaming\Python\Python37\site-packages\scipy\stats\s
tats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional
indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the f
uture this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

(21008, 448)
```



```
In [ ]:
```

Bibliography

1. National Geographic's Education Blog, "Africa's Dazzling Diveristy," 2015. https://blog.education.nationalgeographic.org/2015/02/18/africas-dazzling-diversity/, [Accessed: 26- Feb- 2019].

2. J. Tesfu, "Mali Empire (ca. 1200-)," 2008. https://www.blackpast.org/global-african-history/mali-empire-ca-1200/, [Accessed: 26- Feb- 2019].

3. Michigan State Univeristy: African Studies Center, "Module Seven (B), Activity Two: Colonial Exploration and Conquest in Africa," in *Exploring Africa*, World Press, 2018. http://exploringafrica.matrix.msu.edu/curriculum/unit-two/module-seven-b/, [Accessed: 26- Feb- 2019].

4. OECD, "Violent Events," *MAPS & FACTS: Sahal and West AFrica Club*, 2015.

5. OECD, "Ebola killed more than 11,000 people," *MAPS & FACTS: Sahal and West AFrica Club*, Jan 2016.

6. OECD, "West African Girls are Being Married Off too Young," *MAPS & FACTS: Sahal and West AFrica Club*, Mar 2016.

7. OECD, "Military Expenditures in West Africa," *MAPS & FACTS: Sahel and West Africa Club*, Jul 2018.

8. J. J. O'Connor and E. F. Robertson, "A History of Topology." MacTutor History of Mathematics Archive, 1996.

9. R. Kraft, *Illustrations of Data Analysis Using the Mapper Algorithm and Persistent Homology.* Degree project, Kth Royal Institute of Technology: School of Engineering Sciences, Stockholm, 2016.

10. G. Carlsson, "Three Properties of Topological Analysis," 2014. https://www.ayasdi.com/blog/topology/three-properties-of-topological-analysis, [Accessed: 26- Feb- 2019].

11. A. Gilmore and Ayasdi, "The Shape of Data," 2015. https://www.youtube.com/watch?v=zDe72aINF2s&t=491s,[Accessed: 26- Feb- 2019].

12. F. Chazal and B. Michel, "An introduction to Topological Data Analysis: fundamental and practical aspects for data scientists," *arXiv e-prints*, p. arXiv:1710.04019, 2017.

13. The Central Intelligence Agency (CIA), "The World Factbook," 2018.

14. D. C. Conrad, *Empires of Medieval West Africa.* Chelsea House Publishers, 2010.

15. A. Marc, N. Verjee, and S. Mogaka, *The Challenge of Stability and Security in West Africa.* Washington, DC: Agence Française de Développement/The World Bank, 2015.

16. R. O. Collins, *African History: Text and Readings*, vol. 1. Princeton: Markus Wiener Publishers, 1990.

17. J. M. Kabia, *Humanitarian Intervention and Conflict Resolution in West Africa: From ECOMOG to ECOML.* Burlington, VT: Ashgate Publishing Limited, 2009.

18. I. W. Zartman, T. D. Bakary, A. A. Boahen, A. Gboyega, and D. Rothchild, *Governance as Conflict Management: Politics and Violence in West Africa.* Brookings Institution Press, dec 1996.

19. The World Bank, "World Bank Country and Lending Groups – Country Classification," 2018. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups, [Accessed: 26- Feb-2019].

20. N. Bouchama, G. Ferrant, L. Fuiret, A. Meneses, and A. Thim, "Gender Inequality in West African Social Institutions," *OECD: Sahal and West Africa Club*, no. 13, 2018.

21. International Crisis Group, "Nigeria : Women and the Boko Haram Insurgency," tech. rep., International Crisis Group, dec 2016.

22. D. L. Heymann, L. Chen, K. Takemi, D. P. Fidler, J. W. Tappero, M. J. Thomas, T. A. Kenyon, T. R. Frieden, D. Yach, S. Nishtar, A. Kalache, P. L. Olliaro, P. Horby, E. Torreele, L. O. Gostin, M. Ndomondo-Sigonda, D. Carpenter, S. Rushton, L. Lillywhite, B. Devkota, K. Koser, R. Yates, R. S. Dhillon, and R. P. Rannan-Eliya, "Global Health Security: The Wider Lessons from the West African Ebola Virus Disease Epidemic," *The Lancet*, vol. 385, no. 9980, pp. 1884–1899, 2015.

23. R. Berglee, "Subsaharan Africa," in *World Regional Geography: People, Places and Globalization*, ch. 7, pp. 374–480, University of Minnesota Libraries Publishing, 2012.

24. L. A. Mazzitelli, "Transnational Organized Crime in West Africa: the Additional Challenge," *International Affairs*, vol. 2006, no. April 2006, pp. 1071–1090, 2013.

25. B. Davidson, *A History of West Africa 1000 - 1800.* London: Addison-Wesley Longman Ltd, revised ed., Jul 1978.

26. N. Nunn and L. Wantchekon, “The Slave Trade and the Origins of Mistrust in Africa,” *American Economic Review*, vol. 101, no. 7, pp. 3221–3252, 2011.

27. A. M. Duva, “The Lone Star: The Story of Liberia,” *PBS*, 2002. `http://www.pbs.org/wgbh/globalconnections/liberia/essays/history/`, [Accessed: 26- Feb- 2019].

28. N. Annan, “Violent Conflicts and Civil Strife in West Africa: Causes, Challenges and Prospects,” *Stability: International Journal of Security & Development*, vol. 3, no. 1, 2014.

29. P. Diaz, “The Empire in Africa,” 2006. Documentary: see `https://www.imdb.com/title/tt0495103/`, [Accessed: 26- Feb- 2019].

30. Vice, “The Cannibal Warlords of Liberia,” 2011. `https://www.youtube.com/watch?v=ZRuSS0iiFyo{&}t=693s`,[Accessed: 26- Feb- 2019].

31. CDC, “2014-2016 Ebola Outbreak in West Africa,” tech. rep., CDC, Dec 2017.

32. M. Mankad, Z. Ul-haq, L. Finnegan, F. Checchi, G. Graham, G. Alkema, P. Watt, and F. Goodwin, “A Wake-up Call: Lessons from Ebola for the World’s Health Systems,” tech. rep., Save the Children, 2015.

33. United Nations Development Programme, “Assessing the socio-economic impacts of Ebola Virus Disease in Guinea, Liberia and Sierra Leone: The Road to Recovery,” tech. rep., UNDP, 2014.

34. G. Ferrant and A. Kolev, “Does gender discrimination in social institutions matter for long-term growth? : Cross-country evidence,” *OECD Development Centre Working Papers*, pp. 1–45, 2016.

35. V. M. Hudson and H. Matfess, “In Plain Sight: The Neglected Linkage between Bride Price and Violent Conflict,” *International Security*, vol. 42, pp. 7–40, 2017.

36. N. D. Allen, “Assessing a Decade of U.S. Military Strategy in Africa,” *Orbis*, vol. 62, pp. 655–669, Aug 2018.

37. J. Borger, “US to send troops to Liberia,” *The Gardian*, 2003. `https://www.theguardian.com/world/2003/jul/03/julianborger`, [Accessed: 26- Feb- 2019].

38. G. Myre, “The Military Doesn’t Advertise It, But U.S. Troops Are All Over Africa,” *npr*, 2018. `https://www.npr.org/sections/parallels/2018/04/28/605662771/the-military-doesnt-advertise-it-but-u-s-troops-are-all-over-africa`,[Accessed: 26- Feb- 2019].

39. U.S. Africa Command Public Affairs, “U.S. Africa Command Mission Statement,” 2019. `https://www.africom.mil/media-room/photo/31498/u-s-africa-command-mission-statement`, [Accessed: 26- Feb- 2019].

40. United Nations Security Council (UNSC), “Resolution 2242,” 2015.

41. A. Gelman and J. Hill, “Missing-data imputation,” in *Data Analysis using Regression and Multilevel/Hierarchical Models* (R. M. Alvarex, N. L. Beck, and L. L. Wu, eds.), ch. 25, pp. 529–545, New York, NY: Cambridge University Press, 1st ed., 2007.

42. C. d. J. Oudraat and M. E. Brown, “Women, Gender, and Terrorism: The Missing Links,” tech. rep., Women in International Security, Washington, DC, 2016.

43. J. Krause, W. Krause, and P. Bränfors, “Women’s Participation in Peace Negotiations and the Durability of Peace,” *International Interactions*, vol. 44, no. 6, pp. 985–1016, 2018.

44. L. Woessmann, “The Economic Case for Education,” *Education Economics*, vol. 24, no. 1, pp. 3–32, 2016.

45. G. Psacharopoulos and H. A. Patrinos, “Returns to investment in education: a decennial review of the global literature,” *Education Economics*, vol. 26, no. 5, pp. 445–458, 2018.

46. Ayasdi, “Professor Gunnar Carlsson Intorduces Topological Data Analysis.” Youtube, 2013. `https://www.youtube.com/watch?v=XfWibrh6stw`, [Accessed: 26- Feb- 2019].

47. G. Carlsson, “Topology and Data,” *Bulletin of the American Mathematical Society*, vol. 46, no. 2, pp. 255–308, 2009.

48. J. R. Munkres, *Topology.* Prentice Hall, Inc., 2nd ed., 2000.

49. G. Singh, F. Memoli, and G. Carlsson, “Topological Methods for the Analysis of High Dimensional Data Sets and 3D Object Recognition,” in *Eurographics Symposium on Point-Based Graphics* (M. Botsch, R. Pajarola, B. Chen, and M. Zwicker, eds.), pp. 1–11, The Eurographics Association, 2007.

50. A. Hatcher, *Algebraic Topology.* Cambridge: Cambridge University Press, 2002.

51. K. Brown, D. Doran, R. Kramer, and B. Reynolds, “HELOC Applicant Risk Performance Evaluation by Topological Hierarchical Decomposition,” *CoRR*, vol. abs/1811.1, pp. 1–10, 2018. `https://arxiv.org/abs/1811.10658`, [Accessed: 26- Feb- 2019].

52. A. Bak, “Stanford Seminar - Topological Data Analysis: How Ayasdi used TDA to Solve Complex Problems,” Nov 2013. `https://www.youtube.com/watch?v=x3Hl85OBuc0{&}t=2930s`,[Accessed: 26- Feb- 2019].

53. R. A. Fisher, “The Use of Multiple Measurements in Taxonomic Problems,” *Annals of Eugenics*, vol. 7, pp. 179–188, 1936.

54. D. Dheeru and E. Karra Taniskidou, “{UCI} Machine Learning Repository,” *University of California, Irvine, School of Information and Computer Sciences*, 2017. `http://archive.ics.uci.edu/ml`, [Accessed 26- Feb- 2019].

55. M. Vicolau, A. J. Levine, and G. Carlsson, “Topology based data analysis identifies a subgroup of breast cancers with a unique mutational profile and excellent survival,” *PNAS*, vol. 108, pp. 7265–7270, Apr 2011.

56. L. Li, W.-y. Cheng, B. S. Glicksberg, O. Gottesman, R. Tamler, R. Chen, E. P. Bottinger, and J. T. Dudley, “Identification of Type 2 Diabetes Subgroups through Topological Data Analysis of Patient Similarity — Ayasdi,” *Science Translational Medicine*, vol. 7, pp. 1–16, Oct 2015.

57. Ayasdi, “Credit Card Fraud Detection & Modeling: Reduce overall fraud exposure by the analysis of complex transaction data,” tech. rep., Ayasdi, 2013.

58. T. Hastie, R. Tibshirani, and J. Friedman, “Random Forest,” in *The Elements of Statistical Learning: Data mining, Inference, and Prediction*, Springer Series in Statistics, ch. 15, pp. 587– 603, Springer, New York, 2nd ed., 2009.

59. D. Xu, Y. Wang, Y. Meng, and Z. Zhang, “An Improved Data Anomaly Detection Method Based on Isolation Forest,” *Proceedings - 2017 10th International Symposium on Computational Intelligence and Design, ISCID 2017*, vol. 2, pp. 287–291, 2017.

60. A. Beiden, “Ayasdi Support: t-SNE Lens?,” Jul 2017. `https://ayasdicommunity.force.com/s/question/0D50P00003HCM2WSAX/tsne-lens`, [Accessed: 26- Feb- 2019].

61. L. van der Maaten and G. Hinton, “Visualizing Data using t-SNE,” *Journal of Machine Learning Research*, vol. 9, pp. 2579–2605, Nov 2008.

62. S. Arora, W. Hu, and P. K. Kothari, “An Analysis of the t-SNE Algorithm for Data Visualization,” *arXiv e-prints*, pp. 1–32, Mar 2018. `http://arxiv.org/abs/1803.01768`, [Accessed: 26- Feb- 2019].

63. J. Lawhead, *Learning Geospatial Analysis with Python.* Packt Publishing, 2nd ed., Dec 2015.

64. Ayasdi, "Knowledge: Selecting The Metric." Blog, aug 2018. `https://ayasdicommunity.force.com/s/article/Knowledge-Selecting-The-Metric`, [Accessed: 26- Feb- 2019].

65. Python Software Foundation, "Python Language Reference, version 2.7," 2001. `https://www.python.org/download/releases/2.7/`, [Accessed 26- Feb- 2019].

66. Python Software Foundation, "Python Language Reference, version 3.7," 2008. `https://www.python.org/downloads/release/python-370/`, [Accessed: 26- Feb- 2019].

67. GeoPandas Development Team, "GeoPandas," 2013. `https://github.com/geopandas/geopandas`, [Accessed: 26- Feb- 2019].

68. A. Bilogur, "Geoplot," 2016. `https://github.com/ResidentMario/geoplot`, [Accessed: 26- Feb- 2019].

69. B. Sandvik, "World Borders Dataset," 2009. `http://thematicmapping.org/downloads/world{_}borders.php`, [Accessed: 26- Feb- 2019].

70. Eris, "World Cities," Jun 2013. `https://hub.arcgis.com/datasets/6996f03a1b364dbab4008d99380370ed{_}0`, [Accessed: 26- Feb- 2019].

71. E. H. Boyle, M. King, and M. Sobek, "IPUMS-Demographic and Health Surveys: Version 5 [West Africa - Women]," 2018. `https://www.idhsdata.org/idhs/`, [Accessed 26- Feb- 2019].

72. ICF, "The DHS Program Spatial Data Repository." `https://spatialdata.dhsprogram.com/home/`, [Accessed: 26- Feb- 2019].

73. C. Raleigh, A. Linke, H. Hegre, and J. Karlsen, "Introducing ACLED Armed Conflict Location and Event Data," *Journal of Peace Research*, vol. 47, no. 5, pp. 651–660, 2010.

74. T. D. Program, "Part I: Introduction to DHS Sampling Procedures," Oct 2014. `https://www.youtube.com/watch?v=DD5npelwh80`, [Accessed: 26- Feb- 2019].

75. C. Raleigh and C. Dowd, "Armed Conflict Location and Event Data Project (ACLED) Codebook," 2017. `https://www.acleddata.com/wp-content/uploads/2017/01/ACLED_Codebook_2017.pdf`, [Accessed: 26- Feb- 2019].

76. W. McKinney, “Data Structures for Statistical Computing in Python,” in *Proceedings of the 9th Python in Science Conference* (S. van der Walt and J. Millman, eds.), pp. 51–56, 2010.

77. F. Pedregosa, R. Weiss, and M. Brucher, “Scikit-learn: Machine Learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

78. O. Travis E, “A Guide to Numpy.” `http://www.numpy.org/`, [Accessed 26- Feb- 2019].

79. J. D. Hunter, “Matplotlib: A 2D Graphics Environment.” `https://matplotlib.org/`, [Accessed: 26- Feb- 2019].

80. S. Gillies and Others, “Shapely: manipulation and analysis of geometric objects.” `https://github.com/Toblerity/Shapely`, [Accessed: 26- Feb- 2019].

81. M. Waskom, O. Botvinnik, D. O’Kane, P. Hobson, J. Ostblom, S. Lukauskas, D. C. Gemperline, T. Augspurger, Y. Halchenko, J. B. Cole, J. Warmenhoven, J. de Ruiter, C. Pye, S. Hoyer, J. Vanderplas, S. Villalba, G. Kunter, E. Quintero, P. Bachant, M. Martin, K. Meyer, A. Miles, Y. Ram, T. Brunner, T. Yarkoni, M. L. Williams, C. Evans, C. Fitzgerald, Brian, and A. Qalieh, “mwaskom/seaborn: v0.9.0,” Jul 2018.

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14. ABSTRACT

The relationship between women and stability, if any, is a topic of much debate and research. Several large and influential organizations have all researched women's effect on stability. Furthermore, several of these world organizations, the United Nations, in particular, have declared gender equality to be a driving force in promoting stability and conflict prevention. Due to the United States active involvement in conflict prevention in such regions as West Africa, research concerning the relationship between women and stability is of particular interest the United States Africa Command.
As such, this research applied Topological Data Analysis, combined with other machine learning algorithms, to Demographic and Health Survey Program data combined with Armed Conflict Location and Event Data so as to observe the relationship between women's status and armed conflicts in the West African region. While this team did not observe any direct correlation between women's well-being and stability - defined as a lack of armed conflict events - the chosen methodologies and data usage have potential implications for future research concerning stability and conflict.

15. SUBJECT TERMS

Economics, Women and Stability, West Africa, Topological Data Analysis, Geospatial Analysis

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