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Hunger in Conflict: A Quantitative Analysis of the Effects of Armed Conflict on Food Security in West Africa and Afghanistan

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A Thesis in the Field of Sustainability and Environmental Management

for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

March 2022

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Abstract

Half of the world's undernourished population lives in a country experiencing armed conflict or violence (FAO, 2021). As the main driver of food insecurity, conflict has pushed some 99.1 million people into acute food insecurity in 2020 alone (FSIN, 2021). Additionally, the impacts of COVID-19, climate change, and poverty threaten to exacerbate these already fragile situations, pushing more people towards extreme vulnerability and food crisis (FEWS NET, n.d.). Food insecurity is particularly prevalent in protracted conflicts, where years of violence have worn down government institutions, economies and resources that might otherwise help their populations cope (Peters et al., 2019). Delivering humanitarian assistance is challenging amidst growing needs in increasingly complex environments, and resources are limited. However, response could be improved through a better understanding of how and where violence has the greatest impact on food security, allowing organizations to better target the most vulnerable populations.

My research sought to quantify the statistical significance of armed conflict on food security through case studies in West Africa and Afghanistan. I evaluated the duration and intensity of conflict on Integrated Food Security Phase Classification (IPC) levels at both the province and district levels, as well as a temporal analysis through seasonal and timeline regressions.

My study was guided by three main questions: how would IPC levels change with different accumulations of fatalities? How does the duration and intensity of violence impact IPC levels? Which administration levels show the highest correlation

between IPC level and violence? I hypothesized that there is a strong correlation between conflict and IPC levels with 12 months of aggregated fatalities, showing the most robust results at an admin 1 level. In addition, I hypothesized that correlations would be stronger in the lean season versus other times of the year.

I began my research by producing an attribute table that matched IPC and fatality data to all admin units, which allowed me to analyze data trends and prepare a classification of possible scenarios. Through statistical regression, I quantified the extent to which the duration and intensity of fatalities impacted IPC levels on both province and district levels. Statistical regressions were also performed on seasonal aggregations in addition to a timeline analysis.

The results of the analysis found that the fluctuation in fatality and IPC levels are generally correlated. In Afghanistan this trend was apparent across 24 out of 32 provinces, while in West African countries it was less visible, with three provinces in Nigeria, one in Chad, and none in Mali, Cameroon, or Niger. The strongest correlations were found at the largest admin 1 level with 12 months of aggregated fatalities. However, the results also show that in certain contexts with a prolonged intensity of conflict fatalities, IPC levels and fatalities are correlated and then experience a "tipping point" moment in which IPC levels and fatalities decouple. IPC levels remain high as conflict fatalities decrease. The results of all analyses were transformed into a graduated map that indicates the sensitivity of IPC levels to conflict fatalities. This tool can serve governments, policymakers, and organizations in planning humanitarian food assistance programs, adaptation and mitigation strategies.

Dedication

To my family.

My parents Elizabeth and Phillip Cook, your unconditional love and support has made me feel like anything is possible.

To my husband Paolo and daughters Luna and Emma, thank you for your endless patience. I never could have done it without you.

Acknowledgements

Above all, I wish to thank Dr. Mark Leighton for his dedication to the ALM program. Through all the classes, walks, talks, and advising, I am in awe of your commitment to each and every student.

I would like to thank my thesis director, Krishna Krishnamurthy, for his genuine enthusiasm for my thesis topic and for pushing me out of my comfort zone to learn QGIS. With that, you showed me that being in unfamiliar territory can bring great opportunities to explore. Thank you for your collaborative spirit.

I would never have completed my degree if it weren't for my adviser Lacy Klingensmith. You were always there with optimism and a solution, which was enough to get me through multiple crises, including my last class during the pandemic.

Table of Contents

Dedication v

Acknowledgements vi

List of Tables x

List of Figures xi

I. Introduction 1

Research Significance and Objectives 2

Background 3

Food Security Metrics 3

The Current State of Food Security 4

Highest increase in food insecurity. *5*

Armed Conflict and Food Insecurity 9

Consequences on Food Systems 9

Urban Conflict and Displacement 10

Food as a Weapon of War 10

Protracted Conflict 11

Conflict and Climate Change 12

Causal Relationships and Feedback Loops 14

Food Insecurity Causes Armed Conflict 14

Climate Change Causes Armed Conflict 15

Emerging Data and Research 16

Challenges Going Forward 19

Research Questions, Hypotheses and Specific Aims 19

Specific Aims 20

II. Methods 21

Food Security Data 21

Data Sources for Armed Conflict 23

Armed conflict location and event database (ACLED). *24*

Uppsala conflict database program (UCDP). *24*

Defining the Country Sample Set 26

Research Methods 27

Downloading and Preparing Data. 27

Data Processing in QGIS 28

Statistical Analysis 29

Visualizing Results in Map Form 31

III. Results 33

Trend Analysis 33

Scenario 1: Clear Relationship Between Conflict and Food Insecurity 33

Scenario 2: Tipping Point 34

Scenario 3: No Relationship Between Conflict and Food Insecurity 35

Aggregated Fatalities 36

Spatial Analysis 38

Seasonal Variations 40

Timeline Statistical Analysis 41

IV. Discussion 45

Conflict is Correlated to Food Insecurity 45

Conflict is Correlated to Food Insecurity Until a Tipping Point 51

No Relationship Between Conflict and Food Insecurity 54

Conclusions 55

Appendix 1 Comparison of Food Security Indicators 57

Appendix 2 Regression Results for Nigeria by Season 58

Appendix 3 Timeline Regression Results 59

References 62

List of Tables

Table 1. The 34 countries in major food crises today (IPC = 3 or above). 6

Table 2. Prevalence of severe food insecurity. 7

Table 3. Conflict and climate-related shocks associated with food crises. 14

Table 4. Descriptions of IPC Phase 1-5. 22

Table 5. Step-by-step summary of research methods. 27

Table 6. Index of countries. 28

Table 7. Results of linear regression analyses in Nigeria. 39

Table 8. Regression results using the averaged province level and total aggregated fatalities for three seasons in Niger. 39

Table 9. Regression results using IPC levels by admin 1 and three seasons of aggregated fatalities in Niger. 39

Table 10. Regression results using aggregations of seasonal data from 2011-2021 for each country. 40

Table 11. Comparison of the most commonly used food security and undernourishment indicators. 57

Table 12. Regression results for Nigeria by season, using average admin 1 and 3 seasons of aggregated fatalities 58

Table 13. R^2 values by province in West African countries with 3 aggregated seasons of fatalities, 2011-2021 59

Table 14. R^2 values by province in Afghanistan with 3 aggregated seasons of fatalities, 2011-2021. 61

List of Figures

Figure 1. Number of people in IPC Phase 3 or higher in 2020 (FSIN, 2021). 7

Figure 2. FEWS NET situational report for South Sudan in 2019. 22

Figure 3. A shapefile in QGIS of ACLED conflict events in West African countries. 23

Figure 4. Total conflict-related fatalities in Yemen between 2015-2018. 25

Figure 5. Fatalities and IPC levels in Uruzgan, Afghanistan, 2011-2021. 34

Figure 6. Average IPC levels and fatalities in Borno, Nigeria, 2011-2021. 35

Figure 7. Average IPC levels and fatalities in Brakna, Mauritania, 2011-2021. 36

Figure 8. Average IPC levels and fatalities in Bamyan, Afghanistan, 2011-2021. 36

Figure 9. IPC levels and fatalities in Nigeria, October 2016. 37

Figure 10. Average IPC levels and 12 months aggregated fatalities in Nigeria, October 2016...38

Figure 11. A province-level map of IPC sensitivity to fatalities. 42

Figure 12. A district-level map of IPC sensitivity to fatalities. 42

Figure 13. IPC sensitivity to fatalities by province in Afghanistan. 43

Figure 14. IPC sensitivity to fatalities by district in Afghanistan. 44

Figure 15. IDP populations per state in northeastern Nigeria. 46

Figure 16. Seasonal calendar for Niger by farming, pastoral and labor migration periods. 47

Figure 17. Total seasonal fatalities by season in Afghanistan, 2011-2021. 49

Figure 18. Average IPC levels and fatalities in Badghis, Afghanistan from 2011-2021. 50

Figure 19. Average IPC levels and fatalities levels in Gao, Mali from 2011-2021.....50

Figure 20. The harvest calendar for Mali...51

Figure 21. Fatalities and average IPC levels in Borno state, Nigeria including HA0. 52

Figure 22. Average IPC and fatalities in Yobe, Nigeria, 2011-2016...........................53

Figure 23. Average IPC levels and fatalities in Afghanistan, 2011-2021. 54

Figure 24. Average IPC levels in Mauritania, 2011-2021...55

Chapter I

Introduction

The unprecedented convergence of armed conflict, climate change and the COVID-19 pandemic threaten to reverse the progress made towards achieving the Sustainable Development Goal of Zero Hunger by 2030. In 2020, an estimated 928 million people faced severe food insecurity, with another 1.44 billion at risk (FAO, 2021). The numbers have steadily increased into 2021, with more than 55 countries in food crisis (FSIN, 2021).

Armed conflict remains the number one catalyst of food insecurity: of the top ten food crises today, eight are in countries affected by conflict (FSIN, 2021). The food security outlook looks particularly challenging in situations of protracted conflict, where years of violence have worn down food reserves, government institutions, economies, and coping mechanisms that might otherwise provide support in times of food scarcity (Peters et al., 2019). These conditions, combined with severe climate shocks, have pushed more than 500,000 people to famine in 2021 (FSIN, 2021). With 274 million people projected to require humanitarian assistance in 2022, governments and humanitarian organizations face immense challenges in meeting their growing needs (UNOCHA, 2021).

A robust body of research on food security and conflict has supported the development of food crisis monitoring, humanitarian programming, and policy decisions. The development of hunger indexes, such as the FAO's Integrated Food Security Phase Classification (IPC) scale, has improved humanitarian response to food crises through frequent reporting and analysis at high spatial resolutions (IPC, n.d.). Studies have shown how violent conflict has reduced agricultural production, impacted farmers, disrupted markets, and displaced populations, all of which negatively impact food and income sources. They have also demonstrated how the presence of armed groups limits civilian mobility, reducing consumption, and threatens the transportation of food aid to affected populations. Most recently, the emerging availability of data and technology has allowed advanced quantitative analysis to start untangling the links between multiple causes of food crises. These studies have been able to estimate the relative importance of conflict and drought on food security, disaggregated by livelihood and other variables.

While considerable work has been done to quantify the impact of conflict using various food security metrics, there is still a lack of research that examines how the duration and intensity of conflict affects food insecurity at various timeframes and spatial levels.

Research Significance and Objectives

Using GPS techniques and statistical analysis, my research aims to fill that gap by measuring the correlation between fatalities and IPC levels over various time periods, using West Africa and Afghanistan as case studies. My research sought to quantify the proportion of variation in IPC values that could be explained by fatalities, particularly regarding conflict intensity and duration, as well as temporal patterns of violence. In measuring these values, the model could serve as an additional food crisis early warning tool, with the ability to more precisely identify and target vulnerable populations before they reach an emergency state. This information would serve governments, policymakers, and organizations as they plan more targeted humanitarian assistance programs, adaptation and mitigation strategies for maximum impact.

My research objectives were:

- To quantify the statistical significance of armed conflict on food security through case studies in West Africa and Afghanistan
- To identify trends between fatalities and changes in IPC levels over time
- To develop a model that can estimate the correlation between fatalities and IPC levels in various seasons or time periods
- To produce a map that highlights, by administration level, the correlation between fatalities and IPC levels

Background

The increase in food insecurity is alarming. In 2020, an estimated 928 million people faced severe food insecurity, an increase of 148 million from 2019 (FAO, 2021). The numbers have steadily increased into 2021, with more than 55 countries in food crisis (FSIN, 2021). Evidence suggests that armed conflict and climate change are responsible for the fourth consecutive year of rising food insecurity (FAO, 2021). In addition, the effects of COVID-19 have magnified existing variabilities. This convergence of causes paints a grim portrait for the near future, with concern over famine likely to persist.

Food Security Metrics

Food security is a state in which "all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2008, p. 1). Food security consists of four main pillars, availability, access, utilization, and stability, all of which must be fulfilled to meet this definition (FAO, 2008). Food insecurity occurs when people lack access to sufficient amounts of food, per this definition, and can be "chronic, seasonal or transitory" (FAO, 2017).

With so many food insecurity metrics available, there is a debate among experts about the appropriate application of each. Ranging from Prevalence of Undernutrition (PoU) to Food Insecurity Experience Scale (FIES) to the Integrated Phase Classification (IPC) system, the choice of metric ultimately depends on the purpose of the work (Jones et al., 2013). A table of the most commonly used metrics can be found in Appendix 1.

The IPC system was designed to inform humanitarian agencies and governments so they can more effectively respond to humanitarian crises with targeted intervention. This requires food security information at high spatial resolutions to be available on a regular basis.

The Integrated Phase Classification was first developed by the Food and Agricultural Organization of the United Nations (FAO) in 2004 in Somalia. Today, it is an internationally recognized system based on a standard set of criteria to evaluate acute food security. The scale consists of five IPC phases: 1 – minimal; 2 – stressed; 3 – crisis; 4 – emergency; 5 – famine. IPC levels are only assigned to areas in which at least 20% of the population is experiencing that phase. The comparable Cadre Harmonisé (CH), which is primarily used in West Africa and the Sahel, is often referred to alongside IPC values, as they use similar criteria (IPC, n.d.).

The Current State of Food Security

In 2020, an estimated 2.3 billion people, or 30% of the world's population, faced moderate to severe food insecurity (FAO, 2021). Of the 55 countries considered in food crisis (IPC Phase 3 or higher), 34 were identified as major food crises (Table 1) (FSIN, 2021). To be classified as a major food crisis, one of the following criteria must be filled:

- 20% of the population faces IPC Phase 3 or higher
- at least 1 million people face IPC Phase 3 or higher
- IPC Phase 4 or higher was declared anywhere in the country
- an area of a country was included in the IASC humanitarian system-wide emergency response-level 3, headed by the United Nations Office for the Coordination of Humanitarian Affairs (FSIN, 2021; IASC, n.d.)

In 2021, the Democratic Republic of Congo had the highest number of people facing IPC phase 3 or greater, at 27.3 million (Table 1)). More than 50% of the population in Yemen, South Sudan, Syria, Bangladesh, and Angola have been in IPC Phase 3 or greater. From 2020 to 2021, the number of people estimated to be in Catastrophe IPC Phase 5 quadrupled, rising from 133,000 to 584,000. Over 400,000 of those were in Ethiopia's Tigray region in July-September, followed by South Sudan, Yemen, and Madagascar (FSIN, 2021).

Highest increase in food insecurity. Today, 2.37 billion people face moderate to severe food insecurity. Although the regions of Asia and Africa bear a burden of this population, with 1.2 billion and 799 million respectively, Africa has the highest prevalence of moderate to severe food insecurity, with 60% of the population affected compared to 26% in Asia (FAO, 2021). Moreover, the sub-region of West Africa has experienced the greatest proportional increase in severe food insecurity on the continent, with prevalence jumping from 8.6% in 2014 to 28.8% in 2020 (northern Nigeria, followed by Burkina Faso, Cameroon, Niger, Sierra Leone, and

Mali (Figure 1).
Table 2). Of the 24.8 million people facing food crisis at IPC phase 3 or higher, 37%

were in

Table 1. The 34 countries in major food crises today (IPC = 3 or above).

Country	IPC Phase 3 or above (in millions)	IPC Phase 3 or above (% of population)	Population experienced IPC Phase 4 or 5 in 2020/2021
Dem. Rep. of Congo	27.3	28	Phase 4
Ethiopia	16.8	30	**Phase 5**
Yemen	16.1	54	**Phase 5**
Afghanistan	13.2	42	Phase 4
Nigeria	12.8	12	Phase 4
Syria*	12.4	60	
Sudan	9.8	21	Phase 4
South Sudan	7.2	60	**Phase 5**
Haiti	4.4	46	Phase 4
Pakistan	3.8	26	Phase 4
Guatemala	3.7	23	Phase 4
Somalia	3.5	22	Phase 4
Zimbabwe	3.4	35	Phase 4
Honduras	3.3	35	Phase 4
Mozambique	2.9	16	Phase 4
Burkina Faso	2.9	13	**Phase 5**
Malawi	2.6	15	
Cameroon	2.6	10	Phase 4
Central African Rep.	2.3	47	Phase 4
Zambia*	2.3	24	Phase 4
Niger	2.3	10	Phase 4
Palestine	2	38	Phase 4
Kenya	2	13	Phase 4
Uganda	2	5	Phase 4
Sierra Leone	1.8	22	Phase 4
Burundi*	1.6	14	Phase 4
Madagascar	1.3	35	Phase 4
Mali	1.3	6	Phase 4
Bangladesh (Cox's Bazar)	1.2	87	
Chad	1	7	Phase 4
Angola*	0.6	62	Phase 4
Tanzania	1	20	Phase 4
Eswatini	0.3	30	Phase 4
Lesotho	0.6	40	Phase 4

Countries are listed in descending order by the maximum number of people that faced IPC phase 3 or above. Data has been updated with most recent 2021 figures, except where denoted with an asterisk, which is from 2020. Countries highlighted in pink indicate current armed conflict, while countries in brown indicate protracted conflict. (By author, data from FSNI, 2021; FSIN, 2021b).

northern Nigeria, followed by Burkina Faso, Cameroon, Niger, Sierra Leone, and

Mali (Figure 1).

Table 2. Prevalence of severe food insecurity.

	Prevalence of severe food Insecurity (%)						
	2014	2015	2016	2017	2018	2019	2020
WORLD	**8.3**	**8.1**	**8.3**	**8.7**	**9.6**	**10.1**	**11.9**
AFRICA	**17.7**	**18.3**	**19.8**	**20.5**	**20.6**	**21.9**	**25.9**
Northern Africa	10.2	9.0	10.4	10.6	9.3	8.8	9.5
Sub-Saharan Africa	19.4	20.4	22.0	22.7	23.2	24.9	29.5
Eastern Africa	23.7	24.1	25.8	25.3	25.0	26.0	28.7
Middle Africa	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	35.8
Southern Africa	18.9	18.9	19.0	19.0	19.1	19.2	22.7
Western Africa	8.6	10.8	12.9	15.3	16.8	19.6	28.8

West Africa saw the greatest increase of any other sub-region, more than tripling between 2014-2020 (FAO, 2021).

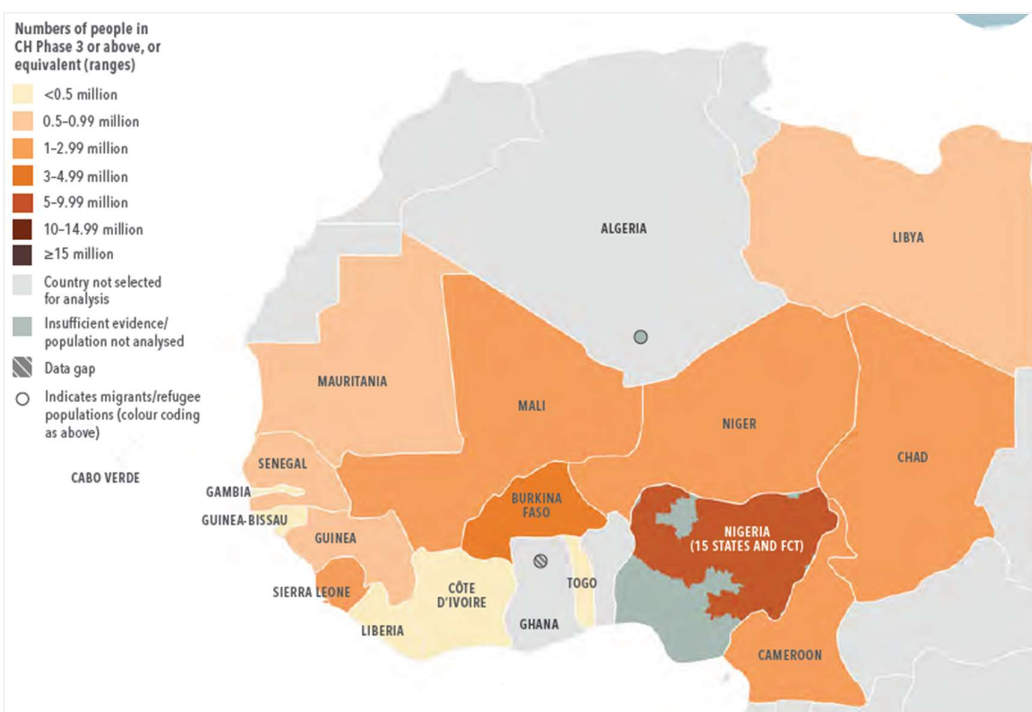

Figure 1. Number of people in IPC Phase 3 or higher in 2020 (FSIN, 2021).

The main cause of West Africa's increase in food insecurity has been a surge in violent conflict and subsequent internal displacement, which rose to 5.7 million people in 2020 - a 2.2 million increase in a single year (FSIN, 2021). A rise in attacks by non-state armed groups has continued to spread across the region since 2010, notably Boko Haram in the Lake Chad area, but also ethnic militias and Jihadist militant groups in Mali and Burkina Faso (George, Adelaja, & Awokuse, 2020; Nsaibia & Duhamel, 2021). Burkina Faso was particularly affected by a surge in internally displaced persons (IDPs), which jumped from 0.2 to 1.1 million people in 2020 (FSIN, 2021). In addition, Chad and Niger are hosts to nearly a million refugees and asylum seekers from the Central African Republic and Sudan (FSIN, 2021). Access to humanitarian assistance has remained challenging amidst rising insecurity as attacks on aid workers continue (Norwegian Red Cross, 2021); 2020 was a record year with 283 documented incidents, 55 of which occurred in West Africa (Aid Worker Security Database, 2021). Moreover, COVID-19 has exacerbated the already fragile situation, with reduced market access, loss of income, and increased food prices (GRFC 2021).

In Asia, Afghanistan has been repeatedly ranked as one of the most serious food crises in terms of numbers of affected people, which has climbed to 13.2 million (FSIN, 2021b). Decades of armed conflict, natural disasters, repeated drought, and COVID-19 pushed 4.3 million people into Emergency IPC Phase 4 in 2020 (FSIN, 2021). Then in 2021, the worst drought of the decade converged with a spike in violence in the first half of the year. An additional 677,000 people were displaced between January and September, cutting many people off from their agriculture-based food and income sources (UNOCHA, 2021b; IFRC, 2021).

Armed Conflict and Food Insecurity

Research has examined the dynamic relationship between food insecurity and armed conflict since the 1980s, primarily focusing on famine relief in Africa, but has grown most significantly in the last 10 years. During this time, the literature has evolved to include the effects of climate change, poverty, characteristics of armed conflict, food policy, coping and resilience, and mental health, among other things. Studies have also addressed the effects hunger and food prices have on increased violence, as food insecurity and conflict can be mutually reinforcing. In the last few years, a growing availability of data and new technology has enabled more innovative, quantitative methods of analysis, which can improve early warning systems and response to food crises. The following analysis includes some of the most significant areas of literature to date.

Consequences on Food Systems

It is well-established that one of the most direct effects of conflict on food security is the disruption of food production. In countries where a large percentage of the population relies on agriculture or livestock, both food supply and income are at risk (Hollerman et al., 2017). Conflict can destroy crops, fields, assets and infrastructure, and contaminate land with mines and ordinance (FAO 2017; Teodosijevic, 2003; Unruh, Heynen, & Hossler, 2003). Farmers may shift to short-term yields in the presence of armed groups, switching from perennial crops to less risky, but lower income-generating activities (Arias, Ibanez, & Zambrano, 2019). In some cases, farmers cultivate less land due to risk of violence or abandon their farms altogether as they flee for safety elsewhere as seen during the Chechen wars (Yin et al., 2019). This phenomenon is also the case in Nigeria as violence has escalated between herders and farmers, driving many farmers to seek safety in urban centers (George, Adelaja, & Awokuse, 2021). A significant number of Fulani herdsmen's cattle have also been stolen or killed by Boko Haram insurgents, a loss of both food and income (International Crisis Group, 2021).

Conflict can also disrupt major transportation routes, affect food supply chains, and local markets (Teodosijevic, 2003; Justino, 2012). People living in proximity to armed groups may reduce their mobility for fear of attack, including traveling to markets to buy or sell food, or looking for work outside of their villages (Tranchant, Gelli, & Masset, 2019).

Urban Conflict and Displacement

Wars in cities put millions of civilians in the line of fire, in addition to vital infrastructure that supplies water and electricity. Conflict in urban areas impacts food security through physical damage to markets, infrastructure and a disruption in the exchange of goods (ICRC, 2017). In Syria, fighting in cities like Aleppo and Idlib has also led to mass exoduses of people who faced food insecurity in camps or other urban areas, or for those who were in besieged areas, food rations would often run out (BBC, 2016; UNHCR, 2021). Unfortunately, the consequences of such large-scale destruction are long term: ten years after the conflict began, 6.8 million people are internally displaced and 12.9 million are food insecure (WFP, 2021).

Food as a Weapon of War

Food has also been used as a weapon of war as food aid has been blocked, with varying intentions (Conley & de Waal, 2019; FAO, 2017). In South Sudan, security threats by armed groups were intentionally used to keep food aid from reaching hard-to-reach communities in the swamps (FAO, 2017). During the 2011-2012 famine in Somalia, which was triggered by drought and resulted in 250,000 deaths, the armed group Al Shabaab blocked international aid from reaching populations under their control (Maxwell & Majid, 2016). Another example is Ethiopia's Tigray region, which has been sealed off by Ethiopian security forces, pushing an estimated 400,000 people into a state of famine in May 2021 (IPC, 2021; Al Jazeera, 2021). In Yemen, warring parties have frequently blocked major ports or denied humanitarian organizations access to populations into opposition-held territory, further limiting food availability (Specia, 2017). This is on top of the country's economic collapse due to the war (Almosawa & Hubbard, 2021). Despite the adoption of U.N. resolution 2417 in 2018 that bans the starvation of civilians and obstruction of humanitarian aid as a war tactic, it still continues today (United Nations, 2018).

Protracted Conflict

Conflict trends have changed significantly over the last few decades, with trends showing not just an increase in conflict, but also in duration. The number of years of armed conflict has increased, which is highly correlated to an increase in food insecurity (Global Peace Index, 2020; FAO, 2017). Of the ten worst food crises today, six are in protracted conflict: Afghanistan, the Democratic Republic of the Congo, Nigeria, South Sudan, Syria, and Yemen (FSIN, 2021).

Protracted conflicts are characterized by either long periods of violence or repeated violence, over many years (ICRC, 2016). The effects are devastating;

government institutions are slowly worn down, as are healthcare systems, food supplies, economies, education, security, infrastructure and the ability for populations to be resilient (ICRC, 2019).

Not only can food become scarce, but prices may become extremely volatile (FAO, 2020). In 2016 in South Sudan, main roads from Uganda were blocked, cutting off food supplies and leading cereal prices to jump tenfold in the span of just one year (FAO, 2017).

In addition, the longevity of conflicts has implications for humanitarian aid organizations. For example, the International Committee of the Red Cross averages 42 years in its ten largest operational contexts (ICRC, 2019). In terms of resources and funding, many organizations must rethink their role (Bennett, 2015; Daar, Chang, Salomon, & Singer, 2018).

Conflict and Climate Change

The effects of climate change have impacted food production around the world in various ways. As seasonal temperatures and precipitation patterns change, the possibility of crop failure increases, especially for farmers who depend on rain-fed agriculture (IPCC, 2019). Agricultural pests and diseases are also a threat to crop production as climate favorably increases their geographical spread and lifecycles (IPCC, 2019). The massive desert locust swarms that threatened crops in the Horn of Africa in 2020, for example, were attributed to an unusually long rainy season and higher temperatures, which created prime conditions for insect reproduction (Wainwright et al., 2020).

Variation in precipitation and temperature also affect arid land that is suitable for pastoral use. Globally, between 200-500 million pastoralists depend on their animals for both food and income. The IPCC reported with high confidence that, particularly in Africa, available pastureland would decrease with rising temperatures, along with animal productivity (IPCC, 2019).

When the impacts of armed conflict are combined with climate-related challenges, the effect of "double vulnerability" can create an extremely high risk of food insecurity (Peters et al., 2019; FAO, 2017a). In these cases, the effects of climate change can magnify existing vulnerabilities, such as access to food, income, and healthcare (Peters et al., 2019; FAO, 2017). Often, such dire situations can further perpetuate violence (FAO, 2017).

Across Africa in particular, a combination of climate change and conflict are taking a toll on the population. Nine of the top 10 countries considered most vulnerable to climate change are in Africa and six of those nine are affected by armed conflict: Somalia, Chad, Central African Republic, Democratic Republic of Congo, Sudan, and Niger (University of Notre Dame, 2019; ICRC, 2019). The repercussions are widespread. In Mali, for example, 800 schools were shut down. Meanwhile, drought was leaving families hungry (UNICEF, 2019). That leaves few good choices for youth, among them migration to find employment, or joining one of Africa's hundred-plus armed groups, perpetuating the cycle of violence (ICRC, 2019).

Forty-one countries needed external food assistance in 2019, due to the double exposure to both conflict and drought (FAO, 2019b). Of the roughly 31 countries in armed conflict, 12 of them are among the most exposed to climate change, or an estimated 669 million people (OECD, 2020). As seen in Table 3, the compounded conflict-climate change shocks in 2016 pushed some 10 countries and 53.5 million people into food crisis.

Table 3. Conflict and climate-related shocks associated with food crises.

Country	Main climate/weather adverse effect on food security	Number of food-insecure people (IPC/CH phase 3+) in millions
Afghanistan	Floods, landslides in winter; drought in Ghor province	8.5
Burundi	El Niño phenomenon	2.3
Central African Republic	Localized floods	2.0
Democratic Republic of the Congo	El Niño phenomenon	5.9
Iraq*	Drought	1.5
Somalia	El Niño-related drought	2.9
South Sudan	Drought and floods	4.9
Sudan	El Niño phenomenon	4.4
Syrian Arab Republic*	Drought in Aleppo, Idlib and Homs	7.0
Yemen	Flooding, heavy rains and tropical cyclones	14.1
Total		**53.5**

(Source: FAO, 2017)

Causal Relationships and Feedback Loops

A considerable part of the literature on conflict and food insecurity addresses the complex interactions between multiple causes. The relationships between conflict, climate change and food insecurity are elaborate and often context specific (Martin-Shields & Stojetz, 2019). For example, an increase in food insecurity in conflict settings is not surprising: reinforcing feedback loops perpetuate the cycle regardless of the original catalyst. However, this also makes it hard to identify root causes and an effective response, in turn (Martin-Shields & Stojetz, 2019). Examining these drivers and how they interact is complex, but necessary in shaping policy solutions and interventions.

Food Insecurity Causes Armed Conflict

Various aspects of food security have been analyzed in relation to violence. There are multiple variables at play, including food prices, percentage of population reliant on agriculture and pastoral activities, food imports, markets, existing or past grievances, and governance. In addition, food insecurity combined with other factors may together result in violence, as it “may become a channel through which wider socio-economic and political grievances are expressed” (Holleman et al., 2017, p.V).

In areas where a large percentage of the population relies on agriculture, tensions could arise over both food supply and agricultural labor. In Afghanistan and Pakistan, for example, tensions were observed to rise outside of the harvest season, when food supplies and employment opportunities diminished. However, the result of such tensions depends on other contextual factors, such as existing grievances, social inequalities, or recent famine (Martin-Shields & Stojetz, 2019).

Underlying resource scarcity can impact access to food sources and livelihoods, resulting in “food insecurity-induced grievances” and conflict (Koren & Bagozzi, 2016). The authors further concluded that, “if future global projections for population growth, consumption, and climate change hold true, then these dynamics suggest that incidences of violent conflict over food scarcity and food insecurity may increase as individuals and groups fight over a continuously shrinking pool of resources, including food” (Koren & Bagozzi, 2016 p. 1007).

Additionally, when resources are exhausted, and people cannot provide for their families, they may be more easily recruited by armed groups, which offer them food and shelter (Humphreys & Weinstein, 2008). Again, this feedback loop only perpetuates the cycle of violence.

Climate Change Causes Armed Conflict

Although there is a lack of substantial research that shows a causal link between climate change and conflict, the effects of climate change have been shown to intensify existing conflict, acting as “threat multipliers” (Buhaug, 2015; Peters et al., 2019). A rise in temperature has also been correlated with an increased risk of conflict (O’Loughlin et al., 2012; Burke et al., 2009) When underlying resource scarcity is further strained by climate events, for example, it can create a “breeding ground” for violence (IPCC, 2019). A population’s ability to cope or absorb the climate shock can determine the likelihood of violence (Peters et al., 2019). Therefore, countries in protracted conflict are less likely to have this ability and are more vulnerable to additional violence. Moreover, in contexts where there are existing tensions, especially those of ethnic origin, and which are accompanied by the conditions of political exclusion and economic inequality, the duration of drought has been strongly correlated to an increased incidence of conflict (Von Uexkull, Croicu, Fjelde, & Buhaug, 2016).

Emerging Data and Research

Within the last few years, an emerging availability of data has led to new research streams trying to quantify relationships between food security and conflict. Improved data and GIS modeling, technological advances in remote sensing, micro-level surveys, and increased use of mobile technology in remote areas have given researchers more tools and information to carry out complex analyses (Martin-Shields & Stojetz, 2019). However, there are still only a handful of relevant papers.

Anderson et al. (2021) used GIS methods to analyze the effects of conflict, drought, and locusts on acute food insecurity across livelihood zones in Sub-Saharan Africa, teasing out the relative importance of each. While the report’s findings showed that the increase in food insecurity could be attributed to armed conflict across all livelihood zones, it also found that it took pastoralists an average of two years to recover from drought – twice as long as agricultural communities. These findings indicate that food security of pastoralists, more than other groups, are potentially at higher risk with the additional onset of conflict. In summary, the findings showed that both drought and conflict were always present during periods of famine, which demonstrates the compounding effect of multiple drivers on food security outcomes.

Brück et al. (2016) evaluated the intensity and duration of conflict on food security outcomes using both a descriptive framework as well as a GIS method that linked various subnational, geocoded data. Two of the findings were that highly localized conflicts results in decreased food production and higher rates of malnutrition, and higher intensity conflicts result in challenges with food distribution and rise in food prices. They also found that the type of conflict affects the characteristics of the food crisis: when the fighting is over government control, the impact is on long-term food security, as opposed to fighting over territory. Therefore, the type of conflict should be considered when assessing food security outcomes. Overall, the authors highlight one research challenge: the lack of adequate, disaggregated food security indicators that match up with the same unit of analysis of conflict data, both geographically and temporally.

George et al. (2020) measured the impact of Fulani Ethnic Militia (FEM) attacks on farmers in Nigeria, a novel case of studying an active conflict zone using longitudinal data versus a post-conflict study. They found that agricultural output decreases with a rise in conflict intensity (measured through fatalities) through a reduction in productive farmland and fewer hours of farm labor. Their research also noted that farmers migrated to urban centers due to the conflict, abandoning farmland. In addition, farmer coping strategies for reducing risk of attack included decreasing the number of owned cattle George et al. (2020).

Recent research has also focused on improving predictive modeling used in early warning systems, which must confront the numerous causal variables that can impact food security. Krishnamurthy, Chaularton and Kareiva (2020) evaluated the precision of FEWS NET outlook reports from 2011-2019, comparing prediction reports to the actual situations that later unfolded. Among other findings, the authors reported that difficulty in predicting armed conflict is a major uncertainty in forecast models. One-fifth of all missed food crises were due to an inaccurate prediction of conflict outcomes. This was especially true in areas that experienced fewer conflicts (0-49 conflicts) and a very high number of conflicts (75 and over). In areas that experienced between 50-74 conflict events, forecasts were more accurate. In addition to seasonal forecasts, the difficulty of predicting conflict is one of the most significant challenges to accurate early warning, and the authors recommend further research to improve understanding around how conflict impacts food security.

These papers conclude with several recommendations. First, livelihoods should be factored into food insecurity vulnerability assessments and assistance strategies, especially when looking at the complex conflict-food insecurity pathways amidst multiple drivers of food crisis. This is especially true when assessing farmer and herder requirements for grazing and agriculture, which is reduced by both conflict and drought. Second, there is a growing need for more precision in data collection and climate forecasting, which would improve the accuracy of conflict predictions and early warning systems. And finally, the type of conflict, as well as the duration and intensity of violence, should be considered when analyzing food security outcomes. This allows for more nuanced understanding of the interaction between different variables depending on context, which is helpful for governments, humanitarian agencies, and policy makers as they develop strategies for intervention before crises emerge.

Challenges Going Forward

These studies have greatly contributed to a growing body of research on conflict and food security, and they have also identified several challenges going forward:

- The incidence and duration of conflict is a growing trend, which implies a future in which food crises continue.
- Interactions between conflict, climate impacts, and other causes of food insecurity will become increasingly complex in protracted crises. There is a need to further characterize the relative importance of different variables and their pathways, including issues of reverse causality and endogeneity.
- Humanitarian organizations lack the necessary funding and resources to address growing humanitarian needs, not to mention the security risks involved when delivering aid in complex conflict settings.

Research Questions, Hypotheses and Specific Aims

My research was guided by the following questions and hypotheses:

1. How sensitive are IPC levels to armed conflict?

   Hypothesis 1: There is a strong relationship between fatalities and a change in IPC levels; however, food insecurity is intensified by additional explanatory variables such as extreme drought.

2. Which of the three aggregations (one, two, or three seasons) of fatalities best explains the variation in IPC levels?

   Hypothesis 2: A model that uses 9-12 months of aggregated fatalities will show the strongest explanatory power of IPC change.

3. And at which admin level in each country will the data prove most robust? The two admin districts analyzed were 1 and 2, the latter being a higher spatial resolution.

   Hypothesis 3: The data will prove most robust at an admin 1 level since the effects of violent conflict can be widespread as opposed to localized, depending on the characteristics of the conflict.

4. Is there any one season that shows a significantly higher correlation between fatalities and a change in IPC levels?

   Hypothesis 4: The period corresponding to lean seasons will show the highest correlation between fatalities and a change in IPC levels.

Specific Aims

To complete my research, I addressed the following aims:

1. Produce an attribute table that matches IPC and fatality data to admin 2 units.
2. Analyze data trends and prepare a classification of possible scenarios.
3. Quantify to what extent the duration and intensity of conflict affects IPC levels.
4. Perform a spatial analysis to discern at which scale data is most robust – admin 1 or admin 2.
5. Identify seasonal patterns that show strongest correlations between fatalities and IPC levels.
6. Based on results, create a graduated map that indicates the level of correlation between IPC levels and fatalities for each admin unit.

Chapter II

Methods

The purpose of this research was to quantify the relationship between armed conflict and acute food insecurity from 2011 to 2021 by assessing the degree of correlation between fatalities and the change in severity of hunger according to the International Phase Classification (IPC) , using West Africa and Afghanistan as case studies. My approach consisted of a series of statistical analyses to better understand how the intensity and duration of conflict, as well as seasonal patterns, impacted IPC levels. The end results were transformed into a graduated map that identifies sensitivity to conflict at the admin 1 or 2 level, as defined by the resulting r-squared values from my statistical analysis.

Food Security Data

FEWS NET, a USAID-funded food crisis monitoring organization, produces IPC-compatible data and analysis on the countries it monitors, using a scale of 1-5 (Figure 2). It produces three different types of situational reports: the current situation (CS), which is based on the actual state of food security; projected near-term situation (ML1), which is a projection for the next season, or four months; and medium-term situation (ML2), which is a projection for the following season, or six to eight months (Figure 3). Currently, the reports are issued three times a year: February, June and October.

FEWS NET changed its original data collection methodology in January 2011, therefore my data set spans from January 2011 to June 2021, the most recent available season at the time of writing. The frequency of FEWS NET CS reports also changed within the ten-year span I analyzed. From 2011 – 2015, they issued four reports per year (January, April, July and October), which were reduced to three after 2016 (February, June, and October). Therefore, my data set includes a total of 37 CS seasons.

Table 4. Descriptions of IPC Phase 1-5.

PHASE 1 **Minimal**	Households are able to meet essential food and non-food needs without engaging in atypical and unsustainable strategies to access food and income.
PHASE 2 **Stressed**	Households have minimally adequate food consumption but are unable to afford some essential non-food expenditures without engaging in stress-coping strategies.
PHASE 3 **Crisis**	Households either: - Have food consumption gaps that are reflected by high or above-usual acute malnutrition; OR - Are marginally able to meet minimum food needs but only by depleting essential livelihood assets or through crisis-coping strategies.
PHASE 4 **Emergency**	Households either: - Have large food consumption gaps which are reflected in very high acute malnutrition and excess mortality; OR - Are able to mitigate large food consumption gaps but only by employing emergency livelihood strategies and asset liquidation.
PHASE 5 **Famine**	Households have an extreme lack of food and/or other basic needs even after full employment of coping strategies. Starvation, death, destitution, and extremely critical acute malnutrition levels are evident. (For Famine Classification, area needs to have extreme critical levels of acute malnutrition and mortality.)

(Source: FEWS NET, n.d.)

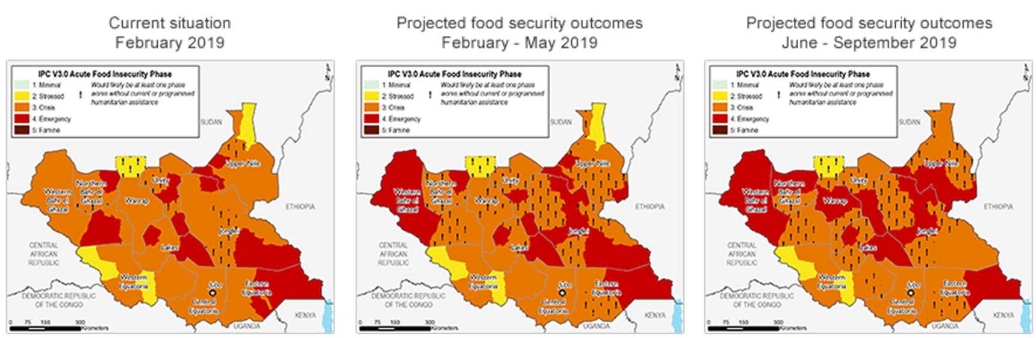

Figure 2. FEWS NET situational report for South Sudan in 2019.

The maps show the Current Situation (CS) at left, the Near Term (ML1) projection in center, and Medium Term (ML2) projection at right (FEWS NET, n.d.).

Since March 2012, FEWS NET has integrated a humanitarian assistance (HA) protocol. which is represented through an “!” exclamation mark after the IPC value.

For example, if HA0 = 1, food security conditions would likely be worse by 1 IPC phase. So if an area is classified as IPC3!, the area would likely be classified as IPC phase 4 in the absence of humanitarian assistance. I incorporate this data into my analysis and refer to it in the results and discussion.

Data Sources for Armed Conflict

Information pertaining to incidences of armed conflict can be found in conflict databases through organizations that monitor and record conflict "events". Various information is included with each event observation, including the date, actors, type of violence, fatalities and event coordinate (Figure 3). The primary database used in my research was Armed Conflict Location and Event Data (ACLED), supplemented by data from the Uppsala Conflict Database Program (UCDP) when necessary (ACLED, n.d.; UCDP, n.d.).

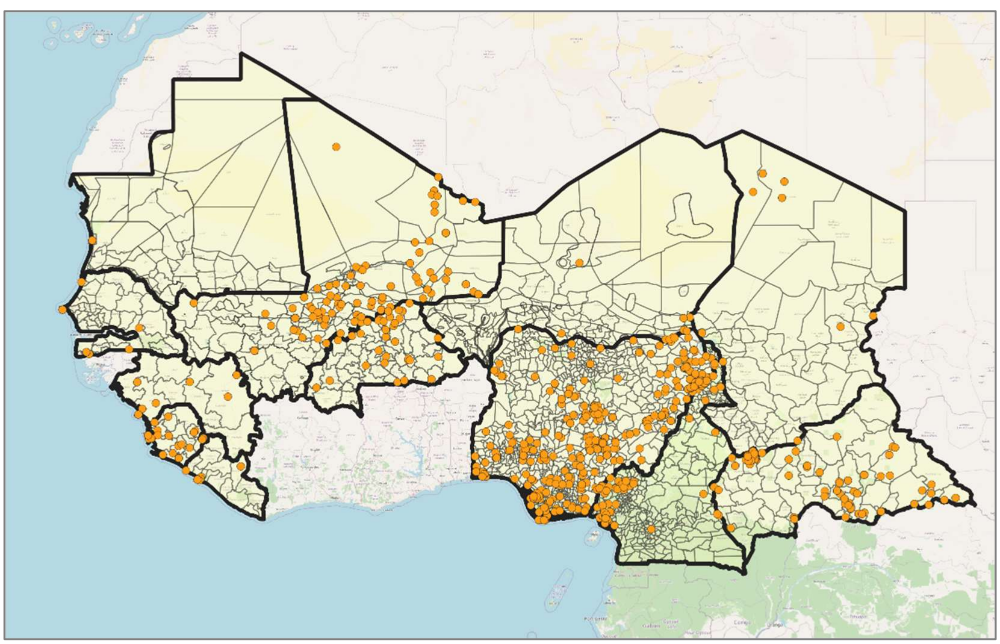

Figure 3. A shapefile in QGIS of ACLED conflict events in West African countries.

The orange dots on the map represent the coordinates of individual conflict events recorded by ACLED from December - February 2018 (by author).

Armed conflict location and event database (ACLED). A database for armed conflict as well as non-violent events, ACLED is a powerful tool to zoom in on details of specific "events", whether violent or non-violent. Similar to UCDP, data is collected, reviewed, and verified by a team. ACLED is unique in that it also monitors non-violent events, such as movements of armed actors, protests, and riots. It also tracks violence against civilians. This is useful for specific sectors, such as International Humanitarian Law (IHL), which looks at the rules of war and protection of civilians (ICRC, 2015).

As opposed to the UCDP, ACLED does not classify an armed conflict by battle deaths, but instead defines the nature of conflict. For example, a battle is defined as, "a violent interaction between two politically organized armed groups at a particular time and location." There is no minimum fatality number to qualify as a battle (ACLED, n.d.). ACLED's data also enables spatial analysis, since violence can impact regions outside of the area directly affected, which is particularly useful in food security evaluations (Raleigh, et al. 2010).

Uppsala conflict database program (UCDP). The Uppsala Conflict Database Program (UCDP) is an online database that collects, verifies and organizes data that relates to armed conflict from 1946 to the present. It is searchable by various filters, including countries, actors, conflicts, number of deaths, and the type of violence, such as state or non-state violence.

The UCDP defines armed conflict as, "a contested incompatibility that concerns government and/or territory over which the use of armed force between the military forces of two parties, of which at least one is the government of a state, has resulted in at least 25 battle-related deaths each year" (Uppsala Conflict Database

Program, 2020). A battle death is defined as “fatalities caused by the warring parties that can be directly related to combat, including civilian losses” (UCDP, n.d.).

Due to UCDP’s strict definitions of battles and conflict, its battle and fatality counts are frequently lower than those captured by ACLED, as seen in Yemen (Figure 4) (Raleigh & Kishi, 2019). ACLED, on the other hand, captures violence regardless of its conflict status, which was important for my analysis in capturing events leading up to food crisis. For this reason, I chose to use ACLED data over UCDP whenever possible.

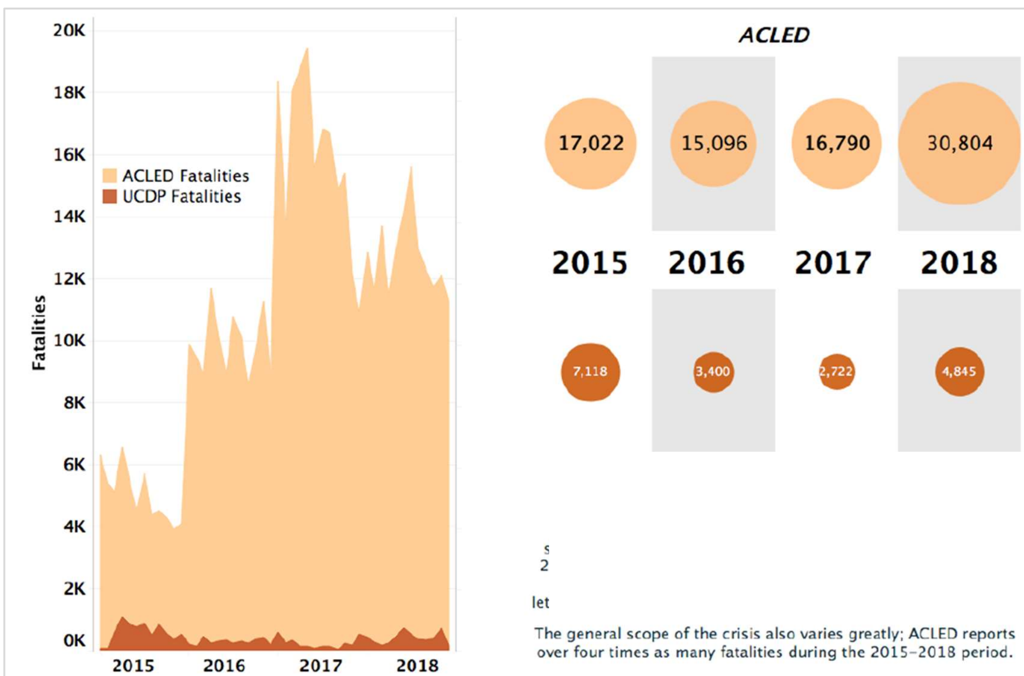

Figure 4. Total conflict-related fatalities in Yemen between 2015-2018.

Fatalities differ greatly between ACLED and the UCDP databases due to their methodological differences (Raleigh & Kishi, 2019).

When deciphering which conflict indicator would best represent conflict intensity, I examined both conflict events and fatalities. ACLED defines an “event” as an observation of armed conflict, but it does not always result in fatalities. On the flip side, an event could result in mass fatalities. Therefore, an event was not a reliable indicator since it could conceal the high impact of numerous fatalities. Thus, I used number of fatalities as the indicator.

For Afghanistan, ACLED data was only available from 2017. Therefore, I supplemented with UCPD data only to ensure completeness. The quality of my results was not impacted negatively by this procedure.

Defining the Country Sample Set

The data set for analysis included countries in West Africa and Afghanistan. West Africa has experienced the highest proportional increase in acute food insecurity over the last decade and provided a wide range of values and country situations for analysis. Included countries were those that have been regularly monitored for food insecurity since 2011: Mali, Niger, Nigeria, Chad, and Mauritania. Nonetheless evaluations were still performed for Cameroon and Burkina Faso when possible due to the high number of people facing IPC Phase 4-5 in 2020-2021.

Afghanistan was included in the study for several reasons. First, it was the deadliest conflict of both 2019 and 2020, with over 20,000 conflict-related deaths annually, and therefore provides the most extreme fatality values for analysis (Strand & Hegre, 2021). Including Afghanistan also allowed a comparison of results to a region outside of Africa with different geographical, climatic, and conflict conditions. It presents clear “conflict seasons” which tend to end in the winter. Moreover, there is increased urgency to understand the relationship between violence and humanitarian needs in Afghanistan given the recent developments (Goldbaum, 2021).

Research Methods

The methods for this paper were the following (Table 5): (1) downloading and preparing data; (2) processing data in QGIS to match IPC regional shapefiles and conflict data with administration units; (3) analysis through statistical regressions of data by different time periods and seasons; (4) based on results, creation of maps that reflect where IPC is most sensitive to fatalities.

Table 5. Step-by-step summary of research methods.

1 → Download and Prepare Data	2 → Process Data in QGIS	3 → Analysis	4 Visualize Results
• Download admin2/LHZ boundaries that correspond to FEWS NET IPC data for each country • Download FEWS NET IPC data for all seasons from January 2011 to June 2021 • Download and aggregate conflict data (ACLED and UCDP) to match FEWS NET seasons	• Merge all admin2/LHZ boundaries into one map • Upload IPC seasonal shapefiles, rasterize, and run zonal statistics to assign a value to admin2/LHZ units • Upload conflict data, convert to shape files, link to corresponding admin2/LHZ • Perform "joins" to create master attribute table	• Identify "hotspots" in each country's admin1, creating line graphs to visualize trends • Linear regressions on 3 sets of fatality aggregations, repeating for admin 1 and admin 2 levels • Linear regressions for 3 main seasons over 10 years, repeating for admin 1 and admin 2 levels • In Afghanistan, additional linear regression over 10 years for 3 sets of fatality aggregations, repeating for admin 1 and admin 2 levels	Creation of maps that reflect where IPC is most sensitive to fatalities by admin1 and admin2

Downloading and Preparing Data.

ACLED data were downloaded from their website using their data export tool, which allows a search to be refined by conflict event "type". I included those with reported fatalities: battles, explosions/remote violence; violence against civilians, protests, and riots. The sub-events I selected included: abduction, air/drone strike, armed clash, attack, chemical weapon, excessive force, looting of property, mob violence, remote explosions, shelling/artillery, suicide bomb, violent demonstration, and grenade.

I aggregated the fatality data to match the time periods leading up to each

FEWS NET reporting month. Aggregating in this way was necessary to understand if IPC levels were sensitive to fatalities that occurred within the same time period. This method also allowed me to easily combine seasons when testing IPC sensitivity to longer periods of conflict.

IPC data were downloaded from the FEWS NET website in the form of West Africa regional shapefiles for all CS seasons between January 2011 and June 2021. I then imported them into QGIS for processing.

Data Processing in QGIS

I processed raw data to match administrative divisions (second-level administrative units and livelihood zones) used by FEWS NET to obtain an IPC classification (Table 6). The most recent admin 2 maps (and third-level administration divisions in the case of Cameroon) were obtained from FEWS NET and GADM. However, FEWS NET IPC shapefiles do not match perfectly to the map polygons. Therefore, I followed the methodologies laid out in Choularton and Krishnamurthy

Table 6. Index of countries.

Country	**No. admin units**	**Boundary type**
Mali	207	Admin 2 + LHZ
Niger	259	Admin 2 + LHZ
Nigeria	774	Admin 2
Mauritania	147	Admin 2 + LHZ
Chad	70	Admin 2
Burkina Faso	45	Admin 2
Cameroon	360	Admin 3
Afghanistan	402	Admin 2

The index includes the number of admin units that comprise the data set and the boundary type (by author).

(2019), which resolved this issue by rasterizing each layer and running zonal statistics with an output as the majority IPC value in each polygon.

Once all country maps were uploaded to QGIS, I merged them to create one regional shapefile for West Africa. I performed the same process for Afghanistan. The number of admin 2/LHZ in each data set was as follows:

Next, I uploaded the conflict data .csv files, adding them as layers to QGIS and then converting to shapefiles. ACLED and UCDP both register an event's coordinates, so each one appears as a point on the map. For each season, I assigned those data points to the corresponding administration unit (vector - analysis tools - points in polygon) which resulted in a sum of points per administration unit. I repeated this process to calculate the total fatalities per season per administration unit, but this time in the processing pane I added the "weight field" as fatalities. Once these steps were completed, I performed "joins - fields" for each of the seasonal IPC, conflict events, and fatalities layers to the West Africa/Afghanistan attribute tables.

Statistical Analysis

In Excel, I created individual country workbooks where I further sorted the data by admin 1 and admin 2 levels. Then I performed a first analysis to evaluate the data for fatality and IPC "hotspots" through a series of IF statements in Excel. I first searched for IPC levels 4 and 5, as these denote emergency and famine, followed by crisis-level IPC 3. I created line graphs for each admin 1 where "hotspot" data was located. This helped me to visualize the conflict and IPC levels over ten years and identify interesting trends for statistical analysis.

In the second phase of my analysis, I wanted to determine the statistical significance between IPC and fatality values in each season. I performed linear regressions to calculate the R^2 and P values, with a statistical significance of $P \leq 0.05$. In order to determine which administrative level would show the best fit (R^2) to the data, I performed the analyses at both admin 1 (hereafter referred to as provinces) and admin 2 levels (hereafter referred to as districts) and compared results. For the linear regressions, the independent variable was fatalities, and the dependent variable was the IPC level. I proceeded with the following three analyses:

1. In each country, I performed linear regressions of all district IPC values and fatalities.
2. Within each province, I performed linear regressions using the district IPC and fatalities values.
3. Within each province, I averaged all district IPC values and totaled the fatalities. Using these values, I performed linear regressions on all provinces.

Next, I took the above analysis one step further to understand if IPC levels were sensitive to periods of conflict outside of the current season. I also wanted to address the issue of reverse causality (Sneyers, 2017). Therefore, my approach was to test two additional aggregations of fatalities – two seasons (6/8 months), and three seasons (9/12 months). Anderson et al.'s (2021) methods used 12 months of previous fatalities, which also prompted me to test this aggregation set. Although this method would not exclude the same season of fatalities that could cause reverse causality, it would include additional fatality seasons to diminish the effect. I expanded each country worksheet with the corresponding accumulation of fatalities and repeated the steps above for each.

The next step was to perform a temporal analysis by aggregating seasonal data to evaluate whether there were seasonal patterns in IPC values and fatalities over ten years. This was an important focus of my research due to previous studies that found vulnerability among pastoral and agriculturally dependent populations (Anderson et al., 2021). Therefore, evaluating seasonal variations linked to planting/harvest/lean seasons or grazing periods could prove insightful.

Due to the discrepancy in the number of seasons from 2001-2015 and 2016-2021, I followed the approach by Krishnamurthy et al. (2020), which combined the closest seasonal months: season 1 combined January and February seasons; season 2 combined June and July seasons; and season 3 consisted of October seasons. The April season was excluded because it was only reported in years 2011-2015. I performed linear regressions with the three scenarios of aggregated fatalities at both province and district levels.

I then performed steps 1-3 in addition to linear regressions with the aggregated fatalities for both West Africa and Afghanistan. However, the results were not statistically significant for Afghanistan, which I will discuss below. This led me to test another model through a 10-year "timeline" linear regression for all seasons for each province and district-level. This would test fatality and IPC sensitivity over time versus within one season. Within each province, I averaged the district IPC values in each season and totaled the seasonal fatalities. I then performed a linear regression on those values for all years. I then performed linear regressions at a district level on IPC values and fatalities for all years to determine the statistical significance at the highest spatial resolution. I then repeated these analyses for the two additional scenarios of aggregated fatalities.

Visualizing Results in Map Form

Once my analysis was complete, I inputted the results into QGIS to create a set of maps that indicated each admin level's sensitivity to conflict through a color gradient. I uploaded a .csv file with the R^2 values and matched them to the corresponding admin unit using the "joins" function. I then created a color ramp in QGIS that corresponded to a range of R^2 values from 0-1. In cases where the IPC level did not change, or there were no fatalities, the regression resulted in 1, and the corresponding unit was left blank. This was the case of Mauritania.

Chapter III

Results

My results are presented in the following order, which follow the sequence of the methods:

1. Trend analysis
2. Aggregated fatalities
3. Spatial analysis
4. Seasonal variations
5. Timeline regression analysis

Trend Analysis

The trend analysis was the first step in evaluating the data to identify patterns between variables and prepare a classification of three possible scenarios.

Scenario 1: Clear Relationship Between Conflict and Food Insecurity

Overall, my results showed a correlation in the relationship between IPC levels and fatalities. In Uruzgan, Afghanistan, IPC levels and fatalities generally rise together starting in 2015 (Figure 5). The fluctuation in fatality and IPC levels appear to be correlated between 2011-2021. There is typically an increase in IPC levels one to two seasons after a spike in fatalities.

Many of the line charts indicated a lag of one to two seasons before an increase in IPC levels was observed. This was an interesting aspect to consider when assessing the appropriate number of seasons to be included in aggregated regressions later in the analysis.

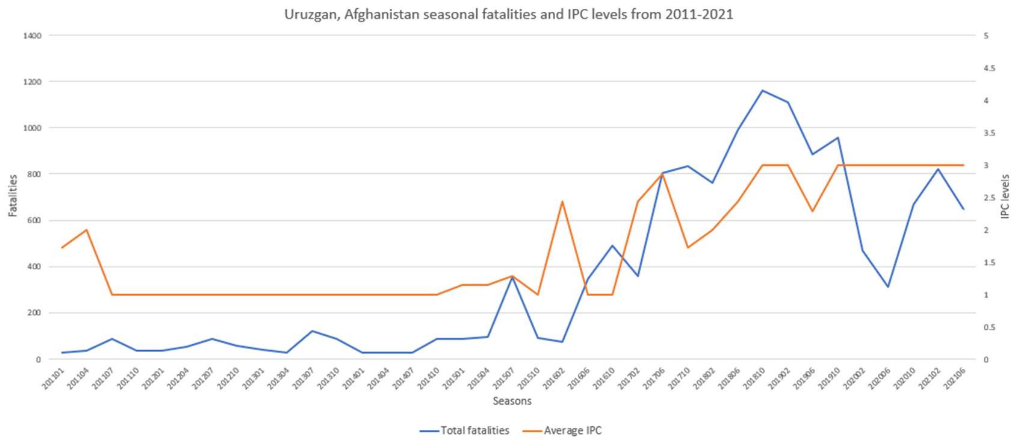

Figure 5. Fatalities and IPC levels in Uruzgan, Afghanistan, 2011-2021.

In Afghanistan this trend was apparent across 24 out of 32 provinces, while in West African countries it was less visible, with three provinces in Nigeria, one in Chad, and none in Mali, Cameroon, or Niger.

Scenario 2: Tipping Point

Although the general trend pointed to highly correlated variables, there were exceptions. For example, in Borno, Nigeria, IPC levels increased with fatalities and remained high despite a later decline in fatalities (Figure 6). There was a sharp spike in fatalities in the first and second seasons of 2015. The average IPC increased from 2.2 in January 2015 to 3.3 by July, after which the average IPC remained above 2.8 until 2020 despite a decrease in fatalities (Figure 6). It is, however, important to note that although fatalities decreased, the lowest number was still comparably high, at 353. This pattern may indicate an inability of the population to recover after a certain threshold of destruction and violence, and the depletion of food reserves and other coping strategies. Additionally, the elevated IPC levels may be due to conflictinduced displacement and food insecurity experienced in IDP camps or host communities.

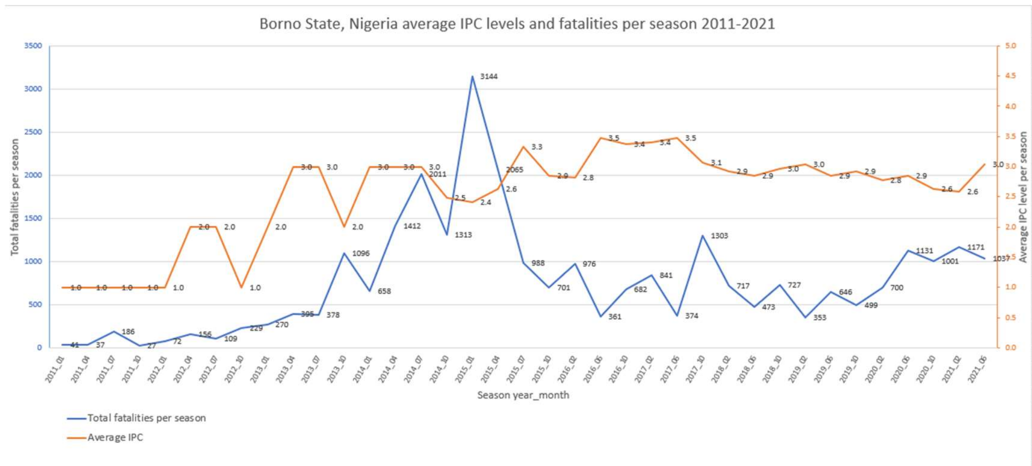

Figure 6. Average IPC levels and fatalities in Borno, Nigeria, 2011-2021.

Scenario 3: No Relationship Between Conflict and Food Insecurity

Where there were few or no fatalities for the entire ten-year period, the IPC level still fluctuated. In Mauritania, for example, IPC levels oscillated between phase 1 and 3 as seen in the province of Brakna (Figure 7). Brakna is an agro-pastoral region located in southwestern Mauritania on the border with Senegal, and food insecurity is likely due to variations in precipitation which has magnified Mauritania's chronic water shortage, as well as the increase in food prices (FEWS NET, 2021).

In Afghanistan, the IPC levels in several districts fluctuated significantly even in years where fatalities were low or absent. For example, in Bamyan the average IPC level was at Phase 3 for several seasons with few fatalities (Figure 8).

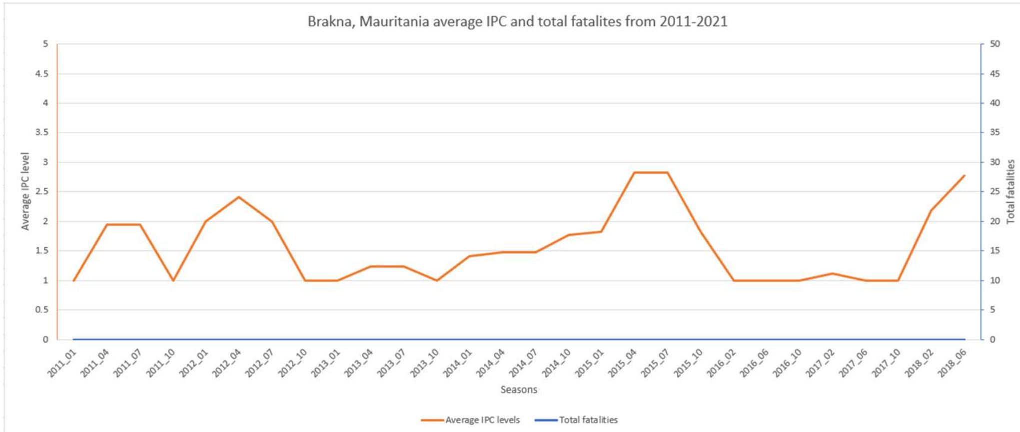

Figure 7. Average IPC levels and fatalities in Brakna, Mauritania, 2011-2021.

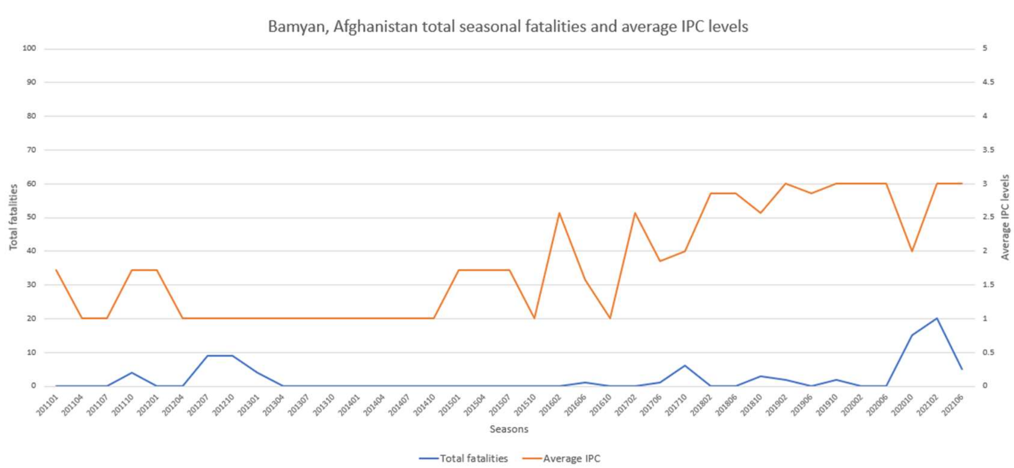

Figure 8. Average IPC levels and fatalities in Bamyan, Afghanistan, 2011-2021.

Aggregated Fatalities

In West Africa, the regression results from three scenarios of aggregated fatalities varied by country for individual seasons across ten years. Mali showed the most statistical significance with one and three seasons of aggregated fatalities; Nigeria with two and three seasons; and Niger and Chad with three seasons. Burkina Faso also showed higher R^2 values with three seasons of aggregated fatalities; however, a lack of data would not allow a complete analysis. Likewise, there were data gaps for Cameroon, but it showed highest correlation with two seasons of aggregated fatalities.

The high R^2 values in Nigeria appear to be driven by IPC and fatalities in Borno state. Figure 9 andFigure 10 show charts for Nigeria in the October 2016 season using three seasons of aggregated fatalities.

Figure 9 represents IPC and fatality values by district units for the whole country, while Figure 10 shows the average IPC values and total fatalities within each province unit. High values in Borno state in both examples drive the slope of the trendline, with a higher R^2 value of 0.6867 (p = 2.42E-10) for the model using average IPC levels versus 0.2335 (p = 1.55E-46). Many districts in Borno state experienced IPC Phase 4 during this season, as reflected in Figure 9.

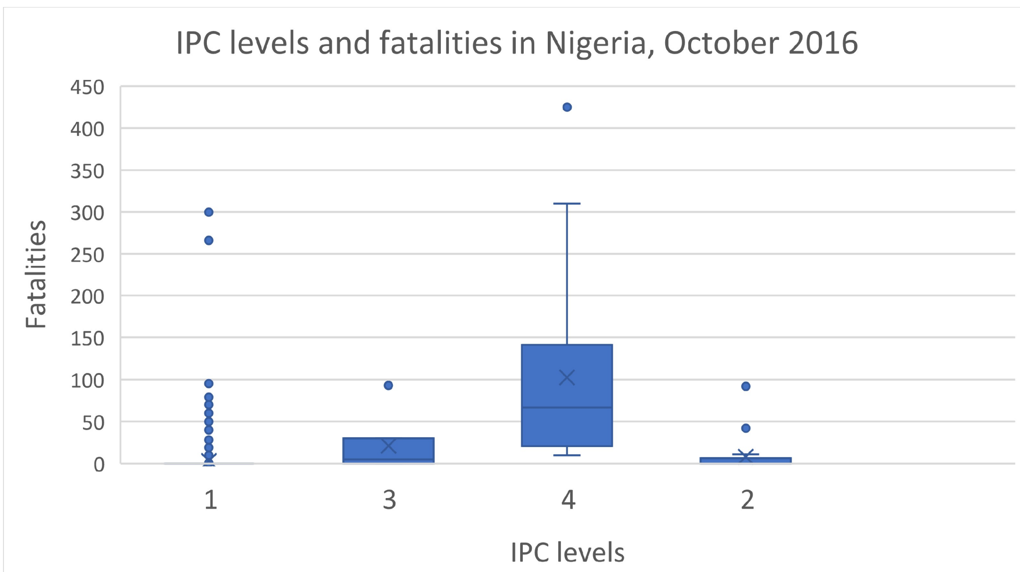

Figure 9. IPC levels and fatalities in Nigeria, October 2016.

In Afghanistan, overall, linear regressions with three seasons of aggregated fatalities resulted in the highest R^2 values. However, the results of regression analysis in Afghanistan differed from West African countries. Despite high numbers of fatalities and elevated IPC levels, it was common to see little variation in IPC values

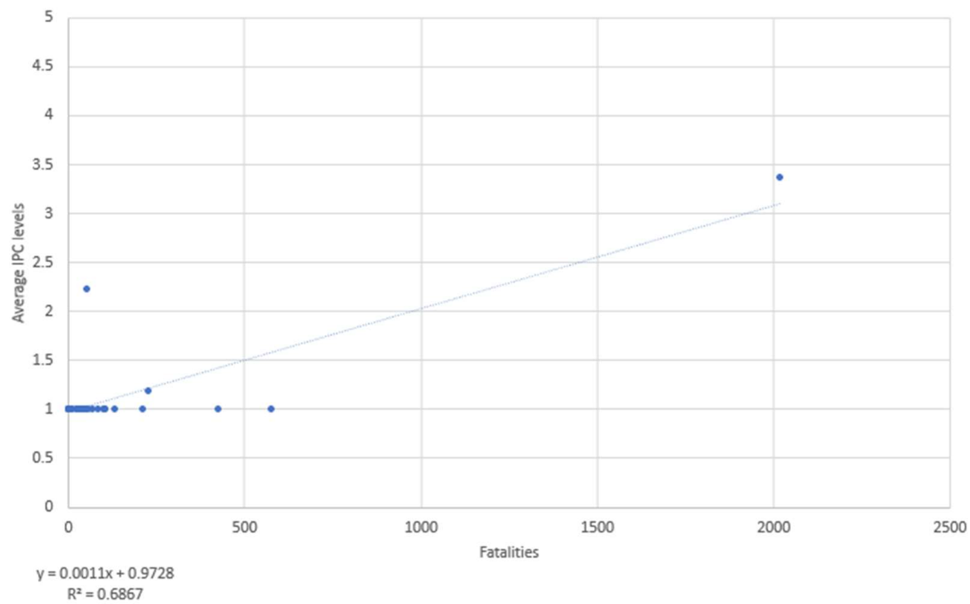

Figure 10. Average IPC levels and 12 months aggregated fatalities in Nigeria, October 2016.

within a single season, which resulted in r=0. The highest R^2 value was 0.277 (three seasons of aggregated fatalities) in June 2016. All other R^2 values, with all scenarios of aggregated fatalities, were less than 0.19. Moreover, in the seasons of October 2011 and January 2012, R^2 values showed a negative correlation between IPC values and fatalities, at 0.1192 and 0.1525 respectively (three seasons of aggregated fatalities).

Spatial Analysis

All seasonal regressions showed the best fit model at a district level, using the average IPC and total fatalities, which I elaborate on in the discussion. For example, Table 7 compares the regression results of all three statistical analyses (described in Methods) in Nigeria, with a district-level example of Borno state, the province with the most fatalities in Nigeria. The R^2 values were highest at a province level for all scenarios of aggregated fatalities (Table 7).

Table 7. Results of linear regression analyses in Nigeria.

February 2017	Analysis 1: all admin 2 IPC and fatality values for Nigeria	Analysis 2: using the admin 2 IPC and fatality values (ex: Borno State)	Analysis 3: using average IPC values and total fatalities for all admin 1. Linear regressions on all admin 1 levels
3 seasons aggregated fatalities	R^2=0.239 ($p \leq$ 0.05)	R^2=0.08 (p =0.147)	R^2=0.67 ($p \leq 0.05$)
2 seasons aggregated fatalities	R^2=0.216 ($p \leq$ 0.05)	R^2=0.084 (p =0.1405)	R^2=0.696 ($p \leq 0.05$)
1 season fatalities	R^2=0.228 ($p \leq$ 0.05)	R^2=0.0775 (p =0.1598)	R^2=0.228 ($p \leq 0.05$)

Aggregated seasonal regressions showed the same results. For example, with three seasons of aggregated fatalities, Niger showed higher R^2 values when using averaged district values and total fatalities (Table 8) than using the district IPC and fatality values (Table 9).

Table 8. Regression results using the averaged province level and total aggregated fatalities for three seasons in Niger.

Season 1		Season 2		Season 3	
R^2	*p*-value	R^2	*p*-value	R^2	*p*-value
0.599828	($p \leq 0.05$)	0.353774	($p \leq 0.05$)	0.670098	($p \leq 0.05$)

Table 9. Regression results using IPC levels by admin 1 and three seasons of aggregated fatalities in Niger.

	Season 1		Season 2		Season 3	
Admin1	R^2	*p*-value	R^2	*p*-value	R^2	*p*-value
Agadez	0.001366	0.558371	0.003846	0.325875	1	N/A
Diffa	0.027284	0.001142	0.021654	0.003807	0.027823	0.00174
Dosso	1	N/A	0.019292	0.007141	0.000216	0.787265
Maradi	0.07733	7.18E-08	0.019474	0.007754	0.132409	9.08E-12
Niamey	1	N/A	0.004352	0.715308	0.097012	0.093845
Tahoua	0.089653	2.13E-12	0.029014	8.37E-05	0.140672	1.76E-17
Tillababeri	0.105436	1.06E-14	0.050702	1.27E-07	0.119913	2.99E-15
Zinder	0.000626	0.629503	0.001412	0.468801	1	N/A

Seasonal Variations

Among West African countries, three countries showed the highest R^2 values with three seasons (9/12 months) of aggregated fatalities: Mali, Nigeria, and Chad (Table 10). The exception was Niger, with a higher R^2 value with two seasons (6/8 months) of fatalities. The results for Chad, Mauritania and Niger were strongest in the October season, with Mali and Nigeria in the January/February season. R^2 values for Nigeria showed the least variation across all three seasons, ranging between 0.267-

Table 10. Regression results using aggregations of seasonal data from 2011-2021 for each country.

	3 Seasons of Fatalities (9/12 months)		
	R^2	R^2	R^2
Country	Season 1	Season 2	Season 3
Mali	0.4637	0.1560	0.1401
Niger	0.5998	0.3538	0.6701
Nigeria	0.3663	0.2679	0.3396
Chad	0.1341	0.0595	0.3086
Burkina Faso	N/A	0.1603	N/A
Afghanistan	0.1000	0.1120	0.1050
	2 Seasons of Fatalities (6/9 months)		
	R^2	R^2	R^2
Country	Season 1	Season 2	Season 3
Mali	0.4465	0.1522	0.1794
Niger	0.3634	0.2976	0.7723
Nigeria	0.3164	0.2809	0.3354
Chad	0.0648	0.0362	0.2505
Burkina Faso	N/A	0.1615	N/A
Afghanistan	0.1156	0.1183	0.1476
	1 Season of Fatalities (3/4 months)		
	R^2	R^2	R^2
Country	Season 1	Season 2	Season 3
Mali	0.3389	0.0948	0.2370
Niger	0.1585	0.2998	0.4248
Nigeria	0.2443	0.2442	0.3288
Chad	0.0384	0.0352	0.2846
Burkina Faso	N/A	0.1724	N/A
Afghanistan	0.0526	0.1248	0.1517

Data was insufficient to calculate results for all seasons in Burkina Faso. Numbers highlighted in green indicate the highest R^2 value of the three seasons for each country with each scenario of aggregated fatalities.

0.366. Nigeria also showed a higher R^2 value in the October season when tested with two seasons of aggregated fatalities. The only country with highest R^2 in June/July season was Burkina Faso, albeit with a low R^2 value of 0.1724 with one season of fatalities. R^2 values for all seasons and aggregations of fatalities for Mauritania were below 0.077, with *P* values greater than 0.05. There was insufficient data to calculate all seasons for Burkina Faso.

Results for Afghanistan were strongest with one season of fatalities, however, all R^2 values were less than 0.15 (Table 10). Again, with this model, a lack of variability in the IPC levels within individual seasons in Afghanistan resulted in low R^2 values overall.

Timeline Statistical Analysis

In addition to aggregated seasonal regressions, I performed a series of "timeline" linear regressions, which analyzed data across ten years at province and district levels. I then transformed the results into map form (Figure 11 & Figure 12). A table of results can be found in Appendix 3.

In West African countries, results at the province level showed the highest R^2 value in Littoral, Cameroon at 0.907, followed by Imo and Oyo, Nigeria at 0.797 and 0.729 respectively. R^2 values for the northwestern provinces of Zamfara (0.461), Sokoto (0.455) and Adamawa (0.368), Nigeria were also significant (Figure 11).

In West African countries, results at the district level showed that the highest R^2 value was 0.68 in the district of Wouri, Littoral, Cameroon. It was closely followed by Guidan Roumdji, Maradi, Niger at 0.625 (Figure 12). Results were also high in Imo, Kaduna, Katsina and Sokoto Nigeria, but Borno state values were lower, with the highest R^2 value of 0.312 in Damboa.

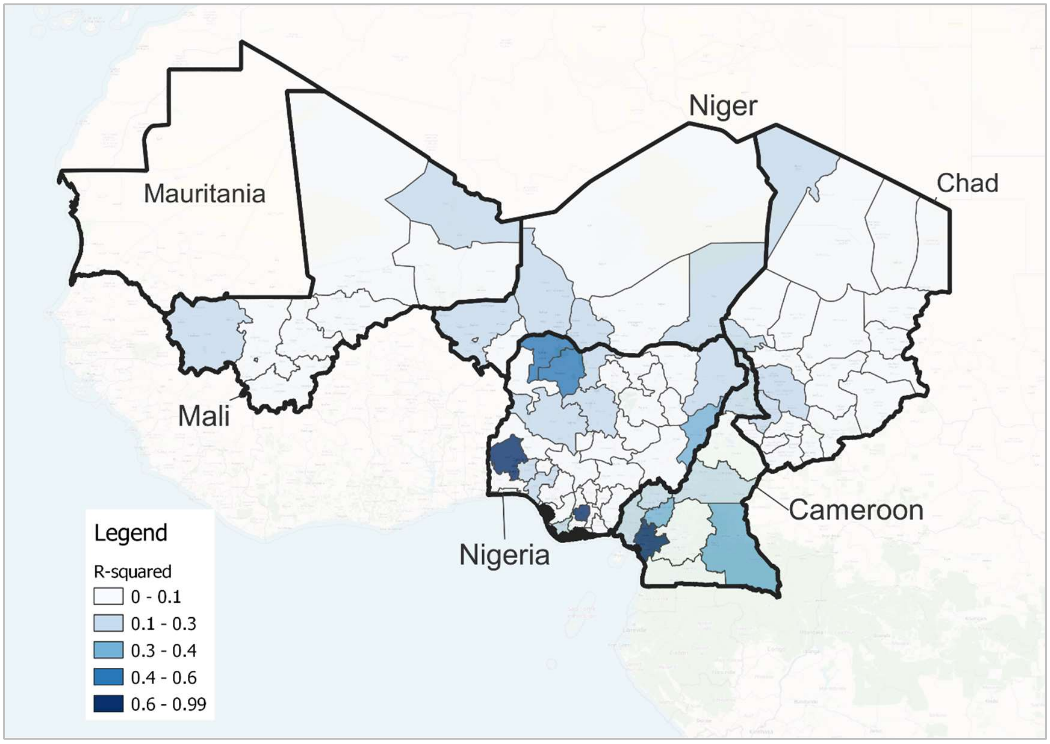

Figure 11. A province-level map of IPC sensitivity to fatalities.

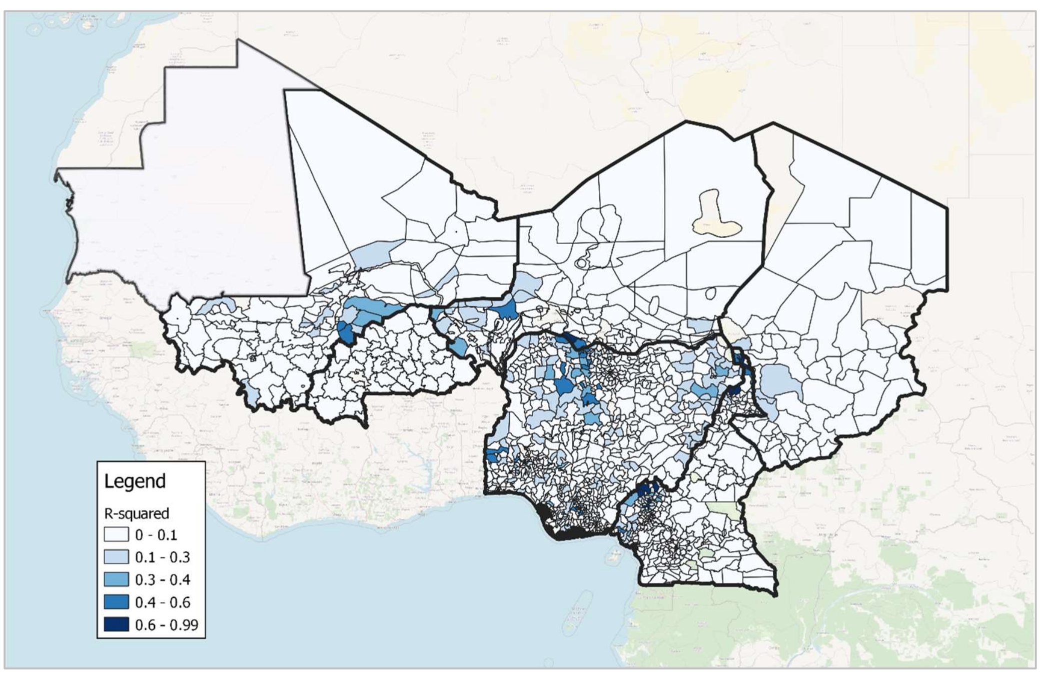

Figure 12. A district-level map of IPC sensitivity to fatalities.

In Afghanistan, the results showed statistical significance with three aggregated seasons of fatalities at both province and district levels (Figure 13 & Figure 14). This model was more successful in the case of Afghanistan because it could capture the variation in IPC levels that could only been seen over a longer time period. R^2 values were calculated for each province and district unit, indicating the proportion of variation in IPC values explained by fatalities.

The highest correlations between IPC levels and fatalities were in the province units of Uruzgan and Farah, with values of 0.6726 and 0.6539 respectively (Figure 13). However, the median R^2 value is 0.47, which means at least 47% of the variation in IPC levels in half of Afghanistan's provinces can be explained by fatalities.

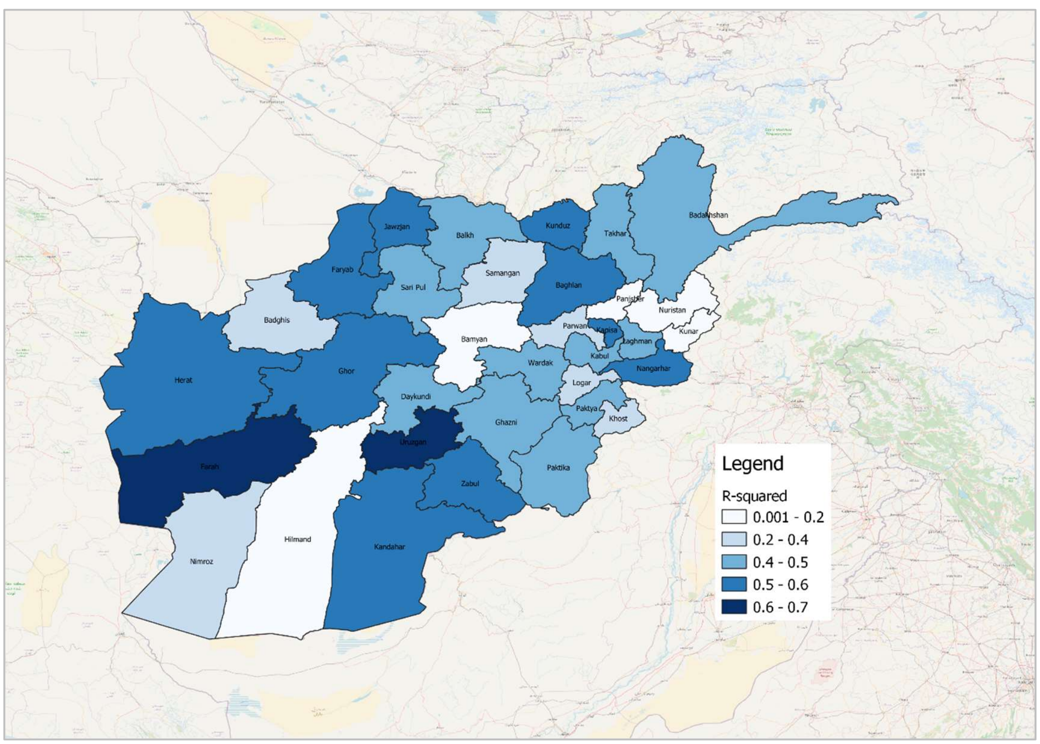

Figure 13. IPC sensitivity to fatalities by province in Afghanistan.

At a district level, the five highest R^2 values were in Ana Dara, Farah, at 0.724, Farah, Farah at 0.666, Khwaja Sabzposh, Faryab at 0.626, and Achin, Nangarhar at 0.618 (Figure 14).

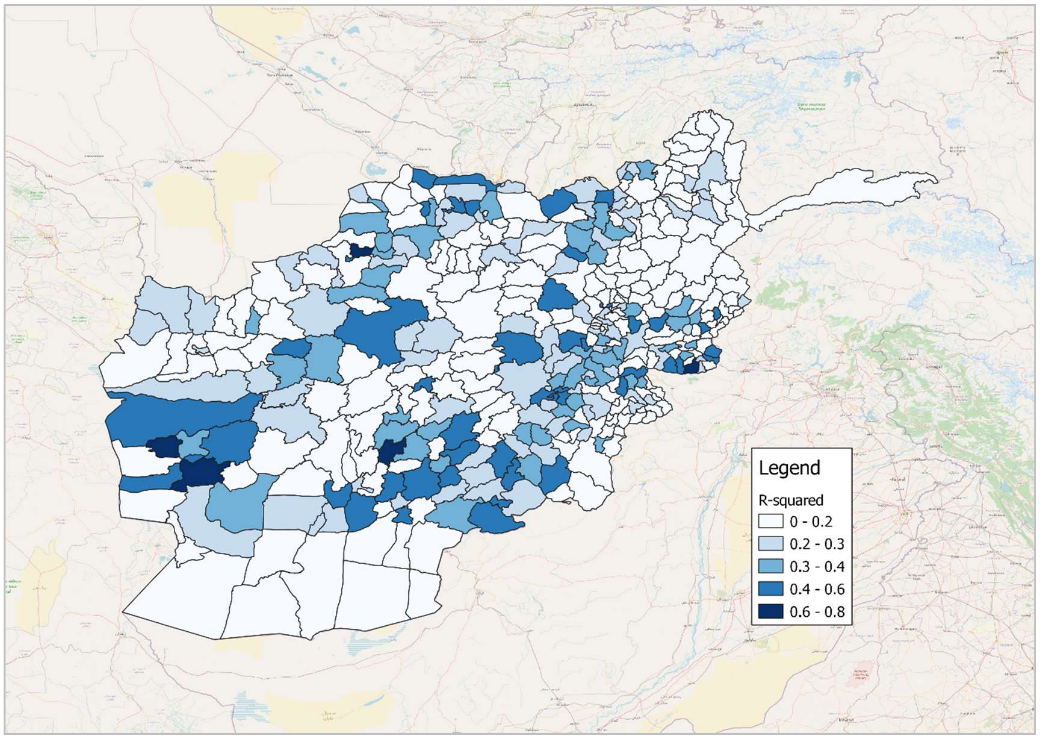

Figure 14. IPC sensitivity to fatalities by district in Afghanistan.

For all timeline regressions, it is important to consider the number of years a context has been experiencing conflict because it will impact how the regression will show fatalities as an explanatory variable over the entire ten-year period. If a country experienced severe drought for several years that leads to food insecurity, and an onset of armed conflict later, the R^2 will be lower because less of IPC change is not explained by fatalities alone. The timeline model appears to show a greater explanatory power in Afghanistan, possibly due to decades of ongoing conflict, versus many parts of West Africa where the greatest increase in conflict intensity has occurred since 2015.

Chapter IV

Discussion

This study found that the increase in severe food insecurity in West Africa over the last decade is significantly correlated to fatalities in Nigeria, Mali, Niger, Cameroon, and Chad. Burkina Faso also shows strong correlation in 2021, but a lack of IPC data did not allow for a full analysis. Regression results for Afghanistan also showed a high correlation between IPC levels and fatalities over time, but not in individual seasons due to a lack of variability in data. The following discussion follows the same order of scenarios as the Results.

Conflict is Correlated to Food Insecurity

Research has shown that the impacts of armed conflict on food security are not straight forward. However, following Anderson et al. (2021), my research found significant correlations between the two variables.

One of the interesting findings from my results was the robustness of data on the province versus district level. In West African countries, a majority of both R^2 and p values ($0.05 \leq$) were statistically significant for provinces with all three aggregations of fatalities in all seasons. These findings are consistent with Anderson et al. (2021) that conflict can have wide-reaching impacts outside of the immediate areas where events or fatalities occur. This may be because fighting (and fatalities) in one district displaces a portion of the population to other, nearby district, where they face food insecurity in IDP camps or host communities. For example, in northern Nigeria, displacement numbers are some of the highest in the region at just over two million people, with more than 75% in Borno state (Figure 15) (IOM, 2021; FSIN, 2021). An estimated 89% of IDPs in northern Nigeria stay within their province, but 56% reside in a district other than their own (IOM, 2021). This means there is significant population movement within a state and therefore the average ICP level across a state may be more robust in statistical regression analysis than those in any given district. Second, fighting in one area may impact food security in a neighboring

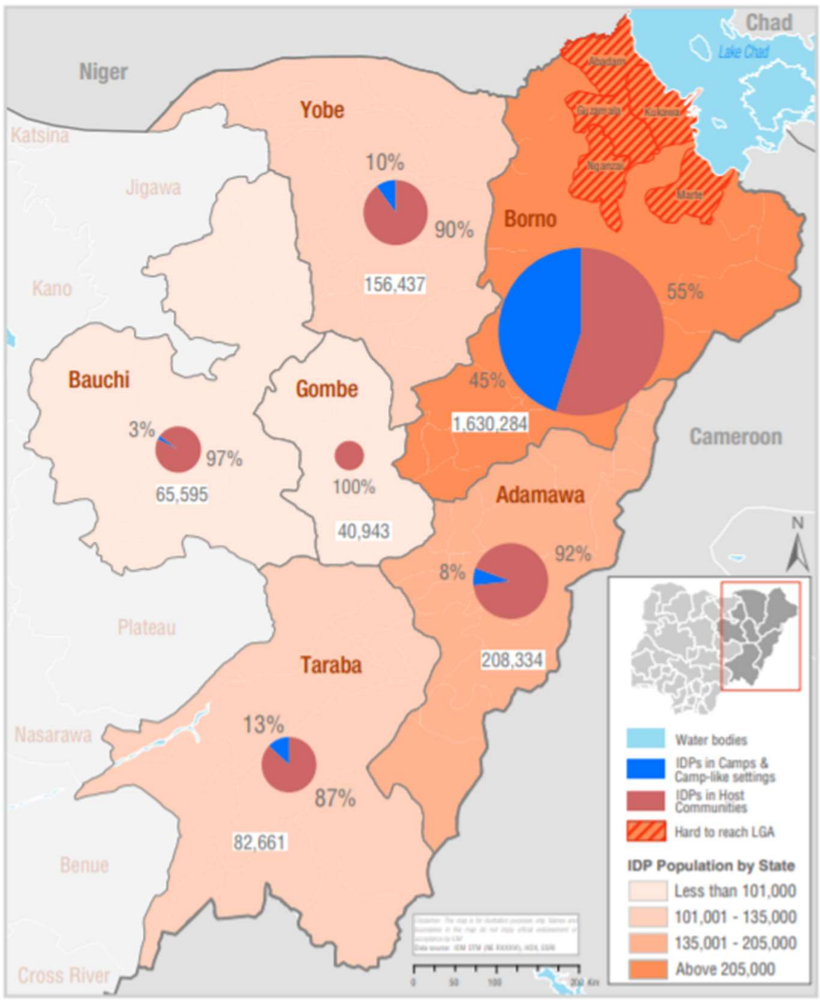

Figure 15. IDP populations per state in northeastern Nigeria.

The map shows IPCs population per state and settlement type (IOM, 2021).

district. As stated in the background, the disruption to local production of food can be affected by several factors, including destruction to crops and agricultural assets, reduced mobility to food markets to buy and sell food, and income shocks due to reduced labor opportunities.

Another interesting aspect of my results was the outcome of the aggregated seasonal analysis, which provided an insight into seasonal patterns of hunger and violence. Of all the analyzed countries, Mali and Niger showed the clearest examples of seasonal disparities. In Mali, the strongest correlation was in the first season (January/February) with an R^2 of 0.46. Niger showed the highest correlation in the third season (October), with the highest R^2 value of 0.77 with two seasons (6/8 months) of aggregated fatalities. As we examine the harvest schedule, there could be a link with the consecutive pastoral and agricultural lean seasons, which begin in mid-March and end at the end of October (Figure 16). These lean season conditions may be exacerbated by climate variation or extreme weather, which further depletes available grazing land and food reserves.

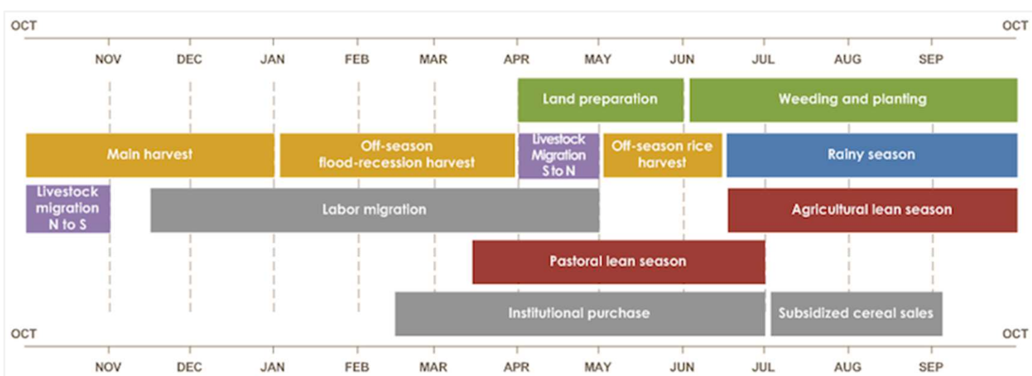

Figure 16. Seasonal calendar for Niger by farming, pastoral and labor migration periods.

(Source: FEWS NET, n.d.)

The R^2 values showed less variation in Nigeria. However, in individual seasons (not aggregated), the R^2 values are noticeably higher starting in 2014, with values ranging between 0.44 – 0.66 (Appendix 2). One reason the results for aggregated seasonal regressions are less significant than individual seasons may be due to different kinds of conflict dynamics across the country. For example, violence carried out by Boko Haram and the Islamic State Group of the Sahel (ISGS) may not be triggered by the same kind of violence seen between herders and farmers in other regions, which tend to flare up around certain seasons of the year (George et al., 2020). This is an important insight when forecasting food insecurity in different contexts.

As previously mentioned, regression analysis depends on variation in data, and the seasonal results for Afghanistan showed low R^2 values. However, the timeline regression analysis showed very strong correlations over time between conflict and food insecurity. In addition, an analysis of conflict data added an insight pertaining to winter-season conflict patterns. Figure 17 shows clear increases in fatalities in the autumn months, followed by a dip in fatalities in the winter season. Fatalities were higher in October than all other seasons from 2015 – 2020. This may be due to harsh winter conditions in some provinces that restrict mobility, and therefore fighting.

Some contexts show a clear correlation between IPC levels and fatalities, but others are more complex and show varying degrees of correlation at different moments over the ten-year time period. There are several cases in which IPC levels

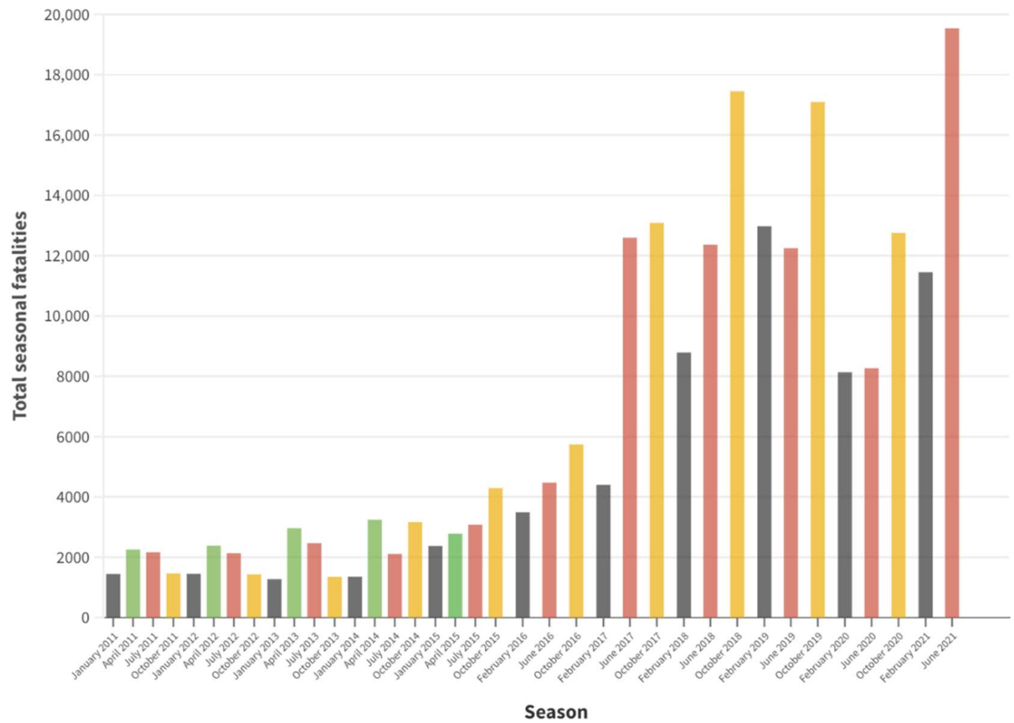

Figure 17. Total seasonal fatalities by season in Afghanistan, 2011-2021.

Note UCDP data was used from 2011 – February 2017 and ACLED data from June 2017-2021 (By author, data from UCDP, n.d.; ACLED, n.d.).

were elevated at Phase 1 before an onset of conflict. In Afghanistan, this was likely due to severe drought in 2008 that preceded my analysis (Figure 18) (USDA, 2008). In 2011, there was an increase in IPC levels in 98% of the country, particularly in the western provinces like Badghis (Figure 18), most likely due to similar drought conditions that continued in 2011-2012 (UNOCHA, 2011). There was still a general absence of fatalities at that time, except for four western provinces where fatalities ranged between 163-318. Devastating floods and landslides also impacted several northern and northwestern areas, including Badghis, which may be the cause of IPC level spikes in 2015 (UNOCHA, 2015; USAID, 2015).

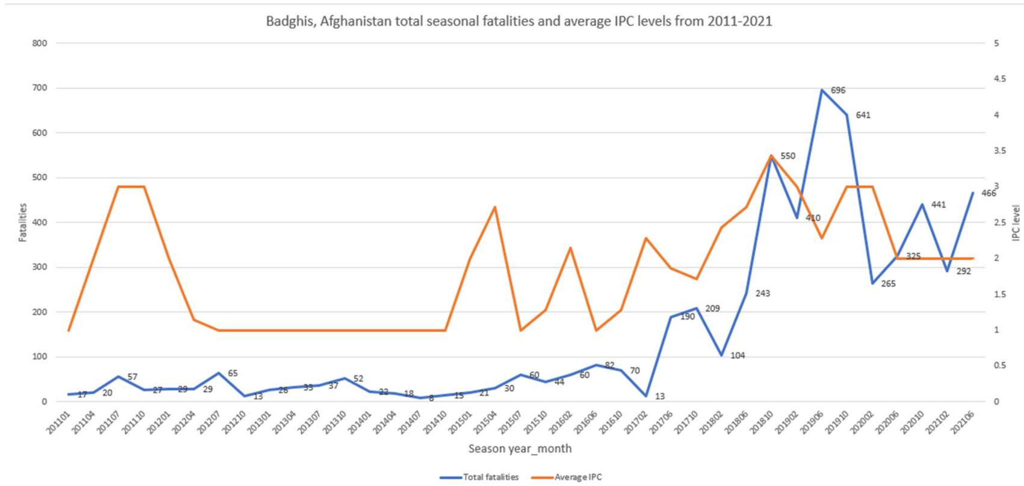

Figure 18. Average IPC levels and fatalities in Badghis, Afghanistan from 2011-2021.

A similar situation was observed in 2001-2017 in Gao, Mali which saw more frequent spikes in IPC levels up to Phase 3 with low fatalities during that time (Figure 19). The increase in food security coincides with Mali's pastoral lean season and land preparation for planting (Figure 20). Spikes in IPC levels are observed every April-July from 2011-2016, and again in the June seasons from 2016-2021, albeit marginally lower. This may also be intensified by drought conditions.

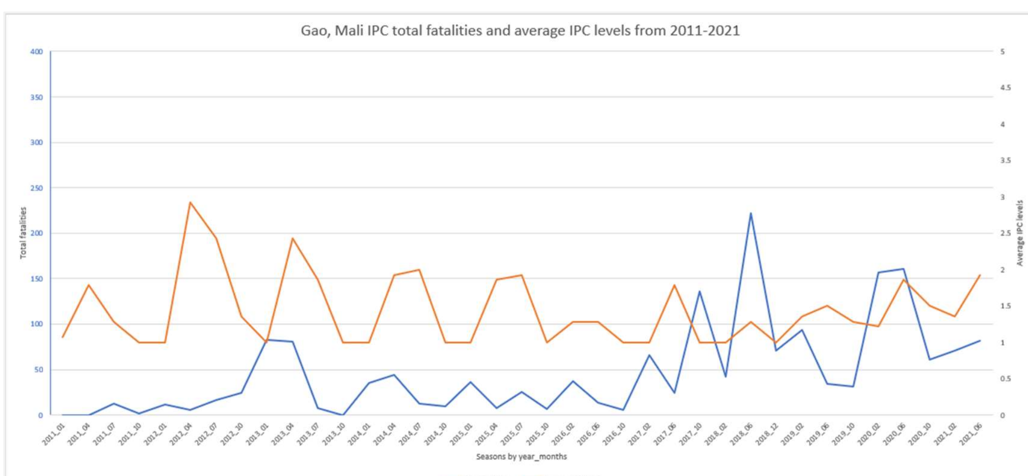

Figure 19. Average IPC levels and fatalities levels in Gao, Mali from 2011-2021.

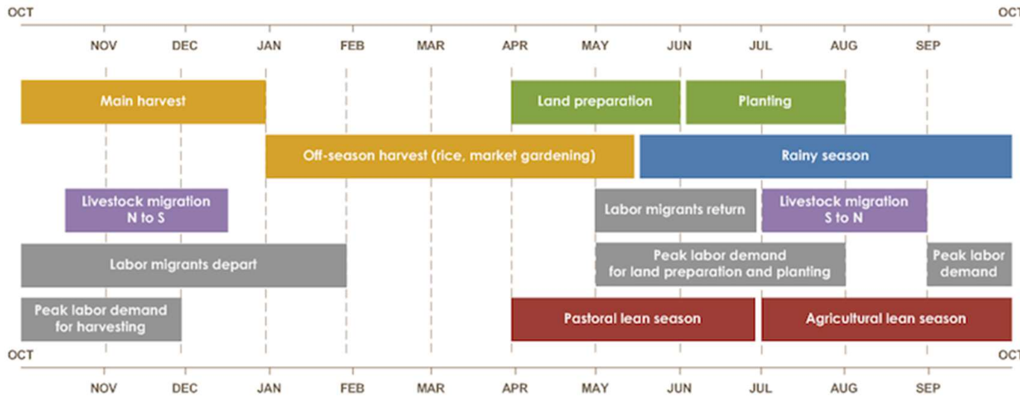

Figure 20. The harvest calendar for Mali (FEWS NET, n.d.)

Elevated or fluctuating baseline IPC levels are important to note because they indicate a pre-existing level of food insecurity before the onset of conflict, which in theory could make the population more vulnerable to food insecurity in the presence of fatalities, commonly referred to as "double vulnerability" (Peters et al., 2019). This also has implications for overall nourishment of the population: countries experiencing more than one driver of food insecurity may have PoU rates of up to 12 times that of countries that are only affected by one driver (FAO, 2021).

In these cases, the results of regression analysis were insightful because they could estimate the degree to which the eventual onset of conflict impacted IPC scores in the presence of drought or other shocks.

Conflict is Correlated to Food Insecurity Until a Tipping Point

Reviewing the results of my analyses, there are strong correlations between variables in many contexts. However, one of my findings involved cases in which IPC values and fatalities were correlated until what seemed like a "tipping point". My results showed several cases in which both fatalities and IPC levels increased and then decoupled: fatalities dropped off and the IPC level remained elevated for years afterwards. Borno state is one such example (Figure 21).

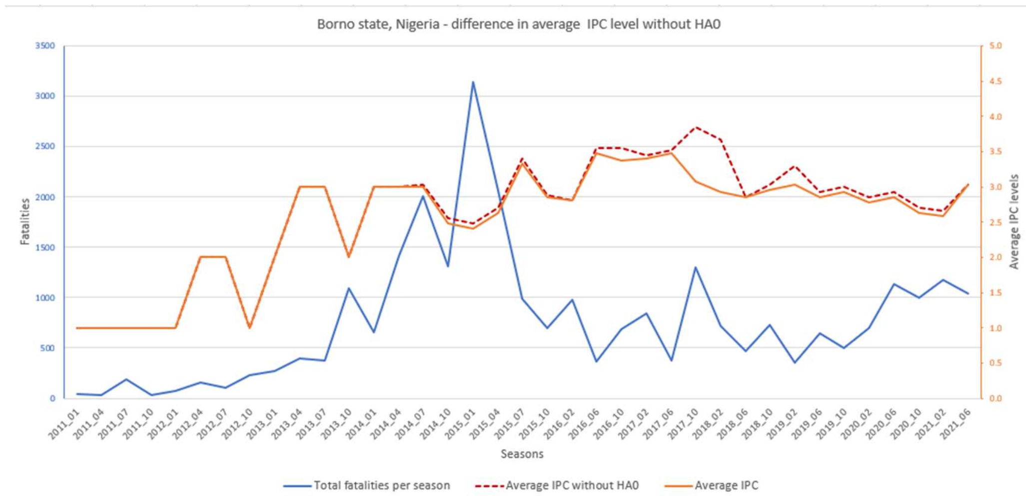

Figure 21. Fatalities and average IPC levels in Borno state, Nigeria including HA0. *(By author, data FEWS NET, n.d., ACLED, n.d.)*

Was this a sign that a threshold had been met, after which the population could no longer recover? Just as there can be a lag time in food insecurity after the onset of conflict, there also appears to be a lag time in rehabilitation. Assets are destroyed, livelihoods, people have to rebuild their lives, their incomes, and their food reserves. This is apparent in Syria: after ten years of conflict damaged farm equipment, canals, machinery, and silos, and the country is now dependent on wheat imports (Bayram & Gök, 2020; Al-khalidi, 2021). Those who can farm must wait for a harvest, and in the meantime, they must pay for food. It can take decades for the food systems to recover.

This pattern was also apparent in Yobe, Nigeria albeit with overall fewer fatalities (Figure 22). Yobe borders Borno to the west and shares a northern border with Niger. It currently hosts more than 156,000 displaced people, most of whom fled fighting in Borno, which is one reason why IPC levels have remained high despite a decrease in fatalities.

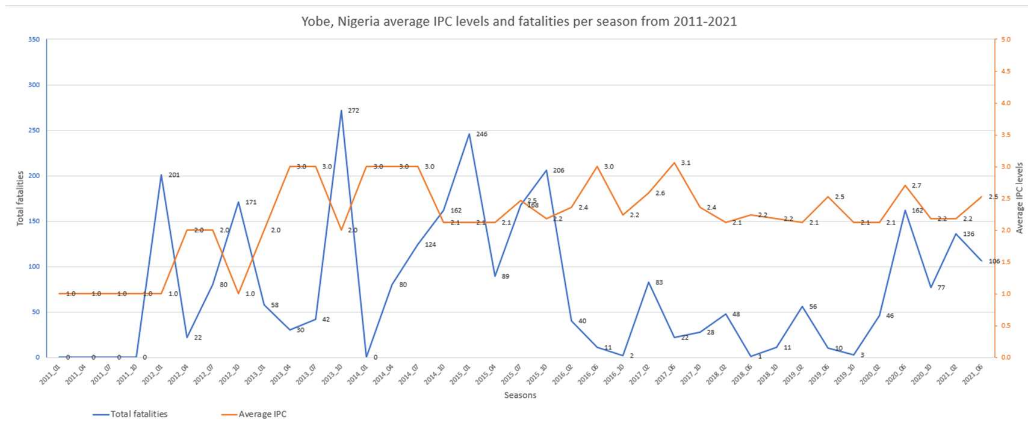

Figure 22. Average IPC and fatalities in Yobe, Nigeria, 2011-2016.

(By author, data FEWS NET, n.d., ACLED, n.d.).

In the case of Afghanistan, where the IPC levels had already been elevated for years, the tipping point has clearly passed. Figure 23 shows fatality and average IPC levels at a country level from 2011-2021. Both IPC levels and fatalities were relatively low until a spike in fatalities in 2016. IPC levels appear to follow the trend, steadily increasing until a spike in June 2017, followed by consecutive, higher peaks in the following years. In June 2021, the last season included in this analysis, the average IPC level hovers between IPC Phase 3-4, with seasonal fatalities at roughly 11,000, just before the Taliban took control of the government in August of this year. Considering the IPC levels are averages, this number indicates millions of people are actually in IPC Phase 4 or higher.

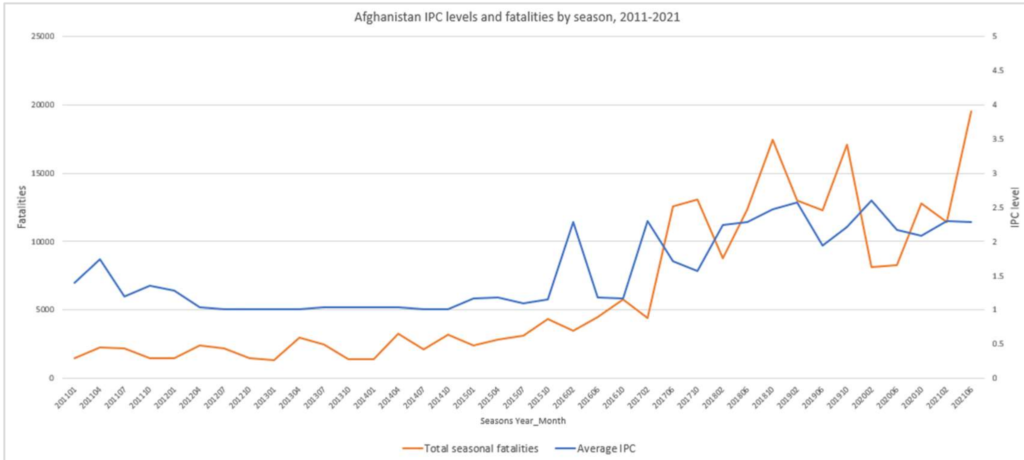

Figure 23. Average IPC levels and fatalities in Afghanistan, 2011-2021.

No Relationship Between Conflict and Food Insecurity

Of the countries analyzed in this study, Mauritania was the only one that had not experienced armed conflict from 2011 to 2020. The average IPC levels fluctuated between Phase 1-2 since 2011, with noticeable increases during the lean season (April - September), which reflects the series of severe droughts that have hit the country over the past decade (Figure 24) (WFP, 2021b). In fact, severe drought has been well-documented in Mauritania, with the most notable period being 1971-1991 when 94 different droughts hit the country, most of them severe, resulting in widespread death of animals and crop failure (Yacoub & Tayfur, 2020).

More than 75% of Mauritania's population lives in rural areas with a majority depending on agricultural activities, and late or irregular rains put a strain on both income and food sources (Yacoub & Tayfur, 2020; WFP, 2021). Drought also affects pastoralists, reducing the available pasture for animals. This has often resulted in the selling of livestock and other assets as a coping mechanism (FEWS NET, 2021b). Rising food prices due to drought and the COVID-19 have affected food accessibility, especially for poor families.

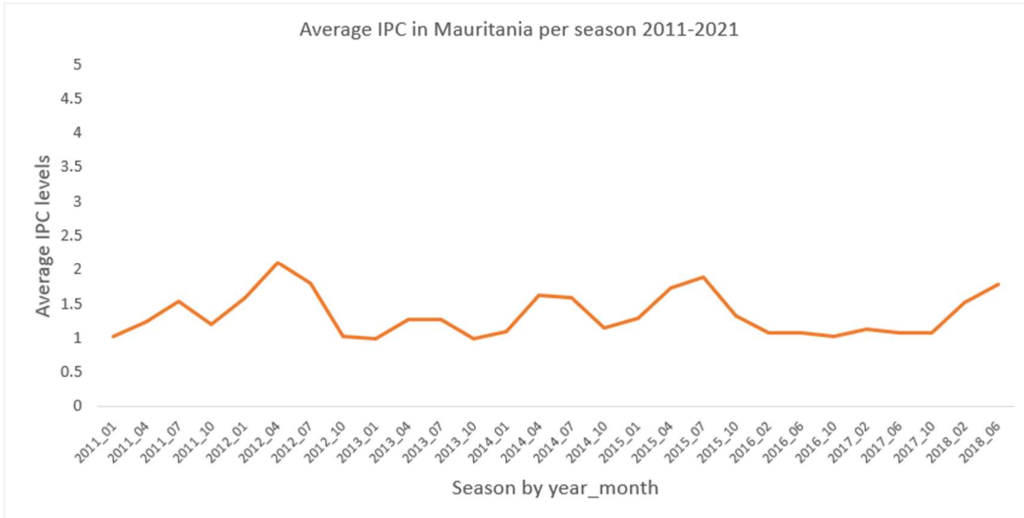

Figure 24. Average IPC levels in Mauritania, 2011-2021.

Along the border with Mali, where scarce pastures are more abundant, herders from both countries compete for resources, made worse by drought (FEWS NET, 2021). Mauritania also hosts an estimated 64,000 refugees in M'bera camp who have fled violence in Mali, and local farmer grievances about the over-use of scarce water resources have been documented (UNHCR, 2021b; Kestler-D'Amours, 2017). As the armed conflict in Mali continues alongside increased resource scarcity, this is a situation that could become more sensitive to increased tensions.

Conclusions

Global hunger has risen to an unprecedented level in 2021 as the impacts of armed conflict, climate shocks, and COVID-19 converge. With more than 500,000 people facing famine in 2021, there is an urgent need to understand the root causes of food crises to avert further human suffering. Armed conflict continues to drive a majority of food crises, and my thesis addressed how the duration and intensity of fighting, measured through fatalities, impacts IPC levels at different temporal and spatial levels.

My research found that Integrated Food Security Phase Classification (IPC) levels, which classifies the severity of food insecurity on a scale of 1-5, and conflict fatalities are generally correlated, but it also found an important exception: after rising together, there seems to be a "tipping point" moment in which IPC levels and fatalities decouple. Fatalities decline and IPC levels remain high - or continue to rise. This was most prominent in regions of Nigeria, Niger and Afghanistan. Another finding was the strength of three seasons of aggregated fatalities and the robustness of data at a province level. The former implies that the accumulated impact of violence on a population can take time to manifest as food insecurity. The latter implies that the spatial scale of conflict's impact on food security extends well beyond the areas in which violence occurs, which concurs with other research findings.

Each of these individual findings provides an insight into the dynamics between conflict and food insecurity. However, when considered together, a bigger picture emerges, one that governments, humanitarian organizations and policymakers alike will need to pay attention to. Populations are able to cope with a certain amount of violent conflict, even spikes that result in hundreds of fatalities. However, the tipping point reflects an immense depth of destruction and human suffering that has taken place not only to a localized population, but a widespread region, and the time and resources it will take to rebuild will be vastly greater than what it would have taken to prevent it in the first place. My research points to the need not only for emergency assistance when food crises peak, but well before they reach that point. Adaptation and mitigation programs are critical in building resilience for when emergencies arise – especially in these increasingly uncertain times.

Appendix 1

Comparison of Food Security Indicators

Table 11. Comparison of the most commonly used food security and undernourishment indicators.

Prevalence of undernourishment (PoU)	• Calculated using a country's available kilocalories using food balance sheets, minimum dietary energy requirement (MDER) and overall population number to calculate a percentage of the population that is considered undernourished (FAO, 2017a).
Prevalence of severe food insecurity	• Calculated through household surveys called Food Insecurity Experience Scale (FIES) as a percentage of the population • Defined as, "the level of severity of food insecurity at which people have likely run out of food, experienced hunger and, at the most extreme, gone for days without eating, putting their health and well-being at grave risk" (FAO, 2019a, p. 189)
Prevalence of moderate or severe food insecurity	• Combines the measurements for both moderately and severely food insecure, and calculated as a percentage of the population • Defined as, "the level at which people face uncertainties about their ability to obtain food and have been forced to reduce, at times during the year, the quality and/or quantity of food they consume due to the lack of money or other resources. It thus refers to a lack of consistent access to food, which diminishes dietary quality, disrupts normal eating patterns, and can have negative consequences for nutrition, health and well-being" (FAO, 2019a, p. 188).
Integrated Phase Classification (IPC)	• Data available at a high spatial resolution, typically at admin 2 or admin 3 level • Based on a standard set of criteria to evaluate acute food security according to a scale of five IPC phases: 1 – minimal; 2 – stressed; 3 – crisis; 4 – emergency; 5 – famine (Figure 1) • IPC Phases are assigned to areas in which at least 20% of the population is experiencing that phase

Appendix 2

Regression Results for Nigeria by Season

Table 12. Regression results for Nigeria by season, using average admin 1 and 3 seasons of aggregated fatalities.

Season	**R2**	**p-value**
201101	0.002381	0.774257
201104	n/a	
201107	n/a	
201110	n/a	
201201	n/a	
201204	0.069988	0.113576
201207	0.025905	0.341279
201210	n/a	
201301	0.1660	0.0123
201304	0.3275	0.0002
201307	0.3365	0.0002
201310	0.2893	0.0006
201401	0.5264	0.0000
201404	0.4431	0.0000
201407	0.4494	0.0000
201410	0.5384	0.0000
201501	0.5313	0.0000
201504	0.5711	0.0000
201507	0.6557	0.0000
201510	0.6767	0.0000
201602	0.6516	0.0000
201606	0.5966	0.0000
201610	0.6867	0.0000
201702	0.6700	0.0000
201706	0.2928	0.0005
201710	0.5894	0.0000
201802	0.6632	0.0000
201806	0.4281	0.0000
201810	0.5310	0.0000
201902	0.5861	0.0000
201906	0.4653	0.0000
201910	0.4774	0.0000
202002	0.6127	0.0000
202006	0.3585	0.0001
202010	0.2936	0.0005
202102	0.5015	0.0000
202106	0.2947	0.0005

(By author)

Appendix 3

Timeline Regression Results

Table 13. R^2 values by province in West African countries with 3 aggregated seasons of fatalities, 2011-2021.

Country	Province	R^2
Mali	Bamako	0.048132
Mali	Gao	0.002073
Mali	Kayes	0.22534
Mali	Kidal	0.113497
Mali	Koulikoro	0.003898
Mali	Mopti	0.064773
Mali	SÃ©gou	0.053885
Mali	Sikasso	0.000788
Mali	Tombouctou	0.020153
Niger	Agadez	0.022153
Niger	Diffa	0.272064
Niger	Dosso	0.081775
Niger	Maradi	0.116432
Niger	Niamey	0.001505
Niger	Tahoua	0.105946
Niger	Tillababeri	0.269208
Niger	Zinder	0.007973
Nigeria	Abia	0
Nigeria	Adamawa	0.368488
Nigeria	Akwa Ibom	0
Nigeria	Anambra	0.002117
Nigeria	Bauchi	0.014137
Nigeria	Bayelsa	0.20108
Nigeria	Benue	0.028554
Nigeria	Borno	0.192145
Nigeria	Cross River	0.000663
Nigeria	Delta	0.025757
Nigeria	Ebonyi	0.000254
Nigeria	Edo	0
Nigeria	Ekiti	0.070911
Nigeria	Enugu	0.001469
Nigeria	Federal Capital Territory	0.01657
Nigeria	Gombe	0.00903
Nigeria	Imo	0.797734
Nigeria	Jigawa	0.009179
Nigeria	Kaduna	0.170731
Nigeria	Kano	0.076119
Nigeria	Katsina	0.207227
Nigeria	Kebbi	0.054558
Nigeria	Kogi	0.012467

Nigeria	Kwara	0.044294
Nigeria	Lagos	0.006724
Nigeria	Nasarawa	0.003783
Nigeria	Niger	0.139991
Nigeria	Ogun	0.008512
Nigeria	Ondo	0.244129
Nigeria	Osun	0.173646
Nigeria	Oyo	0.72963
Nigeria	Plateau	0.007805
Nigeria	Rivers	1.19E-06
Nigeria	Sokoto	0.455689
Nigeria	Taraba	0.002473
Nigeria	Yobe	0.09711
Nigeria	Zamfara	0.461378
Chad	Barh el Gazel	0.005708
Chad	Batha	0.034901
Chad	Borkou	0.006104
Chad	Chari-Baguirmi	0.102292
Chad	Ennedi-Est	0.063497
Chad	Ennedi-Ouest	0.013891
Chad	Guera	0.000129
Chad	Hadjer-Lamis	0.008259
Chad	Kanem	0.00269
Chad	Lac	0.266822
Chad	Logone Occidental	0.004827
Chad	Logone Oriental	0.002325
Chad	Mandoul	0.007383
Chad	Mayo-Kebbi Est	0.104689
Chad	Mayo-Kebbi Ouest	0.018138
Chad	Moyen-Chari	0.011895
Chad	N'Djamena	0.000329
Chad	Ouaddai	0.009728
Chad	Salamat	0.002178
Chad	Sila	0.00171
Chad	Tandjile	0.04499
Chad	Tibesti	0.221072
Chad	Wadi Fira	0.000105
Cameroon	Adamaoua	0.10103
Cameroon	Centre	0.000809
Cameroon	Est	0.306122
Cameroon	ExtrÃªme-Nord	0.160645
Cameroon	Littoral	0.90799
Cameroon	Nord	0.062006
Cameroon	Nord-Ouest	0.236505
Cameroon	Ouest	0.323834
Cameroon	Sud	0
Cameroon	Sud-Ouest	0.169881

(By author)

Table 14. R^2 values by province in Afghanistan with 3 aggregated seasons of fatalities, 2011-2021.

Admin 1	R^2	*p*-value
Badakhshan	0.4794	2.06E-06
Badghis	0.3062	0.000381
Baghlan	0.5965	2.16E-08
Balkh	0.4436	6.81E-06
Bamyan	0.0306	0.30081
Daykundi	0.4577	4.30E-06
Farah	0.6539	1.41E-09
Faryab	0.5458	1.78E-07
Ghazni	0.4771	2.23E-06
Ghor	0.5141	5.96E-07
Herat	0.5123	6.37E-07
Hilmand	0.0250	0.350159
Jawzjan	0.5629	8.98E-08
Kabul	0.4540	4.86E-06
Kandahar	0.5400	2.23E-07
Kapisa	0.5732	5.87E-08
Khost	0.2926	0.000547
Kunar	0.0712	0.110348
Kunduz	0.5503	1.49E-07
Laghman	0.4681	3.03E-06
Logar	0.3344	0.000178
Nangarhar	0.5679	7.31E-08
Nimroz	0.2081	0.00454
Nuristan	0.0008	0.870721
Paktika	0.4978	1.08E-06
Paktya	0.4797	2.03E-06
Panjsher	0.0793	0.091315
Parwan	0.2432	0.001928
Samangan	0.2788	0.000782
Sari Pul	0.4566	4.46E-06
Takhar	0.4910	1.37E-06
Uruzgan	0.6726	5.26E-10
Wardak	0.4562	4.51E-06
Zabul	0.5441	1.90E-07

(By author)

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