Unfed Unrest: Drought, Food Insecurity and Rioting in Sub-Saharan Africa

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Executive Summary

There is broad agreement that climate change represents a severe threat to human civilisation, through the increased frequency of natural disasters such as cyclones, droughts and wildfires. Nonetheless, the second-order effects that this could have on levels of human conflict are still up for debate. Within this research space, much focus has been put on the impacts of drought, including an emerging finding across several studies that drought can lead to an increase in rioting. Past research has suggested that drought leads to water shortage, bringing people into conflict over scarce resources.

This study theorises that instead, the observed increase in rioting following drought could follow a more complex pathway. Rainfall shortage during drought leads to reduced crop yields, and subsequent food insecurity in countries with a dependence on subsistence/smallholder farming. The grievances accumulated due to this food insecurity then lead to rioting. To test this hypothesis, the study combines geolocated riot data from 2011-2020 with measurements of a remotely-sensed agricultural drought index across eight Sub-Saharan African countries, broken down into 120 disaggregated first-level administrative divisions. Across the entire time period, no significant relationship is found, however subsetting the data to investigate the effect that the lean season has on rioting reveals that agricultural seasonality plays a critical role in governing the drought-rioting relationship. During lean season months, a one standard deviation decrease in the index increases the frequency of riots by 12.26 percent, while during non-lean season months, the same decrease in the index decreases the frequency of monthly riots by 15.92 percent.

The findings provide evidence for a more complex food security pathway involved in governing the relationship between drought and rioting. With negative implications concentrated on the lean season, governments and NGOs could use this knowledge to concentrate drought responses to these same periods. Drought resilience efforts in the face of worsening climate change could also focus on improving food and agricultural security to reduce the chance of rioting.

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Abstract

Drought is found to cause an increase in rioting, with water competition seen as the driving cause. But does this ignore a more complex reality? This study theorises an alternative food insecurity pathway, with drought causing crop failure, aggravating grievances and leading to food riots. To explore this hypothesis, the paper uses a remotely sensed index of agricultural drought and geolocated riot data disaggregated across country regions. Following data processing, the study shows an index decline of one standard deviation (signalling drought) during the lean season increases riot frequency by 12.26%. The same index decline during other months of the year causes riot frequency to counterintuitively decline by 15.92%. The findings support the existence of a complex interaction between drought, food security, agricultural seasonality and rioting.

Introduction

Despite doomy proclamations on the matter by the likes of the UN Secretary-General (Guterres, 2021), the debate over whether climate change will cause more conflict and war is far from settled. After over a decade of research on the topic across multiple disciplines, a sea of contradictory findings and acrimonious disputes have emerged (Koubi, 2019). Nonetheless, approaches have evolved, trending towards the investigation of how natural disasters expected to worsen under climate change, such as floods, heatwaves and droughts, have influenced human societies in the recent past. Through an understanding of these past disasters, researchers can more accurately predict the future, something made all the more important in light of the accelerating warming reported by climate scientists (IPCC, 2022).

Newer studies have looked at smaller scales of human conflict, where climatic phenomena may have a more direct impact. Research into a potential link between droughts and riots has emerged as one area of more promising investigation in the climate-conflict field. Two previous studies, Almer et al. (2017) and Unfried et al. (2021), found evidence that drought, expressed as rainfall/surface water deficiency, was linked to a statistically significant higher likelihood of rioting in Sub-Saharan Africa. In both cases, competition over scarce water resources during times of drought was theorised to be the causal mechanism contributing to the increase in riots, backed up by a key finding that areas with low surface water availability experienced more riots in times of drought. However, when Unfried et al. (2021) applied the same methodology to Central America as it did in Africa, no significant link was found between drought and rioting. With Central America unlikely to experience radically different water conflict dynamics compared to Africa, there is reason to think that an alternative mechanism may also be at play.

Understanding the dynamics behind the emergence and spread of riots is important due to their destructive consequences. The 4610 riot events recorded in the dataset resulted in a cumulative 3530 fatalities, as well as potentially significant economic impacts due to property damage. Riots also cause significant ripple effects, which can lead to political collapse or even the breakdown of food supply (Renn et al., 2011, p. 6). Given this, knowing what conditions are conducive to rioting, and preventing them from occurring, is a critical issue for regional stability.

Riots can occur due to grievances accumulated for a wide range of reasons, however, one kind of riot that is of interest to research into the effects of drought is the 'food riot'. In times of severe food insecurity or high food prices (Brinkman & Hendrix, 2011), riots historically have been observed. In some cases, these riots are explicitly linked to a demand for food, but in other cases, the food insecurity serves to amplify existing grievances (Heslin, 2020). With drought often causing crop failures and food insecurity (Ngcamu & Chari, 2020), it is possible that this too could be causing food riots.

Following this line of inquiry, an alternative pathway involving food insecurity is theorised, whereby rainfall shortage leads to agricultural drought, which, if it occurs during the growing season, can lead to crop failures or reduced crop yields, and widespread food insecurity. The impact of this is expected to be higher in Sub-Saharan Africa compared to other parts of the globe, due to the region's reliance on subsistence or smallholder farming (Ngcamu & Chari, 2020). These small, non-irrigated farms are highly vulnerable to drought (do Vale et al., 2020), both due to their lack of infrastructure, and also the fact that most of those who work on these farms subsist to a large degree off the food they grow. Finally, this food insecurity creates grievances that raise the likelihood of rioting in an affected area, with the highest likelihood of riots theorised to occur during the so-called 'lean season' - the period of the agricultural year prior to harvest when food supplies are at their lowest within Sub-Saharan Africa.

To empirically test the plausibility of this food pathway, geographically and temporally disaggregated data is used. Spatially, the unit of analysis is the first-level administrative divisions of eight Sub-Saharan African countries, then temporally split into monthly intervals over the 2011-2020 time period. Fundamentally, the paper seeks to answer the question of whether agricultural drought increases the frequency of rioting in the agricultural year following a poor harvest. Following a substantial precedent in agricultural drought monitoring, the study relies on the remotely sensed Normalized Difference Vegetation Index (NDVI) as a proxy for crop health. NDVI is a measurement obtained by applying a simple formula to the red and near-infrared spectral bands obtained by an earth observation satellite (Huang et al., 2021). Deviations from the long-term 20-year monthly NDVI averages (anomalies) are used as a measure of the severity of agricultural drought. The mean NDVI anomaly recorded over the farmlands of a given first-level administrative division in the most recent growing season serves as the primary independent variable, and its effect is measured against geolocated riot events in the same region obtained from the Armed Conflict Location and Event Data Project (ACLED). Given the significant variance in population between the regions analyzed, rioting frequency is normalized by a linear approximation of population in a given year.

From these sources, a raw dataset covering 120 regions across Sub-Saharan Africa is generated, which is then split into two smaller datasets with one including all data points that occur in the lean season, and another including all of those that do not. The two continuous variables (mean growing season NDVI anomaly and monthly riots per 100,000 people) are regressed against each other with controls for country-level fixed effects necessitated by a significant cross-correlation between riots in different regions of the same country. Contrary to the initial hypothesis, evidence is found for a statistically significant relationship between agricultural drought and a decrease in rioting when applied to the raw dataset. However, when applied to two data subsets focusing on those months during the lean season, and those outside of it, a more complex picture is established. Highly statistically significant results are found demonstrating that agricultural drought increases the frequency of riots during lean season months, with a one standard deviation decrease in mean growing season NDVI anomaly resulting in a 12.26 percent increase in monthly riot frequency. During months outside of the lean season, the effect is reversed, with the same one standard deviation decrease in mean growing season NDVI anomaly reducing the frequency of riots by 15.92 percent.

Thus, the study fits into the existing literature exploring potential relationships between climate change and conflict, and more specifically, drought as a predicted consequence of climate change and its effects on small-scale human conflict. The findings add to the existing body of research on the topic by opening up the plausibility of crop failures and food insecurity as an alternative, or additional, mechanism by which droughts lead to riots beyond simplistic competition over scarce water. The results suggest that the effect of drought in increasing riots is confined to the lean season of the agricultural year, a level of temporal detail not achieved in previous research. Should these findings be backed up by future studies, they would be immensely useful for governments and NGOs seeking to mitigate the impacts of drought, as they could conceivably concentrate resources and responses on the lean season.

Literature Review

Climate change and conflict

The IPCC (2022) Sixth Assessment report estimated that the world has warmed 1.07°C since pre-industrial times, primarily due to greenhouse gas emissions. It found that under 'intermediate' emissions reduction scenarios, the world will have reached 2°C by 2041-2060, and could reach close to 3°C of warming by 2100 (IPCC, 2022). The report notes that *"all life on Earth – from ecosystems to human civilization – is vulnerable to a changing climate [...] Where trends intersect they can reinforce each other intensifying risks and impacts, which affect the poor and most vulnerable people the hardest."* (IPCC, 2022, p. 1). Within this paradigm of vulnerability to current and future warming, researchers have attempted to establish and quantify the impacts this will have on the world and human society. Beyond the first-order effects such as increased natural disaster frequency, heat stress and sea-level rise (IPCC, 2022), a key debate exists within the literature regarding the second-order impacts on human conflict.

Specifically, researchers have investigated the broad question of whether climate change will increase human conflict and produced a series of studies over the last two decades yielding confusing and often contradictory results. Following the release of the IPCC's Fourth Assessment report in 2007 that barely mentioned human conflict, Nordås & Gleditsch (2007) called for new research investigating the various causal chains through which climate change may impact human conflict. They noted that mapping the impacts on human livelihood through the direct impacts of sea-level rise, declining human health and changing weather patterns, as well as indirectly via forced migration was particularly important (Nordås & Gleditsch, 2007, p. 634). Concurrently, government-adjacent advisory groups released reports highlighting the security impacts of climate change, stating that it would cause *"destabilization and violence, jeopardizing national and international security"* (WBGU, 2007, p. 1) and act *"as a threat multiplier for instability in some of the most volatile regions of the world"* (CNA, 2007, p. 6).

Initial studies appeared to confirm these theorised impacts but immediately generated controversy. Looking at historical incidences of civil war in Sub-Saharan Africa, Burke et al. (2009, p. 20670) found *"strong historical linkages between civil war and temperature, with* *warmer years leading to significant increases in the likelihood of war".* The authors went so far as to state that warming by 2030 would cause an approximately 54 percent increase in armed conflict incidence or an additional 393,000 battle deaths (Burke et al., 2009, p. 20672). These results were later challenged by Buhaug (2010) on the basis of a poorly operationalised dependent variable (civil conflict years with greater than 1000 battle deaths), the use of country fixed effects and a poor time period and country selection. An expanded study found that *"aggregate statistics on climate variability do not have a systematic, direct bearing on the short-term risk of civil war"* (Buhaug, 2010, p. 16481). Burke et al. (2010) later acknowledged that post-2002 civil war data showed a much weaker relationship between conflict and climate, however, rejected the majority of Buhaug's criticisms. Separately, Hsiang et al. (2011) presented alternative evidence for the role of climate in conflict through findings that the probability of civil wars starting in the tropics doubles during El Niño years relative to La Niña years.

Following these early studies that examined the direct impact of temperature or large-scale climate patterns on conflict, newer research began examining other pathways through which the consequences of a warmer world influenced conflict. Among the most heavily studied of these was the precipitation pathway. Climate change is forecast to generate decreased rainfall in many regions (IPCC, 2022) and may cause conflict through drought-induced scarcity. As theorised by Couttenier & Soubeyran (2011, p. 15), *"drought, in altering crops and devastating livestock, reduces drastically households home consumption and increases competition for resources such as drinking water and arable land."* The authors also found that the risk of civil war in Sub-Saharan Africa increases by more than 42 percent from a 'normal' climate to one characterised by extreme drought (Couttenier & Soubeyran, 2011, p. 3). This clear result was quickly brought into question by later studies such as Klomp & Bulte (2013), which found little evidence linking weather shocks to the onset of conflict. Similarly, using georeferenced data on civil war onset in a local ethnopolitical context, Theisen et al. (2012) also failed to find evidence of a drought-conflict connection.

At times the debate within the literature became so acrimonious that Solow (2013) urged researchers to stop fighting and work together as part of a 'call for peace' in the field. With so many studies producing conflicting results, key debates boiled down to questions of how data was being used (Solow, 2013, p. 179), how 'conflict' was being operationalised as a variable (Koubi, 2019), and whether the overall decline in interstate conflict was masking climatic effects (Gartzke, 2012, p. 178). This lack of clarity within the research on the matter continues to the present and has led the IPCC (2022, p. 13) to conclude with 'medium confidence' that *"in some assessed regions extreme weather and climate events have had a small, adverse impact on their length, severity or frequency, but the statistical association is weak"*.

Summing up a decade of progress in the field, von Uexkull and Buhaug (2021) highlighted a series of shortcomings identified in a meta-analysis of 35 recent literature reviews. These shortcomings included:

1. Disaggregation: A lack of spatially disaggregated data broken down at a sub-national level being used in research, rather than aggregated country-level data.
2. Diversity of outcomes: Too much of a focus on state-level conflict outcomes (such as civil war) rather than more plausible smaller-scale outcomes.
3. Indirect pathways: A sole focus on direct correlations between climate and conflict, making the investigation of causal pathways difficult.
4. Scope conditions: The assumption that the pervasiveness of the climate–conflict relationship was equal across all time scales, geographical regions, etc.
5. Climate change impacts: The assumption that past climate variability will impact societies in the same manner as current and future climate change.
6. Climate change response impacts: A lack of attention paid to how societies' responses to climate change might moderate its impacts.
7. Methodological diversity: A need for a greater number of research designs able to test how generalisable observed effects are outside of specific countries/regions.

Individual shortcomings from the above list were previously identified by multiple authors, and new studies post-2014 already made use of improved research questions and designs in order to mitigate the problems they introduced. Much of this research was focused on a reassessment of the precipitation pathway, exploring both the different factors which may moderate the relationship between drought and conflict (Vestby, 2019; Ide et al., 2020; von Uexkull et al., 2016), as well as the way droughts lead to smaller-scale conflicts, such as protests, riots and communal violence (Almer et al., 2017; Unfried et al., 2021; Koren et al., 2021). Beyond the existence of a positive causal relationship at all, two broad questions were explored:

1) Do certain social, geographic, developmental or political factors make this positive relationship more prominent?
2) Does this positive relationship exist evenly across all spatial scales and all scales of conflict?

The precipitation pathway & small-scale conflict

On the first question, several factors were found to moderate the precipitation-conflict relationship. Droughts affecting agriculturally dependent and politically excluded groups in impoverished countries were found to increase the likelihood of sustained violence (von Uexkull et al., 2016), while other groups were relatively unaffected. This finding was theorised to be evidence of a *"powerful reciprocal relationship between armed conflict and local drought, whereby each phenomenon makes a group more vulnerable to the other"* (von Uexkull et al., 2016). Ide et al. (2020) also built on this, arguing that drought–conflict links are highly context-dependent, with pre-existing societal cleavages, autocratic regime types or cuts of the public water supply found to be predictors of nonviolent, water-related conflict onset during droughts. Thus, the authors argued drought serves as a 'triggering event' that sets off deeply embedded social grievances (Ide et al, 2021, p. 576). On the level of individual psychology, Vestby (2019) found that people were more willing to participate in politically-motivated violence during times of drought if they perceived their standard of living to have dropped.

Regarding the second question, an interesting trend in the research emerged. While numerous studies continued to look at the interstate/intrastate scale of conflict, with some results appearing to confirm a complex yet positive relationship between drought and conflict (Harari & La Ferrara, 2018; von Uexkull et al., 2016), and others finding little evidence (Ide et al., 2020; Fröhlich, 2020), more concrete findings were made on smaller scales. Almer et al. (2017) found that drought had a significant positive impact on the likelihood of rioting in Sub-Saharan Africa, an effect that was even more pronounced in areas that lacked access to surface water supplies. A similar study conducted by Unfried et al. (2021) backed up this result with a wider geographical range, finding that a one standard deviation decrease in local water mass following drought more than triples the local likelihood of social conflict. Much of this observed increase in social conflict was driven by civil unrest, particularly targeting the government. Both studies also made use of spatially disaggregated data, breaking down the geographical study area into grid cells, an approach which may better capture the localised nature of drought and rioting.

Riots can be understood as a form of contentious collective action by people who *"lack regular access to representative institutions, who act in the name of new or unaccepted claims, and who behave in ways that fundamentally challenge others or authorities"* (Tarrow, 2011, p. 7). Often a triggering event is linked to riots, however, these events can also be viewed as 'the straw that broke the camel's back', and if social tension or discontent is high, these triggering events have a higher probability of causing riots (Berestycki et al., 2015, p. 445). Common causes for this social tension include *"political events or decisions, new or increased taxes, food scarcity, high unemployment, police brutality, or racial tension"* (Berestycki et al., 2015, p. 444).

Beyond this, riots, as a conflict event, are characterised by low barriers to entry. They have been found to *"often occur where resources are scarce, the level of organization is low and individuals have reason not to think highly of the [political] system's responsiveness"* (Holdo & Bengtsson, 2020, p. 165). They also are generally confined to limited geographic areas and short periods of time (Almer et al., 2017). Nonetheless, riots are also observed to occur in 'waves' or 'bursts' where they spread rapidly from a triggering event and can be modelled in a similar way to the spread of a virus. From this modelling, Bonnasse-Gahot et al. (2018) showed that geographic proximity and high-density urban areas are key underlying mechanisms for the spread of riots.

Due to these low barriers to entry, riots may be a better dependent variable to measure the direct impact of climate shocks (such as drought) than larger-scale conflict. However, while there is recent empirical evidence for a drought-rioting connection, the causal mechanism underpinning this is still up for debate. Drawing attention to the fact that areas with low surface water availability experienced higher amounts of rioting, Almer et al. (2017) argued that this supports the hypothesis that competition over limited water supplies during drought led to conflict. While finding that access to surface and groundwater reduces the likelihood of social conflict, an initial hypothesis by Unfried et al. (2021) that water demand factors accelerate water scarcity and intensify the effect of water mass change on conflict was unsupported by the data, leading the researchers to conclude that *"water demand factors contribute to a quicker depletion of water mass in case of drought shocks, but do not intensify* *the link between water decline and conflict itself"* (Unfried et al. 2021, p. 2). Another peculiarity of the findings in Unfried et al. (2021) is that the observed effects were entirely driven by Africa. These anomalous findings create room for alternative or more complex causal mechanisms for drought-intensified riots beyond the standard competition-conflict pathway.

Droughts, crop failure, and food riots

Drought is a broad term that encompasses several discrete, but linked concepts. In its most basic definition, a *"drought means a sustained, extended deficiency in precipitation"* (World Meteorological Organization [WMO], 1986). Within the scientific literature, drought is more commonly broken down into subtypes related to its outcomes, including meteorological, hydrological, agricultural, socio-economic and groundwater drought (Mishra and Singh, 2010). Studies looking at links between drought and conflict have generally focused on either hydrological drought, defined as a period of *"inadequate surface and subsurface water resources for established water uses of a given water resources management system"* (Mishra and Singh, 2010, p. 206), or agricultural droughts, defined as *"a period with declining soil moisture and consequent crop failure"* (Mishra and Singh, 2010, p. 206).

Agricultural droughts, through their damaging effects on crops, can also severely impact food availability. Research focussing on a wide range of countries including Ethiopia (Agidew & Singh, 2018), Sri Lanka (Gunatilake, 2015) and Tanzania (Mdemu, 2021) has shown that drought can have a significant negative effect on food security. Food security in Africa is particularly severely impacted due to poor infrastructure development and dependence on subsistence farming (Ngcamu & Chari, 2020). In addition, droughts can raise both local and international food prices due to a reduction in supply. Examining Indian agricultural markets, Letta et al. (2021) demonstrated that the majority of these price rises occur both before the conclusion of the growing season, with markets pricing in the expected production shortfalls. Access to international markets is found to mitigate drought-induced local price shocks (Schaub & Finger, 2020). Moreover, based on European agricultural data, Brás et al. (2021) found that negative drought impacts on crop production roughly tripled over the last 50 years.

Drought does not affect all agriculture equally. Small-scale subsistence and smallholder farms are particularly vulnerable to drought due to the fact that they are generally rainfed (do Vale et al., 2020), and not able to draw on irrigation resources that enable the uninterrupted supply of water. These farmers are further impacted by drought due to their poverty, remote locations, and their use of land-degrading agricultural practices (Harvey et al., 2014, p. 7). The terms 'subsistence' and 'smallholder' farming do not have agreed-upon definitions within the literature (Morton, 2007). World Health Organisation (WHO) researchers have defined subsistence farming as describing *"farming and associated activities which together form a livelihood strategy where the main output is consumed directly by the household, where there are few if any purchased inputs and where only a minor proportion of output is marketed"* (Barnett et al., 1996, p. 1), however, others acknowledge that marketisation is growing ubiquitous across the world and that such a definition is ill-fitting. On the other hand, 'smallholder farming' is usually classified in terms of the size of the farm, less than 2 hectares under a UN Food and Agriculture Organization (FAO) definition (Rapsomanikis, 2015), or the nature of the workforce, usually small familial groups that derive their principal income from working the land (Morton, 2007).

The impact of drought on crop yields and food production is also mitigated by certain factors. The FAO notes that adaptive drought resilience can be enabled through increased water storage and improved access to irrigation water, improved irrigation technologies and techniques such as water harvesting (Food and Agriculture Organization of the United Nations [FAO], 2015, p. 43). Beyond this, the proliferation of drought-related sensors in vulnerable regions (Gomez-Zavaglia et al., 2020), the installation of early warning systems, and the wide dissemination of climate-related information were also found to mitigate impacts and boost preparedness (Sunday et al., 2021).

One well-established cause of riots is the low availability and high price of food (Brinkman & Hendrix, 2011). Food can be understood as an 'entitlement' by a country's population. In this context, an entitlement refers to the various consumption bundles that can be legally obtained from a person at prevailing prices given their initial resources, both in terms of money or land (Dreze and Sen, 1989). If a group cannot establish their entitlement over an adequate amount of food, either due to rising prices, falling wages or some combination of the two, hunger results (Dreze and Sen, 1989, p. 22). This deprivation of the entitlement of food is seen to classically lead to grievances held by the deprived group, which subsequently is expressed as unrest (Rudolfsen, 2018). In addition, Heslin (2020, p. 1) found evidence that *"a change in food access motivated protest and violence involving existing grievances rather than explicitly addressing food access"*. Violent unrest is also found to be *"the product of both food insecurity and the underlying vulnerability of the state to [food security] shocks"* (Jones et al., 2017, p. 340), with the latter being a more significant predictor than the former.

Jones et al. (2017) established three main reasons that individuals confronted with food insecurity are more willing to participate in violent demonstrations and riots:

1. Food security shocks act as a source of grievance due to the denial of basic necessities, generating competition and subsequent animosity amongst social groups and with the government.
2. The same shocks increase existing grievances, by emphasizing food entitlements, thus highlighting inequalities and conflicts between social groups.
3. Hunger makes people desperate and in doing so reduces the perceived costs associated with taking part in violent demonstrations.

These riots associated with food insecurity or high food prices are generally referred to as food riots. While the term has entered common parlance among researchers, there is disagreement within the literature over the precise definition of a 'food riot' (Raleigh et al., 2015). This study, however, accepts the definition of Barbet-Gros and Cuesta (2014, p. 2) for the World Bank, characterising these riots as *"violent, collective unrest [...] essentially motivated by a lack of food availability, accessibility or affordability [...] and which may have other underlying causes of discontent",* building on earlier conceptualisations by Berazneva and Lee (2013) and Lagi et al. (2011). Much research has focused on the impact of international food prices on food riots in the developing world, however, significantly less has focussed on the impact of local-level food prices or the deprivation of food itself. Nonetheless, Smith (2014, p. 679) found that sudden increases in domestic food prices significantly increase the probability of riots, concluding that these riots were a *"consumer response to economic pressure from increased food prices"*. Interestingly, this research by Smith (2014) used rainfall as one of its indicators for domestic food prices.

A theory of food insecurity and violent riots

Given the established link between rainfall shortages and violent rioting, as well as the well-known effects of food insecurity and food prices in creating conditions favourable to food rioting, a reexamination of the simplistic competition-conflict pathway is due. This updated pathway would need to explain both how rainfall shortages lead to a greater likelihood of riots as well as why this effect appears to only hold true in regions of Africa.

One possible alternative explanation is that food insecurity could play an intermediate role in this causal chain. Droughts are well established in the literature as a cause of both acute and long-term food security crises. Moreover, they are also shown to cause spikes in local food prices. Both of these shocks are theorised to cause food riots. Thus, many of the riots captured by Almer et al. (2017) and Unfried et al. (2021) in their respective studies on droughts and violent unrest may have been better characterised as food riots.

The explanatory power of this characterisation, and that of a more generalised drought-food insecurity-conflict pathway, is made more apparent when Africa is considered. Africa is unique as a region due to its dependence on rainfed non-irrigated farming, as well as its high levels of subsistence or smallholder farming. While reliable data on the exact percentage of food produced through subsistence/smallholder farming is scarce, Antonaci et al. (2014) states that in Sub-Saharan Africa, this figure stands at about 75–80 percent. Alternatively, AGRA (2017) notes that around 70 percent of Africa's population is involved in smallholder farming, producing approximately 80 percent of the continent's food. According to an African Development Bank study focusing on Uganda, Kenya, Ethiopia and Tanzania *"smallholder farmers accounted for over 70 percent of agricultural production and over 75 percent of the labour force"* (Salami et al., 2009, pp. 2-3). Together these statistics are in agreement that the majority of the food grown in Sub-Saharan Africa is produced by these small-scale agricultural operations, which themselves employ the majority of the population.

Smallholder and subsistence farmers are much more vulnerable to drought-related crop failures than larger commercial farms due to their inability to invest in measures such as irrigation or water storage which increase resilience (Mwamakamba et al., 2017). In the case of a drought, areas with a large proportion of these farms may suffer more significant production shortfalls and thus experience more significant local food price shocks due to demand outstripping supply. In addition, these same farmers depend on their own agricultural output for much of their food consumption, with drought-induced production shortfalls directly impacting their caloric intake. Both of these outcomes intensify the three pathways toward food riots in the case of droughts outlined by Jones et al. (2017) and may explain why the effect of rainfall on rioting is present in Africa but not in other regions studied.

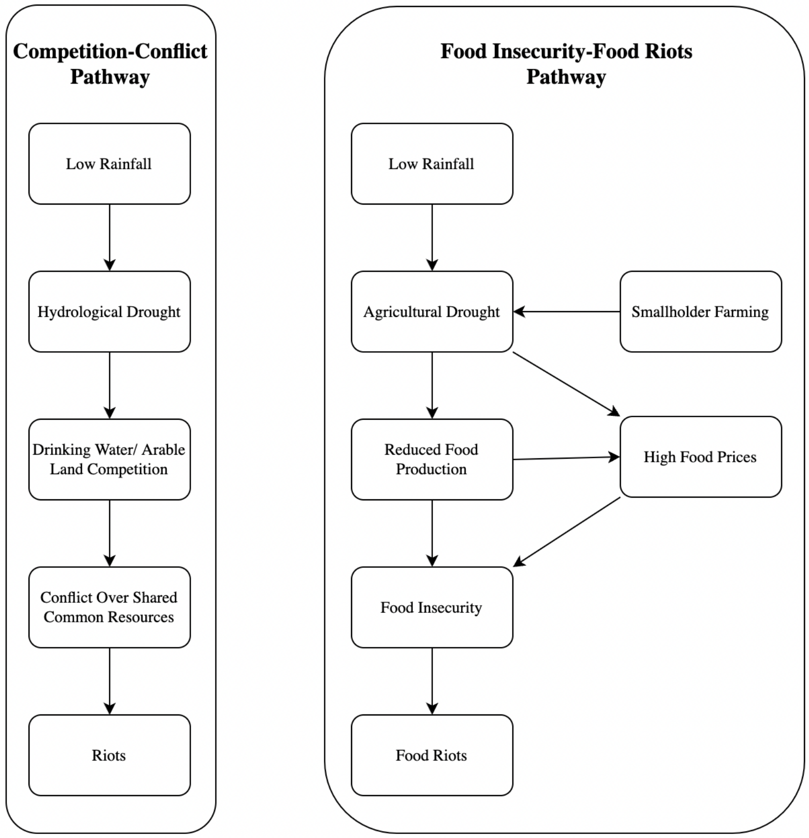


Figure 1. Comparison of drought-rioting pathways

Seasonality also plays a role in food insecurity, due to the fact that in Sub-Saharan Africa the annual harvest often does not yield enough food to last the entire year. The agricultural year is broken down into a sowing period, a growing season and a harvesting period (FAO, 2022). These distinct periods of the agricultural year fall within the same months every year, with some small amounts of variance owing to meteorological conditions. The periods also differ on the basis of the geographic location and the type of crop being planted. Previous studies looking at relationships between drought and conflict (von Uexkull et al., 2016; Linke & Ruether, 2021) have focussed on growing season droughts as the impacts on food production are greatest for droughts that occur during these time periods.

Another important element of the agricultural year is the so-called 'lean season', which comprises the last few months prior to the primary harvest when food supplies are at the lowest. During the lean season in Sub-Saharan Africa, the low availability of food results in an observable reduction in caloric intake and an increase in undernutrition (Lantonirina et al., 2019; Bonuedi et al., 2022). It is during this lean period that the effect of the food insecurity-food riots pathway can be expected to be the most noticeable.

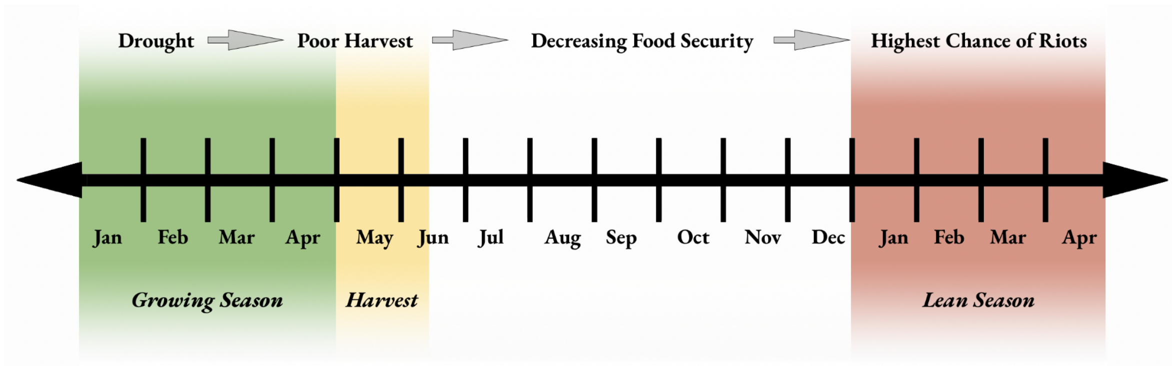


Figure 2: Hypothesized food-rioting effects during the agricultural calendar

This proposed alternative theoretical mechanism leads to the following research question: Is there a relationship between drought-induced crop failures and the frequency of violent rioting?

Based on the food insecurity-food riots pathway the following hypotheses can be made:

H_0: The frequency of monthly rioting does not increase as agricultural drought during the previous growing season worsens.

H_1: The frequency of monthly rioting increases as agricultural drought during the previous growing season worsens.

H_2: The effect of agricultural drought on increased riot frequency is higher in lean season months.

Data Sources and Methodology

Geographic and Temporal Scope

In designing a methodology to test the plausibility of a food insecurity-food riots pathway, hereafter referred to as 'the food insecurity pathway', the study follows several of the suggestions of Uexkull and Buhaug (2021). With the food insecurity pathway likely existing only within regionally-bound scope conditions, ie. in African countries with a dependence on rain-fed agriculture and smallholder farming, the study is confined to the same area. While previous research has established a link between drought and rioting across Africa as a whole, the study focuses on a subset of Sub-Saharan Africa. Much of North Africa is unsuitable for widespread agriculture and depends on imported food, making food riots there more historically linked to international food price shocks (Lagi et al., 2011), that exist outside of the food insecurity pathway, hence it is excluded from the study area.

Given that the theoretical mechanism begins with rainfall shortages causing drought, a climatic phenomenon that is often sub-national in scale (Amarasinghe et al. 2020), it is important to make use of disaggregated data with a finer spatial resolution than at the country level. The food insecurity pathway implies that a rainfall shortage leads to agricultural drought and subsequent crop failures that are widespread enough that either food security is directly impacted or causes food prices to rise due to low supply. This then causes those affected to be more likely to riot. Considering this, the disaggregated spatial unit of analysis needs to be of sufficient size to capture crop failures large enough to set in motion this causal chain, but not so large as to include areas unaffected by the regional rainfall shortage. Moreover, in terms of capturing the incidence of rioting, thought must be paid to where people riot. Almer et. al (2017, p. 201) intuits that riots, in general, require highly populated areas that boast the "presence of a substantial number of individuals with coordinated beliefs". This implies that food riots are more likely to occur in cities and towns rather than in the countryside. Nonetheless, in the context of Sub-Saharan Africa, travel is difficult and expensive due to poor infrastructure (Foster & Briceño-Garmendia, 2010). Within this environment, the distance a food-insecure person may travel to take part in political violence is constrained.

Considering the above conceptualisation, the study utilises first-level administrative divisions as defined by the UN FAO Global Administrative Unit Layers (GAUL) dataset for the spatial unit of analysis, hereafter referred to as 'regions'. These regions are the equivalent of national constituent states, provinces, and regions, usually amounting to between 2 and 25 percent of a nation's total land area. Within the GAUL dataset, they are available as shapefile vector geometries (FAO, 2015). While variable in size and population, these regions generally contain a mixture of land uses, including agriculture, and feature a regional capital city, with significant government presence and administrative offices. Following the food insecurity pathway, after agricultural drought and crop failure, this study theorises that people travel to the regional capitals and larger urban areas of these regions to take part in political violence in the form of rioting.

Due to data processing constraints, the study is limited to a subset of eight Sub-Saharan African countries, distributed across multiple geographic, climatic and cultural zones. These countries included: Kenya, Tanzania, Botswana, Zimbabwe, Mozambique, Zambia, Nigeria and Ethiopia. Together the countries contain a total of 120 regions suitable for analysis, yielding 14400 individual data points in the raw dataset. For a full list of the regions analysed see Appendix I.

A ten-year period of analysis is chosen encompassing the period from 2011 to 2020. This time period is large enough to capture several wet and dry climatic cycles in each region, while recent enough to capture contemporary levels of smallholder farming and locally-grown agricultural dependence.

Descriptive Statistics of Regions:

The regions vary significantly in terms of land area, percentage farmland area, and population. In terms of area, the mean size is 50134 km^2, with a standard deviation of 52845 km^2. The largest region in terms of area is Oromia, Ethiopia (322996 km^2), while the smallest is Hareri, Ethiopia (371.42 km^2). The mean percentage of farmland across the 120 regions is 22.03 percent with a standard deviation of 21.2 percent. The region with the largest farmland percentage is Kano, Nigeria (86.97 percent), and the smallest is Ghanzi, Botswana (0.02 percent). Finally, as for regional populations at the beginning of the study period, the mean is 2,905,221 people, and the standard deviation 3,680,304 people. The most populated region is Oromia, Ethiopia (30,141,971 people), and the least populated is Chobe, Botswana

(23,347 people). See Appendix I for a full breakdown of regional areas, cropland percentages and population data sources.

Agricultural Drought

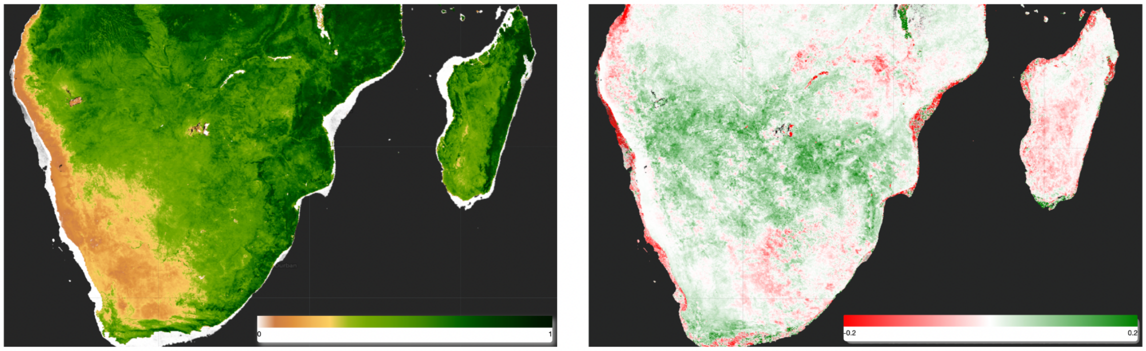
To investigate the food insecurity pathway, and the aforementioned research question, large amounts of data is required on cropland, agricultural drought, and the locations and timing of riots.

To operationalise the independent variable, agricultural drought, remote sensing is used to collect data on large areas of agricultural land. To achieve this, the study makes use of Normalised Difference Vegetation Index (NDVI) data from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard several NASA satellites. NDVI is a measure of vegetation health obtained through a relatively simple calculation derived from measurements of red and near-infrared (NIR) wavelengths of light (Huang et al., 2020), as seen in the formula below:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Figure 3: Normalised Difference Vegetation Index (NDVI) formula. (Huang et al., 2020)

NDVI has a long history of use in remote sensing and is the most cited index for agricultural drought in the literature, and the second most frequently mentioned indicator for drought overall (Kchouk et. al., 2021). As a measure of crop health and crop biomass, NDVI is frequently used as an estimator for crop yields (Roznik et al, 2022). NDVI values range from -1 to 1, and the *"higher the NDVI index in critical growing periods over the growing season, the greater the potential crop yield"* (Roznik et al., 2022, p. 3). As a source of this data, the MODIS instrument has also been used for the purpose of estimating crop yield (Mkhabela et al., 2011) and cross-region comparisons of drought severity (Khan & Gilani, 2021), just to name a few. Within the study, MODIS NDVI data is obtained from Google Earth Engine, a multi-petabyte database of remote sensing imagery (Gorelick et al., 2017). In its initial form, the NDVI data is a single raster mosaic covering the entire planet, updated every 16 days at a spatial resolution of 463.313 meters per pixel (Google Earth Engine, 2022).



MODIS NDVI Raster Image **Derived NDVI Anomaly**

Figure 4: Visualisation of MODIS NDVI and NDVI anomaly raster images of Southern Africa (Data: NASA EOSDIS Land Processes DAAC)

To derive relative crop health information from this data, these raster images are clipped to the geometries of farmlands within selected regions. These farmland geometries are obtained from Global Food Security-Support Analysis Data at 30 m (GFSAD30) a USGS/NASA project to provide high-resolution global cropland data. The GFSAD30 data is derived from a machine learning model applied to imagery from that Landsat 8 satellite (Thenkabail et al., 2021), and is available as tiled raster images. This farmland raster data is vectorised and then used to clip the separate NDVI anomaly rasters, with all other non-farmland areas discarded (See Fig. 5 below). Then, for each month of each study period year, mean NDVI figures are calculated for the farmland areas and then compared with the 20-year (2000-2020) average for the same areas, to derive a mean NDVI anomaly figure for each month of the study period. These spatial and temporal data reductions result in monthly NDVI data points capturing the deviation in crop health from the long-term average or alternatively serve as a measure of agricultural drought.

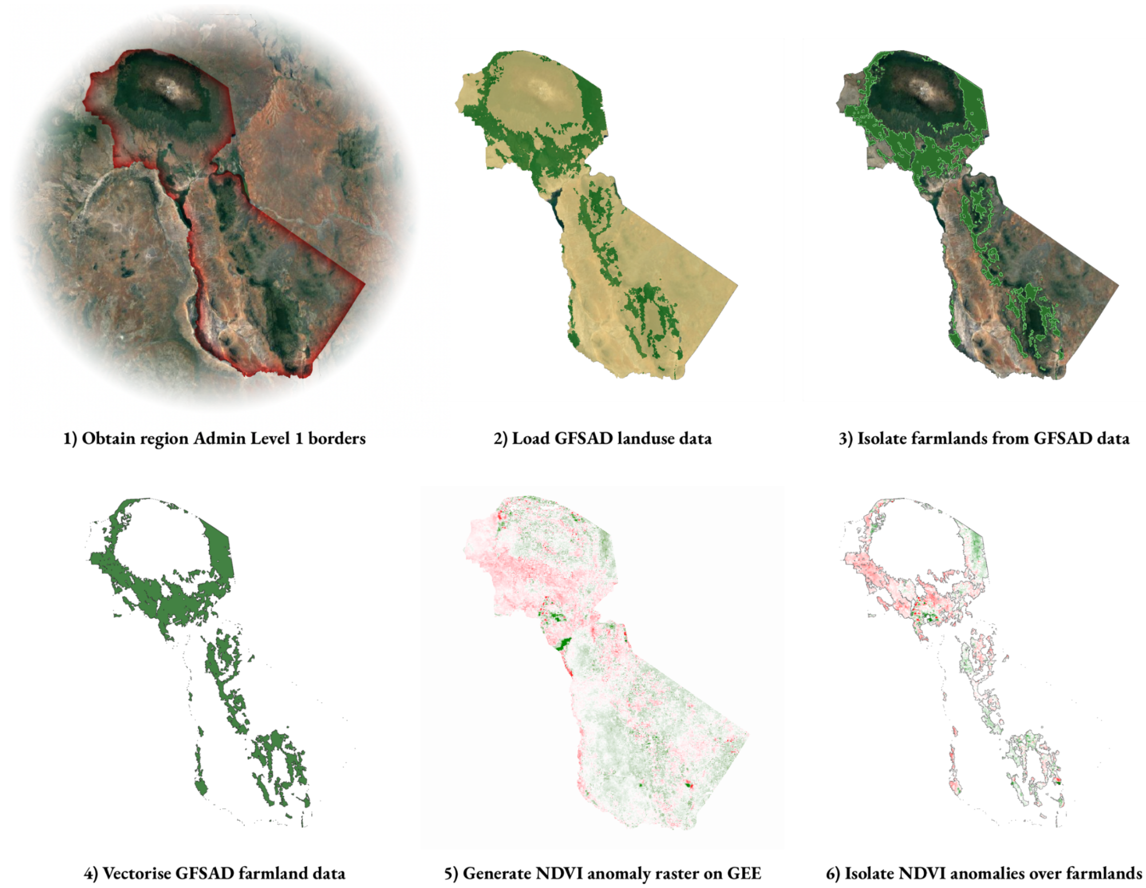


Figure 5: Farmland NDVI anomaly generation process for Kilimanjaro Region, Tanzania
(Data: NASA EOSDIS Land Processes DAAC/Thenkabail, 2021/FAO, 2015)

For the proposed causal mechanism to come into action, drought would need to directly impact food production, or lead to the assumption of lower supply, and high food prices. For this reason, the period of focus is the agricultural growing season, wherein low NDVI readings would translate to reduced crop yield. Moreover, the impact of this crop yield reduction would be felt primarily during the period after the drought-affected crop is harvested through to the harvest of the next crop, given the findings of Lantonirina et al., (2019) and Bonuedi et al. (2022) that food supplies run low prior to harvest. To capture this, a further reduction of the remote sensing data is carried out, resulting in a statistic representing the mean NDVI anomaly over the croplands in each region during the growing season of the preceding agricultural year.

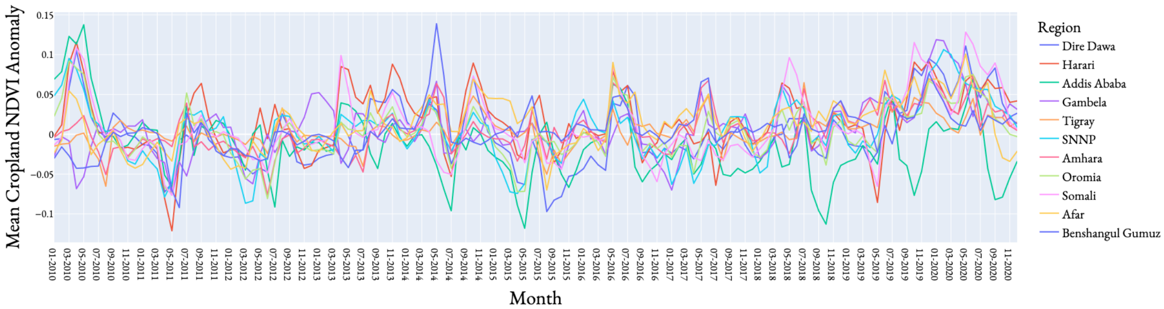


Figure 6: MODIS monthly farmland NDVI anomaly data from Ethiopia 2010-2020
(Data: NASA EOSDIS Land Processes DAAC)

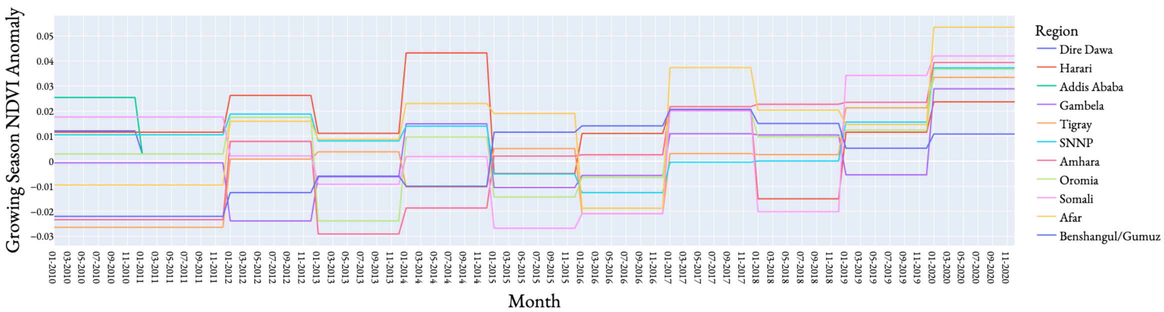


Figure 7: Growing Season farmland NDVI Anomalies from Ethiopia 2010-2020
(Data: NASA EOSDIS Land Processes DAAC)

Data on the duration of the growing season for the major food crop of each country analysed is obtained from the FAO Global Information and Early Warning System (GIEWS) Country Briefs. In cases of multiple major food crops, an approximation of the most important growing months is used. Similar data on the lean season for each country is obtained from the same source. The growing season and lean season months for each country can be seen in the table below:

Country	Growing Season Months	Lean Season Months
Zimbabwe	January, February, March, April	January, February, March, April
Mozambique	January, February, March	January, February, October, November, December
Botswana	February, March, April	January, February, March
Kenya	June, July, August, September	May, June, July, August, September
Tanzania	January, February, March, April, May	January, February, November, December
Nigeria	July, August, September, October, November	April, May, June, July, August
Ethiopia	June, July, August, September	May, June, July, August
Zambia	January, February, March, April	January, February, March, October, November, December

Table 1: Growing season and lean season months across the countries analysed (FAO, 2022)

In addition, while the first-level administrative division is suitable as a unit of analysis in most cases, some regions are deemed special cases for analysis of this causal mechanism. These regions include island regions in Tanzania with limited agriculture that are omitted from the analysis, as well as stand-alone urban regions. The former group depends significantly on trade for food supply, and thus fall outside of the influence of the food insecurity pathway. The latter group of regions are usually associated with the largest city in each country, featuring very little agriculture, and thus, the NDVI anomaly data for the farmlands in these small, urbanised areas would not be representative of the area from which the city draws its food production from. In countries that included regions like these, NDVI anomaly data from the largest adjacent region is used, capturing the effect of crop health in surrounding agricultural regions on rioting in the urban area. Figure 6 below demonstrates how two urban regions in Zimbabwe, Harare (dark blue) and Bulawayo (dark green) take their NDVI data from Mashonaland East (blue) and Matabeleland North (green) respectively.

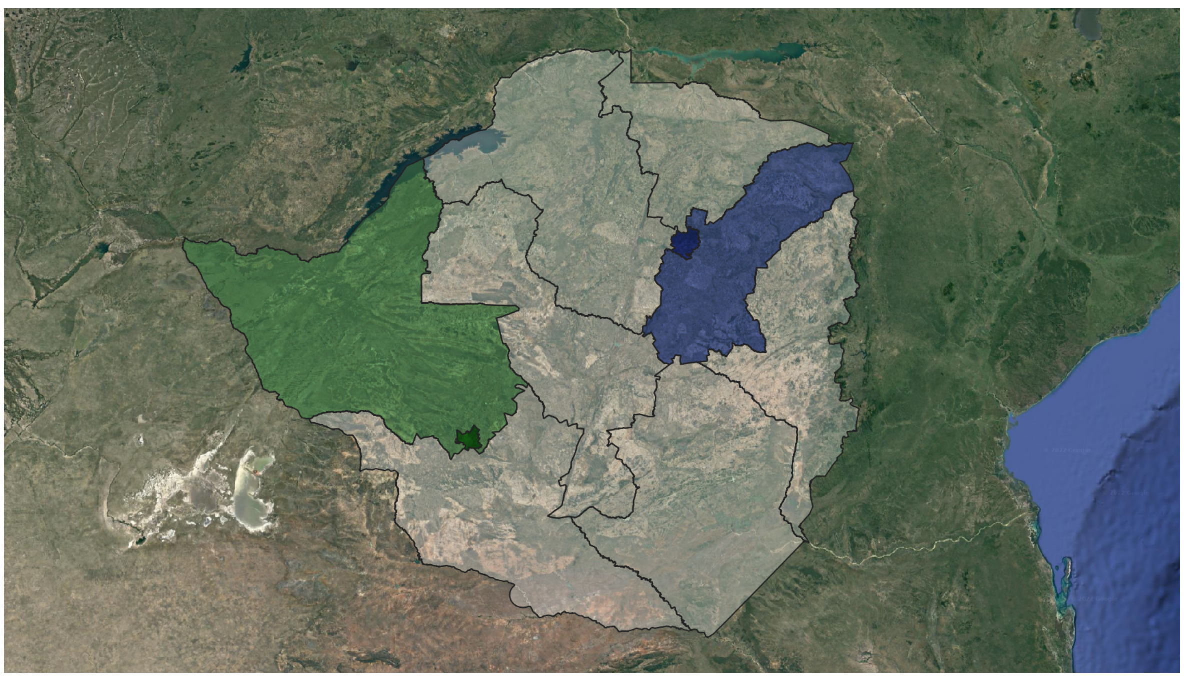


Figure 6: Example of urban area data merges in Zimbabwe (Data: FAO, 2015)

Descriptive Statistics of Growing Season NDVI Anomalies:

Due to the multiple geographic and temporal reductions used to obtain the growing season NDVI anomaly data, each data point is a small fractional number just above or just below zero. Within the raw dataset, the mean value within the data is -0.00052, and the standard deviation is 0.02631. The lowest growing season NDVI anomaly and the most severe agricultural drought within the data is -0.130081 and occurred in Kgatleng, Botswana during the 2015 growing season. Conversely, the highest growing season NDVI anomaly is 0.115555 and took place in Central District, Botswana, during the 2014 growing season. For a full breakdown of the NDVI anomaly data, see Appendix II.

Riots

Data on the dependent variable, riots in Sub-Saharan Africa, is obtained from the Armed Conflict Location & Event Data Project (ACLED). The ACLED database contains data on the locations, dates, actors and number of fatalities of all reported political violence and protest events around the world (ACLED, 2021). Data collection for Africa began in 1997, and has continued through to the present, while coverage has expanded to include all regions of the planet (ACLED, 2022). Critically, for this study, each 'event' is geocoded to first and second-level administrative divisions of a country as well as to a set of latitude/longitude coordinates (ACLED, 2021).

ACLED data is also coded based on the type of event recorded. Within the 'EVENT_TYPE' variable, an event can take the form of battles, explosions/remote violence, violence against civilians, riots and strategic developments (ACLED, 2021). Each event also includes a supplementary 'Notes' field wherein a description of the event is given. Riots are defined by ACLED as violent events where demonstrators or mobs engage in disruptive acts targeting other *"individuals, property, businesses, other rioting groups or armed actors"* (ACLED, 2021, p. 14). This definition is wide enough to capture the kind of food riots involved in the proposed food insecurity pathway, and thus is suitable for use. Following a similar methodology to Almer et al. (2017), the study subsets the data to only include events coded as 'Riot' under EVENT_TYPE. Further filtering of the riot events to exclude those events that do not mention terms like 'food', 'food prices' or 'food riot' is not carried out based on the theoretical understanding introduced by Barbet-Gros & Cuesta (2014, p. 2) that food riots *"may have other underlying causes of discontent"* or could *"motivate protest and violence involving existing grievances"* (Heslin. 2020, p. 1) making them not always obvious as an explicit 'food riot' to an outside observer. Beyond this, filtering events by actor type, or the number of fatalities is also deemed unnecessary as these variables fall outside of the food insecurity pathway.

In several cases, the locations of riot events are coded differently to the FAO GAUL dataset of country regions. These cases relate primarily to administrative boundary changes over the period of study. In such cases, the boundaries at the start of the study period (2011) are used, and the locations of riots are re-coded to the appropriate region.

To account for the fact that the population of the regions selected for study varied significantly, the number of riots each month is normalised for population. Population data is obtained from census data, national statistics agencies, as well as the UN. As reliable yearly population counts are not undertaken in the study regions, two population counts are found within, or slightly outside of the study period, and a linear approximation of population change is derived. From this linear approximation, yearly population counts are generated, and rioting is normalised to a final statistic of 'Riots per 100,000 people'.

Descriptive Statistics of Riots:

Within the 120 first-level country subdivisions analysed, over the ten year 2011-2020 period of analysis, a total of 4388 individual riot events were recorded. The mean number of riots recorded in a given region is 38.21. The highest number of riots (253) is found in the Nyanza Province of Kenya, while in several regions, no riots are recorded at all over the study period. These regions were Ghanzi, Kgalagadi, Chobe and Ngamiland in Botswana, Singida, Katavi and Simiyu in Tanzania. For a year-by-year regional breakdown of riot frequencies, see Appendix III.

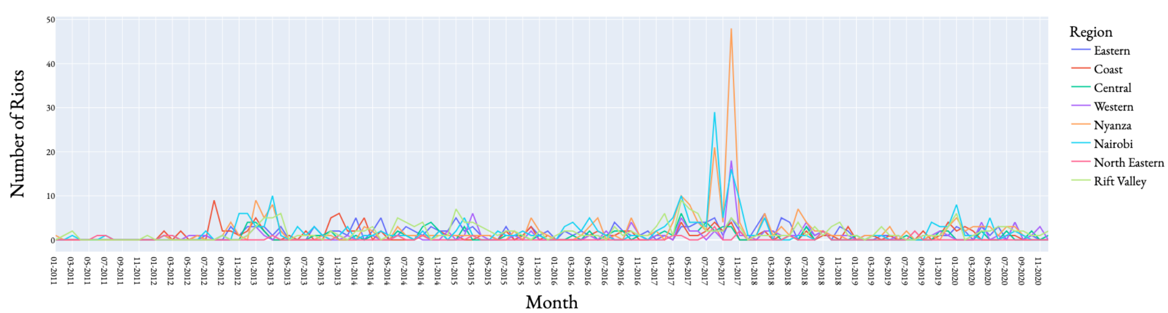


Figure 8: Example of a riot wave visible in Kenya (Data: ACLED)

Plotting the number of riots per month of each region in a given country reveals significant correlation between regions. As well, riots appear to occur in significant ‘waves’: short periods of time where anomalously high numbers of riots occur across multiple regions. Major riot waves observable within the data include April-September, 2016 in Zambia, July-November 2017 in Kenya (see Fig. 6), March-June, 2018 in Zimbabwe and August-November 2014 in Mozambique.

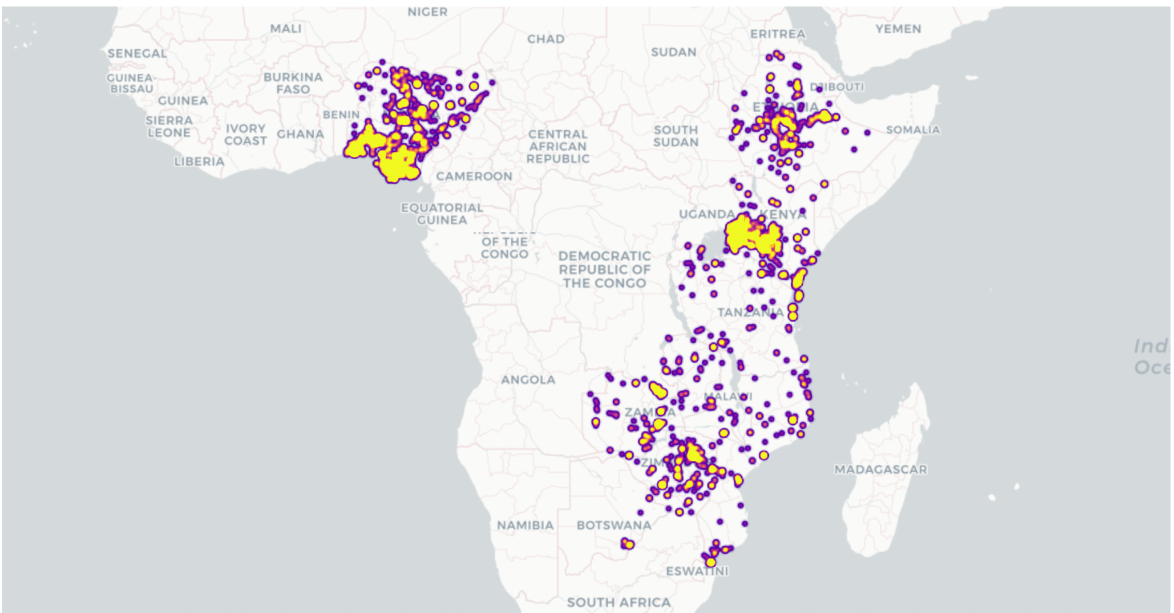


Figure 9: Heatmap of riot events included in the raw dataset (ACLED data)

Basic geospatial visualisation of the riot events within the dataset spanning 2011-2020 shows an uneven spatial distribution of riot events that backs up the methodological approach. Specifically, the riots show substantial clustering around urban areas, particularly regional and national capitals. Moreover, certain regions and countries appear to have a much higher number of riots over the study period (see Fig. 7), corresponding roughly with areas of high population, justifying the normalisation of the riot frequency by population. Beyond this, several regions see no riots at all over the study period, however, are kept in the dataset to avoid selection bias.

Estimation

To test the effect of previous year growing season NDVI anomalies on riot frequency Ordinary Least Squares (OLS) regression is used. This can be expressed as the number of riots per 100,000 people R_{it} in a region *(i)* per month *(t)* being a function of:

$$R_{it} = \alpha + \beta NDVI_{ig} + \gamma_c + \epsilon$$

with intercept α, where $\beta NDVI_{ig}$ captures the effect of the mean NDVI anomaly of a region *(i)* over the previous growing season *(g)*. Beyond this, γ_c represents controls for country-level fixed effects c and ε the error term. The country-level fixed effects control for a significant fraction of the cross-correlation between rioting in different provinces of the same country, and more generally account for country-level political, economic and cultural effects that may influence rioting patterns.

Separately, a similar function is used to test the effect of previous growing season NDVI anomalies on riot frequency confined to the lean season. This can be expressed as the number of riots per 100,000 people R_{il} in a region *(i)* per lean season month *(l)* being a function of:

$$R_{il} = \alpha + \beta NDVI_{ig} + \gamma_c + \epsilon$$

with the same terms as the previous formula.

A third function is used to test the effect of previous growing season NDVI anomalies on riot frequency confined to the non-lean season. This can be expressed as the number of riots per 100,000 people R_{in} in a region *(i)* per non-lean season month *(n)* being a function of:

$$R_{in} = \alpha + \beta NDVI_{ig} + \gamma_c + \epsilon$$

with the same terms as the initial whole-dataset regression formula.

Results

The results of the baseline regression involving the entire dataset of points can be seen in Table 2. The coefficient of interest is 'β' which represents the effect of the mean NDVI anomaly ($NDVI_{ig}$) measured over a region's farmland for the previous growing season on rioting. Lower values of this variable reflect poorer crop health over the growing season and thus lower crop yields, with higher values reflecting the inverse. To confirm H_1, $\beta NDVI_{ig}$ should have a negative coefficient.

	(1) Raw Dataset		(2) Lean Season		(3) Non-Lean Season	
	$Riots_{it}$		$Riots_{il}$		$Riots_{in}$	
	Basic	+ Fixed Effects	Basic	+ Fixed Effects	Basic	+ Fixed Effects
$\beta NDVI_{ig}$	0.0332**	0.0190	−0.0711***	−0.0887***	0.0807***	0.0672***
	(0.0155)	(0.0156)	(0.0254)	(0.026)	(0.0196)	(0.0197)
$\gamma_{Ethiopia}$		−0.0040*		−0.0089***		−0.0024
		(0.0020)		(0.0034)		(0.0024)
γ_{Kenya}		0.0102***		0.0044		0.0126***
		(0.0021)		(0.0034)		(0.0028)
$\gamma_{Mozambique}$		−0.0077***		−0.0120***		−0.0066**
		(0.0020)		(0.0032)		(0.0025)
$\gamma_{Nigeria}$		−0.0045***		−0.0087***		−0.0032
		(0.0016)		(0.0028)		(0.0020)
$\gamma_{Tanzania}$		−0.0110***		−0.0151***		−0.0098***
		(0.0017)		(0.0029)		0.0020
γ_{Zambia}		0.0031		−0.0013		0.0043
		(0.0020)		(0.0032)		(0.0028)
$\gamma_{Zimbabwe}$		0.0108***		0.0080**		0.0116***
		(0.0020)		(0.0034)		(0.0025)
Constant	0.0101***	0.0130***	0.0105***	0.0173***	0.0099***	0.0117***
	(0.0004)	(0.0014)	(0.0006)	(0.0026)	(0.0005)	(0.0017)

Note: $^* p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

Table 2: Regression output comparison across the three datasets

In column (1), it is seen that when applied to the dataset as a whole, $\beta NDVI_{ig}$ has a statistically significant effect on rioting in the opposite to the hypothesised direction ($\beta NDVI_{ig}$ = 0.0341). With the addition of controls for country fixed effects, the effect on rioting is reduced ($\beta NDVI_{ig}$ = 0.0190) and is no longer statistically significant. This can be considered a refutation of H_1.

By contrast, column (2) shows the results of the regression involving the subset of the data points including only those months that fell within the lean season of each region. Here, it is seen that $\beta NDVI_{ig}$ now has a highly statistically significant negative coefficient (-0.0711). With the addition of controls for country fixed effects the coefficient further decreases ($\beta NDVI_{ig}$ = -0.0887), and remains highly statistically significant. This represents a confirmation of H_2, that the effect of agricultural drought on rioting is higher in lean season months

These results would indicate that a one standard deviation decrease in the mean growing season NDVI anomaly would increase the frequency of riots per 100,000 people by 0.00213 for each lean season month. While this amount appears small, given a frequency of observed riots per 100,000 people per month of 0.0173 at mean levels of $NDVI_{ig}$ across the lean season dataset, this would imply that this one standard deviation decrease in $NDVI_{ig}$ increases the frequency of lean season riots (R_{il}) by 12.26 percent.

Exemplifying this from the data, in Dar es Salaam, Tanzania, in the 2013/2014 lean season, which ran four months from November 2013 to February 2014, the region of 4,364,541 people should have expected a baseline of 3.03 riots at mean levels of $NDVI_{ig}$. However, during the preceding growing season, which lasted from January to May 2013, a mean growing season NDVI anomaly of -0.03925 is observed. This would translate to an increased expected riot frequency across the lean season of 3.62 riots.

Finally, in column (3), the regression results for the subset of the data points including only those months that fell outside of the lean season for each region are presented. In a surprising result, here, the coefficient for $NDVI_{ig}$ is positive ($\beta NDVI_{ig}$ = 0.0672), and highly statistically significant. This implies that during non-lean season months, poor crop health in the previous growing season actually has the effect of reducing the frequency of riots. Indeed, a one standard deviation decrease in $NDVI_{in}$ results in a 15.92 percent decrease in the monthly frequency of rioting during non-lean season months. This effect, which operates in an almost equally opposite direction to that seen in the lean season, explains the weak and statistically insignificant effect of $\beta NDVI_{ig}$ on rioting when applied to the dataset as a whole, and serves as a further refutation of H_1.

Discussion

The results described above appear to provide evidence supporting the existence of a food insecurity pathway, however, its effects appear to be conditioned to a far greater degree by seasonality than hypothesised.

The research by Almer et al. (2017) and Unfried et al. (2021), had found that when looking at hydrological drought in Sub-Saharan Africa, rainfall deficiencies led to an observable increase in riots, irrespective of the time of the year. In contrast, the first important finding of this study is showing that this pattern does not hold true when using agricultural drought, measured through remotely-sensed NDVI, as the independent variable. Specifically, the initial broad hypothesis (H_1) that the frequency of monthly rioting increases as agricultural drought during the previous growing season worsens is unsupported by the weak and statistically insignificant effect found in the data.

Despite this, the null hypothesis that there is no significant effect of agricultural drought on rioting can also not be confirmed, in light of the intriguing second and third findings of the study. Most notably, a substantial and highly significant relationship is seen between growing season NDVI anomalies, and rioting, when looking only at the lean season. This period of the year corresponds to the time when food supplies are generally at their lowest, and food insecurity at its highest. The finding that it is only during this period that an increase in riots can be observed, would appear to confirm the second hypothesis (H_2) that the effects of the food insecurity pathway are at their strongest during this period, albeit in a more absolute form - that these effects are only observable at all during the lean season, rather than relatively stronger when compared to the year as a whole.

This evidence that the effect of drought on rioting is conditioned by agricultural and food security seasonality supports the plausibility of a causal mechanism more complex than one involving simple competition for scarce water resources. As hydrological drought and agricultural drought are highly cross-correlated, a simple finding where the low growing season NDVI anomalies are linked to an observable rise in rioting would be insufficient to establish the food insecurity pathway as a plausible causal mechanism. In such a scenario, any observed increase in rioting could be equally explained by increased competition over scarce water resources. The restriction of this effect to simply the lean season months however demonstrates clear evidence for food security playing a role in this drought-enhanced rioting.

One potential caveat to this is the existence of seasonal patterns to high water consumption/demand that correlate closely with the lean season across the countries and regions analysed. Going back to the agricultural calendar (detailed in Fig. 2 and Table 1), it is notable that the growing season often has a significant overlap with the lean season, due to the fact that the last few months up until harvest are the period at which food stocks are at their lowest. This growing season can also be understood to be a time of high water demand, with the majority of Sub-Saharan Africa's water being used by agriculture (Zaki et al., 2018), and this use presumably concentrated during the growing season. Nonetheless, the relationship investigated in this study looks at the frequency of riots that occur in the year after an agricultural drought in the growing season. Given the (up to) one-year time lag between the observation of the independent and dependent variables, for growing season water demand to explain the lean season riot increases (in cases of agricultural drought), the measured agricultural drought would have to affect the availability of water up to a year into the future. Further research is required in order to separate these two effects, and investigate whether a portion of the observed increase in rioting in the face of food insecurity during the lean season, may in fact be driven by cross-correllated growing season water demand competition.

Another possibility is that the observed increase in lean season rioting is the result of the mutually-reinforcing effects of both food insecurity and water scarcity. Recent research by Koren et al. (2021, p. 68) looking at social unrest in Kenya found that *"food insecurity and water insecurity greatly reinforce the other's impact on social unrest, with high degrees of both insecurities increasing the expected counts of unrest events by approximately one or more events per day, on average"*. If this holds true across the other countries analyzed in this study, then the increased rioting during the overlapping lean season-growing season could be explained by the cumulative effects of these staple insecurities, rather than either individually, and thus both theorised pathways may exist simultaneously.

Further questions are raised by the third major finding of the study, that agricultural drought is linked to a counterintuitive and very statistically significant reduction in rioting during the remaining months of the year that fall outside of the lean season. Following the conceptualised food insecurity pathway, it would be expected that during these months, the effect of the agricultural drought increasing rioting would be lesser, but still present. An explanation for the observed effect in the opposite direction may lie outside of this pathway as it was initially theorised.

One potential explanation is that policy responses at the local, national and international levels may temporarily alleviate food insecurity. Local or regional governments may respond by constructing temporary infrastructure such as new wells (del Ninno et al., 2005). At a national level, governments could enact policies such as food subsidies, price caps or the removal of food import tariffs in the wake of agricultural drought and crop failure (del Ninno et al., 2005). Furthermore, national governments with sufficient state capacity may also provide direct cash assistance to struggling drought-affected smallholder farmers, reducing their food insecurity and, following the pathway, their likelihood to riot. These interventions however may be costly serving as only temporary measures, and may not last through to the lean season. Beyond this, international food aid provided by donor states is also a common response to severe droughts within Sub-Saharan Africa (del Ninno et al., 2005). This food aid may fall short of what is required to make up for the decline in production, and may be exhausted by the lean season, leading to the reversal of the relationship between drought and rioting during these months.

Alternatively, or in addition, the observed effect could be the result of a well-established finding of pro-social behaviour in the aftermath of disasters. Mathewman & Uekusa (2021, p. 965), defined this as ‘communitas’, stating that for over a century, researchers have observed *“improvisational acts of mutual help, collective feeling and utopian desires that emerge in the wake of disasters”*. The possibility exists that a drought of sufficient severity could lead to the inhabitants of the affected regions to exhibit more prosocial behaviours, and thus be less willing to take part in riots. This initial effect of ‘communitas’ could then decline over time following the initial poor harvest, and then by the time the next lean season comes around the grievances associated with the food insecurity pathway come back to the fore, and rioting then increases in likelihood.

A final route by which these findings may be influenced is through labour migration. The agricultural calendar in Sub-Saharan African countries is characterised by significant changes in employment, with a greater number of people working in agriculture during the labour-intensive growing season and harvest period compared to the remainder of the year (Rapsomanikis, 2015). During this period of downtime, especially following a drought that impacts crop production, farm labourers who rely on their crops for food, may be incentivised to seek other paid employment off-farm in order to generate income to purchase food should they face a future shortfall. This job-seeking would require farmers to temporarily migrate to urban areas following a harvest, before returning for the next growing season, a period of time that overlaps considerably with the lean season. The impact of these labour migrations is unknown, but their timing opens the possibility of them explaining these effects, and thus makes them an interesting area of study for future research.

Several other sources of error exist which could affect the dataset as a whole, and are worth noting. While the changes in regional population over the study period are normalised, the same cannot be said for changes in cropland size. These changes could influence the accuracy of the $\beta NDVI_{ig}$ values, however are somewhat mitigated by the fact that the GFSAD30 data on cropland areas uses 2015 as its reference year, roughly in the middle of the study period. In addition, further error could be introduced by the data collection methodology used by ACLED, whereby researchers gather data from publicly available secondary reports. This, ACLED admits, "may underestimate the volume of events of non-strategic importance" such as low-level conflict (ACLED, 2019, p. 9). With riots a form of low-level conflict, it is possible that a fraction of the riots that occurred in each region over the study period were not coded into the database, thus introducing error through omission of key data.

Nonetheless, the three findings together reveal that while drought-induced food insecurity plays a role in riot frequency, the mechanism by which it occurs is likely more complex than a simple cause and effect relationship. Conclusively establishing the mechanism through which drought leads to more (or less) riots in Sub-Saharan Africa would likely require additional data looking not just at remote sensing data on crop health, but also comparing this with data on real or perceived food insecurity, possibly using social media sentiment analysis in a similar manner to Koren et al. (2021).

Conclusion

This study presents supporting evidence for the existence of an alternative pathway by which drought can lead to conflict in the form of rioting. Unlike past research on the relationship between rainfall shortages and rioting, the theorised food insecurity pathway involves low rainfall leading to agricultural drought and crop failures. These crop failures, in the context of Sub-Saharan Africa's dependence on smallholder/subsistence farming, lead to food insecurity, both through a reduction in the direct availability of food, as well as high food prices. This food insecurity functions as a source of grievance for those affected, and in addition exacerbates existing grievances creating a situation of high social tension conducive to rioting. Given yearly fluctuations in food availability resulting from the agricultural calendars of Sub-Saharan African countries, this food insecurity and subsequent rioting is theorised to be highest during the lean season.

Using remotely sensed data on agricultural drought across the time period 2010-2020, as well as geocoded data on the locations of riots, eight countries across Sub-Saharan Africa are analysed, broken down into 120 disaggregated first-level administrative divisions. The population-normalised monthly frequencies of riots were compared to mean NDVI anomalies across the farmlands of each region during the most recent growing season while controlling for country-level fixed effects. To test the hypothesised effects of drought on food insecurity and rioting, three individual OLS linear regressions are run on the entire dataset, and subsets for only lean season months, and only non-lean season months.

The results of the study support the existence of a food insecurity pathway playing a role in the observed increase in rioting following droughts, however, they also include counterintuitive findings that indicate underlying complexities within the dynamics linking droughts and riots. Of specific relevance to the field of climate-conflict research is the finding that while the overall effect of agricultural drought on rioting is not statistically significant, during the lean season this effect becomes very apparent and of substantial magnitude. This demonstrates that food insecurity plausibly plays a role in drought-driven rioting in Sub-Saharan Africa and that the different phases of the agricultural calendar have a significant effect on the dynamics of rioting in the region. While conflict over scarce water resources during droughts cannot be conclusively ruled out as a causal mechanism for these observations, the findings show that a more complex interaction between both water scarcity and food insecurity may be occurring.

In addition, the surprising finding that agricultural drought is observed to reduce the frequency of rioting outside of the lean season, challenges existing theories that imply a simplistic linear relationship between drought and rioting. Rather, evidence exists for more complex interactions with a range of potential exogenous variables, including (but potentially not limited to) political drought responses, socio-psychological disaster responses within communities and economic migrations following drought. Future research on this topic will need to control for the potential effects of these variables on rioting, in order to properly ascertain the true effect of drought on rioting. Alternatively, these findings open the door for further research exploring these complex dynamics, with the impact of political drought responses of particular importance in light of the potentially actionable insights it could provide.

These results are of particular importance to policymakers and NGOs given the evidence for a complex relationship between drought and rioting that depends, to a significant degree on periods of the agricultural calendar. While caloric shortfall during the lean season is well-known, the socio-political impacts this can have on Sub-Saharan African countries have been less-understood. With the evidence presented in this study that this lean season food insecurity leads to political grievances and rioting, the provision of aid by NGOs and international donors during this period becomes even more important, as it could reduce not just malnutrition but also improve security as a second-order effect. Similarly, national-level drought responses should be crafted in such a way that concentrates on the lean season, either through programs providing supplementary nutrition, cash payouts allowing subsistence/smallholder farmers to purchase food on the open market, or relaxation of trade barriers that would reduce the price of food on local markets. With droughts expected to become more severe and more frequent due to climate change, resource-constrained players across all levels of government, as well as NGOs and IOs may be forced to make difficult decisions on where and when they allocate the limited aid they have available. Based on this study, there is evidence that a lean season only allocation may have the greatest efficiency in preventing riots following drought and should be considered by policymakers in a resource-constrained environment.

The mechanisms underpinning the drought-rioting relationship are also shown in the study to likely involve a greater complexity than simple competition for water resources. As such, policymakers seeking to improve country or region-level resilience will have to take this into consideration when formulating their plans. Simply improving water access or negotiating better political arrangements for sharing water may not be sufficient to mitigate the effect that drought has on increasing rioting. Instead, attention would likely also need to be placed on improving the general drought resilience of food production in Sub Saharan Africa. Such interventions have been widely covered by researchers in the field of economics, development and agricultural science, and could take many forms, all given yet more importance based on the results of this study.

Overall, this study demonstrates that food security remains a core component of human security and cannot be neglected when assessing the impacts of climate change on conflict. In a period of unprecedented food crisis driven not only by the climate, but also by war, COVID-19 and supply chain collapse, research furthering humanity's understanding of these dynamics is more important than ever.

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Appendix I: Regional Data Statistics

Table 3: Region Statistics

Region	Country	Area (km^2)	% Country Area	Farmland (km^2)	% Farmland
Midlands	Zimbabwe	49359.40	12.63	13754.71	27.87
Matabeleland N.	Zimbabwe	75489.40	19.32	7992.72	10.59
Manicaland	Zimbabwe	35655.58	9.13	15349.89	43.05
Harare	Zimbabwe	1007.75	0.26	80.20	7.96
Mashonaland C.	Zimbabwe	28128.47	7.20	9406.77	33.44
Bulawayo	Zimbabwe	461.43	0.12	80.74	17.50
Masvingo	Zimbabwe	56469.57	14.45	19113.99	33.85
Mashonaland E.	Zimbabwe	32074.24	8.21	13553.57	42.26
Mashonaland W.	Zimbabwe	57742.61	14.78	10649.65	18.44
Matabeleland S.	Zimbabwe	54352.02	13.91	8951.86	16.47
Ghanzi	Botswana	114493.17	19.80	19.90	0.02
Southern	Botswana	27394.74	4.74	3277.09	11.96
South-East	Botswana	2013.92	0.35	189.99	9.43
North East	Botswana	5337.40	0.92	501.22	9.39
Kgatleng	Botswana	7815.74	1.35	1498.01	19.17
Central	Botswana	146668.60	25.36	4548.27	3.10
Chobe	Botswana	20974.65	3.63	250.71	1.20
Ngamiland	Botswana	111503.79	19.28	243.04	0.22
Kweneng	Botswana	36965.62	6.39	2251.95	6.09
Kgalagadi	Botswana	105130.35	18.18	3089.78	2.94
Eastern	Kenya	153046.47	26.27	29762.10	19.45
North Eastern	Kenya	127487.79	21.88	75.35	0.06
Nairobi	Kenya	696.69	0.12	150.30	21.57
Central	Kenya	13175.32	2.26	9358.71	71.03
Nyanza	Kenya	16275.62	2.79	11791.47	72.45
Western	Kenya	8362.81	1.44	7081.64	84.68
Coast	Kenya	82675.75	14.19	2027.87	2.45
Rift Valley	Kenya	180878.01	31.05	26905.55	14.87
Manica	Mozambique	62437.04	7.93	3388.94	5.43
Cabo Delgado	Mozambique	77931.65	9.90	1931.66	2.48
Zambezia	Mozambique	103338.77	13.13	18294.99	17.70
Tete	Mozambique	100735.16	12.80	7869.73	7.81
Niassa	Mozambique	122267.81	15.53	7142.45	5.84
Maputo	Mozambique	23499.57	2.98	2875.55	12.24
Inhambane	Mozambique	68771.08	8.74	2260.99	3.29
Nampula	Mozambique	78179.98	9.93	4402.18	5.63
Sofala	Mozambique	68001.45	8.64	4887.27	7.19
Gaza	Mozambique	75436.44	9.58	6316.93	8.37
Addis Ababa	Ethiopia	539.05	0.05	275.35	51.08
Hareri	Ethiopia	371.42	0.03	141.19	38.01
Somali	Ethiopia	313129.94	27.71	3238.22	1.03
Afar	Ethiopia	95179.20	8.42	881.83	0.93
Beneshangul Gumu	Ethiopia	50091.54	4.43	2416.26	4.82
Dire Dawa	Ethiopia	1055.54	0.09	109.18	10.34
Tigray	Ethiopia	51815.47	4.59	17036.14	32.88
Amhara	Ethiopia	155356.10	13.75	73209.90	47.12
SNNPR	Ethiopia	108648.77	9.62	29808.89	27.44
Gambela	Ethiopia	30702.52	2.72	236.84	0.77
Oromia	Ethiopia	322995.80	28.59	106859.70	33.08
Eastern	Zambia	68615.89	9.13	11105.11	16.18
Southern	Zambia	85820.41	11.42	14146.49	16.48
Luapula	Zambia	48200.54	6.41	5121.75	10.63
Lusaka	Zambia	21527.88	2.86	1787.03	8.30
Central	Zambia	94836.68	12.62	14518.64	15.31
Copperbelt	Zambia	30861.66	4.11	6285.89	20.37
North-Western	Zambia	123442.75	16.43	4018.07	3.26
Western	Zambia	129154.94	17.19	4240.49	3.28
Northern	Zambia	148977.42	19.83	5485.66	3.68

Table 4: Region Statistics (cont.)

Region	Country	Area (km^2)	% Country Area	Farmland (km^2)	% Farmland
Bayelsa	Nigeria	10009.36	1.10	37.06	0.37
Gombe	Nigeria	18203.57	2.00	10667.95	58.60
Delta	Nigeria	16806.83	1.85	2135.55	12.71
Benue	Nigeria	31301.95	3.44	18379.95	58.72
Abuja	Nigeria	7353.14	0.81	1232.43	16.76
Cross River	Nigeria	20995.13	2.31	2068.10	9.85
Kogi	Nigeria	28967.92	3.19	3528.24	12.18
Kebbi	Nigeria	35831.73	3.94	12860.48	35.89
Plateau	Nigeria	27562.53	3.03	11553.83	41.92
Edo	Nigeria	19624.71	2.16	1761.79	8.98
Enugu	Nigeria	7702.29	0.85	1510.23	19.61
Rivers	Nigeria	8731.54	0.96	1263.98	14.48
Lagos	Nigeria	3782.17	0.42	18.33	0.48
Borno	Nigeria	71618.28	7.88	20827.76	29.08
Zamfara	Nigeria	34575.52	3.80	17036.16	49.27
Ekiti	Nigeria	5240.93	0.58	197.89	3.78
Kwara	Nigeria	35420.52	3.90	4563.61	12.88
Katsina	Nigeria	23700.33	2.61	19429.99	81.98
Ogun	Nigeria	16083.98	1.77	93.62	0.58
Kaduna	Nigeria	44306.36	4.87	19104.40	43.12
Taraba	Nigeria	60449.95	6.65	13841.00	22.90
Anambra	Nigeria	4592.56	0.51	706.57	15.39
Yobe	Nigeria	45620.25	5.02	20278.46	44.45
Nassarawa	Nigeria	26313.59	2.89	12323.87	46.83
Niger	Nigeria	71121.47	7.82	26685.48	37.52
Abia	Nigeria	4723.46	0.52	354.66	7.51
Akwa Ibom	Nigeria	6608.82	0.73	234.02	3.54
Imo	Nigeria	5312.16	0.58	299.75	5.64
Oyo	Nigeria	27381.36	3.01	3405.53	12.44
Bauchi	Nigeria	49040.18	5.39	25079.42	51.14
Ebonyi	Nigeria	6185.82	0.68	3704.33	59.88
Adamawa	Nigeria	34433.92	3.79	10623.25	30.85
Osun	Nigeria	9189.26	1.01	452.73	4.93
Jigawa	Nigeria	23985.91	2.64	18540.32	77.30
Ondo	Nigeria	14478.96	1.59	399.91	2.76
Kano	Nigeria	20069.22	2.21	17454.72	86.97
Sokoto	Nigeria	31945.66	3.51	7884.95	24.68
Tanga	Tanzania	27907.69	2.98	4363.86	15.64
Iringa	Tanzania	36523.63	3.90	6679.02	18.29
Dar-es-salaam	Tanzania	1632.53	0.17	39.91	2.44
Singida	Tanzania	48549.54	5.18	13521.06	27.85
Morogoro	Tanzania	70163.65	7.49	8768.63	12.50
Mara	Tanzania	30214.07	3.23	9857.87	32.63
Kagera	Tanzania	36859.43	3.93	1824.46	4.95
Rukwa	Tanzania	28094.17	3.00	6786.67	24.16
Mtwara	Tanzania	17791.19	1.90	5810.39	32.66
Ruvuma	Tanzania	63070.14	6.73	7216.81	11.44
Lindi	Tanzania	64694.38	6.91	3543.94	5.48
Kilimanjaro	Tanzania	13205.84	1.41	2903.97	21.99
Shinyanga	Tanzania	16411.19	1.75	13370.71	81.47
Mwanza	Tanzania	24634.98	2.63	10163.92	41.26
Katavi	Tanzania	49335.53	5.27	3209.33	6.51
Manyara	Tanzania	46952.21	5.01	10457.96	22.27
Tabora	Tanzania	75448.33	8.05	25076.06	33.24
Simiyu	Tanzania	24964.30	2.67	12786.37	51.22
Geita	Tanzania	21053.35	2.25	9415.67	44.72
Mbeya	Tanzania	61396.31	6.55	8428.06	13.73
Pwani	Tanzania	31400.46	3.35	836.60	2.66
Kigoma	Tanzania	44997.46	4.80	2267.76	5.04
Arusha	Tanzania	38146.47	4.07	3476.83	9.11
Dodoma	Tanzania	41940.73	4.48	19894.47	47.43
Njombe	Tanzania	21325.82	2.28	6048.47	28.36

Country	Standalone Urban Area Region	Adjacent Joining Region
Kenya	Nairobi	Central
Ethiopia	Addis Ababa	Oromia
Ethiopia	Dire Dawa	Oromia
Zimbabwe	Harare	Mashonaland East
Zimbabwe	Bulawayo	Matabeleland North
Tanzania	Dar es Salaam	Pwani
Mozambique	Maputo City	Maputo
Nigeria	Lagos	Ogun

Table 5: Standalone urban area region merges used within the dataset.

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Appendix II: NDVI Anomaly Data Statistics

	Growing Season Mean NDVI Anomaly Values				
Region/Country	2010	2011	2012	2013	2014
Matabeleland South, Zimbabwe	0.014996	0.014996	0.002142	-0.036278	-0.026645
Midlands, Zimbabwe	0.022753	0.022753	0.003593	-0.018315	-0.01975
Mashonaland West, Zimbabwe	0.019049	0.019049	0.002872	-0.001457	-0.011694
Mashonaland East, Zimbabwe	0.007659	0.007659	0.005322	-0.00973	0.003618
Matabeleland North, Zimbabwe	0.025085	0.025085	0.007456	-0.02896	-0.017041
Bulawayo, Zimbabwe	0.043097	0.025085	0.007456	-0.02896	-0.017041
Masvingo, Zimbabwe	0.011209	0.011209	-0.022355	-0.045468	-0.028118
Mashonaland Central, Zimbabwe	0.00749	0.00749	0.001737	-0.008998	-0.00624
Manicaland, Zimbabwe	0.003361	0.003361	-0.007249	-0.024872	-0.000801
Harare, Zimbabwe	0.021852	0.007659	0.005322	-0.00973	0.003618
Ghanzi, Botswana	0.020733	0.020733	0.046321	-0.025824	-0.101306
Southern, Botswana	0.03218	0.02825	0.007334	-0.001531	-0.018117
South East, Botswana	0.042113	0.042113	0.088594	-0.027235	-0.07623
Central, Botswana	0.036451	0.021445	0.010986	0.002132	-0.010283
Kgatleng, Botswana	0.028507	0.028507	0.056632	-0.031023	-0.075854
Kweneng, Botswana	0.027067	0.027067	0.047306	-0.038335	-0.080028
Ngamiland, Botswana	-0.000411	-0.000411	0.023487	0.006837	-0.060349
Kgalagadi, Botswana	0.075088	0.075088	0.063963	-0.012411	-0.079352
Chobe, Botswana	0.019661	0.019661	0.002632	0.001892	-0.038746
North East, Botswana	0.013019	0.013019	-0.02096	-0.047776	-0.033335
Eastern, Kenya	0.013004	0.01225	0.008004	-0.005165	-0.023295
Coast, Kenya	0.017788	0.017788	-0.039711	-0.042978	-0.013071
Central, Kenya	0.020455	0.021445	0.010986	0.002132	-0.010283
Western, Kenya	0.004058	0.013082	-0.0029	-0.006785	-0.016424
Nyanza, Kenya	-0.000724	-0.000724	0.012095	0.023854	-0.031019
Nairobi, Kenya	0.023035	0.01402	0.007571	0.049054	0.01209
North Eastern, Kenya	0.015238	0.015238	-0.042731	-0.005608	0.035128
Rift Valley, Kenya	0.008683	0.008683	0.008523	0.03784	0.003583
Nampula, Mozambique	-0.003225	-0.003225	-0.01085	-0.013186	-0.016291
Gaza, Mozambique	0.026988	0.026988	0.01979	-0.001204	0.007619
Tete, Mozambique	0.007656	0.007656	-0.002593	-0.0221	-0.012051
Maputo, Mozambique	0.032606	0.032606	0.004306	0.009873	0.009422
Manica, Mozambique	0.010055	0.010055	-0.004637	-0.040206	-0.011108
Zambezia, Mozambique	0.009971	0.009971	0.002269	-0.017182	-0.007659
Sofala, Mozambique	0.005562	0.005562	-0.001519	-0.043463	-0.014905
Cabo Delgado, Mozambique	-0.011191	-0.011191	-0.007085	-0.013159	-0.017797
Inhambane, Mozambique	0.009633	0.009633	0.013196	-0.022138	-0.010404
Niassa, Mozambique	0.000716	0.000716	-0.001103	-0.010461	-0.022586
Ebonyi, Nigeria	-0.001904	-0.001904	0.011387	-0.003772	-0.002269
Katsina, Nigeria	-0.00022	-0.00022	0.001936	0.018438	-0.006429
Bauchi, Nigeria	0.001513	0.001513	-0.002726	0.007769	-0.003393
Niger, Nigeria	0.00211	0.00211	-0.00152	-0.001695	-0.027642
Adamawa, Nigeria	0.001819	0.001819	-0.002293	0.006194	-0.019797
Kebbi, Nigeria	0.004617	0.004617	-0.003324	0.008938	-0.008248
Edo, Nigeria	-0.000572	-0.000572	-0.000804	0.001831	-0.003079
Abia, Nigeria	0.011185	0.011185	0.009796	0.003221	-0.001036
Ogun, Nigeria	0.010081	0.010081	0.002756	-0.00136	-0.009537
Kwara, Nigeria	-0.002515	-0.002515	0.000276	-0.002384	-0.018931
Ondo, Nigeria	0.001645	0.001645	0.008592	0.01434	0.002172
Delta, Nigeria	0.011284	0.011284	0.006318	-0.023897	0.005144
Kaduna, Nigeria	0.006547	0.006547	0.002126	0.009118	-0.010912
Akwa Ibom, Nigeria	0.017319	0.017319	0.013376	-0.000511	-0.007691
Federal Capital Territory, Nigeria	0.00117	0.00117	-0.001109	0.005297	-0.001975
Oyo, Nigeria	0.004396	0.004396	0.010564	0.00692	-0.011558
Rivers, Nigeria	0.012497	0.012497	0.005126	-0.008122	0.001653
Sokoto, Nigeria	-0.007604	-0.007604	0.001338	0.02524	-0.010581
Imo, Nigeria	0.016697	0.016697	0.008693	-0.005152	-0.003749
Lagos, Nigeria	0.02047	0.010081	0.002756	-0.00136	-0.009537
Plateau, Nigeria	0.004559	0.004559	-0.001012	0.001613	0.01453
Nassarawa, Nigeria	0.005438	0.005438	0.004776	0.003	-0.003012

Table 6: NDVI statistics of first 60 regions (2010-2014)

	Growing Season Mean NDVI Anomaly Values					
Region/Country	2015	2016	2017	2018	2019	2020
Matabeleland South, Zimbabwe	0.028764	-0.011619	-0.023512	0.050125	0.005181	-0.022204
Midlands, Zimbabwe	0.006926	-0.009131	-0.01589	0.052253	0.015867	-0.024437
Mashonaland West, Zimbabwe	0.000027	0.001421	0.002174	0.043733	0.016495	-0.027515
Mashonaland East, Zimbabwe	-0.005879	0.005689	-0.01018	0.046448	0.022164	0.009694
Matabeleland North, Zimbabwe	0.016077	-0.013667	-0.020548	0.048043	0.01397	-0.022414
Bulawayo, Zimbabwe	0.016077	-0.013667	-0.020548	0.048043	0.01397	-0.022414
Masvingo, Zimbabwe	0.024003	-0.024283	-0.041077	0.062266	0.019242	-0.013476
Mashonaland Central, Zimbabwe	-0.00597	0.017919	-0.019153	0.052866	0.010636	-0.010956
Manicaland, Zimbabwe	0.001683	-0.009287	-0.024199	0.047641	0.020316	0.007727
Harare, Zimbabwe	-0.005879	0.005689	-0.01018	0.046448	0.022164	0.009694
Ghanzi, Botswana	0.086095	-0.055848	-0.030517	0.11084	-0.007043	-0.018081
Southern, Botswana	-0.016159	-0.006501	-0.027865	0.028633	-0.006488	-0.057413
South East, Botswana	0.0469	-0.096314	-0.112817	0.081009	0.035998	-0.097204
Central, Botswana	-0.024283	-0.001828	-0.014015	0.021541	-0.017772	-0.037734
Kgatleng, Botswana	0.062157	-0.130081	-0.092026	0.114974	0.039133	-0.065202
Kweneng, Botswana	0.070776	-0.086987	-0.117202	0.094107	0.039732	-0.086721
Ngamiland, Botswana	0.037315	-0.071297	0.020136	0.070963	0.035555	-0.092744
Kgalagadi, Botswana	0.091377	-0.061095	-0.048691	0.07704	-0.032453	-0.113397
Chobe, Botswana	0.091045	0.019105	0.006702	-0.020919	-0.002267	-0.031851
North East, Botswana	0.082168	-0.018293	-0.021356	0.104056	0.03087	-0.016831
Eastern, Kenya	-0.025131	-0.01553	-0.027486	0.013282	-0.011927	-0.014651
Coast, Kenya	0.014858	0.00548	-0.046058	-0.006822	0.049783	0.018542
Central, Kenya	-0.024283	-0.001828	-0.014015	0.021541	-0.017772	-0.037734
Western, Kenya	0.001755	-0.016615	-0.008402	0.018144	0.001079	-0.023397
Nyanza, Kenya	0.006038	0.005645	-0.028873	-0.014571	0.018187	0.040211
Nairobi, Kenya	-0.013198	0.004939	0.011171	0.004466	0.05858	0.041702
North Eastern, Kenya	-0.018696	-0.018698	0.00955	-0.008192	0.063741	-0.003878
Rift Valley, Kenya	-0.009618	0.000853	-0.002983	-0.002042	0.028362	0.036256
Nampula, Mozambique	0.002179	-0.022577	-0.001542	-0.01615	0.015144	0.01743
Gaza, Mozambique	0.009049	-0.023756	-0.073028	0.029766	-0.021238	-0.015276
Tete, Mozambique	-0.023084	-0.002645	-0.033535	0.021612	-0.016291	0.005937
Maputo, Mozambique	0.012993	-0.030427	-0.081643	0.039514	-0.007261	-0.024894
Manica, Mozambique	-0.008429	-0.038525	-0.037715	0.04519	0.014738	0.000403
Zambezia, Mozambique	-0.013973	-0.040567	-0.020134	0.004253	-0.000789	-0.003422
Sofala, Mozambique	-0.003818	-0.038369	-0.040852	0.021528	0.024309	0.012103
Cabo Delgado, Mozambique	0.006323	-0.011462	0.001581	-0.006579	0.019439	0.027562
Inhambane, Mozambique	-0.005586	-0.027838	-0.035364	0.017506	0.000123	-0.018078
Niassa, Mozambique	-0.008348	-0.020671	-0.024107	0.000413	0.002682	0.005145
Ebonyi, Nigeria	0.007098	0.02885	0.003396	0.006067	0.01004	0.013498
Katsina, Nigeria	-0.008937	-0.020962	0.006867	0.007696	0.025813	0.052275
Bauchi, Nigeria	-0.0082	-0.010736	-0.000101	-0.017278	-0.005491	0.016267
Niger, Nigeria	-0.015472	-0.030985	-0.028489	-0.032406	-0.019738	-0.021211
Adamawa, Nigeria	-0.01308	-0.011096	-0.030269	-0.047045	-0.018119	-0.003811
Kebbi, Nigeria	-0.021084	-0.031394	-0.020683	0.001391	0.003523	0.002736
Edo, Nigeria	0.009968	0.008777	-0.000105	-0.015615	-0.004002	0.016518
Abia, Nigeria	0.013742	0.006452	-0.000044	-0.006237	0.005992	0.003936
Ogun, Nigeria	0.007767	-0.012492	0.014967	-0.005535	0.036892	0.040728
Kwara, Nigeria	0.001596	-0.006156	-0.011961	-0.012356	0.005384	0.022501
Ondo, Nigeria	0.00629	0.022574	0.00711	-0.001737	0.002143	0.030619
Delta, Nigeria	0.010751	0.007083	-0.006926	-0.017165	-0.011045	-0.008106
Kaduna, Nigeria	-0.006113	-0.017938	-0.019339	-0.005231	0.017278	0.034923
Akwa Ibom, Nigeria	0.020992	0.007864	0.003783	0.01336	0.001616	-0.004373
Federal Capital Territory, Nigeria	0.003396	-0.008464	-0.026928	-0.02379	-0.005256	-0.00018
Oyo, Nigeria	0.011356	0.005952	-0.004935	-0.007923	0.012192	0.031323
Rivers, Nigeria	0.009231	-0.014857	-0.029717	-0.020101	-0.004119	0.001149
Sokoto, Nigeria	-0.016027	-0.022227	-0.008755	0.008728	0.012015	0.028876
Imo, Nigeria	0.013375	-0.008928	0.005152	-0.013869	0.006651	0.002507
Lagos, Nigeria	0.007767	-0.012492	0.014967	-0.005535	0.036892	0.040728
Plateau, Nigeria	0.010082	0.004069	-0.012607	-0.01718	-0.000761	0.020623
Nassarawa, Nigeria	0.005259	0.003945	-0.026232	-0.020589	-0.003222	-0.004869

Table 7: NDVI statistics of first 60 regions (2015-2020)

	Growing Season Mean NDVI Anomaly Values				
Region/Country	2010	2011	2012	2013	2014
Jigawa, Nigeria	0.000392	0.000392	0.003272	0.01348	-0.002411
Bayelsa, Nigeria	0.015414	0.015414	0.012825	-0.037675	-0.015138
Kogi, Nigeria	0.002611	0.002611	0.007715	-0.016205	0.002112
Yobe, Nigeria	0.000815	0.000815	-0.008516	0.029534	0.00494
Zamfara, Nigeria	0.008304	0.008304	-0.003589	0.011182	-0.013873
Cross River, Nigeria	0.007174	0.007174	0.007793	-0.006994	0.020698
Anambra, Nigeria	0.014101	0.014101	0.017631	-0.034368	0.025228
Borno, Nigeria	-0.005543	-0.005543	-0.013723	0.023339	-0.016277
Gombe, Nigeria	-0.001047	-0.001047	-0.006349	0.009753	-0.014011
Kano, Nigeria	0.002239	0.002239	0.003769	0.009481	0.004248
Benue, Nigeria	-0.00505	-0.00505	0.005919	-0.000626	-0.000911
Ekiti, Nigeria	-0.003401	-0.003401	0.002236	0.0037	-0.000852
Osun, Nigeria	-0.010732	-0.010732	0.009131	0.011119	0.002143
Enugu, Nigeria	0.007544	0.007544	0.006631	0.007289	0.004942
Taraba, Nigeria	-0.00149	-0.00149	0.000479	-0.003119	-0.014
Lindi, Tanzania	-0.008433	-0.008433	-0.008687	0.014551	0.007057
Shinyanga, Tanzania	-0.009922	-0.009922	-0.019879	-0.001139	-0.007632
Mbeya, Tanzania	-0.003747	-0.003747	0.000815	-0.013283	-0.015175
Singida, Tanzania	-0.013815	-0.013815	-0.017475	-0.018475	-0.003311
Njombe, Tanzania	-0.002878	-0.002878	0.00213	-0.004433	-0.008735
Katavi, Tanzania	-0.00433	-0.00433	-0.002242	-0.007188	-0.007482
Kilimanjaro, Tanzania	0.016669	0.016669	-0.014681	-0.042558	-0.015285
Geita, Tanzania	0.00728	0.00728	-0.01242	-0.002571	-0.008623
Arusha, Tanzania	0.016606	0.016606	-0.043595	-0.026771	-0.001022
Iringa, Tanzania	-0.01292	-0.01292	-0.009417	-0.013389	-0.008615
Kigoma, Tanzania	-0.005178	-0.005178	-0.001055	-0.006255	-0.007908
Simiyu, Tanzania	-0.003131	-0.003131	-0.01392	0.002848	-0.004259
Tanga, Tanzania	-0.024411	-0.024411	0.00254	-0.055906	-0.052139
Ruvuma, Tanzania	-0.004909	-0.004909	0.000271	-0.006151	-0.007086
Mwanza, Tanzania	0.003061	0.003061	-0.012886	-0.00179	0.000343
Manyara, Tanzania	-0.000685	-0.000685	-0.002617	-0.010916	-0.019289
Dodoma, Tanzania	-0.012089	-0.012089	-0.000673	-0.007228	-0.023428
Pwani, Tanzania	-0.013204	-0.013204	0.028848	-0.039255	-0.029119
Kagera, Tanzania	0.005174	0.005174	0.006265	0.005401	-0.01282
Dar es Salaam, Tanzania	-0.003791	-0.013204	0.028848	-0.039255	-0.029119
Tabora, Tanzania	-0.010339	-0.010339	-0.009252	-0.016944	-0.015371
Mara, Tanzania	0.019906	0.019906	0.001095	0.009531	-0.018177
Morogoro, Tanzania	-0.007869	-0.007869	0.020137	-0.017119	-0.023659
Rukwa, Tanzania	-0.010441	-0.010441	0.01005	-0.004377	-0.008352
Mtwara, Tanzania	-0.000423	-0.000423	-0.000308	-0.003284	-0.006622
Dire Dawa, Ethiopia	0.012074	0.002858	0.017467	-0.023804	0.009662
Harari, Ethiopia	0.011567	0.011567	0.026222	0.0111	0.04315
Addis Ababa, Ethiopia	0.025387	0.002858	0.017467	-0.023804	0.009662
Gambela, Ethiopia	-0.000672	-0.000672	-0.023833	-0.006218	0.014877
Tigray, Ethiopia	-0.026375	-0.026375	0.00084	0.003713	-0.01032
SNNP, Ethiopia	0.010481	0.010481	0.01876	0.008058	0.013955
Amhara, Ethiopia	-0.02335	-0.02335	0.007876	-0.029042	-0.018658
Oromia, Ethiopia	0.002858	0.002858	0.017467	-0.023804	0.009662
Somali, Ethiopia	0.017623	0.017623	0.002082	-0.009218	0.001835
Afar, Ethiopia	-0.00957	-0.00957	0.015875	0.008675	0.022976
Benshangul/Gumuz, Ethiopia	-0.021993	-0.021993	-0.012542	-0.005974	-0.010023
Eastern, Zambia	0.019575	0.01225	0.008004	-0.005165	-0.023295
Southern, Zambia	0.033351	0.02825	0.007334	-0.001531	-0.018117
Luapula, Zambia	-0.014903	-0.014903	0.002556	-0.00571	-0.012809
Central, Zambia	0.025927	0.021445	0.010986	0.002132	-0.010283
North-Western, Zambia	-0.001409	-0.001409	-0.0007	-0.008126	-0.01558
Western, Zambia	0.017619	0.013082	-0.0029	-0.006785	-0.016424
Lusaka, Zambia	0.02834	0.02834	0.014189	-0.000029	-0.002464
Northern, Zambia	-0.013522	-0.013522	0.006081	-0.005969	-0.010713
Copperbelt, Zambia	0.001892	0.001892	-0.002333	-0.005724	-0.011418

Table 8: NDVI statistics of the second 60 regions (2010-2014)

	Growing Season Mean NDVI Anomaly Values					
Region/Country	2015	2016	2017	2018	2019	2020
Jigawa, Nigeria	-0.013169	-0.010139	0.025343	0.003358	0.023559	0.000392
Bayelsa, Nigeria	-0.013824	-0.072495	0.001788	-0.00248	-0.008495	0.015414
Kogi, Nigeria	0.012925	0.008113	-0.004058	0.00129	-0.01044	0.002611
Yobe, Nigeria	-0.011245	-0.01568	-0.000549	-0.017743	0.004037	0.000815
Zamfara, Nigeria	-0.021058	-0.01567	-0.001256	0.010882	0.01833	0.008304
Cross River, Nigeria	0.005936	0.007683	-0.00066	-0.005065	0.006333	0.007174
Anambra, Nigeria	0.021469	-0.000865	-0.016452	-0.015541	-0.044047	0.014101
Borno, Nigeria	-0.032813	-0.003988	0.024014	-0.006975	0.04408	-0.005543
Gombe, Nigeria	-0.012842	-0.021195	-0.003762	-0.022786	0.000541	-0.001047
Kano, Nigeria	-0.009833	-0.023811	0.008166	0.006181	0.033895	0.002239
Benue, Nigeria	0.003211	0.003769	-0.010348	-0.016499	0.007564	-0.00505
Ekiti, Nigeria	0.008567	0.021669	0.01038	-0.004121	0.006546	-0.003401
Osun, Nigeria	0.017158	0.017083	0.003097	-0.014764	0.009356	-0.010732
Enugu, Nigeria	0.012751	0.015469	-0.001352	-0.009008	0.012997	0.007544
Taraba, Nigeria	0.002063	-0.002684	-0.018332	-0.023637	-0.004256	-0.00149
Lindi, Tanzania	0.021789	-0.017479	0.007712	0.017418	0.017739	-0.008433
Shinyanga, Tanzania	0.001877	0.007114	-0.005275	-0.037826	0.011984	-0.009922
Mbeya, Tanzania	0.011096	-0.005359	-0.00833	-0.009747	0.007616	-0.003747
Singida, Tanzania	-0.002434	-0.014909	0.00244	-0.038718	0.002211	-0.013815
Njombe, Tanzania	0.015486	0.006095	0.011333	0.018159	0.030719	-0.002878
Katavi, Tanzania	-0.009922	-0.002932	-0.015193	0.004722	0.001146	-0.00433
Kilimanjaro, Tanzania	0.006963	-0.012527	-0.011615	0.001886	0.04709	0.016669
Geita, Tanzania	-0.001319	0.000065	-0.011813	-0.04247	0.003292	0.00728
Arusha, Tanzania	0.010151	-0.01218	-0.010253	-0.014922	0.037583	0.016606
Iringa, Tanzania	0.011713	0.001657	0.006815	0.006507	0.026208	-0.01292
Kigoma, Tanzania	-0.009071	-0.009588	-0.016363	-0.015919	-0.003756	-0.005178
Simiyu, Tanzania	-0.007201	0.006136	-0.000729	-0.033664	0.018721	-0.003131
Tanga, Tanzania	0.005502	-0.012095	-0.050026	0.001119	0.035195	-0.024411
Ruvuma, Tanzania	0.010407	-0.012097	-0.006781	0.003864	0.000779	-0.004909
Mwanza, Tanzania	-0.008092	0.009153	-0.007323	-0.041763	0.006164	0.003061
Manyara, Tanzania	-0.008159	-0.025707	-0.002733	-0.05407	0.001313	-0.000685
Dodoma, Tanzania	-0.01592	-0.049239	0.003253	-0.058237	0.002936	-0.012089
Pwani, Tanzania	0.001674	-0.02192	-0.054866	0.011558	0.029122	-0.013204
Kagera, Tanzania	-0.0004	-0.00865	-0.022377	-0.052263	-0.00098	0.005174
Dar es Salaam, Tanzania	0.001674	-0.02192	-0.054866	0.011558	0.029122	-0.003791
Tabora, Tanzania	-0.018472	0.00594	-0.000282	-0.0342	0.011788	-0.010339
Mara, Tanzania	0.004301	-0.001089	-0.007338	-0.056187	-0.000598	0.019906
Morogoro, Tanzania	0.002808	-0.025743	-0.037532	-0.010713	-0.013761	-0.007869
Rukwa, Tanzania	-0.001627	-0.003254	-0.016616	-0.011134	-0.013433	-0.010441
Mtwara, Tanzania	0.017278	0.00065	0.005722	0.000624	0.008591	-0.000423
Dire Dawa, Ethiopia	-0.01429	-0.00648	0.020026	0.009702	0.0124	0.012074
Harari, Ethiopia	-0.004952	0.011054	0.020663	-0.015016	0.01156	0.011567
Addis Ababa, Ethiopia	-0.01429	-0.00648	0.020026	0.009702	0.0124	0.025387
Gambela, Ethiopia	-0.010507	-0.00571	0.010956	0.010438	-0.005445	-0.000672
Tigray, Ethiopia	0.004997	-0.020921	0.003022	0.002613	0.021277	-0.026375
SNNP, Ethiopia	-0.005117	-0.012556	-0.000416	0.000055	0.015565	0.010481
Amhara, Ethiopia	0.002029	0.002554	0.02173	0.022705	0.023461	-0.02335
Oromia, Ethiopia	-0.01429	-0.00648	0.020026	0.009702	0.0124	0.002858
Somali, Ethiopia	-0.026765	-0.020968	0.020037	-0.020154	0.034193	0.017623
Afar, Ethiopia	0.019013	-0.018756	0.03732	0.02032	0.014607	-0.00957
Benshangul/Gumuz, Ethiopia	0.011564	0.014067	0.020578	0.015034	0.005164	-0.021993
Eastern, Zambia	-0.025131	-0.01553	-0.027486	0.013282	-0.011927	0.019575
Southern, Zambia	-0.016159	-0.006501	-0.027865	0.028633	-0.006488	0.033351
Luapula, Zambia	-0.003036	0.00078	-0.005646	0.019846	0.005995	-0.014903
Central, Zambia	-0.024283	-0.001828	-0.014015	0.021541	-0.017772	0.025927
North-Western, Zambia	-0.000891	-0.005728	-0.010437	0.010518	-0.001707	-0.001409
Western, Zambia	0.001755	-0.016615	-0.008402	0.018144	0.001079	0.017619
Lusaka, Zambia	-0.017249	0.004696	-0.013154	0.030077	-0.012311	0.02834
Northern, Zambia	0.002817	-0.000359	-0.003406	0.014053	0.007286	-0.013522
Copperbelt, Zambia	-0.013303	0.003225	-0.009871	0.021363	0.001491	0.001892

Table 9: NDVI statistics of the second 60 regions (2015-2020)

Appendix III: Riot Data Statistics

	Total Recorded Riots									
Region/Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Matabeleland S., Zimbabwe	0	0	0	0	1	1	1	4	5	4
Midlands, Zimbabwe	1	0	3	0	3	2	9	8	1	4
Mashonaland W., Zimbabwe	1	3	1	1	5	3	5	6	3	5
Mashonaland E., Zimbabwe	1	1	2	7	4	4	5	10	4	0
Matabeleland N., Zimbabwe	0	0	0	2	2	1	2	5	0	1
Bulawayo, Zimbabwe	0	1	0	4	7	3	9	9	8	2
Masvingo, Zimbabwe	0	2	3	13	3	3	2	6	2	1
Mashonaland C., Zimbabwe	0	1	0	0	1	3	3	5	3	5
Manicaland, Zimbabwe	0	2	3	3	9	2	2	6	4	6
Harare, Zimbabwe	5	12	8	10	25	25	27	33	15	10
Ghanzi, Botswana	0	0	0	0	0	0	0	0	0	0
Southern, Botswana	0	0	0	0	0	0	0	0	0	1
South East, Botswana	1	0	1	0	0	1	1	2	0	1
Central, Botswana	0	0	0	0	0	0	0	0	0	1
Kgatleng, Botswana	0	0	0	1	0	0	0	0	0	0
Kweneng, Botswana	1	0	0	0	1	0	0	1	1	2
Ngamiland, Botswana	0	0	0	0	0	0	0	0	0	0
Kgalagadi, Botswana	0	0	0	0	0	0	0	0	0	0
Chobe, Botswana	0	0	0	0	0	0	0	0	0	0
North East, Botswana	1	0	0	0	0	1	1	0	0	0
Eastern, Kenya	0	8	19	26	22	17	28	29	5	17
Coast, Kenya	0	21	23	13	10	9	20	12	9	9
Central, Kenya	0	5	10	14	7	9	26	10	6	7
Western, Kenya	0	4	8	7	11	8	33	17	9	13
Nyanza, Kenya	1	8	26	14	15	17	107	29	12	24
Nairobi, Kenya	2	17	29	11	16	19	91	10	12	19
North Eastern, Kenya	2	2	2	2	1	0	8	3	2	0
Rift Valley, Kenya	4	2	25	26	28	16	46	22	13	25
Nampula, Mozambique	2	0	0	14	2	3	10	1	7	1
Gaza, Mozambique	0	0	0	5	0	0	1	3	2	0
Tete, Mozambique	0	0	2	2	0	2	10	2	5	2
Maputo, Mozambique	2	0	0	0	1	4	1	1	2	1
Manica, Mozambique	0	0	0	2	1	0	0	3	5	1
Zambezia, Mozambique	0	1	5	1	1	0	14	2	3	1
Sofala, Mozambique	0	1	4	2	2	0	0	3	7	1
Cabo Delgado, Mozambique	2	0	3	1	1	0	0	1	3	3
Inhambane, Mozambique	0	0	0	0	1	0	0	0	0	1
Niassa, Mozambique	0	0	0	0	0	0	2	1	3	3
Ebonyi, Nigeria	0	0	3	1	4	5	5	2	2	5
Katsina, Nigeria	1	0	0	3	4	0	2	1	7	8
Bauchi, Nigeria	1	0	0	5	7	2	3	3	5	3
Niger, Nigeria	1	3	0	1	6	6	6	4	4	2
Adamawa, Nigeria	6	0	1	2	2	2	0	3	3	5
Kebbi, Nigeria	0	0	0	2	2	0	0	2	1	1
Edo, Nigeria	0	1	1	3	4	10	8	8	3	16
Abia, Nigeria	0	0	0	1	2	8	3	2	2	9
Ogun, Nigeria	0	4	6	9	9	4	5	3	4	16
Kwara, Nigeria	0	1	1	3	7	0	4	1	2	2
Ondo, Nigeria	0	3	6	2	6	12	11	8	6	13
Delta, Nigeria	0	2	3	9	14	19	15	25	8	24
Kaduna, Nigeria	7	4	3	4	16	6	10	7	6	10
Akwa Ibom, Nigeria	0	0	4	4	1	3	8	3	17	7
Abuja, Nigeria	5	0	4	8	11	24	23	20	11	15
Oyo, Nigeria	0	0	3	8	3	8	7	9	9	19
Rivers, Nigeria	1	3	0	7	24	8	26	8	4	5
Sokoto, Nigeria	2	0	0	0	0	0	0	2	3	1
Imo, Nigeria	0	1	1	2	8	6	8	4	8	16
Lagos, Nigeria	0	3	7	20	27	23	21	19	23	32
Plateau, Nigeria	10	7	2	3	11	6	2	6	1	8
Nassarawa, Nigeria	2	0	1	8	2	1	1	2	2	1

Table 10: Yearly riot frequencies of the first 60 regions (ACLED data)

	Total Recorded Riots									
Region/Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Jigawa, Nigeria	0	0	0	0	0	1	3	4	1	6
Bayelsa, Nigeria	0	3	2	10	11	9	9	4	9	4
Kogi, Nigeria	0	0	0	0	7	3	4	3	2	6
Yobe, Nigeria	1	0	0	0	1	0	1	1	1	0
Zamfara, Nigeria	0	1	1	4	0	3	1	4	2	2
Cross River, Nigeria	0	0	1	2	5	1	5	6	5	10
Anambra, Nigeria	0	3	1	8	14	6	3	7	5	12
Borno, Nigeria	2	0	4	4	5	3	3	3	2	1
Gombe, Nigeria	2	0	1	1	1	4	0	1	2	1
Kano, Nigeria	2	2	1	3	8	4	3	3	3	3
Benue, Nigeria	3	0	3	1	9	8	12	10	7	6
Ekiti, Nigeria	0	1	2	5	8	6	12	9	3	6
Osun, Nigeria	0	2	0	7	12	5	10	5	4	13
Enugu, Nigeria	0	0	0	2	4	5	4	6	3	5
Taraba, Nigeria	2	1	0	1	6	1	4	5	3	4
Lindi, Tanzania	0	0	1	0	0	0	0	0	0	2
Shinyanga, Tanzania	2	0	0	0	0	1	0	0	0	0
Mbeya, Tanzania	0	2	0	0	4	0	1	0	1	0
Singida, Tanzania	0	0	0	0	0	0	0	0	0	0
Njombe, Tanzania	0	0	2	0	0	0	0	0	0	0
Katavi, Tanzania	0	0	0	0	0	0	0	0	0	0
Kilimanjaro, Tanzania	0	0	0	1	0	0	0	0	0	1
Geita, Tanzania	0	0	0	0	0	0	2	0	0	0
Arusha, Tanzania	3	1	6	0	2	1	0	1	0	0
Iringa, Tanzania	0	0	1	0	2	0	0	0	0	0
Kigoma, Tanzania	0	0	0	0	1	0	0	1	1	2
Simiyu, Tanzania	0	0	0	0	0	0	0	0	0	0
Tanga, Tanzania	0	0	1	0	0	0	0	0	0	0
Ruvuma, Tanzania	0	2	0	0	1	0	0	0	0	0
Mwanza, Tanzania	1	1	1	3	1	0	0	0	0	0
Manyara, Tanzania	0	1	0	0	0	0	0	0	0	0
Dodoma, Tanzania	1	0	0	0	1	0	0	0	1	0
Pwani, Tanzania	0	1	1	0	1	0	0	0	0	0
Kagera, Tanzania	0	4	2	1	0	1	0	0	2	1
Dar es Salaam, Tanzania	1	5	4	5	3	1	2	5	0	0
Tabora, Tanzania	0	0	0	0	0	0	1	1	0	0
Mara, Tanzania	1	3	1	3	1	0	1	0	0	0
Morogoro, Tanzania	1	0	0	0	0	0	0	0	0	1
Rukwa, Tanzania	0	0	1	1	1	0	0	0	0	0
Mtwara, Tanzania	0	0	4	0	0	0	0	0	0	0
Dire Dawa, Ethiopia	0	0	0	0	0	1	0	1	17	2
Harari, Ethiopia	0	0	0	0	0	1	0	0	2	5
Addis Ababa, Ethiopia	0	3	5	1	2	7	0	14	2	5
Gambela, Ethiopia	0	0	1	0	0	2	0	0	4	1
Tigray, Ethiopia	0	0	6	0	0	0	0	1	0	2
SNNP, Ethiopia	0	0	0	0	0	2	1	8	2	4
Amhara, Ethiopia	0	1	0	0	1	11	5	23	5	3
Oromia, Ethiopia	0	1	2	3	6	81	38	33	31	19
Somali, Ethiopia	1	1	1	0	0	0	1	8	0	2
Afar, Ethiopia	0	0	0	0	0	1	0	1	0	1
Benshangul/Gumuz, Ethiopia	0	0	0	0	0	0	0	1	0	2
Eastern, Zambia	1	1	0	1	2	3	0	2	0	3
Southern, Zambia	0	2	3	1	1	18	1	0	1	9
Luapula, Zambia	1	0	0	2	1	1	0	2	0	5
Central, Zambia	0	2	3	5	2	7	2	2	3	4
North-Western, Zambia	1	1	0	0	1	2	1	1	1	6
Western, Zambia	3	0	1	1	4	3	1	0	1	2
Lusaka, Zambia	8	10	15	12	9	19	4	8	3	24
Northern, Zambia	0	2	1	0	1	1	0	1	0	5
Copperbelt, Zambia	5	10	8	17	9	12	2	7	3	14

Table 11: Yearly riot frequencies of the second 60 regions (ACLED data)

Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated. I confirm that the digital copy of the master thesis that I submitted on 9.05.22 is identical to the printed version I submitted to the Examination Office on 10.05.22.

DATE: 9/5/22

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