FOOD ABUNDANCE AND VIOLENT CONFLICT IN AFRICA

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Scholars debate whether climate change has a consistent effect on the likelihood of armed conflict in Africa. One major pathway by which climatic variability is hypothesized to increase conflict is by decreasing food availability. However, limitations on food access at both the local and national levels in many developing African countries force most armed groups and communities to depend on locally-produced food. These actors are therefore likely to use violence to establish control over more food resources or be stationed where more food is available, suggesting that food abundance might also be driving conflict. The present study employs novel data on wheat and maize yields in Africa measured at the very local level to empirically evaluate this hypothesis on a highly disaggregated conflict indicator. To account for the endogenous relationship between conflict and food production, average local levels of drought are used as an instrument. The findings show that, contrary to previous expectations, conflict is driven by higher yields, on average, and not by scarcity.

Key words: Food security, civil war, resource scarcity, violent conflict, instrumental variable.

JEL codes: D74, Q11, Q18.

A growing number of studies on environmental stressors and conflict posit that future wars will be fought over diminishing resources (Miguel, Satyanath, and Sergenti 2004; Burke et al. 2009; Maystadt and Ecker 2014). These studies draw links between environmental conditions such as variations in temperature and precipitation, and civil war, hypothesizing that these factors operate, among others, through food security mechanisms. By and large, the emphasis is on food scarcities, namely that rising temperature and droughts reduce the amount of food resources available locally, which in turn forces actors to obtain access to food via violent means. For instance, in their analysis of the relationship between climate variability and conflict in Sub-Saharan Africa, Burke et al. (2009) find that "[t]emperature variables are strongly related to conflict incidence over our historical panel." These authors further hypothesize that, "[t]emperature can affect agricultural yields both through increases in crop evapotranspiration (and hence heightened water stress in the absence of irrigation) and through accelerated crop development…reducing African staple crop yields by 10%-30% per °C of warming," (Burke et al. 2009). Somewhat more cautiously, O'Loughlin et al. (2012) note that, "the positive association between instability and temperature may result from the harmful effects of high temperatures on food products such as maize."

The Malthusian notion that food scarcities increase the likelihood of conflict is not a recent one, although it has received increased attention over the last four decades (e.g., Homer-Dixon 1998). In contrast, however, an impressive body of research draws linkages between the abundance of natural resources and conflict (e.g., Bannon and Collier 2003; Blattman and Miguel 2010; Adhvaryu et al. 2017). Food is not only a renewable natural resource; it is crucial to maintaining the daily

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life and activities of a group, be it a military battalion, a rebel contingent, or a rural community. With a large number of studies on social unrest emphasizing the importance of food security (Messer 2009; Bellemare 2015), it thus appears plausible that variations in local crop productivity affect past and future conflict risk. Indeed, recent research lends support to this argument. For instance, Crost and Felter (2016) show that rebels benefit from higher food crop prices, which allow them to expand territorial control and even establish a local monopoly on violence. Despite this and other (e.g., Koren and Bagozzi 2016), important evidence, however, to date few studies have explicitly considered the role of food and its exact effects on conflict, or attempted to evaluate how food resources shape regional and continental conflict patterns over time.

One challenge in evaluating staple crop yields' role in driving conflict is that local food productivity variables are inherently endogenous; food output can influence the propensity of violence, but the associated feedback effects from conflict can in turn influence food output (Homer-Dixon 1998; Messer 2009). To address this concern, the local staple crop yield indicators used here are instrumented using drought intensity levels, which—as recent studies posited—can influence conflict through food production. The causal relationship between local food production and violent conflict is thus identified using this climatic variable (Miguel, Satyanath, and Sergenti 2004). It is important to stress that previous research has suggested that rainfall variations might be not be an ideal instrument of income shocks (Sarsons 2015). While the argument developed here does not necessarily equate local yields with income, I address this concern both theoretically—by discussing some distinctions of African agriculture systems—and empirically, by showing that my drought-based instrumental variable is at least "plausibly exogenous" (Conley, Hansen, and Rossi 2012).

By relying on said approach, this study provides quantitative evidence linking past internal armed conflict incidence to food yields at the very local level while incorporating variations in climatic trends, specifically droughts. Using 0.5 ° grid cells (10,674 cells for Africa; Tollefsen et al.2012), the influence of annual local wheat and maize yields (Ray et al. 2012) on violence is estimated using ordinary least squares (OLS) and two-stage least squares (2SLS) regressions with grid-cell (i.e., unit of analysis) fixed effects. Conflict measures were obtained from the Armed Conflict Location and Event Dataset (ACLED) Version 6, which provides exceptional disaggregated coverage of political violence in Africa at the very local level (Raleigh et al. 2010). Unlike previous studies, which employ only climate-related variables, focus on specific countries, or employ only binary indicators of conflict (Burke et al. 2009; O'Loughlin et al. 2012; Maystadt and Ecker 2014; Koren and Bagozzi 2016), this study relies on subnational analysis of the *annual* effect of local food crop production in Africa on continuous measures of conflict within all 0.5 ° grid cell for the years 1998–2008.[1]

The findings presented here contribute significantly to our understanding of the relationship between food security, violent conflict, inequality, and environmental variability. The estimation procedure accommodates both the non-random assignment of observations and the possible concurrent relationship between climate, food production, and conflict. Overall, the empirical models provide new and nuanced evidence that locally-grown food resources have a particularly strong influence on the frequency of conflict in Africa. In the IV models, where the effect of food resources is exogenized with respect to conflict, *higher* levels of food crop yields are shown to have a substantive effect on violent conflict, all else being equal.

These findings challenge the notion that rising food scarcities increase conflict simply by forcing communities and armed groups to compete over a shrinking pool of food resources. Rather, empirical evidence suggests that—on average—violent conflict is not the direct result of food scarcity, but of abundance. That is, areas with more food resources are more valued by different actors, and as a result attract more conflict. Moreover, these associations are robust to a variety of alternative explanatory mechanisms and specifications. The relationships between climatic variability, food, and violence are therefore complex and warrant careful interpretation.

[1] This is the temporal period for which information on all variables was available. See also Adhvaryu et al. (2017) for a study that relies on similar resolution levels for analyzing conflict across sub-Saharan Africa.

Staple Crop Yields and Local Conflict

The linkage between conflict and food resources is not a recent phenomenon, engendered by climate change, but rather—in many parts of the world—a persistent historical occurrence. Throughout history, armies and militias living off the land were a regular characteristic of warfare. In ancient and medieval times before the development of modern logistic support technologies, living off the land, foraging, and relying on the local population was a military necessity. Although the utilization of logistic supply chains has significantly reduced the need of modern militaries to rely on local populations for support, the bureaucratic and economic capabilities required to maintain such systems has ensured that the vast majority of armed groups in Africa lack regular support (Koren and Bagozzi 2016). Indeed, a detailed background discussion of relationships between food resources and conflict in Africa as well as food-related vulnerabilities—provided in the supplementary online appendix due to space constraints—shows that these issues strongly impact the behavior of different armed actors in contemporary wars.

When discussing conflict over food resources, it is important to distinguish between four different categories, each with different motivations for initiating food-related conflicts or moving into areas with more food during times of ongoing war. The first category includes official military and auxiliary state forces that do not receive (regular) support from the state, a fact which distinguishes them from other, better organized state forces. This category includes most official state forces in Africa (Koren and Bagozzi 2016), as well as political militias. Indeed, numerous militia groups such as the *janjaweed* in Sudan or the *interahamwe* in Rwanda were especially likely to be sent to pray upon the local population, sometimes with logistic support being withdrawn from them intentionally to push them toward violent appropriations of food resources (Koren and Bagozzi 2017). Unsupported state actors are thus likely not only to initiate conflict in areas with abundant food resource, but also gravitate toward these areas in search of necessary food support during times of war.

The second category of actors includes all rebel groups and similar nonstate actors operating against the government. These groups might attack areas with more food in order to possess these resources not only to support themselves or challenge state strongholds, but also to exploit local food resources for profit (Crost and Felter 2016), which sometimes results in high levels of civilian victimization (Koren and Bagozzi 2017). For instance, in Uganda, rebels are likely to appropriate and kill profitable cattle, leading to a shift in local populations' agricultural portfolios (Rockmore 2012). Similarly, the Islamic State in Syria and Iraq (ISIS) fought to establish and maintain control over fertile agricultural areas due to the group's reliance on agricultural income (Jaafar and Woertz 2016).

The third category covers militias and civil defense forces representing *agriculturalist* communities in rural regions. The agriculturalist lifestyle is more characteristic of areas where access to water resources is relatively stable, allowing these communities to grow crops for consumption and to be sold locally (O'Loughlin et al. 2012). Individuals and groups in these localities thus live a stationary lifestyle, and procure livestock mostly as a means of wealth accumulation (i.e., as an equivalent of a savings account; Roncoli, Ingram, and Kirshen 2001; Rockmore 2012). In many countries these communities are less likely to be defended by the state due to the costs involved with sending and supporting armed groups. This in turn means that property rights are rarely enforced (Barrett 2010), pushing many of these communities to resort to self-help. Such self-defense militias can be used not only to defend against potential raids, but also to attack neighboring communities in order to establish control over more arable land and food resources. Indeed, this last point is supported by ample anecdotal evidence, as shown in the online supplementary appendix.

The fourth category includes all militias representing *pastoralist* communities. Pastoralists are highly mobile groups that live in mostly arid regions. As a result, these groups are forced to rely on mobile livestock, especially cattle, rather than on crops, meaning that in this case owning cattle is not a luxury but rather a necessity dictated by their (semi-)nomadic lifestyle (Lybbert et al. 2007). Pastoralists have been at the heart of many previous studies connecting food resources to conflict, with some associating increases in precipitation with higher frequencies of raids (e.g., Adano et al. 2012;

Butler and Gates 2012), and others showing the opposite relationship (O'Loughlin et al. 2012; Maystadt and Ecker 2014). In many cases, regional narratives emphasize how the prevalence of violent conflict is shaped by local conditions such as the precedence of civil war, which floods the region with firearms (Koren and Bagozzi 2017), or the collapse of state authority, especially if external actors move into the vacuum and fund raids (Rockmore 2012). Pastoralist militias might therefore both raid other pastoralists in order to replenish their herds, and attack agriculturalist communities in order to both steal livestock and obtain food crops, which—due to their mobile lifestyle and the arid regions where they reside—these groups are generally incapable of growing independently.

All four actor categories, which—it is important to acknowledge—might exhibit significant overlap, have different motivations to fight over food resources. In the first two cases, given that troops are frequently mobile rather than stationary, they do not have the ability to grow food for personal consumption, and as a result must rely on food grown locally in the region in which they operate (Koren and Bagozzi 2016). Agricultural land can be owned by local civilians who grow food for personal consumption only or by larger producers who grow food for trade, both internationally and domestically. Especially in regions without developed infrastructure and where mobilizing food resources or appropriating food aid is less possible, both government and rebel troops are forced to move into areas that offer access to food in order to support their operations. These limitations intensify the incentives for troops to seek out the few remaining areas that do have high food access for sustenance, and potentially also for rent-extraction (Jaafar and Woertz 2016; Crost and Felter 2016).

In the latter two cases, while agriculturalist and pastoral communities can produce food for personal consumption, they are also under a constant threat of experiencing acute food insecurity (see online supplementary appendix). The eruption of a disease or the onset of drought can suddenly kill crops and decimate herds, placing these communities at the sudden and immediate risk of starvation. Without government support or other safety nets that can mitigate the effects of these unexpected shortages, acute food insecurity is a Damocles Sword over the heads of these groups (Barrett 2010). For example, during the drought in Burkina Faso, "farmers strove to minimize cash investments in agriculture, but in some cases they were unable to do so because many had consumed all their seed before planting," (Roncoli, Ingram, and Kirshen 2001). Such shocks jeopardize *immediate* food security; assuming the community survives this adverse period, it should be able to restore food supply levels. This suggests that cooperation might emerge as a preferred strategy in these contexts (Toft 2006; Adano et al. 2012; Butler and Gates 2012). However, to increase overall resilience, improve capabilities, and be better prepared for the brutal effect of shocks, such groups will be expected to increase competition during periods of abundance.

Without the ability to purchase drought-resistant seeds or livestock, and without government or international support—which in many cases cannot arrive in time or be received by those who need it—that provides a safety net against sudden shocks, the only alternative to free market or aid solutions is to obtain food using violent means. Moreover, the tendency for conflict might also be affected by population growth (Homer-Dixon 1998) or migration (Dell, Jones, and Olken 2014), which increase the pressure to secure more resources just to keep the same level of sustenance, leading to a zero-sum, "Red Queen" scenario.[2] To increase overall resilience, communities must obtain the necessary access to enough food resources during periods of plenty, when more assets could be mustered and when time horizons with respect to the competition over food are relatively long, that is, actors *perceive* that more resources will make them more resilient in the future. This directly relates to the notion of time horizons in interstate war, as put by Toft (2006): "if both actors discount the present but see their fate provided for in the future, then violence is likely" while "[i]f both actors discount the future highly, then violence is unlikely."

Finally, it is important to emphasize that while conflict frequency might increase with higher productivity, food is not always necessarily the cause. For instance, government or

[2] Building on Lewis Carroll's apt description, a "Red-Queen" race is a competitive scenario in which every actor must match or exceed the current expenditures of rivals, so that each is forced by the others to invest even more resources only to maintain the same position (Baumol 2004).

rebel troops might be stationed in more fertile areas in order to protect these areas, or to support themselves. Consequently, other armed actors seeking to attack enemy strongholds will move into these areas not to obtain food resources, but simply because these regions are likely to offer a valuable target. In these contexts, the impact of food resources is indirect; a military base might have been formed in this particular region to protect local food resources or simply because support is more likely there, and fighting arose as enemy forces attacked this base. Moreover, while securing food resources might be a direct cause of armed conflict in some cases, conflict—especially full-scale civil war—is frequently the result of political and socioeconomic issues (Fearon and Laitin 2003). In this context, troops gravitate into areas with more food resources during ongoing war to secure food or prevent these resources from being consumed by the enemy. Therefore, while I make the argument that conflict concentrates in areas with high staple crop yields, I also recognize that groups do not fight *necessarily* over these resources; locations with more food resources might simply attract and sustain a large portion of ongoing violence.

Whether competition over food resources is the direct cause of conflict, or whether it directly or indirectly fuels ongoing violence, in contrast to some previous studies on the climate-conflict nexus (Burke et al. 2009; O'Loughlin et al. 2012; Maystadt and Ecker 2014) the expectation here is that conflict should be positively associated with *more* food resources, all else being equal. However, although multiple studies have suggested that such positive associations exist (e.g., Adano et al. 2012; Butler and Gates 2012; Koren and Bagozzi 2016), making a causal statement with respect to food resources is more challenging because, unlike temperature or precipitation, at the local level, food crops are likely to have an endogenous relationship with conflict. In other words, just as higher local food outputs can cause conflict, conflict can destroy crops and reduce yields.

For instance, as Messer argues, "[f]ood poverty may be exacerbated as violence disrupts migratory labor and remittance patterns over wide regions, as has been the case across multiple African areas, also Afghanistan and Iraq, whose violence, and interruptions to livelihood and security, impact neighboring countries," (2009). Violent conflict can destroy infrastructure, displace large populations, and increase population pressures via movement of different groups and troops into the region (Koren and Bagozzi 2017). Moreover, food insecurity can be used as a weapon of conflict in-and-of itself, as adversaries deliberately starve opponents into submission by siege or destruction of crops, livestock, and markets, and divert food relief from intended beneficiaries to armed groups and their supporters. Indeed, research into the impact of conflict on food choices found significant changes in livestock and crop growing patters in Uganda (Rockmore 2012) and Colombia (Arias, Londoño, and Zambrano 2017). Establishing the *causal* effect of food on conflict—or coming as close to it as possible when observational data are concerned—necessitates a fitting identification strategy and effective data that allow the researcher to isolate the causal arrow flowing from food resources to conflict, rather than the other way around.

Data and Methods

This section discusses the data to be analyzed, the equations to be estimated, and the identification strategy to be used to establish the causal impact of food resources on armed conflict.

Data

For Africa, a grid cell sample encompassing 11 years of data from 1998 to 2008 is used to evaluate the relationship between local food crop yields and violent conflict. The geolocated data used for this analysis were obtained from the PRIO-Grid dataset (Tollefsen et al. 2012). This dataset measures a variety of spatial data at the 0.5 ° resolution, or a geographic squared "cell" of roughly 55 × 55 kilometers at the equator (3025 square kilometers area), which decreases with higher latitudes. This dataset thereby allows one to capture the variation of specific geographic and economic phenomena globally (excluding oceans, Antarctica, and the Arctic) at the very local level. All variables were aggregated to the same grid level and integrated into this dataset for the years analyzed.

The dependent *conflict* variable was obtained from the ACLED Version 6 dataset and measures all incidents of political violence (including those that ended without casualties), with a focus on civil and communal conflicts, violence against civilians, remote violence, rioting, and protesting that occurred both within and outside the civil war context (Raleigh et al. 2010). The actors covered by this dataset are official state forces, rebels, political militias, ethnic and tribal militias, protesters, and rioters, which means that more than any other available dataset, the ACLED Version 6 data correspond directly to the different actor categories discussed in the previous section. The ACLED dataset provides information on geographic specificity, that is, whether an incident was coded at the village/town, district, or province level. To ensure comparability across different cases and variables, I analyze only events coded as occurring at the village/town level, which most closely correspond to my grid-cell level of analysis, and aggregate these incidents to the annual 0.5 ° grid level.

The resulting *conflict* indicator is therefore defined inclusively as the total number of political violence incidents among and between different state and non-state actors within a given cell during a given year coded by the ACLED dataset. This indicator captures many nuances of political violence—including events that ended without casualties, such as strategic developments—and hence provides an improvement over other studies that employ binary indicators of conflict or focus exclusively on the state vs. rebel logic. Additionally, and again in line with the argument presented above, these data capture both instances of conflict onset and violence occurring as part of ongoing campaigns. For summary purposes, histograms and averaged values by grid cell of *conflict* are plotted for the 1998–2008 period in figures A.1 and A.5, respectively, in the online supplementary appendix.

The effect of local food availability on the number of conflict events is evaluated using the annual local productivity of wheat and maize—two cereals that together compose the lion's share of all staple crops consumed in African households (FAO 2016). These continuous *wheat yield* and *maize yield* indicators measure average annual levels of wheat and maize productivity at the highly localized, ~0.08 ° grid level, or approximately 9km x 9km at the equator (Ray et al. 2012).[3]

To identify local areas where cropland is grown, Ray et al. (2012) relied on an earlier high resolution geospatial global cropland map for year 2000 created by Ramankutty et al. (2008). Ramankutty et al. (2008) utilized two sources of data to create their map. The first source consisted of global satellite-based land cover data obtained from two previous datasets, BU-MODIS and GLC2000 (Ramankutty et al. 2008). The second source consisted of national and subnational census data on cropland area and food inventories. The authors then used regression techniques to train the satellite land cover data against the census data. The resulting estimates, along with the satellite data, allowed Ramankutty et al. (2008) to then map cropland areas at the high-resolution five-minute (~0.08 °) level. In the second step, Ramankutty et al. (2008) further adjust their high-resolution maps, scaling up or down all pixels within an administrative unit to exactly match the census data.

To interpolate their time-varying measure of crop-specific area and yield by 0.08 ° grids for wheat and maize, Ray et al. (2012) then expanded the dataset developed by Ramankutty et al. (2008) in two steps. First, Ray et al. (2012) collected an exceptionally large number of datasets' crop area and yields at the subnational and national level, going back to 1961. The average number of census observations over the 1961–2008 period was 600,000 per crop, although the number of observations varied geographically.[4]

Ray et al. (2012) then use the high-resolution cropland map created by Ramankutty et al. (2008) as a spatial reference to disaggregate wheat and maize area and yield data within each administrative unit. The grid of staple crop yields was created "by disaggregating the yield from the smallest political unit with available data in the agricultural inventory by distributing the inventory data for each administrative unit uniformly to each pixel [i.e., 0.08 ° grid] within that administrative unit," (Monfreda, Ramankutty, and Foley 2008). For wheat and maize yields, the process developed by Monfreda, Ramankutty, and Foley (2008) was repeated annually over the 1961–2008 period (Ray et al. 2012). The crop area in each 0.08 ° grid of the final map was set to zero when no reference to a crop existed in the inventory data. Information on

[3] For detailed information on the sources and methods used to compile these data, see Monfreda, Ramankutty, and Foley (2008), Ramankutty et al. (2008), and Ray et al. (2012).

[4] Crop inventory information became more easily available after 1990, the period analyzed here (Ray et al. 2012).

these missing points was then interpolated from the latest five years if at higher administrative units crops reports were present (Ray et al. 2012).[5]

It is important to note that data quality might be poor in some countries, sometimes due to ongoing political strife, which means that some countries do not provide annual reports. These issues, however, are unlikely to affect the specific data used here. First, the geospatial and temporal interpolation of missing data as discussed above should help ameliorate some missing-ness issues resulting from ongoing strife. Moreover, the authors created a useful metric (presented in Ray et al. 2012) to evaluate overall data quality for each political unit. As shown in Ray et al. (2012), the data quality for Africa is generally high at the reported administrative level (averaging within the top 90th percentile) and—with a data quality level that is nearly identical to North America's—is better than any other world region. It is important to emphasize, however, that the vast majority of crop output data on Africa were available only at the national level. Thus, for most African countries Ray et al. (2012) interpolate localized changes in wheat and maize yields within each particular 0.08 ° grid based on national averages, which is less than ideal.

These limitations notwithstanding, the resulting *wheat yield* and *maize yield* indicators provide "a dramatically improved understanding of crop yield and area changes across regional and global scales, which are otherwise often obscured using only national census statistics," (Ray et al. 2012), especially in world regions where subnational statistics are missing or nonexistent, such as Africa. Indeed, as highlighted by 24 food-system experts, a salient problem with current attempts to assess local food security is that "the data collected are rarely comparable across ecological zones because of inconsistencies in methodologies or in the spatial scale at which observations are made" (Sachs et al. 2010). From this perspective, the high-resolution data produced by Ray et al. (2012) provide a significantly and substantively better fit for observed local food production trends, even when compared with other high-resolution datasets such as BU-MODIS or GLC2000. Using a dataset that combines satellite-derived imagery and staple crop inventory data also allows scholars "to capitalize on whichever satellite-based land cover data set is best suited to each region," compared with the constituent datasets, which on their own would provide "reasonably good global results, but would lose accuracy in some regions," (Ramankutty et al. 2008).

To ensure comparability to the other data used in this present study, both the *wheat yield* and *maize yield* indicators were averaged to the 0.5 ° grid cell level to ensure comparability across observations. A value of one thus corresponds to a grid-cell whose total area is entirely covered by wheat or maize crops, respectively, during a given year. For summary purposes, averaged values for *wheat yield* and *maize yield* (by grid cell) are plotted for the 1998–2008 period in figures A.6–A.7 of the online supplementary appendix. Additionally, the correlations between average annual wheat and maize yields, and the number of conflict events per grid cell, are plotted in figure 1 below.

The instrument used to "exogenize" the effect of food on conflict, *drought*, is operationalized using a Standardized Precipitation Index (SPI) that aggregates monthly precipitation data to the cell-year level (Guttman 1999). This SPI-based indicator classifies drought severity as the number of standard deviations below average precipitation levels in a particular grid cell during a given year. The resulting *drought* variable is an ordinal indicator (it can take the values of 0, 1, 1.5, and 2.5 standard deviations below the mean) providing a straightforward measure of rainfall shocks and—correspondingly—their impact on food production.

The models reported below also employ different controls. First, considering the potential impact of population pressures on food availability and the number of conflict events as raised by previous studies (e.g., Homer-Dixon 1998), I account for population density in a given cell during a given year using the variable *population* (Nordhaus 2006). This cell-level variable was originally measured for the years 1995, 2000, and 2005, and then interpolated to the yearly level using a last-value-carried-forward approach (Tollefsen et al. 2012). To control for spatial correlation, I include a binary spatial lag of the dependent variable, *conflict (spatial)*, denoting whether any conflict events occurred in the first-order neighboring

[5] While Ray et al. (2012) also calculate changes in staple crop yield trends using categorical trend indicators, the present article relies on the raw high-resolution yield information underlying the analyses conducted in Ray et al. (2012).

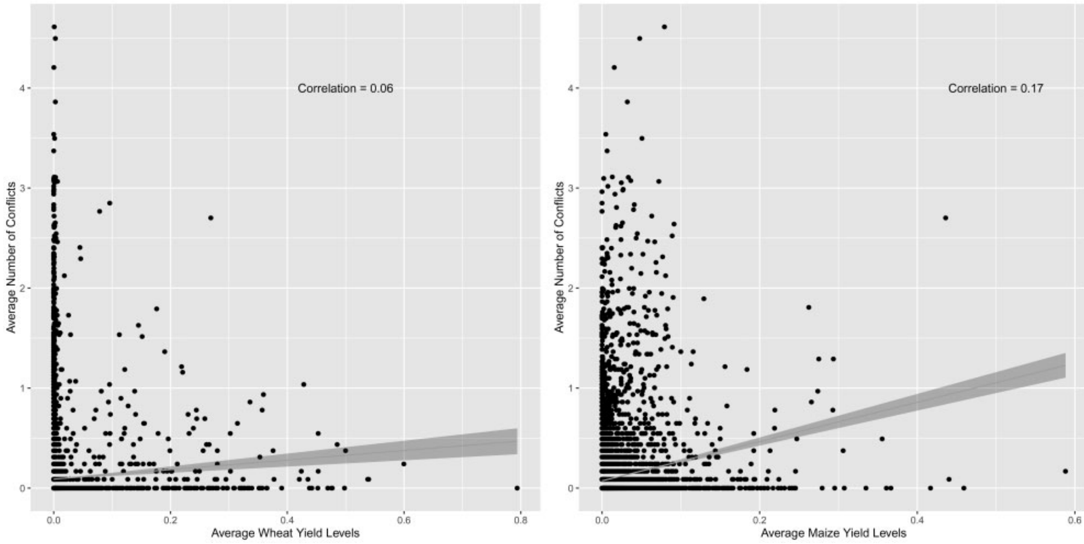

Figure 1. The linear correlation between annual wheat (left) and maize yields (right) and conflict by 0.5 ° grids, 1998–2008.

Note: Conflict measures are presented in natural log form.

cells. I also include a one-year lag of the dependent variable, *conflict (lag)*, to control for the temporal dependence of conflict events, alongside annual and grid cell fixed effects.

Crucially, these variables are all measured at the grid cell, and not country, level. Furthermore, the crop yield measures used for analysis are *time-varying*, which provides a major improvement over past studies of this sort that have favored static measures of cropland at comparable levels of geographic resolution (e.g., O'Loughlin et al. 2012; Koren and Bagozzi 2016). Nevertheless, to account for alternative explanations (e.g., Fearon and Laitin 2003; Bannon and Collier 2003), several country-level indicators were also included in the analysis. The *democracy* measure is the ordinal Polity2 indicator, with higher values corresponding to more democratic regimes (Marshall, Jaggers, and Gurr 2013). The gross domestic product (GDP) per capita measure, *GDP per capita*, was obtained from the World Bank (2015). Finally, a large number of alternative mechanisms are evaluated in the Competing Mechanisms section. For summary purposes, all variables—including those used in sensitivity analyses—are reported in table 1.

Identification Strategy

Local food yields cannot be argued to be exogenous to localized conflict because the latter might devastate infrastructure in the region and generate more population pressures (e.g., via troops moving in). This suggests that the estimates provided by OLS regressions are likely to be biased due to simultaneity between the main explanatory variable and the dependent variable. The identification strategy used in this article therefore relies on the use of an instrumental variable (IV), that is, a variable that is correlated with food production but arguably uncorrelated with the error term of violent conflict. This framework is in line with previous studies of the relationship between agriculture and economic growth, climate, and conflict (e.g., Miguel, Satyanath, and Sergenti 2004; Sarsons 2015; Bellemare 2015).

Recall that an IV must satisfy two requirements. First, it must be correlated with food production at the local level. To this extent, table 3 shows that the instrument is not weak, excluding, perhaps, the full specifications (Stock and Yogo 2003). Second, the IV must only affect violent conflict through food production, a requirement that is also known as meeting the exclusion restriction (Angrist and Pischke 2009).

To account for the potentially endogenous relationship and "feedback effects" between violent conflict and food production, and to obtain consistent estimates, I rely on the ordinal *drought* indicator discussed above, which

Table 1. Summary Statistics of All Variables

Variable	Minimum	Median	Mean	Max.	SD
Grid Cell Level Variables					
Conflict	0	0	0.228	334	2.854
Wheat yield	0	2.63e-05	0.009	0.930	0.047
Maize yield	0	0.004	0.016	0.667	0.034
Drought	0	0	0.229	2.5	0.654
Conflict (lag)	0	0	0.182	334	2.523
Conflict (spatial)	0	0	0.091	1	0.287
Population[1]	0	9.721	9.369	16.268	2.263
Nighttime light	0.021	0.034	0.040	0.941	0.032
Ethnic diversity	0	1	1.325	7	1.177
Terr. change	0	0	0.007	1	0.081
Temperature	3.625	24.675	24.382	32.617	3.774
Temperature (lag)	3.625	24.658	24.364	32.617	3.778
Wheat yield (lag)	0	2.58e-05	0.009	0.930	0.047
Maize yield (lag)	0	0.004	0.016	0.642	0.034
Violent conflict	0	0	0.069	220	1.209
Violent conflict (lag)	0	0	0.055	220	1.038
Military conflict	0	0	0.103	286	1.726
Military conflict (lag)	0	0	0.081	286	1.550
Conflict[1]	0	0	0.062	5.814	0.320
Conflict (lag)[1]	0	0	0.047	5.814	0.289
Any drought	0	0	0.123	1	0.328
Severe drought	0	0	0.088	1	0.283
Extreme drought	0	0	0.062	1	0.241
Country Level Variables					
Democracy	−9	0	0.214	10	5.084
GDP per capita[1]	5.517	7.350	7.547	10.341	1.106
Food imports (%)	0.474	16.493	17.313	62.416	7.510
Agricultural imports (%)	0.146	1.175	1.870	42.322	3.040
Foreign aid[1]	15.713	20.040	19.947	23.240	1.269
Oil production[1]	0	13.592	9.170	18.690	8.075
Gas production[1]	0	0	1.663	7.192	2.369
Military expenditure[1,2]	0	12.612	12.536	15.350	1.645
Cereal prod. index	0.015	91.957	99.050	882.89	57.648
Meat prod. index	0.032	91.620	93.835	737.38	52.157

Note: Superscript [1] indicates a natural log; [2] indicates that this variable is only available for the years 1998–2007.

is crucially measured at the annual grid level, in a manner consistent with previous research (e.g., Miguel, Satyanath, and Sergenti 2004; Crost and Felter 2016). As a climatic indicator, this instrument is highly unlikely to be directly endogenous with violent conflict. At the same time, this instrument is likely to be highly correlated with local wheat and maize yields, which means that the IV models identify the true relationship between food security and conflict, conditional on droughts, and are thus preferred to their OLS counterparts. This is easily ascertained with statistical tests—in effect, tests of the null hypothesis that the instrument is weak—the results of which are shown in table 3. Moreover, the effect of droughts on food production and on increasing food scarcities has been the tenet of previous studies of the climate-conflict nexus (e.g., O'Loughlin et al. 2012). Importantly, as discussed in the online supplementary appendix, droughts are also likely to monotonically affect food production by decreasing yields everywhere they impact.

It is important to recognize, however, that previous research suggested that—in some situations—rainfall shocks might not necessarily pass the exclusion restriction. Sarsons (2015), for instance, relies on information on dam construction in India to illustrate that while income in downstream areas is less sensitive to rainfall fluctuations, rainfall shocks remain a strong predictor of riots in these contexts. As this is not a trivial concern, I address it both theoretically and empirically. First, note that, perhaps even more so than in

India (the focus of Sarson's study), most agriculture in Africa (especially Sub-Saharan Africa) during the 11 year period analyzed here depended almost exclusively on rainfall (FAO 2008; Kastner et al. 2012). As a result of this high dependence on precipitation, the amount of land required to produce food in these regions actually increased over time, as opposed to Asia, where researchers observed notable decreases in the amount of land required to support a certain number of people (Kastner et al. 2012).

These context-specific differences suggest that, at least from a theoretical perspective, the use of *drought* as an instrument for the impact of local food yields on conflict in Africa is defensible. Moreover, rainfall can impact conflict through both positive and negative deviations from the mean, with too much precipitation causing overly high levels of soil moisture, thus increasing the risk of crop disease (FAO 2008). This suggests that the impact of being located down- vs. upstream from irrigation dams as identified by Sarsons (2015) is more likely during positive rainfall shocks. To help account for this concern, I restrict my *drought* instrument to focus only on *negative* rainfall shocks as discussed above.[6]

I also address this concern empirically. First, note that Sarsons shows that the violation of the exclusion restriction for rainfall-based instruments is the result of location, specifically, rather than issues such as conflict spillovers or migration (2015). This is in contrast to the latter's impact of economy-wide effects at the country level, where these and other channels might be at play (Dell, Jones, and Olken 2014; Carleton and Hsiang 2016). To account for constant factors such as geographic locations at the highly disaggregated geo-spatial level, I include fixed effects for each grid-cell in my sample and cluster standard errors at a similar level to address heterogeneities. Considering the relatively small size of this unit of analysis (0.5 x 0.5 grid) compared with, say, the province or even district levels, this approach should help fix much of the geo-spatial variance within my sample, including variance resulting from upstream vs. downstream locations.

[6] This approach also builds on Dell, Jones, and Olken, who note that "[a] promising direction for research on droughts would construct a drought definition based solely on exogenous environmental variables such as precipitation," (2014).

More importantly, however, I rely on the method developed by Conley, Hansen, and Rossi (2012) to allow for departures from the exclusion restriction, that is, allowing the IV to have some direct effect on conflict that is not exclusively restricted to food productivity, to show that this IV is still "plausibly exogenous." Conley, Hansen, and Rossi (2012) identify that, often, the exclusion restriction is suspect because many IVs are endogenous to some extent. To test how much a given IV violates the exclusion restriction, these authors accordingly present several practical methods for performing inference while relaxing the exclusion restriction and showing that an IV can pass a certain threshold of endogeneity but still remain exogenous enough for the purpose of inference. Indeed, as shown in table 4 and discussed in more detail below, the IV *drought* survives local-to-zero approximation tests for "plausible exogeneity," suggesting that—empirically—the use of this IV is defensible (Conley, Hansen, and Rossi 2012).

If the instrument is valid and effectively exogenizes food production relative to conflict, then the coefficients for *wheat yield* and *maize yield* are the weighted average, covariate-specific local average treatment effects (hereafter, "average LATE") of food production on violent conflict, that is, the increase in the extent of violent conflict (as measured by the continuous dependent variable) due to food production in those grid cells and years where droughts induce a change in maize and wheat yields, accounting for other covariates (Angrist and Pischke 2009). Hence, the relationship between food production and conflict at the local level is identified using the following two-equation system in the IV models:

$$(1)\quad \boldsymbol{y_{it}} = \alpha_1 + \beta_{1f}\hat{f}_{it} + \beta_{1y}y_{i,t-1} + \beta_{1s}y_{st} + \beta_{1X}X_{it} + \boldsymbol{\Phi}_{1\mathrm{i}} + \boldsymbol{\Psi}_{1\mathrm{t}} + \epsilon_{1it}$$

$$(2)\quad f_{it} = \alpha_2 + \beta_{2c}\boldsymbol{c_{it}} + \beta_{2y}y_{i,t-1} + \beta_{2s}y_{st} + \beta_{2X}X_{it} + \boldsymbol{\Phi}_{2\mathrm{i}} + \boldsymbol{\Psi}_{2\mathrm{t}} + \nu_{2it}$$

where $\boldsymbol{y_{it}}$ is a vector of violent conflict incidents by grid cell for each year; $y_{i,t-1}$ is the temporal lag of the dependent variable; y_{st} denotes whether conflict occurred in neighboring cells or not each year; $\boldsymbol{X_{it}}$ is a matrix of control variables; $\boldsymbol{\Phi_i}$ are $\boldsymbol{\Psi_t}$ are fixed effects by grid cell and year, respectively;

α are the constants for each equation; ϵ_{1it} is the error term for the second stage regression; and ν_{2it} is the error term of the first-stage regression.[7] In this system, $\hat{f}_{it}$ is the instrumented effect of wheat or maize yields as estimated by equation 2, that is, the increase in the extent of violent conflict (as measured by the dependent variable) due to wheat or maize yields in grid cells and years where drought, captured by the vector $\boldsymbol{c_{it}}$, induces a change in crop yields. As the data for some variables are duplicated over time, grid cell-clustered standard errors for all models are used to assess statistical significance.

To treat the observed quantities on all variables for each cell as non-random, fixed effects for each grid cell were included in all models; and fixed effects for each year covered in the data (1998–2008) were also included to account for potential time dependencies. The use of unit of analysis fixed effects—that is, including binary variables for the units of analysis, in this case grid cells, to capture observed and unobserved influences on an outcome of interest (the frequency of conflict in this case) that are constant over time—is a well-established statistical procedure for identifying causal relationships (Angrist and Pischke 2009). This approach, combined with the use of a valid instrument to "exogenize" the effects of the endogenous explanatory indicators, allows the IV models to isolate localized food production effects and make the case for a consistently significant higher risk of conflict with increased yields.

Results

To evaluate the effect of local food yields on conflict I estimate two separate specifications for each crop. These models build on the availability and access aspects of food security as described by Barrett, two concepts that are "inherently hierarchical, with availability necessary but not sufficient to ensure access" (2010). Considering that food availability is "typically measured in daily calories per person" (Barrett 2010), the baseline—or availability—model includes only food yields, that is, the total amount of wheat or maize available in a given grid cell during a given year (exogenized by *drought* in the IV models) in addition to grid cell and year fixed effects to account for constant observed and unobserved confounders. Building on the definition of food access as "the range of food choices open to the person(s), given their income, prevailing prices, and formal or informal safety net arrangements through which they can access food," (Barrett 2010), the full specifications incorporate a variety of controls (discussed in the previous section) alongside food yields to account for the impact of salient political and socioeconomic conditions.

Table 2 reports the coefficient estimates of four OLS models that each assesses the likelihood of cell-year conflict in Africa. The effect of these variables is then compared to their average LATE in table 3. Due to space constraints, the direct impact of drought on conflict and the first-stage regression estimates for the IV models are reported in tables A.2 and A.3, respectively, in the online supplementary appendix. The hypothesized relationship between food yields and conflict is evaluated against benchmark explanations of conflict risk: socioeconomic and political indicators, and conflict history (Fearon and Laitin 2003; Bannon and Collier 2003). The linear effect of wheat and maize yields on conflict without accounting for endogeneity concerns is estimated in models 1–4. The exogenized effect of these indicators on localized conflict is then estimated in a series of IV regressions in models 1E–4E.

In model 1, *wheat yield* has a negative but statistically insignificant effect on conflict. However, by destroying infrastructure, causing civilian producers to flee, or through "scorched earth" tactics, conflict might also negatively impact food production. This coefficient might thus reflect a reversed relationship, which obscures the true effect of local yields on violence. Model 1E, where the effect of local food production with respect to conflict is instrumented using *drought*, accounts for this likely scenario. Here, *wheat yield* is positively and significantly associated with the incidence of conflict, which suggests that conditional on average conflict in a given cell, localized conflicts arise more often during years of *high* yields.

The full (or "access") specification presented in models 2 and 2E include a variety of controls to show that these results are indeed consistent with the addition of a large

[7] These intercepts are not included in the regression outputs below as all variables are demeaned and the "within transformation" is applied to multiple factors (Gaure 2013).

Table 2. OLS Regression Models for Total Number of Conflict Events per Grid Cell, 1998–2008

Variable	Wheat Yield		Maize Yield	
	1) Baseline	2) Full	3) Baseline	4) Full
Wheat yield	−0.517	−0.528	–	–
	(0.464)	(0.472)		
Maize yield	–	–	−3.749**	−3.111***
			(1.682)	(1.188)
Conflict (lag)	–	0.202**	–	0.202**
		(0.084)		(0.084)
Conflict (spatial)	–	0.337***	–	0.336***
		(0.083)		(0.083)
Population[1]	–	−0.663***	–	−0.633***
		(0.190)		(0.187)
Democracy	–	−0.022**	–	−0.022**
		(0.010)		(0.010)
GDP per capita[1]	–	0.019	–	0.024
		(0.173)		(0.172)
Observations	72,213	68,204	72,213	68,204
R^2	0.454	0.429	0.454	0.429
Adjusted R^2	0.400	0.370	0.400	0.370

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are OLS regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects are included in each regression, though not reported here. Superscript [1] indicates a natural log.

Table 3 IV Regression Models for Total Number of Conflict Events per Grid Cell, 1998–2008

Variable	Wheat Yield		Maize Yield	
	1E) Baseline	2E) Full	3E) Baseline	4E) Full
Wheat yield	75.13***	83.53***	–	–
	(24.35)	(26.05)		
Maize yield	–	–	184.40***	204.74***
			(58.90)	(62.77)
Conflict (lag)	–	0.201**	–	0.206**
		(0.084)		(0.084)
Conflict (spatial)	–	0.343***	–	0.436***
		(0.087)		(0.110)
Population[1]	–	−0.877***	–	−2.762***
		(0.239)		(0.798)
Democracy	–	−0.032***	–	0.007
		(0.011)		(0.013)
GDP per capita[1]	–	−0.048	–	−0.336
		(0.180)		(0.246)
Observations	72,169	68,160	72,169	68,160
Endogenous variables test	9.520***	10.28***	9.809***	10.64***
Weak instrument F-statistic (clustered SEs)	50.22	8.372	51.48	8.955
Weak instrument F-statistic (i.i.d. SEs)	191.39	31.84	88.74	15.26
R^2	0.414	0.351	0.366	0.264
Adjusted R^2	0.354	0.284	0.301	0.187

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects are included in each regression, though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*. Superscript [1] indicates a natural log.

number of socioeconomic, political, and spatial-temporal confounders. Here, the effects of GDP per capita, democratization levels, population density, as well as spatial and temporal conflict dependencies are evaluated, in addition to the *wheat yield* variable included in models 1 and 1E. While the effect of within-grid cell wheat production on violent conflict in model 2 is again statistically insignificant, the instrumented effect of *wheat yield* is positive and statistically significant in model 2E, even with the inclusion of these alternative explanations. This again confirms the argument that, on average, years with *higher* yields increase the frequency of conflict within a given cell during a given year.

Models 3–4 and 3E–4E estimate the same specifications, this time using maize as an approximation of local food availability. The effect of maize yields is negative and significant in the baseline and full models for the OLS regressions. Yet, in the IV models *maize yield* is consistently *positive* and significant across both the baseline and full specifications. These findings again support the hypothesis that conflict within a given grid cell is likely—on average—to arise during years with higher yields, when the conditional impact of droughts on annual crop productivity by grid cell is estimated. Moreover, diagnostic regressions of the instrument *drought* on the endogenous yield variables presented in table A.3 of the online supplementary appendix are significant, suggesting that the IV estimates are indeed informative (Angrist and Pischke 2009).[8]

The estimated impact of staple crop yields on local conflict frequency is sizable: focusing on model 1E as the benchmark, the average marginal effect for *wheat yield* indicates that a 0% to 100% change in wheat yields increases the predicted number of conflict events in a given grid cell during a given year by approximately 75 incidents. This suggests that for a mere 1% increase in *wheat yield*, the predicted number of conflict events by cell increases by approximately 0.75 incidents. Considering that the average number of conflict events for an average grid cell, during a given year for the entire 1998–2008 period is 0.228, this effect is substantive.

More broadly, endogenous variable tests are significant, suggesting that endogeneity between the dependent and explanatory variables likely exists and thus supporting the use of IV models. In models 1E and 3E, the F-statistic for a weak instrument far exceeds the threshold of 10 (Stock and Yogo 2003) for an IV not to be considered weak, while in models 2E and 4E the instrument is borderline weak when clustered standard errors are used, suggesting that this model might be marginally biased toward OLS estimates. Finally, as shown in tables A.7–A.8 of the online supplementary appendix, the results are consistent when each control is added sequentially to arrive at the full specifications. Thus, this analytical framework and the consistency of the results across different specifications suggest that positive local food yields have a strong impact on localized conflict in Africa. This effect is not unique to one crop, but rather characterizes at least two distinct staple foods. Crucially, models 2E and 4E clearly show that this finding is not the result of local population densities, higher levels of state presence, or economic development, all of which are controlled for by these models.

Sensitivity Analyses and Competing Mechanisms

Below I evaluate the sensitivity of my findings to the plausible exogeneity assumption, modeling choices, and a large number of competing mechanisms. Due to space constraints, all other sensitivity analyses, as well as all variables used in this section, are discussed in full in the online supplementary appendix and only briefly below. Additionally, to account for the varying importance of wheat and maize across different African regions, the main analyses are repeated by omitting each African sub-region from the sample at a time in tables A.9–A.13 of the online supplementary appendix to illustrate the findings' robustness to regional bias.

Sensitivity Analyses

I begin by assessing the robustness of my IV regression results to small departures from the strict exogeneity assumption required for those results to be identified. Having discussed these issues theoretically above, I apply the method developed by Conley, Hansen, and Rossi (2012) to deal with plausibly—but not strictly—exogenous instruments. In applying this methodology, it is necessary to impose some sort of prior on said departures from strict exogeneity, with the trade-off being that the less precise the prior, the less precise the resulting models'

[8] For all specifications, statistically significant (to the 5% level) Hausman test estimates suggest the random effects assumption is less likely to be supported by the data, thus supporting the use of a fixed effects framework.

Table 4 IV Regression Models for Total Number of Conflict Events per Grid Cell, LTZ Simulations

Variable	Wheat Yield		Maize Yield	
	5) Baseline	6) Full	7) Baseline	8) Full
Wheat yield	261.17***	150.19**	–	–
	(77.48)	(59.96)		
Maize yield	–	–	312.11***	210.58**
			(90.24)	(81.22)
Population[1]	1.259***	–0.752*	0.541	–1.285**
	(0.326)	(0.383)	(0.474)	(0.595)
Conflict (spatial)	–	36.19***	–	35.37***
		(3.327)		(3.139)
Democracy	–	0.406***	–	–0.112
		(0.128)		(0.086)
GDP per capita[1]	–	–2.184**	–	–0.644*
		(0.840)		(0.340)
Constant	–11.85***	20.22**	–6.973*	13.65*
	(3.008)	(9.171)	(3.878)	(7.167)
Observations	6,680	6,429	6,680	6,429
Endogenous variables test	11.69***	7.437***	12.33***	7.174***
Weak instrument F-statistic (clustered SEs)	22.303	9.404	25.56	7.284
Weak instrument F-statistic (i.i.d. SEs)	11.12	5.931	19.59	5.581
R^2	–0.191	0.063	–0.101	0.069
Adjusted R^2	–0.192	0.062	–0.1012	0.068

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. The variables *wheat yield* and *maize yield* were instrumented using a collapsed binary version of *drought*. Superscript [1] indicates a natural log.

estimates will be. I thus utilize Conley, Hansen, and Rossi's intermediate local-to-zero (LTZ) method, which only requires one to impose a prior on the mean and standard deviation for the parameter measuring the magnitude of the presumed departure from strict exogeneity. In this case, I assume a mean of a zero (i.e., no direct effect) and a standard deviation of 0.1, thus allowing for relatively wide departures from strict exogeneity. However, the LTZ approach relies on particular specifications and a large number of computer simulations. Due to the size of my sample and the complications involved with using grid cell fixed effects under this framework, it was impossible to run LTZ models with available computer resources.

Considering these complications, each LTZ model was estimated on a collapsed sample for the entire 11-year period of analysis. In this sample, a binary indicator for drought, denoting whether a given grid cell experiences drought with one or more standard deviations below the mean of a given cell's precipitation levels, is used as an IV, while all other variables were averaged for the entire period (excluding *conflict*, which was summed). This time-invariant grid cell framework thus nullifies the need for grid cell fixed effects. Additionally, because the LTZ approach requires the inclusion of at least one exogenous variable alongside the endogenous one in the model, all baseline models include *population* in addition to *wheat yield* and *maize yield*. Table A.4 (online supplementary appendix) replicates the main analysis on said collapsed sample to show that each food indicator's coefficient maintains roughly the same substantive size (within one order of magnitude), sign, and significance as reported in table 3, across both the baseline and full specifications. The results of the Conley, Hansen, and Rossi's LTZ estimations presented in table 4 then show that both food indicators are robust to substantive departures from the assumption of strict exogeneity of drought on conflict.

Another methodological concern relates to the structure of my data, which include a large number of units, but a relatively low number of time periods. This might suggest susceptibility to estimation bias when linear fixed effect models—implying unobserved heterogeneity—are used (Blundell and

Table 5. GMM IV Regression Models for Total Number of Conflict Events per Grid Cell, 1998–2008

Variable	Wheat Yield		Maize Yield	
	9) Baseline	10) Full	11) Baseline	12) Full
Wheat yield	0.610***	0.231**	–	–
	(0.174)	(0.108)		
Maize yield	–	–	2.257***	0.309*
			(0.530)	(0.165)
Conflict (lag)	0.382***	0.781***	0.381***	0.780***
	(0.090)	(0.087)	(0.089)	(0.087)
Conflict (spatial)	–	−0.223*	–	−0.220*
		(0.127)		(0.127)
Population[1]	–	−0.0003	–	−0.001
		(0.002)		(0.002)
Democracy	–	0.001	–	−0.0001
		(0.001)	(0.001)	
GDP per capita[1]	–	0.002	–	0.003
		(0.003)		(0.003)
Observations	72,169	68,160	72,169	68,160
Sargan test	73.69***	612.47***	75.436***	613.03***
DF	(39)	(43)	(39)	(43)
R^2	0.082	0.088	0.083	0.088

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with robust standard errors in parentheses. GMM instruments for all models are the $t - 4$ and beyond lags of *conflict*. Superscript [1] indicates a natural log.

Bond 1998). Additionally, the time-demeaning operation of fixed effects in these models means that the error terms of the dependent variable and its lag are correlated, causing an inconsistency in such estimator, referred to as the "Nickel Bias" (Blundell and Bond 1998). Although the use of standard IV regressions within panel-time-series data is a standard practice (e.g., Miguel, Satyanath, and Sergenti 2004; Sarsons 2015), to show that my IV model results are robust to these concerns, I additionally estimate a series of generalized method of moments (GMM) models below (Blundell and Bond 1998).

A key assumption of these GMM models is that the necessary instruments are "internal"; that is, based on lagged values of the instrumented variable(s). The model is accordingly specified as a system of equations, one per time period, where the instruments applicable to each equation differ (in later time periods, additional lagged values of the instruments are available). With the individual fixed effects swept out, a straightforward instrumental variable estimator is available. The system GMM approach also has an advantage over first-differencing GMM models, as the former is much more susceptible to the aforementioned Nickel Bias effects (Blundell and Bond 1998), and was hence preferred within the context of the present analysis.

Following the procedure established by Blundell and Bond (1998) for using endogenous instruments in dynamic panel data, I estimate system GMM models that rely on the past values of yields as instruments for the contemporary effect of yields on conflict. However, to further ensure that these models can claim exogeneity, and considering that the large size of the grid panel suggests a very large number of available lagged instruments and thus overfitting (Arellano 2003; Roodman 2009), I rely on deeper lags of the dependent variable, in a manner suggested by past research (Blundell and Bond 1998; Arellano 2003; Roodman 2009). Therefore, in all models reported in table 5, the GMM instruments are the $t - 4$ and beyond lags of the dependent variable, *conflict*. For robustness purposes, however, table A.5 of the online supplementary appendix also reports similar models where the GMM instruments are the $t - 2$ year lags and beyond of the dependent variable, and the $t - 1$ and beyond lags of *conflict (spatial)*.

The results of the Blundell and Bond (1998) system GMM models presented in table 5 show that both local yield indicators are statistically robust to departures from the 2SLS framework, although marginally so in the full specification of the *maize yield* model. While the results are not statistically

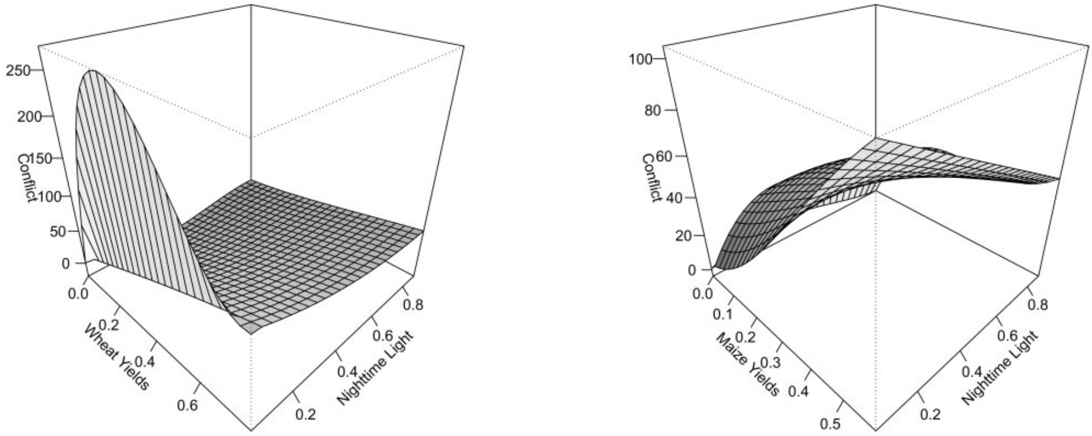

Figure 2. Nonparamteric regression plots of annual nighttime light emissions on violent conflict over the range of (left) wheat yields and (right) maize yields by grid cell in Africa, 1998-2008.

weakened due to the inclusion of a large number of endogenous instruments, Sargan tests do offer evidence of over-identification, even when relying only on deep DV lags, implying that endogeneity may remain a concern within these GMM models. While this can be explained by the sheer size of the grid panel (10,674 cells), by providing an additional way of instrumenting the effect of food on conflict, these GMM models nevertheless show that the relationship between local yields is positive, which complements the IV regressions and LTZ models used previously.

Competing Mechanisms

Having shown that the findings presented in table 3 are generally robust to modeling choices, I now turn to empirically evaluating a large number of alternative mechanisms that could explain the main results. Due to space constraints, these variables are discussed in detail in the online supplementary appendix.

One of the most robust explanations to the onset of conflict connects low development and economic inequalities to conflict frequency (Blattman and Miguel 2010; Fearon and Laitin 2003). Considering that such underdeveloped regions are also more susceptible to limitations on food access and availability (Kastner et al. 2012), low development, economic inequality, and limitations of food are likely to be highly correlated. From this perspective, grid cells with lower economic activity are likely to have more unemployment, more disadvantaged individuals, and hence suffer from more conflict, independently of variation in local yields.

To this end, model 13 in table 6 first replicates the full IV analysis with the inclusion of annual cell-level economic development indicators, *nighttime light*, which measures annual nighttime light emissions in a given cell as a proxy of local development, as used by past studies (Koren and Sarbahi forthcoming). As can be observed, the variables *wheat yield* and *maize yield* maintain their sign and significance across all models, suggesting that their impact is not (only) the result of low development levels and inequalities.

Moreover, in addition to illustrating the validity of this mechanism by the process of elimination—that is, by empirically accounting for a variety of alternative mechanisms—figure 2 further highlights the interactions between economic inequality, food resources, and conflict. Here, nonparametric regression plots—which do not enforce a modeling structure on the data and hence provide a more flexible method of visualizing relationships between different factors—show the correlations of local yields and conflict with respect to economic development as approximated using nighttime light levels. As shown, conflict occurs more frequently in cells with more crop productivity, but relatively low levels of economic development, where—based on anecdotal evidence at least—limitations on food access are more likely (Roncoli, Ingram, and Kirshen 2001).

Second, model 14 in table 6 examines whether the observed effects of the crop yield

Table 6. IV Regression Models for Total Number of Conflict Events per Grid Cell, Additional Robustness Models

Variable	13) Development		14) Resources		15) Aid		16) Violent	
	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield
Wheat yield	83.44***	–	78.50***	–	36.09***	–	25.04***	–
	(26.010)		(24.74)		(12.50)		(7.718)	
Maize yield	–	204.65***	–	178.79***	–	79.85***	–	61.31***
		(62.74)		(54.74)		(26.93)		(18.48)
Nighttime light[1]	−19.04***	−7.945	–	–	–	–	–	–
	(6.154)	(5.185)						
Oil production[1]	–	–	0.006	0.025***	–	–	–	–
			(0.004)	(0.009)				
Gas production[1]	–	–	−0.133***	−0.229***	–	–	–	–
			(0.037)	(0.062)				
Food imports	–	–	–	–	0.011***	0.003	–	–
					(0.004)	(0.003)		
Agricultural imports	–	–	–	–	0.006**	0.006**	–	–
					(0.003)	(0.003)		
Aid[1]	–	–	–	–	0.698**	−0.036*	–	–
					(0.020)	(0.021)		
DV (lag)	0.200**	0.205**	0.200**	0.204**	0.423***	0.426***	0.353**	0.357***
	(0.084)	(0.084)	(0.084)	(0.084)	(0.066)	(0.066)	(0.052)	(0.052)
Conflict (spatial)	0.341***	0.435***	0.328***	0.393***	0.076**	0.099**	0.067***	0.095***
	(0.086)	(0.110)	(0.083)	(0.099)	(0.038)	(0.041)	(0.019)	(0.024)
Population[1]	−0.892***	−2.768***	−0.796***	−2.414***	−0.408**	−1.464***	−0.353***	−0.918***
	(0.241)	(0.798)	(0.228)	(0.697)	(0.159)	(0.0458)	(0.093)	(0.243)
Democracy	−0.031***	0.008	−0.038***	−0.007	−0.035***	−0.018*	−0.011**	−0.001
	(0.011)	(0.013)	(0.011)	(0.010)	(0.013)	(0.010)	(0.005)	(0.005)
GDP per capita[1]	−0.041	−0.333	0.084	−0.165	−0.042**	0.346	−0.030	−0.116
	(0.180)	(0.246)	(0.171)	(0.217)	(0.293)	(0.242)	(0.064)	(0.076)
Obs.	68,160	68,160	68,160	68,160	49,362	49,362	68,160	68,160
End. variables	10.29***	10.64***	10.07***	10.67***	8.34***	8.794***	10.53***	11.01***
WI F-stat. (CSEs)	7.204	7.678	6.354	7.712	5.518	7.846	8.372	8.983
WI F-stat. (ISEs)	27.48	13.08	24.30	13.55	22.24	14.05	31.84	15.30
R^2	0.353	0.265	0.361	0.305	0.588	0.573	0.483	0.442
Adj. R^2	0.285	0.188	0.294	0.232	0.540	0.524	0.429	0.384

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*. Superscript [1] indicates a natural log.

variables are driven by an abundance of lucrative resources such as oil and gas exports (Ross 2011), which previous research connected to higher conflict frequency (e.g., Bannon and Collier 2003; Blattman and Miguel 2010). The effect of localized food production remains positive and significant in these models, suggesting that the availability of other profitable natural resources is not driving the results.

Third, some scholars have highlighted the potential effect of food imports and food aid on conflict (e.g., Nunn and Qian 2014; Bellemare 2015). From this perspective, higher levels of food imports and food aid might increase competition between armed groups over expropriating these resources, and hence explain the pattern observed in table 3. To account for the impact of food and agricultural imports more broadly, as well as total aid, model 15 includes three additional controls—*food imports*, *agricultural imports*, and *aid*—all taken from World Bank (2015). Although the variable *agricultural imports* has a statistically significant effect across all models and *food imports* in the wheat model (*aid* changes its coefficient across the models), the inclusion of these variables does not diminish the sign and significance of *wheat yield* and *maize yield*. The impact of *local* food productivity on the propensity of conflict is again shown to be independent of that of other factors, in this case agricultural and aid dependencies at the national level.

Fourth, recall that my dependent variable incorporates all conflict types and related developments occurring within a given cell during a given year, with or without casualties. A competing explanation might be that the number of conflicts without casualties "inflates" the variable *conflict*, thus affecting the results. To address this concern, model 16 re-estimates the full analyses on a dependent variable that captures only violent incidents, that is, recorded events at the village level with at least one combatant or civilian fatality (Raleigh et al. 2010). The coefficients of both *wheat yield* and *maize yield* maintain their sign, significance, and size (within one order of magnitude), suggesting that the findings are robust to the inclusion of nonviolent conflict events within the dependent variable.

Fifth, previous research has drawn strong linkages between ethnic enmities and localized political violence (e.g., Fjelde and Hultman 2014). To evaluate whether the primary findings were the result of such ethnic enmities, model 17 in table 7 includes two additional controls: *ethnic diversity*, a count of the number of politically relevant ethnic groups settled in a particular cell during a given year (Wucherpfennig et al. 2011); and *terr. change*, denoting whether a new occupier was reported in a given cell (Raleigh et al. 2010). While the coefficients of both *ethnic diversity* and *terr. change* are positive and statistically significant, they do not diminish the effect of local food productivity.

Sixth, recall that my argument does not suggest that scarcity never impacts conflict, but rather that—on average—violence would be more frequent in food-abundant areas. To provide a more empirically thorough evaluation of scarcity's role in driving conflict, model 18 incorporates two additional controls, *temperature* and its lag (Tollefsen et al. 2012), to show that doing so does not diminish the sign or significance of *wheat yield* and *maize yield*. This, again, lends support to the argument that, at least at the local level, on average, it is food abundance that impacts conflict frequency. Additionally, the coefficient signs of *temperature* and *temperature (lag)* change from positive to negative as one moves from the wheat models to the maize models. Interestingly, and shown in table A.6 of the online supplementary appendix, this relationship holds when the one-year lag of each crop is included in the model instead of lagged temperature levels. Considering that R^2 scores suggest that both wheat models are preferred to their maize counterparts, it might be that conflict is more frequent in regions that previously experienced both higher yields and higher temperatures, although these results are far from definite. Alternatively, wheat might be simply more sensitive to higher temperatures.

Interestingly, when cereal and meat production indexes (obtained from FAO 2016) are added in models 19 and 20 (for countries and years for which information is available), the former's effect is positive and significant, while the latter's effect is negative and significant. These results can help reconcile some of this article's seemingly-counterintuitive findings with previous research that emphasizes the role of scarcity. For instance, Maystadt and Ecker (2014) find that droughts induce higher livestock prices, which in turn increases localized frequency of conflict. In contrast, table 3 illustrates that when the same instruments are used for cereals, the

Table 7. IV Regression Models for Total Number of Conflict Events per Grid Cell, Additional Robustness Models (continued)

Variable	17) Ethnic		18) Temperature		19) Production		20) Scarcity	
	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield
Wheat yield	75.59***	–	96.10***	–	35.86***	–	45.36***	–
	(23.79)		(30.47)		(13.84)		(17.11)	
Maize yield	–	186.38***	–	193.48***	–	143.30**	–	132.70***
		(57.97)		(58.64)		(57.77)		(50.39)
Ethnic diversity	0.086***	0.286***	–	–	–	–	–	–
	(0.027)	(0.074)						
Terr. change	5.859***	5.918***	–	–	–	–	–	–
	(0.826)	(0.842)						
Temperature	–	–	0.178***	−0.129***	–	–	0.219***	−0.283**
			(0.057)	(0.047)			(0.073)	(0.088)
Temperature (lag)	–	–	0.049*	−0.151***	–	–	−0.039	−0.283***
			(0.026)	(0.057)			(0.027)	(0.099)
Cereal prod. index	–	–	–	–	0.001**	0.001**	0.001**	0.001**
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
Meat prod. index	–	–	–	–	−0.006***	−0.007***	−0.006***	−0.007***
					(0.002)	(0.003)	(0.002)	(0.002)
DV (lag)	0.182**	0.186**	0.210**	0.215**	0.415***	0.418***	0.418***	0.421***
	(0.080)	(0.080)	(0.090)	(0.090)	(0.073)	(0.074)	(0.077)	(0.077)
Conflict (spatial)	0.182**	0.186**	0.345***	0.456***	0.104***	0.162***	0.108**	0.179***
	(0.080)	(0.080)	(0.091)	(0.117)	(0.042)	(0.006)	(0.046)	(0.060)
Population[1]	−0.675***	−2.360***	−1.031***	−2.488***	−0.490***	−2.122***	−0.718***	−1.611***
	(0.211)	(0.714)	(0.279)	(0.718)	(0.198)	(0.793)	(0.245)	(0.582)
Democracy	−0.022**	0.010	−0.034***	0.007	−0.036*	−0.019	−0.043**	−0.016
	(0.011)	(0.012)	(0.011)	(0.013)	(0.019)	(0.016)	(0.021)	(0.016)
GDP per capita[1]	−0.033	−0.312	−0.087	−0.285	0.847***	1.931***	0.829***	2.183***
	(0.165)	(0.237)	(0.194)	(0.240)	(0.285)	(0.665)	(0.281)	(0.714)
Obs.	67,755	67,755	66,007	66,007	35,936	35,936	34,254	34,254
End. variables	10.09***	10.34***	9.951***	10.89***	6.714***	6.157**	7.031***	6.934***
WI F-stat. (CSEs)	6.269	6.665	5.364	7.656	6.015	3.664	3.912	3.871
WI F-stat. (ISEs)	24.019	11.40	18.89	13.54	22.48	6.908	13.528	8.109
R^2	0.396	0.323	0.327	0.283	0.593	0.534	0.575	0.547
Adj. R^2	0.333	0.253	0.256	0.207	0.552	0.488	0.532	0.501

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*. Superscript [1] indicates a natural log.

results are the opposite. Interestingly, in both models 19 and 20, country-level food production indexes exhibit the same relationship: cereal production has a positive and significant relationship with conflict frequency, while meat production is negative and significant. This suggests that future research should focus not necessarily on whether scarcity vs. abundance drives conflict, but rather on the distinct relationships exhibited by different food resource types with respect to conflict.

Seventh, to address the concern that rebel groups might be more dependent on locally-grown food than official state forces, model 21 in table 8 re-estimates the full specifications, where the dependent variable includes only conflicts waged by official state forces. In these models, the dependent variable (and its lag) were operationalized as the annual number of all conflict events—with and without fatalities—that involved official military forces in a given grid cell. The results are robust to this choice of DV, suggesting that—as previous research (e.g., Koren and Bagozzi 2016) shows—abundance has a noticeable impact even on regular state forces, which are generally considered better organized and well-supported.

Eighth, note that my sample includes a relatively large number of cells with zero values or missing information, which might affect the results. To address these concerns, I first re-estimate the full models on two subsamples that include only grid cells where some wheat or maize, respectively, are grown in model 22. I then repeat this analysis on a subsample that includes only grid cells that experienced conflict at some point during the 1998-2008 period in model 23. As can be observed in both sets of analyses, the coefficients of *wheat yield* and *maize yield* maintain their sign, size, and significance, suggesting that the findings are not driven by a high number of zero values or missing information on conflict events.

Ninth, considering that some studies suggest larger countries are also more likely to suffer from protracted conflict (e.g., Fearon and Laitin 2003), Model 24 re-estimates the full specifications on a sample consisting solely of countries whose geographic size is below the 75% percentile of all African countries. Again, the coefficients of *wheat yield* and *maize yield* maintain their sign, size, and significance, suggesting that the main analysis results are not driven by the inclusion of large countries in the sample.

Table 9 accounts for possible biases that might be caused by the distribution of the dependent variable or the choice of the unit of analysis. To this end, model 25 re-estimates the full specification using a logged version of the dependent variable (and its lag) to verify that the effect of *wheat yield* and *maize yield* is not driven by the range of values on *conflict* ($0 \Longleftrightarrow 344$ annual incidents). Model 26 then re-estimates the full specification on a sample where the top 1% of all values (including zero values, to make this sensitivity test even more robust) on *wheat yield* and *maize yield* was removed from each model, respectively, to account for the effect of outliers (see also figure A.8 in the online supplementary appendix).

Next, considering that political violence measured at the 0.5 ° x 0.5 ° fine-scale level might exhibit higher levels of spatial and serial correlations besides the regressors in equations 1 and 2, model 27 re-estimates the full IV models, where standard errors are clustered at the higher, province level of aggregation. Additionally, to account for both observed and unobserved annual country-level factors, model 28 re-estimates the full model with the inclusion of country $\times$ year fixed effects. Note that this procedure is very likely to generate type II errors, and indeed, the model issues a warning that the resulting standard errors are likely to be inflated, which did not happen with any of the other (numerous) models reported in the article and online supplementary appendix. Nevertheless, the results are robust to the inclusion of country $\times$ year fixed effects in the maize model, although the wheat model drops out of significance ($p = 0.17$).

Finally, recall that the *drought* variable used to instrument food productivity is an ordinal measure of different degrees of drought severity. To illustrate that the effect of drought as an instrument for local food yield is robust to more penalizing thresholds of negative rainfall shocks, several alternative binary IVs are used to instrument the average LATE of *wheat yield* and *maize yield* on *conflict* in table 10 below.

The first alternative instrument used in model 29, *any drought*, is a binary variable operationalized as grid cell years that experienced drought levels of 1 or more standard deviations below average precipitation level, and zero otherwise. The instrument used in model 30, *severe drought*, is a binary variable operationalized as grid-cell years

Table 8. IV Regression Models for Total Number of Conflict Events per Grid Cell, Additional Robustness Models (continued)

Variable	21) Military Conflict		22) Planted Cells		23) Conflict Cells		24) No Large Count.	
	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield
Wheat yield	62.15***	–	77.42***	–	226.55***	–	87.81***	–
	(20.38)		(26.22)		(77.31)		(26.19)	
Maize yield	–	152.44***	–	191.52***	–	643.08***	–	223.02***
		(49.09)		(59.56)		(227.85)		(63.93)
DV (lag)	0.090	0.091	0.204**	0.207**	0.197**	0.213**	0.177	0.183**
	(0.073)	(0.074)	(0.100)	(0.089)	(0.085)	(0.085)	(0.088)	(0.089)
Conflict (spatial)	0.297***	0.366***	0.383***	0.435***	0.351***	0.643***	0.492***	0.729***
	(0.076)	(0.096)	(0.114)	(0.114)	(0.110)	(0.193)	(0.128)	(0.185)
Population[1]	−0.689***	−2.093***	−0.991***	−2.665***	−4.422***	−13.84***	−1.044**	−3.354***
	(0.193)	(0.631)	(0.302)	(0.802)	(1.299)	(4.388)	(0.270)	(0.903)
Democracy	−0.015**	0.014	−0.042***	0.006	−0.085***	0.020	−0.078***	−0.052
	(0.007)	(0.010)	(0.014)	(0.012)	(0.029)	(0.042)	(0.025)	(0.905)
GDP per capita[1]	−0.099	−0.314	−0.445*	−0.459*	−0.291	−1.132	−0.005	0.241
	(0.161)	(0.218)	(0.256)	(0.263)	(0.549)	(0.888)	(0.213)	(0.227)
Obs.	68,160	68,160	50,461	65,367	19,450	19,450	47,613	47,613
End. variables	9.303***	9.644***	8.722***	10.34***	8.587***	7.966***	11.24***	12.17***
WI F-stat. (CSEs)	8.372	8.943	8.300	9.430	3.963	2.963	7.920	10.29
WI F-stat. (ISEs)	31.84	15.23	29.61	16.17	7.961	5.532	29.63	19.45
R^2	0.170	0.069	0.353	0.280	0.083	−0.077	0.310	0.252
Adj. R^2	0.084	−0.028	0.285	0.206	−0.014	−0.190	0.240	0.177

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*. Superscript [1] indicates natural log; [2] indicates this variable is only available for the years 1998–2007.

Table 9. IV Regression Models for Total Number of Conflict Events per Grid Cell, Additional Robustness Models (continued)

Variable	25) Logged DV		26) Outliers Removed		27) Province SEs†		28) Count. × Year Fes‡	
	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield
Wheat yield	4.239**	–	187.17***	–	83.53**	–	423.41	–
	(1.861)		(57.68)		(36.76)		(314.47)	
Maize yield	–	10.37**	–	249.13***	–	204.74**	–	96.45**
		(4.476)		(77.28)		(94.83)		(46.45)
DV (lag)	0.659***	0.662***	0.203**	0.209**	0.201**	0.206**	0.204***	0.207***
	(0.012)	(0.012)	(0.085)	(0.085)	(0.084)	(0.084)	(0.066)	(0.243)
Conflict (spatial)	0.015**	0.019***	0.349***	0.449***	0.343***	0.436***	0.188**	0.228***
	(0.007)	(0.007)	(0.088)	(0.114)	(0.105)	(0.144)	(0.082)	(0.068)
Population[1]	−0.101***	−0.196***	−0.774***	−2.758***	−0.877***	−2.762**	0.636	0.505**
	(0.018)	(0.052)	(0.226)	(0.798)	(0.332)	(1.078)	(0.413)	(0.243)
Democracy	−0.005***	−0.003***	−0.039***	0.010	−0.032**	0.007	–	–
	(0.001)	(0.001)	(0.012)	(0.013)	(0.013)	(0.021)		
GDP per capita[1]	0.012	−0.003	−0.115	−0.612**	−0.048	−0.336	–	–
	(0.013)	(0.017)	(0.191)	(0.305)	(0.300)	(0.406)		
Obs.	68,160	68,160	67,439	67,453	68,160	68,160	70,937	70,937
End. variables	5.186**	5.365**	10.53***	10.39**	5.163**	4.661**	1.813	4.319**
WI F-stat. (CSEs)	8.361	8.979	9.611	9.583	1.951	1.342	0.756	19.20
WI F-stat. (ISEs)	31.81	15.31	30.09	16.08	31.84	15.26	1.034	29.26
R^2	0.661	0.647	0.345	0.276	0.351	0.264	0.114	0.510
Adj. R^2	0.626	0.610	0.276	0.200	0.284	0.187	0.013	0.454

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses unless noted otherwise. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*. † indicates that standard errors are clustered by province/state in parentheses; ‡ is a model warning: standard errors may be too high; superscript [1] indicates a natural log.

Table 10. IV Regression Models for Total Number of Conflict Events per Grid Cell, Additional Robustness Models, Alternative Drought Thresholds

Variable	29) Low Threshold†		30) Medium Threshold‡		31) High Threshold§	
	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield	Wheat Yield	Maize Yield
Wheat yield	78.66***	–	82.06***	–	92.64***	–
	(23.65)		(28.52)		(31.32)	
Maize yield	–	208.01***	–	198.67***	–	203.38***
		(60.95)		(67.27)		(68.54)
DV (lag)	0.201**	0.206**	0.201**	0.206**	0.201**	0.206**
	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
Conflict (spatial)	0.343***	0.438***	0.343***	0.433***	0.343***	0.435***
	(0.086)	(0.109)	(0.087)	(0.111)	(0.087)	(0.112)
Population[1]	−0.865***	−2.796***	−0.873***	−2.700***	−0.873***	−2.749***
	(0.233)	(0.776)	(0.240)	(0.836)	(0.240)	(0.855)
Democracy	−0.032***	0.008	−0.032***	0.006	−0.032***	0.007
	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)
GDP per capita[1]	−0.044	−0.322	−0.047	−0.326	−0.047	−0.334
	(0.180)	(0.245)	(0.181)	(0.249)	(0.181)	(0.250)
Obs.	68,160	68,160	68,160	68,160	68,160	68,160
End. variables	11.06***	11.65***	8.279***	8.724***	8.750***	8.805***
WI F-stat. (CSEs)	8.300	8.778	5.692	6.668	7.533	7.601
WI F-stat. (ISEs)	35.23	14.50	22.32	10.97	20.43	12.21
R^2	0.360	0.259	0.354	0.274	0.334	0.266
Adj. R^2	0.293	0.182	0.287	0.198	0.264	0.190

Note: Asterisk * indicates $p < 0.1$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$ (two-tail test). Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. † indicates that the variables *wheat yield* and *maize yield* were instrumented using *any drought*; ‡ indicates that the variables *wheat yield* and *maize yield* were instrumented using *severe drought*; § indicates that the variables *wheat yield* and *maize yield* were instrumented using *extreme drought*. Superscript [1] indicates a natural log.

that experienced drought levels of 1.5 or more standard deviations below average precipitation level, and zero otherwise. The instrument used in model 31, *extreme drought*, is a binary variable operationalized as grid-cell years that experienced the worst drought levels of 2.5 standard deviations below average precipitation level, and zero otherwise. The sign, size, and significance of each local food yield's coefficient remains practically unchanged, even when droughts are operationalized using these different negative rainfall shock thresholds.

Discussion and Conclusion

The results presented in this article suggest that agricultural regions experience relatively high levels of violent conflict that are, to a large extent, driven by the type and amount of food resources produced there. By exploiting exogenous negative local variations in rainfall that generate local decreases in staple crop yields, this analysis advances knowledge on an important cause of violence: conflict frequency in Africa responds to positive local changes in crop productivity. These findings diverge from the current conceptualizations of this relationship in mainstream literature, which frequently attributes conflict to sudden food shortages (e.g., Burke et al. 2009; Maystadt and Ecker 2014). This article has theorized and shown that scarcity-based explanations are insufficient in explaining localized conflict over food resources, their potential validity notwithstanding.

This, of course, does not mean that prolonged heat waves or lower yields do not impact conflict. Indeed, it might be that the findings here complement previous studies that focus on the country level (e.g., Burke et al. 2009); conflict in areas with higher yields might be more frequent in countries that are more vulnerable to climate-induced scarcities. Moreover, as shown in table 7, different types of food resources might have diverging impacts on the probability of conflict.

Another explanation for the present analysis' findings is the possibility that different aspects of production are associated with distinct types of conflict. Models 16 (table 6) and

21 (table 8) include alternative conceptualizations of conflict, but it is possible that patterns of violence might vary according to the focus on inputs or outputs of production. McGuirk and Burke (2017), for instance, identify lower incidence of “factor conflict” (i.e., over raw inputs) within food-producing cells with higher prices, as armed groups benefit more from harvesting crops than waging violence. However, higher prices can concurrently generate “output conflicts,” as the benefits of using violence to secure food surplus outweigh decreasing wages within these areas (McGuirk and Burke 2017). While the earlier finding (regarding “factor conflict”) is in line with research into how scarcity impacts armed conflict, the latter seems to confirm, at least to some extent, the present analysis.[9]

Future research might thus benefit from analyzing in more detail how these effects vary across different resource types, how the interactions between food abundance and climatic shocks impact conflict, and the degree and extent to which these relationships vary between different levels of analysis, for example, the country and the district. A second direction would build on the approach used by scholars such as McGuirk and Burke (2017) and Fjelde (2015) and create localized (e.g., at the 0.5 ° grid cell) measures of food inputs and outputs. Such analysis would likely benefit from using time-varying measures of crop area and yield such as the ones used here, rather than by relying on satellite images that are constant for the year 2000, as is the case with much of the previous research.

Considering the potentially grim implications of food security for conflict and instability (FAO 2008), highlighting the peace-building challenges imposed by local food-related inequalities using a spatially disaggregated approach can be consequential. International and nongovernmental organizations can use this information to adapt field work to advance both food security and peace through developing local capacity and sustainability alongside traditional peace-building strategies. Hunger and conflict usually go hand-in-hand, but using concrete data about food productivity, the nature of the conflict, the actors, and the context can increase our understanding of how to prevent or mitigate conflict and its consequences.

[9] Interestingly, and similar to the *conflict* variable used in the present analysis, McGuirk and Burke (2017) use ACLED data to code output conflict, but rely on a different dataset to code factor conflict.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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