AJAE Appendix:

"Food Abundance and Violent Conflict in Africa"

Contents

Theoretical Background

Below I discuss the background, anecdotal evidence, and food-related vulnerabilities as they pertain to linkages between food abundance and conflict locally.

Anecdotal Evidence

Deficiencies in access to food have forced many contemporary armed actors to routinely live off the land in times of war and peace. During the Civil War in Sierra Leone, for instance, regular Sierra Leone Army (SLA) troops were paid not with money, but with bags of rice, a meager payment usually appropriated by generals located back in the capital, Freetown. This lack of support pushed the SLA to fight over areas with higher levels of food resources and to perpetrate atrocities against local populations in order to extract sustenance (Keen, 2005). The appropriation of food and the abuse of power by military officials was not unique to Sierra Leone, and very similar situation existed in other African countries such as Angola (Cilliers, 2000, 8-9). In some instances, leaders actively encouraged troops to commandeer such supplies from the population. In Zaire, for instance, Mobutu Sese Seko notoriously replied to his troops when the latter complained about not being paid their wages: "you have guns; you don't need a salary" (Stearns, 2011, 115).

The importance of securing food resources in face of unequal access is not the unique domain of groups that are part of the government vs. rebel logic. Indeed, ethnic and tribal militias and other irregular forces representing local communities and different ethnic groups might be even more likely to initiate conflict over food resources. As discussed below, these communities might be especially dependent on locally grown food resources, and hence more susceptible to the adverse effect of distributional differentials between the core and the periphery (Reardon and Taylor, 1996; Pitt, Rosenzweig and Hassan, 1990). This situation is especially likely in countries and regions where little or no protection of property rights by the government exists, which leads to the formation of these irregular militias (Koren and Bagozzi, 2017).

In the extant literature, conflict between rebel and irregular groups over food resources is usually attributed to competition over livestock, especially cattle. For instance, Rockmore (2012) finds that in Uganda, populations residing in areas of persistent conflict shift from large cattle herds and open grazing to small livestock that can be kept in closed compounds, as well as labor intensive and drought intensive crops.[1] Similar patterns appear in Colombia, where households reduce land allocated to perennial crops and increase production of seasonal crops and pasture in regions with an intense conflict (Arias, Londoño and Zambrano, 2017). As a result of similar dynamics, in the Horn of Africa states applied significant force to combat violent raiders, who attempt to steal food resources or secure access to fertile regions (Leff, 2009; Maystadt and Ecker, 2014). Even in relatively stable countries such as Ghana, competition between farmers and Fulani herders frequently leads to localized conflict (Tonah, 2006).

By attributing livestock and violence dynamics to competition over access to water resources, some studies have drawn links between environmental change, conflict, and food resource abundance (e.g., Butler and Gates, 2012; Adano et al., 2012).[2] For instance, in their analysis of conflict in Kenya and Ethiopia, Adano et al. find that "more conflicts and killings take place in wet season times of relative abundance, and less in dry season times of relative scarcity, when people reconcile their differences and cooperate" (2012, 77). Somewhat in line with this argument, Rowhani et al. find "that conflicts are more frequent in regions with more vegetation," presumably because vegetation increases the ease with which raiders can approach cattle pens unnoticed (2011, 221). These studies and their emphasis on abundance are thus in line with research into the positive impact of profitable natural resources on civil war and civilian victimization (e.g., Bannon and Collier, 2003). In other words, just like areas and countries with abundance of profitable resources such as diamonds or oil attract violence, so should be the case in areas with higher food available—these areas offer more of an especially valuable resource, which not only can be traded for profit, but is also necessary to guarantee survival.

These regional narratives, especially the analyses of Uganda (Rockmore, 2012) and Colombia (Arias, Londoño and Zambrano, 2017), highlight violence resulting not only from cattle raids, but also from food crop resources. Some additional examples include Angola (Cilliers, 2000), Sudan and Ethiopia (Leff, 2009), Somalia (Ahmed and Green, 1999), Sierra Leone (Keen, 2005), and Nigeria (Ofuoku, 2009). Forces initiating conflict in regions where food resources are abundant or moving into these areas in order to control these resources is therefore a modern-day affliction in many African, and other developing, countries and regions (Koren and Bagozzi, 2016). For summary purposes, the total conflict number of incidents, average wheat, and average maize yields by grid cell for all the countries analyzed for the temporal period of concern are reported in Table A.1.

Food Security Vulnerabilities

Constraints on food access are unlikely to lead to acute violence within advanced industrialized democracies due to the existence of safeguards to those in need and a high degree of infrastructure that can transfer more food when needed. However, in many developing African countries and regions, widespread limitations to food access can affect armed conflict. This is because such food insecurity-prone areas are likely to be characterized by three main attributes.[3] First, rural regions in many African countries have poor infrastructure, including an absence of paved roads and refrigeration, which have especially parlous implications in relation to food security (FAO, 2008). Individuals in these regions are therefore at a higher risk of having their immediate access to food impaired.

A second attribute of regions with a high risk of food insecurity is a relative lack of sophisticated agricultural technology, such as heavy machinery and efficient fertilizers (Barrett, 2010; Kastner et al., 2012). This technological gap is narrowing, but current technology is still limited, and the impact of inadequate farming technology is much more severe in underdeveloped regions (Barrett, 2010; Lybbert et al., 2007; Kastner et al., 2012). Without technological improvements, less food can be produced in these regions, and thus they are more prone to food shortages.

Lastly, rural regions in the developing world, and especially in Africa, are arguably most vulnerable to the negative impact of climatic variability on food accessibility (FAO, 2008; Reardon and Taylor, 1996). The weak infrastructure that characterizes many of these regions (e.g. dirt roads) is much more likely to be destroyed due to extreme climatic effects such as flood. For instance, a report by the Food and Agricultural Organization of the United Nations states that, "climate variables also have an impact on physical/human capital—such as roads, storage and marketing infrastructure, houses, productive assets, electricity grids, and human health—which indirectly changes the economic and socio-political factors that govern food access" (2008, 12).

Taking into account these three issues, people in many developing regions are forced to rely on food produced and sold locally and grown using relatively simple technology, which increases asymmetries in access to food, both between urban and rural areas (Pitt, Rosenzweig and Hassan, 1990), and—within rural areas—between commercial producers and smallholders (Jayne et al., 2003). Moreover, although numerous studies highlight the potentially salient effect of food imports on production (Bellemare, 2015; Hendrix and Haggard, 2015), food imports are less relevant to the daily diet of many individuals in these regions compared with foodstuff that are locally grown and sold (see, e.g, Barrett, 2010; Koren and Bagozzi, 2017). This places these individuals at a high risk of experiencing food insecurity (Barrett, 2010; Rowhani et al., 2011), especially from a distributional perspective (Reardon and Taylor, 1996; Pitt, Rosenzweig and Hassan, 1990).

Table A.1: Summaries of conflict events, average wheat, and average maize yields by grid cell, total values for all countries analyzed, 1998-2008

Country	Conflict events	Average wheat yield	Average maize yield	Country	Conflict events	Average wheat yield	Average maize yield
Cabo verde	0	0	0	Burundi	2,463	0.0423	0.4780
Sao Tome	0	0	0	Rwanda	230	0.0380	0.3720
Guinea-Bissau	147	0	0.0817	Somalia	3,397	0.0135	1.0068
Eq. Guinea	14	0	0.0241	Djibouti	24	0	0.0002
Gambia	56	0	0.0506	Ethiopia	794	3.0997	4.5400
Mali	82	0.0353	1.1529	Eritrea	343	0.1095	0.0841
Senegal	305	7.11E-05	0.4805	Angola	2,594	0.0106	3.2023
Benin	21	0.0001	2.5372	Mozambique	155	0.0103	5.9677
Mauritania	57	0.0019	0.0478	Zambia	420	0.0505	2.3872
Niger	190	0.0189	0.1412	Zimbabwe	3,599	0.1884	5.6793
Cote d'Ivoire	846	0	1.2375	Malawi	98	0.0258	6.4863
Guinea	356	0	1.0685	South Africa	757	3.8579	12.9092
Burkina Faso	103	1.91E-05	1.2364	Namibia	156	0.0076	0.1231
Liberia	775	0	0.0259	Lesotho	6	0.1118	0.6114
Sierra Leone	3,416	0	0.1278	Botswana	25	0.0075	0.2449
Ghana	66	0	2.8605	Swaziland	60	0.0008	0.1913
Togo	61	0	1.7980	Madagascar	210	0.0200	1.3267
Cameroon	107	0.0016	2.0153	Comoros	0	0	0
Nigeria	1,978	0.1621	12.6989	Mauritius	0	0	0
Gabon	23	1.65E-06	0.2436	Seychelles	0	0	0
Cen. Af. Rep.	319	0.0002	0.5243	Morocco	188	18.0346	1.6961
Chad	406	0.0080	0.6261	Algeria	1,348	16.8551	0.0116
Rep. Congo	196	9.21E-05	0.1506	Tunisia	47	5.3266	0
Dem. Rep. Con.	3,023	0.0304	7.3598	Libya	61	2.5095	0.0188
Uganda	3,255	0.0474	2.7439	Sudan	2,256	1.6689	0.3036
Kenya	2,095	0.4928	5.8295	Egypt	367	7.9396	5.7286
Tanzania	245	0.2256	8.4878				

Note: A value of "1" corresponds to a quantity that is equal to one 0.5 $\times$ 0.5 degree grid cell that is entirely (i.e., 100%) covered by maize or wheat producing cropland, respectively.

Detailed Discussion of Data and Variables from Robustness Analyses

The first sensitivity analysis reported in the main paper tests whether the main IV analyses results presented are driven by low development levels. Hence, a nighttime light emissions based indicator, *nighttime light*, is used to capture local economic development in a manner used in past research (see, e.g., Chen and Nordhaus, 2011; Koren and Sarbahi, Forthcoming; Elvidge et al., 2014), and was added to Model 13, Table 6. This variable measures the annual (calibrated) average of nighttime light emissions at the 0.5 degree grid cell resolution. It captures average visible (i.e., cloud free and stable) nighttime light emission obtained from the DMSP-OLS Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages).

Original DMSP data were collected by US Air Force Weather Agency, and processed by the NOAA's National Geophysical Data Center (see, e.g., Elvidge et al., 2014). While numerous nighttime light measures are available, the indicator I chose to employ for approximating localized development was calibrated using values from Elvidge et al. (2014) to account for differences between data from different satellites and sensor decay over time, making these measures especially useful for time-series analysis (Tollefsen et al., 2012). Values are standardized to be between zero and one, where one is the highest observed value in the entire time-series, and zero is the lowest for the years 1992-2012, and aggregated to the 0.5 degree grid cell level.

The second set of sensitivity models presented in Model 14, Table 6 in the main paper takes into account the role of natural resources as a potential confounder explaining the relationships between food yields and conflict. The variable *oil production* approximates annual oil production by country (in metric tones), starting in 1932. The variable *gas production* measures annual gas production by country (also in metric tones), starting in 1955. For 1970 to 2000, these data originally obtained from the World Bank's "Wealth of Nations" database, while 2000–2011 data are taken from the US Energy Information Administration website (Ross, 2011).

The robustness models reported in Model 15, Table 6 incorporate three additional variables to account for the impact of agricultural and food imports, as well as the impact of international aid on conflict more broadly. The first variable, *food imports*, measures the annual total share (in percents) of a given country's total food merchandise imports according to the World Bank (2015). The second variable *agricultural imports*, measures raw materials imports (excluding fuel, fertilizer, minerals, and ores), and again operationalized as the annual share of total imports during the same calendar year according to the World Bank (2015). Finally, the variable *aid* is operationalized as the annual net of repayments involving all official development assistance (ODA) and other official aid flows (in constant 2008 USD) provided to a given country (World Bank, 2015).

In Model 16, Table 6 incorporates an alternative dependent variable, *violent conflict*, as well as its one-year lag as a control. This variables was operationalized from the same ACLED Version 6 dataset (Raleigh et al., 2010), where only incidents that included at least one combatant or noncombatant fatality were counted. Like all other conflict variables used in the main and sensitivity analyses, this variable includes only recorded events whose geographic precision was the village—and not district, province, or country—level.

Model 17, Table 7 includes two additional independent variables. The first, *ethnic diversity*, is operationalized as a count of the number of politically relevant ethnic groups settled in a particular cell during a given year (Wucherpfennig et al., 2011). This indicator thus accounts for the number of distinct ethnic groups found within each individual cell, and control for the possibility that conflict was the result of preexisting inter-ethnic divisions. The second variable, *terr. change*, is a binary variable denoting a whole or part of a grid cell exchanged hands between different noncombatants during a fiven year (Raleigh et al., 2010). This variable accounts for some persistent enmities between different groups and the possibility that some armed actors might initiate conflict or move into these regions to recover territories previously lost.

Model 18, Table 7 two additional variables, *temperature* and *temperature (lag)*. This variables measure the average and lagged average annual temperature, respectively, in a given cell (in Celsius) (Fan and Van den Dool, 2008; Tollefsen et al., 2012) to account for the effect of heat waves on local scarcity, and correspondingly, conflict. Model 19, Table 7 adds two production index indicators to the model, capturing production levels of meat and cereals, respectively (FAO, 2016). The FAO indices of agricultural production show the relative level of the aggregate volume of agricultural production for each year in a given country (normalized per capita) in comparison with the base period 1999-2001. These two variables are based on the sum of price-weighted quantities of meat products and cereals, respectively, produced after deductions of quantities used as seed and feed (also weighted against the same base period). The resulting aggregate variables, *meat prod. index* and Cereal prod. index, thus capture disposable production for immediate or long-term consumption (i.e., not as seed or feed). Model 20, Table 7 then incorporates both temperature measures and both indexes.

Model 21, Table 8 reports a set of Full models where the dependent variable includes only conflicts waged by official state forces. The dependent variable, *military conflict*, as well as its one-year lag, was operationalized as the annual number of all conflict events in a given grid cell—with and without fatalities—that involved official military forces.

Additional Diagnostics and Summary Figures

This section provides a discussion of the IV's monotonicity and report some diagnostics on the direct and reduced-form impact of *drought* on food yields and the dependent variable.

Additional Discussion of the Instrumental Variable

Before proceeding to reduced-form regression estimates, it is worth discussing in more detail how the use of the IV *drought* combined with unit-of-analysis fixed effects tackles concerns related to unobserved heterogeneity, measurement error, and reverse causality. First, in addition to the two requirements from a valid IV—that it is exogenous to the dependent variable and that it is correlated with the endogenous explanatory variables, both of which have been discussed and analyzed both qualitatively and quantitatively in the main paper—one can add a third requirement; that the IV will have a monotonic effect on the dependent variable (Angrist and Pischke, 2009; Sovey and Green, 2011). The term "monotonic effect" refers to the notion that the instrument does not impact the instrumented endogenous variable differently in different locations, and does not produce a positive impact in some locations and a negative impact in others. If this requirement is satisfied, then the average LATE of food yields is weighted with respect to conflict throughout the entire sample.

This requirement highlights one advantage of using droughts as the instrument; as mentioned in the main article, drought ought to decrease yields everywhere in Africa, and not to cause decreases in some grid cells, but increases in others. The effect of drought on conflict through maize and wheat yields is thus monotonic, because in every year when drought effected conflict through food production in a given grid cell, it did so in the same way, with higher levels of drought translating to lower food crop yields, while the absence of drought causes higher yields. Moreover, while the use of rainfall shocks as an IV to approximate shocks to growth has been questioned by some due to its predictability (Sarsons, 2015), the annual variation in droughts—strong, negative shocks—is less predictable, and the use of annual fixed effects controls for increases in droughts that are time dependent. Last, recall that although it is plausible that conflict can affect food crop yields, a reverse causality between conflict and drought is quite implausible. Rather, the causal arrow most likely flows from droughts to conflict, a relationship that—as Table A.2 below shows—is significant (Angrist and Pischke, 2009).

Direct Effect of The Instrument on the Dependent Variable

The results of OLS models estimating the direct effect of the instrument *drought* on the frequency of conflict at the grid cell level are reported in Table A.2 to highlight its the validity as an instrument for wheat and maize yields in the primary analysis. This reduced-form analysis supports the decision to use 2SLS models by showing that the reduced-form relationship between the IV and the dependent variable is significant at the 1 percent level. This is evidence in favor of a causal relationship flowing from droughts to conflict, presumably via affecting food production (Angrist and Pischke, 2009, 87-89).

Table A.2: OLS regression models for impact of drought on conflict by grid cell, 1998-2008

Variable	**1D) Baseline**	**2D) Full**
Drought	-0.064***	-0.075***
	(0.019)	(0.021)
Conflict (lag)	–	0.202**
		(0.084)
Conflict (spatial)	–	0.335***
		(0.083)
Population[1]	–	-0.697***
		(0.196)
Democracy	–	-0.022**
		(0.010)
GDP per capita[1]	–	0.034
		(0.172)
Observations	72,213	68,160
R^2	0.454	0.430
Adjusted R^2	0.399	0.370

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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 included in each regression though not reported here.
[1] Natural log

First-Stage Regression Estimates

The first stage regression estimates of the 2SLS models from the main article are provided in Table A.3. As can be clearly observed, *drought* has a highly statistical effect (to the 1 percent levels) on both *wheat yield* and *maize yield*. Moreover, the R^2 values of all models are exceptionally high, with the (adjusted) R^2 of the Baseline models being higher than that of the Full models, suggesting that *drought* is an especially good fit for instrumenting food yields in Africa. Moreover, that effect of the instrument *drought* on both food yield indicators is significant to the 1% level. This latter fact is important because instruments with no observable correlation with the endogenous explanatory variable cannot be considered truly valid (Angrist and Pischke, 2009, 87-89).

Table A.3: IV regression models for total number of violent events per grid cell, 1998-2008 – first stage estimates

Variable	**Wheat Yield**		**Maize Yield**	
	1E) Baseline	**2E) Full**	**3E) Baseline**	**4E) Full**
Drought	-8.539e-04***	-8.966e-04***	-3.478e-04***	-3.658e-04***
	(1.205e-04)	(1.265e-04)	(4.848e-05)	(4.990e-05)
Conflict (lag)	–	6.456e-06	–	-1.998e-05*
		(1.197e-05)		(1.204e-05)
Conflict (spatial)	–	-1.043e-04	–	-4.947e-04***
		(2.444e-04)		(1.448e-04)
Population[1]	–	2.153e-03***	–	1.009e-02***
		(5.726e-04)		(1.067e-03)
Democracy	–	1.230e-04***	–	-1.418e-04***
		(1.099e-05)		(1.779e-05)
GDP per capita[1]	–	9.749e-04***	–	1.807e-03***
		(1.489e-04)		(4.081e-04)
Observations	72,169	68,160	72,169	68,160
R^2	0.959	0.958	0.972	0.972
Adjusted R^2	0.954	0.954	0.970	0.969

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Additional Summary Figures

As alluded to in the main paper, my preliminary efforts in exploring trends of social conflict leads me to examine variation in data on cell-level (i.e., local) conflict in Africa from the Armed Conflict Location and Event Dataset (Raleigh et al., 2010). To this end, four different conceptualizations of the ACLED data are presented in Figures A.1 – A.4 below. These four ACLED conceptualizations correspond to i) the main dependent variable, described in detail in the paper; ii) violent incidents only (i.e., incidents with one or more fatalities) reported in Table 10 in the main paper and discussed in more detail below; iii) a logged version of the dependent variable, described in more detail below; and iv) a conceptualization of the dependent variable that includes only events imitated by military forces, also described in more detail below. For each figure, all values of each variables are plotted on the left, and then again with zero counts removed on the right. Next, the maps showing averaged values by grid cell for i) *conflict*, ii) *wheat yield*, and ii) *maize yield* for the entire 1998-2008 period mentioned in the main paper are provided in Figures A.5 – A.7.

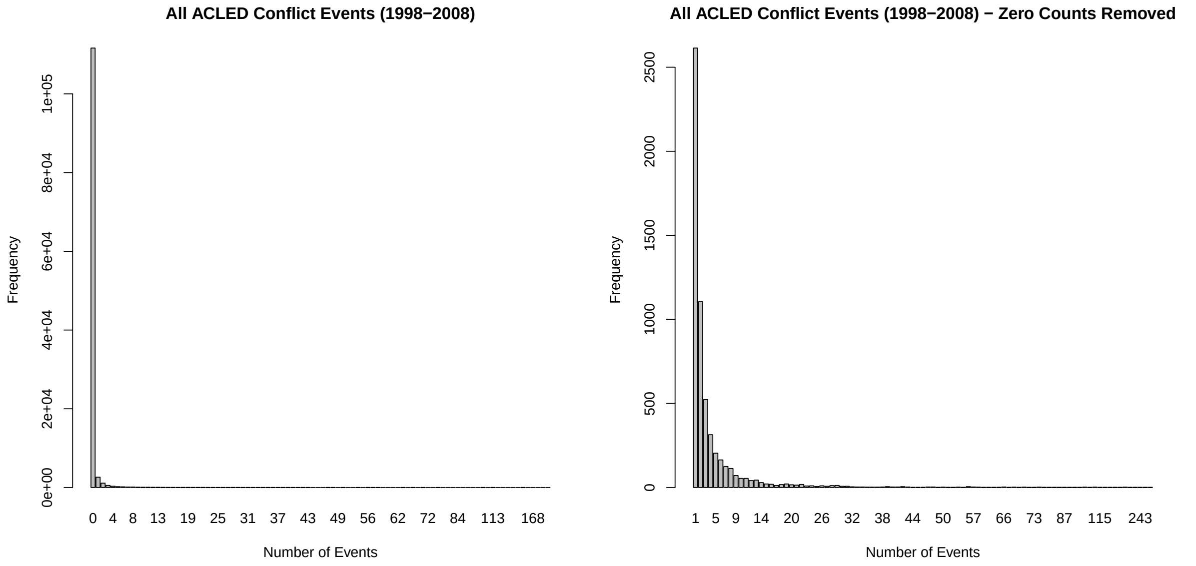

Figure A.1: Annual instances of conflict by grid-cell, 1998-2008

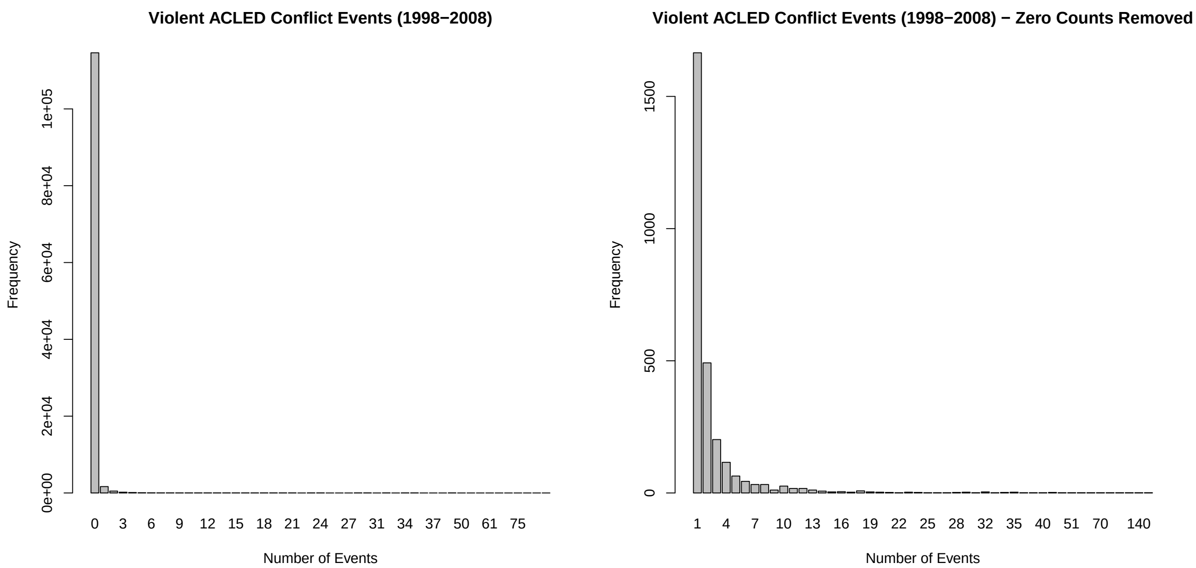

Figure A.2: Annual instances of violent conflict by grid-cell, 1998-2008

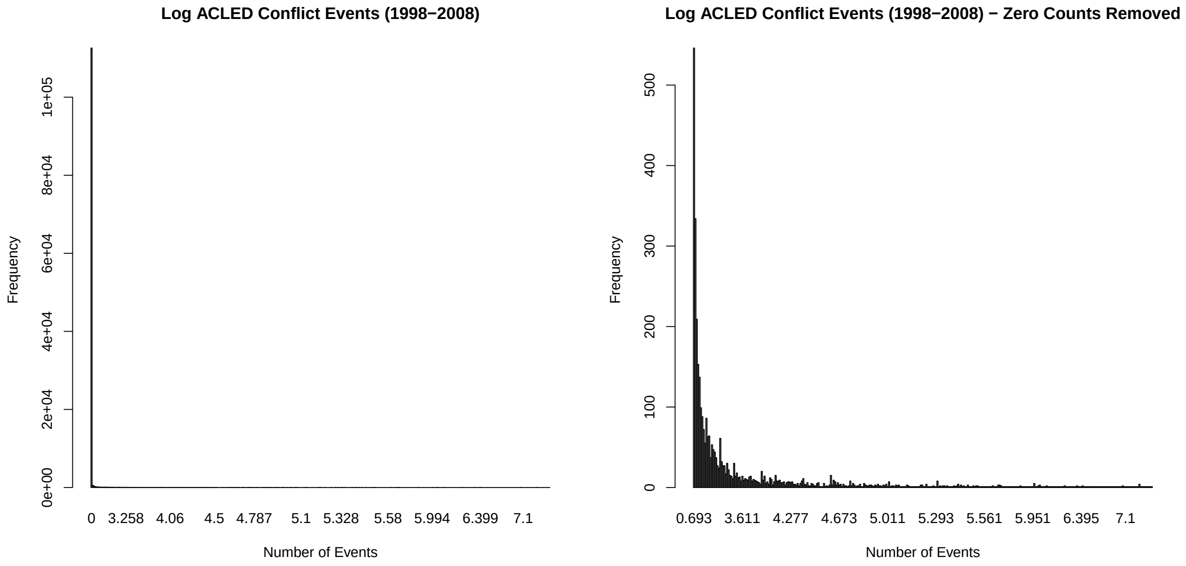

Figure A.3: Annual instances of conflict by grid-cell, 1998-2008 (natural log)

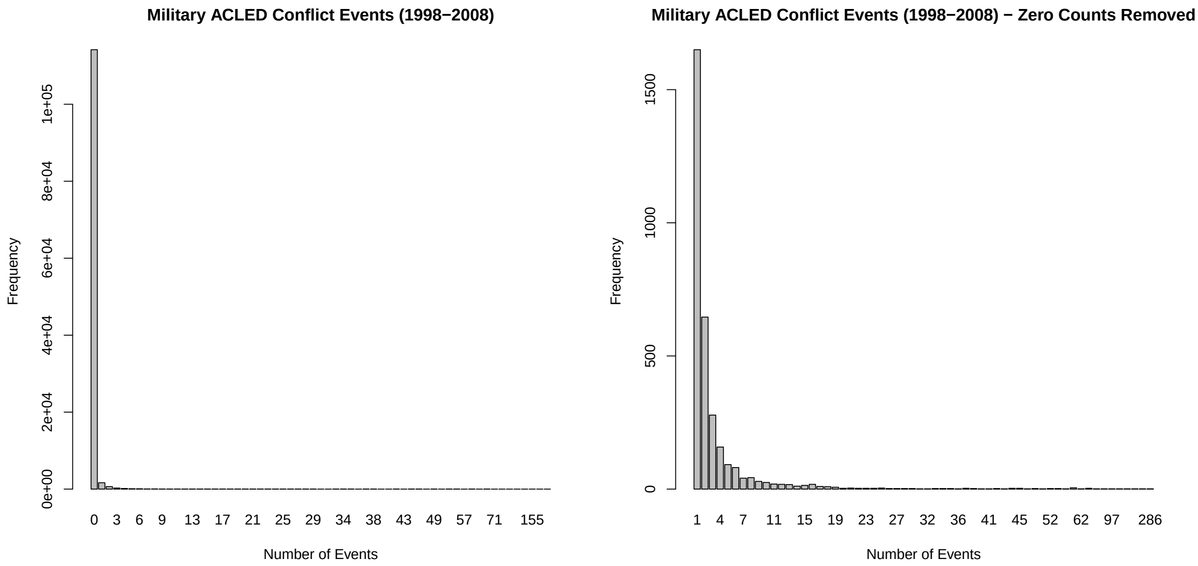

Figure A.4: Annual instances of military-initiated conflict by grid-cell, 1998-2008

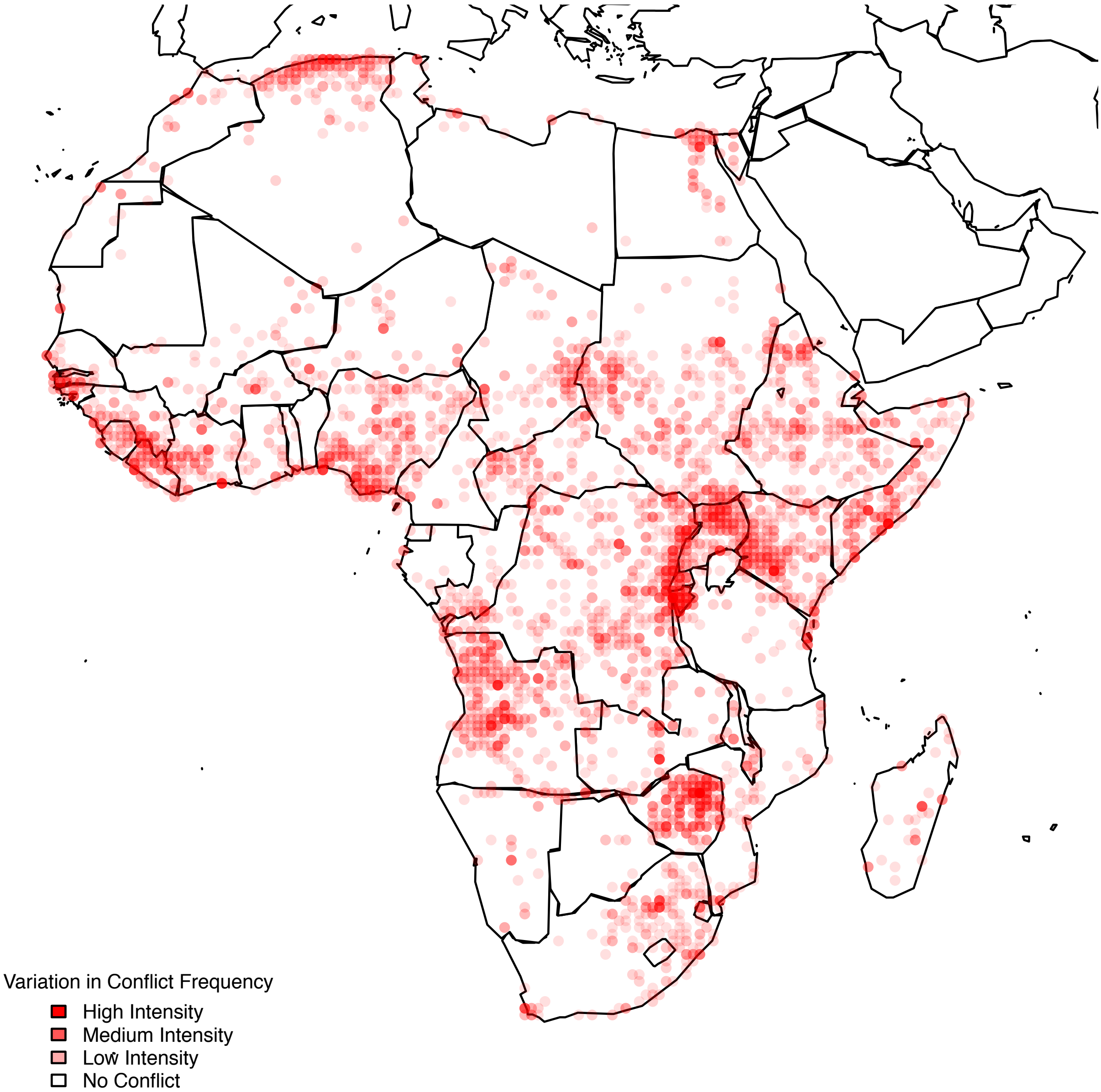

Figure A.5: Average levels of violent conflict from ACLED Version 6 dataset by 0.5 ∘ grids (Raleigh et al., 2010).

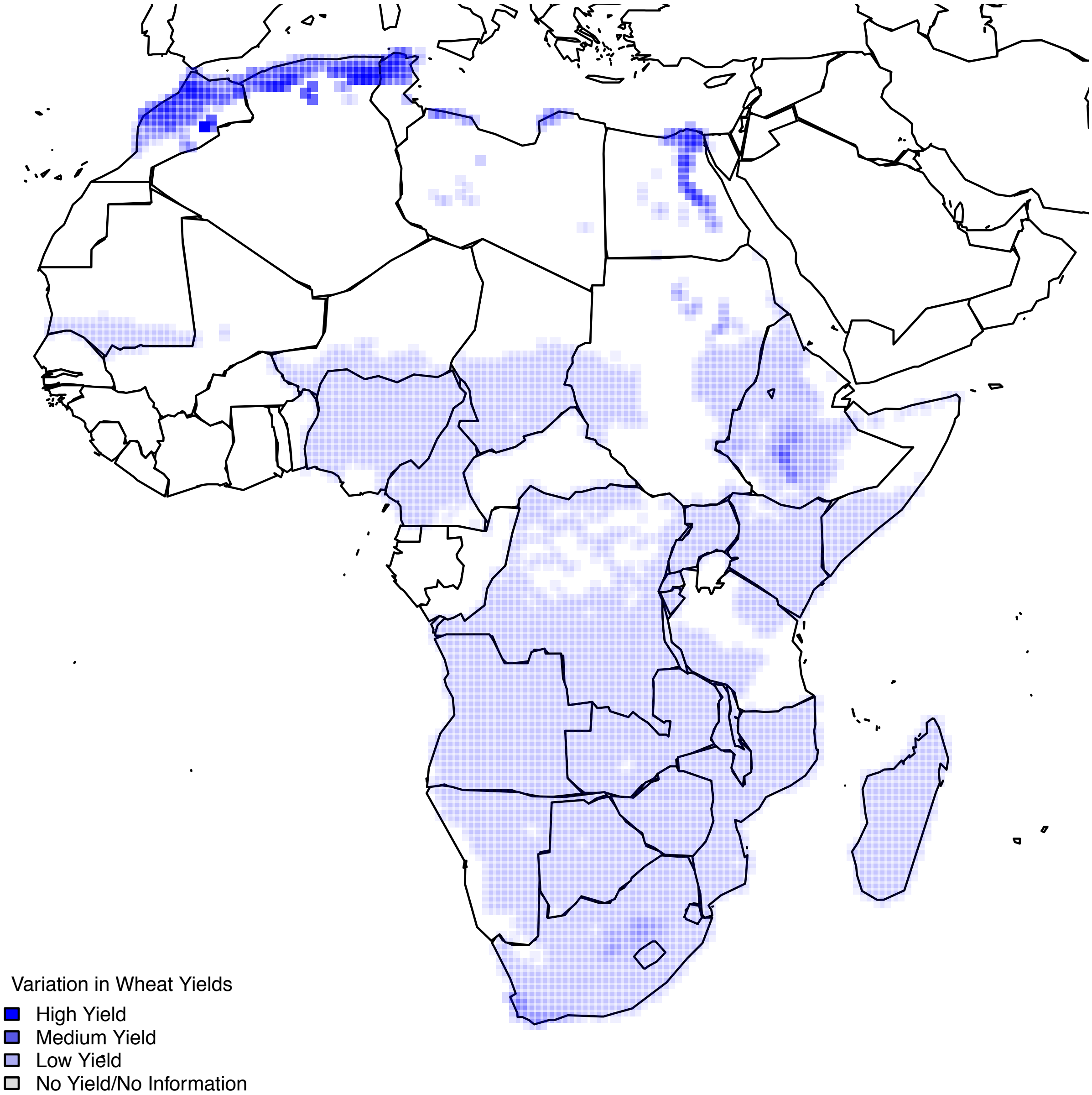

Figure A.6: Average wheat yields by 0.5 ○ grids (Ray et al., 2012).

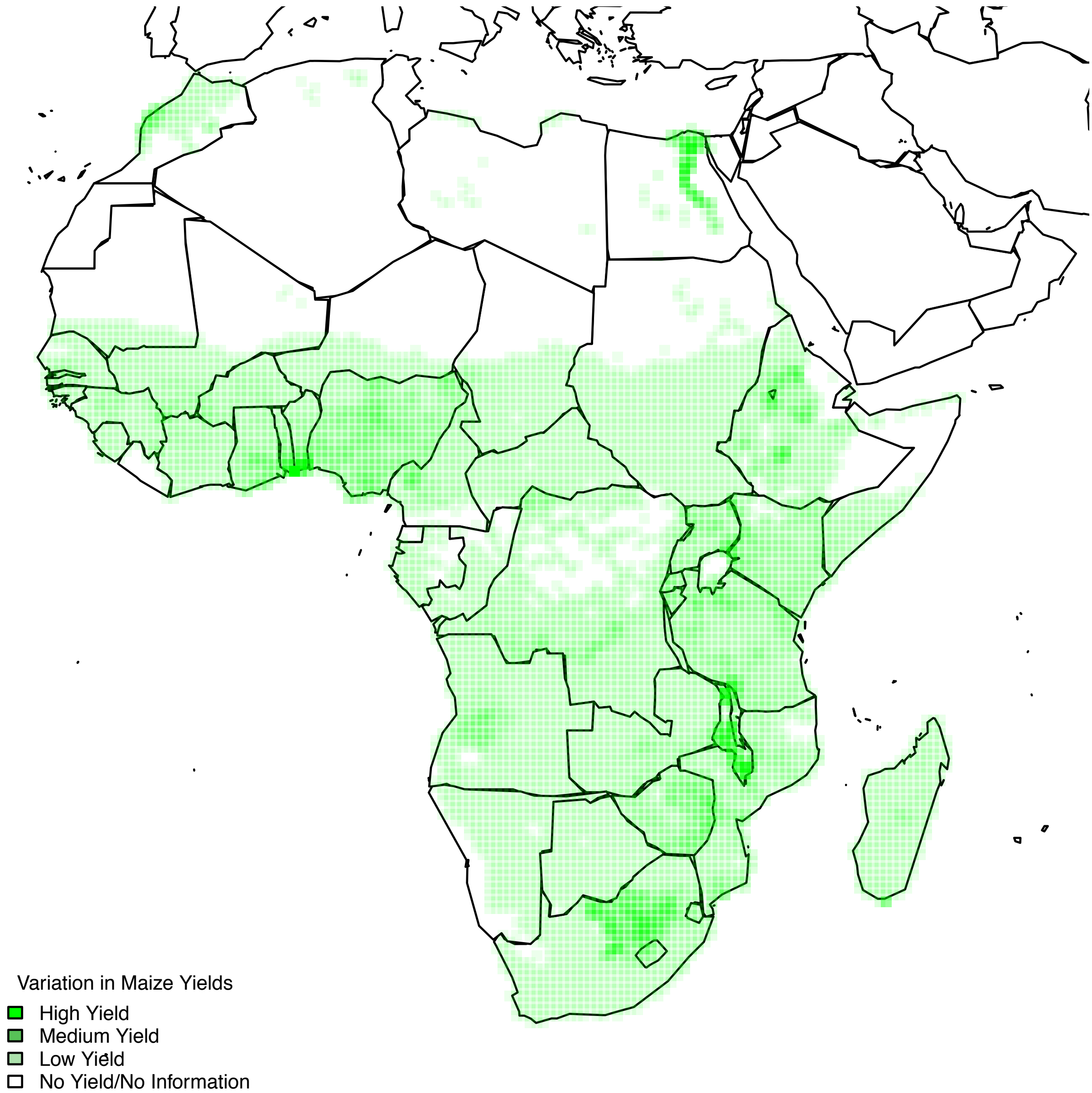

Figure A.7: Average maize yields by 0.5 ○ grids (Ray et al., 2012).

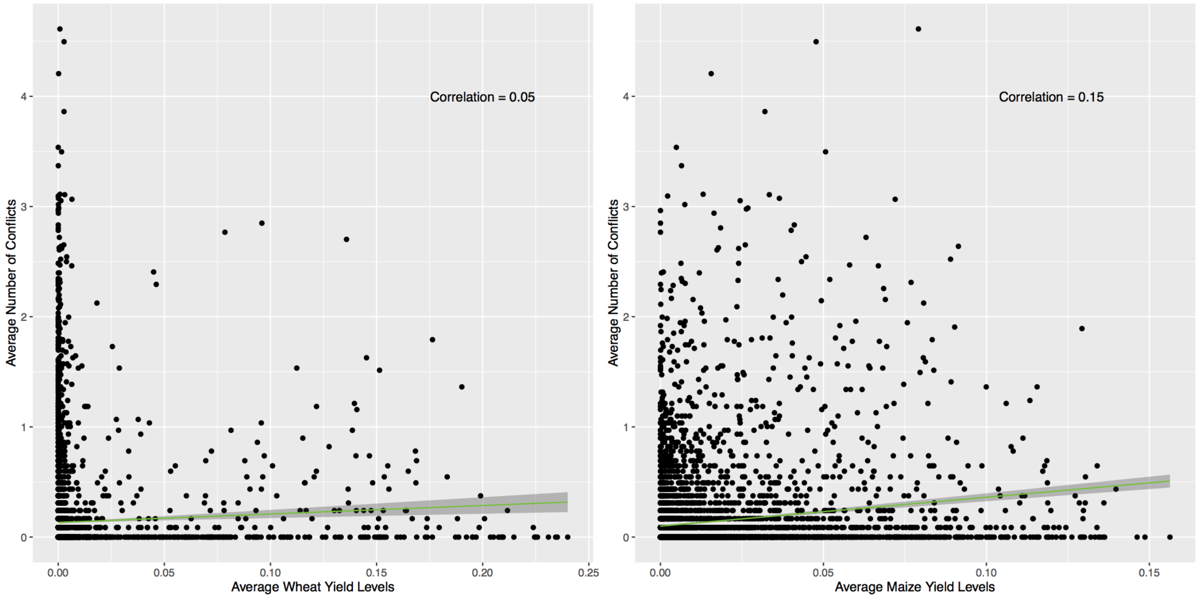

Figure A.8: The linear correlation between annual wheat (left) and maize yields (right) and conflict by 0.5 ○ grids, 1998-2008 with top one percent values for yields removed. Conflict measures are presented in natural log form.

Additional Robustness Analyses

Robustness Analysis: Collapsed Sample

Next, recall that the local-to-zero approximation tests reported in Table 4 in the main paper rely on a collapsed sample and a binary indicator of drought due to the prohibitive computational issues involved with estimating a set of plausible exogeniety simulations that includes fixed effects by grid cell. To show that the results of the main estimation hold in this collapsed sample, in Table A.4 a binary indicator of drought—operationalized according to the guidelines discussed in the main paper—is used to instrument the impact of *wheat yield* and *maize yield* on *conflict*. Table A.4 thus reports a set of models corresponding to the specifications presented in Table 4 in the main paper. As Models 32-37 clearly illustrate, the sign, statistical significance, and size of local food yields all hold even when the sample is average (and conflict events summed) for the entire 1998-2008 period.

Table A.4: IV regression models for total number of conflict events per grid cell, collapsed sample

Variable	**Wheat Yield**			**Maize Yield**		
	32) Baseline	**33) Add population**	**34) Full**	**35) Baseline**	**36) Add population**	**37) Full**
Wheat yield	255.53***	261.17***	150.19***	–	–	–
	(77.07)	(76.39)	(55.07)			
Maize yield	–	–	–	309.18***	312.11***	210.58***
				(90.75)	(88.90)	(78.62)
Population[1]	–	1.259***	-0.752***	–	0.541	-1.285**
		(0.318)	(0.367)		(0.461)	(0.573)
Conflict (spatial)	–	–	36.19***	–	–	35.37***
			(3.328)			(3.340)
Democracy	–	–	0.406***	–	–	-0.111
			(0.125)			(0.083)
GDP per capita[1]	–	–	-2.184**	–	–	-0.644*
			(0.815)			(0.336)
Constant	1.418***	-11.85***	20.22**	-1.251	-6.973*	13.65**
	(0.540)	(2.919)	(8.822)	(1.285)	(3.755)	(6.918)
Obs.	6,680	6,680	6,429	6,680	6,680	6,429
End. variables	10.99***	11.69***	7.437***	11.61***	12.33***	7.174***
WI F-stat. (CSEs)	31.29	22.303	9.404	31.34	25.56	7.284
WI F-stat. (ISEs)	19.28	11.12	5.931	23.95	19.59	5.581
R^2	-0.189	-0.191	0.063	-0.100	-0.101	0.069
Adj. R^2	-0.189	-0.192	0.062	-0.100	-0.1012	0.068

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Robustness Analysis: GMM Instruments

As reported in the main paper, some robustness analyses were moved to this online appendix due to space constraints. The first set of models, reported in Table A.5, replicate the GMM models presented in Table 5 in the main paper using different GMM instruments. Whereas Table 5 aimed to be as parsimonious as possible and rely only on the deep ($t-4$ and beyond) lags of the dependent variable, the models presented in Table A.5 rely on more recent lags, both temporal and spatial, to instrument the effect of food yields internally, in a manner commonly used in the literature (e.g., Arellano and Bond, 1991; Blundell and Bond, 1998; Roodman, 2009). As illustrated in Table A.5, the results presented in Table 5 are robust to the inclusion of more recent temporal and geospatial lags, although the level of potential engoeneity risk increases, as illustrated by the higher Sargan values (which, again, this can be explained by the information available for large number of panel units).

Table A.5: GMM IV regression models for total number of conflict events per grid cell, 1998-2008, recent conflict lags

Variable	**Wheat Yield**		**Maize Yield**	
	38) Baseline	**39) Full**	**40) Baseline**	**41) Full**
Wheat yield	0.586***	0.386**	–	–
	(0.163)	(0.152)		
Maize yield	–	–	1.901***	0.514*
			(0.475)	(0.310)
Conflict (lag)	0.451***	0.384***	0.451***	0.384***
	(0.018)	(0.028)	(0.018)	(0.024)
Conflict (spatial)	–	-0.187***	–	-0.175***
		(0.064)		(0.062)
Population[1]	–	0.029***	–	0.026***
		(0.003)		(0.003)
Democracy	–	0.001	–	-0.0004
		(0.001)		(0.001)
GDP per capita[1]	–	-0.031***	–	-0.028***
		(0.004)		(0.004)
Observations	72,169	68,160	72,169	68,160
Sargan test	924.72***	892.30***	933.25***	898.81***
DF	(117)	(119)	(117)	(119)
R^2	0.021	0.006	0.022	0.006

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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 $t-2$ and beyond lags of *conflict*, and the $t-1$ and beyond lags of *conflict (spatial)*.
[1] Natural log

Robustness Analysis: Lagged Yields

Next, recall that Model 18 reported in Table 7 in the main paper relies on the current and lagged value of local temperature levels to approximate the last year's scarcity effect on conflict in a given cell. To illustrate that the contradictory results across the wheat and maize yield models hold when the actual lagged effects of each crop are taken into account, Table **??** incorporates each crop's one-year-lag alongside its contemporary values. As Models 42-45 clearly illustrate, the sign, statistical significance, and size of local food yields at year t all hold when each crop's one-year-lag is included, while the effect of the latter is—similarly to *temperature (lag)*—positive in the wheat models, but negative in the maize ones.

Table A.6: IV regression models for total number of conflict events per grid cell, 1998-2008, lagged yields

Variable	**Wheat Yield**		**Maize Yield**	
	42) Baseline	**43) Full**	**44) Baseline**	**45) Full**
Wheat yield	66.53***	77.97***	–	–
	(22.24)	(24.19)		
Maize yield	–	–	372.06***	434.20***
			(126.21)	(140.80)
Wheat yield (lag)	12.34**	14.85***	–	–
	(5.043)	(5.564)		
Maize yield (lag)	–	–	-205.48***	-236.90***
			(66.69)	(75.14)
Conflict (lag)	–	0.201**	–	0.204**
		(0.084)		(0.084)
Conflict (spatial)	–	0.336***	–	0.479***
		(0.085)		(0.127)
Population[1]	–	-0.822***	–	-2.735***
		(0.226)		(0.850)
Democracy	–	-0.036***	–	0.008
		(0.011)		(0.013)
GDP per capita[1]	–	-0.044	–	-0.260
		(0.180)		(0.234)
Observations	71,189	66,007	71,189	66,007
Endogenous variables test	8.946***	10.39***	8.690***	9.509***
Weak instrument F-statistic (clustered SEs)	25.93	7.394	14.77	4.282
Weak instrument F-statistic (i.i.d. SEs)	118.18	33.18	15.24	4.287
R^2	0.424	0.364	0.211	-0.080
Adjusted R^2	0.365	0.298	0.129	-0.193

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Robustness Analysis: Sequential Addition of Controls

This section illustrates that the addition of each control variable reported in the Full model specifications does not effect to sign, size, or statistical significance of the results by sequentially adding each control. The estimates of these sequential analyses are presented in Table A.7 for *wheat yield* and A.8 for *maize yield*, and show that the results are consistent across all controls for both staple crops.

Table A.7: IV regression models for total number of conflict events per grid cell, controls added sequentially (wheat)

Variable	**Add conflict (lag)**	**Add conflict (spatial)**	**Add population**	**Add democracy**
Wheat yield	77.38***	71.95***	74.51***	75.21***
	(26.45)	(25.68)	(26.29)	(26.42)
Conflict (lag)	0.244***	0.242***	0.242***	0.242***
	(0.066)	(0.067)	(0.067)	(0.067)
Conflict (spatial)	–	0.308***	0.303***	0.296***
		(0.078)	(0.078)	(0.078)
Population[1]	–	–	-0.907***	-0.758***
			(0.242)	(0.225)
Democracy	–	–	–	-0.035***
				(0.011)
Observations	72,169	70,937	70,937	70,937
Endogenous variables test	8.560***	7.847***	8.034***	8.107***
Weak instrument F-statistic (clustered SEs)	25.11	16.80	12.52	9.987
Weak instrument F-statistic (i.i.d. SEs)	95.70	65.26	48.21	38.39
R^2	0.440	0.447	0.444	0.444
Adjusted R^2	0.383	0.389	0.386	0.386

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.
[1] Natural log

Table A.8: IV regression models for total number of conflict events per grid cell, controls added sequentially (maize)

Variable	**Add conflict (lag)**	**Add conflict (spatial)**	**Add population**	**Add democracy**
Maize yield	190.04***	175.08***	190.20***	190.20***
	(64.10)	(61.60)	(66.61)	(66.21)
Conflict (lag)	0.247***	0.244***	0.244***	0.244***
	(0.067)	(0.066)	(0.066)	(0.066)
Conflict (spatial)	–	0.398***	0.394***	0.394***
		(0.104)	(0.103)	(0.105)
Population[1]	–	–	-2.200***	-2.204***
			(0.677)	(0.704)
Democracy	–	–	–	0.001
				(0.013)
Observations	72,169	70,937	70,937	70,937
Endogenous variables test	8.789***	8.078***	8.153***	8.248***
Weak instrument F-statistic (clustered SEs)	25.73	17.70	11.98	9.750
Weak instrument F-statistic (i.i.d. SEs)	44.35	30.76	20.74	16.85
R^2	0.389	0.404	0.391	0.391
Adjusted R^2	0.327	0.342	0.323	0.328

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Robustness Analysis: Regional Bias

Finally, it is important to emphasize that the local importance of wheat and maize may very across different African regions, depending on availability and the importance different actors attribute to different types of staple crops. To illustrate that the main results are not driven by such regional biases, I repeat the main analyses presented in Table 3, main paper, by omitting each African sub-region from the sample at a time in Tables A.9–A.13. The guidelines of distinction between regions used in these analyses follows these used by previous studies (e.g., Burke et al., 2009). Western Africa includes Sao Tome and Principe, Guinea-Bissau, Equatorial Guinea, Gambia, Mali, Senegal, Benin, Mauritania, Niger, Ivory Coast, Guinea, Burkina Faso, Liberia, Sierra Leone, Ghana, Togo, Cameroon, Nigeria, and Gabon. Central Africa includes the Central African Republic, Chad, the Republic of Congo, and the Democratic Republic of the Congo. Eastern Africa includes Uganda, Kenya, Tanzania, Zanzibar, Burundi, Rwanda, Somalia, Djibouti, Ethiopia, and Eritrea. Northern Africa includes Morocco, Algeria, Tunisia, Libya, Sudan, South Sudan, and Egypt. Finally, southern Africa includes Angola, Mozambique, Zambia, Zimbabwe, Malawi, South Africa, Namibia, Lesotho, Botswana, Swaziland, Madagascar, Comoros, Mauritius, and Seychelles. As Tables A.9–A.13 clearly illustrate, the coefficients of *wheat yield* and *maize yield* maintain their sign, size (within one order of magnitude), and statistical significance, with the possible exception of the Baseline models in Table A.11 (eastern Africa removed), which are borderline significant (p=0.054 and p=0.053, respectively).

Table A.9: IV regression models for total number of conflict events per grid cell, western African countries removed

Variable	**Wheat Yield**		**Maize Yield**	
	42) Baseline	**43) Full**	**44) Baseline**	**45) Full**
Wheat yield	63.06***	72.66***	–	–
	(23.11)	(24.89)		
Maize yield	–	–	253.45***	278.86***
			(98.07)	(100.63)
Conflict (lag)	–	0.204**	–	0.210**
		(0.100)		(0.100)
Conflict (spatial)	–	0.369***	–	0.504***
		(0.111)		(0.152)
Population[1]	–	-1.033***	–	-4.176***
		(0.312)		(1.440)
Democracy	–	-0.035***	–	0.002
		(0.013)		(0.015)
GDP per capita[1]	–	-0.302	–	-1.193**
		(0.234)		(0.474)
Observations	55,856	51,847	55,856	51,847
Endogenous variables test	7.444***	8.520***	6.679***	7.679***
Weak instrument F-statistic (clustered SEs)	50.94	8.515	24.64	4.640
Weak instrument F-statistic (i.i.d. SEs)	178.17	29.71	37.87	7.213
R^2	0.427	0.360	0.311	0.147
Adjusted R^2	0.368	0.293	0.240	0.056

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Table A.10: IV regression models for total number of conflict events per grid cell, central African countries removed

Variable	**Wheat Yield**		**Maize Yield**	
	47) Baseline	**48) Full**	**49) Baseline**	**50) Full**
Wheat yield	85.18***	92.13***	–	–
	(24.53)	(27.04)		
Maize yield	–	–	172.51***	176.17***
			(47.32)	(48.73)
Conflict (lag)	–	0.183**	–	0.188**
		(0.088)		(0.089)
Conflict (spatial)	–	0.364***	–	0.454***
		(0.101)		(0.121)
Population[1]	–	-1.048***	–	-2.872***
		(0.258)		(0.739)
Democracy	–	-0.050***	–	-0.003
		(0.015)		(0.014)
GDP per capita[1]	–	-0.269	–	-0.242
		(0.246)		(0.266)
Observations	60,300	56,291	60,300	56,291
Endogenous variables test	12.06***	11.61***	13.29***	13.07***
Weak instrument F-statistic (clustered SEs)	49.45	7.941	69.93	12.99
Weak instrument F-statistic (i.i.d. SEs)	193.08	30.891	132.53	24.53
R^2	0.405	0.326	0.378	0.296
Adjusted R^2	0.344	0.255	0.314	0.222

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Table A.11: IV regression models for total number of conflict events per grid cell, eastern African countries removed

Variable	**Wheat Yield**		**Maize Yield**	
	51) Baseline	**52) Full**	**53) Baseline**	**54) Full**
Wheat yield	36.92*	50.44**	–	–
	(19.16)	(19.72)		
Maize yield	–	–	123.8*	171.20**
			(64.00)	(67.00)
Conflict (lag)	–	0.121*	–	0.127*
		(0.074)		(0.074)
Conflict (spatial)	–	0.406***	–	0.546***
		(0.095)		(0.144)
Population[1]	–	-0.641***	–	-2.220***
		(0.219)		(0.804)
Democracy	–	-0.009	–	0.020
		(0.008)		(0.014)
GDP per capita[1]	–	-0.251	–	-0.135
		(0.179)		(0.169)
Observations	61,886	60,373	61,886	60,373
Endogenous variables test	3.713*	6.540**	3.739*	6.536**
Weak instrument F-statistic (clustered SEs)	51.27	8.602	40.68	6.930
Weak instrument F-statistic (i.i.d. SEs)	198.85	33.00	74.18	12.576
R^2	0.413	0.245	0.382	0.162
Adjusted R^2	0.354	0.170	0.320	0.078

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Table A.12: IV regression models for total number of conflict events per grid cell, northern African countries removed

Variable	Wheat Yield		Maize Yield	
	55) Baseline	**56) Full**	**57) Baseline**	**58) Full**
Wheat yield	1,631.9***	1,982.8***	–	–
	(587.6)	(667.00)		
Maize yield	–	–	190.50***	207.41***
			(63.00)	(65.07)
Conflict (lag)	–	0.204**	–	0.196**
		(0.086)		(0.085)
Conflict (spatial)	–	0.328***	–	0.507***
		(0.096)		(0.129)
Population[1]	–	-1.615***	–	-2.410***
		(0.507)		(0.740)
Democracy	–	-0.055***	–	-0.002
		(0.015)		(0.001)
GDP per capita[1]	–	-0.260	–	-0.550*
		(0.231)		(0.300)
Observations	63,600	59,619	63,600	59,619
Endogenous variables test	7.713***	8.837***	9.144***	10.16**
Weak instrument F-statistic (clustered SEs)	25.07	5.008	46.36	8.320
Weak instrument F-statistic (i.i.d. SEs)	27.25	7.131	78.41	13.89
R^2	0.186	0.089	0.360	0.253
Adjusted R^2	0.102	-0.006	0.294	0.175

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Table A.13: IV regression models for total number of conflict events per grid cell, southern African countries removed

Variable	Wheat Yield		Maize Yield	
	59) Baseline	**60) Full**	**61) Baseline**	**62) Full**
Wheat yield	44.24***	36.87***	–	–
	(15.31)	(13.86)		
Maize yield	–	–	223.98***	187.87**
			(84.21)	(75.39)
Conflict (lag)	–	0.371***	–	0.374***
		(0.065)		(0.066)
Conflict (spatial)	–	0.141***	–	0.143***
		(0.040)		(0.046)
Population[1]	–	-1.084***	–	-1.276***
		(0.351)		(0.492)
Democracy	–	-0.034***	–	0.017
		(0.011)		(0.016)
GDP per capita[1]	–	0.751***	–	-0.051
		(0.173)		(0.299)
Observations	47,034	44,510	47,034	44,510
Endogenous variables test	8.353***	7.073***	7.074***	6.210**
Weak instrument F-statistic (clustered SEs)	45.30	7.748	22.01	3.802
Weak instrument F-statistic (i.i.d. SEs)	185.38	31.65	36.12	6.173
R^2	0.441	0.544	0.347	0.454
Adjusted R^2	0.383	0.495	0.280	0.396

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** 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*.

[1] Natural log

Notes

[1]See also Finnström (2003) for an anthropological perspective.

[2]Other studies, however, identify a negative relationship. For instance, Maystadt and Ecker (2014) associate droughts with more civil war in Somalia.

[3]The term "food insecurity" refers to situations where food security levels are dangerously low, and there are not enough food resources, due to either distributional or production shortages, to guarantee sufficient dietary intake for all individuals in the region (Barrett, 2010).

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