

Online appendix for

## **Living off the land: The connection between cropland, food security, and violence against civilians**

This supplemental appendix proceeds in five parts. In the section immediately below, we assess the variation in, and provide summary statistics for, our independent and control variables. Following this presentation, we report a set of negative binomial (NB), zero-inflated negative binomial (ZINB), zero-inflated Poisson (ZIP), and logistic model estimates that correspond to the robustness models mentioned in the main paper's Robustness Section. We then list the countries included in our ACLED Africa sample. The fourth section below describes the operationalizations of our cropland,  $\text{civil conflict}_{t-1}$ , and  $\text{violence}_t$  variables in detail. Finally, section five provides an expanded discussion of our theory in relation to (i) existing explanations for civil violence and (ii) food and violence more specifically.

# Summary statistics

Table A.I. Summary statistics for independent variables, 1997-2009

	Median	Mean	Std. dev.	Min	Max
Cropland	2.031	15.225	23.999	0	99.92
Civil conflict <sub>t-1</sub>	0	0.149	0.356	0	1
Ln population <sub>t-1</sub>	9.651	9.308	2.261	0	16.268
Ln travel time	6.129	6.188	0.853	0	8.722
Ln cell area	7.995	7.877	0.600	-1.890	8.039
Ln GCP <sub>t-1</sub>	0.070	0.255	0.471	0	4.455
Ln precipitation <sub>t-1</sub>	6.151	5.974	1.024	4.205	8.417
Drought <sub>t-1</sub>	0	0.273	0.711	0	2.5
Temperature <sub>t-1</sub>	24.575	24.280	3.761	2.625	32.617
Ln distance to border	4.913	4.682	1.137	0	7.574
Spatial lag of DV <sub>t-1</sub>	0	0.081	0.829	0	51.75
Polity <sub>t-1</sub>	-1	-0.279	5.261	-9	9
Polity <sub>t-1</sub> <sup>2</sup>	25	27.751	22.552	0	81
Ln military expenditure <sub>t-1</sub>	12.409	12.452	1.627	7.601	15.350
Ln GDP pc <sub>t-1</sub>	7.280	7.477	1.071	4.614	10.341
Territorial Change	0	0.007	0.082	0	1

Figure A.1. Annual instances of violence against civilians by grid-cell, 1997-2009

(a) All instances

(b) Non-zero instances

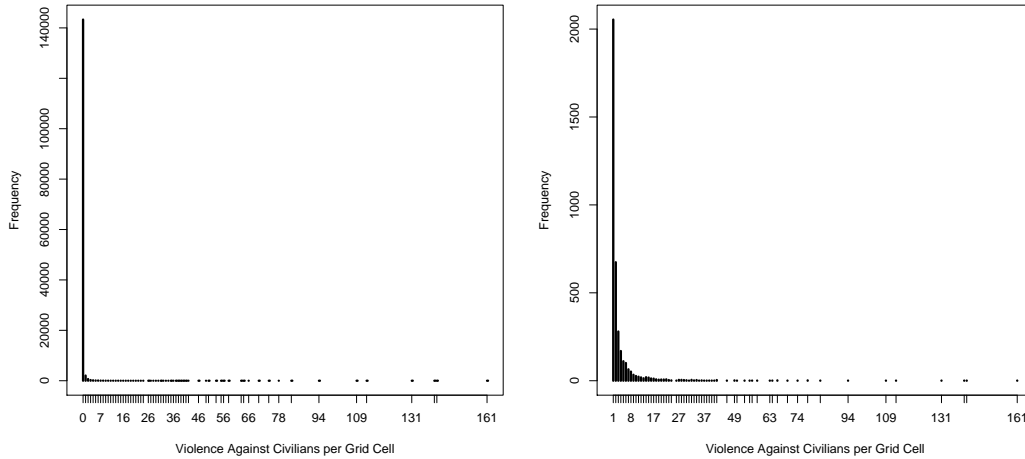
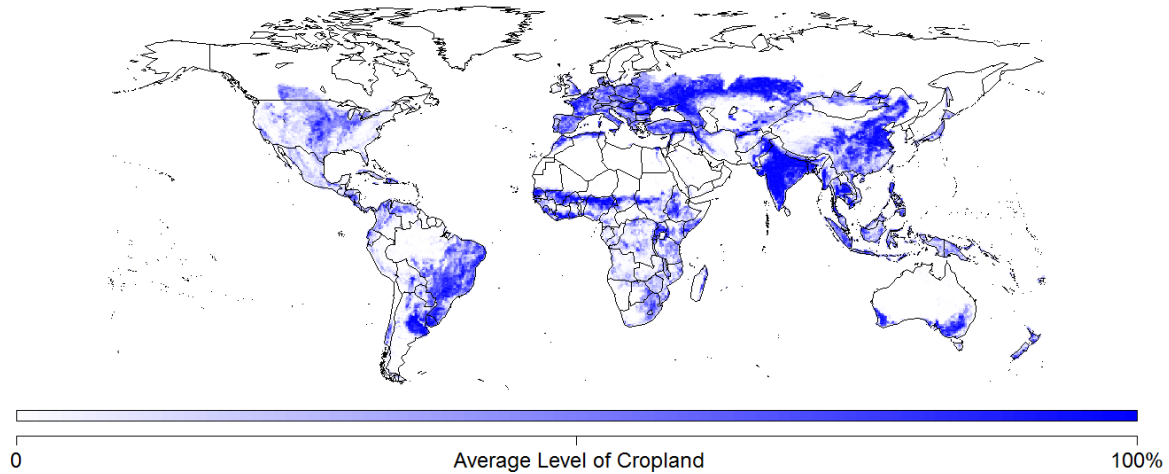
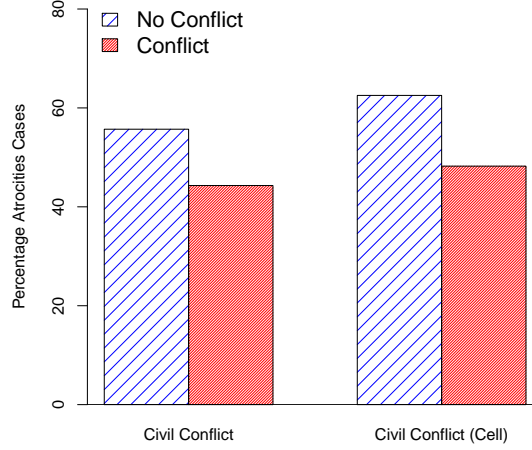


Figure A.2. Global variation in cropland measure



As alluded to in the introduction to the main paper, our preliminary efforts in exploring trends of violence against civilians both during and outside of civil conflict leads us to examine variation in data on cell-level (i.e., local) violence against civilians in Africa from the Armed Conflict Location and Event Dataset (ACLED Raleigh et al., 2010). The ACLED data are presented in Figure A.3 and described in detail in the main paper and further below. Figure A.3 presents the percentage of ACLED’s “violence against civilians” events across (i) African country-years classified as civil conflict or non-civil conflict cases and (ii) 0.5 x 0.5 decimal degree African grid-cell years classified as as civil conflict or non-civil conflict cases. As discussed in the main paper, “civil conflict” is measured and defined based upon the UCDP/PRIO Armed Conflict Dataset’s (ACD) 25-battle death threshold (Gleditsch et al., 2002). Most notably, Figure A.3 reveals that violence against civilians arise as often outside of contemporary African civil conflicts as they do within such conflicts.

Figure A.3. Variation in violence against civilians in Africa, 1997-2009



We next present a set of simple summary statistics for our primary dependent and independent variables (described in more detail in the main paper and further below) that together seek to assess our core theoretical contentions absent the control variables and modeling assumptions that we include within our primary analysis. For this set of comparison statistics, we subset our sample data to include either (i) only non-civil  $\text{conflict}_{t-1}$  grid-cells or (ii) only civil  $\text{conflict}_{t-1}$  grid-cells. We then calculate the proportions of (ACLED-derived)  $\text{violence}_t$  incidents (against civilians) that occurred *both* within *and* outside of cropland areas as based upon three relevant cropland thresholds: (1) classification of a cell as “cropland” if it included *any* percentage of cropland (2) classification of a cell as cropland if its land area was classified as least 15.225% cropland (i.e., the mean of our cropland variable) (3) classification of a cell as cropland if its land area was classified as at least 50% cropland. By comparing the relative proportions of  $\text{violence}_t$  occurring within and outside of each cropland condition separately for both civil  $\text{conflict}_{t-1}$  cells and non-civil  $\text{conflict}_{t-1}$  cells, we can gain a sense of whether the variation in these variables is suggestive of our broader theoretical arguments.

Turning to the first row of Table A.II, we find first that virtually all violence<sub>t</sub> incidents (> 99%) in Africa occur within cells that exhibit at least some degree of cropland. Even so, row one suggests that during times of civil conflict<sub>t-1</sub> a higher relative share of violence<sub>t</sub> occurs within croplands (99.50%) than in non-croplands (0.50%), when compared to times of peace (column two), where we observe that a slightly higher share of violence occurs outside of cropland areas (0.60%). These disparities become more pronounced as we increase our cropland threshold to more reasonable values. For example, row two in Table A.II indicates that again, while a majority of violence<sub>t</sub> incidents in Africa occur within cropland cells based upon our mean-cropland designation, a substantially higher relative share of violence<sub>t</sub> occurs within croplands (85.60%) than in non-croplands (14.40%) during times of civil conflict<sub>t-1</sub>, when compared to times of peace (with only 77.78% of violence<sub>t</sub> incidents occurring within croplands and the remaining 22.22% occurring in non-cropland areas). When we only consider cells with at least 50% area classified as cropland, we now find that violence<sub>t</sub> on the whole is more common in non-cropland locations. Nevertheless, cells classified as civil conflict<sub>t-1</sub> continue to see a far higher share of their incidents of violence<sub>t</sub> against civilians committed within croplands (42.06%) than do peace-designated cells (14.72%), which instead now see roughly 85% of all peace-time atrocities occurring in non-cropland areas. These descriptive statistics are thus consistent with our hypothesis, as well as with the count model findings discussed in the main paper.

Table A.II. Sample variation in violence<sub>t</sub> across (i) civil conflict and (ii) cropland

	<b>Civil conflict<sub>t-1</sub></b>	<b>No civil conflict<sub>t-1</sub></b>
> 0% Cropland threshold	99.50%	99.40%
≥ 15.225% Cropland threshold	85.60%	77.78%
≥ 50.00% Cropland threshold	42.06%	14.72%

Cell values are percentage of violence<sub>t</sub> incidents occurring within “croplands” among column designation cells.

## Robustness models

In this section, we present a range of robustness models for our primary violence<sub>*t*</sub> analysis, beginning first with a set of ZINB models that incrementally include larger sets of additional control variables. We present these additional control variables incrementally as several of these controls are not coded across all sample years under analysis and hence lead us to omit a moderate number of observations due to listwise deletion. The second robustness table below presents a host of alternate specifications of our large ZINB model, as described in the main paper. The third robustness table below re-estimates *all* four primary NB and ZINB specifications from our main paper when we replace our civil conflict<sub>*t-1*</sub> independent variable (and croplandXcivil conflict<sub>*t-1*</sub>) with a more temporally proximate civil conflict<sub>*t*</sub> measure. The fourth table reexamines our full results in light of several alternate approaches to controlling for changes in territorial control among the cells in our sample. We then present a table of results for violence<sub>*t*</sub> disaggregated by perpetrator identity, followed by a set of Bayesian random effects (full) ZINB models.

With respect to the expanded controls used below, ethnic diversity<sub>*t-1*</sub> is operationalized as a count of the number of politically relevant ethnic groups settled in a particular cell (Wucherpfennig et al., 2011; Tollefsen et al., 2012). GDP pc growth<sub>*t-1*</sub> is constructed from the national-level GDP pc measure described in the main paper (World Bank, 2012). Presence peacekeepers<sub>*t-1*</sub> is a binary indicator of whether peacekeeping forces were present in given country during the previous year, taken from Hultman, Kathman & Shannon (2013). Ln oil production<sub>*t-1*</sub> and ln gas production<sub>*t-1*</sub> are country-level measures taken from Ross (2013) and distance to capital is a cell-level measure obtained from (Tollefsen et al., 2012). Political terror scale<sub>*t-1*</sub> is the Amnesty International version of this country-level human rights score (Gibney, Cornett & Reed Wood, 2012), lagged by one year. Presence of informal militias (“Presence inf. militias”) is a binary indicator of whether or not a country was recorded as having an informal militia present within its territory in the previous calendar year by Carey, Mitchell & Lowe (2013), whereas violence<sub>*t-1*</sub> is a one year lag of the dependent variable.

Table A.III. Expanded controls robustness models

	Model 1	Model 2	Model 3	Model 4
<i>Count stage</i>				
Civil conflict <sub>t-1</sub>	-0.348 (0.187)	-0.373* (0.185)	-0.668** (0.180)	-0.308 (0.200)
Cropland	-0.008** (0.002)	-0.010** (0.002)	-0.008** (0.002)	-0.006* (0.002)
CroplandXcivil conflict <sub>t-1</sub>	0.015** (0.003)	0.017** (0.003)	0.014** (0.003)	0.013** (0.003)
Ln population <sub>t-1</sub>	0.208** (0.062)	0.225** (0.067)	0.284** (0.069)	0.206* (0.086)
Ln cell area	-0.939* (0.476)	-0.990* (0.427)	-1.212** (0.409)	-1.624** (0.599)
Ln GCP <sub>t-1</sub>	0.329** (0.112)	0.388** (0.114)	0.462** (0.118)	0.698** (0.138)
Ln travel time	-0.117 (0.146)	-0.180 (0.151)	-0.152 (0.157)	-0.071 (0.147)
Temperature <sub>t-1</sub>	0.011 (0.015)	-0.000 (0.015)	0.028 (0.015)	-0.013 (0.016)
Ln precipitation <sub>t-1</sub>	0.401** (0.086)	0.312** (0.085)	0.220* (0.087)	0.135 (0.101)
Drought <sub>t-1</sub>	-0.095* (0.045)	-0.080 (0.045)	-0.066 (0.044)	-0.157* (0.063)
Ln distance to border	-0.343** (0.046)	-0.308** (0.053)	-0.273** (0.061)	-0.275** (0.041)
Spatial lag DV <sub>t-1</sub>	0.257** (0.051)	0.247** (0.048)	0.200** (0.045)	0.069* (0.032)
Ln GDP pc <sub>t-1</sub>	-0.182* (0.083)	0.093 (0.093)	0.591** (0.113)	0.349* (0.152)
Polity <sub>t-1</sub>	-0.031* (0.012)	-0.033** (0.013)	0.004 (0.013)	-0.085** (0.026)
Polity <sub>t-1</sub> <sup>2</sup>	0.003 (0.002)	0.002 (0.002)	-0.003 (0.002)	-0.008* (0.004)
Ln military expenditure <sub>t-1</sub>	0.126* (0.050)	0.039 (0.053)	-0.039 (0.059)	-0.400** (0.067)
Territorial change	1.849** (0.115)	1.846** (0.110)	1.861** (0.120)	1.964** (0.160)
Ethnic diversity <sub>t-1</sub>	0.133* (0.053)	0.090 (0.053)	-0.031 (0.054)	0.031 (0.052)
Ln oil production <sub>t-1</sub>	-0.028** (0.009)	-0.035** (0.010)	-0.062** (0.010)	-0.013 (0.014)
Ln gas production <sub>t-1</sub>	-0.021 (0.041)	-0.053 (0.043)	-0.160** (0.044)	-0.114* (0.056)
Distance to capital	.	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
Percentage national cropland	.	0.015** (0.005)	0.023** (0.006)	0.029** (0.005)
GDP pc growth <sub>t-1</sub>	.	.	-0.676 (0.827)	0.790 (0.881)
Political terror scale <sub>t-1</sub>	.	.	0.629** (0.058)	0.480** (0.072)
Presence inf. militia <sub>t-1</sub>	.	.	.	0.141 (0.140)
Presence peacekeepers <sub>t-1</sub>	.	.	.	-0.328* (0.143)
Violence <sub>t-1</sub>	.	.	.	0.235** (0.053)
<i>Inflation stage</i>				
Ln travel time	0.234 (0.164)	0.163 (0.179)	0.205 (0.186)	1.075** (0.214)
Ln population <sub>t-1</sub>	-0.618** (0.059)	-0.640** (0.062)	-0.600** (0.062)	-0.483** (0.073)
Ln cell area	-0.688 (0.514)	-0.885 (0.537)	-1.066* (0.540)	-1.227* (0.555)
Civil conflict <sub>t-1</sub>	-1.305** (0.180)	-1.428** (0.196)	-1.382** (0.192)	-1.320** (0.281)
Constant	12.650** (4.414)	14.856** (4.658)	15.419** (4.668)	9.351* (4.527)
<i>N</i>	106,507	106,507	97,769	56,898

Values in parentheses are robust standard errors clustered by cell-id

\*\* indicates  $p < .01$ , \* indicates  $p < .05$ ;

Year fixed effects included in all models though not reported here.

Table A.IV. Additional robustness models

<i>Count stage</i>	Civil conflict countries	Non-civil conflict countries	Zero-inflated Poisson	Alternate temp. controls	PITF atrocities	Outliers removed	Alt. cropland	1-degree cells	Dichotomous spatial lag	Low Mil. expenditure	Low mil. exp. per soldier	Firth logit
Civil conflict <sub>t-1</sub>	-0.036 (0.209)		-0.002 (0.171)	-0.573** (0.196)	0.171 (0.459)	-0.347 (0.201)	-0.063 (0.197)	-0.313 (0.240)	-0.311 (0.206)	0.146 (0.275)	-0.344 (0.249)	0.369** (0.085)
Cropland	-0.005* (0.002)	-0.009* (0.004)	-0.009** (0.002)	-0.005** (0.002)	-0.006* (0.003)	-0.008** (0.002)	-0.001 (0.003)	-0.007* (0.003)	-0.008** (0.002)	-0.009** (0.003)	-0.010** (0.003)	-0.004** (0.001)
CroplandXcivil conflict <sub>t-1</sub>	0.010** (0.003)		0.012** (0.003)	0.016** (0.003)	0.010* (0.005)	0.016** (0.003)	0.015** (0.006)	0.015** (0.005)	0.015** (0.003)	0.010* (0.005)	0.021** (0.005)	0.007** (0.002)
Ln population <sub>t-1</sub>	0.209** (0.077)	0.399** (0.146)	0.181** (0.047)	0.179** (0.053)	0.142 (0.152)	0.243** (0.059)	0.190** (0.063)	0.243** (0.115)	0.233** (0.060)	0.110 (0.086)	0.324** (0.079)	0.596** (0.030)
Ln cell area	-1.222* (0.574)	-1.034 (0.728)	-0.337 (0.455)	-0.304 (0.354)	-0.575 (0.790)	-0.814 (0.458)	-0.698 (0.606)	-0.860 (1.265)	-0.952 (0.526)	-2.537** (0.681)	-1.785** (0.651)	-0.417* (0.197)
Ln GCP <sub>t-1</sub>	0.409** (0.142)	0.389* (0.196)	0.273* (0.122)	0.291** (0.091)	0.062 (0.196)	0.298** (0.115)	0.356** (0.130)	0.368* (0.170)	0.233* (0.114)	0.268 (0.256)	0.196 (0.200)	0.027 (0.057)
Ln travel time	-0.223 (0.176)	0.439 (0.233)	-0.150 (0.111)	0.027 (0.107)	-0.170 (0.428)	-0.047 (0.136)	-0.015 (0.133)	0.158 (0.242)	-0.116 (0.140)	-0.243 (0.212)	0.058 (0.180)	-0.278** (0.052)
Temperature <sub>t-1</sub>	-0.023 (0.015)	-0.035 (0.028)	0.005 (0.014)	-0.002 (0.011)	0.010 (0.019)	-0.010 (0.014)	-0.009 (0.014)	-0.008 (0.021)	-0.010 (0.013)	-0.082** (0.020)	-0.049* (0.021)	-0.003 (0.006)
Ln precipitation <sub>t-1</sub>	0.691** (0.100)	-0.616** (0.194)	0.277* (0.113)	0.305** (0.081)	0.561** (0.134)	0.368** (0.087)	0.380** (0.091)	0.038 (0.130)	0.317** (0.083)	0.345** (0.126)	-0.048 (0.121)	0.369** (0.043)
Drought <sub>t-1</sub>	-0.143** (0.055)	0.003 (0.079)	0.069 (0.066)	-0.133** (0.048)	0.001 (0.071)	-0.085 (0.045)	-0.094* (0.045)	-0.075 (0.047)	-0.112* (0.044)	-0.009 (0.060)	-0.090 (0.056)	-0.100** (0.034)
Ln distance to border	-0.347** (0.047)	-0.334** (0.097)	-0.230** (0.051)	-0.286** (0.040)	-0.224** (0.080)	-0.340** (0.047)	-0.336** (0.048)	-0.262** (0.069)	-0.328** (0.047)	-0.413** (0.073)	-0.312** (0.061)	-0.176** (0.020)
Spatial lag DV <sub>t-1</sub>	0.234** (0.047)	0.524* (0.206)	0.035** (0.008)	0.165** (0.054)	1.500** (0.246)	0.255** (0.053)	0.260** (0.050)	0.316** (0.073)	2.789** (0.227)	0.145** (0.028)	0.197** (0.039)	2.894** (0.126)
Ln GDP pc <sub>t-1</sub>	-0.165* (0.081)	-0.892** (0.245)	-0.198* (0.078)	-0.280** (0.059)	-0.081 (0.165)	-0.238** (0.068)	-0.246** (0.069)	-0.241* (0.114)	-0.221** (0.067)	-0.413** (0.118)	-0.279** (0.098)	-0.121** (0.040)
Polity <sub>t-1</sub>	-0.099** (0.016)	0.111** (0.033)	-0.012 (0.012)	-0.030** (0.009)	-0.015 (0.018)	-0.031** (0.011)	-0.030** (0.011)	-0.018 (0.015)	-0.029* (0.011)	-0.061** (0.020)	-0.064** (0.020)	-0.016** (0.006)
Polity <sub>t-1</sub> <sup>2</sup>	0.001 (0.003)	-0.007 (0.007)	0.004 (0.002)	0.007** (0.002)	-0.000 (0.004)	0.007** (0.002)	0.007** (0.002)	0.004 (0.003)	0.006** (0.002)	0.007 (0.004)	0.012** (0.004)	0.005** (0.001)
Ln military expenditure <sub>t-1</sub>	-0.082 (0.045)	0.311* (0.149)	-0.096** (0.035)	0.061 (0.037)	0.348** (0.073)	0.010 (0.040)	-0.001 (0.042)	0.053 (0.055)	-0.011 (0.040)	0.054 (0.079)	-0.016 (0.060)	0.058** (0.022)
Territorial change	1.945** (0.138)	2.057** (0.593)	0.773** (0.115)	1.681** (0.150)	1.713** (0.175)	1.769** (0.125)	1.888** (0.123)	1.378** (0.127)	1.842** (0.127)	1.921** (0.174)	1.755** (0.158)	2.135** (0.101)
Violence <sub>t-1</sub>				0.352** (0.066)								
Constant				-1.256 (3.079)								
<i>Inflation stage</i>												
Ln travel time	0.708** (0.207)	-0.215 (0.225)	0.116 (0.097)	0.357* (0.161)	0.428 (0.629)	0.294* (0.148)	0.278 (0.147)	0.097 (0.386)	0.243 (0.159)	0.317 (0.196)	0.101 (0.163)	
Ln population <sub>t-1</sub>	-0.512** (0.073)	-0.712** (0.107)	-0.655** (0.046)	-0.629** (0.064)	-0.610** (0.136)	-0.605** (0.058)	-0.605** (0.057)	-0.749** (0.117)	-0.597** (0.060)	-0.627** (0.083)	-0.655** (0.068)	
Ln cell area	-0.346 (0.578)	-0.277 (0.854)	-0.391 (0.461)	-0.572 (0.536)	-0.527 (0.902)	-0.686 (0.508)	-0.845 (0.590)	-6.364* (2.776)	-0.694 (0.497)	-0.045 (0.456)	-0.805 (0.604)	
Civil conflict <sub>t-1</sub>	-0.990** (0.199)		-0.885** (0.078)	-1.464** (0.213)	-1.343** (0.512)	-1.260** (0.172)	-1.256** (0.174)	-1.648** (0.370)	-1.246** (0.188)	-2.518** (0.261)	-1.890** (0.255)	
Constant	5.471 (4.990)	13.479* (6.226)	13.075** (3.730)	10.636* (4.599)	10.999 (9.099)	12.168** (4.297)	13.531** (4.932)	68.768** (25.504)	12.290** (4.241)	7.406* (3.734)	14.974** (4.814)	
N	71,494	35,013	106,507	97,500	106,507	106,503	106,351	24,938	106,507	53,969	62,699	106,507

Models 1-11 are ZINB Models; Model 12 is a logit estimated with penalized maximum likelihood; Values in parentheses are robust standard errors clustered by cell-id; \*\* indicates  $p < .01$ , \* indicates  $p < .05$ ; Year fixed effects included in Models 1-3 and 5-12 though not reported here.



Table A.V. Civil conflict<sub>t</sub> robustness models

	Model 1	Model 2	Model 3	Model 4
<i>Count stage</i>				
Civil conflict <sub>t</sub>	1.022** (0.144)	0.548** (0.195)	0.359 (0.195)	-0.027 (0.205)
Cropland	-0.007** (0.002)	-0.011** (0.002)	-0.011** (0.002)	-0.009** (0.002)
CroplandXcivil conflict <sub>t</sub>	0.020** (0.003)	0.018** (0.003)	0.017** (0.003)	0.015** (0.003)
Ln population <sub>t-1</sub>	0.928** (0.060)	0.589** (0.063)	0.291** (0.063)	0.250** (0.060)
Ln cell area	-0.231* (0.118)	-0.178 (0.179)	-0.250 (0.455)	-0.828 (0.480)
Ln GCP <sub>t-1</sub>	-0.384** (0.090)	-0.387** (0.086)	0.078 (0.097)	0.320** (0.117)
Ln travel time	-0.126 (0.129)	0.182 (0.148)	-0.211 (0.158)	-0.049 (0.147)
Temperature <sub>t-1</sub>	.	.	0.009 (0.014)	-0.009 (0.014)
Ln precipitation <sub>t-1</sub>	.	.	0.550** (0.081)	0.385** (0.087)
Drought <sub>t-1</sub>	.	.	-0.043 (0.050)	-0.084 (0.046)
Ln distance to border	.	.	-0.435** (0.048)	-0.353** (0.047)
Spatial lag DV <sub>t-1</sub>	.	.	.	0.250** (0.050)
Ln GDP pc <sub>t-1</sub>	.	.	.	-0.235** (0.069)
Polity <sub>t-1</sub>	.	.	.	-0.025* (0.011)
Polity <sub>t-1</sub> <sup>2</sup>	.	.	.	0.007** (0.002)
Ln military expenditure <sub>t-1</sub>	.	.	.	0.009 (0.041)
Territorial change	.	.	.	1.698** (0.117)
<i>Inflation stage</i>				
Ln travel time	.	0.372** (0.106)	0.327* (0.127)	0.311 (0.159)
Ln population <sub>t-1</sub>	.	-0.588** (0.047)	-0.582** (0.052)	-0.597** (0.060)
Ln cell area	.	0.096 (0.136)	-0.294 (0.448)	-0.697 (0.513)
Civil conflict <sub>t</sub>	.	-0.653** (0.113)	-0.916** (0.126)	-1.262** (0.176)
Constant	.	5.694** (1.385)	8.996* (3.747)	12.084** (4.372)
N	115,158	115,158	108,321	106,507

Values in parentheses are robust standard errors clustered by cell-id;

\*\* indicates  $p < .01$ , \* indicates  $p < .05$ ;

Year fixed effects included in all models though not reported here.

Table A.VI. Disaggregated robustness models

	Rebel perpetrators	Government perpetrators	Government perpetrators low military exp. per soldier countries	Militia perpetrators	Reb. & gov. perps. (no militias)
<i>Count stage</i>					
Civil conflict <sub>t-1</sub>	-0.328 (0.432)	-0.727 (0.387)	-1.154* (0.486)	-0.514 (0.331)	-0.279 (0.229)
Cropland	-0.018** (0.004)	-0.011** (0.003)	-0.013** (0.004)	-0.006* (0.002)	-0.013** (0.003)
CroplandXcivil conflict <sub>t-1</sub>	0.034** (0.005)	0.003 (0.005)	0.010* (0.005)	0.010* (0.004)	0.020** (0.004)
Ln population <sub>t-1</sub>	-0.071 (0.115)	0.317** (0.098)	0.411** (0.134)	0.353** (0.083)	0.120 (0.073)
Ln cell area	-3.220** (0.888)	-0.987 (0.694)	-1.188 (0.736)	-0.584 (0.463)	-1.395* (0.585)
Ln GCP <sub>t-1</sub>	0.277 (0.180)	0.184 (0.174)	0.538* (0.259)	0.180 (0.133)	0.387** (0.138)
Ln travel time	-0.227 (0.287)	-0.123 (0.207)	-0.017 (0.372)	0.321 (0.188)	-0.345 (0.182)
Temperature <sub>t-1</sub>	-0.065** (0.023)	-0.007 (0.015)	-0.037 (0.025)	0.015 (0.016)	-0.037* (0.015)
Ln precipitation <sub>t-1</sub>	0.522** (0.176)	0.409** (0.118)	0.159 (0.174)	0.341** (0.101)	0.452** (0.108)
Drought <sub>t-1</sub>	-0.105 (0.085)	-0.241** (0.070)	-0.177 (0.101)	0.042 (0.058)	-0.181** (0.059)
Ln distance to border	-0.535** (0.069)	-0.274** (0.054)	-0.190* (0.092)	-0.278** (0.066)	-0.417** (0.049)
Spatial lag DV <sub>t-1</sub>	0.361** (0.090)	0.362 (0.248)	-0.149 (0.178)	0.675** (0.157)	0.253** (0.054)
Ln GDP pc <sub>t-1</sub>	-0.370* (0.172)	-0.238* (0.097)	-0.148 (0.148)	-0.313** (0.085)	-0.273** (0.094)
Polity <sub>t-1</sub>	-0.102** (0.024)	-0.076** (0.016)	-0.017 (0.029)	-0.020 (0.013)	-0.077** (0.015)
Polity <sub>t-1</sub>	0.003 (0.004)	-0.001 (0.004)	-0.016** (0.005)	0.015** (0.002)	-0.001 (0.003)
Ln military expenditure <sub>t-1</sub>	-0.116 (0.107)	-0.088 (0.058)	-0.242** (0.085)	0.061 (0.047)	-0.104 (0.057)
Territorial change	1.890** (0.242)	2.098** (0.179)	1.886** (0.228)	1.975** (0.206)	1.917** (0.154)
<i>Inflation stage</i>					
Ln travel time	0.799* (0.351)	0.124 (0.257)	0.156 (0.397)	0.383 (0.209)	0.330 (0.217)
Ln population <sub>t-1</sub>	-0.520** (0.123)	-0.701** (0.111)	-0.779** (0.157)	-0.618** (0.092)	-0.611** (0.080)
Ln cell area	-1.360* (0.684)	-0.241 (0.583)	-0.199 (0.508)	-0.798 (0.813)	-0.542 (0.421)
Civil conflict <sub>t-1</sub>	-2.093** (0.414)	-1.850** (0.430)	-2.738** (0.894)	-0.592* (0.294)	-1.767** (0.201)
Constant	14.861* (6.006)	11.564* (5.437)	12.367* (5.652)	12.928* (6.530)	11.392** (3.953)
N	106,507	106,507	62,699	106,507	106,507

Values in parentheses are robust standard errors clustered by cell-id;

\*\* indicates  $p < .01$ ; \* indicates  $p < .05$ ;

Year fixed effects included in all models though not reported here.

Table A.VII. Alternate territorial control specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
<i>Count stage</i>								
Civil conflict <sub>t-1</sub>	-0.353 (0.201)	-0.600** (0.200)	-0.294 (0.201)	-0.511* (0.202)	-0.206 (0.183)	-0.412* (0.195)	-0.115 (0.181)	-0.275 (0.197)
Cropland	-0.008** (0.002)	-0.008** (0.002)	-0.009** (0.002)	-0.008** (0.002)	-0.008** (0.002)	-0.008** (0.002)	-0.009** (0.002)	-0.008** (0.002)
CroplandXcivil conflict <sub>t-1</sub>	0.016** (0.003)	0.017** (0.003)	0.016** (0.003)	0.017** (0.003)	0.016** (0.003)	0.016** (0.003)	0.015** (0.003)	0.015** (0.003)
Ln population <sub>t-1</sub>	0.243** (0.059)	0.211** (0.066)	0.235** (0.065)	0.206** (0.068)	0.203** (0.058)	0.200** (0.064)	0.208** (0.061)	0.207** (0.065)
Ln cell area	-0.813 (0.458)	-0.852 (0.497)	-0.836 (0.470)	-0.844 (0.500)	-0.752 (0.459)	-0.794 (0.493)	-0.764 (0.467)	-0.776 (0.492)
Ln GCP <sub>t-1</sub>	0.298** (0.115)	0.305* (0.119)	0.304** (0.117)	0.301* (0.122)	0.272* (0.116)	0.287* (0.120)	0.262* (0.116)	0.264* (0.121)
Ln travel time	-0.048 (0.136)	-0.062 (0.142)	-0.042 (0.151)	-0.064 (0.148)	-0.111 (0.138)	-0.084 (0.144)	-0.071 (0.142)	-0.087 (0.149)
Temperature <sub>t-1</sub>	-0.010 (0.014)	0.006 (0.014)	-0.007 (0.014)	0.007 (0.014)	-0.005 (0.013)	0.008 (0.014)	-0.005 (0.014)	0.009 (0.014)
Ln precipitation <sub>t-1</sub>	0.368** (0.086)	0.372** (0.092)	0.378** (0.089)	0.380** (0.093)	0.374** (0.086)	0.359** (0.093)	0.387** (0.088)	0.365** (0.094)
Drought <sub>t-1</sub>	-0.084 (0.045)	-0.047 (0.048)	-0.083 (0.045)	-0.055 (0.047)	-0.065 (0.044)	-0.044 (0.048)	-0.059 (0.043)	-0.048 (0.048)
Ln distance to border	-0.340** (0.047)	-0.327** (0.047)	-0.339** (0.047)	-0.335** (0.048)	-0.332** (0.046)	-0.323** (0.048)	-0.322** (0.046)	-0.324** (0.049)
Spatial lag DV <sub>t-1</sub>	0.262** (0.051)	0.308** (0.055)	0.248** (0.052)	0.322** (0.057)	0.210** (0.039)	0.281** (0.050)	0.165** (0.030)	0.282** (0.048)
Ln GDP pc <sub>t-1</sub>	-0.236** (0.068)	-0.320** (0.070)	-0.247** (0.069)	-0.318** (0.071)	-0.251** (0.067)	-0.324** (0.070)	-0.253** (0.068)	-0.323** (0.070)
Polity <sub>t-1</sub>	-0.031** (0.011)	-0.033** (0.013)	-0.032** (0.012)	-0.033** (0.013)	-0.027* (0.011)	-0.031* (0.013)	-0.029* (0.012)	-0.032* (0.013)
Polity <sub>t-1</sub> <sup>2</sup>	0.007** (0.002)	0.008** (0.002)	0.007** (0.002)	0.009** (0.002)	0.007** (0.002)	0.009** (0.002)	0.008** (0.002)	0.009** (0.002)
Ln military expenditure <sub>t-1</sub>	0.009 (0.040)	0.042 (0.042)	0.008 (0.041)	0.049 (0.043)	0.005 (0.039)	0.044 (0.042)	0.006 (0.039)	0.051 (0.042)
Territorial change	1.795** (0.119)	.	.	.	0.835** (0.121)	.	.	.
Territorial change <sub>t-1</sub>	.	1.505** (0.159)	.	.	.	0.749** (0.176)	.	.
Count territorial change	.	.	0.399** (0.066)	.	.	.	0.169** (0.024)	.
Count territorial change <sub>t-1</sub>	.	.	.	0.389** (0.107)	.	.	.	0.084* (0.042)
<i>Inflation stage</i>								
Ln travel time	0.294* (0.149)	0.258 (0.141)	0.302* (0.148)	0.260 (0.142)	0.184 (0.128)	0.200 (0.132)	0.201 (0.121)	0.193 (0.130)
Ln population <sub>t-1</sub>	-0.605** (0.058)	-0.617** (0.056)	-0.616** (0.057)	-0.625** (0.056)	-0.638** (0.050)	-0.624** (0.052)	-0.639** (0.049)	-0.625** (0.052)
Ln cell area	-0.687 (0.508)	-0.683 (0.519)	-0.685 (0.510)	-0.679 (0.522)	-0.415 (0.471)	-0.511 (0.502)	-0.409 (0.469)	-0.479 (0.502)
Civil conflict <sub>t-1</sub>	-1.270** (0.173)	-1.293** (0.173)	-1.257** (0.170)	-1.266** (0.176)	-0.873** (0.140)	-0.968** (0.160)	-0.807** (0.129)	-0.868** (0.152)
Territorial change	.	.	.	.	-3.334** (0.522)	.	.	.
Territorial change <sub>t-1</sub>	.	.	.	.	.	-2.209** (0.439)	.	.
Count territorial change	.	.	.	.	.	.	-2.682** (0.376)	.
Count territorial change <sub>t-1</sub>	.	.	.	.	.	.	.	-2.380** (0.585)
Constant	12.182** (4.301)	12.514** (4.351)	12.270** (4.292)	12.511** (4.363)	11.427** (3.896)	11.744** (4.176)	11.435** (3.850)	11.552** (4.165)
N	106507	97500	106507	97500	106507	97500	106507	97500

Values in parentheses are robust standard errors clustered by cell-id;

\*\* indicates  $p < .01$ , \* indicates  $p < .05$ ;

Year fixed effects included in all models though not reported here;

Count territorial change records the number of times a territory changes hands during a given year.

Table A.VIII. Full model with random effects (1997-2009)

	Country REs	Grid cell REs	Country and grid cell REs
<i>Count stage</i>			
Civil conflict <sub>t-1</sub>	-0.788** (-0.897 ⇔ -0.683)	0.354** (0.219 ⇔ 0.521)	-0.915** (-1.023 ⇔ -0.820)
Cropland	-0.005*** (-0.008 ⇔ -0.003)	-0.008** (-0.011 ⇔ -0.006)	-0.002** (-0.004 ⇔ -0.001 )
CroplandXcivil conflict <sub>t-1</sub>	0.017** (0.014 ⇔ 0.019)	0.012** (0.008 ⇔ 0.016)	0.016** (0.012 ⇔ 0.020)
Ln population <sub>t-1</sub>	0.439** (0.380 ⇔ 0.477)	0.360** (0.306 ⇔ 0.420)	0.299** (0.249 ⇔ 0.336)
Ln cell area	-1.462** (-1.970 ⇔ -0.731)	-2.124** (-2.545 ⇔ -1.424)	-1.019* (-1.839 ⇔ -0.152)
Ln GCP <sub>t-1</sub>	0.243** (0.124 ⇔ 0.392)	0.171** (0.026 ⇔ 0.289)	0.195** (0.077 ⇔ 0.310)
Ln travel time	-0.230** (-0.308 ⇔ -0.147)	-0.389** (-0.499 ⇔ -0.276)	-0.528** (-0.583 ⇔ -0.469)
Temperature <sub>t-1</sub>	-0.005 (-0.029 ⇔ 0.012)	-0.049** (-0.066 ⇔ -0.025)	0.001 (-0.010 ⇔ 0.015)
Ln precipitation <sub>t-1</sub>	0.545** (0.495 ⇔ 0.595)	0.366** (0.276 ⇔ 0.498)	0.475** ( 0.414 ⇔ 0.535)
Drought <sub>t-1</sub>	-0.025 (-0.088 ⇔ 0.021)	-0.103** (-0.165 ⇔ -0.058)	-0.006 (-0.073 ⇔ 0.048)
Ln distance to border	-0.417** (-0.446 ⇔ -0.386)	-0.308** (-0.344 ⇔ -0.262)	-0.437** (-0.479 ⇔ -0.393)
Spatial lag DV <sub>t-1</sub>	0.107** (0.077 ⇔ 0.136)	9.152** (0.125 ⇔ 0.179)	0.115** (0.091 ⇔ 0.136)
Ln GDP pc <sub>t-1</sub>	-0.247** (-0.322 ⇔ -0.177)	-0.634** (-0.923 ⇔ -0.384)	-0.163** ( -0.223 ⇔ -0.115)
Polity <sub>t-1</sub>	-0.035** (-0.043 ⇔ -0.026)	-0.021** (-0.037 ⇔ -0.008)	-0.016* (-0.033 ⇔ -0.003)
Polity <sub>t-1</sub> <sup>2</sup>	0.006** (0.004 ⇔ 0.007)	-0.003* (-0.006 ⇔ 7.3E-05)	0.002* (4.1E-04 ⇔ 0.004)
Ln military expenditure <sub>t-1</sub>	-0.010 (-0.062 ⇔ 0.051)	2.1E-04 (-0.106 ⇔ 0.078)	-0.020 (-0.053 ⇔ 0.009)
Terr. change <sub>t</sub>	1.772** (1.556 ⇔ 2.002)	2.638** (2.433 ⇔ 2.892)	1.735** (1.495 ⇔ 2.032)
<i>Inflation stage</i>			
Ln travel time	1.164** (1.001 ⇔ 1.351)	0.712** (0.652 ⇔ 0.788)	-0.239* (-0.437 ⇔ -0.048)
Ln population <sub>t-1</sub>	-1.008** (-1.076 ⇔ -0.946)	-0.936** (-0.959 ⇔ -0.916)	-1.331** (-1.435 ⇔ -1.268)
Ln cell area	-3.637** (-4.912 ⇔ -2.545)	-0.398 (-0.757 ⇔ 0.046)	-1.667* (-3.225 ⇔ -0.521)
Civil conflict <sub>t-1</sub>	-6.300** (-6.576 ⇔ -5.991)	0.066 (-0.036 0.220)	-5.530** (-5.644 ⇔ -5.427)
Constant	36.841** (27.306 ⇔ 47.547)	8.819** (5.644 ⇔ 12.62)	33.027** (23.881 ⇔ 42.726)
N		106,507	
DIC	17,352.59	18,937.7	17,506.73

Values in parentheses are robust standard errors clustered by cell-id;

\*\* indicates  $p < .01$ , \* indicates  $p < .05$ ;

Year fixed effects included in all models though not reported here.

## Sample Countries

Table A.IX. Countries included in ACLED Africa sample, 1997-2009

Algeria	Madagascar
Angola	Malawi
Benin	Mali
Botswana	Mauritania
Burkina Faso	Morocco
Burundi	Mozambique
Cameroon	Namibia
Central African Republic	Niger
Chad	Nigeria
Djibouti	Republic of Congo
DR-Congo	Rwanda
Egypt	Senegal
Equatorial Guinea	Sierra Leone
Eritrea	Somalia
Ethiopia	South Africa
Gabon	South Sudan
Gambia	Sudan
Ghana	Swaziland
Guinea	Tanzania
Guinea-Bissau	Togo
Ivory Coast	Tunisia
Kenya	Uganda
Lesotho	Zambia
Liberia	Zimbabwe
Libya	

## Operationalization of dependent and independent variables

### *Cropland*

The *continuous* cropland independent variable was operationalized as the *percentage of a given cell's* area whose land cover class was denoted as (irrigated and non-irrigated) cropland by the Globcover 2009 project. That is, this measure corresponds to the land cover classes assigned a value of 11-40 by Bontemps et al. (2009). The categories considered as cropland are hence post-flooding or irrigated croplands, rainfed croplands, mosaic cropland (50-70%) / vegetation (grassland, shrubland, forest) (20-50%), and mosaic vegetation (grassland, shrubland, forest) (50-70%) / cropland (20-50%) (Bontemps, Defourny & Van Bogaert, 2009: 4.1). Note that although this variable is coded only for 2009, it is unlikely to vary for the relatively short temporal period covered by the data. We recognize that this measure does not perfectly capture access to food, yet, to our knowledge, this is the best available indicator for approximating food access for our sample-frame at the time of writing.

### *Civil conflict<sub>t-1</sub>*

The *binary* civil conflict<sub>t-1</sub> independent variable is coded as “1” if a particular 0.5 x 0.5 decimal degree African grid cell is classified as an interstate “armed conflict” grid cell by the UCDP/PRIO Armed Conflict Dataset (ACD; Gleditsch et al., 2002) during the previous calendar year, and “0” otherwise. This ACD armed conflict classification was incorporated into the PRIO-GRID cell-level dataset (which we use in our analysis) by Tollefsen et al. (2012). Note as well that our primary analysis further interacted civil conflict<sub>t-1</sub> with cropland to fully test our hypothesis.

We favor this ACD civil conflict classification as our primary indicator of (recent) civil conflict, as opposed to an event count measure (derived from, e.g., Armed Conflict Location and Event Data Project) of civil conflict because our theory anticipates that the general state of a geographic region experiencing civil conflict will contribute to the dynamics discussed in the main paper. As such, using an event data measure of conflict, as opposed to the ACD's civil conflict classification (described in more detail below) poses a number of challenges.

First, note that all event-data based conflict measures, in their disaggregated state, only capture whether a (single) battle or event occurred within a given region. Such an event-record does not necessarily imply that a given region is an actual civil conflict zone, as intermittent battles may occur within even fully non-contested areas of relative peace, or may be too minor in severity to reasonably classify an area as being within a civil conflict zone. While aggregating event data to a particular threshold for a more robust civil conflict classification may help to address these challenges, the fact that the ACD provides a multi-faceted classification scheme for this very purpose largely ensures that using the ACD’s civil conflict classification for our civil conflict measure, as opposed to deriving our own event data-based classification scheme for civil conflict cells, will provide a more accurate, and defensible, coding of civil conflict areas.

Indeed, the ACD classifies armed conflict based upon “a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths” (UCDP/PRIO, 2015: 1) and further uses a verification of (i) the use of armed force, (ii) a 25 battle-deaths per year (and dyad) threshold, (iii) the identities of the (government and opposition organization) conflicting parties, (iv) territorial classifications and control to determine whether or not civil conflict can be considered to be present in a particular location.<sup>1</sup> This nuanced classification of civil conflict appears as the standard civil conflict classification within the PRIO-GRID dataset (Tollefsen et al., 2012), and has been widely used as a measure of civil conflict across an extensive number of studies.<sup>2</sup>

Furthermore, as demonstrated within the robustness models presented earlier, we find that all NB and ZINB models presented in the main paper are robust to the inclusion of  $\text{civil conflict}_t$  in place of  $\text{civil conflict}_{t-1}$ . While the use of  $\text{civil conflict}_t$  offers a measure that is more temporally proximate to our outcome variable ( $\text{violence}_t$ ), and yields highly robust

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<sup>1</sup>We note that the ACD also provides classifications for extrasystemic and interstate conflicts, though our focus here is on internal conflict exclusively.

<sup>2</sup>E.g., see here: <https://www.prio.org/Data/Armed-Conflict/UCDP-PRIO/>.

results, we maintain the use of civil conflict $_{t-1}$  as a primary dependent variable within our main paper for two reasons. First, civil conflict $_{t-1}$  establishes the temporal precedence of our independent variables, and thus helps to minimize simultaneity concerns while also ensuring that in no instances do we include instances of civil conflict that occurred *after* our annually observed instances of violence $_t$ . Second, while civil conflict $_{t-1}$  may indeed include several instances where civil conflict has very recently dissipated (i.e., during the 1-11 months before our observed outcomes), this only provides a higher test for our theory (relative to conflict $_t$ ).

### *Violence $_t$*

The *count-based* violence $_t$  (against civilians) dependent variable is operationalized as the yearly ( $t$ ) count of instances of violence committed against civilians by armed (state or nonstate) actors within a given African (0.5 x 0.5 decimal degree) grid cell. This measure was coded from the Armed Conflict Location and Event Data Project (ACLED) dataset (Version 5), which defines violence against civilians as “deliberate violent acts perpetrated by an organized political group such as a rebel, militia or government force against unarmed non-combatants,” and records any such instance for which civilians are harmed or killed (Raleigh & Dowd, 2015: 13). ACLED uses local and international news sources, Africa-oriented news reports and analyses, and NGO reports to collect and geo-code relational (i.e., source-target) based incidents of armed conflict occurring within the 49 African countries mentioned above (and listed above) for the years 1997-2014, thereby limiting the start of our sample to the year 1997.

From the ACLED data, we subset out all instances of violence directed at civilians as targets, and then further subset out only those incidents that could be credibly seen as being perpetrated by armed state or nonstate actors by omitting any recorded instances of violence against civilians that were instead perpetrated by (i) rioters, (ii) protesters, or (iii) other non-rebel/militia/military based actors. The remaining violence $_t$  perpetrators therefore include formal government-based actors (e.g., militaries, police), rebel groups (defined by ACLED as “political organizations whose goal is to counter an established national governing regime by



violent acts” (Raleigh & Dowd, 2015: 5)), and political militias which the ACLED project notes “operate in conjunction, or in alliance, with a recognized government, governor, military leader, rebel organization or opposition group” (Raleigh & Dowd, 2015: 5). Note however, that as demonstrated in the robustness models presented above, our analysis is robust to an operationalization of violence<sub>t</sub> that does not consider militias as perpetrators (i.e., one that only includes government and rebel perpetrators).

Lastly, we omit any events that do not have sufficient geo-coding accuracy for merging to the 0.5 x 0.5 cell level, and then merge all remaining violence<sub>t</sub> incidents to our African country cell-year dataset based upon their recorded latitude-longitude coordinates, before summing each cell’s remaining violence<sub>t</sub> incidents to the yearly-count level.

## **Comparison of theory to existing explanations for violence**

As mentioned in the main paper, we next provide an expanded discussion previous theories of violence against civilians that seek to explain why violence might arise in cropland regions, specifically. In doing so, we also highlight how our theory complements these existing explanations. In the discussion below, we elaborate upon four alternate theoretical approaches: ethnic rivalries and inter-ethnic violence; the effect of easily lootable valuable resources (e.g. drugs, diamonds) on violence; revenge attacks and indiscriminate violence; and the relationship between militias<sup>3</sup> and human rights violations. Lastly, we also discuss previous works concerned with the relationship between food and violence more broadly, and offer insights into how our theory fits within this larger body of research.

### *Discussion of competing explanations*

From an ethnically centric perspective, the civilian population might offer armed actors that hail from the same group food, support and shelter, and weapons, among others. Especially in countries and regions with high level of ethnic fractionalization, this accentuates existing ethnic or religious divisions, by bringing other ethnicities to view the entire group

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<sup>3</sup>Which might be employed to defend arable areas.

in question—including women and children—as enemy collaborators, as happened, for instance, with the case of the Tutsi in the Democratic Republic of the Congo (Stearns, 2011). Correspondingly, “violence and terror against enemy ethnic constituencies and their property might lower the productive capacity of the civilian population, and thereby undermine their ability to provide material support, such as food, shelter, wartime taxes, and ultimately even recruits to the warring actor” (Fjelde & Hultman, 2014: 1236). From this perspective, when conflict arises in areas and regions where it breaks down along ethnic lines, atrocities are more likely to be used strategically in order to remove potential enemy supporters, and their base of operations (Valentino, Huth & Balch-Lindsay, 2004; Fjelde & Hultman, 2014).

Although this theoretical approach provides a good explanation as to why violence against civilians during conflict is more prevalent in more ethnically diverse countries and localities, it does not necessarily explain why croplands—specifically—are at a higher risk of experiencing violence. Therefore, from a theoretical perspective, the ethnically centric approach does not negate our emphasis on food access, but rather—we believe—complements it; the frequency of atrocities against civilians during conflict in a given region can increase as a result of both ethnic enmities, *and* because the necessity to secure food support becomes acute. Indeed, in numerous conflicts (e.g., in Sierra Leone, see Keen, 2005, India see Pandita, 2011), armed groups have been observed to aim significant degree of violence toward *their own* ethnic group in order to secure food resources. Nevertheless, we account for the possibility that our conclusions can be observed by ethnic enmities in our robustness models by using a measure of ethnic diversity measured *at the cell level*. As the significance of our findings hold in models that include indicators for ethnic diversity, we believe that it is robust to these concerns, and that our the two theories are more likely to be complementary rather than contradictory.

A second alternative explanation relates to the notion that violence is more likely in rural areas that offer abundance of natural resources. Indeed, numerous studies have identified a connection between gemstones, oil, and occasionally drugs, and violence against civilians

during conflict (e.g. Buhaug, Gates & Lujala, 2009; Basedau & Pierskalla, 2014). From this perspective, the increased frequencies of atrocities perpetrated by armed actors during times of conflict are the result of the fact that these resources offer economic independence, and reduce these groups' need to rely on the local population for financial support (Basedau & Pierskalla, 2014). Atrocities are thus used to control the population during times of conflict or to help recruiting a labor force for extracting natural resources during times of conflict. A similar argument is made by Wood (2014) in relation to military capabilities, namely that groups that have access to more advanced technologies (e.g. UNITA acquiring tanks and artillery) are free from the necessity to rely on the local population for support, which leads—again—to civilian victimization.

The focus on valuable resources to explain instances of atrocities against civilians during conflict is insightful and, indeed, has been the subject of a large body of research (e.g. Collier & Hoeffler, 2005; Weinstein, 2007; Wood, 2010). Yet, this approach again falls short in explaining why atrocities are more frequent in *cropland* areas, specifically, and not rural areas more broadly. Again, we view our explanation as complementing this argument rather than seeking to replace the focus on natural resources. We recognize that, during conflict, armed actors might be motivated to perpetrate violence against civilians by both greed, i.e. the incentives of government troops and nonstate actors to maintain economic and logistic independence and enjoy the rents provided by controlling these profitable resources; *and* by the necessity to obtain food resources for the purpose of self sustenance. Correspondingly, our models account for this possibility empirically, by including an indicator of gross cell product (GCP, in billion USD) to account for regional productivity, which is measured, again, at the *cell* level, in our analysis. This GCP indicator captures whether a given cell offers high degree of profitability and high rents that might motivate armed groups to perpetrate civilians.

The third explanation we discuss emphasizes that violence during civil war is more likely to arise in retribution to previous (or current) enmities. This approach highlights the importance of preexisting political divisions, or the crucial role played by civilian support for

the different political factions in generating violence during civil wars. Proponents of this approach argue, for example, that the “variation in levels of violence appears to be largely explained by the incentives of armed groups, which—in these wars—decide to target civilians according to their public identities, but also by the civilian incentives for collaboration with the groups, which are associated with strategic political considerations at the local level” (Balcells, 2010: 307). This approach is therefore similar to explanations that highlight ethnic enmities, only instead of focusing on ethnic divisions, proponents of the retributive violence approach focus on *political* rivalries. One should therefore expect to see more violence occurring in areas and regions where (i) preexisting political parities are large, and hence violence is used to challenge the status quo; and (ii) where violence already occurred earlier during (or before) the war, which incentivizes the actor currently in power to employ violent retribution (Kalyvas, 2006; Balcells, 2010).

The importance of focusing on political factors notwithstanding, we believe that our explanation offers a novel conceptualization of how political parities and preexisting grievances can translate into violence, namely through competition over food resources between armed troops and civilians. In this respect, our argument does relate to the work of scholars such as Kalyvas (2006), who emphasize the coercive logic of using violence to challenge the status quo and generate support, especially in relation to the fact that civil conflict is likely to frequent rural areas (Kalyvas, 2004). Our focus on food as a form of natural resources is thus in line with these expositions, while the focus on croplands provides one explanation as to why violence is more likely in rural areas.

The fourth competing explanation discussed here relates to the role played by pro-government militias and other irregular state groups in generating violence. Indeed, numerous studies have shown that militias, especially informal groups whose connection to the regime is easily concealed, are significantly more likely to be associated with human rights violations (Mitchell, Carey & Butler, 2014) and mass killing (Koren, Forthcoming). From this perspective, atrocities against civilians in rural regions during conflict might occur as the

result of militias or other irregular troops seeking to secure arable land and access to water and food. The focus on militias also helps explaining situations of human rights violations in some countries and regions, for example because the government “may knowingly recruit those with a reputation for violence (for example, criminals) and then refuse to control these agents—rather than actually lose control over them” (Mitchell, Carey & Butler, 2014: 818).

Although the militia centric explanation is useful and highlights the role of groups that until recently have received relatively little attention by scholars, we believe that our theory still offers a novel understanding of the motivations behind violence that cannot be completely explained by the focus on pro-government militias alone. Perhaps most notably, militia based explanations cannot fully account for the lower frequency of atrocities perpetrated in cropland regions during times of relative peace, considering that these groups exist during times of both conflict and relative peace (Ahram, 2011; Koren, Forthcoming).

Nevertheless, our theory and empirics both encompass militias, which frequently operate in the gray area between the state and rebel groups; but at the time it primarily applies to broader actors, namely rebel organizations and governments, which might employ militias for their own ends while intentionally providing lower level of support (Koren, Forthcoming). This allows us to draw on militia based explanations for violence to explain the potentially higher incentive of such groups to obtain food resources grown locally. Empirically, we made sure to analyze only atrocities perpetrated by forces identified as either state or non-state, and omitted atrocities perpetrated by militias from our main analysis. This helps us to ensure that our findings regarding the relationship between conflict, cropland, and atrocities are unlikely to be the result of human rights violations perpetrated by militias. Nevertheless, we account for the potential confounding effect of militia on violence during conflict in a robustness model presented in Table A.III.

#### *Discussion of extant literature on food and violence*

Some deficiencies in the literature related to food security and violence is now being addressed by recent research into the relationship between food import prices and political stability,

especially in developing countries. For instance, in his analysis of the relationship between food prices and social unrest, Bellemare finds that “rising food prices appear to cause food riots” (2014, 18). Hendrix & Haggard (2015) expand on Bellemare’s study by focusing on the role of political institutions in mitigating the effect of global food prices on instability. They find that, “[g]lobal food prices are correlated with urban unrest in democracies, but not in autocracies” because, “food policy in democracies is less biased in favor of urban constituencies” (2015, 145). From a different perspective, Weinberg & Bakker (2015) utilize domestic food prices as an indicator of citizen wellbeing. The authors find that social unrest is indeed more prevalent during periods of heightened food prices, with larger price increases being associated with more pronounced outbreaks of social unrest (2015, 320).

These studies highlight an important mediating factor by which variations in food production can affect political instability, but they are also limited in three respects. First, the reliance on food imports may not capture the true effect of food insecurity in countries and regions where a large number (or indeed the majority) of civilians must, to a large extent, live off locally produced food. Second, the focus on the state as the unit of analysis limits one’s ability to account for global and regional variations that might affect food security. In this respect, we echo Theisen, Gleditsch & Buhaug contention that “more work needs to be put into the geographical disaggregation of the effects of climate change since these effects will not follow national boundaries,” especially as “[a]ctors and agency tend to be vaguely portrayed, or outright ignored, in the relevant empirical literature” (2013, 621-622). Third, these studies are focused primarily on civil disobedience campaigns, and do not directly address the relationship between food security and violence against civilians, specifically.

Our paper complements these existing studies by focusing on one important (mediating) factor, food resources, and the geographic variation of atrocities against civilians both cross-nationally and at the very local level. Whereas extant research on food prices and imports expands our understanding of the relationship between food, a staple commodity, and political resistance, our understanding of food security’s relationship(s) with violent outcomes

such as atrocities is predominately subsumed under the hypothesized effects of trade and/or climate change. The notion that climatic variability affects armed conflict has received much consideration in the extant literature. Numerous studies found that climate-related variables are strongly related to the incidence of conflict (e.g., Burke et al., 2009; Raleigh & Kniveton, 2012; Hendrix & Salehyan, 2012). Others, however, have instead emphasized the importance of political and socioeconomic conditions as moderating or overriding factors (e.g. Buhaug, 2010). Yet, practically absent from this discussion is the question of how climatic variability influences the incidence of civilian victimization, specifically. We contend that the implications of food insecurity for conflict are not only a feature of climate change and trade shocks, but also the result of population growth, local traditions, global increases in consumption, and droughts, all of which exhibit significant amounts of variation independently of climatic factors. Our focus on the relationship between conflict, cropland, and atrocities thus allows us to identify a novel implication of food security across the developing world, and relates to other studies of this kind that focus on (civil) conflict (e.g., Koren & Bagozzi, 2016).

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