

# Climate change, cash crops, and violence against civilians in the Sahel

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## Abstract

The possibility that climate change will increase the risk of civil war by causing agricultural decline, thereby increasing competition over scarce resources, is at the focus of a vastly expanding research agenda. Yet, an emerging body of work suggests that agricultural abundance, not scarcity, drives violence. This study illustrates that debates over whether scarcity or abundance does more to drive violence can be adjudicated with greater attention to actor type (government, rebel, or militia), type of violence, and crop type. It leverages new spatiotemporal monthly data to assess the relationship between local cash crop productivity and violence against civilians by state forces, rebels, and militias, accounting for the impact of climatic and socioeconomic indicators, across 14 countries in the Sahel between January 2006 and December 2018. Aggregating data on local agricultural production for 42 crops alongside a vegetation coverage indicator, a monthly measure of local cash crop productivity is created, and its impact on the monthly rates of violence against civilian by these three actors is estimated. Results indicate that rebel and militia attacks increase by about twofold in cash crop producing locations during peak productivity months, whereas state force attacks do not. This suggests that nonstate actors are more dependent on local sources of revenue and follow demand-based incentives to use violence to facilitate appropriation.

**Keywords:** Agriculture; climate change; georeferenced data; violence against civilians

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## Introduction

The possibility that climate change will intensify violence within developing agricultural regions is a major concern for both researchers and policymakers (e.g., von Uexkull and Buhaug, 2021; UN, 2021). Until relatively recently, researchers were divided on whether climate change will (substantively) impact civil war. Some argued that by inducing scarcities climate change will increase conflict risk (e.g., Burke et al., 2009; Maystadt and Ecker, 2014; Cane et al., 2014; Kelley et al., 2015; Crost et al., 2018), while others claimed that climate change is, at best, a weak predictor of conflict (e.g., Buhaug, 2010; O’Loughlin et al., 2012). Yet others find that – locally – violence is often associated with abundance rather than scarcity (e.g., Hendrix and Salehyan, 2012; Koren and Bagozzi, 2017; Koren, 2018; Crost and Felter, 2020; Linke and Ruether, 2021). Considering that the advantages provided by the scarcity-vs.- abundance debate were limited (Mach et al., 2019), researchers luckily moved beyond this dichotomy to explore where, when, and why we might see a particular impact (von Uexkull and Buhaug, 2021).

A directly related research agenda emphasizes the impact of shifting climate on communal violence, namely clashes between different ethnic, political, or socioeconomic groups within the state without the direct intervention of the military (e.g., Fjelde and Von Uexkull, 2012; Döring, 2020; Detges, 2014; Scheffran, Ide and Schilling, 2014; Petrova, 2022; Theisen, 2012; Van Weezel, 2019). Examples for violent communal violence events include cattle theft raids (Adano et al., 2012; Detges, 2014; Schilling et al., 2014; Döring, 2020), clashes between political parties (Fjelde and Von Uexkull, 2012; Caruso, Petrarca and Ricciuti, 2016; Petrova, 2022) or ethnic communities (Scheffran, Ide and Schilling, 2014), and pastoralist-agriculturalist social conflicts (Theisen, 2012; Schilling et al., 2014). As Van Weezel (2019, 515) explains, “[c]ommunal conflict

is commonly linked to climate as there are fewer constraints in engaging in violence with other groups compared to the state.”

One area that deserves further consideration is the impact of agricultural pressures in developing regions on violence specifically targeted at unarmed civilians. Although both the focus on armed conflict between the state and rebels and empirical definitions of communal violence may sometimes cover violence against civilians (VAC) incidents, understanding the motivations that lead to such violence, specifically, over other choices (e.g., engaging with armed groups, attacking nonmilitary installments), especially by more capable organizations, requires further investigation. For instance, armies and rebel groups, which are mostly focused on achieving broad political goals such as toppling a regime (for rebels) or ensuring its stability (armies) (Selby and Hoffmann, 2014), may be less impacted by local agricultural variations. In contrast, the incentives to target civilians are more immediate and localized, and may arise, for instance, due to the willingness or need to loot or secure revenues and logistical support (Koren and Bagozzi, 2017).

Studying if the rate of violence against civilians is sensitive to agricultural productivity in developing regions can not only yield important insights into improving human security, but also link across bodies of research that focus on climate’s impact on armed conflict involving armed actors and those that focus on communal social conflict. Such analyses require moving beyond the oft-used state-vs-rebel dichotomy, where military forces are synonymous with the state while rebels are actors who specifically mobilize against the state. This dichotomy ignores a host of pro-government and nonaligned actors who are not an official part of the state and that are prevalent in many areas around the globe, especially in (sub-Saharan) Africa (Carey, Mitchell and Lowe, 2013; Raleigh, Choi and Kniveton, 2015; Magid and Schon, 2018). These actors – often referred to as “militias” in the extant research – are not rebels; they might even be created or co-opted by

the government under a semi-independent or informal status (i.e., not being part of the military or police) to assist in specific operations where the state lacks capacity or information. Rebels and militias may share key similarities with respect to the potential sensitivity of their behavior to environmental variability. Whereas state forces are more likely, on average, to enjoy some level of support, rebels and militias often arise or concentrate in rural agricultural areas, and are much more dependent on locally sourced crops for sustenance and funding (Jaafar and Woertz, 2016; Koren and Bagozzi, 2017).

This study therefore extends on past research, paying close attention to local and temporal differences in agricultural productivity, climate, and violence against civilians. VAC is often implemented not strategically as part of a war plan, but rather tactically, to facilitate looting and appropriation based on more immediate pressures or war dynamics. Although such possibilities have been hypothesized in past research (Koren and Bagozzi, 2017; Crost and Felter, 2020; Linke and Ruether, 2021), this study tests their viability directly and systematically by examining trends within the 14 countries that enclose the African Sahel<sup>1</sup> –highlighted as an area heavily susceptible to both agricultural variability and conflict (Benjaminsen et al., 2012; Raleigh and Dowd, 2013) – for every month between January 2006 and December 2018. Considering that agricultural productivity varies intra-annually, it introduces an important empirical contribution, assessing how *monthly* (as opposed to annual) changes in the productivity of valuable crops from Spatial Production Allocation Model (SPAM) (Yu et al., 2020) impact VAC at the 0.5-degree grid cell level, distinguishing these effects across official state (military and police), rebel, and (pro-government, political, ethnic, and nonaligned) militias.

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<sup>1</sup> Mali, Senegal, Mauritania, Niger, Burkina Faso, Cameroon, Nigeria, Central African Republic, Chad, Ethiopia, Eritrea, Algeria, Sudan, and South Sudan.

### **Cash crops, resource dependence, and violence against civilians: three mechanisms**

The primary link between climate insecurity (e.g., heatwaves, droughts, and floods) and both civil war and social-communal conflicts is often hypothesized to work by inducing scarcity and exacerbating competition over resources across different socioeconomic and political contexts. The latter include regions with ethnically and economically marginalized groups (Adano et al., 2012; Theisen, 2012; Schilling et al., 2014; von Uexkull et al., 2016), locations where state responses to climate shocks are limited or politicized (Adano et al., 2012; Raleigh and Dowd, 2013; Petrova, 2022), and urban areas where mostly consumers reside (Hendrix and Salehyan, 2012). Rural low development contexts are especially vulnerable to armed conflict and communal violence, and climate stress can potentially exacerbate these dynamics (von Uexkull et al., 2016; Van Weezel, 2019; Raleigh and Dowd, 2013).

Examining violence against civilians (VAC), specifically, researchers show that strategic behaviors concerning resource availability will impact the decisions of armed actors to engage in VAC differently than they would in armed conflicts (Kalyvas, 2006; Weinstein, 2007; Koren and Bagozzi, 2017). This suggests that the impact of climate and agriculture on VAC is distinct from their impact on armed conflicts or other types of communal violence, although we recognize that some overlap between the three phenomena (armed conflict, communal social conflict, and VAC). From this perspective, VAC is used to facilitate resource appropriation as to improve the organization's operational capacity, or due to more immediate rapacious needs, such as looting.

Researchers who emphasize the exacerbating impact of climate change on violence in rural developing contexts highlight agricultural *supply*, and hence often focus on the potential conflict risk associated with decreases in agricultural input. For instance, Burke et al. (2009, 20670)

hypothesize that “[b]ecause the vast majority of poor African households are rural, and because the poorest of these typically derive between 60% and 100% of their income from agricultural activities, such temperature-related yield declines can have serious economic consequences for both agricultural households and entire societies that depend heavily on agriculture,” presumably with direct impacts on increasing armed conflict. Similarly, in their analysis of the Syrian civil war, Kelley et al. (2015, 3241) note that, “in 2003, before the drought’s onset, agriculture accounted for 25% of Syrian gross domestic product. In 2008, after the driest winter in Syria’s observed record, wheat production failed and the agricultural share fell to 17%,” which presumably contributed to conflict onset. These analyses suggest that, if climate stress does pose a risk, we should observe violence intensifying in cash-crop producing locations when fewer crops are produced (i.e., reduced yields and yield shocks), accounting for population densities and development. In these times, the value of these resources increases, suggesting heightened competition and therefore incentives for violence.

At the same time, some researchers who focus on the importance of *demand* for valuable crops, and who study their importance both as a source of sustenance and as valuable commodities, argue that logistical support (Hendrix and Salehyan, 2012; Koren and Bagozzi, 2017; Koren, 2018; Linke and Ruether, 2021) or rapacity driven (Jaafar and Woertz, 2016; Crost and Felter, 2020) models provide better fit for the observed trends, namely, that conflict rates increase where and when resources are more abundant. For instance, as Koren and Bagozzi (2017, 352) explain, “[a]s the need to sustain a continuous supply of food is perhaps the most acute aspect of this deficiency in logistical support, we suggest that interactions with local populations over food access will generate specific dynamics that can affect the rates of troop violence against civilians.”

Thinking specifically about violence against civilians, both perspectives can be extended to identify three possible mechanisms linking variations in agricultural productivity to VAC. The first relates to the intersection between armed actors' strategic calculations, and the more immediate needs that may arise as part of these calculations to engage in resource appropriation to secure support, using VAC as a means to this end. Researchers emphasize the strategic incentives of actors, such as achieving broad political goals such as toppling a regime (for rebels) or ensuring its stability (armies) (Selby and Hoffmann, 2014). To succeed in these endeavors, they need to secure sources of logistic and financial support. State forces are more likely to enjoy regular logistic support, whereas rebels (and other nonstate organizations fighting for the state or who are nonaligned) will be much less likely to receive such regular support, forcing the latter to often "live off the land." This suggests that rebels and militias – and possibly state forces as well – might seek to source agricultural resources strategically to support their fighting operations, but will engage in VAC to facilitate appropriation on more ad hoc tactical basis, when and where vulnerable agricultural crops are available for the taking, even if they plan to sell them at a later date (Croston and Felter, 2020; Buhaug and von Uexkull, 2021). For instance, in northeastern Nigeria, Boko Haram often engages in violence against farmers to secure resources to sell or for personal consumption (Eke-okocha and Eze, 2023).

A second mechanism relates to shifts in the behaviors of nonstate (rebel and militia) actors, and how they may increase the rates of their violent appropriation behaviors. Researchers that focus on communal violence emphasize that many communities in the Sahel and in eastern Africa are heavily dependent on access to locally sourced agriculture and pastureland, which explains why they may shift their farming or roaming due to changing frequency of climate shocks and disasters (Adano et al., 2012; Theisen, 2012; Detges, 2014; Van Weezel, 2019; Ide et al., 2020;

Döring, 2020). Land grabs by state-backed producers or potential shifts in roaming dynamics due to climate change can create opportunity for more competition and raiding, where local militias may engage in violence against farmers and pastoralists to chase them off the land, or where pastoralists might raid farms for sustenance and to loot resources (or cash available on the premise to pay workers during harvest times) (Theisen, 2012; Detges, 2017). In these situations, VAC is one tactic available to armed organizations, and may be used when and where the situation calls for resource appropriation or preemptive violence (Linke and Ruether, 2021).

Finally, it is possible that soldiers, rebels, or militia troops may engage in VAC due to rapacity-based incentives: where the opportunity arises, they might look cash crops (or money to pay for workers) simply because they wish to, and their commanders cannot or do not wish to prevent this behavior (Weinstein, 2007). The incentives here are more individual-focused, but they should similarly lead to violence where and when opportunity and willingness for rapacity intersect.

These three mechanisms share: (i) a focus on VAC, specifically, rather than other forms of conflict; and (ii) immediacy, namely that violence is often not planned long time in advance, unlike, for instance, strategic plans for conquering “breadbasket territories,” which often can involve long periods of fighting and where VAC rates may even be reduced to facilitate local support (Jaafar and Woertz, 2016). From this perspective, individuals residing in regions characterized by very low socioeconomic development and who depend on locally sourced crops are easy targets for armed actors seeking to attack or prey on local populations. If they are primarily supply driven (as the climate-scarcity-conflict perspective suggests) then they should increase their VAC rates when and where sudden *declines* in cash-crop productivity happen. If they are more demand driven (as the conflict-abundance perspective hypothesizes) then their VAC rates should



be more sensitive to positive changes cash-crop productivity. Finally, if they are driven mostly by logistical incentives, then either one of these expectations (scarcity breeds violence or abundance breeds violence) should be more valid for nonstate actors, which are less likely to be supported compared with state troops.

One aspect of agriculture that researchers often emphasize with respect to conflict is cash crops. Examples for cash crops analyzed in past research include cereals and grains (Jaafar and Woertz, 2016; Koren, 2018; Linke and Ruether 2021), fruit (Crost and Felter, 2020), and coffee (Dube and Vargas, 2006), among others. The importance of cash crops is twofold. First, some crops (cereals and grains, fruit, sugarcane) can be used for consumption, to support and feed armed troops (Koren and Bagozzi, 2017; Koren, 2018). Second, cash crops can be converted to revenue, which can assist in purchasing equipment and paying troops (Jaafar and Woertz, 2016; Crost and Felter, 2020). This provides a major advantage for the state or rebel and militia organizations fighting in developing rural areas, considering that – unlike other natural resources such as diamond or oil – cash crops are rarely if ever sanctioned (Biersteker, 2018). From this perspective, cash crops are one of the most relevant aspects of agricultural productivity as they pertain to armed actors’ incentives to engage in violence for appropriation. Finally, cash crop locations in the Sahel produce the highest yields during the May – July months, suggesting that these periods should experience high VAC rates in locations with greater productivity, especially considering that output can bring in high revenues several months after the harvest (Aune and Batino, 2008).

Testing tactical appropriation dynamics accordingly necessitates data that are focused on relatively sparse temporal periods and geospatial resolution. As discussed in the next section, this study leverages a newly available data framework to do exactly that. Building on past agricultural economic research (Koren, 2018; Crost and Felter, 2020), the focus is specifically placed on cash

crops, rather than agricultural productivity or pastoral land. Cash crop productivity is easier to measure across space and time, provides the greatest “bang for buck” for appropriation, and is specifically sensitive to potential revenue streams from selling produce (Croston and Felter, 2020). Monthly variations are also more reflective of these hypothesized tactical incentives compared with annual ones. As such, the monthly variation of local cash crop productivity is an effective proxy of tactical looting incentives, one that can be measured across multiple states for the first time (to our knowledge) at this level of temporal and spatial resolution.

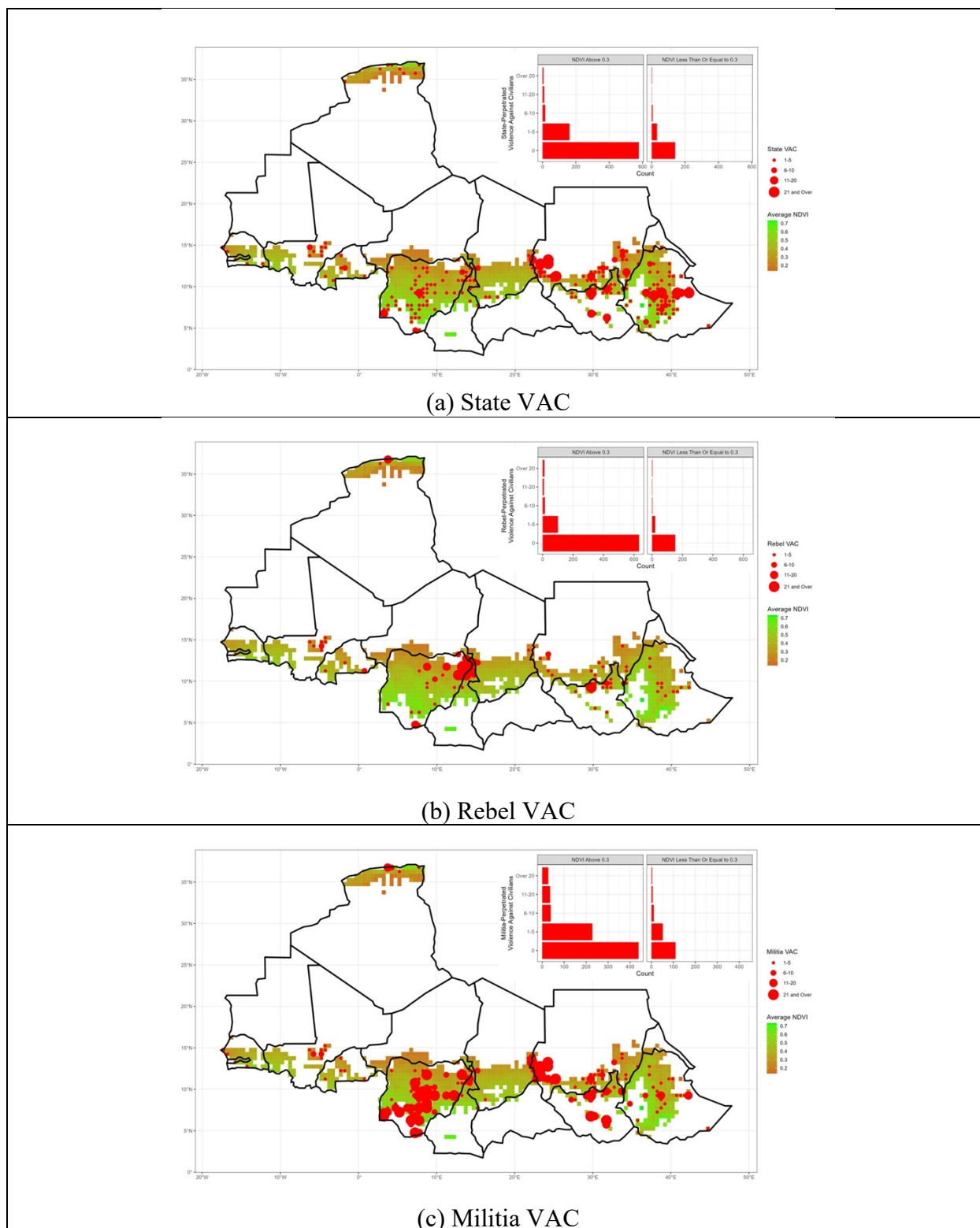
## **Materials and methods**

The unit of observation is the 0.5-degree agricultural grid cell month (*it*) in the Sahel. Agriculturally productive areas are identified using the Spatial Production Allocation Model (SPAM) (Yu et al., 2020) and aggregated into AfroGrid, a 0.5-degree grid month framework for climate-conflict analysis (Schon and Koren, 2022). SPAM identifies 42 primary crops produced annually in each 0.5 AfroGrid cell. The analysis is hence focused only on agriculturally active locations in the Sahel, identified by SPAM as producing some type of crops (robustness models that ensure the results are robust to this choice is reported in the supplementary material file).

The dependent variables are created using data from Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al., 2010), which records all VAC events involving state forces, rebels and insurgents, and ethnic and identity militias. Specifically, the three dependent variables corresponding to the theoretical expectations discussed previously are created based on a classification included in AfroGrid (Schon and Koren, 2022) to identify the initiating actor in each event. For each actor, all initiated VAC events are summed as the total count in 0.5-degree grid cell  $i$  during a given month  $t$  for the period of interest for each respective VAC indicator. The

resulting *State VAC<sub>it</sub>*, *Rebel VAC<sub>it</sub>*, and *Militia VAC<sub>it</sub>* accordingly have means of 0.004, 0.004, and 0.011 and ranges of  $0 \Leftrightarrow 25$ ,  $0 \Leftrightarrow 9$ , and  $0 \Leftrightarrow 16$ , respectively.

The key explanatory variable, *cash crop productivity<sub>it</sub>*, is constructed in three steps. First, SPAM data are used to identify all locations where cash crops were grown based on the 2005 survey, assigning these locations a score of =1, =0 otherwise. As discussed in the theoretical section, based on past research, the crops included in the cash crop category are: cereals (e.g., wheat, maize, rice and millet), oil crops (e.g., sunflower, rapeseed), cotton, coffee, and sugarcane. To reduce the (low) risk that VAC can affect crop planting choices by civilians, crop values from 2005 are used, and the sample is limited to the January 2006 – December 2018 period. Robustness models that account for this choice are reported in the appendix. To create *cash crop productivity<sub>it</sub>*, this variable is then interacted with a vegetation health variable, constructed using the Normalized Difference Vegetation Index (NDVI). NDVI is a continuous indicator of vegetation and agricultural productivity, which ranges from 0 (no vegetation) to 1 (the entirety of the cell-month is covered by vegetation) on land. NDVI information was obtained from the MODIS Terra monthly satellite data, downloaded and processed with the MODISTsp R package (Busetto and Ranghetti, 2016; Didan et al., 2015) and included in AfroGrid (Schon and Koren, 2022). The same data are also used to create the NDVI anomaly indicator and its corresponding agricultural productivity variable used in Table A8, supplementary material file. Due to the inclusion of grid cell fixed effects, the constitutive term for the cash crop variable is omitted from analysis, but considering our interest in the impact of productivity within these regions, specifically, this is not an econometric concern (Angrist and Pischke, 2009).



**Figure 1.** The rates of violence against civilians by state, rebel, and militia forces within agricultural areas over the 2006-2018 period.

Figure 1 gives a visual representation of the correlation between agricultural productivity and VAC by state forces (top), rebels (center), and militias (bottom) in cropland areas in the Sahel, collapsed over the entire January 2006 – December 2018 period.<sup>2</sup> At the top-right of each plot, bar graphs reporting the rates of VAC events within more and less productive cropland areas are additionally reported. Generally, the highest risk for civilians from armed combatants appears to be in Nigeria, Sudan, South Sudan, and Ethiopia. From a visual explanation of subfigure (a), it appears that the highest rates of state VAC are largely concentrated in areas with ongoing major civil wars, especially in Darfur (southwestern Sudan), South Sudan, and Ethiopia, as well as in central and southwestern Nigeria (around Lagos). These clusters do not seem to overlap heavily with agricultural productive locations.

Turning to the central subfigure, which shows the rates of rebel VAC, the frequencies and locations of intensified violence are largely similar, although they are far lower in Darfur and central Ethiopia. The most notable difference from the state VAC plot is that the greatest rates of rebel VAC across the entire region are found around Lake Chad, in the border area between Chad, Niger, Nigeria, and Cameroon, where the rebel group Boko Haram operates. This region has been analyzed in past studies, including those that examine the viability of potential linkages between climate change and conflict and lack thereof, and which highlight the potential relationship between agriculture and armed conflict (Benjaminsen et al., 2012; Raleigh and Dowd, 2013; Detges, 2017). Finally, turning to examine militia VAC (bottom plot) we observe higher VAC rates are concentrated in central Nigeria (agriculturalist-pastoralist and ethnic and political violence), Darfur (*janjaweed*), and the agricultural areas of South Sudan, central Mali, and central

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<sup>2</sup> For the specific crops grown in each location see Figure A1, supplementary material.

Ethiopia. Overall, then, the data reveal large cross-sectional variation, with higher rates of nonstate (rebel and militia) VAC potentially more likely in cropland areas that are, on average, more productive compared with state VAC (as illustrated by the bar plots).

To measure the impact of climate and weather, variables measuring average monthly temperature and precipitation (log10 transformed) in a cell  $i$  during month  $t$ , created by AfroGrid using data from the CRU TS monthly high-resolution gridded multivariate climate dataset (Harris et al. 2020), are included in some specifications. For environmental stress more generally, a variable measuring whether a grid cell was included in the Sahara transition zone during a given year, created by Schon, Koehnlein, and Koren (2023), is deployed. Other controls – included in AfroGrid – are added, including total average annual nighttime light emissions (adjusted for VIIRS data) and population densities (Lloyd et al., 2019), both log10 transformed, as well as GDP per capita indicator (World Bank, 2022). Summary statistics for all variables (including those used in the sensitivity analysis) are reported in Table A1, supplementary materials file.<sup>3</sup>

The identification strategy implicitly assumes a relationship between agricultural variability and VAC, which can be confounded by climate and socioeconomic factors. In line with this logic, a series of fixed effects linear models is estimated using the ordinary least squares (OLS) estimator, where controls for climate and then socioeconomics are added sequentially. Drawing on standard econometric approaches (Angrist and Pischke, 2009), the identification equations are:

$$\mathbf{y}_{it} = \beta_1 \mathbf{n}_{it} + \beta_2 \mathbf{p}_{it} + \beta_3 \mathbf{y}_{it-1} + \omega_i + \phi_m + \tau_t + \epsilon_i \quad (1)$$

$$\mathbf{y}_{it} = \beta_1 \mathbf{n}_{it} + \beta_2 \mathbf{p}_{it} + \beta_3 \mathbf{y}_{it-1} + \beta_{4-6} \mathbf{C}_{it} + \omega_i + \phi_m + \tau_t + \epsilon_i \quad (2)$$

$$\mathbf{y}_{it} = \beta_1 \mathbf{n}_{it} + \beta_2 \mathbf{p}_{it} + \beta_3 \mathbf{y}_{it-1} + \beta_{4-6} \mathbf{C}_{it} + \beta_{7-9} \mathbf{X}_{it} + \omega_i + \phi_m + \tau_t + \epsilon_i \quad (3)$$

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<sup>3</sup> Data curation and replication files are available on Harvard Dataverse: <https://doi.org/10.7910/DVN/LDI5TK>.

$y_{it}$  is a vector of state, rebel, or militia VAC event counts and  $y_{it-1}$  their corresponding one-month lags;  $n_{it}$  is a vector capturing vegetation coverage;  $p_{it}$  is an interaction between vegetation health and cells denoted as cash crop producing in the SPAM data for the 2005 coverage (omitted from the models due to the inclusion of 0.5 grid fixed effects), which denotes monthly levels of cash crop productivity within a particular 0.5 degree cell;  $C_{it}$  is a matrix of climate controls (average temperature, average log precipitation, and whether a given cell was part of the Sahara desert during a given year);  $X_{it}$  is a matrix of our socioeconomic controls of interest (log nighttime light emissions, log local population, and log GDP per capita);  $\omega_i$  and  $\phi_m$  are fixed effects by grid cell and month, respectively;  $\ln \tau_t$  is the (log) linear time trend; and  $\varepsilon_i$  are standard errors clustered by 0.5-degree grid cell.<sup>4</sup>

One relevant identification aspect relates to the potential impact of endogeneity. First, as mentioned above, the possibility that VAC affects civilian crop choices is addressed by deploying 2005 cropland values and analyzing violence starting in 2006, while ensuring the results are robust to this decision in Figure 2 and Table A3, supplementary material file. Perhaps more likely, violence could also reduce vegetation coverage (e.g., because farms are destroyed when civilians are killed). Crucially, however, this will push estimates downward, meaning that endogeneity would be a concern in case of a negative relationship between cash crop productivity and violence is identified (we account for this possibility in Table A11, supplementary material file); but not so in the case of a positive coefficient, which means – if anything – that the true effects might be stronger than said coefficients suggest. All analysis were conducted in R.

## Results

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<sup>4</sup> The models do not include an intercept due to the reliance on the method designed to facilitate estimation of models with fixed effects developed by Gaure (2013).

Table 1 attempts a systematic evaluation of the relationship between cash crop productivity, specifically, and VAC within agricultural areas in the Sahel. For the Sahel from Jan. 2006 to Dec. 2018, a linear model with grid cell and month fixed effects and grid clustered standard errors shows a negative but statistically insignificant relationship between *Cash crop productivity<sub>it</sub>* and violence against civilians (VAC) by state actors (columns (a) – (c), Table 1). This coefficient maintains its negative sign and lack of significance as controls for climate stress (columns (d) – (f)) and then socioeconomics (column (g) – (i)) are added to arrive at the fully specified models.

**Table 1.** Determinants of violence against civilians (VAC) in the Sahel

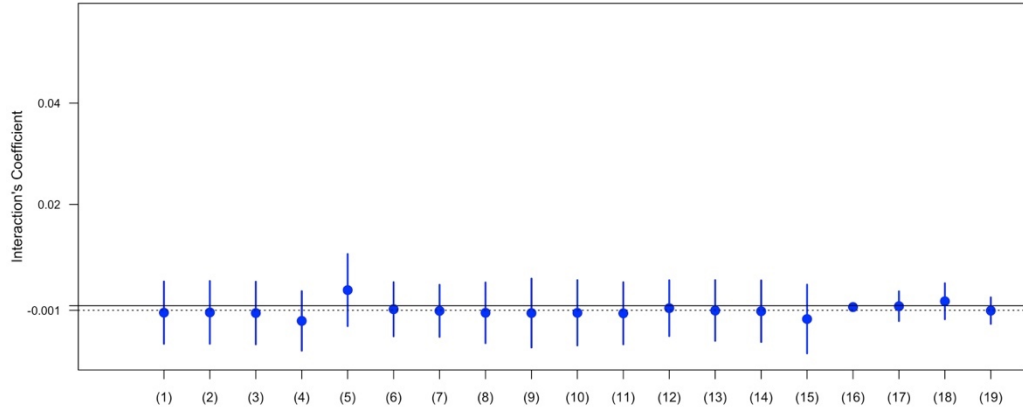
	<i>Baseline</i> (1)			<i>Climate</i> (2)			<i>Full</i> (3)		
	State (a)	Rebels (b)	Militia (c)	State (d)	Rebels (e)	Militia (f)	State (g)	Rebels (h)	Militia (i)
<i>Vegetation coverage<sub>it</sub></i>	.001 (.003)	-.002 (.002)	-.019*** (.007)	.001 (.003)	.001 (.003)	.020*** (.007)	.001 (.003)	.001 (.003)	-.020*** (.007)
<i>Cash crop prod.<sub>it</sub></i>	-.001 (.003)	.008** (.003)	.024*** (.007)	-.001 (.003)	.007*** (.003)	.022*** (.007)	-.001 (.003)	.007*** (.003)	.023*** (.007)
<i>DV<sub>it-1</sub></i>	1.300*** (.177)	1.304*** (.189)	0.239*** (.020)	1.300*** (.177)	1.304*** (.189)	.239*** (.020)	1.296*** (.176)	1.303*** (.189)	.239*** (.021)
<i>Temperature<sub>it</sub></i>				.00001 (.0001)	.0002*** (.0001)	.0001 (.0001)	.00005 (.0001)	.0002*** (.0001)	.0001 (.0001)
<i>Precipitation<sub>it</sub><sup>1</sup></i>				-.0001 (.001)	.001** (.0004)	.002*** (.001)	-.00005 (.001)	.001* (.0004)	.002*** (.001)
<i>Sahara TZ<sub>it</sub></i>				.001 (.001)	.001 (.004)	.002 (.002)	.001 (.001)	.001 (.004)	.003 (.002)
<i>Nighttime light<sub>it</sub><sup>1</sup></i>							-.0005 (.001)	-.0003 (.0004)	.002 (.001)
<i>Population<sub>it</sub><sup>1</sup></i>							-.0004 (.006)	.006 (.006)	.003 (.024)
<i>GDP per capita<sub>it</sub><sup>1</sup></i>							-.367*** (.112)	.132 (.080)	-.502*** (.153)
$\tau$	.0001*** (.00001)	.0001*** (.00001)	.0003*** (.00002)	.0001*** (.00001)	.0001*** (.00001)	.0003*** (.00002)	.0002*** (.00003)	.00002 (.00003)	.0004*** (.00001)
R <sup>2</sup>	.121	.177	.183	.121	.177	.183	.121	.177	.183
Adjusted R <sup>2</sup>	.115	.172	.178	.115	.172	.178	.115	.172	.178

*N*: 342,108 observations; coefficients reported with standard errors clustered by grid cell in parentheses; grid cell and month fixed effects were included in each regression but are not reported here. \*  $p < .1$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$ . <sup>1</sup> Log base 10.

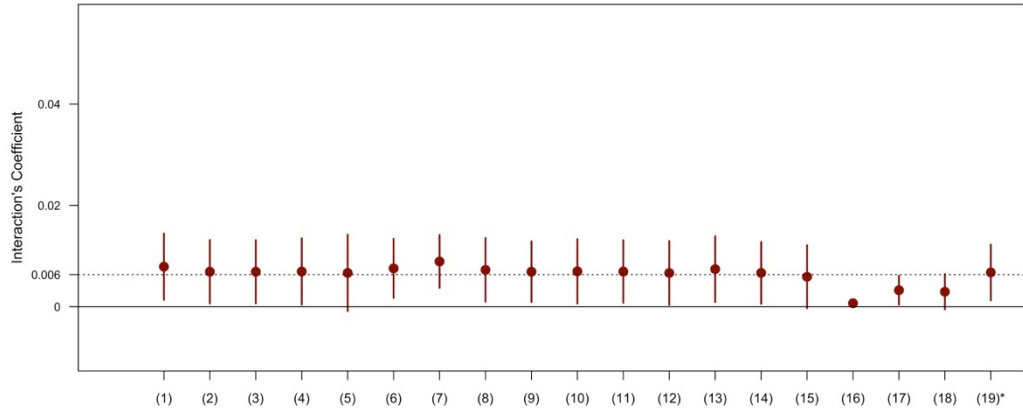


Considering these results, the estimates from the rebel VAC models provide a strikingly different picture. Across all three main models (Table 1, columns (b), (e), and (h)), the coefficient of *Cash crop productivity<sub>it</sub>* is positive and statistically significant to at least the  $p < .05$  level, suggesting rebel VAC in the Sahel increases in cash crop producing grids in months during the year when these areas are more productive. The same results hold when the militia VAC models (Table 1, columns (c), (e), and (i)) are examined: the *Cash crop productivity<sub>it</sub>*'s coefficient is positive and statistically significant to the  $p < .01$  level. These results suggest that VAC initiated by nonstate actors is sensitive to higher cash crop productivity, potentially due to immediate needs to ensure logistic support or rapacity-based incentives, while VAC by state actors is not.

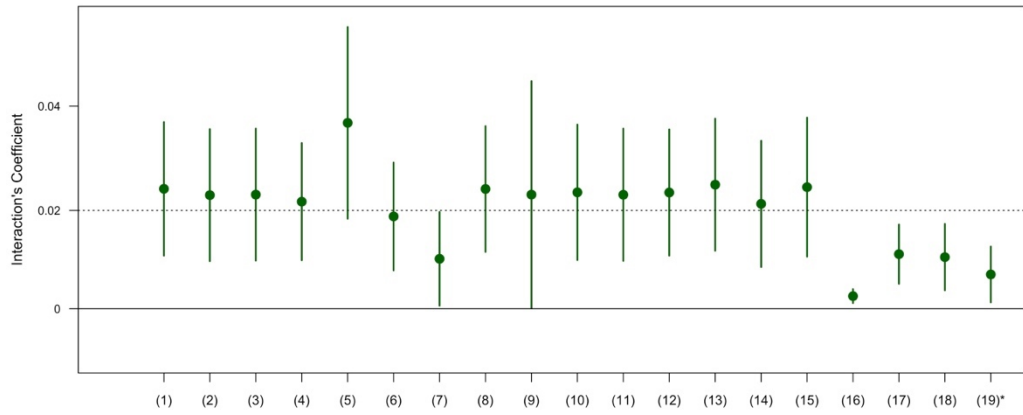
Interestingly, the effects of the climate stress controls are also generally in line with the same rapacity logic. In all state VAC models (Table 1, columns (a), (d), and (g)), *Temperature<sub>it</sub>*'s, *Precipitation<sub>it</sub>*'s, and *Sahara transition zone<sub>it</sub>*'s coefficients are statistically insignificant, suggesting violent state actors' behavior are not noticeably responsive to climate shocks. In contrast, *Precipitation<sub>it</sub>*'s coefficient is statistically significant (to the  $p < .1$  level) for both rebel and militia VAC, suggesting violence by nonstate actors increases when there is more rainfall. *Temperature<sub>it</sub>*'s coefficient is positive and statistically significant (to the  $p < .01$  level) across the medium and full rebel VAC models, suggesting violence by rebels may be more likely in warmer (spring and summer) months. Looking at the socioeconomic controls, countries with higher GDP per capita appear less likely to suffer violence by state actors, potentially because militaries in such states are more likely to be supported (Koren and Bagozzi, 2017); and militias, potentially because the existence of and need for support from such groups is lower in strong states.



(a) State VAC



(b) Rebel VAC



(c) Militia VAC

**Figure 2:** Evaluating the sensitivity of *Cash Crop Productivity<sub>it</sub>*'s coefficient. (1) Baseline; (2) Climate; (3) Full; (4) Cereals; (5) High crops; (6) All grids; (7) TVCs; (8) Civil war; (9) CSEs; (10) No Algeria and Mauritania; (11) YFEs; (12) Country FEs; (13) Country FEs x YFEs; (14) Spatial lag; (15)  $t - 2$  and  $t - 3$  VAC lags; (16) NDVI anomalies; (17) Log DVs; (18) Binary DVs; (19) GED. \* Reports the same coefficient obtained from the nonstate VAC GED models for both the rebel and militia plots.

To evaluate the sensitivity of these results, numerous robustness tests are performed. These tests are reported in full in the supplementary material file, and the sensitivity of each *Cash crop productivity<sub>it</sub>*'s coefficient estimate across each of these models is summarized in Figure 2, with 95% confidence intervals to illustrate whether these effects are statistically different from zero. The three plots in this figure correspond to robustness models where the dependent variables are state VAC, rebel VAC, and militia VAC, respectively. The first three models in each plot (1, 2, and 3) report each of *Cash crop productivity<sub>it</sub>*'s coefficients from the baseline, climate, and full specifications in Table 1.

The ensuing models, in order, account for: using only cereals productivity (Model 4); high cropland locations only (Model 5); all Sahel grid cells (Model 6); time varying cropland indicators (Model 7); civil war impacts (Model 8); country level clustered errors (Model 9); removing Algeria and Mauritania (Model 10); year fixed effects (Model 11); socioeconomic country level impacts (Model 12); all country level factors using country x year fixed effects (Model 13); including a binary spatial lag of each VAC type (Model 14); including two- and three-month lags of each dependent variable (Model 15); operationalizing productivity using vegetation health anomalies (Model 16);<sup>5</sup> logging all dependent variables and their lags (Model 17) ; using a binary (VAC/no VAC) version of each dependent variables and their lags (Model 18); and using the Geolocated

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<sup>5</sup> The coefficient and 95% confidence intervals decrease in size in these models due to the wider range on this anomaly-based variable ( $-5.886 \Leftrightarrow 7.306$ ) compared with the standard *Crop productivity<sub>it</sub>* indicator ( $0 \Leftrightarrow 1$ ).

Event Dataset to construct (GED) state and nonstate VAC (Sundberg and Melander, 2013) (Model 19). Substantively, cash-crop producing grids during peak productivity months are expected to experience no noticeable increase in state VAC events; but to experience about 94% increase in the monthly rate of rebel (an average coefficient size of 0.007 and a sample average of 0.0036 monthly events) and militia (an average coefficient size of 0.022 and a sample average of 0.011 monthly events) VAC events.

In addition to these sensitivity tests, two additional exercises – also reported in the supporting materials file – were conducted to account for modeling choices and endogeneity. First, while OLS estimation procedures were chosen considering econometric research overwhelmingly recommends these estimators in the context of fixed effects regressions (Angrist and Pischke, 2009), a set of zero-inflated negative binomial (ZINB) models corresponding to the full specifications are estimated in Table A10, with country fixed effects in the count stage, and vegetation coverage and all climate and socioeconomic controls in the inflation stage. The results of the OLS analyses hold in these models, and substantively become even stronger, suggesting the findings are robust to modeling choices. Finally, considering potential endogeneity concerns with respect to negative coefficients in these models (see Materials and methods), a set of system generalized methods of moments (GMM) models that more directly account for simultaneous relationships in is estimated Table A11. In each case, the instrumented coefficient of cash crop productivity remains negative, which confirms the results in Table 1.

### **Discussion of scope conditions**

The results should be interpreted with the following scope conditions in mind. First, the analysis focuses on the Sahel, considering this region is often highlighted as an area at high risk of

intensified violence due to shifting climate patterns. The region is also generally underdeveloped and primarily rural (Raleigh, Choi and Kniveton, 2015), suggesting that the results might not be applicable to more developed or more urbanized contexts. For instance, these dynamics are unlikely to be relevant to researchers and policy experts analyzing the war in Ukraine, where the conflict is carried primarily by official state forces, in developed, urban and peri-urban locations. They might, however, be useful in analyses that focus on rebel groups operating in agrarian regions, such as the Naxalites in India (Wischnath and Buhaug, 2014), or rural defense militias, for example, vigilantes in Nigeria (Magid and Schon, 2018). Further testing can rely on similar data to the ones used here to assess whether and to what extent the relationships we identify are valid in other global contexts.

Second, the observational data and proxies used here are highly effective in that they allow us to capture geographically and empirically disaggregated variations in both VAC and the hypothesized VAC drivers. As explained in Materials and methods, endogeneity is unlikely to be a concern considering the direction and strength of the relationship we identify between cash crop productivity and VAC by rebels and militias, but it does suggest that this relationship is “plausibly exogenous,” and is hence fully consistent with a causal interpretation (Angrist and Pischke, 2009). Additionally, while the empirical focus here is on cash crops, it is possible that – within and across agrarian regions – other types of primary or agricultural resources can have varying effects on VAC, or be associated with greater sensitivity of violence due to climatic variations.

## **Conclusion**

Moving beyond the analytical dichotomy of whether climate change uniformly drives conflict risk, this study provides three important extensions by (i) focusing on tactical violence perpetrated

specifically against unarmed civilians, (ii) expanding on the government-vs.-rebel dichotomy to also analyzing numerous nonaligned and pro-government militias, and (iii) measuring intra- (as opposed to inter-) annual variations in cash crop productivity. The analysis has detected a consistent statistical pattern, whereby VAC attacks initiated by rebels and militias are more sensitive to positive monthly variations in cash crops within a world region especially susceptible to climate change's impacts.

Importantly, these results are more in line with demand-based arguments of conflict, which emphasize agricultural abundance and its impact on violence (Hendrix and Salehyan, 2012; Jaafar and Woertz, 2016; Koren and Bagozzi, 2017; Koren, 2018; Crost and Felter, 2020; Linke and Ruether, 2021) rather than supply-based arguments that emphasize how climate change can increase the risk of violence by inducing scarcity and competition (Burke et al., 2009; Maystadt and Ecker, 2014; Kelley et al., 2015). Indeed, the climate indicators also included in the models do not point to a clear impact of rising environmental scarcities. Moreover, that the coefficient estimates are positive and significant across both the rebels and militias categories but not state forces suggest that the logistical framework (Jaafar and Woertz, 2016; Koren and Bagozzi, 2017; Koren, 2018; Linke and Ruether, 2021) is an effective explanation of these tactical VAC trends.

Qualitative evidence from specific cases drawn from the data underscores the validity of these dynamics. For example, in northeastern Nigeria, Boko Haram often engages in violence against farmers to secure resources to sell or for personal consumption (Eke-okocha and Eze, 2023), and both pro- and anti-government nonstate actors (vigilantes and rebels) use violence against civilians to garner support and appropriate resources (Felbab-Brown, 2020). Similarly, in Burkina Faso, the number and size of Jihadist groups has seen a sharp rise since 2019, including not only homegrown groups but also groups that originated in Mali and Niger and regional al-

Qaeda-affiliated JNIM Islamist group (Schmauder, 2021). As the rate of conflict events doubled since 2020, armed insurgents have engaged in violence and human rights violations, often designed to facilitate pillaging and resource appropriation (HRW, 2022; Durmaz, 2022).

There are, importantly, non-climate explanations and drivers that can also explain this study's results. As mentioned above, rural regions in the Sahel are often undeveloped, and state capacity is weak. The controls included in the model should largely account for these confounders, but the lack of rule-of-law enforcement, for instance, can still intensify the incentives of groups that are not part of the state to engage in resources appropriation regardless of climate pressures. Another issue relates to pastoralist-agriculturalist tensions and ethnic marginalization, which underlie the risk of communal conflict (Adano et al., 2012; Detges, 2014; Schilling et al., 2014; Döring, 2020) as well as VAC. In these contexts, climate shifts can intensify pressures to engage in appropriative violence (Benjeminsen et al. 2012), but the key drivers remain – for now – socioeconomic and political.

The results broadly speak to the importance of strengthening adaptive and state-protective capacities of agriculturally-dependent communities, especially those that rely on their own civil defense militias. They also suggest that expanding state capacity and development are more likely to exert preventive influence on violence against civilians that will be, at least currently, greater than that of climate change mitigation capacities, although we emphasize the key importance of the latter for addressing concerns other than civilian victimization.

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