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Climate variability, crop and conflict: Exploring the impacts of spatial concentration in agricultural production

Paola Vesco

Department of Peace and Conflict Research, Uppsala University & CMCC, Euro-Mediterranean Center on Climate Change

Malcolm Mistry

Department of Economics, Ca' Foscari University of Venice & CMCC, Euro-Mediterranean Center on Climate Change

Matija Kovacic

Department of Economics, Ca' Foscari University of Venice & European Commission, Joint Research Centre (JRC), Ispra

Mihai Croicu

Department of Peace and Conflict Research, Uppsala University

Abstract

Although substantive agreement exists on the role of climate variability and food scarcity in increasing violence, a limited number of studies have investigated how food resources affect violent conflict. This article explores the complex linkages between climate variability, agricultural production and conflict onset, by focusing on the spatial distribution of crop production in a cross-country setting. We hypothesize that spatial differences in crop production within countries are a relevant factor in shaping the impact of climate variability on conflict in agriculturally - dependent countries. To test this hypothesis, we rely on high-resolution global gridded data on the local yield of four main crops for the period 1982–2015 and aggregate the grid-cell information on crop production to compute an empirical indicator of the spatial concentration of agricultural production within countries. Our results show that the negative impacts of climate variability lead to an increase in the spatial concentration of agricultural production within countries. In turn, the combined effect of climate extremes and crop production concentration increases the predicted probability of conflict onset by up to 14% in agriculturally dependent countries.

Keywords

agriculture, food, climate variability, conflict

Introduction

Substantial agreement exists that climatic conditions can impact security through intermediate pathways and/or under some specific conditions (Mach et al., 2019). Yet, the mechanisms connecting climate to conflict and the conditions that make this link more likely to arise are rather unclear (Koubi, 2019). Among the examined channels through which climate variability can influence conflict, agriculture and food security have received great attention (Wischnath & Buhaug, 2014; Koren et al., 2021). This is not surprising as conflict is arguably most widespread in developing countries, which are not only heavily dependent on agriculture (Lotze-Campen & Schellnhuber, 2009), but also disproportionately affected by changes in climatic conditions (Porter et al., 2014). However, studies of the climate–conflict nexus still lack explicit incorporation of agricultural variables in the models, which is essential to improve the specifications of their theoretical argumentations (Meierding, 2013).

Corresponding author:
paola.vesco@pcr.uu.se

The main argument of this study follows three steps, leading from climate extremes to conflict. First, the negative impacts of climate variability increase the spatial concentration of crop production across locations. Second, the spatial distribution of crop production, which measures how food access and livelihood conditions vary across locations, is a relevant factor to shape the impact of climate on conflict in agriculturally dependent countries. Third, the combined effect of climate extremes and spatial concentration of crop production increases the likelihood of conflict onset.

We test this argument by constructing a time-variant Gini Index of crop production (GICP henceforth) within countries. GICP provides a measure of the spatial distribution of crops, that is, how concentrated or dispersed crop production is across locations. Higher values of GICP correspond to food output being concentrated in few areas of the country, while lower levels of GICP indicate that crop production is more homogeneously distributed. GICP enables us to examine how the spatial distribution of agricultural resources shapes the effect of climate on conflict over time. A set of validation tests proves that GICP is a good measure of populations' livelihood and access to food.

To this end, the present analysis contributes to the previous literature to several extents. First, the study introduces a novel, time-varying measure of spatial dispersion/concentration of crop production at the country level. The use of GICP enables us to explicitly examine the effect of climate extremes on the spatial distribution of crop production within countries and over time. Growing scientific evidence suggests that the impact of climate variability on agricultural production will vary considerably across space (Lobell, Schlenker & Costa-Roberts, 2011), yet this relationship has seldom been tested empirically. Second, our analysis complements both country-level studies and disaggregated analyses of the climate–conflict nexus, by capturing a spatial dimension of vulnerability related to crop production. Specifically, this article thoroughly investigates the effect that geographical patterns of crop production may exert on conflict; these patterns have been generally overlooked by other investigations, although implicitly assumed to occur. Finally, our study makes use of new time-varying data of agricultural production at the grid-cell level, along with a wide set of climatic indicators which are explicitly relevant to agricultural production.

The rest of the article proceeds as follows: the first section elaborates our argument on climate variability, crop production and conflict; the second section presents the data and illustrates the construction and validation of GICP; the final part discusses our empirical models and presents the results.

Climate variability, crop production concentration and conflict

The impacts of climate variability[1] on agricultural production are well established in the scientific literature. Natural extremes and anomalies in weather conditions that result from climate variability are already reducing crop productions at the global level, a trend that is projected to continue as temperatures rise further (Lobell, Schlenker & Costa-Roberts, 2011). If no adaptation takes place, global yields are expected to decrease at a pace of 1.5% per decade (Lobell & Gourdji, 2012) and losses in aggregate production will affect wheat, rice and maize in both temperate and tropical regions by 2°C of local warming (Challinor et al., 2014). Crop-level adaptation and technological innovation can moderate losses to some extent (Rosenzweig & Parry, 1994) but adaptive capacity is projected to be exceeded in regions closest to the equator if temperatures increase by 3°C or more (Porter et al., 2014).

However, when one moves from a global to a local (e.g. national or regional) focus, the impacts of climate variability become more complex. While climate anomalies are expected to have spatially heterogeneous impacts on agriculture, yielding a net negative effect at the global level (Lobell, Schlenker & Costa-Roberts, 2011), their impacts at a local scale are less straightforward, and they are expected to vary across both time and space (Kang, Khan & Ma, 2009).

Not only the impacts of climate on food production may vary across space (Iglesias et al., 2009, 2012), but countries' adaptive capacity to weather shocks is unlikely to be spatially homogeneous and rather differs across locations and strata of the populations within the same country (Alam, 2017). One key aspect that can restrain a country's resilience to climate variability is represented by the spatial distribution of food; the negative impacts of climate variability are likely to increase relative

[1] Climate change involves persistent shifts in the mean and variation of surface weather conditions, such as temperature, precipitation and wind, observed at a multidecadal scale or longer (WMO, 2017). Climate variability refers to short-term or interannual changes in surface weather conditions, which can lead to anomalies in climatic statistics and the occurrence of extremes beyond those of individual weather events. Although climate variability denotes a different concept than climate change, it is an effect of long-term variations in climate.

differences in food access and supply at both the global and local levels, as the degree of climate variation and the extent of its impacts on populations will differ from one community to another, and between rural and urban areas (Wheeler & von Braun, 2013).

Adding to this complexity, a combination of contrasts in the impacts of climate variability across regions (e.g. weather extremes) along with a high concentration of crop production in limited areas are also plausible. This could increase the risk of spatial propagation of localized crop failures (Alcamo et al., 2007), especially due to the high food teleconnectivity between regions (Bren D'Amour et al., 2016).

Overall, the vulnerability of a country to changes in climatic conditions may not only be shaped by the quantity of food production *on average*, but rather by how this production is spatially distributed relative to the distribution of population.[2] Accounting for the spatial heterogeneity of food production is therefore paramount to increase our understanding of countries' vulnerability to climate impacts. As decreases in one region may be compensated by the increase in another region (Alcamo et al., 2007), the national amount of food production may not capture all the relevant dimensions of countries' vulnerabilities.

Country-level empirical studies are thus unequipped to represent spatial differences in the production of food, as national statistics are too aggregated to reveal such differences. Disaggregated studies may partially overcome this measurement problem by examining the effect of climate shocks locally (e.g. Harari & La Ferrara, 2018), but they cannot directly investigate the effect of a change in the spatial distribution of crop production. In fact, to calculate any measure of spatial dispersion, the unit of analysis at which the main input is measured (e.g. subnational) must be lower than the relevant unit at which that distributional measure is calculated (e.g. national). Although previous studies have investigated the relationship between climate anomalies, food and conflict (e.g. Koren & Bagozzi, 2016), a systematic analysis of the *spatial* dynamics and distributional implications of food cannot be undertaken in traditional empirical settings.

Due to these complexities, the previous literature has not adequately accounted for the role of spatial variation in resources' distribution and further research needs to target the geographical disaggregation of the impacts of climatic conditions (Raleigh, Choi & Kniveton, 2015). Guariso & Rogall's (2017) study of the impacts of inequality in rainfall across ethnic groups and McGuirk & Burke's (2017) analysis of climate impacts on conflicts across food producing and non-food producing regions provide good attempts in this direction, but they do not specifically discuss how the spatial distribution of crops may shape the impacts of climate on conflict.

As illustrated in what follows, we posit that the effect of climate is especially detrimental in those countries that are dependent on agriculture and where food production is concentrated in few areas. Schematically, the line of reasoning proposed in the article proceeds as follows: climate anomalies (e.g. warm spells, droughts) have a heterogeneous effect on crop production across locations, leading to a disproportionate harvest decrease in some regions compared to others. Spatially heterogeneous crop failures will disproportionately restrain local populations' access to food, reduce rural households' means of sustenance, induce peaks in food prices (Arezki & Brueckner, 2014) which reduce consumers' purchasing power (Berazneva & Lee, 2013), and affect agricultural income (Roche et al., 2020), all in all leading to a heavier deterioration of the local livelihood in some regions, while others are relatively better off. The relative deprivation induced by a heterogeneous livelihood impairment and shifts in food entitlements will in turn (a) foster grievances, especially when intertwining with extant societal fractures (Heslin, 2020) or ethnic exclusion (Ide, Kristensen & Bartusevĉius, 2021), (b) trigger resource competition and deliberate efforts to deny adversaries' access to harvests (Linke & Ruether, 2021), and (c) decrease the opportunity cost of conflicts for the poor and thereby motivate the use of collective violence and increase the predisposition to armed conflict (Pinstrup-Andersen & Shimokawa, 2008).

We test this argument by constructing a Gini Index of crop production (GICP), which provides a measure of how the agricultural output is spatially distributed within countries, and how access to food and livelihood conditions may differ across regions. GICP enables us to capture a wide range of scenarios characterizing countries' crop production in the aftermath of a climate extreme.

Before delving into the theoretical mechanisms in detail, a caveat is necessary. The proposed steps connecting climate and crop production to conflict are far from deterministic; in particular, the association between the spatial distribution of crops and conflict is conditioned by agricultural dependence, to the extent that countries which strongly rely on agriculture are more vulnerable to climate shocks (Thomas & Twyman, 2005). We thereby

[2] This specification may be relevant for sizeable countries with large shares of arid land (e.g. deserts).

expect our argument to be especially relevant for, and our results to be driven by, agriculturally dependent countries; we explore this condition explicitly in our empirical analysis.

Even in stable climatic conditions, in those settings where agricultural production is concentrated in few regions, some households would be more vulnerable to fluctuations in food supply and/or prices, as they would have lower opportunities to access local food resources or complement their diet with locally grown crops, and limited income opportunities from agriculture. Conversely, other households would be relatively better off and more resilient to shocks. Regions with lower crop production may be more vulnerable a priori to the harmful effect of climate extremes, as they are characterized by less fertile soils, poorer technological capacities and irrigation infrastructures, and in general by weather and land conditions less suitable to agriculture. Climate extremes may therefore disproportionately reduce crop output in regions that were already disadvantaged and lead to an increase in the territorial concentration of agricultural production.

Schematically, we can think of three scenarios characterizing the agricultural production of a country in the aftermath of a climate extreme: harvests decrease in one region while remaining stable in others; the country experiences an average crop decline, but this decrease is higher in one or few regions compared to others; finally, crop production may even increase in regions less or not severely hit by a drought, while yields decrease in affected locations, thus leading to a sharper gap across space.

Climate-driven crop failures are expected to decrease food supplies and put communities' access to food at stake (Lesk, Rowhani & Ramankutty, 2016), thus shifting populations' food entitlements (Berazneva & Lee, 2013) and directly affecting households' livelihoods.

Climate shocks can not only affect food supply and demand; they can also increase the variance of agricultural incomes (Roche et al., 2020) and induce spikes in food prices which destabilize the agricultural labor market and reduce consumers' purchasing power (Swinnen & Squicciarini, 2012).

As a result, climate shocks to crop production will affect livelihood conditions both directly, through changes in the availability of and access to food, and indirectly, through related changes in agricultural income, food price fluctuations and changes in consumers' purchasing power. Heterogeneously distributed crop failures due to climate shocks will hence lead to unequal impairments in food entitlements and livelihood conditions across locations and communities (Wheeler & von Braun, 2013).

Adverse changes in food entitlement and livelihood have a highly destabilizing potential (Berazneva & Lee, 2013), and conflicts tend to occur in areas experiencing increased demand and lower supply of food resources (Koren & Bagozzi, 2016). Sharpened differences in food supply/demand and livelihood conditions can be even more likely to increase the probability of conflict, by fomenting feelings of relative deprivation, which will encourage individuals to mobilize upon previous grievances, and fuel competition for resources.

First, the disproportionate livelihood deterioration induced by climate extremes will widen the gap between what individuals perceive to be a fair condition and what they acknowledge to be their actual status (Fjelde, 2015). The relative deprivation felt by already poor farmers can add to pre-existing inequalities and exacerbate societal fragmentation (Jones, Mattiacci & Braumoeller, 2017), and thereby encourage mobilization to obtain a fairer distribution of resources. Relative differences in crop production will possibly intertwine with pre-existing grievances, as group leaders will have increased opportunity to emphasize the group's identity while disparaging, discriminating against and besetting outsiders (Homer-Dixon, 1991).

Next, groups with lower than average crop production will be more willing to compete for resources against resource-wealthier groups (De Juan, 2015). Resource competition may result either directly or indirectly, via an increase in migration flows. Negative shocks to agricultural productivity caused by weather variation have been shown to positively affect net migration outflows, mainly from poor countries (Falco, Galeotti & Olper, 2019). In the aftermath of a climate-induced crop failure, rural labourers may resort to out-migration as an adaptation strategy. Climate-induced migration can steer resource competition in the receiving areas and foster ethno-political tensions between migrants and host communities, increasing the probability of conflict (Brzoska & Fröhlich, 2015).

As an illustrative example, the civil conflict in Darfur did not erupt in the northern or eastern regions, which were the most hit by droughts, but in those which experienced an improvement in resource availability (Brown, 2010). The relative deterioration of resources in some regions compared to the others triggered nomadic movements of affected groups towards resource-abundant regions, fostered reciprocal accusations of overexploiting local resources, and reinforced pre-existing societal and ethnic cleavages, thus contributing to the conflict (De Juan, 2015).

Finally, destitute individuals may become more willing to fight for overthrowing the government and/or getting increasing control over the productive capacity (Robinson & Acemoglu, 2006). Also, the government can deliberately manipulate households' access to food to undermine the insurgents, by distributing food relief and aid only to supporting groups and excluding regions which are known to host the insurgents – as happened in both Darfur and Ethiopia (Keller, 1992; Hendrix & Brinkman, 2013). As rebel groups generally propagandize material incentives as a reward for engagement (Kalyvas, 2006), individuals who were already worse off due to the uneven distribution of agricultural output will be particularly attracted to narratives of personal enrichment put forward by rebel leaders. Especially in the lack of viable economic alternatives, the opportunity cost of joining the fight will be thus reduced.

All in all, exacerbated differences in crop production will shape the spatial distribution of livelihood opportunities, trigger resource competition (De Juan, 2015), exacerbate previous grievances upon which individuals are willing to act (Heslin, 2020), ease rebels' effectiveness in recruiting and, in turn, increase the probability of violence.

What type of conflict is likely to be triggered by these dynamics depends on who is identified as 'liable', that is, who the affected individuals are likely to blame for their conditions (Theisen, 2017). If individuals perceive the government or the political elite as responsible for their status, they will more likely seek to overthrow the current political settings and the mobilization may thus increase the risk of civil conflict. Exogenous shocks to crop productions may especially destabilize political settings if the government lacks the will or the capacity to satisfy the most basic needs (e.g. Gleick, 2014) or if citizens perceive food price increases as a government's failure to provide basic means of sustenance (Lagi, Bertrand & Bar-Yam, 2011). In the case where the members of the government coincide with a specific ethnic group, or when a particular ethnic group is perceived as the 'culprit' of the livelihood deterioration, however, the mobilization is more likely to occur along ethnic borders and thus ethnic conflict will be more likely. Deteriorated livelihood conditions may also push individuals to rely on the members of their group for sustenance, triggering feelings of solidarity within the groups to the detriment of others (De Juan & Hänze, 2021). Relative differences in access to food may raise resentment in some groups against those that are perceived to be better-off, thus easing rebels' effectiveness in mobilizing people, especially around a common identity (Homer-Dixon, 1991), which may increase the likelihood of non-state and communal conflicts.

The line of reasoning articulated above leads us to formulate the following hypotheses:

Hypothesis 1: Climate variability increases the spatial concentration of crop production within countries.

Hypothesis 2: High levels of concentration in crop production are associated with a higher probability of conflict onset.

Hypothesis 3: The impact of climate variability on conflict onset is conditional on the spatial concentration of crop production.

Hypothesis 3a: The combined impact of climate variability and spatial distribution of crop production on conflict is higher in agriculturally dependent countries.

We test these hypotheses empirically by means of a probit model, as illustrated in the following sections.

Data

The main dependent variable is *Armed conflict onset*, defined broadly as a contested incompatibility where the use of armed force between two parties results in at least 25 battle-related deaths in one calendar year (UCDP, 2019). *Onset* is a binary variable coded as 1 for every year in which a conflict breaks out in a given country and 0 otherwise. We explore different types of conflicts in our empirical models. *Civil conflict* is defined as a state-based conflict that involves at least a government of a state as an active part (Pettersson, Högbladh & Öberg, 2019). *Non-state conflict* is defined as the use of armed force between two organized armed groups, neither of which is the government of a state, which results in at least 25 battle-related deaths in a year (Sundberg, Eck & Kreutz, 2012). *Communal conflicts* are defined as non-state conflicts between two or more informally organized groups, which identify themselves along identarian lines (Pettersson, 2019).[3] Data for these conflict types are drawn from UCDP Armed Conflict Dataset. Finally, *Ethnic conflicts* are violent episodes where rebels pursue

[3] Communal conflicts correspond to non-state conflicts where the organizational level is coded as 3 in the Non-State UCDP data (Sundberg, Eck & Kreutz, 2012; Pettersson, Högbladh & Öberg, 2019).

ethno-nationalist aims and recruit along ethnic lines in order to achieve ethno-national self-determination, a more favorable ethnic balance of power in government, ethno-regional autonomy, the end of ethnic and racial discrimination, or a more balanced division of resources along ethnic lines within society. We utilize country-level data on ethnic conflicts from the latest version of the EPR dataset (Vogt et al., 2015).

To build the GICP, we utilize annual production (tonnes) of four main crops (maize, wheat, soybean, rice) in a given grid cell. Global gridded data of annual crop yields (tonnes/hectare) at 0.5-degree resolution ($\sim$ 55km$\times$55km at the equator), covering 1982–2015, are drawn from a hybrid dataset (Iizumi et al, 2014, 2018; Iizumi & Ramankutty, 2016; Iizumi & Sakai, 2020 – details in Online appendix).[4] Although the data include only four major calorie crops, thereby partly limiting our analysis, the trade-off permits us to assemble consistent long panel data, necessary to investigate the conditional effect of climate variability on conflict onset.[5]

As for climate data, we employ selective climatic indicators considered most relevant for agriculture. Isolating the climate component which effectively impacts local agriculture is fundamental to disentangle the effect of climate variability on conflict (Harari & La Ferrara, 2018). Our main vector of climate variables (Table II) includes standardized annual anomalies of growing degree-days (GDD) and precipitation anomalies from their long-term mean (P). GDD (McMaster & Wilhelm, 1997) are heat-units measuring the cumulative amount of time a crop is exposed to temperatures favorable for phenological growth. Compared to other thermal measures such as average growing season temperatures, GDD better captures non-linearities in the relationship between temperature and agricultural productivity (Roberts, Schlenker & Eyer, 2012). Other agroclimatic indicators such as the Warm Spell Duration Index (WSDI), self-calibrating Palmer Drought Severity Index (PDSI) and Standardized Precipitation Evapotranspiration Index (SPEI) were also examined as alternative measures of climate variability for our study period (details in Online appendix). In line with common practice in climate–conflict literature (Buhaug, 2015), meteorological variables from both observations (Harris, 2014) and reanalysis data products (Rodell et al., 2004; Mistry, 2019), as well as different functional forms of climatic indicators (standardized anomalies, coefficient of variation, empirical probability) were utilized as sensitivity checks (details in Online appendix). The climatic indicators and the various operationalizations used in our study not only capture variations in climate extremes due to both natural and anthropogenic causes, but are also documented to be exacerbated by global warming (Seneviratne et al., 2012).

As a number of factors can influence conflict, we include a battery of explanatory and control variables in our empirical models. First, regions can be naturally endowed with fertile soils and climate suitable to agriculture, making them more resilient to climate variability impacts. Hence, we control for the share of agricultural land over the total country area. In those regions whose climatic conditions are less suitable for agriculture, irrigation can compensate for water scarcity and environmental shocks, increasing populations' resilience to climate extremes (Mendelsohn & Seo, 2007). Share of irrigation is also a suitable measure of technological development in agriculture (e.g. Dinar & Zilberman, 1991). Suitability for agriculture and irrigation technologies may thus increase countries' resilience to climate variability impacts; therefore, we control for the amount of irrigated land as a proportion of total cultivated land (extensive description of the variable and data sources can be found in the Online appendix, Table A.I). As rural populations and regions with a high dependence on agriculture may be more vulnerable to climate variability impacts (von Uexkull, 2014), we include controls for the proportion of the rural population and agricultural added value as a share of GDP. In the next sections, we also explicitly test the validity of our argument for agriculturally dependent countries.

Further, governmental policies can have great influence in agricultural distribution, not only through the allocation of property rights (Butler & Gates, 2012) but also by shaping micro-level decisions in agricultural production, for example by providing incentives and subsidies to farmers, or implementing insurance schemes to protect farmers against climate shocks (Dinar & Mendelsohn, 2011). The state can direct relief programs to help some groups cope with the negative impacts of climate variability, while purposefully excluding others (Theisen, Holtermann & Buhaug, 2012). Next, countries' trade policies and storage strategies can be directed to compensate for crop failures and stabilize food prices (Schewe, Otto & Frieler, 2017). To account for these factors, our models include controls for regime type, sociopolitical discrimination and trade volume in food. The following sections detail the steps of our main argument, leading from climate anomalies to higher conflict risk.

[4] The 0.5°$\times$0.5° spatial resolution is the most commonly used unit of analysis in social science and conflict research, as it corresponds with the average precision of conflict data.

[5] A discussion of the implications of this choice can be found in the Online appendix.

Climate variability and spatial concentration of crop production

To the best of our knowledge, this study is the first to compute a time-varying indicator of the spatial distribution of agricultural production and explore how it correlates to conflict. Some studies did focus on land distribution as a potential predictor of insurgency, but they only concentrated on the maldistribution of land tenure (e.g. Boix, 2003; Hidalgo et al., 2010), while neglecting differences in land productivity and agricultural production. Land maldistribution is not necessarily a good proxy of crop production; indeed, higher agricultural outputs can be achieved without necessarily expanding the amount of land per capita, through enhanced agronomic practices, improved crop varieties and other technological innovations (Tilman et al., 2011).

We compute GICP as a measure of spatial distribution of crop production at the country level, and as a sensitivity test, across ethnic groups (the 'between-groups' GICP is discussed in the Online appendix). GICP for a country's area consisting of n grid-cells with values of crop production y_i is defined as:

$$G = \frac{1}{n}\left[n + 1 - 2\left(\frac{\sum_{i=1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n}y_i}\right)\right] \quad (1)$$

where gridded crop production values y_i are indexed in non-decreasing order such that $y_i \leq y_{i+1}$.[6] A GICP value of 0 corresponds to a perfectly homogeneous distribution of crop growth within the country, while a GICP of 1 indicates that the crop production is concentrated in one or few producing areas.

We construct two basic measures of GICP: the first uses information on crop production from all grid-cells; the second is limited to rural grid-cells and excludes urban areas from the sample. We also compute the same measures weighted by population size (details in Online appendix).[7] Urban areas will have low or null production of crops and could erroneously be interpreted as 'poor' in agricultural value compared to rural locations. As our main goal is to observe the effect of the distribution of crop across space, including urban areas in the analysis may potentially influence the construction of GICP, as it would consider urban cells equal to rural locations which have a low or null level of crop production. Consistently, we perform our empirical analysis by using both measures – the GICP computed for the entire sample, as well as for the subset of the sample that only includes rural areas.

Figure 1 visualizes the values of GICP for both the full sample and only rural cells.[8] The distribution of crop production is not considerably affected by the exclusion of urban areas from the sample, as the values of the GICP tend to follow the same pattern whether urban areas are included or not. High values of spatial concentration of crop production are evenly distributed across the world.

The high value of GICP in developed countries, as in the United States, is coherent with the technological advances in cultivation techniques and the shift to intensive farming that characterize the latest stages of economic development, leading to an oligopolistic concentration of crop production in the hands of few producers (Sexton et al., 2007).

Although climate variability may have disruptive effects for farmers in the USA, due to the concentration of crop production in relatively few areas, the effect of the shock will still be limited in the overall socio-economic system, where only 11% of the population is employed in the agricultural sector, and food accounts for less than 13% of households' expenditures (USDA, 2020).

However, the same value of GICP may arguably have a more detrimental effect in Mali, where almost 80% of people are employed in agriculture (FAO, 2017) and highly vulnerable to climate extremes (von Uexkull, 2014). This points to our framework condition relative to the importance of agricultural dependence for our argument (Hypothesis 3a). We explicitly test for this condition in our empirical models, by observing how the effect of climate variability and crop concentration varies across countries with high and low dependence on agriculture.

Validation of the Gini Index of agricultural production

Before testing the link between climate variability, agricultural production and conflict empirically, we first

[6] Data on crop production are drawn from grid-cell-level data on four main crops (Iizumi & Sakai, 2020), as described in the previous section.

[7] Rural cells are defined as those whose land surface is not covered by any urban structure, according to GlobCover categorization (Bontemps, Defourny & Van Bogaert, 2009). Urban cells are any cells for which the extension of the urban area is greater than zero.

[8] The map for between-group GICP is reported in Online appendix, Figure A.7.

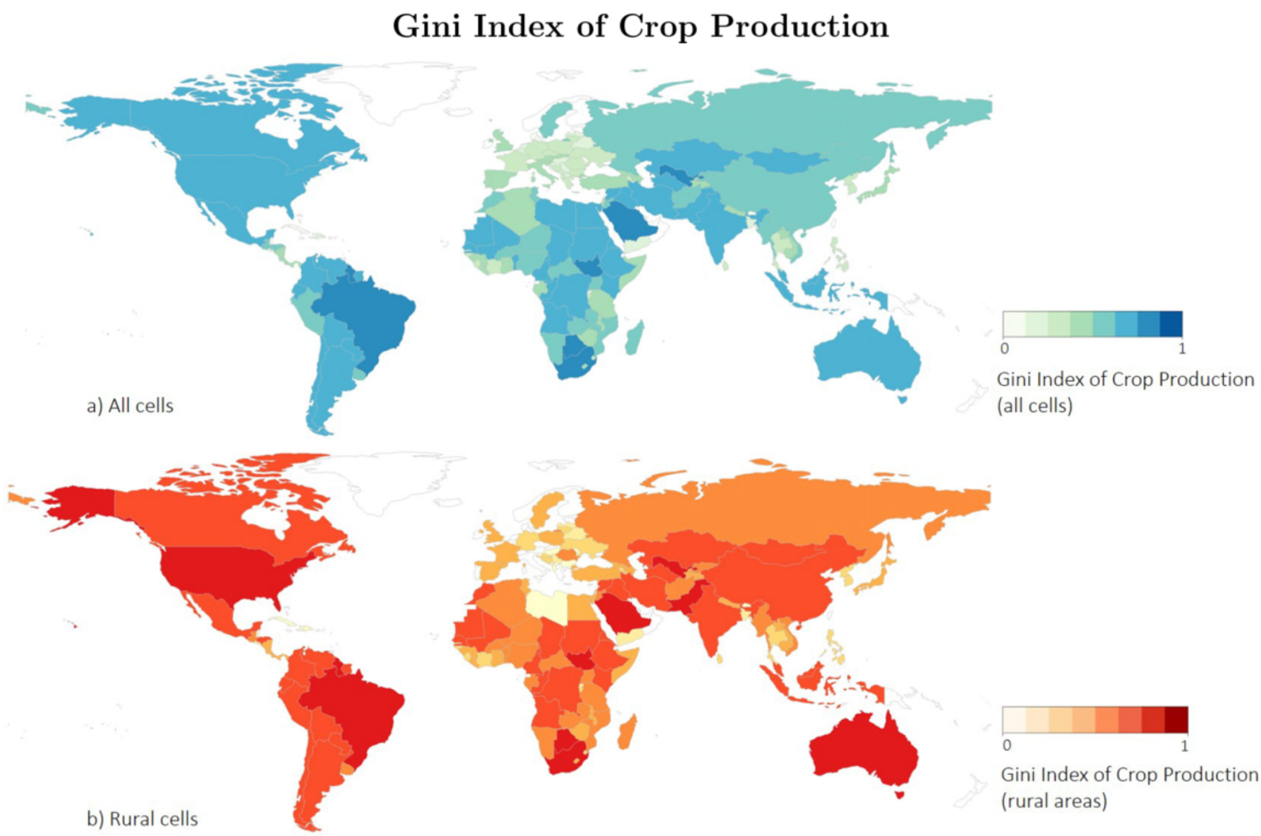

Figure 1. Gini Index of crop production computed at the country level, for grid-cells nested within countries: (a) all cells; (b) rural cells only

verify whether GICP is indeed a good measure of populations' livelihood and access to food.

We verify the validity of this measure through two tests: first, by observing the correlation of GICP with the spatial differences in economic activities; second, by exploring how climate variability affects the sustainability of national food systems. The first test is meant to validate the ability of GICP to capture differences in populations' livelihoods across the country; the second aims at validating our claim that the spatial distribution of crop production is relevant to individuals' access to food and may be impacted by climate extremes.

Spatial differences in crop production and livelihood

Agricultural production may represent an important source of income in several societies and a key factor in populations' livelihood. If this assumption holds, differences in the spatial distribution of crops should be reflected by similar patterns in the spatial distribution of countries' GDP. Given the complexity of economic and social systems, this is not expected to be a one-to-one relationship, as otherwise the concentration of income may be used as a perfect substitute for crop production concentration.

In order to explore the potential relationship between crop and income spatial concentration, we estimate a simple model that regresses the country-year Gini coefficient of GDP on the Gini Index of agricultural production (details in Online appendix). Both Gini coefficients are calculated for the same grid-cells to guarantee the highest possible level of comparability.

Table A.IV and Figure A.6 in the Online appendix report the conditional correlation coefficients between crop production spatial concentration and the extent of inequality in the distribution of gross domestic products. The coefficients suggest that spatial inequality in income distribution reflects the patterns of the spatial concentration of crops. This relationship is accentuated among countries where agriculture constitutes a significant share of national employment. We observe that a one standard deviation (1σ) increase in crop concentration is followed by an increase in (standardized) income inequality index of 0.5 points (which corresponds to a 0.1 point increase in the non-standardized measure). The above evidence indicates that GICP may be a relevant measure of differences in populations' livelihoods across space and it is especially germane to agriculturally dependent countries, where large shares of populations are employed in agriculture.

Climate variability, spatial differences in crop production and food

One key assumption of our analysis concerns the effect of climate variability on the spatial concentration of agricultural production across locations. As the negative impacts of climate variability are expected to affect communities' ability to satisfy their basic needs and their choices concerning food consumption, we should also observe a relationship between the climatic indicators and the sustainability of food systems.

To this end, we validate the GICP by regressing a cross-country indicator of food sustainability (Béné et al., 2019) on the vector of agroclimatic indicators. The food sustainability indicator (FSE) provides a synthetic but comprehensive representation of national food systems, encompassing measures of food security along with socio-economic dimensions. Regressing FSE against climate variability enables us to test how climate influences the sustainability and security of food systems across countries. Table A.V in the Online appendix presents the results. We find that a 1σ increase in GDD variation increases the sustainability of food systems approximately by 0.02, while a 1σ increase in precipitation variability leads to a similar decrease in food sustainability. The robust, although small, association between climate variability and the sustainability of food systems underscores our first hypothesis on the effect of climate on crop distribution and increases our confidence in the ability of GICP to measure populations' access to food.

We also find that this association is stronger in agriculturally dependent regions, strengthening the relevance of agricultural dependence as a framework condition for our argument.

Climate variability and spatial concentration of crop production

The main argument of this study follows three steps, leading from negative impacts of climate variability to conflict. It is important to note that our empirical models cannot be interpreted in terms of an indirect causal link between climate extremes and conflict, but they provide insight on how climate may impact the spatial distribution of food resources, and how this in turn may increase the likelihood of violence.

In order to test our hypotheses we proceed as follows: (i) as climate variability may alter the distribution of crops across locations, we first estimate a set of empirical models in which crop production concentration, measured by GICP, is regressed on the climate variability indicators (details in Online appendix); (ii) we estimate the effect of crop spatial concentration and climate on the probability of conflict outbreak; (iii) we quantify the joint effect of climate and crop spatial concentration on conflict onset.

As for (iii) we estimate the following empirical model:

$$Y_{i,t} = \alpha_0 + \alpha_1 GICP_{i,t-1} + \alpha_2 A_{i,t-1} + \alpha_3 [GICP_{i,t-1} * A_{i,t-1}] + \alpha_4 X_{i,t} + \alpha_5 C_{i,t} + \epsilon_{i,t} \quad (2)$$

where $GICP_{i,t-1}$ is the standardized GICP in country i in year $t-1$; A is the vector of standardized agroclimatic anomalies (lagged precipitation and lagged GDD), X contains a set of country-specific variables, and C is the vector of spatial (continent-level) and time controls. This empirical strategy enables us to account for the dynamic aspect of crop concentration and time-varying climate anomalies, as well as their joint effect on conflict, both within countries over time and across countries. As our goal is to observe the impacts of climate variability on crop production, temporal within-country variation is especially important – relative to cross-sectoral variation. Within-country GICP considerably varies over time, especially from year to year (Figure A.5 in Online appendix). This time-varying, cross-country framework allows us to properly take into account differences in countries' vulnerability to climate extremes, which may be due to their differing agroclimatic conditions, the suitability of their land for agriculture, and varying degrees of irrigation development and technological endowments. Needless to say, other factors can affect countries' adaptive capacity to climate extremes as well as their latent risk of conflict, and we appropriately include controls for these elements (illustrated in section 3).

Finally, to test the hypothesis that societies characterized by higher levels of concentration in crop production may be more vulnerable to climatic shocks, we interact GICP with standardized anomalies of precipitation and GDD. As a dependent variable Y we consider the onset of four different types of conflicts, namely civil, ethnic, non-state and communal conflicts.

In our main model specifications, we lagged GICP and climate variables by one year, consistently with the wider literature on the climatic–agricultural impacts in a panel data setting (e.g. Deschênes & Greenstone, 2012).

Table I. OLS Model: GICP crop (country level/non-standardized) regressed on climate (Models 1–3 all cells – GICP_all; Models 4–6 rural cells – GICP_r)

Variable	*(1) GICP_all*	*(2) GICP_all*	*(3) GICP_all*	*(4) GICP_r*	*(5) GICP_r*	*(6) GICP_r*
GDD (spatial)	0.044**		0.024†	0.045**		0.026*
	(0.015)		(0.013)	(0.015)		(0.013)
PREC (spatial)		0.074**	0.067**		0.072**	0.064**
		(0.013)	(0.013)		(0.014)	(0.014)
GDP	0.075*	0.047†	0.048†	0.061*	0.032	0.035
	(0.029)	(0.026)	(0.026)	(0.029)	(0.027)	(0.026)
Population	0.022†	0.014	0.010	0.023*	0.015	0.011
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Rural pop.	–0.000	–0.001	–0.001	–0.000	–0.001	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agr. AV	0.038	0.016	0.017	0.014	–0.012	–0.009
	(0.024)	(0.023)	(0.022)	(0.025)	(0.024)	(0.023)
Trade (food)	0.001	0.003	0.004	0.013†	0.015**	0.015*
	(0.009)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)
Irrig. land	–0.110	–0.159†	–0.155†	–0.172	–0.223†	–0.218†
	(0.097)	(0.090)	(0.091)	(0.106)	(0.117)	(0.117)
N. Observations	3,606	3,606	3,606	3,225	3,225	3,225
R^2	0.443	0.506	0.516	0.407	0.467	0.480
Continent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Significance levels: † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Precipitation and GDD are here defined as coefficients of variation (details in Online appendix).

Persistence in soil conditions, especially in rain-fed cultivation regimes with a prolonged drought-like condition, can result in a lagged effect on crop productivity (Hatfield et al., 2011). Moreover, climatic conditions prior to the crop planting window (e.g. warm spell) are also known to have detrimental effects on the eventual seasonal harvest.

Results

The results from Table I show that a 1σ increase in precipitation variation is associated with a 0.07 point increase in GICP, while the effect of a 1σ increase in GDD variation is somewhat lower (0.04). The same regressions have been performed for GICP calculated at the ethnic group level, as well as for alternative climate indicators (Table A.XV).

The results from Table I substantiate Hypothesis 1, confirming that the negative impacts of climate variability alter the spatial distribution of crop production and lead to an increase in the spatial concentration of crops.

Table II reports the results of Equation 2 for the full set of countries over the period 1982–2015. Crop production concentration correlates positively with civil and ethnic conflict onset, suggesting that a 1σ increase in GICP raises the probability of civil (ethnic) conflict outbreak by 2.1% (1%). As for communal conflicts, the effect is mostly driven by rural areas: the coefficient of GICP calculated over rural cells (Model 8) is higher than the one referring to GICP calculated over all cells (Model 4).

The coefficients of agroclimatic indicators (Table A.VII in the Online appendix) indicate that climate seems not to have a strong independent effect on the likelihood of conflict onset, except for ethnic conflicts where this association is negative. The lack of a strong correlation between climate variability and conflict may be due to the impact of climate being mediated by agricultural concentration. As climate variability has a positive effect on GICP (Table I), crop concentration may partially absorb the effect of climate on conflict and thus explain why we do not find a strong effect in the first set of models. We test this intuition by interacting the climatic variables with GICP. The results of these models, including interactions between climate variables and GICP, are presented in Figure 2.

The findings suggest that spatial differences in crop production may act as a bridge between climate extremes and conflict, but the effect is statistically significant only

Table II. Probit model: conflict onset regressed on climate variables, GICP (country level; all cells and rural cells) and the interaction between GICP and climate variables

Variable	*(1) Civil*	*(2) Ethnic*	*(3) NS*	*(4) Comm.*	*(5) Civil*	*(6) Ethnic*	*(7) NS*	*(8) Comm.*
GICP	0.021**	0.012**	0.009	0.014*				
	(0.007)	(0.004)	(0.008)	(0.007)				
GICP_r					0.020**	0.011*	0.011	0.017*
					(0.008)	(0.005)	(0.009)	(0.008)
GDD	–0.001	–0.003	–0.003	0.004	–0.003	–0.004	–0.004	0.003
	(0.006)	(0.004)	(0.005)	(0.003)	(0.006)	(0.004)	(0.005)	(0.003)
PREC	–0.002	–0.006*	–0.006†	–0.008†	–0.002	–0.006*	–0.006†	–0.008†
	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
GDD*GICP	0.001	0.005	0.002	0.000				
	(0.005)	(0.004)	(0.004)	(0.002)				
PREC*GICP	0.002	0.004†	0.008**	0.009*				
	(0.004)	(0.002)	(0.003)	(0.004)				
GDD*GICP_r					0.004	0.007†	0.004	0.001
					(0.006)	(0.004)	(0.005)	(0.002)
PREC*GICP_r					0.001	0.004	0.010**	0.010*
					(0.004)	(0.003)	(0.004)	(0.005)
GDP	–0.018	–0.017*	–0.000	0.025*	–0.019	–0.018†	–0.000	0.029*
	(0.012)	(0.008)	(0.019)	(0.012)	(0.013)	(0.009)	(0.021)	(0.014)
Population	0.015**	0.007*	0.037**	0.025**	0.017*	0.007*	0.041**	0.027**
	(0.006)	(0.003)	(0.009)	(0.005)	(0.007)	(0.004)	(0.010)	(0.006)
Anocracy	0.025*	0.006	0.027*	0.019**	0.026*	0.007	0.029*	0.021**
	(0.010)	(0.007)	(0.010)	(0.007)	(0.011)	(0.007)	(0.012)	(0.008)
Discrim.	0.054†	0.019	0.086**	0.033	0.057†	0.019	0.093**	0.034
	(0.029)	(0.015)	(0.032)	(0.022)	(0.032)	(0.017)	(0.035)	(0.024)
Rural pop.	0.000	–0.000	–0.000	0.001	0.000	–0.000	–0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Agr. AV	0.004	–0.003	0.041*	0.037**	0.002	–0.005	0.045*	0.042**
	(0.011)	(0.007)	(0.017)	(0.011)	(0.013)	(0.007)	(0.018)	(0.012)
Trade (food)	0.004	0.004	–0.003	–0.000	0.005	0.004	–0.003	0.000
	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
Irrig. land	0.035	0.008	–0.004	–0.036	0.034	0.014	–0.006	–0.035
	(0.028)	(0.023)	(0.043)	(0.026)	(0.038)	(0.027)	(0.059)	(0.034)
N. Obs.	3,571	3,571	3,571	3,571	3,211	3,211	3,211	3,211
Pseudo R^2	0.133	0.154	0.3070	0.382	0.113	0.144	0.289	0.370
Continent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Significance levels: † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Precipitation and GDD are here defined as standardized annual anomalies from their long-term means (details in Online appendix).

for non-state and communal conflicts. Locations that suffer from a 1σ decrease in precipitation, combined with a 1σ increase in agricultural concentration, have nearly a 6% higher probability of experiencing non-state conflict outbreak and a 5% higher probability of communal conflict onset (Figure 2). Likewise, when introducing the interaction terms, the stand-alone GICP remains roughly the same for all types of conflict onsets but gains significance for communal conflicts (Models 4, 8). Similar results are found when we replicate the model for the between-group GICP (Tables A.IX–X, Online appendix) and the population-weighted GICP (Table A.XI, Online appendix).

Results of these models indicate that the combined effect of climate variability and crop production provides incentives to mobilization between rebel groups, especially along identarian lines. This is consistent with previous studies advancing that changes in local livelihood and food access may not be the primary motivation to join rebel groups, but rather contribute

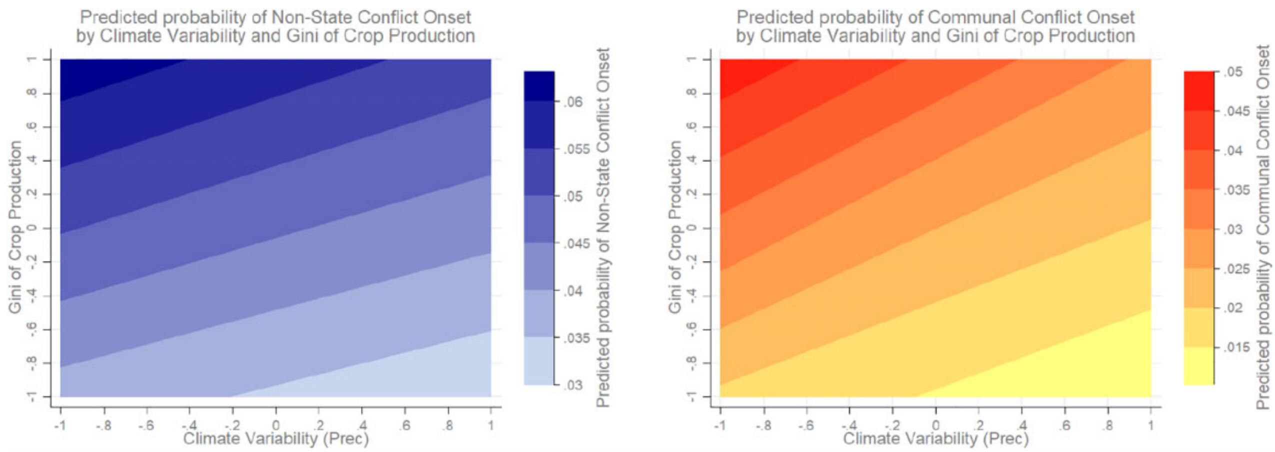

Figure 2. Combined marginal effect of climate variability (precipitation anomaly) and spatial concentration of crop production on non-state and communal conflict onset

The effects are significant at the 1% level for non-state and 5% level for communal conflicts

to mobilizing protests around pre-existing grievances (Heslin, 2020).

However, the lack of a robust effect of climate and agricultural concentration on civil conflicts may also be due to contextual factors. The impact of climate variability may be conditional to agricultural dependence, whereby populations relying on agriculture as their primary source of income are disproportionately vulnerable to environmental hardships. The next section discusses this framework condition further.

Dependence on agriculture

The results of our validation tests (Tables A.IV and A.V in Online appendix) point to crop production as an important mean of sustenance, especially among countries which are highly dependent on agriculture. Hence, we expect the joint effect of climate extremes and GICP to be mainly relevant for societies that heavily rely on agriculture.

Tables A.XIII–A.XIV in the Online appendix replicate the models in Table II for two subsets of countries defined in terms of their dependence on agriculture, proxied by high or low share of agricultural employment in the national workforce. Crop production concentration and climate anomalies are found to be particularly important for agriculturally dependent societies, while their effect is null or very weak among the countries with low agricultural dependence.

In countries that strongly rely on agriculture, the combined effect of a 1σ decrease in GDD and a 1σ increase in GICP leads to an increase in the probability of civil conflict of 14% and of non-state conflict by around 10% (Figures A.8 and A.9, Online appendix). This substantiates our framework condition relative to the importance of agricultural dependence in shaping the effect of climate variability and crop production concentration on conflict onset and shows that the results for the full sample are mainly driven by the set of agriculturally dependent countries.

The Online appendix reports the results of multiple sensitivity tests. First, we replicate the models presented in Table II with alternative climate specifications and by including several different controls; the results do not change substantially. Second, we test the empirical validity of the GICP by replicating the models in Table II with the absolute value of crop production as the main independent variable (Table A.XVII). The coefficients suggest that crop production alone does not correlate significantly with conflict outbreak (Models 1–4, Table A.XVII in the Online appendix). Moreover, even when controlling for the absolute quantity of crop production (Models 5–8), the magnitude and statistical significance of GICP are similar to those presented in Table II, thus substantiating our confidence in the importance of the spatial distribution of crops, rather than the absolute quantity, in explaining conflict.

We further explore the robustness of GICP by looking at the contribution it brings in improving predictive performance in an out-of-sample setting. Such a test would allay concerns of both model overfitting on the sample data and reducing the risk of errors originating from statistical distributional assumptions inherent with in-sample analytics, such as over-reliance on p-values (Ward, Greenhill & Bakke, 2010). Results of these tests confirm the importance of GICP as a predictor of conflict onset, strengthen its empirical validity, and highlight the importance of agricultural dependence as a contextual factor (details in Online appendix).

Conclusions

This study investigates whether the spatial distribution of crop production shapes societies' capacity to deal with climate extremes and makes them more vulnerable to violence in turn. A key finding of the study is that climate variability increases the spatial concentration of crop production, exacerbating the relative differences in crop output across locations. Increased spatial differences in crop production shape populations' livelihood opportunities and ease rebels' effectiveness in mobilizing individuals, especially along identarian lines. We find that higher concentrations of crop production increase the likelihood of conflict onset and condition the effect of climate variability on violence. This effect is greater in countries that rely heavily on agriculture.

One main caveat of the present analysis is that the suggested linkage from climate variability to conflict is far from deterministic and strongly depends on contextual factors, mostly agricultural dependence. Differences in food access across locations can likely aid in mobilizing protests around pre-existing grievances, some unrelated to food access, rather than developing new grievances.

In this perspective, the analysis can be extended to test how socio-economic and institutional characteristics may influence the relationship between climate, the spatial distribution of crops and conflict onset. More efficient institutional systems, able to guarantee a fair distribution of property rights and enforce cooperative agreements to manage resources, can mediate the negative consequences of climatic changes and attenuate tensions.

Finally, a limitation of the present study is represented by data availability; indeed, grid-cell-level information on crop production, utilized to compute the agricultural distribution at the country level, does not correspond to the agricultural output available to each household. To this end, the study of spatial distribution in crop production will surely benefit from ongoing progress in data collection, which will hopefully make available high-quality time-variant survey data on agricultural production.

Replication data

The dataset and scripts for the empirical analysis in this article, along with the Online appendix, can be found at http://www.prio.org/jpr/datasets.

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ORCID iD

Paola Vesco https://orcid.org/0000-0002-0368-0633
Malcolm Mistry https://orcid.org/0000-0003-3345-6197
Mihai Croicu https://orcid.org/0000-0002-5372-7129

References

Alam, Monirul (2017) Livelihood cycle and vulnerability of rural households to climate change and hazards in Bangladesh. *Environmental Management* 59(5): 777–791.

Alcamo, Joseph; Nikolai Dronin, Marcel Endejan, Genady Golubev & Andrei Kirilenko (2007) A new assessment of climate change impacts on food production shortfalls and water availability in Russia. *Global Environmental Change* 17(3–4): 429–444.

Arezki, Rabah & Markus Brueckner (2014) Effects of international food price shocks on political institutions in low-income countries: Evidence from an international food net-export price index. *World Development* 61(9): 142–153.

Béné, Christophe; Steven Prager, Harold Achicanoy, Patricia Alvarez Toro, Lea Lamotte, Camila Bonilla & Brendan Mapes (2019) Global map and indicators of food system sustainability. *Scientific Data* 6(1): 279.

Berazneva, Julia & David Lee (2013) Explaining the African food riots of 2007–2008: An empirical analysis. *Food Policy* 39(April): 28–39.

Boix, Carles (2003) *Democracy and Redistribution*. Cambridge: Cambridge University Press.

Bontemps, Sophie; Pierre Defourny & Eric Van Bogaert (2009) GlobCover: Products description and validation report. European Space Agency (http://due.esrin.esa.int/Files/Globcover2009_validation_report_2.2.pdf).

Bren D'Amour, Christopher; Leonie Wenz, Matthias Kalkuhl, Jan Christoph Steckel & Felix Creutzig (2016)

Teleconnected food supply shocks. *Environmental Research Letters* 11(3).

Brown, Ian (2010) Assessing eco-scarcity as a cause of the outbreak of conflict in Darfur: A remote sensing approach. *International Journal of Remote Sensing* 31(10): 2513–2520.

Brzoska, Michael & Christiane Fröhlich (2015) Climate change, migration and violent conflict: Vulnerabilities, pathways and adaptation strategies. *Migration and Development* 5(2): 190–210.

Buhaug, Halvard (2015) Climate–conflict research: Some reflections on the way forward. *Climate Change* 6(3): 269–275.

Butler, Christopher & Scott Gates (2012) African range wars: Climate, conflict, and property rights. *Journal of Peace Research* 49(1): 23–34.

Challinor, Andrew; J Watson, David Lobell, SM Howden, DR Smith & Netra Chhetri (2014) A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* 4(4): 287–291.

De Juan, Alexander (2015) Long-term environmental change and geographical patterns of violence in Darfur, 2003–2005. *Political Geography* 45: 22–33.

De Juan, Alexander & Niklas Hänze (2021) Climate and cohesion: The effects of droughts on intra-ethnic and inter-ethnic trust. *Journal of Peace Research* 58(1): 151–167.

Deschênes, Olivier & Michael Greenstone (2012) The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Reply. *American Economic Review* 102(7): 3761–3773.

Dinar, Ariel & Robert Mendelsohn, eds (2011) *Handbook on Climate Change and Agriculture*. Cheltenham: Edward Elgar.

Dinar, Ariel & David Zilberman (1991) Effects of input quality and environmental conditions on selection of irrigation technologies. In: Ariel Dinar & David Zilberman (eds) *The Economics and Management of Water and Drainage in Agriculture*. Boston, MA: Springer, 229–250.

Falco, Chiara; Marzio Galeotti & Alessandro Olper (2019) Climate change and migration: Is agriculture the main channel? *Global Environmental Change* 59(11): 101995.

FAO (2017) Country fact sheet on food and agriculture policy trend – Mali. Food and Agriculture Organization (FAO) (http://www.fao.org/3/a-i7617e.pdf).

Fjelde, Hanne (2015) Farming or fighting? Agricultural price shocks and civil war in Africa. *World Development* 67(3): 525–534.

Gleick, Peter (2014) Water, drought, climate change, and conflict in Syria. *Weather, Climate, and Society* 6(3): 331–340.

Guariso, Andrea & Thorsten Rogall (2017) Rainfall inequality, political power, and ethnic conflict in Africa. *LICOS Discussion Paper Series* 391.

Harari, Mariaflavia & Eliana La Ferrara (2018) Conflict, climate, and cells: A disaggregated analysis. *Review of Economics and Statistics* 100(4): 594–608.

Harris, Ian (2014) Climatic Research Unit (CRU): Time-series version 4.01 of high-resolution gridded data of month-by-month variation in climate. Centre for Environmental Data Analysis (CEDA) (https://catalogue.ceda.ac.uk/uuid/58a8802721c94c66ae45c3baa4d814d0).

Hatfield, Jerry; Kenneth Boote, B Kimball, L Ziska, Roberto Izaurralde, Donald Ort, Allison Thomson & D Wolfe (2011) Climate impacts on agriculture: Implications for crop production. *Agronomy Journal* 103(2): 351–370.

Hendrix, Cullen & Henk-Jan Brinkman (2013) Food insecurity and conflict dynamics: Causal linkages and complex feedbacks. *Stability: International Journal of Security & Development* 2(2): 26.

Heslin, Alison (2020) Riots and resources: How food access affects collective violence. *Journal of Peace Research*. https://doi.org/10.1177/0022343319898227.

Hidalgo, Daniel; Suresh Naidu, Simeon Nichter & Neal Richardson (2010) Economic determinants of land invasions. *Review of Economics and Statistics* 92(3): 505–523.

Homer-Dixon, Thomas (1991) On the threshold: Environmental changes as causes of acute conflict. *International Security* 16(2): 76–117.

Ide, Tobias; Anders Kristensen & Henrikas Bartusevîčius (2021) First comes the river, then comes the conflict? A qualitative comparative analysis of flood-related political unrest. *Journal of Peace Research* 58(1): 83–97.

Iglesias, Ana; Luis Garrote, Sonia Quiroga & Marta Moneo (2009) Impacts of climate change in agriculture in Europe. PESETA-agriculture study. Luxembourg: European Commission Joint Research Centre.

Iglesias, Ana; Sonia Quiroga, Marta Moneo & Luis Garrote (2012) From climate change impacts to the development of adaptation strategies: Challenges for agriculture in Europe. *Climatic Change* 112(1): 143–168.

Iizumi, Toshichika & Navin Ramankutty (2016) Changes in yield variability of major crops for 1981–2010 explained by climate change. *Environmental Research Letters* 11(3): 1–10.

Iizumi, Toshichika & Toru Sakai (2020) The global dataset of historical yields for major crops 1981–2016. *Scientific Data* 7(1): 97.

Iizumi, Toshichika; Mizuki Kotoku, Wonsik Kim, Paul West, James Gerber & Molly Brown (2018) Uncertainties of potentials and recent changes in global yields of major crops resulting from census- and satellite-based yield datasets at multiple resolutions. *PLOS One* 13(9): 1–15.

Iizumi, Toshichika; Masayuki Yokozawa, Gen Sakurai, Maria Isabel Travasso, Vladimir Romanenkov, Pascal Oettli, Terry Newby, Yasushi Ishigooka & Jun Furuya (2014) Historical changes in global yields: Major cereal and legume crops from 1982 to 2006: Historical changes in global yields. *Global Ecology and Biogeography* 23(3): 346–357.

Jones, Benjamin; Eleonora Mattiacci & Bear Braumoeller (2017) Food scarcity and state vulnerability: Unpacking the link between climate variability and violent unrest. *Journal of Peace Research* 54(3): 335–350.

Kalyvas, Stathis (2006) *The Logic of Violence in Civil War*. Cambridge: Cambridge University Press.

Kang, Yinhong; Shahbaz Khan & Xiaoyi Ma (2009) Climate change impacts on crop yield, crop water productivity and food security: A review. *Progress in Natural Science* 19(12): 1665–1674.

Keller, Edmond (1992) Drought, war, and the politics of famine in Ethiopia and Eritrea. *Journal of Modern African Studies* 30(4): 609–624.

Koren, Ore & Benjamin Bagozzi (2016) From global to local, food insecurity is associated with contemporary armed conflicts. *Food Security* 8(5): 999–1010.

Koren, Ore; Benjamin Bagozzi & Thomas Benson (2021). Food and water insecurity as causes of social unrest: Evidence from geolocated Twitter data. *Journal of Peace Research* 58(1): 67–82.

Koubi, Vally (2019) Climate change and conflict. *Annual Review of Political Science* 22(1): 343–360.

Lagi, Marco; Karla Bertrand & Yaneer Bar-Yam (2011) The food crises and political instability in North Africa and the Middle East. IMF Working paper.

Lesk, Corey; Pedram Rowhani & Navin Ramankutty (2016) Influence of extreme weather disasters on global crop production. *Nature* 529(7584): 84–87.

Linke, Andrew & Brett Ruether (2021) Weather, wheat and war: Security implications of climate variability for conflict in Syria. *Journal of Peace Research* 58(1): 114–131.

Lobell, David & Sharon Gourdji (2012) The influence of climate change on global crop productivity. *Plant Physiology* 160(4): 1686–1697.

Lobell, David B; Wolfram Schlenker & Justin Costa-Roberts (2011) Climate trends and global crop production since 1980. *Science* 333(6042): 616–620.

Lotze-Campen, Hermann & HJ Schellnhuber (2009) Climate impacts and adaptation options in agriculture: What we know and what we don't know. *Journal für Verbraucherschutz und Lebensmittelsicherheit* 4(2): 145–150.

Mach, Katharine; Caroline Kraan, Neil Adger, Halvard Buhaug, Marshall Burke, James Fearon, Christopher Field, Cullen Hendrix, Jean-Francois Maystadt, John O'Loughlin, Philip Roessler, Jurgen Scheffran, Kenneth Schultz & Nina von Uexkull (2019) Climate as a risk factor for armed conflict. *Nature* 571(7764): 193–197.

McGuirk, Eoin & Marshall Burke (2017) The economic origins of conflict in Africa. NBER Working paper W23056 (January).

McMaster, Gregory & Wallace Wilhelm (1997) Growing degree-days: One equation, two interpretations. *Agricultural and Forest Meteorology* 87(4): 291–300.

Meierding, Emily (2013) Climate change and conflict: Avoiding small talk about the weather. *International Studies Review* 15(2): 185–203.

Mendelsohn, Robert & Niggol Seo (2007) Changing farm types and irrigation as an adaptation to climate change in Latin American Agriculture. DOI:https://doi.org/10.1596/1813-9450-4161

Mistry, Malcolm (2019) A high-resolution global gridded historical dataset of climate extreme indices. *Data* 4(1): 41.

Pettersson, Therése (2019) UCDP Non-State Conflict codebook version 19.1 (https://ucdp.uu.se/downloads/).

Pettersson, Therése; Stina Högbladh & Magnus Öberg (2019) Organized violence, 1989–2018 and peace agreements. *Journal of Peace Research* 56(4): 589–603.

Pinstrup-Andersen, Per & Satoru Shimokawa (2008) Do poverty and poor health and nutrition increase the risk of armed conflict onset? *Food Policy* 33(6): 513–520.

Porter, JR et al., eds (2014) *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press, 485–533.

Raleigh, Clionadh; Hyun Jin Choi & Dominic Kniveton (2015) The devil is in the details: An investigation of the relationships between conflict, food price and climate across Africa. *Global Environmental Change* 32(2015): 187–199.

Roberts, Michael; Wolfram Schlenker & Jonathan Eyer (2012) Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics* 95(2): 236–243.

Robinson, James & Daron Acemoglu (2006) *Economic Origins of Dictatorship and Democracy*. Cambridge: Cambridge University Press.

Roche, Kevin; Michele Mueller-Itten, David Dralle, Diogo Bolster & Marc Mueller (2020) Climate change and the opportunity cost of conflict. *Proceedings of the National Academy of Sciences* 117(4): 1935–1940.

Rodell, Matthew; PR Houser, U Jambor, J Gottschalck, K Mitchell, C-J Meng, K Arsenault, B Cosgrove, J Radakovich, M Bosilovich, JK Entin, JP Walker, D Lohmann & D Toll (2004) The Global Land Data Assimilation System. *Bulletin of the American Meteorological Society* 85(3): 381–394.

Rosenzweig, Cynthia & Martin Parry (1994) Potential impact of climate change on world food supply. *Nature* 367(6459): 133–138.

Schewe, Jacob; Christian Otto & Katja Frieler (2017) The role of storage dynamics in annual wheat prices. *Environmental Research Letters* 12(5): 54005.

Seneviratne, Sonia; N Nicholls, D Easterling, CM Goodess, S Kanae, J Kossin, Y Luo, J Marengo, K McInnes, M Rahimi, M Reichstein, A Sorteberg, C Vera & X Zhang (2012)

Changes in climate extremes and their impacts on the natural physical environment. In: *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change* (IPCC). New York City: IPCC, 109–230.

Sexton, Richard; Ian Sheldon, Steve McCorriston & Humei Wang (2007) Agricultural trade liberalization and economic development: The role of downstream market power. *Agricultural Economics* 36(2): 253–270.

Sundberg, Ralph; Kristine Eck & Joakim Kreutz (2012) Introducing the UCDP Non-State Conflict dataset. *Journal of Peace Research* 49(2): 351–362.

Swinnen, Johan & Pasquamaria Squicciarini (2012) Mixed messages on prices and food security. *Science* 335(6067): 405–406.

Theisen, Ole Magnus (2017) Climate change and violence: Insights from political science. *Current Climate Change Reports* 3(4): 210–221.

Theisen, Ole Magnus; Helge Holtermann & Halvard Buhaug (2012) Climate wars? Assessing the claim that drought breeds conflict. *International Security* 36(3): 79–106.

Thomas, David & Chasca Twyman (2005) Equity and justice in climate change adaptation amongst natural-resource-dependent societies. *Global Environmental Change* 15(2): 115–124.

Tilman, David; Christian Balzer, Jason Hill & Belinda Befort (2011) Equity and justice in climate change adaptation amongst natural-resource-dependent societies. *Proceedings of the National Academy of Sciences* 108(50): 20260–20264.

UCDP (2019) UCDP definitions (https://pcr.uu.se/research/ucdp/definitions/).

USDA (2020) Agriculture and food sectors and the economy. United States Department of Agriculture, Economic Research Service (https://www.ers.usda.gov).

Vogt, Manuel; Nils-Christian Bormann, Seraina Ruegger, Lars-Erik Cederman, Philipp Hunziker & Luc Girardin (2015) Integrating data on ethnicity, geography, and conflict: The Ethnic Power Relations data set family. *Journal of Conflict Resolution* 59(7):1327–1342.

von Uexkull, Nina (2014) Sustained drought, vulnerability and civil conflict in sub-Saharan Africa. *Political Geography* 43: 16–26.

Ward, Michael; Brian Greenhill & Kristin Bakke (2010) The perils of policy by p-value: Predicting civil conflicts. *Journal of Peace Research* 47(4): 363–375.

Wheeler, Tim & Joachim von Braun (2013) Climate change impacts on global food security. *Science* 341(6145): 508–513.

Wischnath, Gerdis & Halvard Buhaug (2014) Rice or riots: On food production and conflict severity across India. *Political Geography* 43(November): 6–15.

WMO (2017) What is climate? World Meteorological Organization (http://www.wmo.int/pages/prog/wcp/ccl/faq/faq_doc_en.html).

PAOLA VESCO, PhD in Science and Management of Climate Change (Ca' Foscari University of Venice, 2020); Post-doctoral researcher, Department of Peace and Conflict Research, Uppsala University (2020–).

MATIJA KOVACIC, PhD in Economics (Ca' Foscari University of Venice, 2013); Researcher at the Joint Research Centre (JRC), European Commission (2019–).

MALCOLM MISTRY, PhD in Science and Management of Climate Change (Ca' Foscari University of Venice); Post-Doctoral Researcher, Ca' Foscari University of Venice (2017–).

MIHAI CROICU, MA in Peace and Conflict Studies (Uppsala University, 2016); PhD candidate, Department of Peace and Conflict Research, Uppsala University (2017–).