INTERNATIONAL MONETARY FUND

Climate Shocks and Domestic Conflicts in Africa

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WP/22/250

2022
DEC

WORKING PAPER

 WP/22/250

IMF Working Paper
African Department

Climate Shocks and Domestic Conflicts in Africa
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Authorized for distribution by Boileau Loko
December 2022

ABSTRACT: This paper analyzes the interlinkages between climate shocks, domestic conflicts, and policy resilience in Africa. It builds on a Correlated Random Effect model to asess these interrelationships on a broad sample of 51 African countries over the 1990-2018 period. We find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of domestic conflicts, by as high as up to 38 percent. However, the effect holds only for intercommunal conflicts, not for government-involved conflicts. The effect is maginified in countries with more unequal income distribution and a stronger share of young male demographics. The results are robust to a wide set of sensitivity checks, including using various indicators of weather shocks and domestic conflicts, and alternative estimation techniques. The findings shed light on key policy resilience factors, including steadily improving domestic revenue mobilization, strengthening social protection and access to basic health care services, scaling up public investment in the agriculture sector, and stepping up anti-desertification efforts.

JEL Classification Numbers:	Q54, D74, J11
Keywords:	Weather shocks; Domestic conflicts; Demographics; Resilience
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* The paper was initiated when Yoro Diallo was intern in the IMF Resident Representative Office in Mali. We are grateful to B. Loko, M. Marshalls and participants at the African Department's seminar for valuable comments and suggestions. All remaining errors are our own.

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I. Introduction

The economic and social damages of climate change (CC) have taken center stage in the public and academic debates. The adverse consequences of climate shocks (droughts, floods, severe weather events) are felt with greater frequency and intensity worldwide (Masson-Delmotte and others, 2018). Developing countries, and more particularly rural areas across Africa, appear among the hardest hit by the adverse consequences of CC **(Helgeson, Dietz, et Hochrainer-Stigler 2013; IMF 2019; 2020)**. According to the International Monetary Fund, sub-Saharan African economies contract by one percent when average temperature rises 0.5 above its long-term trend, or a 60 percent greater impact compared to other developing countries (IMF, 2020b). Relatedly, the International Panel on Climate Change (IPCC) documented that the CC-driven locust invasion worsened food insecurity in East African countries in 2019 (IPCC, 2020).

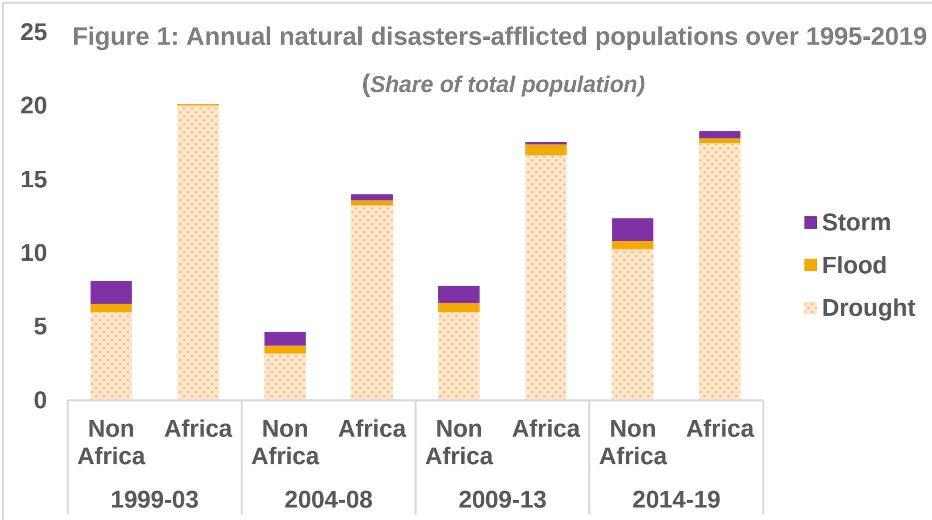
This paper adds to the literature and policy debate by focusing on the CC-domestic conflict nexus. Domestic conflicts are often referred to as one of the most serious social consequences of CC, given their increasingly frequent occurrence on account of competition for access to natural resources (Reuveny, 2007; Kniveton and others, 2008; and Scheffran and others, 2012).[1] However, as pointed out by von Uexkull and others (2016), "*to date, the research community has failed to reach a consensus on the nature and significance of the relationship between climate variability and armed conflicts*".[2] The present paper aims to expand our understanding as to whether and to what extent climate shocks affect domestic conflicts incidence, and how policymakers can develop resilience strategies to break this vicious linkage. This is one of the first paper to address directly these questions at the macro-level, as existing studies rather built on grid-cell data (McGuirk and Burke, 2020; McGuirk and Nunn, 2020; Mach and others, 2019; Harari and Ferrara, 2018; Carlton and others, 2016; Von Uexkull and others, 2016; Burke and others, 2015; Hsiang and others, 2014; and Raleigh and Urdal, 2007). Although grid-cell data analyses feature greater granularity, our macro-level investigation complements these existing studies by allowing to go beyond locality-specific regularities and infer more generalized patterns across the cross-country sample at hand. We build on a broad panel of 51 Africa countries over the 1990-2018 period to investigate the interlinkages between climate shocks, domestic conflicts, and policy resilience in Africa. Another key novelty of our study stems from our reliance on a broader indicator of weather shock that accounts jointly for both precipitation and temperature at the macro-level. Moreover, we rely on intercommunal conflicts instead of strictly focusing on herder-farmer conflicts.

We focus on Africa as it stands out as one of the hardest-hit continents by both climate shocks and domestic conflicts over the past decade. On the one hand, the annual number of people afflicted by natural disasters (drought, floods, and cyclones) is higher in Africa compared to other developing countries, although to varying intensity depending on the nature of the weather shock (Figure 1). Drought episodes appear to be weighing more severely on population's assets (Von Uexkull and others , 2016), thus making weather shocks, as captured through the *aridity index*, a relevant proxy for CC throughout this study. On the other hand, a good number of African countries experienced at least one conflict[3] per year over the 2010-18

[1] Migration is also referred to as another serious consequence of these conflicts for access to natural resources.
[2] The existing literature focused on the role of institutional, demographic and political factors, with ethnic diversity found as the main historical causes of civil conflicts incidence and duration (Horowitz, 1989; Esteban and Ray, 1999; Collier and Hoeffler, 2001). Other recent studies point to poverty, inequality, institutional weaknesses and dependence on natural resources as primary causes of civil wars (Elbadawi, 2000).
[3] *Type 1 (State-based conflict)* refers to "the use of armed force between two armed parties, of which at least one is the government of a state, which results in at least 25 battle-related deaths in a calendar year". *Type 2 (non-state* conflict) refers to

(continued…)

period (Figure 2), encompassing terrorism incidents and intercommunal clashes, including because of competition to access scarce natural resources (OECD, 2013; Africa report, 2020).[4]



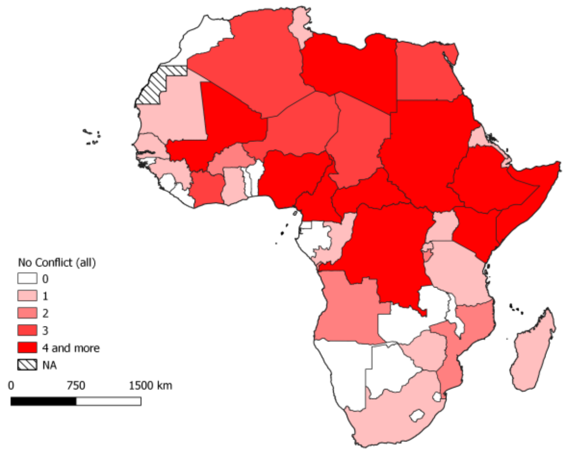
Source: EMDAT, WDI, and authors' calculations

"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."; and *Type 3 (One-sided violence)* refers to "the use of armed force by the government of a state or by a formally organized group against civilians, which results in at least 25 deaths". More details in section 3.1.

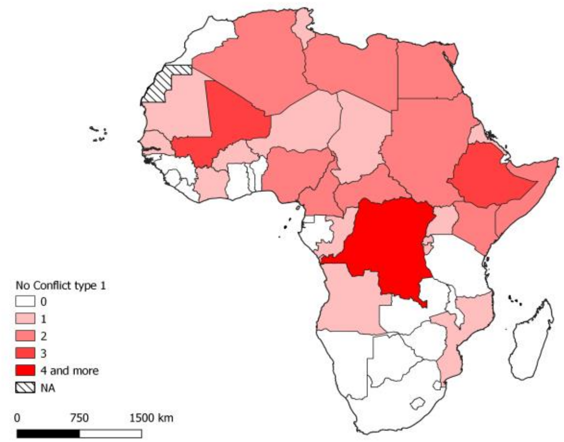
[4] Terrorism incidents and intercommunal clashes are increasingly threatening social cohesion in several Western and Central African countries (Burkina Faso, Cameroon, C.A.R., Chad, Mali, Niger, Nigeria, etc.).

Figure 2: Annual average number of conflicts over the period 2010-18

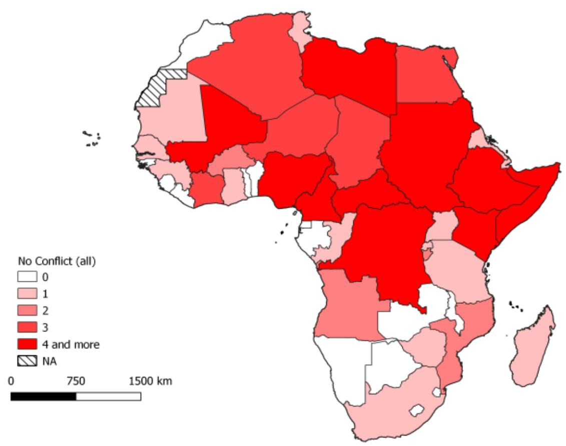
(a) *All* conflicts



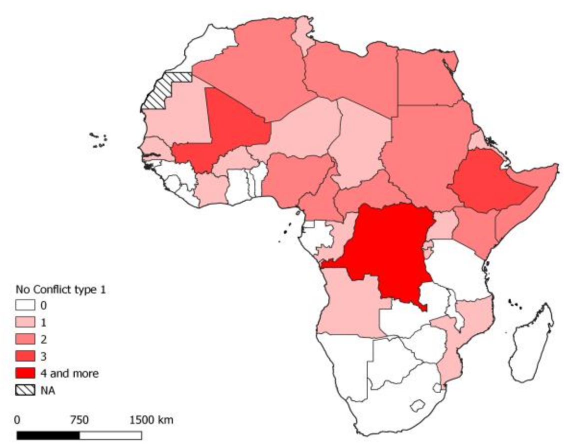
(b) Conflict *type 1*



(c) Conflict *type 2*



(d) Conflict *type 3*



Source: UCDP/PRIO and authors' calculations. Conflict type 1, type 2 and type 3 refer respectively to *state, non-state,* and *one-sided* conflict according to UCDP/PRIO classification.

We find key results with far-reaching policy implications. First, we find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of domestic conflicts by as high as up to 38 percent. Second, the effect holds only for intercommunal conflicts, not for government-involved conflicts. Third, the effect is magnified in countries with more unequal income distribution and a stronger share of young male demographics, while higher quality social protection and access to basic health care services, stronger tax revenue mobilization, scaled up public investment in the agricultural sector, and stepped-up anti-desertification efforts appear as relevant resilience factors to climate shocks. Fourth, the results are robust to a wide set of sensitivity checks.

The remainder of the paper is organized as follows. Section II briefly reviews the literature on the determinants of domestic conflicts. Section III introduces the dataset, while section IV presents the methodological approach used to assess the interlinkages between weather shocks, domestic conflicts, and resilience factors. Section V discusses the main results and some robustness checks, while section VI briefly concludes and draws some policy recommendations.

II. Literature Review

The existing literature points to both institutional and economic determinants of domestic conflicts. A common finding in the literature is that countries with weak institutions and low level of economic development face a higher risk of experiencing civil and military conflicts (Fearon and Laitin, 2003; Collier and Hoeffler, 2004, 2005; Hegre and Sambanis, 2006).

- **Regarding economic factors**, high level of economic development and strong economic growth are found to be associated with greater government's ability to upgrade human capital and reduce domestic (income and social) inequalities through a more adequate delivery of basic social services such as education and health (Cammeraat, 2020). Relatedly, stronger economic growth, along with its induced greater employment opportunities, increases the opportunity cost for young people to be recruited into rebellions, thereby reducing the incidence of domestic conflicts (Collier and Hoeffler, 2004).

- **As regards institutional factors**, a commonly found result is that weaker institutions are more conducive to inefficient resource allocation, which leads to economic exclusion of segments of the population, and in turn, to revolts. Stronger democratic institutions help reduce the risk of domestic conflicts through facilitating effective negotiation and credible engagement in conflict resolution (Fearon, 2004). In a similar vein, Hegre and Sambanis (2006) and Colaresi and Carey (2008) show that States with stronger democratic institutions rely less on violence and repression against civilians. However, several papers pointed to some heterogeneity in this relationship, in the form a U-inverted relationship between the level of democracy and the probability of domestic conflict. Particularly, a semi-democratic regime, that is, a regime that combines both autarchy and democracy, faces a higher risk of domestic conflict compared to a purely autarchic or democratic regime (Hegre, 2014).

Beyond economic and institutional factors, climate variability is also increasingly pointed out as a key source of domestic conflicts in poorer countries. Most empirical studies point to a converging finding that climate shocks pose a significant threat to domestic stability in developing countries (Hendrix and Glaser, 2007; Gleick, 2014; Von Uexkull and others, 2016). A key channel behind this empirical regularity lies in these countries' large dependence on the agricultural sector, which is also one of the most affected sectors by climate variability. In rural Africa for example, agricultural-based income remains the norm and occupies about 52% of rural populations, thus rendering economic and social stability highly vulnerable to climate shocks. In addition, CC also drives domestic conflicts through accelerating the competition to access scarce natural resources such as fresh water, arable land, forest, and water for irrigation (Homer-Dixon, 1994). According to the International Panel on Climate Change, the reduced water availability in the semi-arid savanna ecosystems across tropical Africa is likely to exacerbate conflicts between herdsmen and farmers (IPCC, 2001)

- **Some non-linearity is also present in the relationship between climate shocks and domestic conflicts**. Country-specific social and economic characteristics, including the demographics structure, the strength of the social protection system and policy resilience, affect the relationship between climate shocks and domestic conflicts. *Urdal (2011)* documents that the population growth rate as well as its density contribute a great deal to the growing pressure on renewable natural resources such as arable land, fresh water, forests, and fisheries.

- Moreover, countries' ability to reap the demographic dividend depends on the implementation of well-anticipated policies allowing to improve human capital and create appropriate employment opportunities *(Homer-Dixon, 1999; Zakaria, 2001; and Urdal, 2005)*. Failing to implement such policies reduces the opportunity cost for young people to be enlisted in rebellion *(Collier, 2000)*.

- The persistence of domestic inequalities and poverty along with the availability of policies to tackle them also stand as major catalysts of social tensions (*Østby and others, 2009; and Ikejiaku, 2012)*. Indeed, climate shocks negatively affect households' well-being through their adverse effects on income, food security, and human capital. This negative impact does not necessarily lead to conflicts, as it depends on the availability of adequate social protection to cope with the adverse consequences of climate shocks. Particularly, domestic conflicts are more likely to arise when some population groups are excluded from government social programs *(Von Uexkull and others, 2016)*.

- The intensity of conflicts is also a function of domestic factors that can accelerate the formation of conflicting groups, which in turn fuels conflicts. A factor found in the literature to drive the formation of conflicts and political groups in developing countries is ethnic fragmentation *(Stewart, 2016; Schleussner and others, 2016; and Fearon, 2006)*. Furthermore, in some African countries, decisions on specialization in economic sectors are often made on an intercommunal basis, thus adding to the complexity of the relationship between competition for access to natural resources and domestic conflicts. In the Sahel for example, conflicts often arise between the Peulhs (who are predominantly herders) and the Dogons (who are predominantly farmers), on account of competition to access scarce natural resources *(Sangaré and McSparren, 2018)*.

III. Data

Our study covers 51 African countries over the 1990-2018 period, based on data availability. We rely on the following variables.

3.1. Dependent variable: *Intercommunal conflict*

Our dependent variable is the **incidence of *intercommunal conflicts***, defined as conflicts arising between two social groups (e.g., ethnicity, religious) within the borders of a state.

- We use data from Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP GED Version 19.1), which records information on fatal violence at event level around the world over the 1989-2018 period (Sundberg and Melander, 2013; Pettersson and others, 2019).

Recorded fatal violence refers to conflict events that result in at least 25 battle-related deaths in a calendar year. For each event, the dataset provides information about the actors, the type of conflict, the geographical location and coordinates, and the specific occurrence dates of the violence. UCDP classifies conflict events into three categories: *state-based conflict, non-state conflict and one-sided violence*. These three categories of events are mutually exclusive and differentiated based on the identity of participating actors in the conflict.

(i) ***State-based armed conflict*** refers to the use of armed force between two armed parties, of which at least one is the government of a state.

(ii) ***Non-state conflict*** refers to "the use of armed force between two organized armed groups, neither of which is the government of a state".

(iii) ***One-sided violence*** refers to the use of armed force by the government of a state or by a formally organized group against unarmed civilians.

- Our dependent variable is circumscribed to *non-state conflicts ((ii) above)*, covering conflicts between communal groups within a country, or so-called *intercommunal clashes* **(Yilmaz 2005)**. We focus on this type of conflicts as it is the most associated with the consequences of climate change (e.g., resources scarcity, tensions around water and land management).

- For robustness purpose, we also rely on alternative variables. On the one hand, we carried out a *placebo* test using the other two types of conflicts ((i) and (iii) above) to explore whether the effect of climate shocks on domestic conflicts holds only for intercommunal clashes or for all types of conflicts.[5] On the other hand, for the sake of further robustness check, we also rely on conflict data from *Armed Conflict Location Events Dataset (ACLED)*, which compiles real time data on the locations, dates, actors, fatalities, and types of all conflict events across the world (Eck, 2012). Two main reasons explain the reliance on UCDP GED as primary database in this study compared to ACLED. First, unlike UCDP GED, ACLED does not provide a distinction between the intensity and the nature of violence, nor does it clarify whether the involved actor reports to the state. As such, to conduct this robustness check, we filter the "INTERACTION"[6] variable from ACLED to obtain data on intercommunal conflicts, through selecting only conflicts between communal militia groups (Raleigh and Dowd, 2015).[7] Second, ACLED covers a shorter period, starting only from 1997, compared to 1989 for UCDP.

3.2. Interest variable: *Weather shocks*

Weather shocks can materialize through several forms, including drought, floods, extreme temperatures, storms, etc. As such, differentiated effects may arise from conflicts incidence, depending on the nature of weather shocks (Buhaug and others, 2014; and Selby, 2014). Droughts appear as the most frequent climate shock in Africa (Figure 1), hence the greater reliance on drought-related variable in the literature when it comes to assessing the influence of climate shocks on conflicts in Africa. We rely on the *aridity index* as proxy for weather shock.

- Aridity is viewed as a climatic phenomenon reflected mostly through low rainfall, with rainfall in arid or dry regions standing out below potential evapotranspiration – evapotranspiration

[5] The placebo test consists of repeating our analysis on different types of conflicts: *State-based conflict, One sided violence, and all types of conflicts*. This test allows assessing the validity of our assumption that climate shock is only related to intercommunal conflicts and not to the other types of conflicts.

[6] "INTERACTION" allows identifying the parties (Civilians, Armed-State, Armed-Social group) in conflicts.

[7] In ACLED codebook, for variable interaction, we select code 44 "- COMMUNAL MILITIA VERSUS COMMUNAL MILITIA" and 47 "COMMUNAL MILITIA VERSUS CIVILIANS", which corresponds to intercommunal conflicts.

referring to the amount of water that evaporates through the soil, groundwater, and plant transpiration.

- Santoni (2017) calculates the aridity index as the ratio between precipitation and evapotranspiration, using data from the Climate Research Unit (CRU). To allow for a more direct interpretation, we use the inverse of the initial aridity index. As such, the higher the value of the aridity index used in our study, the greater the degree of aridity in this region. In addition, we normalized the index using a min-max transformation, allowing for a less dispersed distribution, with the index now ranging between 0 to 10.[8]

For robustness purposes, we also use two alternative proxies to capture drought. First, we use the *drought intensity* indicator from EM-DAT, measured as the share of the population affected by drought. The underlying idea is that droughts may lead to conflicts between groups if and only if the impact on people's property is substantial. Second, we rely on *extreme dry episodes* (during calendar year), calculated as the number of months, for a given country during a given calendar year, over which the Standard Evapotranspiration Index (SPEI, from CRU) reaches a level meeting Ye and others (2015)'s criteria for an extreme dry episode.[9]

3.3. Control variables

We account for potential drivers of intercommunal conflicts, in line with the literature review above. First, we control for country's level of economic development, captured through per capita GDP and access to electricity, based on data availability, as well as for real GDP growth rate.[10] Second, we account for variables related to the demographic structure, namely the population size, population growth rate, population density and ethnic fractionalization.[11] Third, we control for income distribution, captured through disposable and market Gini index, using the Standardized World Income Inequality Database (SWIID). Fourth, we take account of factors measuring the quality of institutions. Finally, we control for a time fixed effect and the lagged value of the dependent conflict variables, with a view to accounting for any likely persistency in conflicts occurrence, in line with Von Uexkull and others (2016). Table (A1) provides a more detailed description of variables along with their summary statistics.

3.4. Pairwise Correlation

A steady pattern supportive of a weather shocks-domestic conflicts nexus seems to emerge from preliminary correlations (Figures 3.a and 3b). It stands out that on average over the 1990-2018 period, conflict-year observations are associated with greater value in the aridity index. This apparent correlation will be assessed more rigorously in the next sections through appropriate econometric analyses.

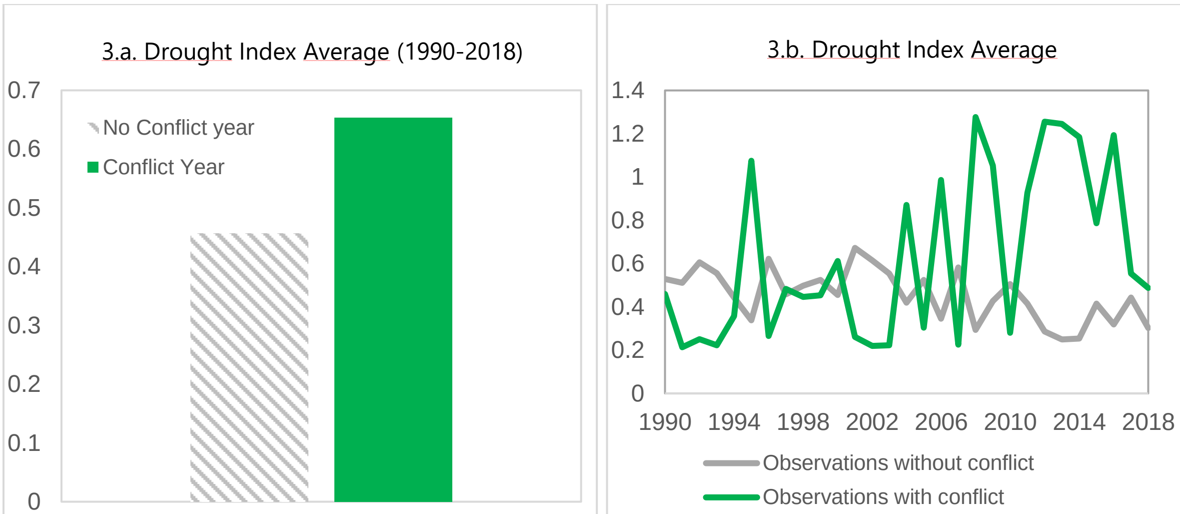
[8] Min-Max transformation for X consists of transforming it into an index Z through the following formula: $Z = 10 * \frac{X-\min(X)}{Max(X)-Min(X)}$

[9] A period is considered as an extreme dry episode when the SPEI value is inferior to -2.

[10] Access to electricity proxies not only for poverty (along the lines of access to basic public services) but also for access to quality infrastructure. Data paucity prevented us from accounting for more direct poverty indicators such as poverty rates. Data on access to electricity come from the World Development Indicators (WDI).

[11] Data on the size, growth and density of population are taken from WDI dataset. Data on ethnic fractionalization, viewed as the degree of ethnic diversity within a country, come from Drazanova (2019).

Figure 3. Aridity Index and Domestic Conflicts over 1990-2018: Pairwise Correlations



IV. Methodology

We build on a Logit binary discrete choice model, with the dependent binary variable equaling 1 for all observations corresponding to a domestic conflict occurrence, and 0 otherwise. Specifically, we consider the following equation:

$$Pr(Y_{it}|X_{it}, Z_{it-1}) = G(\alpha + \beta_0.X_{it} + \sum_{k=1}^{n}\beta_k.Z_{ikt-1}) = \alpha + \beta_0.X_{it} + \sum_{k=1}^{n}\beta_k.Z_{ikt-1} + year + \mu_i + \varepsilon_{it},$$

Where $\boldsymbol{Y_{it}}$ is a binary variable taking the value 1 if an intercommunal conflict occurs in a country i at year t. X_{it} stands for the weather shock proxy (aridity index, drought intensity, and extreme dry episode, respectively, as discussed above). The exogenous nature of these weather variables (e.g., Miguel and Sergenti, 2004; Dube and Vargas, 2013; and Ritter and Conrad, 2016) allows identifying the causal effect between climate and conflict incidence. Z_{it} represents the set of control variables. That said, we also use the one-year lagged value of some of our control variables to further mitigate endogeneity concerns. $Year$ stands for the time trend, while β captures the estimated parameters, μ_i an unobserved time-invariant country specificity and ε_{it} the residual term.

We rely on the Correlated Random Effect (CRE) to estimate Equation (1), to overcome estimation challenges posed by standard Fixed effect (FE) and Random effect (RE) models. Basically, the CRE combines properties from both the FE and RE models, through estimating within effects in random effects (Mundlak, 1978; Allison, 2009; and Wooldridge, 2010). This hybrid model consists of adding to the right-hand side of equation (1), the mean value of each covariate ($\overline{X_i}$ and $\overline{Z_i}$) at the country level *i*. We briefly discuss below the rationale behind the preference for the CRE over both FE and RE models.

- Under RE, μ_i is assumed not to be correlated with the covariates, namely $Cov(\mu_i, X) = 0$. However, this independence assumption between country's unmeasured features and covariates is rather strong, as unobserved country specificity may well be correlated with covariates (Wooldridge, 2019a). For instance, country's unmeasured historical features such as colonization might explain its contemporaneous level of economic development and institutional quality

(Acemoglu and others, 2001), so might its geographical structure for when it comes to its degree of vulnerability to climate shocks.

- Although FE allows for a correlation between individual specific effects and the covariates, namely Cov(μ_i, X)≠0, it also carries some drawbacks that limit its use. First, FE is not fit for variables that do not vary over time such as our binary dependent variable. Relatedly, FE may lead to selection bias, as countries having experienced zero intercommunal conflict throughout the study period (43% of our sample) will be excluded from the analysis (Caballero, 2016), while one cannot rule out the possibility of a correlation between the factors explaining the lack of time-variation in the dependent binary variable for these observations and the factors driving weather shocks. Second, FE suffers from the incidental parameters problem, in that FE in discrete choice models leads to inconsistent estimates when the length of the panel is fixed (Chamberlain, 1979; and Wooldridge, 2019).

With CRE, Equation (1) above is transformed into Equation (2) below.

$$Pr(Y_{it}|X_{it}, Z_{it-1}) = \alpha + \beta_0 . X_{it} + \sum_{k=1}^{n} \beta_k . Z_{ikt-1} + \overline{X_\iota} + \overline{Z_\iota} + year + \mu_i + \varepsilon_{it} \quad (2)$$

$\overline{X_\iota}$ *and* $\overline{Z_\iota}$ stand for country's i mean average for X_{it} *and* Z_{it}, respectively.

Including mean values of independent variables allows controlling for unobserved country specificity that may be correlated with the interest and/or control variables. This helps embolden the validity of the independence assumption between country's unmeasured features and covariates (Cov(μ_i, X)=0). The added variables (mean values of time-varying covariates) are constant for a given country over the study period but vary across countries. As such, we thus control not only for time-constant unobserved heterogeneity —as under FE—, but also for the vector of time-averaged variables, thereby overcoming the abovementioned incidental parameters problem in nonlinear models. Another appealing feature of the CRE is that it allows estimating the effects of time-constant independent variables, just as in a traditional random effects model (Wooldridge, 2019). It follows that CRE allows for differences within and between-country, through accounting for country-specific and time-invariant features affecting the likelihood of domestic conflicts as well as weather shocks occurrence, or both (Caballero, 2016). Finally, unlike FE, CRE helps avoid likely selection bias in the face of time-invariant binary dependent variable.

V. Econometric results

5.1. Baseline results

Table 1 below reports the baseline results on the relationship between weather shocks and domestic conflicts occurrence. Weather shocks, as captured through the drought (aridity) index, are positively associated with domestic conflicts occurrence (columns 1-6), with a statistical significance of one percent, suggesting that weather shocks increase the likelihood of intercommunal conflicts. This effect does not hold only for contemporaneous drought episode, but for past drought episodes (one-year lag of the aridity index), as captured through the significantly positive coefficients associated with both variables (columns 8).[12] The bottom panel of the table reports statistics capturing the area under the ROC curve (AUROC) (along with their associated

[12] Controlling jointly for past aridity and current aridity (column 8) particularly allows disentangling the effect of a conflict starting at the beginning of a given calendar year from the effect of a conflict that carried from the end of the previous calendar year.

standard errors), meant to gauge the predictive power of the CRE estimations.[13] The reported AUROC statistics stand above 0.88 in all columns – except column 1 (where only the aridity index is included as regressor), pointing to a rather good fit of the model.

We rely on odds ratio to provide a quantitative interpretation of the estimated coefficients, the latter not standing directly for marginal effects in logit models.[14] One minus the odds ratio provides the percent change in odds for each unit increase in the drought index. The estimated odds ratio ranges between 1.22 and 1.38, which points to a rather sizable effect. This suggests that each unit increase in the drought index enhances the chance of experiencing an intercommunal conflict by a magnitude ranging between 22 and 38 percent.[15]

Besides the influence of weather shocks, additional interesting results stand out as drivers of domestic conflict occurrence, in line with the existing literature (columns 2-12).

- First, intercommunal conflicts persist over time, as reflected in the significantly positive coefficient associated with the one-year lag of the dependent variable (columns 7-12).

- Second, the higher a country's economic development level, the lower its probability of experiencing an intercommunal conflict, as reflected in the negative and significant coefficient associated with per capita GDP. This finding holds when using access to electricity as proxy for access to quality infrastructure (hence for economic development) or for poverty (through the lens of access to basic public services) (column 4). Relatedly, economic buoyancy (real GDP growth) is associated with lower likelihood of domestic conflict occurrence, though the statistical significance of the estimated coefficient is rather weak (the coefficient is significant in one out of three columns).

- Third, Institution quality[16] mitigates the incidence of domestic conflict. Indeed, the coefficient associated with the quality of institutions is significantly negative.

- Fourth, social and demographic factors also matter for intercommunal conflict incidence. On the one hand, ethnic fractionalization stands out as a catalyst for domestic conflicts, as evident from its associated positive and statistically significant coefficient. On the other hand, larger population size is associated with higher probability of experiencing intercommunal conflicts. The estimated coefficient associated with population density is positive but not statistically significant.

- Sahel countries do not behave differently compared to other African countries when it comes to the influence of drought episodes on intercommunal conflicts occurrence. The coefficient associated with the Sahel dummy variable is statistically insignificant (column 12). It is however worth noting that when focusing on government-involved domestic conflicts, Sahel countries do experience higher occurrence probability compared to their African peers (see Placebo test-based robustness check in Table 5).

[13] ROC stands for Receiver Operating Characteristic. AUROC statistics range between zero and one, with higher values reflecting greater predictive power of the model.

[14] In a logit model, the odds ratio refers to the exponential value of estimated coefficients.

[15] In other terms, a one (within country)-standard deviation increase in the aridity index raises the likelihood of experiencing an intercommunal conflict by as high as between 7 percent and 11.4 percent.

[16] Institutional quality is computed as a simple average of the six indicators from the World Governance Indicators, namely (i) voice and accountability, (ii) regulatory quality, (iii) political stability, (iv) government effectiveness, (v) rule of law and (vi) control of corruption.

Table 1: Baseline results

VARIABLES	(1) Conflict type 2	(2) Conflict type 2	(3) Conflict type 2	(4) Conflict type 2	(5) Conflict type 2	(6) Conflict type 2	(7) Conflict type 2	(8) Conflict type 2	(9) Conflict type 2	(10) Conflict type 2	(11) Conflict type 2	(12) Conflict type 2
Drougth index	0.251**	0.248**	0.253***	0.191**	0.248**	0.227*	0.243*	0.238*				
	(0.115)	(0.118)	(0.0943)	-0.0959	(0.117)	(0.124)	(0.145)	(0.145)				
Drought index (t-1)								0.272***	0.275***	0.298**	0.318**	0.319**
								(0.101)	(0.102)	(0.121)	(0.153)	(0.151)
Log GDP pc(t-1)		-2.665***			-2.459***	-2.482***	-2.010***	-2.012***	-2.002***	-1.934**	-2.249***	-2.224**
		(0.880)			(0.889)	(0.807)	(0.718)	(0.713)	(0.716)	(0.858)	(0.860)	(0.870)
Growth (t-1)			-2.425**	-1.84	-1.737							
			(1.187)	-1.229	(1.209)							
Electricity access (t-1)				-0.037**								
				-0.0171								
EFI index		8.131*	10.07**	8.012**	10.12**	6.078	6.397*	6.373*	6.377*	9.777	8.224**	7.941*
		(4.269)	(4.380)	-3.827	(4.682)	(3.952)	(3.492)	(3.483)	(3.487)	(6.064)	(4.090)	(4.357)
ln Pop. (t-1)		3.004**	3.013***	2.388***	3.319***		2.406***	2.415***	2.399***		2.841***	2.823***
		(1.218)	(1.135)	-0.927	(1.259)		(0.931)	(0.937)	(0.930)		(0.967)	(0.970)
ln Pop. Density (t-1)						0.105				6.186		
						(0.352)				(4.539)		
Sahel												0.239
												(1.133)
Conflict all (t-1)							1.992***	2.020***	2.023***	2.130***	1.449***	1.451***
							(0.372)	(0.375)	(0.375)	(0.392)	(0.537)	(0.532)
Institution (t-1)											-3.132***	-3.146***
											(0.868)	(0.891)
Constant	-5.417***	-36.34*	-44.40**	-38.18**	-34.75*	9.304	-31.68*	-31.79*	-31.69*	3.217	-39.39**	-39.22**
	(1.117)	(21.18)	(18.57)	(15.22)	(20.50)	(6.184)	(16.50)	(16.54)	(16.45)	(7.069)	(17.95)	(18.01)
CRE Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,479	1,146	1,145	884	1,142	1,120	1,146	1,146	1,146	1,120	741	741
Number of countries	51	46	47	46	45	45	46	46	46	45	45	45
Log likelihood	-434.8	-289.3	-292.9	-226.1	-285.6	-292.8	-271.1	-270.6	-271	-280.4	-158.3	-158.2
Wald Chi2	131847	88588	53924	108634	1004000	75195	45812	118938	16396	16232	2740	2853
Rho(LR)	0.797	0.583	0.617	0.599	0.573	0.535	0.458	0.457	0.457	0.647	0.457	0.458
P-value	0	0	0	0	0	0	0	0	0	0	0	0
AUROC	0.578	0.890	0.886	0.886	0.894	0.874	0.921	0.922	0.921	0.877	0.935	0.935
seAUROC	0.018	0.011	0.012	0.013	0.011	0.013	0.009	0.009	0.009	0.012	0.010	0.011

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2. Conditional effects

We now turn onto exploring factors that could exacerbate or mitigate the influence of weather shocks on intercommunal conflicts occurrence. We explore the following heterogeneity factors, which are likely to alter the climate shocks-conflicts nexus.

$$Pr(Y_{it} = 1|X_{it}, Z_{it-1}) = \alpha + \beta_0.X_{it} + \beta_1.C_{it} + \varphi.X_{it} * C_{it} \sum_{k=1}^{n} \beta_k.Z_{ikt-1} + year + \mu_i + \varepsilon_{it}, \quad (3)$$

Table 2 below reports results on the weather shocks-domestic conflicts nexus, conditional on the influence of factors related to the demographic structure. We focus on the role of youth share (aged 15 to 24) in the population, which is ambiguous à priori. On the one hand, a larger youth share can turn out as a blessing, as a larger youth share can be a powerful growth engine through labor supply and hence contribute to reducing intercommunal conflict occurrence ("peace dividend" channel), should it benefit from appropriate education and professional training. On the other hand, large youth cohorts could give rise to greater probability of domestic conflict occurrence, should governments fail to provide them with opportunities to participate in education, labor market, and in governance, rendering cheaper the recruitment cost of unemployed young people into armed conflict groups (Urdal, 2012; and Collier and others, 2000).

- We divided our sample into two groups around the median size of youth share. In Table 2 (columns 1 and 2), Group 1(2) refers to countries with a youth share below (above) 20 percent of the population. It stands out that the coefficient associated with the drought index is significantly positive under Group 2, while it is positive but not statistically significantly under Group 1. This finding suggests that the catalyst effect of weather variability on intercommunal conflicts is magnified in countries with a larger share of youth.

- When tweaking further the result, it turns out that within the subsample of youthly populated countries (Group 2), the catalyst role of weather shocks on domestic conflicts occurrence is stronger when the share of male youth outweighs that of female youth (columns 3 and 4).

Table 2: Role of Demographic structure factors on the weather shocks-conflicts nexus

	(1)	(2)	(3)	(4)
	Youth Share		Youth Gender	
Dependent variable : Intercommunal conflict	Group 1 (<20%)	Group 2 (≥20%)	Female	Male
Drought index (t-1)	0.024	0.692***	-0.729	0.367**
	(0.155)	(0.224)	(1.239)	(0.152)
Controls variables included	Yes	Yes	Yes	Yes
Number of observations	527	614	599	542
Number of countries	39	42	32	32
Log likelihood	-140.2	-135.3	-111.7	-161.4
Wald Chi2	131.7	44.59	72.22	126
Rho(LR)	0.314	0.522	0.562	0.281
P-value	0	2.57e-06	0	0
AUROC	0.917	0.903	0.884	0.913
seAUROC	0.009	0.010	0.013	0.010

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

Table 3 below presents results on the likely role of macroeconomic factors on the weather shocks-domestic conflicts nexus. We explore the influence of tax revenue mobilization, liquidity constraints (access to credit, and remittances), social spending, income inequality, social protection, investment in agriculture sector, and forest coverage.

- **Tax revenue mobilization**

The coefficient associated with the interactive term between the drought index and tax revenue is negative and statistically significant, suggesting that greater tax revenue mobilization mitigates the catalyst role of weather shocks on intercommunal conflicts occurrence. Tax revenue is critical for creating fiscal space to expand social safety nets and upgrade public infrastructure, which in turn help preserve social cohesion and speed up recovery from damages caused by natural disasters and climate change (IPCC, 2007; McIntyre, 2009; and Cabezon and others, 2015). More broadly, enhanced tax revenue collection stands as a resilience-strengthening factor, in that it allows building fiscal buffers for smoothening out effects of adverse shocks to the economy, including weather shocks. Improved tax revenue collection also helps ease financial constraints, especially in developing countries, given their limited access to international market and the shallowness of their domestic financial markets (Catalano and others, 2020).

- **Liquidity constraints: Remittances and access to credit**

Financial constraints for adapting to climate change can be relaxed through access to credit and/or remittances. Remittances or access to credit might help households smoothen out consumption, and thus cope with adverse shocks, through easing financial constraints (Le De and others, 2013; and Bendandi and Pauw, 2016). As such, remittances or access to credit might mitigate the conflict catalyst role of weather shocks. As expected, the interactive term between the drought index and remittances is negative. However, the estimated coefficient is not statistically significant (column 2). A similar result was found for access to credit (column 3).

- **Social spending, social protection, and inequality**

Government spending in priority social sectors such as health can improve households' access to quality health care services, thus reducing their exposure to poverty and vulnerability to shocks (Celikay and Gumus, 2017). It can thus be expected that enhanced priority social spending helps lessen the catalyst effect of weather shocks on domestic conflicts occurrence. The estimated coefficient associated with the interactive term between health spending and the drought index is significantly negative, in line expectations (column 4). This finding holds when relying on an alternative proxy for access to health care services, namely the number of hospital beds per 1000 people (column 5).[17] Relatedly, stronger social protection systems are found to mitigate the influence of weather shocks on domestic conflicts occurrence. Indeed, income redistribution, which stands out as a key factor towards preserving the very fabric of the society, is essential for holding back the materialization of the weather shocks-domestic conflicts nexus. The coefficient associated with the interactive term between the drought index and state redistribution effort is significantly negative (column 6), underscoring that the more income is distributed the lower the likelihood of weather shocks igniting intercommunal conflicts.[18] These findings suggest that improved public basic services such as expanded social safety nets and upgraded health care services contribute to strengthening social cohesion and softening by the same token the catalyst effect of weather shocks on domestic conflicts occurrence through rendering it less likely that segments of the population feel marginalized to the point of getting themselves recruited into armed groups.

- **Agriculture sector: Employment and Investment**

Most developing countries remain largely dependent on the agricultural sector, which also remains highly subject to the vagaries of the weather (Mendelsohn and others, 2000; and IMF, 2017). With a large segment of active labor force still employed in the agriculture sector, this makes weather shocks a pivotal driver of changes in poverty and income inequality in Africa. Moreover, several studies documented that climate change reduces agriculture sector productivity, increases malnutrition and heightens food insecurity (Mendelsohn and others, 2000; Ringler and others, 2010; and Tumushabe, 2018). Enhanced public investment in the agricultural sector, in the forms of well-targeted subsidies to facilitate access to inputs (irrigation system, tractors, seeds, fertilizers, etc.), technical capacity building, or well-targeted cash transfers to farming groups in the aftermath of an adverse shock, could thus prove essential for strengthening the sector's resilience or adaptability to weather shocks, through improving farmers' ability to recover more quickly from damages caused by climate shocks (IPCC, 2007; and McIntyre, 2009, IMF, 2020).As expected, the estimated coefficient associated with the interactive term between the drought index and agricultural sector investment is negative and statistically significant (column 7) as expected, confirming that scaled up public investment in agriculture sector reduces the probability of experiencing an intercommunal conflict following weather shocks.

[17] We estimated the interaction term with the education expenditure variable. The coefficient of the interaction is not significant. We found the same result with the interaction between the drought index and defense spending. We are not surprised by the latter result because we considered inter-communities groups conflict as the dependent variable. Thus, improving people's living conditions seems to mitigate this type of conflict more than purchasing military equipment.

[18] Redistributive effort refers to the weight of government social safety nets framework including taxes, subsidies, and transfers to reduce inequality. In SWIID database, it is proxied by the difference between Gini on disposable income (post-tax, post-transfer) and Gini on market income (pre-tax, pre-transfer).

- **Forest coverage**

Forests are identified as powerful instruments towards strengthening adaptability and resilience to climate change, through their pivotal roles as carbon sequestrator as well as vehicle of economic and sociocultural opportunities (Canadell and Raupach, 2008). As such, expanded forest coverage may be expected to mitigate the materialization of the weather shocks-domestic conflicts nexus. Our results confirm this expectation, with the estimated coefficient associated with the interactive term between the drought index and forest coverage turning out negative and statistically significant (column 8). This finding underscores the prominence of reforestation efforts for slowing down desertification and its catalyst role on domestic conflicts occurrence.

Table 3: Conditional effects and resilience factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	X=Tax Revenue	X=Remittances	X=Credit to private sector (%GDP)	X=Health expenditure	X=Hospital beds per 1000 people	X= Redistribution effort	X=Investment in agriculture	X=Forest coverage
VARIABLES	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict
Drought index (t-1)	3.134***	0.107	0.713**	0.992**	1.579***	1.915***	0.920***	0.327***
	(0.803)	(0.148)	(0.348)	(0.433)	(0.572)	(0 .475)	(0.297)	(0.125)
Drought index(t-1)*X(t-1)	-0.164***	-0.006	-0.009	-0.132*	-0.669***	-0.126***	-0.568*	-0.403**
	(0.049)	(0.022)	(0.009)	(0.078)	(0.248)	(0.035)	(0.293)	(0.201)
Controls variables included	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
CRE variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	695	944	724	704	221	838	742	1,117
Number of countries	44	45	45	46	46	43	38	45
Log likelihood	-131.18	-219.9	-148.6	-153.9	-50.03	-206.176	-171.8	-261.810
Wald Chi2	63379.72	62.67	125956	1125	2.112e+06	105.1	5.990e+08	56091.91
Rho(LR)	0.309	0.420	0.410	0.501	0.615	0.156	0.342	0 .271
P-value	0	8.71e-08	0	0	0	0	0	0
AUROC	0.955	0.928	0.938	0.926	0.927	0.928	0.933	0.929
seAUROC	0.008	0.009	0.011	0.011	0.016	0.011	0.010	0.009

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively. “X” representing the variable used to interact with the drought index, is included not only in isolation but also in interaction with the drought index.

5.3. Robustness checks

We test the robustness of our baseline results to alternative specifications.

5.3.1. Using alternative variables and models

First, we check the robustness to the reliance on alternative proxies for domestic conflicts.

(i) We start by using the number of intercommunal conflicts experienced during a calendar year as dependent variable, with a view to going beyond the simple occurrence of conflicts and rather capturing the intensity of conflicts. In the sample at hand, countries experience on average 11 domestic conflicts per calendar year. We re-arranged this variable into five categories based on the number of recorded domestic conflicts. Specifically, we set "Number of Conflicts" equal to 0 when no domestic conflict occurs in a country on a given year; 1 when the number of conflicts per year ranges between one and three; 2 when the number of conflicts per year ranges between four and five; 3 when the number of conflicts per year ranges between six and eight; and 4 when the number of conflicts per year exceeds 9. We build on an ordered *probit* model to estimate the relationship between the drought index and the re-arranged "Number of Conflicts" variable. Table 4 below reports the corresponding results, which confirm that the higher the drought index, the greater the probability of experiencing more intense intercommunal conflicts.

(ii) In addition, we use different binary discrete choice models to test the sensitivity of the baseline results. We estimate equation 2 using four econometric methods: (i) Probit Correlated Random Effect; (ii) Logit Random Effect (CRE); (iii) Probit Random Effect (RE) and (iv) Logit Fixed Effect (FE). The results are reported from column 3 to column 6, respectively. We find that the coefficients associated with drought index are still positive and significant except for the result from the FE model in column 6 – as explained in section IV, the FE presents many shortcomings.

(iii) We also explore whether the catalyst role of weather shocks on domestic conflicts occurrence holds only for intercommunal conflicts or applies to all types of domestic conflicts. We run *placebo* tests, where the dependent variable in the baseline model remains intercommunal conflicts. This choice is predicated on the most-commonly held assumption, namely that climate variability is more likely to drive conflicts among various groups because of competition to access natural resources (Reuveny, 2007; Kniveton and others, 2008; and Scheffran and others, 2012). The validity of this assumption can be confirmed through the UCDP/PRIO database that allows classifying conflicts into three categories, namely *State-based armed conflict, non-state conflict and One-sided violence*, in line with the discussion from section 3.1. above. Table 5 below reports the corresponding estimations results. In column 3, the dependent variable is as in the baseline ("*non-state conflict"*). In column 1, the dependent variable refers to all conflicts, irrespective of the type of domestic conflicts, while columns 2 and 4 feature results for "*State-based armed conflict"* and *"One-sided violence"*, respectively. The results point to significant heterogeneity: the catalyst role of weather shocks on domestic conflicts occurrence holds true only for intercommunal conflicts (column 3) and one-sided violence (column 4), not for the "State-based armed conflict". The coefficient associated with the drought index is significantly positive when focusing on intercommunal conflicts and one-sided violence (columns 3 and 4), but it is no longer statistically significant when considering State-based armed conflicts (columns 2). The statistical insignificance of the coefficient associated with government-involved conflicts may reflect the fact that such conflicts in our sample mostly do not occur because of competition for scare resources such as land and water, but rather because of socio-demographic and institutional factors such as ethnic fragmentation, religious considerations, or revolt on account of weak institutions and resentments over social or economic exclusions (Stewart, 2016; Schleussner and others, 2016; Colaresi and Carey, 2008; Fearon, 2006 and 2004; Hegre and Sambanis, 2006). This result is particularly important, given the heavy human toll of intercommunal clashes: in the Sahel for example, intercommunal conflicts are costing thousands of lives and causing millions of population displacements.[1] Also, it is worth noting that while the Sahel dummy is not statistically significant under the baseline, it turns out significantly positive when focusing on state-based armed conflicts (column 2), suggesting that compared to their African peers, Sahel countries face higher probability of experiencing government-involved domestic conflicts.

Table 4: Using "Number of conflicts per year" as dependent variable

VARIABLES	(1) Number of conflicts	(2) Number of conflicts	(3) Conflict (Dummy)	(4) Conflict (Dummy)	(5) Conflict (Dummy)	(6) Conflict (Dummy)
Drought index (t-1)	0.524**	0.293***	0.175**	0.570**	0.300**	0.260
	(0.211)	(0.107)	(0.0788)	(0.287)	(0.151)	(0.380)
log GDP (t-1)	-2.164**	-1.243***	-1.244***	-0.441	-0.267	-1.705
	(0.845)	(0.470)	(0.479)	(0.565)	(0.304)	(1.429)
EFI	8.092**	3.980**	3.981*	6.271**	3.132*	4.722
	(3.513)	(1.890)	(2.122)	(3.010)	(1.611)	(32.60)
log Pop. (t-1)	2.432***	1.328***	1.562***	2.492***	1.379***	-1.741
	(0.642)	(0.368)	(0.551)	(0.590)	(0.318)	(3.843)
Conflict all (t-1)	1.625***	0.905***	0.823***	1.528***	0.863***	1.140**
	(0.591)	(0.293)	(0.284)	(0.538)	(0.284)	(0.468)
Institution (t-1)	-3.215***	-1.763***	-1.673***	-3.039***	-1.634***	-3.558***
	(0.740)	(0.415)	(0.500)	(0.881)	(0.494)	(1.037)
Constant			-21.36**	-45.60***	-24.89***	
			(10.24)	(10.24)	(5.534)	
Year dummies	yes	yes	yes	yes	yes	yes
Modele	Ordered probit+CRE	Ordered logit+CRE	Probit+CRE	Logit+RE	Probit+RE	Logit+FE
Observations	741	741	741	741	741	287
Number of countries	45	45	45	45	45	17
Log likelihood	-284.2	-282.7	-158.5	-161.8	-161.8	-98.76
Wald Chi2	1113	2315	2758	593.8	665.3	50.16
P-value	0	0	0	0	0	0

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

[1] According to UNHCR (2020): The Central Sahel countries of Burkina Faso, Mali, and Niger are the epicenter of the forced displacement crisis. More than 1.5 million internally displaced people (IDPs) and 365,000 refugees have fled violence in the Central Sahel, including over 600,000 for 2021 alone.

Table 5: Placebo test

VARIABLES	(1) All types of conflict	(2) Conflict type 1 (State-based conflict)	(3) Conflict type 2 (Non-State conflict)	(4) Conflict type 3 (One sided violence)
Drought index (t-1)	0.686**	-0.0536	0.319**	0.621**
	(0.336)	(0.332)	(0.151)	(0.299)
Sahel	1.001	1.656*	0.239	0.738
	(0.724)	(0.922)	(1.133)	(0.612)
Control variables	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Model	CRE	CRE	CRE	CRE
Observations	741	741	741	741
Number of countries	45	45	45	45
Log likelihood	-232.2	-203.6	-158.2	-238.8
Wald Chi2	164.1	457.8	2853	351.2
Rho(LR)	0.229	0.516	0.458	0.158
P-value	0	0	0	0
AUROC	0.897	0.852	0.935	0.876
seAUROC	0.0126	0.0160	0.0106	0.0151

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

(iv) For the sake of further robustness check, we also rerun the baseline regression, using this time ALCED-based conflicts data instead of UCDP GED data used so far (see discussion in section 3.1. above). The results are qualitatively similar to the benchmark estimates, confirming that drought-led weather shock increases the likelihood of experiencing intercommunal conflicts (Table 6, column 4).

5.3.2. Using alternative indicators of weather shock and conflict variables

Second, we carry out some sensitivity analysis using alternative weather shock indicators. First, we replace our interest variable with alternative measures of weather shocks discussed above, namely the “Drought intensity” index, SPEI, and “Extreme drought episode” index dry. Table 6 below (columns 1, 2 and 3) reports the corresponding estimation results. The coefficients associated with the drought intensity index (column 1) and the extreme drought episode (column 2) are qualitatively similar to the baseline estimates (positive, though not statistically significant for the drought intensity and SPEI index), somewhat upholding the catalyst role of weather shocks on intercommunal conflicts occurrence.

Table 6: Using alternative weather shock indicators
(Drought intensity, Extreme Drought episodes, and ACLED-based database weather shock)

	(1)	(2)	(3)	(4)
VARIABLES	Conflict type 2	Conflict type 2	Conflict type 2	Conflict type 2 from ACLED
Drought index (t-1)				0.477*
				(0.219)
Drought intensity (t-1)	0.00768			
	(0.0333)			
SPEI (t-1)		-0.0128		
		(0.439)		
Extreme dry episode (t-1)			0.634**	
			(0.305)	
Control variables	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Modele	CRE	CRE	CRE	CRE
Observations	741	741	741	705
Number of countries	45	45	45	42
Log likelihood	-159.4	-159.5	-159	-240.293
Wald Chi2	5029	2098	3068	219.25
Rho(LR)	0.496	0.496	0.492	0.404
P-value	0	0	0	0
AUROC	0.929	0.930	0.931	0.872
seAUROC	0.0106	0.0107	0.0106	0.0158

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

5.3.3. Controlling for further covariates

Finally, we check the results robustness by controlling to the extent possible for variables that are likely to matter simultaneously for both weather shocks and domestic conflicts. Controlling for such covariates help mitigate concerns of likely omitted variables bias. We account for three groups of covariates: those reflecting macroeconomic resilience factors (capital stock), resources scarcity (share of agriculture and arable lands), and socio-economic factors (youth unemployment, male youth versus female unemployment, share of rural population), respectively. Accounting for these additional covariates left the estimate of the influence of the drought index qualitatively unchanged, upholding the weather shocks-intercommunal conflicts nexus from the baseline results (Table 7).

Table 7: Robustness Check: Controlling for further Covariates

	(1)	(2)	(3)	(4)	(6)	(7)	(8)
	X=Capital stock	X= Youth Unemployement	X= Male Youth Unemployement	X= Female Youth Unemployement	X= Agriculture land (%Total land)	X=Arable land (% Total land)	X= Rural population (%Total population)
VARIABLES	Conflict type '2'	Conflict type '2'	Conflict type '2'	Conflict type '2'	Conflict type '2'	Conflict type '2'	Conflict type '2'
Drought index (t-1)	0.400**	0.296*	0.297*	0.299*	0.308**	0.316**	0.358**
	(0.177)	(0.154)	(0.152)	(0.163)	(0.148)	(0.151)	(0.162)
X (t-1)	-1.119*	0.020	0.024	0.009	-0.104	-0.146*	0.236***
	(0.638)	(0.049)	(0.040)	(0.062)	(0.087)	(0.076)	(0.083)
Control variables	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes
Model	CRE	CRE	CRE	CRE	CRE	CRE	CRE
Observations	662	739	739	739	722	722	739
Number of countries	40	44	44	44	43	43	44
Log likelihood	-134.2	-157.6	-157.6	-157.4	-154.2	-155.2	-155
Wald Chi2	9.185e+06	5892	7685	7578	45879	30346	3532
Rho(LR)	0.266	0.436	0.438	0.432	0.377	0.413	0.460
P-value	0	0	0	0	0	0	0
AUROC	0.950	0.936	0.936	0.936	0.931	0.930	0.937
seAUROC	0.00969	0.0106	0.0106	0.0107	0.0115	0.0116	0.0106

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

VI. Concluding Remarks

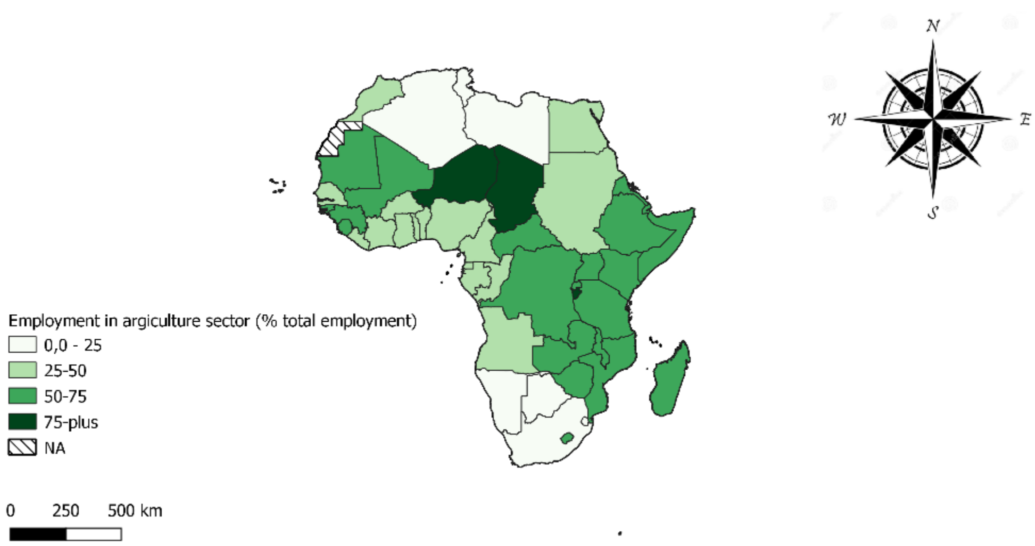
This paper adds to the policy debate by providing one of the first macro-level empirical evidence on the climate change-domestic conflicts nexus in Africa. We build on a broad panel of 51 Africa countries over the 1990-2018 period. We unveil key results with far-reaching policy implications.

First, we find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of domestic conflicts, by as high as up to 38 percent. Second, the effect holds only for intercommunal conflicts, not for government-involved conflicts. Third, the effect is magnified in countries with more unequal income distribution and a stronger share of young male demographics, while higher quality social protection and access to basic health care services, stronger tax revenue mobilization, scaled up public investment in the agricultural sector, and stepped-up anti-desertification efforts appear as relevant resilience factors to this vicious climate-conflicts nexus. The results are robust to a wide set of sensitivity checks.

From a policy standpoint, these findings call for holistic reforms geared towards strengthening African countries' adaptability and resilience to climate shocks and macroeconomic shocks more broadly, including notably steadily improving tax revenue mobilization, unleashing job creation opportunities for the youth, and tackling the root causes of social inequalities. The latter, which requires bold steps towards expanding social safety nets, improving access to quality health care services, and scaling up public investment in the agricultural sector, is critical for preserving the fabric of the society, developing a greater sense of belonging to a "Nation", and ultimately warding off the catalyst role of climate shocks on intercommunal conflicts. The results also call for stepped-up anti-desertification efforts, echoing the global policy agenda of mitigating climate change-driven natural disasters (United Nations' 13th Sustainable Development Goal), including through greater resource mobilization worldwide to support developing countries to this end.

Annex

Figure A.1. Employment in agriculture sector (% total employment) in 2015



Source: WDI and author's calculation

Table A.1. List of countries

Algeria	Eswatini	Mozambique
Angola	Ethiopia	Namibia
Benin	Gabon	Niger
Botswana	Gambia	Nigeria
Burkina Faso	Ghana	Rwanda
Burundi	Guinea	Senegal
Cabo Verde	Guinea-BiAfricau	Sierra Leone
Cameroon	Kenya	Somalia
Central African Republic	Lesotho	South Africa
Chad	Liberia	South Sudan
Congo, Dem. Rep.	Libya	Sudan
Congo, Rep.	Madagascar	Tanzania
Cote d'Ivoire	Malawi	Togo
Djibouti	Mali	Tunisia
Egypt, Arab Rep.	Mauritania	Uganda
Equatorial Guinea	Mauritius	Zambia
Eritrea	Morocco	Zimbabwe

Table A.2. Data description and sources

Variables	Description	Sources
Control variables		
GDP per capita	Gross Domestic Product constant 2010	World Economic Outlook (IMF)
GDP growth	Annual growth of Gross Domestic Product	World Economic Outlook (IMF)
EF index	EF index measures the ethnicity fragmentation within a country	Drazanova (2019)
Population	Total population	World Development Indicator (WDI-World Bank)
Institution	Average of institution variables from WGI	World Governance Indicators (WGI)
Conditional variables		
Tax revenue (%GDP)	Total Tax revenue as percentage of GDP	World Economic Outlook (IMF)
Remittances (%GDP)	Total personal remittances received (current US$)	World Development Indicator (WDI-World Bank)
Credit to private sector (%GDP)	Total financial resources provided to the private sector by financial corporations	World Development Indicator (WDI-World Bank)
Health Expenditure (%GDP)	Level of current health expenditure expressed as a percentage of GDP	World Development Indicator (WDI-World Bank)
Hospital beds per 1000 people	Total Hospital beds per 1000 people. Hospital beds include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centers.	World Development Indicator (WDI-World Bank)
Redistribution effort	Difference between Gini market and disposable Gini.	Standardized World Income Inequality Database (SWIID)
Investment in agriculture (%GDP)	Percentage of agriculture expenditure in total GDP	International Food Policy Research Institute (IFPRI)
Forest coverage (%)	Share of total land under forest cover	World Development Indicator (WDI-World Bank)
Covariates variables		
Capital stock	Total capital stock (private and public), in billions of constant 2011 international dollars.	IMF
Length of paved road	Length of total paved roads in kilometers	International Road Federation; World Bank
Youth Unemployment	Youth unemployment refers to the share of the labor force ages 15-24 without work but available for and seeking employment.	World Development Indicator (WDI-World Bank)
Youth Unemployment Male	Unemployment rate in Male youth cohorte	World Development Indicator (WDI-World Bank)
Youth Unemployment Female	Unemployment rate in Female youth cohorte	World Development Indicator (WDI-World Bank)
Employment in agriculture sector	Employment in agriculture sector in percentage of total employment.	World Development Indicator (WDI-World Bank)

Agriculture Land (%)	Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures	World Development Indicator (WDI-World Bank)
Arable Land (%)	The share of land area that is arable	World Development Indicator (WDI-World Bank)
Rural population (%)	Rural population refers to people living in rural areas as a percentage of total population	World Development Indicator (WDI-World Bank)

Table A.3. Descriptive Statistics

Variables	Observations	Mean	Std. Dev.	Min	Max
Dependent variables					
Conflict type 1	1,479	.3089926	.4622344	0	1
Conflict type 2	1,479	.2129817	.4095533	0	1
Conflict type 3	1,479	.3536173	.4782539	0	1
Drought index	1,377	.5050179	1.16678	0	10
SPEI	1,479	-.1679904	.600806	-2.496004	2.317462
Extreme Dry Months	1,479	.0628803	.5681869	0	11
Drought intensity	1,479	1.462908	4.236494	0	16.951
GDP per capita	1,37	4474.611	5447.501	438.6431	40368.08
GDP growth	1,374	4.192457	8.200983	-62.07592	149.973
EF index	1,219	.6187605	.2463901	.014	.89
Total population	1,472	1.80e+07	2.53e+07	337950	1.96e+08
Institution	989	-.6686225	.6152929	-2.449376	.8798928
Conditional variables					
Tax revenue (%GDP)	1,206	15.46551	8.42928	.5855501	53.32792
Remittances	1,156	4.193562	11.77208	0	167.4317
Credit to private sector	1,358	18.71697	17.22069	0	106.3065
Health Expenditure	820	7.250061	3.843578	0	23.24532
Hospital beds per 1000 people	270	1.476799	1.05411	.1	6.3
Relative redistribution	919	10.04701	3.804742	-7.778729	15.77442
Investment in agriculture	804	1.295056	1.207912	.0015456	9.464178
Forest coverage (%)	1,32	27.84946	23.10903	.0442011	90.03765
Covariates variables					
Capital stock	1,118	130.9442	238.2048	1.448561	1353.867
Youth Unemployment	1,428	16.54519	14.32871	.4	60.83
Youth Unemployment Male	1,428	15.61686	12.85227	.59	55.89
Youth Unemployment Female	1,428	18.24705	17.15754	.16	69.52
Employment in agriculture sector	1,428	52.13839	22.39818	4.6	92.557

Agriculture Land (%)	1,317	46.0377	21.48512	2.655081	82.67134
Arable Land (%)	1,317	12.56063	12.39098	.0431406	48.72219
Rural population (%)	1,472	60.78488	17.67953	10.63	94.584

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