Water Wars*

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May 14, 2024

Abstract

We study the relationship between access to water resources and local violence in Africa. Due to limited irrigation, rural communities rely on rainfall, rivers, and lakes for their economic needs. Rainfall scarcity can make access to water from rivers and lakes more valuable, thereby generating conflicts in rural settings. We explore this hypothesis by integrating granular data on the river network with high-resolution data on rainfall and violent conflict events in Africa from 1997 to 2021. We find that reduced rainfall in a location leads to more conflict in neighboring areas that are water-rich and located upstream along the river network. These are the sites that exert more control over the river flow. The effect is more pronounced in regions experiencing a long-term decline in water presence. Consistent with the proposed mechanism, conflicts concentrate in areas with higher returns to water access, as proxied by the presence of agricultural production. Additionally, the impact is more pronounced in regions with unequal water distribution among ethnic groups, highlighting how cooperation costs are an important friction preventing peaceful sharing of water resources. In terms of policy responses, we find that the effects tend to be mitigated in countries with stronger democratic institutions, better rule of law, higher state capacity and less corruption.

Keywords: Conflict, water, climate change, rivers, resource competition, Africa.
JEL-Classification: D74, Q25, N47, O13, Q34.

*We are grateful for helpful comments from Leander Heldring, Rama Dasi Mariani, Ameet Morjaria, Bernhard Nöbauer, Dominc Rohner, Edoardo Teso, from workshop participants at the Northwestern Applied Micro Lunch, Northwestern Development Lunch, Prato Summer School in Development Economics 2023 and the International Conference on "Economics of Global Interactions" 2023.

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1 Introduction

Access to water is essential for human life and economic activity. Estimates suggest that four billion people experience at least one month per year without access to sufficient water (Mekonnen and Hoekstra, 2016). Climate change is likely to exacerbate this situation, thereby drawing attention to the potential for conflicts over access to water (United Nations, 2023; World Economic Forum, 2023). This is a natural concern, given the role of climatic shocks and competition over resources in fostering violence (Burke, Hsiang and Miguel, 2015; McGuirk and Burke, 2020). However, we lack systematic evidence on whether, and how, climatic shocks can induce conflicts over water resources.

In rural Africa, where the economy is largely dependent on agriculture and pastoralism, this issue is particularly salient. Due to the lack of large irrigation infrastructures, these economic activities rely mainly on rainfall, wells and surface water. In this context, those residing close to rivers and lakes can use surface water for their needs. For instance, farmers construct irrigation channels from rivers or practice recession agriculture, which involves cultivating lands enriched by river sediments. Pastoralists similarly exploit these water bodies as drinking points for their livestock.

This paper investigates systematically the occurrence of conflicts over water resources in Africa from 1997 to 2021. There are specific locations and time periods where we expect conflicts over water resources to occur. They are more likely to arise during years of low rainfall, when the value of accessing surface water increases. In such scenarios, drought-affected individuals are likely to seek water access in adjacent, water-abundant cells. Additionally, those experiencing a drought primarily contend for access to water in upstream locations, as upstream they can exert more control over the river flow and water quality is generally better. Summing up this argument, we expect that a location is more likely to experience conflict over water resources if it is water rich and a drought happens in a region located downstream.

In our empirical analysis, we bring this argument to the data. Utilizing cells of $0.5^\circ \times 0.5^\circ$ degrees in latitude and longitude as units of observation, we measure the incidence of conflict using geocoded event data across all African countries from Armed Conflict Location Events Data Project (ACLED), which provides details on the date, location, and type of conflicts. For assessing surface water resource distribution, we employ hydrological data from the Global Floods Awareness System (Harrigan et al., 2020). Additionally, we rely on the HydroBASINS dataset (Döll et al., 2003) to determine for each pair of cells their up-downstream relationship along the rivers network.

For each cell, we define its neighborhood as all surrounding cells within a 180 km radius and assign a measure of water richness to the cell itself. Our preferred measure is *Water Discharge*, representing the annual average water flow through a cell. We assess whether the impact on violence of low rainfall in a downstream neighboring cell is amplified in cells that are *water rich*. By employing geographically disaggregated data, we can estimate a specification that includes grid-cell fixed effects, to account for local time-invariant factors, and country-year fixed effects, to control for common macro-level factors that vary by country and year. Our approach also allows us to control for any direct effects of rainfall occurring in the grid-cell itself.

Our main result is that rainfall shocks in a downstream cell increase the likelihood of conflict differentially more in locations that have higher *Water Discharge*. Our preferred specification implies that when a downstream cell experiences a rainfall shock, the likelihood of conflict is 0.6 percentage points larger for a cell with high *Water Discharge*, compared to one with low *Water Discharge*, corresponding to 7.30% of the conflict incidence mean.[1] These findings are robust to alternative coding of the water richness measure, to using alternative conflicts data and to controlling for other relevant confounders like temperature and population.

In light of these findings, we further delve into the economic incentives behind conflicts over water resources. We expect a higher likelihood of conflict in areas where the benefits of water access are larger. Given Africa's predominantly agrarian economy, water exploitation is primarily linked to agricultural activities. Therefore, cells with significant agricultural output are likely to offer higher returns from water access. To investigate this channel we split the sample between cells with high and low agricultural production. We find that, consistently with our expectations, the effects are driven by places characterized by higher presence of agriculture.

Surface water resources may be distributed unequally across space, yet individuals from different areas can cooperate and manage them together. We thus expect that conflict arises in contexts in which the costs of cooperation are higher. To explore this possibility, we use data from Giuliano and Nunn (2018) to identify the linguistic groups residing in each cell. Ethnic grievances might imply too high cooperation costs. Indeed, we observe that effects are stronger in areas with more unequal distribution of water resources across different ethnic groups, measured as polarization, Gini and Theil indexes. This evidence suggests that high cooperation costs contribute to the failure of peaceful water sharing and lead to an increased reliance on violence.

Climate change poses a multifaceted threat to water resources, not only through

[1] For this quantification high discharge corresponds to the third quartile of the discharge distribution, whereas low discharge corresponds to the first quartile level.

more frequent droughts but also via long-term desertification processes. In order to examine this extended impact, we have developed a simple metric for long-term water depletion. We find that the effect of droughts on conflict over water resources is stronger in regions where water availability has diminished over the past forty years. The findings suggest that adaptation costs exacerbate the problem, and that conflict over water resources may become a more urgent issue as climate change intensifies the desertification process in certain areas.

In the final section of the paper, we explore the ability of formal institutions to mitigate conflicts induced by climate change. Stronger state presence might be essential not only for the effective redistribution of resources but also for the development and implementation of infrastructural solutions designed to mitigate crisis situations. We look at whether countries with better institutional characteristics are less likely to experience conflict over water resources. Considering various measures of formal institutions, such as democratic governance, rule of law, absence of corruption and government effectiveness, reveals a consistent pattern: conflicts triggered by droughts are primarily a concern in countries with relatively weaker institutions.

Our research contributes to the literature on climate and conflict by presenting new evidence that identifies a precise mechanism through which climate change (Hsiang and Burke, 2014; Burke, Hsiang and Miguel, 2015) and weather shocks (Miguel et al., 2004; Sarsons, 2015; Almer et al., 2017; Unfried et al., 2022) influence local violence. Recent works by Eberle et al. (2020) and McGuirk and Nunn (2020) have emphasized the impact of heat and changing rainfall patterns on conflicts between farmers and pastoralists. In our study, we focus on the effects of low rainfall years, which are becoming more frequent in Africa due to climate change, and how they increase competition for accessing and controlling surface water resources. A key aspect of our analysis involves investigating spillovers, wherein low rainfall in one area leads to heightened conflict in water-rich territories located upstream. By identifying this specific mechanism, we provide insights into the spatial spillovers observed in existing climate-conflict research (Guariso and Rogall, 2017; Harari and Ferrara, 2018). In doing so, we complement the specific mechanisms of conflicts diffusion studied by König et al. (2017) and McGuirk and Nunn (2020).

We also speak to the literature on the determinants of conflict, which has focused on the importance of ethnic or social factors (Esteban et al., 2012; Rohner et al., 2013; Depetris-Chauvin and Özak, 2020; Moscona et al., 2020; Arbatlı et al., 2020), of historical factors (Besley and Reynal-Querol, 2014; Michalopoulos and Papaioannou, 2016; Depetris-Chauvin, 2015), and economic factors, especially shocks to resources value and conflict opportunity cost (Dube and Vargas, 2013; Berman et al., 2017; McGuirk and Burke, 2020; Adhvaryu et al., 2021). We demonstrate that controlling and accessing surface water resources can be a determinant of conflict.

In a nutshell, our paper contribution to the literature of the economics of conflict is manifold. To the best of our knowledge, we are the first to show that the control of surface water resources is a mechanism linking climate shocks and conflict. Additionally, we find that, under unfavorable climatic conditions, water can induce a resource curse. Finally, leveraging on new fine grained data, we document how the rivers network structure can shape the spatial spillovers observed in existing climate-conflict research.

The remainder of the paper is organized as follows. Section 2 provides a description of the context and of how rivers and lakes' water is used for economic activity in rural Africa. In Section 3 we introduce our data sources and we detail how we build the variables used in the analysis. Section 4 describes the empirical strategy and the results of the paper. Finally, Section 5 concludes.

2 Background and Context

2.1 Using surface water resources to smooth water consumption

Water is an essential resource for agriculture, pastoralism, and daily consumption. In rural Africa, the absence of infrastructures such as piped water and irrigation systems necessitates heavy reliance on rainfall, wells, and surface water. In this context, we provide examples illustrating how households utilize surface water resources for their economic activities and everyday life. Our aim here is to illustrate concretely the significance of controlling water resources.

An example is flood-based farming systems (for more details refer to Puertas et al., 2021). This agricultural practice capitalizes on the nutrient-rich soil deposited by river floods. Another variant of this approach is the use of inundation canals, where land is irrigated through canals supplied by temporary high water levels in rivers. These methods become particularly crucial during low rainfall periods, stressing the importance for farmers to maintain control over land near surface water sources, enabling them to effectively utilize these agricultural techniques.

In general, the construction of canals plays a vital role in bringing water from rivers to arid regions. An example of this is the initiative undertaken by the World Food Programme (WFP) in Kenya, where paved canals have been built from the Turkwell River. These canals efficiently channel water to farms in neighboring areas, benefiting over 45,000 farmers. As a result, farmers can effectively irrigate their fields even during seasons with limited rainfall (World Food Programme, 2023). Farmers located near rivers have the advantage of lower canal construction costs and can harness the water flowing through them to a greater extent.

Likewise, water resources are crucial for pastoralists. Rivers and lakes act as natural hydration points for livestock, and the areas around these water bodies often maintain vegetation even in dry seasons. This availability of vegetation enables herders to provide reliable nourishment for their livestock.

Securing land along a river grants farmers enhanced access to water resources, yet such control can significantly affect water availability further downstream. One extreme example is the Omo River which flows between Ethiopia and Kenya (Climate Diplomacy, 2023*c*). In the rural communities of the Lower Omo River Valley, a combination of flood recession agriculture and pastoralism is practiced, both of which depend on the seasonal floods of the Omo River to replenish crop and grazing lands along the riverbank. The establishment of irrigated sugar plantations in Ethiopia (situated upstream) has the potential to impact the water availability in these regions, as water diversion for these plantations can disrupt the natural flow downstream.

2.2 Climate change and conflicts over water resources

Freshwater resources may be distributed unequally, yet different groups can cooperate and manage them together. For instance, according to the hydraulic theory, the formation of early states was partly motivated by the necessity of institutions for large-scale irrigation projects.[2] Moreover, a symbiotic system has often existed between farmers and herders, with herders migrating to farmers' land during dry seasons. This traditional arrangement, especially when farmers' land is situated near rivers, can be seen as a norm that enables efficient sharing of water resources among different groups during periods of limited rainfall.

However, climate change-induced rainfall scarcity in Africa is undermining these established water-sharing institutions, leading to their deterioration. For instance, herders migrate earlier to water-rich lands, causing conflicts with farmers still cultivating crops (Eberle et al., 2020 and McGuirk and Nunn, 2021). Additionally, farmers may extract more water for irrigation during rainfall shortages, reducing downstream water flow. As recently happened in Laikipia county, in Kenya, or in Fayoum, in north Egypt, this can induce groups located downstream to resort to violence to destroy the irrigation infrastructure or scare the farmers upstream, especially if the government does not take actions (Nation, 2023, Monitor, 2022). Climate change also creates new

[2] See Allen et al. (2020) for econometric evidence supporting this theory in the case of ancient Mesopotamia.

situations requiring cooperation over water resources without preexisting arrangements. A notable example of this is observed when droughts force pastoral groups to modify their migratory routes, often leading to competition with other pastoralists over the same water sources. An illustration of this situation can be found in the Lower Omo and Turkana region along the Kenyan-Ethiopian border. Local communities in search of water and grazing land have expanded their ranges, leading to increased proximity and frequent clashes with other groups over these resources. From 1989 to 2011, conflicts between the Nyangatom, Daasanach, and Turkana groups alone resulted in over 600 direct deaths (Climate Diplomacy, 2023*b*).

3 Data

This section describes the data sources and the construction of the variables used in the analysis. Our empirical analysis is based on a geo-referenced, annual panel that divides the African continent into 10,229 grid cells (see Figure A.2). These grid cells have a size of $0.5^\circ \times 0.5^\circ$ degrees, equivalent to approximately 55 km $\times$ 55 km at the equator. Throughout our analysis, the unit of observation is a cell-year pair.

3.1 Data Sources

Conflict Our study utilizes georeferenced conflict events from the Armed Conflict Location & Event Data Project (ACLED) covering the period from 1997 to 2021 (Raleigh et al., 2010). The ACLED data has no requirement for a specific number of fatalities within a calendar year or for a conflict event. As a result, the ACLED data is very apt for capturing smaller-scale, localized conflict events. ACLED gathers information on conflict events from multiple sources, including regional and national media outlets, NGOs, and humanitarian organizations. The ACLED data includes the date and geographic coordinates of each event. We retain only events that are precisely geolocalized. In our main analysis, we consider only events categorized as "battles", and "violence against civilians", excluding thereby less violent events like "riots" and "protests". In fact, according to the mechanism we are considering when a shock occurs, individuals tend to move upstream to access water resources, resulting in the emergence of more lethal and intense conflicts compared to mere riots or protests.[3] Figure A.3 reports the average yearly incidence for ACLED conflict data.

In some robustness checks, we use georeferenced conflict events from the Uppsala

[3] In Table A.4 we show that we do not observe any effect using riots or protests incidence as dependent variables.

Conflict Data Program (UCDP) (Sundberg and Melander, 2013) covering the period from 1989 to 2020. In the UCDP data, conflict events are characterized as either two-sided battles or one-sided attacks that fulfill specific criteria. In order to be included, a conflict event must involve at least one fatality, and the conflict dyad (i.e., the pair of actors involved) must have caused a minimum of 25 fatalities within at least one calendar year during the series. Moreover, at least one of the actors involved must be an "organized actor," such as a state or a politically organized rebel group or militia. These data are compiled following a two-step process, by which global newswire sources are consulted first, and then confirmed consulting local/specialized sources, such as translations of local news performed by the BBC, local media, NGO reports, and field reports. Like ACLED data, UCDP data includes the date and geographic coordinates of each event. We consider only precisely geolocalized events.[4]

By utilizing the date and geographic location (longitude and latitude) we are able to assign each event to a specific cell-year pair. For both data sources, we aggregate the information at the cell-year level. We code conflict incidence as 1 if any conflict event occurred within a cell-year and as 0 otherwise.

Hydrology In our analysis, we include data on river discharge obtained from the Global Floods Awareness System.[5] River discharge refers to the volume of water passing through the section of a river per unit of time, measured in cubic meters per second. The data we utilize provides daily average river discharge on a global scale, with a spatial resolution of $0.05° \times 0.05°$ decimal degrees. The data are produced by combining information from satellites, in-situ measurements, and hydrological models. Notice that the quantity of water reported in the data takes into account all types of surface water bodies, including lakes, ponds, rivers and streams. We aggregate this information at the cell-year level (see Figure A.4). To incorporate information on the river network topology, we rely on the HydroBASINS dataset.[6] This dataset offers a shapefile of drainage basins, which are globally consistent geospatial units frequently employed in environmental and hydrology studies. Each basin represents the land area that collects and channels precipitation, such as a valley. The shapefiles are available at different levels of aggregation; we use level 7 as in Eberle (2020). We allocate each cell to a specific basin based on the amount of water in the overlapping area. Specifically, for every intersection between a river basin and a square grid cell, we as-

[4]To be more specific, our analysis includes only those events that have been geolocated with a minimum precision of the town level (precision level 3).

[5]Accessible from Harrigan et al. (2020).

[6]Part of the HydroSHEDS environment and accessible from `https://www.hydrosheds.org/`; for further details, see Döll et al. (2003).

sign the cell to the basin if that particular intersection contains the greatest amount of water. Then, we construct a matrix that describes the relationship between each pair of cells along the rivers' network exploiting the Pfafstetter coding system.[7] This matrix enables us to identify whether a pair of cells is connected upstream, downstream, or not connected at all.[8] We are the first, to the best of our knowledge, to use the Pfafstetter coding system to pin down the upstream-downstream relationships between uniform squared cells. This allows us to employ the standard units of observations from the conflict literature and at the same time to integrate them with the spatial structure imposed by the rivers network.

Rainfall Following Harari and Ferrara (2018) we use precipitation data from ERA5 (Hersbach et al., 2023). ERA5, a reanalysis dataset, offers comprehensive weather data for the period 1959 through 2021. It provides data at various grid resolutions and temporal resolutions as fine as 6 hours. The dataset is derived from a combination of high-frequency observations collected from diverse sources, including weather stations, satellites, and probes. ERA5 represents a notable improvement over gauge data, particularly in regions with limited weather station coverage like Africa. In fact, it is important for us not to rely exclusively on raw gauge data for two reasons. Firstly, due to the scarcity of weather stations across Africa, extensive interpolation would be required, potentially resulting in artificial patterns of spatial correlation in weather shocks. Secondly, the availability of gauge data itself may be influenced by the presence of conflict.

Other Data We assign ethnic groups to territories across the continent using the geographic distribution of linguistic groups from Giuliano and Nunn (2018). These data are built by linking manually ethnic groups to languages and dialects; the geographic distribution of languages and dialects is from Gordon and Grimes (2009). Additionally, we use information about agricultural land cover from the replication package of McGuirk and Burke (2020). Temperature data are from Hersbach et al. (2023). Population data are from Center for International Earth Science Information Network - CIESIN - Columbia University (2018). Finally, state capacity indicators are taken from Kaufmann et al., 2011.

[7]The Pfafstetter coding system is widely used in hydrology to determine the up-downstream relationship between rivers' basins, see for example Verdin and Verdin (1999).

[8]See appendix Section A.1 for further details about the construction of the river network matrix.

3.2 Variables Definition

For each cell of our grid, we define a neighborhood as all the cells in a 180 km radius. We choose this buffer to be consistent with the seminal work of Harari and Ferrara (2018). In the top panel of Figure A.1 we report an example of how we build a neighborhood (all the highlighted cells) around the reference cell (in dark yellow). Then, as a way of example, we overlap hydrographic data of a section of the Niger River with our grid, showing how we establish which cells are upstream (orange) or downstream (red) to the reference cell (see appendix Section A.1 for further details).

Water Richness We propose different definitions of water richness. Notice that these measures change over time, because of the time-varying dimension of our hydrological data. Our preferred measure of water presence is *Water Discharge*, a continuous measure of water abundance corresponding to the natural logarithm of the mean amount of freshwater present in a cell during a year (see Figure A.4). More precisely, it is the sum of the water passing through the sections of all the rivers flowing in a given cell, measured in cubic meters per second. In order to understand the impact of shocks in places that are extremely water rich, we also consider two alternative measures using a simple dummy. *Water Monopolist* (see Figure A.5) is a dummy which indicates cells that have the largest quantity of water in their neighborhood. To be specific, *Water Monopolist* is equal to one for cell i in neighborhood n, if *Water Discharge* of cell i is the highest of the neighborhood. Finally, *Water Monopolist +* (see Figure A.6) requires the additional condition that a cell has abundance of water also in absolute terms. Specifically, *Water Monopolist +* takes value one for cells which are *Water Monopolist* and whose *Water Discharge* is above the median of the continent in a year.

Rainfall Shocks To identify rainfall shocks, we adopt the methodology outlined in Burke, Gong and Jones (2015) and Corno et al. (2020). We utilize a long-term time series spanning from 1959 to 2021, consisting of rainfall observations. For each geographical cell, we fit a gamma distribution to the calendar year rainfall data. This distribution estimation allows us to characterize the typical rainfall patterns for a specific location. Using the estimated gamma distribution, we determine which location-years experienced rainfall levels below the 15th percentile of the distribution. We code these instances as rainfall shocks.

Ethnic Inequality in Water Access An imbalanced allocation of water among distinct ethnic groups could potentially hinder the sharing of this resource in case of adverse climate shocks raising cooperation costs. To gain a better understanding of this process, we calculate various indexes that describe water allocation within each neighborhood among different ethnic groups. Specifically, we use the geographic distribution of linguistic groups from Giuliano and Nunn (2018) and overlap it with the shapefile of each cell's neighborhood. For each linguistic group within a neighborhood, we determine their water ownership. Finally, we calculate different statistics at the neighborhood level based on the water ownership of each ethnic group. In particular, we compute polarization following the index proposed by Reynal-Querol (2002). Differently from the original measure, which relies on population shares, our approach considers water shares as a proportion of the total water quantity in a neighborhood. Consequently, the index takes its maximum value if in a given area there are only two groups owning 50% of the total water amount. As alternative measures to account for inequality in water distribution between ethnic groups we compute the Gini and Theil indexes. We report the spatial distribution of these three variables in Figure A.7.

4 Rainfall Scarcity and conflict over water resources

4.1 Empirical Strategy

Our objective is to test systematically the occurrence of conflicts related to water resources at a local level. There are specific locations and time periods where we expect conflicts over water resources to occur. They are more likely to arise during years of low rainfall, when the value of surface water increases. It is in such cases that individuals affected by drought conditions are more inclined to seek access to water in neighboring cells, particularly if these cells are abundant in water. Additionally, those experiencing a drought primarily contend for access to water in upstream locations, as upstream they can exert more control over the river flow and water is normally more abundant and of higher quality. Summing up this argument, we expect that a cell is more likely to experience conflict over water resources if it is water rich and a drought happens in a cell located downstream.

We present here our baseline equation which estimates whether adverse rainfall shocks in downstream territories have a differentially higher impact on cells that are water rich.

$$\begin{aligned} y_{it} = \lambda_1 \text{Water Rich}_{it} + \lambda_2 Shock_{it}^{Down} + \\ \beta Shock_{it}^{Down} \times \text{Water Rich}_{it} + \\ \mathbf{X}_{it}' \Gamma + \mu_i + \mu_{ct} + \varepsilon_{it} \end{aligned} \tag{1}$$

Where y_{it} is a dummy variable for conflict incidence in cell i during year t, Water Rich$_{it}$ is a time varying measure of water richness in a given cell, and $Shock_{it}^{Down}$ takes value one if a cell in the neighborhood located downstream to cell i is hit by a rainfall shock during year t. We include in the regression cell fixed effects μ_i and country-year fixed effects μ_{ct} to account for time invariant cell characteristics and country specific yearly shocks that might affect conflicts. $\mathbf{X}'_{it}$ are additional cell specific time-varying variables. In some specifications, we control for rainfall shocks happening in cell i, which may have direct effects on local violence. We also show that results are unaffected by including rainfall shocks happening in cells located upstream to i, and we allow them to have differential impact depending on water presence (Water Rich$_{it}$). In sensitivity analysis we include additional time varying controls, that we introduce in Section 4.3. Our hypothesis is that if a drought happens downstream, water rich cells are more likely to experience conflict. Thus, we expect $\beta > 0$.

4.2 Baseline Results

In Table 1 we present results with our preferred measure of water richness: *Water Discharge*. *Water Discharge* corresponds to the average quantity of water present in a cell during a given year. In column 1 we estimate the main regression equation 1, testing our hypothesis that a cell is more likely to experience conflict over water resources if it is water rich and a drought happens in a cell located downstream. The coefficient β is positive and statistically significant at the 1% level. In column 2 we check whether our hypothesis that only downstream shocks have an impact on conflict incidence is valid interacting our measure of water presence with shocks happening upstream. We cannot find any significant impact of upstream shocks on conflict. In columns 3 and 4 we control for any direct effect of rainfall shock happening in the cell, results are unaffected. Finally, in column 5 we test whether groups located downstream and upstream have different incentives to fight when hit by a drought, including both shocks in the same regression. We can appreciate how upstream shocks do not display the same patterns as downstream shocks. Moreover, our coefficient of interest is very stable and, if anything, it becomes larger and more precisely estimated. Interpreting the magnitude of the coefficient in our preferred specification (column 5) we have that when a downstream cell experiences a rainfall shock, the likelihood of conflict is 0.6 percentage points higher for a cell with high *Water Discharge*, compared to one with low *Water Discharge*,[9] corresponding to 7.30% of the dependent variable mean. This is in line with a predatory mechanism of seeking control over the water flow of the river when the resource becomes scarcer. In Table A.2, we include the same specifica-

[9]For this quantification high discharge corresponds to the third quartile of the discharge distribution, whereas low discharge corresponds to the first quartile level.

tions of Table 1 but reporting spatially clustered standard errors, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). While the estimates become generally less precise, the coefficient β from equation 1 retains statistical significance at the 5% level.

Table 1: Precipitation shocks and water discharge

	Incidence (ACLED)				
	(1)	(2)	(3)	(4)	(5)
Water Discharge	0.0010	0.0007	0.0010	0.0009	0.0009
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Water Discharge × Shock Down	0.0011***		0.0011***		0.0012***
	(0.0004)		(0.0004)		(0.0004)
Water Discharge × Shock Up		0.0003		0.0003	-0.0002
		(0.0005)		(0.0005)	(0.0005)
Shock Down	0.0008		0.0010		0.0009
	(0.0017)		(0.0018)		(0.0018)
Shock Up		-0.0018		-0.0024	-0.0014
		(0.0020)		(0.0021)	(0.0021)
Shock Own			-0.0005	0.0020	0.0000
			(0.0017)	(0.0016)	(0.0017)
Cell FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201	0.08201	0.08201
R^2	0.42101	0.42095	0.42101	0.42096	0.42101
Cells	10,228	10,228	10,228	10,228	10,228
Observations	255,700	255,700	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Sensitivity Analysis

Alternative Measures of Water Richness In Table 2 we estimate equation 1 using all the three measures of water presence. Column 1 corresponds to column 5 of Table 1, while in columns 2 and 3 we interact weather shocks with a binary variable. Specifically, in column 2, *Water Measure* takes value one if a cell is the one with the highest water discharge in its neighborhood during a given year. Finally, in column 3, we focus on cells that not only have the highest water discharge in their neighborhood but also exceed the median value in the sample. This methodology effectively excludes cells with minimal discharge, in particularly desert areas. In all columns, we observe a positive coefficient for the interaction term between downstream precipitation shocks and water presence. In cells with particularly high levels of water presence (column 3) a precipitation shock causes an increase in conflicts of 3.4 percentage points, which corresponds to about 42% of the dependent variable mean. Reassuringly, all the three measures aimed at capturing water richness deliver consistent results.

Table 2: Precipitation shocks all measures

	Incidence (ACLED)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	0.0009	0.0120	0.0151
	(0.0009)	(0.0098)	(0.0106)
Water Measure × Shock Down	0.0012***	0.0181	0.0336**
	(0.0004)	(0.0123)	(0.0170)
Water Measure × Shock Up	-0.0002	-0.0020	-0.0046
	(0.0005)	(0.0118)	(0.0144)
Shock Own	0.0000	-0.0004	-0.0004
	(0.0017)	(0.0017)	(0.0017)
Shock Down	0.0009	0.0049***	0.0048***
	(0.0018)	(0.0015)	(0.0015)
Shock Up	-0.0014	-0.0018	-0.0018
	(0.0021)	(0.0017)	(0.0017)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201
R^2	0.42101	0.42101	0.42103
Cells	10,228	10,228	10,228
Observations	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Measure* indicates generically a measure of water quantity which varies between columns. In column (1) it is the natural logarithm of the average water discharge present in a cell during a given year (*Water Discharge*). In column (2) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year (*Water Monopolist*). In column (3) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year and the discharge is higher than the median level in the sample for that year (*Water Monopolist +*). *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Alternative conflict dataset In Table A.3 we replicate our baseline analysis using alternative conflict data from the UCDP georeferenced Event Dataset (Sundberg and Melander, 2013) that focuses on violence perpetrated by larger-scale and more structured groups. Our coefficient of interest remains positive, large and precisely estimated in all three specifications.

Alternative conflict definitions In Table A.4 we replicate our main regression results using different conflict categories from the ACLED dataset. In column 1 we replicate column 5 of Table 1, in column 2 we consider only battles (the most deadly type of conflicts present in our data) in column 3 other kind of violent attacks against civilians by organized groups, while in the last two columns we look at less intense and deadly conflict types like protests (column 4) and riots (column 5). In line with the mechanism we have in mind, we observe an effect only for larger scale type of conflicts. Individuals do not move upstream just for rioting or protesting against the government, but to fight over access to water resources.

Additional controls In Table A.9 we show that our results are robust to controlling for other factors which have been associated with conflict. Specifically, we control for (log) population, yearly average temperature and yearly average temperature during the day. Finally, we check whether results are robust to controlling for lagged conflict incidence. The estimates of our main coefficient of interest are unaffected by the inclusion of the controls.

Alternative neighborhood and rainfall shocks In the appendix, from Table A.5 to Table A.8, we conduct additional robustness checks to ensure that our results are not influenced by the specific parameter choices we have made. Specifically, Tables A.5 and A.6 explore alternative thresholds for defining a rainfall shock, using different percentiles as cutoff points in the distribution. Conversely, Tables A.7 and A.8 examine the effects of using alternate radii of 160 km and 200 km, respectively, to define a cell neighborhood. Across all these analyses, our primary coefficient of interest maintains a magnitude and significance level similar to that estimated in our main specification (column 5 of Table 1).

4.4 Heterogeneous characteristics affecting conflicts

In this section, we explore the characteristics that increase the likelihood of conflicts arising over water resources.

Agricultural land and returns to water access We expect a higher likelihood of conflict in areas where the returns to accessing water are higher. Given the agrarian nature of the African continent, one of the main ways to exploit water resources is agriculture. To scrutinize this channel we split the sample between cells with high and low level of agricultural ground cover. In particular, in columns 1 and 2 of Table 3 we split the sample according to whether agriculture is present or totally absent in the cell. On the other hand, in columns 3 and 4 we separate the sample according to the median level of agricultural ground cover. We can detect an impact of downstream shocks only in localities where there is at least a minimum level of agriculture. This finding is in line with these conflicts being over the control of factors for economic production (McGuirk and Burke, 2020). Indeed, the joint presence of water and agricultural land, makes these cells particularly attractive targets for invasion in case of droughts downstream.

Table 3: Agricultural Land

	Incidence (ACLED)			
	Agri Yes	Agri No	Agri50 H	Agri50 L
	(1)	(2)	(3)	(4)
Water Discharge	0.0010	0.0019**	0.0016	0.0010
	(0.0012)	(0.0009)	(0.0015)	(0.0011)
Water Discharge × Shock Down	0.0014**	0.0001	0.0018**	0.0010
	(0.0006)	(0.0019)	(0.0007)	(0.0007)
Water Discharge × Shock Up	-0.0003	0.0000	-0.0005	-0.0008
	(0.0006)	(0.0020)	(0.0008)	(0.0007)
Shock Own	-0.0024	0.0000	-0.0028	-0.0015
	(0.0023)	(0.0013)	(0.0028)	(0.0017)
Shock Down	-0.0009	0.0008	-0.0058	0.0025
	(0.0033)	(0.0016)	(0.0046)	(0.0017)
Shock Up	-0.0010	0.0001	0.0016	-0.0007
	(0.0038)	(0.0016)	(0.0053)	(0.0018)
Cell FE	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
Dep. Var. Mean	0.11341	0.00995	0.13336	0.03066
R^2	0.41907	0.28129	0.43298	0.33517
Cells	7,124	3,104	5,114	5,114
Observations	178,100	77,600	127,850	127,850

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. In columns (1) and (2) we split the sample according to the presence or absence of agricultural land. In columns (3) and (4) we split the sample according to higher-lower than the median presence of agricultural land. Data for agricultural land are taken from McGuirk and Burke (2020). *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Ethnic diversity and cooperation costs Freshwater resources may be distributed unequally, yet different groups can still cooperate and manage them together. For instance, according to the hydraulic theory, the formation of early states was partly motivated by the necessity of institutions for large-scale irrigation projects (Allen et al., 2020). Moreover, a symbiotic system has often existed between farmers and herders, with herders migrating to farmers' land during dry seasons. This traditional arrangement, especially when farmers' land is situated near rivers, can be seen as a norm that enables efficient sharing of water resources among different groups during periods of limited rainfall. Scarce rainfall in Africa due to climate change threatens established water-sharing institutions, leading to their collapse.

We explore this potential mechanism in Table 4, considering three different measures of imbalance water allocation as detailed in Section 3.2. In columns 1 and 2 we split the sample between cells belonging to neighborhoods with high-low levels of polarization in water access between different ethnic groups. This measure takes the maximum value if in the neighborhood are present two groups owning 50% of the total existing water. The more polarized the access to water is, the higher should be the incentive for groups to appropriate the resource from other populations when they are hit by a shock. As we can observe in Table 4 we only can detect an impact of rainfall shocks in highly polarized neighborhoods. In columns 3 to 6 we do a similar exercise splitting the sample on the basis of two different measures of inequality in water ownership: Gini and Theil indexes. As expected, only shocks happening in markets where inequality in water access is higher have an impact on conflicts incidence. The coefficients corresponding to the interaction *Water Discharge* $\times$ *Shock Down* are way larger and significant in odd columns, indicating that cooperation in water sharing becomes more complex in a context where there is inequality in access to water across different ethnic groups.

Table 4: Ethnic diversity and cooperation costs

	Incidence (ACLED)					
	RQ H	RQ L	Gini H	Gini L	Theil H	Theil L
	(1)	(2)	(3)	(4)	(5)	(6)
Water Discharge	0.0014	0.0016	0.0010	0.0022**	0.0017	0.0019*
	(0.0013)	(0.0015)	(0.0016)	(0.0011)	(0.0016)	(0.0011)
Water Discharge × Shock Down	0.0017***	0.0003	0.0017**	0.0006	0.0018***	0.0008
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Water Discharge × Shock Up	-0.0001	-0.0008	-0.0006	-0.0004	-0.0008	-0.0001
	(0.0007)	(0.0006)	(0.0008)	(0.0007)	(0.0008)	(0.0007)
Shock Own	-0.0010	-0.0012	-0.0033	0.0007	-0.0031	0.0007
	(0.0025)	(0.0024)	(0.0027)	(0.0020)	(0.0027)	(0.0019)
Shock Down	-0.0026	0.0028	-0.0029	0.0022	-0.0044	0.0025
	(0.0031)	(0.0023)	(0.0040)	(0.0019)	(0.0039)	(0.0019)
Shock Up	0.0028	-0.0031	0.0022	-0.0018	0.0036	-0.0026
	(0.0034)	(0.0026)	(0.0046)	(0.0022)	(0.0045)	(0.0021)
Cell FE	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.08727	0.07869	0.11787	0.04808	0.11907	0.04687
R^2	0.41479	0.44586	0.42949	0.39843	0.42989	0.39681
Cells	5,054	5,052	5,054	5,052	5,054	5,052
Observations	126,350	126,300	126,350	126,300	126,350	126,300

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. In columns (1) and (2) we split the sample according to high-low value of Reynal-Querol polarization index, computed as detailed in Section 3. In columns (3) and (4) we split the sample according to high-low values of Gini index, computed as detailed in Section 3. In columns (5) and (6) we split the sample according to high-low values of the Theil index computed as detailed in Section 3. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Water stress Climate change might generate an increase in conflicts over water resources not just through more frequent droughts, but in the longer run, by depleting the quantity of water present in a given area. Desertification processes are well known to affect some areas of the continent like the Sahel region and more in general, a decrease in water quantity in given areas might break economic equilibria existing among the populations living along river bodies. To explore this possible mechanism, we create a measure of water stress at cell level. In particular, we consider the difference in discharge between the average water presence in a cell during our sample period and the first 10 years for which the variable discharge is available (from 1979 to

1988). Looking at the spatial distribution of the variable (see Figure A.8) we can notice how, in most of the continent, there has been a reduction in water quantity over the last 40 years. In columns 1 and 2 of Table 5 we divide the sample according to higher or lower than the median increase in water presence, while in columns 3 and 4 we split the sample according to a positive or negative change over time in discharge. We can estimate a significant impact of precipitation shocks only in those cells which have experienced a reduction in water presence over time.

Table 5: Water Stress

	Incidence (ACLED)			
	Above Median Change	Below Median Change	Positive Change	Negative Change
	(1)	(2)	(3)	(4)
Water Discharge	0.0017*	-0.0013	0.0019*	0.0007
	(0.0010)	(0.0023)	(0.0010)	(0.0019)
Water Discharge × Shock Down	0.0001	0.0019***	-0.0007	0.0015***
	(0.0007)	(0.0006)	(0.0010)	(0.0005)
Water Discharge × Shock Up	0.0003	-0.0004	0.0012	-0.0005
	(0.0007)	(0.0006)	(0.0010)	(0.0006)
Shock Own	-0.0007	-0.0002	0.0064**	-0.0046**
	(0.0026)	(0.0023)	(0.0028)	(0.0021)
Shock Down	0.0055**	-0.0028	0.0023	-0.0001
	(0.0026)	(0.0026)	(0.0028)	(0.0024)
Shock Up	-0.0004	-0.0023	-0.0025	-0.0007
	(0.0028)	(0.0030)	(0.0028)	(0.0029)
Cell FE	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
Dep. Var. Mean	0.08827	0.07593	0.07136	0.08813
R^2	0.43971	0.41519	0.42857	0.42647
Cells	5,106	5,105	3,670	6,541
Observations	127,650	127,625	91,750	163,525

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. In columns (1) and (2) we split the sample according to higher-lower than the median water stress as defined in Section 4. In columns (3) and (4) we split the sample according to positive or negative change in water presence between our sample period and the first ten years of water discharge data (1979-1988). *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Institutions A key aspect that might ease the consequences of a drought is the ability of the state to redistribute resources, build infrastructures apt to prevent crises and ensuring property rights protection to avoid violent appropriation of water. In line with the research by Michalopoulos and Papaioannou (2014), we employ the Worldwide Governance Indicator from the World Bank (Kaufmann et al., 2011) as measures of institutional quality,[10] recognizing its potential significance in facilitating water redistribution under conditions of scarcity. Our analysis primarily considers four key

[10]In order to avoid reverse causality issues we consider values of the indexes for the pre-sample period (year 1996).

elements: the type of institutional governance, rule of law guarantee, absence of corruption and government effectiveness. In the first two columns of Table 6 we split the sample according to high-low level of democratic governance in a country.[11] We explore whether more democratic systems, characterized by stability and participatory governance, are better equipped to encourage cooperative responses to climate-related challenges. In columns 3 and 4 the focus shifts on high-low levels of rule of law. The idea is that, a better definition and enforcement of property rights are fundamental to managing resources efficiently and resolving disputes, especially in times of environmental stress. In columns 5 and 6 we look into a metric of state capacity, government effectiveness, reflecting the quality of public services and the efficacy of policy formulation and implementation. Higher government effectiveness might contribute to the construction of appropriate infrastructures to cope with climate shocks, but also to respond more rapidly to crises. Lastly, in columns 7 and 8 we split the sample according to high-low levels of corruption. The underlying idea is that property rights protection and government effectiveness necessitate an environment free from corruption. Across all these dimensions, we observe a sizable and significant effect for our primary coefficient of interest only in even columns, indicating countries with weaker institutional quality metrics.

Even if this is mostly correlational evidence and despite we do not have specific data related to effectiveness in water management by states, these results seem to suggest that better institutions might be effective in preventing local violence for water resources in case of climate shocks.

[11] In particular, we create a measure of democratic governance by computing the mean between "voice and accountability" and "political stability" indexes at country level.

Table 6: Institutional Quality

	Incidence (ACLED)							
	Dem H	Dem L	RLaw H	RLaw L	Gov Eff H	Gov Eff L	Corrupt H	Corrupt L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Water Discharge	0.0004	0.0016	-0.0007	0.0031	0.0018**	-0.0007	-0.0008	0.0036*
	(0.0008)	(0.0022)	(0.0009)	(0.0019)	(0.0009)	(0.0023)	(0.0009)	(0.0020)
Water Discharge × Shock Down	0.0001	0.0017***	0.0006	0.0016***	0.0005	0.0017***	0.0005	0.0012**
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Water Discharge × Shock Up	0.0003	-0.0005	0.0005	-0.0006	-0.0004	0.0002	-0.0003	-0.0001
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Shock Own	0.0012	-0.0015	-0.0011	0.0007	0.0036	-0.0033	-0.0015	0.0012
	(0.0023)	(0.0025)	(0.0024)	(0.0024)	(0.0023)	(0.0025)	(0.0020)	(0.0027)
Shock Down	-0.0027	0.0056*	-0.0025	0.0049*	0.0027	-0.0006	-0.0015	0.0052
	(0.0022)	(0.0029)	(0.0024)	(0.0027)	(0.0022)	(0.0030)	(0.0019)	(0.0033)
Shock Up	-0.0041	0.0010	-0.0035	0.0003	0.0015	-0.0050	-0.0017	-0.0008
	(0.0025)	(0.0033)	(0.0027)	(0.0032)	(0.0024)	(0.0034)	(0.0022)	(0.0037)
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.05527	0.11018	0.06696	0.09751	0.06949	0.09575	0.05603	0.10840
R^2	0.36197	0.44512	0.37419	0.45222	0.41544	0.42323	0.41074	0.41853
Cells	5,247	4,981	5,188	5,040	5,351	4,877	5,154	5,074
Observations	131,175	124,525	129,700	126,000	133,775	121,925	128,850	126,850

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. In different columns we split the sample according to higher or lower than the median values in the sample of different variables indicating institutional quality. In particular in columns (1) and (2) we consider democratic governance (which takes into account measures of political stability and voice and accountability), in columns (3) and (4) rule of law, in columns (5) and (6) government effectiveness and in columns (7) and (8) corruption. The indexes are taken from Kaufmann et al. (2011). *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in Section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusion

This paper examines the influence of competition for water resources on local violence across the African continent over the period 1997-2021. By combining detailed data on hydrology, river network topology, and weather patterns, we demonstrate that adverse rainfall conditions drive individuals to seek water access in upstream areas with abundant water resources. Our analysis focuses on major conflict events such as battles and violence against civilians. When a downstream cell experiences a rainfall shock, the likelihood of conflict is 0.6 percentage points larger for a cell with high water presence with respect to a cell where water is scarce. This translates to a 7.30% increase in conflict likelihood with respect to the mean conflict incidence in our sample. Notably, our results remain robust across various "water richness" measures, diverse conflict datasets, and when considering other possible confounders like temperature and population.

Given Africa's predominantly agrarian economy, the economic returns from water access should be higher in areas with significant agricultural output. Consistently with our expectations, we find that the effects are driven by places characterized by higher presence of agriculture.

Additionally, we find that conflict over water resources is more likely in regions characterized by higher cooperation costs, i.e. when water is unevenly distributed across different ethnic groups. Employing three distinct measures of water distribution across ethnicities - polarization, Gini, and Theil indexes - our analysis reveals that greater disparity in water access among different ethnic groups is associated with an increased risk of conflict.

Climate change plays a role not only by increasing the frequency of droughts, but also altering the distribution of surface water, giving rise to desertification processes. We find that the effect is mainly concentrated in those areas where water has been decreasing in the last forty years, possibly destabilizing pre-existing equilibria in terms of water sharing and management.

Finally, we show that institutions, assessed by various World Bank indices, can play a pivotal role in this context. Stronger institutions can mitigate the challenges posed by water scarcity through the development of appropriate infrastructures and the implementation of redistribution schemes. Such strategies can facilitate the equitable allocation of water resources between regions abundant in water and those facing scarcity.

Our results suggest that policymakers should take into account the unequal distribution of freshwater resources when thinking about climate-conflict relationship.

Moreover, we highlight the rivers network's structure as an important transmission channel for climate shocks. While we focus on local violence, this structure can shape the relationship between water scarcity and conflict at a larger scale. A prime example is the ongoing geopolitical tensions surrounding the construction of the Grand Ethiopian Renaissance Dam (Climate Diplomacy, 2023*a*). More generally, taking into account the river network is key to understanding how water management policies will affect neighboring regions and countries. This is crucial in a future where climate-related shocks are expected to become increasingly frequent and water scarcity a more acute problem.

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A Appendix

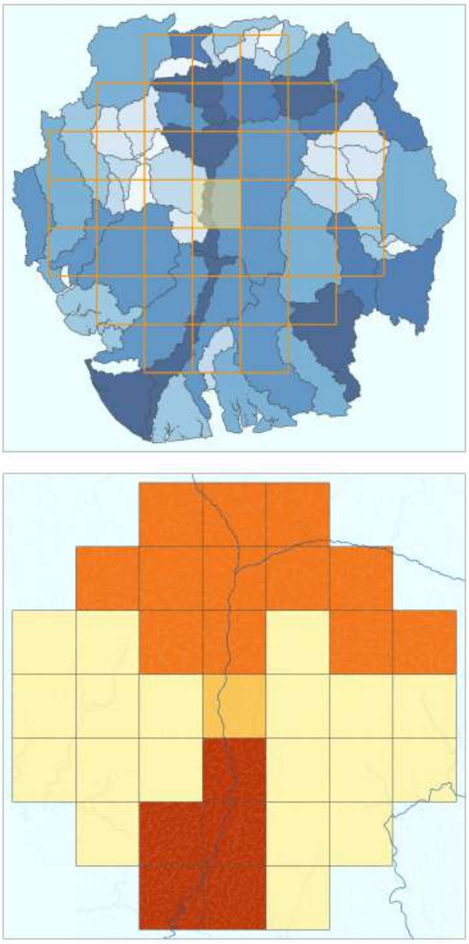
A.1 Upstream - Downstream

In this section we describe in detail the construction of the rivers network relationships between grid cells sample units. From the hydrology literature (Harrigan et al., 2020), as mentioned in section 3, we take the spatial breakdown of the entire African continent in river basins. A basin can be defined as the area of land drained by a river and its branches. The basins shapefiles are available at different levels of disaggregation; following Eberle (2020) and Strobl and Strobl (2011) we choose level 7 whose basins have an average area comparable to the cells we use in the analysis. Following the Pfafstetter classification system (see Verdin and Verdin, 1999 for a comprehensive explanation about how the system works), for each basin we have information about its position along the river network. In order to understand the relative positioning of our grid cells in terms of up-downstream relationship, we need to assign each cell to a river basin. Given the irregular shape of river basins, there are many different criteria one can use to perform this matching. Since our main objective is to study the interdependence of water resources between different regions, our main criterion to assign a cell to basin is the relative importance in terms of water discharge of the cell's area drained by the basin. In particular, for each intersection between river basins and a given cell we compute the average discharge quantity; then, we assign each cell to the basin whose intersection contains the highest water amount.

We illustrate the methodology by taking as example the confluence of Niger and Benue rivers. In the top panel of Figure A.1 we overlay the neighborhood of all the cells whose centroid is within 180 Km from the dark yellow cell at the center of the figure, with the river basins present in the area. The orange grid represents the neighborhood of cells, while the basins are colored on the basis of the average discharge presence. In the bottom panel we display the corresponding assignment of the cells. In light yellow are represented cells whose centroid is located within 180 Km from the reference cell (the cell in the middle in dark yellow) and that do not have any up-downstream relationship with respect to it. The orange (red) cells are those located upstream (downstream) according to our definition. The blue lines represent the rivers with highest water presence in the area (which are indeed the Niger and Benue).

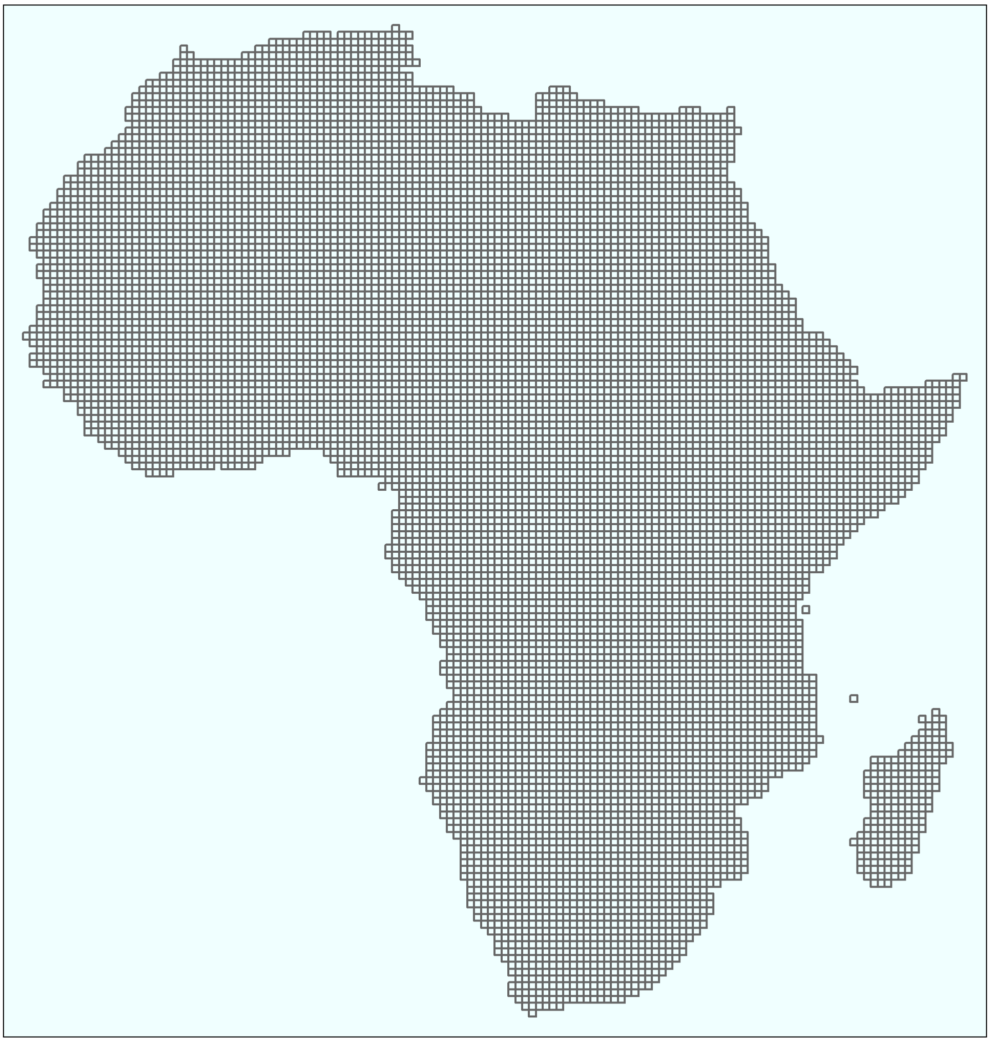
A.2 Figures

Figure A.1: Niger river upstream and downstream relationship



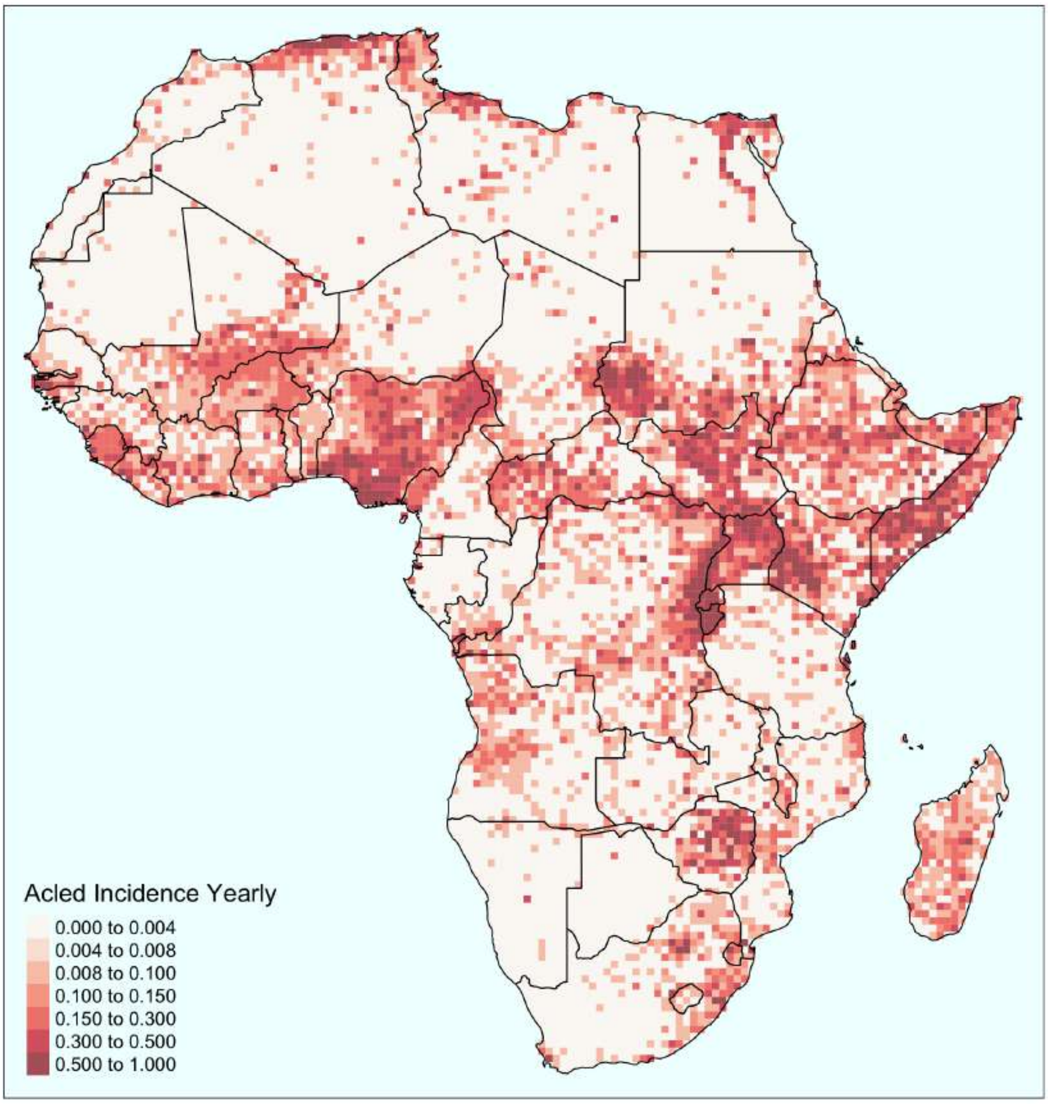
Notes: The figure shows, by way of example, a section of Niger river to illustrate how we build the upstream-downstream relationships. In the top panel we superimpose the grid for the neighborhood (cells within 180 Km radius) of the yellow cell in the center of the figure with the river basins shapefile colored according to the average water discharge present in each of them. In the bottom panel we show the resulting upstream-downstream relationships between the different cells according to the methodology explained in appedix A.1. Orange cells are those located upstream within the neighborhood of the main cell (in dark yellow), while the red cell are those that we consider downstream with respect to it. Light yellow cells are those coded as neither upstream nor downstream with respect to the main cell.

Figure A.2: The grid



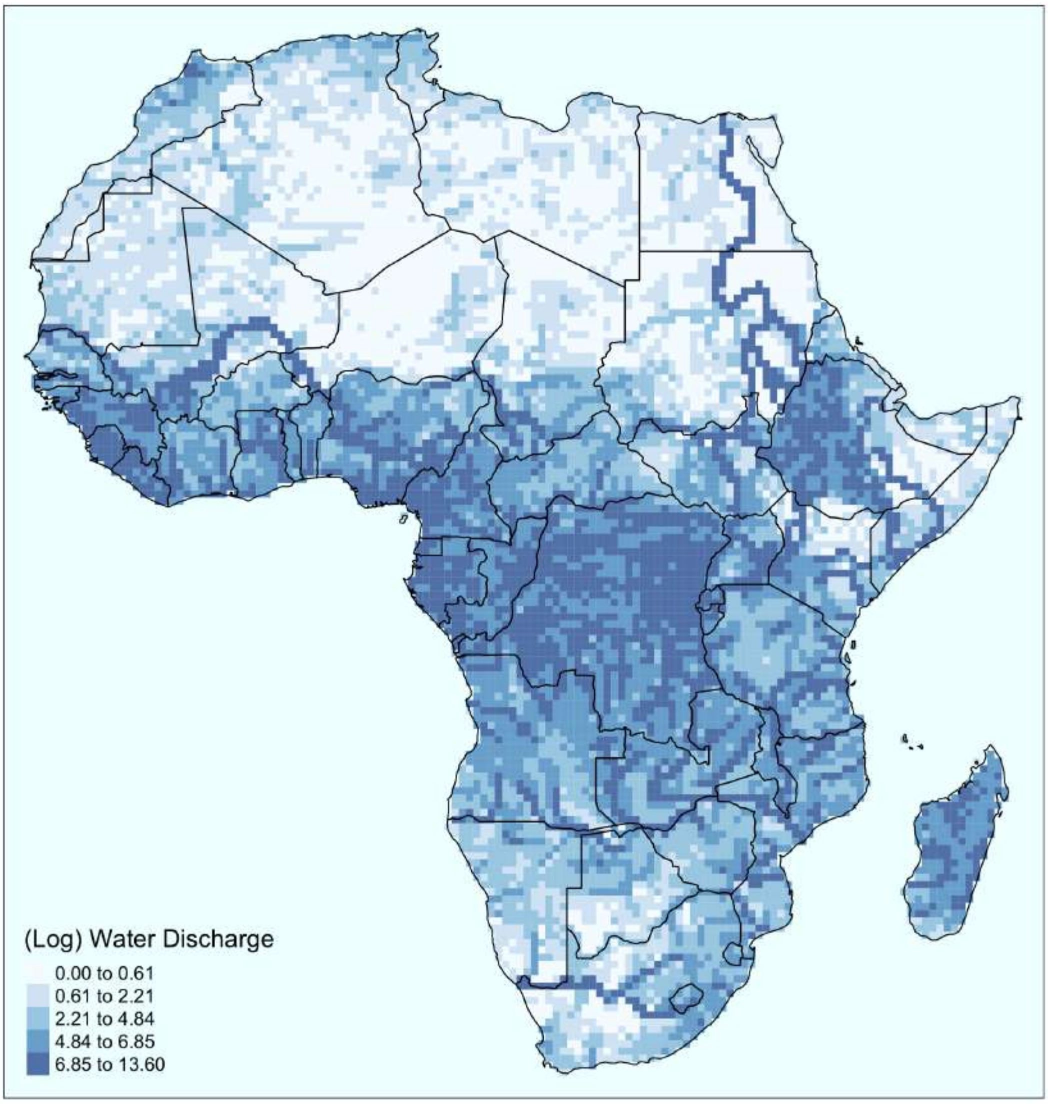
Notes: Grid of $0.5^\circ \times 0.5^\circ$ cells covering the African continent that we use for the analysis.

Figure A.3: Conflict (ACLED)



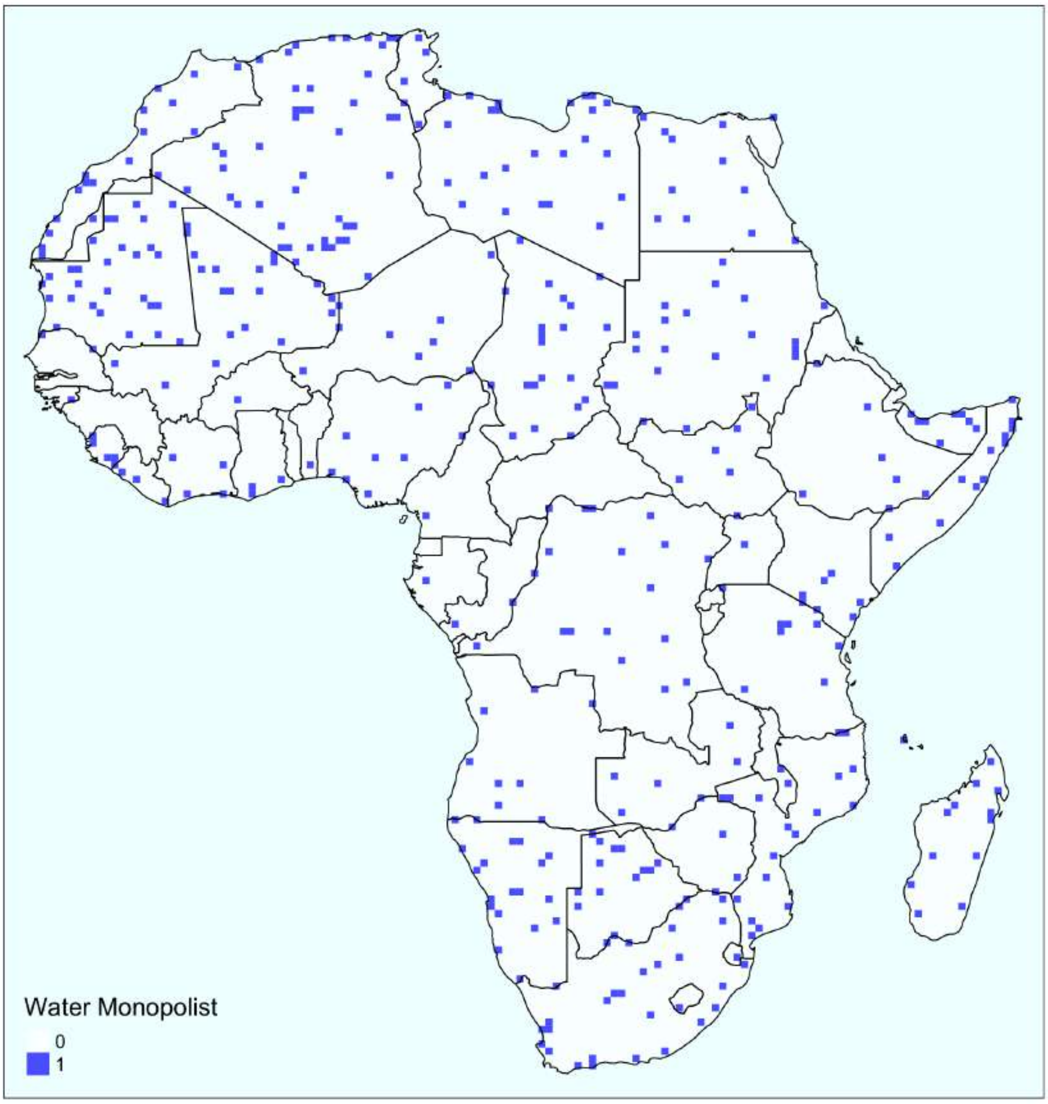
Notes: Spatial distribution of our main dependent variable, conflict incidence, for the period 1997-2021. Darker shadings indicate cells with a higher proportion of years with at least one conflict incident, based on data from the Armed Conflict Location and Event Data Project (ACLED).

Figure A.4: Average discharge (cell level)



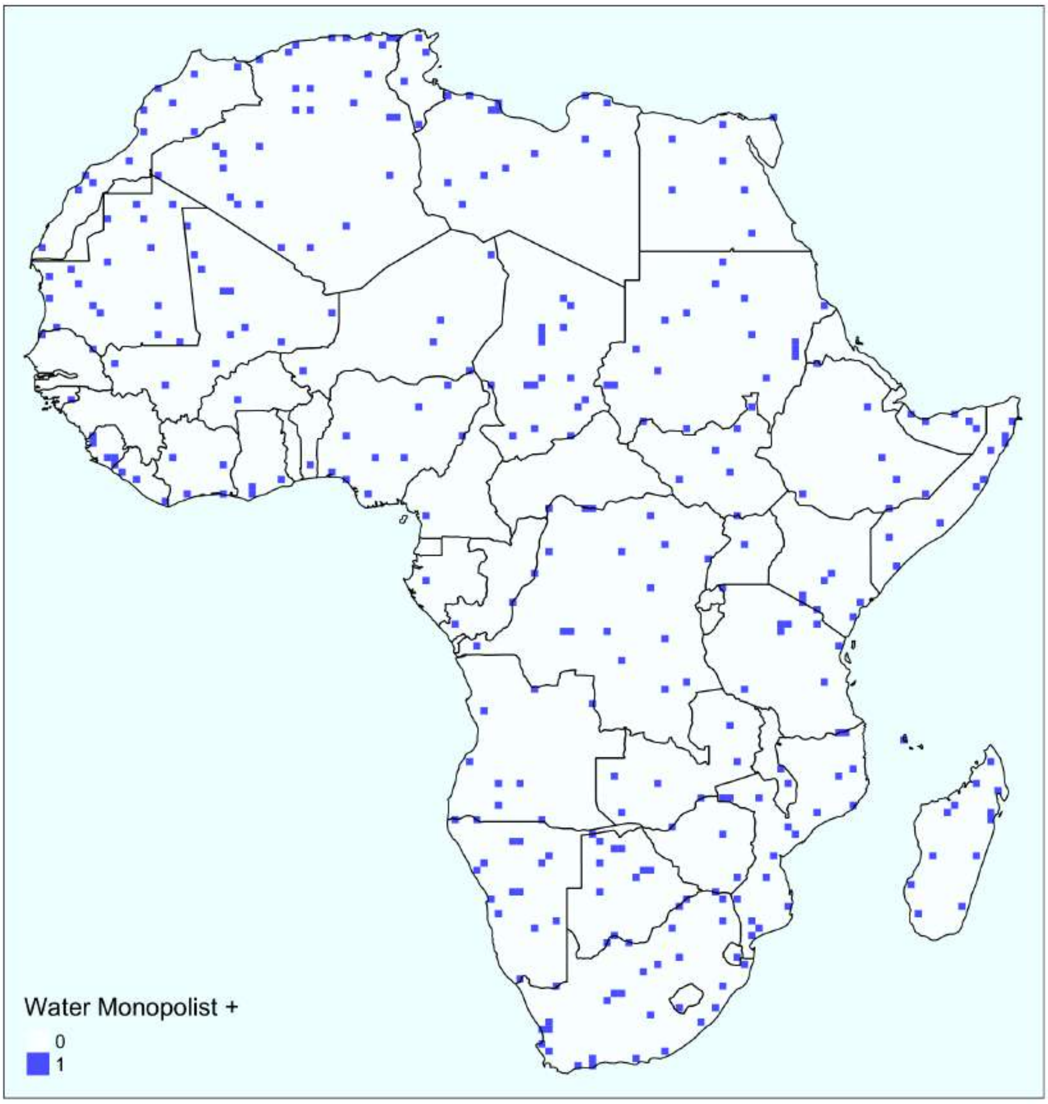
Notes: Cell-level (Log) average yearly discharge in m3/s over the sample period 1997-2021. Darker color indicates areas with higher average discharge. Water discharge data have been taken from Harrigan et al. (2020).

Figure A.5: Water Monopolist



Notes: In the map are represented in blue cells which are coded as water monopolist (see Section 3 for details on the definition) for the majority of the years during the sample period 1997-2021.

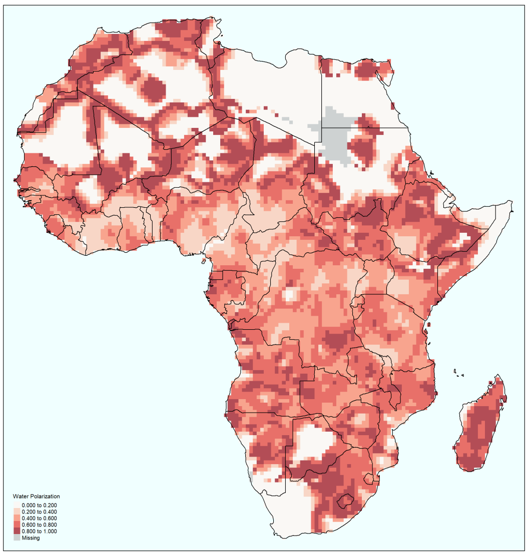
Figure A.6: Water Monopolist +



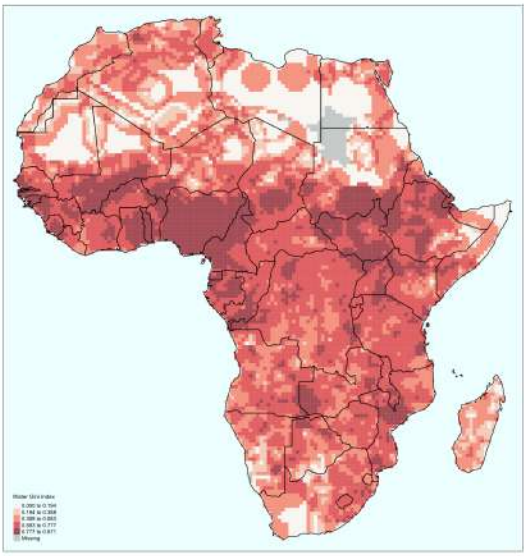
Notes: In the map are represented in blue cells which are coded as water monopolist + (see Section 3 for details on the definition) for the majority of the years during the sample period 1997-2021.

Figure A.7: Water Inequality and Polarization

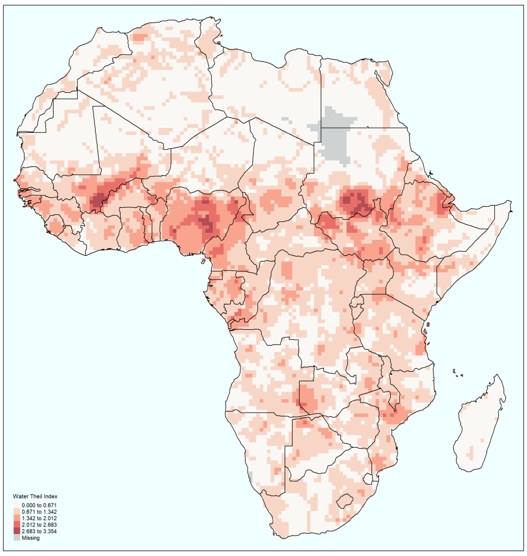
(a) Polarization index



(b) Gini index

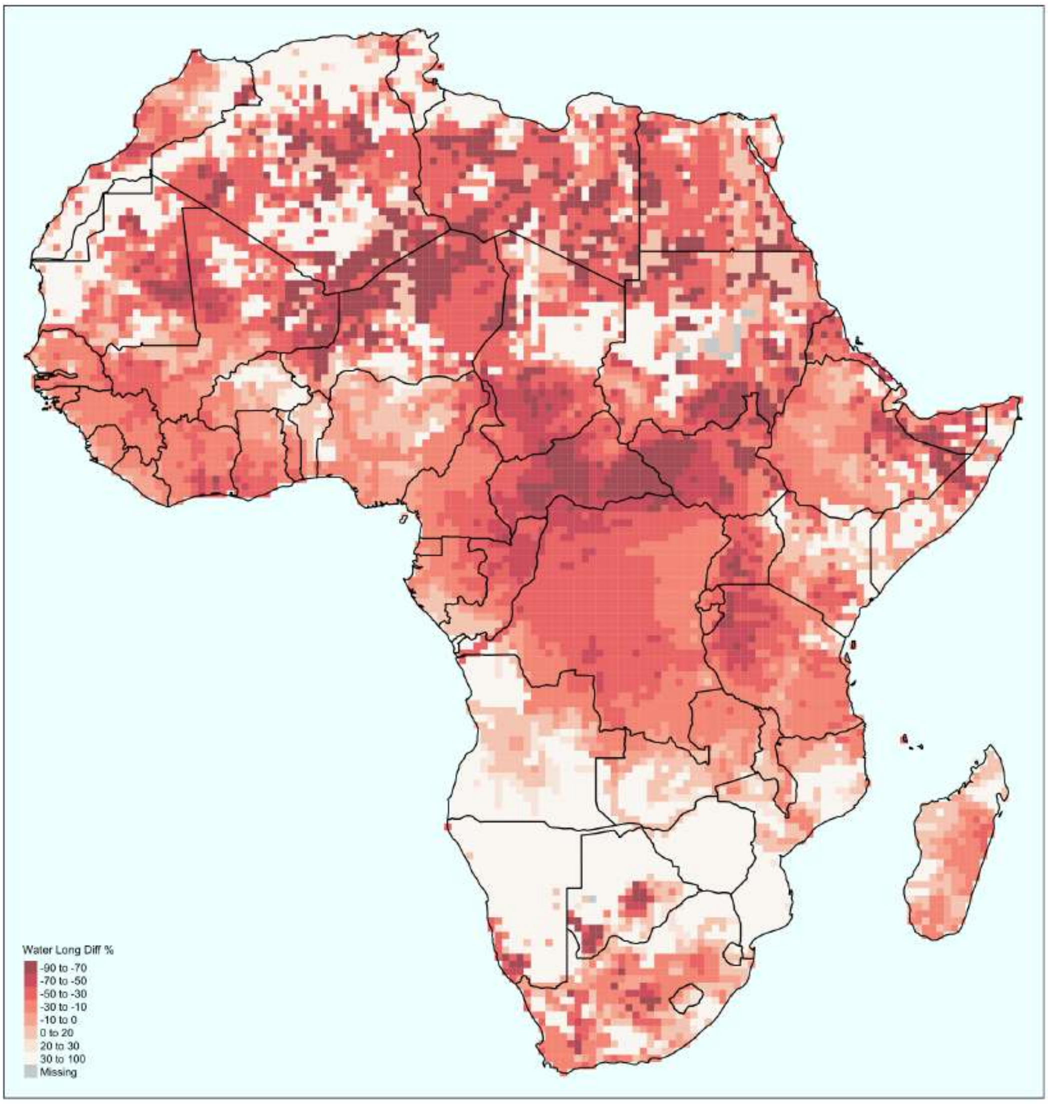


(c) Theil index



Notes: The maps display the spatial distribution of three different measures of water allocation between different ethnic groups at neighborhood level. In top panel (a), we report polarization measure of water ownership, in panel (b) the Gini index, while in panel (c) we report the Theil index distribution. Darker colors indicate higher values of the respective indexes. Grey cells represent missing values.

Figure A.8: Water Stress



Notes: The map displays the spatial distribution of the measure of water stress that we use. Darker colors indicate higher level of long term negative changes in water availability. The construction of the measure is detailed in section 4. Discharge data are taken from Harrigan et al. (2020).

A.3 Tables

Table A.1: Summary statistics

Variable	Mean	SD	Min	Median	Max	N
Panel A: *Conflicts*						
Incidence (ACLED)	0.0820	0.2744	0	0	1.0000	255,700
Incidence Battles	0.0543	0.2266	0	0	1.0000	255,700
Incidence Violence	0.0557	0.2293	0	0	1.0000	255,700
Incidence Protests	0.0415	0.1995	0	0	1.0000	255,700
Incidence Riots	0.0351	0.1840	0	0	1.0000	255,700
Incidence (GED)	0.0304	0.1716	0	0	1.0000	337,524
Panel B: *Water measures*						
Water Discharge (ln)	3.6334	3.2151	0	3.0318	14.131	255,700
Water Monopolist	0.0172	0.1299	0	0	1.0000	255,700
Water Monopolist +	0.0125	0.1113	0	0	1.0000	255,700
Panel C: *Rainfall shocks*						
Shock Down	0.2556	0.4362	0	0	1.0000	255,700
Shock Down p10	0.1742	0.3793	0	0	1.0000	255,700
Shock Down p20	0.3337	0.4715	0	0	1.0000	255,700
Shock Own	0.1971	0.3978	0	0	1.0000	255,700
Shock Own p10	0.1273	0.3333	0	0	1.0000	255,700
Shock Own p20	0.2664	0.4421	0	0	1.0000	255,700
Shock Up	0.1755	0.3804	0	0	1.0000	255,700
Shock Up p10	0.1225	0.3278	0	0	1.0000	255,700
Shock Up p20	0.2235	0.4166	0	0	1.0000	255,700
Panel D: *Other variables*						
Agricultural Cover	15.889	24.458	0	2.3642	99.917	255,700
Discharge Long Diff	195.79	2,479.2	-100.00	-16.739	99,670	255,275
Democratic	-0.9225	0.8486	-2.2008	-0.9961	0.9389	255,700
Rule of Law	-0.9089	0.6794	-2.1447	-1.0216	0.5845	255,700
Government Effectiveness	-0.7418	0.6503	-1.9599	-0.9236	1.0205	255,700
Corruption	-0.7347	0.6259	-1.6479	-0.8607	0.8180	255,700
RQ Index	0.5050	0.3053	0	0.5665	1.0000	252,650
Gini Index	0.5614	0.2472	0	0.6171	0.9712	252,650
Theil Index	0.8042	0.5596	0	0.7192	3.3539	252,650
Temperature (day)	27.306	3.4748	10.836	27.239	37.245	255,700
Temperature	24.462	3.4479	8.1089	24.596	34.057	255,700
Population	94,578	317,839	0	20,116	18,604,352	255,700

Notes: The table reports summary statistics for the main variables used in the analysis. The unit of observation is a $0.5° \times 0.5°$ grid cell and year. In *Panel A* we report summary statistics for the measures of conflicts used as dependent variables. In *Panel B* we report the summary statistics for the measures of water presence. In *Panel C* we report summary statistics for the measures of rainfall shocks. Finally, in *Panel D* we report summary statistics for the rest of the variables used for the heterogeneity analysis or as controls.

Table A.2: Conley standard errors

	Incidence (ACLED)				
	(1)	(2)	(3)	(4)	(5)
Water Discharge	0.0010	0.0007	0.0010	0.0009	0.0009
	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Water Discharge × Shock Down	0.0011**		0.0011**		0.0012**
	(0.0006)		(0.0006)		(0.0006)
Water Discharge × Shock Up		0.0003		0.0003	-0.0002
		(0.0006)		(0.0006)	(0.0006)
Shock Down	0.0008		0.0010		0.0009
	(0.0024)		(0.0024)		(0.0023)
Shock Up		-0.0018		-0.0024	-0.0014
		(0.0025)		(0.0025)	(0.0024)
Shock Own			-0.0005	0.0020	0.0000
			(0.0021)	(0.0021)	(0.0021)
Cell FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201	0.08201	0.08201
R^2	0.42101	0.42095	0.42101	0.42096	0.42101
Cells	10,228	10,228	10,228	10,228	10,228
Observations	255,700	255,700	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Conley standard errors with a spatial lag of 500 Km and infinite serial correlation are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Alternative data on conflict

	Incidence (GED Geo3)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	-0.0003	0.0147**	0.0129*
	(0.0006)	(0.0072)	(0.0070)
Water Measure $\times$ Shock Down	0.0005*	0.0143*	0.0305**
	(0.0003)	(0.0086)	(0.0124)
Water Measure $\times$ Shock Up	-0.0004	-0.0018	-0.0058
	(0.0003)	(0.0079)	(0.0095)
Shock Own	0.0012	0.0012	0.0012
	(0.0011)	(0.0011)	(0.0011)
Shock Down	0.0001	0.0017*	0.0016*
	(0.0011)	(0.0010)	(0.0010)
Shock Up	-0.0007	-0.0021*	-0.0021**
	(0.0013)	(0.0011)	(0.0011)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.03039	0.03039	0.03039
R^2	0.28764	0.28768	0.28771
Cells	10,228	10,228	10,228
Observations	337,524	337,524	337,524

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° $\times$ 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. Differently from our main analysis we construct the dependent variable using GED dataset. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1989-2020. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Alternative conflict categories

	Incidence (ACLED) (1)	Incidence Battles (2)	Incidence Violence (3)	Incidence Protests (4)	Incidence Riots (5)
Water Discharge	0.0009	0.0013*	-0.0008	0.0006	-0.0006
	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0006)
Water Discharge × Shock Down	0.0012***	0.0013***	0.0011***	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Water Discharge × Shock Up	-0.0002	-0.0003	0.0002	0.0002	0.0005
	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Shock Own	0.0000	0.0004	-0.0011	-0.0011	-0.0030**
	(0.0017)	(0.0015)	(0.0015)	(0.0013)	(0.0012)
Shock Down	0.0009	0.0005	0.0001	-0.0004	-0.0010
	(0.0018)	(0.0016)	(0.0015)	(0.0014)	(0.0012)
Shock Up	-0.0014	-0.0032*	-0.0011	-0.0007	-0.0016
	(0.0021)	(0.0018)	(0.0018)	(0.0016)	(0.0014)
Cell FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Dep. Var. Mean	0.08201	0.05431	0.05570	0.04152	0.03507
R^2	0.42101	0.36651	0.38268	0.39875	0.37082
Cells	10,228	10,228	10,228	10,228	10,228
Observations	255,700	255,700	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one conflict event occurs in a cell and year. In column (1) we report estimates using our main dependent variable which includes ACLED battles and violence against civilians. In columns (2) and (3) we separate the two components of the main dependent variables and consider battles and violence against civilians separately. In columns (4) and (5) we consider less deadly type of conflict events such as protests and riots. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1989-2020. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Alternative rainfall shocks G10

	Incidence (ACLED)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	0.0010	0.0125	0.0163
	(0.0009)	(0.0095)	(0.0104)
Water Measure × Shock Down	0.0014***	0.0275**	0.0458***
	(0.0005)	(0.0137)	(0.0172)
Water Measure × Shock Up	0.0003	-0.0073	-0.0104
	(0.0005)	(0.0120)	(0.0138)
Shock Own	0.0006	0.0002	0.0002
	(0.0020)	(0.0020)	(0.0020)
Shock Down	-0.0003	0.0043**	0.0043**
	(0.0022)	(0.0017)	(0.0017)
Shock Up	-0.0008	0.0009	0.0009
	(0.0024)	(0.0020)	(0.0020)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201
R^2	0.42102	0.42101	0.42103
Cells	10,228	10,228	10,228
Observations	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Measure* indicates generically a measure of water quantity which varies between columns. In column (1) it is the natural logarithm of the average water discharge present in a cell during a given year (*Water Discharge*). In column (2) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year (*Water Monopolist*). In column (3) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year and the discharge is higher than the median level in the sample for that year (*Water Monopolist +*). *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). Differently from the main analysis we define precipitation shocks as precipitation level in a cell-year below the 10th percentile in the long term distribution (see 3 for further details in the construction of precipitation shocks). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Alternative rainfall shocks G20

	Incidence (ACLED)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	0.0010	0.0095	0.0115
	(0.0010)	(0.0100)	(0.0108)
Water Measure × Shock Down	0.0013***	0.0218**	0.0386***
	(0.0004)	(0.0104)	(0.0143)
Water Measure × Shock Up	-0.0007	-0.0009	-0.0027
	(0.0005)	(0.0105)	(0.0128)
Shock Own	0.0031**	0.0028*	0.0028*
	(0.0015)	(0.0015)	(0.0015)
Shock Down	-0.0031*	0.0008	0.0008
	(0.0017)	(0.0014)	(0.0014)
Shock Up	0.0003	-0.0023	-0.0023
	(0.0019)	(0.0016)	(0.0016)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201
R^2	0.42100	0.42100	0.42103
Cells	10,228	10,228	10,228
Observations	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Measure* indicates generically a measure of water quantity which varies between columns. In column (1) it is the natural logarithm of the average water discharge present in a cell during a given year (*Water Discharge*). In column (2) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year (*Water Monopolist*). In column (3) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year and the discharge is higher than the median level in the sample for that year (*Water Monopolist +*). *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). Differently from the main analysis we define precipitation shocks as precipitation level in a cell-year below the 20th percentile in the long term distribution (see 3 for further details in the construction of precipitation shocks). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Alternative radius 160 Km

	Incidence (ACLED)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	0.0009	0.0102	0.0125
	(0.0009)	(0.0080)	(0.0087)
Water Measure × Shock Down	0.0014***	0.0133	0.0224
	(0.0005)	(0.0109)	(0.0144)
Water Measure × Shock Up	-0.0001	-0.0059	-0.0066
	(0.0005)	(0.0104)	(0.0125)
Shock Own	-0.0001	-0.0005	-0.0005
	(0.0017)	(0.0017)	(0.0017)
Shock Down	0.0002	0.0049***	0.0049***
	(0.0020)	(0.0016)	(0.0016)
Shock Up	-0.0015	-0.0015	-0.0016
	(0.0022)	(0.0018)	(0.0018)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201
R^2	0.42102	0.42100	0.42101
Cells	10,228	10,228	10,228
Observations	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. Differently from the main analysis, as robustness exercise, we use 160 Km radius to define a cell neighborhood. *Water Measure* indicates generically a measure of water quantity which varies between columns. In column (1) it is the natural logarithm of the average water discharge present in a cell during a given year (*Water Discharge*). In column (2) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year (*Water Monopolist*). In column (3) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year and the discharge is higher than the median level in the sample for that year (*Water Monopolist +*). *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Alternative radius 200 Km

	Incidence (ACLED)		
	Water Discharge	Water Monopolist	Water Monopolist +
	(1)	(2)	(3)
Water Measure	0.0009	0.0104	0.0093
	(0.0009)	(0.0106)	(0.0112)
Water Measure $\times$ Shock Down	0.0010**	0.0217*	0.0341**
	(0.0004)	(0.0123)	(0.0168)
Water Measure $\times$ Shock Up	-0.0001	-0.0053	-0.0061
	(0.0005)	(0.0114)	(0.0133)
Shock Own	0.0003	-0.0001	-0.0001
	(0.0017)	(0.0017)	(0.0017)
Shock Down	0.0008	0.0042***	0.0041***
	(0.0018)	(0.0015)	(0.0015)
Shock Up	-0.0018	-0.0018	-0.0019
	(0.0020)	(0.0017)	(0.0017)
Cell FE	✓	✓	✓
Country-Year FE	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201
R^2	0.42100	0.42100	0.42101
Cells	10,228	10,228	10,228
Observations	255,700	255,700	255,700

Notes: The table reports estimated coefficients from equation (1). The unit of observation is a 0.5° $\times$ 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. Differently from the main analysis, as robustness exercise, we use 200 Km radius to define a cell neighborhood. *Water Measure* indicates generically a measure of water quantity which varies between columns. In column (1) it is the natural logarithm of the average water discharge present in a cell during a given year (*Water Discharge*). In column (2) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year (*Water Monopolist*). In column (3) it is an indicator variable equal to 1 if the cell is the one with the highest water discharge in a neighborhood in a given year and the discharge is higher than the median level in the sample for that year (*Water Monopolist +*). *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Additional Controls

	Incidence (ACLED)			
	(1)	(2)	(3)	(4)
Water Discharge	0.0009	0.0013	0.0015	0.0008
	(0.0009)	(0.0010)	(0.0010)	(0.0009)
Water Discharge × Shock Down	0.0012***	0.0012***	0.0012***	0.0011**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Water Discharge × Shock Up	-0.0001	-0.0002	-0.0002	-0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Shock Own	0.0000	-0.0004	-0.0006	-0.0002
	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Shock Down	0.0009	0.0007	0.0005	0.0004
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Shock Up	-0.0014	-0.0015	-0.0015	-0.0002
	(0.0021)	(0.0021)	(0.0021)	(0.0020)
Log pop.	0.0046			
	(0.0048)			
Temp.		0.0044**		
		(0.0022)		
Temp. (day)			0.0059***	
			(0.0020)	
Lagged Incidence				0.1701***
				(0.0051)
Cell FE	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
Dep. Var. Mean	0.08201	0.08201	0.08201	0.08366
R^2	0.42102	0.42103	0.42104	0.44153
Cells	10,228	10,228	10,228	10,228
Observations	255,700	255,700	255,700	245,472

Notes: The table reports estimated coefficients from equation (1) with additional controls. The unit of observation is a 0.5° × 0.5° grid cell and year. The dependent variable is a dummy that takes value 1 if at least one violent conflict occurs in a cell and year. *Water Discharge* is the natural logarithm of the average water discharge present in a cell during a given year. *Shock* is an indicator variable taking value 1 if a location experiences a drought (as defined in section 3), upstream (*Up*), downstream (*Down*) or within the unit of observation (*Own*). In different columns we introduce additional controls to our baseline regression equation. In particular in column (1) we control fro (Log) population in the cell, in column (2) we controls for average temperature over the year, in column (3) we control for average daily temperature over the year and in column (4) we control for conflicts happening in the previous year. The sample covers the years in the interval 1997-2021. Clustered standard errors by cell are reported in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.