Niger, 2014 ©Mercy Corps

ADDRESSING THE CLIMATE-CONFLICT NEXUS IN FRAGILE STATES:

Understanding the role of governance

NOVEMBER, 2020

Introduction

Climate-related causes of conflict are increasingly undermining peace, stability, and development in low-income countries, which are the most at-risk of experiencing the negative effects of climate change. Estimates by various experts suggest that climate change has increased conflict risk by approximately 3-20% over the last century (Mach et al. 2019). While there is widespread support for the idea that climate change increases the risk of conflict, the mechanisms by which this occurs is less clear (Gleditsch 2012). Some research points to the role that quality governance and political institutions may play in mediating the relationship between climate change and conflict, but this idea rests primarily on theoretical grounds and lack empirical testing.

We seek to help address this evidence gap by conducting data analyses to examine the relationships between climate change, conflict, and governance. Specifically, the present study looks at the relationship between climate variability[1] and violent conflict, and the extent to which state capacity is able to mediate this link within five countries in Sub-Saharan Africa that have experience conflict or instability in recent years: Kenya, Mali, Nigeria, Uganda, and Zimbabwe. Because most studies look at these relationships cross-nationally, we recognize that there is much variation at the subnational level in terms of climate variability, conflict, and local governance and seek to examine subnational differences.

Trying to understand the links between climate variability and conflict is admittedly an ambitious undertaking, especially considering that most experts agree that this link is an indirect one.[2] Despite variation across and within countries, two key insights stand out from our analyses. First, we find support for a link between higher temperature variability and greater violent conflict. Precipitation variability, however, shows results that are more mixed. Second, we observe a general trend whereby stronger state capacity appears, in some cases, to reduce the likelihood that climate variability will lead to conflict. Keeping in mind that our findings are indicative and not conclusive, the correlations (and the lack thereof) found in the analysis of these specific contexts can contribute to better understanding the climate-conflict nexus, including the specific role that governance plays in it.

First, we find support for a link between higher temperature variability and greater violent conflict. Second, we observe a general trend whereby stronger state capacity appears, in some cases, to reduce the likelihood that climate variability will lead to conflict.

Taken together, these findings can inform programming and policymaking, first, by supporting activities that improve our understanding of the local drivers of conflict and, specifically, how environmental factors may exacerbate them. Secondly, the analysis points to the potential benefits of strengthening local governance as a way of mediating the effects of climate change on conflict. Although improving governance has long been seen as an important factor in preventing various other forms of conflict (Mercy Corps, 2019), it has not been a central focus of investments and policies focused on addressing climate-

[1] While the term “climate change” is used widely in the relevant literature, “climate variability” is a more nuanced and precise term for our discussion here. Climate variability refers to climatic variations and extreme weather events experienced over shorter periods of time (months or years), whereas climate change refers to the longer process experienced over decades and centuries.

[2] For more on this see work by: Buhaug 2016; Schleussner et al. 2016; Abrahams & Carr 2017; Feitelson & Tubi 2017; Jones et al. 2017; Van Baalen & Mobjörk 2018; and Mach et al. 2019

related challenges.[3] Yet, our research suggests that strengthening local governance may have a role to play in policies and programs aimed at promoting climate adaptation and security in fragile states.

Evidence and Research Gaps

In recent years, the notion that climate change is linked to increased violent conflict has gained traction as more and more studies point to this link. Much of this research indicates that the relationship between climate change and conflict is an indirect one that may operate through different mechanisms. Some of these hypothesized mechanisms include: food insecurity and general economic uncertainty and disruption (Buhaug (2016); low socioeconomic development, low state capacity, and a recent history of violence (Mach et al. 2019); and elite exploitation of local grievances and tactical considerations by armed groups (Van Baalen & Mobjörk 2018). Social and political contexts—ranging from land rights institutions to intergroup inequality—are also important parts of the nexus (Buhaug 2016; Schleussner et al. 2016; Jones et al. 2017; Feitelson & Tubi 2017; Van Baalen & Mobjörk 2018; Mach et al. 2019). Finally, studies have also posited that quality governance and political institutions may play a mediating role, in that they may be able to interrupt the link between climate variability and conflict by offering forums for conflict resolution (Gizelis & Wooden 2010; Buhaung 2016; Jones et al. 2017; Van Baalen & Mobjörk 2018).

Despite growth in research on this topic, there is still a dearth of empirical studies that are rooted in local factors. The bulk of existing research rests largely on theoretical grounds, is cross-national in scope, or is based on antiquated data. With the exception of a few studies (see for example Cuni-Sanchez et al.'s (2019) research in Kenya), there is a lack of local-level analyses that focus on the context-specific interplays of climate and conflict. We contribute to this discourse by offering an empirical analysis using newly collected subnational data to examine the links between climate variability, governance and conflict in five sub-Saharan African countries—Kenya, Mali, Nigeria, Uganda, and Zimbabwe.

Case Selection, Data, and Methodology

This study focuses on five countries—Kenya, Mali, Nigeria, Uganda, and Zimbabwe—in sub-Saharan Africa, the region most severely affected by climate change (Collier et al. 2008; Barrios et al. 2010; Henderson et al. 2017; Cook 2018) and also critically affected by conflict. Merging various secondary data sources on climate variability, governance and conflict from these countries, we are able to test the hypothesis that governance is a key mechanism linking climate change and conflict.

For our climatic variables, we use daily temperature data from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset, and precipitation data from the NCEP Daily Global Analyses of the U.S. National Oceanic and Atmospheric Administration (NOAA). We use daily temperature data to create mean values for each country per year, over 2000-2017. We then calculated

[3] As an exception, some Natural Resource Management (NRM) programs focus on building local government capacity to dispute resource-based conflicts, but many focus on informal institutions.

daily standard deviations from those mean values. This approach allows us to capture the daily extremes at an annual level, rather than being absorbed by an annual average. For precipitation, we calculate the mean values for each country per year, and then calculate daily standard deviations from those mean values in order to capture precipitation variability.

Conflict data is from the Armed Conflict Location and Event Data (ACLED) project, which collects dates, actors, locations, fatalities and modalities of all reported political violence and protests events across various regions. We restrict our analysis to violent conflicts (battles, violence against citizens, and remote violence), omitting protests, riots, and other non-violent events.

Governance indicators are from Afrobarometer public opinion surveys for available years over 1999-2017[4]. Afrobarometer collects survey data on public attitudes by conducting face-to-face interviews with randomly selected individuals that constitute nationally representative samples of the voting age population, with approximately 1,200-2,400 respondents per country. In order to capture localized state capacity we use two types of variables: (1) *reach or penetration,* measured by the presence of a police station and a post office (as opposed to the presence of schools and hospitals, for example, which could have been built by external actors) and (2) *performance,* measured by perceptions of how well the local government handles corruption, as this offers an assessment of local governance quality, rather than perceptions of national-level governance.

Using these data, we conduct a series of panel regression analyses with three regression models. While causality can be inferred regarding conflict and climate—i.e., it is unlikely that conflict affects the variability of temperature and precipitation—the direction of causality between conflict and governance is likely a bit more tangled (e.g. indirect). Moreover, for the sake of parsimony we rely on straightforward correlations in our models, and do not include statistical causality tests. We therefore avoid using casual language altogether in our interpretations.

In our models, we first look at the relationships between our climate variables (temperature and precipitation variability) and violent conflict, and then look at the relationship between our governance indicators (presence of a police station, presence of a post office, perception of corruption) and violent conflict. Next, we include sets of interaction terms between our climatic variables and our governance indicators in order to better explore whether governance has a mediating effect on the link between climate variability and violent conflict. We also control for year and subnational region fixed effects, in order to discern if time or place have significant correlations with violent conflicts.

We run five models in total (see below). Model 1 simply places violent conflicts and the independent variable and temperature and precipitation as the dependent variables. Model 2 adds the governance indicators (police station, post office, and corruption). Model 3 includes interaction terms between the climatic variables and the presence of a police station (i.e., temperature*police station and precipitation*police station). Model 4 adds interaction terms between the climatic variables and the presence of a post office. Lastly, Model 5 adds interaction terms between the climatic variables and perception of corruption.

Model 1: $conflict = (climate\ variability_{i,t} + \alpha_i + \delta_t + \nu_{i,t})$
Model 2: $conflict = (climate\ variability_{i,t} + governance_{,t} + \alpha_i + \delta_t + \nu_{i,t})$
Model 3: $conflict = (climate\ variability_{i,t} + governance_{i,t} + interactionA_{i,t} + \alpha_i + \delta_t + \nu_{i,t})$
Model 4: $conflict = (climate\ variability_{i,t} + governance_{i,t} + interactionB_{i,t} + \alpha_i + \delta_t + \nu_{i,t})$
Model 5: $conflict = (climate\ variability_{i,t} + governance_{i,t} + interactionC_{i,t} + \alpha_i + \delta_t + \nu_{i,t})$

[4] Years available for Kenya: 2003, 2005, 2008, 2011, 2014, 2016; for Mali: 2001, 2002, 2005, 2008, 2013, 2014, 2017; for Nigeria: 2000, 2003, 2005, 2008 2013, 2015, 2017; for Uganda: 2000, 2002, 2005, 2008, 2012, 2015, 2017; for Zimbabwe: 1999, 2004, 2005, 2009, 2012, 2014, 2017.

In the next section, we highlight findings where there is a statistically significant relationship in one or more of the models above for a country (see summary in Table 1). While acknowledging that there is variation across and even within the countries, we try to describe general trends that emerge in the direction of the correlations (or lack thereof).

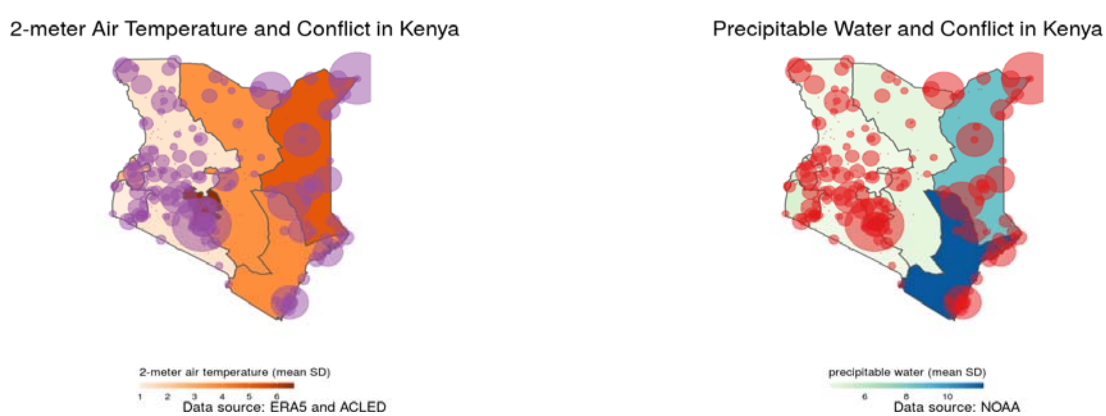
Case Findings

Kenya

In Kenya, higher variability in precipitation is associated with a higher incidence of violent conflict.[5] Several reports indicate that conflicts in Kenya tend to be dispersed but often arise over land and water resources, particularly over riverlands (New Security Beat 2012). Flooding and landslides have been devastating and frequent in recent years (Floodlist 2020). As both droughts and floods reduce the viability of land, this could contribute to conflicts over arable land, which may explain in part our finding that higher levels of variability of precipitation are associated with more violent conflicts.

This relationship appears to be mediated by factors related to state capacity. Importantly, each interaction with precipitation (police station, post office, and corruption) is negative and significant in at least one of the three models[6]. This lends support to the idea that the types of state capacity and governance represented here are able to reverse the positive relationship between precipitation variability and violent conflicts. While precipitation's interaction with presence of a police station loses significance in Models 4 and 5, the interaction with presence of a post office stays consistently significant. The interaction between control of corruption and temperature variability is also negative and significant, as is the interaction between temperature variability and presence of a police station; although the relationship between temperature variability and conflict, while positive, is not significant in our baseline model[7].

Figure 1: Kenya Climate Variability and Violent Events



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5 Specifically, for each unit increase in precipitation variability the log odds of experiencing violent conflict increases by between 0.4 (Model 1) and 0.3 (Model 2).

6 For each unit increase in the interaction between precipitation variability and police station, the log odds of experiencing violent conflict decreases by 0.47 (Model 3); for each unit increase in the interaction between precipitation variability and post office, the log odds of experiencing violent conflict decrease by between 1.15 (Model 4) and 1.05 (Model 5); for each unit increase in the interaction between precipitation variability and police station, the log odds of experiencing violent conflict decreases by 0.18 (Model 5).

7 For each unit increase in the interaction between temperature variability and corruption, the log odds of experiencing violent conflict decreases by 0.2 (Model 5); for each unit increase in the interaction between temperature variability and police station, the log odds of experiencing violent conflict decreases by between 0.64 (Model 3), 0.94 (Model 4), and 1.4 (Model 5).

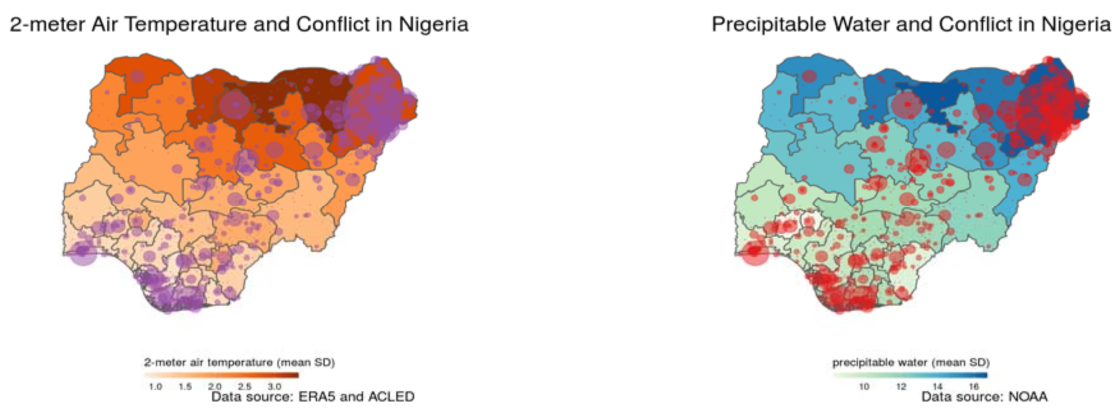
Nigeria

In Nigeria, higher variability in temperature is associated with more violent conflicts[8], whereas lower variability in precipitation is associated with greater violent conflicts[9]. The former finding is in line with our expectations, and the hypothesis that higher temperatures to negatively impact land viability, resulting in conflicts over increasingly scarce resources. The latter finding, however, is somewhat counterintuitive. State capacity variables, for their part, appear to have little effect on violent conflicts in Nigeria. None of them are significant on its own. The only significant interaction is between precipitation variability and the presence of a police station[10], and while this relationship is negative the relationship between precipitation variability and conflicts is already negative. It is therefore helpful to take a deeper look at the context in which specific outbreaks of conflict are couched throughout Nigeria.

Looking closer at the data, geography stands out as an important factor for the incidence of violent conflict in Nigeria. ACLED data shows that violent conflicts tend to be concentrated in the Northeast, in the Southern region, around the megacity Lagos, and dispersed across the Middle Belt. This is not surprising given the multiple and varied conflicts that exist in Nigeria. For example, Boko Haram attacks, beginning in 2009, have been concentrated in the Northeast, particularly in Borno state (Global Conflict Tracker 2020). Violent clashes between farmers and herders has been increasing in the Middle Belt (ICG 2018). The Niger Delta in the Southern region is characterized by conflict over oil production, which has manifested in various forms of inter- and intra-ethnic conflict (Folami 2017). The oil-producing Bayelsa, Delta, and River states are especially prone to this type of violence, though an amnesty introduced in October 2005 has been successful in quelling some of the conflict. It is worth noting that all of the above-mentioned states (apart from Nasarawa) have positive and significant relationships with violent conflicts across all of our statistical models.

This suggests that while climate may indeed be an important factor in some of these cases—particularly regarding the conflicts between farmers and herders in the Middle Belt—it does not fully explain the various types of violent conflict across Nigeria. Other conduits—e.g., economic or political grievances—are in some cases be stronger drivers of conflict, on their own. Hence, while our findings do not suggest that local governance has been able to mediate the link between temperature variability and violent conflicts in this context, this could be due in part to the prevalence of other drivers of conflict (often geographically specific) that are omitted from our models.

Figure 2: Nigeria Climate Variability and Violent Events



[8] For each unit increase in temperature variability the log odds of experiencing violent conflict increases by between 0.67 (Model 1) and 0.61 (Model 2).

[9] For each unit increase in precipitation variability the log odds of experiencing violent conflict decreases by around 0.4 (Models 1 & 2).

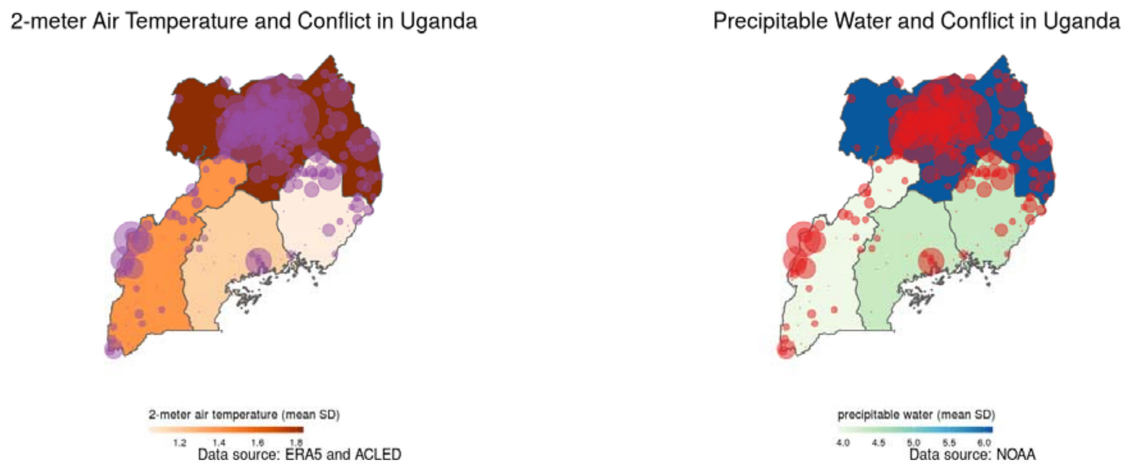
[10] For each unit increase in the interaction between precipitation variability and police station the log odds of experiencing violent conflict decreases by 0.33 (Model 3).

Uganda

In Uganda, higher temperature variability may be associated with greater violent conflicts[11], whereas lower levels of precipitation variability may be associated with greater violent conflicts[12]. As with Nigeria, this is contrary to expectations.

State capacity as measured by the presence of a post office and a better handling of corruption are both associated with a lower incidence of conflict[13]. Taken on its own, the presence of a police station is associated with greater violent conflicts[14], but lacks significance when interacted with the climatic variables. There is also no significant relationship when corruption is interacted with either climatic variable. Importantly, however, the interaction between temperature variability and presence of a post office is significant and negative[15], suggesting that state capacity (as proxied by a post office) may be able to reverse the positive relationship between temperature variability and violent conflicts.

Figure 3: Uganda Climate Variability and Violent Events



Zimbabwe

In Zimbabwe, higher variability in precipitation may be associated with greater violent conflicts[16]. Handling of corruption stands out as the most important governance factor represented here. While it is not significant on its own, a better handling of corruption tends to reverse the positive relationship between precipitation variability and conflict[17].

Though temperature variability lacks a significant relationship with conflict and demonstrates inconsistent signs in our base models, the interaction between temperature variability and corruption is negative and

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[11] For each unit increase in temperature variability the log odds of experiencing violent conflict increases by 2.6 (Model 2).

[12] For each unit increase in precipitation variability the log odds of experiencing violent conflict decreases by 1 (Model 1).

[13] For each unit increase in post office presence the log odds of experiencing violent conflict decreases by between 10.14 (Model 2) and 15.41 (Model 3); for each unit increase in perceptions of better handling corruption the log odds of experiencing violent conflict decreases by between 6.34 (Model 2) and 3.08 (Model 4).

[14] For each unit increase in police station presence the log odds of experiencing violent conflict increases by 6 (Model 2).

[15] For each unit increase in temperature variability the log odds of experiencing violent conflict decreases by 26.17 (Model 5).

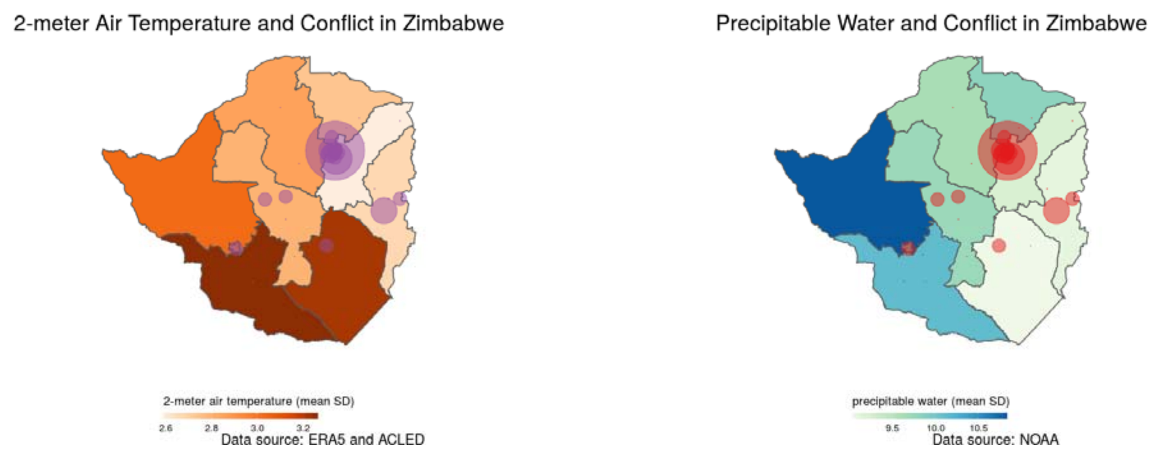
[16] For each unit increase in precipitation variability the log odds of experiencing violent conflict increases by 0.53 (Model 2).

[17] For each unit increase in the interaction between precipitation variability and corruption the log odds of experiencing violent conflict decreases by 1.244 (Model 5).

significant[18]. This lends further support that controlling corruption may be a key component of reducing conflict in Zimbabwe. Surprisingly, the interaction between temperature variability and presence of a police station is positive and significant, but this may potentially be due to the view that the police are not a trusted or positively viewed state institution in Zimbabwe[19].

Our findings for corruption are not surprising, given that Zimbabwe has been plagued by high levels of corruption for the past two decades. Based on the World Bank's governance indicator for "control of corruption"—which ranks countries along a 2.5 to -2.5 scale—Zimbabwe has ranged from -0.98 to -1.40, with a low in 2000 and a high in 2013. While rivaled by Nigeria in the early 2000s, from 2005 to 2018 Zimbabwe stands out as the most corrupt government of our five country cases, based on this indicator. Corruption within the police force is especially problematic in Zimbabwe. Likely stemming from low salaries, limited training, poor working conditions, and a culture of impunity (GAN Integrity 2019), the police are viewed by a majority of Zimbabweans as the most corrupt institution in the country (Afrobarometer 2015).

Figure 4: Zimbabwe Climate Variability and Violent Events



Mali

While Mali is often cited as a case exemplifying how climate change can amplify conflict[20], our models suggest that other factors—perhaps political, ideological, and ethnic—may be stronger drivers of conflict. Neither temperature variability nor precipitation variability has a significant relationship with violent conflicts in Mali in our baseline models. Indicators for local governance, for their part, show mixed and inconsistent results.

[18] For each unit increase in the interaction between temperature variability and corruption the log odds of experiencing violent conflict decreases by 1.24 (Model 5).

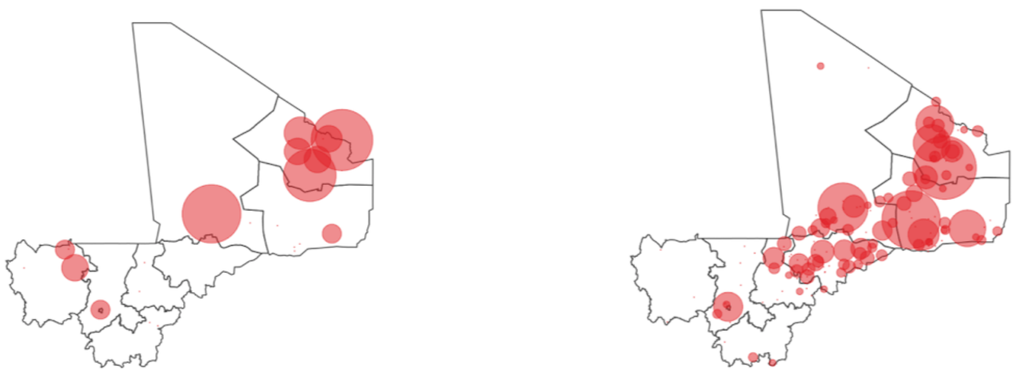
[19] For each unit increase in temperature variability the log odds of experiencing violent conflict increases by 10.34 (Model 5).

[20] See for example: Arsenault, C. (2015). "Climate change, food shortages, and conflict in Mali." Al Jazeera, April 27, 2015. link (last accessed: Aug 10, 2020); Doucet, L. (2019). "The battle on the frontline of climate change in Mali." BBC News, Jan 22, 2019. link (last accessed: Aug 10, 2020); ICRC. (2019). "Mali-Niger: Climate change and conflict make an explosive mix in the Sahel." International Committee of the Red Cross. link (last accessed: Aug 10, 2020); Kalkavan, B. (2019). "The when and how of climate conflict: The case of Mali." ECDPM Great Insights magazine, Autumn 2019: 8:4. link (last accessed: Aug 10, 2020).

As with all our models, we control for yearly fixed effects. A clear pattern emerges for these time dummy variables, in that they are consistently significant after 2012, indicating a significant change at that time driving violent conflict. This is likely driven by the aftermath of the 2012 coup d'état and insurgency in the north. Despite a 2015 peace deal, conflicts have increased as the Islamist insurgency expanded southward from the North. The ramifications of this event continue as ethnic militias have carried out massacres, in addition to an uptick in terrorist attacks (CRS 2020).

The figures below show the rather stark contrast in violent conflicts before and after the delineating event of the 2012 coup d'état. Note that the first map of Figure 5 represents 12 years (2000-2011), second map represents only half as many years and displays a much higher incidence of violent conflicts.

Figure 5: Conflict Events Pre- and Post- 2012



Conflict Events: 2000-2011 | Conflict Events: 2012-2017

General Findings and Implications

A few general implications can be gleaned from these case findings. First, regarding the relationship between climate variability and conflict, we see that higher temperature variability stands is linked to greater violent conflicts, whereas higher precipitation variability presents results that are more mixed. This aligns with research by Hsiang et al. (2015), who find that, of all climatic variability, contemporaneous temperature has the biggest effect (they find that for every one standard deviation in temperature, interpersonal conflict increases by 2.4% on average, and intergroup conflict increases by 11.3% on average).

A number of different hypotheses may explain the mixed and at times counter-intuitive relationship in which greater temperature variability is associated with less conflict, though testing these hypotheses is beyond the scope of this study. For example, it may be the case that that the specific type of precipitation variability captured in Nigeria and Uganda—where lower precipitation variability is associated with more violent conflicts—tends to represent periods of more rainfall, rather than less. If the "new normal" is characterized by droughts and dry spells, variation away from this could be welcomed and therefore reduce competition over arable land. Another interpretation could follow Salehyan and Hendrix (2012), who find that water scarcity has a pacifying effect on organized conflict and that water abundance is associated with more political violence; armies, for example, require plenty of water. While they do not test rain variability, their findings could suggest that less variability may be positive for tactical considerations and strategic planning in conflict. Though these are two possible explanations for counter-intuitive findings, further research must be done to validate or disconfirm them.

Second, regarding the mediating effects of governance, we see that indicators of local state capacity (i.e. increased local presence and a better handling of corruption) may be able to mediate the link between climate variability and conflict—*in the absence of other, stronger factors*. A possible explanation for this is that, as environmental changes drive competition for limited resources, the presence of legitimate and trusted state institutions at the local level may help prevent or mediate disputes. In these contexts, strengthening state capacity and improving local governance, more generally, may be effective ways of moderating climate-related violent conflicts. Beyond this, our analysis suggests that efforts that address conflict ought to be highly context-specific. The large amount of variation observed highlights the importance of context, even as the presence of a functioning and less corrupt local government stands out as a general finding.

Table 1: Summary of Relationships with Conflict (Violent Events)

	Climatic Variables		***Climate and Governance Variables Interacted***					
Country	**Precipitation**	**Temperature**	**Temperature * Police Station**	**Temperature* Post Office**	**Temperature* Handling Corruption**	**Precipitation* Police Station**	**Precipitation*Post Office**	**Precipitation* Handling Corruption**
Kenya	+		–		–	–	–	–
Nigeria	–	+				–		
Uganda	–	+		–				
Zimbabwe	+		+		–			–
Mali				+		+		

Legend:

- *Plus signs (+) indicate a positive relationship, and minus signs (–) indicate a negative relationship with conflict (violent events)*
- ***Black +/– indicate statistical significance across all models***
- *Gray +/– indicate statistical significance in one or some, but not all models that variable is included in*

Future research would offer valuable insights by collecting more disaggregated local-level data. For instance, it would be beneficial to collect local governance indicators at higher resolutions to show more localized variation, as Afrobarometer's subnational data represent broader regions than those captured by ACLED data. Additionally, future research can also focus on how other context-specific factors (environmental, social, and political) interact with climate variability and conflict. For example, taking the case of Nigeria, it would be enlightening to explore whether policies like anti-grazing laws reduce or increase conflict between pastoralists and farmers, and whether this is more prominent during times of drought.

For development policymakers interested in addressing the challenges of climate change and its effects on conflict, two takeaways emerge from this study. First, development actors should conduct or commission conflict analysis to identify both the immediate triggers and the root causes of conflict, as well as examining how climate variability and climate related issues (such as resource competition) might exacerbate those causes. While our research indicated that there are links between higher temperature variation and more violent conflict, the causes of conflict are highly localized and complex. More in-depth, sector neutral analysis that take into account the interaction between environmental factors, resource access and conflict within a specific context will reveal different pathways by which climate change may amplify conflict, or other factors that may be more important. Secondly, development actors should explore investing in strengthening local governance as part of climate adaptation programs in fragile states. When designing approaches to mitigate conflict, donors and implementers commonly look to governance programs. However, governance programs are not often considered part of the menu of solutions related to climate change. In places where environmental factors are exacerbating conflict, donors and partners ought to consider investing in governance programs that strengthen local state capacity to address the new challenges brought about by climate change. Our research suggests that enhancing local presence to provide services like security and minimizing mismanagement and corruption are important indicators of improved state capacity that can help address these challenges.

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Appendix

Kenya Regression Results

	(1) violent_events	(2) violent_events	(3) violent_events	(4) violent_events	(5) violent_events
temperature	0.839	0.787	1.451•	0.782	1.201•
	(1.11)	(1.08)	(2.21)	(1.35)	(2.25)
precipitation	0.756•••	0.701•••	1.019•••	0.939•••	1.209•••
	(4.69)	(3.93)	(8.25)	(9.06)	(8.77)
police		0.738	6.689•••	2.744	5.642•
		(0.89)	(4.35)	(1.24)	(2.35)
post office		-0.407	0.295	6.830	4.729
		(-0.18)	(0.17)	(1.88)	(1.28)
fighting corruption		0.131	0.622	0.507	2.519•••
		(0.33)	(1.90)	(1.58)	(3.50)
temp*police			-0.637••	-0.939•	-1.391••
			(-2.66)	(-2.38)	(-3.20)
precip*police			-0.486••	0.234	0.158
			(-3.13)	(1.00)	(0.64)
temp*post office				0.748	0.754
				(0.99)	(1.03)
precip*post office				-1.151••	-1.049••
				(-3.08)	(-3.08)
temp*corrupt					-0.199•
					(-2.11)
precip*corrupt					-0.179•
					(-1.98)
Year					
2005	0.499	0.608	1.053••	1.050••	1.360••
	(1.82)	(1.27)	(2.63)	(2.61)	(3.20)
2008	1.486•••	1.462•	1.505•••	1.272••	1.555•••
	(5.91)	(2.50)	(3.33)	(3.15)	(3.90)
2011	0.564•	0.484	0.957	0.484	0.972•
	(2.26)	(0.76)	(1.96)	(1.10)	(2.04)
2014	1.498•••	1.462•	2.075•••	1.878•••	1.969•••
	(5.26)	(2.30)	(4.47)	(4.31)	(4.47)
2016	0.764•	0.783	1.214•	1.157•	1.434••
	(2.14)	(1.24)	(2.54)	(2.55)	(3.07)
Region					
Coast	-2.243	-1.917	-1.422	-2.684	-2.595
	(-0.76)	(-0.66)	(-0.61)	(-1.40)	(-1.26)
Eastern	3.130	3.031	4.945••	3.164	2.581
	(1.35)	(1.36)	(2.58)	(1.82)	(1.58)
Nairobi	2.945	2.711	4.018•	2.314	1.855
	(1.44)	(1.33)	(2.32)	(1.50)	(1.21)
Northeastern	-0.386	-0.293	0.472	-0.468	-0.551
	(-0.25)	(-0.19)	(0.41)	(-0.45)	(-0.50)
Nyanza	4.391	4.186	7.164•	3.521	2.778
	(1.01)	(0.99)	(1.97)	(1.10)	(0.90)
Riftvalley	7.024	6.729	9.752••	6.215•	5.296
	(1.72)	(1.71)	(2.80)	(2.01)	(1.80)
Western	2.664	2.434	4.472	1.873	1.175
	(0.86)	(0.80)	(1.75)	(0.81)	(0.53)
Constant	-8.240	-8.077	-15.59•••	-10.51•	-13.96•••
	(-1.74)	(-1.58)	(-3.42)	(-2.51)	(-3.54)
Observations	48	48	48	48	48

t statistics in parentheses
• $p < 0.05$, •• $p < 0.01$, ••• $p < 0.001$
Constant: year=2003 region= Central

Nigeria Regression Results

	(1) violent_events	(2) violent_events	(3) violent_events	(4) violent_events	(5) violent_events
temperature	0.668•••	0.612•••	0.475•••	0.476•••	0.608
	(6.82)	(5.67)	(3.78)	(3.74)	(1.91)
precipitation	-0.392•	-0.394•	-0.145	-0.147	-0.431
	(-2.22)	(-2.11)	(-0.69)	(-0.71)	(-1.72)
police		-0.190	2.937•	3.294•	2.381
		(-0.70)	(2.46)	(1.99)	(1.54)
post office		0.512	0.494	-0.602	-1.360
		(1.15)	(1.27)	(-0.25)	(-0.56)
fighting corruption		-0.164	-0.239	-0.198	-1.391
		(-0.76)	(-1.21)	(-0.99)	(-1.94)
temp*police			0.503	-0.0982	-0.0336
			(1.51)	(-0.20)	(-0.06)
precip*police			-0.327•	-0.266	-0.188
			(-2.41)	(-1.48)	(-1.11)
temp*post office				0.880	0.707
				(1.75)	(1.27)
precip*post office				-0.0439	0.0468
				(-0.18)	(0.18)
temp*corrupt					0.0162
					(0.07)
precip*corrupt					0.0969
					(1.35)
Year					
2008	0.973	0.948	0.993	0.954	0.964
	(1.44)	(1.44)	(1.58)	(1.51)	(1.55)
2012	1.834•••	1.735•••	1.846•••	1.816•••	1.760•••
	(3.76)	(3.56)	(4.00)	(3.84)	(3.86)
2014	2.156•••	2.067•••	2.081•••	2.067•••	2.009•••
	(4.60)	(4.51)	(4.65)	(4.58)	(4.61)
2017	2.435•••	2.533•••	2.485•••	2.386•••	2.369•••
	(4.76)	(5.09)	(5.25)	(4.91)	(5.01)
Region					
Adamawa	2.530•••	2.567•••	2.091••	2.125••	2.100••
	(3.70)	(3.80)	(2.98)	(3.00)	(2.98)
Akwa Ibom	0.341	0.387	0.418	0.440	0.511
	(0.69)	(0.84)	(0.77)	(0.79)	(0.95)
Anambra	0.345	0.313	0.149	0.207	0.158
	(0.88)	(0.85)	(0.34)	(0.45)	(0.35)
Bauchi	0.935	1.253•	0.814	0.948	0.710
	(1.44)	(1.96)	(1.20)	(1.34)	(0.87)
Bayelsa	2.170•••	2.234•••	2.141•••	1.855••	1.924••
	(3.71)	(3.92)	(3.71)	(3.02)	(3.14)
Benue	1.703•••	1.851•••	1.594•••	1.589•••	1.516•••
	(4.31)	(4.74)	(3.73)	(3.50)	(3.40)
Borno	4.840•••	5.053•••	4.101•••	4.143•••	3.886•••
	(4.31)	(4.67)	(3.62)	(3.68)	(3.42)
Cross River	0.0963	0.248	0.272	0.187	0.176
	(0.16)	(0.42)	(0.42)	(0.26)	(0.25)
Delta	1.228••	1.230••	1.123•	1.082•	1.113•
	(2.79)	(2.94)	(2.37)	(2.16)	(2.28)
Ebonyi	-0.720	-0.617	-0.776	-0.754	-0.901
	(-1.68)	(-1.50)	(-1.81)	(-1.62)	(-1.90)
Edo	0.427	0.410	0.348	0.349	0.346
	(0.97)	(0.95)	(0.75)	(0.72)	(0.73)
Ekiti	-1.642••	-1.724••	-2.175•••	-2.018••	-1.958••
	(-2.85)	(-2.83)	(-3.37)	(-3.11)	(-2.98)
Enugu	0.121	0.167	-0.0694	-0.0723	-0.143
	(0.26)	(0.38)	(-0.13)	(-0.13)	(-0.26)
Federal Capital Territory	0.254	0.289	-0.0208	0.0527	0.0227
	(0.67)	(0.85)	(-0.05)	(0.12)	(0.05)
Gombe	1.455	1.693•	1.030	1.122	1.085
	(1.85)	(2.12)	(1.17)	(1.23)	(1.20)

Imo	-0.200	-0.241	-0.211	-0.214	-0.275
	(-0.41)	(-0.48)	(-0.43)	(-0.43)	(-0.54)
Jigawa	-0.00490	0.225	-0.823	-0.788	-0.627
	(-0.00)	(0.20)	(-0.68)	(-0.66)	(-0.54)
Kaduna	1.647***	1.837***	1.497**	1.575**	1.394**
	(3.84)	(4.63)	(3.26)	(3.27)	(2.80)
Kano	1.138	1.398	0.869	1.031	0.853
	(1.59)	(1.96)	(1.16)	(1.32)	(1.03)
Katsina	0.244	0.510	-0.347	-0.0580	-0.151
	(0.21)	(0.46)	(-0.28)	(-0.05)	(-0.12)
Kebbi	-0.824	-0.600	-1.057	-0.952	-1.135
	(-1.20)	(-0.90)	(-1.48)	(-1.30)	(-1.54)
Kogi	0.718*	0.684*	0.449	0.479	0.417
	(2.04)	(2.05)	(1.11)	(1.11)	(0.97)
Kwara	-0.655	-0.602	-0.760	-0.754	-0.864
	(-1.56)	(-1.52)	(-1.80)	(-1.65)	(-1.92)
Lagos	0.734	0.798	0.908	0.850	0.837
	(1.10)	(1.22)	(1.33)	(1.18)	(1.18)
Nassarawa	0.756	0.830	0.768	0.767	0.718
	(1.11)	(1.29)	(1.11)	(1.08)	(1.04)
Niger	0.563	0.648	0.271	0.267	0.241
	(0.87)	(1.06)	(0.43)	(0.42)	(0.37)
Ogun	-0.286	-0.262	-0.0435	-0.0427	-0.187
	(-0.48)	(-0.47)	(-0.08)	(-0.07)	(-0.31)
Ondo	-0.0798	-0.129	-0.0523	-0.00234	-0.0909
	(-0.17)	(-0.31)	(-0.12)	(-0.00)	(-0.18)
Osun	-0.691	-0.642	-0.563	-0.517	-0.600
	(-1.24)	(-1.16)	(-0.94)	(-0.82)	(-1.01)
Oyo	-0.0507	-0.0331	-0.0642	-0.0540	-0.117
	(-0.11)	(-0.08)	(-0.15)	(-0.11)	(-0.26)
Plateau	2.219***	2.401***	2.110***	2.126***	2.061***
	(5.38)	(6.40)	(5.04)	(4.85)	(4.74)
Rivers	1.715***	1.809***	1.683***	1.438**	1.488**
	(3.67)	(4.11)	(3.54)	(2.80)	(2.93)
Sokoto	0.462	0.748	0.149	0.460	0.190
	(0.50)	(0.80)	(0.15)	(0.46)	(0.18)
Taraba	1.653***	1.915***	1.694***	1.532**	1.500**
	(3.69)	(4.06)	(3.42)	(3.01)	(3.02)
Yobe	2.460**	2.575**	1.614	1.212	0.876
	(2.70)	(3.06)	(1.66)	(1.26)	(0.87)
Zamfara	0.600	0.893	0.358	0.580	0.359
	(0.79)	(1.22)	(0.41)	(0.71)	(0.39)
Constant	2.897	3.300*	0.938	0.904	4.088
	(1.69)	(2.05)	(0.47)	(0.46)	(1.68)
Observations	176	176	176	176	176

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Constant: year=2005 region= Abia

Uganda Regression Results

Uganda Regression Results, Violent Events

	(1) violent_events	(2) violent_events	(3) violent_events	(4) violent_events	(5) violent_events
temperature	1.831	2.595•	7.116•	10.84•	25.40
	(1.73)	(2.38)	(2.33)	(2.36)	(1.75)
precipitation	-1.000•••	0.00375	-0.738	-1.418	2.235
	(-3.52)	(0.01)	(-1.11)	(-1.78)	(0.83)
police		5.983•••	22.29•	24.79••	37.66•••
		(3.49)	(2.44)	(3.07)	(5.14)
post office		-10.14••	-15.41•••	-2.709	14.86
		(-3.29)	(-3.61)	(-0.14)	(0.53)
fighting		-6.341•••	-3.250	-3.081•	8.811•
corruption		(-7.74)	(-1.67)	(-1.97)	(2.09)
temp*police			-16.97	-23.19	-11.09
			(-1.52)	(-1.66)	(-0.59)
precip*police			1.103	2.101	-2.556
			(0.69)	(0.84)	(-0.57)
temp*post office				-22.85	-26.17•••
				(-1.88)	(-3.59)
precip*post office				2.981	1.149
				(1.23)	(0.18)
temp*corrupt					-8.032
					(-1.34)
precip*corrupt					-0.749
					(-0.64)
Year					
2005	0.854	1.338••	0.681	0.651	1.576•
	(1.19)	(2.95)	(1.37)	(1.31)	(2.24)
2008	-0.0283	-1.003•••	-0.583	-0.470	-1.040•
	(-0.05)	(-4.10)	(-1.61)	(-1.42)	(-2.46)
2012	-0.528	-3.807•••	-2.428•	-2.264•	-3.919••
	(-0.57)	(-8.74)	(-2.56)	(-2.57)	(-3.11)
2015	-0.805	-2.286•••	-1.925•••	-1.928•••	-1.981•••
	(-0.97)	(-6.40)	(-5.74)	(-5.49)	(-4.08)
2017	-2.882•••	-5.141•••	-4.004•••	-3.733•••	-6.790•••
	(-4.76)	(-10.40)	(-4.65)	(-4.46)	(-4.23)
Region					
Eastern	-2.362•	0.983	-0.120	-0.316	2.536
	(-2.01)	(0.73)	(-0.10)	(-0.39)	(1.49)
Central	-3.007••	-1.316	-1.713•	-1.765••	0.483
	(-2.80)	(-1.36)	(-2.31)	(-3.27)	(0.33)
Western	-3.979•••	0.465	-1.123	-1.266	1.789
	(-4.07)	(0.51)	(-1.00)	(-1.49)	(0.78)
Constant	7.301••	11.68•••	4.368	2.987	-33.19•
	(2.73)	(7.47)	(1.02)	(0.66)	(-2.18)
Observations	22	22	22	22	22

t statistics in parentheses
• $p < 0.05$, •• $p < 0.01$, ••• $p < 0.001$
Constant: year=2002 region= Northern

Zimbabwe Regression Results

Zimbabwe Regression Results, Violent Events

	(1) violent_events	(2) violent_events	(3) violent_events	(4) violent_events	(5) violent_events
temperature	-0.195	0.432	0.656	0.0996	6.254***
	(-0.35)	(0.72)	(0.86)	(0.14)	(3.48)
precipitation	0.514	0.534*	0.371	0.404	2.571***
	(1.95)	(2.15)	(1.18)	(1.31)	(4.13)
police		-1.013	-6.386	-27.28	-26.60
		(-0.86)	(-0.60)	(-1.28)	(-1.42)
post office		-0.742	-0.572	30.15	12.54
		(-0.61)	(-0.45)	(0.99)	(0.45)
fighting corruption		-0.847	-0.725	-1.047	22.93***
		(-1.41)	(-1.18)	(-1.55)	(4.78)
temp*police			-0.272	9.353	10.34*
			(-0.16)	(1.70)	(2.07)
precip*police			0.603	-0.127	-0.293
			(0.77)	(-0.07)	(-0.16)
temp*post office				-11.15	-6.853
				(-1.79)	(-1.19)
precip*post office				0.275	0.559
				(0.11)	(0.23)
temp*corrupt					-4.138***
					(-3.97)
precip*corrupt					-1.244**
					(-3.24)
Year					
2009	-0.506	1.076	1.129*	0.986	0.748
	(-1.77)	(1.90)	(1.96)	(1.79)	(1.95)
2012	-0.639**	0.0966	0.170	-0.202	-0.268
	(-2.61)	(0.30)	(0.49)	(-0.47)	(-0.71)
2014	-1.337***	-0.926**	-0.840*	-0.823*	-1.174***
	(-5.79)	(-2.60)	(-2.26)	(-2.28)	(-4.16)
2017	-0.470**	0.176	0.262	0.417	0.264
	(-2.89)	(0.50)	(0.66)	(1.09)	(0.91)
Region					
Matabeleland South	0.491	0.252	0.184	-0.0483	-0.120
	(0.96)	(0.46)	(0.32)	(-0.10)	(-0.24)
Manicaland	2.694***	2.950***	3.003***	2.714***	2.428***
	(3.80)	(3.34)	(3.50)	(3.94)	(4.11)
Mashonaland Central	1.785**	2.140***	2.113***	1.990***	1.668***
	(3.11)	(3.65)	(3.61)	(4.02)	(3.82)
Masvingo	1.923**	1.703*	1.639*	0.957	0.625
	(3.22)	(2.56)	(2.33)	(1.04)	(0.66)
Midlands	1.660**	1.769**	1.813**	1.421*	1.158*
	(3.17)	(2.59)	(2.66)	(2.22)	(2.19)
Bulawayo	1.016	1.369*	1.377*	0.935	0.385
	(1.77)	(2.24)	(2.19)	(1.63)	(0.79)
Mashonaland West	2.225***	2.497***	2.501***	2.135***	1.748***
	(4.98)	(4.29)	(4.35)	(4.25)	(3.76)
Mashonaland East	2.114**	2.593***	2.646***	2.212***	1.846**
	(3.24)	(3.37)	(3.50)	(3.31)	(3.21)
Harare	3.728***	4.454***	4.564***	3.885***	3.768***
	(7.55)	(6.12)	(6.27)	(5.58)	(5.99)
Constant	-3.484	-4.329	-3.633	-1.513	-39.94***
	(-0.97)	(-0.97)	(-0.73)	(-0.34)	(-4.50)
Observations	50	50	50	50	50

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Mali Regression Results

	(1) violent_events	(2) violent_events	(3) violent_events	(4) violent_events	(5) violent_events
temperature	0.936	1.030	3.651	0.672	-5.149
	(0.43)	(0.56)	(1.56)	(0.66)	(-1.79)
precipitation	0.0716	0.994	1.066	0.0745	0.831
	(0.15)	(1.48)	(1.34)	(0.10)	(0.16)
police		-3.572•	-37.22•	28.86	-20.36
		(-2.15)	(-2.34)	(1.21)	(-0.27)
post office		4.035••	3.165	-207.9•	-65.94
		(3.02)	(1.88)	(-2.03)	(-0.35)
fighting corruption		2.450•	2.357	1.400	-16.11
		(1.98)	(1.41)	(0.84)	(-0.43)
temp*police			3.673	0.936	-1.489
			(1.62)	(0.38)	(-0.86)
precip*police			1.482•	-2.763	2.006
			(2.32)	(-1.13)	(0.33)
temp*post office				9.135••	9.499••
				(2.88)	(2.89)
precip*post office				13.62	1.718
				(1.85)	(0.12)
temp*corrupt					2.665
					(1.55)
precip*corrupt					0.617
					(0.22)
Year					
2005	0.220	0.543	-0.00536	-0.605	2.119
	(0.18)	(0.33)	(-0.00)	(-0.35)	(0.64)
2008	2.905•	1.816	0.820	2.197	-0.0317
	(2.38)	(1.24)	(0.49)	(1.51)	(-0.01)
2012	1.749	3.402	-5.579	2.145	6.746
	(0.26)	(0.63)	(-0.76)	(0.49)	(1.32)
2014	4.737•••	4.469•••	5.052•••	4.505•••	4.863
	(4.52)	(3.47)	(3.93)	(3.93)	(1.79)
2017	6.068•••	7.050•••	7.571•••	7.581•••	8.239••
	(5.54)	(4.92)	(4.87)	(5.73)	(2.89)
Region					
Gao	0.295	1.658	-5.947	-0.939	6.420
	(0.06)	(0.44)	(-1.00)	(-0.19)	(1.45)
Kayes	-16.22•••	-17.43•••	-19.92•••	-18.91•••	-16.47•••
	(-15.32)	(-16.10)	(-10.50)	(-11.35)	(-11.69)
Kidal	-0.670	-1.195	-12.04	-3.489	3.482
	(-0.10)	(-0.20)	(-1.35)	(-0.60)	(0.66)
Koulikoro	-0.622	-1.940	-4.741	-3.911	-0.901
	(-0.78)	(-1.84)	(-1.68)	(-1.14)	(-0.41)
Mopti	1.232	-0.230	-4.485	-1.517	2.718
	(0.71)	(-0.12)	(-1.22)	(-0.52)	(1.03)
Ségou	0.512	-0.321	-2.809	-1.237	1.766
	(0.60)	(-0.31)	(-1.29)	(-0.54)	(0.95)
Sikasso	-1.953	-2.794•	-2.550••	-1.522	-2.261
	(-1.42)	(-2.02)	(-2.72)	(-1.34)	(-1.10)
Timbuktu	-1.628	-1.499	-13.75	-2.964	4.641
	(-0.20)	(-0.23)	(-1.39)	(-0.49)	(0.79)
Constant	-6.575•	-22.77•	-27.28	-6.567	1.206
	(-1.97)	(-2.11)	(-1.73)	(-0.48)	(0.02)
Observations	51	51	51	51	51

t statistics in parentheses
• $p < 0.05$, •• $p < 0.01$, ••• $p < 0.001$
Constant: year=2002 region= Bamako

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