Conflict versus Disaster-induced Displacement: Similar or Distinct Implications for Security?

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Abstract

Recent research has found evidence for a linkage between conflict induced-displacement and violence. Yet, displacement is also caused by natural disasters, whose implications for security have until now not received much attention. Drawing on spatial data on flood-induced disasters and forced migration in Africa, we investigate the impact of migration caused by natural disasters on social conflict. We show that disaster-induced displacement differs from conflict-induced displacement and raises distinct security implications. We also consider if areas simultaneously affected by conflict and disaster-induced migration are particularly at risk of conflict. The results suggest that there is no such amplifying effect.

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Introduction

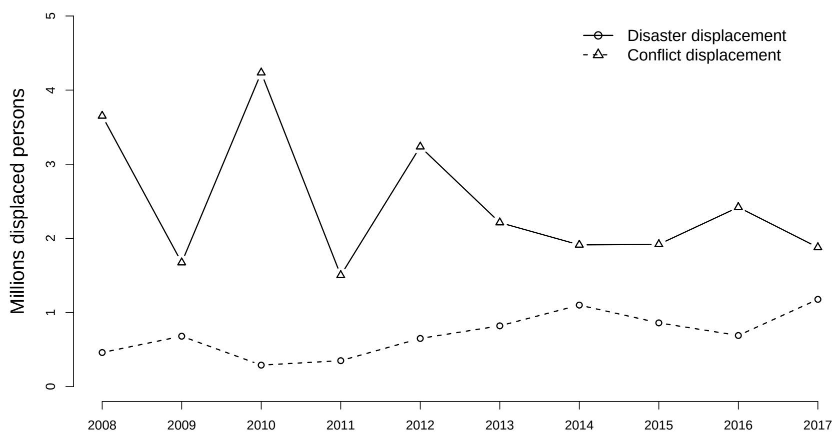
Worldwide, more people than ever before have been displaced because of conflict (UNHCR, 2018: 2). And yet, every year, the total number of newly displaced persons due to disasters, such as droughts and floods, is considerably higher, as Figure 1 reveals. In 2017, for instance, 18.8 million people had been newly displaced by disasters, exceeding the total for displacement due to conflict by more than 7 million (IDMC and NRC, 2018: 2). As a result of climate change, the World Bank expects that more than 140 million people could be forced to move internally by 2050 (Rigaud et al., 2018). Thus, disaster-induced displacement has become a prominent issue which raises grave protection and security concerns (International Rescue Committee, 2019).

Yet, while conflict researchers have investigated the role of conflict-displacement on violence dynamics (e.g. Lischer, 2005; Salehyan and Gleditsch, 2006; Bohnet, Cottier and Hug, 2018; Fisk, 2019; Braithwaite, Salehyan and Savun, 2019), these have to a large extent ignored disaster-induced displacement until recently (Ghimire, Ferreira and Dorfman, 2015; Koubi et al., 2018; Nordqvist and Krampe, 2018; Brozska, 2018; Brzoska, 2019). In fact, fewer still have analysed the effect of both conflict and disaster-induced displacement together, even though these forms of displacement routinely occur simultaneously in some countries, such as South Sudan and Colombia (IDMC and NRC, 2018). We aim to fill this gap and, thus, consider the following research questions:

> *Does disaster-induced displacement play a significant role in social conflict dynamics? And, how does this role differ compared to conflict-induced displacement?*

While disaster-hit countries benefit from international aid, negative externalities might still appear when tensions between the displaced and host communities arise. IDMC and NRC (2013: 6) warn that populations displaced due to a disaster are at 'increased risk of being neglected, unprotected and left without durable solutions the longer they are displaced.' In addition, people displaced by natural disasters are not covered by existing international protection regimes (Thomas, 2014; Ferris, 2019). Furthermore, when natural disasters and conflict strike together, high levels of insecurity

Figure 1. New conflict and disaster-induced displacement (IDMC and NRC, 2018: 2).



can arise, because of the inability to distribute aid and reduced levels of social cohesion (Walch, 2013).

In the following, we carry out an analysis of the effects of flood-induced displacement on social conflict, relying on data on flood-affected first-order administrative units in Africa from 1991 to 2011. Our contribution is two-fold. First, we develop a theoretical argument linking flood-induced displacement to social conflict. Second, we then examine the empirical validity of our argument. We focus on flood-induced displacement as floods present one of the major types of disasters, and their frequency as well as intensity is generally rising (UNESCO, 2012: 23). Between 2008 and 2018 floods were the primary cause of weather-related displacement (IDMC and NRC, 2018: 32). Africa faces particularly high risk of flood-induced displacement even at low- to mid-level flood exposure (Kakinuma et al., 2020). Across Sub-Sahran Africa, an estimated 2.6 million were forced to move because of disasters in 2017, with Somalia and Ethiopia among the ten countries most affected by disasters. For instance, Cyclone Idai is estimated to have displaced a quarter of a million inhabitants in Mozambique, Malawi and Zimbabwe (OCHA, 2019).

In the next section, we review the literature on the link between disasters and social conflict. We then present the theoretical underpinnings of our empirical study. Next, we introduce the research design and discuss the results of the empirical analysis. We conclude with putting our results in a broader context of forced migration and sketching avenues for future research.

Literature Review: The link between environmental change, disasters and social conflict

Concerns about the environment, migration and domestic, as well as international security have become increasingly salient both in policy-making and academic research (McLeman and Gemenne, 2018: 3). Yet, few scholars have considered the impact of disaster-induced displacement on security and conflict. In fact, the existing literature has until recently been largely restricted to studies conducted by international organizations or national governments (e.g. Clark, 2007; Walch, 2010), indicating that disaster-induced displacement until now has been mostly approached through a humanitarian lens.

While research on the link between environmental change and conflict has rarely considered disaster-induced displacement (Homer-Dixon, 1999; Goldstone, 2001; Kahl, 2006; Hendrix and Salehyan, 2012; Fjelde and von Uexkull, 2012; Raleigh and Kniveton, 2012; Salehyan and Hendrix, 2014), migration has often featured as a potential intervening factor. In general, the arguments found in the literature have centered on the role of '[...] resource scarcity and competition over the means to sustain livelihoods' (Salehyan, 2008: 316). Moreover, large-scale population movements could also cause group identity conflicts, in particular when natives hold a distinct ethnic or political identity (Homer-Dixon, 1999: 141; Goldstone, 2001: 100).

For its part, the literature on disasters and conflict has largely ignored the issue of displacement and has reported divergent empirical results (Brozska, 2018). For example, Theisen and Slettebak (2011: 21), focusing on Indonesia, find support for the claim that climatic disasters such as floods, in contrast to geological disasters, increase the risk of violence, as disasters increase inequalities between groups. Similarly, Nel and Righarts (2008) and Besley and Persson (2011: 1433) argue that disasters are positively associated with violence. Eastin (2016), moreover, shows that natural disasters can prolong conflict. By contrast, Slettebak (2012) and Bergholt and Lujala (2012) reach the opposite conclusion, that disasters are not linked to conflict, even though they observe that disasters have adverse effects on economic growth.

Nel and Righarts (2008) point out that different dynamics might apply in minor and major conflicts, but most studies on disasters until now do not consider lower levels of violence, including social unrest and communal violence. Indeed, Ghimire, Ferreira and Dorfman (2015) did not find evidence for a link between flood-induced displacement and the onset of armed conflict. As Suhrke (1997) has indicated, however, people displaced by disasters are often powerless, making protests or riots more likely than armed conflict (see also Hendrix and Salehyan, 2012). Blocker, Rochford and Sherkat (1991) similarly underline that natural disasters need to be regarded within a social movement framework.

Koubi et al. (2018) and Spilker et al. (2020) are some of the few who have recently advanced the analysis of disaster-induced displacement, the latter underlining that the reason for migration can determine the social acceptance of migrants. Those moving because of sudden-onset disasters, the authors argue, might be more accepted by the host population than those of slow-onset (e.g. drought) as they will most likely leave again. Yet, both studies focus on perceptions of migrants by host populations, rather than on conflict *per se*. In this article, we fill this gap and present, what is to our knowledge, the first disaggregated study of both disaster- and conflict-induced displacement and their effects on the social conflict dynamics.

Theory

Although forced migration is viewed as an important causal variable linking disasters with conflict (Gleditsch, Nordas and Salehyan, 2007; Ghimire, Ferreira and Dorfman, 2015), the exact causal mechanisms remain poorly understood (Brzoska and Fröhlich, 2016: 192) and empirical findings have been mixed (Koubi et al., 2018; Brozska, 2018).

Unequal distribution, state failure and deterioration of livelihoods

Drawing on the environmental change literature, we propose in this section that disaster-induced displacement may lead to conflict via three distinct mechanisms or pathways: *unequal distribution and competition over resources*, *the worsening effects of disaster on livelihoods* and *state failure*, whereby state capacity can also function as a mediator between the first two. While we assume that disaster-induced displacement can heighten the risk of conflict, we acknowledge that theoretical arguments exist that predict either no or the opposite association. We take into account some of these counterarguments, yet our hypotheses focus on the former as 'solid evidence' exits that disasters can cause violence, not by themselves (Brozska, 2018: 323), but possibly through displacement and its effect on hosting communities. Subsequently, we discuss how conflict-induced internally displaced persons (IDPs) may affect the risk of social conflict and derive expectations about how the joint presence of disaster- and conflict-induced displaced persons may reinforce the risk of of social conflict.

Three potential outcomes for disaster-induced displacement can occur: acceptance, return or conflict (Clark, 2007). In general, disaster-induced displaced persons can self-settle in spontaneous camps, live with relatives, or be assisted by aid organizations in organized camps. The newcomers can then either be accepted at the new location to which they travel to or be rejected. Often those who have family ties or who receive assistance by aid agencies can make a smooth transition to a new, even if temporary, life in their new surroundings. The acceptance at the new location depends partly on the attitudes of the host population, including the expectations that displaced persons will not represent an economic burden (Spilker et al., 2020). Yet, many people displaced by disasters are not able to return home shortly and remain stranded (IDMC, 2020).

It has also been argued that exposure to a disaster might increase solidarity (Drury et al., 2016) and that those fleeing because of sudden onset disasters may be less likely to perceive conflict at their new location as they are exposed to adverse consequences of environmental disasters only shortly (Koubi et al., 2018). Yet, competition over scarce resources might still generate grievance, particularly where populations are concentrated or where different ethnic groups come together (Hsiang, Burke and Miguel, 2013; Clark, 2007; Salehyan, 2008; Goldstone, 2001; Bhavnani and Lacina, 2015). Shifts in ethnic settlement patterns and competition over housing and jobs —that might arise because of the influx of disaster-induced displaced persons into a new region— could potentially lead to conflict 'between newcomers and members of local communities' (Swain et al., 2011: 96; Reuveny, 2007; Hendrix and Salehyan, 2012; Schleussner et al., 2016). In addition, as Mobjoerk, Krampe and Tarif (2020) underline, when affected populations are marginalized, those losses can increase the risk of local tensions and violence.

Moreover, flooding, by destroying crops and reducing arable land, has the potential to cause conflicts over food prices (Hendrix and Salehyan, 2012; Fjelde, 2015; Smith, 2014; Brozska, 2018: 6) and access to land (Walch, 2010; Thomas, 2014). In Mozambique after the 2000 floods violence arose out of a post-flood resettlement program due to a conflicting land tenure regime (Wiles, Selvester and Fidalgo, 2005: 6). Disasters can also create tensions between communities by contaminating water supply (Walch, 2010: 16).

Grievances may also arise when aid —from governments or international agencies— is unequally distributed. For instance, local elites, such as influential landowners, might use their political networks to redirect disaster aid distribution in their favor (Nordqvist and Krampe, 2018; Mobjoerk, Krampe and Tarif, 2020). Unequal access to aid could lead marginalized groups, such as displaced persons, to mobilize in protest. In this regard, Brzoska (2019: 9) underlines that violent conflict is especially likely where 'degrees of income loss and resource availability tend to differ among various potentially conflicting groups' and aid is unequally distributed (see also Ide, 2015; Brozska, 2018). Sri Lanka offers an illustration of the mechanism. In the aftermath of the 2004 tsunami, the 'Tamils complained that the government failed to provide adequate assistance and Muslims felt ignored and discriminated against,' which led to renewed intercommunal tensions and conflict (Mitra and Vivekananda, 2015: 4).

Typically, the state is responsible for providing help when disasters strike (Bhavnani, 2006; Siddiqi, 2018). However, when the state or political institutions fail to perform, ensures the delivery of external aid or privileges one group over the other, discontent among displaced communities could emerge (Kahl, 2006; Harris, Keen and Mitchell, 2013; Mobjoerk, Krampe and Tarif, 2020). Goldstone (2001: 93f) asserts that the response of regimes to disasters is key in predicting conflict outbreak: 'Natural disasters provide an opportunity for the regime to display its flaws or to demonstrate its competence. Where the latter is shown, natural disasters can be a cause of increased support of the government; but where the flaws come to the fore, political unrest and violence is a widely observed response' (see also Bhavnani, 2006; Mobjoerk and van Baalen, 2016; Brzoska, 2019). Because of both grievances and opportunity, poor responses by governments to natural disasters may thus increase the risk of conflict.

Recent floods in Côte d'Ivoire demonstrate how the failure of the state to provide assistance may generate resentment. In this case, displaced persons voiced anger at the lack of adequate response by the state after floods in 2014 (IRIN, 2014). Similarly, urban food riots arose in Maputo, Mozambique due to food shortages and heightened food prices after floods in September 2010 (Swain et al., 2011: 90). Repeated floodings in Mozambique in the past had demonstrated the government's inability to provide basic public goods and food, as well as organize rescue operations, generating substantial discontent among segments of the population.

Furthermore, armed groups can present themselves as 'alternative service and relief providers where governments are unresponsive' (Mobjoerk, Krampe and Tarif, 2020) or weak. Armed groups might thus use natural disasters for their tactical purposes. These include increased recruitment tactic, as well as using violence to secure their own food security (Nordqvist and Krampe, 2018; Walch, 2018*b*; Mobjoerk, Krampe and Tarif, 2020). This has been observed, for example, after extreme floods in the Philippines and Pakistan. While disasters can also temporarily weaken the position of armed groups (Walch, 2018*b*), the long-term effects are less clear (Nordqvist and Krampe, 2018). By contrast, support or aid by the government can mitigate the negative impact of disasters on the livelihoods of people affected, which can, in turn, reduces the motivation for them to mobilize (Barnett and Adger, 2007; Brzoska, 2019) or join armed groups.

Most studies on disasters stress the large adverse impact on livelihood conditions due to the loss of lives and economic assets (Brozska, 2018: 324). In Nigeria, for example, people affected by floods have had to search for alternative sources of income because farmlands were destroyed and crops washed away (Adeagbo et al., 2016). In addition, hikes in food prices can heighten local competition over scarce resources. Both these factors have been shown to be linked to collective violence because of heightened grievances (van Baalen and Mobjbörk, 2017; Ghimire, Ferreira and Dorfman, 2015).

While Koubi et al. (2018) posit that those affected by sudden-onset disasters have only 'short-term' grievances in contrast to those affected by slow-onset disasters (e.g. drought), we contend that the former are less well prepared to adapt to changes in the environment and, thus, can also hold strong grievances. In general, communities that can diversify their livelihoods (e.g. are not solely dependent on agriculture) have the highest capacity to adapt to the impact of disasters (Wisner et al., 2003; Few, 2003; Barnett and Adger, 2007; Armah et al., 2010; Krishnamurthy, 2012). Yet, those who lack these resources may be particularly vulnerable. In this context, communities that have been particularly severely hit by disasters may develop strong grievances because their livelihood options are very limited or non-existent. For instance, resource-dependent communities in North Mali, which had to cope with severe droughts and erratic rainfall, had incentives to join the Turaeg rebellion because of the severe effects on their livelihoods, as well as the economic and political marginalization they faced (Mitra and Vivekananda, 2015).

In this regard, floods can be particularly detrimental for people's livelihoods as they have less time to adapt or develop peaceful resource sharing mechanism in contrast to slow-onset disasters (Mobjoerk and van Baalen, 2016; Mobjoerk, Krampe and Tarif, 2020). Consequently, we argue that people whose livelihoods are threatened as a result of disasters, including floods, might mobilize in protest and potentially resort to violence or join armed groups. As they are forcefully displaced, their willingness to adjust at their new location might also be reduced. Hence, they may be more willing to engage in conflict and violence. This is particularly likely when people are affected by both gradual and sudden events (Koubi et al., 2021). In addition, a large influx of disaster-induced displaced persons may be perceived as threatening to the host community as they may fear for the security of their livelihood, which can lead to tensions. (Nordqvist and Krampe, 2018). Hence, not just availability of livelihoods, but perceptions also determine conflict (Nardulli, Peyton and Bajjalieh, 2015; Brzoska, 2018).

In sum, disaster-induced displacement could lead to social conflict because of (1) increased resource competition and unequal distribution of aid, (2) state failure and (3) loss of livelihoods and perception of livelihood insecurity. Consequently, we hypothesize that:

> *H1: Administrative regions affected by flood-induced displacement face an increased risk of social conflict.*

Instead of expecting civil war violence, we argue that disaster-induced displacement rather leads to lower-level conflict, such as demonstrations and riots. Although the former cannot be ruled out, we believe it unlikely in the case of disaster-induced displacement because '[protests] and riots do not require the high levels of organizations or funding typical of rebellion' (Hendrix and Salehyan, 2012: 37, see also Fjelde and von Uexkull, 2012). In fact, people displaced by disasters are frequently vulnerable and have access to only limited resources for mobilization.

Disaster- versus conflict-induced displacement

Does disaster-induced displacement raise distinct security implications, compared to displacement due to violence and civil war? In general, extant research suggests that conflict-induced displacement affects hosting areas through grievances and opportunity mechanisms for violence (Bohnet, Cottier and Hug, 2018). Opportunity factors, for example, include supply of personnel to rebel groups, while motivational factors comprise loss of land and marginalization. Ferris (2008) outlines that both conflict- and disaster-induced displacement, have the same protection needs. However, she emphasizes that appropriate responses may differ. First, those displaced by disaster might be able to return more rapidly than those displaced by conflict. Second, disaster-induced displaced persons often receive more assistance as governments accept international aid, while they tend to restrict the amount of aid provided to conflict IDPs (Ferris, 2008). Field (2018) shows that, within the same country, people displaced by disasters are considered to be more deserving of aid, while those displaced by conflict are often ignored (see also

Spilker et al., 2020). Third, persons internally displaced by conflict are often not formally recognized as persons of concerns. Consequently, they might hold particularly strong grievances. At the same time, and similarly to people displaced by disasters, conflict-induced displaced persons often have to cope with unequal access to aid, discrimination, forced relocation, sexual and gender-based violence, loss of documentation, recruitment and issues of property, which might lead to tensions and new conflict (Ferris, 2008).

In this regard, a rich literature has found evidence for a link between refugee and IDP flows and security, in particularly if displaced populations are concentrated and when the state capacity is low (Whitaker, 2003; Lischer, 2005; Salehyan and Gleditsch, 2006; Böhmelt, Bove and Gleditsch, 2019; Rüegger, 2019; Fisk, 2019; Braithwaite, Salehyan and Savun, 2019). Although most IDPs situations do not result in violence, some could lead to the expansion of rebel networks, facilitate the spread of arms and ideologies conducive to conflict, as well as alter the local ethnic balance.[1] Hence, we hypothesize that:

> *H2: Administrative regions affected by conflict-induced displacement face an increased risk of social conflict.*

The question thus arises: *What if an administrative region is struck by both conflict and disaster?* The lack of attention in the literature to this question is problematic. Harris, Keen and Mitchell (2013: vii) point out that from 2005 to 2009 more than 50 percent of people displaced were affected by both natural disasters and conflict, and that disasters have the potential to 'exacerbate pre-existing conflicts.' At the same time, disasters might produce a ripe moment for conflict resolution and, thus, rather than causing new conflict, might make peace agreements more likely. Yet, the failure to find support for the hypothesis in the literature casts doubt on its validity. In fact, while 'the aftermath of disasters may temporarily stop hostilities,' it often does not 'lead to a formalized settlement of the conflict issues' (Kreutz, 2012: 484, see also Walch, 2018*a*). On balance, Siddiqi (2018: S168) highlights that 'disasters in conflict areas are constructed, created and sustained in the pursuit of political goals.'

Although people affected by both disaster and conflict might 'just try to survive' and therefore not necessarily have the capacity to engage in contentious actions, they still might hold strong grievances (for an illustration in the case of South Sudan, see Davies, 2014). Walch (2013) outlines five ways in which disasters might causes news grievances in conflict areas. First, early-warning systems might be neglected. Second, in addition to hindering the flow of emergency aid, national and international financial and human resources could be diverted. In this regard, Mabiso et al. (2014) points out that conflict situations can also hinder the flow of emergency aid and hamper food security. Third, infrastructure could be disrupted, reducing the ability to quickly reach those in need. Fourth, disaster and conflict striking together can undermine social cohesion. Particularly, where ethnic groups are already divided and ethnic tensions exist, disaster occurrence may increase the likelihood of conflict (Schleussner et al., 2016). Fifth, disasters create insecurity as humanitarian actors could become targets of violence by rebel groups (Walch, 2013).

In fact, Ghimire, Ferreira and Dorfman (2015) and Eastin (2016) report that natural disasters, such as floods, can lengthen the duration of civil wars by negatively impacting state capacity and facilitating recruitment among aggrieved populations displaced by the state. Also, Barnett and Adger (2007) underline that those deprived by disasters might more easily be recruited by rebel groups.[2] Furthermore, disasters can intensify pre-existing inequalities (Wisner et al., 2003; Ide, 2015) and with this raising grievance levels. Consequently, we hypothesize that:

> *H3: Administrative regions affected by both flood- and conflict-induced displacement face an increased risk of social conflict. The risk is higher than in those administrative regions that are affected by flood- or conflict-induced displacement alone.*

Data and methods

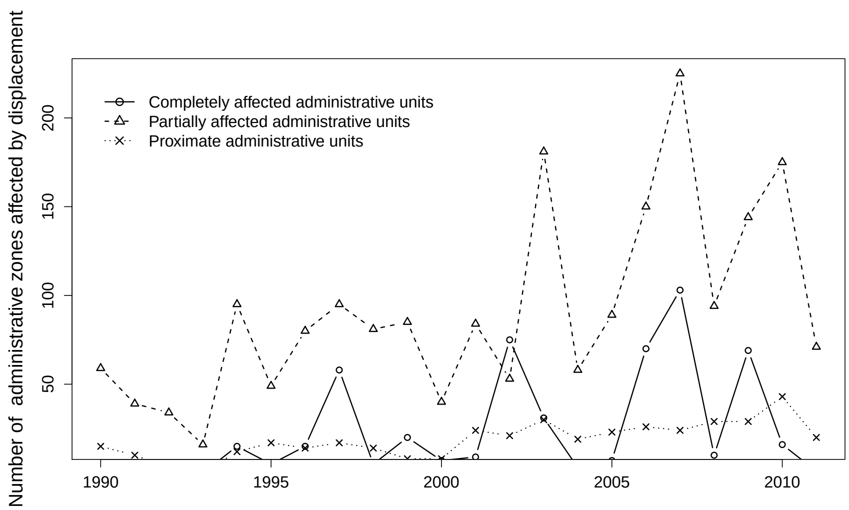
Our empirical analysis is carried out on a sample of first-order administrative units (e.g. province, state or district depending on the country) comprising the whole African continent over the period 1991–2011. This allows us to examine whether locations affected by flood-induced displacement experience a heightened risk of social conflict and compare it to previous research on the security implications of internal displacement (Bohnet, Cottier and Hug, 2018). In addition to drying trends over the course of the 21$^{\text{th}}$ century, the intensity of rainfalls on the continent is predicted to increase as well (Stocker et al., 2013: 1234, 1267–8). Studying how flood-induced displacement affects social conflict in Africa — a continent highly exposed to flood-induced displacement (Kakinuma et al., 2020) — may thus contribute to our understanding of how climate change may influence social outcomes in contexts characterized by high vulnerability and a limited adaptive capacity.[3]

Independent variables

Data on flood-induced displacement is provided by the Global Archive of Large Flood Events of the *Dartmouth Flood Observatory* (Brakenridge, 2014).[4,5] The dataset provides estimations of displaced persons and, more importantly, geo-references each disaster since 1985 (see also Ghimire, Ferreira and Dorfman, 2015). Using the *Dartmouth Flood Observatory*, we compute three independent dichotomous (and mutually exclusive) variables, which respectively indicate if an administrative zone has been a) fully or b) partially affected by a large flood event recorded in the Global Archive of Large Flood Events dataset, or c) is located in its direct vicinity ($\leq$ 25 km).[6] We use a 25 km threshold as the literature on displacement caused by sudden-onset natural disasters generally holds that displacement normally occurs over a short distance, as people above all attempt to flee from destruction and physical harm caused by floods (Findley and Geddes, 2011: 143; Piguet, 2020). The breakdown of public infrastructure and transport systems, as well as resource scarcity makes more distant travel difficult. Moreover, evidence from Bangladesh has shown that persons displaced due to floods seek shelter within just a few kilometers from the disasters (Zaman and Weist, 1991). Maps of first-order administrative zones are provided by the 2008 Global Administrative Unit Layer (GAUL) dataset (FAO, 2008).[7]

In a second step, we disaggregate our indicators further by generating three additional dichotomous indicators that record if any of these three types of administrative zones have been affected by a flood event that led to a displacement of at least 1'000 persons

Figure 2. Frequency of flood-induced displacement (1990-2011)



during the corresponding year.[8] As before, these variables are mutually exclusive.[9] By proceeding in this way, we hope to isolate the impact on social conflict caused by displacement from distinct effects resulting from the destruction and damage brought about by floods. Figure 2 plots the annual frequencies of all three displacement variables. Despite the high variability of the data, there is some evidence for an increase of the frequency of disaster-induced displacement over-time, a fact which is consistent with current rainfall predictions in Africa (Stocker et al., 2013: 1267).

To investigate the interaction between conflict and flood-induced displacement we draw on the *Global Internal Displacement Patterns* (GIDP) dataset (Bohnet, Cottier and Hug, 2018). The GIDP dataset is a geo-referenced dataset, which systematically records if an administrative unit hosts conflict-induced IDPs in a given year.[10] The variable, *Conflict IDPs*, takes the value of 1, whenever an administrative zone in a given year is hosting conflict IDPs.

Dependent variable

The dependent variable, *social conflict incidence*, is a dichotomous variable. We generate the variable based on the *Social Conflict in Africa Dataset* (SCAD v. 3.0, Hendrix and Salehyan, 2012) and code individual administrative zones as affected by social conflict if they experience at least one social conflict event (i.e protests, strikes, riots or communal violence), in the corresponding year.[11,12]

Control variables

We control for the following confounding factors.[13] First, the frequency with which an administrative unit is exposed to floods may affect its ability to react to future displacements-induced by floods, as damage wrought by floods might negatively impact infrastructure. Hence, we control for the number of past occurrences of floods that have either affected the administrative zones or have occurred in its direct vicinity (within a distance of 25 kilometers) since 1990. In addition, we add a square term of this variable for the expectation that inhabitants of administrative zones, which regularly experience floods, may have adapted coping mechanisms to limit the impact of floods, thereby resulting in an inverted U-shaped relation between the frequency of floods and the risk of social conflict (Findley and Geddes, 2011; Brzoska, 2019).[14] In keeping with the literature, we control for the (log) population per administrative zone, as well as the (log) level of economic development. To do so, we draw on the *Gridded Population of the Word* (GPW v.3) dataset (CIESIN, 2005), which provides disaggregated data on population at a 2.5 arc-minute resolution. We derive the indicator of economic development from the G-Econ dataset (Nordhaus, 2006).[15,16]

In order to control for spatial and temporal diffusion effects, we add two dummy variables. The first measures whether a contiguous administrative zone located in the same country was affected by social conflict during the previous year, while the second is a temporally lagged dependent variable. Finally, we add a *peace years* variable, which counts the number of years since the last conflict in the same administrative unit, along with two polynomials of orders two and three (Carter and Signorino, 2010).

At the country level, we control for democracy, economic development (log GDP per capita at PPP constant) and economic growth, as well as (log) population and population growth. The data for the democracy variable comes from the the Polity IV (Gurr, Jaggers and Moore, 1989; Marshall, Jaggers and Gurr, 2011). We recode the *Polity* variable to attenuate possible concerns regarding endogeneity (Vreeland, 2008). The resulting variable, *xpolity*, varies between -6 and $+7$. We add a dichotomous variable, *anocracy*, that is coded positively, whenever a country's democracy score falls between -2 and $+3$ inclusive. The data for the economic and demographic variables come from the *World Development Indicators* (World Bank, 2013).

Finally, we add a control for the incidence of civil war-years at the country level, as armed conflict could have an impact on social conflict, either by restricting media reports on social conflict events that did not involve the use of violence, or by heightening the costs for actions, such as protests or strikes to potential participants (Hendrix and Salehyan, 2012: 42). The data on civil war years is obtained from the UCDP Onset of Intrastate Conflict Dataset (v4-2012, Gleditsch et al., 2002; Themnér and Wallensteen, 2013).

Methodology

The empirical analysis is carried out using binary cross-sectional times series logistic regressions with heteroskedasticity robust standard errors. The unit of analysis is the first order administrative zone – year.[17] In the first model, we test hypothesis H1.[18] Because of the potential presence of temporal dynamics, the model includes both lagged and immediate variables for disaster-induced displacement. The regression frame covers the whole period 1991–2011 or a total of 13,179 observations, structured around 44 African countries. A total of 1,785 cases of social conflict incidences are recorded. Table A.1 in the Appendix presents descriptive statistics for Model 1.

Due to the sparser data for conflict-induced displacement, subsequent models restrict the analyses to the period 2008–2011. The sample for these models contains a total of 2'663 observations in 43 countries, with 410 instances of social conflict. Model 2 replicates Model 1, while Model 3 provides tests of hypothesis 2, which states that conflict-induced displacement increases the risk of social conflict. Finally, with Model 4 we test hypothesis H3, which postulates that administrative zones jointly affected by flood- and conflict-induced displacement are particularly likely to witness incidences of social conflict. We therefore interact the conflict-induced IDPs variable, with each variable for flood events and flood-induced disaster displacement.

Results

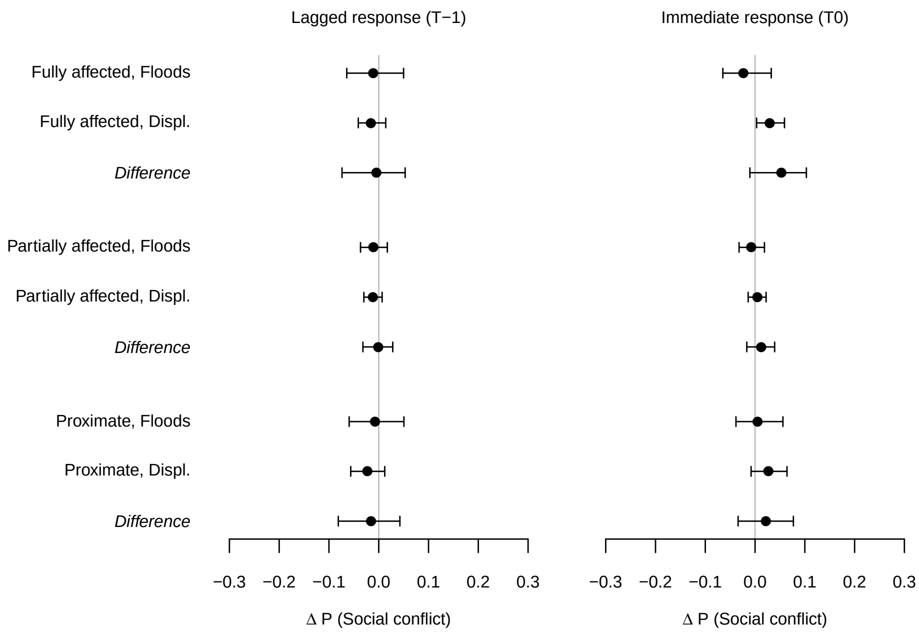
Table I presents our main results. In general, the results of Model 1 do not support hypothesis H1. Administrative zones affected by a flood or those near such zones are no more likely to experience social conflict if displacement has occurred. This is illustrated in Figure 3, where we depict average predictive differences in the probabilities of conflict for both contemporary and lagged variables (Gelman and Hill, 2006; Hanmer and Kalkan, 2013). The first two point estimates and the confidence intervals depict by how much the conflict probability would increase in our sample if an administrative zone was affected by a flood, respectively by flood-induced displacement, compared to a situation where no flood would have occurred. The third point estimate, and of primary interest for this paper, depicts the difference between the two previous estimates; in other words by how much the conflict probability would change, if an administrative zone had witnessed significant displacement following a flood, compared to a flood, which had not caused significant displacement.[19] As the figure shows, for each type of administrative zones affected by flood-induced displacement, we fail to find evidence for a specific effect of disaster-displacement. The point estimates of the differences in the average predicted differences are all close to zero, when it comes to both a *lagged* and a *immediate* effect on social conflict probability. The findings are coherent with claims in the literature, that disaster-induced displaced persons are too weak to voice dissent (Suhrke, 1997). Thus, fears that disaster-induced displacement will cause political instability is not supported by the data. There is, nevertheless, one exception to this trend, namely administrative zones fully affected by flood-induced displacement appear to face a higher risk of social conflict *immediately* after the disaster. This finding arguably signals that large displacements due to floods may lead to particularly strong grievances right after a disaster. The lack of a similar result for the lag displacement variable may be suggestive

Table I. Logistic Regression - social conflict incidence

	1991-2011	2008-2011		
	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Admin level				
disaster displ. (full overlap) $_{T0}$	0.668*	0.002		−0.081
	(0.396)	(0.614)		(0.531)
* conflict IDPs				0.813
				(0.644)
flood (full overlap) $_{T0}$	−0.333	0.636		0.800*
	(0.368)	(0.519)		(0.466)
* conflict IDPs				−1.402***
				(0.469)
disaster displ. (part. overlap) $_{T0}$	0.119	−0.122		−0.393
	(0.150)	(0.298)		(0.309)
* conflict IDPs				1.262**
				(0.601)
flood (partial overlap) $_{T0}$	−0.076	−0.084		0.066
	(0.134)	(0.263)		(0.268)
* conflict IDPs				−0.993*
				(0.556)
disaster displ. (near area) $_{T0}$	0.252	0.380		0.121
	(0.327)	(0.742)		(0.624)
* conflict IDPs				1.092*
				(0.607)
flood (near area) $_{T0}$	0.034	−0.200		−0.005
	(0.273)	(0.686)		(0.585)
* conflict IDPs				−0.987*
				(0.507)
disaster displ. (full overlap) $_{T-1}$	−0.044	0.473		0.458
	(0.395)	(0.791)		(0.546)
* conflict IDPs				−0.599
				(0.915)
flood (full overlap) $_{T-1}$	−0.146	−0.791		−0.817
	(0.366)	(0.761)		(0.527)
* conflict IDPs				0.677
				(0.874)
disaster displ. (part. overlap) $_{T-1}$	−0.001	0.305		0.155
	(0.146)	(0.274)		(0.284)
* conflict IDPs				0.340
				(0.554)
flood (partial overlap) $_{T-1}$	−0.104	−0.354		−0.312
	(0.133)	(0.263)		(0.266)
* conflict IDPs				−0.148
				(0.531)
disaster displ. (near area) $_{T-1}$	−0.158	0.602		0.487
	(0.364)	(0.723)		(0.564)
* conflict IDPs				0.166
				(0.482)
flood (near area) $_{T-1}$	−0.096	−0.836		−0.630
	(0.308)	(0.657)		(0.499)
* conflict IDPs				−0.511
				(0.363)
conflict IDPs			0.340**	0.324
			(0.164)	(0.242)
past floods	0.126***	0.083	0.062	0.095
	(0.032)	(0.060)	(0.057)	(0.059)
past floods ^{2}	−0.010***	−0.005	−0.005	−0.006
	(0.003)	(0.004)	(0.004)	(0.004)
income pc (log)	0.577***	0.416**	0.448**	0.408**
	(0.098)	(0.191)	(0.188)	(0.182)
population (log)	0.464***	0.174**	0.194**	0.180**
	(0.045)	(0.085)	(0.087)	(0.083)
temporal lag	0.974***	1.101***	1.098***	0.942***
	(0.122)	(0.267)	(0.267)	(0.184)
spatial lag t-1	0.286***	0.319**	0.303**	0.300**
	(0.067)	(0.144)	(0.144)	(0.145)
Country level				
xpolity t-1	0.012	0.005	0.0002	0.006
	(0.010)	(0.022)	(0.022)	(0.022)
anocracy t-1	−0.107	−0.072	−0.068	−0.064
	(0.069)	(0.175)	(0.172)	(0.173)
GDP pc (log) $_{T-1}$	−0.386***	−0.341**	−0.357**	−0.290*
	(0.072)	(0.157)	(0.154)	(0.148)
GDP growth t-1	0.001	−0.039**	−0.037**	−0.036**
	(0.004)	(0.017)	(0.017)	(0.017)
population (log) $_{T-1}$	−0.078**	0.074	0.067	0.074
	(0.038)	(0.081)	(0.081)	(0.079)
pop growth t-1	−0.135***	−0.269**	−0.272**	−0.244**
	(0.031)	(0.127)	(0.125)	(0.122)
civil war incidence	−0.112	0.142	0.061	0.042
	(0.073)	(0.160)	(0.170)	(0.171)
peace years	Yes	Yes	Yes	Yes
intercept	−3.901***	−2.227	−2.378*	−2.657*
	(0.679)	(1.450)	(1.430)	(1.420)
Observations	13,179	2,663	2,663	2,663
Log Likelihood	−3,815.217	−859.623	−863.600	−852.941
Akaike Inf. Crit.	7,688.434	1,777.246	1,763.201	1,789.883

Notes: heteroskedasticity robust standard errors in parentheses, $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

Figure 3. Average predictive differences in conflict probability due to floods and disaster displacement (1991-2011)



that a large share of the population displaced by a disaster is able to return within a year.[20]

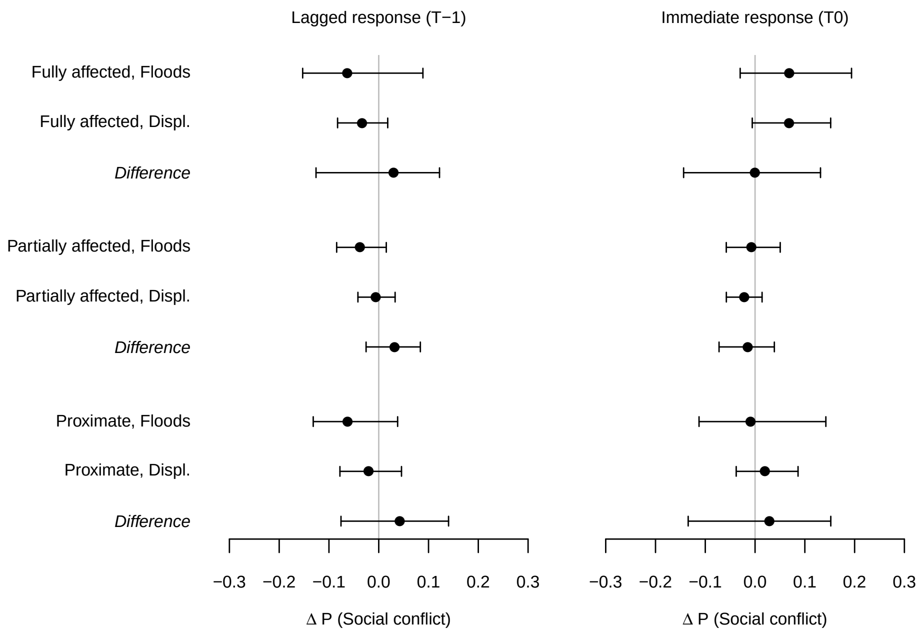
We now briefly discuss the control variables. As expected, we find an inverted U-shaped relationship between the number of past floods events and the risk of social conflict. This suggests that, while past flood events may increase the risk of social conflict, administrative zones exposed to recurrent flooding may have devised adaptation strategies to reduce the negative impacts of floods (Brzoska, 2019).[21] Unexpectedly, we find a positive association between the level of development of an administrative zone and the risk of social conflict. Without surprise, demographically larger administrative zones are more at risk of social conflict. As regards the temporal and spatial lag variables, these are positively and significantly related with the dependent variable, highlighting the importance of diffusion effects.

At the country level, neither the coefficient for *democracy*, nor the coefficient for *anocracy* are associated with social conflict. In general, the estimated coefficients indicate that democracies may possibly face a higher risk of social conflict. However, this may be the consequence of democracies tolerating, and, welcoming demonstrations, while non-democracies might repress them (see, for example, Wood and Wright, 2016). In addition, the results show that a higher GDP per capita at the country level is associated with a lower risk of social conflict, although no such association is found for economic growth. We also find that countries with a larger population or a higher population growth face a smaller risk of social conflict incidence. The latter could, however, be an artifact of the sample composed of African countries, with a generally high rate of population growth. Finally, despite a negative coefficient, ongoing civil wars do not appear to affect the likelihood of disruptive actions.

To assess hypotheses H2 and H3, we draw on conflict displacement data provided by the GIDP dataset. This has as consequence that the sample is reduced to the period 2008–2011. Model 2 reports in Table I the results of an identical specification as Model 1, estimated on the basis of the reduced time period. We depict in Figure 4 the immediate and lagged effects of floods and flood-induced displacement on average predictive differences in conflict probabilities. The point estimates for the estimated differences in the average predicted differences signals that the occurrence of flood-induced displacement does not substantially increase the likelihood of social conflict, as compared to administrative zones only affected by a flood, which did not cause any substantial displacements. While the results appear to show that an administrative zone fully affected by flood-induced displacement may face an *immediate* higher risk of conflict compared to not being hit by a flood, this effect is not distinguishable from the direct effect of a flood as depicted by the confidence interval for the estimated differences in the average predicted differences.

Taking this into account, we next present with the results of Model 3 a direct test of whether conflict IDPs increase the likelihood of conflict. As in previous analyses (Bohnet, Cottier and Hug, 2018), we find that the presence of conflict IDPs increases the risk of conflict diffusion, here measured as the incidence of social conflict. This result supports our second hypothesis. The average predicted difference shows that if all

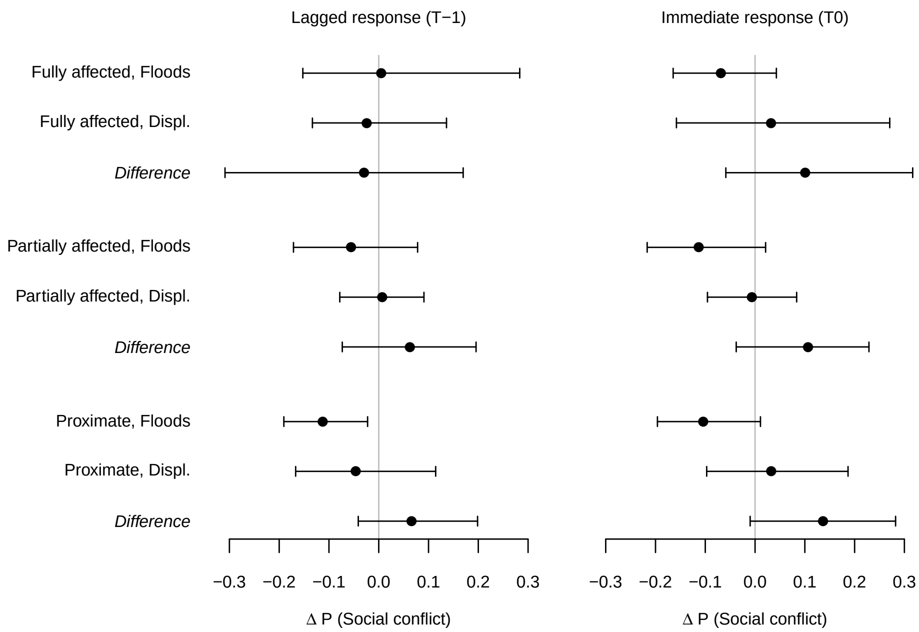
Figure 4. Average predictive differences in conflict probability due to floods and disaster displacements (2008-2011)



administrative units were to host conflict IDPs the average probability of social conflict would increase by 3.5 percentage point.[22]

Does the joint occurrence of conflict and displacement have a particularly large effect on the risk of social conflict? Combining the specifications of Models 2 and 3, we assess in Model 4 our third hypothesis by interacting the variable measuring whether conflict IDPs are present with the flood and disaster displacement variables.[23] In general, the point estimates depicted in Figure 5 suggest that flood-induced displacement, in regions already hosting IDPs, results in an *immediate* increase in the risk of social conflict, compared to the effect of a flood not having caused any large-scale displacement. Yet, the large uncertainty in the estimates does not permit to conclude that the joint occurrence of conflict- and flood- induced displacement increase the risk of social conflict. Interestingly, the results of Model 4 suggest that when a flood hits an administrative

Figure 5. Average predictive differences in conflict probabilities due to floods and disaster displacement in the presence of conflict IDPs



zone hosting conflict IDPs, but does not cause any displacement, the probability of conflict diminishes *immediately*.[24] This effect is, however, only statistically significant for administrative zones in close proximity to a flood event.[25]

The results of Model 4 do not appear to differ substantially from those of Model 2, when the same sets of simulations are carried out to reveal the effects of disaster-induced displacement in the absence of conflict IDPs.[26] Overall, the results of Model 4 lead to the rejection of hypothesis H3. Thus, we find no evidence that the simultaneous presence of conflict- and disaster-induced displacement has an amplifying effect on the incidence of social conflict, compared to the sole presence of conflict IDPs. In supplementary analyses, we examine the sensitivity of the results to alternative specifications, including separating peaceful from violent events, using a fixed effect linear regression or a negative binomial estimator, as well as re-estimating the models, but with an alternate source of data, the UCDP GED (Sundberg and Melander, 2013).[27] With minor caveats, the results of the sensitivity analysis do not alter the main conclusions of the analysis.

Conclusion

In this paper, we have assessed whether forced displacement due to floods increases the likelihood of social conflict. While earlier studies focusing almost exclusively on single countries have found mixed evidence for such a link, we offer more general evidence stemming from a large sample of African countries. Our novel analysis is currently in our knowldege the most comprehensive assessing the link between disaster displacement and conflict. Our results have shown that contrary to conflict IDPs, disaster-induced displacement does not significantly increase the likelihood of social conflict. In general, disaster-induced displaced persons seem too weak to voice dissent and engage in contentions actions (Suhrke, 1997). They may more easily rely on local support (e.g. extended family, community) than those displaced by conflict, explaining the low risk of conflict. Thus, based on our broader-based study, we find that alarmist claims that disaster displacement will lead to increased social conflict are currently exaggerated.

Conflict displacement, however, clearly increases the likelihood of conflict. Yet IDPs do not heighten conflict risks in administrative zones affected by disaster-induced displacement as hypothesized. Furthermore, the immediate effects of floods, absent any displacement, in areas hosting IDPs was generally negative. In this regard, the absence of displacement, following a 'large flood event,' may function as a crude indicator of the quality of a state's response to a flood event, as better disaster planning, early-warning systems and timely response may dramatically reduce the scale of any displacement. Thus, the state's reaction and support to populations affected by natural disasters, such as floods, might have a crucial impact on the likelihood of social conflict.

Future research should examine possible intervening factors, such as relief aid and social networks. In particular, social networks may help displaced persons mitigating the negative effects of disasters on their livelihoods. Conversely, it is also conceivable that these social networks might facilitate mobilization for contentious actions (Nardulli, Peyton and Bajjalieh, 2015: 327). Moreover, researchers should also consider the consequences of protracted displacement, in which people displaced by disasters remain stranded, unable or unwilling to return to their previous place of residence (IDMC, 2020). Indeed, there are reasons to fear that such a form of displacement may have particularly detrimental effects of political stability and the likelihood of social conflict.

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Declaration of interest statement

No potential conflict of interest was reported by the authors.

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Notes

1. For an overview of the link between conflict-induced displacement and violence, see Rüegger and Bohnet (2020) or the 2019 *Journal of Peace Research* special issue on 'Refugees, Forced Migration, and Conflict.'

2. In Pakistan, for example, Islamist militants have provided aid in return for membership, in addition to relying on forced recruitment

3. Adams et al. (2018) warns that research on climate change generally focuses on areas already experiencing frequent armed conflicts, such as Africa, which may lead to biased inferences. We do not wish to downplay these concerns. Yet, we believe these concerns are limited here, since we primarily examine the plausibility of our hypotheses, but cannot directly test the postulated mechanisms.

4. We refer to the appendix for a discussion of alternative data sources on flood-induced displacement.

5. By 'large' flood events, the Brakenridge (2014) refers to episodes, which have caused 'significant damage, to structures or agriculture, long (decades) reported intervals since the last similar event, and/or fatalities.'

6. We chose this coding scheme to generate a more granular measure of the extent to which an area has been affected by flood-induced displacement. We do not have *a priori* expectations as to which of these three types of zones is more likely to be associated with social conflict (see also the discussion in the appendix).

7. For more information on the FAO GAUL dataset, we refer to footnote 3 in the appendix.

8. We chose 1'000 persons as a threshold to exclude floods that might have led to population displacement but the scale of which is unlikely to have caused a significant burden for the state and local authorities.

9. These three displacement variables displacement are by definition a subset of the corresponding flood variables. In other words, if an administrative zone is completely affected by flood- induced displacement, the same zone is also coded as fully affected by floods. Nevertheless, because a few administrative zones may have been affected by more than one flood in a given year, which may not all have caused displacement, there is a risk of a discrepancy in the coding of the flood and displacement variables. To solve this issue, we force the coding of the flood variables to reflect the coding of the flood-induced displacement variables.

10. For more information about the content of the GIDP dataset, see Bohnet, Cottier and Hug (2018).

11. Social conflict events that revolved exclusively around any of the five following issues were systematically

excluded, as they are unlikely to be related to disaster-induced displacement : 'Elections,' 'foreign affairs/relations,' 'domestic wars,' 'violence, terrorism,' 'pro-government' (Salehyan and Hendrix, 2012). Social conflict events, which involved 'pro-government violence' or 'intra-governmental violence,' are also exclused, because the theory does not address repression, nor conflict within the state. Finally, we removed events which could not be geo-located at a level of precision equal or higher to the first order administrative zone.

12. We note that the SCAD is not exempt of limitations. In particular, its reliance on newswires from the Agence France Presse and Associated Press is susceptible to induce a selection bias with events occurring in major urban areas, as well as events of larger magnitude, more likely to be reported (Weidmann, 2015). In spite of its limitations, we opted for the SCAD to measure social conflict events over existing alternatives, such as the ACLED (Raleigh et al., 2010; ACLED, 2019), because its exclusive reliance on newswires make events reporting more consistent over time and space.

13. While it would have been interesting to examine how these control variables may moderate the effects of disaster-induced displacement on social conflict, we are here primarily interested in how displacement *directly* affects the odds of conflict. Moreover, extending the empirical analysis to the examination of interaction effects would have gone beyond the scope of the present article. We thus leave this aspect for future research.

14. We also replaced the flood count variable by a variable counting the number of flood events having caused a displacement of at least a 1'000 persons, but the results are similar to those we report in Table I.

15. The 1 degree cell resolution of the G-Econ dataset is problematic as the G-Econ cells frequently overlap administrative boundaries. Therefore, we generate a population-weighted dataset with a resolution equal to a 2.5 arc-minute.

16. Both the GPW and the Nordhaus datasets are available at five year intervals (from 1990 to 2000 for the former, respectively 2005 for the latter). We extrapolate interval years for the entire period 1990-2011.

17. Variables at the country level only serve as controls and, given the hierarchical structure, will yield coefficients with standard errors that are underestimated.

18. Unfortunately, our data only allows us to examine the link between disaster-displacement and social conflict, but we cannot directly test the causal mechanisms posited.

19. In order to obtain conservative estimates, each set of simulations was conducted only on the sub-sample of administrative zones, which has been fully, respectively partially affected by floods, or was located in close proximity to one.

20. The estimated differences in the average predicted differences for fully affected administrative zones is distinct from zero at the 90 percentile for the immediate response.

21. We provide further illustration in Figure A.1 in the Appendix, which depicts average simulated probabilities at varying levels of past occurrence of floods.

22. The 95% confidence interval extends over the interval bounded between +0.001 and +0.070.

23. Because we encounter a problem of separation due to the large number of interaction terms included in this specification and the restricted time range, we estimate this model using Bayesian generalized linear models (see arm package in R, Gelman and Hill, 2006).

24. This result must be interpreted in light of the fact that administrative units hosting conflict IDPs already possess a higher than average risk of conflict.

25. The point estimate of the difference in the average predicted differences for administrative zones in proximity to a flood is distinct from zero at the 90% confidence interval.

26. Average simulated probabilities for the effects of flood-induced displacement in the absence of conflict IDPs are depicted in Figure A.2 of the Appendix.

27. Models 5–16 in Table A.2–A.3 of the Appendix present the results of the sensitivity analysis.

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Conflict versus Disaster-induced Displacement: Similar or Distinct Implications for Security? *Online appendix*

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In this Appendix, we present additional information on the sample and discuss the results of the sensitivity analysis. Section 1 provides complementary information on the *Dartmouth Flood Observatory* data and outlines the process used to generate the variables measuring the occurrence of floods and flood-induced displacement. Next, in Section 2, we report the descriptive statistics for the variables used in the analyses presented in the main text and the sensitivity analyses (see Table A.1). Additionally, Figure A.1 depicts average simulated probabilities for the effects of the past exposure of an administrative zone to floods on social conflict (based on estimates from Model 1), while Figure A.2 depicts average simulated probabilities for the effects of flood-induced displacement in the absence of conflict IDPs (based on estimates from Model 4). Finally, the last section, Section 3, presents and discuss the results of the sensitivity analyses.

1 Flood-induced displacement

In this section, we review available data on disaster displacement. We then provide an in-depth discussion of the *Dartmouth Flood Observatory*'s Global Archive of Large

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Flood Events (Brakenridge, 2014) and the operationalization of the main independent variables, which measure whether an administrative zone has been affected by flood-induced displacement.

To assess the effect of natural disaster-induced displacement, we need data on the location of people displaced by natural disasters. Unfortunately, to our knowledge, the only existing dataset on the precise location of displaced populations in Africa, the *IOM Displacement Matrix* (DTM), is available for only selected cases of disasters and conflict-induced displacements in Africa (e.g. Sudan, Nigeria, Mali).[1] In fact, the coverage of the DTM is often limited to specific areas of a given countries, where displacement has occured frquently in recent times, such as north-eastern Nigeria. Systematic data on disaster-induced displacement remains thus limited, particularly when it comes to spatial information on the location of natural disasters and displaced persons.

The most obvious source of data with a broad spatial coverage on environmental disasters is the *EM-DAT International Disaster Database* hosted by the *Center for the Research on the Epidemiology of disasters* at the Catholic University of Louvain, Belgium (CRED, 2009). Unfortunately, the data only provides information on the number of affected persons and those made homeless. The latter category has been shown to substantially under-estimate the scale of displacement, while over-estimating it for the former (IDMC and OCHA, 2009, 8; see also IDMC, 2019, 38). In addition, the data provided is aggregated at the country-level and therefore does not allow for the spatial localization of disasters. A recent extension to the EM-DAT, the Geocoded Disasters (GDIS) dataset, provides georeferenced information on the locations of disasters listed in the EM-DAT dataset at the first-order administrative level, and in some cases down to the second- and third-administrative unit levels (Rosvold and Buhaug, 2021). While a major contribution for future research on disasters, this newly available dataset suffers from the same limitations as the EM-DAT when it comes to data on displacement.

Other existing datasets on natural disasters suffer from similar limitation. While *MunichRE* has also collected data on natural disasters, its dataset is to our knowledge not publicly available, and data on displacement is not systematically provided (IDMC, 2019, 34). Similarly, the data collected by the *International Federation of Red Cross*

[1] For access to the data, see `https://dtm.iom.int/`.

and Red Crescent Societies does not systematically provide information on the scale of displacement resulting from disasters (IDMC, 2019, 33).

The *UN High Commissioner for Refugees* appears to have been collecting data as well, but the coverage has remained restricted to countries having been affected by massive emergencies (such as the Haiti earthquakes or the 2010 floods in Pakistan), for which UNHCR was asked to provide assistance (UNHCR, 2013). Finally, the *Internal Displacement Monitoring Center*, an offshoot of the Norwegian Refugee Council, has been collecting high quality data on disaster-induced displacement for all sudden-onset disasters, which have affected at least 100'000 persons. This data, however, is only available from 2008 onwards and does not explicitly map the location of these disasters within countries (IDMC and OCHA, 2009).

In general, we chose the *Dartmouth Flood Observatory*'s Global Archive of Large Flood Events to construct our measure of displacement in light of its extent and systematic coverage of floods, disaggregated data on locations, and estimation of the number of displaced persons (Brakenridge, 2014). In particular, the dataset records every instance of floods reported by news or governmental agencies that are perceived by coders as 'large' (Dartmouth Flood Observatory, 2014). By 'large' flood event, the *Dartmouth Flood Observatory* refers to episodes, which did cause 'significant damage, to structures or agriculture, long (decades) reported intervals since the last similar event, and/or fatalities.' Flood events included in the *Dartmouth Flood Observatory* data are related to the following 'root' causes: heavy rain, tropical cyclone, extra-tropical cyclone, monsoon rain, snowmelt, ice-jam/break-up, dam/levy break or release, brief torrential rain, tidal surge or avalanche related (Dartmouth Flood Observatory, 2014). Estimates of the number of displaced persons are computed on the basis of media reports, or, if not available, by relying on the number of houses destroyed or damaged.[2] In addition, the dataset also geo-references the extent of the area affected by floods.

Using the *Dartmouth Flood Observatory* data, we generate two sets of dichotomous variables. The first set of dichotomous variables measures whether an administrative

[2]It should be mentioned that estimates of displaced persons provided by the *Dartmouth Flood Observatory* are probably conservative, as it evaluates that for each house destroyed or damaged only four persons are displaced (Dartmouth Flood Observatory, 2014).

zone was affected by a flood-event, which has caused the displacement of at least a thousand persons, while the second set codes whether an administrative zone was affected by a large flood event, irrespective of whether any displacement induced by a flood occurred and its the magnitude. Each set of dichotomous variables contains three mutually exclusive variables, which indicate if an administrative zone has been a) fully or b) partially affected by an instance of flood-induced displacement, respectively by a flood event, or c) is located in its direct vicinity ($\leq$ 25 km). We generate three indicators for each set of independent variables, as opposed to pool them together, because the effect of a flood event, respectively an instance of flood-induced displacement, may differ depending on the extent to which administrative zones have been affected by floods. To the extent that floods and flood-induced displacement vary considerably according to their magnitude, it may be that the spatial extent to which an administrative zone is affected by a flood influences the probability of social conflict. Similarly, administrative zones not directly affected by a disaster but located in close proximity to a flood event may possibly exhibit a differing ethnic make-up. In such a situation, an inflow of ethnically distinct displaced persons may also contribute to raise the risk of violence. As mentioned in the article, by generating two sets of independent variables, we hope to separate and isolate the impact on social conflict caused by displacement specifically, from distinct effects resulting from the destruction and damage brought about by floods.

To compute the two sets of independent variables on flood-induced displacement and flood-induced disaster, we rely on an indirect strategy by overlaying Global Archive of Large Flood Events with the Global Administrative Unit Layer (GAUL) (FAO, 2008),[3] which maps the first-order administrative zones of every country throughout the world. The spatial analysis to compute the independent variables was carried out in ArcGIS 10.1. To minimize distortion due to earth curvature, a 'world sinusoidal' projection was used for the source maps.

[3]'The Global Administrative Unit Layers (GAUL) is an initiative implemented by FAO within the EC-FAO Food Security Programme funded by the European Commission. The GAUL aims at compiling and disseminating the most reliable spatial information on administrative units for all the countries in the world, providing a contribution to the standardization of the spatial dataset representing administrative units [...] The GAUL keeps track of administrative units that have been changed, added or dismissed in the past for political causes' (FAO, 2008).

2 Summary statistics and additional statistics

Table A.1 presents descriptive statistics based on Model 1, Table 1 in the main text. Next, Figure A.1 depict average simulated probabilities of social conflict, as a function of the number of past flood events (based on the estimates of Model 1, Table 1 in the main text). Finally, Figure A.2 depicts average predictive differences in social conflict probabilities as a result of floods and flood-induced displacement in the absence of conflict-induced IDPs (based on the estimates of Model 4, Table 1 in the main text).

Table A.1: Descriptive statistics

Statistic	N	Mean	Median	St. Dev.	Min	Max
Dependent variables						
Social conflict incidence	13,179	0.131	0	0.338	0	1
Social conflict count	13,179	0.306	0	1.271	0	39
Peaceful conflict incidence	13,179	0.072	0	0.258	0	1
Violence conflict incidence	13,179	0.085	0	0.279	0	1
Non-state conflict incidence	12,532	0.030	0	0.172	0	1
Civil war incidence	12,532	0.103	0	0.304	0	1
Displacement and flood variables						
Disaster displ. (full overlap)	13,179	0.037	0	0.189	0	1
Disaster displ. (partial overlap)	13,179	0.128	0	0.334	0	1
Disaster displ. (near)	13,179	0.026	0	0.158	0	1
Flood (full overlap)	13,179	0.045	0	0.208	0	1
Flood (partial overlap)	13,179	0.177	0	0.381	0	1
Flood (near)	13,179	0.036	0	0.188	0	1
Control variables — Administrative level						
Past flood count	13,179	2.268	1	2.501	0	19
Admin gdppc (ln)	13,179	1.093	0.811	0.678	0.138	5.557
Admin pop (ln)	13,179	13.150	13.143	1.306	7.497	17.135
Spatial lag (social conflict)	13,179	0.288	0	0.453	0	1
Spatial lag (peaceful conflict)	13,179	0.177	0	0.382	0	1
Spatial lag (violent conflict)	13,179	0.205	0	0.404	0	1
Spatial lag (non-state conflict)	12,532	0.095	0	0.293	0	1
Spatial lag (civil war)	12,532	0.204	0	0.403	0	1
Contol variables — Country level						
Xpolity (lag)	13,179	0.078	−2	3.280	−6	7
Anocracy (lag)	13,179	0.553	1	0.497	0	1
Country gdppc (ln lag)	13,179	7.431	7.111	0.948	5.331	10.216
Country gdp growth (lag)	13,179	4.992	4.686	6.764	−50.248	106.280
Country pop (ln lag)	13,179	16.401	16.551	1.234	12.832	18.889
Country pop growth (lag)	13,179	2.559	2.659	1.070	−7.597	10.258
Civil war	13,179	0.367	0	0.482	0	1

Note: Summary statistics based on the sample of Model 1

Figure A.1: Average simulated probabilities of social conflict: past exposure to floods — Model 1 (1991–2011)

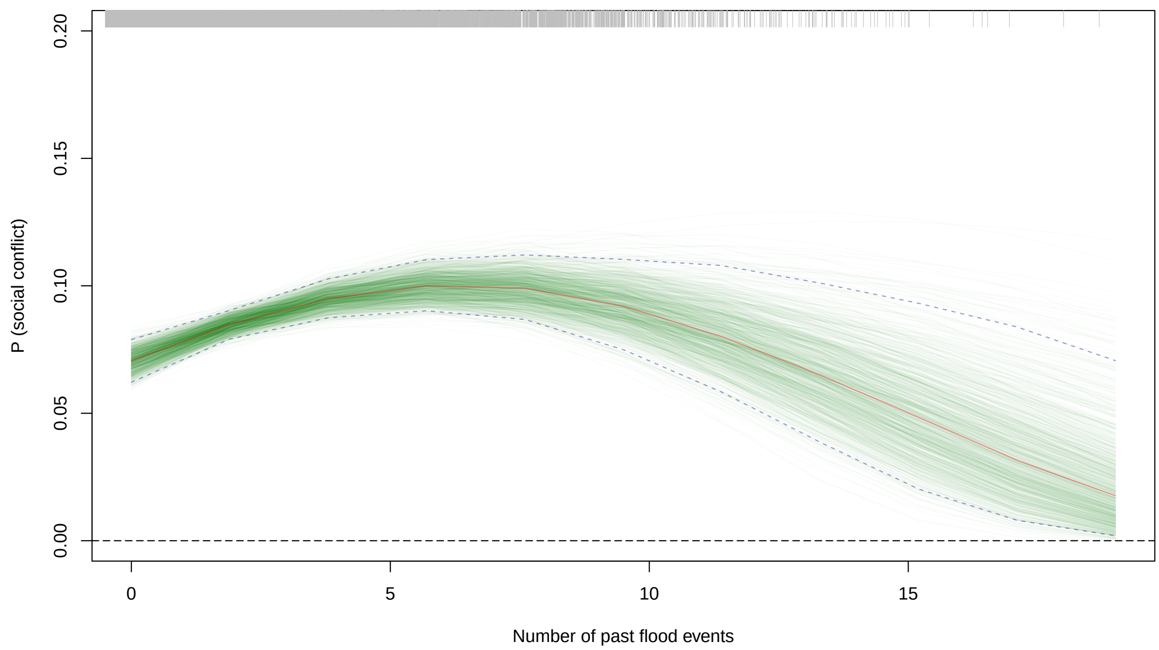
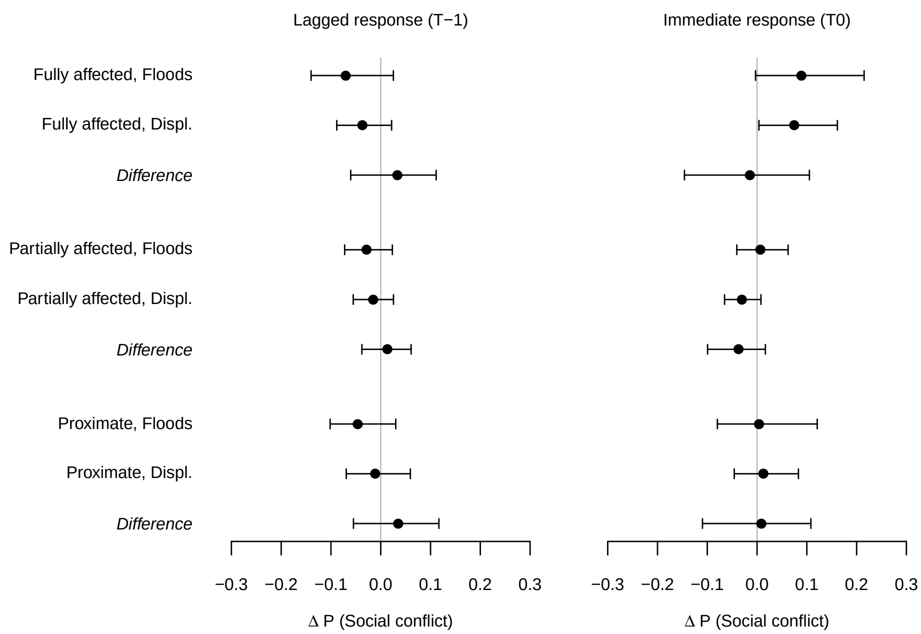


Figure A.2: Average predictive differences in conflict probabilities due to floods and disaster displacement in the absence of conflict IDPs — Model 4 (2008–2011)



3 Sensitivity analysis

In this section, we present the results of the sensitivity analysis. To assess the sensitivity of the results to alternative specifications, we carried out additional analyses for both Models 1 and 4. Table A.2 (Models 5–10) and Table A.3 (Models 11–16) present the results of the additional analyses for Model 1, respectively Model 4. In the ensuing section, we discuss in turn the results of the sensitivity analysis for each model. In discussing the results of the supplementary analysis, we focus, in general, only on the effects of flood-induced displacement relative to a flood (i.e. the difference in the estimates of the effect on the risk of social conflict of displacement induced by floods compared to the sole effect of floods).[4]

3.1 Sensitivity analysis: Model 1

The first two models examine whether restricting the measurement of the dependent variable to only social conflict events, which do not exhibit the use of violence (Model 5),[5] or are conversely coded as involving violence between distinct social groups or against the government (Model 6) affects our results.[6] The results of the analyses are depicted in Figures A.3–A.4. In general, neither the results of Model 5, nor of Model 6 appear to substantially alter the conclusions of Model 1 with regards to hypothesis H1. If anything, it would appear that the results of Model 1 more closely reflect the incidence of violent social conflict (Model 6). Thus, the results of these first two sensitivity checks suggest that disaster-induced displacement does not, in general, modify the probability of either peaceful social conflict, nor violent social conflict, compared to the direct impact of a flood.

Next, Model 7 reproduces Model 1 using a negative binomial regression with a

[4]We, however, comment occasionally on the estimates of the total effect of a flood or of a displacement, if these are particularly noteworthy.

[5]Under this specification, the dependent variable is restricted to only events categorized in the SCAD as ‘organized demonstration’, ‘spontaneous demonstration’, ‘general strike’ or ‘limited strike’ (Salehyan and Hendrix, 2012).

[6]Under this latter specification, the dependent variable is restricted only to events categorized in the SCAD as ‘spontaneous riot’, ‘organized riot’, ‘anti-government violence’ and ‘extra-government violence’ (Salehyan and Hendrix, 2012).

count dependent variable for social conflict.[7] Under this specification, we find qualified support for hypothesis H1 in Model 7. Administrative zones, which are fully affected by flood-induced displacement, as well as those located in direct proximity to a zone affected by flood-induced displacement, face an *immediate* higher frequency of social conflict (Figure A.5).[8] As before, we do not find evidence that these effects carry over time, as depicted by the confidence intervals for the difference between the lag effects on social conflict of disaster-displacement and floods in the left column of Figure A.5. In Model 8, we assess the sensitivity of Model 1 to unit heterogeneity. To this end, we implement a conditional (fixed effects) logistic estimator, with administrative zones fixed effects (Chamberlain, 1980).[9] Under this conservative specification, we cannot show the results of Model 1 graphically, as the conditional logit does not provide estimates for the fixed-effects. We thus are limited to inspect the coefficients shown in Table A.2. In general, the conclusions with regards to Hypothesis H1 are not affected by this conservative specification. With the exception of the estimate for the immediate effect of areas fully affected by a flood, which led to the displacement of at least a 1'000 people, none of the coefficients are statistically significant at conventional levels. Thus, we find little evidence that disaster-induced displacement systematically raises the odds of conflict.

Finally, the last two models examine the sensitivity of Model 1 to alternate forms of political violence. First, in Model 9, we rely on event data on non-state violence provided by the UCDP GED v1.5 (Sundberg, Lindgren and Padskocimaite, 2011; Sundberg, Eck and Kreutz, 2012; Sundberg and Melander, 2013). Reliance on the UCDP GED on non-state violence instead of the SCAD data does not appear to otherwise alter the previous conclusions as average predictive differences indicate in Figure A.6. Indeed, the occurrence of flood-induced displacement does not appear to have any distinct effect on the risk of non-state conflict compared to the effects of a flood. Last, but

[7]In the negative binomial models, the temporal and spatial lag variables no longer measure the incidence of social conflict in the previous year in the same administrative zone, respectively in neighboring administrative zones, but the number of such events.

[8]Nevertheless, these results should be cautiously approached, as we do not detect a similar immediate effect for zones, which are partially affected by disaster-induced displacement.

[9]We estimate the model using the `survival` package in R.

not least, Models 10 replaces the dependent variable with a variable measuring the incidence of civil war violence in an administrative zone, drawing again on the UCDP GED (Gleditsch et al., 2002; Sundberg, Lindgren and Padskocimaite, 2011; Sundberg and Melander, 2013). In line with theoretical expectations, we generally do not observe any evidence that the probability of civil war violence increases in the aftermath of flood-induced displacement (Figure A.7). There is, nevertheless, one exception to this trend. The results of Model 10 suggest that the incidence of disaster-displacement in an administrative zone located in proximity to a flood is susceptible to have an unexpected *immediate* pacifying effect on the incidence of civil war events, compared to the direct effect of a nearby flood.

3.2 Sensitivity analysis: Model 4

To evaluate the sensitivity of Model 4, which examines whether the presence of conflict IDPs amplifies the effect of flood-induced displacement on social conflict, we simply replicate the previous sensitivity analysis for Model 1. In general, it should be noted that, as a consequence of the problem of separation (Gelman and Hill, 2006), we alluded to in the main section of the article, the interval of confidence of some the models are substantial, or conversely, extremely small. This issue subsists in spite of the fact that all the models, except the negative binomial and conditional (fixed-effect) logit, are implemented based on a Baysian generalized linear specification (Gelman and Hill, 2006).[10]

As before, Model 11–12 examine the sensitivity of Model 4 to limiting the dependent variable to only peaceful social conflict events, respectively to only those events involving the use of violence. Unfortunately, the results of Model M11, which examines the association between disaster-displacement and the incidence of peaceful social conflict, are strongly affected by the problem of separation as depicted in Figure A.8. In general, it appears that these are neither coherent with the previous results for Model 4, nor with hypothesis H3. Interestingly, as revealed by Table A.3, not only is the coefficient for conflict IDPs not significant, its sign is also negative. This indicates that the presence

[10]As a result, we have adjusted the scale of the x-axis for the figures depicting the effect of floods and disaster-induced displacement for Models 11–16.

of conflict IDPs does not generally affect the risk of peaceful social conflict. The results of Model 12, which examines the effects of flood-induced displacement on violent social conflict, appear to be less affected by separation. In general, the estimates are broadly coherent with the results of Model 4. If anything, the results depicted in Figure A.9 suggest that the occurrence of flood-induced displacement in administrative zones fully affected by flooding and hosting conflict IDPs leads to a *delayed* increase in the risk of violent social conflict, relative to the impact of a flood. Finally, the results of Model 12 also indicate that the presence of conflict IDPs generally raises the risk of violent social conflict.

Next, Models 13 and 14 re-estimate Model 4 with a negative binomial estimator, respectively a conditional (fixed-effects) logit. Unfortunately, as these models are unable to account for separation, a number of coefficients display large estimates with even larger standard errors. We thus refrain from depicting the results of average predictive differences and do not interpret the coefficients.

Model 15 replicates Model 4, but replaces the dependent variable with the incidence of non-state conflict using the UCDP GED. In general, we find little evidence of a systematic association between disaster-displacement and an increased risk of non-state conflict, in presence of conflict IDPs. Nevertheless, the findings suggest that administrative zones hosting conflict IDPs and located in proximity to a flood, which caused significant displacement, face a *delayed* upward risk of non-state conflict, as compared to the direct effect of a flood (Figure A.10). Finally, in Model 16, we replace the dependent variable with a variable measuring the incidence of civil war violence. Unexpectedly, it appears that the incidence of flood-induced displacement in administrative zones hosting conflict IDPs may cause a decrease in the *immediate* risk of civil war conflict events, in particular for administrative zones fully affected by floods, or in close proximity to one (Figure A.11). By contrast, we find no evidence for a lagged effect.

Table A.2: Sensitivity analysis (Model 1)

	P. conflict	*V. conflict*	Social conflict		*Non-state*	*Civil war*
	(Model 5)	(Model 6)	(Model 7)	(Model 8)	(Model 9)	(Model 10)
Admin. level						
disaster displ. (full overlap) $_{T0}$	0.559	0.736	0.800^{**}	0.911^{*}	0.240	-0.222
	(0.462)	(0.476)	(0.357)	(0.502)	(1.087)	(0.564)
flood (full overlap)	-0.037	-0.448	-0.451	-0.812^{*}	-0.185	0.021
	(0.422)	(0.449)	(0.321)	(0.476)	(1.028)	(0.509)
disaster displ. (part. overlap) $_{T0}$	-0.400^{**}	0.180	-0.067	0.124	0.406	0.142
	(0.188)	(0.173)	(0.155)	(0.171)	(0.299)	(0.203)
flood (partial overlap) $_{T0}$	0.293^{*}	-0.138	-0.007	-0.116	0.153	0.242
	(0.153)	(0.157)	(0.141)	(0.154)	(0.290)	(0.172)
disaster displ. (near area) $_{T0}$	0.732^{*}	0.282	0.694^{**}	-0.041	-0.170	-1.174^{***}
	(0.431)	(0.394)	(0.285)	(0.361)	(0.604)	(0.399)
flood (near area) $_{T0}$	-0.345	-0.245	-0.427^{*}	0.039	0.403	0.913^{***}
	(0.362)	(0.330)	(0.235)	(0.307)	(0.489)	(0.293)
disaster displ. (full overlap) $_{T-1}$	0.114	-0.084	0.177	0.056	0.656	0.603
	(0.467)	(0.437)	(0.347)	(0.473)	(0.948)	(0.442)
flood (full overlap) $_{T-1}$	0.038	-0.153	-0.153	-0.342	0.015	-0.777^{**}
	(0.429)	(0.406)	(0.306)	(0.442)	(0.904)	(0.384)
disaster displ. (part. overlap) $_{T-1}$	0.012	0.020	0.011	0.012	-0.048	0.119
	(0.202)	(0.163)	(0.136)	(0.170)	(0.279)	(0.210)
flood (partial overlap) $_{T-1}$	-0.158	-0.159	-0.218^{*}	-0.001	0.416	-0.115
	(0.180)	(0.149)	(0.124)	(0.153)	(0.272)	(0.183)
disaster displ. (near area) $_{T-1}$	-0.254	-0.161	0.049	-0.424	0.478	0.374
	(0.465)	(0.410)	(0.287)	(0.384)	(1.056)	(0.461)
flood (near area) $_{T-1}$	0.205	-0.037	-0.179	0.044	-0.467	-0.094
	(0.387)	(0.347)	(0.238)	(0.327)	(0.997)	(0.392)
past floods	0.157^{***}	0.129^{***}	0.146^{***}	-0.094	0.005	-0.065
	(0.045)	(0.036)	(0.031)	(0.061)	(0.065)	(0.046)
past floods ^{2}	-0.014^{***}	-0.009^{***}	-0.006^{**}	-0.003	-0.002	0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
income pc (log)	0.883^{***}	0.429^{***}	0.377^{***}	2.035^{***}	-0.905^{***}	-0.405^{**}
	(0.128)	(0.113)	(0.085)	(0.660)	(0.340)	(0.192)
population (log)	0.572^{***}	0.422^{***}	0.298^{***}	1.910^{***}	0.309^{***}	0.330^{***}
	(0.065)	(0.050)	(0.050)	(0.641)	(0.073)	(0.051)
temporal lag	0.988^{***}	0.704^{***}	0.220^{***}	0.489^{***}	1.149^{***}	1.200^{***}
	(0.161)	(0.145)	(0.011)	(0.137)	(0.274)	(0.175)
spatial lag $_{T-1}$	0.126	0.557^{***}	0.018^{***}	0.433^{***}	0.897^{***}	1.091^{***}
	(0.097)	(0.079)	(0.007)	(0.091)	(0.155)	(0.107)
Country level						
xpolity $_{T-1}$	0.016	0.025^{**}	0.001	0.056^{***}	0.045^{**}	0.064^{***}
	(0.013)	(0.012)	(0.011)	(0.020)	(0.022)	(0.018)
anocracy $_{T-1}$	-0.115	-0.085	-0.136^{*}	0.567^{***}	-0.126	-0.076
	(0.090)	(0.080)	(0.070)	(0.131)	(0.143)	(0.096)
GDP pc (log) $_{T-1}$	-0.497^{***}	-0.343^{***}	-0.252^{***}	-0.936^{***}	0.310	0.530^{***}
	(0.092)	(0.082)	(0.065)	(0.342)	(0.206)	(0.134)
GDP growth $_{T-1}$	0.005	0.002	-0.0003	0.006	-0.034^{***}	0.005
	(0.006)	(0.005)	(0.004)	(0.006)	(0.009)	(0.007)
population (log) $_{T-1}$	-0.231^{***}	0.011	-0.023	-0.477	0.412^{***}	-0.367^{***}
	(0.052)	(0.044)	(0.040)	(0.736)	(0.093)	(0.063)
pop growth $_{T-1}$	-0.111^{***}	-0.144^{***}	-0.121^{***}	-0.303^{***}	0.041	-0.109^{***}
	(0.042)	(0.034)	(0.026)	(0.049)	(0.063)	(0.030)
civil war incidence	-0.162	-0.072	-0.078	0.097	0.693^{***}	2.851^{***}
	(0.099)	(0.084)	(0.075)	(0.112)	(0.136)	(0.163)
peace years	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	-2.574^{***}	-5.468^{***}	-2.685^{***}		-15.771^{***}	-5.403^{***}
	(0.881)	(0.786)	(0.705)		(1.880)	(1.257)
Observations	13,179	13,179	13,179	13,179	12,532	12,532
θ	—	—	0.465^{***} (0.024)	—	—	—
Log Likelihood	$-2{,}343.175$	$-3{,}067.736$	$-6{,}335.309$	-2257.646	$-1{,}116.873$	$-2{,}086.018$
Akaike Inf. Crit.	4,744.350	6,193.472	12,728.620	4571.291	2,291.745	4,230.037

Notes: heteroskedasticity robust standard errors in parentheses, †p<0.1; *p<0.05; **p<0.01

Figure A.3: Average predictive differences in conflict probability due to floods and disaster displacement (1991-2011) — Model 5

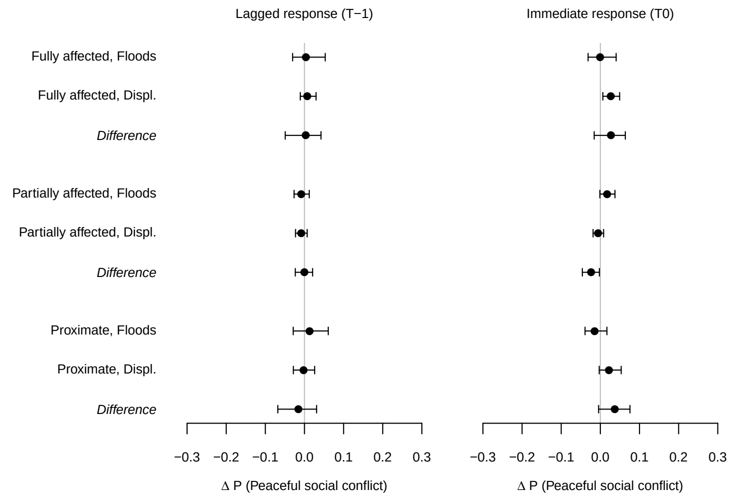


Figure A.4: Average predictive differences in conflict probability due to floods and disaster displacement (1991-2011) — Model 6

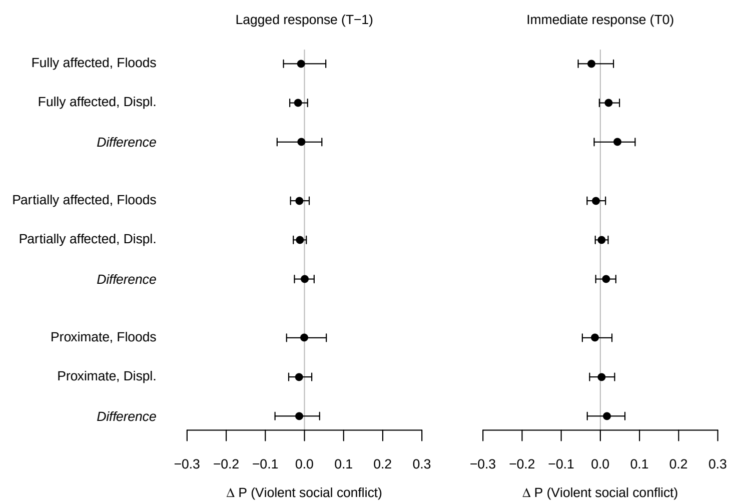


Figure A.5: Average predictive differences in number of conflict events due to floods and disaster displacement (1991-2011) — Model 7

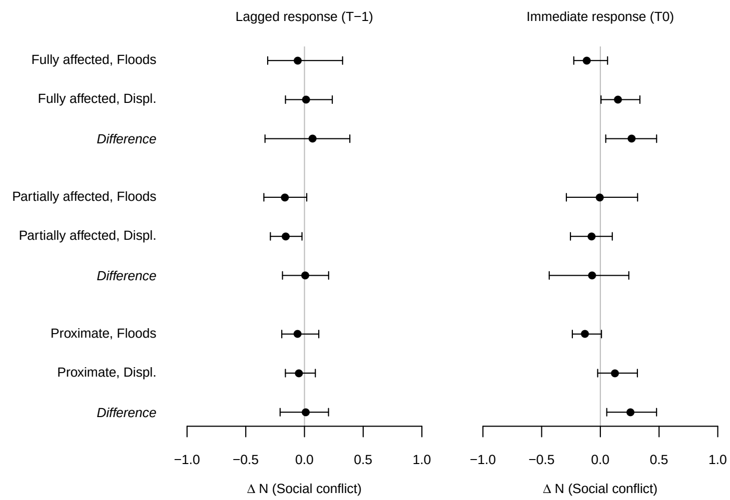


Figure A.6: Average predictive differences in conflict probability due to disaster displacement (1991-2011) — Model 9

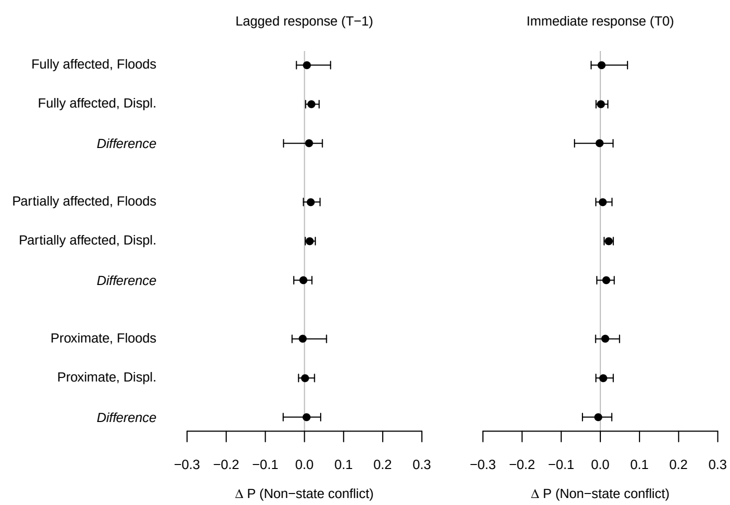


Figure A.7: Average predictive differences in conflict probability due to disaster displacement (1991-2011) — Model 10

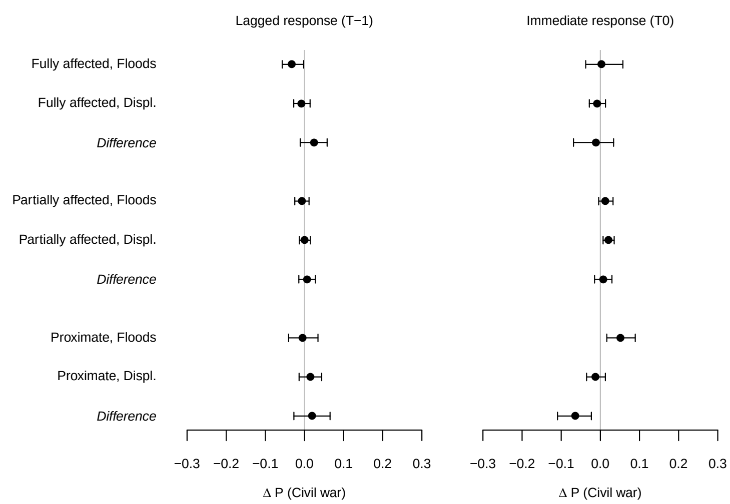


Table A.3: Sensitivity analysis (Model 4)

	P. conflict	*V. conflict*	Social conflict		*Non-state*	*Civil war*
	(Model 11)	(Model 12)	(Model 13)	(Model 14)	(Model 15)	(Model 16)
Admin. level						
disaster displ. (full overlap) $_{T0}$	0.194	−0.069	0.281	−1.447	−0.553	−0.931
	(0.545)	(0.617)	(0.536)	(1.625)	(0.831)	(0.854)
* conflict IDPs	−0.170*	0.992	32.205***	20.772	−0.234	−1.354*
	(0.095)	(0.693)	(0.721)	(5,279.303)	(0.183)	(0.715)
flood (full overlap) $_{T0}$	0.425	0.429	0.298	0.717	1.124	0.318
	(0.450)	(0.570)	(0.465)	(1.529)	(0.924)	(0.564)
* conflict IDPs	−0.495**	−0.985**	−32.914***	−16.786	−0.655	−0.013
	(0.217)	(0.474)	(0.524)	(5,279.303)	(0.409)	(1.016)
disaster displ. (part. overlap) $_{T0}$	−0.940**	−0.340	−0.845**	0.405	−1.124	−0.453
	(0.446)	(0.367)	(0.388)	(0.561)	(0.875)	(0.515)
* conflict IDPs	1.469***	1.031*	2.029**	−0.091	2.201***	0.577
	(0.496)	(0.601)	(0.868)	(1.249)	(0.796)	(0.641)
flood (partial overlap) $_{T0}$	0.275	−0.090	0.157	−0.724	0.694	1.034**
	(0.359)	(0.318)	(0.339)	(0.567)	(0.904)	(0.477)
* conflict IDPs	−1.082***	−0.596	−1.183	0.168	−1.859**	−0.458
	(0.392)	(0.552)	(0.826)	(1.154)	(0.805)	(0.613)
disaster displ. (near area) $_{T0}$	0.894	−0.527	0.381	−0.075	−0.575	−2.017***
	(0.722)	(0.716)	(0.595)	(1.052)	(0.787)	(0.774)
* conflict IDPs	−0.213	1.478**	34.857***	15.497	−0.079	0.410
	(0.456)	(0.611)	(0.788)	(7,030.632)	(0.557)	(0.583)
flood (near area) $_{T0}$	−0.371	−0.022	−0.388	−0.223	1.803**	1.916***
	(0.697)	(0.655)	(0.517)	(0.956)	(0.715)	(0.689)
* conflict IDPs	−0.563	−0.484	−34.609***	−15.105	−0.964*	−0.272
	(0.409)	(0.490)	(0.719)	(7,030.632)	(0.515)	(0.469)
disaster displ. (full overlap) $_{T-1}$	0.447	0.651	0.564	0.612	−0.118	0.139
	(0.558)	(0.600)	(0.810)	(1.310)	(0.672)	(0.482)
* conflict IDPs	−3.115***	0.438	−0.629	−2.213	−0.197	−1.357*
	(1.203)	(0.429)	(1.345)	(3.432)	(0.461)	(0.798)
flood (full overlap) $_{T-1}$	−0.262	−0.883	−0.344	−1.582	1.890***	0.657
	(0.534)	(0.580)	(0.774)	(1.283)	(0.686)	(0.410)
* conflict IDPs	1.591	−0.481	0.312	1.921	−0.547	−0.757
	(1.497)	(0.341)	(1.252)	(3.277)	(0.433)	(0.544)
disaster displ. (part. overlap) $_{T-1}$	0.137	0.493	0.001	0.622	0.622	−0.341
	(0.388)	(0.355)	(0.298)	(0.572)	(0.521)	(0.492)
* conflict IDPs	1.135***	−0.066	0.691	0.042	0.081	−0.151
	(0.389)	(0.564)	(0.632)	(1.024)	(0.668)	(0.600)
flood (partial overlap) $_{T-1}$	−0.092	−0.685**	−0.020	−1.188**	−0.084	0.489
	(0.350)	(0.334)	(0.282)	(0.600)	(0.487)	(0.474)
* conflict IDPs	−0.732**	0.275	−0.785	0.610	0.243	0.191
	(0.327)	(0.546)	(0.609)	(0.992)	(0.620)	(0.563)
disaster displ. (near area) $_{T-1}$	0.022	0.428	0.264	0.581	0.071	−0.842
	(0.606)	(0.628)	(0.641)	(1.260)	(0.219)	(0.780)
* conflict IDPs	−1.048***	0.240	31.479***	0.091	0.942***	0.138
	(0.264)	(0.485)	(0.869)	(1.075)	(0.354)	(0.872)
flood (near area) $_{T-1}$	−0.135	−0.516	−0.189	−1.456	−0.541**	0.868
	(0.438)	(0.560)	(0.562)	(1.184)	(0.262)	(0.873)
* conflict IDPs	−1.241***	−0.391	−32.101***		0.660**	−0.358
	(0.272)	(0.364)	(0.622)	(0.000)	(0.310)	(1.048)
conflict IDPs	−0.358	0.477*	0.350	−0.561	2.186***	0.935**
	(0.381)	(0.254)	(0.262)	(0.537)	(0.659)	(0.399)
past floods	0.101	0.104	0.052	0.386	0.294**	−0.128
	(0.081)	(0.064)	(0.058)	(0.502)	(0.117)	(0.110)
past floods ^{2}	−0.006	−0.008*	−0.001	−0.026	−0.021***	0.011*
	(0.006)	(0.004)	(0.004)	(0.024)	(0.007)	(0.007)
income pc (log)	0.513**	0.237	0.101	11.298	−2.624***	−0.326
	(0.236)	(0.193)	(0.136)	(7.748)	(0.738)	(0.408)
population (log)	0.370***	0.097	0.130	19.270	0.480***	0.135
	(0.110)	(0.092)	(0.097)	(14.281)	(0.179)	(0.178)
temporal lag	0.961***	0.143	0.260***	1.468***	1.339***	1.320***
	(0.261)	(0.214)	(0.030)	(0.431)	(0.437)	(0.328)
spatial lag $_{T-1}$	−0.172	0.490***	0.021	0.527*	0.744*	0.735**
	(0.225)	(0.164)	(0.023)	(0.289)	(0.426)	(0.295)
Country level						
xpolity $_{T-1}$	−0.025	0.039	−0.037*	0.184	0.043	0.029
	(0.029)	(0.026)	(0.021)	(0.387)	(0.064)	(0.040)
anocracy $_{T-1}$	0.172	−0.201	−0.327*	2.005	0.081	−1.804***
	(0.229)	(0.205)	(0.177)	(1.953)	(0.376)	(0.577)
GDP pc (log) $_{T-1}$	−0.254	−0.236	−0.070	1.249	1.258***	0.256
	(0.186)	(0.159)	(0.120)	(4.516)	(0.389)	(0.359)
GDP growth $_{T-1}$	−0.026	−0.045**	−0.042***	−0.018	0.007	−0.083
	(0.023)	(0.021)	(0.015)	(0.045)	(0.057)	(0.058)
population (log) $_{T-1}$	−0.176*	0.178**	0.106	−9.467	0.324	−0.129
	(0.103)	(0.086)	(0.084)	(11.644)	(0.258)	(0.184)
pop growth $_{T-1}$	−0.222	−0.283**	−0.284**	−0.233	0.081	−0.340
	(0.158)	(0.141)	(0.130)	(1.555)	(0.376)	(0.333)
civil war incidence	0.156	0.079	0.146	0.423	0.382	2.795***
	(0.237)	(0.195)	(0.173)	(0.338)	(0.407)	(0.523)
peace years	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−1.419	−3.410**	−2.793**		−25.368***	−2.961
	(1.952)	(1.553)	(1.354)		(5.700)	(3.602)
Observations	2,663	2,663	2,663	2,663	2,016	2,016
θ	—	—	0.363*** (0.034)	—	—	—
Log Likelihood	−433.261	−714.951	−1,497.133	−202.472	−119.371	−252.057
Akaike Inf. Crit.	950.522	1,513.902	3,078.266	484.9439	322.742	588.114

Notes: heteroskedasticity robust standard errors in parentheses, †p<0.1; *p<0.05; **p<0.01

Figure A.8: Average predictive differences in conflict probabilities due to floods and disaster displacement in the presence of conflict IDPs — Model 11

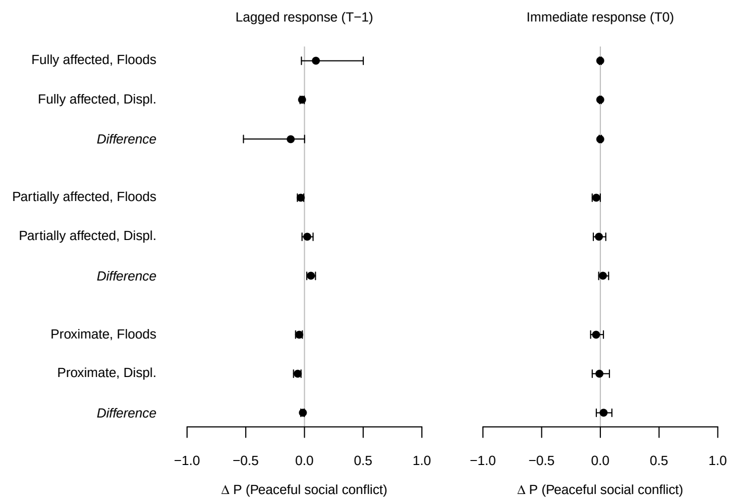


Figure A.9: Average predictive differences in conflict probabilities due to floods and disaster displacement in the presence of conflict IDPs — Model 12

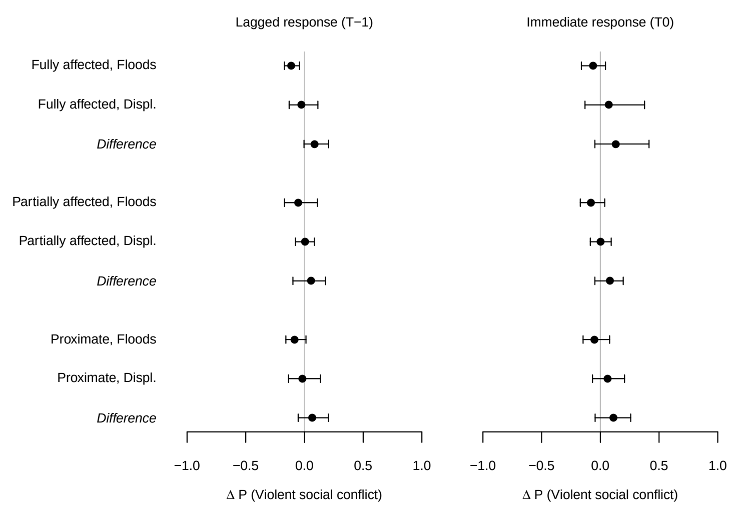


Figure A.10: Average predictive differences in conflict probabilities due to floods and disaster displacement in the presence of conflict IDPs — Model 15

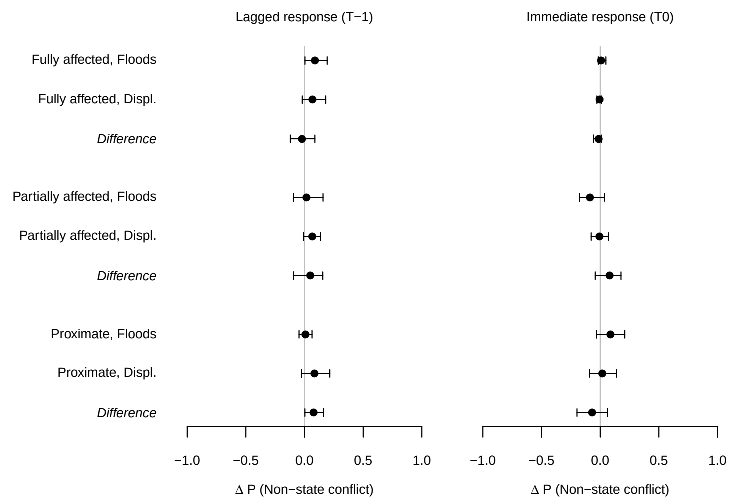
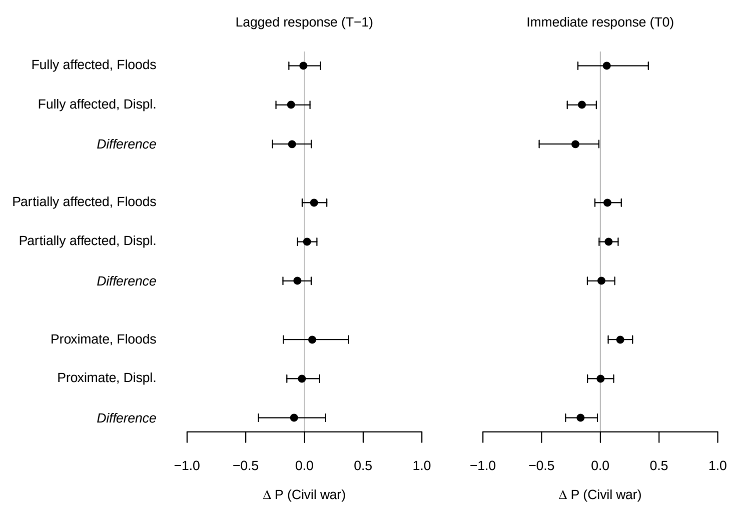


Figure A.11: Average predictive differences in conflict probabilities due to floods and disaster displacement in the presence of conflict IDPs — Model 16



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