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by

Mariagrazia D'Angeli, Giovanni Marin, Elena Paglialunga

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Climate Change, Armed Conflicts and Resilience[*]

Mariagrazia D'Angeli[†] Giovanni Marin[‡] Elena Paglialunga[§]

Abstract

In recent years, there has been rapid development of the literature linking climate change and armed conflicts. Although no conclusionary evidence has been found of a direct link between climate change and armed conflicts, still climate change has been addressed as an important trigger, exacerbating underlying social, economic and institutional conditions and thus resulting in higher risk and magnitude of violent activities. In this context, while more research is needed to further disentangle how climatic changes combine with socio-economic and institutional elements to induce conflicts, an important pathway to be explored is the role that building resilience can play in preventing and/or breaking the negative relationship between climate change and violent activity. In this context, resilience refers to the capacity of a system to come back to its original conditions after a shock and relies on the combination of socioeconomic, institutional and technological dimensions. In our paper we provide empirical evidence on the role played by resilience-building investments in attenuating the emergence of armed conflicts as a consequence of climate-related anomalies and natural disasters.

Keywords: resilience, armed conflicts, natural disasters, climate change

JEL: D74, O13, Q54

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[†] Corresponding author. Department of Economics, Society and Politics, University of Urbino Carlo Bo, Italy; SEEDS. E-mail: m.dangeli7@campus.uniurb.it

[‡] Department of Economics, Society and Politics, University of Urbino Carlo Bo, Italy; SEEDS. E-mail: giovanni.marin@uniurb.it

[§] Department of Economics, Society and Politics, University of Urbino Carlo Bo, Italy; SEEDS. E-mail: elena.paglialunga@uniurb.it

1 Introduction

Climate change has been extensively recognized as one of the most pressing issues of our time. Indeed, the IPCC has stated that *"the warming of the climate system is by now unequivocal"* (IPCC, 2007). In its latest 2021 Report, the IPCC uses even stronger words; in fact, it states that *"human influence has warmed the climate at a rate that is unprecedented in at least the last 2000 years"* (IPCC, 2021). Human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels (IPCC, 2018). Among the numerous long-term changes that have been observed in the global climate there are changes in temperature and precipitation amounts (IPCC, 2007) and aspects of extreme weather including droughts, floods, heavy precipitation, heatwaves and increased intensity and frequency of tropical cyclones (IPCC, 2007). Warmer temperatures have been linked to a reduction in economic growth and economic output (Dell et al., 2012). Climate change impacts on human systems include – but are not limited to – effects on agricultural output, labour productivity, health, but also conflicts and political instability (Dell et al., 2014).

Indeed, in recent years there has been a rapid development of the literature linking climate change and armed conflicts. Although no conclusionary evidence has been found of a direct link between climate change and armed conflicts, still climate change has been addressed as an important trigger, exacerbating underlying social, economic and institutional conditions and thus resulting in higher risk and magnitude of violent activities (IPCC, 2014). While more research is needed to further disentangle how climatic changes combine with socio-economic and institutional elements to induce conflicts, resilience can play a crucial role in preventing and/or breaking the vicious cycle between climate change and violent activity. In this context, resilience refers to the capacity of a system to come back to its original conditions after a shock and relies on the combination of socioeconomic, institutional and technological dimensions. This constitutes an important pathway to be explored in the relationship between climate-related extreme events and their socio-economic impacts, with particular reference to the factors that determine the ability of affected systems to anticipate, mitigate and recover from natural hazards (Lazzaroni and Van Bergeijk, 2014), especially if such extreme events are related to the insurgence of violent activities.

Building on this framework, our paper aims at providing empirical evidence on the link between the emergence of climate-related extreme events and violent conflicts, and whether resilience affects this relationship, considering a panel of 151 countries over the period 1995-2013.

The paper is organized as follows. Section 2 reviews the relevant literature on the link between climate change and violent conflicts, focusing in addition on the role played by resilience. Section 3 develops a novel taxonomy of countries in terms of a complex indicator of both resilience and vulnerability compiled within the ND Global Adaptation Initiative (ND-GAIN) and of ethnic fractionalization by means of a cluster analysis. Section 4 provides evidence on the empirical link between climate-related extreme events and violent conflicts accounting for cross-country differences based on which cluster they belong to. Section 5 concludes.

2 Related literature

In recent years there has been a rapid increase in the literature linking climate change and armed conflicts. In this regard, no conclusionary evidence has been found of a direct link between climate change and conflicts (Bernauer et al., 2012; IPCC, 2014; Buhaug, 2015). However, several authors (e.g., Koubi, 2019) do find that, under specific circumstances, climate change might, albeit indirectly, influence violent conflicts. Indeed, climate change has been systematically recognized as a potential threat multiplier of underlying social, economic and political conditions, thereby contributing to the worsening of the conditions that might spark armed conflicts. The IPCC (2014) has stated that *"climate change can indirectly increase risks of violent conflicts by amplifying well-documented drivers of these conflicts, such as poverty and economic shocks."*

Hsiang et al. (2013) were the first to assemble this rapidly growing strand of literature by assessing more than 60 studies causally relating climate to conflicts and finding a certain degree of convergence in the results. They find strong causal mechanisms linking climatic events to human conflicts across a range of spatial and temporal scales and across all major regions of the world. Although these results were contested (Buhaug et al., 2014), the study does highlight the fact that climate change can be a crucial factor in sparking the onset of violent activities, however not the sole culprit. In fact, several mechanisms might play a role in the climate change-armed conflict nexus, either mediating or worsening the relationship.

2.1 Natural disasters, risk factors and socio-economic consequences

Among the several consequences of climate change, one that has been identified is the increase in the frequency and magnitude of extreme events and natural disasters (IPCC, 2007). The IPCC (2012) defines natural disasters as *"severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery* (IPCC, 2012, p.31); such events include, but are not limited to, natural disasters such as droughts, heavy precipitation and heat waves.

Climate-related extreme events have been increasing over the last decades. This constitutes an issue, not only because of the natural disaster *per se,* which can be considered exogenous to some extent (even though the influence of man-made climate change seems to be contradicting even the exogenous nature of natural disasters), but also because of the socio-economic effects a natural disaster produces. As Cavallo and Noy point out, *"the very occurrence of disasters is an economic event"* (Cavallo and Noy, 2009, p. 64). This is because natural disasters occur within a certain well-defined social, economic and political context, and this raises interesting questions on whether their effects are mitigated, or heightened, because of the specific context in which they occurred. This and other related questions are relevant for the social researcher. Additionally, since it is impossible – at least in the present moment – to foresee the occurrence of natural disasters, it is important to gain insight into the risk that natural disasters pose and the mechanisms through which these risks manifest themselves, since this will be useful for the design of better response actions when a natural disaster indeed occurs (Nel and Righarts, 2008).

Natural disasters generate socio-economic damages which are very difficult to assess. An element which further complicates this assessment is the complexity of the impacts related to natural disasters; in fact, we can distinguish between direct and indirect, as well as short and long term impacts (Cavallo and Noy, 2009). Direct impacts include the mortality and morbidity as an immediate consequence of the natural disaster, but also damages to fixed assets and capital, as well as raw materials (*Ibidem*). Indirect damages, on the other hand, refer to the economic activity that will not take place because of the disaster (*Ibidem*). Moreover, we have to consider not only the most immediate consequences of natural disasters – e.g., the number of deaths and injured, the physical damages to the infrastructures, the cost of emergency operations, socio-economic and environmental impacts (Marin et al., 2021) – but longer-term impacts as well, such as the reduction in population size and a lower average income (*Ibidem*). As it can be noted, direct effects of natural disasters usually coincide with short-term ones (as for the number of deaths and damage to infrastructures), but this is not always the case. The issue lies in the fact that the usual methods used to measure the impact of natural disasters are related to quantifying only the direct economic losses – i.e., the monetary value of the damage to physical assets (Markhvida et al., 2020). However, considering only direct economic losses greatly underestimates the impact of natural disasters, and does not take into account that some subgroups, such as low-income households, might be disproportionally affected (*Ibidem*).

Natural disasters have been linked to a series of effects, such as migration, political instability and, ultimately, violent activity in the form of armed conflicts. Pre-existing conditions, such as poverty, income inequality and ethnic fractionalization might further enhance the risk of violent activity after a natural disaster occurs (Cappelli et al., 2021; Schleussner et al., 2016; IPCC, 2014). Even though the literature has explored these relations extensively, no conclusionary evidence has been reached. This may be due mainly to the complexity of the interrelationship between natural disasters, the underlying socio-economic context and, eventually, violence and the related difficulty in empirically assessing them.

An element related to the role that pre-existing conditions play with respect to the effects of a natural disaster is the fact that there is evidence that their effects vary across countries, especially across developed and developing nations. For example, Cavallo and Noy (2009) report that while the damages caused by natural disasters are heterogeneous across countries, there is a smaller effect in advanced economies with respect to developing ones. Moreover, even though the number of disasters occurred in the period 1970-2008 is comparable across developed and developing countries, the latter seem to be more affected in terms of lives lost with respect to advanced economies. In fact, *"developing countries bear the lion's share of the burden, in terms of both casualties and direct economic damages"* (Cavallo and Noy, 2009, p. 74). This further raises the question of whether there are some pre-existing conditions that enable these different results, to what extent they are related to the different levels of development across countries, and ultimately if policy interventions can be made to amend such imbalances.

Nel and Righarts (2008) ask if the occurrence of a natural disaster increases the risk of violent civil conflict in a society. They look at data for 187 political units for the period 1950-2000 and conclude that natural disasters significantly increase the risk of violent civil conflict both in the short and medium term. Moreover, they find that such dynamics are especially relevant in low and middle-income countries with high levels of inequality, mixed political regimes, and sluggish economic growth (Nel and Righarts, 2008). Bergholt and Lujala (2012) find that climate-related natural disasters have a negative effect on economic growth and that the effect is indeed considerable. However, they do not find evidence to support the hypothesis that climate-related natural disasters increase the likelihood of conflict onset through their effect on slower economic growth.

Natural disasters might facilitate conflict onset through natural resource depletion, which often occurs as a consequence of natural disasters. According to the *resource curse hypothesis* resource-rich countries are characterized by slow economic growth and high likelihood of armed conflict onset because of weak leadership, rent-seeking behaviours and failing institutions (Brunnschweiler and Bulte, 2008). While some authors reject the hypothesis that natural resource endowment is automatically bad news for development and conflict, others (e.g., Vesco et al., 2020) do find that both resource scarcity (especially of agriculturally related resources) and abundance are associated with a higher probability of conflict. Natural resource scarcity – especially in the case of vital resources such as water – might spur competition to access such resources; additionally, it might increase inequality among those who can more easily access such resources and those who cannot, thereby increasing social fragmentation and enhancing pre-existing grievances which, if not adequately managed, can lead to conflict (Vesco et al., 2020).

In this respect, Eastin (2016) analyzes the effects of natural disasters on the duration of civil conflicts and concludes that natural disasters indeed prolong conflict duration by both *"diminishing the state's capacity to suppress insurgency, while reinforcing insurgent groups' ability to evade capture and avoid defeat*" (Eastin, 2016, p. 322).

Finally, another element related to the climate change – violent activity nexus is ethnic fragmentation. While there is a great deal of literature on the subject and a direct relationship has not yet been found empirically, it might be, as Schleussner et al. (2016) note, that the disruptive nature of extreme climatic events might have severe consequences in terms of violent activities particularly in ethnically fractionalized societies. The main reasons behind the link between ethnic fractionalization and conflict risks are associated to horizontal inequality and relative deprivation across groups (Cederman et al., 2011; Østby, 2008), slower economic growth and inequal access to resources (Alesina et al., 2016) and lower provision of public goods (Habyarimana et al., 2007).

Migration is a further relevant mechanism since it is expected that the effects of climate change will impact people's livelihoods in such a way that they will be forced to migrate in search of better living conditions. The increased number of migrants is linked to higher probability of conflict onset, since it is argued that migrants will create additional competition for natural resources that could bring to conflicts in the receiving regions. However, such association does not find enough empirical support, mainly because of the increased complexity of the issues regarding the links between climate change, migration and conflicts and because in most cases people do not migrate only because of climate-related conditions; environmental reasons are compounded most of the time by other reasons, mainly economic (Brzoska and Fröhlich, 2015).[1]

While natural disasters have been positively linked to conflicts, there are indeed some elements that have been recognized as being able to mitigate the relationship between natural disasters and conflicts. Quality institutions and sound governance have been considered as one of the main factors mitigating the probability of conflict onset after a natural disaster occurs. High quality institutions can more effectively help resolve grievances and redistribute resources in face of an adverse climatic event, which in turn can diminish people's grievances and hence avoid those tensions degenerate in violent

[1] Furthermore, they note that there are different types of migrations, differing for motives, goals and timing. It would not be appropriate to consider such relationships as deterministic because that would mean an oversimplification of the issues at hand.

activities. Quality institutions are also important in the correct management of vital public resources. For example, Gizelis and Wooden (2010) find that political institutions might influence the impact of water scarcity on the probability of conflict, by mitigating conflicts of interest that could potentially escalate to intrastate wars. On the other hand, the literature has also considered natural disasters as a possible cause of political instability which in the worst scenario could lead to violence and, ultimately, conflict. Omelicheva (2011) sets out to analyze whether natural disasters can be considered triggers of political instability. The analysis yields some interesting results, in that she finds that it is the pre-existing country-specific conditions, including the resilience of a state's political and economic institutions to crisis, that are the most important in terms of their effect on political instability, suggesting that *"natural disasters can trigger political instability in only those states which already exhibit the attributes of the conflict-prone societies"* (Omelicheva, 2011, p. 23). Thus, the concept of resilience starts becoming more relevant for the climate change-armed conflict nexus literature, in that – as we will discuss more in detail – resilience might prove to be an excellent asset against the emergence of climate-related armed conflicts. For this reason, it is important to provide policymakers and institutions with all the information needed to implement actions aimed at improving resilience and decreasing vulnerability to both climate events and violent activity.

2.2 Vulnerability, resilience, risk and exposure

The concepts of vulnerability, resilience, risk and exposure are often discussed in relation to natural disasters and their consequences on socio-economic systems. Even though it is not the aim of this paper to engage in a thorough review of these concepts, still it is important to present a short overview on them in order to give a clearer picture of the framework in which this analysis is carried out in.

Firstly, it must be highlighted that the relationships among the concepts we will discuss in this paragraph – especially resilience and vulnerability – are not well defined (Cutter et al., 2008). In fact, *"some researchers believe these notions to be part of the same concept, while other authors claim that each is the outcome of another or that they are separate but linked concepts"* (Modica and Zoboli, 2016, p. 60).

It is useful to think of these concepts in relation to the ex-ante and ex-post situation relating to a natural disaster: vulnerability and resilience refer to the pre-event situation; hazard and risk refer to the disaster itself; finally, damage and loss refer to the post-event situation (*Ibidem*). The IPCC defines vulnerability as *"the propensity or predisposition to be adversely affected"* (IPCC, 2014, p. 5). Instead, Sarewitz et al. (2003) define it as *"the inherent characteristics of a system that create the potential for harm but are independent of the probabilistic risk of occurrence of any particular hazard or extreme event"* (Sarewitz et al., 2003, p. 805). Resilience has, instead, taken on several slightly different – but still compatible – meanings from when it was first used by Holling in 1973. Holling (1973) defined resilience as *"the ability to absorb change and disturbance and still maintain the same relationships between population or state variables"*, while Pimm (1984) defined it as the ability of a system to recover after a shock. Holling's definition of resilience qualifies it as ecological resilience, in that it considers a system adaptive in the sense that *"it can evolve from a stable domain to another after being hit by a shock"* (Caschili et al., 2015, p. 208). Pimm's approach to resilience, instead, can be qualified as engineering resilience, in that it *"studies a system in its stable equilibrium and evaluates its ability to return to a stable equilibrium after a shock"* (*Ibidem*).

In the IPCC definition, vulnerability comprises aspects of resilience as well, because it is said that *"vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt"* (*Ibidem*). According to other authors, however (e.g., Modica and Zoboli, 2016; Miller et al., 2010) vulnerability and resilience, while sharing some common characteristics, cannot be considered as one concept because there might be some aspects that refer to both vulnerability and resilience, while others do not (Modica and Zoboli, 2016).

Hazard, instead, refers to the extreme event in itself and indicates *"the potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources"* (IPCC, 2014, p.5).

Exposure is defined a *"all the assets and people that can be harmed by a natural disaster"* (Marin et al., 2021, p. 2). It is a key component in determining the risk arising from a shock, since it gives an account of the potential losses that can result from a natural disaster if it indeed occurs; exposure varies among areas and can be quite differentiated at the sub-national level as well. Exposure is influenced by both physical and socio-economic elements, such as population, GDP and infrastructure. Exposure eventually determines whether an *hazard* becomes a *disaster*. In this instance, it is interesting to note how some authors (e.g. Kelman, 2019) advocate to avoid the use of the term "natural disaster" as disasters are not natural but depend on the vulnerability and exposure of a system, and not from the hazard itself.

Risk needs to be understood as a complex concept, i.e., the product of the interaction between the hazard (and, in particular, its severity and frequency), the system's exposure to shocks and its vulnerability (IPCC, 2014; Marin et al., 2021; Modica and Zoboli, 2016). The level of risk varies in terms of potential losses with respect to the severity of the hazard and the vulnerability of the system (Marin et al., 2021).

The two post-disaster concepts are, instead, damage and loss. Damage refers to the measurement, in economic terms, of the degree of harm which infrastructures and other physical assets might have suffered after a shock (Modica and Zoboli, 2016); loss is, instead, the *"change in wealth"* (Modica and Zoboli, 2016; Kliesen, 1994) as a result of the damage to infrastructures and/or physical assets after a shock.

As it can be seen from this brief overview, if on the one hand these concepts might share some communalities, on the other hand they each represent a specific aspect of a multifaceted framework which needs to be explored in full in order to be used proficuously in assessing the consequences of external shocks and/or natural disasters.

2.3 Resilience as a mediating factor in the climate-conflict nexus

As we have seen above, the question of the meaning and implications of resilience and of its relation to vulnerability and adaptive capacity are at the center of debate in the literature. While a more holistic view on the concept of resilience might better capture the complexities and what it entails from an economic, social, ecological, and in some way, philosophical point of view (what does it mean to recover? Is the return to the pre-shock conditions really the best objective to achieve?), on the other hand it is imperative to give a practical sense to the theoretical debate and try to assess what it means to be resilient and how resilience can be measured.

There is extensive literature describing indexes of resilience (e.g., Cutter et al., 2008; Cutter et al., 2014) and how they can be applied at different scales to asses systems' resilience and help in understanding which factors enhance or limit systems' recovery capacity. Many such indicators acknowledge the multi-dimensional nature of resilience and thus compile a complex picture of different dimensions. For example, Cutter et al. (2014) compile an empirically-based resilience index named Baseline Resilience Indicators for Communities (BRIC) based on six different domains – social, economic, housing and infrastructure, institutional, community and environmental (Cutter et al., 2014). Applying this measure to US counties, they find that *"the predominant drivers of the lower inherent resilience are lower rankings on housing/infrastructure, institutional, community capital, and environmental resilience"* (Cutter et al., 2014, p. 75). Joerin et al. (2014) try to assess abilities of people and institutions to respond to potential climate-related disasters in the city of Chennai, India, by devising the Climate Disaster Resilience Index (CDRI). Such index consists of five dimensions (economic, institutional, natural, physical and social), as well as 25 parameters and 125 variables. They find that the communities living in the northern parts of Chennai are less resilient with respect to communities living along the urban fringes.

Additionally, there is some empirical literature trying to assess resilience at different scales and in different regions of the world. For example, Akter et al. (2013) try to empirically assess the vulnerability and resilience to natural disasters in a tropical cyclone-prone coastal community in Bangladesh. They find that *"the cyclone in question has negative impacts on the community, particularly in terms of income, employment and access to clean water and sanitation"* (Akter et al., 2013, p. 114). Additionally, they find that the poor were more impacted and suffered more damages. However, they showed a greater ability to withstand the shock compared to their non-poor neighbors. Hence, their greater vulnerability did not necessarily lead to lower resilience (*Ibidem*). This is an interesting result since it rebuts the argument that resilience and vulnerability are two opposite concepts, implying that if a system is more resilient it is automatically less vulnerable; instead, it shows that this is not always the case.

Apart from the empirical strategies devised to assess resilience in practical terms, in the context of climate change research, and especially in the climate-conflict literature, it becomes particularly important to understand if, and to what extent, high levels of resilience can help in mitigating climate change impacts and if this can, ultimately, indirectly affect other climate-related violent events. In this sense, it becomes important to understand which are the factors that determine the ability of affected systems to anticipate, mitigate and recover from natural hazards (Lazzaroni and Van Bergeijk, 2014), especially if such extreme events might be related to the insurgence of violent activities. It becomes crucial, then, to answer two questions:

- Do natural disasters increase the probability of the emergence of new conflicts?
- Do different levels of vulnerability and resilience to natural disasters affect differently the disaster-conflict relationship?

3 Paving the way towards (climate) conflicts: a taxonomy

According to the literature reviewed in the previous paragraph, the impact of climate change on the probability that climate conflicts emerge depends on the vulnerability, coping capacity (i.e., resilience) and social context of the area hit by a climate-related extreme event. These dimensions are clearly not independent but quite strongly interconnected. To account for these interdependencies, we classify different countries in a multi-dimensional way by means of a cluster analysis, to identify groups of countries with similar combinations of relevant variables that are expected to be related to the disaster-conflict nexus.

3.1 Data and indicators

Data on the number of conflicts are taken from the UCDP/PRIO Armed Conflicts Dataset, which contains information on armed conflicts from 1946 to 2020. The UCDP/PRIO Dataset contains information on both state and non-state armed conflicts. A state-based armed conflict is defined by UCDP/PRIO as *"a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in a calendar year"* (Pettersson, 2021b, p.1). A non-state conflict, instead, is defined as *"the use of armed force between two organized armed groups, neither of which is the government of a state, which results in at least 25 battle-related deaths in a year"* (Pettersson, 2021a, p.2).

Data on natural disasters are taken from the EM-DAT Database on natural disasters managed by the Center for Research on the Epidemiology of Natural Disasters (CRED). The EM-DAT Database contains information on several types of natural disasters (geophysical, meteorological, hydrological, climatological, biological, extra- terrestrial, technological) from 1900 to 2020 (EM DAT Guidelines, 2020). In order for a disaster to be entered in the database, at least one of the following criteria have to be fulfilled:

- deaths: 10 or more people died as a result of the disaster;
- affected: 100 or more people affected/injured/homeless;
- declaration/international appeal: declaration by the country of a state of emergency and/or an appeal for international assistance.

In our analysis we have included all climatological, meteorological and hydrological disasters, as they are more related to the changing climate with respect to other events such as earthquakes. Climatological disasters include droughts, glacial lake outbursts and wildfires (forest fires, land fires); meteorological disasters include storms (tropical storms, extra-tropical storms, convective storms) and extreme temperatures (cold waves, heat waves, severe winter conditions). Finally, hydrological disasters include fog, floods (coastal floods, riverine floods, flash floods, ice jam floods), landslides and wave actions (rogue wave, seiche).

As for the variables related to the disaster-conflict nexus, we identify three different dimensions to be considered in classifying countries. First, the coping capacity of a country in case of climate-related extreme events is a pre-requisite to limit or even avoid socio-economic losses in the aftermath of an extreme event or, at least, to recover quickly. However, an important issue to be discussed is determining what influences the coping capacity of a country. In fact, it might be that the extent to which a country is capable to limit the risk of adverse socio-economic impacts and/or to recover quickly following a natural hazard is, to a certain extent, context-specific and hence a synthetic indicator will not capture the specificities of each region. On the other hand, in order to have a certain degree of generalization in the analysis it is important to consider an indicator which is widely available, comprehensive in considering the dimensions to be taken into account and comparable across regions.

To this end, we first take into account the dimension related to the vulnerability of a certain area or country to climate-related extreme events. As proxy of a country's vulnerability to climate change impacts we used a synthetic vulnerability index developed within the ND Global Adaptation Initiative (ND-GAIN) developed by the University of Notre Dame, Indiana (USA).[2] This index is a synthetic indicator of a country's vulnerability, which is defined as *"the propensity or predisposition of human societies to be negatively impacted by climate hazards*" (*Ibidem*, p. 3). We consider this indicator to be quite useful because it takes into account multiple dimensions of vulnerability – exposure, sensitivity and adaptive capacity – across six different strategic sectors (Health, Food, Ecosystems, Habitat, Water, Infrastructure). The exposure component refers to the *"the extent to which human society and its supporting sectors are stressed by the future changing climate conditions"* (*Ibidem*, p. 3) and hence refers to the physical factors which contribute to vulnerability. The sensitivity component refers instead to the *"degree to which people and the sectors they depend upon are affected by climate related perturbations"* and deals primarily with the dependance of both economic sectors and the population to climate-related perturbations. Finally, the adaptive capacity component refers to the *"ability of society and its supporting sectors to adjust to reduce potential damage and to respond to the negative consequences of climate events"* (*Ibidem*, p. 4). Each component of the index for each sector is represented with one or more indicators, and they are then combined and scaled to obtain an index of vulnerability which ranges from 0 to 1.[3]

The second dimension we take into account as a proxy for a country's resilience is the "*readiness*" indicator from ND-GAIN. This is a synthetic measure of a country's readiness, defined as *"the readiness to make effective use of investments for adaptation actions thanks to a safe and efficient business environment*" (Chen et al., 2015, p. 4). In this sense, the ND-GAIN indicator of readiness focuses on the ability to leverage investments for adaptation actions and is based on three main dimensions: economic readiness, governance readiness and social readiness. Economic readiness refers to the *"investment climate that facilitates mobilizing capitals from private sector"* (*Ibidem*, p.

[2] An in-depth description of the data can be found in Appendix A

[3] The scaling and weighting procedure used to build the vulnerability index is the same as the one used to build the readiness index (see footnote n. 4 and Appendix A for more details).

4); governance readiness refers to *"the stability of the society and institutional arrangements that contribute to the investment risks"* (*Ibidem*, p. 4), while social readiness refers to the *"social conditions that help society to make efficient and equitable use of investment and yield more benefit from the investment"* (*Ibidem*, p. 4). Each dimension making up the index is based on one or multiple indicators – e.g., Rule of Law, Control of Corruption, Social Inequality – which are then combined and scaled in order to obtain an index which ranges from 0 to 1.[4] It is important to point out that this definition of readiness refers only to the objective of leveraging investments, which is an important component – but not the sole – of a resilient community, as it can be seen from the definitions discussed earlier. However, this index has the advantage of being available for many countries worldwide, hence guaranteeing a high level of comparability across nations.

A third relevant dimension relates to the possibility to count on the cooperation among different social and ethnic groups in reducing vulnerability ex ante, in dealing with and recovering after the emergency situations in the occurrence of an extreme event. It is interesting, in this respect, to assess whether a high variety of ethnic groups within a country or a region (i.e., ethnically fractionalized countries) can be a useful asset in the face of a natural disaster, enhancing adaptive capacity through cooperation and mutual help or, conversely, might deteriorate the consequences of natural disasters, thereby increasing armed conflict risk (Schleussner et al., 2016). Here we rely on an indicator of ethnic fractionalization as a proxy for ethnic diversity within a country and use the Historical Index of Ethnic Fractionalization (HIEF) index, compiled as the probability that two randomly drawn individuals within a country are not from the same ethnic group, with a range from 0 to 1. The dataset was compiled by Drazanova (2019, 2020) and contains data for 162 countries across all continents for the years 1945-2013.

[4] The procedure to obtain the readiness index is as follows: first, raw data are collected and, if necessary, interpolated. Then, baseline for minimum and maximum values are identified. Then, a reference point is identified for each indicator. Then, raw data are scaled to score data, ranging from 0 to 1. A score is computed for each dimension (economic, social, governance readiness) as the arithmetic mean of its components, with equal weights. Finally, the readiness score is computed as the arithmetic mean of the scores of each dimension, all weighted equally (See Appendix A for more details).

3.2 Cluster analysis

To group together countries with similar characteristics we employ a cluster analysis, which is a statistical tool aimed at creating groups of observations that share similar characteristics, while guaranteeing that groups are distinct from one another. Following Hair et al. (2009), as a first step we run a hierarchical cluster analysis on the cross section of 151 countries based on data for year 1995.[5] By means of hierarchical cluster analysis we identify the optimal number of clusters, that is a compromise between how distinct the clusters are and how similar the units are within the same cluster. Given the optimal number of clusters, the centroids (i.e., the average values of the clustering variables within each cluster) are used as starting point for the non-hierarchical cluster analysis (k-means algorithm in our case). More specifically, we use the centroid linkage algorithm for the hierarchical clustering analysis, considering the squared Euclidean distance between each country and the centroids of countries belonging to each cluster.

To identify the optimal number of clusters, we consider both the Duda-Hart Je(1)/Je(2) index and the Calinski-Harabasz pseudo-F test. Regarding the former, the rule of thumb suggests to consider a number of cluster such that the Je(1)/Je(2) index is among the highest values while the pseudo T-squared is a local minimum. Both criteria are satisfied for the solution with 2, 5, 6 and 9 clusters. However, the Calinski-Harabasz pseudo-F, according to which the optimal solution is among the ones with the largest pseudo-F, suggests that the 5-clusters solution is the best one.

As a final step, we use the k-means algorithm to perform the non-hierarchical clustering with 5 clusters, using centroids from the hierarchical clustering as a starting point.

Table 1 reports the internal profiling of the five clusters, that is the characteristics of the different groups in terms of the clustering variables. From the table it can be noted that there is quite a distinction in terms of clustering profile among the clusters. Cluster 1 has the lowest level of readiness (0.27) and the highest level of vulnerability (0.56) and ethnic fractionalization (0.76) among the five clusters. On the other hand, cluster 5 has the highest level of readiness (0.62) and the lowest level of vulnerability (0.33) and ethnic fractionalization (0.10) among the five clusters. Both clusters 2 and 4 have a quite low

[5] Time-varying results based on longitudinal data are available upon request.

level of readiness (0.32 in both cases) and high of vulnerability (0.44 and 0.46, respectively). However, while cluster 2 also shows a high level of ethnic fractionalization (0.54), cluster 4 is instead characterised by a low level of ethnic fractionalization (0.19). Finally, cluster 3 has a quite high level of readiness (0.57) and low level of vulnerability (0.36), while the level of ethnic fractionalization is quite high (0.44).

Table 1: Internal profiling of clusters

Cluster	Readiness	Vulnerability	Ethnic fractionalization
1	0.27	0.56	0.76
2	0.32	0.44	0.54
3	0.57	0.36	0.44
4	0.32	0.46	0.19
5	0.62	0.33	0.10
Total	**0.36**	**0.46**	**0.45**

Notes: Internal profiling of the five clusters according to the clustering variables. The clustering variables (readiness, vulnerability and ethnic fractionalization) are all expressed in index form ranging from 0 to 1, with 0 being the lowest value and 1 being the highest value.

We can then begin to characterize each cluster based on its attributes. A possible characterization is as follows:

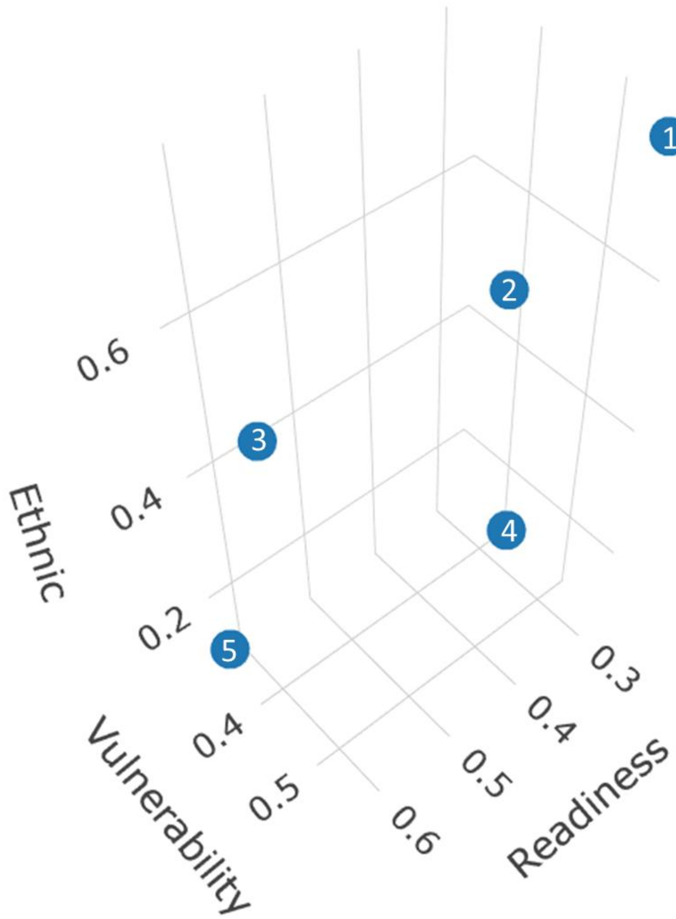
- **Cluster 1: Highly problematic countries.** This cluster is characterized by low levels of readiness and high levels of vulnerability, with a high level of ethnic fractionalization. The countries belonging to cluster 1 are mostly located in the Sub-Saharan Africa region (501.41 million people, about 50%). Finally, countries in cluster n.1 are prevalently low-income countries. About 77% of the people living in low-income countries in our sample are located in countries in cluster 1. Based on these characteristics, we expect the countries in this cluster to be unable to properly react to the consequences of extreme climate-related events in case they occur, and thus be the most likely to suffer negative impacts, with the possibility of tensions resulting in violent activities.
- **Cluster 2: Still problematic, but in slightly better conditions.** The countries in this cluster are still characterized by high levels of vulnerability and low of readiness, but to a lesser extent when compared to cluster n.1. As for ethnic fractionalization, it is still high but not as high as cluster 1. As for the composition

of countries in this cluster, most countries in cluster 2 are upper-middle income countries. The majority of people lives in Latin America and the Caribbean (396.83 million people, about 55%). Although the clustering variables show a better picture with respect to cluster 1, we still expect countries in this cluster to be unable to properly react to climate-related extreme events, but there is a possibility that the consequences related to natural disasters might be less pronounced in this case.

- **Cluster 3: Wealthy countries with some concerns.** The countries in this cluster are, on average, high income countries characterized by medium-high levels of readiness and medium-low levels of vulnerability and ethic fractionalization. Although rich, these countries may present some issues in terms of impacts related to natural disasters. We expect these countries to experience some mild effects of natural disasters on new conflicts.
- **Cluster 4: Problematic countries with an homogeneous ethnic composition.** These are countries mainly located in the Eastern Asia region, mostly upper-middle income countries. These are characterized by low levels of resilience and high of vulnerability (even though they are not in the conditions of countries in cluster 1) but have a really low level of ethnic fractionalization. We expect consequences of natural disasters to be relevant in terms of increasing the risk of conflict, even though we expect them to be less pronounced with respect to cluster 1 and 2.
- **Cluster 5: Wealthy, resilient countries.** These are high-income countries mainly located in Europe and in the Easter Asia/Pacific region. They are characterized by the highest level of resilience and the lowest level of vulnerability among all the clusters. We expect countries in this cluster to be able to adequately deal with the consequences of climate-related natural disasters.

We then report the distribution of the five clusters in space across the three different clustering variables as an additional informative tool (Figure 1).

Figure 1: Distribution of clusters in space



To gain a better understanding about the general features of clusters, we also report statistics for other relevant variables that were not used to build the different clusters (i.e., external profiling) for the years 1995-2013. We consider four variables: Human Development Index (HDI), GDP per capita (taken from ND – Gain) and the number of state and non-state conflicts and disasters in a year (all on average). Results, reported in Table 2. shows that, on average, countries in cluster 1 have the lowest level of HDI (0.47) and are among the poorest countries in the world (the average GDP per capita is only 4,752 USD). On the opposite, clusters 3 and 5 include the richest countries (25,731 and 29,730 USD per capita, respectively) with the highest level of HDI (0.83 and 0.86, respectively). The last two clusters, clusters 2 and 4, show similar level of HDI (0.67 and 0.64, respectively), but in terms of GDP per capita the former is richer than the latter (13,238 and 8,369, respectively). By looking at the last two columns in Table 2, cluster 1 emerges as the most affected by violent conflicts (0.93 conflicts on average in year), while clusters 3 and 4 show the highest occurrence of natural disasters (2.62 and 2.02 natural disasters respectively).

Table 2: External profiling of clusters

Cluster	HDI	GDP per capita (US$, PPP)
1	0.47	4,752
2	0.67	13,238
3	0.83	25,731
4	0.64	8,369
5	0.86	29,730
Total	**0.65**	**12,954**
Cluster	**Average number of yearly state and non-state conflicts**	**Average number of yearly natural disasters**
1	0.93	1.77
2	0.33	1.39
3	0.18	2.62
4	0.21	2.02
5	0.003	1.64
Total	**0.41**	**1.82**

Notes: external profiling of the clusters according to four variables (HDI, GDP per capita, number of state and non-state conflicts and number of natural disasters) for the period 1995-2013. The clusters were the result of a cluster analysis performed on 152 countries in the year 1995. All variables included in the external profiling are expressed in yearly average over the entire period of analysis.

Then, we consider the distribution of the population within the clusters (in millions) according to income level and world region (Table 3). Almost half of the population in cluster 1 lives in lower-middle income countries (it has also to be noted that 233.88 out of the 302.50 million people living in low-income countries, that is about 77%, are grouped in cluster 1). In clusters 2 and 4 we mainly find people living in upper-middle income countries, while clusters 3 and 5 include (mainly and exclusively, respectively) high income countries. By looking at the geographical distribution, Table 3 shows that on average most of the population in cluster 1 belongs to countries in the Sub-Saharan Africa region (501.41 million people, about 50%). The majority of people living in countries in cluster 2 is in Latin America and the Caribbean (396.83 million people, about 55%), while the majority of people living in countries in cluster 3 is from North America (295.63 million, about 57%) and, to a lesser extent, Europe and Central Asia (133.65 million, about 25%). People living in countries in cluster 4 are located mainly in the East Asia and

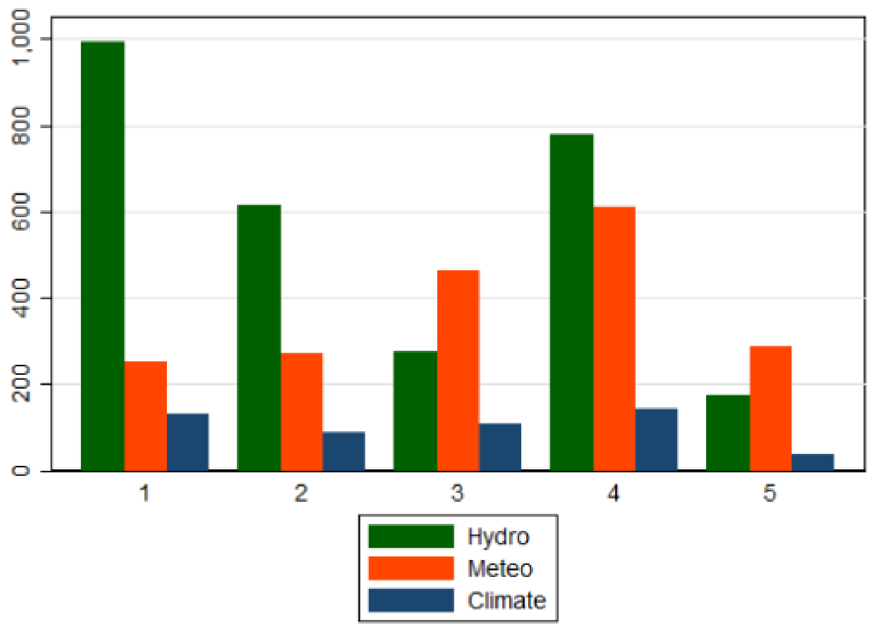
Pacific region (1293.36 million, about 67%), while people living in countries in cluster 5 are located mostly in Europe and Central Asia (250.01 million, about 57%).

Table 3: Distribution of population (in millions) by cluster and world region/income level

By income level	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Total
High income	1.61	9.72	457.45	65.24	438.61	972.63
Upper middle income	303.12	520.40	59.49	1444.28		2327.30
Lower middle income	459.35	176.86		340.75		976.96
Low income	233.88	5.76		62.85		302.50
Total	**997.96**	**712.75**	**516.94**	**1913.12**	**438.61**	**4579.39**
By world region	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Total**
East Asia and Pacific	271.65	64.51	66.69	1293.36	188.60	1884.81
Europe and Central Asia		184.99	133.65	224.34	250.01	793.00
Latin America and Caribbean	0.76	396.83	14.30	68.17		480.06
Middle East and North Africa	62.82	53.01	5.54	162.69		284.07
North America			295.63			295.63
South Asia	161.33	0.51		136.95		298.79
Sub-Saharan Africa	501.41	12.89	1.12	27.60		543.03
Total	**997.96**	**712.75**	**516.94**	**1913.12**	**438.61**	**4579.39**

Notes: Distribution of population (in millions) by cluster and world region/income level. The distribution relates to a sample of 151 countries for the year 2010.

Figure 2: Cumulative number of climate-related disasters by cluster and type of disaster

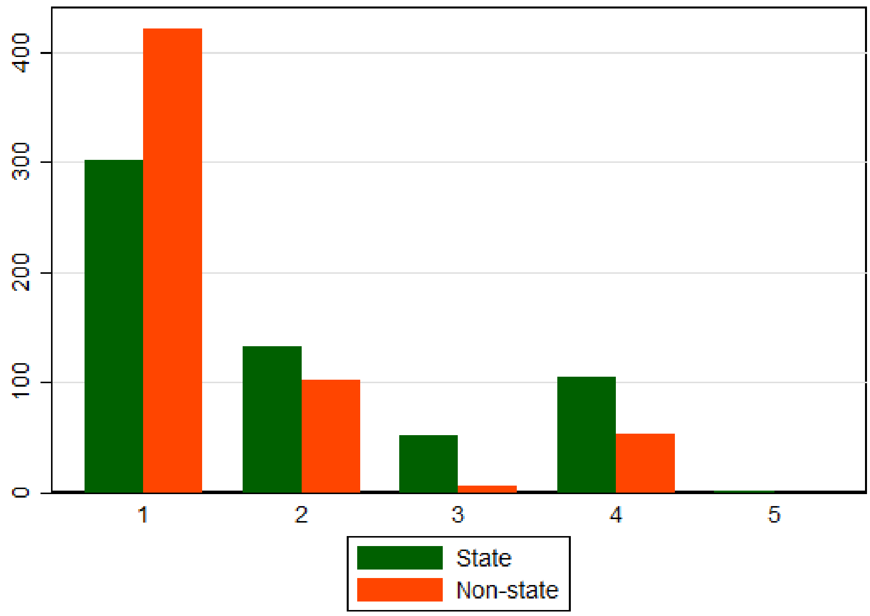


Notes: Cumulative number of climate-related disaster by cluster and disaster type for the period 1995-2013. Disasters are distinguished by type (hydrological, meteorological and climatological).

As a final step, we display some descriptive statistics regarding the distribution of natural disasters across the five clusters. Figure 2 shows the relative composition of the natural disasters occurred across the five clusters. Hydrological and meteorological disasters are the most common across all five clusters, even with evident differences in the number of events across clusters. For example, 993 and 780 hydrological disasters occurred in cluster n. 1 and 4 respectively, while only 175 occurred in cluster n. 5. Climate disasters instead are less frequent. For example, 130 climatic disasters occurred in cluster n. 1, while only 37 in cluster n. 5.

Finally, in Figure 3 we report information on the relative distribution of conflicts across clusters, with additional information on the differentiation between state and non-state conflicts.

Figure 3: Cumulative number of conflicts by cluster and type of conflict



Notes: Cumulative number of conflicts by cluster and conflict type over the period 1995-2013. Conflicts are distinguished between state and non-state conflicts.

An interesting point to note here is that while in cluster n. 1 non-state conflicts are more prevalent with respect to state conflicts, this does not occur in the other clusters.

4 The role of resilience for the link between natural disasters and conflicts: an empirical exploration

As a final step of our analysis, we investigate whether climate-related extreme events are correlated to the emergence of violent conflicts and whether such a nexus is contingent on which cluster each country belongs to. To this aim, we estimate a probit model on the pooled panel of 151 countries over the period 1995-2013. We estimate the following regression:

$$Conflict_{it} = \alpha_i + \rho Tot\_conflicts_{i;t_0} + \beta Disaster_{i;t,t-2} + \sum_j \theta_{it}^{j} Clus_i^j + \psi HDI_{it} + \delta_{i \in Reg} + \tau_t + \epsilon_{it} \quad (1)$$

where:

- $Conflict_{it}$ is a dummy equal to one if at least one new violent conflict occurred in country *i* in year *t;*
- $Tot\_conflicts_{i;t_0}$ is the number of conflicts registered in 1995 in country *i;*
- $Disaster_{i;t,t-2}$ is the number of climate-related natural disasters registered in a 3 years window;
- $Clus_i^j$ is a dummy variable for country *i* belonging to cluster *j*;
- HDI_{it} is Human Development Index of country *i* in year *t*;

Additionally, we included a series of control variables in order to account for unobservable characteristics and countries/year fixed effects. We included world region (as in second panel of Table 2) dummies ($\delta_{i \in Reg}$) and year dummies (τ_t). The pre-sample mean of total conflicts controls for the existence of a certain degree of path-dependence in conflicts across time (the so-called conflict trap hypothesis, see Collier et al., 2003), while HDI controls for the level of human development of countries. In estimating this equation, we are interested both in capturing the effect of natural disasters on the probability of new conflicts (i.e., the coefficient β associated with the $Disaster_{i;t,t-2}$ variable). Standard errors are clustered by country to account for within-country correlation of the residuals.

As a second step in our analysis, we also estimate the heterogeneous effect of natural disasters on the probability of new conflicts for different levels of resilience, vulnerability and ethnic fractionalization as summarized by cluster dummies. This is done by interacting our indicator of disasters with cluster dummies. Finally, we estimate another specification of the same equation including the total number of natural disasters broken down by type. The rationale here is to account for the differentiated effects of different disasters on the probability of new conflicts. We repeat these steps for three different outcome variables, namely state conflicts, non – state conflicts and the sum of the two. We do this in order to account for the effect of natural disasters on different violent outcomes and not just state – based conflicts.

We first estimate the first specification of our equation (i.e., the direct effect of natural disasters on the probability of new conflicts). Average marginal effects are reported in Table 4, while estimated coefficients are shown in Table C1 in the Appendix C.

Table 4: Average marginal effects for specification n. 1

	(1) New total conflicts	**(2) New state conflicts**	**(3) New non-state conflicts**
Pre-sample mean of total conflicts	0.0426***	0.0225***	0.0640***
	(0.00619)	(0.00547)	(0.0108)
HDI	-0.142**	-0.120**	-0.138*
	(0.0692)	(0.0479)	(0.0741)
Cluster n. 1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n. 2 (dummy)	-0.00823	-0.0207	0.0232
	(0.0218)	(0.0134)	(0.0243)
Cluster n. 3 (dummy)	-0.0108	-0.00508	-0.00112
	(0.0346)	(0.0248)	(0.0405)
Cluster n. 4 (dummy)	-0.0170	-0.0162	0.000191
	(0.0173)	(0.0122)	(0.0204)
Cluster n. 5 (dummy)	-0.0621***	-0.0377**	[empty]
	(0.0241)	(0.0154)	
Total number of disasters in a 3-year period	0.00246***	0.000627	0.00199***
	(0.000666)	(0.000393)	(0.000663)
N of observations	2454	2454	2182

Notes: Marginal effects based on a pooled probit model (see Table C1 in Appendix C for coefficients). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies. The number of observations differs across the three estimations because the year dummies, world region dummies and cluster dummies perfectly predict the zero outcome, hence they have been dropped.

Our results point to a positive and statistically significant effect of natural disasters in *t*, *t-1* and *t-2* on the probability of the emergence of new conflicts in *t*. The average marginal effect of natural disasters is positive and indicates that 1 additional natural disasters in the last 3 years increases (on average) the probability of a new conflict of 0.246%. Notice that the effect is positive and statistically significant for non – state conflicts as well (0.00199), while this the marginal effect is small and not significantly different from zero for state conflicts. This is a first interesting result, as it seems to imply that natural disasters are more likely to increase the probability of small, non – state conflicts arising from local tensions/grievances than they are to spark state conflicts. The average marginal effects is also positive and significant for the pre-sample mean of total conflicts for all specifications, indicating that past conflicts positively influence the emergence of new conflicts. This seems to at least partly confirm the so-called "conflict trap" hypothesis, according to which there is quite a persistence of conflicts over time, in that past conflicts hinder development, and this in turn can facilitate subsequent violent events (Collier et al., 2003). Finally, the average marginal effect for the HDI index is negative and statistically significant for all three specifications, in line with previous literature on the positive effect that a high level of human development has on lowering the probability of the emergence of violent activities (e.g. Collier et al., 2003; Kim and Conceicao, 2010).[6]

Then, we estimate the second specification, in which we include both the effect of natural disasters in *t, t-1, t-2* on the probability of a new conflict in *t* and the differentiated effect of natural disasters in *t, t-1, t-2* on the probability of the insurgence of a new conflict in *t* for different levels of readiness, vulnerability and ethnic fractionalization (i.e., for different clusters). Average marginal effects are reported in Table 5, while the coefficients are reported in Table C2 in Appendix C. Table 5 shows that there is an heterogeneous effect of natural disasters on the probability of insurgence of new conflicts for different clusters. Indeed, the marginal effects of natural disasters for column 1 (total conflicts) are positive and significant for all clusters, but the magnitude of the effects is differentiated across clusters and is larger for cluster n. 1 and 2: one natural disaster in the last three years increases the probability of insurgence of new conflicts by 0.299% in cluster 1 and 1.05% in cluster 2, while this value drops to just 0.263% for cluster 3 and 0.105% for cluster 4. These results show that the effect of a natural disaster on the probability of new

[6] As a robustness check, we also estimate the same specification by adding as time-varying control variables our three clustering variables (resilience, vulnerability and ethnic fractionalisation). Results, reported in Table C4 of Appendix C, confirm the ones shown in Table 4.

conflicts is stronger in magnitude in cluster 1 and 2, which are the less resilient and more vulnerable clusters.[7]

Table 5: Marginal effects for specification n. 2

Marginal effects of total number of disasters in a 3-year period:	**(1) New total conflicts**	**(2) New state conflicts**	**(3) New non-state conflicts**
At Cluster n. 1	0.00299***	-0.000949	0.00326***
	(0.00105)	(0.00118)	(0.000692)
At Cluster n. 2	0.0105***	-0.00151	0.00909***
	(0.00189)	(0.00144)	(0.00231)
At Cluster n. 3	0.00263*	0.00789**	-0.0183
	(0.00143)	(0.00328)	(0.0153)
At Cluster n. 4	0.00105*	0.000533**	0.000855*
	(0.000583)	(0.000251)	(0.000461)
N of observations	2182	2182	2182

Notes: Marginal effects based on a pooled probit model (see Table C2 in Appendix C for coefficients). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies.

As a final step, we compute the same specification as shown in Table 4, but differentiating for different types of disasters. The goal is to capture whether there are some particular types of natural disasters that have more effect on the probability of insurgence of conflicts with respect to others. By looking at Table 6, it seems that for total conflicts the number of floods has a positive and significant effect on the probability of insurgence of new conflicts, while for state conflicts it is instead the number of fires. Finally, for non – state conflicts the number of landslides seems to have a positive effect on the insurgence of conflicts. One conclusion that can be drawn is that different disasters might increase the likelihood of different violent activities to different extents, according to distinct socio-economic backgrounds and contextual factors. Again, the role of the persistence of violence and of high human development in, respectively, increasing and lowering the probability of violent activities is confirmed.

[7] As a robustness check, in Table C5 in Appendix C we report results where we add as additional control variables our three time-varying clustering variables. Overall, results are in line with our baseline results in terms of both statistical significance and magnitude. Moreover, In Table C6 in Appendix C we show results where climate-related disasters are further interacted with time-varying clustering variables. The aim is to provide evidence about the independent role played by each clustering variable as a mediator of climate-related disasters. For what concerns non-state conflicts, we estimate that the marginal effect of climate-related disasters is increasing with the level of vulnerability and ethnic fractionalisation while it is decreasing with the level of readiness, while results for state conflicts appear to be less clearcut.

Table 6: Marginal effects for specification n. 3

	(1) New total conflicts	(2) New state conflicts	(3) New non-state conflicts
Pre-sample mean of total conflicts	0.0415***	0.0222***	0.0638***
	(0.00622)	(0.00527)	(0.0114)
HDI	-0.152**	-0.126***	-0.147**
	(0.0716)	(0.0477)	(0.0735)
Cluster n. 1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n. 2 (dummy)	-0.00231	-0.0204	0.0273
	(0.0205)	(0.0135)	(0.0237)
Cluster n.3 (dummy)	0.000599	-0.00432	0.0140
	(0.0353)	(0.0252)	(0.0455)
Cluster n.4 (dummy)	-0.00881	-0.0172	0.00888
	(0.0160)	(0.0129)	(0.0213)
Cluster n.5 (dummy)	-0.0542**	-0.0390***	[empty]
	(0.0240)	(0.0145)	
Total number of droughts in a 3-year period	-0.000175	0.00121	-0.00480
	(0.00989)	(0.00676)	(0.00960)
Total number of fires in a 3-year period	0.00825	0.0107***	-0.000799
	(0.00606)	(0.00390)	(0.00672)
Total number of floods in a 3-year period	0.00385**	0.00152	0.00175
	(0.00194)	(0.00126)	(0.00165)
Total number of landslides in a 3-year period	0.00638	-0.00477	0.0137***
	(0.00508)	(0.00363)	(0.00461)
Total number of extreme temperature events in a 3-year period	-0.00677	-0.00661	-0.0106
	(0.00853)	(0.00482)	(0.00985)
Total number of storms in a 3-year period	0.000828	0.000203	0.00125
	(0.00148)	(0.00105)	(0.00176)
N of observations	2454	2454	2182

Notes: Marginal effects based on a pooled probit model (see Table C3 in Appendix C for coefficients). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies.

5 Conclusions

Climate change impacts are disruptive and will have unprecedented consequences on both natural and socio-economic systems. While mitigation actions strive to move forward, adaptation will become an inevitable path to consider in the current climatic crisis. In this perspective, research on resilience and on the factors that might improve systems' resilience capacity is a crucial issue to be assessed, because resilience-building might prove to be an essential policy option in the face of unprecedented, exceptional climatic changes and tipping points. In this respect, and in the face of the complex interconnections which the climate crisis is bringing about – socioeconomic impacts, migration issues, and security concerns in the form of conflicts – it is vital to understand whether building resilience to climate related extreme weather events might prove to be an effective policy action not only in counteracting the negative effects of climate change, but also in preventing that the aftermath of a disaster might offer the conditions for tensions and, ultimately, conflict to arise.

In this context, the aim of this paper was to assess whether building resilience to climate change impacts could also have a positive effect in terms of limiting the probability of the insurgence of new conflicts as a result of a natural disaster. Our results seem to suggest that, firstly, there is a positive impact of natural disasters on the probability of new conflicts. Secondly, the effects of natural disasters on the probability of insurgence of new conflicts might be differentiated for different levels of resilience, vulnerability and ethnic fractionalization. In particular, the probability that a natural disaster increases the likelihood of conflicts is higher for more vulnerable, less resilient countries than in more resilient, less vulnerable countries. Finally, as for ethnic fractionalization, its role appears interesting and deserves further exploration because, even though there is no evidence of a direct link between ethnic fractionalization and armed conflicts, our results suggest that natural disasters occurring in highly vulnerable, low resilient countries with high ethnic fractionalization are more likely to result in new conflicts. This is definitely a result that needs further testing, but is in line with the literature assessing high ethnic fractionalization as an additional trigger to the possibility of violent activities to arise, given pre-existing vulnerable social, economic and political conditions.

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Appendix A – Details on data sources[8]

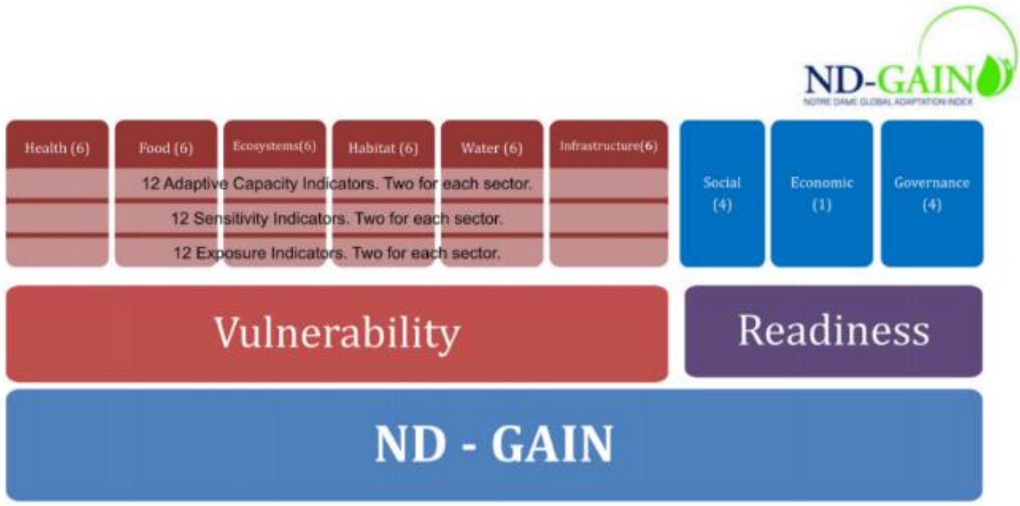
The ND Gain Global Adaptation Initiative compiles a Country Index, which shows a country's vulnerability to climate disruptions and readiness to leverage private and public sector investment for adaptive actions. ND-GAIN brings together over 74 variables to form 45 core indicators to measure vulnerability and readiness of 192 UN countries from 1995 to the present.

ND Gain measures vulnerability taking into account three dimensions (exposure, sensitivity, adaptive capacity) and six key sectors (food, water, health, ecosystem services, human habitat and infrastructure).

Each sector is represented by six indicators which represent the three dimensions of vulnerability: two indicators for sensitivity, two for exposure, two for adaptive capacity. Each component has 12 indicators, 2 for each of the 6 sectors, for a total of 36 indicators.

Readiness is divided in economic, social and governance readiness. Each component is represented by 3 indicators for a total of 9 indicators.

Figure A1: Summary of ND Gain Vulnerability and Readiness indicators. Source: ND GAIN Technical document



[8] This appendix is based upon the ND Gain Technical document (Chen C., Noble I., Hellmann J., Coffee J., Murillo M., Chawla N. (2015). University of Notre Dame Global Adaptation Index Country Index Technical Report.)

In order to obtain the final result – i.e., an indicator which ranges from 0 to 1 for both readiness and vulnerability – the procedure is as follows:

1. Selection of raw data;
2. Interpolation of missing data;
3. Identification of baseline minimum and maximum for raw data;
4. Definition of reference point for each indicator;
5. Scaling of raw data to scores, with values ranging from 0 to 1;
6. Computation of readiness and vulnerability score;
7. Computation of the Country Index

Scaling follows the following formula:

$$\text{score} = |\text{"direction"} - \frac{\text{"}raw\text{"}\ data\ -\ reference\ point}{baseline\ maximum - baseline\ minimum}|$$

Where “direction” is either 0 when calculating the score of the vulnerability indicator or 1 when calculating the readiness indicator, so that a higher vulnerability score means higher vulnerability (worsening) and a higher readiness score means higher readiness (improvement) (Chen et al, 2015, pp. 6-8).

Appendix B – List of countries belonging to different clusters

Cluster 1: Highly problematic countries. Afghanistan, Angola, Benin, Burkina Faso, Central African Republic, Chad, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Djibouti, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Guyana, Indonesia, Iran, Kenya, Kuwait, Laos, Liberia, Malawi, Mali, Mauritania, Namibia, Nepal, Niger, Nigeria, Pakistan, Philippines, Senegal, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Uganda, Zambia

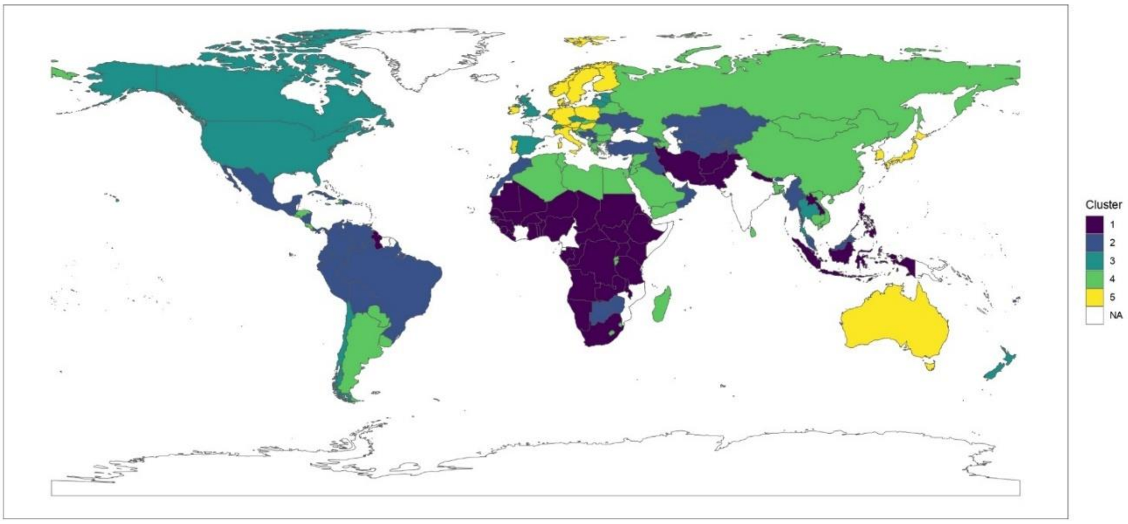
Cluster 2: Still problematic, but in slightly better conditions. Bahrain, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Colombia, Cuba, Dominican Republic, Ecuador, Fiji, Georgia, Guatemala, Iraq, Kazakhstan, Kyrgyz Republic, Malaysia, Mexico, Moldova, Morocco, Myanmar, Nicaragua, North Macedonia, Oman, Panama, Peru, Qatar, Serbia, Tajikistan, Trinidad and Tobago, Turkey, Turkmenistan, Ukraine, United Arab Emirates, Uzbekistan, Venezuela, Zimbabwe

Cluster 3: Wealthy countries with some concerns. Belgium, Canada, Chile, Cyprus, Czech Republic, Estonia, Israel, Latvia, Lithuania, Mauritius, New Zealand, Singapore, Spain, Switzerland, Thailand, United Kingdom, United States

Cluster 4: Problematic countries with an homogeneous ethnic composition. Albania, Algeria, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Bulgaria, Burundi, Cambodia, China, Comoros, Costa Rica, Croatia, Egypt, El Salvador, Eswatini, Greece, Haiti, Honduras, Jamaica, Jordan, Lebanon, Lesotho, Libya, Madagascar, Mongolia, Paraguay, Romania, Russian Federation, Rwanda, Saudi Arabia, Slovak Republic, Solomon Islands, Sri Lanka, Syrian Arab Republic, Tunisia, Uruguay, Vietnam, Yemen

Cluster 5: Wealthy, resilient countries. Australia, Austria, Denmark, Finland, Germany, Hungary, Ireland, Italy, Japan, Korea, Rep, Netherlands, Norway, Poland, Portugal, Slovenia, Sweden

Figure B1: Visual representations of the 5 clusters. Source: authors' own elaboration on the data.



Appendix C – Additional results and robustness checks

In this appendix we report the results for the estimations of specification 1,2 and 3, which correspond to the marginal effects in Table 4, 5 and 6 of paragraph 4 in the paper. Additionally, we report additional robustness checks for specifications 1 and 2.

Table C1: Estimation results for specification n. 1

	(1) New total conflicts	**(2) New state conflicts**	**(3) New non-state conflicts**
Pre-sample mean of total conflicts	0.349***	0.315***	0.650***
	(0.0513)	(0.0744)	(0.111)
HDI	-1.167**	-1.679***	-1.401*
	(0.562)	(0.649)	(0.728)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	-0.0626	-0.283	0.219
	(0.166)	(0.181)	(0.228)
Cluster n.3 (dummy)	-0.0832	-0.0585	-0.0123
	(0.275)	(0.292)	(0.448)
Cluster n.4 (dummy)	-0.136	-0.209	0.00208
	(0.135)	(0.155)	(0.223)
Cluster n.5 (dummy)	-0.715*	-0.712*	[empty]
	(0.387)	(0.399)	
Total number of disasters in a 3-year period	0.0202***	0.00879	0.0202***
	(0.00513)	(0.00550)	(0.00633)
N of observations	2454	2454	2182

Notes: pooled probit model for state and non-state conflicts, both together (column 1) and separately (columns 2 and 3). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies.

Table C1 shows that the total number of natural disasters has a positive and significant effect on the probability of total conflicts. Additionally, the pre-sample mean of total conflicts has a positive and significant effect in all the specifications, signaling a certain degree of persistence of violent activities. Finally, the coefficient for HDI is negative and significant, meaning that a higher HDI corresponds to a lower probability of conflicts.

Then, we report the estimation results for specification n. 2. Results are shown in Table C2.

Table C2 shows that there is a differentiated effect of natural disasters on the probability of violent conflicts; while we cannot comment on the magnitude of the effects from these results (see Table 5 in paragraph 4 for the marginal effects), still the effect of natural disasters on the probability of conflicts seems to be positive for cluster n. 1 and 2, while it seems negative (but not very significant) for clusters 3 and 4.

Table C2: Estimation results for specification n. 2

	(1) New total conflicts	(2) New state conflicts	(3) New non-state conflicts
Pre-sample mean of total conflicts	0.328***	0.392***	0.583***
	(0.0507)	(0.0809)	(0.113)
HDI	-1.400**	-1.567**	-1.787**
	(0.555)	(0.677)	(0.707)
Cluster n. 1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n. 2 (dummy)	-0.307	-0.413*	0.170
	(0.190)	(0.234)	(0.257)
Cluster n. 3 (dummy)	-0.0392	-0.766**	0.723
	(0.271)	(0.307)	(0.542)
Cluster n. 4 (dummy)	-0.0118	-0.403*	0.293
	(0.147)	(0.206)	(0.238)
Total number of disasters in a 3-years period	0.0213***	-0.00895	0.0385***
	(0.00758)	(0.0104)	(0.00859)
Total number of disasters in a 3-year period	0.0581***	-0.0236	0.0356**
x Cluster n. 2	(0.0148)	(0.0301)	(0.0181)
Total number of disasters in a 3-year period	-0.00146	0.109***	-0.393*
x Cluster n. 3	(0.0105)	(0.0277)	(0.223)
Total number of disasters in a 3-year period	-0.0129*	0.0170*	-0.0299***
x Cluster n. 4	(0.00784)	(0.00990)	(0.00810)
N of observations	2182	2182	2182

Notes: pooled probit model for state and non-state conflicts, both together (column 1) and separately (column 2 and 3). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies. Cluster n. 5 was omitted as it contained only 1 conflict (Australia).

Finally, we report the estimation of specification n. 3 Results are shown in Table C3. Table C3 shows that the only significant effects, excluding HDI and the pre-sample mean of total conflicts which we have discussed earlier, are the total number of floods for total conflicts, total number of fires for state conflicts and total number of landslides for non-state conflicts. While these results are not easy to interpret, they do point out to the possibility of the differentiated effects of different natural disasters on violent activities, hence the importance of accounting for this dimension of heterogeneity in the analysis.

Table C3: Estimation results for specification n. 3

	(1) New total conflicts	(2) New state conflicts	(3) New non-state conflicts
Pre-sample mean of total conflicts	0.341***	0.315***	0.658***
	(0.0520)	(0.0726)	(0.119)
HDI	-1.247**	-1.786***	-1.515**
	(0.579)	(0.644)	(0.732)
Cluster n. 1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n. 2 (dummy)	-0.0181	-0.278	0.270
	(0.161)	(0.181)	(0.232)
Cluster n. 3 (dummy)	0.00462	-0.0496	0.149
	(0.272)	(0.295)	(0.454)
Cluster n. 4 (dummy)	-0.0713	-0.226	0.0982
	(0.129)	(0.166)	(0.234)
Cluster n. 5 (dummy)	-0.625*	-0.771**	[empty]
	(0.379)	(0.370)	
Total number of droughts in a 3-year period	-0.00143	0.0171	-0.0495
	(0.0812)	(0.0959)	(0.0990)
Total number of fires in a 3-year period	0.0678	0.152***	-0.00824
	(0.0504)	(0.0536)	(0.0693)
Total number of floods in a 3-year period	0.0316**	0.0216	0.0181
	(0.0158)	(0.0173)	(0.0169)
Total number of landslides in a 3-year period	0.0524	-0.0675	0.141***
	(0.0413)	(0.0494)	(0.0458)
Total number of extreme temperature events	-0.0556	-0.0936	-0.109
in a 3-year period	(0.0705)	(0.0655)	(0.101)
Total number of storms in a 3-year period	0.00680	0.00288	0.0129
	(0.0120)	(0.0149)	(0.0180)
N of observations	2454	2454	2182

Notes: pooled probit model for state and non-state conflicts, both together (column 1) and separately (column 2 and 3). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies.

As additional robustness checks, we have estimated the equations for specification 1 and 2 with some modifications. For specification 1, we have added saturated interactions among the clustering variables as regressors, along with the cluster dummy variables. We have done this in order to assess the sign and significance of different interactions among the clustering variables on our dependent variables. Marginal effects are reported in Table C4.

Table C4: Robustness check for specification n. 1 (controlling for time-varying clustering variables)

	(1) New total conflicts	**(2) New state conflicts**	**(3) New non-state conflicts**
Pre-sample mean of total conflicts	0.0328***	0.0150**	0.0533***
	(0.00714)	(0.00619)	(0.0107)
HDI	-0.0471	-0.0558	-0.0223
	(0.124)	(0.0704)	(0.130)
Readiness	-0.488***	-0.294***	-0.431***
	(0.104)	(0.0646)	(0.117)
Vulnerability	-0.313	-0.235*	-0.193
	(0.190)	(0.122)	(0.182)
Ethnic fractionalization	0.0693	-0.0197	0.190**
	(0.0763)	(0.0457)	(0.0864)
Cluster n. 1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n. 2 (dummy)	0.00491	-0.0269	0.0525**
	(0.0273)	(0.0262)	(0.0266)
Cluster n. 3 (dummy)	0.0292	0.0102	0.108
	(0.0604)	(0.0525)	(0.0835)
Cluster n. 4 (dummy)	0.0181	-0.0202	0.117*
	(0.0436)	(0.0353)	(0.0636)
Cluster n. 5 (dummy)	-0.0482	-0.0500*	[empty]
	(0.0398)	(0.0291)	
Total number of disasters in a 3-year period	0.00227***	0.000332	0.00198***
	(0.000675)	(0.000379)	(0.000573)
N of observations	2454	2454	2182

Notes: Marginal effects as a robustness check for a pooled probit model for state and non-state conflicts, both together (column 1) and separately (column 2 and 3). Saturated interactions were used together with cluster dummy variables. Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies.

First and foremost, accounting for time-varying readiness, vulnerability and ethnic fractionalization (in addition to time-invariant cluster dummies) has no influence on the sign, magnitude and significance of our indicator of natural disasters. Second, higher levels of readiness on average are linked to a reduction in the probability of state and non – state conflicts of 48.8% compared to the lowest level; if we take state and non – state conflicts separately, the effect is stronger for non – state conflicts (43.1%) than state conflicts (29.4%). Marginal effects for vulnerability are negative but not significant, except for state conflicts. Finally, marginal effects for ethnic fractionalization are positive and significant only for non – state conflicts, showing that the likelihood of non – state conflicts is influenced more by ethnic tensions with respect to state conflicts. This points to the possibility of ethnic tensions being relevant in influencing only non – state conflicts, in which the two opposing sites do not belong to a government or a state and hence are more local.

Then, we performed a robustness check for specification n. 2, adding time-varying clustering variables along with the interaction between the total number of disasters and the cluster dummy variables, which are time-invariant. Marginal effects are reported in Table C5.

Table C5: Robustness check for specification n. 2 (controlling for time-varying clustering variables)

Marginal effects of total number of disasters in a 3-year period	**(1) New total conflicts**	**(2) New state conflicts**	**(3) New non-state conflicts**
At Cluster n. 1	0.00220**	-0.00138	0.00204***
	(0.000989)	(0.00131)	(0.000557)
At Cluster n. 2	0.0104***	-0.00106	0.00982***
	(0.00208)	(0.00141)	(0.00247)
At Cluster n. 3	0.00320*	0.00853**	-0.0334*
	(0.00177)	(0.00350)	(0.0188)
At Cluster n. 4	0.00101	0.000326	0.00161*
	(0.000775)	(0.000352)	(0.000897)
N of observations	2182	2182	2182

Notes: Marginal effects as robustness check for a pooled probit model for state and non-state conflicts, both together (column 1) and separately (column 2 and 3). Time-varying cluster variables were added as controls together with cluster dummy variables (time invariant). Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies. Cluster n. 5 was omitted as it contained only 1 conflict (Australia).

Also in this case, our main results are robust to the inclusion of time-varying clustering dummies. The differentiated effects for different clusters are still driven by cluster n. 2 (1.04%), while the effect for cluster n. 3 is stronger here (0.32%) than in specification 2 in the paper (0.263%). The effect is still strong for cluster n. 1 (0.22%), while it is not significant for cluster n. 4.

Finally, as a last robustness check we have estimated specification n. 2 by interacting the total number of disasters to each clustering variable (readiness, vulnerability, ethnic fragmentation) and then we have estimated the marginal effects of the total number of disasters for different relevant values of the clustering variables, distinguishing for state and non – state conflicts.[9] The idea here is to understand whether the cross-cluster

[9] We also saturate the model by controlling for the time-varying clustering dummy.

heterogeneity in the effect of natural disasters on conflicts is driven by one (or more) specific clustering variables. Marginal effects are reported in Table C6.

Table C6: Robustness check for specification n. 2

Panel A – State conflicts			
Average marginal effects of total number of disasters in a 3-year period	**Readiness**	**Vulnerability**	**Ethnic fractionalization**
At 10th percentile	-0.00476***	0.00315***	0.00137**
	(0.00173)	(0.00116)	(0.000685)
At 25th percentile	-0.00201**	0.00185***	0.00110**
	(0.000930)	(0.000692)	(0.000517)
At 50th percentile	0.000245	0.000445	0.000486
	(0.000415)	(0.000488)	(0.000413)
At 75th percentile	0.00144***	-0.000942	-0.00000913
	(0.000539)	(0.000666)	(0.000538)
At 90th percentile	0.00148	-0.00126*	-0.000195
	(0.000916)	(0.000720)	(0.000604)
N. of observations	2454	2454	2454
Panel B – Non-state conflicts			
Average marginal effects of total number of disasters in a 3-year period	**Readiness**	**Vulnerability**	**Ethnic fractionalization**
At 10th percentile	0.00542***	-0.0000668	0.000269
	(0.00171)	(0.00148)	(0.000230)
At 25th percentile	0.00379***	0.00107	0.000549*
	(0.00109)	(0.000940)	(0.000290)
At 50th percentile	0.00207***	0.00236***	0.00195***
	(0.000561)	(0.000743)	(0.000455)
At 75th percentile	0.000605**	0.00384***	0.00471***
	(0.000252)	(0.00125)	(0.00126)
At 90th percentile	0.00000305	0.00420***	0.00640***
	(0.0000567)	(0.00149)	(0.00193)
N. of observations	2182	2182	2182

Notes: Marginal effects as robustness check for pooled probit model for state and non-state conflicts for different relevant levels of the clustering variables. Standard errors clustered by country. *p<0.1, **p<0.05, ***p<0.01. Additional control variables: world region dummies, year dummies along with the other standard controls (HDI index, pre-sample mean of total conflicts).

For non – state conflicts the higher the level of readiness the less likely it is that a natural disaster will result in a conflict, while results are mixed for state conflicts. As for vulnerability, results show that for non – state conflicts the higher the vulnerability the more likely it is that a natural disaster will result in a conflict. Again, results are mixed for state conflicts. Finally, as ethnic fractionalization increases, so does the probability that a natural disaster will result in a non – state conflict; instead, lower ethnic fractionalization increases the probability that a natural disaster will result in a state conflict, pointing to the already mentioned differentiated role of ethnic tensions in state and non – state violent activities.