Università degli Studi di Urbino Carlo Bo

Department of
Economics, Society, Politics (DESP)

Ph.D. PROGRAMME IN:
Global Studies. Economy, Society and Law

CYCLE: XXXV

Essays on Climate Change, Armed Conflicts and Vulnerability

SSD: SECS-P/06

Coordinator: Ch.mo Prof. Antonello Zanfei
Supervisor: Ch.mo Prof. Giovanni Marin
Co-supervisor: Ch.ma Prof.ssa Valeria Costantini

Ph.D. student: Mariagrazia D'Angeli

ACADEMIC YEAR 2021/2022

Essays on Climate Change, Armed Conflicts and Vulnerability

Mariagrazia D'Angeli

Abstract

Climatic changes continue to pose significant challenges to the global community. The detrimental effects of climate change have resulted in devastating consequences, both in terms of loss of human life and long-term harm to economic and social systems. In particular, the security implications of climate change have gained increased attention in recent years. It is commonly acknowledged that the most vulnerable regions of the world are disproportionately affected by these distressing events, both in terms of climatic shocks and violent activities. Research has established that the relationship between climatic changes and conflict is not direct, but rather contingent on the vulnerability of a country. Vulnerability manifests itself both as a pre-existing condition and as a determinant of the more severe impacts of climatic changes in certain areas of the world and is a key element in certain regions' susceptibility to tensions and potential escalation into violent activities. Indeed, recent research has focused on the climate-conflict-vulnerability nexus, highlighting that the key connection between the drivers of conflict risk, the determinants of severe climatic impacts and the consequences of armed conflicts manifests as increased socioeconomic vulnerability. In this context, this work contributes to the literature on climate change, armed conflicts and vulnerability. Its objective is to examine the link between climate change and conflicts, evaluate the factors of vulnerability in one of the world's most susceptible regions, and empirically examine the impact of climate change and conflicts on subsequent socioeconomic vulnerability. To achieve these goals, a comprehensive analysis will be conducted by utilizing a diverse range of methodologies.

Dedication

I would like to take this opportunity to thank some wonderful people in my life that have motivated me and helped me complete this Dissertation.

To my supervisor and co-supervisor, Giovanni Marin and Valeria Costantini, thank you for your suggestions to improve my Thesis, but also for the light-hearted moments we have shared together. To Elena Paglialunga and Federica Cappelli, thank you for sharing your wisdom with me during my Phd journey and contributing with many useful insights to improve my work. To my wonderful colleagues and friends from the Phd Programme in Urbino, thank you for sharing laughs and stimulating conversations during our time together in Urbino before the pandemic started. To the people that I met during my time at Uppsala University, first of all my tutor, Paola Vesco, for her immense support both professionally and personally and for teaching me a lot - not just in terms of forecasting. To my family, thank you for being so supportive and helping me recover when times got hard. A special thank you goes to my mom, for her strenuous eagerness to motivate me and for her curiosity in the work I was doing. And finally, to myself. Despite everything, we did it.

Acknowledgements

This Thesis would have not been completed without the contribution of several people that I am extremely grateful to have met during my Phd journey. All of them have contributed with advice, manuscript revisions, methodological discussions and technical support. I wish to thank them all here.

First Chapter: Thank you to Giovanni Marin, my supervisor, and Elena Paglialunga for their help while I attempted my first efforts at implementing an empirical analysis. Thank you for your support and for having shown me how to get started with Stata.

Second Chapter: Thank you, again, to Giovanni Marin, Valeria Costantini, my co-supervisor, and Elena Paglialunga for teaching me everything I know about spatial econometrics. Thank you to Federica Cappelli for her support and for her helpful feedback.

Third Chapter: A huge thank you goes to Paola Vesco, my tutor during my visiting period at Uppsala University, for initiating me to the world of forecasting and for helping me discover the unknown (by me) potential of R. Thank you for your huge support and for your crucial feedback and professionalism.

All models are wrong,
but some are useful.
George E. P. Box

Contents

List of Figures

List of Tables

1

Introduction

1.1 General Framework

It is widely acknowledged that climate change is one of the most pressing issues of our time. The Intergovernmental Panel on Climate Change (IPCC) has stated that *"the warming of the climate system is by now unequivocal"* (IPCC, 2007, p.2). Human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels (IPCC, 2018). In its latest 2021 Report, the IPCC has stated that *"human influence has warmed the climate at a rate that is unprecedented in at least the last 2000 years"* (IPCC, 2021, p.6). Despite the participation of numerous countries in the signing of the Paris Agreement at COP21 in 2015, which aimed to *contain* the warming of the climate to below 2°C - ideally 1.5°C - compared to pre-industrial levels by 2030, it is highly unlikely that this goal will be achieved by that date, given the current rate of greenhouse gas (GHG) emissions.

Climate change is characterized by various long-term shifts in global climate patterns, including changes in temperature and precipitation levels, as well as increased frequency and intensity of extreme weather events such as droughts, floods, heavy rainfall, heatwaves and tropical cyclones (IPCC, 2007). In 2021, 432 disasters related to natural hazards were recorded in the EM-DAT Database (CRED, 2022). These changes have been and will increasingly affect both natural and human systems to an extent that could require radical adaptation responses in the future. Additionally, warming temperatures have been linked to a range of negative socioeconomic outcomes, including a reduction in economic growth and output (Dell et al., 2012) and negative consequences on agricultural yields, labor productivity, health, conflicts and political instability (Dell et al., 2014).

Organized violence has also been on the rise worldwide since 2020, reversing the downward trend in fatalities observed after the peak in 2014 (Pettersson et al., 2021). The Uppsala Conflict Data Program (UCDP) recorded 56 active conflicts in 2020, a record high since 1946 (Strand and Hegre, 2021). The decrease in fatalities in some areas, such as Syria, was offset by an upsurge in violence in other regions of the world, mainly in Africa (Pettersson et al., 2021). Armed conflicts have been referred to as "development in reverse" (Collier et al., 2003) and have been associated with a decline in economic growth (Gupta et al., 2004), development failures (Gates et al., 2012), food insecurity (FAO, 2020), migration and displacement (Schutte et al., 2021), as well as declining educational attainment (Davies, 2005; Diwakar, 2015).

In recent years, there has been growing research linking climate change and armed conflicts. Although no conclusive evidence has been found of a direct link between them, still climate change has been identified as an important trigger that exacerbates underlying social, economic, and institutional conditions and results in a higher risk and magnitude of violent activities (IPCC, 2014). In fact, climate change has been deemed as a "threat multiplier" that intensifies pre-existing drivers of conflicts, such as poverty or economic shocks (IPCC, 2014). This is particularly relevant in countries where the effects of climate change are more severe, as these regions are often also the most susceptible to both climate-related and conflict-related risks.

In fact, climate change impacts are not distributed equally across countries worldwide. Some countries and regions within countries are more affected by detrimental climatic effects than others, due to differences in geographic and socioeconomic conditions. The African continent, for instance, is one of the most vulnerable areas to climate change impacts (Chen, 2015), and it is also an area heavily affected by all types of climatic changes (IPCC, 2021) and violent events (Pettersson et al., 2021). The intersection of these complex dynamics can result in a vicious cycle of heightened climate impacts, higher conflict risk, and increased socio-economic vulnerability (Buhaug and Uexkull, 2021).

Vulnerability is both a pre-existing condition and a determinant of the more severe impacts of climate change in certain regions of the world. In the current context, where mitigation and adaptation options are necessary to cope with the changing climate, understanding the role of vulnerability, its drivers, and its consequences is crucial, particularly for regions of the world that may be affected by multiple concurrent crises - humanitarian, climatic, and economic. This is particularly important for regions that are already vulnerable, as it will help to identify the most at-risk communities and target efforts to reduce vulnerability and build resilience.

These are the reasons that explain the paramount importance of investigating the relationship between climatic changes, socioeconomic vulnerability, and violent activities, especially at this moment in time. We are at a "crossroad of crises": a changing climate is contributing to harmful economic and societal impacts, which in turn create increased migration and conflict risk. These events are more likely to occur in regions of the world that are already more vulnerable from both a socio-economic perspective and from previous adverse climatic impacts. Unfortunately, these areas of the world are paying a higher price for the ongoing climate crisis with respect to other parts of the world, not just in terms of harmful climatic effects but also in terms of economic and social collapse. All of these crises are currently occurring and unfortunately they may compound with each other, possibly creating complex and unprecedented consequences. Future predictions are not reassuring unless quick and decisive action is taken today. It is important to stress on the immediate need of acting and implementing policies that will address the current state of the climate and its challenges, while simultaneously considering peacekeeping efforts. This way, we can ensure that the most vulnerable populations will be protected and that the future of the planet will be more sustainable.

In this context, it is of the utmost importance to thoroughly examine these complex and encompassing relationships, in order to grasp how all these phenomena are linked and which actions can be taken to better understand and possibly prevent adverse effects from occurring, both in terms of violent activities, harmful climatic impacts, and increased socioeconomic vulnerability. A deeper understanding of these issues can help inform policies and strategies that address climatic goals while simultaneously taking into consideration peacekeeping objectives. This includes addressing the underlying social, economic and political factors that contribute to socioeconomic vulnerability and conflict risk, as well as investing in mitigation and adaptation measures that can help reduce the impacts of climate change on vulnerable populations.

Given the general framework outlined above, the goals of this work are as follows: first, to understand if and to what extent high vulnerability (or, conversely, resilience) can play a role in the climate-conflict nexus (Chapter 2); second, to analyze the local sources of vulnerability in the climate-conflict nexus with a high level of spatial granularity in one of the most vulnerable regions of the world, Eastern Africa (Chapter 3); finally, to assess how climate-related natural disasters and conflicts can affect subsequent socioeconomic vulnerability (Chapter 4).

This will be achieved through the use of several different methodologies across this work. First, Chapter 2 examines historical patterns of countries and assesses whether a high level of vulnerability (or, conversely, resilience) can have a conditional effect on the relationship between climate-related hazards and conflict risk. The methodological approach employed in this chapter includes a combination of cluster analysis to group together countries with similar levels of relevant variables and non-linear regression to examine the extent to which being resilient (or, conversely, vulnerable) has an effect on the probability of new conflicts to arise. Chapter 3 focuses on investigating the local sources of vulnerability that increase conflict risk as a consequence of long-term climatic variations in one of the most vulnerable regions of the world, Eastern Africa. By understanding the local sources of vulnerability in such a fragile context, it may be possible to develop policies that take both climate adaptation and peacekeeping efforts into account. Further, it might be possible to extend this approach to other vulnerable regions of the world, and identify location-specific sources of vulnerability to better tailor adaptation and conflict prevention policies. The methodology used in this chapter is a georeferenced approach in the context of spatial analysis, employed to better disentangle climatic, vulnerability and conflict dynamics at the local level and study the existence of spatial spillovers in the region. Finally, Chapter 4 looks at the future by investigating whether climate-related natural disasters and conflicts influence subsequent socioeconomic vulnerability. This is done by employing a forecasting approach in a machine learning framework.

This work finds several interesting results that are worth commenting on:

1. The impact of climate-related disasters on the probability of conflict is contingent upon the level of resilience and/or vulnerability of a country. Specifically, natural disasters are more likely to increase conflict risk in vulnerable countries as compared to resilient countries, *ceteris paribus*;
2. Climate change does not impact conflicts *per se*, but it is through the conditional intervention of pre-existing vulnerability factors that long-term climate variability is able to affect conflict risk in the Eastern Africa region;
3. Climate-related natural disasters and conflicts affect subsequent socioeconomic vulnerability, mainly through population-related dynamics.

These results are in line with the literature on the existence of a vicious cycle among high levels of vulnerability, increased conflict risk and harmful climatic impacts (Buhaug and Uexkull, 2021). All the results in this work are relevant because they all point out to the need to implement *"joined"* policies that address both climate adaptation and peace preservation. Furthermore, these results highlight the conditional relationship between climate change and conflict, which is strongly influenced by pre-existing vulnerability factors. All these results empirically demonstrate the existence of a vulnerability-conflict-harmful impacts vicious cycle and indicate the importance of fully comprehending these complex relationships when formulating future climate policies.

This introduction is structured as follows: Section 1.2 delineates the general theoretical framework of this work, connecting the main channels linking climate and conflict to considerations on socioeconomic vulnerability, while Section 1.3 details the contents of each chapter, each linked to a specific focus in the climate-conflict-vulnerability nexus.

1.2 Climate, vulnerability and conflicts

Long-term climate variability has been a major topic of public debate not only due to its direct effects, such as warming, ocean acidification and biodiversity loss, but also due to its potential impact on national security. In recent years, policymakers have become increasingly interested in the security implications of climate change, as it has the potential to escalate pre-existing tensions into crises.

Numerous research studies have been conducted in recent years on the relationship between climate and conflict (see for example Gleditsch 2012; Koubi 2019; Mach et al. 2019; Von Uexkull and Buhaug 2021). While no conclusionary evidence has been reached on the existence of a direct link between climatic variations and conflict outcomes (Hsiang et al., 2013; Buhaug et al., 2014), still it has been acknowledged that there is a conditional relationship between climate shocks and violent activities. In particular, pre-existing vulnerability plays a critical role in shaping this relationship. For example, climatic changes might increase conflict risk through a decrease in crop yield due to extensive drought periods (Raleigh et al., 2015; Von Uexkull et al., 2016). This will be particularly harmful in areas of the world where affected people rely their livelihoods mainly on the agricultural sector, which is particularly susceptible to climatic conditions. Additionally, the consequences of climate on conflict are more detrimental in regions that already suffer from pre-existing vulnerabilities, such as poverty and low levels of development (Gates et al., 2012). As a result, there may be a vicious cycle between climate impacts, conflict risk and socioeconomic vulnerability(Buhaug and Uexkull, 2021). This implies that vulnerable societies have a higher risk of experiencing more pronounced climatic impacts and detrimental conflict effects, which in turn will increase future levels of societal vulnerability, creating the aforementioned vicious cycle.

According to the notion of vulnerability, which is defined as *"the propensity or predisposition to be adversely affected"*(IPCC, 2014, p.5), vulnerable societies may be more prone to suffer detrimental effects as a consequence of climatic changes compared to less vulnerable ones (IPCC, 2022b). Such predisposition ultimately depends on structural economic and political relationships as well as historical cultural values and praxes, assigning a strong societal connotation to the concept of vulnerability (Gaillard 2010; Wisner et al. 2014).

Buhaug and Uexkull (2021) are, to the best of our knowledge, the first to establish a theoretical connection among climate change, conflicts and socioeconomic vulnerability. In their paper, Buhaug and Uexkull (2021) detail the existence of a vicious cycle between harmful climatic impacts, increased conflict risk, and enhanced socioeconomic vulnerability. They demonstrate that many of the conditions that shape socioeconomic vulnerability to subsequent hazards also influence conflict risk, and are exacerbated by the consequences of violent activities, which further increase socioeconomic vulnerability to subsequent hazards, trapping affected societies in a vicious cycle of harmful conflict impacts, increased climate-related risks and heightened vulnerability. This seminal paper is the starting point of this dissertation, which aims at exploring the complex interrelations among socioeconomic vulnerability, conflict risk and harmful climatic impacts.

In this section, we delineate the main channels linking climate change and violent activities, with particular attention to the role of vulnerability in this conditional relation. Despite a large number of studies investigating the relationship between climate change and conflict, evidence of an unmediated effect of climate change on violent activities is still insufficient (Hsiang and Burke 2014; Buhaug et al. 2014; Koubi 2019; Ide et al. 2020). However, some preliminary conclusions have been reached. For example, researchers have distinguished between direct and indirect

effects of climate change on conflict risk (Koubi, 2019). Direct effects include physiological/psychological factors and resource scarcity. The latter, in particular, has been the focus of many studies (e.g., Maxwell and Reuveny 2000; Berger 2003; Audu 2014; Vesco et al. 2020; Fatima et al. 2022). It has been argued that resource scarcity will increase the likelihood of conflict as communities struggle to meet their most basic needs, or as different communities with different lifestyles compete for access to resources (e.g. farmers versus pastoralists) (Audu, 2014). However, it is important to note that disputes over access to scarce resources are not always the main driver of conflicts. More often, these grievances compound with pre-existing vulnerabilities such as ethnic polarization, high levels of inequality and poverty (UN, 2012).
Among the indirect factors linking climate change to conflicts, Koubi (2019) mentions poor economic outcomes and migration. In fact, on the one hand, high income inequality, sluggish economic growth, and low levels of development are all factors that can serve as pre-existing vulnerabilities in shaping the relationship between climate change and conflict, thus increasing the risk of violent activities as a result of climate-related shocks. On the other hand, while migration is a complex phenomenon, environmental change can influence people's decision to migrate both directly and indirectly through its influence on other drivers, such as the disruption of people's economic livelihoods (Black et al., 2011). This disruption is likely the result, for example, of pre-existing vulnerabilities in the agricultural sector, which is particularly dependent on climatic variables. As a result, affected population may decide to migrate as an adaptation measure against climate change and its adverse effects on living conditions (Koubi et al. 2016, Conigliani et al. 2021). Additionally, climate-induced migration may lead to higher conflict risks in receiving areas due to competition for access to scarce resources, especially if this is compounded by underlying ethnic and socioeconomic cleavages (Brzoska and Fröhlich, 2016; Schleussner et al., 2016; Koubi, 2019). However, whether migration leads to conflicts in the receiving regions depends largely on political, economic, and social contextual factors and thus needs to be analyzed on a case-by-case basis (Abel et al., 2019).

Although there is some research on the direct effects of increased temperatures on different forms of violence (Mares and Moffett 2016, 2019), most studies have focused on the *indirect, conditional* impacts of climate variability on conflict outcomes. Specifically, a major pathway that has been identified as being a source of vulnerability in the climate - conflict nexus is the agricultural sector (Raleigh et al., 2015; Koubi, 2019; Sharifi et al., 2021a; Sharifi et al., 2021b; Vesco et al., 2021).

In particular, climate-related reduction in agricultural productivity can in turn *"cause unemployment, diminish economic capacity and/or reduce availability, accessibility and affordability of essential needs such as food"* (Sharifi et al., 2021b, p.9). The impacts associated with food systems are particularly pronounced in countries where the economic system is heavily dependent on agriculture, as this sector is particularly vulnerable to the effects of climate change. In this case, the loss of agricultural output could produce serious consequences in terms of both economic and food security, which can eventually result in violent outcomes (Von Uexkull et al. 2016; Harari and Ferrara 2018; Vesco et al. 2021). Reduced crop yields may also lead to changes in food prices (Raleigh et al., 2015) and/or livestock displacement which could further increase land use competition (Maystadt et al., 2014), as well as tensions between different modes of living (Kirkbride 2008; Scheffran et al. 2019). Harari and Ferrara (2018) also suggests that the timing when climate change manifests its effects is relevant, as the growing season is the period in the year in which crops are most sensitive to shocks. This is especially relevant for communities that rely on traditional agricultural practices, and hence are more vulnerable to seasonal changes. For example, Von Uexkull et al. (2016) focus on the drought-conflict relationship during the growing season and find that, while under most conditions droughts do not influence conflict risk, in the case of agriculturally dependent groups and politically excluded ethnic groups in poor countries droughts do increase the risk of violent activities.

In addition to these factors, various other contextual elements have been identified as playing a significant role in exacerbating or alleviating the relationship between climate and conflict, such as state capacity and institutions (Cappelli et al. 2022b; Gizelis and Wooden 2010; Jones et al. 2017, Petrova 2022), economic growth and development (Miguel et al., 2004), previous conflicts (Collier et al., 2003). All of these elements contribute to shaping pre-existing socioeconomic vulnerability and ultimately have a significant impact on the relationship between climatic impacts, conflict risk, and subsequent socioeconomic vulnerability (Buhaug and Uexkull, 2021).

1.3 Dissertation Structure

Given the theoretical background presented above, the goals of this dissertation are the following: first, to shed light on the conditional relationship intervening between climate-related shocks and conflict outcomes; second, to understand the role of local vulnerability factors in conditioning the climate - conflict relationship; third, to understand if, conversely, climate-related shocks and conflicts can have a role in affecting subsequent socioeconomic vulnerability. Each chapter in this dissertation departs from the general theoretical framework on climate, conflict and vulnerability to explore some specific aspects in the climate-conflict-vulnerability relationship.

1.3.1 Climate change, armed conflicts and resilience: a conditional link

Chapter 2 analyses the conditional effect of climate-related hazards on the risk of new armed conflicts, considering specific levels of relevant variables in the climate - conflict relationship, including the level of resilience, vulnerability and ethnic fractionalization of a country. This is accomplished by first conducting a cluster analysis based on the aforementioned variables. As a result of this procedure, five distinct groups of countries are identified. Then, a non - linear regression is performed to, firstly, understand the impact of natural disasters on the probability of armed conflicts; second, analyze if such impact is contingent upon various combinations of the clustering variables, specifically for varying levels of resilience, vulnerability, and ethnic fractionalization. This paper examines historical patterns among countries and emphasizes the role of resilience as a mediating factor in the relationship between climate and conflict. In fact, it finds that, *ceteris paribus*, it is more likely that a natural disaster might result in a conflict in more vulnerable, less resilient countries with respect to more resilient, less vulnerable ones.

1.3.2 Local sources of vulnerability to climate change and armed conflicts in East Africa using spatial analysis

This chapter delves into the relationship between climate, conflict, and vulnerability on a more granular level, with a focus on the East Africa region. A spatial analysis approach is employed to firstly analyze whether long-term climate variability has an impact on conflict risk in Eastern Africa; then, evaluate the role of vulnerability in the climate - conflict relationship in the region; finally, pinpoint local sources of vulnerability specific to the Eastern Africa region that could help explain the conditional effect of long term climate variability on conflict risk. This chapter focuses on the *agriculture* and *resource* channels as potential vulnerability factors influencing the climate - conflict relationship in the region. The findings suggest that climatic variability does not impact on the probability of conflict *per se*, but conditional on some other pre-existing sources of vulnerability. In particular, in the case of the Eastern Africa region, such sources of vulnerability include the presence of shared water resources and spatial inequality in resource access.

1.3.3 Predicting the impact of armed conflict on vulnerability: a Machine Learning approach

This chapter examines the relationship between climate-related natural disasters, conflicts, and vulnerability from a predictive perspective. Specifically, it investigates the potential impact of both conflicts and climate-related hazards on subsequent levels of socioeconomic vulnerability with the objectives of, firstly, understanding if armed conflicts affect predictions of subsequent socioeconomic vulnerability. Secondly, it analyzes if climate-related hazards improve predictions of subsequent socioeconomic vulnerability; finally, it combines the effects of conflicts and climate-related hazards on the one hand, and gender inequality on the other, to examine if they improve predictions of subsequent socioeconomic vulnerability, employing a machine learning approach. The findings confirm the intricate connections between climate impacts, violent activities, and socioeconomic vulnerability.

2

Climate change, armed conflicts and resilience: a conditional link

2.1 Introduction

This chapter aims at providing empirical evidence on the link between the emergence of climate-related extreme events and violent conflicts, and whether resilience and vulnerability affect this relationship, considering a panel of 151 countries over the period 1995-2013. The chapter is organized as follows: Section 2.2 lays out the relevant theoretical background; Section 2.3 sets out the methodological approach; Section 2.4 provides evidence on the empirical link between climate-related extreme events and violent conflicts accounting for differences based on which cluster countries belong to. Finally, Section 2.5 concludes.

2.2 Theoretical Background

2.2.1 Vulnerability, resilience, risk and exposure: a taxonomy

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 chapter 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.

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 (Modica and Zoboli, 2016). IPCC (2014) 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). We refer to vulnerability taking into account the definition of the IPCC, hence we consider it as the propensity to be negatively affected by climate-related hazards. Resilience has, instead, taken on a slightly different meaning 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. In this analysis, we take into account resilience as defined by Pimm (1984). Hence, we intend resilience as the ability of a system to recover after a shock. Accordingly, we expect that more resilient communities might confront lower risks of violent activities as resulting from natural disasters (Ide et al., 2020). Conversely, more vulnerable countries might be affected by the detrimental consequences of natural disasters to such an extent that tensions might more easily result in violent activities.

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 as *"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 a 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 rather depend on the vulnerability and exposure of a system, and not from the hazard itself. Risk needs to be understood as the product of the interaction between the hazard, 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"*(Kliesen and Mill 1994; Modica and Zoboli 2016) as a result of the damage to infrastructures and/or physical assets after a shock.

2.2.2 Natural disasters, risk factors and socioeconomic 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). Natural disasters are defined as *"severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions"* (IPCC, 2012, p.31).

In recent decades, there has been a noticeable rise in the frequency of extreme climate events. This constitutes a significant concern, not only due to the event itself, but also because of its socio-economic consequences. In fact, as Cavallo, Noy, et al. (2011, p.64) point out, *"the very occurrence of disasters is an economic event"*. This is because natural disasters occur within a certain well-defined social, economic and political context, leading to 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 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, since this will be crucial for designing effective response strategies in the event of a natural disaster (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, Noy, et al., 2011). 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 (Cavallo, Noy, et al., 2011). Indirect damages, on the other hand, refer to the economic activity that will not take place because of the disaster (Cavallo, Noy, et al., 2011).

In addition to immediate consequences, the long-term effects of natural disasters should also be taken into account, such as population decline and reduced average income. These impacts, along with the number of deaths and injuries, infrastructure damage, and emergency operation costs, must be considered in order to fully understand the overall impact of a disaster (Marin et al., 2021). 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 (Markhvida et al., 2020).

Natural disasters have been linked to a series of negative consequences, 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 (IPCC 2014; Schleussner et al. 2016; Cappelli et al. 2021). For example, despite a lack of consensus on the relationship between ethnic fractionalization and conflict, it might be that the disruptive nature of extreme climatic events might have severe consequences in terms of violent activities particularly in ethnically fractionalized societies (Schleussner et al., 2016). The main mechanisms 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).

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 that tensions degenerate in violent 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 tensions and, ultimately, conflict.

Given the theoretical background presented above, it becomes then important to understand if, and to what extent, high levels of resilience or vulnerability can play a role in the probability of violent activities resulting from climate-related shocks. Hence, we formulate the following hypotheses:

Hypothesis 1. Natural disasters increase the likelihood of new conflicts.

Hypothesis 2. Different levels of vulnerability and resilience to natural disasters differently affect the disaster-conflict relationship.

2.3 Methodology

According to the literature reviewed in the previous section, 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. As a second step, we employ the classification derived from the cluster analysis to assess the likelihood of new conflicts as a function of natural disasters, both independently and in conjunction with varying degrees of vulnerability and/or resilience. This approach aims to investigate the potential interplay between climate-related disasters and social vulnerability and resilience in shaping the occurrence of conflicts.

2.3.1 Data and indicators

Data on the number of conflicts are drawn from the UCDP Armed Conflicts Dataset, which contains information on armed conflicts from 1946 to 2020 (Pettersson, 2021b). The UCDP Dataset contains information on both state and non-state armed conflicts. A state-based armed conflict is defined by UCDP 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 come from the EM-DAT Database on natural disasters managed by the Center for Research on the Epidemiology of Natural Disasters[1] (CRED, 2022). The EM-DAT Database contains information on several types of natural disasters (geophysical, meteorological, hydrological, climatological, biological, extra- terrestrial, technological) from 1900 to the present day (Guha-Sapir, 2020). In order for a disaster to be entered in the database, at least one of the following criteria have to be fulfilled:

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

[1] Data from EMDAT are widely used, but still present some limitations (for example, see Jones et al. 2022). Still, we rely on this dataset as it provides relevant information on natural disaster events and other pertinent exposure-related variables, such as the number of people impacted. Moving forward, it would be interesting to expand upon this research by incorporating data on heatwaves and droughts from climate datasets such as ERA5.

In our analysis we focus on all climatological, meteorological and hydrological disasters, as they are more related to the changing climate with respect to other events such as earthquakes [2]. Within these different disaster types, we have distinguished between slow-onset disasters (droughts, extreme temperatures) and rapid-onset disasters (fires, floods, landslides and storms), as the literature highlights that the latter are more likely to trigger repression dynamics (Wood and Wright, 2016), civil unrest (Nardulli et al., 2015), political instability (Omelicheva, 2011) and violent conflicts (Nel and Righarts, 2008). Moreover, research has found that the distinction between rapid and slow-onset disasters is relevant for conflict dynamics, as rapid onset disasters require reactive actions and can easily show the government's inadequate preparation for disaster response (Lee et al., 2022).

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 degree, 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 consider as proxy for a country's resilience the *readiness* indicator from the ND Global Adaptation Initiative (ND-GAIN) developed by the University of Notre Dame, Indiana (USA) [3] (Chen, 2015). This is a synthetic measure defined

[2] 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).

[3] An in-depth description of the data can be found in Appendix **??**.

as *"the [country] readiness to make effective use of investments for adaptation actions thanks to a safe and efficient business environment"* (Chen, 2015, p.4). In this sense, this indicator focuses on the ability to leverage investments for adaptation actions and is based on three main dimensions: economic, governance and social readiness. Economic readiness refers to the *"investment climate that facilitates mobilizing capitals from private sector"* (Chen, 2015, p.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 with high coping capacity, as discussed earlier. However, this index has the advantage of being available for many countries worldwide, hence guaranteeing a high level of comparability across nations. Additionally, as a synthetic indicator that captures a crucial aspect of resilience, namely the ability to limit or rapidly recover from the impacts of a climate-related shock, it is valuable to incorporate this measure into the classification we are conducting. By doing so, we can account for a country's capacity to recover quickly, which in turn reduces the likelihood of natural disasters contributing to an increased probability of conflicts.

The second indicator we take into account refers to the vulnerability of a certain country to climate-related shocks and we use as proxy the vulnerability index developed within the ND-GAIN. This index is a synthetic indicator of a country's

[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.

vulnerability, which is defined as *"the propensity or predisposition of human societies to be negatively impacted by climate hazards"* (*Ibidem*, p. 3), hence referring to the IPCC definition of vulnerability. The advantage of using this indicator is given by the fact that 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 dependence 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. [5] We believe that this indicator of vulnerability is an essential component to be included in the cluster analysis, as there is a wide literature on the conditional effects of climate-related shocks on the probability of conflicts as mediated by vulnerability (for example, see Buhaug and Uexkull 2021). The concept of vulnerability is instrumental in determining the pre-existing conditions that impact the likelihood of tensions escalating into violent conflicts following a natural disaster. Vulnerability can arise from a variety of factors such as socio-economic inequalities, weak institutional frameworks, and inadequate disaster preparedness measures. These factors can exacerbate the impacts of natural disasters and increase the likelihood of conflicts emerging. Therefore, understanding the extent to which a society is vulnerable to environmental hazards is crucial in predicting the potential for conflicts to arise in the aftermath of a natural disaster.

[5] The scaling and weighting procedure used to build the vulnerability index is the same as the one used to build the readiness index.

A third relevant dimension for understanding the disaster-conflict nexus is the ability to foster cooperation among different social groups in reducing vulnerability and facilitating recovery in the event of an extreme event. Ethnicity is a strong determinant of social identity and political preferences and, as a consequence, of societal cleavages (Von Uexkull et al., 2016). In this regard, it is essential to investigate whether having a diverse range of ethnic groups within a country or region can be a valuable asset in the face of natural disasters, promoting adaptive capacity through cooperation and mutual aid. Alternatively, it is also possible that a high level of ethnic diversity could exacerbate the effects of natural disasters, thereby increasing the risk of armed conflict (Schleussner et al., 2016). Therefore, it is important to analyze the potential impact of ethnic diversity on the ability to cope with natural disasters and determine whether it is a contributing factor to either mitigating or exacerbating conflict risks. Hence, the third indicator we include in our cluster analysis is a measure of ethnic fractionalization, as a proxy for ethnic diversity within a country, and use the Historical Index of Ethnic Fractionalization (HIEF), 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), and contains data for 162 countries across all continents for the years 1945-2013.

2.3.2 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. The motivation for employing a cluster analysis as a first step is that it allows to perform a non-parametric combination of the relevant variables that are chosen to perform the cluster analysis. This approach is preferable to just employing control dummies, since it enables the identification of only the significant combinations of interactions among the variables included in the cluster analysis. Following Hair (2009), as a first step we run a hierarchical cluster analysis on the cross section of 151 countries based on data for year 1995. [6]. 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 each 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 2.1 reports the internal profiling of the five clusters, that is the characteristics of the different groups in terms of the clustering variables, Table 2.2 shows average values by cluster of 'external' variables and Table 2.3 reports the distribution of population across different clusters, broken down by income level and world region.

[6]Comparison between the cluster analysis for the year 1995 and 2013 yields an overlap among countries of 86.6 %. This goes up to 91.1 % if the comparison is made adding population weights.

Table 2.1: 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.

Table 2.2: External profiling of clusters

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Total**
Human Development Index	0.519	0.673	0.858	0.640	0.862	0.662
GDP per capita in PPS, constant USD, 2011	4306	10061	33421	6742	28906	11578
GINI index	39.3	47.8	38.8	39.2	31.8	39.9
Non-state conflicts (dummy)	0.214	0.166	0.010	0.050	0	0.099
State conflicts (dummy)	0.126	0.0378	0.084	0.050	0.002	0.066
Slow onset disasters (average per year)	0.226	0.370	0.793	1.277	0.400	0.751
Rapid onset disasters (average per year)	4.065	2.740	12.654	13.123	2.573	8.33

Notes: Average values over the period 1995-2013, weighted by country's population.

Table 2.3: 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.

Based on results shown in Tables 2.1, 2.2 and 2.3, we characterise the five clusters as follows [7]:

- **Cluster 1: Highly problematic countries.** This cluster is characterized by the lowest levels of readiness and highest levels of vulnerability, with the highest level of ethnic fractionalization. Countries in this group have very low GDP per capita and HDI and an intermediate degree of inequality. The countries belonging to cluster 1 are mostly located in the Sub-Saharan Africa region (501.41 million people, about 50%) and are prevalently low-income economies. 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

[7]The complete list of countries belonging to each cluster can be found in Appendix A.2

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 if compared to cluster 1. As for ethnic fractionalization, it is still high but not as high as cluster 1. Countries in this group have intermediate levels of HDI and GDP per capita but appear to be the most unequal countries. 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 internal profiling shows 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. Yet, 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. Countries in this group have the largest average GDP per capita and very high HDI, with intermediate levels of inequality. 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 a 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 vulnerability (even though they are not in the conditions of countries in cluster 1) but have a really low level of ethnic fractionalization. Countries in this group also have very low GDP per capita and HDI. We ex-

pect 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 clusters 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. Countries in this group are very wealthy and have the largest levels of HDI and, at the same time, they look very 'equal' on average. We expect countries in this cluster to be able to adequately deal with the consequences of climate-related natural disasters.

2.3.3 Empirical analysis

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.[8] 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:

$$\begin{aligned} Conflict_{it} = {} & \alpha_i + \rho TotConflict_{it0} + \beta Disaster_{i,t,t-2} \\ & + \sum_{j=1}^{n} \theta_{it}^{j} Clus_i^j + \Psi HDI_{it} + \delta_{i\in Reg} + \tau_t + \epsilon_{it} \end{aligned} \tag{2.1}$$

where:

[8] For future research, it would be interesting to broaden the scope of our estimation by incorporating the magnitude of extreme events. This could be achieved by including variables such as the number of fatalities resulting from a natural disaster. By doing so, we can gain a more comprehensive understanding of the relationship between natural disasters and conflicts, and how the severity of the former impacts the likelihood of the latter.

- $Conflict_{it}$ is a dummy equal to one if at least one new violent conflict occurred in country i in year t;
- $TotConflict_{it0}$ is the number of active 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 to account for unobservable characteristics of countries. We included world region dummies ($\delta_{i\in Reg}$) and year dummies (τ_t) to account, respectively, for unobserved factors common to all countries within a region (e.g. environmental hazards) and for trends common to all countries. HDI controls for the level of human development of countries, which is likely to affect both the expected impacts from disasters (and, thus, the likelihood to be included in the EM-DAT list) and the probability of conflicts arising for socio-economic reasons. 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). Moreover, the pre-sample mean is a proxy for time-invariant unobservable individual factors (Blundell et al., 1995), as it summarizes information about systematic historical differences in conflict intensity across different countries which depend on structural (and likely time-invariant) features.[9] We also control for the number of earthquakes, volcanic activity and epidemics in a 3-year period, since they are not strictly related to climate change but still cause damages and diminish a country's pool of resources to face other disasters. In estimating this equation, we are interested 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

[9] Additionally, the pre-sample mean allows to indirectly control for the time-invariant component of other relevant variables, such as food security.

of the residuals.

As a second step in our analysis, we estimate the heterogeneous effect of natural disasters on the probability of new conflicts for different combinations of resilience, vulnerability and ethnic fractionalization as summarized by cluster dummies. This is done by interacting our indicator of disasters with cluster dummies. 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 types of violence. Finally, we estimate the heterogeneous effect of natural disasters on the probability of new conflicts by distinguishing between rapid and slow onset disasters. The difference between slow (e.g., droughts) and rapid onset disasters (e.g., storms, cyclones) is relevant because they might compel different responses in terms of disaster prevention and recovery, which might thus entail different consequences in terms of conflict risk.

2.4 Results

Table 2.4: Average marginal effects for specification n. 1

	New total conflicts	**New state conflicts**	**New non-state conflicts**
Pre-sample mean	0.0399***	0.0233***	0.0594***
	(0.00599)	(0.00544)	(0.00995)
HDI	-0.117*	-0.107**	-0.114
	(0.0681)	(0.0483)	(0.0702)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.00167	-0.0229*	0.0313
	(0.0207)	(0.0134)	(0.0231)
Cluster n.3 (dummy)	-0.00387	-0.00727	0.00607
	(0.0324)	(0.0239)	(0.0382)
Cluster n.4 (dummy)	-0.00741	-0.0176	0.0112
	(0.0167)	(0.0127)	(0.0192)
Cluster n.5 (dummy)	-0.0555**	-0.0390***	
	(0.0224)	(0.0149)	
Number of earthquakes in a 3-year period	-0.0000394	0.00258	-0.00484
	(0.00338)	(0.00191)	(0.00341)
Number of epidemics in a 3-year period	0.00889***	0.00305	0.00743***
	(0.00245)	(0.00216)	(0.00201)
Number of volcanic eruptions in a 3-year period	0.00356	-0.0179*	0.0149
	(0.0104)	(0.0106)	(0.00922)
Total number of climate-related disasters in a 3-year period	0.00217***	0.000377	0.00216***
	(0.000729)	(0.000446)	(0.000720)
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, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period. The number of observations differs across the three estimations because countries in cluster n.5 perfectly predict the zero outcome, hence they have been dropped

Average marginal effects for the baseline specification are reported in Table 2.4, while estimated coefficients are shown in Table A.1 in Appendix A.3. Our results point to a positive and statistically significant effect of recent natural disasters (at time t, t-1 and t-2) on the probability of the emergence of new conflicts at time t. The average marginal effect of natural disasters is positive and indicates that 1 additional natural disaster in the past 3 years increases (on average) the probability of a new conflict of 0.217 %. Notice that the effect is positive and statistically significant for non – state conflicts (0.216 %), while it 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 conflicts between (formally or informally) organised groups due to rising tensions and grievances, rather than to spark conflicts involving the government of a state. The average marginal effect of the pre-sample mean of total conflicts is also positive and statistically significant in all specifications (total, state and non – state conflicts). This confirms the existence of the so-called "conflict trap" hypothesis, according to which violence is persistent over time since past conflicts are a strong predictor of the emergence of new conflicts (Collier et al., 2003). Finally, the average marginal effect for the HDI index is negative and statistically significant in 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; Conceição et al. 2020). The cluster dummies rarely show any significance, except for cluster 2 for state conflicts and cluster 5 for state and total conflicts. In both cases, the coefficients are negative, implying that if a country belongs to cluster 2, it is less likely to experience a new state conflict. Countries in cluster 5, instead, are less likely to experience new conflict. This is in line with our hypothesis, since cluster 5 is made up of wealthy and resilient countries. As for cluster 2, it might be that countries in that cluster are more likely to be subject to local tensions with respect to state conflicts. As for other non – climatic disasters, only the coefficients for the number of epidemics and volcanic eruptions in a 3-year period show statistical significance. As for the number of epidemics, the coefficient is positive and significant for new total conflicts and non – state conflicts, implying that epidemics can increase the likelihood of conflicts, as they might create serious health and economic crises, especially among the most vulnerable. This, in turn, might increase tensions and exacerbate conflict risk. As for volcanic eruptions, the coefficient is negative and significant only for state conflicts. This might imply that when a volcanic eruption occurs, all the resources of a country are moved to respond to the needs of the affected population. Hence, less resources are available to engage in violent activities among countries. [10]

In our second specification we account for both the homogeneous and the differentiated effect of natural disasters occurred in the past 3 years on the probability of the insurgence of a new conflict at time t for different combinations of readiness, vulnerability and ethnic fractionalization (i.e., for different clusters). We do this by interacting the number of disasters ($Disaster_{i,t,t-2}$) with the cluster dummies ($Clus_i^j$). Average marginal effects are reported in Table 2.5, while the coefficients are reported in Table A.2 in Appendix A.3. The relationship between natural disasters and the probability of insurgence of new conflicts is heterogeneous across clusters. Indeed, the marginal effects of natural disasters on total conflicts (column 1) are positive and significant for all clusters except cluster 4. Moreover, the magnitude of the effects is differentiated across clusters and is larger for countries more at risk of societal cleavages due to the higher level of ethnic fractionalization (i.e., clusters 1, 2 and 3): one natural disaster in the past three years increases the probability of insurgence of new conflicts by 0.219 % in cluster 1 and 1.01 % in cluster 2, while this value drops to 0.253 % for cluster 3 and is not significant for cluster 4. These results show that the effect of a natural disaster on the probability of new conflicts is stronger in magnitude in cluster 2, i.e., the low-resilience, high-vulnerability cluster characterised by the highest level of income inequality. This result confirms previous

[10] 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 A.6 of Appendix A.3, confirm the ones shown in Table 2.4.

evidence showing that countries with an unequal income distribution are likely to suffer the greatest damages when hit by a natural disaster (Cappelli et al., 2021). Additionally, if we look at non-state conflicts (column 3), we see that the effect of a natural disaster on the probability of conflicts is stronger for cluster 1 with respect to column 1; additionally, while for column 1 the effect was positive and significant for cluster 3, this is not the case for non-state conflicts. This is in line with the literature on the relationship between climate-related shocks and non-state conflicts, and points to stronger effects on non-state conflict risk for countries that are highly vulnerable and not very resilient.

Table 2.5: Marginal effects for specification n. 2

Marginal effects of total number of disasters in a 3-year period	**New total conflicts**	**New state conflicts**	**New non-state conflicts**
At Cluster n.1	0.00219*	-0.00106	0.00274***
	(0.00120)	(0.00129)	(0.000865)
At Cluster n.2	0.0101***	-0.00314*	0.00926***
	(0.00192)	(0.00167)	(0.00215)
At Cluster n.3	0.00253*	0.00836**	-0.0171
	(0.00133)	(0.00344)	(0.0140)
At Cluster n.4	0.000298	-0.000719	0.00131
	(0.000936)	(0.000590)	(0.000908)
N. of observations	2182	2182	2182

Notes: Marginal effects based on a pooled probit model (see Table A.2 in Appendix A.3 for coefficients). Standard errors clustered by country. $*p < 0.1, **p < 0.05, ***p < 0.01$. Additional control variables: world region dummies, year dummies, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period.

Table 2.6: Marginal effects for specification n. 3

	New total conflicts	**New state conflicts**	**New non-state conflicts**
Pre-sample mean	0.0400***	0.0233***	0.0597***
	(0.00602)	(0.00543)	(0.0102)
HDI	-0.120*	-0.111**	-0.117*
	(0.0684)	(0.0484)	(0.0704)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.00276	-0.0223*	0.0322
	(0.0203)	(0.0131)	(0.0233)
Cluster n.3 (dummy)	-0.00139	-0.00523	0.00830
	(0.0327)	(0.0244)	(0.0392)
Cluster n.4 (dummy)	-0.00563	-0.0163	0.0124
	(0.0162)	(0.0126)	(0.0193)
Cluster n.5 (dummy)	-0.0539**	-0.0379**	[empty]
	(0.0223)	(0.0148)	
Number of earthquakes in a 3-year period	0.000265	0.00276	-0.00443
	(0.00328)	(0.00183)	(0.00339)
Number of epidemics in a 3-year period	0.00890***	0.00311	0.00736***
	(0.00244)	(0.00214)	(0.00204)
Number of volcanic eruptions in a 3-year period	0.00245	-0.0201	0.0141
	(0.0108)	(0.0123)	(0.00971)
Number of slow-onset disasters in a 3-year period	-0.00197	-0.00318	-0.00151
	(0.00518)	(0.00450)	(0.00570)
Number of rapid-onset disasters in a 3-year period	0.00245***	0.000629	0.00237***
	(0.000877)	(0.000603)	(0.000842)
N. of observations	2454	2454	2182

Notes: Marginal effects based on a pooled probit model (see Table A.3 in Appendix A.3 for coefficients). Standard errors clustered by country. $*p < 0.1, **p < 0.05, ***p < 0.01$. Additional control variables: world region dummies, year dummies, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period. The number of observations differs across the three estimations because countries in cluster n.5 perfectly predict the zero outcome, hence they have been dropped.

Then, we estimate the last specification, in which we differentiate between rapid-onset (fires, floods, landslides and storms) and slow-onset disasters (drought, extreme temperature). Marginal effects are reported in Table 2.6, while coefficients are reported in Table A.3 in Appendix A.3. Table 2.6 shows that the number of rapid-onset disasters in a 3-year period has a positive and significant effect on the probability of total conflicts. One rapid- onset natural disaster in the last 3 years increases the probability of new conflicts by 0.245 %. The effect stays positive and significant for non-state conflicts (0.00237), while it is not significant for state conflicts. On the other hand, the effect of slow-onset disasters is never significant. This is in line with the literature on the effects of slow and rapid onset disasters on conflict risk, as they require different responses and influence different mechanisms in disaster management.

2.5 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, vulnerability and their role in shaping the conditional link between climatic changes and violent outcomes is a crucial issue to be assessed. In fact, resilience-building might prove to be an essential policy option in the face of unprecedented, exceptional climatic changes and tipping points. Given the multifaceted connections emerging from the climate crisis, such as socioeconomic impacts, migration challenges, and security concerns manifested through increased conflict risk, it is crucial to understand whether developing resilience to climate-related extreme events can be an effective policy response. This approach not only might help societies adapt to the adverse socioeconomic effects of climate change but can also prevent the conditions that may lead to tensions and, ultimately, conflict to arise in the aftermath of a disaster. Understanding the disaster-conflict nexus is a critical area of research, particularly in light of the interconnected and complex relationships arising from climate change. By examining the potential effectiveness of building resilience to natural disasters, we can identify strategies to minimize the risks of conflicts triggered by extreme climatic events. In this way, policy interventions that promote resilience can enhance the stability and security of regions vulnerable to the impacts of climate change.

In this context, the aim of this chapter 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 climate-related shock. Our results suggest that, firstly, there is a positive impact of natural disasters on the probability of new conflicts. In particular, natural disasters have a positive effect on the risk of new non-state conflicts arising, while this is not the case for state-conflicts. Secondly, even though there is no evidence of a direct link between ethnic fractionalization and armed conflicts, our results suggest that natural disasters occurring in countries with high ethnic fractionalization are more likely to result in new conflicts. This is in line with pre-existing literature linking natural disasters, ethnic fractionalization and violent activities and might be connected to ethnic differences serving as conflict lines in case of societal tensions arising from climate-related shocks (Schleussner et al., 2016).

Third, the effects of natural disasters on the probability of insurgence of new conflicts is differentiated for different levels of resilience and vulnerability. In particular, the probability that a natural disaster increases the likelihood of conflicts is higher for more vulnerable and less resilient countries, and it is magnified by high level of income inequality. Furthermore, the effects on conflict risk is differentiated across slow and rapid-onset disasters. These two types of disasters necessitate distinct responses, with slow-onset disasters requiring proactive measures, and rapid-onset disasters requiring reactive measures. This distinction in response strategies could have varying effects on conflict risk, especially in regions that are already vulnerable. Overall, our results are in line with the existing literature that highlights the significant impact of pre-existing social, economic, and political vulnerabilities on the likelihood of violent activities following natural disasters. These vulnerabilities can create a conducive environment for tensions to escalate and ultimately result in violent conflicts. Hence, focusing on improving resilience to climatic changes might have positive impacts on peace-keeping efforts as well, and provides a potential cost-effective policy approach that could help counteract both disruptive climatic impacts and detrimental conflict effects.

3

Local sources of vulnerability to climate change and armed conflicts in East Africa using Spatial Analysis

3.1 Introduction

The aim of this chapter is to provide empirical evidence on the role of long-term climate variability on the probability of conflict in Eastern Africa using a spatial analysis approach. The choice to focus on Eastern Africa was determined by the fact that this region is particularly vulnerable both in terms of climate change and violent activities (O'Loughlin et al. 2012; Raleigh and Kniveton 2012). Secondly, this chapter aims at providing empirical evidence on the local sources vulnerability to the climate-conflict nexus in the region. The specific focus is on the *agriculture* and *resource* channels, as they are quite relevant in the context of Eastern Africa, whose economy is primarily based on the agricultural sector (ADB, 2021). This will be done using a spatial analysis approach. Such methodology allows to consider spatial interactions among relevant variables, as well as spatial spillover effects.

The rest of the chapter is structured as follows: Section 3.2 summarizes the literature on climate, conflict and vulnerability in Eastern Africa; Section 3.3 presents the data and the methodology used; Section 3.4 presents the main results while Section 3.5 concludes.

3.2 Theoretical Background

3.2.1 Eastern Africa in the climate - conflict nexus

The African continent has been the focus of a great amount of research on the climate – conflict relationships for a number of reasons. First, the African continent can be considered a conflict hot-spot, where many conflicts have occurred in the last several decades (e.g. the Rwanda Genocide in 1994, the Second Congo War between 1998 and 2003, the Darfur conflict since 2003 and the Arab Spring in 2011). Second, it will unfortunately be one of areas of the world more harmed by climate change effects. For example, it is likely that land temperatures will rise more in Africa with respect to the global land temperature average, and precipitations will likely reduce instead (IPCC 2014, 2018, 2022). This would have great implications in terms of negative effects on both natural and human systems. Third, the African region is unfortunately characterized by high levels of pre-existing socio-economic vulnerabilities, for example low economic growth, widespread poverty and high income inequality. Most African countries, in fact, rank very low both in terms of human development (Conceição et al., 2020) and multidimensional poverty.

Within the Africa continent, Eastern Africa has been increasingly recognized as a particularly vulnerable region, both in terms of climatic changes and violent activities. Eastern Africa is the region that has experienced the highest number of conflicts over the period 1997-2018 (Mack et al., 2021). However, while temperature and precipitation deviation from long-term means have been linked to an increase in conflict risk in this area, they seem to display a weaker role with respect to other socio-economic and political drivers (O'Loughlin et al., 2012).

The climate – conflict nexus in this region has been the object of analysis of many scholars over the past several years, with mixed results. For example, while Raleigh and Kniveton (2012) analyze rainfall variability and disaggregated conflicts in East Africa over the period 1997-2009 and find that the frequency of such conflicts is exacerbated both by extreme wet and dry conditions, Brown (2010) assessed "eco-scarcity" as a possible cause of the conflict in Darfur, finding no evidence for it. Others have found mixed results, in that climate change cannot be deemed the only cause of violent activities in the region, but it is certainly a concurring exacerbating factor (Ayana et al. 2016; Owain and Maslin 2018; Seter et al. 2018).

One of the reasons for the scholarly interest in the Eastern Africa region is certainly the fact that this is a relatively restricted geographical area which is characterized by a *"history of violence, high dependence on natural resources for livelihoods, widespread poverty, and limited adaptive capacity"* (Van Baalen and Mobjörk, 2018, p. 3). All of these factors make this region a particularly interesting object of analysis in order to understand the mechanisms driving the climate – conflict nexus in this area and how it relates to context-specific economic, political and social dynamics. Moreover, another important aspect might be related to investigating the local sources of socio-economic vulnerability in the region which might be detrimental for communities in the face of increasing climate change, and could also increase conflict risk. Vulnerability is defined as *"the propensity or predisposition to be adversely affected"*(IPCC, 2014, p.5). In fact, it might be that communities that display high levels of socio-economic vulnerability are also more affected by climatic impacts, and this further deteriorates adaptive capacity, increasing conflict risk, creating a vicious cycle of vulnerability and harmful climate and conflict impacts (Buhaug and Uexkull, 2021). In order to better understand the complex interplay between climate change, vulnerability, and conflict in the region, it is necessary to investigate the sources of vulnerability at the local level. By assessing local sources of vulnerability, it may be possible to identify specific areas where targeted policies and interventions can be implemented to improve the adaptive capacity of communities and reduce the risk of conflict. Thus, investigating the possible sources of vulnerability in Eastern Africa can prove to be a useful exercise to untangle the climate-vulnerability-conflict nexus in the region. This process can help policymakers to develop more targeted and effective policies to improve adaptive capacity at the local level.

Building on the reviewed literature, this chapter aims at identifying a specific set of socioeconomic and context-specific factors that foster vulnerability to both climate change and conflicts in East Africa at the local level. In addition, it explicitly addresses the interaction between local vulnerability factors and climate change impacts to understand how they enhance conflict risk and lead to the emergence of conflict hot-spots.

Accordingly, we formulate the following research questions:

1. *Why are some locations more likely to engage in armed conflicts than others in the presence of a similar level of exposure to climatic changes?*
2. *What are the local sources of vulnerability of the East Africa region?*

3.3 Methodology

3.3.1 Data

For the purpose of our analysis, we build a georeferenced panel database for East Africa,[1] covering the time span from 1997 to 2016. Our grid is composed of 8,217 cells with resolution of 25x25 km (15 arc-min).

In our analysis, we are interested in assessing the effect of long-term climatic conditions mediated by specific vulnerability mechanisms on the probability of conflict in the Eastern Africa region. In order to do so, we gather data on armed conflicts from the Armed Conflict Location & Event Data Project (ACLED), which provides disaggregated incident information on political violence, demonstrations, and select related non-violent developments around the world. In particular, the events

[1] Countries included are Burundi, Djibuti, Eritrea, Ethiopia, Kenya, Rwanda, Sudan, Somalia, Tanzania and Uganda.

collected in the ACLED database can belong to six categories:

i) political violence;

ii) battles;

iii) explosion/remote violence;

iv) violence against civilians;

v) riots;

vi) protests.

We associate these data to our grid and calculate the number of conflicts for each cell and year (*nc*) as well as the number of conflicts experienced by each cell in the previous year (*nc_lag1*). In addition, to analyse the factors that influence the probability of violent activities, we create a dummy variable (*cd*) equal to 1 if $nc>0$ and 0 otherwise, which will be used as our main dependent variable.

Explanatory variables belong to three main classes: i) climatic variables; ii) vulnerability factors related to agriculture and resource access; iii) socio-economic characteristics and vulnerability factors.

Climatic variables

For this set of variables we ground on the African Flood and Drought Monitor (AFDM) database, which provides monthly values of temperatures and precipitations at 0.25° grid resolution from 1970 to 2016. Starting from these variables, to obtain an overall measure of anomalous climatic variations experienced by a given cell across one year, we calculate the average level of monthly anomalous variations of temperatures and precipitations (*tempmvy* and *precmvy*, respectively).

The occurrence and severity of droughts are another meteorological phenomenon deserving attention. Their gradual occurrence makes droughts one of the easiest meteorological phenomena to monitor over a prolonged time horizon and, at the same time, one of the costliest hazards in terms of their economic and social impacts (Svoboda, Fuchs, et al., 2016). Hayes et al. (2011) define droughts as *"a deficiency of precipitation relative to what is expected that, when extended over a* *season or a longer period of time, results in the inability to meet the demands of human activities and the environment"* (Hayes et al., 2011, p.1). A number of indices and indicators have been developed to monitor droughts[2]. Among these, the most widely accepted and employed in the literature are the Standardized Precipitation Index (SPI), developed by McKee et al. (1993), and the Standardized Precipitation Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010). Both indices are very flexible, as they can be calculated for any geographical region and over any timescale, each associated to a different type of drought impact (Pandey and Ramasastri, 2001). For instance, basic droughts impacts can be monitored over a timescale up to 3 months; agricultural impacts over a timescale up to 6 months; while hydrological impacts are usually calculated for a timescale equal to or higher than 12 months (WMO and GWP, 2016). Further, both SPI and SPEI provide indications for both dry (negative values) and wet events (positive values). The main difference between the two indices lies in the inputs needed to calculate drought events: while the SPI only requires historical precipitation data, the SPEI also accounts for the impacts of temperatures on drought events, based on a basic water balance calculation (Vicente-Serrano et al., 2010). Based on the difference in calculation among the two indices, we mainly rely on the SPEI, as it offers a comprehensive consideration of the variables that refer to drought conditions.

By employing the R code developed and provided by Begueria and Serrano (2017), we calculate monthly values of the SPEI for 12 months and aggregate them to obtain yearly values (*spei_#y*). [3] Then, we relied on the classification of the SPI formulated by McKee et al. (1993) to denote droughts of different entities and also extended it to the SPEI. Accordingly, as reported in Table 3.1, we divided the monthly values of SPEI into three classes of increasing precipitation intensity (from *f1* to *f3*) as representative of flood events, and other three classes of increasing drought severity

[2] An overview of these indices and indicators can be found in the Handbook of drought indicators and indices by the WMO (2016).

[3] To further improve the accuracy and precision of the estimates of climate-related variables, future expansions of this work could consider employing the count of drought months instead of the annual Standardized Precipitation Evapotranspiration Index (SPEI).

Table 3.1: SPEI classification

SPI and SPEI values	Drought and flood condition	Class names
2.0 and more	Extremely wet	*f3*
1.5 to 1.99	Very wet	*f2*
1.0 to 1.49	Moderately wet	*f1*
-0.99 to 0.99	Near normal	
-1.0 to -1.49	Moderately dry	*d1*
-1.5 to -1.99	Severely dry	*d2*
-2.0 and less	Extremely dry	*d3*

Source: authors' elaboration from McKee et al. (1993)

Table 3.2: Descriptive statistics of climate-related variables

Variable	Obs	Mean	Std. Dev.	Min	Max
tempmvy	230,076	0.701915	0.99394	-4.78143	12.17524
precmvy	230,076	2.529062	14.33995	-81.4295	195.2336
spei_12y	230,076	-0.23054	0.875976	-3.83467	3.50051
spei_12yp	230,076	0.238146	0.432069	0	3.50051
spei_12yn	230,076	-0.46869	0.597843	-3.83467	0

(from *d1* to *d3*).

Again, we aggregate monthly values of the SPEI for 12 months at the annual level, by distinguishing between positive values of SPEI (*spei_#yp*) that account for annual exposure to flood hazards, and negative values of SPEI (*spei_#yn*) that account for annual exposure to drought hazards. Table 3.2 reports main descriptive statistics for climate-related variables. [4]

[4]The SPEI allows to indirectly consider additional factors that are not explicitly accounted for in the analysis but that have the potential to affect the climate - conflict nexus, such as food insecurity.

Vulnerability factors related to agriculture and resource access

Another set of explanatory variables regards land use and agriculture. We gathered data on different land cover typologies from the USGS, which provides global land cover data at 15 arc-min resolution, based on a 10-year collection (from 2001 to 2010). Starting from these data we create a dummy variable assuming the value of 1 if the prevalent land cover of cells' centroids is made of water basins (*water*), as water resources might be a particularly interesting source of vulnerability to analyze in this region.

As for agriculture-specific features, we gathered information of land use devoted to agriculture from the History Database of the Global Environment (HYDE) (Goldewijk et al., 2017). This database provides data at 5 arc-min resolution (approximately 10 km) for 1990 and for the time span ranging from 2000 to 2015, hence we interpolate the original data to obtain information for the whole period of our analysis, from 1990 to 2016. In particular, from the HYDE database we collect data on total irrigated area (*irri*) expressed in km^2.

Then, to account for the exposure of the agricultural sector to climatic hazards, we include a set of variables aimed at evaluating cell-specific risks of floods and droughts during the growing season of main crops, i.e., the period in which crops are more sensitive to external variations (Harari and Ferrara, 2018). In particular, we combine climatic information provided by the SPEI index with information on the initial and last month of growing season of each cell's main crops, provided by the UCDP-PRIO (Peace Research Institute Oslo) grid database. As a first step, we build a monthly dummy variable equal to 1 if, in a given month, each cell's main crop is in the growing season. Then, for each class and timescale of the SPEI index, we create a monthly dummy variable equal to 1 if the index exceeds the underlying threshold for each cell, and we interact it with the dummy variable indicating the months of growing season. To obtain yearly values, we sum the interaction variable by year and get a set of count variables that represent the number of months in each year in which the drought or flood condition occurs during the growing season of

Table 3.4: Descriptive statistics of land cover and agriculture variables

Variable	Obs	Mean	Std. Dev.	Min	Max
water	230,076	0.018133	0.133433	0	1
irri	230,076		2.250829	0	81.48996
grspei_12d1_sh	230,076	0.205684	0.338174	0	1
grspei_12d2_sh	230,076	0.085199	0.242553	0	1
grspei_12d3_sh	230,076	0.04084	0.17591	0	1
grspei_12f1_sh	230,076	0.114931	0.256159	0	1
grspei_12f2_sh	230,076	0.046269	0.167498	0	1
grspei_12f3_sh	230,076	0.016957	0.104037	0	1

each cell's main crop. Finally, to have a measure of the length of the growing season affected by extreme climatic conditions, we divide the number of months where the threshold is exceeded by the total number of months of growing season in each cell and year (variables from *grspei_12d1_sh* to *grspei_12f3_sh* in Table 3.4).

Socio-economic characteristics and vulnerability factors

We compile data on socio-economic characteristics from several different sources. Data on GDP come from the Gridded global dataset for Gross Domestic Product and Human Development Index, developed by Kummu et al., 2018. This dataset contains information on spatially disaggregated GDP for the years 1990–2015.[5] Hence, to extend the analysis to 2016 we interpolate data and aggregate the cells of the Kummu dataset to our 0.25°x0.25°C grid cell (approximately 25 km^2 and 15 arc-min) in order to make them coherent with the rest of our data.

As for information regarding population, our dataset contains data on the total population number ($popc\_AD$), population density for each km^2 ($popd\_AD$) and ru-

[5]Kummu et al., 2018 provide 5 arc-min resolution (approximately 10 km grid) data for two main variables: cell-based GDP per capita (PPP) and Total GDP (PPP), both expressed in constant international 2011US$. They started from country-level GDP data gathered from the World Bank's World Development Indicators (WDI) database and the CIA's World Factbook for missing countries. Then, they downscaled the national GDP data to obtain 5 arc-min resolution data on sub-national GDP per capita by first calculating population-weighted national GDP per capita from sub-national GDP per capita data from Gennaioli et al., 2013 and the HYDE 3.2 population dataset. This measure was then used to calculate the ratio between population-weighted national GDP and reported sub-national GDP. Then they estimated the total GDP per capita for each cell by multiplying this ratio with the reported sub-national GDP and thus obtained georeferenced data for GDP per capita (PPP) for the time span ranging from 1990 to 2015. To obtain data on GDP, they multiplied the GDP per capita by grid-specific population data.

ral population numbers (*rurc_AD*). From this variable, we calculate the share of rural population for each cell (*rur_sh*). The original source of data is the HYDE 3.2 Database (Goldewijk et al., 2017). Data are provided only for 1990 and for the period from 2000 to 2015 and with a spatial resolution of 5 arc-min (about 10 km), which correspond to 36 micro cells for each of our 25x25 km cell grid. Consequently, in order to have data for the entire period 1990 – 2016, we interpolate and aggregate the original data by cell, summing the values of the 36 micro cells for each cell of our grid.

Other significant information regarding the possible social vulnerability of a territory is ethnic fragmentation. Ethnic division is relevant because the literature has found that climatic-related extreme events might act as a threat multiplier of violent activities in a particularly violent way in ethnically fractionalized contexts (Schleussner et al., 2016). To take this aspect into account, we create a time-invariant count variable (*n_ethnic*) in order to have information about the number of distinct ethnic groups coexisting within a single cell. The original source of data is the Geo-referenced of ethnic groups (GREG) dataset provided by Weidmann et al., 2010.[6]

A relevant dimension regarding spatial inequality in access to resources is related to the presence and intensity of night lights. Nights lights have been widely used in the literature as proxies of economic activity, development, economic growth and income inequality (Henderson et al., 2012; Pinkovskiy and Martin, 2016; Mveyange, 2018) but also resilience to shocks after natural disasters (Qiang et al., 2020). Scholars have been increasingly employing night light data, especially given the unavailability of statistical information in many developing countries. Night lights data have the advantage of being measured objectively and being available at a high spatial resolution for the entire globe since 1992 (Chen and Nordhaus, 2011). Night light data have been used in the literature to measure human activities at several levels, including urbanization (Li et al. 2019; Stathakis et al. 2015), electrification (Doll and

[6]In the GREG dataset, data are divided into zones (represented by polygons), within which there can be a maximum of three ethnic groups. However, our cells do not perfectly match the polygons, hence our cells may include more than three distinct ethnic groups.

Pachauri 2010; Dugoua et al. 2018;Min et al. 2013) and several dimensions of socio-economic development, such as poverty (Weidmann and Schutte 2017; Andreano et al. 2021) and inequality (WB 2018; Ivan et al. 2019). Further, night light data have been shown to be a particularly useful proxy of economic output and economic growth, especially in developing countries where statistical systems are lacking or absent (Chen and Nordhaus 2011; Doll et al. 2000; Henderson et al. 2012).

Night light data are mainly available from two different data sources, i.e. the Defense Meteorological Satellite Program (DMSP) until 2013 and the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument after 2013. The issue lies in the fact that these two sources of data are not comparable. To remedy this, Li et al. (2020) were the first to provide a global harmonized dataset for night light data for the period 1992-2018, and this provides valuable information and new pathways to be explored in the use of night light data, as it makes the two sources of night light data comparable for the first time.

The way in which night light data have been operationalized to be used as proxy varies in the social sciences (see Gibson et al. 2021 and Dugoua et al. 2018 for a summary). Night light data are often expressed in several modalities and used as proxies of different relevant variables. For example, night lights are often expressed as a logarithmic transformation of their sum to represent GDP and economic growth (Doll et al., 2006) and rural electrification (Min et al., 2013) and as average to represent a plethora of phenomena, such as local economic development (Michalopoulos and Papaioannou, 2014) and impacts of natural disasters (Cole et al., 2017).

For the purpose of our analysis, we aggregate data in order to make them compatible with our grid cell resolution and as a final step we calculate the standard deviation of night-time light data for each grid cell expressed in Digital Number (DN) values (*sd_nl*). Statistically, standard deviation represents a measure of dispersion, i.e. it gives a measure of how much the data are spread out around the mean. Thus, we interpret the standard deviation of night lights as a measure of vulnerability because, according to our hypothesis, it represents dispersement in access to resources that enable development. Specifically, we interact *sd_nl* with relevant climatic variables representing exposure to droughts (*spei_12yn*) and floods (*spei_12yp*) to obtain a measure of climatic vulnerability.

Together with night lights, we have included other variables to represent vulnerability, with a specific focus on the *agriculture* and *resource* channels. In addition to *sd_nl* we include *rur_sh*, i.e. the share of rural population in each cell to account for vulnerability in the agricultural sector, as rural population is usually more vulnerable to climate change impacts as it mostly derives its livelihoods from climate-sensitive activities and has less access to resources, including electricity and sanitation (IPCC, 2022b). Then, to account for the vulnerability of the agricultural sector we have included the variables *grspei_12d3_sh* and *grspei_12f3_sh* to take into account the share of months of the growing season with SPEI below -2 (prolonged drought exposure) and above 2 (prolonged flood exposure). This gives an account of the vulnerability of the agricultural sector when exposed to climate extremes during the most vulnerable period, i.e. the growing season (Harari and Ferrara, 2018). Finally, we include the variable *water*, i.e. the share of land covered in water basins for each cell; we do this to account for the vulnerability deriving from competing groups claiming access to water resources, especially in a situation of prolonged drought exposure ($water \cdot spei\_12yn$).

Finally, we include the number of ethnic groups in a cell (*n_ethnic*), as a high ethnic fractionalization could worsen the effects of climate-related shocks on the probability of conflicts (Schleussner et al., 2016), hence becoming a source of vulnerability. Table 3.6 reports main descriptive statistics of socio-economic variables and vulnerability factors.

Table 3.6: Descriptive statistics of socioeconomic characteristics

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
gdp_pc	164,340	16.28259	10.15217	0	93.0036
popc_AD	164,340	3438.448	9839.137	0	350673.7
rur_sh	164,340	.8795083	.2720016	0	1
sd_nl	164,340	.4679066	1.401314	0	24.22019
n_ethnic	164,340	1.36461	.7023711	0	6

According to the literature reviewed above, we formulate the following hypotheses:

Hypothesis 1. *Agriculture-related factors increase vulnerability in the climate-conflict nexus in Eastern Africa.*

Hypothesis 2. *Resource-related factors increase vulnerability in the climate-conflict nexus in Eastern Africa.*

3.3.2 Data visualization

In order to further explore our dataset and have a deeper understanding of the data we will be using in our analysis, we have performed some visualization exercises on relevant variables for our study.

Figure 3.1 (a) shows the total number of conflicts in East Africa across the entire period of analysis, i.e. 1997-2016. Conflicts are mainly located in the centre of the region, especially in the Horn of Africa and in the Western area, while the Northern and and Southern regions are less prone to conflicts, mainly linked to the presence of deserts. Figure 3.1 (b), instead, shows the number of cells with multiple years of conflicts over the period 1997-2016. Cells in blue are those that experienced at least one conflict in more than one year, while red cells did not. Figure 3.1 (a) and (b) display almost the same conflicts, meaning that if a conflict occurred in the region, it primarily occurred for more than one year. This might be a visual representation

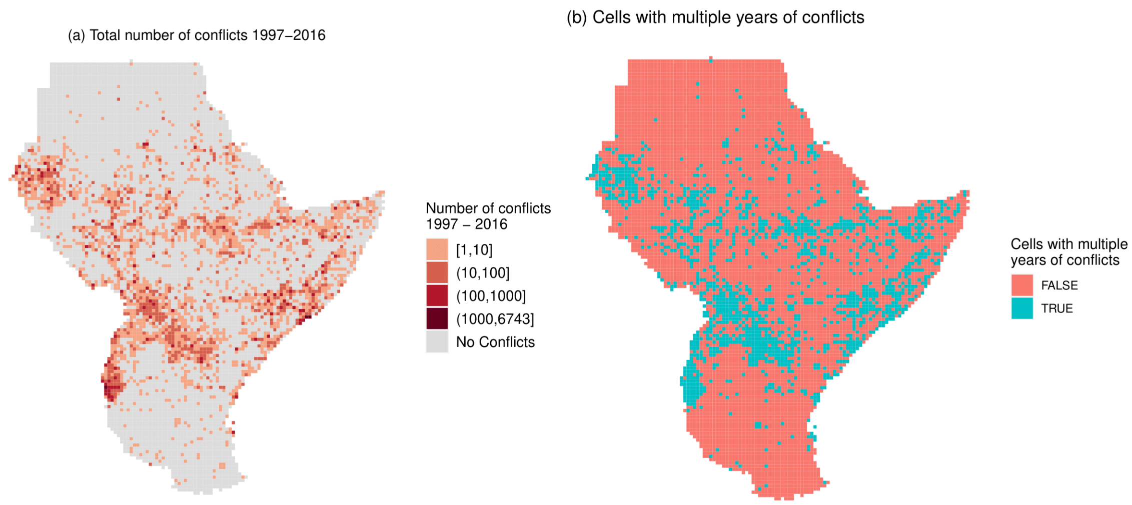


Figure 3.1: (a) Total number of conflicts, 1997-2016; (b) Cells with multiple years of conflicts (blue), 1997-2016

of the so-called *"conflict-trap"* hypothesis proposed by (Collier et al., 2003), which states that areas that experience conflict are then more likely to experience it consecutively.

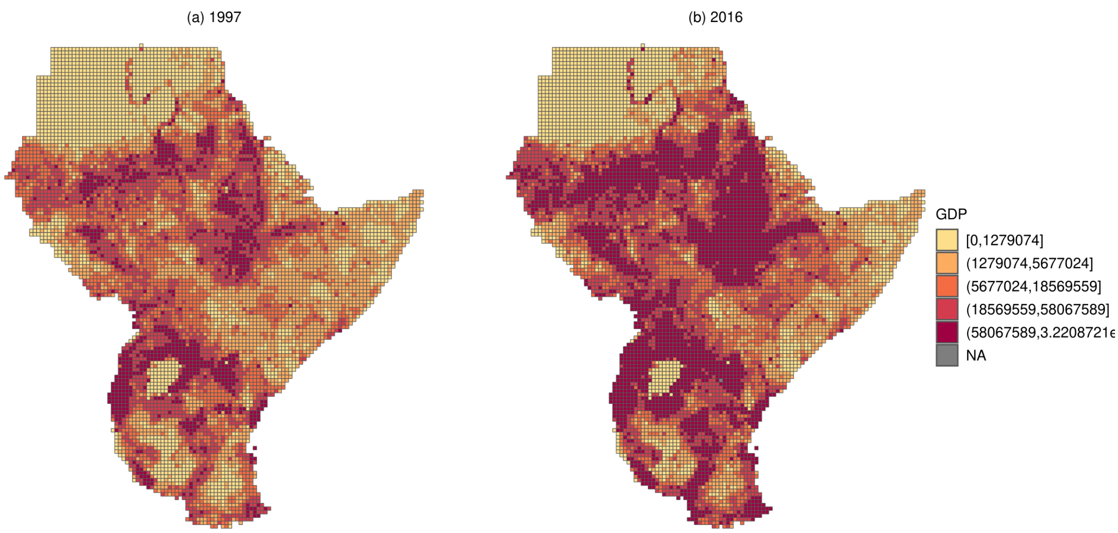


Figure 3.2: (a) GDP in 1997 (expressed in millions USD); (b) GDP in 2016 (expressed in millions USD)

Figure 3.2 shows the GDP in our region of interest, for 1997 (a) and 2016 (b) respectively. Figure 3.2 shows that the GDP has increased on average in the region, even though in some areas the increase was more consistent than in others.

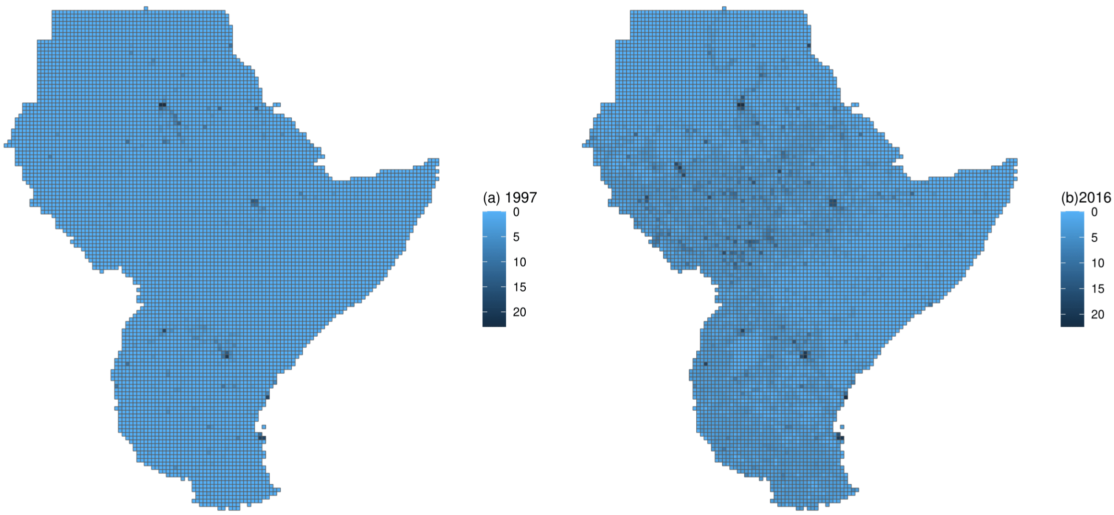


Figure 3.3: Night lights expressed in standard deviation in (a) 1997 and (b) 2016

Finally, figure 3.3 depicts the standard deviation of night lights for East Africa, in 1997 and 2016 respectively. Again, Figure 3.3 shows that on average the standard deviation of night light increased from 1997 to 2016, with some internal heterogeneities. This might point to unequal development processes and differences in access to resources in our region of interest.

3.3.3 The empirical model

According to Mach et al. (2020), future research on the climate-conflict nexus should exploit growing access to micro-level data from diverse sources, such as satellite and drone imagery, social media and population surveys. These new types of data could be useful in understanding fine-scale variations in elements that determine neighbouring societies to experience potentially different levels of vulnerability. For instance, high spatial resolution data allow to detect the presence of water basins and irrigation facilities, as well as the number of ethnic groups co-inhabiting a small area. In addition, the identification of factors giving rise to the emergence of conflict hot-spots requires the adoption of a local perspective. This local perspective allows to account for the spatial dimension in the distribution of the data and to consider spatial autocorrelation before proceeding in the analysis [7]. In particular, to understand the origin of conflict hot-spots, Silve and Verdier (2018) suggest to consider two channels jointly. First, regional conflict hot-spots usually result from the clustering of similar internal features, such as geographical or social characteristics, resource endowments, and climatic conditions that can make a regions especially vulnerable to climate change and conflicts. Second, the geographical distribution of armed conflicts is largely dependent on the contagion effect induced by the spatial spillovers between neighbouring regions. Previous studies have established that spatial spillovers play a crucial role in shaping the complex dynamics between climate change and conflict (e.g., Cappelli et al. 2020, Cappelli et al. 2022a). Therefore, it is essential to consider spatial interactions in this case to gain a more comprehensive understanding of the underlying mechanisms that contribute to conflict in the region. To date, only a few quantitative studies at a highly disaggregated level and encompassing large datasets directly address contagion effects and spatial propagation of armed conflicts (Harari and Ferrara, 2018). In spatial econometrics, the contagion effect among neighbouring locations can be shaped in different ways, ac-

[7] Results of both global and local spatial autocorrelation indices for our data are available in Appendix B.

cording to the type of interaction effects used (Elhorst et al., 2014). In our case, we are interested in understanding the emergence of conflict hot-spots as resulting from local vulnerability factors as well as from the direct contagion effect of conflicts themselves. Accordingly, we employ a Spatial Autoregressive Model (SAR) for panel data. The SAR model takes into consideration how the occurrence of conflict in one cell can affect the likelihood of conflict in neighboring cells, as well as how local vulnerability factors can indirectly influence the probability of conflict. We introduce the direct interaction effect by means of an inverse distance row-normalized weight matrix W. By using this model, we are able to capture the complex interplay between these variables and provide a more comprehensive understanding of the underlying mechanisms that contribute to conflict in the region. Furthermore, the use of panel data in the SAR model allows us to analyze changes over time and account for potential confounding variables that may impact the relationship between long-term climate variability, vulnerability and conflict. The econometric model we estimate is the following:

$$\begin{aligned} Conflict_{it} = \alpha + \rho \sum_{j=1}^{n} W_{ij} Conflict_{jt} + X_{it}^{CC}\beta_{CC} + X_{it}^{SE-V}\beta_{SE-V} \\ + X_{it}^{AR-V}\beta_{AR-V} + X_{it}^{OC}\beta_{OC} + \gamma_t + \mu_i + \epsilon_{it} \end{aligned} \tag{3.1}$$

Where:

- $Conflict_{it}$ is the probability of conflict onset in cell i and time t;
- ρ is the endogenous spatial interaction effect (introduced by means of the spatial weight NxN matrix W) associated to conflicts occurred in cell j and time t;
- X_{it}^{CC} is the set of variables related to climate change and variations experienced by cell i in time t;
- X_{it}^{SE-V} is the set of covariates representing socio-economic characterstics and vulnerability factors of cell i in time t;
- X_{it}^{AR-V} is the set of covariates accounting for vulnerability related to agricul-

ture and resource access in cell i and time t;

- X_{it}^{OC} is the set of control variables in cell i in time t;
- μ_i are cell-specific fixed effects;
- γ_t are year-specific fixed effects;
- ϵ_{it} is the error term.

3.4 Results

Table 3.7: SAR baseline model

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
GDP_pc (ln)	-0.0851***	-0.0855***	-0.0856***	-0.0859***	
	(0.0071)	(0.0071)	(0.0072)	(0.0071)	
Population (ln)	0.1399***	0.1409***	0.1406***	0.1413***	0.1156***
	(0.0146)	(0.0147)	(0.0147)	(0.0147)	(0.0144)
Nightlights (sd)	0.0033***	0.0034***	0.0034***	0.0034***	0.0009
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Tempmvy		0.0011	0.0025**	0.0023*	0.0000
		(0.0011)	(0.0012)	(0.0012)	(0.0012)
Precmvy		-0.0000	0.0000	0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tempmvyˆ2			-0.0004*	-0.0004*	-0.0004
			(0.0003)	(0.0003)	(0.0002)
Precmvyˆ2			0.0000		
			(0.0000)		
SPEI_12_neg				0.0034	0.0026
				(0.0033)	(0.0033)
SPEI_12_pos				0.0037	-0.0005
				(0.0039)	(0.0039)
GDP_pc_growth					-0.1540***
					(0.0122)
Spatial ρ	0.8269***	0.8270***	0.8256***	0.8248***	0.8392***
	(0.0137)	(0.0137)	(0.0137)	(0.0137)	(0.0128)
Variance σ^2	0.0331***	0.0331***	0.0331***	0.0331***	0.0332***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
N	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05
Rˆ2	0.0386	0.0392	0.0391	0.0394	0.0485

This Table shows coefficients for a SAR model with a rw11 matrix across the years 1997-2016. Additional controls include year dummies and a structural break dummy in 2013. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7 reports results for the *baseline* SAR model on a panel of 8,217 grid-cells for the years 1997-2016, while Table 3.8 reports results for the *vulnerability* SAR model computed on the same dataset and the same timespan.

The baseline model includes climatic as well as night light data. As for basic control factors, we find a negative and significant effect of GDP per capita and GDP growth on the probability of conflicts. The effect is robust across all specifications and it is in line with the literature linking higher levels of development to a lower

Table 3.8: SAR vulnerability model

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
GDP_pc (ln)	-0.0783***	-0.0860***	-0.0860***	-0.0860***	-0.0866***	-0.0862***
	(0.0072)	(0.0071)	(0.0071)	(0.0071)	(0.0072)	(0.0071)
Population (ln)	0.1250***	0.1416***	0.1409***	0.1377***	0.1397***	0.1407***
	(0.0140)	(0.0148)	(0.0147)	(0.0147)	(0.0148)	(0.0148)
Nightlights (sd)	0.0032***	0.0034***	0.0034***	-0.0030	0.0031***	0.0034***
	(0.0010)	(0.0010)	(0.0010)	(0.0021)	(0.0010)	(0.0010)
Tempmvy	0.0020	0.0023*	0.0023*	0.0022*	0.0023*	0.0023*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Tempmvy^2	-0.0005*	-0.0005*	-0.0004*	-0.0004*	-0.0004*	-0.0004*
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Precmvy	-0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SPEI_12_neg	0.0782***	0.0030	0.0030	-0.0007	0.0022	0.0038
	(0.0113)	(0.0033)	(0.0033)	(0.0032)	(0.0046)	(0.0033)
SPEI_12_pos	0.0892***	0.0032	0.0037	-0.0004	-0.0189***	0.0035
	(0.0175)	(0.0040)	(0.0039)	(0.0038)	(0.0056)	(0.0039)
Rural population (%)	-0.0710**					
	(0.0337)					
Rural population*SPEI_12_neg	-0.0850***					
	(0.0114)					
Rural population*SPEI_12_pos	-0.0970***					
	(0.0180)					
GrSPEI_12d3_sh		0.0024				
		(0.0057)				
GrSPEI_12f3_sh		0.0023				
		(0.0050)				
SPEI_12_negs#Water			0.0223*			
			(0.0118)			
Water			0.0000			
			(.)			
Nighlights (sd)*SPEI_12_pos				0.0072**		
				(0.0028)		
Nightlights (sd)*SPEI_12_neg				0.0082***		
				(0.0023)		
N_ethnic					0.0000	
					(.)	
1.n_ethnic#SPEI_12_neg					-0.0048	
					(0.0050)	
2.n_ethnic#SPEI_12_neg					0.0153**	
					(0.0078)	
3.n_ethnic#SPEI_12_neg					0.0214*	
					(0.0125)	
4.n_ethnic#SPEI_12_neg					-0.0596	
					(0.0415)	
5.n_ethnic#SPEI_12_neg					-0.1297*	
					(0.0696)	
6.n_ethnic#SPEI_12_neg					-0.0655***	
					(0.0049)	
1.n_ethnic#SPEI_12_pos					0.0198***	
					(0.0071)	
2.n_ethnic#SPEI_12_pos					0.0303***	
					(0.0096)	
3.n_ethnic#SPEI_12_pos					0.0303*	
					(0.0168)	
4.n_ethnic#SPEI_12_pos					-0.0144	
					(0.0592)	
5.n_ethnic#SPEI_12_pos					0.2305	
					(0.1781)	
6.n_ethnic#SPEI_12_pos					0.0797***	
					(0.0076)	
Irrigation						0.0024*
						(0.0014)
Irrigation#SPEI_12_neg						-0.0015**
						(0.0007)
Spatial ρ	0.8260***	0.8248***	0.8251***	0.8235***	0.8255***	0.8245***
	(0.0136)	(0.0138)	(0.0137)	(0.0138)	(0.0137)	(0.0137)
Variance σ^2	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
N	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05
R^2	0.0427	0.0395	0.0391	0.0391	0.0390	0.0393

This Table shows coefficients for a SAR model with a rw11 matrix across the years 1997-2016.

conflict risk (e.g. Collier and Rohner 2008, Ray and Esteban 2017). On the other hand, as expected, an increase in population has a positive effect on conflict risk, as in more populated places tensions are more likely to arise.

Turning to climatic factors, temperature anomalies have a positive effect on conflict risk but, as we can see in Models 3-5, their effect is quadratic: after a certain threshold (which, in our case, corresponds to 3.125°C), the effect of temperature anomalies turns negative. However, cells characterized by these extreme anomalous variations in temperatures correspond to less than 5% of our sample. Therefore, results for about 95% of our cells are in line with the literature linking higher variations in temperature to conflict outcomes (Burke et al. 2015, O'Loughlin et al. 2012). Finally, long-term conditions of drought and/or flood do not seem to have an impact on conflict risk *per se*.

In Table 3.7 we include the standard devation of night lights as a first factor of vulnerability at the local level. Interestingly, its coefficient is positive and significant, indicating that a greater spatial inequality in access to key resources (e.g., energy and infrastructures) increases the likelihood of conflict outbreak. This result adds new verve to the acknowledgement of vulnerability as a social construction, being inequality in access to resources that are key for adaptation a pillar of this strand of literature (Thomas et al., 2019).

Table 3.8 adds on to Table 3.7, concentrating on possible sources of vulnerability that drive the climate-conflict nexus. In particular, we introduce several interaction terms between local sources of vulnerability and climatic factors to test whether climate change impacts bring about different conflict outcomes in the presence of a similar level of exposure but a different level of vulnerability. Marginal effects for Table 3.8 are available in Appendix B. Results in this case are especially interesting. We find that long-term climatic stress such as prolonged droughts and excessive terrain humidity, for instance in the aftermath of floods or water bombs, are possible channels of increased conflict risk not *per se*, but in combination with some specific sources of vulnerability. This is the case if we look at Model 3, in which we test the effect of the presence of water basins on the probability of conflict outbreak. While in normal weather conditions the presence of water basins does not constitute a source of increased conflict risk, when we test the effect of water basins in combination with extremely dry climatic conditions the coefficient turns positive and significant. Prolonged drought and flood conditions also increase conflict risk when coupled with spatial inequality in access to resources, as proxied by the standard deviation of night lights.

On the other hand, contrary to our hypotheses, we did not find evidence of a climate-conflict nexus mediated by vulnerability in the agricultural sector. This is evident from the negative and significant effect of a higher share of rural population, both *per se* and in combination with extreme climatic (both dry and wet) conditions in Model 1. In a similar vein, the non-significant effect of the share of crops' growing season affected by either prolonged drought or flood conditions in Model 2 contributes to excluding the agricultural sector as a source of increased vulnerability to climate change and conflicts in East Africa. This, especially if read in conjunction with the increased risk of conflict posed by spatial inequality in access to infrastructures, might indicate that conflict dynamics in the East Africa region are mainly located in urban areas, as opposed to rural areas. Finally, prolonged drought conditions coupled with irrigation systems seem to decrease conflict risk, implying that technical innovation in agriculture might be a source of resilience in the region.

A final source of social vulnerability is related to the co-presence of different ethnic groups in a given area (Model 5). Our results highlight different behaviours in response to different climatic conditions. In extremely dry conditions, we find an increased risk of conflicts if an area is co-inhabited by two or three different ethnic groups, and a diminished risk of conflicts in the presence of five or six different ethnic groups. In this case, the explanation for such a different response may be related to the competition over power acquisition. To illustrate, when a limited number of ethnic groups (e.g., two or three) is present in a same territory, competition for prevailing over the others increases; on the other hand, in the presence of a multitude of ethnic groups it is more likely for everyone to get a share of power, hence tensions quieten. A different picture emerges when a given area is affected by extremely wet conditions: in this case, irrespective of the number of ethnic groups, the likelihood of conflict outbreak is greater. Arguably, in the case of extremely wet conditions, the environmental hazard manifests itself in a very short time span and is very destructive. This will require to take immediate actions to counteract the adverse impacts. Accordingly, if the society exposed to such hazards is not adequately prepared to adapt to this kind of extreme events, the eventuality of a conflict becomes a much more plausible outcome (Buhaug et al., 2008).

3.5 Conclusions

This chapter sheds new light on the climate-conflict nexus by investigating why some locations are more likely to engage in armed conflicts than others in the presence of a similar level of exposure to climatic changes. In particular, the focus of this chapter is on the concept of vulnerability to both climate change and armed conflicts and, accordingly, on the identification of a specific set of factors that enhance vulnerability of certain shares of the population at the local level. Grounding on the literature studying vulnerability to climate change, we consider vulnerability as a combination of socioeconomic and context-specific factors. Further, instead of relying on a composite indicator of vulnerability, we include separately different aspects that shape vulnerability, in order to identify key factors where policy makers can intervene to improve local resilience.

From a methodological perspective, a Spatial Autoregressive Model was employed to capture the spatial and context-specific dimension of vulnerability factors in driving the climate-conflict nexus in East Africa. Results from this analysis provide some interesting insights: first, climate change does not increase conflict risk *per se*, but only in presence of pre-existing vulnerability. This result is especially relevant, as it can help explain the disagreement in the literature about the impact of climate change on conflict propensity. In particular, results seem to suggest that there is no generalisable direct link between climate change and conflicts, but rather climate change acts as a threat multiplier in the presence of vulnerability. However, the relationship is more complex than this, in that climate change can certainly exacerbate pre-existing vulnerabilities. Hence, as also suggested in a recent paper by Buhaug and Uexkull (2021), future research should further investigate the relationship among climate change, conflict risk and vulnerabilities by also accounting for mutual influences and the possibility of vicious cycles.

Second, in line with the literature on climate change vulnerability, socioeconomic factors play a key role in the climate-conflict nexus. In particular, vulnerability is enhanced whenever power is not distributed in such a way as to ensure an equitable distribution of resources. This is true, for instance, in relation to resources such as water basins, which are essential for the livelihood of some agricultural and farmer communities, as well as infrastructures, which are key to ensure a decent life in urban contexts. Also, the importance of power distribution emerges in relation to the number of ethnic groups co-inhabiting a given place: conflicts and vulnerability arise only when ethnic groups are present in a number which is not sufficiently small or sufficient large to ensure a share of power to each one.

In conclusion, this chapter highlights the need to carefully evaluate local sources of vulnerability when designing measures to both improve adaptation to climate change and to enhance peace and stability. Becoming a climate-resilient society implies targeting the same sectors that are plausible channels in the climate - conflict nexus. If societies exposed to adverse climatic impacts are unprepared or lack adaptive capacity, tensions over resources turn out to be increasingly likely, with the increased possibility of resulting into conflicts. Therefore, the risk of violent activities resulting from disruptions of economic livelihoods, unequal access to resources, and other factors are ultimately extreme manifestations of vulnerability. It is clear that becoming more resilient to climate change requires a multi-faceted approach that takes into account the complex interplay between climate change impacts, vulnerability, and conflict. Policy approaches that aim at addressing these underlying vulnerabilities could have the potential to improve societal resilience to climate change impacts, while at the same time reducing conflict risk in a cost-effective way.

4

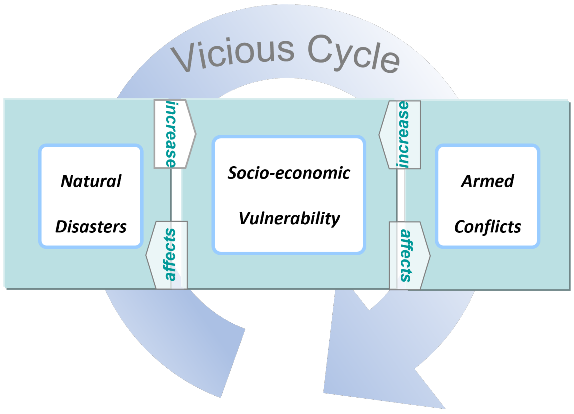
Predicting the impact of armed conflict on vulnerability: a Machine Learning approach

4.1 Introduction

This chapter aims at empirically exploring the impact of armed conflict on societal vulnerability to natural disasters by analysing the impact of armed conflicts, alone or in combination with the occurrence of natural disasters, on socio-economic vulnerability. This chapter argues that the impacts of conflicts and disasters – including reduced economic growth, impaired access to healthcare and infrastructure, forced displacement, and widespread material and immaterial destruction – increase societal vulnerability to subsequent climate hazards. Societal vulnerability is understood as *"the propension or predisposition to be adversely affected"* (IPCC, 2022a, p.5). Following this notion, socio-economic vulnerability is a multifaceted concept, which encompasses several different dimensions.

Global, yearly data on 189 countries from 1995 to 2019 are employed to test the out-of-sample performance of armed conflict and natural disasters indicators in predicting the ND-GAIN country vulnerability index. The rest of the chapter is structured

Figure 4.1: The complex theoretical relationships among societal vulnerability, armed conflicts and natural disasters.



as follows: Section 4.2 sets up the theoretical framework; Section 4.3 illustrates the data and methodology used; Section 4.4 reports results and Section 4.5 discusses and concludes.

4.2 Theoretical Background

4.2.1 Integrating the literature: a complex framework

Armed conflicts have been linked to a variety of negative outcomes that may increase subsequent socio-economic vulnerability to other hazards. First, conflicts have detrimental effects on many critical dimensions of human development, such as food security and livelihood: they have been associated with hunger crises and increased undernourishment, higher infant mortality rates, lower educational attainment, and livelihood deprivation (Gates et al., 2012). In turn, socio-economic development is one of the main drivers of vulnerability, as poor countries with low levels of development lack the resources to adapt to and recover from climate hazards and disasters (Yohe and Tol, 2002). At a macro-level, violence increases economic inequality, as the disruption of market mechanisms and threats to rule of law during and after conflicts hinder government effectiveness (Bircan et al., 2017). Armed conflicts dampen economic growth and have adverse effects on inflation, tax revenues and investments (Gupta et al., 2004). This diminishes state capacity and it results in a lower pool of resources being available to adapt to and/or prevent climatic-related risks (Buhaug and Uexkull, 2021). Conflicts have long-lasting effects on civilian health and well-being (Ghobarah et al., 2003; Wagner et al., 2018). Not only do conflicts kill people directly, but they also spread destruction and death indirectly, for example through the disruption of health services and increased risks of disease outbreaks or spread of epidemics due to poor sanitation and impaired access to freshwater (Murray et al., 2002; Iqbal, 2006). The long-term impairment in public health causing long-lasting effects on the surviving individuals is likely to make them more vulnerable to future climatic hazards. Moreover, armed conflicts can trigger migration and displacement, perceived either as a coping strategy or as a last resort in case of violence (Augsten et al., 2022).

In turn, migration can increase affected people's vulnerability to climate hazards. Not only refugees and displaced communities living in temporary camps are more exposed to natural disasters (UNHCR, 2017); migrants are also more likely to accept riskier jobs (Orrenius and Zavodny, 2009; Johnson and Ostendorf, 2010) that make them more vulnerable to shocks. The inflow of migrants might destabilize the ethnic and social equilibria of host societies, especially in case of pre-existing marginalization (Rüegger, 2019; Schleussner et al., 2016). The destabilization induced by migrants' inflow might deteriorate states' willingness or ability to devote resources to disaster risk management and thereby increase the vulnerability of displaced and host communities (Marktanner et al., 2015).

We expect long-lasting and more intense conflicts to have particularly dire implications on societal vulnerability. First, longer and more severe conflicts are associated with greater material destruction and higher casualties and deaths, leading to higher macro-economic damages (Besley and Mueller, 2012; Mueller, 2016). Greater life losses and economic damages increase the risk of economic decline, as they progressively divert public resources away from other spheres (Lavi and Bar-Tal, 2015). Longer, severe conflicts are also more likely to change societal norms, and lead to a normalization of violence as an accepted behavioural pattern (Lavi and Bar-Tal, 2015). Protracted conflict exposure and the normalized use of violence in conflict-ridden societies might increase the risk of experiencing PTSD and major depression, especially in the case of resource loss and individual lost of trust in the government (Canetti et al., 2010). The individual and community level erosion of trust further destroys economic ties, increases social and political polarization, and overall heightens the risk of precipitating societies into conflict recurrence (Cederman and Pengl, 2019) and 'conflict traps' (Collier and Sambanis, 2002) which further reduce societal adaptive capacity and preparedness to respond to subsequent shocks.

The above arguments yield the following hypothesis:

Hypothesis 1. *Armed conflicts increase societal vulnerability to climate hazards.*

Hypothesis 1a. *More intense armed conflict are associated with higher levels of societal vulnerability to climate hazards.*

Hypothesis 1b. *Protracted armed conflicts are associated with higher levels of societal vulnerability to climate hazards.*

Climate-related natural disasters are an additional driver of societal vulnerability that can deteriorate the capacity of societies to adjust to future hazards. An important distinction needs to be made between hazards and disasters. Hazards are extreme events - such as storms, cyclones and droughts - that occur because of climatic forces; their frequency and magnitude is increasing as a result of climate change (IPCC, 2014). Disasters, on the other hand, are the product of hazards occurring within socio-economic systems. Disasters manifest themselves as people and resources are affected and damaged. As disasters strictly depend on the vulnerability of the exposed system, some scholars argue that no disaster can be deemed "natural" (Kelman, 2019).

In other words, while climate hazards relate to the intensity and severity of a climate phenomenon, natural disasters are dependent on the populations' response to the hazard, and thus are closely related to the magnitude of the impacts suffered by the population. The present analysis thus focuses on climate-related natural disasters as a main driver of socio-economic vulnerability.

Similarly to conflicts, natural disasters can trigger migration flows. Natural disasters in combination with loss of households' assets increase the likelihood of internal migration (Petrova, 2021). Likewise, drought induced crop failures or prolonged arid conditions in rural areas may push people to migrate to urban centers, putting urban wages under pressure. (Marchiori and Schumacher, 2011).

Natural disasters are also associated with increased volatility in the agricultural market and peaks in food prices (Fuglie, 2021), which can result in income losses and increased poverty for urban residents, especially in already poor countries characterized by high-income inequality (Dessus et al., 2008). Poverty, poor access to resources and food insecurity limit the capacity of communities to respond to climate-related shocks. For example, communities that rely on agricultural-dependent activities as their main source of livelihood confront higher levels of vulnerability when exposed to natural disasters (Von Uexkull et al., 2016).

Natural disasters can damage residential properties and infrastructures and cause both loss of lives and structural destruction. The economic loss may in turn reduce both individuals' and governments' resource availability, and thus lead to a deterioration in adaptive capacity. At an individual level, natural disasters can have long lasting psycho-social and mental-health impacts on exposed populations, particularly on women and children (Morrissey and Reser, 2007)

The human and economic damages induced by natural disasters, and the individual distress associated with them, can undermine social capital and reduce social trust (Albrecht, 2018), threaten state capacity and deteriorate government stability (Khurana et al., 2022). In turn, the lack of accountable governance and weak institutions constitute a major driver of vulnerability (Augsten et al., 2022). Research has in fact shown that state capacity prevents human losses caused by natural disasters, especially predictable ones such as floods and storms (Lin, 2015), and countries with better institutions experience less human and economic costs from natural disasters

(Raschky, 2008).

Overall, natural disasters may exacerbate and perpetuate societal vulnerability and deteriorate the resilience of affected societies to future climate hazards. Crucially, multiple climate-related disasters and their effects might compound with each other; not only multiple natural disasters might occur consecutively, but their impacts might overlap both spatially and temporally, hindering the possibility of recovery and further increasing societal vulnerability to subsequent events (Ruiter et al., 2020; Zscheischler et al., 2020).

This leads us to formulate the following hypothesis:

Hypothesis 2: *Natural disasters increase societal vulnerability to future climate hazards.*

Not only natural and human induced disasters have the potential to increase societal vulnerability to future natural hazards, but the effect of a *compound* exposure to armed conflict and natural disasters can be even more detrimental to societal vulnerability. The combination of social and natural events can in fact give rise to a cascade of temporally or spatially dependent risks (Zscheischler et al., 2018), which might compound and further increase socio-economic vulnerability to future hazards.

In fact, natural disasters can increase the risk of conflicts, especially in regions characterized by high levels of inequality, sluggish economic growth and mixed political regimes (Nel and Righarts, 2008). Natural disasters can also increase the duration of civil wars, by dampening state capacity and reducing available resources for peace efforts (Eastin, 2016). In turn, as disasters are a product of social constructs beyond the natural event itself, the devastation induced by violence can contribute to shaping natural hazards into disasters (Peters, 2022). The compound effect of violence and climate-related natural disasters may therefore be more detrimental to societal vulnerability than the occurrence of a single event. It is not a coincidence that the most severe humanitarian crises are found in areas exposed to a combination of human and natural disasters (von Uexkull and Busby, 2018). For example, some of the most acute hunger crises are located in conflict-affected regions that were exposed to prolonged or severe natural hardships, such as conflict-ridden South Sudan and Northern Nigeria (Buhaug and Uexkull, 2021).

Lastly, women are particularly vulnerable to the impacts of both climate natural disasters and armed conflicts (Augsten et al., 2022). Climate related natural disasters, especially in agricultural dependent communities, disproportionately expose women to forced migration, discrimination, land and income loss, and food insecurity (Chandra et al., 2017). On average, women are more affected by natural and human disasters due to their weakened capacity to recover (Chandra and Gaganis, 2016), impaired access to land rights, financial resources and social protection mechanisms (Molyneux and Razavi, 2002; Shah et al., 2013), as well as cultural and societal barriers to disasters adaptation and response (Zake and Hauser, 2014).

These arguments yield the following hypotheses:

Hypothesis 3: *The combination of natural disasters and armed conflict increases societal vulnerability to climate hazards relatively more than the occurrence of natural disasters or conflicts individually.*

Hypothesis 3a: *Gender inequality increases societal vulnerability to climate hazards.*

4.3 Data and Methodology

4.3.1 A machine learning approach

Extreme, rare events such as armed conflicts or climatic extremes, which can cause devastating impacts, are generally characterized by a complex chain of causal steps, the effects of which often propagate beyond the event itself in both space and time (Zscheischler et al., 2018). Understanding the overall impacts of compound events requires an analysis of complex causal mechanisms and interactions among various

components.Traditional statistical methods that rely on reduced form regressions are not fully equipped to grasp the complexities of these linkages and are especially unsuitable to characterize endogenous relationships (Schutte et al., 2021).
In contrast, predictive models reliant on machine learning algorithms are flexible enough to overcome the limitations of reduced form regressions, while maintaining high interpretability. Out-of-sample predictions can successfully contribute to the testing of theoretical arguments as an alternative or supplement to null hypothesis significance tests (Hegre et al., 2017; Ward et al., 2010).

We examine the out-of-sample performance of four models employing the same machine learning algorithm but varying sets of features to predict societal vulnerability to climate hazards [1], measured by the yearly vulnerability score from ND-GAIN (Chen, 2015, see section 4.3.3). To measure the contribution of various sets of independent variables in predicting vulnerability, we compare the four models to the baseline model, which only includes the population size per country as predictor. We expect population size to be a strong predictor, as vulnerability is highly dependent on exposure.
The 'armed conflict' model includes the annual, national count of armed conflict events of any type (state-based, one-sided, non-state) from the Uppsala Conflict Data Program (UCDP), the related number of fatalities, and the duration of ongoing conflicts for every country and year (Pettersson and Öberg, 2020). The second set of features in the 'natural disasters' model, used to test Hypothesis *2*, includes the count of natural disasters for every country-year, the related number of 'affected' people, i.e. those injured, killed or in need of assistance, and the total estimated damages in USD, drawn from the EM-DAT Database (Guha-Sapir, 2020). The third set of features characterizing the 'compound events' model, and employed to test Hypothesis *3*, combines both armed conflict and natural disasters indicators. To test hypothesis 3a, we specify a 'gender' model that includes measures of gender inequality from the World Development Indicators in addition to armed conflict and

[1] To perform our analysis, we employ the R code devised and utilized by Schutte et al. (2021).

natural disasters predictors. Specifically, we include the proportion of seats held by women in national parliaments, female unemployment as a percentage of the female labour force and the under-5 female mortality rate (World Bank, 2019). As we cannot assume an immediate effect of human or natural disasters on countries' response, all predictors included in the model are lagged by one year. More information on the main data sources is provided in section 4.3.3.

4.3.2 Modelling design

We train, evaluate and test the models using global data for each country and year in the 1995-2019 period. We utilize a 'leave-the-future-out' cross validation with a random forest machine learning algorithm that closely approximates the task of predicting the real near-future vulnerability. To maximise the amount of data while avoiding leakage, we trained the models on 21 partially overlapping sub-sets of the samples within the period 1996-2018, as in Schutte et al. (2021) (e.g. 1996-1998,...,2016-2019) and predict for one year ahead within the range 1999-2019.
All models are trained with a random forest regressor (rf). Random forest is a 'bagging' method where decision trees are added simultaneously to the ensemble and fit to correct the prediction errors made by prior models (Breiman, 2001).
For each model, we evaluate predictive performance as the absolute difference between predicted and actual outcomes (*'mean absolute error' or MAE*), averaged across all sub-sets of the samples. Better-performing models have lower average errors, such that an increase in the average error of a model specification when dropping a set of features from the overall model indicates a positive contribution of those features in predicting the vulnerability score. As the modelling set-up is equivalent to dropping a particular set of features from the combined model, the difference in predictive error between the compound model and the armed conflict or natural disasters models provides an indication of the marginal contribution of that particular set of features in predicting vulnerability. Likewise, as a test for Hypothesis *3a*, we can therefore compare the predictive performance of the *com-*

pound events and the *gender compound* models. A lower error of the latter model would indicate a positive contribution of gender features in predicting societal vulnerability in exposed societies. In order to test Hypothesis *1a* and *1b*, we compute and present the accumulated local effects (ALE) plots for all the features in the compound model, including the duration of ongoing conflicts (1a) and the intensity of violence, proxied by the count of battle-related deaths (1b). ALE plots describe how features influence the prediction of a machine learning model on average, and represent an efficient and unbiased alternative to partial dependence plots (PDPs) that are not suitable in presence of highly correlated features. (Molnar, 2021).

4.3.3 Data

Vulnerability data

The vulnerability data are drawn from the country-year ND-GAIN vulnerability score (Chen, 2015). The ND-GAIN aggregate index assigns a 0-1 vulnerability score to each country and year from 1995 to 2019. Consistently with the IPCC's definition, vulnerability is defined as the *'propensity or predisposition of human societies to be negatively affected by climate hazards'* (Chen, 2015, p.3). The index encompasses six macro sectors that assess the vulnerability of a country with respect to food, water, health, ecosystem services, human habitat and infrastructure. For each sector, the ND-GAIN score results from the aggregation of three macro components: adaptive capacity, sensitivity and exposure, each including a number of sub-indicators. For each sub-indicator, 0-1 scores are assigned according to each country-year's performance against an optimal benchmark. The aggregated vulnerability score, ranging from 0 (low) to 1 (high vulnerability) is computed for each country-year as the arithmetic, unweighted mean of all the sub-indicators.

The ND-GAIN vulnerability index is well established in the literature and has been used extensively to answer various research questions, including to explore how countries' vulnerability respond to climate change perception (Azócar et al., 2021) and to investigate the effect of macro-level characteristics on societal vulnerability to climate shocks (Halkos et al., 2020), with a particular focus on the challenges faced by developing countries (Namdar et al., 2021). ND-GAIN data have also been used to study the nexus between adaptation, readiness, and vulnerability of countries over time (Sarkodie and Strezov, 2019), and to identify challenges in adaptation options (Amegavi et al., 2021).

Although several other indices of vulnerability are available, we have opted for ND-GAIN data because of their broader temporal and spatial coverage, among other reasons. Still, ND-GAIN data are not without limitations; hence, starting from ND-GAIN sub-indicators we have constructed a "disaster and conflict sensitive" vulnerability indicator. Details on the comparison of ND-GAIN with other indices as well as on the construction of our new vulnerability indicator can be found in Appendix C.

Armed conflict data

Data on violence are drawn from UCDP (Pettersson and Öberg, 2020), and follow their definition of armed conflict as an incompatibility concerning the government and/or territory of a state where the use of armed force results in 25 or more battle-related deaths per country-year (Gleditsch et al., 2002). We include all types of violent events coded by UCDP: state-based armed conflicts involving at least the government of a state, non-state violence between non-governmental actors such as rebel groups, and one-sided violence where a governmental or non-state actor attacks unarmed civilians. UCDP data are extracted from a multitude of sources, including news articles, reports from United Nations agencies and international organisations, Truth and Reconciliation Commissions and case-oriented research studies (Eck, 2012). Despite being obviously subject to the same limitations as its sources, UCDP applies a strict definition of conflict events and a rigorous coding approach that ensures that every event is carefully vetted before inclusion to guarantee data quality (Eck, 2012).

Natural disasters data

Information on natural disasters is drawn from the publicly accessible EM-DAT Database (Guha-Sapir, 2020) maintained by the Centre for Research on the Epidemiology of Disasters (CRED) of the University of Louvain, Belgium.[2] EM-DAT includes disasters that caused more than 10 fatalities, left more than 100 people in need of emergency assistance, and involved either the declaration of a state of emergency, or a call for international assistance. EM-DAT data are coded from a collection of sources such as United Nations agencies, governmental and non-governmental organizations, insurance companies, research centers, and the press (Guha-Sapir and Below, 2002). Being focused on humanitarian needs, EM-DAT data may fail to comprehensively cover disasters in developed countries that experienced high economic and material losses, but lower deaths and no call for international aid (Kousky, 2014). Despite this caveat, EM-DAT is to date the best source for consistent, cross-national data on natural disasters (Kousky, 2014). We exclude from the analysis natural disasters that are not strictly linked to climatic changes, e.g. earthquakes and epidemics, and we account only for climate-related ones, such as storms and droughts. The complete list of climate-related disasters considered in the analysis can be found in Appendix C.2

4.4 Results

The results of the forecasting models are presented in Figure 4.2. The map (a) illustrates the best predictive models for each country, averaged over the test sets in 1999-2019. Results are displayed in section a of Figure 4.2. As Figure 4.2 shows, the best predictive model varies across countries worldwide. The *conflict* model is the best predictive in the Russian Federation, in some vulnerable countries of the

[2] Data from EMDAT are widely used, but still present some limitations (for example, see Jones et al. 2022). Still, we rely on this dataset as it provides relevant information on natural disaster events and other pertinent exposure-related variables, such as the number of people impacted. Moving forward, it would be interesting to expand upon this research by incorporating data on heatwaves and droughts from climate datasets such as ERA5.

Middle East, like Afghanistan and Turkmenistan, and of Latin America, such as Argentina, Uruguay and Ecuador. The *conflict* model is also the best predictive model of vulnerability in the African continent, especially in East Africa, such as in Somalia, Kenya, Ethiopia, Djibouti and Sudan, but also in Central-West Africa, such as in Central African Republic, Congo and Camerun. As many of these countries have been ravaged by long-lasting conflicts for many years, it is not surprising that vulnerability to subsequent hazards is best explained by the exposure to conflicts.

The *disaster* model is the best predictive one in some countries of Latin America, like Mexico, Nicaragua, Colombia and Peru, and in southern Africa, like Namibia, Botswana, Zimbabwe and Zambia. Similarly, the *disaster* model is the best predictive model of vulnerability for some countries in the Eastern Europe/Middle East region, like Turkey, Iraq, Georgia and Armenia.

The *compound* model is the best predictive model in Senegal, Angola and some countries of South-East Asia, like Indonesia, Thailand and South Korea. This is not surprising, since these are countries that are historically both been subject to conflicts and natural disasters.

The *gender* model is the best predictive model in the rest of the world. Gender inequalities are a driver of subsequent vulnerability in most of the developed world, but also in most of Asia and some parts of Latin America. As gender equality is associated with socio-economic development, these results shed light on the importance of an inclusive, egalitarian and sustainable human development for reducing societal vulnerability.

The importance of gender variables in predicting vulnerability is confirmed by the scatter plot in Figure 4.2 c, showing that predictions from the *gender* model have the highest correlation with observed vulnerability. Consistently, the mean absolute error in predictions (Figure 4.2 d) reiterates that the *gender* model is the best predictive model of vulnerability on average across all countries and test sets, immediately followed by the *compound* model. The *conflict* model exhibits a slightly better performance than the *disasters* model, and all models are more accurate in predicting than the baseline, in line with our hypotheses. Broadly, all models have a tendency to under-predict vulnerability relative to the actual scores, as evident in Figure 4.2 c.

Figure 4.2 b reports the feature importance of the *compound* model. Accordingly, the most important predictor in the *compound* model is population, followed by people affected by climate-related disasters, conflict events, deaths, and duration, disaster counts, and lastly, disaster damages. The importance of population in predicting vulnerability is likely a reflection of exposure: populated areas are more exposed to all sources of vulnerability, and vulnerability in itself is strictly dependent on the presence of human activities. Similarly, the magnitude of people that are affected by natural disasters is an important predictor of vulnerability, as the affected population may be less able to respond to future disasters. People might die as a result of a disaster, become homeless or be severely injured – all factors that contribute to increasing subsequent vulnerability to future shocks. The number of disasters is less important in predicting vulnerability than the number of people affected, suggesting that a good response system that reduces the impact on affected people could, at least partly, help alleviate societal vulnerability to subsequent disasters.

The model also assigns a high importance to conflict events and deaths as predictors of vulnerability. These findings shed light on the possible mechanisms through which armed conflict and natural disasters may affect vulnerability, illuminating the importance of population related dynamics rather than strictly economic losses.

Figure 4.2: a) Best predictive model of 'disasters and conflict sensitive' vulnerability by country averaged over the test sets in 1999-2019; b) Feature importance of the compound model; c) Scatterplot of predicted and actual 'disasters and conflict sensitive' vulnerability scores across models; d) Average prediction error averaged across the test sets in 2001-2019. Model 'g': gender; 'd': disaster; 'v': conflict; 'c': compound; 'b': baseline.

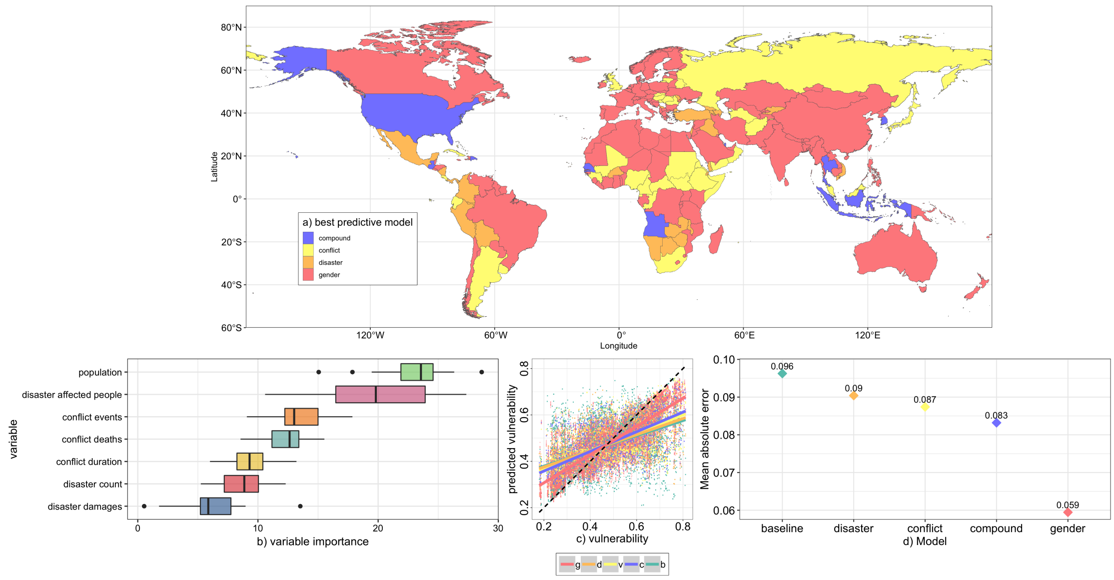


Figure 4.3 depicts the Accumulated Local Effect (ALE) plots for each component of the *compound* model (without the baseline). ALE plots describe how input features (horizontal axis) influence the prediction of a machine learning model on average (vertical axis) (Molnar, 2021). Figure 4.3 shows that when conflict duration increases, the average prediction of vulnerability increases steadily, suggesting that the duration of a conflict increases societal vulnerability. Similarly, when the number of conflict deaths rise, the average vulnerability prediction also increases. The average vulnerability prediction also rises when the number of conflicts increase, but then decreases as conflict events continue to rise. This non-linear relationship might indicate an adaptation effect: when a conflict breaks out in a previously peaceful country, this might have a very negative effect on affected people and the economic system, but the effect is much less devastating when an additional violence episode occurs in countries with a strong conflict legacy. Figure 4.3 also shows a positive relationship between natural disasters and vulnerability, mostly driven by the number of affected people. The ALE plot shows that the prediction of vulnerability

increases steadily at the increase in the number of affected people, confirming the pivotal role of affected population in predicting societal vulnerability. By contrast, the average vulnerability prediction tends to remain constant when disaster damages are very limited, and then rapidly declines when the damages are over 2700 USD (10 on log+0.001 scale). The effect of disaster counts on vulnerability exhibits a similar trend. This might again indicate an adaptation effect: while vulnerability is very responsive to the shock induced by the first disaster, societies may be able to adapt and prepare to subsequent shocks, and thereby reduce the negative impact on vulnerability. Although the ALE plots remain reliable even when the features are correlated (Molnar, 2021), the magnitude of the effect of individual features on the average prediction might be capturing some indirect effects, due to the interaction of an individual variable with others in the model.

Figure 4.3: Accumulated Local Effect (ALE) plots, compound model without baseline. The observed value is reported on a *log+0.001* scale.

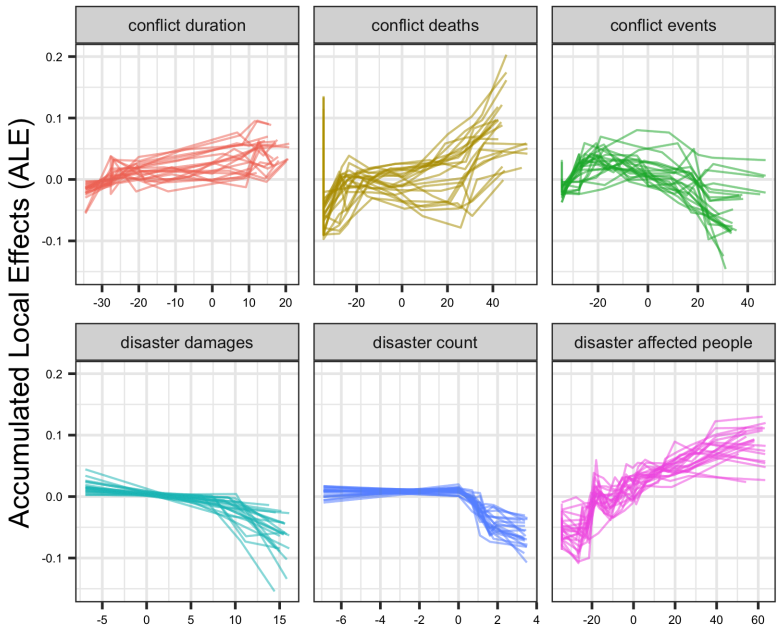
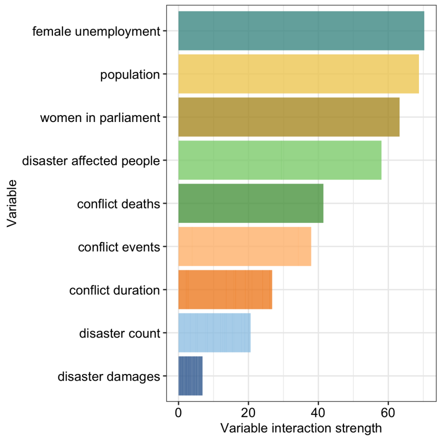


Figure 4.4 presents the strength of the interaction in the features of the *compound* model. The interaction between two features is measured as the change in prediction that occurs by permuting the features values, after accounting for the individual feature effects (Molnar, 2021). The plot shows that the population variable exhibits

a very strong interaction with all the other features, while disaster count and disaster damages show the weakest interactions with the other features. This confirms that the amount of people affected by conflicts and disasters is one of the main drivers of vulnerability, but also suggests that part of their effect on vulnerability is indirect, and may operate though their interactions with other features.

Figure 4.4: Interaction strength of the features in the compound model.



4.5 Conclusions

Armed conflict, climate-related impacts and societal vulnerability are inherently connected in an endogenous, complex relationship. Although past studies have illuminated how climate shocks and its adverse consequences affect the risk of conflict, existing evidence on the inverse relationship is scant.

This chapter fills this gap by presenting the first systematic study of the impact of violence and natural disasters on subsequent levels of societal vulnerability to climate hazards. Hypotheses were made regarding how both armed conflict and natural disasters increase societal vulnerability to future hazards, especially when they mutually compound, and when they affect gender unequal countries where women have less resources and capacity to adapt. These hypotheses are then tested in a predictive framework that leverages on the explanatory power of machine learning tools. Five random forest models are trained, tested and evaluated in a leave-the-future-out cross validation to predict a country-year disaster and conflict sensitive vulnerability index, derived from ND-GAIN data.

Results show that both armed conflict and natural disasters increase societal vulnerability to climate hazards. The compound model, accounting for the combined effect of both violence and climate-related disasters, predicts vulnerability more accurately than the models including conflict or disasters related features alone. A gender model, encompassing information on the level of gender equality and inclusion in a country, is the best predictive model of vulnerability, especially in developed countries.

The findings also show that armed conflict and natural disasters' effect on vulnerability operates through their impacts on population rather than via economic losses. This suggests that policies aimed at improving individual and collective well-being, livelihood, and overall adaptive capacity, and especially providing support to women as one of the most affected segment of society, may prove more fruitful to decrease the impacts of climate hazards than economically-centered relief programs.

5

Conclusion

Climate change has been in the spotlight for several decades as the most important challenge humanity faces. For the first time in history, human activity has - and will have - long lasting impacts on the planet, shaping it to such an extent that a term for a new era - the Anthropocene - was coined (Lewis and Maslin, 2015). The magnitude of these impacts might develop to such an extent that new phenomena and tipping points might be reached, bringing both the human and environmental systems to never-seen-before conditions. The potential (and still partly unknown) dangers arising from the warming of the planet urge the academic community to pay particular attention to such phenomena and to study them extensively in order to propose effective solutions.

One of the most relevant lines of research in the study of climate change related impacts is how it relates to vulnerability, to what extent pre-existing vulnerabilities worsen climate-related impacts, and how these phenomena contribute to the increase in conflict risk. If careful attention is not devoted to the design of effective adaptation policies that also take into account peace-keeping efforts, affected populations in the most vulnerable regions of the world risk being trapped in a vicious cycle of heightened conflict risk, harmful climate impacts and increased socio-economic vulnerability, that might compound with each other and further influence one another to a potentially destructive extent (Buhaug and Uexkull, 2021). The future of the planet might be one of increased climate-related risks, violent conflicts, scarce economic outcomes and environmentally-related migration from the Global South to the North, and this might pose serious questions as to how to deal with such interconnected challenges.

In this context, this thesis is integrated in the literature regarding the climate-conflict-vulnerability relationship that has been explored in each chapter in different ways.

Chapter 2 looks at the conditional relationship between climate-related hazards and conflict risk. First, it asks if natural disasters can have an effect on the probability of new armed conflicts. Second, it asks whether high resilience to climate change could mitigate the effect of natural disasters on the probability of conflicts. Chapter 2 finds several insights: first, there is a positive impact of natural disasters on the probability of new conflicts. In particular, natural disasters have a positive effect on the risk of new non-state conflicts, while this is not the case for state-conflicts. Second, even though there is no evidence of a direct link between ethnic fractionalization and armed conflicts, results suggest that natural disasters occurring in countries with high ethnic fractionalization are more likely to result in new conflicts. This is in line with pre-existing literature linking natural disasters, ethnic fractionalization and violent activities and might be connected to ethnic differences serving as conflict lines in case of societal tensions arising from climate-related shocks (Schleussner et al., 2016). Finally, the effect of natural disasters on the probability of insurgence of new conflicts is differentiated for different levels of resilience and vulnerability. In particular, the probability that a natural disaster increases the likelihood of conflicts is higher for more vulnerable and less resilient countries. Furthermore, the effects on conflict risk is differentiated across slow and rapid-onset disasters, as they require different responses (proactive vs reactive) and might thus differently influence conflict risk, especially in already vulnerable regions.

Chapter 3, instead, goes into a finer level of detail, looking at the relationship between climatic changes, armed conflicts and vulnerability in Eastern Africa. This is accomplished with the use of a spatial analysis approach that allows to look in detail at the relationships among variables, going beyond national level averages. Chapter 3 investigates why some locations are more likely to engage in armed conflicts than others in the presence of a similar level of exposure to climatic changes and, accordingly, attempts to identify a specific set of factors that enhance vulnerability of certain shares of the population at the local level. Different aspects of vulnerability are included in order to identify key factors where policy makers can intervene to improve local resilience. Results of chapter 3 provide some interesting insights: first, climate change does not increase conflict risk *per se*, but only in presence of pre-existing vulnerability. In particular, results seem to suggest that there is no generalisable direct link between climate change and conflicts, but rather climate change acts as a threat multiplier in the presence of vulnerability. Second, in line with the literature on climate change vulnerability, socioeconomic factors play a key role in the climate-conflict nexus. In particular, vulnerability is enhanced whenever power is not distributed in such a way as to ensure an equitable distribution of resources. Ultimately, chapter 3 highlights the need to evaluate local sources of vulnerability when designing measures to both improve adaptation to climate change and to enhance peace and stability.

Finally, chapter 4 looks at another aspect of the climate-conflict-vulnerability vicious cycle, and from a prediction perspective. Specifically, chapter 4 looks at whether climate-related hazards, conflicts and gender inequality influence subsequent levels of socioeconomic vulnerability. This is done through a machine learning approach: data on conflicts, climate-related hazards and gender inequalities are used to predict subsequent levels of socioeconomic vulnerability, proxied by the country vulnerability index ND-GAIN, through five different models that are trained, tested and evaluated in a leave-the-future-out cross validation.

Results show that both armed conflict and natural disasters increase societal vulnerability to climate hazards. The compound model, accounting for the combined effect of both violence and climate-related disasters, predicts vulnerability more accurately than the models including conflict or disasters related features alone. A gender model, encompassing information on the level of gender equality and inclusion in a country, is the best predictive model of vulnerability, especially in developed countries.

Cumulatively, this thesis has looked at different aspects of the climate-conflict-vulnerability nexus. The study of the interrelations among these phenomena is crucially relevant in our current world. In fact, for the first time in history the human race is dealing with concurrent crises which to be understood, and possibly prevented, require new and improved perspectives and solutions. This thesis has attempted to provide such new perspectives by focusing on the importance of taking into account the conditional relationship between climatic changes, socioeconomic vulnerability and conflict risk and taking into consideration the unprecedented interrelations intervening between them to devise improved and comprehensive policies. By focusing on these interrelated factors and taking a comprehensive approach, we can develop more effective policies and adaptive measures to build resilience and reduce the risk of conflict in the face of unprecedented climate change impacts, while at the same time taking into consideration peace and stability objectives. If holistic and cost-effective policies that consider both climate change adaptation and peacekeeping efforts are implemented, we can ensure that the future that lies ahead will be one of less pronounced climate impacts and a more stable and peaceful world.

Bibliography

Abel, Guy J, Michael Brottrager, Jesus Crespo Cuaresma, and Raya Muttarak (2019). "Climate, conflict and forced migration". *Global environmental change* 54, pp. 239–249.

ADB (2021). *East Africa Economic Outlook 2021*.

Albrecht, Frederike (Apr. 2018). "Natural Hazard Events and Social Capital: The Social Impact of Natural Disasters". *Disasters* 42.2, pp. 336–360.

Alesina, Alberto, Stelios Michalopoulos, and Elias Papaioannou (2016). "Ethnic inequality". *Journal of Political Economy* 124.2, pp. 428–488.

Amegavi, George Babington, Zechariah Langnel, Jerome Jeffison Yaw Ofori, and Daisy Rose Ofori (2021). "The impact of adaptation on climate vulnerability: Is readiness relevant?" *Sustainable Cities and Society* 75, p. 103325.

Andreano, Maria Simona, Roberto Benedetti, Federica Piersimoni, and Giovanni Savio (2021). "Mapping poverty of Latin American and Caribbean countries from heaven through night-light satellite images". *Social Indicators Research* 156.2, pp. 533–562.

Anselin, Luc (1995). "Local indicators of spatial association—LISA". *Geographical analysis* 27.2, pp. 93–115.

Audu, Sunday Didam (2014). "Freshwater scarcity: A threat to peaceful co-existence between farmers and pastoralists in northern Nigeria". *International journal of development and sustainability* 3.1, pp. 242–251.

Augsten, Leanna, Karine Gagné, and Yvonne Su (June 2022). "The human dimensions of the climate risk and armed conflict nexus: a review article". en. *Regional Environmental Change* 22.2, p. 42.

Ayana, Essayas K, Pietro Ceccato, Jonathan RB Fisher, and Ruth DeFries (2016). "Examining the relationship between environmental factors and conflict in pastoralist areas of East Africa". *Science of The Total Environment* 557, pp. 601–611.

Azócar, Gabriela et al. (2021). "Climate change perception, vulnerability, and readiness: inter-country variability and emerging patterns in Latin America". *Journal of Environmental Studies and Sciences* 11.1, pp. 23–36.

Begueria, S and V Serrano (2017). "SPEI: Calculation of Standardised Precipitation-Evapotranspiration index. R package version 1.6". March, p. 16.

Berger, Rachel (2003). "Conflict over natural resources among pastoralists in northern Kenya: a look at recent initiatives in conflict resolution". *Journal of International Development: The Journal of the Development Studies Association* 15.2, pp. 245–257.

Besley, Timothy and Hannes Mueller (2012). "Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland". *The American Economic Review* 102.2, pp. 810–833.

Bircan, Çağatay, Tilman Brück, and Marc Vothknecht (2017). "Violent conflict and inequality". *Oxford Development Studies* 45.2, pp. 125–144.

Black, Richard et al. (2011). "The effect of environmental change on human migration". *Global environmental change* 21, S3–S11.

Blundell, Richard, Rachel Griffith, and John Van Reenen (1995). "Dynamic count data models of technological innovation". *The economic journal* 105.429, pp. 333–344.

Boix, Carles (2008). "Economic Roots of Civil Wars and Revolutions in the Contemporary World". *World Politics* 60.3. Publisher: Cambridge University Press, pp. 390–437.

Breiman, Leo (2001). “Random Forests”. *Machine learning* 45.1, pp. 5–32.

Brown, Ian A (2010). “Assessing eco-scarcity as a cause of the outbreak of conflict in Darfur: a remote sensing approach”. *International Journal of Remote Sensing* 31.10, pp. 2513–2520.

Brown, Molly E., Kathryn Grace, Trey Billing, and David Backer (2021). “Considering climate and conflict conditions together to improve interventions that prevent child acute malnutrition”. *The Lancet Planetary Health* 5.9, e654–e658.

Brzoska, Michael and Christiane Fröhlich (2016). “Climate change, migration and violent conflict: vulnerabilities, pathways and adaptation strategies”. *Migration and Development* 5.2, pp. 190–210.

Buhaug, Halvard, Nils Petter Gleditsch, and Ole Magnus Theisen (2008). “Implications of climate change for armed conflict”. *Washington, DC: World Bank*.

Buhaug, Halvard and Nina von Uexkull (2021). “Vicious circles: violence, vulnerability, and climate change”. *Annual Review of Environment and Resources* 46, pp. 545–568.

Buhaug, Halvard et al. (2014). “One effect to rule them all? A comment on climate and conflict”. *Climatic Change* 127.3, pp. 391–397.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015). “Climate and conflict”. *Annu. Rev. Econ.* 7.1, pp. 577–617.

Canetti, Daphna et al. (2010). “Exposure to prolonged socio-political conflict and the risk of PTSD and depression among Palestinians”. *Psychiatry: Interpersonal and Biological Processes* 73.3, pp. 219–231.

Cappelli, Federica, Caterina Conigliani, Davide Consoli, Valeria Costantini, and Elena Paglialunga (2022a). “Climate change and armed conflicts in Africa: temporal persistence, non-linear climate impact and geographical spillovers”. *Economia Politica*, pp. 1–44.

Cappelli, Federica, Valeria Costantini, and Davide Consoli (2021). “The trap of climate change-induced “natural” disasters and inequality”. *Global Environmental Change* 70, p. 102329.

Cappelli, Federica, Valeria Costantini, Elena Paglialunga, Giorgia Sforna, and Anil Markandya (2022b). "The Climate–Conflicts Nexus and the Role of Geographical Spillovers". In: *Climate And Development*. World Scientific, pp. 221–255.

Cappelli, Federica et al. (2020). "Do spatial interactions fuel the climate-conflict vicious cycle? The case of the African continent". *Journal of Spatial Econometrics* 1.1, pp. 1–52.

Cavallo, Eduardo, Ilan Noy, et al. (2011). "Natural disasters and the economy—a survey". *International Review of Environmental and Resource Economics* 5.1, pp. 63–102.

Cederman, Lars-Erik and Yannick Pengl (2019). "Global Conflict Trends and Their Consequences". *Background Paper to the United Nations Sustainable Development Outlook 2019*.

Cederman, Lars-Erik, Nils B Weidmann, and Kristian Skrede Gleditsch (2011). "Horizontal inequalities and ethnonationalist civil war: A global comparison". *American political science review* 105.3, pp. 478–495.

Chandra, Alvin and Petros Gaganis (May 2016). "Deconstructing Vulnerability and Adaptation in a Coastal River Basin Ecosystem: A Participatory Analysis of Flood Risk in Nadi, Fiji Islands". *Climate and Development* 8.3, pp. 256–269.

Chandra, Alvin, Karen E. McNamara, Paul Dargusch, Ana Maria Caspe, and Dante Dalabajan (Feb. 2017). "Gendered Vulnerabilities of Smallholder Farmers to Climate Change in Conflict-Prone Areas: A Case Study from Mindanao, Philippines". *Journal of Rural Studies* 50, pp. 45–59.

Chen C.; Noble, I.; Hellmann J.; Coffee J.; Murillo M.; Chawla N. (2015). *Notre Dame-Global Adaptation Index (ND-GAIN) Country Index*. ND-Gain technical document.

Chen, Xi and William D Nordhaus (2011). "Using luminosity data as a proxy for economic statistics". *Proceedings of the National Academy of Sciences* 108.21, pp. 8589–8594.

Cherniack, E Paul (2008). “The impact of natural disasters on the elderly”. eng. *Am J Disaster Med* 3.3, pp. 133–139.

Cole, Tony A, David W Wanik, Andrew L Molthan, Miguel O Román, and Robert E Griffin (2017). “Synergistic use of nighttime satellite data, electric utility infrastructure, and ambient population to improve power outage detections in urban areas”. *Remote Sensing* 9.3, p. 286.

Collier, Paul and Dominic Rohner (2008). “Democracy, development, and conflict”. *Journal of the European Economic Association* 6.2-3, pp. 531–540.

Collier, Paul and Nicholas Sambanis (2002). “Understanding civil war: A new agenda”. *Journal of Conflict Resolution* 46.1, pp. 3–12.

Collier, Paul et al. (2003). *Breaking the conflict trap: Civil war and development policy*. Vol. 41181. 4. World Bank Publications.

Conceição, Pedro et al. (2020). “Human Development Report 2020: The Next Frontier Human Development and the Anthropocene”. *UNDP: New York, NY.*

Conigliani, Caterina, Valeria Costantini, and Giulia Finardi (2021). “Climate-related natural disasters and forced migration: a spatial regression analysis”. *Spatial Economic Analysis*, pp. 1–24.

CRED (2022). *2021 Disasters in Numbers.*

Davies, Lynn (2005). “Evaluating the Link between Conflict and Education”. *Journal of Peacebuilding & Development* 2.2, pp. 42–58.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2012). “Temperature shocks and economic growth: Evidence from the last half century”. *American Economic Journal: Macroeconomics* 4.3, pp. 66–95.

— (2014). “temfrom the weather? The new climate-economy literature”. *Journal of Economic Literature* 52.3, pp. 740–98.

Dessus, Sébastien, Santiago Herrera, and Rafael de Hoyos (Nov. 2008). “The Impact of Food Inflation on Urban Poverty and Its Monetary Cost: Some Back-of-the-Envelope Calculations”. *Agricultural Economics* 39, pp. 417–429.

Diwakar, Vidya (2015). "The Effect of Armed Conflict on Education: Evidence from Iraq". *The Journal of Development Studies* 51.12, pp. 1702–1718.

Doll, Christopher NH, Jan-Peter Muller, and Jeremy G Morley (2006). "Mapping regional economic activity from night-time light satellite imagery". *Ecological Economics* 57.1, pp. 75–92.

Doll, Christopher NH and Shonali Pachauri (2010). "Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery". *Energy policy* 38.10, pp. 5661–5670.

Doll, ChristopherN H, Jan-Peter Muller, and Christopher D Elvidge (2000). "Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions". *AMBIO: a Journal of the Human Environment* 29.3, pp. 157–162.

Drazanova, Lenka (2019). "Historical index of ethnic fractionalization dataset (HIEF)". *Harvard Dataverse* 1.

Dugoua, Eugenie, Ryan Kennedy, and Johannes Urpelainen (2018). "Satellite data for the social sciences: measuring rural electrification with night-time lights". *International journal of remote sensing* 39.9, pp. 2690–2701.

Dureab, Fekri et al. (June 2019). "An Overview on Acute Malnutrition and Food Insecurity among Children during the Conflict in Yemen". en. *Children (Washington, D.C.)* 6.6, p. 77.

Eastin, Joshua (2016). "Fuel to the fire: Natural disasters and the duration of civil conflict". *International Interactions* 42.2, pp. 322–349.

Eck, Kristine (Mar. 2012). "In Data We Trust? A Comparison of UCDP GED and ACLED Conflict Events Datasets". *Cooperation and Conflict* 47.1, pp. 124–141.

Elhorst, J Paul et al. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*. Vol. 479. Springer.

Eurostat (2018). *Handbook of Spatial Analysis - Theory and Application with R.*

FAO (2020). "The state of food security and nutrition in the world. Transforming food systems for affordable healthy diets". In: Last accessed 05.05.21. Rome: FAO.

Fatima, Noor, Aamir Alamgir, Moazzam Ali Khan, and Muhammad Owais (2022). "Evaluating dual exposure by using climate-conflict vulnerability index on the coastal districts of Sindh, Pakistan". *Environmental Monitoring and Assessment* 194.8, pp. 1–27.

Franziska Atwii Kristin Bergtora Sandvik, Lotte Kirch Beata Paragi Katrin Radtke Soren Schneider Daniel Weller (2022). *World Risk Report*. Institute for International Law of Peace and Armed Conflict.

Fuglie, Keith (Apr. 2021). "Climate change upsets agriculture". *Nature Climate Change* 11.4, pp. 294–295.

Gaillard, Jean-Christophe (2010). "Vulnerability, capacity and resilience: Perspectives for climate and development policy". *Journal of International Development: The Journal of the Development Studies Association* 22.2, pp. 218–232.

Garry, S and F Checchi (Aug. 2020). "Armed Conflict and Public Health: Into the 21st Century". *Journal of Public Health* 42.3, e287–e298.

Garschagen, Matthias, Deepal Doshi, Jonathan Reith, and Michael Hagenlocher (2021). "Global patterns of disaster and climate risk—an analysis of the consistency of leading index-based assessments and their results". *Climatic Change* 169.1, pp. 1–19.

Gates, Scott, Håvard Hegre, Håvard Mokleiv Nygård, and Håvard Strand (2012). "Development consequences of armed conflict". *World Development* 40.9, pp. 1713–1722.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer (2013). "Human capital and regional development". *The Quarterly journal of economics* 128.1, pp. 105–164.

Ghobarah, Hazem Adam, Paul K. Huth, and Bruce M. Russett (2003). "Civil wars kill and maim people–Long after the shooting stops". *American Political Science Review* 97.2, pp. 189–202.

Gibson, John, Susan Olivia, Geua Boe-Gibson, and Chao Li (2021). "Which night lights data should we use in economics, and where?" *Journal of Development Economics* 149, p. 102602.

Gizelis, Theodora-Ismene and Amanda E Wooden (2010). "Water resources, institutions, & intrastate conflict". *Political Geography* 29.8, pp. 444–453.

Gleditsch, Nils Petter (2012). "Whither the weather? Climate change and conflict". *Journal of Peace Research* 49.1, pp. 3–9.

Gleditsch, Nils Petter, Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg, and Håvard Strand (2002). "Armed conflict 1946-2001: A new dataset". *Journal of peace research* 39.5, pp. 615–637.

Goldewijk, Kees Klein, Arthur Beusen, Jonathan Doelman, and Elke Stehfest (2017). "Anthropogenic land use estimates for the Holocene–HYDE 3.2". *Earth System Science Data* 9.2, pp. 927–953.

Gosling, Simon N. and Nigel W. Arnell (Feb. 2016). "A global assessment of the impact of climate change on water scarcity". *Climatic Change* 134.3, pp. 371–385.

Guha-Sapir, Debarati (2020). *EM-DAT: The Emergency Events Database*. Brussels, Belgium, www.emdat.be.

Guha-Sapir, Debarati and Regina Below (2002). "Quality and Accuracy of Disaster Data: A Comparative Analyse of 3 Global Data Sets". *Working paper prepared for the Disaster Management facility, World Bank, Brussels.* CRED Working Paper.

Gupta, Sanjeev, Benedict Clements, Rina Bhattacharya, and Shamit Chakravarti (2004). "Fiscal consequences of armed conflict and terrorism in low-and middle-income countries". *European Journal of Political Economy* 20.2, pp. 403–421.

Habyarimana, James, Macartan Humphreys, Daniel N Posner, and Jeremy M Weinstein (2007). "Why does ethnic diversity undermine public goods provision?" *American political science review* 101.4, pp. 709–725.

Hair, Joseph F (2009). *Multivariate data analysis.*

Halkos, George, Antonis Skouloudis, Chrisovalantis Malesios, and Nikoleta Jones (2020). "A hierarchical multilevel approach in assessing factors explaining country-level climate change vulnerability". *Sustainability* 12.11, p. 4438.

Hallegatte, Stephane and Julie Rozenberg (Apr. 2017). "Climate change through a poverty lens". en. *Nature Climate Change* 7.4, pp. 250–256.

Harari, Mariaflavia and Eliana La Ferrara (2018). "Conflict, climate, and cells: a disaggregated analysis". *Review of Economics and Statistics* 100.4, pp. 594–608.

Hayes, Michael, Mark Svoboda, Nicole Wall, and Melissa Widhalm (2011). "The Lincoln declaration on drought indices: universal meteorological drought index recommended". *Bulletin of the American Meteorological Society* 92.4, pp. 485–488.

Hegre, Håvard, Nils W. Metternich, Håvard Mokleiv Nygård, and Julian Wucherpfennig (2017). "Introduction: Forecasting in peace research". *Journal of Peace Research* 54.2, pp. 113–124.

Henderson, J Vernon, Adam Storeygard, and David N Weil (2012). "Measuring economic growth from outer space". *American economic review* 102.2, pp. 994–1028.

Holling, Crawford S (1973). "Resilience and stability of ecological systems". *Annual review of ecology and systematics*, pp. 1–23.

Hsiang, Solomon M and Marshall Burke (2014). "Climate, conflict, and social stability: what does the evidence say?" *Climatic change* 123.1, pp. 39–55.

Hsiang, Solomon M, Marshall Burke, and Edward Miguel (2013). "Quantifying the influence of climate on human conflict". *Science* 341.6151, p. 1235367.

Ide, Tobias, Michael Brzoska, Jonathan F Donges, and Carl-Friedrich Schleussner (2020). "Multi-method evidence for when and how climate-related disasters contribute to armed conflict risk". *Global Environmental Change* 62, p. 102063.

IPCC (2007). *Climate change 2007-The Physical Science Basis. Working group I contribution to the fourth assessment report of the IPCC*. Vol. 4. Cambridge university press.

— (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change.* Cambridge University Press.

— (2014). *AR5 Climate Change 2014: Impacts, Adaptation, and Vulnerability, Global and Sectoral Aspects, Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.*

— (2018). *Summary for Policy Makers. In Global warming of 1.5°C. An IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways.*

— (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Vol. In Press. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

— (2022a). *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*

— (2022b). "Summary for Policymakers In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change".

Iqbal, Zaryab (2006). "Health and human security: The public health impact of violent conflict". *International Studies Quarterly* 50.3, pp. 631–649.

Ivan, Kinga, Iulian-Horia Holobâcă, József Benedek, and Ibolya Török (2019). "Potential of night-time lights to measure regional inequality". *Remote Sensing* 12.1, p. 33.

Jawad, Mohammed et al. (Dec. 2020). "Estimating indirect mortality impacts of armed conflict in civilian populations: panel regression analyses of 193 countries, 1990–2017". en. *BMC Medicine* 18.1, p. 266.

Johnson, Shelly and Judith Ostendorf (Jan. 2010). "Hispanic Employees in the Workplace". *AAOHN Journal* 58.1, pp. 11–16.

Jones, Benjamin T, Eleonora Mattiacci, and Bear F Braumoeller (2017). "Food scarcity and state vulnerability: Unpacking the link between climate variability and violent unrest". *Journal of Peace Research* 54.3, pp. 335–350.

Jones, Rebecca Louise, Debarati Guha-Sapir, and Sandy Tubeuf (2022). "Human and economic impacts of natural disasters: can we trust the global data?" *Scientific data* 9.1, p. 572.

Kelman, Ilan (2019). "Axioms and actions for preventing disasters". *Progress in Disaster Science* 2.

Khurana, Ritika, Douglas Mugabe, and Xiaoli L. Etienne (2022). "Climate change, natural disasters, and institutional integrity". *World Development* 157, p. 105931.

Kirkbride, Mary (2008). *Survival of the fittest: pastoralism and climate change in East Africa*. Vol. 116. Oxfam.

Kliesen, Kevin L and John Stuart Mill (1994). "The economics of natural disasters". *The regional economist* 332.

Kling, Gerhard, Ulrich Volz, Victor Murinde, and Sibel Ayas (2021). "The impact of climate vulnerability on firms' cost of capital and access to finance". *World Development* 137, p. 105131.

Koubi, Vally (2019). "Climate change and conflict". *Annual Review of Political Science* 22, pp. 343–360.

Koubi, Vally, Gabriele Spilker, Lena Schaffer, and Tobias Böhmelt (2016). "The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries". *Population and environment* 38.2, pp. 134–163.

Kousky, Carolyn (2014). "Informing climate adaptation: A review of the economic costs of natural disasters". *Energy Economics* 46, pp. 576–592.

Kummu, Matti, Maija Taka, and Joseph H A Guillaume (2018). "Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015". *Scientific Data* 5.1, p. 180004.

Lavi, Iris and Daniel Bar-Tal (2015). "Violence in prolonged conflicts and its socio-psychological effects". In: *Violence and mental health*. Springer, pp. 3–25.

Lee, Bomi K, Sara McLaughlin Mitchell, Cody J Schmidt, and Yufan Yang (2022). "Disasters and the dynamics of interstate rivalry". *Journal of peace research* 59.1, pp. 12–27.

Lewis, Simon L and Mark A Maslin (2015). "Defining the anthropocene". *Nature* 519.7542, pp. 171–180.

Li, Xuecao, Yuyu Zhou, Jiyong Eom, Sha Yu, and Ghassem R Asrar (2019). "Projecting global urban area growth through 2100 based on historical time series data and future Shared Socioeconomic Pathways". *Earth's Future* 7.4, pp. 351–362.

Li, Xuecao, Yuyu Zhou, Min Zhao, and Xia Zhao (2020). "A harmonized global nighttime light dataset 1992–2018". *Scientific Data* 7.1, p. 168.

Lin, T.-H. (Mar. 2015). "Governing Natural Disasters: State Capacity, Democracy, and Human Vulnerability". *Social Forces* 93.3, pp. 1267–1300.

Mach, Katharine J et al. (2019). "Climate as a risk factor for armed conflict". *Nature* 571.7764, pp. 193–197.

Mach, Katharine J et al. (2020). "Directions for research on climate and conflict". *Earth's future* 8.7, e2020EF001532.

Mack, Elizabeth A et al. (2021). "Conflict and its relationship to climate variability in Sub-Saharan Africa". *Science of the Total Environment* 775, p. 145646.

Magee, Christopher S P and Tansa George Massoud (Jan. 2011). "Openness and internal conflict". en. *Journal of Peace Research* 48.1, pp. 59–72.

Marchiori, Luca and Ingmar Schumacher (Apr. 2011). "When Nature Rebels: International Migration, Climate Change, and Inequality". *Journal of Population Economics* 24.2, pp. 569–600.

Mares, Dennis M and Kenneth W Moffett (2016). "Climate change and interpersonal violence: a "global" estimate and regional inequities". *Climatic change* 135.2, pp. 297–310.

— (2019). "Climate change and crime revisited: An exploration of monthly temperature anomalies and UCR crime data". *Environment and Behavior* 51.5, pp. 502–529.

Marin, Giovanni, Marco Modica, Susanna Paleari, and Roberto Zoboli (2021). "Assessing disaster risk by integrating natural and socio-economic dimensions: A decision-support tool". *Socio-Economic Planning Sciences* 77, p. 101032.

Markhvida, Maryia, Brian Walsh, Stephane Hallegatte, and Jack Baker (2020). "Quantification of disaster impacts through household well-being losses". *Nature Sustainability* 3.7, pp. 538–547.

Marktanner, Marcus, Edward Mienie, and Luc Noiset (2015). "From armed conflict to disaster vulnerability". *Disaster Prevention and Management* 24.1, pp. 53–69.

Maxwell, John W and Rafael Reuveny (2000). "Resource scarcity and conflict in developing countries". *Journal of peace research* 37.3, pp. 301–322.

Maystadt, Jean-François, Giacomo De Luca, Petros G Sekeris, and John Ulimwengu (2014). "Mineral resources and conflicts in DRC: a case of ecological fallacy?" *Oxford Economic Papers* 66.3, pp. 721–749.

McKee, Thomas B, Nolan J Doesken, and John Kleist (1993). "The relationship of drought frequency and duration to time scales". In: *Proceedings of the 8th Conference on Applied Climatology*. Vol. 17. 22. Boston, pp. 179–183.

Mendelsohn, Robert and Niggol Seo (2007). *Changing farm types and irrigation as an adaptation to climate change in Latin American agriculture*. Tech. rep. WPS 4161. Washington, D.C.: World Bank Group.

Michalopoulos, Stelios and Elias Papaioannou (2014). “National institutions and subnational development in Africa”. *The Quarterly journal of economics* 129.1, pp. 151–213.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti (2004). “Economic shocks and civil conflict: An instrumental variables approach”. *Journal of political Economy* 112.4, pp. 725–753.

Min, Brian, Kwawu Mensan Gaba, Ousmane Fall Sarr, and Alassane Agalassou (2013). “Detection of rural electrification in Africa using DMSP-OLS night lights imagery”. *International journal of remote sensing* 34.22, pp. 8118–8141.

Modica, Marco and Roberto Zoboli (2016). “Vulnerability, resilience, hazard, risk, damage, and loss: a socio-ecological framework for natural disaster analysis”. *Web Ecology* 16.1, pp. 59–62.

Molnar, Christoph (2021). *Interpretable Machine Learning. A guide for making black box models explainable*. https://christophm.github.io/interpretable-ml-book/.

Molyneux, Maxine and Shahra Razavi, eds. (Nov. 2002). *Gender Justice, Development, and Rights*. Oxford University Press.

Montserrat, Marin Ferrer, Vernaccini Luca, and Poljansek Karmen (2017). “INFORM Index for Risk Management: Concept and Methodology, Version 2017”.

Morrissey, Shirley A. and Joseph P. Reser (2007). “Natural disasters, climate change and mental health considerations for rural Australia”. *Australian Journal of Rural Health* 15.2, pp. 120–125.

Mueller, Hannes (July 2016). “Growth and Violence: Argument for a Per Capita Measure of Civil War”. *Economica* 83.331, pp. 473–497.

Murray, Christopher JL, Gary King, Alan D Lopez, Niels Tomijima, and Etienne G Krug (2002). “Armed conflict as a public health problem”. *Bmj* 324.7333, pp. 346–349.

Mveyange, Anthony (2018). "Measuring and Explaining Patterns of Spatial Income Inequality from Outer Space: Evidence from Africa". *World Bank Policy Research Working Paper* 8484.

Namdar, Razieh, Ezatollah Karami, and Marzieh Keshavarz (2021). "Climate change and vulnerability: the case of MENA countries". *ISPRS International Journal of Geo-Information* 10.11, p. 794.

Nardulli, Peter F, Buddy Peyton, and Joseph Bajjalieh (2015). "Climate change and civil unrest: the impact of rapid-onset disasters". *Journal of Conflict Resolution* 59.2, pp. 310–335.

Nel, Philip and Marjolein Righarts (2008). "Natural disasters and the risk of violent civil conflict". *International Studies Quarterly* 52.1, pp. 159–185.

Omelicheva, Mariya Y (2011). "Natural disasters: triggers of political instability?" *International Interactions* 37.4, pp. 441–465.

Orrenius, Pia M. and Madeline Zavodny (Aug. 2009). "Do Immigrants Work in Riskier Jobs?" *Demography* 46.3, pp. 535–551.

Østby, Gudrun (2008). "Polarization, horizontal inequalities and violent civil conflict". *Journal of Peace Research* 45.2, pp. 143–162.

Owain, Erin Llwyd and Mark Andrew Maslin (2018). "Assessing the relative contribution of economic, political and environmental factors on past conflict and the displacement of people in East Africa". *Palgrave Communications* 4.1, pp. 1–9.

O'Loughlin, John et al. (2012). "Climate variability and conflict risk in East Africa, 1990–2009". *Proceedings of the National Academy of Sciences* 109.45, pp. 18344–18349.

Pandey, R P and K S Ramasastri (2001). "Relationship between the common climatic parameters and average drought frequency". *Hydrological Processes* 15.6, pp. 1019–1032.

Peters, Laura ER (2022). "Disasters as Ambivalent Multipliers: Influencing the Pathways from Disaster to Conflict Risk and Peace Potential Through Disaster Risk Reduction". *Journal of Peacebuilding & Development*, p. 15423166221081516.

Petrova, Kristina (2021). "Natural hazards, internal migration and protests in Bangladesh". *Journal of Peace Research* 58.1, pp. 33–49.

— (2022). "Floods, communal conflict and the role of local state institutions in Sub-Saharan Africa". *Political Geography* 92, p. 102511.

Pettersson, Therese (2021a). *Non-state Conflict Codebook v 21.1.*

— (2021b). *UCDP/PRIO Armed Conflict Dataset Codebook v 21.1.*

Pettersson, Therése et al. (July 2021). "Organized Violence 1989–2020, with a Special Emphasis on Syria". *Journal of Peace Research* 58.4, pp. 809–825.

Pettersson, Therése and Magnus Öberg (2020). "Organized violence, 1989–2019". *Journal of Peace Research* 57.4, pp. 597–613.

Pimm, Stuart L (1984). "The complexity and stability of ecosystems". *Nature* 307.5949, pp. 321–326.

Pinkovskiy, Maxim and Xavier Sala-i Martin (2016). "Lights, camera... income! Illuminating the national accounts-household surveys debate". *The Quarterly Journal of Economics* 131.2, pp. 579–631.

Qiang, Yi, Qingxu Huang, and Jinwen Xu (2020). "Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster". *Sustainable Cities and Society* 57, p. 102115.

Raleigh, Clionadh, Hyun Jin Choi, and Dominic Kniveton (2015). "The devil is in the details: An investigation of the relationships between conflict, food price and climate across Africa". *Global Environmental Change* 32, pp. 187–199.

Raleigh, Clionadh and Dominic Kniveton (2012). "Come rain or shine: An analysis of conflict and climate variability in East Africa". *Journal of peace research* 49.1, pp. 51–64.

Raschky, P. A. (July 2008). "Institutions and the Losses from Natural Disasters". *Natural Hazards and Earth System Sciences* 8.4, pp. 627–634.

Ray, Debraj and Joan Esteban (2017). "Conflict and development". *Annual Review of Economics* 9, pp. 263–293.

Regan, Patrick M and Hyun Kim (2020). "Water scarcity, climate adaptation, and armed conflict: insights from Africa". *Regional Environmental Change* 20.4, pp. 1–14.

Rüegger, Seraina (Jan. 2019). "Refugees, Ethnic Power Relations, and Civil Conflict in the Country of Asylum". *Journal of Peace Research* 56.1, pp. 42–57.

Ruiter Marleen C, Couasnon Anaïs de, Marc JC van den Homberg, James E Daniell, Joel C Gill, and Philip J Ward (2020). "Why we can no longer ignore consecutive disasters". *Earth's future* 8.3, e2019EF001425.

Sarewitz, Daniel, Roger Pielke Jr, and Mojdeh Keykhah (2003). "Vulnerability and risk: some thoughts from a political and policy perspective". *Risk Analysis: An International Journal* 23.4, pp. 805–810.

Sarkodie, Samuel Asumadu and Vladimir Strezov (2019). "Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries". *Science of the Total Environment* 656, pp. 150–164.

Scheffran, Jürgen, Peter Michael Link, and Janpeter Schilling (2019). "Climate and conflict in Africa". In: *Oxford Research Encyclopedia of Climate Science.*

Schillinger, Juliane, Gül Özerol, Şermin Güven-Griemert, and Michiel Heldeweg (Nov. 2020). "Water in war: Understanding the impacts of armed conflict on water resources and their management". *WIREs Water* 7.6.

Schleussner, Carl-Friedrich, Jonathan F Donges, Reik V Donner, and Hans Joachim Schellnhuber (2016). "Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries". *Proceedings of the National Academy of Sciences* 113.33, pp. 9216–9221.

Schutte, Sebastian, Jonas Vestby, Jørgen Carling, and Halvard Buhaug (Apr. 2021). "Climatic Conditions Are Weak Predictors of Asylum Migration". *Nature Communications* 12.1, p. 2067.

Seter, Hanne, Ole Magnus Theisen, and Janpeter Schilling (2018). "All about water and land? Resource-related conflicts in East and West Africa revisited". *GeoJournal* 83.1, pp. 169–187.

Shah, Kalim U., Hari Bansha Dulal, Craig Johnson, and April Baptiste (June 2013). "Understanding Livelihood Vulnerability to Climate Change: Applying the Livelihood Vulnerability Index in Trinidad and Tobago". *Geoforum* 47, pp. 125–137.

Sharifi, Ayyoob, Dahlia Simangan, and Shinji Kaneko (2021a). "Three decades of research on climate change and peace: A bibliometrics analysis". *Sustainability Science* 16.4, pp. 1079–1095.

Sharifi, Ayyoob et al. (2021b). "Climate-induced stressors to peace: a review of recent literature". *Environmental Research Letters.*

Silve, Arthur and Thierry Verdier (2018). "A theory of regional conflict complexes". *Journal of Development Economics* 133, pp. 434–447.

Stathakis, Demetris, Vassilis Tselios, and Ioannis Faraslis (2015). "Urbanization in European regions based on night lights". *Remote Sensing Applications: Society and Environment* 2, pp. 26–34.

Strand, Håvard and Håvard Hegre (2021). "Trends in Armed Conflict, 1946–2020". *Conflict Trends* 3.

Svoboda, Mark D, Brian A Fuchs, et al. (2016). *Handbook of drought indicators and indices.* World Meteorological Organization Geneva, Switzerland.

Thomas, Kimberley et al. (2019). "Explaining differential vulnerability to climate change: A social science review". *Wiley Interdisciplinary Reviews: Climate Change* 10.2, e565.

UN (2012). "Environmental Scarcity and Conflict Renewable Resources and Conflict The United Nations Interagency Framework Team for Preventive Action. Toolkitand Guidance for Preventing And Managing Land And Natural Resources Conflict with funding and support from the European Union".

UNHCR (2017). *UNHCR, Displacement and Disaster Risk Reduction (DRR).* Policy Brief. Geneva: UNHCR, The UN Refugee Agency.

Van Baalen, Sebastian and Malin Mobjörk (2018). "Climate change and violent conflict in East Africa: Integrating qualitative and quantitative research to probe the mechanisms". *International Studies Review* 20.4, pp. 547–575.

Vesco, Paola, Shouro Dasgupta, Enrica De Cian, and Carlo Carraro (June 2020). "Natural Resources and Conflict: A Meta-Analysis of the Empirical Literature". *Ecological Economics* 172, p. 106633.

Vesco, Paola, Matija Kovacic, Malcolm Mistry, and Mihai Croicu (2021). "Climate variability, crop and conflict: Exploring the impacts of spatial concentration in agricultural production". *Journal of Peace Research* 58.1, pp. 98–113.

Vicente-Serrano, Sergio M, Santiago Beguería, and Juan I López-Moreno (2010). "A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index". *Journal of climate* 23.7, pp. 1696–1718.

Von Uexkull, Nina and Halvard Buhaug (2021). "Security implications of climate change: A decade of scientific progress". *Journal of Peace Research* 58.1, pp. 3–17.

von Uexkull, Nina and Joshua W. Busby (2018). "Climate Shocks and Humanitarian Crises: Which Countries Are Most at Risk?" *Foreign affairs (New York, N.Y.)* Journal, Electronic.

Von Uexkull, Nina, Mihai Croicu, Hanne Fjelde, and Halvard Buhaug (2016). "Civil conflict sensitivity to growing-season drought". *Proceedings of the National Academy of Sciences* 113.44, pp. 12391–12396.

Wagner, Zachary et al. (2018). "Armed conflict and child mortality in Africa: a geospatial analysis". *The Lancet* 392.10150, pp. 857 –865.

Ward, Michael D., Brian D. Greenhill, and Kristin M. Bakke (2010). "The perils of policy by p-value: Predicting civil conflicts". *Journal of Peace Research* 47.4, pp. 363–375.

WB (2018). “Measuring and Explaining Patterns of Spatial Income Inequality from Outer Space: Evidence from Africa”. *World Bank Policy Research Working Paper* 8484.

Weidmann, Nils B, Jan Ketil Rød, and Lars-Erik Cederman (2010). “Representing ethnic groups in space: A new dataset”. *Journal of Peace Research* 47.4, pp. 491–499.

Weidmann, Nils B and Sebastian Schutte (2017). “Using night light emissions for the prediction of local wealth”. *Journal of Peace Research* 54.2, pp. 125–140.

Wisner, Ben, Piers Blaikie, Terry Cannon, and Ian Davis (2014). *At risk: natural hazards, people’s vulnerability and disasters*. Routledge.

WMO and GWP (2016). *West Australia*. Vol. 1. 2366, pp. 1068–1069.

Wood, Reed M and Thorin M Wright (2016). “Responding to catastrophe: Repression dynamics following rapid-onset natural disasters”. *Journal of Conflict Resolution* 60.8, pp. 1446–1472.

World Bank (2019). *World Development Indicators*. Washington DC: The World Bank.

Yohe, Gary and Richard S.J. Tol (2002). “Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity”. *Global Environmental Change* 12.1, pp. 25–40.

Zake, J. and M. Hauser (July 2014). “Farmers’ Perceptions of Implementation of Climate Variability Disaster Preparedness Strategies in Central Uganda”. *Environmental Hazards* 13.3, pp. 248–266.

Zscheischler, Jakob et al. (2018). “Future climate risk from compound events”. *Nature Climate Change* 8.6, pp. 469–477.

Zscheischler, Jakob et al. (2020). “A typology of compound weather and climate events”. *Nature reviews earth & environment* 1.7, pp. 333–347.

Appendices

Appendix A

Supplementary Material for Chapter 2

A.1 Details on data sources

The ND Gain Global Adaptation Initiative[1] 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.

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]Appendix A is based upon the ND Gain Technical document by Chen (2015)

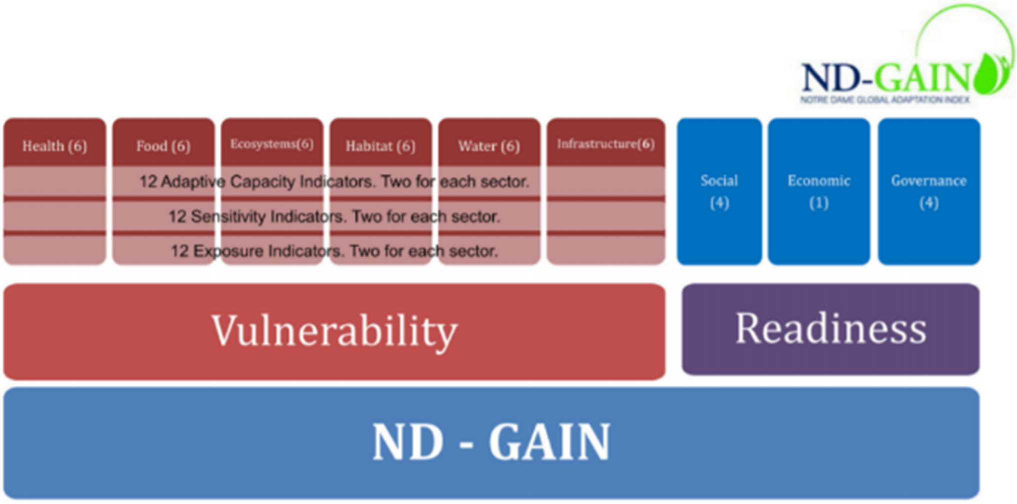


Figure A.1: Summary of ND Gain Vulnerability and Readiness indicators.

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 is performed using the following formula:

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

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, 2015, pp. 6-8).

A.2 Additional information on cluster analysis

A.2.1 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

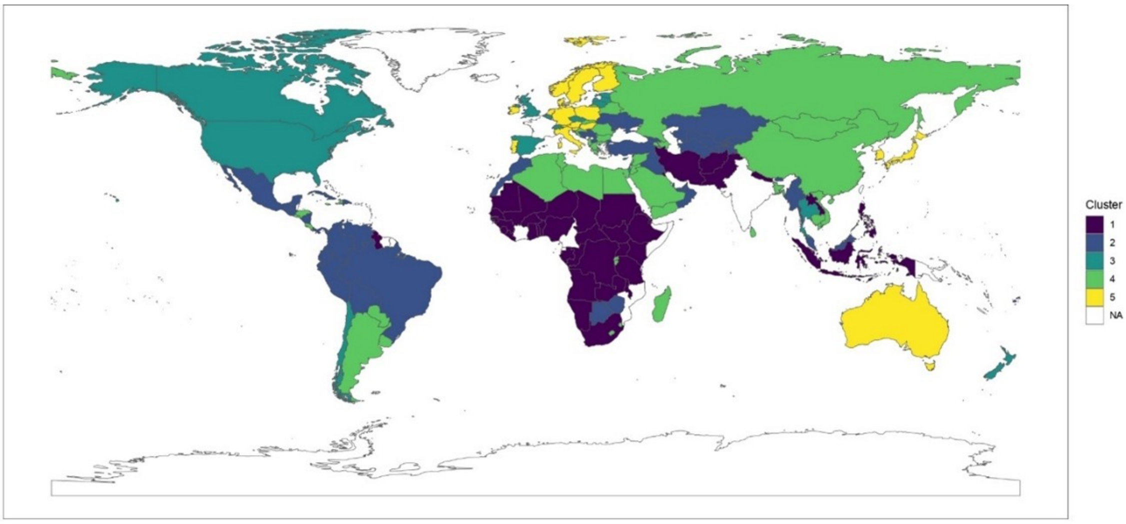
Cluster 2: Still problematic, but in slightly better conditions. Bahrain, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Colombia, Cuba, Dominican Republic, Ecuador, Fiji, Georgia, Guatemala, Iraq, Kazakhstan, Kyrgyz Republic, Malaysia, Mexico, Moldova, Morocco, Myanmar, Nicaragua, North 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 A.2: Visual representations of the 5 clusters.



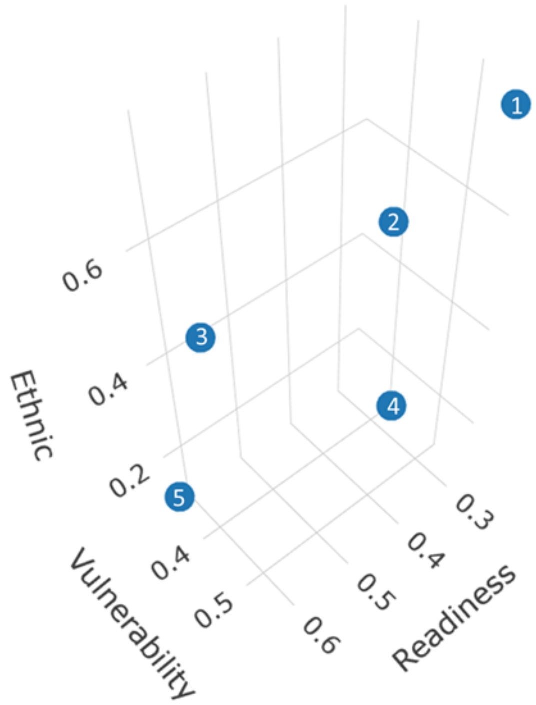
Source: authors' own elaboration on the data.

A.2.2 Additional characterisation of clusters

We first report the distribution of the five clusters in space across the three different clustering variables as an additional informative tool (Figure A.3), as well as a map visually representing the cluster divisions across countries worldwide (Figure A.2)

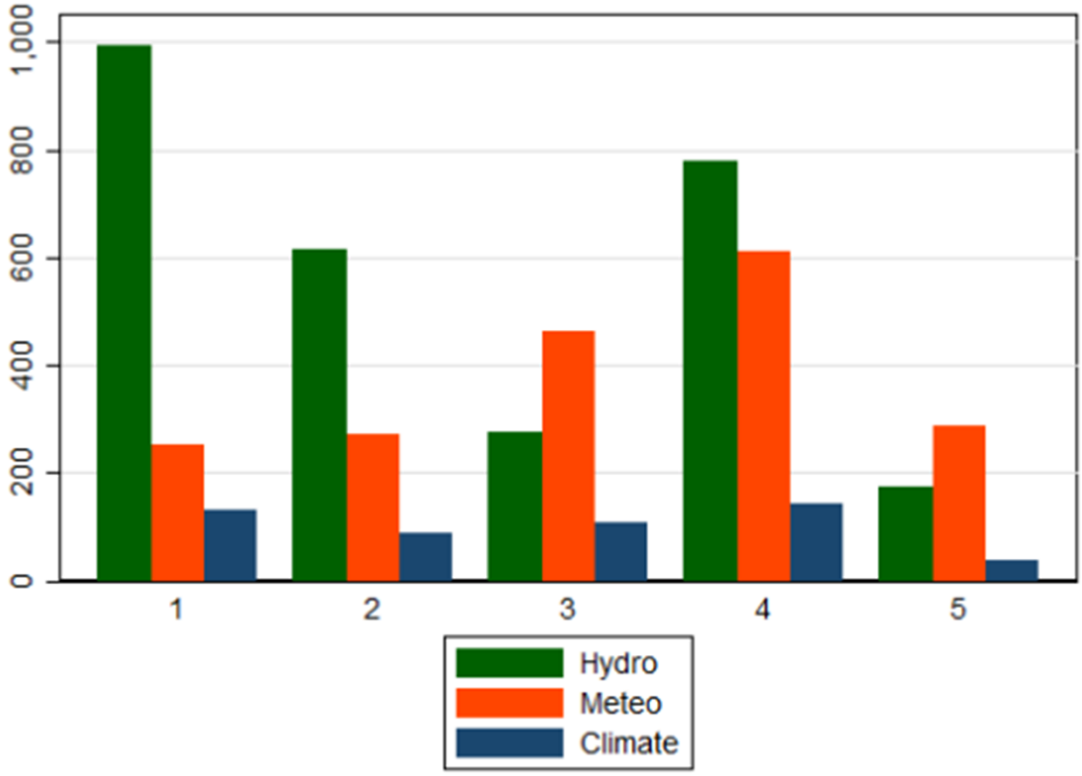
As a final step, we display some descriptive statistics regarding the distribution of natural disasters across the five clusters. Figure A.4 shows the relative composition of the natural disasters occurred across the five clusters. Hydrological and meteorological disasters are the most common across 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. Figure A.5 instead shows the relative composition of natural disasters across the five clusters according to slow and rapid onset disasters. As it can be seen from A.5, there is a prevalence of rapid onset disasters for all five clusters, while slow-onset disasters are less frequent.

Figure A.3: Distribution of clusters in space



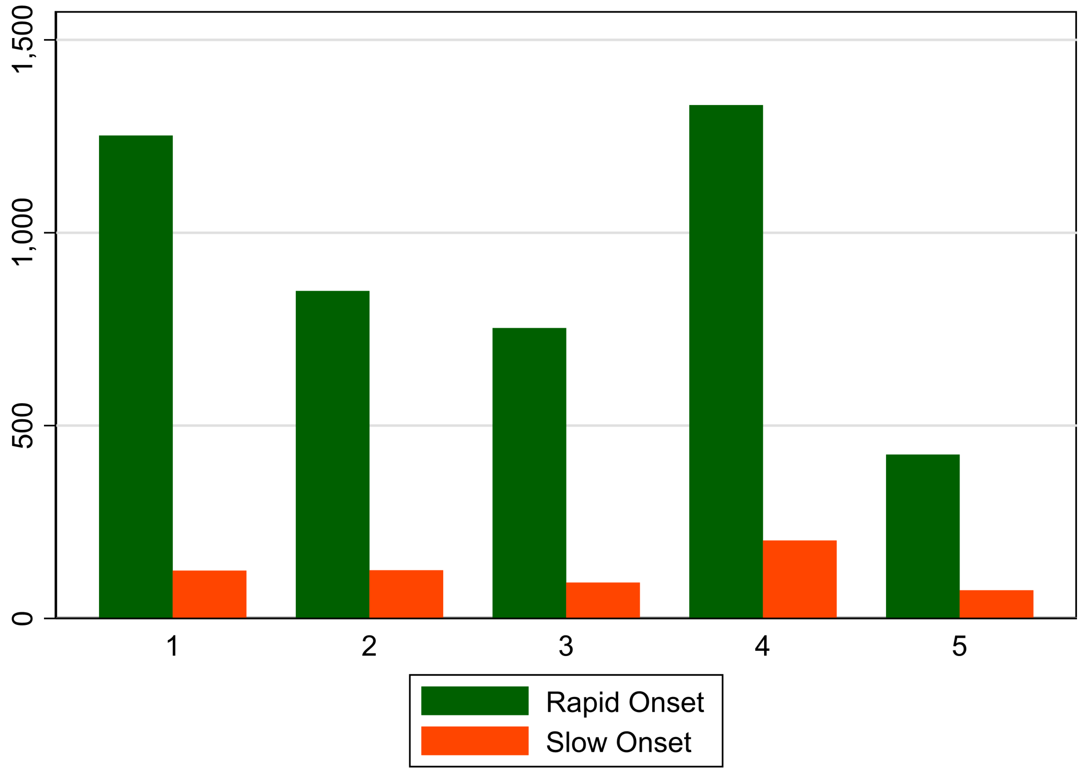
Finally, in Figure A.6 we report information on the relative distribution of conflicts across clusters, with additional information on the differentiation between state and non-state conflicts. An interesting point to note here is that while in cluster n. 1 non-state conflicts are more prevalent with respect to state conflicts, this does not occur in the other clusters.

Figure A.4: Cumulative number of climate-related disasters by cluster and type of disaster



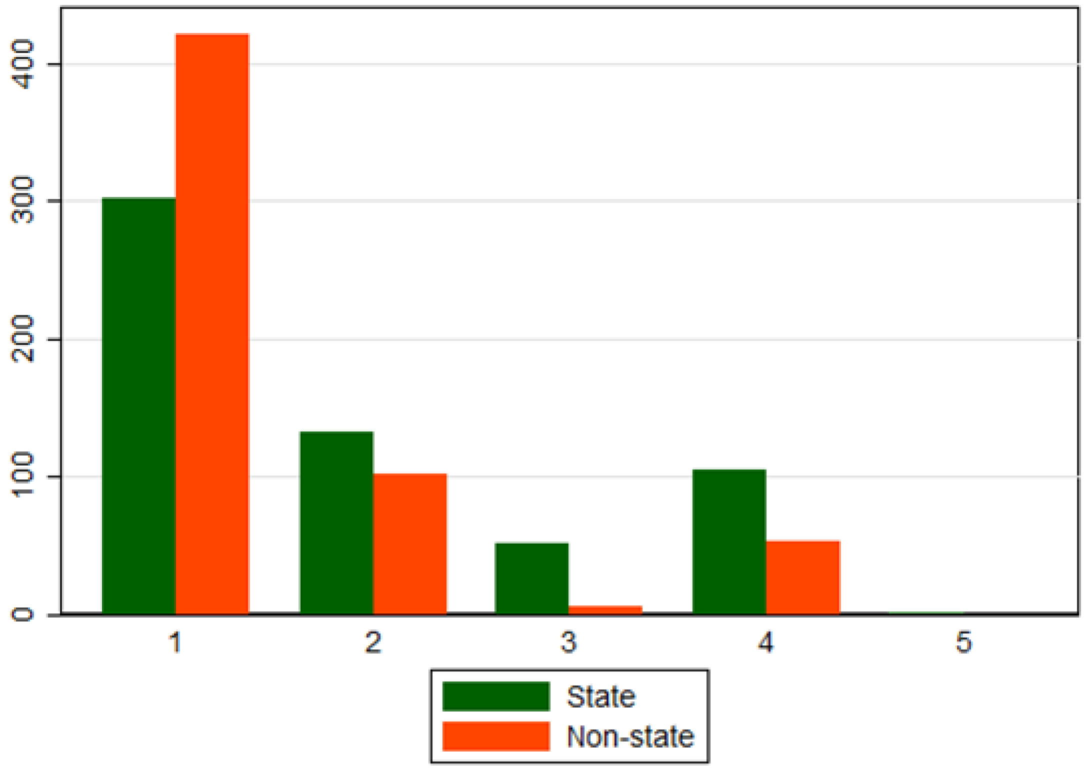
Notes: Cumulative number of climate-related disaster by cluster and disaster type for the period 1995-2013. Disasters are distinguished by type (hydrological, meteorological and climatological).

Figure A.5: Cumulative number of slow and rapid onset disasters across the five clusters



Notes: Cumulative number of climate-related disaster by cluster and disaster type for the period 1995-2013. Disasters are distinguished by slow onset (droughts, extreme temperature) and rapid onset disasters (fires, floods, landslides and storms).

Figure A.6: 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.

A.3 Additional results and robustness checks

In this section we report the results for the estimations of specification 1, 2 and 3, which correspond to the marginal effects in Table 2.4, 2.5 and 2.6 in the paper. Estimations are reported in Tables A.1, A.2 and A.3. Additionally, we report additional robustness checks for specifications 1 and 2. Results are reported in Tables A.4 and A.5. Finally, we report marginal effects for specification 1, 2, and 3 estimated using a RE estimator. Marginal effects are reported in Tables A.6, A.7 and A.8.

Table A.1: Estimation results for specification n. 1

	New total conflicts	New state conflicts	New non-state conflicts
Pre-sample mean	0.331***	0.329***	0.619***
	(0.0509)	(0.0746)	(0.107)
HDI	-0.969*	-1.507**	-1.183*
	(0.560)	(0.665)	(0.707)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.0130	-0.315*	0.310
	(0.161)	(0.183)	(0.222)
Cluster n.3 (dummy)	-0.0310	-0.0840	0.0704
	(0.263)	(0.286)	(0.428)
Cluster n.4 (dummy)	-0.0605	-0.226	0.125
	(0.135)	(0.163)	(0.215)
Cluster n.5 (dummy)	-0.666*	-0.735*	[empty]
	(0.373)	(0.385)	
Number of earthquakes in a 3-year period	-0.000327	0.0364	-0.0504
	(0.0281)	(0.0269)	(0.0356)
Number of epidemics in a 3-year period	0.0738***	0.0430	0.0773***
	(0.0199)	(0.0299)	(0.0200)
Number of volcanic eruptions in a 3-year period	0.0296	-0.253*	0.155
	(0.0866)	(0.148)	(0.0993)

Total number of disasters in a 3-year period	0.0180***	0.00533	0.0225***
	(0.00571)	(0.00630)	(0.00724)
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 A.2: Estimation results for specification n. 2

	New total conflicts	New state conflicts	New non-state conflicts
Pre-sample mean	0.313***	0.397***	0.543***
	(0.0512)	(0.0847)	(0.110)
HDI	-1.206**	-1.574**	-1.513**
	(0.554)	(0.736)	(0.709)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	-0.227	-0.227	0.189
	(0.191)	(0.237)	(0.270)
Cluster n.3 (dummy)	0.0197	-0.615**	0.712
	(0.264)	(0.311)	(0.526)
Cluster n.4 (dummy)	0.0826	-0.208	0.302
	(0.153)	(0.214)	(0.252)
Number of earthquakes in a 3-year period	0.0231	0.0843***	-0.0330
	(0.0266)	(0.0266)	(0.0399)
Number of epidemics in a 3-year period	0.0747***	0.0449	0.0787***
	(0.0194)	(0.0306)	(0.0199)
Number of volcanic eruptions in a 3-year period	0.00104	-0.177	0.0699
	(0.117)	(0.142)	(0.142)
Total number of disasters in a 3-year period	0.0169***	-0.0111	0.0343***
	(0.00930)	(0.0129)	(0.0108)

Total number of disasters in a 3-year period * Cluster n. 2	0.0585***	-0.0575*	0.0415**
	(0.0143)	(0.0333)	(0.0168)
Total number of disasters in a 3-year period * Cluster n. 3	0.00186	0.108***	-0.369*
	(0.0117	(0.0289)	(0.206)
Total number of disasters in a 3-year period * Cluster n. 4	-0.0146	0.000884	-0.0212
	(0.0115)	(0.0146)	(0.0141)
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).

Table A.3: Estimation results for specification n. 3

	New total conflicts	New state conflicts	New non-state conflicts
Pre-sample mean	0.332***	0.329***	0.622***
	(0.0511)	(0.0745)	(0.109)
HDI	-1.001*	-1.571**	-1.215*
	(0.562)	(0.664)	(0.708)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.0217	-0.311*	0.321
	(0.160)	(0.181)	(0.225)
Cluster n.3 (dummy)	-0.0111	-0.0603	0.0958
	(0.263)	(0.288)	(0.431)
Cluster n.4 (dummy)	-0.0461	-0.210	0.140
	(0.132)	(0.163)	(0.216)
Cluster n.5 (dummy)	-0.648*	-0.713*	[empty]
	(0.372)	(0.384)	
Number of earthquakes in a 3-year period	0.00220	0.0390	-0.0462
	(0.0273)	(0.0258)	(0.0355)
Number of epidemics in a 3-year period	0.0739***	0.0439	0.0767***

	(0.0199)	(0.0296)	(0.0204)
Number of volcanic eruptions in a 3-year period	0.0203	-0.283*	0.147
	(0.0898)	(0.171)	(0.104)
Total number of slow-onset disasters in a 3-year period	-0.0163	-0.0449	-0.0157
	(0.0429)	(0.0630)	(0.0592)
Total number of rapid-onset disasters in a 3-year period	0.0204***	0.00889	0.0247***
	(0.00685)	(0.00845)	(0.00837)
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.

As additional robustness checks, we have estimated the equations for specification 2 (Table 2.5) with some modifications. In particular, we have added 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 A.4.

Table A.4: Robustness check for specification n. 2 (controlling for time-varying clustering variables)

Marginal effects of total number of disasters in a 3-year period	New total conflicts	New state conflicts	New non-state conflicts
At Cluster n.1	0.00166	-0.00126	0.00169***
	(0.00105)	(0.00134)	(0.000621)
At Cluster n.2	0.0100***	-0.00221	0.00982***
	(0.00204)	(0.00154)	(0.00224)
At Cluster n.3	0.00297*	0.00936**	-0.0339*
	(0.00169)	(0.00390)	(0.0188)
At Cluster n.4	0.000307	-0.000803	0.00248
	(0.00102)	(0.000639)	(0.00151)
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).

Table A.5: 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	-0.00536***	0.00249*	0.000628
	(0.00183)	(0.00132)	(0.000747)
At 25th percentile	-0.002621***	0.00136*	0.000540
	(0.00101)	(0.000820)	(0.000597)
At 50th percentile	-0.000281	0.000145	0.000340
	(0.000492)	(0.000568)	(0.000466)
At 75th percentile	0.00110*	-0.00102	0.000170
	(0.000594)	(0.000722)	(0.000629)
At 90th percentile	0.00127	-0.00127*	-0.000105
	(0.000959)	(0.000770)	(0.000725)
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	0.00521***	0.00135	0.000372
	(0.00167)	(0.00165)	(0.000392)
At 25th percentile	0.00383***	0.00202*	0.000637
	(0.00113)	(0.00116)	(0.000444)
At 50th percentile	0.00231***	0.00269***	0.00190***
	(0.000665)	(0.000891)	(0.000587)
At 75th percentile	0.000862**	0.00317***	0.00430***
	(0.000385)	(0.00121)	(0.00146)
At 90th percentile	0.0000612	0.00315***	0.00575***
	(0.000115)	(0.00147)	(0.00217)
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).

Then, as a last robustness check we have estimated specification n. 2 by estimating the marginal effects of the total number of disasters for different relevant values of the clustering variables, distinguishing for state and non – state conflicts. The idea here is to understand whether the cross-cluster heterogeneity in the effect of natural disasters on conflicts is driven by one (or more) specific clustering variables. Marginal effects are reported in Table A.5. For non – state conflicts the lower the level of readiness the more 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.

As a final step, we include marginal effects for specifications 1, 2 and 3 estimated using a RE estimator. Marginal effects are reported in Tables A.6, A.7 and A.8. Marginal effects are quite consistent with those obtained with the pooled probit estimator used in our main results.

Table A.6: Marginal effects for specification n. 1 with RE estimator

	New total conflicts	**New state conflicts**	**New non-state conflicts**
Pre-sample mean	0.0429***	0.0240***	0.0623***
	(0.00751)	(000711)	(0.0131)
HDI	-0.129	-0.108*	-0.151*
	(0.0813)	(0.0563)	(0.0839)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.000499	-0.0213	0.0222
	(0.0266)	(0.0188)	(0.0272)
Cluster n.3 (dummy)	-0.00692	-0.00811	-0.0000167
	(0.0372)	(0.0284)	(0.0387)
Cluster n.4 (dummy)	-0.00754	-0.0173	0.00521
	(0.0225)	(0.0168)	(0.0211)
Cluster n.5 (dummy)	-0.0539*	-0.0377*	[empty]
	(0.0286)	(0.0195)	
Number of earthquakes in a 3-year period	0.000647	0.00316	-0.00456
	(0.00353)	(0.00235)	(0.00387)
Number of epidemics in a 3-year period	0.00622**	0.00270	0.00365
	(0.00281)	(0.00208)	(0.00246)
Number of volcanic eruptions in a 3-year period	-0.00162	-0.0214*	0.00398
	(0.0101)	(0.0125)	(0.00830)
Total number of natural disasters in a 3-year period	0.00206***	0.000423	0.00187**
	(0.000788)	(0.000562)	(0.000774)
N. of observations	2454	2454	2182

Notes: Marginal effects based on a probit random effect estimator. Standard errors clustered by country. $*p < 0.1, **p < 0.05, ***p < 0.01$. Additional control variables: world region dummies, year dummies, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period. The number of observations differs across the three estimations because countries in cluster n.5 perfectly predict the zero outcome, hence they have been dropped.

Table A.7: Marginal effects for specification n. 2 with RE estimator

	New total conflicts	**New state conflicts**	**New non-state conflicts**
At Cluster n.1	0.00229	-0.00122	0.00268***
	(0.00142)	(0.00158)	(0.00103)
At Cluster n.2	0.00836***	-0.00326	0.00768**
	(0.00292)	(0.00240)	(0.00309)
At Cluster n.3	0.00261	0.00761**	-0.0165
	(0.00169)	(0.00363)	(0.0115)
At Cluster n.4	0.000266	-0.000625	0.00150
	(0.00130)	(0.000848)	(0.00116)
N. of observations	2182	2182	2182

Notes: Marginal effects based on a probit random effect estimator. Standard errors clustered by country. $*p < 0.1, **p < 0.05, ***p < 0.01$. Additional control variables: world region dummies, year dummies, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period.

Table A.8: Marginal effects for specification n. 3 using a RE estimator

	New total conflicts	**New state conflicts**	**New non-state conflicts**
Pre-sample mean	0.0430***	0.0240***	0.0626***
	(0.00749)	(0.00707)	(0.0131)
HDI	-0.132	-0.110**	-0.153*
	(0.0813)	(0.0563)	(0.0835)
Cluster n.1 (dummy)	[base cat.]	[base cat.]	[base cat.]
Cluster n.2 (dummy)	0.00138	-0.0209	0.0228
	(0.0264)	(0.0185)	(0.0270)
Cluster n.3 (dummy)	-0.00471	-0.00690	0.00174
	(0.0375)	(0.0285)	(0.0392)
Cluster n.4 (dummy)	-0.00595	-0.0166	0.00648
	(0.0225)	(0.0168)	(0.0212)
Cluster n.5 (dummy)	-0.0525*	-0.0370*	[empty]
	(0.0288)	(0.0195)	
Number of earthquakes in a 3-year period	0.000893	0.00324	-0.00422
	(0.00355)	(0.00234)	(0.00389)
Number of epidemics in a 3-year period	(0.00281)	(0.00208)	(0.00246)
	(0.0251)	(0.0313)	(0.0294)
Number of volcanic eruptions in a 3-year period	-0.00226	-0.0224*	0.00359
	(0.0102)	(0.0127)	(0.00832)
Total number of slow-onset disasters in a 3-year period	-0.00172	-0.00165	-0.00160
	(0.00593)	(0.00445)	(0.00588)
Total number of rapid-onset disasters in a 3-year period	0.00230***	0.000567	0.00204**
	(0.000873)	(0.000638)	(0.000829)
N. of observations	2454	2454	2182

Notes: Marginal effects based on a probit random effect estimator. Standard errors clustered by country. $*p < 0.1, **p < 0.05, ***p < 0.01$. Additional control variables: world region dummies, year dummies, number of epidemics in a 3-year period, number of volcanic eruptions in a 3-year period, number of earthquakes in a 3-year period. The number of observations differs across the three estimations because countries in cluster n.5 perfectly predict the zero outcome, hence they have been dropped.

Appendix B

Supplementary Material for Chapter 3

B.1 Measures of spatial autocorrelation

Spatial autocorrelation is the positive or negative correlation of a variable with itself due to the spatial location of the observations (Eurostat, 2018). Two types of spatial autocorrelation can be detected: global spatial autocorrelation and local spatial autocorrelation. While global spatial correlation measures correlation among all units in space, and assumes that such correlation remains stationary, local spatial autocorrelation detects the local autocorrelation between the value of a variable in a spatial unit and the value of the same variable in the surrounding spatial units (Eurostat, 2018). Usually, spatial autocorrelation among the sampled data is analysed before adopting a spatial analysis approach.

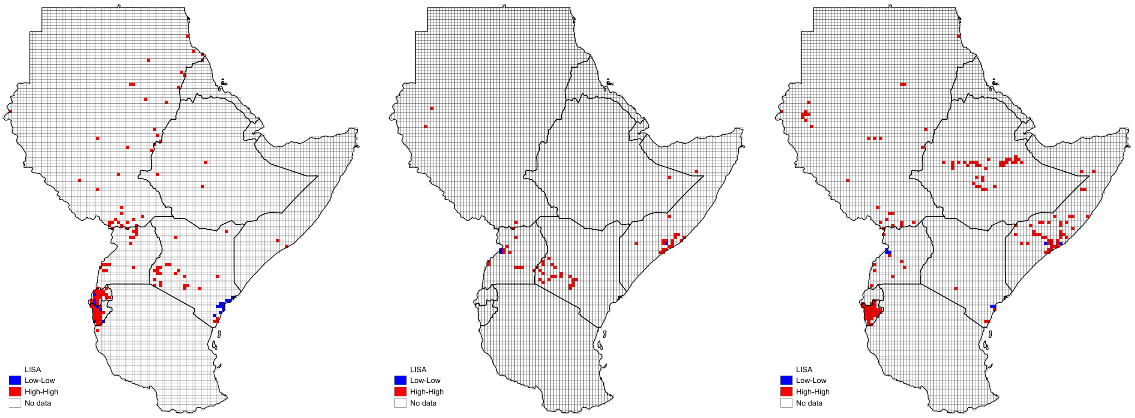
In our case, we examine both global spatial autocorrelation and local spatial autocorrelation. Table B.1 displays the Moran's I as a measure of global spatial autocorrelation for the years 1997, 2007 and 2016. A positive value of the Moran I's indicator signals the presence of positive spatial autocorrelation, i.e. similar values are grouped together in space. As Table B.1 shows, global spatial autocorrelation is present in all the variables we consider in our analysis, hence prompting the adoption of a spatial analysis approach.

Table B.1: Global measure of spatial autocorrelation

Moran's I					
Variables	**I**	**E(I)**	**sd(I)**	**z**	**p-value***
1997					
nc_acled	0.051	0	0.001	49.682	0
gdp_pc	0.283	0	0.001	263.101	0
sd_nl	0.038	0	0.001	35.604	0
tempmvy	0.922	0	0.001	857.79	0
precmvy	0.76	0	0.001	707.151	0
spei_12yp_mean	0.604	0	0.001	562.095	0
spei_12yn_mean	0.749	0	0.001	696.318	0
2007					
nc_acled	0.005	0	0	17.284	0
gdp_pc	0.296	0	0.001	274.896	0
sd_nl	0.034	0	0.001	31.846	0
tempmvy	0.774	0	0.001	719.944	0
precmvy	0.742	0	0.001	690.265	0
spei_12yp_mean	0.594	0	0.001	552.682	0
spei_12yn_mean	0.734	0	0.001	682.385	0
2016					
nc_acled	0.104	0	0.005	20.777	0
gdp_pc	0.502	0	0.006	88.349	0
sd_nl	0.394	0	0.006	69.46	0
tempmvy	0.817	0	0.006	143.777	0
precmvy	0.831	0	0.006	146.249	0
spei_12yp_mean	0.869	0	0.006	152.904	0
spei_12yn_mean	0.872	0	0.006	153.413	0

As a further step, we calculate a measure of local spatial correlation, i.e. the Local Spatial Autocorrelation Index (Anselin, 1995) for our conflict variable. This is useful in order to detect the presence of hotsposts in our data.

Figure B.1: Local Index of Spatial Autocorrelation (LISA)



(a) 1997 (b) 2007 (c) 2016

Figure B.1 depicts the Local Index of Spatial Autocorrelation (LISA) as defined by (Anselin, 1995) for 1997, 2007 and 2016 (Figure B.1). Figure B.1 clearly shows the presence of hotspots, i.e. the red cells (High-High combinations). These are cells with a high number of conflicts surrounded by neighbouring cells with high numbers of conflicts.

B.2 Marginal effects for Table 3.8

Table B.2: Vulnerability. Marginal effects

	M1	**M2**	**M3**	**M4**	**M5**	**M6**
GDP_pc (ln)	-0.0783***	-0.0860***	-0.0860***	-0.0860***	-0.0866***	-0.0862***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Population (ln)	0.1250***	0.1416***	0.1409***	0.1377***	0.1397***	0.1407***
	(0.0080)	(0.0079)	(0.0079)	(0.0079)	(0.0079)	(0.0079)
Nightlights (sd)	0.0032***	0.0034***	0.0034***	-0.0030**	0.0031***	0.0034***
	(0.0006)	(0.0007)	(0.0006)	(0.0012)	(0.0007)	(0.0006)
Tempmvy	0.0020*	0.0023**	0.0023**	0.0022**	0.0023**	0.0023**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Tempmvy2	-0.0005**	-0.0005**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Precmvy	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SPEI_12_neg	0.0782***	0.0030	0.0030	-0.0007	0.0022	0.0038
	(0.0065)	(0.0024)	(0.0024)	(0.0024)	(0.0119)	(0.0024)
SPEI_12_pos	0.0892***	0.0032	0.0037	-0.0004	-0.0189	0.0035
	(0.0094)	(0.0029)	(0.0028)	(0.0030)	(0.0216)	(0.0028)
Rural population (%)	-0.0710***					
	(0.0169)					
Rural population*SPEI_12_neg	-0.0850***					
	(0.0069)					
Rural population*SPEI_12_pos	-0.0970***					
	(0.0102)					
GrSPEI_12d3_sh		0.0024				
		(0.0041)				
GrSPEI_12f3_sh		0.0023				
		(0.0047)				
SPEI_12_neg_#Water			0.0223*			
			(0.0117)			
Water			0.0000			

	(.)			
Nighlights (sd)*SPEI_12_pos		0.0072***		
		(0.0015)		
Nighlights (sd)*SPEI_12_neg		0.0082***		
		(0.0013)		
N_ethnic			0.0000	
			(.)	
1.n_ethnic#SPEI_12_neg			-0.0048	
			(0.0119)	
2.n_ethnic#SPEI_12_neg			0.0153	
			(0.0124)	
3.n_ethnic#SPEI_12_neg			0.0214	
			(0.0137)	
4.n_ethnic#SPEI_12_neg			-0.0596***	
			(0.0230)	
5.n_ethnic#SPEI_12_neg			-0.1297**	
			(0.0553)	
6.n_ethnic#SPEI_12_neg			-0.0655	
			(0.1524)	
1.n_ethnic#SPEI_12_pos			0.0198	
			(0.0218)	
2.n_ethnic#SPEI_12_pos			0.0303	
			(0.0222)	
3.n_ethnic#SPEI_12_pos			0.0303	
			(0.0238)	
4.n_ethnic#SPEI_12_pos			-0.0144	
			(0.0337)	
5.n_ethnic#SPEI_12_pos			0.2305**	
			(0.1008)	
6.n_ethnic#SPEI_12_pos			0.0797	
			(0.3010)	
Irrigation				0.0024***
				(0.0009)
Irrigation#SPEI_12_neg				-0.0015**

						(0.0007)
Spatial rho	0.8260***	0.8248***	0.8251***	0.8235***	0.8255***	0.8245***
	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)
Variance sigma2_e	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05
r2	0.0427	0.0395	0.0391	0.0391	0.0390	0.0393
r2_a						

This table shows coefficients for a SAR model with a rw11 matrix across the years 1997-2016. Additional controls include year dummies and a structural break dummy in 2013. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C

Supplementary Material for Chapter 4

C.1 Comparison of ND-GAIN with other vulnerability indices

Other country-level indexes are available to measure trends in vulnerability and resilience, including the World Risk Index (WRI) and the INFORM Risk Index. WRI provides information on risk as a function of exposure and vulnerability (Franziska Atwii, 2022). The INFORM Risk Index assesses the risk of humanitarian crises, operationalized along the dimensions of hazards and exposure, vulnerability, and lack of coping capacity (Montserrat et al., 2017). Despite a slightly different conceptualization, the vulnerability scores assigned by these indexes are largely overlapping and strongly correlated, especially as concerns their vulnerability component (Garschagen et al., 2021). Our choice of ND-GAIN data over alternative indicators is motivated by a number of factors that we summarise here. First, the definition and operationalization of ND-GAIN are explicitly consistent with the IPCC's definition of vulnerability as *'the propensity or predisposition to be adversely affected'* and encompassing *'a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt'* (Glossary IPCC, 2022a, p. 52). Second, the availability of ND-GAIN scores across multiple sectors is advantageous over the other indices, as it allows for a selection of sub-indicators relevant to a specific research question. For example, Regan and Kim (2020) select a subset of ND-GAIN sub-indicators relevant for water stress to study the impact of climate drivers on the risk of armed conflict, and find that higher levels of adaptive capacity decrease the probability of conflict risk in response to water stress.

As we are interested in how societal vulnerability responds to both natural disasters and conflict events, the provision of disaggregated information on sectoral vulnerability is fundamental for the purpose of this study. Among these sectoral indicators, ND-GAIN includes information on some fundamental components of societal vulnerability that are very sensitive to natural disasters and armed conflict, such as water, infrastructure, and food. In particular, ND-GAIN encompasses data on access to electricity, energy dependency, agricultural capacity, and food import dependency, which not only represent a significant component of a country's vulnerability but are also impacted by both armed conflict and natural disasters. Although the WRI and the INFORM index include many dimensions of societal vulnerability linked to economic development (such as GNI per capita or the HDI index), they do not account for a number of other components that are critical to analyse societal responses to natural disasters and armed conflicts, such as infrastructure, water, and food/agriculture.

Lastly, the temporal span of ND-GAIN data (1995-2019) enables us to maximise the amount of information for training and testing the predictive models. ND-GAIN consistently reports data for the period 1995-2019; WRI have updated and consistent data (including all the sub-indicators) available for the years 2000-2022, and INFORM collects data from 2014 to 2022. As we have conflict data available since 1989, using WRI or INFORM would cause a loss of 3 and 16 years, respectively, in the overall data available for the analysis relative to the temporal span covered by the ND-GAIN index.

C.1.1 Disasters and conflict sensitive vulnerability index

Despite the broader temporal and spatial coverage of ND-GAIN as well as the provision of sectoral information on vulnerability, ND-GAIN is not exempt from limitations. Crucially, not all sub-indicators that are included to compute the ND-GAIN aggregate vulnerability score might be relevant for our research question, as some dimensions may be un-affected by the material and immaterial destruction caused by violence. To isolate the vulnerability shock suffered by sectors that are sensitive to the impacts of conflict and climate hazards, we draw from the sub-indicators of ND-GAIN and re-construct a 'disasters and conflict sensitive' vulnerability index, following a similar procedure to the one used in Kling et al. (2021).

To this end, our 'disasters and conflict sensitive' vulnerability index is constructed by averaging the ND-GAIN sub-indicators that are responsive to conflict and natural disasters. The sub-indicators are selected based on an evaluation of their relevance, and according to the existing empirical literature on the impacts of armed conflict and natural disasters, as summarized in column 3, Table C.1. To minimise the risk of data leakage, the re-constructed indicator also excludes all sub-indicators that are derived from projected data. The final sub-indicators taken into account to construct the new index are presented in Table C.1.

Table C.1: ND-GAIN indicators included in the aggregate disasters and conflict sensitive indicator of vulnerability.

Sector	Indicator	Relevance
Food	Food import dependency	Food consumption is affected by conflict and climate hazards (Dureab et al., 2019; Fuglie, 2021)
	Rural population	Rural population are more vulnerable to the conflict and climate nexus (Von Uexkull et al., 2016)
	Agricultural capacity	Agricultural technology (e.g. irrigation) can mediate the impacts of natural hazards (Mendelsohn and Seo, 2007)
	Child malnutrition	% Conflicts and natural disasters can both increase child malnutrition (Brown et al., 2021, e.g.)
Water	Water dependency	Climate change, natural disasters, and conflicts can affect water resources, access, and management (Gosling and Arnell, 2016; Schillinger et al., 2020) and thus countries' dependency on foreign water resources
	Dam capacity	Armed conflicts can target dams as a weapon (Schillinger et al., 2020)
	Access to drinking water	Climate hazards, natural disasters and conflicts can increase water scarcity (Gosling and Arnell, 2016; Schillinger et al., 2020)
Health	Dependency on external resource for health services	Conflicts impact public health services directly and indirectly (Garry and Checchi, 2020)
	Slum population	Conflicts, climate change, and natural disasters increase poverty, slow socio-economic development (Hallegatte and Rozenberg, 2017; Gates et al., 2012) and trigger refugee flows (Schutte et al., 2021) that may all contribute to increased the share of slum population
	Medical staffs	Conflicts may directly target or harm medical staff and health facilities (Garry and Checchi, 2020)
	Access to improved sanitation facilities	Armed conflict and natural disasters may disrupt the access to sanitation facilities
Ecosystem services	Natural capital dependency	Societies that are dependent on natural resources may be more at risk of armed conflict (Boix, 2008)
	Engagement in international environmental conventions	it proxies the political ability to reach decisions, which is lowered in conflict-affected countries
Habitat	Urban concentration	Densely inhabited areas suffer relatively more destruction from conflicts and climate hazards due to increased exposure
	Age dependency ratio	Children and the elderly are more vulnerable to the impacts of conflict and natural disasters (Jawad et al., 2020; Cherniack, 2008)
	Quality of trade and transport infrastructure	Trade is negatively affected by conflict (Magee and Massoud, 2011)
	Paved roads	Roads can be destructed by conflicts and natural disasters
Infrastructure	Dependency on imported energy	Armed conflict and natural disasters can disrupt energy facilities and increase dependency on imported sources.
	Electricity access	The destruction caused by armed conflict and natural hazards can disrupt access to grid-power
	Disaster preparedness	Armed conflict can lower state capacity, lower development (Gates et al., 2012), and thus reduce disaster preparedness

C.2 Disasters included in the analysis

Table C.2 displays the types of disasters included as features in our analysis. As Table C.2 shows, only metereological, hydrological and climatological disasters have been included, as they are the ones more closely related to climatic changes. Geophysical, biological and extraterrestrial disasters, on the other hand, have been excluded.

Table C.2: Natural disasters included in the analysis

Disaster Type	**Disaster sub-group**	**Disaster group**	**Inclusion in the analysis**
Earthquake	Geophysical	Natural	Not included
Mass Movement (dry)	Geophysical	Natural	Not included
Volcanic activity	Geophysical	Natural	Not included
Extreme temperature	Meteorological	Natural	Included
Fog	Meteorological	Natural	No data
Storm	Meteorological	Natural	Included
Flood	Hydrological	Natural	Included
Landslide	Hydrological	Natural	Included
Wave action	Hydrological	Natural	No data
Drought	Climatological	Natural	Included
Glacial lake outburst	Climatological	Natural	Included
Wildfire	Climatological	Natural	Included
Epidemic	Biological	Natural	Not included
Insect infestation	Biological	Natural	Not included
Animal accident	Biological	Natural	Not included
Impact	Extraterrestrial	Natural	Not included
Space weather	Extraterrestrial	Natural	Not included