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

Mariagrazia D'Angeli[1] and Paola Vesco[2†]

[1]Department of Economics, Society, Politics, University of Urbino Carlo Bo
[2]Department of Peace and Conflict Research, Uppsala University[*]

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Abstract

Armed conflicts have been associated with a variety of detrimental impacts on human security and development, and represent a crucial vector of societal vulnerability to subsequent climate hazards. The burgeoning literature on climate security has highlighted that climate variability and natural disasters may indirectly increase conflict risk in vulnerable locations. However, scientifically sound knowledge of the impacts of armed conflicts on socio-economic vulnerability remains sparse, and more research is needed to understand the complex linkages between natural disasters, armed conflict, and societal vulnerability. This study fills the gap by empirically investigating the impacts of armed conflicts and natural disasters on subsequent levels of societal vulnerability to climate hazards. The paper uses global, time-varying data for 189 countries between 1995 and 2019, combining information on natural disasters, armed conflict, and socio-economic vulnerability. We apply a leave-the-future-out cross validation and an extreme gradient boosting algorithm to test the out-of-sample performance of armed conflict, alone or in combination with natural disasters, as a predictor of vulnerability. This machine learning approach enables us to overcome some of the empirical challenges that traditional statistical methods relying on reduced form regressions fail to solve.

*† Corresponding author: *paola.vesco@pcr.uu.se*
The authors contributed equally to the paper and are listed in alphabetical order.

1 Introduction

Climate change is one of the most pressing issues of our time. The Intergovernmental Panel on Climate Change (IPCC) has estimated that human activities have caused approximately 1°C of global temperature increase with respect to pre-industrial levels, and that the rate of warming has been unprecedented in the last 2000 years (IPCC, 2021). A number of climatic changes have already been observed in the last decades, including changes in temperature and precipitation patterns, and the increase in frequency and magnitude of extreme weather events (IPCC, 2021). 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 and major adjustments in current social, political and economic systems.

Organized violence has also been increasing 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), as the decrease in fatalities in some areas, such as Syria, was counteracted by the upsurge in violence in other regions of the world, mainly in Africa (Pettersson et al., 2021).

Armed conflicts are *"development in reverse"* (Collier et al., 2003): they 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), public health crises and the outbreak of diseases (Ghobarah et al., 2004), the deterioration in social, physical and mental well-being of affected individuals (Cheung et al., 2020), and declining educational attainments (Davies, 2005; Diwakar, 2015). In turn, low levels of development, poor livelihood conditions, increased migration flows, and weak state capacity are associated with heightened vulnerability to climate hazards (Augsten et al., 2022).

Armed conflicts can therefore be a major driver of societal vulnerability, but they are also a consequence of development failure, displacement, economic inequality and poor state capacity. As illustrated in Figure 1, disasters, socio-economic vulnerability and armed conflicts might thus compound with each other in a self-reinforcing feedback loop that breeds higher vulnerability, increased conflict risk and harmful climate-related impacts (Buhaug and von Uexkull, 2021). The result may be a vicious circle, trapping affected societies in a spiral of violence, vulnerability, and harmful impacts (Buhaug and von Uexkull, 2021).
In particular, the literature on vulnerability has seen a surge in the last several years, following the increasing concerns regarding climate change and numerous reports by international institutions. The IPCC defines vulnerability as *"the propension or predisposition to be adversely affected"* (IPCC, 2022, p.5). We rely on this definition and understand societal vulnerability as the predisposition of human systems to be negatively affected by the impacts of natural disasters. Following this notion, socio-economic vulnerability is considered a multifaceted concept, which encompasses several different dimensions.

Although research on the climate-conflict nexus has surged in the past decades (e.g. Koubi, 2019; Mach et al., 2019; von Uexkull and Buhaug, 2021), this literature has mostly focused on the impacts that climate change, coupled with societal vulnerability, can have on the risk of violence, while the effects of armed conflict on vulnerability to climate hazards remain poorly understood.

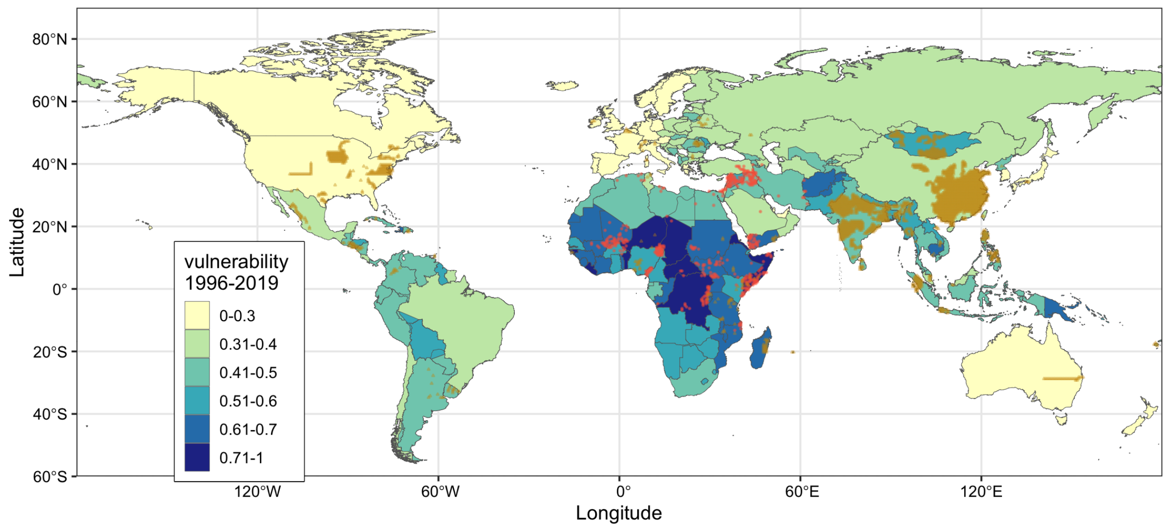

Figure 1. The map visualizes the locations hit by at least 3 climate-related natural disasters in 2018 (purple) from GDIS, a geo-coded extension of the EM-DAT database (Rosvold and Buhaug, 2021); the count of fatal political events of any type (red) recorded by UCDP-GED in 2018 (Croicu and Sundberg, 2015), and the 'disasters and conflict sensitive' vulnerability score reconstructed from Notre Dame Global Adaptation Initiative (2022) one year later, in 2019.

To the best of our knowledge, only one empirical study (Marktanner et al., 2015) has analysed the impact of armed conflict on societal vulnerability to natural disasters. Understanding the complex feedback loops involving armed conflict and vulnerability to climate related hazards is, however, paramount to meaningfully predict and possibly prevent future impacts in conflict-exposed, vulnerable communities. More systematic empirical research is therefore needed to fully understand the mutual association between armed conflict and vulnerability to climate shocks (Buhaug and von Uexkull, 2021; Augsten et al., 2022, p.16).

The present work aims at filling this research gap by analysing the impact of armed conflicts, alone or in combination with the occurrence of natural disasters, on socio-economic vulnerability. We use global, yearly data on 189 countries from 1995 to 2019 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 paper is structured as follows: the first section sets up the theoretical framework; the second illustrates the data and methodology used; the third reports results and the final section discusses and concludes.

2 Theoretical Framework

2.1 Climate, vulnerability and conflict

Climate variability and related impacts have been increasingly at the forefront of the public debate thrusting security risks into the spotlight. Climate as a security issue allegedly involves threats to national stability, livelihoods and health conditions of millions of people across the globe (Barnett, 2003). In the past decade, a burgeoning literature on climate security has advanced common knowledge of the relationship between climate variability and the risk of various conflict outcomes (Mach et al., 2019; von Uexkull and Buhaug, 2021). The most recent empirical studies have shed light on the indirect, conditional relationship between climate shocks and conflict outcomes, and highlighted the role of societal vulnerability in mediating the security risks posed by climate stressors (Koubi, 2019; von Uexkull and Buhaug, 2021). Scholars agree that climate change may indirectly contribute to an increase in conflict risk, through a complex causal chain involving socio-economic, political and cultural factors (Field et al., 2014, IPCC, 2022). Vulnerable populations that are heavily dependent on agricultural production, and are characterized by weak institutions, poor state capacity, and pre-existing ethnic or societal cleavages, are more likely to experience conflict risk when exposed to natural disasters. For example, climate-related resource scarcity and crop failures could have severe impacts on communities' livelihoods and thereby increase conflict risk (Raleigh et al., 2015 von Uexkull et al., 2016 Vesco et al., 2020 Vesco et al., 2021). Additionally, climate-induced migration might result in higher conflict risks in receiving areas because of competition for access to scarce resources, especially if this is compounded by underlying ethnic and socio-economic cleavages (Brzoska and Fröhlich, 2016; Koubi, 2019).

Climate changes and shocks are thus a 'threat multiplier' that may exacerbate the main underlying socio-economic, cultural and political drivers of conflict (Field et al., 2014). In the short term however, socio-economic and governance-related factors will continue to represent the main causes of violent conflict (IPCC, 2021, p.13).

Most of the factors that drive insecurity and conflict risk, such as low socio-economic development, poverty, and weak governance and institutions, are also crucial drivers of societal vulnerability to natural disasters. Since vulnerability represents the predisposition to be adversely affected (Field et al., 2014), it is likely that numerous factors within different realms can have an effect on it; in turn, heightened socio-economic vulnerability can be detrimental when future climatic shocks occur. As exemplified in Figure 1, the association between armed conflict, climate impacts, and societal vulnerability is hence inherently endogenous: past impacts of both conflicts and climate-related shocks increase societal vulnerability to future climate hazards (Buhaug and von Uexkull, 2021).

The following section reviews the main mechanisms connecting armed conflict, natural disasters, and societal vulnerability to climate hazards, and lays out our theoretical expectations.

2.2 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., 2010). 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

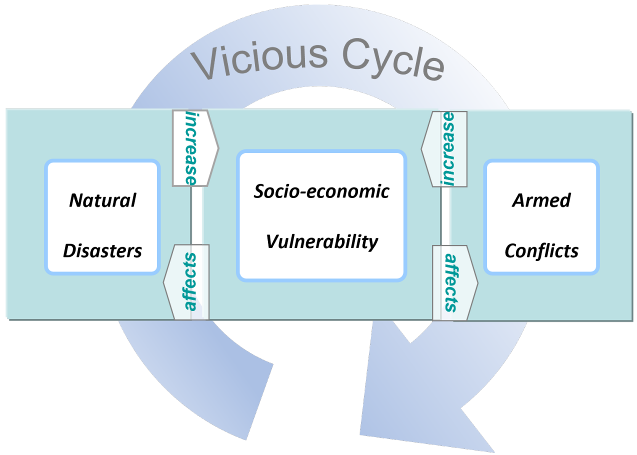

Figure 2. This figure represents the complex theoretical relationships among societal vulnerability, armed conflicts and natural disasters: both natural disasters and armed conflicts increase socio-economic vulnerability; heightened socio-economic vulnerability, in turn, affects the subsequent impacts of climate-related hazards and might even increase future conflict risk.

climatic-related risks (Buhaug and von Uexkull, 2021).

'Civil wars kill and maim people—long after the shooting stops' and they 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. Armed conflicts do not only cause physical injuries and traumas, but have a wide range of psychological and mental health-related effects, including the exacerbation of previous mental health conditions and a decreased ability to cope with problems generated by conflict-related violence (Garry and Checchi, 2020a). As psychological preparedness and resilience are fundamental in shaping individuals' response to natural disasters, psychological distress and mental-health conditions can exacerbate vulnerability to subsequent shocks (Morrissey and Reser, 2007).

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), whereby populations will try to flee conflict-ridden regions in search of a safer environment and better opportunities (Adhikari, 2012). 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 first set of hypotheses:

Hypothesis 1. *Exposure to armed conflict improves predictions of 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 (Field et al., 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, force the interruption or relocation of business activities, and disrupt firms' capital and production (Kousky, 2014). The loss of lives and structural destruction caused by natural disasters can result in economic losses, with average annual costs ranging between 94 billion (EM-DAT) to over 130 billion USD (Kousky, 2014). 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), leading to an additional impairment in individual coping mechanisms and heightened vulnerability to future hazards.

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 institutional integrity, and deteriorate government stability and democratic accountability (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: *Exposure to natural disasters improves prediction of societal vulnerability to 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, p.2). 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 von 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 combined exposure to natural disasters and armed conflict improves prediction of societal vulnerability to climate hazards better than the exposure to a single event.*

Hypothesis 3a: *Gender inequality improves prediction of societal vulnerability to climate hazards.*

3 Data and Methodology

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, and approaches that rely on good social science data are necessary to allow for effective interventions (Janes et al., 2012). 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). Examining the variables that increase the predictive performance of the models provides insight on the aspects of the models and underlying theories that generalize well on unseen data (Colaresi and Mahmood, 2017). For example, the increase in prediction error when removing a variable from the overall model indicates a positive marginal contribution of that variable in predicting the outcome (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, measured by the yearly vulnerability score from ND-GAIN (Chen, 2015, see section 3.3.1). 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 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. As the choice of lags may affect the prediction results, we test the robustness of our models by varying the lag structure (see section 4.1). More information on the main data sources is provided in section 3.3.

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). Random forest is less prone to overfitting than other algorithms, and by combining multiple decision trees through a bootstrap aggregate, it increases predictive accuracy. The random selection of features and the resulting diversity of the trees make this algorithm highly interactive and able to capture complex feature patterns. The gradient boosting increases predictive accuracy while going beyond stringent functional forms assumptions.

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 *compound 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).

3.3 Data

3.3.1 Vulnerability data

The vulnerability data are drawn from the country-year ND-GAIN vulnerability score (Notre Dame Global Adaptation Initiative, 2022). 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). 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 and adaptation options (Amegavi et al., 2021).

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, 2022).

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.

3.3.2 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).

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, 2020b)
	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, 2020b)
	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

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

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 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 1.

3.3.3 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).

3.3.4 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. 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 Table 2.

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

Table 2. Table 2. Correlation between ND Gain sub-indicators used to calculate the new conflict-sensitive vulnerability indicator in 2019 and total fatalities and total conflict count in 2018.

4 Results

The results of the forecasting models are presented in Figure 3. 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 3. As Figure 3 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 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 3 c, showing that predictions from the *gender* model have the highest correlation with observed vulnerability. Consistently, the mean absolute error in predictions (Figure 3 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 3 c.

Figure 3 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 to predict 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. Further research is needed to understand how and under what conditions violence and disasters affect the individual and collective ability to respond to, prevent, and mitigate subsequent climate hazards.

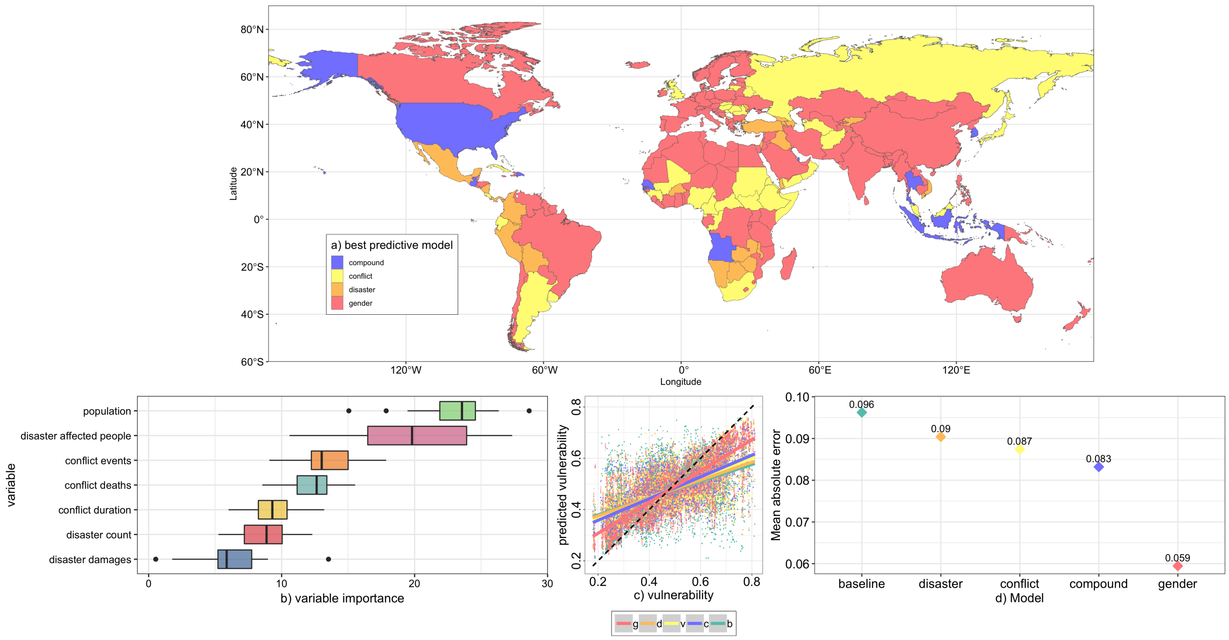

Figure 3. a) Best predictive model of 'disasters and conflict sensitive' vulnerability by country averaged over the test sets in 1999-2019; b) Feature importance of the compound model; c) Scatterplot of predicted and actual 'disasters and conflict sensitive' vulnerability scores across models; d) Average prediction error averaged across the test sets in 2001-2019. Model 'g': gender; 'd': disaster; 'v': conflict; 'c': compound; 'b': baseline.

Figure 4 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 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 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.

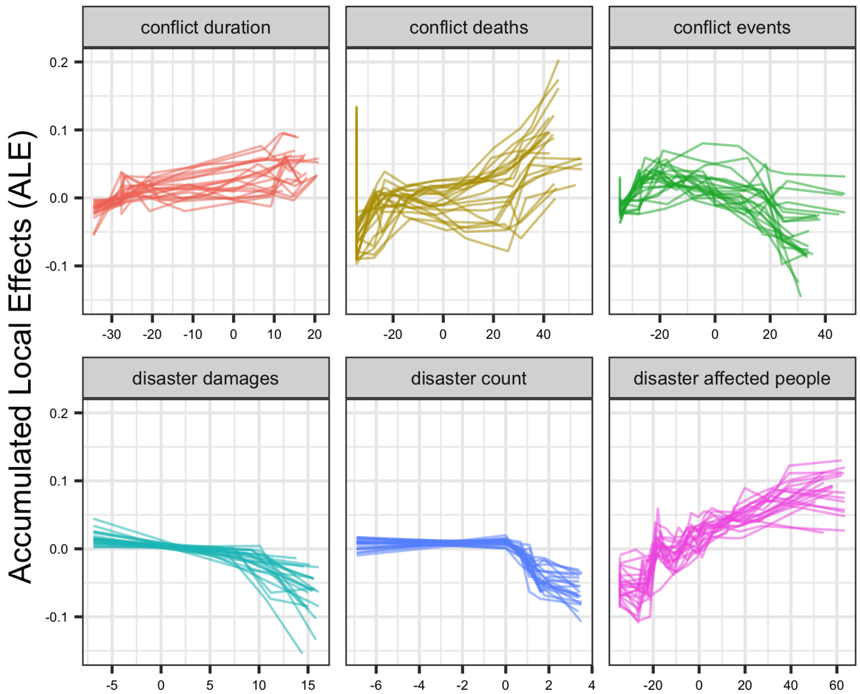

Figure 4. Accumulated Local Effect (ALE) plots, compound model without baseline. The observed value is reported on a*log+0.001* scale.

Figure 5 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.

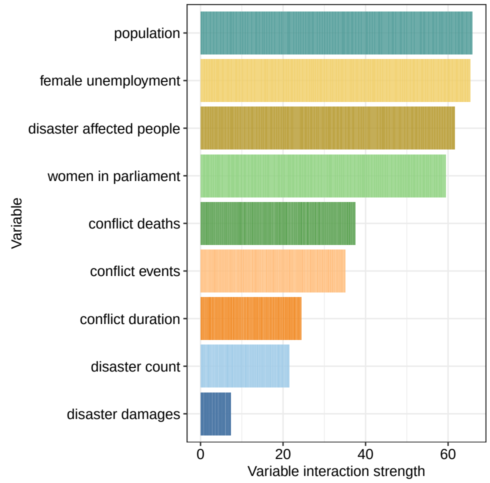

Figure 5. Interaction strength of the features in the compound model.

4.1 Sensitivity tests

We conduct a number of tests to verify the robustness of our findings. First, to evaluate whether the models are sensitive to the selected 1-year lag structure, we re-run the same models by lagging all predictors by 2 years. Second, we test the sensitivity of our results by re-training and testing our models to predict an alternative operationalization of the vulnerability indicator. Specifically, we train and test alternative models to predict the ND-GAIN vulnerability score per each country and year, as reported in section 3.3.1. Next, as higher levels of vulnerability can translate into higher losses of lives from a natural disaster, we specify a set of models that use the number of people killed by natural disasters as outcome. Lastly, to rule out the possibility that population size is driving the results, we specify an alternative set of model that uses per capita predictors in place of their absolute values. The results of these alternative specifications do not substantially differ from the main findings. Results of these tests are presented in Appendix.

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.

We fill 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. By advancing our knowledge of the drivers of societal vulnerability, this study contributes to both the literature on climate security, and the scholarship on climate impacts, vulnerability and adaptive capacity.

We argue that 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.

We test these hypotheses in a predictive framework that leverages on the explanatory power of machine learning tools. We train, test and evaluate five random forest models in a leave-the-future-out cross validation to predict a country-year disaster and conflict sensitive vulnerability index, derived from ND-GAIN data.

We find 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 illuminate 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, trust, 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. However, investigating how and under what conditions conflict and disasters affect vulnerability was outside the scope of this study. Another limitation of this country-year study is to use an aggregated level of analysis that preempts a refined investigation of the spatial and temporal dynamics affecting vulnerability.

Some promising avenues for future research are thus to delve into the causal pathways connecting armed conflict, natural disasters, and societal responses, with a particular focus on the *human* dimension of the climate-conflict nexus, as well as to understand how these impacts spread and diffuse over space and time.

References

Adhikari, Prakash (2012). "The plight of the forgotten ones: Civil war and forced migration". *International Studies Quarterly* 56.3, pp. 590–606.

Albrecht, Frederike (Apr. 2018). "Natural Hazard Events and Social Capital: The Social Impact of Natural Disasters". *Disasters* 42.2, pp. 336–360. DOI: 10.1111/disa.12246.

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.

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. DOI: 10.1007/s10113-022-01888-1.

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.

Barnett, Jon (2003). "Security and climate change". *Global environmental change* 13.1, pp. 7–17.

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, Cagatay, Tilman Brück, and Marc Vothknecht (2010). "Violent conflict and inequality".

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, 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. DOI: https://doi.org/10.1016/S2542-5196(21)00197-2.

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 and Nina von Uexkull (2021). "Vicious Circles: Violence, Vulnerability, and Climate Change". *Annual Review of Environment and Resources* forthcoming.

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.

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

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. DOI: 10.1080/17565529.2015.1016884.

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. DOI: 10.1016/j.jrurstud.2016.12.011.

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.

Cherniack, E Paul (2008). “The impact of natural disasters on the elderly”. eng. *Am J Disaster Med* 3.3, pp. 133–139.
Cheung, Felix et al. (Dec. 2020). “The Impact of the Syrian Conflict on Population Well-Being”. *Nature Communications* 11.1, p. 3899. DOI: 10.1038/s41467-020-17369-0.
Colaresi, Michael and Zuhaib Mahmood (2017). “Do the Robot: Lessons from Machine Learning to Improve Conflict Forecasting”. *Journal of Peace Research* 54.2, pp. 193–214.
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.
CRED (2022). *2021 Disasters in Numbers.*
Croicu, Mihai and Ralph Sundberg (2015). “UCDP Georeferenced Event Dataset Codebook Version 4.0”. *Journal of Peace Research* 50.4, pp. 523–532.
Davies, Lynn (2005). “Evaluating the Link between Conflict and Education”. *Journal of Peacebuilding & Development* 2.2, pp. 42–58. DOI: 10.1080/15423166.2005.469016216322. eprint: https://doi.org/10.1080/15423166.2005.469016216322.
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. DOI: 10.1111/j.1574-0862.2008.00348.x.
Diwakar, Vidya (2015). “The Effect of Armed Conflict on Education: Evidence from Iraq”. *The Journal of Development Studies* 51.12, pp. 1702–1718. DOI: 10.1080/00220388.2015.1056786. eprint: https://doi.org/10.1080/00220388.2015.1056786.
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. DOI: 10.3390/children6060077.
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. DOI: 10.1177/0010836711434463.
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.
Field, CB et al. (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.*
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. DOI: 10.1038/s41558-021-01017-6.
Garry, S and F Checchi (Aug. 2020a). “Armed Conflict and Public Health: Into the 21st Century”. *Journal of Public Health* 42.3, e287–e298. DOI: 10.1093/pubmed/fdz095.
— (Aug. 2020b). “Armed conflict and public health: into the 21st century”. en. *Journal of Public Health* 42.3, e287–e298. DOI: 10.1093/pubmed/fdz095.

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. DOI: 10.1016/j.worlddev.2012.04.031.

Ghobarah, Hazam Adam, Paul K. Huth, and Paul Russett (2004). "The Post-War Public Health Effects of Civil Conflict". *Social Science and Medicine* 59, pp. 869–884.

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.

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.

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. DOI: 10.1007/s10584-013-0853-x.

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.

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. DOI: 10.1038/nclimate3253.

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.

IPCC (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. DOI: 10.1017/9781009157896.

— (2022). *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.

Janes, Craig R, Kitty K Corbett, James H Jones, and James Trostle (2012). "Emerging infectous disease: the role of social science". *The Lancet* 380 (9857), pp. 1884–1886.

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. DOI: 10.1186/s12916-020-01708-5.

Johnson, Shelly and Judith Ostendorf (Jan. 2010). "Hispanic Employees in the Workplace". *AAOHN Journal* 58.1, pp. 11–16. DOI: 10.3928/08910162-20091216-01.

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. DOI: https://doi.org/10.1016/j.worlddev.2022.105931.

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* 22.1, pp. 343–360.

Kousky, Carolyn (2014). "Informing climate adaptation: A review of the economic costs of natural disasters". *Energy Economics* 46, pp. 576–592. DOI: https://doi.org/10.1016/j.eneco.2013.09.029.

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.

Lin, T.-H. (Mar. 2015). "Governing Natural Disasters: State Capacity, Democracy, and Human Vulnerability". *Social Forces* 93.3, pp. 1267–1300. DOI: 10.1093/sf/sou104.

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

Magee, Christopher S P and Tansa George Massoud (Jan. 2011). "Openness and internal conflict". en. *Journal of Peace Research* 48.1, pp. 59–72. DOI: 10.1177/0022343310388834.

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. DOI: 10.1007/s00148-009-0274-3.

Marktanner, Marcus, Edward Mienie, and Luc Noiset (2015). "From armed conflict to disaster vulnerability". *Disaster Prevention and Management* 24.1, pp. 53–69. DOI: https://doi.org/10.1108/DPM-04-2013-0077.

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.

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. DOI: 10.1093/0199256454.001.0001.

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. DOI: https://doi.org/10.1111/j.1440-1584.2007.00865.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1440-1584.2007.00865.x.

Mueller, Hannes (July 2016). “Growth and Violence: Argument for a Per Capita Measure of Civil War”. *Economica* 83.331, pp. 473–497. DOI: 10.1111/ecca.12193.

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.

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.

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

Notre Dame Global Adaptation Initiative (2022). *Notre Dame-Global Adaptation Index (ND-GAIN) Country Index*. ND-Gain Country Index.

Orrenius, Pia M. and Madeline Zavodny (Aug. 2009). “Do Immigrants Work in Riskier Jobs?” *Demography* 46.3, pp. 535–551. DOI: 10.1353/dem.0.0064.

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. DOI: 10.1177/0022343320973741. eprint: https://doi.org/10.1177/0022343320973741.

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. DOI: 10.1177/00223433211026126.

Pettersson, Therése and Magnus Öberg (2020). “Organized violence, 1989–2019”. *Journal of Peace Research* 57.4, pp. 597–613. DOI: 10.1177/0022343320934986. eprint: https://doi.org/10.1177/0022343320934986.

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.

Raschky, P. A. (July 2008). “Institutions and the Losses from Natural Disasters”. *Natural Hazards and Earth System Sciences* 8.4, pp. 627–634. DOI: 10.5194/nhess-8-627-2008.

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.

Rosvold, Elisabeth L. and Halvard Buhaug (Dec. 2021). “GDIS, a Global Dataset of Geocoded Disaster Locations”. *Scientific Data* 8.1, p. 61. DOI: 10.1038/s41597-021-00846-6.

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. DOI: 10.1177/0022343318812935.

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.

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.

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”. en. *WIREs Water* 7.6. DOI: 10.1002/wat2.1480.

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. DOI: 10.1038/s41467-021-22255-4.

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. DOI: 10.1016/j.geoforum.2013.04.004.

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

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

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. DOI: 10.1016/j.ecolecon.2020.106633.

Vesco, Paola, Matija Kovacic, Malcolm Mistry, and Mihai Croicu (Jan. 2021). "Climate Variability, Crop and Conflict: Exploring the Impacts of Spatial Concentration in Agricultural Production". *Journal of Peace Research* 58.1, pp. 98–113. DOI: 10.1177/0022343320971020.

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. DOI: 10.1177/0022343320984210. eprint: https://doi.org/10.1177/0022343320984210.

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. DOI: https://doi.org/10.1016/S0140-6736(18)31437-5.

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.

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. DOI: https://doi.org/10.1016/S0959-3780(01)00026-7.

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. DOI: 10.1080/17477891.2014.910491.

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.