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Climate Change and Conflict:

Exploring Indirect Pathways and Future Scenarios

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PhD Program Coordinator
Prof. Carlo Carraro

Supervisor
Prof. Carlo Carraro

Co-Supervisors
Prof. Halvard Buhaug
Prof. Enrica De Cian
Dr. Shouro Dasgupta

Paola Vesco
ID 956299

Thesis advisor: Professor Prof. Carlo Carraro Paola Vesco

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Abstract

Despite attracting increasing attention from the research community and the mediatic arena in recent years, the security implications of climate change remain still controversial. Yet, understanding the impacts of climatic anomalies on the risk of conflict is fundamental to inform adequate policy actions and adaptation strategies. Going beyond the traditional approach that investigates the direct climate-conflict nexus, the dissertation explores some of the possible indirect connections between climate change and conflict. The thesis finds that climate change has an indirect effect on conflict, but this is very modest compared to socio-economic, demographic and contextual conditions. Shocks to agricultural production and unequal entitlements in crop yields, especially when coupled with socio-political discrimination, seem to be more relevant to security than slow-onset shifts in temperature and precipitation patterns. The results of the projections also show that the African and Asian continents will continue to be the most violent areas in the long-term future.

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Executive Summary

In his lucid analysis of The Consequences of Modernity, Anthony Giddens sketches the risks that post-modern societies are likely to face along their path towards utopian realisms. In Giddens' view, the collapse of economic growth, the upsurge of totalitarianisms, large-scale warfare and ecological decay will be the main threats affecting the decades to come.

At the time of writing, a plume of smoke rising from the fires of the Amazon forest, the Arctic ice melting due to unprecedentedly hot summers, the enduring violence in Syria and the spreading of low-level conflicts which risk spiraling out of control, together with a diffuse rise in populist parties and a creeping climate of intolerance against migrants and refugees, they all may evocate the sound of Lord Gidden's grim bell. For societal dimensions being multi-faceted and inter-connected, as the sociologist points out, each can adversely affect the others and possibly influence millions of human lives. In 2018, 52 active conflicts were registered all over the globe and the economic impact of violence was estimated to reach 14 trillion, equivalent to over 1, 800 per person. Likewise, the Earth's climate is changing at an accelerated rate and the chances to meet the Paris Agreement's objective of limiting the increase in average temperature to 2°C are more and more hanging by geo-engineering techniques, reforestation measures and paradigmatic shifts in energy consumption. Needless to say, there is an urgency to understand the complexities of human-climate interactions and systematically study the destabilizing factors that are likely to pave the way of future societies. Although inferring from the past to understand the future is rather heuristic in scope, scientifically-sound and empirically-driven investigations of historical trends can constitute a fertile ground to grow a reasonable picture of how the future will look like – beyond utopian and dystopian accounts.

The present research effort aims at contributing to a greater understanding of the complex relations between climate change impacts and human societies. Specifically, I hereby focus on some possible conditions that can make the climate-conflict nexus more likely to arise. The main focus is on agricultural production shocks – as they are linked to food availability – and on natural resources that represent the main input to agriculture (water, land). To this end, the work will contribute to the existing conflict research by delving deeper into some indirect mechanisms or pathways that can lead from climate change to an increased probability of violence. At first, the empirical literature on climate and conflict has attempted to find evidence of a direct connection between temperature/precipitation anomalies and the risk of civil war. After a failure to converge on a robust consensus, scholars have lately shifted their focus to rather indirect or conditional linkages between climatic variability and security. The debate is far from exhausted, however, as both theorists and empiricists disagree on the existence of a correlation between climate and conflict, whether direct or indirect. On the other hand, the scientific community is facing a growing demand from the policy arena to construct scientifically sound and empirically grounded tools to forecast security risks in general and conflict in particular. Clarifying the impacts of climate conditions on violence is a necessary step in the daunting climb towards fostering peace and security, preventing and mitigating mayhems, boosting communities' resilience to climate change impacts and increasing adaptive capacities. However, no forecasting attempt has so far been conducted to test the long-term impacts of climatic and environmental conditions on future political stability. This is to some extent surprising, considering that the task of conflict predictions raises similar challenges than those borne by the climate research community, forever devoted to the cause of modelling and scenarios' projections. The ultimate goal of the thesis is therefore to bridge this gap and build on the insight acquired from the historical analysis to forecast the likelihood of conflicts which can be driven, among others, by climate anomalies and agricultural production shocks.

The thesis is structured as a collection of four individual papers. The first one, co-authored with Professor Buhaug, reviews the literature to draw the state of the art in the climate-conflict research. The chapter identifies some major research pitfalls and gaps of existing studies, illustrates the most recent findings and opens up new and needed research avenues.

The second paper, co-authored with Professor Carraro, Enrica De Cian and Shouro Dasgupta, explicitly focuses on a possible indirect mechanism connecting climate to conflict and attempts to systematically and quantitatively answer the questions of how natural resource scarcity/abundance is linked to violence and what is the role of climate in conditioning this relationship. As the connection between natural resources and conflict has been extensively debated in academia, I perform a meta-analysis of the existing studies, with a view to reconcile the differing findings and clarify whether there is a true genuine relationship between natural resource scarcity/abundance and conflict, what is the influence that climate can exert on this link and what methodological characteristics of the studies may help explain the difference in the results. I find that both natural resource abundance and scarcity are genuinely correlated to conflict. The abundance of highly-valuable resources such as minerals and oil appears to be associated with an increased likelihood of conflict, whereby the prospect of material wealth and the incentive of enrichment advertised by rebel groups' leaders attract individuals' mobilization and incentivize greed. The scarcity of renewable resources such as water and land, conversely, is shown to be linked to conflict. Also, climate variables do have an influence on the relationship between natural resources and conflict, although obviously limited to renewable resources (water, land). As water and land are the primary input of agriculture, the results of the analysis suggest that food insecurity and environmentally-related shocks to agricultural production can have a destabilizing effect on socio-economic systems, as they foster grievances and encourage collective mobilization. Therefore, the third chapter of the thesis precisely focuses on agricultural production as a possible predictor of conflict.

In chapter 3, co-authored with Matija Kovacic and Malcolm Mistry, I empirically investigate agricultural production as an alternative indirect pathway linking climatic changes to conflict. I argue that the reasons for the literature connecting climate, crop and conflict being inconclusive so far need to be researched in a misleading operationalization of the independent variable: I therefore posit that it is not the absolute quantity in agricultural output but rather the relative differences in crop yields between identity-based groups, which are relevant to explain conflict outbreaks. By constructing an empirically-driven Gini Indicator of agricultural output, I test the correlation between unequal distributions of crops and conflict onset, and investigate whether the influence of climatic changes on conflict outbreak is conditional upon the level of crop production inequality. Next, I delve deeper into the contextual factors that may make climate more destabilizing, and especially investigate how inequality in agricultural production interact with political discrimination to shape the impact of climatic changes on conflict onset. The analysis finds that inequality in agricultural output is in fact a good predictor of violence, although climate anomalies seem to have a rather moderate influence compared to socio-economic and ethnic factors. Climate variability is shown to increase the risk of conflict onset when agricultural production is especially unequal and communities are considerably discriminated. This finding suggests that the relationship between climate and conflict is dependent upon a set of contextual factors, rather than operating through a single pathway, and that socio-political conditions still have a major role in explaining violence. Moreover, as temperature and precipitation deviations from their long-term mean capture a slow-moving effect, the results may indicate that communities and governments have sufficient time to adapt to climate impacts before they trespass a destabilizing limit.

Chapter 4, in collaboration with Gabriele Accarino, Maria Luisa Gabrielli, Edoardo Arnaudo and Malcolm Mistry, thus analyses the long-term scenario and projects the probability of conflict up to 2050. I take advantage of the potential of Machine Learning techniques and new data availability to improve forecasting accuracy. The chapter finds that AI techniques, especially deep learning, are a valid tool to forecast violence, as they are able to grasp the hidden complexity that characterize human interactions. The projections find that Africa and the Middle-East, Latin America and Southeast Asia will remain the major conflict hotspots in the upcoming decades. Forecasting results again show that climate variables are not likely to have a direct influence on conflict probability in the future and especially the effect of temperature anomalies seem to be conditional upon the level of economic output and crop production. However, further research is needed to understand the impact of alternative climate scenarios which will not comply to the Paris agreement and may thus lead to a warmer planet than the one envisaged in 2015 by global leaders.

The innovative approach applied in the research work builds on different methodologies and offers a solid quantitative framework to assess the historical trends, test and validate theories connecting climate to conflict and eventually build on the knowledge of the past to heuristically project the probability of violence under climatic changes. I conclude that although climate variability has some influence on security, the effect is modest compared to socio-economic and contextual factors. Agricultural production, especially whenever is unequally distributed between groups, is in fact a much better predictor of conflict than temperature and precipitation anomalies. This may possibly suggest that, although on a theoretical ground climate change can increase the likelihood of conflict by altering the availability and distribution of crop yields, communities are capable of adapting to the destabilizing effect of climate anomalies in the long-term. Also, the effect of climate variability is likely to be dependent upon multiple and interrelated conditions and climatic shocks are shown to be especially detrimental for communities and individuals which are already worse off and subject to socio-political discrimination. This does not exclude, however, that more sustained warming and resulting impacts on ecologies and societies could potentially lead to increased probability of conflicts, or even lead to the rise of new and unexpected forms of violence. A possibility also exists that climate will have a non-linear impact on security, leading to an initial increase in the risk of conflict, followed by greater stability. Different mitigation strategies may also be associated with different security scenarios, whereby communities may bear uneven costs for emissions reductions and be subject to disproportionate impacts of climatic changes.

As such, two main conclusions can be drawn from this research work: first, on an academic level, there is a need to not only explore the impacts of less optimistic climatic scenarios on the stability of future societies, but also clarify the destabilizing potential of natural disasters and extreme weather events – which may have far more disruptive consequences than temperature and precipitation anomalies, whereby they do not give societies enough time to adjust. Second, on the policy side, as far as renewable resources (water, land, and therefore crops) are predicted to become increasingly scarce, governments shall invest in common and coordinated adaptation efforts to put individuals and groups in the condition to cope with shocks and be sufficiently resilient to changes, should they be climatic, political or socio-economic. The role of government and institutions appears to be a major element in encouraging cooperation and disincentivizing rebellion; healthy institutions can promote a fairer allocation of resources, eradicate socio-political discrimination, implement cooperative agreements on resource management, contribute to close the gap between wealthy and poor strata of society, better equip communities to cope with environmental shocks and provide relief aids after natural disasters. Policies that intend to increase societal resilience to climate change on the one hand, and actions and strategies aimed at promoting socio-economic development on the other, may thus be mutually supportive, as the effects of the former could complement and enhance the latter and *viceversa*. Scholars need therefore investigate further the complex feedbacks characterizing these policies to shed light on their combined effect for the climate-human system as a whole.

Then crop failure, drought, and flood were no longer little deaths within life, but simple losses of money. And all their love was thinned with money, and all their fierceness dribbled away in interest until they were no longer farmers at all, but little shopkeepers of crops, little manufacturers who must sell before they can make.

Steinbeck (1939)

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Climate and Conflict: A Review of the Literature

Climatic conditions have profound impacts on human activity and well-being, and adverse climatic changes can have devastating societal consequences. It is no coincidence that scholars have connected the collapse of many, if not most, ancient human civilizations to adverse climatic conditions, including the Maya (Douglas et al., 2016); the Tang dynasty (Yancheva et al., 2007); and the Roman empire (Harper, 2017). More recently, the drought-induced Dust Bowl that swept across the American Great Plains in the 1930s caused severe agricultural decline and starvation and forced poor farmworker families to abandon their land in large numbers (Gregory, 1991), as epitomized in the opening quote from Steinbeck's grand novel.

The more recent history seems to be no exception. Studies have highlighted the broader implications of climate variability for security and investigated the influence of climate changes on the risk of conflict. Inflamed by the Arab Spring and the so-called 'bread riots', a dense narrative of climate driven violence has increasingly taken central stage in the academic, mediatic and political arena. Florid anecdotic evidence draws a fil-rouge connecting climatic conditions to violence, passing through poverty, hunger, migration flows and societal disruption.

Regularly, such examples involve narratives of violent competition over scarce resources and land access, if not civil war between communal groups. A prominent example is the conflict in Darfur at the beginning of the century, which was labelled the world's first "climate change conflict" by then-Secretary General of the UN, Ban Ki-Moon (2007). The initial Syrian upheavals in 2011 that led to the devastating civil war also have been linked to a prolonged drought and subsequent loss of agricultural livelihood and forced displacement of disgruntled rural populations to already-strained urban areas (Femia and Werrell, 2013; Gleick, 2014; Kelley et al., 2015). Other examples that have been reported to follow a similar logic include the Rwandan genocide in 1994 (Diamond, 2005) and the recent upsurge in maritime piracy off the Somali coast (Moore, 2017), although it should be mentioned that the role of environmental conditions in causing these conflicts remains contested.

Upon reviewing the literature on climate and conflict, it immediately becomes evident that what scholars mean with "climate" and "climate change" varies significantly across studies, and the usage of the terms sometimes breaks with established definitions. The World Meteorological Organization defines climate as the statistical description in terms of the mean and variability of weather conditions, such as temperature, precipitation and wind, over a period of thirty years or longer (WMO, 2019). Climate change thus involves persistent shifts in such mean conditions, observed at a multi-decadal scale or longer. Studies investigating the security implications of climate habitually refer to climate change as a predictor of conflict, even though the operationalized concept usually captures changes short-term, or yearly/monthly shifts in mean conditions (Koubi, 2018). Such changes are instead representing climate variability, which denotes deviations in climatic statistics and occurrence of extremes beyond that of individual weather events.

This chapter reviews the literature that connects climate change and/or variability to the probability of civil conflict. We exclude from the review studies of inter-national wars, since scholars have generally neglected the effect of climatic and environmental determinants on international conflicts or considered it as a very remote possibility (Homer-Dixon, 1999; Gleditsch, 2012; Theisen et al., 2012). Although there is a considerable literature on impacts of climatic variables on other types of violence, including communal conflicts (Fjelde and von Uexkull, 2012), range wars (Butler and Gates, 2012), and criminal activities (Mares and Moffett, 2016), the majority of extant research concentrates on civil, or state-based, armed conflicts as the outcome variable. This chapter therefore restricts the focus to civil conflicts, defined as a contested incompatibility between the government of a state and an organized, non-state actor involving the use of armed force. This definition includes both conventional civil wars and anti-governmental challenges on lesser scales, including urban rioting.

The chapter is organized as follows: first, we highlight the state of the empirical literature on climate and conflict; next, we discuss the current debates around the climate-conflict nexus; and finally, we conclude with some reflections on possible future research trajectories.

1.1 State of the literature on climate and conflict: A direct link?

We may think of links between climatic conditions and conflict risk in two stylized manners. The first represents a direct relationship, whereby anomalies in surface weather conditions compared to long-term means directly affect the probability of armed conflict. The second and more nuanced notion prescribes an indirect connection, where a climate-conflict link materializes only under certain conditions or via certain indirect causal pathways. Until recently, quantitative and comparative climate-conflict research belonged almost exclusively to the first category. This literature is now sufficiently mature that we are in a position to conclude on the strength and robustness of a general climate-conflict link in the contemporary era.

The first attempts to systematically investigate the relationship between climate and civil conflict were characterized by quite coarse measures of climatic variability, generally limited to temperature means or anomalies (e.g. Burke et al., 2009; Hsiang et al., 2013), and were mostly concerned with the African continent or part of it (Gleditsch, 2012; Adams et al., 2018). These first studies generally found a positive effect of average temperature increase on the risk of conflict, but the alleged relationship appeared to be barely generalizable, as it was sensitive to the type of conflict to be predicted, held only for specific regions of the world, and was rather likely to be ascribed to precise methodological choices and model specifications, such as the definition and measurement of the main variables.

For instance, Burke et al. (2009) found a significant positive effect of the average surface temperature on the risk of civil conflict, but the results were proven not to be robust to alternative model specifications and failed to pass various sensitivity tests performed by Buhaug (2010). Maystadt et al. (2015), found that temperature anomalies, measured at the grid-cell level, are linked to a higher risk of violence in Sudan. However, their dependent variable, i.e. the number of violent episodes per quarter, was not standard in the climate-conflict scholarship. Moreover, the relationship between temperature anomaly and violence is extremely sensitive to the type of conflict to be predicted; for instance, O'Loughlin et al. (2012), who used a grid-cell index of temperature anomaly from the long-term mean, found that while extremely hot climates are associated with higher risk of violence against civilians, temperature does not impact the odds of military confrontations between two armed actors.

Not only the type of conflict, but also the measurement and range of values of the independent variable can affect the significance and even the direction of the relationship. O' Loughlin and co-authors (2012; 2014) found that if extremely high temperatures increase the likelihood of conflict, moderately warmer (and colder) temperatures are associated with a lower risk of violence. Similar results were found by Bolfrass and Shaver (2015) who detected a positive effect of large temperature differences on the probability of conflict at the subnational level, but only a modest impact of incremental temperature change on conflict risk.

Moreover, the direct impact of temperature on security is likely to be region-specific and dependent upon countries' characteristics. Using data on temperature mean at a monthly resolution, Landis (2014) found that prolonged periods of stable, warm weather are associated with a higher risk of civil war onset in countries displaying strong seasonal trends. Nevertheless, the results did not hold either for other countries or alternative model specifications, and the author himself declared the effect to be a very poor predictor of conflict risk compared to socio-economic factors (Landis, 2014). The relationship between temperature and conflict may in fact be driven by specific regions of the world; when disaggregating the analysis at the regional level, O' Loughlin and co-authors (2012, 2014) found that out of the whole African continent, the impact of temperature anomalies on conflict risk remains valid only for the Sahel, while is not significant in other regions.

The evidence of a link between rainfall patterns and conflict is even more nuanced, with some studies finding that wetter, rather than drier, conditions are associated with increased risk of conflict (Hendrix and Saleyhan, 2012; O'Loughlin et al., 2012), some detecting no significant impact of precipitation on violence (Burke et al., 2009; Maystadt et al., 2015), and others showing a positive association between dryer conditions and conflict (O'Loughlin et al., 2014). Again, the effect varies according to the conflict type to be predicted; for instance, extremely dry weather increases the likelihood of rioting and violence against civilians, while moderately dry conditions reduce the risk of conflict between two armed actors (O'Loughlin et al., 2014). Moreover, the effect is likely to be mediated by location and time periods (O'Loughlin et al., 2012); for instance, Hendrix and Glaser (2007) found that the previous year's increase in rainfall reduced the risk of war, while changes in the same year had no statistically significant effect.

In an attempt to clarify the divergencies in the literature, a number of scholars refined the operationalization of the independent variable and proxied climate conditions with more complex measures of water availability and drought. These studies generally detected a very modest effect of drought on violence, especially when compared with socio-economic and contextual factors. Couttenier and Soubeyran (2013), who used the Palmer Drought Severity Index (PDSI), revealed that the effect of drought on civil conflict in Sub-Saharan Africa was insignificant. By combining measures of suitability to agriculture, land degradation and water availability, Hendrix and Glaser (2007) found that neither long-term climate trends nor short-term meteorological triggers are associated with the onset of conflict in the absence of economic, political and demographic control variables. Raleigh and Urdal (2007), who used data on freshwater availability and land allocation, showed that environmental variables have only a moderate effect on the risk of conflict, although water scarcity appears to have a somewhat stronger impact. Even when an effect is found, is likely to be ascribed to model specifications and highly sensitive to socio-economic conditions or other contextual factors; Wischnath and Buhaug (2014), who applied the SPI6 drought index, found that, all else held constant, Asian regions that experienced a drought are more likely to be affected by conflict in the subsequent year. Yet, the results did not hold for different proxies of climate variability and alternative model specifications, leading the authors to conclude that, although significant results can be achieved under some specifications, the median effect is null. Gizelis and Wooden (2010) and von Uexkull et al. (2016) similarly detected null or very modest direct effect of water scarcity on the risk of conflict, but found that the effect could be conditional on other contextual factors, as we will see more extensively in the next section.

Other studies have opted for alternative measures of climatic conditions to test the existence of a direct relationship between climate variability and conflict. Hsiang and co-authors

(Hsiang et al., 2011) employed data on sea surface temperature anomalies associated with El Niño episodes, when meteorological conditions get warmer and dryer, to analyse the effect of climate variations on the risk of conflict. They showed that the probability of civil conflict onset doubles during El Niño events and argued in favour of a strong impact of the global climate on the stability of modern societies. However, the authors themselves warned against the generalizability of their study, highlighting that ENSO has a considerable influence on a variety of climatological variables, each of which can potentially influence other conflict-related factors; generalizing their results to global climate changes phaenomena other than ENSO would therefore require a better understanding of the underlaying mechanisms. In a different study, Nel and Righarts (2008) tested the impact of natural disasters on the risk of civil conflict. They found that disasters are positively related with the risk of civil conflict both in the short and medium term, and that rapid-onset disasters related to geology and climate pose the highest overall risk to security. However, to what extent natural disasters can be attributed to human-induced climate variability rather than natural cycles is still controversial (Otto et al., 2012). Hauge and Ellingsen (1998) used data on deforestation, land degradation, and freshwater supply to test the hypothesis, already advanced by Homer-Dixon (1999), that environmental scarcity exacerbates the incidence of conflict. The study found that all measures increase the risk of domestic conflict and that the results are robust to the inclusion of economic and political controls, such as the level of economic development and the type of political regime. Nevertheless, the study's results could not be replicated by Theisen (2008), which found little support to the alleged eco-scarcity argument. Instead, the analysis revealed that poverty, instability and fuel exports are better predictors of conflict than environmental variables in general, although high levels of land degradation may significantly raise the risk of conflict.

As this review has hopefully clarified, the literature testing a direct impact of climatic variability on the probability of intra-state conflict is inconclusive. Although studies employed different climate measures, ranging from simple temperature means to refined meteorological indicators, the effect of climate is generally found to be insignificant, modest, or controversial. Moreover, even when a direct effect is found, it tends to be limited to specific regions of the world or particular time periods, heavily sensitive to the type of conflict under investigation, as well as to the way of measuring the key predicting variables, and largely ascribed to model specifications and methodological settings.

1.2 Current debates: Assessing key indirect pathways

From the reviewed literature, it is clear that climate variability, such as short-term anomalies in rainfall and temperature patterns, exerts a weak direct influence on the average baseline conflict risk across societies. However, lack of robust evidence for a general climate-conflict effect does not preclude the possibility that climatic conditions can have a measurable influence on the likelihood of violent conflict in more subtle and complex ways. Indeed, claims that link climatic extremes to civil conflicts in the contemporary era usually stress the interactive role of extremes in combination with adverse political and socioeconomic conditions on the ground. For this reason, the empirical climate-conflict literature has increasingly shifted focus toward assessing the empirical merit of plausible indirect connections between climate and conflict.

We may synthetically classify current thinking about climate-conflict linkages in two broad, complementary manners (Figure 1.1): The first denotes conditional pathways, whereby a

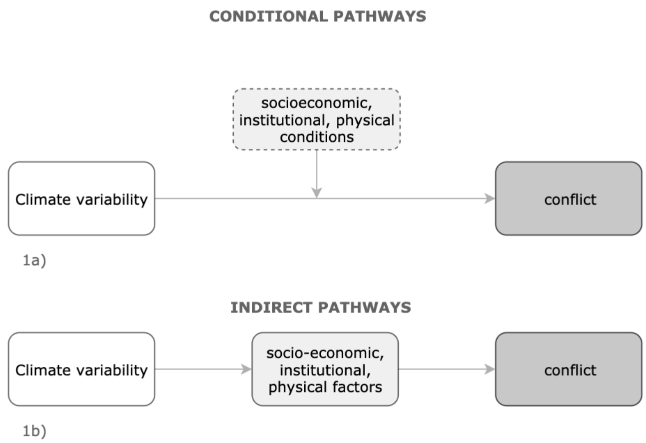

Figure 1.1: Potential mechanisms connecting climate variability to conflict risk: a) conditional pathways; b) indirect connections.

given climate effect (e.g., a flood) is moderated by contextual factors (e.g., quality of infrastructure); the second implies indirect effects, where climatic conditions and events (e.g., a flood) affects violence risk via intermediate impacts on social systems (e.g., loss of livelihood). We review the relevant literature as follows.

1.2.1 Conditional Pathways

A number of recent studies of the climate-conflict nexus highlight the possible role of location-specific factors in moderating a climate effect. In other words, rather than assuming a sweeping, context-insensitive effect of climate variability on civil conflict, they investigate whether the climate effect varies by context, typically proposing that a relationship is most likely to materialize in the most vulnerable societies, characterized by poverty, low state capacity, high demographic pressures, ethno-political exclusion, and considerable dependence on agriculture. Table 1 provides a snapshot of some commonly tested conditional factors and their influence on the estimated climate-conflict link.

Conditional Factor	Moderating Role	Study
Ethno-political exclusion	No moderating role	O'Loughlin et al., 2012
	Decreases climate effect	Bell and Keys, 2016
Ethnic fractionalization	Increases climate effect	Couttenier and Soubeyran, 2013
Socio-Economic Development (GDP/ infant mortality rate)	No moderating role	Slettebak, 2012
Democracy	No moderating role	Theisen et al., 2011-12
	Increases climate effect	Bell and Keys, 2016
State capacity	Increases climate effect	Bell and Keys, 2016
	Decreases climate effect	Gizelis and Wooden, 2010
Population	Increases climate effect	Slettebak, 2012.
	Decreases climate effect	Theisen et al., 2011-12
Urbanization	Increases climate effect	Bell and Keys, 2016
	Increases climate effect	Bell and Keys, 2016
Mountainous terrain	Increases climate effect	Couttenier and Soubeyran, 2013

Table 1.1: Studies exploring some possible conditional mechanisms affecting the link between climate and conflict. Column 1 identifies the conditional mechanism explored by the reviewed studies; column 2 reports the direction of the mechanism; column 3 lists one example reference per type and direction of link.

Only a limited number of studies test the conditional effect of temperature on the risk of conflict. For instance, Buhaug (2010) interacts temperature anomaly with ethnopolitical exclusion and GDP per capita, but finds no support to the conditional argument. Similarly, O'Loughlin et al. (2012) finds no evidence of the effect of temperature anomaly on conflict being conditional to ethnic leadership and political rights.

Other studies test the conditional effect of rainfall levels or anomalies on the likelihood of conflict. Hendrix and Glaser (2007) interact rainfall anomaly, a measure of what they call short-term trigger, with proxies of long-term climate trends, operationalized as climate suitability for Eurasian agriculture, land degradation, and freshwater availability per capita. They find that the effect of rainfall anomalies on the onset of civil conflict in Sub-Saharan Africa is not conditioned by different ecological and natural endowments. Using an instrumental variable approach, Miguel et al. (2004) test both the direct and conditional effect of rainfall levels on conflict. The analysis finds the impact of rainfall (instrumenting income shocks) on civil conflict to be not significantly different in richer, more democratic, more ethnically diverse, or more mountainous African countries, or in countries with a range of different political institutional characteristics. By contrast, the study finds modest support to the argument that rainfall growth affects the risk of conflict via agricultural production.

Some other analyses build on the literature that investigated the impact of natural resource scarcity on conflict risk and test the conditional effect of eco-scarcity induced by climate conditions on the likelihood of violence. Raleigh and Urdal (2007) interact a measure of land degradation and water scarcity with population pressures, socio-economic conditions and governmental settings. Consistently with the Neo-Malthusian hypothesis, the analysis reveals that the interaction between eco-scarcity and population growth significantly, although modestly, increases the risk of conflict. Unexpectedly, the analysis also finds that resource scarcity has a stronger effect on conflict in wealthier states rather than in poorer countries. By contrast, institutional factors have a mediating impact on environmental-related conflicts; strong democracies and autocracies are shown to be at lower risk of conflict, confirming the existence of a U-shaped relationship between the degree of democracy and violence (Hegre et al., 2001). Consistently, Gizelis and Wooden (2010) test the conditional effect of water scarcity on the risk of conflict and find support for the argument that democratic and institutionally solid countries are less at risk of experiencing violence related to water scarcity.

The bulk of the literature testing the conditional effect of climate on conflict uses drought indicators as measure of climate variability. Von Uexkull et al. (2016) use remote-sensing data to investigate how droughts occurring in the growing season impact ethnic conflict. They find that, although drought is a poor predictor of conflict when controlling for socio-economic conditions, it has a more destabilizing impact on agriculturally dependent and politically excluded groups in poor countries. Von Uexkull (2014) similarly show the effect of droughts to be higher in regions dependent on rainfed agriculture.

Couttenier and Soubeyran (2013) investigates the effects of interactions between drought and country characteristics on the risk of civil war. They find that relatively poor countries are as prone to civil conflict when hit by droughts than relatively wealthy ones. Countries with more ethnic fractionalization, lower levels of democracy, and higher share of mountainous terrain are instead more prone to conflict when experiencing droughts. These results contradict the findings of a previous analysis by Theisen et al. (2011-12) which found no effect, either direct or conditional, of drought on the onset of conflict; with the exclusion of population density, none of the interaction term between drought and different socio-economic, political, ethnic, or institutional conditions is found to be significant.

A more recent study by Bell and Keys (2016) tests the conditional impact of drought on conflict in Sub-Saharan Africa. Surprisingly, the analysis find that droughts are more likely to lead to conflict in more stable societies, characterized by better living conditions, greater food security, larger-enduring governments, inclusive political systems, smaller rural populations, and longer histories of peace. A possible explanation to these counter-intuitive findings lays in the so-called "endowment effect" theorized by behavioural economists; the higher the value of the perceived status quo, the higher the destabilizing effect of the shock; in other words, the more a society has to lose, the higher the risk of conflict induced by climatic adversities (Bell and Keys, 2016).

Another possible interpretation of droughts being a "risk equalizer" across stable and solid versus unstable and divided societies would back the argument advanced by disaster sociology (Durkheim, 1956; Fritz, 1996), which claims that harsh conditions trigger a sense of solidarity and unity, while reducing the strength of societal divides that may otherwise lead to violence.

Building on the tradition of disaster sociology, some studies also investigate the conditional

Indirect link	Direction	Study
Natural resource scarcity	Increases climate effect	Eastin, 2016
	Decreases climate effect	Salehyan and Hendrix, 2014
	Unlikely impact	Bernauer and Sigfried, 2012
Food-related shocks	Increases climate effect	Raleigh et al., 2015
Local livelihood deterioration	Increases climate effect	Harari and La Ferrara, 2018
	No impact	Bollfrass and Shaver, 2015
Income shocks	Increases climate effect	Miguel et al., 2004
	No impact	Koubi et al., 2012
Migration	No impact	Cattaneo and Bosetti, 2017

Table 1.2: Studies exploring some possible indirect links between climate and conflict. Column 1 identifies the indirect mechanism explored by the reviewed studies; column 2 reports the direction of the mechanism; column 3 lists one example reference per type and direction of link.

impact of natural disasters on conflict. For instance, Slettebak (2013) consistently find that countries experiencing disasters are less likely to face conflicts, but the risk of violence is higher in highly populated countries. While the interaction term for population is significant in the model, the effect of disasters on conflict does not vary in poorer countries and authoritarian regimes. Contrasting the findings of the above studies, Schleussner et al. (2016) detect no general and global effect of natural disasters on conflict, but find that the destabilizing effect of natural hazards is significantly more likely in highly ethnically fractionalized societies.

1.2.2 Indirect pathways

The second and complementary approach to studying more nuanced climate-conflict links reflected in current scholarship reframes the nexus as a multi-stage pathway, usually examined through instrumentation or two-stage statistical modeling. The mechanisms that have received most attention to date are the following: resource scarcity, agricultural livelihood and food-related shocks, income and changes in economic conditions, and migration (Figure 1.2). Table 1.2 summarizes the main evidence supporting each of these mechanisms.

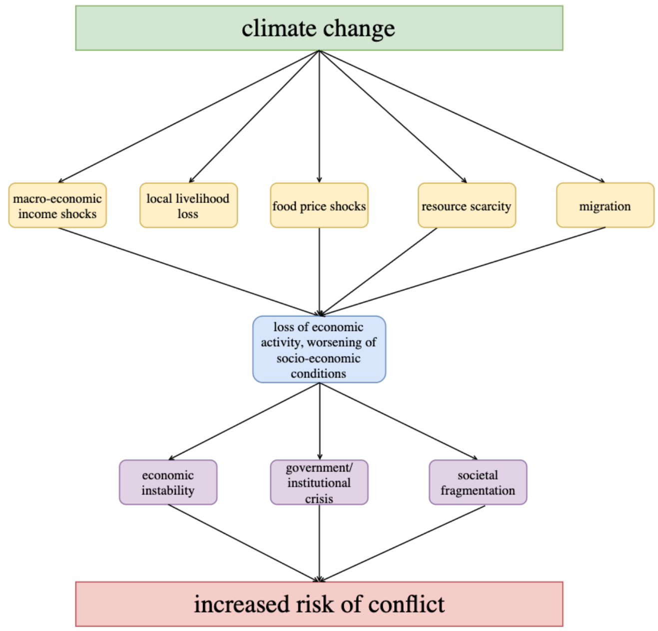

Figure 1.2: Possible indirect pathways from climate change to conflict (adapted from Theisen et al., 2012).

Natural resource scarcity

Climate change is likely to affect the quality and quantity of natural resources and determine resource scarcity in many regions of the world (IPCC, 2014), especially in ecologically fragile regions as well as where resource management and land use policies are poorly developed. Resource scarcity, in turn, can spur conflict through several pathways: triggering destabilizing migration flows (Reuveny, 2007), lowering the opportunity costs of fighting (Eastin, 2016), and accentuating popular grievances that people become willing to act upon (Homer-Dixon, 1999). On the other hand, as conflict is costly, the vulnerability resulting from resource deprivation can decrease both individuals' willingness and opportunity to join rebel groups (Salehyan and Hendrix, 2014).

Not surprisingly due to the predicted impact of climate change on freshwater resources (Bates et al., 2008; Jiménez Cisneros et al., 2014), the main focus of this branch of the literature is on water. Analysts of water issues generally predict a raise in hydro-political tensions due to the adverse consequences of climate change and the increased variability in the access to freshwater (Farinosi et al., 2018; De Stefano et al., 2017).

However, the link between climate, resource scarcity and conflict may be attenuated by institutions, which can mitigate the odds of violence by promoting adaptation and cooperation (Wolf et al., 2003; Yoffe et al., 2004; Tir and Stinnett, 2012). As climate change impact to natural resources is likely to manifest through slow, long-term variations, governments can have enough time to enforce cooperative agreements and institutions to promote an efficient adaptation to resource scarcity (Bernauer and Siegfried, 2012).

Food-related shocks

Climate change is likely to decrease food production and will especially threaten food security in developing countries, whereby governments may lack resources to implement adequate adaptation measures (Rosenzweig and Perry, 1994; Lobell et al., 2008). Climate driven food scarcity may generate grievances or exacerbate already existing ones (Malthus, 1798); deepen inequalities and social fragmentation (Jones et al., 2017); destabilize political settings by increasing the volatility of food prices and making developing countries more dependent on food imports (Hendrix and Haggard, 2015) and reduce the perceived opportunity costs of violence (Brinkman and Hendrix, 2011). On the other hand, also the wealth of food resources may trigger looting strategies and result in higher levels of violence, as combatants rely on local agricultural resources for sustenance (Koren and Bagozzi, 2017).

Studies of this mechanism tend to operationalize climate variability in terms of rainfall anomaly, due to the relevance of precipitation for food production. Raleigh et al. (2015) find that lower than expected levels of rainfall, as well as droughts, during the preceding months indirectly increase conflict through its impact on food price. By contrast, Koren and Bagozzi (2017) find that increased levels of rainfall, rather than drier conditions, are positively associated with violence against civilians. Yet, the link between climate-induced food shocks and conflict is likely to be moderated by multiple factors: Raleigh and co-authors (2015) also show that the relationship is complicated by loop feedbacks, as conflicts reversely have a detrimental effect on food security, and conditional to socio-economic and political factors, as more democratic and wealthier regions are less likely to experience food-related violence. Hendrix and Haggard (2015), instead show that the negative effect of global food prices on protests and riots is higher in democracies than in autocracies, due to the windows of opportunities opened by more democratic countries.

Jones and co-authors (2017) models food insecurity as the conjunct product of climatic shocks (both short-term precipitation fluctuations and rainfall deviations from the long-term mean) and instable global prices and find that climate-induced food insecurity raises the risk of conflict, although the negative impact of weather shocks is counterbalanced by state capacity and governance.

The impact of food security on violence is further complicated by spillover effects spreading through global commodity markets. For instance, Sternberg (2012) uses the Standard Precipitation Index (SPI) to track the 2011 drought in the wheat-growing region of eastern China and argues that the raise in bread prices resulting from the Chinese drought propagated to Egypt and contributed to trigger the mobilizations in the Arab Spring.

Macro-economic income shocks

One possible pathway linking climate variability to conflict runs through negative macro-economic income shocks. Although there is ample empirical evidence linking poor economic conditions to higher rates of civil conflict (Collier and Hoffler, 2004; Fearon and Laitin, 2003; Hegre and Sambanis, 2006), the evidence of a link between climate-induced economic shocks and conflict is debated.

As the first real test of this pathway (although within the context of using exogenous instruments for economic shock rather than assessing the influence of climate variability per se), Miguel et al. (2004) found that lower levels of interannual rainfall reduce economic growth, which in turn is associated with an increased risk of civil conflict.

By contrast, Ciccone (2011) fails to detect a robust link between interannual growth in precipitation and civil conflict, arguing that past research has failed to account for the mean-reverting nature of rainfall patterns, whereas Jensen and Gleditsch (2009) report that the results in Miguel et al. (2004) appear to be driven by their particular definition of the sample. More recent studies similarly conclude on a weak moderating role of macro-economic performance. For example, Koubi et al. (2012) find no support for the hypothesis that climatic variability increases the risk of conflict by depressing economic growth. Relatedly, Buhaug et al. (2015), who consider the agricultural sector specifically, conclude that loss of revenues from food production does not seem to transmit adverse drought impacts into increased risk of violent conflict. This non-finding is corroborated by Van Weezel (2015), who report weak and inconsistent effects of rainfall on conflict onset through both the agricultural and the industrial sector. Again, Bergholt and Lujala (2012), who uses an instrumental variable strategy, do not find any evidence that economic shocks caused by natural disasters have an effect on conflict onset, although they confirm their detrimental consequences for growth.

This mixed and mostly weak evidence may be partially driven by the complex, multi-directional nature of the relationship: climatic variables, economic growth and civil conflict are inherently endogenous and mutually related, and isolating and understanding the role played by each factor is challenging (Dell et al., 2012; Devitt and Tol, 2012).

Rural livelihood and agriculture

An other possible indirect pathway links climate to conflict through adverse impacts on agricultural production and rural livelihoods at the local level. Climatic variations may cause crop failures, reduce income from food production, threaten food security, and in other ways hurt the local economy and thus sow the seed of conflict via various mechanisms: by lowering the opportunity costs of joining rebel groups (Busby, 2018); by increasing the chances to recruit fighters among deprived farmers (Wischnath and Buhaug, 2014); by pushing deprived communities to mobilize for advancing their social grievances (Hendrix and Brinkman, 2013); or by inducing outmigration towards urban areas (Bollfrass and Shaver, 2015).

Most of the studies of this pathway isolate the effect of climate change on agriculture by temporally circumscribing the sample to the growing season. For instance, Harari and La Ferrara (2018) construct specific indicators for drought during the growing season and find evidence that agricultural failures drive the local relationship between climate conditions and conflict episodes, while climatic shocks occurring outside the growing season have no impact on conflict dynamics.

Similarly, von Uexkull et al. (2016) use remote-sensing data to investigate how droughts occurring in the growing season impact ethnic conflict. They find that, although drought is a poor predictor of conflict when controlling for socio-economic conditions, it has a more destabilizing impact on agriculturally dependent and politically excluded groups in poor countries. Von Uexkull (2014) similarly show the effect of droughts to be higher in regions dependent on rainfed agriculture.

Using temperature variations as a measure of climatic conditions, Jun (2017) finds evidence that a high temperature during maize growing season reduces the crop's yield in Sub-Saharan Africa, which in turn increases the incidence of civil conflict. By contrast, Bollfrass and Shaver (2015) cast doubt on the alleged indirect channel at the subnational level, showing that the link between temperature variation and conflict is significantly positive for both regions that experience fluctuations in agricultural output and those which do not exhibit any variation.

Forced migration

A final proposed indirect pathway that has been subject to significant scrutiny links climate variability to conflict through migration. Extreme weather events frequently trigger forced displacement, and degradation in response to gradual climate change may also motivate exodus from increasingly uninhabitable areas (Gleditsch et al., 2007). On the other hand, as migration is costly, the consequences of climatic shocks may stress highly vulnerable populations to the point they get "trapped" (Nawrotzki and DeWaard, 2018).

As such, the link between climate-induced migration and conflict is far from deterministic and rather conditional to a number of factors relating to societal vulnerability, particularly the role of the state (Suhrke, 1997), the local economic context (Bates, 2002), the existence of participatory resource management regimes (Martin, 2005), the conditions in potential receiving regions, as well as familiar and social boundaries (Brzoska and Fröhlich, 2016). A proper understanding of the complex linkages and feedbacks involved in this nexus therefore requires adequate consideration of the adaptation options available to tackle vulnerability (Perch-Nielsen et al., 2008).

Insufficient data on environmental migration flows have so far hampered a thorough empirical assessment of the security implications emanating from environmentally induced migration (Warnecke et al., 2010). In an attempt to counteract the lack of data on migration, Cattaneo and Bosetti (2017) empirically derives an estimate of climate-induced migrant flows. The study detects no significant relationship between the presence of international climate migrants and conflict in destination countries. However, the non-findings may be driven by the construction of the indicator for migration; isolating the effect of climate on the decision to migrate is problematic, especially in the case of cross-national or global analyses (Raleigh et al., 2008; Werz and Conley, 2012).

Moreover, migration decisions often mirror individual perceptions other than objective risks. Koubi et al. (2016) relies on survey data to examine whether and how individual perceptions of different types of environmental stressors induce internal migration in Vietnam. The results suggest that perceptions of long-term environmental events, such as droughts, significantly discourage migration, while perceptions of sudden-onset environmental events, akin floods, significantly enhance outmigration.

An additional challenge is due to the multidirectional nature of this link; if migration can trigger hostility in the receiving communities, conflict is also likely to drive migration. Recent studies by Missirian and Schlenker (2017) and Abel et al. (2019) propose the existence of a two-stage mechanism whose causality runs from climate-induced droughts to conflict and, as a second step, from conflict to outflows of asylum seekers.

1.3 Conclusions and way forward

There are many reasons to be worried about climate change and there is no shortage of alarming statements about how climatic conditions and events will be a dominant cause of conflicts and wars in the future (Dyer, 2009; Welzer 2012). Indeed, some have even connected contemporary conflict events to adverse climatic conditions (Gleick, 2014; Kelley et al., 2015). Yet, as articulated in this review, the conclusions of the scientific literature exhort us to exercise caution when discussing security implications of climate change. The first wave of empirical studies, which considered a direct and sweeping climate effect on conflict largely failed to uncover robust evidence linking the two. More recent investigations, which increasingly adopt theoretically informed research designs that propose more nuanced, conditional and indirect pathways, still have not converged on a robust, context-sensitive statistical association. This lack of a robust evidence does not necessarily mean that the influence of climate change on conflict is exactly zero, nor does it mean that social sensitivity to climatic events cannot increase in the future. A key challenge for future research is to delve deeper into the complexities surrounding nature-society dynamics and refine existing theoretical and methodological frameworks to better understand this complex nexus. Here, we suggest some possible research avenues and present the main challenges that await future scholars.

First, the link between climate variability and conflict is, by no means, deterministic. Future work should build on existing results to theorize and test the numerous steps of this multi-stage process and gain a better understanding of the role played by different socio-economic and physical factors in influencing the relationship between climate and conflict.

Clarifying the direction of the complex linkages intertwining climate, conflict and other conditioning factors may help answer questions of conflict recurrence and explain the persistence of conflict "traps". This involves a careful consideration of numerous methodological issues, not the least endogeneity and reverse causality, which complicates determining strength and direction of the dominant pathway in the relationship. For instance, whether climate has an impact on conflict risk through economic conditions, or rather undermines security, and therefore depresses economic growth, it is often hard to tell from empirical investigations.

Comprehensive research programs that are able to combine case-studies with comparative analyses, and to feature a number of approaches that range from qualitative in-depth analysis to quantitative and generalizable analyses at a global scale, may contribute to achieve a better understanding of the mechanisms at play (Ide, 2017). In this perspective, the information provided by theoretical models may inform the construction of survey-based, case-oriented studies, and the knowledge acquired through local results can lay the ground for further theorization and generalization through empirical analyses.

Second, the empirical literature has so far focused mainly on civil conflict, although a few studies attempt to investigate other types of violence, including social conflict, riots and protests (e.g. Meier et al., 2007; Scheffran et al., 2012; Hendrix and Salehyan, 2012; Fjelde and von Uexkull, 2012). Expanding the focus to include different types of violence may advance the existing knowledge on security and inform more efficient adaptation measures. In particular, learning more about how climatic conditions and events shape livelihood security and social cohesion on the ground is essential if we are to understand when, why, and under what conditions, adverse social impacts translate into overt social conflict. Moreover, new, unexpected forms of conflict may raise in the future due to socio-economic transformations; the pervasive application of artificial intelligence in ordinary life, which is likely to exclude low-skilled workers from the labor market; the increasing availability of "big data"; the demographic pressures induced by population ageing and migratory patterns; the advance of technological changes which can boost energy efficiency and eradicate previous energy sources are only a few patterns which can sow the seed of change and potentially disclose unprecedented forms of discontent.

In this transitory environment, the attempt to forecast the outbreak of conflict may seem a foolish undertaking. However, the instability that potentially arise from socio-economic, physical and climatic changes can be offset by the design of efficient institutions and the implementation of participatory, inclusive frameworks aimed to increase societal resilience, enforce early warning systems and set up adequate coping mechanisms. Policies of this kind strongly need the support of solid research aimed at offering guidance to decision-makers, and capable of exhorting urgent action when needed, while avoiding alarmist threats. Aided by the increasing improvement in data availability and technology, future research should therefore increase the effort to forecast the risk of conflict in the short and long-term future (cf. Hegre et al. 2016).

Finally, increased research efforts should be invested in understanding the implications of climate change for positive peace, beyond the mere absence of conflict. While the bulk of research has focused on conflictual outcomes, there is a need to understand the consequences that fostering peace and security in conflictual areas can have on food security, migration, resource quantity and quality, economic growth and governmental stability. By improving socio-economic conditions and fostering development, peace and stability may in fact improve populations' ability to adapt to climate change impacts and decrease their vulnerability to environmental hardships. The measures put in place to adapt to climate change and the actions enforced to prevent conflict may be, in some cases, complementary; increasing education levels, for instance, may reduce the probability of conflict (Hegre and Sambanis, 2006), while raising environmental awareness and promoting adaptation to environmental stresses (Luthans, 2006). On the other hand, adaptation to climate variability may superimpose societal transformations that are costly, abrupt or radical, and thus may higher the chance of violence. As an example, big infrastructure projects such as dams or bridges may contribute to adapt to climate shocks (Bachner, 2017), but may also have huge economic and social costs, detrimental of population welfare (Flyvbjerg et al., 2003) and thus have a negative impact on stability.

A key focus of future research should therefore be placed in clarifying the role that socio-economic factors can play in promoting adaptation both to conflict and to climate variability, with a view to better understand the security implications of adapting to climate change, and to discover possible complementarities and mutual benefits between measures undertaken to adapt to climate change and conflict-prevention strategies[*].

[*] An adapted version of the chapter, co-authored with Halvard Buhaug, is to be published as part of "The Routledge Handbook of Peace, Security and Development" (Routledge, forthcoming).

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Whiskey is for drinking—water is for fighting.

Mark Twain

2

Natural Resources and Conflict: A Meta-Analysis of the Empirical Literature

Conflicts in developing countries represent one of the major threats to global security in the twenty-first century. Although the number of international wars has steadily declined since 1945 (Pettersson and Wallensteen, 2015), 52 conflicts were still active in 2018, leading to 52000 fatalities (Strand et al., 2018). After the decline in the number of conflicts following the end of the Cold War, the number of major civil wars has almost tripled in the past decade, while associated battle-related deaths rose from four to eleven times in 2015 (Einsiedel et al., 2017).

A considerable part of the academic literature in recent years has been trying to unravel the Gordian knot that links climate and conflict (Dell et al., 2014; Salehyan, 2014; Buhaug et al., 2015). However, there is still a need to systematically investigate how climate may possibly influence conflicts (Hsiang et al., 2013; Adger et al., 2015). Resource availability has been identified as one of the possible channels through which climate may impact conflict risk (Raleigh and Urdal, 2007; Hsiang et al., 2013; Buhaug et al., 2015).

This paper conducts a meta-analysis of the literature on natural resources and conflict, with a view to clarifying whether there is evidence of a relationship between natural resource abundance or scarcity and violence, and whether this relationship is conditioned by climate. While our study is similar to O'Brochta (2019) in the methodology, we advance the literature by including resource scarcity, along with abundance, as a potential driver of conflict and investigate the factors that influence the relationship between natural resources and violent outcomes. Specifically, a major contribution of the present study is to analyze the role of climate in affecting the link between renewable natural resources and conflict.

Climate is strongly intertwined with the availability and distribution of natural goods, and climate variability is likely to have a strong impact on the quantity and quality of resource endowments such as freshwater, arable land, and vegetation (Jiménez Cisneros et al., 2014; Porter et al., 2014). Changing climatic conditions may affect the global and local distribution of resources, increasing the availability of primary goods in some regions of the world and decreasing it in others (IPCC, 2014). As climate-induced shocks to natural resource quantity and allocation are likely to affect stability, natural resources may represent a pathway connecting climate variability to conflict (Raleigh and Urdal, 2007; Hsiang et al., 2013; Buhaug et al., 2015). Building on these considerations, this paper quantitatively reviews the empirical literature to understand how resources are related to conflict and if climatic stressors such as temperature and precipitation affect this relationship.

A rapidly growing literature currently investigates the impact of weather shocks and climate change-driven temperatures and rainfall anomalies on the risk of conflict (Gleditsch, 2012; Hsiang et al., 2013; Hsiang and Burke, 2014; Hsiang et al., 2014; Buhaug et al., 2015; Buhaug, 2016). In our quantitative review, we do not focus directly on climate-change related studies, but we aim to understand whether climatic parameters influence the relationship between natural resources and conflict, and hence, to clarify whether climate variability can potentially increase the risk of conflict indirectly through natural resources.

Although extensive reviews have surveyed the literature on natural resources or more generally, environmental factors and conflict (Nillesen and Bulte, 2014; Mildner et al., 2011; Gleditsch, 2012; Cuvelier et al., 2014; Dell et al., 2014; Gleditsch, 2012) and a number of meta-regression analyses has recently addressed the literature on the climate-conflict nexus (Hsiang et a., 2013; Buhaug et al., 2014; Hsiang et al., 2014), to the best of our knowledge, only a recent study by O'Brochta (2019) has targeted the link between natural resource abundance and conflict. However, O'Brochta (2019) is limited to resource wealth and does not investigate the role of climate in affecting the relationship. Our study is the first attempt to quantitatively systematize the entire empirical literature on the link between natural resources abundance/scarcity and security issues, and to assess the role of multiple factors, including climate, in influencing this relationship.

The remainder of this paper is organized as follows; first, we review the main mechanisms leading from natural resource abundance or scarcity to conflict; next, we present the methodology and materials; the final part summarizes the results and concludes.

2.0.1 Linking natural resources to conflict risk

The relationship between natural resources and conflict can be viewed in two stylized manners; one possible pathway links the scarcity of a resource to increased odds of violence, while the other connects the abundance of natural goods to security threats. Traditionally, "neo-Malthusians" and political ecologists have supported the first hypothesis, while neo-classical economists have argued in favor of the second (Figure 2.1).

On the one hand, resource wealth may trigger looting and create incentives for profit-seeking groups to mobilize and fight for seizing natural goods. In this perspective, individuals will be prone to fight for "greed", as opposed to the traditional motives of creed and need (Collier and Hoffler, 1998). Once looted, profitable resources can be traded to finance conflicts (Nillesen and Bulte, 2014); hence, marginalized groups have low opportunity costs of joining the fight, compared to the better prospect for personal enrichment through resource looting (Collier and Hoffler, 1998; Collier et al., 2008; Fjelde and von Uexkull, 2012).

Also, resource rents may boost political corruption, slow the economic growth, and enhance related "development pathologies" (Kahl, 2006, p. 15), which in turn can fuel societal grievances (Figure 2.1). Resource-rich states may have an incentive to operate according to "rentier logics", leading to widespread corruption, lack of transparency, poor rule of

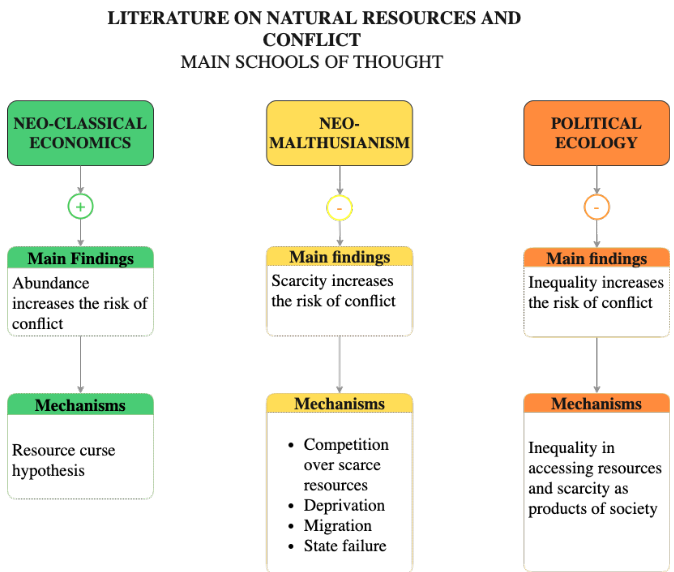

Figure 2.1: Schools of thought within the literature on natural resources and conflict.

law, and weak institutions (Fearon and Latin, 2003; Basedau and Lay, 2009; Ross, 2013; Bayramov, 2018). Moreover, the natural resources sector can steal capital from other economic sectors that could have positive externalities, inducing the so-called "Dutch disease" (Mehlum, Moene and Torvik, 2006; Robinson, Torvik and Verdier, 2006) and slowing economic growth (Sachs and Warner, 2001).

On the other hand, resource scarcity can encourage political turmoil, especially when occurring in fragile contexts characterized by demographic pressures and economic insecurities (Raleigh and Urdal, 2007; Almer et al., 2017). Absolute or relative deprivation, driven by supply contraction and environmental degradation or by demand increase, may trigger competition of poor people over increasingly scarce resources and encourage conflicts, as well as rebellions against the government (Hauge and Ellingsen, 1998; Percival and Homer-Dixon, 1998).

Demographic pressures and environmental changes are also likely to increase inequality and societal fragmentation by widening the existing gaps between rich and poor and deteriorating economic conditions (Homer-Dixon, 1999). Moreover, resource scarcity can trigger food crises and induce livelihood deterioration that forces people to migrate from the most vulnerable areas in a quest for better living conditions (Adger et al., 2015). For instance, Dallmann and Millock find that drought frequency in the origin location increases within-country migration in India, especially in agricultural states (Dallmann and Millock, 2019). Meze-Hausken (2000) shows that, in Ethiopia, household heads are likely to emigrate from dry areas as a response to drought-related famines; Feng and co-authors (2010) prove that a decrease in crop production is causally related with the decision to migrate from Mexico to the United States. Water scarcity is also associated with increasing migration flows: for example, persistent droughts in the Sahel in the 1950s significantly encouraged outmigration (Scheffran et al., 2012), although environmental changes are more likely to affect regional migration within country borders rather than inter-national migration flows (Millock, 2015).

By lowering agricultural production and slowing economic growth, while increasing societal discontent, resource scarcity can destabilize political and institutional settings, whereby governments may lack adequate resources to address popular dissatisfaction (e.g. Gleick, 2014). Violence can thus result from a combination of population growth, resource depletion and disrupted state authority that escalates to intra-elite competition (Homer-Dixon, 1999).

Finally, resource scarcity may be exasperated by the persistence of structural factors rooted in larger processes of material transformation and power relations. Socio-political dynamics steeped in human constructs define the entitlements by which individuals or communities get access to resources in different political economies (Peluso and Watts, 2001; Benjaminsen, 2008); as a result, even if endowed with an abundance of natural goods, poor and indigenous communities may be subject to scarcities for distributional reasons, related to how political economies structure the access to resources (Kahl, 2006).

When reviewing this literature, we may be prone to think that the studies that focus on abundance of natural resources and analyses of resource scarcity are not comparable, as they are examining different mechanisms and driven by different types of resources. However, as illustrated in Figure 2.2, the dynamics activated by abundance and scarcity of a resource often intertwine. Moreover, the intuition that the resource curse is activated only by highly-profitable resources akin minerals, while renewables can impact conflict only if scarce, is often contradicted by scientific evidence, as studies unexpectedly find that the abundance rather than the scarcity of renewable resources, such as water, land and vegetation, is linked to conflictual outcomes (Brown, 2010; Hendrix and Salehyan, 2012; Theisen, 2012). Evidence from case studies also supports the argument that wet seasons, when pasture and water are abundant and when the livestock is in good health, are associated with higher risks of violent episodes such as cattle raiding (Witsenburg and Adano, 2009).

The present study therefore aims at being broad enough to consider different types of resources (both renewables and non-renewables) and differing distributive patterns (both resource abundance and scarcity) as potential causes of conflict, while thorough enough to carefully examine the divergencies between studies as concerns the definition of the resource variable and the type of resource under investigation. Moreover, the analysis attempts to identify the methodological choices that may impact the literature findings and contribute to explaining the divergence within the academic community.

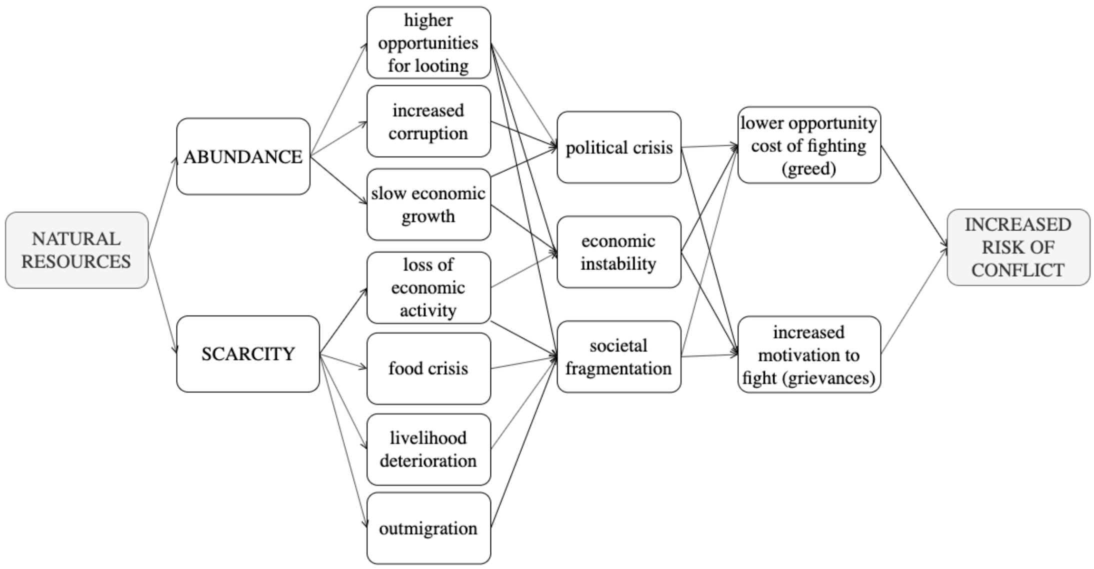

Figure 2.2: Main pathways connecting natural resources to conflict risk.

Specifically, our meta-analysis evaluates the role of three sets of factors leading to divergent findings in the literature. First, we aim to understand whether differences in research design and methods drive the results. The specification of the regression model, the sample selection, the inclusion or exclusion of some control variables, and the choice of employing location or time fixed-effects are all expected to influence the relationship between natural resources and conflict risk. The sample selection represents a critical factor, since it is a measure of the extent to which a study's results can be generalized and considered to be valid across a wider population (Adams et al., 2018). While the findings of a global analysis can have a considerable degree of generalizability, results from a case-study conducted at a national scale are barely generalizable.

Second, we examine if the operationalization of the dependent variable affects the results reported. The definition of conflict is generally associated with violence but may also include non-violent outcomes. Some authors, particularly within the literature focusing on water issues, prefer a broader definition of case or event, one that encompasses both conflictual and cooperative dynamics, classified along a continuous scale of violence intensity (Wolf et al., 2003; Bring and Sjoberg, 2017; Ravnborg et al., 2012). Even when conflict is more strictly interpreted as a non-cooperative status, definitions vary with respect to the number of casualties or deaths that need to occur in order to categorize the event as a conflict. The most commonly adopted thresholds are either a thousand or twenty-five battle-related deaths, corresponding to the coding system adopted by the UCDP/PRIO dataset (Sundberg and Melander, 2003). The choice of the threshold to define conflicts has considerable potential to affect the results, as limiting the definition to the one thousand battle-related deaths would not only exclude all the minor violent events but may also result in a possible intermittent admission and exclusion of the same conflict into the dataset along the time span considered. Moreover, we can expect that natural resources have an influence on the probability of small conflicts but less so on wars. For instance, an unexpected reduction in water availability will negatively affect yields and result in a deterioration of rural livelihoods that in turn may fuel riots, although it is not necessarily going to escalate into war (von Uexkull et al., 2016).

Third, we expect that the measurement of natural resources availability/scarcity will influence results (Brunnschweiler and Bulte, 2008; Salehyan, 2014). A tradition of the literature investigating the link between resources and conflict has specified resources as the ratio of primary commodity exports over GDP (Collier and Hoffler, 1998; Fearon and Laitin, 2003; De Soysa and Neumeyer, 2007). However, as claimed by Brunnschweiler and Bulte (2008), this specification of the independent variable is endogenous to conflict and captures the dependence of economies on natural goods rather than resource availability. Moreover, Brunnschweiler and Bulte (2008) have demonstrated that the connection between resources and conflict disappears when the independent variable is operationalized as stock, and thus the endogeneity problem is addressed.

The type of resource can also have an impact on results. Profitable resources such as minerals, diamonds, gems, hydrocarbons, and drugs, have been generally associated with the resource curse (Humphreys et al., 2005; Lujala, et al., 2005; Lujala, 2009), while renewables tend to be connected to the neo-Malthusian argument (Samset, 2009). However, the distinction is not straightforward and assuming that the resource curse is activated only by minerals and lootable resources, while renewable resources can be connected to conflict only through scarcity is, at least, simplistic. In fact, while there is anecdotal evidence for the claim that land or water scarcity are potential drivers of conflict, rigorous empirical research is still inconclusive (Gartzke and Bohmelt, 2015; Benjaminsen, 2008; Van Leeuwen and Van der Haar, 2016).

A further specification points to the lootability of resources, i.e. the degree to which resources can be expropriated. The easier it is to loot a resource, the less capital intensive the process of extracting it, and the higher market value it has (McNeish, 2012). For instance, Welsch (2008) predicts that the probability of armed conflict varies directly with the size and value of 'lootable' resource allocation and inversely with variables that increase labour productivity. The author argues that, unlike mineral resources, abundance of agricultural resources reduces the probability of conflict by raising labour productivity (Welsch, 2008).

A possible driver of differences in results across studies could be temporal lags, as unlike non-renewable resources, renewables such as freshwater and land are intertwined with agricultural productivity. Hence, exogenous shocks to resource availability may have a mediated impact, following the seasonality of crop growth (see, for instance, Harari and La Ferrara, 2018; von Uexkull et al., 2016). Including or excluding temporal lags may have an impact on studies' results. Therefore, we investigate how the indicator chosen as proxy for resources impacts the study's findings.

Finally, we assess whether the studies' findings are driven by publication bias, which arises when studies with relevant and significant results are more likely to be published. In fact, the tendency of authors or editors not to publish non-significant results may bias findings on the distribution of effects (Klomp and Valckx, 2014).

2.1 Materials and Methods

2.1.1 Methodology: meta-analysis

A meta-analysis is a statistical combination of results from multiple studies to answer a common question (Bowman, 2012). It involves the pooling of data that quantitatively examine whether causal relations described in individual papers remain valid across a wider spectrum of the literature (Romero-Lankao et al., 2012). Although well-rooted in the health sciences, meta-analysis has only recently started to be applied in climate change research. Unlike traditional literature reviews, meta-analyses require reviewing and selecting documents according to systematic, and explicit criteria; they need to include a detailed description of the review procedures employed (e.g. databases searched, articles excluded, search terms used) in order to facilitate study replication, and they adopt statistical techniques to summarize the results of the selected studies (Ford et al., 2011).

2.1.2 Selection of articles and definition of the sample

The selection of articles aims at being as broad as possible. As a first step, we input the selected keywords (environ* and conflict, climate and conflict, natural resource* and conflict, resource* and conflict, land and conflict, water and conflict, scarcity and conflict, abundance and conflict, crop and conflict) into three databases, screening study title, abstract, and keywords: EBSCO, Scopus and Web of Knowledge. The search returned 660 articles (the Appendix provides additional information). A first screening of titles and abstracts resulted in an exclusion of 511 studies. Studies were classified as "included", "excluded", and "uncertain"; those falling into the last category were reviewed independently by the authors and either included or excluded by common decision. As a next step, we examined the remaining articles and categorized them as quantitative or qualitative. Finally, the articles classified as quantitative were assessed in-depth to verify their eligibility according to the following criteria.

1. Articles were required to focus on both natural resources and human conflict, i.e. the objective of the analysis. Articles dealing with other types of conflicts, such as conflicts between other living species or wilderness, were excluded.

2. Articles focusing specifically on methods and frameworks for providing solutions to resource-related conflicts were passed over. Furthermore, studies that test the link between climatic variables (e.g. precipitation) and conflict were included only if the authors consider the variables of interest as a proxy of natural resources (e.g. water).

3. Articles investigating the inverse relationship (from conflict to the environment) were excluded. Quantitative studies were required to report regression results. Studies that,

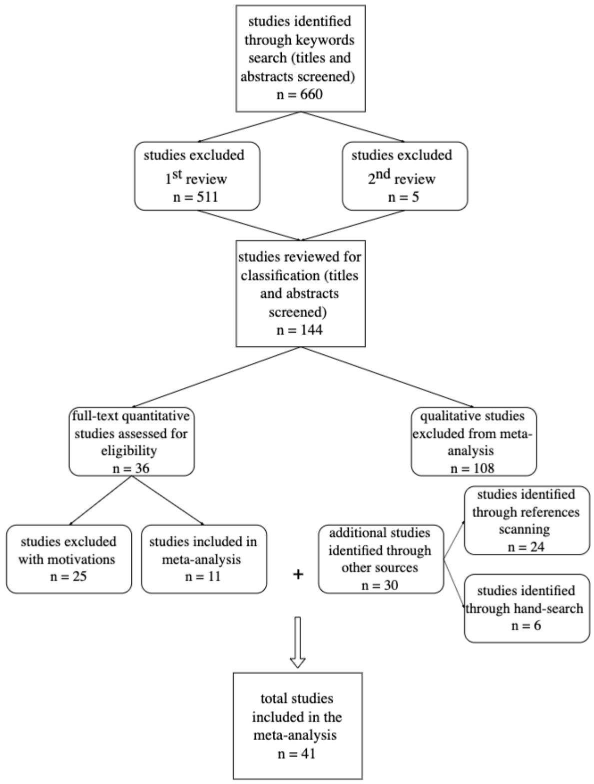

Figure 2.3: Process of articles' selection.

despite adopting a quantitative or semi-quantitative method, did not report statistical coefficients and t-statistics (or standard errors) were excluded from the analysis. Table S.2.2 reports the studies that were excluded from the original selection after this in-depth analysis.

Finally, we expanded the sample by reviewing the references of the selected papers as well as some other systematic reviews (Gleditsch, 2012; Cuvelier et al., 2014 and Dell et al., 2014) to ensure the inclusion of all relevant studies. The overall selection process identified 41 papers.

Studies differ in the way they define both the resource and the conflict variable. As a result, the interpretation of the regression coefficients, i.e. the estimate of the effect that natural resources exert on conflict, is not homogeneous across studies and varies according to the models specifications and the operationalization of the main variables. In order to ease the comprehension and the comparability of the coefficients across different studies, as well as to understand the different mechanisms leading from resources to conflict, we clustered the sample according to the specification of the main independent variable as resource abundance or scarcity.

Moreover, as the definition of conflict varies across studies, we have included a dummy variable to capture different specifications of the predicted outcome. Conflict onset indicates the outbreak of conflict and the dependent variable is coded as 1 if a conflict starts in year (or period) t, and otherwise 0. Incidence defines the occurrence of conflict and signals if a location is experiencing a conflict at time t, without consideration of when it started. Regarding these two specifications, coefficients are interpreted as probabilities – they represent the marginal change in the probability of conflict onset (incidence) due to a one-unit increase in the resource variable. Conflict intensity is a broader category that is generally intended as a measurement of violence and may encompass the frequency, duration, or severity of conflict.

This division of the sample into subsets resulted in the reduction in the number of observations available for each regression. This choice is motivated by two main factors; one is purely methodological, the other one is related to the research goals of the chapter. First, in the empirical model, natural resource abundance/scarcity represents the main meta-regressor, whose effect on conflict is encapsulated in the statistical coefficient. A positive and significant statistical coefficient associated with natural resource abundance suggests that higher amounts of natural resources are likely to increase the risk of conflict, while a positive and significant coefficient associated with natural resource scarcity implies that lower amounts of a resource are associated with conflict. It is evident that the two statistical coefficients are not strictly comparable, as the operationalization of the meta-regressor as either abundance or scarcity points to different directions of the relationship. Performing the meta-analysis for the full sample would therefore break the assumption of cross-comparability that lays at the foundation of the meta-analytic study.

As a consequence, disregarding the divergences across studies and conducting the meta-regression on the basis of the full sample would result in inconsistent and non-comparable results, while manipulating the estimates to homogenize the effect sizes reported by studies would add further subjectivity and potential bias to the analysis (Koricheva et al., 2013). Moreover, avoiding the sample sub-setting would preempt a proper interpretation of the results, as the direction of the effect would not be retrievable from the sign of the statistical coefficients. As a key goal of the chapter is to assess the effect of both resource abundance and scarcity on conflict, sub-dividing the sample according to the operationalization of the natural resource variable enables us to correctly identify both the magnitude and the direction of the relationship between natural resource abundance/scarcity and conflict.

2.1.3 Information extraction and coding

The first step of the analysis is to extract the relevant information from the selected studies. Based on the review of the literature, we defined several fundamental categories to code the information contained in each study: dependent and independent variable, type of resource, time and space coverage, controls introduced (e.g. ethnic fractionalization), and methodology applied.

At the first stage, information was collected qualitatively under each category. The qualitative information enclosed under each category was then coded as a dummy variable, taking the value of 1 if the estimate drawn from the study presented that specific feature, and 0 if it did not. Dummy variables identify the potential independent variables of our meta-regression (Table S.2.3) although only the most relevant ones were included in the final meta-regression model. The coded binary variables identify the main methodological features that exhibit potential to affect the results.

2.1.4 Meta-regression specification

The purpose of our meta-analysis is to synthetize the magnitude and direction of the effect that natural resource abundance and scarcity have on conflict, including or excluding climate controls, to understand if climate may impact conflict through natural resource availability. To this end, we ideally need a single metric of the effect size. Recent research on meta-analytic methods argues in favour of the use of beta coefficients for this purpose (Peterson and Brown, 2005; Bowman, 2012). In this paper, we choose the standardized t-statistic as a measure of the beta coefficients reported by the studies. Whenever studies do not report t-statistics, we computed it as the ratio of the beta coefficients over the standard error. To ensure that estimates are comparable, we removed from the samples the model specifications that included interaction terms, testing for the conditional impact of the independent variable on conflict, as they are not directly comparable with the others (Klomp and Valckx, 2014). However, as robustness tests, we checked the effect of these conditional models by including them in the sample.

Similar to multiple regression analysis, meta-regressions require the assumption of independence of observations (Hox and de Leeuw, 2003). Scholars consider empirical estimates as statistically independent if they are reported by different authors or if the same author reports them but uses different samples. Estimates reported by the same study and employing the same dataset are not statistically independent (Doucouliagos and Ulubasoglu, 2006). Although estimating the model by neglecting the issue of non-independence would not necessarily produce biased results, it would affect the variance of the coefficients and hence lead to an incorrect interpretation of the significance levels. To account for these issues, some authors suggest computing the average effect size of all estimates within the same study or selecting a single estimate from each article (Lipsey and Wilson, 2001). However, these methods would result in a reduction of the sample size and require subjective selection of the single estimate to be sorted out from each study. Furthermore, these techniques would remove all within-study variation, which is a valuable source of information of potential drivers of the studies' results.

In this chapter, we adopted an unrestrained Weighted Least Square (WLS) with robust standard errors clustered at the study level to address the non-independence of observations. The unrestricted WLS is shown to be less biased than traditional meta-regression methods (fixed or random-effects models) when the reported research literature contains selection for statistical significance, i.e. 'publication' bias (Stanley and Doucouliagos, 2012), which is common in many areas of research (Sterling et al., 1995). When a selection for statistical significance exists, and as long as variances are known (as in meta-analyses), unrestricted WLS models are proven to have statistical properties at least comparable with or superior to traditional meta-analytic models such as random or fixed-effects; they are invariant to the magnitude of known or unknown heterogeneity across estimates; and retain desirable properties even when a bad estimate of variance is used (Stanley and Doucouliagos, 2017). To account for variations across studies, our WLS model clusters estimate by study and assume independence among clusters. Our meta-regression model is:

$$t_{i,t} = \beta_0 + \beta_1 \frac{1}{SE_{js}} + \beta_2 \zeta_{js} + \varepsilon_{i,t} \tag{2.1}$$

for estimates $s = 1, , j$, nested within study s. ζ_{js} represents the vector of the studies' methodological features and model specifications, i.e. the dummy variables that we coded and SE_{js} is the vector of standard errors. The coefficient estimates are obtained as:

$$\beta_n = min \sum_{j=1}^{1} W_j e_j^2 \tag{2.2}$$

with $W_j 1 = \frac{1}{SE_{js}^2}$ where β_n denotes the vector of meta-regression coefficients. In the unrestricted WLS approach, weights are calculated as the inverse of the squared standard error, rather than the inverse of the standard deviation (Davidson and MacKinnon, 2004): in this way, the approach allows but does not assume the variance between studies to differ by a proportional constant, unlike random and fixed effect models (Stanley and Doucouliagos, 2017).

In our specification, β_1 is a measure of the so-called precision, which represents the genuine relationship between natural resources and conflict found by the studies, while the constant term is a measure of the so-called publication bias (Klomp and Valckx, 2014; Stanley and Doucouliagos, 2017). Whenever we detect an association between the probability of being published and the statistical significance of the studies' results, a publication bias exists. In fact, assuming no publication bias occurs, the effect sizes should vary randomly and not be proportional to the standard errors of the estimates; conversely, if studies are published according to the significance of the results, estimates of the effect size will vary proportionally to the standard errors.

The Egger test (Egger et al., 1997) is the most commonly used test to check whether the results of a meta-analysis are genuine or driven by publication bias. It consists of regressing the measurement of the effect size against a measurement of the estimate's precision, i.e. the inverse of the standard errors, and is incorporated into our meta-regression model (eq. 2.1 - see also the Appendix). Results of the Egger test from our meta-regressions suggest that there is a significant and genuine relationship between natural resources and conflict, although this varies according to different methodological choices adopted by the studies and different types of natural resources chosen as key predictors.

2.2 Results

2.2.1 Descriptive statistics

We collected 922 estimates of standardized effect size from the 41 studies we selected. More than half of these studies are based on a global sample, while only a limited number of articles focus on single countries (Figure 2.4).

However, of all articles with a narrower focus (regional or national), 85% concentrates on Africa; this may indicate that recent findings of a "streetlight effect" in climate-conflict research (Adams et al., 2018) applies more broadly to the resources-conflict scholarship. The limited variation of the studies spatial coverage thus posits some challenges concerning the degree of generalizability of a study's results and, in our analysis, we controlled for the sample

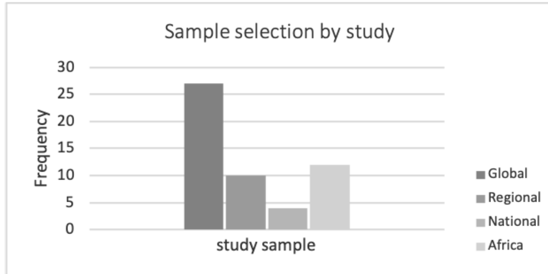

Figure 2.4: Sample selection by study: studies are classified as global, regional or national according to the spatial coverage of the analysis. "Africa" indicates whether the article focuses on the African continent, either a specific country or a cluster of African countries.

	abundance	significance	threshold	time	space	lags
No. of observations	838	343	268	206	139	70
Minimum	-56.33	-56.33	-13.64	-13.64	-13.64	-3.27
Maximum	46.83	31.72	31.72	8.57	8.57	6.38
Median	1.13	2.31	2.18	2.15	0.00	-0.95
Mean	1.24	1.55	1.40	1.22	0.62	0.30
Variance	18.00	28.23	17.35	11.04	12.64	11.07
1st quartile	-0.78	-2.02	-2.16	-2.04	-2.27	-2.39
3rd quartile	2.68	3.24	3.18	3.08	2.98	3.08

Table 2.1: Summary statistics referring to progressive reductions of the sample.

selection as a measure of the extent to which a study's findings can be generalized *.

The range of t-statistics varies considerably across studies, between -56.33 and 46.83. To provide an enhanced understanding of the drivers of the variance, we created a nested structure as illustrated in Figure S.2.1. Starting from the abundance subset, i.e. the one with the largest sample size, we progressively limited the sample according to specific methodological characteristics of the estimates. This process allows us to check for the effect of some methodological aspects on the variance: the operationalization of the dependent and independent variable, the significance level, the spatial and temporal coverage, the operationalization of

*Specifically, we included a dummy variable coded as one if studies adopt a global sample and otherwise zero. We explored the possibility of including further proxies of generalisability as regressors (e.g. regional/cross-national sample, studies limited to African countries) but, due to lack of sufficient variation and multicollinearity issues, we could not compute the coefficients for these extra variables.

indep. var.	abundance	scarcity
N	838	84
Minimum	-56.33	-10.73
Maximum	46.83	16.33
Range	103.16	27.07
Median	1.13	0.20
Mean	1.24	0.89
SE mean	0.15	0.43
Variance	18.00	15.19
1st quartile	-0.78	-1.33
3rd quartile	2.68	3.49

Table 2.2: Descriptive statistics according to the pre-defined subsets of the sample, based on the specification of the resource variable.

the conflict variable, and the inclusion of lags in the model may influence the variance of the effect size.

We find that, when limiting the sample to significant estimates (at 5% level), the variance almost doubles, possibly indicating the existence of some selection bias. By contrast, when excluding from the sample studies that choose five-year periods as their unit of analysis, the variance of the t-statistics decreases by over 30%, and when we limit the sample to studies that investigate major conflicts, defined as events causing at least one thousand battle-related deaths per year, the variance of the t-statistics decreases by almost 40%. This suggests that studies that focus on wars or major conflicts tend to find more homogeneous results than studies that investigate lower-intensity conflicts. Also, when restricting the sample to cross-national or country-level studies, we find that the variance of the t-statistics increases, indicating that non-global studies find more heterogeneous conclusions.

Moreover, excluding estimates containing lagged-terms reduces the variance of the t-statistics, possibly suggesting that the effect of natural resources on conflict is sensitive to the temporal

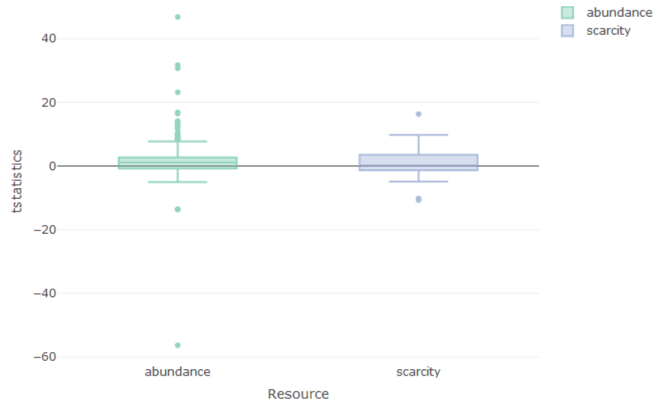

Figure 2.5: Boxplot of the t-statistics reported by studies.

span under consideration and the inclusion or exclusion of lagged coefficients.

Figure 2.5 shows that the effect of resources on conflict is generally small but positive. The average and the median values of the *t*-statistics are positive for both resource abundance and resource scarcity, although they tend to be smaller for the scarcity subset of the sample. In general, it is therefore evident (Table 2.2) that the studies collected in our sample mirror the divergency that is characterized in the literature, as the average value of the *t*-statistics suggests that conflict is associated with both abundance and scarcity of natural resources.

2.2.2 Regression results

Table 2.3 and 2.4 present the main regression results, while results for the other pre-defined subsets of the sample, along with robustness tests, are reported in the Appendix. In order to better understand the link between natural resources and conflict as well as the influence that climatic and socio-economic variables exert on this relationship, we gradually increase the set of predictors. First, we evaluate whether including different types of natural resources (water, mineral and drugs, land and vegetation), identified as key predictors, affects the literature's results about the relationship between resources and conflict.

Second, we include climatic exposure in the form of a dummy variable coded as 1 if the literature controls for climate factors (e.g. temperature, precipitation, droughts) and 0 otherwise. Table 2.3 summarizes the results of these model specifications. In Table 2.4 we focus on the abundance-conflict subset of the sample; we include all types of natural resources in the same model specification (column 1) and then introduce the climate controls (column 2). Next, we add the binary variables identifying the main study features to assess their influence on the results (column 3, Table 2.4).

All regression results report the constant term as a measure of the publication bias and the coefficient for precision, which represents the genuine effect of natural resources on conflict. Our results show that the constant term is always positive but not always statistically significant, indicating that a publication bias may be affecting the results to some extent, but the effect varies according to the study design and its methodological specifications. The results prove that the type of resource that studies chose as predictor has a considerable impact on the findings. The effect of the abundance of mineral resources on conflict is consistently positive and statistically significant across all specifications and is not affected by climate. Unfortunately, due to the lack of studies on the link between scarcity of mineral resources and conflict, we could not test this mechanism in our model.

Hence, our results substantiate the hypothesis that the resource curse is activated by *lootable*, highly profitable resources, whose rents could be sold and contribute to finance the costs of fighting. Although the results also suggest a positive association between land abundance and conflict risk, the effect does not always reach significance at the 10% level. The land/vegetation

Variable	ABUNDANCE		SCARCITY	
	Effect without climate	Effect with climate	Effect without climate	Effect with climate
Minerals, drugs	+	+	n.a.	n.a.
Water	-	-	-	-
Land, vegetation	+	+	+	+

Table 2.3: Mean effect of natural resources (abundance or scarcity) on conflict according to the explored literature, when studies do or do not control for climatic conditions and/or trends. Some effects could not be computed due to lack of sufficient variability of some control variables (n.a.). Grey cells indicate that the effect is significant; darker shades correspond to greater significance levels. For a definition of the resource variables, refer to Table S.2.3 in the Appendix.

regressor in the empirical model broadly includes many operationalizations of the resource variable, such as the availability of arable land (Binningsbø et al., 2007; Østby et al., 2011; Rowhani et al., 2011), the amount of 'agricultural resources' akin forests, croplands and pasturelands (Welsch, 2008; Hauge and Ellingsen, 1998), the degree of agricultural productivity (Bohmelt et al., 2014) or the amount of growing vegetation proxied by indicators such as the NDVI (Meier et al., 2007). This finding hence seems to confirm the results of an extensive academic literature on land invasions, arguing in favor of a positive association between the amount of arable land and the likelihood of conflict (e.g. Robinson and Acemoglu, 2006; Hidalgo, 2010).

In general, we find that the scarcity of land and vegetation is significantly associated with conflict, according to the reviewed studies. Specifically, the effect of land scarcity on conflict is significant and positive both in presence and absence of controls for climate, signaling that highly degraded or scarce land and vegetation may induce a higher risk of conflict. These results would confirm the Neo-Malthusian arguments, advancing that eco-scarcity is associated with increased likelihood of violence (Homer-Dixon, 1999). However, this does not seem to hold true for water scarcity: the coefficient for water scarcity is significant but negative, suggesting that lower levels of freshwater are associated with reduced odds of violence. This may be explained by the vital importance of water for human needs, such that water scarcity could inhibit the outbreak and continuation of a conflict. By contrast, the scarcity of land would cause no such inhibition.

Furthermore, the relationship between renewable natural resources and conflict is considerably affected by climatic factors/trends. In fact, results from the scarcity subset of the sample show that the dummy variable for climate controls is significant across all the specifications, suggesting that climate has a mediating role in the relationship between renewable natural resource scarcity and conflict. As we may expect, inclusion of climatic variables does not change the direction of the relationship between natural resource scarcity and conflict. However, the coefficients for resource scarcity reach higher statistical significance when climate controls are introduced, possibly suggesting that climatic conditions increase the strength of the effect.

This seems to limitedly confirm the hypothesis that climate alters the probability of conflict by affecting resource availability (Raleigh and Urdal, 2007; Burke et al., 2009; Raleigh and Kniveton, 2012; Hsiang et al., 2014). The possible influence of climate on conflict through natural resources appears to have an effect only through scarcity, while abundant goods are not conditioned by climatic changes. Since climatic conditions do not influence the amount or allocation of minerals or fossil fuels, this result is consistent with the previous finding that only the abundance of minerals and highly profitable resources increases the odds of violence. Also, the role of climate in conditioning the relationship between renewable resource scarcity and conflict is consistent with the predicted impact of climate change on natural resources, which is likely to shrink rather than increase the availability of freshwater and arable land in many regions of the world (IPCC, 2014).

We now focus on the full meta-regression specification that includes the regressors for the study features (Table 2.4). First, the coefficient for precision is negative but not statistically significant, suggesting that the effect of natural resource abundance on conflict found by studies is driven by publication bias (the constant term is positive and significant). However, the coefficient for minerals remain positive and significant across all specifications, confirming that the impact of resource abundance on the likelihood of conflict is confined to lootable resources, whose rents could be profitable for the groups who seize them and thus lower the opportunity costs of fighting.

The results also suggest that other methodological choices affect the studies' findings. In particular, the inclusion or exclusion of specific variables as controls has a significant impact on the response. The coefficient for climate is again significant, indicating that controlling for climatic conditions affects the results, although the effect seems to vary according to the controls that are introduced . We could interpret this change in the sign of the climate coefficient as a proof that the effect of climatic conditions is mediated by socio-economic, institutional and political factors: once the studies control for contextual conditions akin the economic development or the degree of ethnic homogeneity, the climate variable points to a different direction.

This is consistent with the findings from the conflict literature, which shows that the effect of climatic shocks on conflict risk is conditional upon socio-economic and contextual factors (Koubi, 2018); human systems can be more or less vulnerable to environmental hardships due to a variety of political, economic, institutional dynamics, which can absorb or

Table 2.4: Impact of methodological features of the studies on the relationship between resource wealth and conflict.

	(1)	(2)	(3)
Precision	-11.476	-12.498	-3.602
	(9.704)	(8.198)	(3.593)
Minerals, drugs	4.681**	6.366***	3.298*
	(1.786)	(0.064)	(1.905)
Water	4.953	6.318	4.057
	(4.081)	(4.113)	(3.254)
Land, vegetation	1.631***	1.638***	2.548
	(0.067)	(0.057)	(2.511)
Climate		-6.180***	3.652**
		(0.066)	(1.519)
Economic context			1.658
			(7.314)
Type of Conflict			-2.211
			(1.964)
Fractionalization			3.182***
			(0.614)
Geography			2.552
			(1.775)
History			1.218
			(2.138)
Location Fixed Effects			0.885***
			(0.152)
Time Fixed Effects			-11.562
			(10.076)
Lags			-0.968
			(1.487)
Institutions			-11.482*
			(5.874)
Resources: stock			-3.0216**
			(1.436)
Conflict specification: incidence			-0.985*
			(0.524
Conflict specification: intensity			-1.110**
			(0.503)
Conflict threshold: 25 BRDs			-3.270***
			(0.002)
UCDP/PRIO Data			-0.239***
			(0.000)
Resources as GDP share			-1.608
			(1.276)
Global analysis			-0.221
			(0.196)
Unit: 5-year			0.234
			(0.298)
Unit: grid-cell			26.533
			(29.674)
Method: logit			-5.889***
			(0.726)
Data: World Bank			1.553
			(2.05113)
Constant	0.283***	0.283***	10.520
	(0.001)	(0.001)	(11.314)
N	825	825	825
R-squared	0.687	0.958	0.995

Notes: Stepwise regressions results relative to the abundance subset of the sample. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

exacerbate the negative impacts of climatic variability. For instance, we observe that the coefficient for institutions is statistically significant and negative: the presence of institutions can moderate the relationship between resources and violence and increase the community's resilience against environmental shocks (e.g. Gizelis and Wooden, 2010).

Controlling for ethnic and/or religious heterogeneity increases the probability of finding a positive and significant relationship between resource abundance and conflict incidence. This indicates that the availability of resources is indeed intertwined with group-specific features and mirrors the findings of the literature that connects ethnic fractionalization and groups inequality with higher risks of conflict (Østby, 2008).

The inclusion of location fixed-effects increases the strength of the relationship between resources and conflict, which may partially reflect the claims advanced by Buhaug (2010) that fixed-effects raise multicollinearity issues: studies that include fixed effects in the model seem to be more likely to find a significant relationship between resource abundance and conflict but the effect may also capture the influence of other factors than only natural resources.

Next, the specification of the main variables appears to have an influence on the study's results: analyses focusing on the incidence or the intensity of violence (rather than the onset of conflict) are less likely to find a robust relationship with resource abundance; however, the coefficients are barely significant at 10%. Studies that adopt a threshold of twenty-five battle-related deaths to define an event as conflict are associated with a lower probability of finding a significant response; this indicates that when focusing on smaller conflictual events, studies find a weaker impact of resources on conflict. Also, the operationalization of the resource variable has a significant influence on the response: studies that operationalize resource availability as a stock tend to find less significant results. This substantiates Brunnschweiler and Bulte's (2008) argument that the climate/resources-conflict nexus vanishes when studies operationalize the resource variable as stock rather than using the ratio of primary commodities over GDP as the main independent variable. Therefore, the choice of the indicator has a particularly strong influence on the results and studies that adopt a relative proxy risk to inflate the significance of the response, as their resource variable presumably captures some economic or market-related effects rather than a pure resource influence on the risk of conflict.

Furthermore, the choice of the data employed in the analysis has an impact on the study's results; analyses that draw conflict data from the UCDP/PRIO dataset tend to find a weaker relationship between resources and conflict. This may be due to the more comprehensive and disaggregated nature of the UCDP/PRIO data as compared to other data sources, which allow to uncover the relationship at a greater level of detail.

The regression methodology adopted also has an effect on the findings; studies that apply a logistic regression tend to find less significant results compared to studies that adopt other methodologies, such as ordinary least squares. Unexpectedly, we do not find support for the claim that the spatial definition of the sample influences the results, as the coefficient for global analyses is not significant. This may be however motivated by the poor variation of the variable across studies.

In the case of the resource scarcity subset of the sample (Table S.2.5), including specific controls reverses the direction detected in the abundance subset. For instance, we find that institutions have a positive and significant effect, which seems to indicate that studies that control for institutional factors are more likely to find a relationship between resource scarcity and violence. This may be due to the tendency of the literature on resource scarcity to focus on institutionally-related conflicts, such as water issues, which are generally classified as the dyadic dispute over transboundary water resources (e.g. De Stefano et al., 2017). This may also indicate that studies that do not include proper controls for institutional factors suffer from omitted variable biases; institutions do play a role in mediating environmentally-related conflicts and failing to consider them is likely to produce inconsistent estimates.

Moreover, historical and geographic factors have a significant impact on the association between resource scarcity and conflict, unlike in the abundance subset of the sample. Specifically, the coefficient for geography is positive; since this binary variable mostly refers to the inclusion of controls for the roughness of terrain of the region under investigation, this result reflects the argument that conflicts would be more likely to erupt in mountainous areas, where rebels can hide more easily (Fearon and Laitin, 2003).

The Appendix reports the regression results discussed here as well as some robustness tests. A first test meant to verify the existence of a "peer" effect is performed by excluding from the sample studies that are not published in peer-reviewed journals; a second robustness check excludes those studies that operationalize the resource variable as a share of GDP, as we have observed that such a methodological choice has a considerable influence on the results. Finally, a third test is performed by reintroducing the conditional estimates, i.e. estimates from those model specifications that include interaction terms. Results from the robustness tests confirm the importance of the above-mentioned methodological features of the studies in affecting the findings, mainly the inclusion of socio-economic or institutional variables as controls (i.e. controlling for ethnic heterogeneity), the operationalization of the resource variable (particularly when measuring the resources as stock), the method adopted for estimating the regression coefficients, the inclusion of lags in the model, and the specification of the threshold to define an event as conflict.

2.3 Discussions and Conclusions

The results of our analysis reflect some major issues that have been at the center of the academic dispute on environment and conflict. Our findings confirm that the inclusion of fixed-effects have an influence on study's results, as discussed in the broader academic debate on the evidence of a climate-conflict nexus (Buhaug, 2010; Buhaug et al., 2014; Hsiang et al., 2013; 2014). Similarly, the definition of the dependent variable in terms of the number of deaths per year chosen as threshold to define an event as conflict, has a significant impact on the findings (Buhaug et al., 2014). Concerning the debate between neo-classical economists, who support the resource-curse hypothesis, and neo-Malthusians, who argue in favour of resource scarcity as a driver of conflict, our analysis shows that both resource wealth and shortage have an impact on conflict but vary according to the type of resources. While the abundance of minerals and drugs – lootable resources – increases the risk of conflict, the scarcity of renewable resources such as land and vegetation is associated with higher probability of violence.

In those settings characterized by abundance of highly-valuable resources such as minerals and fossil fuels, individuals may be more prone to fight for taking control over precious goods or achieve a fairer redistribution of resources. Moreover, rebel leaders generally provide material rewards as an incentive to join the fights (Kalyvas, 2006) and the prospect of material enrichment will likely foster mobilization, especially in destitute areas or among discriminated communities. Particularly in the lack of viable economic alternatives, the opportunity cost of joining the fight will thus be reduced (Collier and Hoeffler, 2004; Brinkman and Hendrix, 2011).

Moreover, the results of the analysis seem to confirm that the Neo-Malthusian argument holds for renewable resources (land in particular), whereby we find a genuine correlation between renewable resource scarcity and conflict. While the findings on mineral resources give support to theorists of greed, the results on renewable resources backs supporters of grievances as a motive for conflict, as they point towards lack of essential goods and environmentally - induced livelihood deterioration as potential conflict-inducing factors.

Furthermore, as water and land represent the primary input of agricultural and food production, our findings might also be a sign of a positive association between food scarcity and violence. Acute food insecurity can in fact increase social grievances and provide reasons for engaging in rebellions. Societal grievances may have a particularly destabilizing effect when government responses to food insecurity are politicized and aid or relief programs are distributed unequally or directed to alternative uses (Hendrix and Brinkman, 2013). Also, the scarcity of water and land may induce crop shocks that translate into food price peaks, and in many other ways exacerbate grievances that individuals may be willing to act upon (Lagi et al., 2011).

Finally, a possibility exists that natural resource scarcity is associated with conflict through a non-linear relationship; in fact, it is not unlikely that the shrinkage in natural goods would initially encourage some degree of cooperation aimed to efficiently manage the resource use and plan its allocation, while cooperation would gradually degenerate into a more conflictual relationship when the amount of the resource becomes so scarce that any solidary or cooperative sharing would be unfeasible (Dinar and Dinar, 2017).

The findings also suggest that some methodological elements are likely to drive the study's results and therefore need to be carefully vetted by future empirical analyses. Empirical research should thoroughly evaluate the choice of the sample and the data to be used, the socio-economic variables to be included as controls, and the proxy chosen to define both the dependent and the independent variables, as all these factors have a strong impact on the results.

Specifically, the inclusion of location fixed effects in the empirical model is associated with a higher probability to find positive and significant results, while studies that operationalize the independent variable as a stock or an absolute quantity tend to find weaker correlations. Interestingly, studies that control for state capacity, democracy or other elements describing the institutional setting of a country are less likely to find a positive relationship between natural resources and conflict. This suggests that governments play an important role in moderating the effect of exogenous shocks to resources and may thereby increase communities' resilience to environmental hardships. In fact, governments can provide relief aids to affected populations, support a fairer redistribution of resources through taxation and fiscal incentives, promote a more equitable allocation of property rights, implement international agreements that foster cooperation on resources management and all in all reduce the opportunity cost of violence and disincentivize rebellions.

Evidence from the literature also supports the hypothesis that climate has an influence on the probability of conflicts related to resource scarcity. Climate change is likely to decrease the availability of natural resources, leading to increased scarcity of some primary goods such as fresh water in many regions of the world (Jiménez Cisneros et al., 2014). As our results suggest, if climatic conditions impact the risk of conflict via resource scarcity, the reduced availability of resources triggered by climate change is likely to amplify the risk of conflict. Further research should therefore explore the availability of natural resource as a possible contributory pathway through which climate patterns and change may increase the risk of conflict or magnify pre-existing tensions.

Finally, our systematic investigation of the literature allows us to identify some further research priorities that should be addressed by future research. The research community agrees on the need to have more disaggregated and high-resolution datasets on social and climatic variables (Buhaug and Lujala, 2005; Buhaug et al., 2008; Levy and Sidel, 2014; Ide, 2017; Bayramov, 2018). Researchers also call for investigating the dynamics that decrease societal vulnerability (Warnecke et al., 2010; Hsiang et al., 2014), and the socio-economic and political factors that could promote adaptation to the likely magnification of conflict risk, other than just to climate change (Scheffran et al., 2012; Hsiang et al., 2014; Adger et al., 2015). Research should also specifically target the complex mechanisms linking climate to conflict, including for instance natural resources, migration, and psychological dynamics (Burke et al., 2009; Kahl, 2006; Dell et al., 2014; Hsiang et al., 2014).

One task for future research is to consider socioeconomic variables that have been investigated only to a limited extent, such as factors reallocation and international trade (Gleditsch, 1998; Dell et al., 2014), while at the same time carefully accounting for both endogeneity and reverse causality issues (Buhaug et al., 2008; Kousky, 2014). In addition, studies need to be broad enough to gather sufficient data but focused enough to capture the effects of subnational or local climatic conditions on the occurrence of violence (Buhaug et al., 2014; Levy and Sidel, 2014). Similarly, they need to better bridge the results of panel data analyses from short to medium and long term (Dell et al., 2014). Future research should therefore refine existing methods and explore new methods for investigating environment–conflict links (Schilling et al., 2010). A possibility is offered by adopting more than one methodology and taking advantage of a pluralistic integration of quantitative and qualitative studies (Van Vuuren, 2015; Ide, 2017). Finally, to increase the robustness of results, studies could target cases that exhibit all the preconditions hypothesized to potentially lead to conflict but that did not result in violent outcomes (Gleditsch, 1998; Kahl, 2006). [†].

[†] A slightly different version of this chapter, co-authored with Shouro Dasgupta, Enrica De Cian and Carlo Carraro, is currently under review by *Ecological Economics*.

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2.6 Appendix

2.6.1 Conflict Data

This section presents a brief description of the most commonly used datasets on conflictual events. Three main datasets on violence and conflict are used: the ACLED database from the Armed Conflict Location and Event Data Project of the University of Sussex, the Correlates of War dataset, and the UCDP/PRIO Database (Table S.2.1). ACLED reports disaggregated data on political violence and protest events and does not constrain the coding of violence to a minimum number of casualties. However, data are only available for 60 developing countries in Asia and Africa, starting from 1997. The Correlates of War main dataset, which was the sole source of conflict data for the first studies on environmental security, does not report minor conflicts and only includes wars causing at least 1000 battle related deaths. The UCDP/PRIO Dataset, by contrast, defines a conflict as the use of armed forces that results in at least 25 battle deaths (Gleditsch et al., 2002; Themnér and Wallensteen, 2013). Table S.2.1 summarizes the main features of the three datasets.

2.6.2 Selection of Articles

This section provides additional details on the process of study selection, with a particular focus on studies authored by the same researchers. The selection of articles has been aimed at being as broad as possible. As a first step, we input the selected keywords (environ* and conflict, climate and conflict, natural resource* and conflict, resource* and conflict, land and conflict, water and conflict, scarcity and conflict, abundance and conflict, crop and conflict) into three databases, screening study title, abstract, and keywords: EBSCO, Scopus and Web

Dataset	Overview	Resolution	Threshold
ACLED	This dataset codes dates and locations of all reported political violence and protest events in over 60 developing countries in Africa and Asia. Political violence and protest include events that occur within civil wars and periods of instability, public protests and regime breakdowns. The dataset covers all African countries from 1997 to the present, and South and South-East Asia in real-time.	Daily-monthly, point coordinates	No causality minimum
Correlates of War	The Correlates of War dataset was originally developed by Singer and Small (1972), who defined war as a "sustained combat, involving organized armed forces, resulting in a minimum of 1,000 battle-related fatalities" (Singer and Small, 1972). The original dataset included inter-state, extra-state and civil wars. Inter-state wars were those conducted between one or more countries. Extra-systemic wars were those that were conducted between a system member and a non-state entity. Civil wars were conducted between a state and a group within its borders. Subsequently, the category of civil wars has been expanded to include intra-state wars, and a new category of non-state wars has been added (Sarkees and Wayman, 2010). The most recent version of the dataset covers the period from 1816 to 2007.	Yearly, country	1000 battle-related deaths
UCDP-PRIO	The dataset is developed by the Department of Peace and Conflict Research at Uppsala University, in collaboration with the Peace Research Institute of Oslo, and covers the period from 1946 onwards. It codes different types of conflicts, including international and conflicts. It applies a threshold of 25 battle-related deaths, which allows for the inclusion of lower-intensity conflicts. A conflict is defined as a "contested incompatibility that concerns government or territory or both, where the use of armed force between two parties results in at least 25 battle-related deaths. Of these two parties, at least one is the government" (Gleditsch et al., 2002).	Yearly, dyads	25 battle-related deaths

Table S.2.1: Overview of the most common datasets on conflict.

of Knowledge.

We included "climate" and climate-related keywords to capture the recent literature on climate and conflict, which may not emerge from a different keyword selection, although including some interesting studies on resources. However, our focus is limited to the link between natural resources and conflict, and we reviewed studies so as to include only those related to the object of interest, while removing those that focus on the climate-conflict nexus. Specifically, we included studies that consider climatic variables, temperature and rainfall as predictors of conflict, only if the authors consider these variables as proxies for resources (e.g. water). As regards the type of publication, we excluded books and book reviews because of, first, time constraint (including books would have required a much longer process) and, second, limited availability (most books and book chapters are not fully open-access). By contrast, we included the gray literature since it is "an important forum for disseminating studies with null or negative results that might not otherwise be disseminated" (Paez, 2017, p.233). Hence, including non-peer reviewed articles may contribute to reduce publication bias and enhance a balanced picture of the available evidence (Quirion and Branger, 2013; Paez, 2017).

Some studies are authored by the same researchers (Lujala, 2009; 2010; Collier and Hoffler, 1998; 2002; Collier and Hoffler, 2004). This may potentially raise concerns as regards the assumption of independence across studies. However, the studies differ either for the method, sample, and/or spatial and temporal coverage, or for the type of resources they link to conflict. By contrast, studies authored by the same scholars and meant to update/review a former version of the analysis were excluded to avoid biases in the meta-regression.

Specifically, Collier and Hoffler (1998) adopts a Tobit and Probit method to investigate the duration of conflict; the 2002 study from the same authors adopts a different sample that is limited to Sub-Saharan Africa, while the 2004 study investigates the onset of conflict by using a logit analysis. Moreover, their study published in 2004 covers 750 episodes of conflict while their first one is limited to a cross-section analysis of 98 countries. As the authors themselves declare, the theoretical assumptions behind the two papers are different.

As concerns the studies by Lujala, they focus on distinguished independent variables: the earlier study examines the risk of conflict linked to the availability of different types of natural resources (minerals, oil, diamonds, gems...), while the study published in 2010 is limited to oil. Moreover, while the first study (Lujala, 2009) defines the conflict variable as the total number of combat deaths accumulated during the conflict and the average daily death rate

Quantitative studies excluded from the meta-analysis.

Study	Motivation for exclusion				Notes
	Obj	*Sol-oriented*	*Inverse rel*	*No-quant*	
Almeida et al., 2014	X			X	The case study aims to obtain and analyse values from the indexes of water-use conflict in managing and planning the water resources of the Grande River Basin, Brazil. The main goal is to identify potential water-use conflicts.
Bjorvatn and Naghavi, 2010				X	The study develops a theoretical model of conflict demonstrating that high cost of conflicts associated with high resource rents can promote peace.
Bretthauer, 2014				X	The study employs a set-theoretical approach of QCA to capture the conjunctural causation between resource scarcity and six conditions to explain previous contradictory empirical results.
Brunnschweiler and Bulte, 2008				X	The study explores how the operationalization of the resource variable affects the regression results of models testing the link between resources, economic growth and conflict but. does not report the t-statistic or the standard errors of the effect size.
Butler and Gates, 2012				X	The study employs a contest success function (CSF) game-theoretical model to analyse the logic of range wars.
Collier et al., 2009	X				The study conducts an empirical analysis of the potential factors leading to war, including primary commodities. However, it is meant to update a former version of the analysis by the same authors (Collier and Hoffler, 2004) and cannot thus be considered as independent.
De Soysa, 2002				X	The study empirically tests the impact of natural resources on conflict. However, it does not report the t-statistics or the standard errors of the effect size (only the z-scores – but we could not retrieve the t-statistics without the standard errors).
Dimelu et al., 2016	X			X	Based on field work, it presents a statistical analysis of perceived causes of conflicts among farmers and herdsmen - does not report relevant coefficient or standard errors (only mean values out of a Likert scale).
Eck, 2014	X			X	The study focuses on the effect of the legal framework on land-use conflicts. In robustness checks, the authors find a positive and significant effect of agriculture and rainfall deviation, but they don't report coefficients and standard errors.
Grossman, 2001				X	The study develops a model of resource scarcity and conflict that integrates explicitly the positive intertemporal effect of consumption on the probability of survival.
Hassani-Mahmooei and Parris, 2013				X	The study advances an agent-based model to study whether resource scarcity is likely to lead to an increase in the appropriation of resources in environments where adaptive agents can allocate a fraction of their efforts to predatory behaviours.
Hsiang, Burke and Miguel., 2014	X				The meta-analysis focuses on the climate-conflict nexus (not on resources).
Keenan, 2014	X				The study presents a theory of pillage that is applied to Congo wars (legal analysis).
Krakowka et al., 2012	X			X	The study investigates the impact of resources on non-conflictual episodes. Morever, it does not report standard errors.
Malley et al., 2008				X	The study contributes to the game theoretical conflict literature by performing a graphical and a chi-square analysis, but it does not report coefficients or standard errors.
Maxwell and Reuveny, 2000				X	The study presents a simple dynamic model of renewable resource and population interaction featuring per capita triggered conflict.
Okpara et al., 2017				X	The study presents a composite index of vulnerability to climate/water-related conflicts, based on a double exposure framework. It reports vulnerability scores and indicators for fishermen, farmers, and pastoralists, but not t-statistics or standard errors.
Ravnborg et al., 2012				X	The study develops comprehensive inventories of water-related conflict and cooperation for five districts. It investigates what uses (domestic use, irrigation...) are mostly associated with water events (conflictive-cooperative) but does not report coefficients or standard errors.
Reuveny, 2002				X	The study presents a mathematical model to describe a society that exhibits a conflict over resources. The goal is to assess whether economic growth alleviates or promotes resource-based conflicts. It concludes that economic growth exacerbates environmental degradation and can therefore increase the likelihood of conflict.
Ross, 2006				X	The study examines thirteen recent civil wars to explore the mechanisms behind the resource-conflict correlation. However, it does not report the t-statistics or the standard errors of the estimates.
Roy, 2017	X				The study tests the relationship between natural resources and stability duration after conflict.
Ruelas-Monjardin et al., 2009					The study applies a conflict assessment approach (semi-quantitative) to a Mexican case study.
Rustad et al., 2012	X				The study tests the relationship between natural resource-related conflict and the duration of post-conflict peace.
Theisen and Brandsegg, 2007				X	The study investigates the effect of population density and precipitation patterns on non-state conflicts in Sub-Saharan Africa. It does not report the t-statistics or the standard errors of the estimates.
Urdal, 2008				X	The study tests whether high population pressure on natural resources, youth bulges and different growth rates between religious groups have an impact on conflict. It does not report the t-statistics or the standard errors of the estimates.

Table S.2.2: Notes: Quantitative studies excluded from the meta-analysis after full text screening. Columns 2 to 5 report the reason for exclusion: "obj" refers to the object of the analysis, "sol. oriented" concerns studies that examine possible solutions to resource-related conflicts; "inverse rel." identifies studies that investigate the link between conflict and resources; "no quant" means that the studies do not meet the methodological criteria for inclusion.

over the whole conflict (intensity), the second analysis investigates the duration of conflict (Lujala, 2010).

More broadly, any dependencies between studies should be efficiently accounted for in our Weighted Least Square Model with clustered standard errors. Table S.2.2 enlists the studies that were excluded from the analysis according to the criteria we have illustrated in the main text of the paper. A motivation for exclusion is provided, as well as a short explanation.

2.6.3 Information Coding

Binary variables coded from the studies

Category	Binary variable	Definition
Reference	Literature type	Binary variable coded as one if the study is published in a peer-reviewed journal, and otherwise zero.
Type of conflict	Dependent variable	Binary variable coded as one if the dependent variable is an intra-national (civil) conflict, and otherwise zero. Intra-state conflict is defined as a conflict between a government and a non-governmental party.
Dependent variable specification	Onset	Binary variable coded as one if the dependent variable is specified as conflict onset, and otherise zero. Onset identifies the outbreak of conflict.
	Incidence	Binary variable coded as one if the dependent variable is specified as conflict incidence.
	Intensity	Binary variable coded as one if the dependent variable is specified as conflict intensity.
	Conflict threshold: 25 BRDs	Binary variable equal to one if the conflict is defined as any violent event causing the death of at least 25 people per year.
Resource type	Minerals, drugs	Binary variable coded as one if the main independent variable is represented by mineral resources and drugs (mainly opium, cocaine).
	Water	Binary variable coded as one if the main independent variable is represented by water. Total availability of water is intended per human use and can be measured in absolute terms (as total water available for consumption) or in relative terms (e.g. per capita).
	Land, vegetation	Binary variable equal to one if the main independent variable is the availability of land or the vegetation cover. Land refers to all resources associated with agricultural production and crops. It includes measures of agricultural productivity and intensity. Vegetation refers to diverse vegetation forms, mainly timber and forestry, and may also indicate the status of soil fertility and degradation.
Explanatory variable specification	Resources: stock	Binary variable coded as one if the explanatory variable is expressed as a stock, and otherwise zero. It may include different types of resources, but expressed in absolute value, e.g. mineral deposits, agricultural stock, total forest coverage, or fish stock.
	Resources as GDP share	Binary variable coded as one if the independent variable is defined as the ratio of primary commodities over GDP.
Controls	Institutions	Binary variable set equal to one if the standard controls for historical factors and governance-related factors are introduced. It includes controls for colonial past, level of corruption, democracy, and suchlike.
	Economic context	Binary variable set equal to one if the standard controls related to economic factors are included. These controls are related to the economic structure and development (GDP, income growth, openness to trade).
	Fractionalization	Binary variable set equal to one if controls related to ethnic, linguistic or religious fractionalization/polarisation and dominance are introduced. Fractionalization is generally referred to as the distance between sub-groups inhabiting the same country or region.
	Geography	Binary variable set equal to one if the standard controls for geographic features are included. These refer to geographic conditions that may have an impact on the risk of conflict (mainly affecting parties' capability to control the territory), e.g. presence of roads, terrain roughness, distance to the capital.
	Climate	Binary variable coded as one if climatic variables (mainly temperature, precipitation) are included as controls.
	Location fixed effects	Binary variable set equal to one if location fixed effects (such as country fixed effects) are introduced.
	Time fixed effects	Binary variable set equal to one if temporal fixed effects (such as years fixed effects) are introduced.
Spatial coverage	Global analysis	Binary variable set equal to one if the study presents a global sample, and otherwise zero. This is a measure of the degree to which the study's results can be generalized and considered valid across a wider population. Global analyses have a greater generalizability than cross-national and national studies.
Temporal coverage	Time coverage	Binary variable coded as one is the study focuses on a time-span starting from the end of the Cold War.
Unit of analysis	Unit: 5-year	Binary variable equal to one if the unit of analysis is the country averaged over five year-periods, and otherwise zero.
	Unit: grid-cell	Binary variable coded as one if the analysis is performed at the gridded cell level, by using geo-referenced data, and otherwise zero.
Method	Method: logit	Binary variable coded as one if the study adopts a logistic regression method, and otherwise zero.
Data	UCDP/PRIO Data	Binary variable set equal to one if conflict data are drawn from the UCDP/PRIO Dataset.
	Data: World Bank	Binary variable set equal to one if resources data are drawn from the World Bank Dataset.
Coefficient specifications	Lags	Binary variable equal to one if the regression model includes temporal lags (e.g. one-year lag to one or more independent variables).
	Squared terms	Binary variable coded as one if the independent variable is squared.
	Interactive effects	Binary variable equal to one if the regression model includes interactive effects (applied only in robustness checks).

Table S.2.3: **Notes**: Definition of the binary variables coded from the study estimates, representing the potential regressors in our analysis (only the most relevant have been included in the regression analysis)

2.6.4 Publication Bias

The Egger's test is the most commonly used test to check whether the results of a meta-analysis are genuine or driven by publication bias (Egger et al., 1997). It consists of regressing the measure of the effect size against a measure of the precision of the estimate, i.e. the inverse of the standard errors and it's hence incorporated into our meta-regression model (eq. 2.1). A β_1 statistically different from zero proves that there is a genuine link between natural resources and conflict.

In our regression model, we have included a term for precision, capturing the genuine effect of natural resource on conflict, and the constant term, measuring the publication bias. The parameter for precision is positive and statistically significant, although not throughout all model specifications. This suggests that there is a significant and genuine relationship between natural resources and conflict, but this varies according to the research design and methodological choices. Similarly, the intercept is not always significant, demonstrating that a publication bias is likely to affect the results but the proportion of the effect changes according to the types of study.

2.6.5 Descriptive Statistics

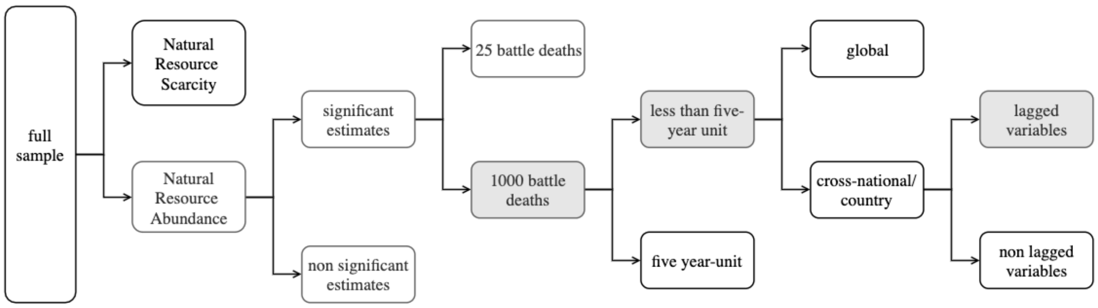

Figure S.2.1: Nested structure to explore the variance of the standardized coefficients reported by studies according to progressive limitations of the sample: grey cells indicate a decrease in variance compared to the previous step.

2.6.6 Regression Results

This section presents all the regression results discussed in the main text of the article. First, we report the results for the model specifications including only natural resources, with and without climate controls; results for the models with the methodological features of the studies follow.

Abundance-conflict. Effect of natural resource abundance with and without climate controls on the risk of conflict.

Resource Abundance	(1)	(2)	(3)	(4)	(5)	(6)
Precision	-10.570	-11.503	29.801	30.710	28.774	29.669
	(9.399)	(7.941)	(27.375)	(28.244)	(26.833)	(27.700)
Minerals, drugs	4.680**	6.364***				
	(1.783)	(0.064)				
Climate		-6.180***		-0.412		-0.412
		(0.066)		(0.763)		(0.764)
Water			-11.792	-12.097		
		(11.950)	(12.262)			
Land, vegetation					0.786	0.767
				(0.838)	(0.879)	
Constant	0.283***	0.283***	0.843	0.857	0.843	0.857
	(0.001)	(0.001)	(0.721)	(0.75428)	(0.721)	(0.754)
N	825	825	825	825	825	825
R-squared	0.687	0.958	0.001	0.003	0.001	0.003

Table S.2.4: **Notes**: Stepwise regressions results relative to the abundance subset of the sample. Regressions focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Scarcity-conflict. Effect of natural resource scarcity with and without climate controls on the risk of conflict.

Resource Scarcity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	-1.075*	-0.272*	-1.075*	-0.272*	-0.996*	-0.136	-0.996*	-0.136
	(0.482)	(0.143)	(0.482)	(0.143)	(0.497)	(0.099)	(0.498)	(0.099)
Climate		2.963***		2.963***		3.012***		3.012***
		(0.080)		(0.080)		(0.091)		(0.092)
Water					-2.393*	-3.728***		
					(1.162)	(0.510)		
Land, veg							2.393*	3.728***
							(1.162)	(0.510)
Constant	3.965***	1.000***	3.965***	1.000***	3.964***	0.950***	1.571	-2.777***
	(0.003)	(0.080)	(0.00309)	(0.080)	(0.003)	(0.091)	(1.162)	(0.510)
N	84	84	84	84	84	84	84	84
R-squared	0.178	0.946	0.178	0.946	0.193	0.982	0.193	0.982

Table S.2.5: Notes: Stepwise regressions results for the scarcity subset of the sample. Regressions focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Scarcity-conflict. Impact of methodological features of the studies on the relationship between natural resource scarcity and conflict.

Resource Scarcity	(1)	(2)	(3)
Precision	-0.996*	-0.136	-0.039
	(0.498)	(0.099)	(0.052)
Water	-2.393*	-3.728***	0.160
	(1.162)	(0.511)	(0.191)
Climate		3.012***	-1.667***
		(0.092)	(0.104)
Fractionalization			0.388*
			(0.207)
Geography			0.636*
			(0.294)
History			-1.202**
			(0.399)
Time Fixed Effects			4.384***
			(0.108)
Lags			0.034
			(0.061)
Institutions			2.508**
			(0.242)
Conflict specification: incidence			0.349
			(0.378)
Conflict specification: intensity			0.317**
			(0.140)
Conflict threshold: 25 BRDs			0.507***
			(0.003)
UCDP/PRIO Data			-0.672***
			(0.008)
Unit: grid-cell			-0.338
			(0.244)
Constant	1.571	-2.777***	-1.287*
	(1.162)	(0.510)	(0.667)
N	84	84	84
R-square	0.193	0.982	0.999

Table S.2.6: **Notes**: Stepwise regression results for the scarcity subset. Due to limited number of observations for the scarcity subset, results for the land variables could not be computed. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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2.6.7 Robustness tests

a) Robustness tests performed by including only the peer-reviewed studies in the analysis.

Abundance-conflict (only peer-reviewed studies). Effect of natural resource abundance with and without climate controls on conflict.

Resource Abundance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	36.943	38.070	-13.293	-14.565	37.691	38.842	36.603	37.739
	(34.119)	(35.196)	(12.007)	(10.174)	(34.895)	(35.996)	(34.397)	(35.497)
Climate		-0.445		-6.645***		-0.446		-0.445
		(0.823)		(0.071)		(0.824)		(0.824)
Minerals, drugs			5.033**	6.845***				
			(1.923)	(0.069)				
Water					-13.186	-13.597		
					(13.507)	(13.950)		
Land, vegetation							0.807	0.784
							(0.929)	(0.974)
Constant	0.840	0.854	0.239***	0.239***	0.840	0.854	0.840	0.854
	(0.776)	(0.812)	(0.002)	(0.002)	(0.777)	(0.812)	(0.777)	(0.813)
N	700	700	700	700	700	700	700	700
R-squared	0.002	0.003	0.687	0.956	0.002	0.003	0.002	0.003

Table S.2.7: **Notes**: Robustness tests performed by including in the sample only the estimates from peer-reviewed studies. Stepwise regressions results are presented for the abundance subset of the sample and focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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Abundance-conflict (only peer-reviewed studies). Effect of natural resource abundance with and without climate controls on conflict.

Resource Abundance	(1)	(2)	(3)
Precision	-14.366	-15.672	-4.934
	(12.350)	(10.466)	(4.924)
Minerals, drugs	5.034**	6.846***	3.038
	(1.926)	(0.069)	(2.252)
Water	5.577	6.107	3.615
	(4.637)	(4.141)	(3.562)
Land, vegetation	1.768***	1.777***	2.159
	(0.086)	(0.073)	(3.063)
Climate		-6.645***	3.596*
		(0.071)	(2.055)
Economic context			40.447
			(35.392)
Type of Conflict			-2.035
			(1.865)
Fractionalization			3.073***
			(1.038)
Geography			2.230
			(2.010)
History			1.655
			(2.502)
Location Fixed Effects			1.037***
			(0.248)
Time Fixed Effects			21.061
			(28.965)
Lags			-1.171
			(2.132)
Institutions			-16.704**
			(6.984)
Resources: stock			-2.810
			(1.700)
Conflict specification: incidence			-1.273*
			(0.633)
Conflict specification: intensity			-1.422**
			(0.611)
Conflict threshold: 25 BRDs			-3.514***
			(0.003)
UCDP/PRIO Data			-0.256***
			(0.000)
Resources as GDP share			-1.929
			(1.486)
Global analysis			-0.429
			(0.356)
Unit: 5-year			0.314
			(0.424)
Unit: grid-cell			33.798
			(36.315)
Method: logit			-6.392***
			(0.844)
Data: World Bank			1.283
			(2.442)
Constant	0.238***	0.238***	-22.045
	(0.002)	(0.001)	(27.167)
N	700	700	700
R-squared	0.687	0.958	0.995

Table S.2.8: **Notes**: Robustness tests performed by including in the sample only the estimates from peer-reviewed studies. Stepwise regression results are presented for the abundance subset. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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Scarcity-conflict (only peer-reviewed studies). Effect of natural resource scarcity with and without climate controls on conflict.

Resource Scarcity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	-1.075*	-0.272*	-1.075*	-0.272*	-0.996*	-0.136	-0.996*	-0.136
	(0.482)	(0.143)	(0.482)	(0.143)	(0.497)	(0.099)	(0.498)	(0.099)
Climate		2.963***		2.963***		3.012***		3.012***
		(0.080)		(0.080)		(0.091)		(0.092)
Water					-2.393*	-3.728***		
					(1.162)	(0.510)		
Land, veg							2.393*	3.728***
							(1.162)	(0.510)
Constant	3.965***	1.000***	3.965***	1.000***	3.964***	0.950***	1.571	-2.777***
	(0.003)	(0.080)	(0.00309)	(0.080)	(0.003)	(0.091)	(1.162)	(0.510)
N	84	84	84	84	84	84	84	84
R-squared	0.178	0.946	0.178	0.946	0.193	0.982	0.193	0.982

Table S.2.9: **Notes**: Robustness tests performed by including in the sample only the estimates from peer-reviewed studies. Stepwise regression results are presented for the abundance subset. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Scarcity-conflict (only peer-reviewed studies). Impact of methodological features of the studies on the relationship between resource scarcity and conflict.

Resource Scarcity	(1)	(2)	(3)
Precision	-0.996*	-0.136	-0.039
	(0.498)	(0.099)	(0.052)
Water	-2.393*	-3.728***	0.160
	(1.162)	(0.511)	(0.191)
Climate		3.012***	-1.667***
		(0.092)	(0.104)
Fractionalization			0.388*
			(0.207)
Geography			0.636*
			(0.294)
History			-1.202**
			(0.399)
Time Fixed Effects			4.384***
			(0.108)
Lags			0.034
			(0.061)
Institutions			2.508**
			(0.242)
Conflict specification: incidence			0.349
			(0.378)
Conflict specification: intensity			0.317**
			(0.140)
Conflict threshold: 25 BRDs			0.507***
			(0.003)
UCDP/PRIO Data			-0.672***
			(0.008)
Unit: grid-cell			-0.338
			(0.244)
Constant	1.571	-2.777***	-1.287*
	(1.162)	(0.510)	(0.667)
N	84	84	84
R-square	0.193	0.982	0.999

Table S.2.10: Notes: Robustness tests performed by including in the sample only the estimates from peer-reviewed studies. Stepwise regression results are presented for the scarcity subset. Due to the lack of sufficient variations, the regression coefficients for some methodological features of the studies have been omitted. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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b) Robustness tests performed by including conditional estimates.

Abundance-conflict (with conditional estimates). Effect of natural resource abundance with and without climate controls on conflict.

Resource Abundance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	151.968	157.518	-47.290	-45.044	155.298	160.945	151.582	157.171
	(137.042)	(140.574)	(37.400)	(33.517)	(140.360)	(143.966)	(137.918)	(141.523)
Climate		-3.526		-26.792***		-3.527		-3.525
		(5.156)		(0.173)		(5.159)		(5.161)
Minerals, drugs			22.974***	27.577***				
			(5.544)	(0.157)				
Water					-64.512	-66.352		
					(62.635)	(63.938)		
Land, vegetation							1.418	1.271
							(5.414)	(5.658)
Constant	6.284	6.392	2.198***	2.198***	6.284	6.392	6.284	6.392
	(4.908)	(5.119)	(0.006)	(0.006)	(4.910)	(5.121)	(4.911)	(5.122)
Observations	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081
R-squared	0.002	0.005	0.787	0.973	0.002	0.005	0.002	0.005

Table S.2.11: Notes: Robustness test performed by including results from conditional estimates. Stepwise regressions results are presented for the abundance subset of the sample and focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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Abundance-conflict (with conditional estimates). Impact of methodological features of the studies on the relationship between natural resource abundance and conflict.

Resource Abundance	(1)	(2)	(3)
Precision	-50.335	-48.249	-19.421
	(38.532)	(34.568)	(19.63)
Minerals, drugs	22.978***	27.581***	12.534
	(5.549)	(0.157)	(8.645)
Water	21.794	24.951	16.343
	(16.642)	(16.931)	(14.247)
Land, vegetation	6.934***	6.919***	8.446
	(0.268)	(0.241)	(12.596)
Climate		-26.793***	14.591**
		(0.173)	(7.096)
Economic context			2.333
			(36.781)
Type of conflict			-9.478
			(8.242)
Fractionalization			12.922***
			(3.313)
Geography			10.347
			(7.849)
History			6.422
			(9.737)
Location Fixed Effects			3.053***
			(0.638)
Time Fixed Effects			-52.700
			(51.942)
Lags			-4.234
			(6.987)
Institutions			-48.666
			(30.977)
Resources: stock			-12.837**
			(6.161)
Conflict specification: incidence			-3.828
			(2.506)
Conflict specification: intensity			-4.464*
			(2.296)
Conflict threshold: 25 BRDs			-13.864***
			(0.012)
UCDP/PRIO Data			-0.721***
			(0.002)
Resources as GDP share			-7.478
			(6.489)
Global analysis			-1.038
			(0.860)
Unit: 5-year			0.883
			(1.359)
Unit: grid-cell			133.162
			(150.738)
Method: logit			-24.513***
			(3.576)
Data: World Bank			5.852
			(9.557)
Constant	2.196***	2.196***	52.209
	(0.005)	(0.004)	(58.246)
N	1,081	1,081	1,078
R-squared	0.788	0.974	0.996

Table S.2.12: Notes: Robustness tests performed by including results from conditional estimates. Stepwise regression results are presented for the abundance subset. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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Scarcity-conflict (with conditional estimates). Effect of natural resource scarcity with and without climate controls on conflict.

Resource Scarcity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	-8.313	-7.737	-8.313	-7.737	-8.515	-7.941	-8.515	-7.941
	(7.718)	(8.571)	(7.718)	(8.571)	(8.292)	(9.124)	(8.292)	(9.124)
Climate		2.542		2.542		2.564		2.564
		(4.606)		(4.606)		(4.554)		(4.554)
Water					4.253	4.409		
					(11.073)	(10.938)		
Land, vegetation							-4.253	-4.409
							(11.073)	(10.938)
Constant	7.164***	4.622	7.164***	4.622	7.164***	4.600	11.417	9.009
	(0.002)	(4.608)	(0.002)	(4.608)	(0.002)	(4.556)	(11.075)	(14.858)
N	124	124	124	124	124	124	124	124
R-squared	0.012	0.012	0.011	0.012	0.011	0.012	0.011	0.012

Table S.2.13: **Notes**: Robustness test performed by including results from conditional estimates. Stepwise regressions results are presented for the scarcity subset of the sample and focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Scarcity-conflict (with conditional estimates). Impact of methodological features of the studies on the relationship between natural resource scarcity and conflict.

Resource Scarcity	(1)	(2)	(3)
Precision	-8.515	-7.941	-30.547
	(8.292)	(9.124)	(34.648)
Water	4.253	4.409	150.961
	(11.073)	(10.938)	(180.241)
Climate		2.564	36.567
		(4.554)	(73.074)
Type of Conflict			253.030
			(294.001)
Fractionalization			-130.982
			(145.911)
Geography			-206.799
			(254.177)
History			-260.755
			(285.391)
Location Fixed Effects			66.097
			(109.540)
Time Fixed Effects			107.322
			(140.990)
Lags			21.189
			(47.248)
Institutions			153.668
			(173.035)
Conflict specification: incidence			-269.605
			(304.172)
Conflict threshold: 25 BRDs			-4.686
			(10.781)
UCDP/PRIO Data			7.978
			(12.522)
Unit: grid-cell			-159.227
			(174.128)
Constant	11.417	9.009	197.843
	(11.075)	(14.858)	(271.681)
N	124	124	124
R-squared	0.011	0.012	0.036

Table S.2.14: **Notes**: Robustness tests performed by including results from conditional estimates. Stepwise regression results are presented for the scarcity subset. Due to the lack of sufficient variation, the regression coefficients for land and some methodological features of the studies have been omitted. Robust standard errors clustered by study are reported in parentheses..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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c) **Robustness tests performed excluding estimates from the studies that operationalize the resource variable as a share of GDP.**

Abundance-conflict (no gdp-share). Effect of natural resource abundance with and without climate controls on conflict.

Resource Abundance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	1.405	0.642	0.749	0.94204	1.426	0.686	0.864	1.086
	(1.248)	(1.217)	(1.182)	(1.196)	(1.287)	(1.248)	(1.178)	(1.196)
Climate		-0.732		0.332***		-0.732		0.335***
		(0.601)		(0.035)		(0.601)		(0.038)
Minerals, drugs			-1.409***	-1.737***				
			(0.032)	(0.021)				
Water					-0.285	-0.603		
					(0.632)	(0.679)		
Land, vegetation							1.414***	1.745***
							(0.028)	(0.012)
Constant	0.513***	1.234**	1.909***	1.907***	0.513***	1.234**	0.500***	0.167***
	(0.031)	(0.600)	(0.020)	(0.021)	(0.031)	(0.601)	(0.018)	(0.021)
N	707	707	707	707	707	707	707	707
R-squared	0.004	0.099	0.221	0.229	0.004	0.099	0.222	0.230

Table S.2.15: **Notes**: Robustness tests performed by excluding from the sample estimates from models that operationalize the resource variable as a share of GDP. Stepwise regressions results are presented for the abundance subset of the sample and focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses. Note that the effect of mineral resource abundance on conflict is negative, unlike in the main findings: this indicates that studies defining resources as a share of GDP are capturing some economic-related effects..
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Abundance-conflict (no gdp-share). Impact of methodological features of the studies on the relationship between natural resource abundance and conflict.

Resource Abundance	(1)	(2)	(3)
Precision	0.870	1.074	-1.199
	(1.218)	(1.232)	(1.20132)
Minerals, drugs	0.254	-0.046	3.739***
	(0.214)	(0.183)	(1.194)
Water	0.199	0.100	6.847***
	(0.392)	(0.457)	(0.675)
Land, vegetation	1.668***	1.700***	3.454***
	(0.193)	(0.195)	(0.705)
Climate		0.335***	-1.090
		(0.036)	(1.403)
Economic context			6.440***
			(1.405)
Type of Conflict			0.005
			(0.062)
Fractionalization			3.949***
			(0.125)
Geography			-3.623**
			(1.463)
History			-2.547***
			(0.653)
Location Fixed Effects			-2.349
			(3.725)
Time Fixed Effects			1.551
			(4.491)
Lags			0.257
			(0.235)
Institutions			-0.633
			(1.186)
Resources: stock			-0.171
			(0.561)
Conflict specification: incidence			0.585
			(1.213)
Conflict specification: intensity			3.942***
			(0.818)
Conflict threshold: 25 BRDs			0.824
			(1.006)
UCDP/PRIO Data			-0.990
			(0.795)
Global analysis			-0.031
			(0.034)
Unit: 5-year			1.002
			(2.167)
Unit: grid-cell			12.649**
			(5.851)
Method: logit			0.059
			(0.780)
Data: World Bank			-2.113
			(1.254)
Constant	0.246	0.213	-5.137***
	(0.200)	(0.203)	(1.566)
Observations	707	707	707
R-squared	0.222	0.230	0.931

Table S.2.16: Notes: Robustness tests performed by excluding from the sample the estimates from models that operationalize the resource variable as a share of GDP. Stepwise regression results are presented for the abundance subset. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
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Scarcity-conflict
(no gdp-share). Effect of natural resource scarcity with and without climate controls on conflict.

Resource Scarcity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precision	-0.995*	-0.252*	-0.995*	-0.252*	-0.922*	-0.126	-0.922*	-0.126
	(0.446)	(0.132)	(0.446)	(0.132)	(0.461)	(0.091)	(0.461)	(0.091)
Climate		2.742***		2.747***		2.787***		2.787***
		(0.074)		(0.074)		(0.085)		(0.085)
Water					-2.214*	-3.449***		
					(1.075)	(0.472)		
Land, vegetation							2.214*	3.449***
							(1.075)	(0.472)
Constant	3.592***	0.850***	3.592***	0.850***	3.592***	0.804***	1.378	-2.645***
	(0.003)	(0.074)	(0.003)	(0.074)	(0.003)	(0.085)	(1.075)	(0.472)
N	84	84	84	84	84	84	84	84
R-squared	0.178	0.946	0.178	0.946	0.193	0.982	0.193	0.981

Table S.2.17: Notes: Robustness tests performed by excluding from the sample estimates from models that operationalize the resource variable as a share of GDP. Stepwise regressions results are presented for the scarcity subset of the sample and focus solely on the resource variables and the climate controls. Robust standard errors clustered by study are reported in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Scarcity-conflict (no gdp-share). Impact of methodological features of the studies on the relationship between natural resource scarcity and conflict.

Resource Scarcity	(1)	(2)	(3)
Precision	-0.922*	-0.126	-0.036
	(0.461)	(0.091)	(0.048)
Water	-2.214*	-3.449***	0.148
	(1.075)	(0.473)	(0.177)
Climate		2.780***	-1.543***
		(0.085)	(0.096)
Fractionalization			0.359*
			(0.191)
Geography			0.589*
			(0.272)
History			-1.112**
			(0.369)
Time Fixed Effects			4.057***
			(0.100)
Lags			0.0316
			(0.056)
Institutions			2.320***
			(0.224)
Conflict specification: incidence			0.323
			(0.350)
Conflict specification: intensity			0.294**
			(0.130)
Conflict threshold: 25 BRDs			0.470***
			(0.002)
UCDP/PRIO Data			-0.622***
			(0.008)
Unit: grid-cell			-0.313
			(0.226)
Constant	1.378	0.804***	-1.118
	(1.075)	(0.085)	(0.793)
N	84	84	84
R-squared	0.193	0.982	0.999

Table S.2.18: **Notes**: Robustness tests performed by excluding from the sample the estimates from models that operationalize the resource variable as a share of GDP. Stepwise regression results are presented for the scarcity subset. Due to the lack of sufficient variation, the regression coefficients for land and some methodological features of the studies have been omitted. Robust standard errors clustered by study are reported in parentheses..

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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The worst form of inequality is to try to make unequal things equal.

Aristotle

3

Climate Variability, Crop and Conflict:

exploring the Impacts of Inequality in Agricultural Production

Contributing to the long debate on the root causes of conflict, an increasing academic effort has been undertaken to investigate the role of climatic and environmental determinants in fostering violence (Hsiang et al., 2013; Buhaug et al., 2014a; Hsiang and Meng, 2014; O'Loughlin et al., 2014). While the empirical literature has failed to find a robust direct association between climatic variability and the likelihood of conflict, scholars have recently shifted their attention towards the possible indirect and conditional pathways leading from climate change to political instability (Theisen, 2017). A substantial agreement exists that climatic conditions can impact security through intermediate pathways and/or under some specific conditions (Mach et al., 2019). However, the mechanisms connecting climate to conflict and the conditions that make this link more likely to arise are rather unclear and further research efforts should aim at understanding how climatic changes interact with and are influenced by socio-economic, political and other factors (Koubi, 2019). In this paper, we delve deeper into the contextual factors that can make climate especially detrimental to security and investigate under which conditions climate anomalies are likely to increase the risk of violence. As climate change is expected to have considerable impact on the quantity and quality of crops produced (Porter et al., 2014), and this impact is likely to greatly vary across different regions of the world (Zhao et al., 2017), we are especially concerned with the role of uneven distributions of agricultural yields in increasing societal vulnerability to climatic changes.

Climate change is likely to increase the frequency, duration and intensity of heatwaves (Perkins et al., 2012; IPCC et al., 2014) and cold spells (Islam et al., 2009; Cohen et al., 2018); alter the quantity and allocation of water and fertile land (IPCC, 2014); reduce freshwater supply (Elliott et al., 2014) and in other ways harm agricultural production (Challinor et al., 2014). While the negative impact of climatic change on global agricultural output is well-established in the literature (IPCC, 2014), the evidence on the implications of crop yield's shocks for security is still sparse (Bollfrass and Shaver, 2015; Buhaug et al., 2015) and additional uncertainty results from the heterogeneous effects of climate variability on agricultural production both in space and time (Jimenez Cisneros et al., 2014).

As it will be argued in the paper, we hypothesize that the destabilizing effect of climatic anomalies arises especially in those settings where the distribution of agricultural output is unequal, as relative differences in crops between locations and groups - rather than absolute scarcity - will more easily lead to relative deprivation. In this perspective, our empirical approach enables us to go beyond the conventional absolute measurement of crop production and explicitly focus on the effect of relative differences in agricultural yield. Agricultural inequality may be especially relevant to the climate-conflict nexus as, when climatic changes reduce the amount of available resources, communities who were already poorer in agricultural production than the average will arguably be more prone to fight for taking control over additional goods, and more likely to join rebel groups in the prospect of material rewards.

The relative deprivation induced by agricultural inequality could also exacerbate extant grievances and add to pre-existing societal fractures, which can be especially destabilizing whereby the government lacks the means or the political will to alleviate popular discontent (as, for instance, in the case of Syria - Gleick, 2014). We therefore go a step further and posit that inequality in agricultural production per se may not be a sufficient condition to shape the effect of climate on conflict, to the extent that it does not take any identarian dimension or socio-political fractures into account. Discriminated ethnic groups do not only lack proper capacities and assets to cope with climatic hardships (Fjelde and von Uexkull, 2012), but are also more likely to be left at the margins of governmental responses and relief programs (Raleigh, 2010). In this perspective, discrimination and agricultural inequality will mutually reinforce each other and extensively diminish societal coping capacities to tackle climate change impacts. The effect of climatic changes will thus be highly destabilizing in those settings where agricultural production is unevenly distributed and characterized by higher political discrimination.

To test this hypothesis, we collect an annual, global dataset including information on the local yield of four main crops relative to the period 1982-2010 and country-level data on ethnic and civil conflict, as well as information on temperature and precipitation anomalies from the long-term mean and political discrimination. Taking advantage of the spatially disaggregated, time-variant measure of production of four main crops (maize, soybeans, wheat and rice), we aggregate the gridded crop value to obtain an annual estimate of agricultural output for each country and ethnic group. This enables us to compute a time-variant, empirically-driven indicator measuring inequality in crop production at both the country and ethnic group level.

The paper contributes to the literature in many regards. First, our study is the first to compute a data-driven, dynamic measure of inequality in agricultural production and investigate how this measure can increase societal vulnerability to climatic anomalies. To this end, we introduce a more flexible definition of agricultural production as predictor of conflict, which is not a priori concerned with scarcity or abundance as absolute quantities but follows the spirit of Selby and Hoffman's notion of relative differences (Selby and Hoffman, 2014). Finally, we delve deeper into the contextual factors that may make climate more destabilizing, and especially investigate how inequality in agricultural production interact with political discrimination to shape the impact of climatic changes on conflict onset.

The remainder of the paper is organized as follows: first, we present the main conditions under which climatic variability may increase the likelihood of conflict; next, we illustrate the data and methods used to build the inequality indicator; the final section presents the results and concludes.

3.1 Climate, Crop and Conflict

Most of the empirical literature investigating the impact of climatic and environmental conditions on organized violence theoretically originates from the environmental security tradition, which links scarcity of renewable resources to conflict, be it induced by climate variability and anomalies, natural hazards or environmentally related migration (Homer-Dixon, 1999; Kahl, 2006). The main argument of these studies advances that climatic and environmental shocks are likely to trigger violence via a number of possible pathways: by reducing the availability of essential natural resources like water (De Stefano et al., 2017), by depressing economic output and growth (Miguel et al., 2004), by fostering migration (Abel et al., 2019) and by deteriorating food production (Harari and La Ferrara, 2018) and/or shocking food prices (Wischnath and Buhaug, 2015). Climatic changes and their broader socio-economic implications may hence increase the likelihood of conflicts by *i)* decreasing the opportunity cost of violence, as they make individuals or groups more attracted to the prospect of gains promoted by rebel leaders; *ii)* triggering a sense of relative deprivation that forces individuals to mobilize to redress their grievances, especially when some specific groups are or perceive to be worse off (Theisen, 2017).

The underlying assumption behind this argument is that some conditions or contextual factors need to pre-exist for climatic shocks to act as a destabilizing force. In other words, climatic changes are a 'threat multiplier' (CNA, 2007), as they may ignite conflicts only when and where they find an inflammable ground. Although scholars agree on the importance of contextual factors in affecting the climate-conflict nexus, most of the recent effort has intended to identify the causal mechanisms connecting climatic conditions to violence, while further attention needs also be paid to understanding under which conditions this relationship is likely to manifest itself (Koubi, 2019).

The impacts of climatic changes are in fact likely to be spatially heterogeneous (IPCC, 2014), not ultimately as they depend on countries' coping capacities and communities' resilience to exogenous shocks (Adger et al., 2003; 2014). Extant studies addressing the contextual factors that may increase vulnerability to climate shocks have so far mostly focused on socio-political and economic settings, such as development (Slettebak, 2012), ethnic fractionalization (Schleussner et al., 2016), ethno-political exclusion (Theisen et al., 2011-12; von Uexkull et al., 2016) and state capacity (Gizelis and Wooden, 2010). Some studies have recently targeted the vulnerability that may raise from agricultural-related conditions, such as agricultural dependency (Bell and Keys, 2016; von Uexkull et al., 2016) and crops' growing season (Harari and La Ferrara, 2018).

Few empirical study specifically address how the effect of climatic variability on conflict varies according to agricultural production (von Uexkull, 2014; Bollfrass and Shaver, 2015). Among those studies, von Uexkull (2014) finds that droughts have a higher impact on African conflict in regions with rainfed agriculture, while a global, disaggregated study by Bollfrass and Shaver (2015) contends that the impact of climatic anomalies on conflict does not exhibit any heterogeneity across different levels of agricultural production and it is consistently positive for both regions that do experience changes in agricultural output and regions that do not.

This paper attempts to gain insight on how vulnerability to climate change is affected by different agricultural-related patterns and especially investigates how inequality in agricultural production can make communities more vulnerable to conflict when hit by climatic shocks. As climate change is expected to have an increasing influence on global agricultural production (Porter et al., 2014), a better understanding of the vulnerability induced by agricultural related patterns is essential to foster communities coping capacities and increase resilience against climatic shocks.

The impacts of climate variability on agricultural production are well established in the scientific literature. Climate change is already reducing crop yields at the global level, a trend that is projected to continue as temperatures rise further (IPCC, 2014). If no adaptation takes place, global yields are expected to decrease at a pace of 1.5% per decade (Lobell and Gourdji, 2012) and losses in aggregate production will affect wheat, rice and maize in both temperate and tropical regions by 2°C of local warming (Challinor et al., 2014). Crop-level adaptation and technological innovation can moderate losses to some extent (Rosenzweig and Perry, 1994) but adaptive capacity is projected to be exceeded in regions closest to the equator if temperatures increase 3°C or more (Porter et al., 2014). For instance, rain shocks have been proven to be equally strong predictors of riot incidence in India, in both districts which are equipped with dams that supply irrigation (and thus more resilient to climate-driven agricultural income shocks) and those which are not (Sarsons, 2015). Adaptive capacities are also likely to be constrained due to the spatial and temporal variability of climate-induced shocks to agriculture, as the negative impacts of climate changes on crop production are expected to vary across both time and space (Kang et al., 2009). Coping capacities will be especially overstepped in developing countries, whereby vulnerable populations characterized by low levels of socio-economic developments may be less resilient to the destabilizing shock of environmental and climatic hardships (Ramankutty et al., 2002; Arnell, 2004; Scheffran and Battaglini, 2011) and governments may lack resources to implement adequate measures (Rosenzweig and Perry, 1994; Morton, 2007; Lobell et al., 2008; Mendelsohn, 2008).

Climate induced shocks to agriculture may cause crop failures (Tigchelaar et al., 2018), reduce farmers' income (Di Falco et al., 2012), deteriorate the local livelihood (Jones and Thornton, 2009), increase the volatility of food prices (Smith, 2014) and make developing countries more dependent on food imports (Hendrix and Haggard, 2015). Although it is unlikely that climate-induced shocks to agricultural production are a sufficient cause for mobilization (Buhaug et al., 2015), they can intertwine with pre-existing grievances thereby making conflict more likely, as well as provide incentives for destitute farmers to join or support rebellion (von Uexkull, 2014). By contrast, increases in agricultural productivity seem to decrease the incidence of conflict, as higher levels of production per land unit could reduce the value of land, increase the opportunity cost of arming and in many ways loosen Malthusian links (Iyigun et al., 2017).

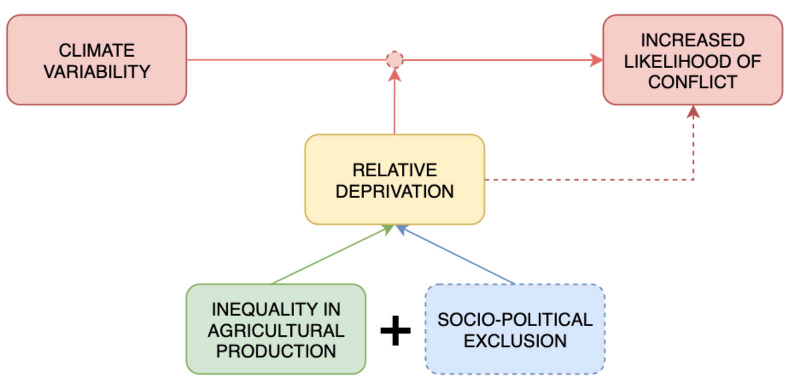

Figure 3.1: Main pathways leading from climate variability to increased likelihood of conflict through inequality in crop production. For simplicity, the links are kept at a minimum.

Moreover, as climatic variability and extreme weather events are unlikely to affect all individuals and households within a country equally (Koubi, 2019), the negative effect of climate shocks can be particularly detrimental in those settings characterized by already high levels of inequality in agricultural production.

Land inequality, for instance, has been linked to an increased likelihood of conflict in Latin America (Jensen and Sørensen, 2012) and maldistribution of land tenure can encourage land invasions after climate-induced economic shocks (Hidalgo et al., 2010). Likewise, variations in soil productivity induced by spikes in fertilizers' prices have been shown to trigger conflict in Sub-Saharan Africa, especially in areas where land endowments are more heterogeneous, both across and within grups (Berman et al., 2019).

Even in stable climatic conditions, in those settings where agricultural production is particularly unequal, individuals only benefit from a small fraction of the available resources; when crop yields become increasingly scarce as an effect of climatic shocks, destitute individuals may thus be more willing to fight for overthrowing the government and getting an increasing control over the productive capacity (Robinson and Acemoglu, 2006). Also, as rebel groups generally propagandize material incentives as a reward for engagement (Kalyvas, 2006) individuals who were already worse off due to the uneven distribution of agricultural output will be particularly attracted to the personal enrichment prospected by rebel leaders. Especially in the lack of viable economic alternatives, the opportunity cost of joining the fight will be thus reduced (Collier and Hoeffler, 2004; Brinkman and Hendrix, 2011).

Moreover, when livelihood conditions are deteriorated by climatic shocks, the gap between what individuals perceive to be a fair condition and what they acknowledge to be their actual status will be even higher (Fjelde, 2014). The relative deprivation felt by already poor farmers can add to pre-existing inequalities and exacerbate societal fragmentation (Jones et al., 2017), and will thereby encourage mobilization to obtain a fairer distribution of resources.

What type of conflict is likely to be triggered by these dynamics, depends on whom is identified as 'liable', i.e. whom the affected individuals are likely to blame for their conditions (Theisen, 2017). If individuals perceive the government or the political elite as responsible for their status, they will more likely seek to overthrow the current political settings and the mobilization may thus increase the risk of civil conflict. Exogenous shocks to crop yields may especially destabilize political settings if the government lacks the will or the capacity to satisfy the most basic needs (e.g. Gleick, 2014). In the case where the members of the government coincide with a specific ethnic group, or whenever a particular ethnic group is perceived as the 'culprit' of the livelihood deterioration, however, the mobilization is more likely to occur along ethnic borders and thus ethnic conflict will be more likely.

The line of reasoning illustrated in this section enables us to formulate the following hypotheses:

Hypothesis 1a. Higher levels of inequality in crop production at the country level are associated with a higher probability of civil conflict onset.

Hypothesis 1b. Higher levels of inequality in crop production between ethnic groups are associated with a higher probability of ethnic conflict onset.

Hypothesis 2. Locations characterized by high inequality in agricultural production will be more likely to experience conflict when hit by climatic changes.

3.1.1 Inequality in crop production, discrimination and conflict

Environmental issues can act as 'threat multiplier' (CNA, 2007), but climatic variability may still not be a sufficiently destabilizing element even where agricultural production is unevenly distributed, unless relative differences in agriculture overlap with other forms of cleavages. Socio-political factors represent in fact a key condition for environmental issues to trespass the threshold of violence (Baechler, 1999). When groups are subject to intentional and targeted discrimination - either formally or informally - with the intent of excluding them from power, they are generally more prone to adopt violent means to overthrow the regime or in other ways alter the current political setting (Cederman et al., 2010). Therefore, countries where ethnic groups which are sensibly worse off than the average experience discrimination or exclusion from central politics have a significantly higher risk of violent anti-governmental opposition (Buhaug et al., 2014b). Climatic hardships reveal and emphasize the ways in which inequalities and coping strategies form the basis of livelihoods, as response actions - both from the local community and from the central government - will be shaped according to socio-political dynamics (Raleigh, 2010).

Politically insignificant and discriminated ethnic groups do not only lack alternative means of livelihood and sources of income but are also more likely to be neglected by government-sponsored redistribution programs and relief aid (Theisen et al., 2011-12). Hence, socio-politically discriminated groups and marginalized communities tend to be less resilient to climatic changes (Fjelde and von Uexkull, 2012) and are likely to experience most conflicts related to environmental pressures (Schleussner et al., 2016; von Uexkull et al., 2014; Raleigh, 2010).

Where agricultural production is unequal, politically discriminated groups will be especially worse off, as they will lack the means and capacities to handle climate change negative impacts. The relative deprivation triggered by inequality in agricultural production and accentuated by climatic shocks will thereby acquire a collective dimension which is the key trigger point of violence, to the extent that conflicts are collective phenomena (Stewart, 2008).

This leads us to advance the following hypothesis:

Hypothesis 3. The joint effect of climate anomalies and inequality in agricultural production on civil (ethnic) conflict onset is especially high for higher levels of political discrimination.

To test our main hypotheses, we compute a Gini index of inequality in agricultural production at two spatial levels: i) country; ii) ethnic group. The next paragraph illustrates the construction of the inequality indicator in more detail.

3.2 Research design

3.2.1 Indicator of Inequality in Crop Production

Our study is the first to compute an empirically-driven, time-varying indicator of inequality in agricultural production and observe how it correlates to conflict, as the dimension of inequality related to agricultural resources have never been tested as a predictor of violence. Studies have extensively examined the destabilizing effect of economic inequalities across identity-based groups (Gurr, 1970; Collier & Hoeffler, 2004; Cramer, 2003; Østby, 2008), but much less attention has been paid to the conflict potential of agrarian inequality. Some studies did focus on land inequality as a potential predictor of insurgency, but they only concentrated on the maldistribution of land tenure (Russett, 1964; Scott, 1976; Muller

& Seligson, 1987; Boix, 2003; Hidalgo, 2010), while totally neglecting the differences in land productivity and agricultural production. Nevertheless, land maldistribution is not necessarily a good proxy of crop production; indeed, higher agricultural outputs can be achieved without necessarily expanding the amount of land per capita, through enhanced agronomic practices, improved crop varieties, and other technological innovations (Tilman et al., 2011). Moreover, despite framing their theories in regional terms, these studies generally compute the measure of inequality only at the country level (Paige, 1978); however, as sharing a common identity is essential for a group to mobilize (Tilly, 1978; Gurr, 2000), between-groups agrarian inequality may be especially relevant for conflict.

This study tries to avoid some of the limitations of the previous literature by using disaggregated, geo-referenced data on crop production covering years 1982-2010 (Iizumi et al., 2018) and aggregating them at both the country and the ethnic group level. These data allow us to build a set of empirically based indicators of inequality in crop production. We compute two main measures of inequality: i) the simple Gini coefficient as a measure of inequality in crop production at the country level; ii) the Gini coefficient across ethnic groups.

The plain *vanilla* Gini coefficient is computed on the basis of the value of crop production for each grid-cell, nested within national countries, and thus measures the inequality in yields across grid-cells as individual units. The between-groups Gini index for a country's population consisting of n groups with values of crop production y_i is defined as:

$$G = \frac{1}{n}(n+1-2)\frac{\sum_{i=1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n}y_i}. \tag{3.1}$$

where group-level values of crop production y_i are indexed in non-decreasing order such that

$y_i \leq y_{i+1}$. The between-groups Gini index captures differences in the mean crop production across ethnic groups (Alesina et al., 2016) and aims precisely at uncovering group-level grievances as underlined in the above sections.

The between-groups Gini index relies on the assumption that each ethnic group has the same access to agrarian products, or in other words, that the benefits deriving directly or indirectly from crop production are gained locally by each group, rather than being appropriated by the central government. Although this is quite a strong assumption, the lack of data on property rights and degrees of access to agricultural benefits by each group prevents us from conducting a more detailed analysis. Moreover, while the issue of rents' redistribution is surely worth-considering in the case of profitable resources like oil and minerals, it is less relevant to agricultural production, whose gains are likely to be accessed homogeneously by groups - especially in the least developed areas, not yet characterized by the oligopolistic structure and the dominance of few big crop producers that is more frequent in developed areas.

For our purpose, we group individuals by 'non-agrarian' characteristics, *i.e.* features which are different than the variable for which the inequality is being calculated: first, by regional identity, and second, by ethnicity. To compute the mean value of crop production for each n group within country's population, we spatially overlay groups' geo-referenced polygons with gridded data on crop production (Iizumi et al., 2018) and aggregate the cell-level crop yield to obtain the mean value of agricultural production by ethnic group. Ethnic groups are defined by using the spatial polygons provided by the 2019 version of the Geo-EPR dataset (Vogt et al., 2015).

For each spatial group, we construct two basic measures of the Gini index: the first one

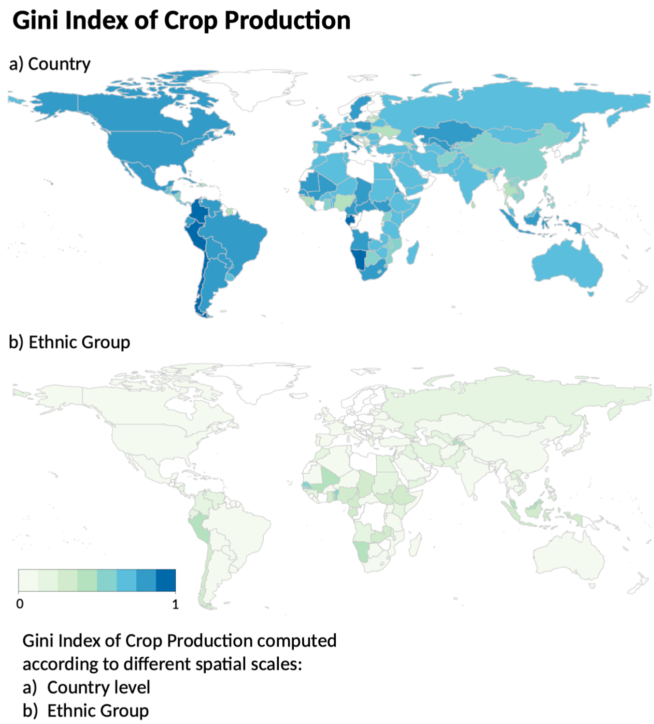

Figure 3.2: Gini index of crop production. a) Simple Gini Coefficient, computed for grid-cells nested within countries; b) Between-groups Gini Coefficient computed for ethnic groups nested within countries.

uses the information on crop production from all grid-cells; the second measure is limited to rural grid-cells and excludes urban areas from the sample.[*] Indeed, when measuring the inequality in crop production across groups, a potential issue may arise concerning the different crop yield levels that characterize urban vs. non-urban areas: urban areas will have low or null production of crops and could therefore erroneously be interpreted as 'poor' in agricultural value compared to rural locations. As our main goal is to observe the effect of an unequal distribution of crop among spatial locations and ethnic groups, including urban

[*]Rural cells are defined as those whose land surface is not covered by any artificial/urban structure, according to Globcover categorization of land-use areas (Bontemps et al., 2009). Urban cells are any cells for which the extension of artificial/urban area is greater than zero.

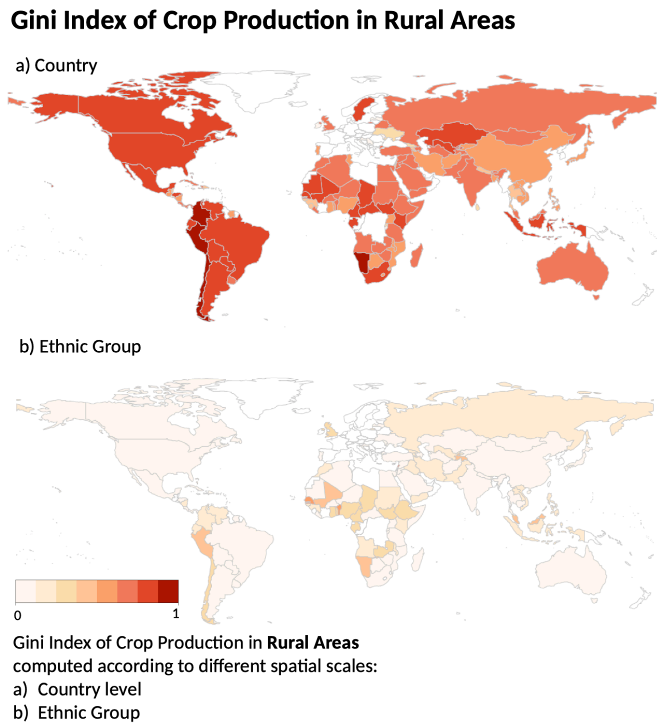

Figure 3.3: Gini index of crop production in rural areas. a) Simple Gini Coefficient, computed for grid-cells nested within countries; b) Between-groups Gini Coefficient computed for ethnic groups nested within countries.

areas in the analysis may potentially influence the construction of the Gini index, as it would consider urban cells equal to rural locations which have a low or null level of crop production. Consistently, we perform our empirical analysis by using both measures of inequality, the Gini index computed for the entire sample, as well as for the sub-set of the sample that only includes rural areas.

Figures 3.2 and 3.3 visualize our measures of inequality for both the full sample and only rural cells. Even a quick glance at the maps enables us to realize that the values of the Gini coefficient vary considerably according to the way of measuring inequality in space, either at the country level or between ethnic groups. By contrast, the distribution of inequality in crop production is not considerably affected by the exclusion of urban areas from the sample, as the values of the Gini index tend to follow the same pattern whether urban areas are included or not. While inequality in crop production between ethnic groups is generally low, inequality at the country level displays the highest variation.

The inequality in crop production within countries seem to be homogeneously high all over the world and especially in developed states. At first, we may be surprised to observe that wealthy countries such as the United States have higher levels of inequality in crop production than poor countries. However, this is coherent with the technological advances in cultivation techniques and the switch to intensive farming that characterize the latest stages of economic development, leading to an oligopolistic concentration of crop production in the hands of few producers (Sexton et al., 2007). Economic inequality has been shown to observe a similar trend, with developed countries featuring higher levels of income inequality than nations at lower levels of development, according to a U-shape relationship (Anand & Kanbur, 1993; Stiglitz, 2013).

A potential issue in measuring inequality between groups is represented by the heterogeneous dimension of groups within countries; as the number of individuals in each group is likely to differ, an unweighted index would assign the same weight to the relative position of small and large groups (Stewart, 2008). To account for differences in size across groups, in our robustness tests we construct a population-weighted index, by replacing the standard group-level mean with a population-weighted average of crop production for each group. Regression results relative to the population-weighted index are available upon requests.

3.2.2 Empirical model and Data sources

The empirical analysis is performed at the country-year level for both types of spatial inequality, i.e. both when the Gini index is computed between the grid-cells within a country, and when it is calculated as a measure of inequality across ethnic groups. We start by testing the effect of crop inequality on the probability of conflict onset (Hypothesis 1) by means of the following empirical model:

$$Y_{i,t} = \alpha_0 + \alpha_1 G_{i,t} + \alpha_2 A_{i,t} + \alpha_3 (G_{i,t} \cdot A_{i,t}) + \alpha_4 X_{i,t} + \alpha_5 E_{i,t} + \alpha_6 D_{i,t} + \alpha_7 C_{i,t} + \varepsilon_{i,t} \tag{3.2}$$

where $G_{i,t}$ is the Gini coefficient of crop production inequality (as described in the previous section) in country i in year t; $A_{i,t}$ is the vector of climatic anomalies (precipitation and temperature anomaly), $X_{i,t}$ contains controls for a country's level of development, population size and other country-specific variables; $D_{i,t}$ identifies political discrimination; $E_{i,t}$ is the vector of ethnic diversity and ethnic politics variables, and C_{it} contains a complete set of geographical and time controls.

Next, we introduce interaction terms to test for hypotheses 2 and 3, as in the following:

$$Y_{i,t} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 G_{i,t} + \alpha_3 D_{i,t} + \alpha_4 Z_{i,t} + \alpha_5 A_{i,t} \cdot D_{i,t} + \alpha_6 G_{i,t} \cdot D_{i,t} + \alpha_7 A_{i,t} \cdot G_{i,t} + \alpha_8 A_{i,t} \cdot G_{i,t} \cdot D_{i,t} + \varepsilon_{i,t} \tag{3.3}$$

where $Z_{i,t}$ identifies all the controls of eq. 3.2. To test the hypothesis that societies characterized by higher level of inequality in agricultural production would be more vulnerable to climatic shocks, we interact the measure of inequality in crop production with data on temperature and precipitation anomalies. To verify our third hypothesis, we interact both climatic anomalies and the Gini index of agricultural production with political discrimination.

The three-way interaction term $A_{i,t} \cdot G_{i,t} \cdot D_{i,t}$ identifies the variation of the joint effect of climate anomalies and inequality on the probability of conflict onset at different levels of discrimination. If the coefficient associated to the interaction term (α_8) is positive and significantly different from zero, then we can say that the joint effect of climate anomalies and inequality increases with discrimination. In other words, the adverse effects of climate change in combination with existing levels of inequality in territorial distribution of agricultural production will be significantly higher in societies with larger shares of disadvantaged and discriminated populations with respect to more inclusive societies. It is important to note that adding an interaction term to a model significantly changes the interpretation of *all* of the coefficients. If there were no interaction terms, for instance, the effect of discrimination on conflict would be equal to α_3. As the three way interaction may also be interpreted as the effect of discrimination for different values of climate anomalies and inequality in crop production the marginal impact of discrimination is not limited to α_3 but also depends on the value of G and climatic variables. In order to capture this, we can rewrite the above equation in the following form:

$$Y_{i,t} = (\alpha_0 + \alpha_1 A_{i,t} + \alpha_2 G_{i,t} + \alpha_7 A_{i,t} G_{i,t} + \alpha_4 Z_{i,t}) + (\alpha_3 + \alpha_5 A_{i,t} + \alpha_6 G_{i,t} + \alpha_8 A_{i,t} G_{i,t}) \cdot D_{it} \tag{3.4}$$

where the first term is the intercept and the composite term associated to $D_{i,t}$ represents the slope, *i.e.,* the marginal effect of discrimination on the probability of conflict outbreak.

The main dependent variable Y is civil conflict as defined by the Uppsala Department of Peace and Conflict Research (UCDP, 2019). Civil conflict is here defined as a state-based conflict, which involves at least a government of a state as an active part, and results in a minimum of 25 battle-related deaths in a year. We consider all conflict episodes over the period 1982 - 2010. Specifically, civil conflict onset is a binary variable coded as 1 for every year in which a conflict breaks out in a given location and 0 otherwise. Data on conflict are drawn from the most recent version of the UCDP database gathered by Uppsala University (Gleditsch et al., 2002; Pettersson et al., 2019). Furthermore, we also consider the onset of ethnic civil conflicts, defined as a binary variable that takes the value of 1 in the first year of an armed ethnic conflict and 0 otherwise. A conflict episode is defined as ethnic whenever rebel organizations pursue ethno-nationalist aims and recruit along ethnic lines in order to achieve ethno-national self-determination, a more favorable ethnic balance of power in government, ethno-regional autonomy, the end of ethnic and racial discrimination, or a more balanced division of resources along ethnic lines within society. We utilize country-level data on ethnic conflicts from the latest version of EPR dataset (Vogt et al., 2015).

To build the crop production inequality indicators (Gini), we rely on information on the annual production of four main crop types (maize, wheat, soybean, rice) in a given grid cell, expressed in tonnes per hectare (t/ha). Global gridded data at 0.5 degree resolution (55 km by 55 km at the equator) are drawn from Iizumi et al. (2018) which improves upon the spatial resolution of the previous versions of their dataset (Iizumi et al., 2014; Iizumi & Ramankutty, 2016) . Although the coverage of the data, which includes only four crop types, may represent a limitation to the analysis, we believe this is an acceptable price to pay for building a time-variant dataset, which is necessary to investigate the conditional effect of climatic variability on conflict onset.

We define climatic anomalies as the standardized deviation of annual temperature and precipitation from their long-term climatologic mean, conventionally defined as the mean over a period of almost thirty years (WMO, 2017). Climatologic data on temperature and precipitation are retrieved from meteorological statistics developed by the University of East Anglia Climatic Research Unit (Harris et al., 2014).

Discrimination is defined as in Cederman et al. (2010), i.e. as the political exclusion directly targeted at an ethnic community - thus disregarding indirect discrimination based, for example, on educational disadvantage. Such active discrimination can be either formal or informal (Cederman et al., 2010). Data on discrimination are drawn from the most recent version of the GeoEPR-ETH dataset (Vogt et al., 2015).

Solid scientific evidence holds that poverty and low levels of development are detrimental for countries' peace and stability (Collier & Hoeffler, 1998; Hegre, 2001; Fearon & Laitin, 2003; Miguel et al., 2004; Collier & Rohner, 2008). Consistently, in our analysis we do control for the role of socio-economic conditions (GDP, population size) in affecting the risk of civil conflict.

Finally, we include a number of control variables to account for other contextual factors that can increase or decrease the odds of violence. A full list of the controls and descriptive statistics are presented in Tables S.3.11 - S.3.12 in the Appendix. Our main covariates are standard in conflict research: other than the GDP per capita and population size, we control for the characteristics of the political system, educational attainment of the population, oil rents, incidence of international trade in domestic GDP, and geophysical characteristics (mountainous terrain).

Data on GDP per capita are drawn from the World Bank Development Indicators (World Bank, 2012), complemented with the Penn World Tables (Feenstra et al., 2015). Data for the missing years are linearly interpolated and variables are lagged by one year to cope with endogeneity.

In order to characterize the political systems, we use the 2019 version of V-Dem data set (Coppedge et al., 2019) based on an expert evaluation of the countries' level of democracy. Specifically, we code a variable for autocracy, corresponding to regime types 0 and 1 in V-Dem Regimes of the World measure.

As for additional country characteristics, we consider the share of the territory covered by water and terrain roughness. Geophysical or structural characteristics such as terrain roughness, which enhance rebels' chances of hiding, may indeed favor rebellions and insurgencies (Fearon & Laitin, 2003). Finally, since countries which rely heavily on the agricultural sector will be more sensitive to changes in crop yields and therefore more subject to exogenous shocks to agricultural production, we control for the degree of agricultural dependence. As a crude proxy for agricultural dependence, we use data on the value added of agricultural production (World Bank, 2012) and we also add a control for the share of irrigated land as a fraction of the cultivated land (World Bank, 2012).

As ethnic competition is likely to affect conflict risk (Cederman et al., 2013), we include controls for the ethnic composition of the population and the intensity of competition between different power groups defined along ethnic lines. Specifically, we control for the degree of ethnic fractionalization (Vogt et al., 2015); and the number of power sharing groups (Vogt et al., 2015), represented by ethnic elites at the central government, which proxies the political competition between groups in the decision making process.

Finally, we consider a set of country-specific controls for the geographic region (macro-area), regional time trend, and cubic splines of the number of peace years since the outbreak of a previous conflict.

3.3 Results

The results of the regression analysis are presented in Tables 3.1 - 3.2. We consider two main types of conflicts: civil conflict and conflicts that are considered purely ethnic in nature. Results relative to alternative specifications of the dependent variable are presented in the Appendix. Results are presented for both the country-level Gini and the Gini between ethnic groups, and for two different cell sub-samples: *i)* all cells with no distinction between urban and rural areas, and *ii)* only rural areas (reported in the Appendix). The models step-wisely increase the set of predictors; we start by including the Gini index together with a full set of country-specific controls and geo-physical characteristics, as well as a complete battery of climatic variables; the models are then gradually enriched to include the interaction terms between the Gini index and proxies for climatic variability, as well as with political discrimination. In all model specifications we control for geographic macro-area and regional time trends, and correct for error correlation over time for a given country by calculating cluster - robust standard errors.

3.3.1 Inequality in Crop Production and Conflict

Results of the empirical analysis confirm our first hypotheses (Hypothesis 1a and 1b). In fact, we find that both country-level and ethnic group-level inequality in crop production are associated with a higher probability of conflict onset. A marginal increase in inequality of agricultural production at the country level (considering both urban and rural areas), holding the other variables at their mean, leads to a 12.6% higher probability of civil conflict outbreak (Model 5, Table 3.1), and the effect is almost 2% points higher when we compute the Gini index considering only rural areas (Model 5, Table S.3.1).

Table 3.1: Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the COUNTRY level, 1982 - 2010.

Conflict Onset	Ethnic	Ethnic	Ethnic	Ethnic	Civil	Civil	Civil	Civil
GINI	0.068**	0.053*	0.050*	0.052*	0.119***	0.126***	0.103***	0.107***
	(0.030)	(0.030)	(0.028)	(0.030)	(0.035)	(0.037)	(0.036)	(0.036)
Discr.*GINI		0.254**	0.255**	0.270**		0.125	0.130	0.132
		(0.117)	(0.111)	(0.122)		(0.110)	(0.139)	(0.131)
Temp.(dev.)*GINI		-0.014		-0.014		-0.008		-0.004
		(0.023)		(0.022)		(0.033)		(0.032)
Prec.(dev.)*GINI			0.009	0.007			0.001	0.001
			(0.022)	(0.021)			(0.029)	(0.029)
Temp.(dev.)*Discr.*GINI		0.173*		0.152		0.092		0.045
		(0.092)		(0.103)		(0.177)		(0.181)
Prec.(dev.)*Discr.*GINI			0.063	0.074			0.068	0.097
			(0.080)	(0.077)			(0.126)	(0.119)
Temperature (lag)	0.000	0.000		0.000	0.001	0.001		0.001
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)
Temperature (dev.)	0.002	0.011		0.009	-0.005	-0.001		-0.005
	(0.005)	(0.015)		(0.014)	(0.006)	(0.023)		(0.023)
Precipitation (lag)	-0.000		-0.000	-0.000	-0.000***		-0.000**	-0.000***
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)	-0.003		-0.009	-0.007	-0.002		0.000	0.000
	(0.003)		(0.014)	(0.014)	(0.004)		(0.019)	(0.019)
Temp.(dev.)*Prec.(dev.)	-0.005				-0.002			
	(0.004)				(0.005)			
Temp.(dev.)*Discr.		-0.103		-0.085		-0.013		0.027
		(0.069)		(0.080)		(0.119)		(0.122)
Pre.(dev.)*Discr.			-0.057	-0.063			-0.093	-0.117
			(0.062)	(0.060)			(0.093)	(0.089)
Water Coverage (%)	-0.000	-0.001	-0.000	-0.000	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mountains (%)	0.032*	0.028*	0.027	0.030*	0.046**	0.044*	0.031	0.046**
	(0.018)	(0.016)	(0.016)	(0.017)	(0.023)	(0.023)	(0.022)	(0.023)
GDP per Capita (log, lag)	-0.004	-0.007	-0.006	-0.006	-0.009	-0.013	-0.013	-0.010
	(0.007)	(0.007)	(0.008)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Population (log, lag)	0.011	0.012	0.012	0.012	0.023**	0.026**	0.026**	0.024**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)	(0.010)
Education (%)	0.001	0.001	0.001	0.001	0.000	-0.001	0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Oil (share GDP)	0.004***	0.004***	0.004***	0.004***	0.002	0.003	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Trade (share GDP)	0.002	0.004	0.003	0.003	-0.000	0.001	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Discrimination (%)	0.030	-0.142	-0.146*	-0.156*	0.039	-0.022	-0.053	-0.042
	(0.020)	(0.089)	(0.083)	(0.093)	(0.029)	(0.082)	(0.104)	(0.098)
Autocracy	-0.004	-0.003	-0.003	-0.003	0.009	0.010	0.008	0.009
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Ethnic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2720	2720	2720	2720	2998	2998	2998	2998

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This is consistent with the previous literature's findings that rural regions tend to be more vulnerable to environmental issues (von Uexkull et al., 2016); an exogenous stress to agriculturally dependent populations would hit them more heavily than urban groups, who can rely on a diversified set of resources.

The inequality in crop production is therefore shown to have a destabilizing impact on societies even when it does not overlap with ethnic cleavages: crop maldistribution across spatial units (grid-cells) within the same country is in fact conducive of conflict even when there is no clear-cut idea of group identification. In other words, maldistribution in agricultural output is per se a destabilizing factor, without necessarily overlapping with ethnic-based dynamics to trigger frustration and exacerbate grievances.

Inequality in agricultural production has a slightly lower effect on ethnic conflict than civil conflict, although the coefficient remains positive and statistically significant at the 5% level (Model 1, Table 3.1). Likewise, when we compute the Gini index between ethnic groups, we find that a marginal increase in agricultural inequality results in around 9% increase in the likelihood of civil conflict and 8% higher probability of ethnic conflict (Model 1, Table 3.2).

This suggests that inequality in agricultural production is more likely to trigger civil conflict than to push mobilization along ethnic lines. This may also indicate, however, that socio-political conditions need to be thoroughly taken into account to explain ethnic conflicts; the relative deprivation induced by agricultural inequality, in line with our third hypothesis, may in fact not be a sufficient factor to trigger ethnic mobilization, unless it interacts with other forms of marginalization and discrimination.

This line of reasoning seems to be confirmed by the regression results, as we find that the interaction term between the Gini index of agricultural production and political discrimination is considerably higher than the stand-alone effect of agricultural inequality (Tables 3.1 - 3.2). A marginal increase of crop inequality leads to around 25% higher risk of ethnic conflict in countries characterized by higher political discrimination.

The pattern does not changes when we perform the analysis by using the Gini index computed for only rural regions; likewise, we find that the Gini index of agricultural production is associated to an increased risk of civil conflict onset, while the effect on ethnic conflict is slightly lower (Table S.3.1).

Moreover, when the Gini index is computed between ethnic groups and restricted to rural cells, a marginal increase in agricultural inequality is shown to increase the probability of ethnic and civil conflict outbreak by 9.6% and 11% respectively (Models 1, 6, Table S.3.2).

As for the other common determinants of conflict onset, the level of GDP per capita is not always significantly correlated with the probability of conflict outbreak; this is not surprising after all, since part of the effect of GDP is absorbed by agricultural production. Consistently with a well-established conflict scholarship, we find that the size of the population and the number of peace years since the outbreak of the previous conflict are significantly related to conflict onset. We also find that socio-political and identity-based characteristics, akin ethnic competition and discrimination, are important predictors of conflict outbreak. As in Fearon & Laitin's (2003) insurgency model, oil production per capita and mountainous terrain receive support here as predictors of violence, and they are confirmed to increase the likelihood of conflict. Finally, although the coefficients associated to autocracy have the expected sign, they do not reach significance at the 0.10 level.

3.3.2 Vulnerability to Climatic Changes and Conflict

We now focus on the combination of factors that is likely to increase societal vulnerability to climatic shocks. First, the empirical evidence presented in Tables 3.1 - 3.2 shows that Hypothesis 2 is not supported, either for civil conflict or for ethnic conflict onset. In fact, the interaction term between temperature or precipitation anomalies and inequality in agricultural production is not significantly correlated with conflict onset. This means that countries with uneven crop endowments are not considerably more vulnerable to conflict than the global average when subject to climatic shocks. A possible explanation for this non-finding lies in the temporal dimension of our climatic variables: temperature and precipitation anomalies are in fact slow-onset events, to the extent that their effect unfolds at a relatively slow pace. The results may therefore suggest that countries are resilient enough to cope with slow variations in temperature and precipitation patterns; however, this may not hold for more rapid-onset events such as floods, heat waves and cold spells, whose impacts on crop productions may be particularly challenging for local communities. More abrupt climatic shocks may indeed have a higher destabilizing effect as they further stress societal coping capacities.

As argued in Hypothesis 3, we do find that countries' vulnerability to climatic anomalies is considerably increased by the combined effect of between-groups inequality in agricultural production and political discrimination. Temperature anomalies are shown to increase civil conflict onset by 36 percentage points in locations characterized by more uneven crop yields and higher levels of political discrimination than the average (Model 6, Table 3.2). Precipitation seems to have a more moderate effect on civil conflict; our results show that a marginal increase in precipitation anomaly leads to an increase of around 25 percentage points where crop production is more unequal and groups suffer from higher discrimination than in

Table 3.2: **Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the ETHNIC group level, 1982 - 2010.**

Conflict Onset	**Ethnic**	**Ethnic**	**Ethnic**	**Ethnic**	**Civil**	**Civil**	**Civil**	**Civil**
GINI	0.079**	0.070**	0.074**	0.071*	0.078*	0.090**	0.085*	0.083*
	(0.033)	(0.036)	(0.036)	(0.036)	(0.043)	(0.045)	(0.047)	(0.045)
Discr.*GINI		0.139	0.162	0.157		-0.067	-0.080	-0.027
		(0.131)	(0.122)	(0.132)		(0.164)	(0.182)	(0.169)
Temp.(dev.)*GINI		-0.017		-0.017		0.006		0.004
		(0.026)		(0.026)		(0.032)		(0.032)
Prec.(dev.)*GINI			0.025	0.021			0.017	0.016
			(0.025)	(0.024)			(0.029)	(0.029)
Temp.(dev.)*Discr.*GINI		0.104		0.109		0.362***		0.351***
		(0.088)		(0.099)		(0.125)		(0.129)
Prec.(dev.)*Discr.*GINI			0.108	0.145			0.226*	0.281**
			(0.083)	(0.091)			(0.129)	(0.136)
Temperature (lag)	-0.001	-0.001		-0.001	0.000	-0.001		0.000
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)
Temperature (dev.)	-0.003	-0.000		-0.001	-0.005	-0.008		-0.008
	(0.006)	(0.008)		(0.008)	(0.008)	(0.011)		(0.011)
Precipitation (lag)	-0.000		-0.000	-0.000	-0.000***		-0.000***	-0.000***
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)	-0.003		-0.007	-0.007	0.003		0.003	0.003
	(0.004)		(0.005)	(0.005)	(0.005)		(0.009)	(0.008)
Temp.(dev)*Prec.(dev.)	-0.007				-0.007			
	(0.005)				(0.006)			
Temp.(dev.)*Discr.		0.004		0.009		-0.054*		-0.040
		(0.029)		(0.038)		(0.033)		(0.042)
Prec.(dev.)*Discr.			-0.033	-0.043			-0.110**	-0.124**
			(0.025)	(0.033)			(0.054)	(0.060)
Water Coverage (%)	-0.000	-0.000	-0.000	-0.000	0.001	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mountains (%)	0.016	0.009	0.028	0.011	0.018	0.009	0.016	0.019
	(0.025)	(0.025)	(0.027)	(0.025)	(0.031)	(0.031)	(0.032)	(0.032)
GDP per Capita (log, lag)	-0.009	-0.011	-0.007	-0.011	-0.011	-0.011	-0.011	-0.012
	(0.012)	(0.012)	(0.013)	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
Population (log, lag)	0.011	0.012	0.009	0.012	0.022	0.020	0.022	0.021
	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Education (%)	0.002	0.002	0.002	0.002	-0.003	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Oil (share GDP)	0.006***	0.006***	0.006***	0.006***	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Trade (share GDP)	0.007	0.008	0.007	0.009	0.004	0.004	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Discrimination (%)	0.070**	0.039	0.023	0.035	0.062	0.090	0.077	0.071
	(0.029)	(0.044)	(0.041)	(0.044)	(0.046)	(0.067)	(0.075)	(0.070)
Autocracy	-0.010	-0.010	-0.007	-0.010	0.008	0.006	0.009	0.009
	(0.020)	(0.020)	(0.018)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Ethnic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1624	1624	1624	1624	1908	1908	1908	1908

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

average settings (Models 6-7, Table 3.2). Similarly, a combined increase in precipitation anomalies and agricultural inequality increase the likelihood of ethnic conflict by 17 percentage points in communities experiencing higher levels of political discrimination.

Expectedly, the effect is stronger when the Gini index considers only rural areas (Tables S.3.1-S.3.2). When the Gini index is computed only for rural cells, in fact, climate anomalies have a greater impact on both civil and ethnic conflict outbreak. Specifically, the combined effect of temperature anomalies and inequality in agricultural production leads to a 38% higher probability of civil conflict outbreak and a 0.18% greater likelihood of ethnic conflict onset in communities characterized by higher degree of political discrimination.

Precipitation anomalies are shown to increase the likelihood of civil conflict by around 25% when interacted with agricultural inequality and discrimination, although the effect on ethnic conflict is not statistically significant. These results overall confirm the high vulnerability of rural areas to climatic and environmental shocks, consistently with the previous literature (von Uexkull et al., 2016).

The evidence presented in Tables 3.1 - 3.2 thus confirm our third hypothesis. Although crop inequality does not prove to be a sufficient condition to reduce societal coping capacity, our results show that the joint effect of uneven crop yields and political discrimination has a role in shaping the impact of climatic variability on both ethnic and civil conflict. This suggests that agricultural inequality needs to coincide with pre-existing societal fractures and cleavages to turn the relative deprivation induced by climate change into violence.

Discriminated groups are not only more vulnerable to climatic shocks, but also likely to be excluded from relief programs and interventions organized by the central government. Moreover, discriminated groups will be especially worse off when hit by climatic and environmental issues, as they have less viable economic alternatives to support their livelihood. When climate changes reduce the amount of available resources, the relative deprivation induced - even in normal conditions - by agricultural inequality will add to the frustration borne by discriminated group and push them to mobilize to obtain a fairer distribution of resources.

More broadly, our results highlight the importance of multiple factors, rather than a single element, in reducing countries' vulnerability to climate changes and increase the likelihood of conflict. As a number of conditions are likely to decrease societal coping capacities in dealing with climate anomalies, further research needs to explore the possible combination of contextual factors under which climatic changes are especially likely to trigger conflict, and understand the various and mutually reinforcing interactions between these factors.

3.4 Conclusions

This study investigates whether relative differences in crop production, alone or coupled with political discrimination, reduce societies' capacity to deal with climatic changes and make them more vulnerable to violence in turn. We find that, although crop inequality is a good predictor of conflict outbreak, the effect of climatic anomalies is not significantly different for countries with highly unequal levels of crop production than countries with more fairly distributed crop yields. However, our results show that the combined effect of unequal crop endowments and political discrimination shapes the impact of climate on conflict, thus suggesting that societal vulnerability to climatic changes is a function of multiple and complexly interacting factors, rather than a single condition.

In this perspective, the analysis can be extended to test how socio-economic characteristics, such as the level of development, and institutional elements, such as governance and trust, may further influence the relationship between climate change, inequality in crop production and conflict onset. More efficient institutional systems, able to guarantee a fair distribution of property rights and the enforcement of cooperative agreements to manage resources, can in fact mediate the negative consequences of climatic changes and attenuate tensions.

Further research efforts need to delve deeper into this complexity and go beyond the usual empirical test of stand-alone contextual factors. Also, studies shall shed light on the impact that more rapid-onset climatic changes, such as heat waves and cold spells, can have on the distribution of agricultural yields and, in turn, on the likelihood conflict.

Finally, a limitation of the present study is represented by data availability; indeed, grid-cell level information on crop production, utilized to compute the agricultural inequality at the country level, do not correspond to the agricultural output available to each household. To this end, the study of inequality in crop production will surely benefit from ongoing progresses in data collection, which will hopefully make available high-quality time-variant survey data on agricultural production at the household level, thus enabling to more thoroughly investigate the impact of inequality in cultivation on the probability of conflict.[†].

[†]A slightly different version of this chapter, co-authored with Matija Kovacic and Malcolm Mistry, is currently under review by the *Journal of Peace Research.*

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3.6 Appendix

3.6.1 Regression Tables: alternative specifications and other conflict types

Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the COUNTRY level RURAL CELLS, 1982 - 2010.

Conflict Onset	**Ethnic**	**Ethnic**	**Ethnic**	**Ethnic**	**Civil**	**Civil**	**Civil**	**Civil**
GINI	0.070*	0.053	0.043	0.050	0.135***	0.149***	0.115***	0.129***
	(0.040)	(0.040)	(0.038)	(0.039)	(0.044)	(0.048)	(0.044)	(0.046)
Discr.*GINI		0.241	0.299**	0.307**		0.106	0.126	0.135
		(0.151)	(0.132)	(0.139)		(0.109)	(0.151)	(0.143)
Temp.(dev.)*GINI		0.012		0.008		0.042		0.042
		(0.028)		(0.027)		(0.040)		(0.039)
Prec.(dev.)*GINI			-0.029	-0.031			-0.041	-0.038
			(0.037)	(0.036)			(0.045)	(0.044)
Temp.(dev.)*Discr.*GINI		0.090		0.100		-0.004		-0.058
		(0.126)		(0.129)		(0.217)		(0.245)
Prec.(dev.)*Discr.*GINI			0.275**	0.309***			0.251	0.271
			(0.115)	(0.114)			(0.205)	(0.210)
Temperature (lag)	0.001	0.001		0.001	0.002*	0.001		0.002*
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)
Temperature (dev.)	0.000	-0.008		-0.006	-0.009	-0.039		-0.040
	(0.006)	(0.019)		(0.019)	(0.007)	(0.029)		(0.028)
Precipitation (lag)	-0.000		-0.000	-0.000	-0.000***		-0.000**	-0.000***
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)	-0.003		0.018	0.020	-0.001		0.032	0.029
	(0.004)		(0.025)	(0.024)	(0.005)		(0.031)	(0.030)
Temp.(dev.)*Prec.(dev)	-0.006				-0.003			
	(0.005)				(0.006)			
Temp.(dev.)*Discr.		-0.038		-0.040		0.062		0.109
		(0.096)		(0.102)		(0.147)		(0.167)
Prec.(dev.)*Discr			-0.219**	-0.243***			-0.238	-0.254
			(0.090)	(0.090)			(0.154)	(0.158)
Discrimination	0.042*	-0.118	-0.169*	-0.171*	0.055*	0.009	-0.040	-0.030
	(0.025)	(0.110)	(0.096)	(0.103)	(0.033)	(0.079)	(0.113)	(0.106)
All controls from Table 3.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2161	2161	2161	2161	2490	2490	2490	2490

Table S.3.1: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the ETHNIC group level RURAL CELLS, 1982 - 2010.

Conflict Onset	Ethnic	Ethnic	Ethnic	Ethnic	Civil	Civil	Civil	Civil
GINI	0.096**	0.072	0.082*	0.073	0.109**	0.110*	0.108*	0.104*
	(0.039)	(0.045)	(0.043)	(0.045)	(0.052)	(0.056)	(0.057)	(0.056)
Discr.*GINI		0.222	0.220	0.238		0.071	0.013	0.122
		(0.153)	(0.139)	(0.151)		(0.211)	(0.230)	(0.224)
Temp.(dev.)*GINI		-0.042		-0.043		-0.003		-0.008
		(0.032)		(0.032)		(0.036)		(0.036)
Prec.(dev.)*GINI			0.036	0.033			0.007	0.004
			(0.034)	(0.034)			(0.035)	(0.035)
Temp.(dev.)*Discr.*GINI		0.181*		0.195*		0.384**		0.375**
		(0.104)		(0.113)		(0.150)		(0.151)
Prec.(dec.)*Discr.*GINI			0.110	0.146			0.253*	0.307**
			(0.104)	(0.114)			(0.140)	(0.145)
Temperature (lag)	0.000	-0.000		-0.000	0.002	0.001		0.002
	(0.001)	(0.001)		(0.001)	(0.002)	(0.002)		(0.002)
Temperature (dev.)	-0.003	0.005		0.004	-0.008	-0.010		-0.009
	(0.009)	(0.012)		(0.012)	(0.009)	(0.013)		(0.013)
Precipitation (lag)	-0.000		-0.000	-0.000	-0.000***		-0.000**	-0.000***
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)	-0.003		-0.010	-0.010	0.004		0.007	0.007
	(0.005)		(0.007)	(0.007)	(0.006)		(0.011)	(0.010)
Temp.(dev.)*Prec.(dev.)	-0.008				-0.007			
	(0.006)				(0.006)			
Discrimination	0.096***	0.040	0.032	0.036	0.079	0.068	0.070	0.045
	(0.036)	(0.048)	(0.047)	(0.048)	(0.051)	(0.076)	(0.086)	(0.081)
Temp.(dev.)*Discr.		-0.016		-0.013		-0.061		-0.046
		(0.034)		(0.043)		(0.041)		(0.047)
Prec.(dev.)*Discr.			-0.038	-0.050			-0.128**	-0.142**
			(0.031)	(0.040)			(0.063)	(0.069)
All controls from Table 3.1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1319	1319	1319	1319	1618	1618	1618	1618

Table S.3.2: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies and conflict onset. GINI index calculated at the COUNTRY level, 1982 - 2010.

Conflict Onset	Ethnic	Civil	Ethnic	Civil
GINI	0.069**	0.120***	0.071**	0.121***
	(0.030)	(0.035)	(0.030)	(0.035)
Temp.(dev.)*GINI			0.008	0.011
			(0.023)	(0.030)
Prec.(dev.)*GINI			-0.003	-0.010
			(0.025)	(0.027)
Temp.(dev.)*Prec.(dev.)	-0.007*	-0.004	-0.018	-0.012
	(0.004)	(0.005)	(0.017)	(0.023)
Temp.(dev.)*Prec.(dev.)*GINI			0.018	0.012
			(0.025)	(0.035)
Temperature (lag)	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Temperature (dev.)	0.000	-0.007	-0.005	-0.014
	(0.005)	(0.006)	(0.016)	(0.021)
Precipitation (lag)	-0.000	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation (dev.)	-0.002	-0.001	0.000	0.005
	(0.003)	(0.004)	(0.017)	(0.018)
Water (% territory)	-0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Mountains (% territory)	0.032*	0.046**	0.033*	0.046**
	(0.018)	(0.023)	(0.018)	(0.023)
GDP per Capita (real, log, lag)	-0.005	-0.009	-0.005	-0.009
	(0.007)	(0.010)	(0.007)	(0.010)
Population (log, lag)	0.011	0.023**	0.012	0.023**
	(0.008)	(0.010)	(0.007)	(0.010)
Education (% total pop.)	0.001	0.000	0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Oil Prod. (% GDP)	0.004***	0.002	0.004***	0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Trade (% GDP)	0.002	-0.000	0.002	-0.000
	(0.003)	(0.005)	(0.003)	(0.005)
Ethnic frac.	0.024	0.004	0.025	0.004
	(0.020)	(0.027)	(0.020)	(0.027)
Center Segmentation	0.001	0.004	0.001	0.004
	(0.002)	(0.003)	(0.002)	(0.003)
Discrimination	0.030	0.039	0.031	0.039
	(0.020)	(0.029)	(0.021)	(0.029)
Autocracy	-0.004	0.009	-0.004	0.008
	(0.013)	(0.013)	(0.013)	(0.013)
Agriculture (% GDP)	0.001	0.000	0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.001)
Irrigated land (% agr. land)	0.082*	0.092*	0.082*	0.092*
	(0.042)	(0.052)	(0.042)	(0.052)
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Cubic Splines peace yrs.	Yes	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes	Yes
N	2720	2998	2720	2998

Table S.3.3: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies and conflict onset. GINI index calculated at the ETHNIC group level, 1982 - 2010.

Conflict Onset	Ethnic	Civil	Ethnic	Civil
GINI	0.081**	0.079*	0.084**	0.081**
	(0.033)	(0.043)	(0.034)	(0.041)
Temp.(dev.)*GINI			-0.005	0.030
			(0.023)	(0.033)
Prec.(dev.)*GINI			0.033	0.030
			(0.022)	(0.024)
Temp.(dev.)*Prec.(dev.)	-0.004	-0.005	-0.006	-0.000
	(0.005)	(0.006)	(0.009)	(0.008)
Temp.(dev.)*Prec.(dev.)*GINI			0.004	-0.022
			(0.032)	(0.042)
Temperature (lag)	-0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Temperature (dev.)	-0.001	-0.003	0.001	-0.009
	(0.006)	(0.008)	(0.008)	(0.010)
Precipitation (lag)	-0.000	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation (dev.)	-0.004	0.002	-0.012**	-0.004
	(0.004)	(0.005)	(0.006)	(0.008)
Water Coverage (% territory)	-0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Mountains (% territory)	0.016	0.019	0.016	0.019
	(0.025)	(0.031)	(0.025)	(0.032)
GDP per Capita (real, log, lag)	-0.008	-0.011	-0.009	-0.011
	(0.012)	(0.015)	(0.012)	(0.015)
Population (log, lag)	0.011	0.021	0.011	0.021
	(0.012)	(0.014)	(0.013)	(0.014)
Education (share tot. pop.)	0.002	-0.003	0.002	-0.003
	(0.004)	(0.003)	(0.004)	(0.003)
Oil (% GDP)	0.006***	0.004	0.006***	0.004
	(0.002)	(0.003)	(0.002)	(0.003)
Trade (% GDP)	0.007	0.004	0.007	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Ethnic Fractionalization	0.018	0.029	0.016	0.026
	(0.034)	(0.039)	(0.033)	(0.039)
Center Segmentation	-0.007*	-0.007	-0.007*	-0.006
	(0.004)	(0.005)	(0.004)	(0.005)
Discrimination (% total pop.)	0.069**	0.062	0.070**	0.064
	(0.029)	(0.046)	(0.029)	(0.045)
Autocracy	-0.010	0.008	-0.010	0.009
	(0.020)	(0.019)	(0.020)	(0.019)
Agr. Share, Irrigated land	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Cubic Splines peace yrs.	Yes	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes	Yes
N	1624	1908	1624	1908

Table S.3.4: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies and conflict onset. GINI index calculated at the COUNTRY level, 1982 - 2010.

Conflict Onset	Non-state	Non-state	Non-state	One-Sided	One-Sided	One-Sided
GINI	-0.071	-0.104	-0.088	-0.089	-0.116	-0.080
	(0.064)	(0.065)	(0.063)	(0.073)	(0.076)	(0.074)
Discr.*GINI	0.130	0.146	0.144	0.553***	0.436**	0.627***
	(0.177)	(0.181)	(0.185)	(0.208)	(0.175)	(0.229)
Temp.(dev.)*GINI	0.016		0.021	0.021		0.015
	(0.026)		(0.026)	(0.054)		(0.052)
Prec.(dev.)*GINI		0.008	0.008		-0.067*	-0.065*
		(0.032)	(0.032)		(0.040)	(0.039)
Temp.(dev.)*Discr.*GINI	-0.218		-0.260	0.675**		0.718**
	(0.169)		(0.183)	(0.342)		(0.341)
Prec.(dev.)*Discr.*GINI		0.082	0.082		0.200	0.297
		(0.123)	(0.114)		(0.207)	(0.225)
Temperature (lag)	0.005**		0.006**	0.008***		0.007***
	(0.003)		(0.002)	(0.002)		(0.002)
Temperature (dev.)	-0.002		-0.006	-0.028		-0.027
	(0.018)		(0.019)	(0.035)		(0.034)
Precipitation (lag)		-0.000	-0.000**		0.000*	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)		-0.003	-0.002		0.032	0.029
		(0.019)	(0.019)		(0.028)	(0.027)
Discrimination	-0.017	-0.042	-0.040	-0.278*	-0.169	-0.320*
	(0.100)	(0.096)	(0.097)	(0.148)	(0.113)	(0.163)
Temp.(dev)*Discr.	0.140		0.171	-0.494**		-0.526**
	(0.127)		(0.140)	(0.244)		(0.246)
Prec.(dev.)*Discr.		-0.069	-0.074		-0.193	-0.251
		(0.094)	(0.088)		(0.145)	(0.163)
All controls from Table 3.1	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines peace yrs.	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2094	2094	2094	2501	2501	2501

Table S.3.5: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Inequality in crop production, climate anomalies and conflict onset. GINI index calculated at the ETHNIC group level, 1982 - 2010.

Conflict Onset	Non-state	Non-state	Non-state	One-Sided	One-Sided	One-Sided
GINI	0.091	0.083	0.079	-0.190**	-0.194**	-0.194**
	(0.065)	(0.063)	(0.066)	(0.094)	(0.093)	(0.090)
Discr.*GINI	-0.588**	-0.676***	-0.643**	0.863***	0.567**	0.815***
	(0.266)	(0.239)	(0.264)	(0.276)	(0.275)	(0.294)
Temp.(dev.)*GINI	0.018		0.013	-0.042		-0.057
	(0.034)		(0.031)	(0.057)		(0.053)
Prec.(dev.)*GINI		-0.024	-0.020		-0.114**	-0.121**
		(0.041)	(0.039)		(0.051)	(0.053)
Temp.(dev.)*Discr.*GINI	-0.088		-0.113	0.636		0.675
	(0.138)		(0.148)	(0.571)		(0.654)
Prec.(dev.)*Discr.*GINI		0.309*	0.297*		0.642***	0.661***
		(0.167)	(0.165)		(0.152)	(0.208)
Temperature (lag)	0.002		0.003	0.009***		0.009***
	(0.003)		(0.003)	(0.003)		(0.003)
Temperature (dev.)	0.009		0.008	-0.015		-0.016
	(0.012)		(0.012)	(0.014)		(0.014)
Precipitation (lag)		-0.000	-0.000		0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Precipitation (dev.)		0.003	0.005		0.011	0.011
		(0.010)	(0.010)		(0.013)	(0.013)
Discrimination	0.296***	0.319***	0.312***	-0.139	0.015	-0.101
	(0.104)	(0.089)	(0.102)	(0.092)	(0.105)	(0.100)
Temp.(dev.)*Discr.	0.007		0.027	-0.176		-0.163
	(0.055)		(0.064)	(0.180)		(0.197)
Prec.(dev.)*Discr.		-0.123**	-0.125**		-0.231***	-0.216***
		(0.056)	(0.057)		(0.053)	(0.056)
All controls from Table 3.1	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Splines peace yrs.	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1398	1398	1398	1629	1629	1629

Table S.3.6: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the COUNTRY level, 1982 - 2010.

Conflict Onset	**All**	**All**	**All**
GINI	0.073^{**}	0.059^{**}	0.061^{**}
	(0.028)	(0.030)	(0.029)
Discr.*GINI	0.366^{**}	0.410^{***}	0.434^{***}
	(0.151)	(0.133)	(0.138)
Temp.(dev.)*GINI	0.003		0.005
	(0.028)		(0.027)
Prec.(dev.)*GINI		-0.016	-0.015
		(0.029)	(0.028)
Temp.(dev.)*Discr.*GINI	0.216^{*}		0.138
	(0.128)		(0.135)
Prec.(dev.)*Discr.*GINI		0.314^{***}	0.324^{***}
		(0.097)	(0.108)
Temperature (lag)	0.000		0.000
	(0.001)		(0.001)
Temperature (dev.)	-0.011		-0.013
	(0.019)		(0.019)
Precipitation (lag)		-0.000^{*}	-0.000^{*}
		(0.000)	(0.000)
Precipitation (dev.)		0.013	0.012
		(0.019)	(0.018)
Discrimination	-0.223^{**}	-0.273^{***}	-0.281^{***}
	(0.114)	(0.102)	(0.106)
Temp.(dev.)*Discr.	-0.111		-0.047
	(0.096)		(0.104)
Prec.(dev.)*Discr.		-0.257^{***}	-0.262^{***}
		(0.074)	(0.083)
All controls from Table 3.1	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes
N	2971	2971	2971

Table S.3.7: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the ETHNIC group level, 1982 - 2010.

Conflict Onset	**All**	**All**	**All**
GINI	0.042	0.038	0.038
	(0.038)	(0.040)	(0.039)
Discr.*GINI	0.131	0.138	0.131
	(0.115)	(0.115)	(0.120)
Temp.(dev.)*GINI	0.005		0.004
	(0.029)		(0.028)
Prec.(dev.)*GINI		0.005	-0.000
		(0.030)	(0.029)
Temp.(dev.)*Discr.*GINI	0.136		0.151
	(0.108)		(0.125)
Prec.(dev)*Discr.*GINI		0.311***	0.383***
		(0.120)	(0.129)
Temperature (lag)	-0.001		-0.001
	(0.001)		(0.001)
Temperature (dev.)	-0.013		-0.013
	(0.009)		(0.008)
Precipitation (lag)		-0.000**	-0.000*
		(0.000)	(0.000)
Precipitation (dev.)		0.004	0.004
		(0.007)	(0.007)
Discrimination	0.038	0.014	0.031
	(0.046)	(0.046)	(0.046)
Temp.(dev.)*Discr.	0.015		0.025
	(0.036)		(0.046)
Prec.(dev.)*Discr.		-0.104***	-0.125***
		(0.036)	(0.042)
Time Controls	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes
N	1852	1852	1852

Table S.3.8: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the COUNTRY level RURAL CELLS, 1982 - 2010.

Conflict Onset	**All**	**All**	**All**
GINI	0.078**	0.058	0.068*
	(0.037)	(0.038)	(0.038)
Discr.*GINI	0.390*	0.466***	0.498***
	(0.201)	(0.154)	(0.164)
Temp.(dev.)*GINI	0.022		0.019
	(0.032)		(0.030)
Prec.(dev.)*GINI		-0.036	-0.035
		(0.039)	(0.037)
Temp.(dev.)*Discr.*GINI	0.196		0.202
	(0.148)		(0.149)
Prec.(dev.)*Discr.*GINI		0.517***	0.552***
		(0.132)	(0.131)
Temperature (lag)	0.001		0.001
	(0.001)		(0.001)
Temperature (dev.)	-0.025		-0.023
	(0.022)		(0.021)
Precipitation (lag)		-0.000	-0.000*
		(0.000)	(0.000)
Precipitation (dev.)		0.027	0.026
		(0.026)	(0.024)
Discrimination	-0.229	-0.306***	-0.321***
	(0.145)	(0.114)	(0.122)
Temp.(dev.)*Discr.	-0.089		-0.086
	(0.112)		(0.116)
Prec.(dev.)*Discr.		-0.412***	-0.435***
		(0.102)	(0.101)
All controls from Table 3.1	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Cubic Splines Peace Years	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes
N	2383	2383	2383

Table S.3.9: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Inequality in crop production, climate anomalies, discrimination and conflict onset. GINI index calculated at the ETHNIC group level RURAL CELLS, 1982 - 2010.

Conflict Onset	All	All	All
GINI	0.042	0.038	0.038
	(0.038)	(0.040)	(0.039)
Discr.*GINI	0.131	0.138	0.131
	(0.115)	(0.115)	(0.120)
Temp.(dev.)*GINI	0.005		0.004
	(0.029)		(0.028)
Prec.(dev.)*GINI		0.005	-0.000
		(0.030)	(0.029)
Temp.(dev.)*Discr.*GINI	0.136		0.151
	(0.108)		(0.125)
Prec.(dev)*Discr.*GINI		0.311***	0.383***
		(0.120)	(0.129)
Temperature (lag)	-0.001		-0.001
	(0.001)		(0.001)
Temperature (dev.)	-0.013		-0.013
	(0.009)		(0.008)
Precipitation (lag)		-0.000**	-0.000*
		(0.000)	(0.000)
Precipitation (dev.)		0.004	0.004
		(0.007)	(0.007)
Discrimination	0.038	0.014	0.031
	(0.046)	(0.046)	(0.046)
Temp.(dev.)*Discr.	0.015		0.025
	(0.036)		(0.046)
Prec.(dev.)*Discr.		-0.104***	-0.125***
		(0.036)	(0.042)
All controls from Table 3.1	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes
Reg. Dummies	Yes	Yes	Yes
N	1852	1852	1852

Table S.3.10: *Significance levels:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Summary statistics: 1982 - 2010

	Mean	Std. Dev.	Min.	Max.	N
Dependent Variables					
Onset (ethnic conflict)	0.029	0.167	0	1	3211
Onset (civil conflict)	0.058	0.234	0	1	3211
Onset (one-sided violence)	0.114	0.318	0	1	3211
Onset (non-state)	0.041	0.199	0	1	3211
Onset (all types of violence)	0.042	0.201	0	1	3211
Inequality Indicators					
Gini (country level)	0.615	0.169	0.049	0.953	3211
Gini Rural (country level)	0.64	0.159	0.011	0.952	2667
Gini (ethnic level)	0.178	0.149	0.011	0.614	2070
Gini Rural (ethnic level)	0.191	0.154	0.011	0.642	1761
Climatic Variables					
Precipitation	89.209	71.215	0.003	583.791	3211
Temperature	18.48	8.027	-8.029	29.541	3211
Precipitation (deviation)	0.009	0.981	-3.188	3.611	3211
Temperature (deviation)	0.056	0.98	-2.781	3.03	3211
Country Characteristics					
Water Coverage (% territory)	5.67	6.722	0.025	30.814	3211
Mountains (% territory)	0.321	0.274	0	0.961	3211
GDP per Capita (log)	11.237	1.988	5.971	16.545	3211
Population (log)	16.379	1.439	12.796	21.014	3211
Education (share total pop.)	15.432	1.688	9.324	20.768	3211
Oil (share GDP)	20.931	2.998	9.76	27.148	3211
Trade (share GDP)	24.726	1.899	16.826	29.439	3211
Ethnic Fractionalization	0.391	0.261	0	0.872	3211
Discrimination (% total pop.)	0.045	0.126	0	0.87	3211
Center Segmentation	1.955	2.219	0	15	3211
Agriculture (share GDP)	17.404	14.25	0.551	79.286	3211
Irrigated Land (% agr. land)	0.084	0.124	0	0.799	3211
Other Controls					
North America	0.027	0.162	0	1	3211
Central America	0.045	0.208	0	1	3211
Latin America	0.126	0.332	0	1	3211
West Europe	0.121	0.326	0	1	3211
East Europe	0.099	0.299	0	1	3211
North Africa and Middle East	0.097	0.297	0	1	3211
Sub-Saharan Africa	0.28	0.449	0	1	3211
Asia	0.194	0.396	0	1	3211
Oceania	0.009	0.095	0	1	3211

Table S.3.11: Descriptive Statistics for the full sample.

Definition of the main variables included in the analysis and corresponding data-sources.

VARIABLE	DEFINITION	DATA SOURCE
Onset of civil conflict	Binary variable coded as 1 for each new intra-state conflict out breaking in a country-year and 0 otherwise. Intra-state conflict involves the use of the armed force by either the government or a formally organized group, and results in at least 25 battle-related deaths in a year.	UCDP v19.1 (Gleditsch et al., 2002; Pettersson et al., 2019).
Onset of ethnic conflict	Binary variable coded as 1 for each new intra-state ethnic conflict out breaking in a country-year and 0 otherwise.	GeoEPR 2019 (Vogt et al., 2015).
Population	Population size for each country.	World Development Indicators (World Bank, 2012).
Excluded groups	Number of excluded groups (discriminated or powerless) as defined in the GeoEPR/EPR data on the status and location of politically relevant ethnic groups settled in the country for the given year.	GeoEPR (Vogt et al., 2015).
GDP	Total GDP (constant 2011 international USD	World Development Indicators (World Bank, 2012) and the Penn World Tables (Feenstra et al., 2015)
GDP per capita	GDP per capita (constant 2011 international USD)	World Development Indicators (World Bank, 2012) and the Penn World Tables (Feenstra et al., 2015).

VARIABLE	**DEFINITION**	**DATA SOURCE**
Oil rents	Difference between the value of crude oil production at world prices and total costs of production.	World Development Indicator (World Bank, 2012).
Trade	Trade volume.	World Bank Development Indicator (World Bank, 2012).
Education	Share of the population, aged over 25 years, which has compleated at least the primary education (percentage)	World Bank Development Indicator (World Bank, 2012).
Autocracy	Variable identifying autocracies. The classification is performed according to V-Dem Indices of political systems and corresponds to regime types 0 and 1 (closed autocracy).	Coppedge et al., 2019.
Discrimination	Sum of discriminated population in each country (as a fraction of total population).	GeoEPR-ETH (Vogt et al., 2015.
History of conflict	Binary variable coded as 1 if the country experienced a conflict in the previous year, and 0 otherwise.	Our computation from UCDP v19.1 (Gleditschet al., 2002; Pettersson et al., 2019).
Number of peace years	Number of years since the last conflict experienced by the country.	UCDP v19.1 (Gleditsch et al., 2002; Pettersson et al., 2019).
Mountainous terrain	Proportion of mountainous terrain within the cell based on elevation, slope and local elevation range, taken from high-resolution mountain raster data.	UNEP's Mountain Watch Report (Blyth et al., 2003).

VARIABLE	DEFINITION	DATA SOURCE
Share of the Excl. Pop.	Indicator of the degree of exclusion along ethnic lines, computed as the natural logarithm of the share of the population excluded from central government.	GeoEPR-ETH (Vogt et al., 2015).
Center Segmentation	Number of ethnic groups in power, represented by ethnic elites at the central government. The variable is termed as the degree of center segmentation.	GeoEPR-ETH (Vogt et al., 2015).
Ethnic Fractionalization	Degree of ethnic fractionalization.	GeoEPR-ETH (Vogt et al., 2015.
Crop	Annual production of four main crop types within the 0.5x0.5 degrees grid cell (maize, soybean, wheat, rice) given in tons per hectare.	Iizumi et al., 2018.
Irrigated Land	Share of Irrigated Land as fraction of total agricultural area	Siebert et al., 2015.
Water (gc)	Coverage of water areas in each cell.	Globcover v2.3. (Bontemps et al., 2009)
Agr. value added	Net output of the agricultural sector as a share of the national GDP. Agriculture includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production.	World Bank Development Indicators (World Bank, 2012)
Precipitation anomaly	Precipitation anomaly, computed as the standardized annual deviation from the long-term mean.	CRU University of East Anglia (Harris et al., 2014).
Temperature anomaly	Temperature anomaly, computed as the standardized annual deviation from the long-term mean.	CRU University of East Anglia (Harris et al., 2014).

Table S.3.12: Definition of the Variables included in the Empirical Model

I have seen the future and it is very much like the present,
only longer.

Kehlog Albran

4

Projecting Conflict under Climate Change: An Artificial Intelligence Application

A recent study soliciting experts' opinion on the climate-conflict nexus suggests that climatic change has already increased the probability of violence and it might increase conflict risk even further in the future, although the effect is deemed to be modest compared to the influence of other factors such as unexpected economic events and food scarcity (Mach et al., 2019). Yet, not only the mechanisms through which the pressure of climate will be exerted are rather unclear (Busby, 2018; Koubi, 2018), but the task of predicting the possible future impacts of climate on security has so far remained unattained by the academic community.

As the bifold instability induced by the detrimental effects of climatic change on crop production (Challinor and Weeler, 2008) and rising food prices (OECD and FAO, 2018) summons the ghost of food wars in the future (Lagi et al., 2011), there is a need to implement conflict forecasting tools that can consider climatic determinants as well as their impacts on agricultural production and food security. Moreover, understanding the long-term effects of changes in agricultural production and other determinants of a persistent change in conflict trends are important and feasible avenues of research (Iyigun et al., 2017).

Predicting conflicts could not only contribute to inform decision makers about the feasibility and desirability of preventive actions, but can also help test and validate statistical and theoretical models (Montgomery et al., 2012).

Although the literature on conflict and peace research has increasingly shifted their focus from the explanation to the prediction of violence (Chadefaux, 2017), attempts to forecast the likelihood of conflicts in the future tend to focus on a very limited set of predictors (e.g. Weidmann and Ward, 2010) and apart from sporadic exceptions (Hegre et al., 2016; Witmer et al., 2017; Farinosi et al., 2018), they neglect the possible impact of climatic and environmental stressors. Moreover, despite the recent progresses in forecasting violence, the results of predictions tend to be quite grim in terms of both reliability and accuracy.

The present study attempts to fill this gap and evaluates three orders of factors that could help improve current forecasts: *i)* the inclusion of 'baseline' climatic conditions and agricultural variables as conflict predictors; *ii)* the consideration of spatial and temporal context, and *iii)* the use of Artificial Intelligence (AI) as a forecasting methodology. First, we estimate the probability of conflict in the long-term by including exhaustive information on key drivers of violence rather than being limited to the standard "suspects", and specifically integrating climatic anomalies and agricultural production shocks among the predictors. In doing so, three types of variables are used to train the models: socio-economic conditions, temporal and spatial contiguity, and climatic and agricultural factors. As concerns climatic variables, it should be noted that the study's goal is not to compare the impact of different climate scenarios - or different levels of global warming - on stability, but rather to set a ground-truth or a baseline that could support this comparison. To this end, the analysis is limited to a high-mitigation scenario (Representative Concentration Pathway - RCP 2.6), which is fairly optimistic in terms of the global warming that may be expected at the end of the century and lies on the assumption that considerable carbon emission reductions could be achieved. In other terms, RCP 2.6 is not the Business-as-Usual scenario and we selected it precisely as it could give an indication of the minimum impact of future climatic changes on armed conflicts. This will hopefully set the ground for further research aiming to investigate the influence of more sustained climatic changes on future societies.

Second, our models for forecasting takes into adequate consideration the spatio-temporal context, by means of a dynamic setting which iteratively updates the spatial and temporal variables according to the predictions. This is made possible through the use of fine-grained data and spatial disaggregation, which enable us to anchor the predictions to a higher spatial resolution compared to conventional national-level analyses.

Third, to increase the predictive power of the model, we apply and compare the results from two AI derived tools: *i)* Decision Trees-based models and *ii)* Artificial Neural Networks. A fundamental goal of the analysis is in fact to test the predictive potential of Machine Learning techniques compared to traditional statistical methods. As such, the study aims not only to understand the impact that climatic variables and agricultural output may exert on future stability but also to evaluate whether AI could improve current forecasting techniques and achieve increased accuracy in conflict predictions compared to the results of the existing literature.

4.1 Conflict Forecasting: doomed to failure?

Despite the growing academic effort in forecasting, most statistical studies of militarized disputes still perform very poorly out-of-sample (Ward et al., 2007), and the task of predicting conflict in the future is daunting to the point that it appears a "foolish" undertaking to even experienced scholars (Collier, 2007, p. 19). Understanding the reasons explaining these poor results is fundamental in improving forecasting reliability and accuracy.

Schematically, the limited progresses achieved so far in violence predictions can be reconnected to two orders of motivations: first, on a ground level, a lack of adequate consideration of the theory and motivations behind conflict, which has so far been explored only in the domain of empirical analyses; second, on a technical level, the existence of some inherent methodological challenges in predicting the occurrence of violence, which scholars tend to address one by one, neglecting the big picture. So far, most of the attempts to improve the accuracy of predictions have been concerned with the second issue, each study addressing a specific methodological challenge separately, in a gold rush to the approach that could achieve the most reliable forecasts. In fact, current researches on conflict predictions systematically frame the problem as a mere methodological issue, which leads to theories and motivations behind conflict occurrence being almost totally absent from the discussion.

This quest for a more robust method to deal with the inherent challenges involved in conflict predictions is of undoubted value to increase the accuracy of conflict forecasts. However, the emphasis on methodological aspects risks overestimate the importance of finding statistically significant results to the detriment of including variables that can improve our forecasting abilities (Ward et al., 2010; Gleditsch and Ward, 2013). Forecasting efforts should therefore couple appropriate methodological approaches with sound theories and a thorough exploration of the motivations behind conflict (Gleditsch and Ward, 2013; Guo et al., 2018).

Existing attempts to forecast conflict and peace have so far focused on a rather limited set of conditions that affect violence, which can be generally brought back to different variants of the Kantian peace (Russett and Oneil, 2001): democracy, international trade and participation in international organizations (Gurr, 1974; Schrodt, 1991; Beck et al., 2000). Recent studies on conflicts have extended their focus to include some additional predictors of violence, such as economic growth, population size, education, and human rights (Montgomery et al., 2012; Rost et al., 2009; Hegre et al., 2016) and to account for spatial and temporal contiguity (Weidmann and Ward, 2010; Gleditsch and Ward, 2013).

It is no coincidence that this literature has regularly neglected the possible destabilizing consequences that climatic variability can exert on future socio-economic systems, especially by hurting agricultural production. If it is true, on the one hand, that empiricists have so far failed to find a robust consensus on the role played by climate change in triggering conflict, forecasting techniques can precisely help validate and test theories, whereby they ultimately allow scholars to go beyond the traditional quest for statistically significant coefficients (Goldstone et al., 2010; Montgomery et al., 2012).

As far as the second aspect is concerned, the task of forecasting conflicts is inherently challenging for various reasons, but two main methodological issues can be identified: first, the choice of the unit of analysis and the influence of spatial and temporal context, which should be given proper account and, second, the rare nature of violent episodes. Studies have shown that conflict-prone areas significantly affect the risk of conflict in the neighbouring locations (Buhaug and Gates, 2002; Hegre and Sambanis, 2006), indicating that both temporal and spatial contexts do play a role in explaining and predicting violence. Yet, political scientists tend to only focus on temporal persistence to the detriment of spatial dependence (Weidmann and Ward, 2010). Moreover, most of the studies in peace and conflict research are still conducted at the country-level (Buhaug et al., 2011) and neglect spatial dependencies among different geographical settings. The choice of the spatial unit of analysis, however, is far from neutral. Country-level studies implicitly assume that national trends will hold in the future and apply this implicit assumption of constancy to both the interaction between territorial units and the effect of causal mechanisms (Cederman and Weidmann, 2017). Disaggregated spatial analyses can enable to go beyond the implicit assumption of constancy in national trends and thus contribute to achieve greater accuracy in the predictions.

Furthermore, characteristics or processes occurring at the national level are influencing characteristics or processes occurring at higher and lower spatial levels. For instance, the economic growth experienced locally is affected by the broader economic wealth of the country, or the effect of agricultural production shocks in sub-national locations is influenced by national dynamics (Figure 4.1). Including careful consideration of neighbouring areas and reciprocal spatial influences can provide valuable insight in conflict forecasts (Weidmann and Ward, 2010; Gleditsch and Ward, 2013).

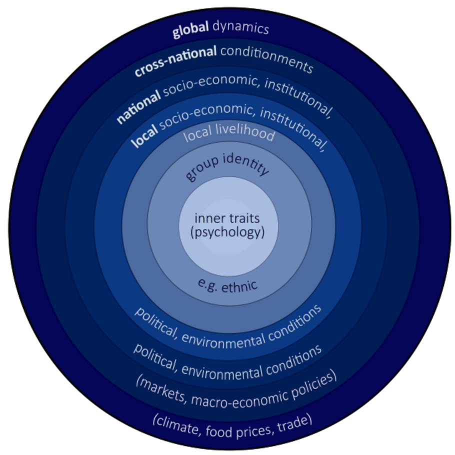

Figure 4.1: Multi-level factors that may affect the likelihood of conflict. Adapted from Luke, 2011.

A second main challenge in forecasting is represented by the rare nature of conflictual events compared to peaceful years (Beck, 2000). Scholars have addressed the problem of "excess of zeroes" in conflict data (Bagozzi, 2015) by means of various techniques, which can be synthetically brought back to one of these two categories: *i)* methods to under- and oversample data in a way to reduce the unbalance between conflictual and peaceful cases (King and Zeng, 2001) akin case control (Goldstone, 2010) or clustering (Schrodt and Gerner, 2000); *ii)* models that modify the probability threshold above which we predict that the minority event will occur (Beck et al., 2000).

However, existing studies tend to overlook the choice of the proper performance metrics to be used in evaluating and comparing the results of predictions and generally stick to accuracy to assess forecasting outcomes (e.g. Goldstone et al., 2010). Nevertheless, as conflicts are rare events, accuracy does not give any indication about the goodness of out-of-sample predictions: even a model that failed to predict all conflicts in the test set, or in other words that was able to predict zero conflicts, can achieve an accuracy close to 100% (Berk and Sorenson, 2019). The choice of more relevant metrics for evaluating the predicting power of the model, as well as the inclusion of a baseline to be used for a comparative assessment of forecasts, need to be addressed clearly if we aim to achieve higher quality and reliability in the predictions (Brandt et al., 2014; Cederman and Weidmann, 2017).

The challenges highlighted so far may appear too daunting to be reasonably addressed by a single study. Nevertheless, we believe that some elements put today scholars in a position to deal with the above issues in a more comprehensive and harmonic way than in the past: first, the literature on conflict has made significant progresses in elaborating theories and hypotheses that can and need to be validated by forecasting tools (Berk and Sorenson, 2019); second, recent advances in data collection and the increasing availability of fine-grained data enable studies to go beyond the standard national analyses and take advantage of more refined, disaggregated information (Buhaug et al., 2011); third, technological and computational innovation provides analysts with new and powerful tools to better handle uncertainty, deal with increasing amount of observations and manage complexity (Guo et al., 2018).

The present study intends to take advantage of these opportunities in order to comprehensively target the obstacles to high-quality forecasting results and explore the potential of Machine Learning in providing sound and reliable predictions, which can thus help prevent and mitigate violence. The study makes a number of contributions to the existing literature on conflict forecasting. First, the analysis does not limit the set of predictors to the two or three usual variables (e.g. GDP, population, education) but is based on a sound consideration of the theoretical pathways that can motivate violence. Specifically, our main focus is on the influence of climatic conditions and agricultural production shocks on the likelihood of conflict in the future. Although long-term predictions are valuable more as heuristic tools than precise recommendations to policy makers (Cederman and Weidmann, 2017), we aim to provide at least a general indication of where conflicts are likely to occur driven, among others, by 'baseline' climatic conditions and agricultural production shocks in the long-term future. The inclusion of climate and crop variables in the analysis serves a bifold purpose: they do not only provide the forecasting model with broader information on the context and conditions that can influence the incidence of conflict, in order to achieve higher accuracy in the predictions, but also serve the purpose of testing the role of these factors in influencing violence. Second, spatial and temporal contexts are explicitly taken into account to include both geographical and temporal dependencies in the forecasts. Also, we exploit the recent release of fine-grained datasets to perform the analysis at the grid-cell level. This enables us to break with the assumption of consistency involved in national analyses and to higher the reliability and accuracy of the forecasts by taking advantage of an increased amount of observations.

Third, we apply different Machine Learning tools to address the inherent methodological challenges of conflict predictions. As they benefit from increasing amounts of data, and can be trained to learn from historical observations, these techniques are better suited to deal with the intrinsic complexity of human interactions and are able to detect the intricate paths and trends which are likely to higher the probability of conflict.

Finally, to increase the reliability of predictions, we explicitly include a baseline model to be used as a reference for performance comparison and select the most suitable metrics for performance assessment. The next section moves on to illustrate the theoretical framework and explain the possible linkages between climatic conditions, agricultural production and conflict.

4.2 Forecasting conflict: testing the impact of climate

Grim mediatic narratives are increasingly depicting a future of bread riots and climate wars (Mills, 2015; Pearce, 2019), which will supposedly be driven by frequent and intense natural hazards, droughts, famines and rising food scarcity. Notwithstanding this growing narrative taking the stage in the media, only limited attention has been devoted by scientists to project the impacts that climate change may exert on future conflict risk. However, acquiring a solid understanding of the security implications of climate change is fundamental to implement proper coping strategies and increase the resilience of vulnerable communities. The present study represents the first attempt to include climatic conditions and agricultural production in conflict forecasts, with a view to understand the baseline or minimum effect of climatic changes in the future and hopefully open up further investigations on the effect of alternative climatic scenarios on security. As the impacts of climate change are likely to be observed in the long-term (WMO, 2019), we project the likelihood of conflict up to 2050, with the aim to give a heuristic indication about the areas of the world that may be more vulnerable to experiencing conflict.

According to the IPCC – whose reports are the most authoritative summary of scientific evidence on climate - climate variability and environmental conditions may indirectly increase the risk of conflict, especially through their influence on well-documented drivers of violence, such as poverty (Adger et al., 2015). Here, we are especially concerned with the conflict potential of climatic anomalies and agricultural shocks. It is not necessary to go as far as assuming catastrophic scenarios (Schwartz and Randall, 2003) to understand that climate variability may have a destabilizing impact on society. Although on a theoretical level the possible connections between climate anomalies and violence are known and generally agreed, scholars still struggle to verify them empirically (Busby, 2018; Koubi, 2018). Forecasting techniques represent a valuable tool to validate and test this theoretical reasoning (Beck et al., 2000) and can thus contribute to clarify the impact of climate change on future societies.

Climate change is predicted to affect (and evidence suggests that it is already affecting) patterns and trends of rainfall and temperature, impact the quantity and distribution of renewable resources akin water and arable land, and is thus likely to have profound implications on a number of economic sectors, including hydropower, energy, transportation and agriculture (Arent et al., 2014). Moreover, increasing temperature and erratic precipitation patterns can affect crop yield (Zhang and Cai, 2011).

In turn, climate-induced agricultural shocks can deepen pre-existing socio-economic grievances (Hendrix and Brinkman, 2013; Jones et al., 2017); they can destabilize food prices and make developing countries highly dependent on food imports (Hendrix and Haggard, 2015; Raleigh et al., 2015); they can push people to migrate towards urban areas (Bollfrass and Shaver, 2015), and they can in many other ways lower the opportunity costs of joining rebel groups and increase the chances to recruit fighters among disgruntled farmers (Brinkman and Hendrix, 2011; Wischnath and Buhaug, 2014; Busby, 2018). The effect of climatic extremes on the risk of conflict may be especially detrimental when occurring during the growing season (Jun, 2017; Harari and La Ferrara, 2018). Also, the impacts of climatic changes may be more heavily borne by agriculturally dependent or rural societies (von Uexkull et al., 2016), whereby the consequences of food insecurity may be particularly destabilizing, as governments lack the resources to implement adequate adaptation strategies (Rosenzweig and Perry, 1994; Lobell et al., 2008).

However, the connections between climate, crop yield and conflicts remain debated. For instance, Jun (2017) finds that a high temperature during maize growing season increases the incidence of conflict in Sub-Saharan Africa by reducing agricultural production. By contrast, Buhaug et al. (2015), which adopts food production rather than food price as a key predictor of conflict incidence, finds no support to the claim that decreased agricultural production induced by climatic variability spurs conflict in Sub-Saharan Africa. Bollfrass and Shaver (2015) also cast doubt on the alleged relationship at the subnational level, showing that the correlation between temperature variation and conflict is significantly positive for both regions that experience fluctuations in agricultural output and those which do not exhibit any variation.

The proposed analysis tests the impact of climatic conditions together with agricultural production on the probability of conflict in the long-term future and applies forecasting to validate the possible connections between climate, crop and violence. The following section provides details on the data and methodology applied for the predictions.

4.3 Methodology

Our approach builds on Hegre et al. (2016) as for the general forecasting design and consists of three main steps: *i)* data collection; *ii)* model set-up and assessment; *iii)* simulations process and update to forecast future conflict probabilities.

4.3.1 Data

First, we collect a joint dataset of historical and projected variables, covering all countries in the world for the period 1950-2050. For the model tuning and testing, we focus only on the historical observations (1950-2017) and leave the subsequent years for conflict predictions. To increase the accuracy of the forecast, we use geo-referenced disaggregated data at a high resolution (0.5° x 0.5° gridded cells).

Our dependent variable, the incidence of conflict, is a binary variable coded as 1 for every year in which a conflict occurs in a given location and otherwise 0. Conflict is here defined as the episode of violence which involve the use of the armed force by either the government or a formally organized group, and results in at least twenty-five battle-related death in a dyad-year. Data on conflict are drawn from the geo-referenced version of the Uppsala Conflict Dataset (UCDP-GED; Croicu and Sundberg, 2017) and are available for the period 1989 – 2017. We complement the UCDP-GED dataset with the PRIO-UCDP data for the period 1950-1989, as reported in the PRIO-GRID structure (Tollefsen et al., 2012). Although some issues of inconsistency may arise from using a combination of two datasets (for instance, conflicts tend to be more frequent after 1989, and this may due to an improved reporting and measurement system), the inconsistency is supposedly limited, as UCDP-GED and PRIO-UCDP data apply the same definition of conflict, follow the same coding process, and even ease the mutual connections and inter-change by reporting the same grid-cell identification number.

Our main predictor, climatic conditions, is operationalized in terms of climate anomalies, i.e. as the standardized annual temperature and precipitation deviation from their long-term mean (the mean throughout the entire 1950-2050 period). In order to test for the effect of agricultural production shocks, we include data on the production of all main crops (non-irrigated) expressed in tons/hectare. We draw, whenever possible, all the variables of interest from the same data-source, in order to ensure as much consistency as possible in the dataset and minimize the bias. To this end, geo-referenced data on climate anomalies and crop production are extracted from the ISIMIP Project for both historical time-series as well as for future projections (Frieler et al., 2017) and they are based on hadgem2 climate model (the Appendix provides more information).

Likewise, all variables are consistent with RCP2.6 scenario of carbon emissions (Figure S.4.2) which would allow to reach the objective of limiting the increase of global mean temperature to 2°C, as established by the Paris agreement (Van Vuuren et al., 2011). This scenario is rather optimistic in terms of emission reductions, as it would require strong and harmonized mitigation efforts from all countries and assumes even negative emissions in the second half of the century (Nakićenović and Swart, 2000). Less stringent emission scenarios like RCP6 or 8.5 may determine a much higher increase in temperature and consequently lead to greater impacts from climate change. Although comparing how different carbon emission and climatic scenarios can affect the probability of conflict in the future would be a relevant contribution in the conflict literature, this goes beyond the scope of the analysis. Possible extensions of this project may assess and compare how different climate scenarios, corresponding to more sustained warming, will affect the probability of conflict. Here, we rather want to set up a zero-ground*, to understand the minimum impact of climatic conditions and agricultural shocks on conflict incidence in the long-term. This will hopefully open up further research efforts aimed at comparing the impact of more sustained climatic

*Note that we follow the standard convention in climate science according to IPCC reports (IPCC, 2014) to define RCP 2.6 the 'minimum' or zero-ground climate scenario.

changes and higher levels of global warming on future stability.

At the time of writing, such a comparison would be unfeasible according to our research design, due to data limitations. In fact, ISIMIP does only make available information on climate variables (temperature and precipitation), crop production and essential input data (i.e. GDP and population) for RCP 2.6 (further details on climatic and crop data are provided in the Appendix).

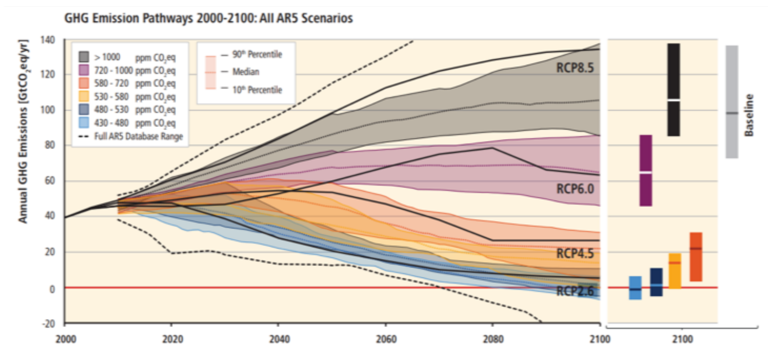

Figure 4.2: Greenhouse Gases Emission Pathways consistent with alternative scenarios. IPCC, 2014.

As we cannot assume that climatic and agricultural changes will be the only or primary drivers of conflicts in the future, across all our model specifications we introduce controls for the socio-economic context, i.e. GDP, population and education. There is in fact sufficient consensus in the conflict literature that high population pressure, poor economic conditions and low level of human development are positively correlated with the risk of conflict (Hegre and Sambanis, 2006; Hegre et al., 2016). For the reasons of consistency illustrated above, we extract data on GDP and population size at the 0.5° grid-cell level from the ISIMIP platform and make sure that GDP growth and demographic trends are compatible with RCP2.6 emission scenario.

Education is defined as the number of people who have at least attained primary education across all age ranges. Data on education are drawn from IIASA projections (Stonawski et al., 2018) in line with a Business-as-Usual scenario. IIASA only provides data at the country-level and every five years; to recover annual observations at the grid cell level, we first filled in missing data (between year t and $t+4$) by linear interpolation. Next, we spatially disaggregated the yearly national value to recover the number of literate people at the grid-cell level. Our basic spatial disaggregation is performed by weighting the country-level number of people with at least primary education by the share of national population who is living in each cell. As IIASA provides the estimate of educated people in terms of population size across all age ranges rather than reporting the number of people currently enrolled in primary education, our basic spatial disaggregation could give a reasonable estimate of the amount of literate people in each gridded cell.

Finally, as countries that are close to conflict areas are subject to greater risk of experiencing violence (Buhaug et al., 2011) and conflict is likely to re-occur in the future (Hegre et al., 2011), we include variables for both spatial and temporal contiguity. Specifically, we add a binary variable coded as 1 for all grid-cells that are neighboring a conflictual cell and we include a one-year temporal lag of conflict incidence. In our simulation protocol, temporal and spatial contiguity are iteratively updated for all grid-cells and all subsequent years up to 2050 according to the conflict prediction in year t. This iteration enables us to re-classify both temporal and spatial contiguity according to the prediction; should a cell be predicted to experience conflict in year t, the algorithm updates the temporal contiguity variable as 1 in the subsequent year and similarly re-classify the spatial contiguity variable for all cells neighboring the one which is predicted to experience conflict.

In the next two sections, we clarify the model set-up and the simulation protocol we apply to forecast conflict.

4.3.2 Model set-up and performance assessment

Although Machine Learning allegedly shows potential to improve the accuracy and reliability of conflict forecasting (Guo et al., 2018), its performance has never, to the best of our knowledge, been comparatively tested against other statistical models for conflict predictions. This paper represents the first attempt to assess AI potential in improving conflict forecasts, by applying and assessing the performance of two Supervised Machine Learning tools to forecast conflict probability up to year 2050: Decision Trees-based algorithms and Artificial Neural Networks (ANNs). Schematically, we can think of the main costs and benefits of these types of models as follows: while ANNs have the merit of being able to deal with increasingly complex tasks, they can also potentially be "black boxes" (Mittelstadt et al., 2016) and due to their complexity, ANNs make it difficult to establish the influence of different conflict predictors. Conversely, Decision-Trees based models are easier to interpret and they can be more efficiently applied to understand the importance of the different features in influencing the outcome.

All models are performed on the same subsets of the data, to avoid any possible inconsistencies due to data pre-processing. Specifically, we split the historical dataset into training, validation, and test subsamples, using a proportion of 70:15:15 which is standard in the Machine Learning literature (Russell et al., 2010); data on future variables are kept for conflict forecasts. We use a ten-fold cross-validation and utilize an under-sampling strategy to deal with the highly imbalanced panel data[†].

[†]Under-sampling consists in randomly removing some observations of the over-represented class, or the zero class.

First, we established a baseline against which to compare the performance of the different models in correctly predicting conflict, and we selected a set of common metrics for evaluation. Ideally, we would like to choose the most basic statistical approach as possible, against which we can compare the results of the AI models; for this purpose, we selected a generalized linear model (GLM), which is one of the most commonly used regression models for binary variable estimation [‡] (GLM model specifications and results are presented in Appendix).

The accuracy and reliability of the models are tested out-of-sample by means of the Area Under the Curve (AUC) and the F1-score. From a statistical point of view, the AUC represents the probability that a model ranks a randomly drawn positive instance higher than a randomly chosen negative one. An AUC of 1 corresponds to a perfect prediction, or an accuracy of 100%. F1 is computed as the weighted average of precision and recall, and thus gives an indication of the model's ability to balance the trade-off between being able of predicting as many positive cases as possible, and correctly discriminating between positive and negative cases, without exceeding in false positives. These metrics are particularly suitable for performance evaluation in the case of highly unbalanced datasets, i.e. when positive instances are very sparse (Frery et al., 2017). Hence, they are especially appropriate to our case, as the panel data of historical observations contains 121,766 instances of conflicts at the cell-year unit, accounting for nearly 3% of total observations.

The GLM which is used as a baseline performs quite well, reaching an AUC of 0.78 and an F1-score of and is able to correctly predict 73% of conflict instances on the test set (Figure 4.3). The considerably accurate prediction achieved even by a basic GLM seem to confirm our

[‡]As we want our baseline to be the most "standard" as possible, we select the most widely known regression model, i.e. GLM, rather than, for instance, polynomial regression – which would arguably be more suitable to conflict prediction as it would be better able to capture non-linear relationships. A quick search in Scopus gives an idea of the popularity of GLM compared to polynomial regression: the search "logistic regression" returns 310,974 records, while "polynomial regression" only 6332 documents [accessed on 26 September 2019].

hypotheses that considering both spatial and temporal context, enriching the set of conflict predictors, and taking advantage of a higher spatial resolution compared to national level analyses, could help increase forecasting accuracy.

Second, we compare and evaluate the performance of two types of Decision Trees-based algorithms: Random Forest and Extreme Gradient Boosting (Figure S.4.1). Random Forest is a supervised Machine Learning tool that grows multiple decision trees and predicts the target by averaging the outcomes of randomly grown trees. Every tree is constructed from a bootstrap sample of the original dataset (Sammut and Webb, 2010); each time a split in a tree is considered, a random sample of m predictors is selected from the full set of predictors. As such, using a random selection of features to split each node allows to reduce the error rate (Breiman, 2001).

Extreme Gradient boosting (XgBoost) constructs additive regression models by sequentially fitting an objective function and minimizing the least square errors at each iteration (Friedman, 2002). Unlike Random Forest, which grows each tree independently, Gradient Boosting algorithms grow trees additively; this means that these algorithms allow to correct the error made by previous trees, until no further improvement can be obtained (Kuhn and Johnson, 2016). The target is thus reached by optimizing an objective function, rather than using traditional optimization method in the Euclidean space (Chen and Guestrin, 2016). XgBoost has shown to be considerably faster than other algorithms (Friedman, 2002), has been efficiently used for anomaly detection (Frery et al., 2017) and has successfully been applied to deal with sparse data (Chen and Guestrin, 2016). On the other hand, Random Forest is generally considered less prone to overfit (Kuhn and Johnson, 2016).

Table 4.1 reports the main hyper-parameters selected from the tuning process for each

HYPER-PARAMETERS
Random Forest
number of rounds: 100
maximum depth: 6
number of trees: 500
mtry (number of variables selected at each split): 4
Extreme Gradient Boosting
number of rounds: 200
maximum depth: 4
number of trees = 500
eta (learning rate): 0.01
gamma (regularization to avoid overfitting): 15

Table 4.1: Hyperparameter of Random Forest and XgBoost models.

model. XgBoost and Random Forest exhibit a slight improvement in performance compared to the GLM used as a baseline and the most significant contributions are represented by the number of correctly classified and misclassified observations. Specifically, XgBoost outperforms Random Forest in terms of F1 score (Table 4.2) but exhibits a slightly lower AUC. Both Decision Tree based algorithms correctly identifies around 74% of conflictual cases out-of-sample, which is not significantly higher than the proportion of cases identified by the baseline (Figure 4.3). However, the proportion of false positives and false negatives is shown to be slightly lower for XgBoost and Random Forest compared to the baseline – especially as concerns the former algorithm – indicating that a reduced amount of grid-cells are erroneously expected to experience conflict (no conflict) when they are actually peaceful (conflictual).

Finally, we set-up and compare the performance of an Artificial Neural Network (ANN)

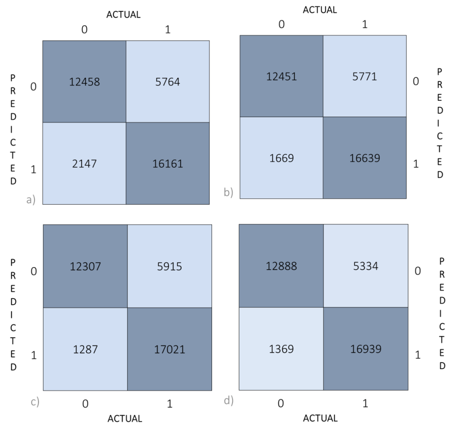

Figure 4.3: Confusion Matrices of conflict predictions from different models. a) GLM Baseline; b) Random Forest; c) XgBoost; d) Artificial Neural Network.

to predict the probability of conflict up to 2050 (the Appendix provides further information on the ANN structure). ANNs have shown higher predictive accuracy than physical, statistical and regression methods in a number of different fields, including prices (Nguyen-ky et al., 2018; Wang et al., 2019), energy and building efficiency (Paudel et al., 2014; Ascione et al., 2017), engineering techniques (Abbas et al., 2019; Gholami et al., 2019) and even astrophysics (De Smet and Scheeres, 2019). However, compared to other fields of study, the application of ANNs to socio-economic research has been rather limited. The ANN model used in this study is a feed-forward Multi-Layer Perceptron, composed of three layers and thus with only one hidden layer (Figure 4.4). The number of hidden neurons is detected by means of 'trial-and-error'. This parameter can highly influence the model performance: when it increases, the error decreases but so does the generalizability of the model (see the Appendix for more information).

The Feed-forward Neural Network is composed of one hidden layer with 32 neurons and has been trained with back-propagation coupled with regularization in order to minimize the binary cross-entropy cost function (eq. 4.1).

$$\theta = -\frac{1}{m}\sum_{i=1}^{m}\left(y_i \cdot \log \hat{y}_i + (1-y_i)\cdot log(1-\hat{y}_i)\right) + \frac{\lambda}{2m}\sum_{l=1}^{L}\sum_{j=1}^{s_l}\sum_{k=1}^{s_{l+1}} + \theta_{k,j}^{(l)^2} \tag{4.1}$$

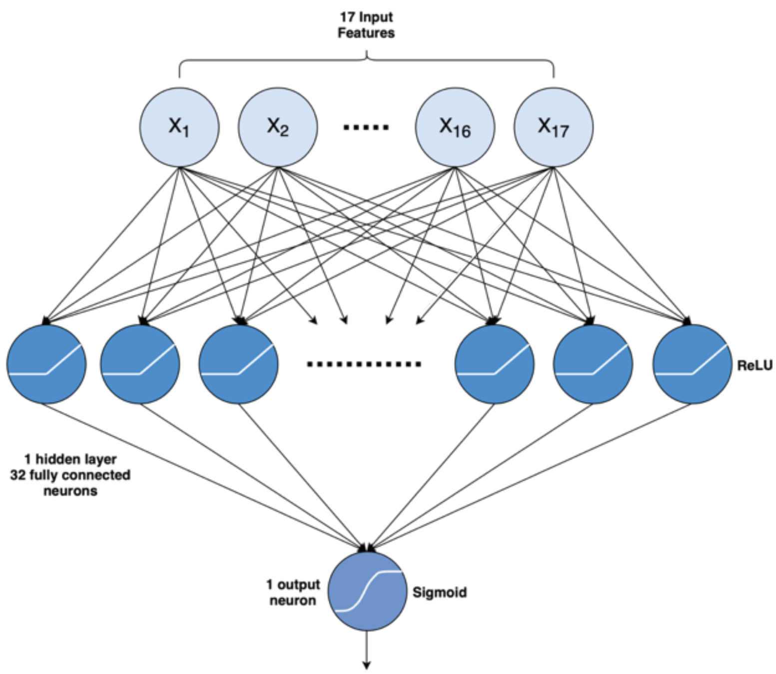

Figure 4.4: Artificial Neural Network structure used to predict conflict.

Non-linear functions are used as transfer functions; a Rectified Linear Unit (ReLu) activation function for the hidden layer and a sigmoidal function for the output layer. The sigmoidal function makes sure that the final output is a binary variable distinguishing between cells that experience conflict and cells that do not and applies a standard 0.5 probability

Model	AUC-ROC	F1
GLM	0.78	0.80
Random Forest	0.80	0.82
Extreme Gradient Boosting	0.80	0.83
Artificial Neural Network	0.82	0.83

Table 4.2: Performance of different models in conflict prediction on the test set: GLM (Baseline), Random Forest, XgBoost, Artificial Neural Network.

threshold.

The ANN structure shows good potential in improving forecasting performances. In fact, the ANN model correctly identifies almost 17000 instances of conflict (Figure 4.3), reaching an AUC equal to 0.82 and an F1 of 0.83 (Table 4.2). Considering the performance on the test set, ANN gives the most reliable and accurate results; hence we select this model to perform the conflict forecast for the period 2018-2050. Although this does not mean that the predictions on future scenarios will be as accurate as in the test set, especially in the long term, we can be confident that the forecasting results of the ANN are at least to some extent more reliable and accurate than traditional statistical techniques and can thus provide a valuable tool for violence prevention and mitigation.

4.3.3 Simulation Protocol

We set up the simulation procedure on the basis of the ANN architecture, to generate annual projections of conflict for each cell-year over the period 2018–2050. Schematically, the procedure *i)* calculates the probabilities for a given cell-year for each of the two classes, 0 (no-conflict) and 1 (conflict); *ii)* applies a 0.5 threshold to draw a binary outcome from these probabilities; *iii)* consistently update the conflict-related variables, i.e. the spatial and tem-

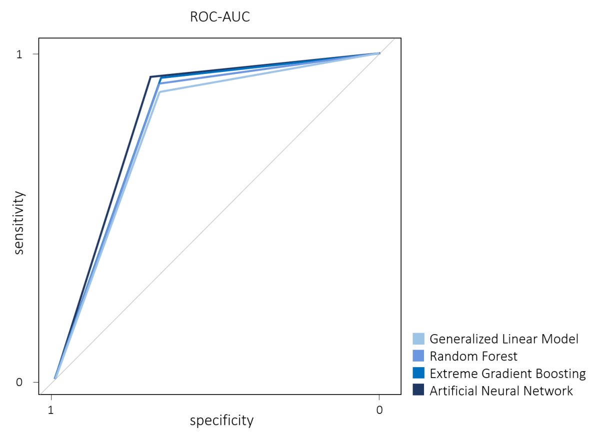

Figure 4.5: AUC-ROC curves of the models applied to conflict prediction.

poral context; *iv)* inputs the updated spatial and temporal variables into the original dataset, and *v)* starts over the predictions in time *t+1* by using these updated variables. This is repeated for all grid-cells and all years.

The updating protocol embedded in the simulations allows an iterative re-consideration of both spatial and temporal context. Ideally, as conflicts are likely to deteriorate socio-economic conditions, we would need to similarly update other input variables, akin GDP and population. However, a trade-off exists between the increase in forecasting reliability thanks to the inclusion of the spatio-temporal context, and the uncertainty increase due to the updating process.

As the input variables in year *t* depend on the predictions in year *t-1*, the uncertainty of the predictions will exponentially increase over time. Figure 4.6 reports an estimate of the mean decrease in confidence (or increase in uncertainty) of predictions over time. The mean decrease in confidence is obtained by averaging the confidence value associated with the predictions for each class (conflict, no conflict) in the 2018-2050 period and across all cells. Confidence is set equal to one for the last year of the historical dataset (for which we have the true realization of conflict); for each subsequent year and for all cells, the confidence of prediction is computed as:

$$Confidence_{it} = Confidence_{it} \cdot [P(x_{it}|x_{it-1} \cdot P(X_{it} = x)] \tag{4.2}$$

where $[P(x_{it}|x_{it-1} \cdot P(X_{it} = x)]$ derives from the chain rule of probability. As we know that each prediction in time t depends on the predicted probability associated with each 0-1 class in year *t-1*, and as the simulation assumes as true the highest probability predicted on each class i to draw a binary outcome (conflict/absence of conflict), the probability computed for each 0-1 class in year t can be seen as conditional on the probability in *t-1*. Next, if one would like to know the probability of all the 0-1 instances, for all cells and across all years, it could simply compute it as a joint probability distribution, which by construction is defined as the second multiplicative term in eq. 4.2.

Figure 4.6 clarifies that the uncertainty in predictions exponentially increases over time, due to the dependency of each annual observation upon the previous time-step. This leads to mean confidence associated with the probability of class i in year 2050 getting as low as nearly 30%. This increase in uncertainty as a function of time exhorts us to exercise caution when interpreting the forecasting results over the long-term, and invite to read them rather as heuristic in scope than indicative of actual conflict risks. This caveat shall open the final section, which presents and discusses the results. Before illustrating the conflict projections, however, we discuss the importance attributed to conflict predictors by Decision Tree based algorithms.

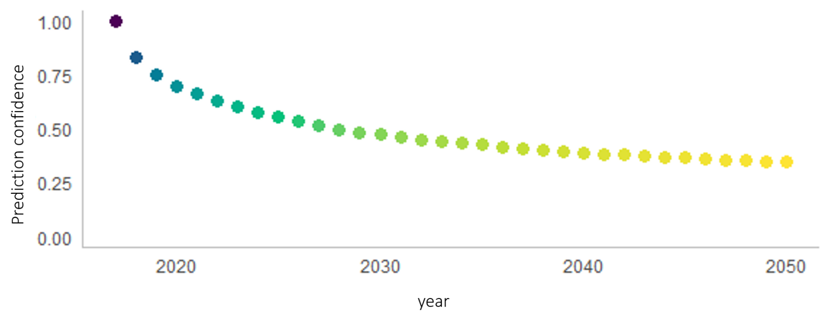

Figure 4.6: Estimate of the decrease in prediction confidence over time, ANN model.

4.4 Results

4.4.1 Importance of conflict predictors

Figure 4.7 presents the importance of different predictors in influencing conflict, as obtained from the Random Forest and XgBoost models. In Decision Trees based algorithms, the importance is computed by observing how the error varies when a specific feature increases or decreases *ceteris paribus* (Archer and Kimes, 2008). Specifically, here we use the "Gini Impurity" measure of variables' importance, which represents the probability of classifying the dependent variable incorrectly at each node split (Strobl et al., 2007). Gini impurity is calculated as:

$$G = \sum_{i=1}^{C} p(i) \cdot (1 - p(i)) \tag{4.3}$$

Where C is the number of classes (2 in our case) and $p(i)$ is the probability of selecting an observation within class i (0, 1). Unlike coefficients in standard regressions, the importance attributed to each feature in Decision Trees Based methods does not give any indication on the direction of the relationship but only offers a general indication of the marginal influence of each predictor when keeping the others constant. Variables' importance is reported in Figure 4.7 on a normalized 0-1 scale. The ranking confirms the primary role of spatial and temporal contiguity, as well as the influence of socio-economic conditions in affecting the probability of conflict. Temporal and spatial context are respectively assigned an importance of 0.93 and 1 on a normalized 0-1 scale and account for over 60% of all variables' importance. This gives support to our hypothesis that taking the spatial and temporal context into consideration contributes to increase the accuracy and reliability of conflict forecasts. Yet, this gap in importance between spatio-temporal contiguity and the rest of predictors risks making the comparison rather uninformative, whereby the importance of the contextual variables might mask the influence of other factors.

For instance, the most important variable after temporal and spatial contiguity is represented by population size, which however gets a score of only 0.16. To gain a better understanding of the relative importance of socio-economic and climatic conditions in influencing the probability of conflict, we can observe their scores separately, setting aside the importance attributed to the spatio-temporal contiguity (Figure 4.7, bottom graph). When we exclude

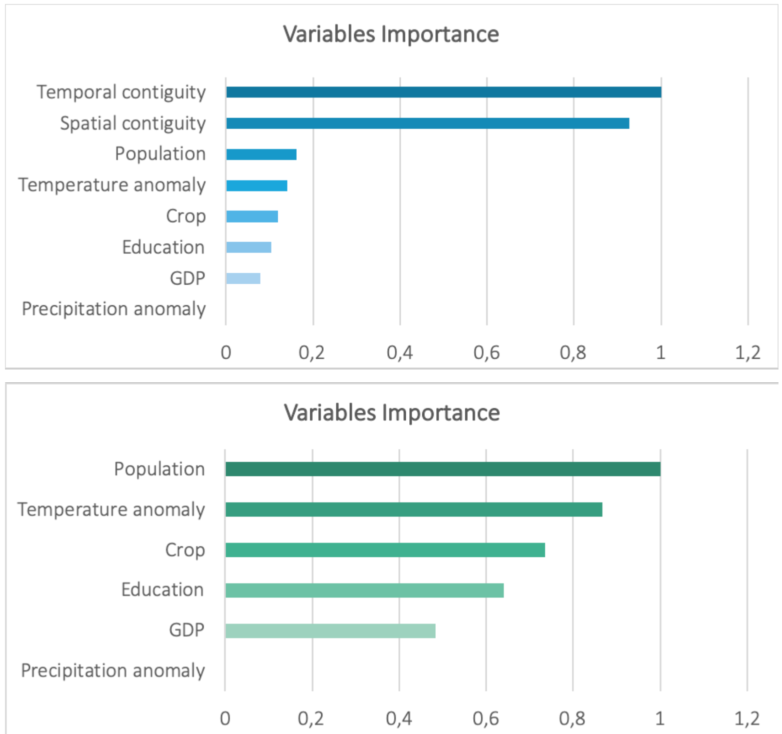

Figure 4.7: Conflict predictors' importance as extracted from Random Forest and XgBoost Models. The top graph reports all variables' importance normalized on a 0-1 scale. The bottom graph reports the variables' importance excluding spatial and temporal context.

spatial and temporal contiguity from the computation, population size is assigned the maximum importance on a normalized 0-1 scale, accounting for 23% of the total estimated influence of the predictors. The other socio-economic variables are shown to be less influent in conditioning conflict probability: education scores approximately 0.63 on an 0-1 scale of importance, representing nearly 18% of the overall influence, while GDP gets a value of 0.48 – accounting for around 15% of the total importance. Although the relative differences between socio-economic factors tends to be quite small, the moderate role of GDP in influencing violence is quite surprising and at odds with the existing literature. We hypothesize that this modest importance of economic output compared to the other predictors may be due to the effect of GDP being partially absorbed by temperature anomaly and crop production, which conversely present a considerable importance value, of 0.87 and 0.74 respectively.

As temperature patterns might affect security through crop production and economic output (Miguel et al., 2004; Dell et al., 2014), the relative importance of GDP is likely to be to some extent absorbed or mediated by these two other variables. One possible explanation is therefore that temperature patterns may negatively impact the economic output, especially by affecting crop production, and the negative economic shock caused by climatic anomalies may in turn increase the risk of violence. In this perspective, the high importance assigned to temperature anomaly and crop production is probably capturing a hidden effect of GDP on security, which may explain why economic output receives a lower score than climatic and agricultural variables. This is arguably confirmed by the almost null importance attributed to the other climatic variable, precipitation anomaly, which is the least influent factor in predicting conflict and accounts for around 7% of features' importance, excluding the spatio-temporal context.

Interestingly, the significance levels reached by coefficients in the GLM (Table S.4.1) are consistent with the variables' importance attributed by Decision Trees-based algorithms for all predictors, except for temperature anomaly, which does not reach significance at the 10% level. This seems to confirm our hypothesis that the influence of temperature anomaly on conflict is inflated and capturing, at least partially, some other economic effect. Overall our results may indicate that the impact of temperature and precipitation is rather indirect or conditional on other factors, which is in line with the results of the existing literature (Koubi, 2018). Also, our predictions are based on the assumption of a rather optimistic climatic scenario, consistent with an increase in temperature of less than 2°C; a possibility exists that warmer scenarios could carry a higher destabilizing influence on future societies.

4.4.2 Conflict Forecasts

As the ANN outperforms the other methodologies in predicting the probability of conflict on the test set, we build our simulation protocol and present the final conflict predictions on the basis of this model. To avoid misleading interpretation of the forecasts and prevent alarmist notes, we do not point at the single grid-cells which are predicted to experience conflict, but present the results aggregated by country.

Figure 4.8 visualizes the mean predicted conflict probability by country up to 2050. Different colors correspond to different conflict incidence probabilities across the overall period 2018-2050. According to our model, the southern hemisphere is predicted to continue experiencing the highest number of conflicts in the world, with the African continent continues to have the higher count of conflict-prone areas. Specifically, Rwanda, Nigeria, Gambia, Malawi, Lesotho, Eritrea, Ethiopia and Sierra Leone exhibit the highest probability of conflict (all above 0.89), while Algeria and Libya are predicted to experience a slightly lower incidence of violence (0.6 and 0.4 respectively).

Middle-East is shown to continue topping the global rank of conflict likelihood, as Lebanon is projected to experience conflict with a probability of over 0.9, and Syria scoring only modestly better, with a probability of conflict equal to 0.87. Unexpectedly, Iran displays a lower probability of conflict on average (0.6), which however crosses the standard 0.5 threshold. This may be due to the lack of information on ethnic and religious fractionalization, for which we do not have projected data in the future, which makes difficult for the model to capture the destabilizing potential of identarian cleavages.

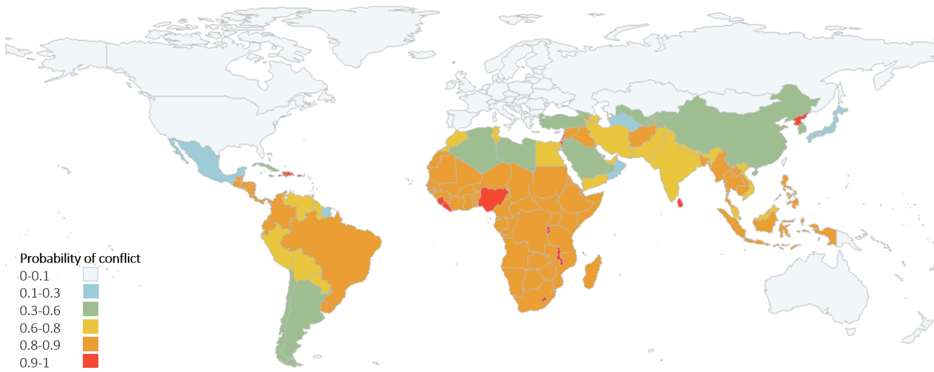

Figure 4.8: Projections of average conflict probability by country for the 2018-2050 period, based on ANN results.

In Central and Latin America, Haiti, Puerto Rico and the Dominican Republic are projected to witness the highest incidence of conflict across the period. This is arguably due to the importance that the model has been trained to assign to temporal and spatial context. As the model learns from historical observations, when Haiti experienced conflicts - especially after the failed coup d'état in 1989 - it tends to transfer this information both in time (to the future) and space (to neighboring countries).

Among Latin-American countries, Suriname, Chile and Argentina are predicted to be relatively less affected by conflict incidence, with an average probability of conflict of around 0.45 and 0.50 respectively, while Brazil, Venezuela (p = 0.8) and Colombia (0.86) show high signs of instability. Although a high probability of conflict in Brazil may sound surprising, this is probably due to the great influence that the model attributes to population size over the other conflict predictors.

North-American countries are, by contrast, predicted to be peaceful, with only Mexico experiencing a slightly higher probability of conflict than the other north-American countries. The low incidence of conflict projected for Mexico compared to Central and Latin American countries confirms the importance that the model attributes to spatial proximity.

Generally, rich, industrialized countries in Europe and North-America, along with Australia and New Zealand, are predicted to have a null or very low probability of conflict for the decades to come. In Asia, North Korea, and Sri Lanka top the conflict ranking, followed by Bangladesh and India, which present a probability of conflict of over 0.85, and Indonesia, Vietnam, and Pakistan (with a probability of nearly 0.80).

In general, we find that Africa, Central and Latin America, and Southeast Asia will likely experience the highest incidence of conflict in the world, while Europe, North-America, and Australia are found to be safe, as the associated probability of conflict in the decades to come is expected to be almost null. The recent tensions in India, rising communal conflicts in Nigeria, threats of violence mounting in Ethiopia and protests spreading in Brazil, just to mention a few, seem to indicate that our forecasts go in the right direction.

However, the model is not able to significantly distinguish the average probability of conflict across countries of the world - and this is especially true for Africa, where the ANN assigns almost the same probability of conflict to every country. Again, this is probably explained by the importance that the model learns to assign to the spatial and temporal context, which is likely to mask to some extent the influence of other predictors.

A limitation of our forecasting is therefore represented by the difficulty to delve deep into possible conflict triggers or forcing, as by looking at the results of the predictions we could not be certain of what factors – other than the spatial and temporal proximity – are most likely to drive the prediction. In fact, countries that are predicted to have higher levels of conflicts in the future differ as for socio-economic, demographic and climatic conditions. Hence, the task of identifying the fundamental motivations behind conflicts in the future remains daunting to the point that forecasting attempts cannot be seen as nothing more than an educated guess.

Moreover, new and unexpected conditions may arise, which can either mitigate or exacerbate tensions. For example, although our analysis casts doubt on the direct impacts of climate anomalies on the likelihood of conflicts, we cannot exclude that less stringent pathways of carbon emission reductions than the one envisaged in RCP2.6, leading to an increasingly warmer planet, will have disruptive consequences for socio-economic systems. Moreover, different Representative Concentration Pathways can be associated with different trends in international security and it is not unlikely that the relationship between carbon emission scenarios and conflict would be non-linear. For instance, one possibility is that high mitigation plans and considerable emission reductions could be achieved at great initial costs which would eventually lead to a more sustainable and stable society at a later stage. Accordingly, the great societal and economic changes required before carbon emissions peak could initially have disruptive consequences for the global socio-economy system, thereby increasing the risk of conflict at an early stage, and then leading to more stable and peaceful societies only further in the future.

Therefore, increasing academic efforts shall focus on the impact of alternative climatic scenarios on future societies, and scholars shall refine existing research to understand how adaptation strategies can moderate the destabilizing consequences of climate anomalies thereby reducing the likelihood of violence.

4.5 Conclusions

The present study forecasts the probability of conflict in the long-term future, under 'baseline' climatic changes. We apply and compare different Machine Learning tools and base the simulation protocol on an Artificial Neural Network structure, which reaches the best accuracy and reliability in out-of-sample predictions. The study shows that Machine Learning techniques outperform standard Generalized Linear Models in conflict predictions, although the difference is modest. The Artificial Neural Network model, in particular, seems to be the most suitable algorithm to capture non-linear relationships and is found to provide the most reliable predictions out-of-sample.

The analysis finds that Africa, Latin America, and Southeast Asia will continue to be the major conflict hotspots in the future, and identifies North Korea, Nigeria, Rwanda and Lebanon as the most violent countries in the decades to come. The results also highlight that spatial and temporal contexts are the most influential factors influencing future conflict probability and suggest that, although temperature anomalies have an influence on future conflict risk, this effect is mediated by socio-economic variables and overall modest compared to the impact of population size. Yet, further research is needed to understand how less optimistic climatic scenarios, corresponding to greater increases in temperature, will impact future societies, as well as to integrate climate change adaptation strategies in the forecasts. As the methodological framework that have been developed in this chapter is flexible enough to be adapted to different data sources, future extensions of this research can include a comparison of the effects of alternative climate change scenarios, which at the present time is not possible.

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4.7 Appendix

The following section provides further detail on the methodology used to forecast conflict. First, we focus on the main data on climate anomalies and crop production. Next, we explain the functioning of Decision Trees, which represent the underlaying structure of Random Forest and XgBoost; finally, we detail the Artificial Neural Network model set-up.

4.7.1 Climate and Crop Data

We utilize climate and crop yield data from the 'Inter-Sectoral Impact Model Intercomparison Project' (ISIMIP) (Warszawski et al., 2013; Frieler et al., 2015). Specifically, we use the data made available by the most recent ISIMIP-2b (Frieler et al., 2017) simulation protocol which uses Global Gridded Crop Models (GGCMs) to simulate annual crop yields (tons/hectare, t/ha) on a 0.5° grid for historical and future years, under various management rules. We focus on crop yields spanning years 1950-2050 for all major crops under rainfed regime as simulated by GGCM GEPIC (Liu et al., 2007).

Our two bias-corrected climate variables: *i)* near-surface average daily temperature (°C) and *ii)* near-surface daily total precipitation (mm/day) are also obtained from ISIMIP-2b, at the same spatial resolution and spanning the same years as the crop yield data. We utilize the bias-corrected daily temperature and precipitation as simulated by HadGEM2-ES (Jones et al., 2011; Lange, 2018) Earth System Model, and match them to the corresponding grid-cell where crop yields are reported by GGCM GEPIC.

The daily temperature and precipitation are aggregated to annual mean temperature (°C) and annual total precipitation (mm) at our sample grid-cells, before computing the standardized anomalies. Standardized anomalies are calculated as the deviation of the annual mean temperature (precipitation) of a grid cell from the long-term mean (over the 1950-2050 period), divided by the standard deviation of the temperature (precipitation) for the overall period.

Climate and crop data are consistent with RCP2.6, i.e. the highest-mitigation scenario according to IPCC convention (IPCC, 2014). The use of RCP2.6 deserves a clarification, as it has definite implications for our analysis. Climate scenarios differ greatly as for their potential impacts to social and economic systems (IPCC, 2014). The effects of climatic change on conflict are likely to be indirect and dependent on a number of contextual factors (Koubi, 2019), thus adding further complexity to the forecasting of climate change implications, especially in the long-term. Although we can hypothesize that high-carbon emission pathways such as RCP 8.5 are likely to have more disruptive security impacts than high-mitigation pathways, the implications of different climatic scenarios on security in the long-term are still rather unclear.

The reasons for the evidence on the long-term impacts of climate on security being scant are multiple and can be reconnected to two main constraints: *i)* limited data availability; *ii)* uncertainty. Although increasing efforts from climate scientists have been invested in modelling climate change costs and impacts, long-term forecasts are in fact limited by the lack of data on long-term trends for many fundamental variables, including demographics and socio-economic factors, especially at a disaggregated spatial level. Moreover, the uncertainty of climate models tends to increase over time (Tinker et al., 2016), which makes the task of forecasting extremely daunting. Specifically, extending the analysis performed in Chapter 4 to alternative climate scenarios would be unfeasible at the time of writing, as ISIMIP has not released data on more carbon-intensive climate scenarios together with the corresponding data on agriculture and consistent information on socio-economic input variables (Frieler et al., 2017). In fact, ISIMIP does only make available information on climate variables (temperature and precipitation), crop production and essential input data (i.e. GDP and population) consistent with RCP 2.6. As the methodological framework that I have developed in Chapter 4 is flexible enough to be adapted to different data sources, future extensions of this project can include a comparison of the effects of alternative climate change scenarios, which at the present time is unfortunately not possible.

4.7.2 Generalized Linear Model: Baseline

As a primary goal of the study is to test whether AI tools can advance current forecasts compared to statistical analyses, we set our baseline to the most commonly used model in conflict predictions: a Generalized Linear Model. The GLM reads as follows:

$$Y_{i,t} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 C_{i,t} + \alpha_3 S_{i,t} + \theta_i + \varepsilon_{it} \tag{4.4}$$

where $A_{i,t}$ is the vector of climate (temperature and precipitation) anomalies, or the deviation from their long-term mean in cell i in year t; $C_{i,t}$ is the value of crop production for all main crops (non-irrigated) in cell i and year t; $S_{i,t}$ contains standard controls for each grid-cell GDP, population size and educational attainment; and ϑ_i identify the geographical controls for macro-regions. Results of the GLM are presented in Table S.4.1. The results confirm the importance of spatio-temporal contiguity in influencing conflict and, similarly to the results of the Random Forest model, highlight the influence of population size on conflict probability. By contrast, the role that Decision Trees attribute to temperature anomalies is not confirmed by the GLM, in which we find that temperature deviation does not reach significance at the 10% level – while precipitation anomalies are barely significant.

This seems to confirm our hypothesis that the importance attributed by Machine Learning algorithms to temperature anomaly is rather due to a hidden effect of economic conditions; if Random Forest gives higher importance to temperature anomaly than economic conditions as conflict predictors, this is probably due to the effect of temperature on security being indirect or conditional upon GDP and crop production levels.

Regression Results of GLM Model

Conflict Incidence	(1)
GDP	0.318***
	(0.071)
Population	74.779***
	(0.074)
Crop	2.132***
	(0.045)
Temperature anomaly	0.002
	(0.071)
Precipitation anomaly	0.156*
	(0.082)
Education	0.059
	(1.081)
Spatial Contiguity	5.351***
	(0.031)
Temporal Contiguity	26.782***
	(0.067)
Constant	2.027***
	(0.520)

Table S.4.1: **Notes: Results are presented as odd ratios. Macro-regional dummies are included. Standard Errors in parentheses.** ***Significance levels:*** * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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4.7.3 Machine Learning

Machine Learning is a method of statistical learning that falls under the general umbrella of "Artificial Intelligence" and is characterized by the ability to automate a learning process. The foundations of Machine Learning lay in the capacity of the model to learn from a set of training examples, i.e. to improve its performance in accomplishing a specific task by means of experience (Mitchell, 1997). Machine Learning algorithms are trained by observing large amounts of data, and thus have the advantage not to require time-consuming hand-coding of software routines to input a specific set of instructions.

Machine Learning techniques can be distinguished in Supervised or Unsupervised learning types (Olawoyin and Chen, 2018). Supervised learning is performed whenever the goal is to detect the function that best approximates the relationship between the so-called ground truth (or the outcome y) and the features (the set of independent variables x). By contrast, the goal of unsupervised learning is to infer and represent the intrinsic structure and patterns that characterize a set of data points, for instance by clustering observations. In the present analysis, we apply two different Supervised Machine Learning tools, Decision Trees-based models and Artificial Neural Networks, to perform a classification of conflict cases.

4.7.4 Decision trees-based Models

Typical examples of Machine Learning tools are the so-called Decision Trees akin Random Forest and Gradient Boosting techniques. Decision Trees are decision classification tools that map a set of features into a target and proceed by evaluating each feature's ability to make more and more accurate predictions (James et al., 2013). Machine Learning tools like Random Forest and Boosting are learning methods that grow an ensemble of trees to progressively reduce the range of possible values of the target, by minimizing the error of the overall model. They proceed by means of subsequent if-then statements to progressively split the observations in terminal nodes or leaves, until reaching the final target (Figure S.4.1).

Decision Trees are becoming increasingly popular for a number of reasons: first, the set of rules or conditions they establish to reach the target are highly interpretable and easy to implement; second, the models can effectively deal with different types of predictors without the need to pre-process them; finally, they do not need any explicit specification of the function to be used in predictions like, for example, a linear regression model requires (Kuhn

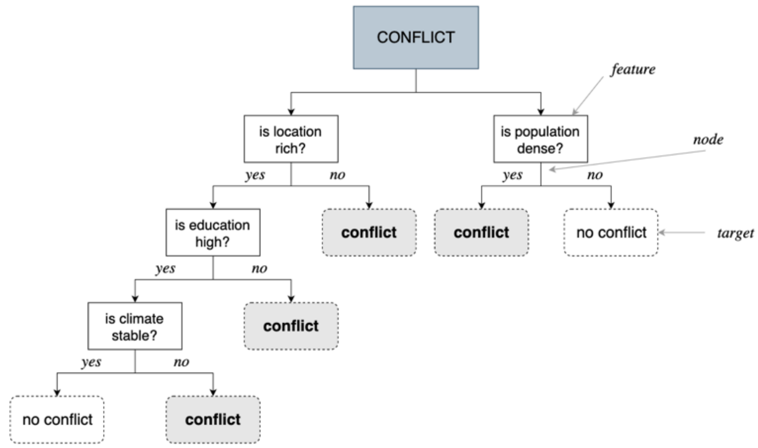

Figure S.4.1: Example of a Decision Tree Structure for classifying conflict onset.

and Johnson, 2016).

4.7.5 Artificial Neural Networks

Under the umbrella of Machine Learning, Deep Learning identifies a variety of algorithms that simulate the complex neural networks of human brain and are able to deduct their own rules from the combination of large amounts of data supplied as inputs (Haykin, 2009).

The quintessential Deep Learning algorithm is represented by Artificial Neural Networks (ANNs). ANNs are massively parallel distributed processors consisting of simpler units (neurons) that can store experiential knowledge and make it available for use. An ANN mimics the functioning of the human brain in its ability to learn from the environment by means of weighted connections linking its basic components, the so-called synapses, which allow the information to be transmitted and manipulated (Ascione et al., 2017). Each computation unit, the neuron, receives information from the previous ones through the synapses, manages the pieces of information and combines them through a transfer function to generate an output which is transmitted to the following neurons (Figure S.4.2).

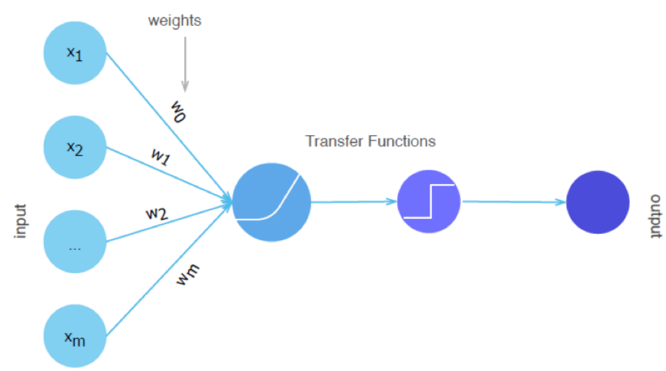

Figure S.4.2: Structure of a single-layer Neural Network. Adapted from Olawoyin and Chen, 2018.

The ANN learns from input and output neurons by means of training. The training is an iterative process that sets the optimal weights of the synaptic connections by minimizing the cost or error, for instance the sum of squared errors (SSE) (Magnier and Haghighat, 2010) or the root mean squared error (RMSE) (Asadi et al., 2014). In our ANN structure, a binary cross-entropy function is used to minimize the costs and choose the optimal weights for the synapses.

As ANNs gain knowledge by experience, they do not need pre-defined sets of rules to be established a priori. In data analysis, extracting high-level information from raw data can often be a tall order; Deep Learning shows great potential to face these challenges, since it allows for a progressive knowledge acquisition, leading from basic notions to extremely complex patterns, along a "hierarchy" of concepts (Goodfellow et al., 2016). In this regard, neural networks are especially convenient when an extended array of variables is investigated (Ascione et al., 2017). This also means that these tools do not require a limitation or an a priori selection of the features to be used as input, since they can manage high amounts of data and parameters.

ANNs are flexible enough to capture long-term and recurrent patterns among data both in space and time and they are particularly useful in capturing non-linear relationships between input variables. Moreover, as every neuron is potentially influenced by the global activity of all other neurons in the network, contextual information is dealt with naturally by ANNs (Deka, 2019). This makes these models particularly suitable for solving multicollinearity issues which are common in statistical analysis (Haykin, 2009).

4.7.6 References

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Estratto per riassunto della tesi di dottorato

L’estratto (max. 1000 battute) deve essere redatto sia in lingua italiana che in lingua inglese e nella lingua straniera eventualmente indicata dal Collegio dei docenti.

L’estratto va firmato e rilegato come ultimo foglio della tesi.

Studente: Paola Vesco ______________________________ matricola: 956299____________

Dottorato: Science and Management of Climate Change ________________________________

Ciclo: 32

Titolo della tesi[1] : **Climate Change and Conflict: Exploring Indirect Pathways and Future Scenarios**

Abstract:

ITALIANO

A discapito di un’attenzione crescente da parte sia della comunità scientifica che del panorama mediatico, le implicazioni che il cambiamento climatico potrebbe esercitare sulla sicurezza globale rimangono, ad oggi, incerte. Tuttavia, una comprensione esaustiva degli impatti dei cambiamenti climatici sul rischio di conflitti appare fondamentale ai fini di disegnare iniziative politiche lungimiranti. La presente tesi di ricerca va oltre l’approccio accademico usuale, per esplorare le potenziali connessioni indirette tra variabili climatiche e probabilità di conflitto. La tesi dimostra che i cambiamenti climatici esercitano un effetto modesto sulla probabilità di conflitto, ancor più se confrontato con il potenziale destabilizzante dei condizionamenti socio-economici, demografici e contestuali. I risultati delle proiezioni sottolineano come nel lungo periodo i continenti africano e asiatico rimangano le aree maggiormente a rischio di conflitto nel lungo termine.

ENGLISH

Despite attracting increasing attention from the research community and the mediatic arena in recent years, the security implications of climate change remain still controversial. Yet, understanding the impacts of climatic anomalies on the risk of conflict is fundamental to inform adequate policy actions and adaptation strategies. Going beyond the traditional approach that investigates the direct climate-conflict nexus, the dissertation explores some of the possible indirect connections between climate change and conflict. The thesis finds that climate change has an indirect effect on conflict, but this is very modest compared to socio-economic, demographic and contextual conditions. Shocks to agricultural production and unequal entitlements in crop yields, especially when coupled with socio-political discrimination, seem to be more relevant to security than slow-onset shifts in temperature and precipitation patterns. The results of the projections also show that the African and Asian continents will continue to be the most violent areas in the long-term future.

Firma dello studente

Paola Vesco

[1] Il titolo deve essere quello definitivo, uguale a quello che risulta stampato sulla copertina dell’elaborato consegnato.