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Climate Change – Agrifood – Conflict Nexus Pathways: A Scoping Review of the Literature*

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Abstract

This paper explores the pathways linking climate change and conflict, shedding light on the critical role the agrifood system can play as an intermediary. By conducting a scoping review of recent literature (2014-2024), this paper identifies two main pathways: increased competition over natural resources used in agriculture and decreased agricultural productivity. While some relationships, such as those examining the immediate causes of conflict – like threats to livelihoods, increased migration, and food insecurity – have been extensively studied, others, such as the impact of price changes and market forces, remain surprisingly underexplored. Various empirical approaches have been employed to identify these pathways, including ordinary least squares and logit/probit regressions as well as instrumental variables and structural equation modeling. Recently, the availability of high-resolution georeferenced datasets including socio-economic, environmental and conflict data, along with methodological advancements like spatial econometrics, have prompted more detailed and rigorous analyses. Current research gaps include the paucity of empirical studies at the micro level and the insufficient exploration of how market-based mechanisms influence the dynamics between climate change and conflict through the agrifood sector. The paper discusses future research directions, emphasizing the need for multidisciplinary approaches.

Keywords: Climate change, conflict, agrifood system, agricultural production, resource scarcity.

JEL codes: Q54; Q25; Q18; D74; O13.

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1. Introduction

Climate change shocks and conflicts have both been increasing in recent years. As emphasized by the Intergovernmental Panel on Climate Change (IPCC, 2022: 9), "widespread, pervasive impacts to ecosystems, people, settlements, and infrastructure have resulted from observed increases in the frequency and intensity of climate and weather extremes" with a high level of confidence. Moreover, the World Meteorological Organization reports that there has been a sevenfold increase in the reported disaster losses from extreme weather since the 1970s (reported in Newman and Noy, 2023). Similarly, the Peace Research Institute Oslo (PRIO) has reported a general increase in global conflicts over the past decades both in terms of state-based and non-state-based conflicts (Rustad, 2024), with increasing levels of internationalization. In particular, the increase in the number of conflict events is mostly concentrated in agriculture-dependent or resource rich regions such as Sub-Saharan Africa, which historically account for the largest share of conflicts, and the Americas, that record a sharp increase over the last decade. Therefore, it is no surprise that correlation between extreme weather events[1] and conflict has recently drawn the attention of many scholars who showed that deviations from normal temperatures and precipitation patterns significantly increase the risk of conflict (see, *inter alia*, Koubi, 2019; Carneiro et al., 2021; Buhaug et al., 2023).[2] However, the pathways linking climate change and conflict are complex and very context-specific, involving numerous environmental, economic, and social factors and different mechanisms (Burke et al., 2015; 2024a).

The analysis of the relationships between climate change and conflict has recently emerged as a hot topic in contemporary research, increasingly emphasizing the critical role played by the agrifood system (Maystadt and Ecker, 2014; Carneiro et al., 2021). However, this fast-growing body of literature has often focused only on reduced forms of the relationship – e.g. the effect of climate change on conflict insurgence (Hsiang et al., 2013; Wischnath and Buhaug, 2014; Burke et al., 2015) – or only on specific subsets of the complex cobweb of relations linking climate change to conflict through the mediation of the agrifood system (Helman et al.,

[1] Extreme weather events such as droughts and floods are the most easily recorded – and felt by people in the short run – climate change manifestations while slow changes in climate patterns (i.e., climatic stressors) can be less easily felt and usually require much longer time to be assessed. This is why, when trying to estimate the relationship between climate change and conflicts, authors usually use weather shocks as proxies for climate change.

[2] For instance, Hsiang et al. (2013) estimated that each standard deviation increase in temperature is on average associated to a 2.4% rise in interpersonal violence and 11.3% rise in intergroup conflict. Similarly, Almer et al. (2017) showed that a decrease of the Standardized Precipitation and Evapotranspiration Index (SPEI) by one standard deviation, i.e. a negative water shock, increases the likelihood of rioting by 8.3%.

2020; Pacillo et al., 2022). Some studies have emphasized that adverse climatic conditions strain agricultural systems, leading to lower yields and food shortages (Caruso et al., 2016; Harari & La Ferrara, 2018; Cappelli et al., 2023; Bedasa & Deksisa, 2024). This might undermine socio-economic stability and increase the likelihood of conflict (Buhaug et al., 2015) or make existing tensions worse and trigger conflicts across communities struggling to secure their livelihood (Kim & Garcia, 2023). Some others show that climate change can lead to disputes arising from competition over scarcer agricultural resources – particularly water and arable land – and eventually lead to escalated tensions and societal disruptions by threatening food security and livelihoods (Burke et al., 2015; Cappelli et al., 2024; McGuirk & Nunn, 2020). This competition is particularly pronounced in regions where resource distribution is unequal, further exacerbating existing vulnerabilities (Thalheimer, 2023). In addition, this interplay is complicated by the fact that conflicts can adversely affect agricultural productivity, leading to a cyclical pattern of vulnerability and violence (Buhaug & von Uexkull, 2021).

Given the rapid growth of this literature, particularly in the empirical domain, a comprehensive and systematic scoping review of the existing knowledge is demanded. A few excellent reviews and conceptual studies have been already published over the last decade or so. However, some of these works adopt a specific viewpoint, such as Ray & Esteban (2017), who focus on the relationship between conflict and development, Shemyakina (2022) who looks at the two-way relationship between conflict and food security, or Buhaug et al. (2023) who propose a general conceptual discussion of what risks to peace entail. Some others (Hsiang et al., 2013; Burke et al., 2015; Sakaguchi et al., 2017; Kouby, 2019) are outdated with respect to more recent contributions. Moreover, all the above-mentioned studies, except Sakaguchi et al. (2017), do not adopt an a priori review protocol as required by scoping review methodology to ensure a transparent and unbiased analysis (Tricco et al., 2018).[3] Furthermore, although most papers highlight an important mediation role played by agriculture and food, none of the above reviews explicitly and systematically focus on disentangling the specific roles played by various agriculture and food dimensions – e.g. agricultural productivity, competition over water and land, agrifood prices, agricultural household income, food security, etc. – and how they shape the pathways linking climate change and conflicts. Indeed, the need for a more focused and critical assessment stems out from the increasing complexity and heterogeneity of climate

[3] For instance, the recent metanalysis carried out by Burke et al. (2024a: 23) focuses "on a smaller number of studies that are particularly distinctive or influential in their approach", neglecting a more systematic approach to the literature.

impacts on the agrifood system (Yang et al., 2024), which eventually might influence conflict dynamics. As argued by several authors (Thalheimer, 2023; Cappelli et al., 2024; McGuirk & Nunn; 2020), climate change *per se* does not directly escalate conflict risk; it is rather the interaction with already existing socioeconomic and institutional vulnerabilities – most of them characterizing the agrifood systems – that determines conflict outcomes.

By and large, the literature emphasizes the changes in resource availability and accessibility (Burke et al., 2015; Cappelli et al., 2024; McGuirk & Nunn, 2020) as well as reduced agricultural productivity (Buhaug et al., 2015; Caruso et al., 2016; Cappelli et al., 2023; Bedasa & Deksisa, 2024) as potential pathways linking climate change to conflict through agriculture. While some conceptualization exists about these mechanisms, the empirical evidence on how they operate remain scanty and somewhat mixed. However, the last decade has brought about some improvements as recent studies introduced methodological advancements that allow for a more detailed analysis of the climate-agriculture-conflict nexus. For instance, empirical analyses have benefitted by the availability of increasingly detailed georeferenced datasets spanning the three different realms needed for such analyses, namely: agro-environmental data, conflict, and socioeconomic data. The increasing availability of high-resolution georeferenced datasets coupled with spatial econometrics techniques offer opportunities for more detailed analyses on the localized impacts of climate change and the context-specific conditions under which these impacts might lead to conflict (Cappelli et al., 2024; Song et al., 2024).

Our primary objective is to disentangle the complex set of relationships between climate change, the agrifood system, and conflicts. As such it differentiates from most existing reviews and metanalyses that focus primarily at reduced form relationships between climate change and conflicts (Hsiang et al., 2013; Burke et al., 2015 and 2024a), treating underlying mechanisms primarily as "moderators" – i.e. interacting factors that affect the strength of the estimated relationship between climate change and conflict – and to a much lesser extent as "mediators" – i.e. conducive intermediate factors that are essential in explaining the sequence of relationships linking climate change and conflict. In this study we focus mostly on the so-called "indirect association" climate-conflict literature (Koubi et al., 2012), that seeks to unravel the relative contribution of climate variability/anomalies on conflict as mediated by other factors – specifically, agrifood related factors – rather than studies that analyze the "direct association" between climate change and conflict. This is crucial especially for agriculture-dependent contexts , such as many low- and middle-income countries. Furthermore, indirect association studies can in principle offer the opportunity to estimate causal relationships and inform the design of conflict prevention/reducing interventions by policymakers and development community.

We aim to fill an important research gap (Hsiang et al., 2013; Burke et al., 2024a), by addressing three specific objectives / research questions. First, clarify what are the pathways and underlying mechanisms through which climate change influences the agrifood system and thus conflict. Second, provide a critical assessment of which pathways (or part of) have been empirically studied so far and how – e.g., methods of analysis, data – thus identifying remaining research gaps in empirical studies. Third, provide a systematic review of the direction and magnitude of the association between climate change and conflict through the mediation of agrifood system.

These objectives are pursued carrying out a scoping review of the more recent studies, published between 2014 and 2024. In doing this, we adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009; Levac et al., 2010) and, specifically, its extension for essential reporting items for scoping reviews (PRISMA-ScR, Tricco et al., 2018) to address the first research question, i.e. the identification of climate-agrifood-conflict nexus pathways, and we adopt the most updated version of the PRISMA guidelines (Page et al., 2021) to answer to the other two research questions, i.e. the collection of empirical evidence on a more focused domain of research by using a relatively smaller number of studies.

The paper is organized into five sections. Section 2 outlines the scoping review methodology and presents the main findings with respect to the type of studies and their geographical scope. Section 3 examines the two main pathways – resource competition and agricultural production – through which climate change influences conflict through the agrifood system, discussing the various mechanisms at work. Section 4 delves into the main empirical estimation issues, such as data, estimation strategies and identification challenges. Section 5 reports the results of the most recent empirical studies aiming at identifying the effect of climate change on conflicts through the mediation of the agrifood system. The final section summarizes the main insights gathered, highlighting research gaps and offering recommendations for future research.

2. Scoping review methodology

Scoping reviews aim at mapping the existing literature to identify key concepts, gaps, and evidence. To do this, they adopt a methodological framework[4] that involves several stages (Arksey and O'Malley, 2005; Levac et al., 2010), that can be grouped differently by the various authors, but include at least the following:

1. *Identifying the research question:* The scoping review begins with a clearly articulated research question, leading to the development of a detailed protocol that outlines the review's scope, objectives, and methods. This protocol ensures that the procedure is predefined and transparent, thereby reducing bias and enhancing reproducibility (Peters et al., 2015).
2. *Identifying and selecting relevant studies:* The core of the scoping review methodology lies in crafting a meticulous search strategy using a blend of keywords and standardized indexing terms to ensure the thorough identification of pertinent studies. This is followed by a rigorous screening and evaluation process against set eligibility criteria (Tricco et al., 2018).
3. *Collating, summarizing, and reporting results:* The extraction of data is a critical step involving the systematic gathering of necessary information from the selected studies. This stage includes a thorough coding and assessment of each study to evaluate its quality and obtain an accurate interpretation of the findings. Guidelines are usually used for a transparent reporting process, which is a necessary condition for either qualitative synthesis or quantitative meta-analysis (Levac et al., 2010; Peters et al., 2015).

The research question behind this study can be stated as follows: "What are the conceptual frameworks and empirical applications studying the relationships between climate change and conflict focusing on the agrifood system pathways and with specific reference to socio-economic analyses?". We operationalized it through search queries applied to the Elsevier-Scopus and the Clarivate Analytics' Web of Science (WoS) databases.[5] Opting for such databases while ensuring a streamlined, high-quality selection of peer-reviewed literature may result in a narrower scope, potential publication bias, and the exclusion of innovative findings

[4] All materials for this study, including the pre-registered protocol, full search strategies, and data extraction form, were pre-published on the Open Science Framework (OSF), available at https://osf.io/prcxz/?view_only=681d5ba1f7554333b606f6913f7526c2.

[5] Elsevier-Scopus and Clarivate-WoS are the two major database indexing journals, books, and proceedings. They are considered largely overlapping, though there are some differences between the two. For instance, Scopus focuses more on humanities and social sciences than WoS, while the WoS database goes back further in the past as compared to Scopus. Considering these differences, we decided to administer our search on both databases.

and diverse perspectives found in some gray literature studies like working papers from international organizations or research institutes not indexed in traditional databases. To partially overcome this, we conducted an expert consultation, asking two non-academic experts to identify important studies that match the research question.

The initial search query in Scopus and WoS yielded 2,743 records (2,084 and 659, respectively).[6] By refining the search criteria to include only publications from January 1st, 2014, onwards,[7] the number of records was reduced to 2,288 (1,720 in Scopus and 568 in WoS). Further narrowing the search to specific subject areas – i.e., Environmental Science, Economics, Social Sciences, and Agricultural and Biological Sciences – resulted in 1,735 records (1,398 in Scopus and 337 in WoS). Finally, limiting the search to English-language publications brought the total to 1,694 records, (1,357 in Scopus while WoS figures stay unchanged) (Figure 1).

Search terms included variations of the key concepts of interest. For instance, the concept of "climate change" is captured by *weather*, *temperature*, *rain**, *SPEI* and *climat** for "climate", and *shock*, *change*, *drought* and *flood** for "change". Similarly, the concept of "conflict" is captured by *conflict**, *violen**, *unrest**, *war*, *theft** and *dispute**. The "agrifood system" is identified using *agricultur**, *food*, *farm** and *livestock**, which allows us to specifically address the link between climate change and conflict via the mediation of the agrifood system. Furthermore, considering prior information about the possible mechanisms operating through the agrifood system, the terms *resource competition* and *yield** are also included. Finally, given the focus of our analysis on the possible "pathways" linking climate change and conflict, the terms *pathway*, *mechanism*, *channel** and *linkage** are included in the search string to ensure a more targeted search.

A second set of records was provided through expert consultation to be sure that no important source was left out of our search. This consultation yielded 176 records that, added to the 1,694 records identified from Scopus and WoS search, result in a total of 1,870 records

[6] These figures reflect the situation of the two databases as per January 30th, 2025.
[7] We decided to restrict our search to the period 2013 onward because we would like to focus on more recent studies and because this is the last period considered in the excellent Burke et al. (2015) metanalysis. Although Burke et al. (2024a) released an update of their metanalysis, our scoping review is still needed considering the differences between the two in terms of: (i) *aim*: our study focuses primarily on unravelling pathways, while Burke's et al. (2024a) is a metanalysis; (ii) *scope and depth*: our review specifically focuses on the climate change – agrifood – conflict nexus, while Burke et al. (2024a) have a broader scope not delving into a detailed identification of agrifood mediated pathways; (iii) *selection method*: we adopted a structured a priori protocol ensuring a systematic selection of all studies that meet the predefined selection criteria, while Burke et al. (2024a) opted for a selection of studies based on their own judgement about the most distinctive or influential studies.

(Figure 2). After eliminating duplicate 262 records (193 duplicates in the two datasets and 69 expert records already included among the ones selected from Scopus and WoS), we got a set of 1,608 ready-for-screening items.

The study screening and selection was carried out in three stages: title-only, title and abstract, and full-text. Two independent reviewers screened all identified studies at all stages. During each stage of the selection process, discrepancies between the two reviewers were resolved by a third, independent reviewer. Studies were excluded if they met any of the following criteria: 1) not focusing on the relationship (or a specific aspect of it) between climate change and conflict; 2) not showing socio-economic focus; 3) not dealing with contemporary conflicts (i.e. from 1945 on).[8]

Title-only screening identified 1,221 titles that did not meet our criteria, leaving 387 records for further title and abstract screening. This second stage of the selection process resulted in the exclusion of a further 158 records. Thus, 229 full-text articles were assessed for eligibility, with 108 being excluded because not explicitly focusing on the relationship between climate change and conflict (87), not having a socio-economic focus (8), not focusing on contemporary conflicts (6), and because some entries just replicate the contents of already included studies at different publication stages (7). Eventually, 121 studies were deemed eligible and included in the review. These studies represent the basis for analysis of the pathways linking climate change to conflict through the mediation of the agrifood system (Section 3). The full list of studies is reported in Table A1 in the Appendix.

A subset of these papers (56 studies), namely the ones whose focus is on quantitative estimates of the relationship between climate change and conflict or of specific links along the pathways, were further analyzed to identify the data used and the estimation procedures (Section 4) and the main results (Section 5). This required a careful coding procedure. For each study we identify: (i) the geographic scope (e.g., involved countries or regions) as well as the spatial unit of analysis (e.g., grid-based, subnational administrative units, countries); (ii) the temporal coverage (i.e., start date – end date of empirical observations) and the temporal unit examined (e.g., day, month, year); (iii) the hypotheses of research, noting the variables used (i.e., dependent, independent, and control variables); (iv) a summary of main findings (i.e. a verbatim description of the main results, a summary evaluation of the impact coding the

[8] There are, indeed, some studies that focus on longer temporal scale, going back in the past centuries such as those of Zhang et al. (2011) and Jia (2013) on China, Besley & Reynal-Quenol (2014) and Dincecco et al. (2019) on Africa, and Damette & Goutte (2023) on Europe.

relationship between climate change and conflict as positive, negative, or neutral,[9] and quantitative estimates, if available, including the statistical significance of such estimates). These features of the quantitative studies are summarized in Table A2 in the Appendix.

The recent surge in climate change-conflict studies is evident from the publication trends depicted in Figure 3, where we extended the time frame of published studies back to 2004 to put the last decade in perspective. This figure shows an increase in the number of studies over the past two decades. Being a relatively recent research field, literature reviews are quite steady over the analyzed period. Vice versa, there is a notable increase in conceptual studies and empirical quantitative analyses after the drop due to the Covid-19 pandemic. These data hide important changes taking place in the literature, especially empirical, such as the shifting from a macro level of analysis to meso and micro analyses, from reduced form analyses (i.e. studies estimating the direct relationship from climate change to conflicts) to the estimation of relationships along the pathways linking climate change and conflict (i.e., unravelling the specific mechanisms at work), and more recently shifting from the estimation of pure association to causal relationships.

Out of the 121 studies selected, 11 were books or book chapters, and the remainder were journal articles. The diversified publication outlets of peer-reviewed articles underscore the multidisciplinary nature of the field, spanning political science, environmental and geographical studies, and development research. This emphasizes an important feature of research on the climate change – agrifood – conflict nexus, that is the need for collaboration between different disciplines to analyze such a complex phenomenon.

The geographical focus of the studies varies, with a clear predominance of Africa. Excluding records of studies with a global coverage or no explicit geographical focus, Figure 4 shows that most studies focus on Africa (61% of total), Asia (23%), and Middle East and North Africa (MENA) (13%), while Latin America and Europe are relatively less represented. While this clustering reflects the prevalence of conflict across regions (e.g., Africa), it neglects other regions (e.g. Latin America) which are also prone to instability. This may limit our understanding of how pathways linking climate change and conflict might operate in contexts other than the pones most studies.

[9] The empirical quantitative studies provide mixed evidence, mostly due to different estimation approaches as well as the heterogeneity of dependent and independent variables used in the studies. Therefore, we decided to adopt a more nuanced approach in evaluating these effects coding them as positive, neutral or negative, as suggested by Sakaguchi et al. (2017).

3. Pathways Linking Climate Change to Conflicts via the Agrifood System

The 121 studies identified through the selection process serve as the basis for the following in-depth analysis, which delves into the pathways and mechanisms through which climate change may lead to conflicts via the mediation of the agrifood system. To further enrich the analysis and substantiate the pathways identified through the scoping review, we also refer to selected works published before 2014 when deemed useful.

3.1. Main pathways

The literature identifies two main pathways through which climate change can lead to conflict via the agrifood system: natural resource competition and agricultural productivity. Figure 5 illustrates these pathways, highlighting several key mechanisms through which climate-induced shocks and stressors may translate into conflict.

The first pathway, shown in the upper part of Figure 5 as resource availability/competition, is driven by the increased scarcity of / reduced access to renewable resources (Node B) such as water, arable land, and pastures due to climate change (Buhaug et al., 2023). The second pathway, shown in the lower part of Figure 5, focuses on the impact of climate change on agricultural productivity. As climate conditions deteriorate, crop yields and livestock productivity (Node C) decline, directly threatening the livelihoods of those dependent on agriculture (Carneiro et al., 2023). Displacement and migration (Node D) are often an immediate response to resource scarcity as well as reduced agricultural productivity, with affected populations seeking refuge in areas with greater resource availability, potentially creating tensions in host communities. Food insecurity and malnutrition (Node H) represent critical outcomes of reduced food availability (Node F) and declining crop yield productivity, both of which increase vulnerability and may push affected populations toward conflict.

Figure 5 emphasizes the central role played by agrifood price changes (Node E) and worsened livelihood (Node G) in increasing the likelihood of conflict. Indeed, the nexus between climate change and conflict is strongly influenced by market-related effects. However, it is worth highlighting that this component of the identified pathway seems to be one of the least explored in the empirical literature, leaving a significant gap in research.

Additionally, we observe two key bidirectional relationships in Figure 5: the links between migration and livelihood (Link 13) and between livelihood and malnutrition (Link 14). Specifically, deteriorating livelihood conditions due to conflict can worsen food insecurity

(George et al., 2020), potentially leading to displacement. In turn, food insecurity (and/or migration) further strains livelihoods, thereby increasing the risk of conflict (Shemyakina, 2022).

Lastly, in Figure 5 we also highlight critical factors (moderators) that can exacerbate or dampen the identified relationships in the climate-agrifood-conflict nexus, notably the agent's position towards the market (i.e., net buyers vs. net sellers), the opportunity cost of joining a conflict, and ethnic divide / political marginalization. For instance, net food buyer households are more vulnerable to food price spikes, which can rapidly destabilize their food security and increase the likelihood of unrest. Conversely, net sellers might benefit from higher prices, though they also face risks if climate change undermines agricultural productivity. Similarly, the opportunity cost of joining conflict becomes a significant factor; when livelihoods are severely impacted by resource scarcity or market disruptions, the costs of not participating in conflict may decrease, pushing individuals towards violent engagement as a means of survival. At the same time, in years of high harvest, violence could increase because the agent has a higher payoff in engaging in conflict. Ethnic divides and political marginalization play a key role, especially in magnifying the negative consequences of heightened competition for resources at home as well as at destination sites (in case of displacement/migration).

Table 1 classifies empirical and conceptual studies according to the pathways, nodes and links as depicted in Figure 5. The studies are grouped into four clusters, namely: (i) resource competition pathway (and part of); (ii) agricultural productivity pathway (and part of); (iii) studies not explicitly referring to one of the two pathways but nevertheless focusing on specific mechanisms belonging to the pathways as illustrated in Figure 5; and (iv) direct association studies, that are the ones estimating the direct effects of climate change on conflicts (Koubi et al., 2012).[10] The following subsections delve into the pathways' empirical evidence, discussing how the selected literature aligns with and elaborates on the relationships depicted in Figure 5.

3.1.1. Resource competition

Climate change exacerbates the scarcity of essential resources such as water, arable land, and pastures, intensifying competition among communities that depend on these resources for their survival. In agrarian settings, where the reliance on these resources is essential, this competition can escalate quickly, contributing to conflict (Buhaug et al., 2015; Koubi, 2019).

[10] In this last category, in Table 1 we report interacting and contextual factors, which can play the role of moderators as defined above.

The situation can be further worsened by the uneven distribution of resources and hazards, that frequently deteriorates intergroup relations (Almer et al., 2017; Shemyakina, 2022).[11]

The strain on resources that are critical for agriculture can trigger conflicts primarily in the area affected by the environmental shock. For example, Ikhuoso et al. (2020) discuss the conflict between herdsmen and crop farmers in Nigeria, and Olagunju et al. (2021) and Okunade & Kohon (2023) show that in northern Nigeria drought and desertification drive herders southward, igniting violent conflicts over land and resources. McGuirk & Nunn (2020) emphasize how climate change can transform a preexisting cooperation relationship between farmers and nomadic transhumant herders into a conflictual one in Sub-Saharan Africa. Eberle et al. (2025) provide further evidence that conflict between herders and farmers emerges because of competition over increasingly scarce productive land, especially at the frontier between fertile and barren lands. Similarly, Fjelde & von Uexkull (2012) highlight that rainfall anomalies create incentives for violent attacks against other communities in a direct effort to alter the allocation of scarce resources in Sub-Saharan Africa. Vargas et al. (2021) argue that climate-induced aridity in central Chile has intensified conflicts over pasture resources between livestock husbandry and guanaco conservation activities.

At the same time, climate change induced shocks can have far-reaching consequences also in places distant from the areas directly affected by the weather shocks through displacement and migration. As people are compelled to move in search of more secure living conditions, this might eventually lead to conflicts in destination areas, where the influx of migrants may exacerbate pressure on existing resource (Myers, 2002; Reuveny, 2007) or aggravate pre-existing grievances in host areas, as evidenced in Syria where drought-induced migration exacerbated social tensions (Ide, 2018; Ash & Obradovich, 2020). However, the evidence of this mechanism is scanty and inconclusive. Reuveny (2008) shows that settling Bengali flood and storm victims on native land in the Chittagong Hill Tracts aggravated a drawn-out guerrilla war which ended in the late 1990s. In India, Assam and Tripura states also experienced violence between Bengali immigrants and the native population (Bhattacharyya & Werz, 2012), because of the upsetting of the ethnic balance in the region as well as competition over resources between natives and immigrants. However, Petrova (2021) shows that flood hazards in combination with loss of assets increased the likelihood of internal migration in Bangladesh. However, unlike other types of domestic mobility, hazard-related migration does not increase

[11] As emphasized by Conca (2023), traditional conflict management approaches may be inadequate for addressing the new forms of climate-driven resource competition.

the frequency of protests in migrants' destination districts. Similarly, Bosetti et al. (2021), in a global sample, show that migrant inflows are not associated with increased conflict in host countries. Brzoska & Fröhlich (2016) argue that, despite case studies showing that natural hazards may contribute to the likelihood of conflict through migration, quantitative studies generally do not agree on whether the pathway is causal or even exists.

Finally, it is worth noting that some authors have emphasized that the availability and abundance of natural resources as opposed to resource scarcity can lead to conflict, potentially intensified by the effects of climate change, which alters the balance and accessibility of resources, creating new points of contention (Salehyan & Hendrix, 2014; Freeman, 2017; Abrahams, 2020).

3.1.2. Agricultural productivity

Climate change's impact on agricultural productivity represents another critical pathway to conflict. Although the net effect of mean potential crop yield on conflicts is theoretically ambiguous (Iyigun et al., 2017),[12] there is some evidence of a higher probability to be in conflict when annual temperature deviates from its long-term average in a country with low agricultural potential relative to a country with high agricultural potential (Goyette & Smaoui, 2022). Furthermore, the variability of potential crop yield has been proved to affect the likelihood of conflicts (Ang & Gupta, 2018). Alterations in temperature, precipitation patterns, and the increased frequency of extreme weather events directly reduce crop yields and livestock productivity (Schlenker & Lobell, 2010; Iqbal et al., 2018), which can reduce the opportunity cost of initiating and engaging in conflicts and civil wars (Collier & Hoeffler, 1998 and 2004).[13] Caruso et al. (2016) show that in Indonesia the increase in the minimum temperature during the core month of the growing season leads to an increase in violence driven by the reduction in future rice production per capita. Jun (2017) shows that in Sub-Saharan Africa, a high temperature during maize growing season reduced the crop's yield, which in turn increased the incidence of civil conflict. Similarly, Harari & La Ferrara (2018) show that higher temperatures and lower rainfall during growing seasons disproportionately increased the risk of conflict in Africa. Eastin (2018) shows that precipitation shocks increase violence in armed intrastate

[12] On the one hand, lower agricultural productivity can increase the incidence of conflict through increasing the requirement for land; on the other hand, the cost of maintaining fighting groups increases as food becomes more expensive, leading to fewer conflict events.

[13] However, the exact mechanism through which the opportunity cost argument operates can work differently in different contexts and needs to be unraveled. For instance, Guardado & Pennings (2025) show that a harvest shock in Afghanistan, Iraq, and Pakistan reduces the probability of insurgent attacks because it is associated with positive labor demand shocks.

conflict in the Philippines, as conflict incidents, battle deaths, and casualties rise in the case of excess rainfall, typhoons, and declines in agricultural productivity. For the same country, Crost et al. (2018) highlight that a shift towards extreme wet or dry seasons leads to a higher level of civil conflict even if annual rainfall totals remain stable. Pacillo et al. (2022) show that a key mechanism in Mali is climate variability that reduces the agricultural productivity of a staple crop such as maize and ultimately increases the intensity of conflict. Similarly, Gatti et al. (2021) show that poor rainfall can trigger local conflicts in Indonesia; however, they provide evidence that in areas served by better functioning irrigation infrastructure, which are key for rice production, the relationship is dampened, thus confirming the operating mechanism.

Climate-induced disruptions in agricultural productivity are likely to cause both adverse agrifood price changes and decreased accessibility to natural resources, which in turn can lead to reduction of livelihood (e.g., Minale et al., 2024; Wischnath & Buhaug, 2014). The decline in agricultural productivity is especially devastating in regions that are highly dependent on agriculture for economic stability and food security (Breckner & Sunde, 2019; Buhaug & von Uexkull, 2021). As agricultural yield and output decrease, food becomes scarcer, heightening food insecurity either directly, for self-consuming households, or indirectly because of price increase that can make unaffordable the usual diet of net-buyer households (Smith, 2014) or agricultural income decrease of net-seller households. Interestingly, McGuirk & Burke (2020) show that an increase in an agricultural production price index reduced local conflicts, while an increase in the consumer price index increases conflict, emphasizing the importance of economic agents' position towards the market in differentially transmitting a price shock. This places immense pressure on livelihoods, particularly in rural areas where agriculture is the primary source of income (Busby, 2018). Significant fluctuations in the prices of food and essential commodities aggravate economic hardships and lead to increasing tensions at the microeconomic level (Ateba Boyomo et al., 2023), while fueling macroeconomic shocks that further increase the risk of conflict (Vesco & Buhaug, 2020). Worsening people's livelihood can be per se a potent trigger for unrest, particularly in regions with weak governance structures (Jones et al., 2017). Food insecurity, exacerbated by the inability to locally produce enough food, often forces communities to rely on external food sources, further straining household finances and increasing the potential for conflict (Gilmore & Buhaug, 2021; Vesco et al., 2021). Eventually, the economic strain caused by declining agricultural productivity can destabilize communities, potentially leading to social unrest and even violent conflict (Hendrix & Salehyan, 2012; Buhaug, 2015).

3.2. Other factors

The literature on the climate change – agrifood – conflict nexus highlights that, beyond the factors shown in Figure 5, several critical elements can shape the mechanisms at play. These include moderators – such as ethnic divide (including linguistic diversity), economic inequalities (including gender disparities), and political marginalization; corruption and trust; technical innovations/solutions – that can play a crucial role in aggravating or mitigating socio-economic tensions induced by climate shock and stressors. Additionally, broader contextual drivers – such as economic development, poverty, and state institutional capacity – can influence the way climate-induced shocks and stressors translate into conflict. Finally, an important role (and an analytical challenge) is represented by feedback mechanisms – such as the impact of conflict on food insecurity or vulnerability – as they can create vicious circles where conflict exacerbates the very conditions that led to its outbreak, thereby increasing the likelihood of further violence.

Most interacting factors suggested in the literature refer to various dimensions of horizontal inequality (Stewart, 2008).[14] Specifically, ethnic divides and political marginalization are significant drivers that can intensify the impacts of climate change on conflict. For instance, Schleussner et al. (2016) highlight that in ethnically fractionalized societies, climate-related disasters often serve as catalysts for conflict by deepening existing societal tensions such as in North and Central Africa. Similarly, Moscona et al. (2020) further elaborate on this showing that segmentary lineage societies, i.e. societies characterized by strong allegiances to distant relatives, experience more conflicts, and particularly ones that are retaliatory, long in duration, and large in scale in Sub-Saharan Africa. Fjelde & von Uexkull (2012) argue that regions experiencing political marginalization are more prone to conflict when faced with environmental stresses, as the lack of state support leaves specific groups vulnerable.[15]

Economic disparities as well as cultural diversity and social norms are crucial in understanding conflict dynamics, as inequalities among different groups in their access to financial, livestock, or agricultural assets can serve as significant triggers. For instance, Song et al. (2024) demonstrate that districts characterized by mixed linguistic groups are more prone to conflict, particularly during droughts, with fatalities rising depending on the severity of the

[14] More recently, Arbatli et al. (2020) argue that interpersonal population diversity, rather than fractionalization or polarization across ethnic groups, has been pivotal to the emergence, prevalence, recurrence, and severity of intra-societal conflicts.

[15] This vulnerability is often exacerbated by land disputes, which are prevalent in areas where agricultural expansion obstructs traditional land use, as observed by Benjaminsen et al. (2012) with reference to Sahel.

drought. This increase is even more pronounced near linguistic borders, suggesting that linguistic diversity interacts with climate shocks to make conflict more likely, particularly over resource competition in agro-pastoral communities. Gender inequality has also been identified as a critical factor. For instance, Munala et al. (2023) argue that climate-induced stresses, such as droughts, can exacerbate violence against women, particularly intimate partner violence, in agricultural regions of East Africa, further compounding the vulnerabilities faced by marginalized populations.

In addition to economic and gender factors, corruption and trust play significant roles in shaping conflict dynamics. According to von Uexkull and Buhaug (2021), individual trust in government and institutions can significantly influence social stability, especially under climate-induced stress. On the other hand, Benjaminsen et al. (2012) focus on corruption in the context of rural Mali, where opportunistic behaviors by local actors and rent-seeking by government officials substantially contribute to land-use conflicts. In their study on the Niger River Delta, they find that factors like agricultural encroachment and a weakening political structure, rather than climate variability, are the primary drivers of conflicts, underscoring the importance of addressing governance issues to mitigate violence.

Furthermore, political and economic factors and technical solutions to climate challenges can exacerbate or mitigate climate change effects on conflicts. For example, Petit et al. (2023) discuss how the implementation of weather modification techniques in Burgundy, France, led to disputes among farmers, thereby highlighting the unintended consequences of such interventions within the broader context of climate change. Conversely, the availability of technical solutions, like better infrastructures that ease access to inputs, markets, and information services, can reduce the risk of conflicts in the context of climate change (Abid et al., 2016; Gatti et al., 2021).

Contextual drivers such as economic development, poverty and state capacity can also influence the likelihood of conflict. For instance, several authors (O'Loughlin et al., 2014; Wischnath and Buhaug, 2014) showed that country's income poverty can explain significant differences in the risk of civil war among countries. Similarly, Koubi (2019) notes that low levels of economic development and weak state institutions are often associated with a higher risk of conflict, as these conditions significantly deepen the vulnerabilities of communities to various stressors, including those not related to climate change. Scheffran (2022) emphasizes that societies characterized by low human development and limited coping capacities are particularly susceptible to conflict as they struggle to manage the socioeconomic and political pressures that arise from environmental and other challenges. More recently, Burke et al. (2024b), with reference to Sub-Saharan Africa, show that higher living standards reduce the sensitivity to climate shocks, possibly also through better policy response to climatic shocks, including effective employment opportunity provision. Low economic development, widespread poverty, and weak institutional capacity all refer to a reduced opportunity cost of engaging in conflict, i.e., people facing such circumstances are more likely to participate in violence (Blattman and Miguel, 2010).

Finally, feedback mechanisms can play an important role as they can create vicious circles. Figure 5 illustrates how low food security and reduced livelihood can lead to conflict. However, several authors have argued that the reverse is also true. For instance, Dabalen & Paul (2014) find significant evidence of households in the worst-hit conflict areas and individuals who are the direct victims of the conflict having lower dietary diversity in Côte d'Ivoire. Similarly, George et al. (2020) discuss how conflict can directly impact food security by disrupting agricultural production and markets, leading to increased malnutrition in Northeastern Nigeria. Ecker et al. (2023) further elaborate on the detrimental effects of conflict on child nutrition, demonstrating how ongoing violence worsens health and development issues, creating a vicious circle of poverty and vulnerability.[16] Similarly, Akresh et al. (2011) show that children born during periods of conflict are significantly more likely to suffer from stunted growth, which in turn affects their long-term health and economic prospects. This cyclical relationship between conflict and food insecurity is compounded by the fact that food scarcity can itself become a driver of further conflict, as Wischnath & Buhaug (2014) argue, illustrating how the loss of food production can escalate ongoing violence by lowering the opportunity costs of rebellion and increasing social grievances. Thus, understanding and addressing these feedback mechanisms is essential for breaking the vicious circle of conflict.

3.3. Concluding remarks

Table 1 reveals that some relationships have been studied more than others. Notably, much of the research has focused on abridged pathways, such as how climate-induced resource scarcity or agricultural decline can lead to conflict. Conversely, market-related mechanisms, particularly the effects of price changes and livelihood disruptions, have been studied less extensively within the climate-conflict literature. For instance, Harari & La Ferrara (2018)

[16] This argument mimics the one proposed within the so-called "nutritional trap" literature (Dasgupta & Ray, 1986).

discuss how economic disparities within countries can fuel conflict, but the empirical examination of how these disparities evolve in response to climate-induced market changes remains underexplored. McGuirk & Burke (2020) is an exception, as they focus specifically on the impact of agricultural production prices and food consumption prices in generating conflict, emphasizing the differential distributional consequences of these two sets of prices. This gap in the climate-conflict literature is particularly striking considering the significant attention the relationship between price changes and livelihoods received in other fields such as agricultural economics after the 2007-2008 global food price crisis (see, *inter alia*, Headey & Fan, 2008; von Braun et al., 2012)

The relatively scanty number of studies focusing on the role of market related variables and people's livelihood is likely due to the lack of detailed, high-frequency data, which are not always available, especially in developing countries, as well as to the inherent complexity of the involved mechanisms that deal with a range of variables that are not only difficult to measure but also deeply intertwined with feedback mechanisms. As suggested by Martin-Shields & Stojetz (2019), Scheffran (2022) and Thalheimer (2023), feedback loops between conflict, food insecurity, and market dynamics can create issues of endogeneity and reverse causality, making it challenging to isolate the effects of climate change on market conditions. Finally, the complexity is further compounded by the dynamic nature of markets, which can respond non-linearly to climate shocks.

4. Empirical strategies and challenges

While the pathways discussed in the previous section were identified by analyzing recent literature, whether they were conceptual or empirical studies, in this section, we instead focus exclusively on empirical studies to critically discuss the empirical strategies and challenges faced in such studies. In doing this, we begin with the datasets and the variables employed and then we turn to the identification strategies adopted.

4.1. Datasets and variables

4.1.1. Climate

Table 2 lists the key climate datasets used in the reviewed studies, each capturing various aspects of climate through different variables, which makes possible identify climate pattern deviations (i.e. deviations from long-term averages). According to the type of information they provide, the datasets can be grouped into four categories: simple indicators deviations (e.g.

precipitation or temperature); composite indicators deviations (e.g. drought or flood conditions); climate-related extreme events and disasters (e.g. hurricanes or catastrophic flooding); and consequences of altered climate processes (e.g. vegetation loss and land degradation).

The choice of the climate dataset critically depends on the research questions being addressed and key data features, such as the spatial resolution, temporal range, and focus. Generally, climatic data have a broad spatial coverage that is usually either global or regional, with data that are all georeferenced at different spatial resolutions (Table 2). The temporal coverage is variable, but it goes back at least to 1970s-1980s, with some datasets providing information that dates as far as the early nineteenth century. Although most available datasets provide simple indicator data, most recent studies use composite indicators deviations such as SPEI and PDSI, while disaster datasets are used the least.

Studies focusing on precipitation deviations/variability and its links to food security and conflict have used datasets such as CHIRPS and CMAP. In particular, CHIRPS' high spatial resolution (0.05°) and tropical focus makes it well suited for research in regions where rainfall variability is a critical driver of socio-economic instability (Ayana et al., 2016; Pacillo et al., 2022; Song et al., 2024). On the other hand, CMAP, with a coarser resolution of 2.5° x 2.5°, is better suited for broader, global analyses aiming to capture large-scale precipitation trends, which are less sensitive to small-scale spatial differences but crucial for understanding global precipitation patterns (Raleigh et al., 2015). Similarly, the choice between datasets providing temperature data depends largely on the spatial precision required and on the temporal scale of analysis. MODIS Terra, with its fine spatial resolution (1 km) and global coverage since 2000, has been utilized in studies where localized temperature variations play a critical role, such as those focusing on agricultural stress or regional temperature anomalies (Koren & Schon, 2023).

In contrast, CRU TS, with its broader temporal coverage (1901–present) and a resolution of 0.5° x 0.5°, is a popular choice in studies requiring both temperature and precipitation data over extended periods (e.g., Ash & Obradovich, 2020; Wang et al., 2023). Two more interesting datasets providing both precipitation and temperature data are the ERA Interim dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) and the NOAA's NCEP/NCAR dataset. Both of them provides reanalysis data[17] and are particularly useful for

[17] Climate reanalysis combines past observations with models to generate consistent time series of multiple climate variables. It involves a variety of data synthesis methods that are used to incorporate different datasets into one regularly spaced grid, thus being able to fill the time and spatial gaps existing in each dataset.

studies focusing on extreme weather conditions as it offers detailed historical weather data that are able to capture rapid-onset events like storms and droughts (Harari & La Ferrara, 2018; Breckner & Sunde, 2019) and/or analyze the link of long-term global weather patterns and socio-political outcomes (Landis, 2014).

Composite climatic indicators such as SPEI and PDSI are selected when researchers need to capture more complex climate interactions, especially those involving water stress and drought. SPEI, with its resolution of 0.5° x 0.5°, has been favored in studies that require both precipitation and evapotranspiration data to assess agricultural productivity and drought conditions (Cappelli et al., 2023; Almer et al., 2017; De Juan & Hänze, 2021). Its global and longtime coverage (1901–present) make it a robust dataset for analyzing water balance in various contexts, particularly where researchers need to understand both drought and unusually wet conditions. Similarly, PDSI, with its long temporal span (1895–present) and its ability to measure soil moisture and drought severity over extended periods, makes it suitable where prolonged drought conditions are key (Couttenier & Soubeyran, 2014; Salehyan & Hendrix, 2014; Vesco et al., 2021). Finally, NatCatSERVICE provides proprietary data on climate-related natural disasters and is useful in research that investigates the socio-economic impacts of such events (Schleussner et al., 2016). This dataset offers insights into the economic damage caused by climate extremes, making it crucial for studies that focus on the financial and social toll of natural disasters.

In addition to the datasets on climate-related anomalies, several important datasets track changes in soil and biomass, which are vital for understanding the effects of climate change on land and vegetation. The AVHRR (Advanced Very High-Resolution Radiometer), operated by NOAA, provides global data on vegetation health through indicators such as the Normalized Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI). It has been instrumental in studies like Linke et al. (2015), where it helped monitor vegetation conditions in Kenya and assess their implications for resource-based conflicts. Similarly, the Copernicus Global Land Service dataset offers weekly data on dry matter vegetation (phytomass), providing insights into biomass productivity and changes over time. McGuirk & Nunn (2020) utilize this dataset to examine how rainfall variability impacts phytomass production, which in turn affects the risk of conflict in transhumant pastoralism regions. These datasets are often used along with composite indicators to capture the complex dynamics of environmental change, offering a more detailed understanding of how both short-term climate shocks and long-term trends influence socio-economic systems.

Table 3 organizes key climate-related variables used by empirical studies published since 2014 into the same four broad categories – simple indicator deviations, composite indicators deviations, extreme events, and effects of altered climatic regimes – mirroring the dataset classification (Table 2). As with the choice of climate dataset, the selection of these variables depends on their features in terms of spatial resolution, temporal coverage, and data structure.[18]

For instance, temperature deviation measures are useful for understanding of heat stress / drought conditions impact on crop yields (e.g., Koren & Schon, 2023) or the impact of heat waves on migration as well as prices (e.g., Ash & Obradovich, 2020; Bosetti et al., 2021; Ateba Boyomo et al., 2023; Wang et al., 2023). Similarly, precipitation deviations are critical for understanding variations in water availability that are key for assessing changes in agricultural yields in rainfed agriculture regions and their consequences on agricultural household food security (Ayana et al., 2016; Raleigh et al., 2015). Undoubtfully the most useful climatic variables used to assess the impact of climate change through the agrifood system are composite index deviations, such as SPEI and PDSI, that better capture the effect of drought severity and water stress (Almer et al., 2017), especially in regions where water scarcity exacerbates pre-existing vulnerabilities (Cappelli et al., 2024). Event-based variables are better suited to estimate the socio-economic and political consequences of rapid-onset extreme weather events such as floods and hurricanes (Schleussner et al. 2016) or the effect of large-scale climatic anomalies such as ENSO[19] and their cascading impacts on food production, migration, and conflict at global level (Landis, 2014). Variables capturing the negative consequences of climate change on vegetation health or productivity are better at analyzing the change in resource availability as determinants of resource-based conflicts in traditional agricultural settings.

It is important to emphasize that these variables can be expressed in many ways. Mean values, standard deviations from mean values, and percentiles of the distribution are the primary measures for simple and composite indicators, whereas counts of the occurrence per year are common for extreme weather events. Another important difference is measuring deviations from the long-term average vs. measuring change in the variability of climate, i.e. climate uncertainty (e.g., Hendrix & Salehyan, 2012). Adopting one measure or the other implies

[18] It is worth noting that some variables, such as extreme events and climatic patterns deviations, can be derived through the combination of data contained in a dataset, although this does not directly identify such events. For example, it is possible to identify storms and hurricanes or the ENSO within the NOAA's NCEP/NCAR or the ECMWF's ERA data.

[19] ENSO stands for El Niño–Southern Oscillation, a climate pattern which significantly influences global weather patterns, agricultural productivity and water availability.

different theoretical assumptions, that is identifying variability/uncertainty rather than the level of the climatic variables as the mechanism through which climate change affects conflicts.

4.1.2. Conflict

Table 4 summarizes the main features of the conflict datasets used in the empirical literature, grouping them into those with a global scope or with a narrower coverage. The two most important conflict databases are the Uppsala Conflict Data Program (UCDP), jointly compiled by the Department of Peace and Conflict Research at Uppsala University and by the Centre for the Study of Civil War at the Peace Research Institute in Oslo, and the Armed Conflict Location & Event Data Project (ACLED), compiled by the Armed Conflict Location & Event Data Project organization.

The choice of conflict datasets, much like climate ones, critically depends on the research objectives, with key considerations being spatial granularity, temporal and geographical coverage, and the frequency of updates (Table 4). In general, conflict datasets that offer subnational detail and georeferenced data are preferred for understanding localized dynamics, as they provide better insights into how conflicts evolve in specific locations and can be used to account for spatial spillover effects. Global datasets such as ACLED and UCDP Georeferenced Event Dataset (UCDP-GED) are particularly suited as they provide highly detailed, georeferenced event data, which enables spatial analysis of conflict trends (see for example, Cappelli et al., 2023). ACLED is well known for mapping events of varying intensity given its broad inclusion criteria and its high update frequency, making it suitable for real-time analyses of political violence, protests, and social unrest (Raleigh et al., 2015; Song et al., 2023). The high spatial resolution of this dataset, down to the village level, makes it a valuable tool for researchers looking to explore micro-level conflict dynamics (McGuirk & Nunn, 2020).

In contrast, UCDP/PRIO provides longer temporal coverage, stretching back to 1946, which is crucial for studies that require historical context and long-term trends (Bazzi & Blattman, 2014; Couttenier & Soubeyran, 2014). Conflicts are recorded at the country level when they meet certain criteria – including a minimum threshold of 25 casualties in a year. Complementarily, UCDP-GED provides georeferenced data on individual events related to the recorded conflicts, bridging the need to localize them (von Uexkull et al., 2016).

GDELT and ICEWS are other global coverage datasets well known for their real-time event updates. GDELT, which captures conflict events from news articles globally, is updated daily, providing a valuable resource for real-time analyses of global political and social conflicts

(Ecker et al., 2023). However, its coarser resolution compared to ACLED and UCDP-GED may make it not ideal for highly localized studies. Similarly, ICEWS offers frequent updates and global coverage but lacks the fine spatial detail provided by ACLED (Landis, 2014). However, this dataset is quite peculiar in that it focuses on event prediction and instability.

Datasets having a narrower scope have been used for the analysis of conflicts at regional, national and subnational levels. For instance, SCAD focuses on social conflicts in Africa, offering valuable insights into unrest and political instability in this region (Almer et al., 2017; Jones et al., 2017). However, its lack of subnational detail and georeferencing may limit its use for studies requiring micro-level spatial analysis. Similarly, country-specific datasets like UNSFIR, which tracks violent events in Indonesia, and the Varshney-Wilkinson Dataset on Hindu-Muslim riots in India, provide detailed conflict data but are limited to their respective geographic areas and are often not updated regularly (Mary, 2022; Caruso et al., 2016). Lastly, newspaper articles could be an invaluable source of information for tracking conflict at local level (Petit et al., 2023).

Table 5 provides an overview of the conflict-related variables commonly extracted from datasets like UCDP, ACLED, and SCAD. These variables include the number of conflict events, fatalities, types of conflict, and geographic spread, which are instrumental in analyzing the dynamics and intensity of conflict in relation to climatic changes.

Events and conflicts - encompassing different types of violence, for example, following the widely used distinction proposed by UCDP, between state-based conflict, non-state conflict, and one-sided violence - are commonly used to measure direct confrontations between armed groups and/or against civilians. However, they can be limited by the focus on frequency and fatalities, which may overlook strategic developments, such as cooperation between conflicting groups. For example, using archival data from different Israeli institutions, Tubi and Feitelson (2016) highlight that in the semi-arid northern Negev, drought-induced conflict between Bedouin herders and Jewish farmers did not always lead to violence, as cooperation in resource-sharing sometimes replaced battles. This suggests that violent events and conflicts per se, while useful for measuring violence (Bazzi & Blattman, 2014), may not capture the full complexity of interactions between conflicting groups, including the potential for temporary peace or cooperation driven by environmental or political circumstances. In this sense, considering events that do not necessarily imply a minimum threshold of violence can allow for a more comprehensive description of the dynamics underway.

Protests are frequently analyzed to measure social unrest, often in response to political, economic, or environmental stressors. However, treating all protests as equally significant can obscure important distinctions. For instance, Petrova (2021) shows that internal migration following natural hazards may increase social tensions in urban areas, yet not all protests escalate into violent conflict. Thus, focusing only on frequency overlooks the strategic developments behind protests, such as leadership organization or migration-related grievances (see, Ash & Obradovich, 2020), which are crucial for understanding the likelihood of escalation. Additionally, duration may not always be the best indicator of the significance of protests, as even short-lived demonstrations can lead to long-term political consequences in certain contexts.

Riots are inherently violent outbursts of social unrest, typically triggered by immediate grievances such as economic hardships or political repression. However, measuring frequency alone can overlook the underlying political or economic conditions that make regions prone to riots (Buhaug et al., 2015). For example, while food price volatility (e.g., Ateba Boyomo et al., 2023) may increase the likelihood of riots, the broader socio-political context often determines whether these events escalate. Fatalities can also be misleading, as the economic and social consequences of riots, such as infrastructure damage and governance challenges, may be more significant than the death toll. Therefore, analyzing strategic developments, such as government responses and the role of organized groups, is critical to understanding the full impact of riots.

Explosions and violence against civilians typically involve more targeted acts of violence, often intended to create fear rather than achieve direct military objectives. Explosions, particularly those used in terrorism or insurgency, are designed to disrupt governance and weaken state legitimacy (Pacillo et al., 2022). Analyzing frequency without considering the broader strategic developments, such as the objectives of insurgent groups, can give a distorted view of conflict intensity. Similarly, fatalities alone may not capture the psychological and political effects of these acts, which often have long-term consequences for civilian populations and governance structures (Sharifi et al., 2021).

Violence against civilians, especially one-sided violence, is a critical aspect of conflict that requires careful analysis beyond just frequency and fatalities. Koren & Schon (2023) demonstrate that in the Sahel, violence against civilians is often driven by the competition for agricultural resources, particularly during peak cash crop harvest. This suggests that one-sided violence is not merely about targeting civilians but can be part of a broader strategy of resource appropriation. Relying solely on fatalities as an indicator of conflict severity can overlook other forms of violence, such as intimidation or displacement, which can have equally devastating effects. It is essential to analyze the strategic motivations behind one-sided violence, particularly the economic and political incentives that drive both state and nonstate actors to target civilians. Further, one-sided violence is often used as a proxy for conflict intensity, but it requires more nuanced analysis since this form of violence can also include non-lethal forms of coercion, such as forced displacement or intimidation, which have long-lasting social and economic effects that are not captured by death tolls alone.

State-based and non-state conflicts often involve large-scale violence, but focusing on duration and fatalities may not capture the full scope of these conflicts. Vesco et al. (2021) highlight how climate variability and agricultural production contribute to the onset of state-based conflicts, particularly in regions heavily dependent on agriculture. However, fatalities alone may not reflect the broader socio-economic disruptions caused by these conflicts, such as forced migration or economic collapse. Additionally, strategic developments, such as shifts in territorial control or peace negotiations, are critical to understanding the evolution of these conflicts (Maystadt et al., 2015).

In conclusion, variables like battles, protests, riots, explosions, violence against civilians, and one-sided violence provide critical information for conflict analysis, but they should not be used in isolation. Relying solely on frequency and fatalities can lead to oversimplified conclusions about the nature of conflict. Researchers should incorporate a broader range of indicators, including onset, duration, and strategic developments, to better capture the complex dynamics of driving conflict. Additionally, understanding the economic, political, and social contexts of these variables is crucial for a more comprehensive analysis of how violence unfolds and affects populations over time.

4.1.3. Socio-economic data

Socioeconomic and administrative datasets, like those listed in Table 6, are fundamental for analyzing the broader social, economic, and demographic factors that influence the institutional context, socio-economic governance and conflict. These datasets cover a wide range of variables, including GDP, demography, well-being, food security, and household-level data, providing essential insights into how economic and social conditions interact with climatic changes and political instability. Table 6 organizes these datasets into three clusters, namely socio-economic data, agrifood data, and other important dimensions such as ethnic and cultural data[20].

Socioeconomic datasets exhibit significant variation in both spatial and temporal coverage, ranging from global to subnational levels and from annual updates to periodic surveys. The resolution of these datasets is a crucial factor in their applicability to conflict analysis. Fine-grained datasets, such as LSMS or Gridded GDP, are more suitable for micro-level studies, providing detailed insights into localized conditions. In contrast, broader datasets like WDI or FAOSTAT are better suited to macro-level, long-term analyses. Moreover, to fully capture the various dimensions needed for robust econometric analysis, these socioeconomic datasets often need to be used in combination, as no single dataset can provide a comprehensive picture on its own.

Macro socioeconomic data, such as those derived from GDP and population datasets, provide critical information for understanding the broader socioeconomic conditions of the region under study. For instance, the International Monetary Fund Statistics and World Bank's World Development Indicators (WDI) offer comprehensive macroeconomic data that researchers can use to assess the economic health status of a country. These data are reported at the country level and usually updated annually, which makes them suitable for longitudinal studies where macro-level changes, such as economic growth or contraction, are being tracked over time (Bazzi & Blattman, 2014). However, their resolution is not fine enough for subnational analyses. In this case, gridded datasets such as the Gridded GDP Dataset (Kummu et al., 2018) are better suited to capture subnational variations or local socio-economic disparities that can drive conflicts at local level (Cappelli et al., 2023; Cappelli et al., 2024). Moreover, the International Food Policy Research Institute (IFPRI), through the Statistics on Public Expenditures for Economic Development (SPEED) database, provides statistics on public expenditure specifically allocated to development, reported at the country level.

Household well-being status can be retrieved using the data from the World Bank's Living Standards Measurement Study (LSMS), the UNICEF's Multiple Indicator Cluster Surveys (MICS) data or the Integrated Public Use Microdata Series (IPUMS) project that makes available the USAID's Demographic and Health Survey (DHS) data. All those agencies contribute with national statistical agencies to provide high-quality, standardized household-

[20] This list aims to summarize the most relevant datasets used in the literature, but it is not exhaustive as the sources are numerous and some studies can focus on very specific aspects, such as institutional settings, or - especially if based at country level - can benefit from national data.

level data that make possible to get insights into income, consumption, education, and health. These data allow for an in-depth analysis of socio-economic conditions across different socio-demographic groups and regions, giving researchers the ability to link micro-level economic factors to macro-level conflict trends (George et al., 2020; Mounirou, 2022; Munala, 2023).

More recently, nighttime light emission datasets, such as the Visible Infrared Imaging Radiometer Suite (VIIRS) or the Defense Meteorological Program Operational Line-Scan System (DMPS-OLS) datasets provided by the US National Oceanic and Atmospheric Administration (NOAA) and by the university of Colorado, have been made available in order to proxy economic activity at subnational level, even in area where it is difficult to administer surveys (Cappelli et al, 2024). The same is done at Africa level by the AfroGrid (Koren & Schon, 2023).

Other datasets, like those from Afrobarometer Surveys are particularly important for understanding the socio-political sentiments and living conditions at the household or subnational level. Afrobarometer provides data on public opinion regarding governance, economic conditions, and social issues across Africa, making it essential for studies examining how governance failures or economic dissatisfaction contribute to conflict or social unrest (De Juan & Hänze, 2021).

Agrifood data also play a crucial role in linking environmental changes to economic vulnerabilities and conflicts. Datasets like FAOSTAT and FAO GAEZ (Global Agro-Ecological Zones) provide detailed data on agricultural production and potential crop yields, helping to assess the impact of climate change on food security (Buhaug et al., 2015; Helman et al., 2020). FAOSTAT, updated annually at the country level, offers broad coverage, making it a suitable choice for studies focusing on national-level food security and economic stability. Additionally, the USDA National Nutrient Database supplies annual information on the caloric and nutritional value of crops, enabling analyses of dietary energy supply across different contexts (e.g., Ang & Gupta, 2018), while the History Database of the Global Environment (HYDE) 3.2 Database offers long-term, spatially explicit data on historical population and land use, supporting studies on the evolution of human-environment interactions over millennia (Cappelli et al., 2023; Cappelli et al., 2024).However, for more disaggregated analysis, the World Bank's LSMS-ISA and the Comprehensive Food Security and Vulnerability Analysis datasets by FAO and WFP offer household or subnational-level data on food security and vulnerability in regions most affected by climate change, such as Sub-Saharan Africa (Pacillo et al., 2022; Mounirou, 2022). Very important for the analysis of the mediation of agrifood prices are the data provided by WFP under the Vulnerability Analysis and Mapping (VAM). The subnational resolution of these datasets is crucial for identifying hotspots of food insecurity and their potential role in fueling social unrest or migration.

Ethnic and cultural variables, such as those found in the Geo-Referenced Ethnic Groups (GREG) and Ethnic Power Relations (EPR) datasets, are indispensable for understanding the political and social structures that can lead to conflict. GREG provides a spatial mapping of ethnic groups worldwide, and when combined with political data from EPR, researchers can explore how ethnic power imbalances or territorial disputes contribute to conflict (Cappelli et al., 2023; von Uexkull et al., 2016). These datasets, updated periodically with global or subnational spatial coverage, are essential for studies that analyze how ethnic divisions and political marginalization overlap with economic vulnerabilities to heighten the risk of conflict (von Uexkull et al., 2016).

Table 7 presents key socioeconomic variables that have been used in the empirical quantitative papers identified in the scoping review. Those variables are essential for understanding the dynamics of economic activity, agricultural production and well-being in conflict-affected areas. The variables range from macroeconomic indicators like GDP per capita and government expenditures at the country level to micro-level variables such as household income and child nutrition at the household and individual levels.

At the macro level, three main variables are considered strong correlates of conflict and are therefore regularly included as control variables: GDP-related variables, government expenditures, and population-related variables. GDP per capita is a widely used measure of economic output per person and is essential for understanding disparities in economic development across countries or regions. Its relationship to conflict onset becomes evident when economic conditions deteriorate or inequalities become pronounced (Bazzi & Blattman, 2014; Salehyan & Hendrix, 2014). Government expenditures is another critical macroeconomic variable, used to proxy a state's capacity to deliver public goods and services. Jones et al. (2017) emphasize that government investments can mitigate or exacerbate conflict risks via their effects on people's vulnerability. However, the effectiveness of these investments often hinges on their equitable distribution. Population density data adds another layer of complexity by providing insights into how densely populated areas may experience specific conflict dynamics due to competition over scarce resources (Breckner & Sunde, 2019; Sarsons, 2015). While high population density might suggest increased competition and potential for conflict, it is essential to consider other contextual factors, such as governance quality and resource availability, which significantly influence conflict outcomes.

Country-level macroeconomic or demographic data usually hides differences and heterogeneity in the context of analysis. This is why in recent years scholars have started to use variables disaggregated at subnational and household levels, using gridded variables from Gridded GDP Dataset or the CIEN Gridded population of the World. Furthermore, variables like nighttime light emissions and household income offer critical insights into local economic activities and living standards. Nighttime light emissions, sourced from the VIIRS dataset, serve as a proxy for economic activity and infrastructure development (Koren & Schon, 2023). This metric is particularly useful in regions where formal economic data may be lacking, yet it may not fully capture informal economic dynamics, which are often prevalent in conflict-affected areas. Similarly, household income and off-farm income data from surveys like LSMS or Afrobarometer illuminate economic conditions at the micro-level, providing valuable insights into household resilience during periods of instability (George et al., 2020; De Juan & Hänze, 2021). However, these variables must be interpreted alongside broader socio-political factors to understand how households navigate economic shocks.

Food insecurity, measured at the country or subnational level using sources like FAOSTAT or LSMS-ISA, is a key variable, particularly in agriculture-dependent regions. It helps assess how agricultural or access to food disruptions contribute to conflict risk, especially in areas facing extreme climatic conditions (Buhaug et al., 2015; Pacillo et al., 2022). Indeed, when food supplies are threatened, the likelihood of unrest increases, unless effective policy responses to contrast food insecurity are implemented. In this contexts, agricultural and food prices are essential for tracking adverse change in household livelihoods (Raleigh et al., 2015). Meanwhile, market access and access to credit variables further illuminate the economic opportunities available to households, showing how economic marginalization can drive social unrest.

Finally, ethnic group distribution variables, sourced from datasets like GREG and the Ethnic Power Relations Dataset, can shed light on how ethnic divide and political exclusion can increase conflict likelihood (Cappelli et al., 2023; von Uexkull et al., 2016).

4.2. Estimation strategies

The methods employed in climate-conflict research over the last decade cover a wide range of empirical strategies selected according to the specific research questions to be addressed and the analytical contexts, primarily available data. Each method group has distinct features, strengths, and limitations, that guiding researchers in choosing the most appropriate tool (Table 8).

Linear and panel models are among the most widely used methods for estimating the effect of climate variables on conflict outcomes. These models, particularly the ordinary least squares (OLS) and its variants, such as fixed effects (FE) and two-way fixed effects (2FE), control for unobserved heterogeneity by incorporating time and unit-specific effects. This makes them particularly effective for analyzing time-series or panel data where the goal is to estimate the impact of climatic changes over time across different regions (Breckner & Sunde, 2019). The simplicity and interpretability of these models are key strengths, allowing for straightforward estimation of linear relationships. However, a significant limitation is their assumption of linearity and their difficulty in addressing endogeneity issues, which can lead to biased estimates if unobserved confounding variables are not properly controlled (Koren & Schon, 2023).

Binary and count models are used when the outcome is dichotomous (e.g., conflict onset) or represents event counts . These models, including logit and probit for binary outcomes and negative binomial regression for count data, are particularly well-suited for predicting conflict occurrence or frequency. for example, zero-inflated negative binomial (ZINB) models are frequently used to handle datasets with an excess of zero counts, a common occurrence in conflict data where many regions may experience no violence (Cappelli et al., 2023). While these models are powerful for predicting event likelihood and frequency, they can be computationally intensive and are sensitive to the data distribution assumptions.

Causal inference models - such as instrumental variables (IV), difference-in-differences (DiD), and structural equation models (SEM) - are employed to address endogeneity in climate-conflict research, which is a common challenge. For example, using instrument variable two-stage least squares with fixed effects (IV-2SLS) helps mitigate bias by isolating exogenous variation in climate variables that can be used to identify causal effects (Maystadt & Ecker, 2014). While effective, these methods rely on strong instruments, which are not always available, and their results can be highly sensitive to model misspecification (Pacillo et al., 2022).

Spatial and non-linear models such as spatial lag models and generalized additive models (GAMs), are designed to address spatial dependence and non-linear relationships that are often present in climate-conflict datasets. For example, spatial autoregressive models (SAR) account for the influence of neighboring regions, making them particularly valuable when conflicts in one area are influenced by conflicts in adjacent regions (Song et al., 2024). These models can capture complex, spatially dependent relationships and are well-suited for understanding how climate extremes such as droughts and floods propagate across regions and impact conflict. However, their computational complexity and the need for large datasets can be limitations, particularly in regions with sparse data coverage (Cappelli et al., 2024).

The selection of empirical methods in climate-conflict research ultimately depends on the research question, data availability and the complexity of the relationships under investigation. While linear and panel models are commonly employed to assess the effects of climate variables such as temperature or rainfall over time and across regions, they do not establish causality (von Uexkull et al., 2016). Instrumental variables and 2SLS methods are used for causal inference (Caruso et al., 2016), though these are critiqued for depending on strong assumptions (Buhaug et al., 2014). To account for spatial dependence, spatial lag models and Moran's I are useful (Song et al., 2024), whereas structural equation models are suitable for exploring multi-level causal pathways (Pacillo et al., 2022). Finally, combining quantitative and qualitative methods can capture both broad patterns and deeper contextual factors, as suggested (Ide, 2017), addressing more complex questions. This mixed approach is especially useful for examining conflict pathways at different socio-economic levels.

5. Results

In this section we focus on the results as they emerge from the empirical quantitative literature of the last decade. These results crucially depend on the adopted dependent (i.e., the conflict variable) and independent (i.e. the climate change indicator) variables as well as on the estimation approaches employed in the studies. Therefore, drawing general conclusions is difficult, as emphasized also by other reviews (Sakaguchi et al., 2017, Burke et al., 2024a). In what follows, we try to organize the high heterogeneity of the empirical evidence by breaking the results down into different groups according to the independent variables – i.e., temperature and precipitation levels, temperature and precipitation anomalies (i.e., deviations from the long-term average), and extreme events. In doing this, we will report the literature results looking first at the impact of climate change on conflicts and then singling out the effects at different stages of the pathways.

5.1. Direct relationship between climate change and conflicts

Figure 6 presents the estimated impacts of the level of temperature and precipitation on conflict, showing mixed results. There are several motivations for this result heterogeneity. Firstly, temperature and precipitation impact conflict differently, with floods being fast-onset climatic change manifestations while droughts are slow-onset manifestations. Additionally, while floods generally affect the whole economy, droughts primarily affect the agricultural sector. Secondly, the agro-ecological context proves crucial, as high precipitations not necessarily imply a negative impact in arid and semi-arid environments. Thirdly, what is relevant about the mediation through the agrifood system is the combined effect of temperature and precipitation changes rather than the separate effect of each of them. Finally, in the reported studies the temperature direction of change is always positive (i.e., high temperature), while the precipitation can be in either direction (i.e., low or high precipitation). This may explain why precipitation's effect on conflicts remains ambiguous while that of temperature is clearer.

Couttenyer & Soubeyran (2014) highlight how the proportion of countries in civil war is positively correlated to the increase of temperature. Similarly, Ang and Gupta (2018) link rising temperatures to conflict, but emphasize that variations in potential crop yield, influenced by regional agro-ecological factors, are key drivers rather than temperatures alone. These findings align with those of Bollfrass and Shaver (2015), although they also note that agricultural disruption alone cannot fully explain this relationship, suggesting instead that other mechanisms, such as macroeconomic shocks or behavioral responses, play a role. Further, Landis (2014) shows that prolonged periods of stable warm weather, by providing an opportunity to organize and coordinate violent activities, are associated with a heightened risk of civil war and non-state conflict.

Looking at precipitation, Devlin and Hendrix (2014) find that joint precipitation scarcity, a situation when both conflicting parties experience below-average rainfall, can have a dampening effect on conflict, challenging the assumption that rainfall scarcity directly leads to violence. Similar results are showed by Bosetti et al., (2018), Crost et al. (2018), and Jun (2017). However, according to these authors, it is the long-term rainfall variability, rather than immediate scarcity, that influences the onset of militarized interstate (mostly civil) disputes. Koren and Schon (2023) show that reduced rainfall in agricultural areas reduces cash crop productivity, thereby heightening the risk of conflict, particularly in agricultural dependent regions. Notably, they also introduce a novel perspective by showing that agricultural abundance, rather than scarcity, can intensify violence, as non-state actors attempt to seize resources during high-yield periods. While Döring (2019) emphasizes that in the context of groundwater access, higher precipitations increase the likelihood of communal conflict.

Figure 7 reports the results of the studies that use climate anomalies, defined as significant deviations from mean temperature and precipitation rather than absolute levels. Altogether, three core insights can be derived from these studies. First, temperature anomalies (i.e., positive deviations from long-term average temperature) are associated with a higher risk of conflict, particularly in agriculture-dependent regions. Second, precipitation anomalies exhibit a dual effect on conflict risk: moderate (both negative and positive) deviations (see Balestri & Caruso, 2024; Pacillo et al., 2022), can mitigate the likelihood of conflicts, while excessive rainfall can similarly increase the risk of conflict through the pressures induced by flooding (e.g., Salehyan & Hendrix, 2014). Finally, the impacts of climate anomalies on conflict are markedly context-dependent and non-linear, with governance structures and institutional resilience serving as critical mediators that shape these dynamics across different regional settings.

The relationship between temperature anomalies and conflict is enriched by studies like Maystadt and Ecker (2014), which reveal that temxperature deviations influence conflict risk in Somalia. Warmer temperatures tend to exacerbate tensions and increase conflict, while cooler anomalies appear to reduce conflict incidence. Similarly, Ateba Boyomo et al. (2023) argue that climate-induced disruptions, such as food price volatility and deforestation linked to temperature anomalies, further exacerbate conflict risks through socioeconomic mechanisms.

Precipitation anomalies are equally important, with studies like Salehyan and Hendrix (2015) demonstrating that positive precipitation anomalies increase the likelihood of conflict in agriculture-dependent regions, while droughts exert a pacifying rather than a triggering effect on armed conflicts. Hence, there are cases where negative precipitation anomalies can alleviate these pressures and reduce conflict risk (Pacillo et al., 2022). Ghimire and Ferreira (2015) also emphasize that excessive rainfall can spark conflict in already fragile regions by causing floods, reinforcing the notion that significant climatic deviations – whether excess or scarcity – can strain resources and ignite violence, illustrating a dual nature in how rainfall deviations impact conflict.

A critical takeaway from these findings is that climate anomalies do not operate in isolation but interact with local socioeconomic and institutional contexts to influence conflict outcomes. While deviations from climate normals can stress resources and lead to conflict, these effects are mediated by governance and institutional capacity. For example, Ateba Boyomo et al. (2023) argue that weak governance can amplify conflict risks, even under minor climate anomalies. Similar results are found by Cappelli et al. (2024) with specific reference to Africa. In contrast, Raleigh et al. (2015) show that stronger institutions may be better equipped to manage these climatic shocks, mitigating the impact of climate variability on conflict. Moreover, the magnitude and direction of the relationship between climate anomalies and conflict are not uniform across studies and may critically depend on the scale of analysis. For example, studies focusing on localized violence or smaller-scale conflicts (e.g., Maystadt & Ecker, 2014) often show stronger effects of climate anomalies, particularly in fragile states, whereas research on larger-scale civil wars where institutional and political factors can play a more prominent role (e.g. Caruso et al., 2016) often reports weaker or insignificant findings.

Figure 8 illustrates the effect of specific climate events, such as droughts and floods, in contrast to Figure 7, which focuses on large climatic deviations from long-term averages. Unlike long-term deviations, these events capture the acute effects of discrete climatic shocks. These are captured either through composite indices like SPEI or PDSI, which reflect the combined extreme deviations in precipitation and temperature, or as discrete extreme events, i.e. droughts and floods. The literature reveals that drier conditions are consistently associated with a higher risk of conflict, particularly in regions vulnerable to climatic stress, such as Sub-Saharan Africa. Additionally, extreme climatic events, like prolonged dry spells, are shown to heighten conflict risk, especially in agriculturally reliant regions with limited infrastructure. For instance, Almer et al. (2017) report a significant association between drier conditions (negative SPEI) and increased riot incidence in Sub-Saharan Africa. In contrast, Couttenier and Soubeyran (2014) find a positive link between floods, measured through PDSI, and the onset of civil war, particularly in countries facing high social vulnerability to water scarcity. Similarly, Harari and La Ferrara (2018) find that more positive SPEI values (i.e., more humid conditions) can exacerbate underlying tensions and correlate with a rise in civil violence.

Several studies also address the impact of extreme climatic events. Detges (2016) show that prolonged dry spells tend to intensify civil and communal violence, particularly in regions reliant on agriculture and marked by weak infrastructure. Additionally, von Uexkull (2014) underscores the vulnerability of rainfed agricultural areas, where droughts significantly increase the likelihood of civil conflict due to the economic strain on farming communities. However, the severity of effects of a drier climate are context-specific: while droughts can trigger civil violence, studies also suggest that community-level interventions may mitigate these effects. For instance, Linke et al. (2015) demonstrate that in regions prone to resource-based communal conflicts, inter-community dialogue can reduce the likelihood of drought-driven violence, highlighting the importance of social interventions in conflict mitigation.

Lastly, Figure 8 does not include the study by Munala et al. (2023), as their analysis reports confidence intervals rather than standard deviations in logistic regression estimates—a standard epidemiological practice that emphasizes the magnitude and precision of odds ratios over formal significance testing. Thus, they constitute a specific case within the reviewed studies. Their research focuses on the relationship between severe weather events, specifically droughts and floods, and intimate partner violence at the subnational level across cities and districts. The findings indicate a significant positive association, with odds ratios of 1.23 in Uganda, 1.28 in Zimbabwe, and 1.91 in Mozambique, highlighting the impact of climatic shocks on domestic violence dynamics.

The overall relationship between climate anomalies and conflict (Table A.2, qualitative effect column) is mostly positive, particularly in regions with a high dependence on agriculture. Most studies (38 out of 51, or 74.5% of total direct association studies) report that climate anomalies, such as droughts, temperature variability, and precipitation anomalies, tend to increase the likelihood of conflict. However, a few studies identify negative (5.9% of total) or neutral (19.6%) relationships, introducing complexity into the analysis. Despite these mixed results, the general conclusion indicates a positive relationship between climate anomalies and conflict via the mediation of the agrifood system. This is largely attributed to the direct impacts of climatic shocks on agricultural yields and the indirect effects mediated through economic stress, food insecurity, and resource competition. While localized exceptions and context-specific dynamics exist, the evidence supports the conclusion that climate anomalies generally increase the risk of conflict, particularly in regions that are heavily reliant on agriculture and characterized by socioeconomic vulnerability.

Figure 9 presents a forest plot summarizing the meta-analysis of the relationship between climate anomalies and conflict, including direct estimates with and without controls.

Using the *metafor* package in R, our analysis standardizes effect size estimates, expressing them as the percentage change in the outcome variable due to a one standard deviation change in the climate variable (as in Burke et al. 2024a), to ensure comparability across studies. Our findings align with theirs, confirming a statistically significant association between climate shocks, particularly temperature anomalies, and conflict risk. However, our findings diverge in the strength of the estimated effects. While Burke et al. (2024a) report an average effect of 2.5% increase in intergroup conflict per standard deviation temperature increase, we identify a weaker effect size: a 1.52% (95% CI: 0.36 to 2.68) increase in conflict outcomes per one-standard-deviation change in climate variables. Possibly, this difference depends not only on our smaller sample of studies (covering only the 2014-2024 period)[21] but also on the specific focus regions with high agricultural dependence. However, this average effect hide a huge heterogeneity among studies as reflected in the wide range of effect sizes.[22] This is usually linked to the differences in contextual factors, such as socioeconomic conditions, governance quality, and the specific nature of the climate variable under study. However, while Burke et al. (2024a) emphasize the moderating role of economic conditions and political institutions, our analysis highlights the crucial role of agricultural dependence. Negative precipitation anomalies and droughts exhibit a weaker but still positive association with conflict, contrasting with Burke et al. (2024a), who find that global rainfall variability generally has insignificant effects. These differences underline the context-dependency of climate-conflict dynamics.

Figure 10 presents the results of the meta-analysis categorized by climate variability, including temperature anomalies, precipitation anomalies, and droughts.

Although all positive, only temperature anomalies show statistically significant estimates. Specifically, temperature anomalies display the strongest positive association with conflict, with effect sizes frequently exceeding 2% per standard deviation, particularly in agriculture-dependent regions. Positive precipitation anomalies exhibit mixed effects, with some studies showing an increase in conflict due to intensified competition over unevenly distributed resources, while others report neutral or stabilizing effects depending on the context. However, this effect is not statistically significant. This is also the case for negative precipitation anomalies and droughts, which reveal a generally positive but even weaker and not significant association with conflict.

By incorporating both direct and indirect pathways, this analysis—which includes direct estimates with and without controls, various empirical models, and different variables for both temperature and conflicts—demonstrates that while the strength and direction of effects vary, the overall emerging pattern supports the hypothesis that climate anomalies increase the likelihood of conflict.

[21] This seems to be consistent with another result by Burke et al. (2024a), who found lower point estimates in more recent studies as compared to older studies (Burke et al., 2015).
[22] The random-effects model employed in the meta-analysis accounts for this heterogeneity and provides a statistically significant aggregated estimate, emphasizing the overall trend of a positive climate-conflict relationship.

5.2. The role of mediators

Table 9 offers an extension of the results presented in Figures 6, 7, and 8 by exploring the mediating role of some intermediate mechanisms such as migration, food security, economic shocks, and political instability in shaping the relationship between climatic shocks/stressors and conflict. For example, Ateba Boyomo et al. (2024) highlight that temperature variations negatively impact livestock production, which in turn can eventually escalate tensions, particularly in regions heavily dependent on pastoralism. Authors such as Bohmelt et al. (2014) and Wischnath & Buhaug (2014) contribute by exploring how agricultural productivity and food growth serve as indirect links between climate and conflict, adding depth to the direct relationships discussed earlier.

It is also worth noting that these mediators are sometimes embedded directly within the climate or conflict variables. For instance, Guariso and Rogall (2017) introduce a new measure of inequality based on rainfall in ethnic homelands during the plant-growing season. This measure, a Gini-type between-group rainfall inequality index, quantifies disparities in rainfall distribution across ethnic homelands by comparing the amount of rainfall each homeland receives. While designed to capture inter-group differences, it inherently mixes climatic variability with structural inequalities, making it challenging to isolate the direct effect of rainfall inequality on conflict.

Abnormal rainfall patterns and droughts drive migration, often resulting in escalated social tensions, protests, or even riots in receiving regions (Bhavnani and Lacina, 2015; Mounirou, 2022). Similarly, Petrova (2021) highlights that climate-induced harvest losses result in heightened internal migration, eventually leading to protests in urban centers, though not necessarily escalating into violent conflict.

Economic shocks, particularly climate-related price increases, indirectly fuel conflict by deepening economic inequalities and social instability. For example, Bazzi and Blattman (2014) report that climate-related price shocks weaken state stability by widening economic inequalities, which then raise the likelihood of conflict onset. Similarly, McGuirk & Burke (2020) show that the increase in farmgate output prices reduces local conflicts, while an increase in food consumer prices increases conflict.

All studies above analyze specific relationships along the pathways going from climate change to conflict through the agrifood system. However, some studies have also emphasized that some relationships can go in the opposite direction. For instance, Ecker et al. (2023)

demonstrate how civil conflict exacerbates child malnutrition. George et al. (2020) further illustrate this point by showing how Boko Haram-related violence in Nigeria leads to deteriorating food consumption scores, emphasizing that conflict can have cascading effects on critical aspects of livelihood, further entrenching instability.

In conclusion, our results on indirect relationships align with Sakaguchi et al. (2017), confirming that agricultural production decreases as climate change increases, and rising food price or migration increase conflict risk, particularly in agriculture-dependent regions. Both analyses emphasize the complexity of these dynamics, which are shaped by contextual and mediating factors such as governance, resource abundance, and food security.

6. Conclusions

The research on the climate change – agrifood - conflict nexus has experienced significant evolution, both conceptually and methodologically, over the past decade. Earlier studies primarily relied on macro-level analyses to establish broad patterns between climate variability and conflict. However, recent advancements show a shift toward localized and mechanism-based approaches, leveraging high-resolution datasets, more advanced econometric techniques, and interdisciplinary frameworks. These advancements allowed researchers to explore more nuanced, context-specific interactions that drive conflict. This evolution reflects a growing recognition of the complex, multifaceted nature of the climate change – agrifood - conflict nexus, where context, governance, and social structures play critical roles in shaping outcomes.

The empirical literature provides robust evidence that two main pathways operate linking climatic variability to conflict via the agrifood system: natural resource competition and disruptions to agricultural productivity. Several studies highlight that deviations in temperature and precipitation adversely affect agricultural yields, leading to food insecurity and economic instability (Ayana et al., 2016; Cappelli et al., 2024). Other studies emphasize the role of resource scarcity, particularly in pastoralist and agriculture-dependent communities, where competition for water and arable land often exacerbates pre-existing vulnerabilities (Eberle et al., 2025; McGuirk & Nunn, 2020). Quantitative analyses further reveal that market mechanisms, such as price volatility, play a critical but underexplored role in driving conflict. Only a few studies (Maystadt & Ecker, 2014; Ghimire & Ferreira, 2015) demonstrate how climate-induced food price increases intensify social tensions, indirectly contributing to conflict, particularly in regions with weak institutional capacities.

Despite these advances, significant research gaps persist. Particularly, the empirical analysis of indirect pathways—i.e., the specific role of the agrifood system in mediating the relationship between climate change and conflict—and mechanisms such as food price fluctuations, market structure, and institutional responses remain inadequately examined (Crost et al., 2025; Boege, 2023). As argued by Abrahams (2020), the integration of climate and conflict data with governance and development programming is also essential to capture the broader systemic impacts of climate variability, but it is still widely underexplored. Many studies infer but do not measure the transmission of shocks through prices, trade, and input costs. Integrating high-frequency market data with georeferenced conflict records can help quantify how resource stress propagates across space and social groups. Also, quasi-experimental designs—such as spatial difference-in-differences, natural experiments, or instrumented panels—are essential to isolate the specific mechanisms at work. Furthermore, research must offer practical and effective solutions: for example, evaluating the impact of interventions—such as climate insurance, irrigation upgrades, or adaptive safety nets—can clarify whether they dampen the conflict potential of climate shocks. Finally, the literature is still grappling with establishing robust causal links at the micro level, where data scarcity and variability in conflict definitions present persistent challenges. Future research should focus on addressing these gaps through interdisciplinary approaches, combining insights from economics and other social sciences, agronomy and climatology, and peace studies. This agenda can help translate existing evidence into actionable guidance for policy and adaptation planning.

Figures and Tables

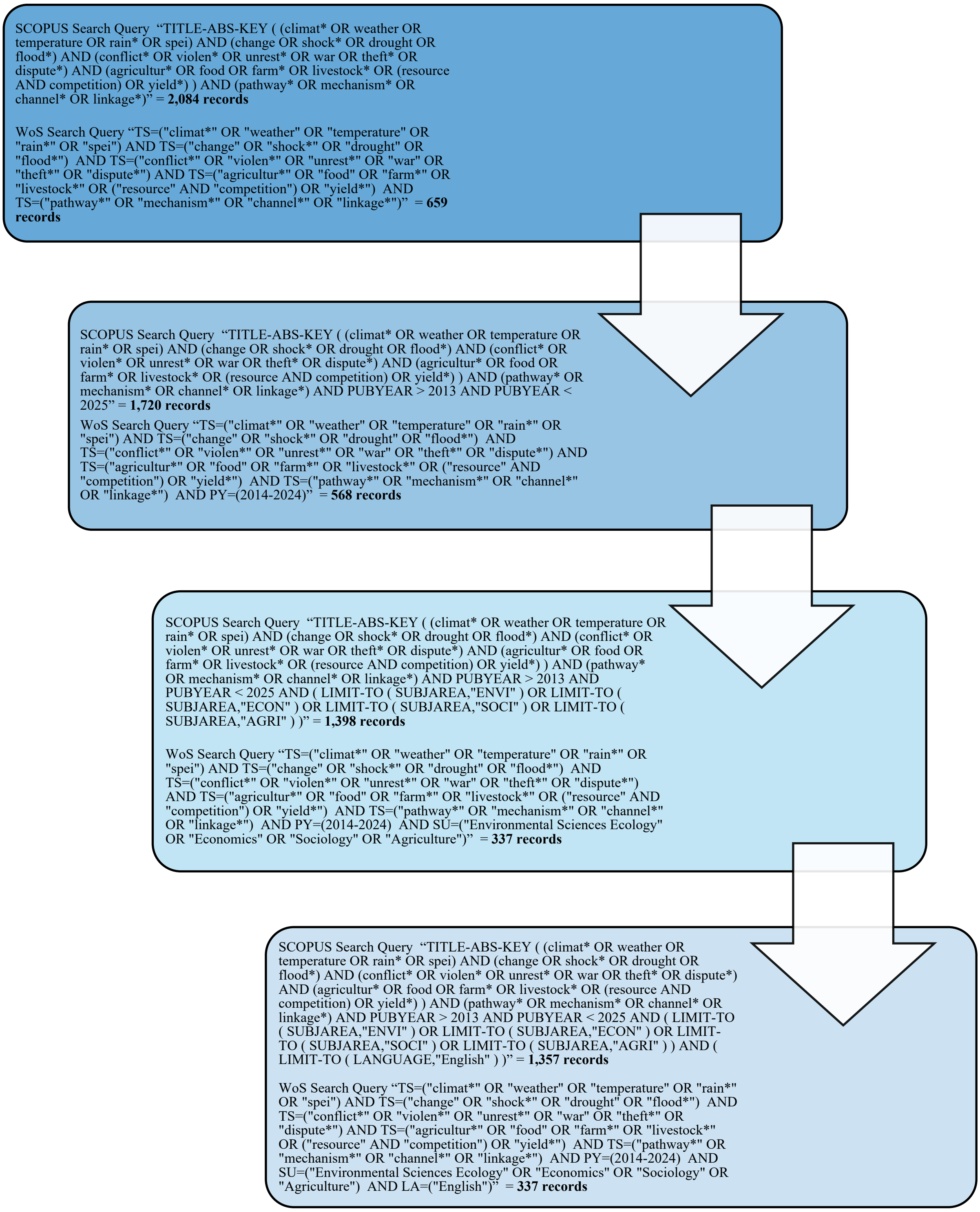


Figure 1. Scopus and WoS databases search queries.

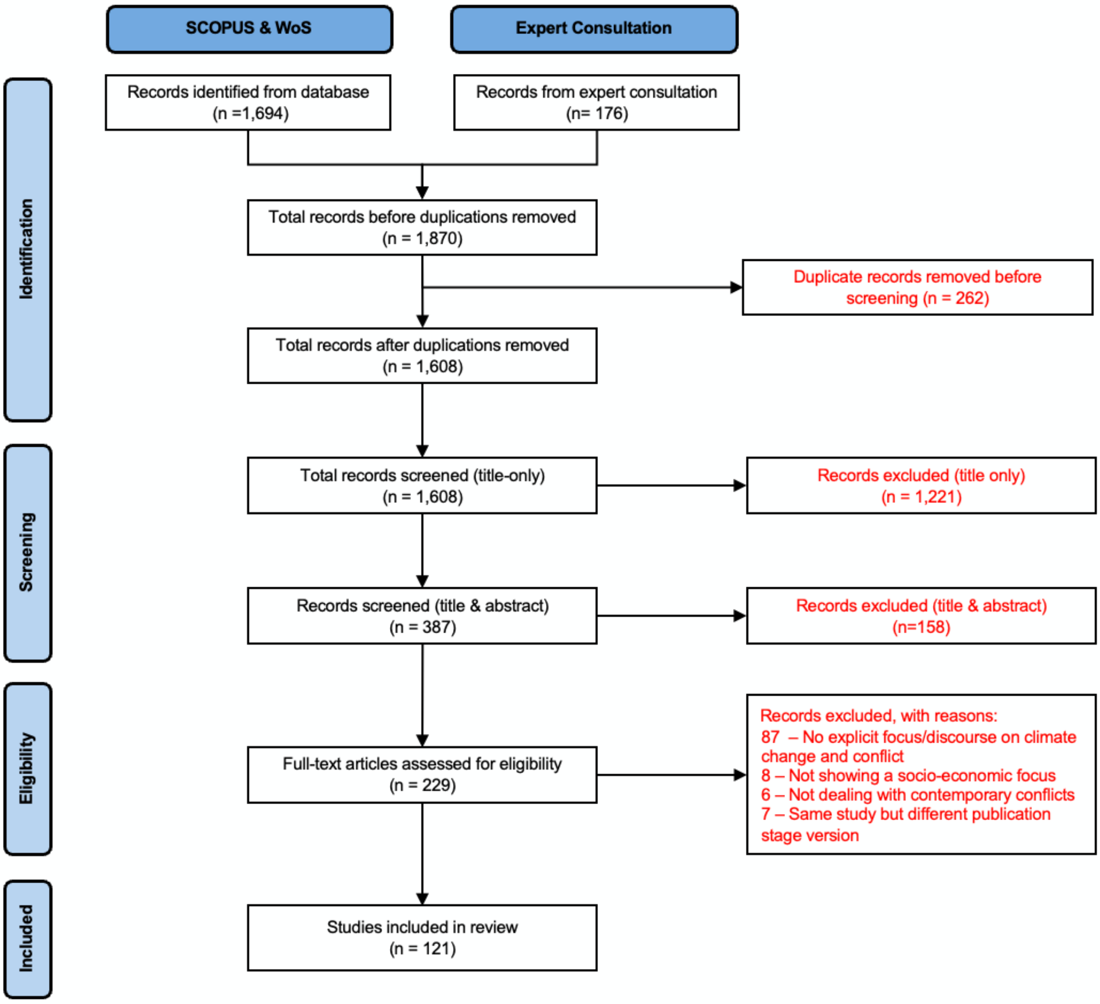


Figure 2. Flow diagram of the paper selection process.

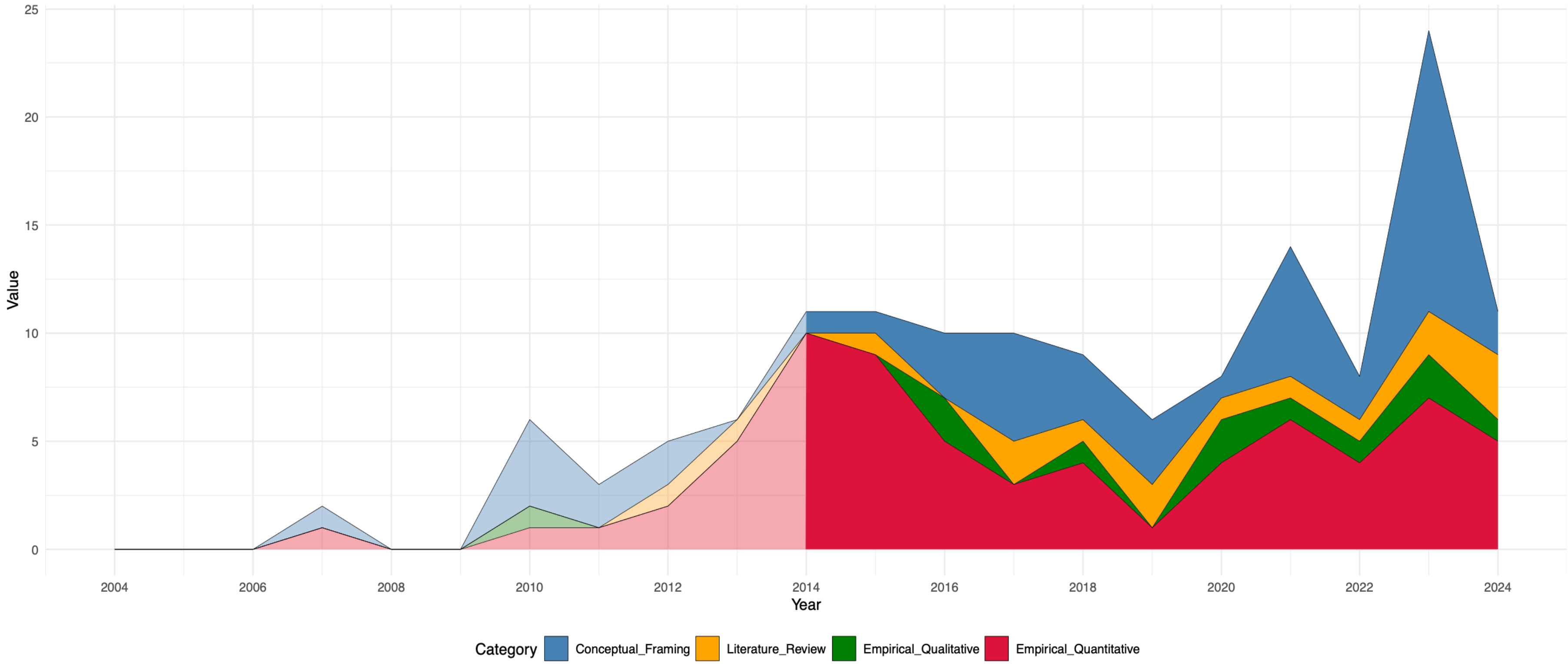


Figure 3. Distribution of studies across publication years and types.

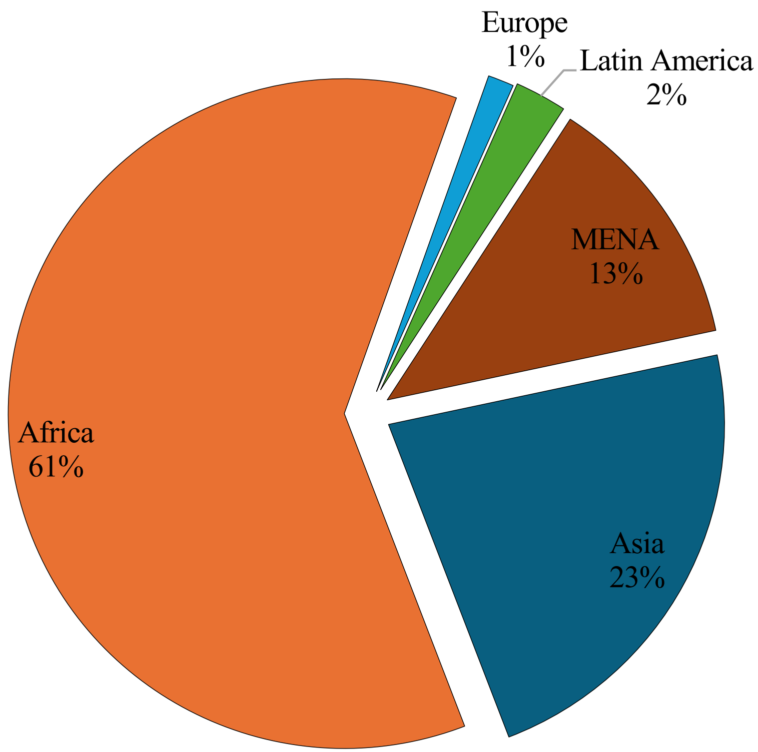


Figure 4. Distribution of studies' regional focus.

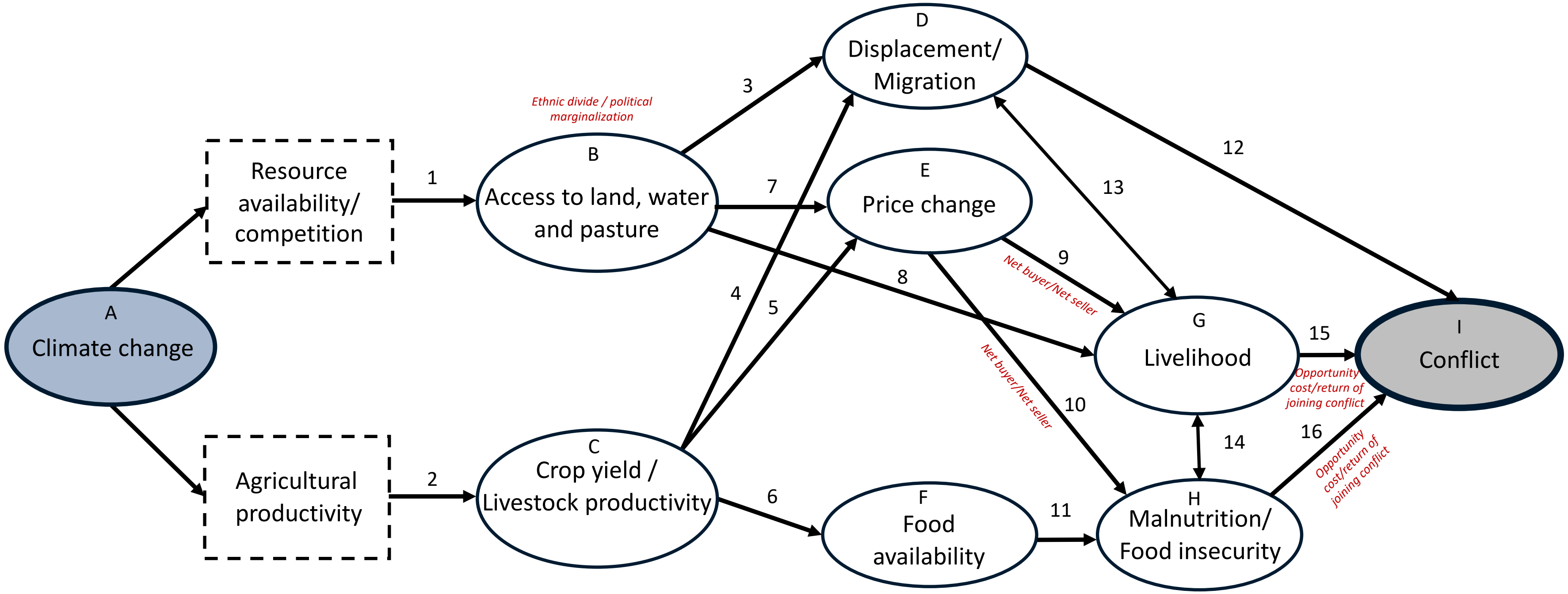


Figure 5. Pathways linking climate change to conflicts via the agrifood sector.

Figure 6. Coefficients for temperature and precipitation on conflict outcomes.

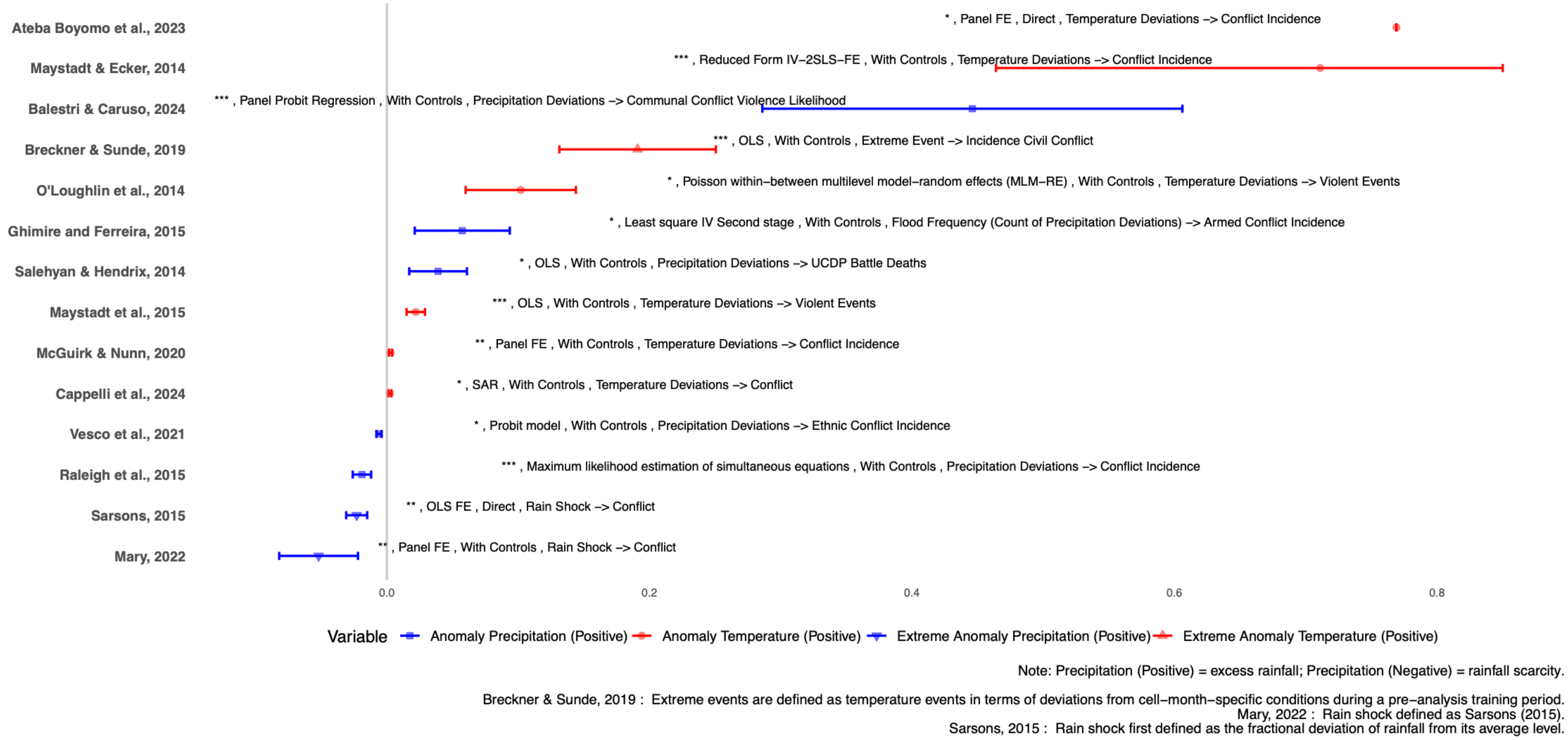


Figure 7. Coefficients for temperature and precipitation anomalies on conflict outcomes.

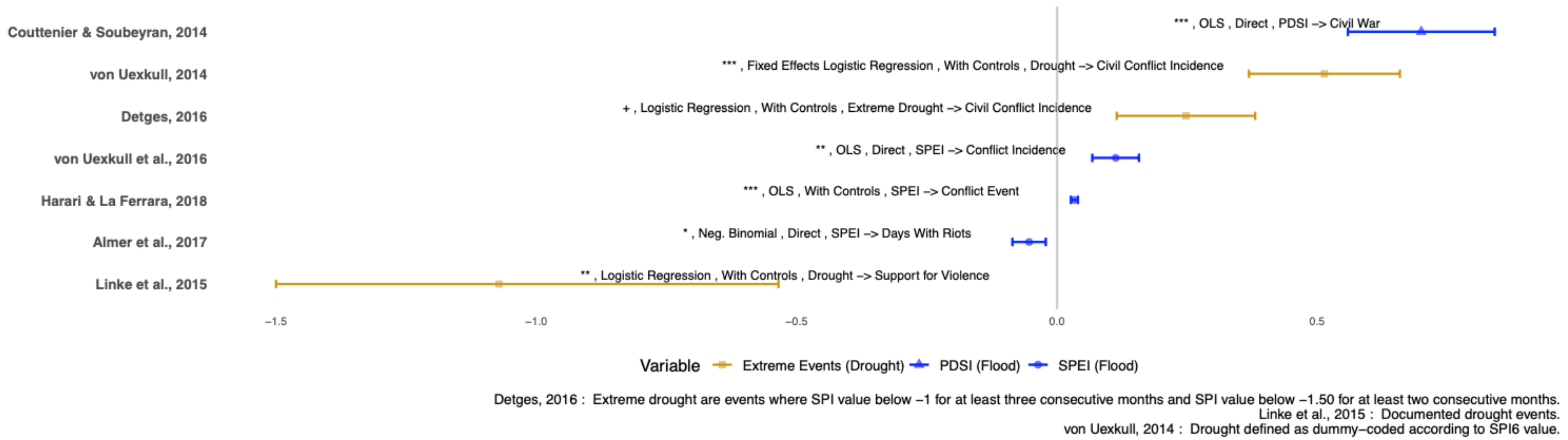
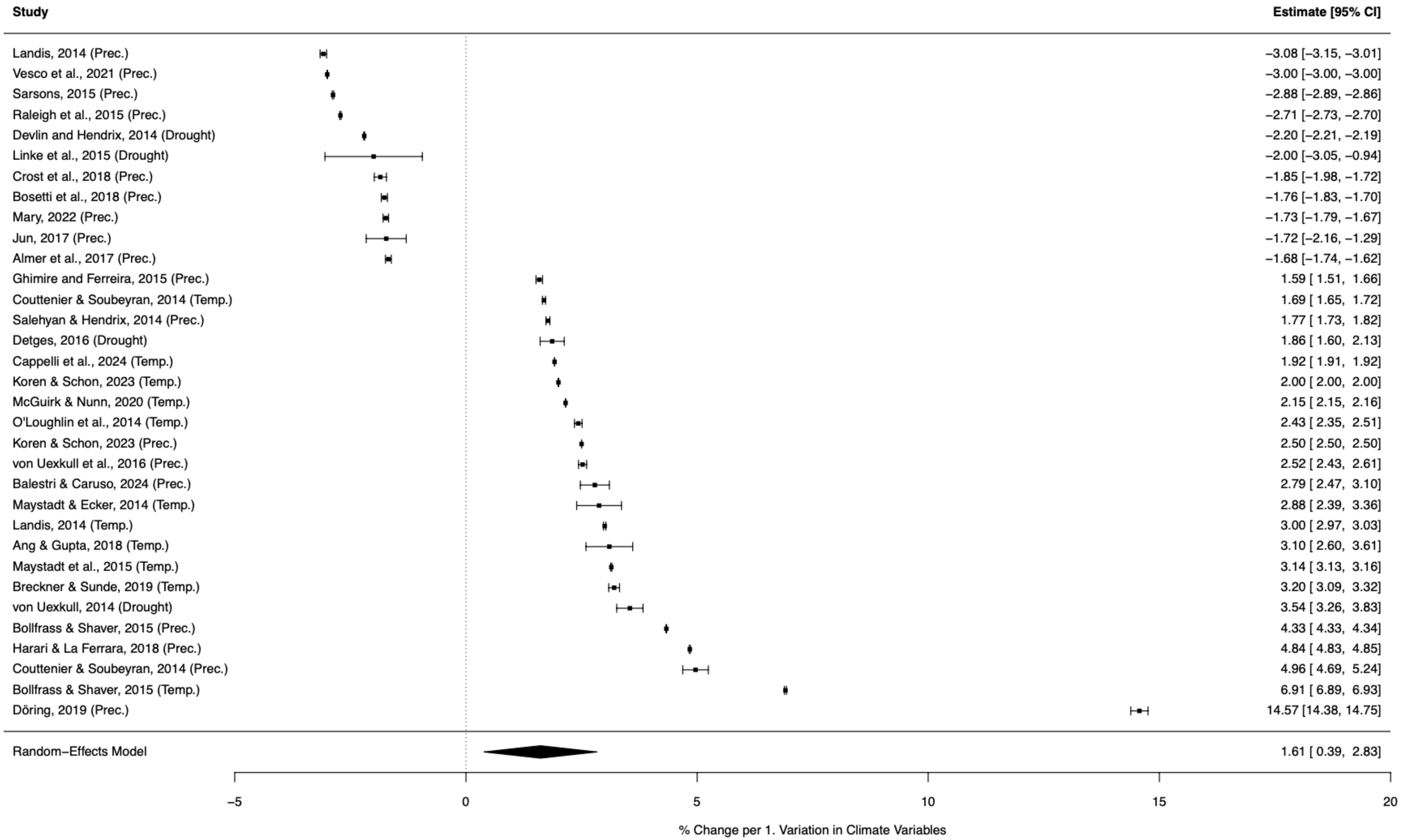


Figure 8. Coefficients for extreme events on conflict outcomes.



Note: Random−effects meta−analysis using REML estimator. Interpretation should consider between−study heterogeneity.

Figure 9. Metanalysis of results of climate change on conflict outcomes.

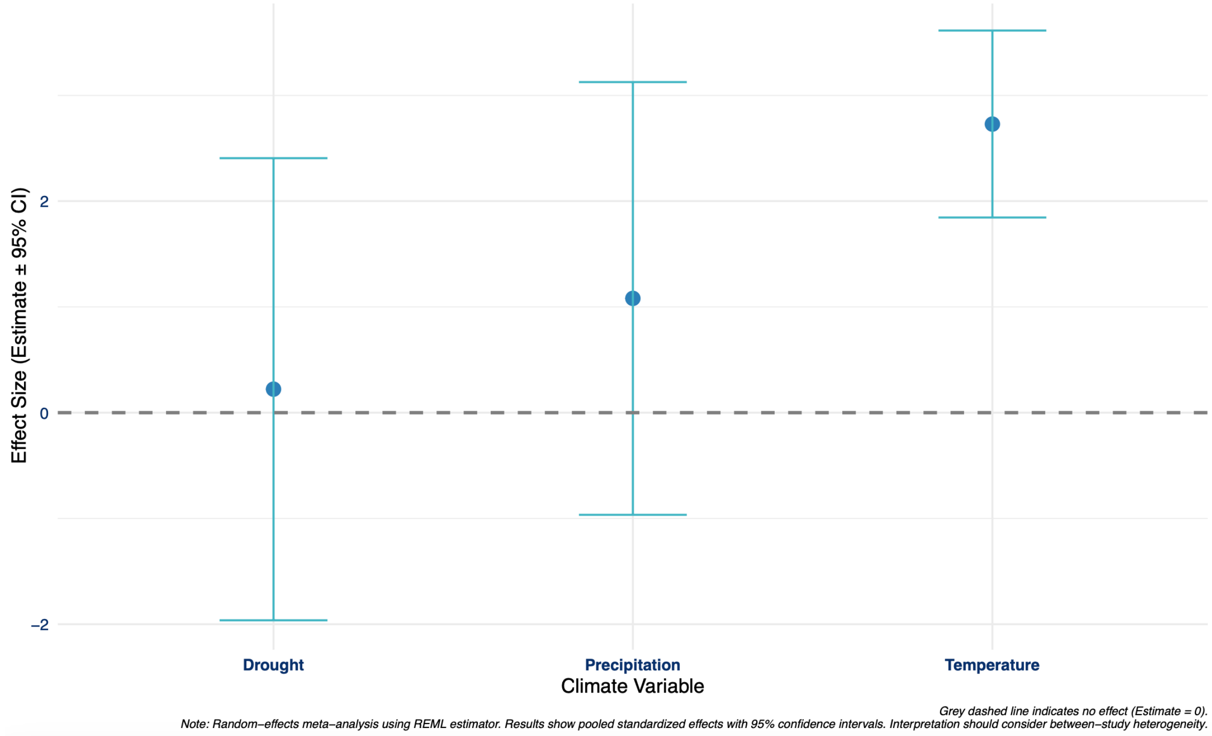


Figure 10. Metanalysis results distinguished by climate event type.

Table 1. Pathways conceptual mapping.[23]

Nodes	Links	Pathway	Interacting Factors	Conceptual framing studies	Empirical studies
Resource availability/Competition					
A-B-I		Resource availability/competition		Abdullahi et al., 2024; Abrahms et al., 2023; Abrahams & Carr, 2017; Berchin et al., 2017; Brzoska & Fröhlich, 2016; Buhaug, 2015; Conca, 2023; Froese & Schilling, 2019; Gómez-Álvaro & Caro-Carretero, 2024; Ibrahim-Olesin et al., 2021; Ikhuoso et al., 2020; Martin-Shields & Stojetz, 2019; Plänitz, 2019; Post et al., 2016; Sitati et al., 2021; Thalheimer, 2023; Vargas et al., 2021; Xie et al., 2024	Almer et al., 2017; Ayana et al., 2016; Balestri & Caruso, 2024; Bohmelt et al., 2014; Bosetti, Cattaneo, & Peri, 2021; Cappelli et al., 2023; Cappelli et al., 2024; Couttenier & Soubeyran, 2014; De Juan & Hänze, 2021; Devlin and Hendrix, 2014; Doring, 2020; Eberle et al., 2025; Ghimire and Ferreira, 2015; Landis, 2014; Linke et al., 2015; Maystadt & Ecker, 2014; Maystadt et al., 2015; McGuirk & Nunn, 2020; Minale et al., 2024; O'Loughlin et al., 2014; Salehyan & Hendrix, 2014; Tubi and Feitelson, 2016; Vesco et al., 2021; von Uexkull, 2014; Wang et al., 2023
A-B-D-I	1-3-12	Resource availability/competition *via Migration*		Boege, 2023; Clack et al., 2023; Freeman, 2017; Okunade & Kohon, 2023; Olagunju et al., 2021	Ani & Uwizeyimana, 2020; Roy et al., 2022
A-B-E-G-I	1-7-9-15	Resource availability/competition *via Price change – Livelihood*		Buhaug et al., 2023	
A-B-G-H-I	1-8-14-16	Resource availability/competition *via Livelihood - Food insecurity*		Carneiro et al., 2023	

[23] Literature review studies are not included in the table as they refer to collections of studies. Similarly, Hsiang & Burke (2014), who state that no clear pathway emerges from the literature, is not included in this table.

Agricultural productivity					
A-C-I		Agricultural productivity		Abdullahi et al., 2024; Abrahams & Carr, 2017; Ahmed et al., 2023; Bedasa & Deksisa, 2024; Buhaug, 2015; Buhaug, 2016; Busby, 2018; Homer-Dixon, 2023; Ibrahim-Olesin et al., 2021; Mach et al., 2019; Martin-Shields & Stojetz, 2019; Plänitz, 2019; Post et al., 2016; Sitati et al., 2021; Thalheimer, 2023; Xie et al., 2024	Ateba Boyomo et al., 2024; Ang & Gupta, 2018; Balestri & Caruso, 2024; Bohmelt et al., 2014; Bollfrass & Shaver, 2015; Breckner & Sunde, 2019; Buhaug et al., 2015; Cappelli et al., 2023; Caruso et al., 2016; Crost et al., 2018; George et al., 2020; Jun, 2017; Koren & Schon, 2023; Mary, 2022; Nardulli et al., 2015; Pacillo et al., 2022; Tubi and Feitelson, 2016; von Uexkull, 2014; Wang et al., 2023
C-E/D-G-H-I	2-4/5-13/9-14-16	Agricultural productivity *via Migration / Price change - Livelihood – Malnutrition / Food Insecurity*		von Uexkull & Buhaug, 2021	Wischnath & Buhaug, 2014
Not explicitly specified pathway					
A-D-I		*via Displacement / Migration*		Issifu et al., 2022; Scheffran, 2022	Ash & Obradovich, 2020; Bhavnani and Lacina, 2015; Iqbal et al., 2018; Koubi et al., 2018; Madu & Nwankwo, 2021; Petrova, 2021
A-E-I		*via Price change*			Ateba Boyomo et al., 2023; Bazzi & Blattman, 2014; Raleigh et al., 2015
A-G-I		*via Livelihood*		Castells-Quintana et al., 2017; Gilmore & Buhaug, 2021; Huber et al., 2023; Koubi, 2017; Mfon, 2023	Guariso & Rogall, 2017; Mounirou, 2022; Sarsons, 2015
A-F-I		*via Food availability / Food insecurity*		Buhaug & von Uexkull, 2021; Martin-Shields & Stojetz, 2019; van Baalen & Mobjörk, 2018	Ecker et al., 2023; Helman et al., 2020; Jones et al., 2017; Koren et al., 2021; Okafor et al., 2023
A-G-D-I	13-15	*via Livelihood – Displacement / Migration*		Ide, 2018	

Direct Association					
A-I			Ethnic divide/Political marginalization/Land disputes	Nyiayaana & Okoh, 2023	von Uexkull et al., 2016; Schleussner et al., 2016
A-I			Technical solutions/Infrastructure	Phyffer, 2024; Thalheimer, 2023	Abid et al., 2016; Detges, 2016; Harari & La Ferrara, 2018; Petit et al., 2023
A-I			Gender disparity		Munala et al., 2023
A-I			Linguistic diversity		Song et al., 2024

Table 2. Climate datasets.

Datasets	Definitions	Spatial coverage	Temporal coverage	Spatial Resolution	Mentioned in
Simple indicators deviations					
Rainfall only					
CHIRPS (Climate Hazards Group InfraRed Precipitation with Stations)	**Description**: Precipitation data developed combining satellite and station observations. **Availability**: Public. **Update frequency**: Daily. **Provider**: UCSB's Climate Hazards Group.	Global (focus on tropics)	1981–present	0.05°; ~5.6 km	Ayana et al., 2016; Song et al., 2024
CPC Merged Analysis of Precipitation (CMAP)	**Description**: Precipitation data based on satellite estimates and station observations. **Availability**: Public. **Update frequency**: Monthly. **Provider**: NOAA's Climate Prediction Center.	Global	1979–present	2.5°; ~278 km	Raleigh et al., 2015
Global Precipitation Climatology Project (GPCP)	**Description**: Precipitation data based on a combination of satellite and gauge-based observations. **Availability**: Public. **Update frequency**: Monthly. **Provider**: NASA and World Climate Research Programme.	Global	1979–present	2.5°; ~278 km	Ayana et al., 2016
Global Precipitation Climatology Centre (GPCC)	**Description**: High-resolution precipitation data based on global weather stations. **Availability**: Public. **Update frequency**: Updated annually. **Provider**: German Meteorological Service.	Global	1901–present	0.5°; ~55.6 km	Bohmelt et al., 2014; Detges, 2016
Temperature only					
MODIS Terra	**Description**: Land surface temperature data via NASA's EOS satellite Terra.	Global	2000–present	0.0083°; ~1 km	Ayana et al., 2016; Koren & Schon, 2023

	Availability: Public. **Update frequency**: Daily. **Provider**: NASA.				
Both rainfall and temperature					
Climatic Research Unit (CRU TS 3.24)	**Description**: Temperature and precipitation data. **Availability**: Publicly available. **Update frequency**: Monthly. **Provider**: University of East Anglia's Climatic Research Unit.	Global	1901–present	0.5°; ~55.6 km	Ash & Obradovich, 2020; Maystadt & Ecker, 2014; Maystadt et al., 2015; Wang et al., 2023
ECMWF (European Centre for Medium-Range Weather Forecasts)	**Description**: Reanalysis data for temperature and precipitation. **Availability**: Public. **Update frequency**: Real-time. **Provider**: ECMWF's ERA Interim.	Global	1979–2019	0.75°; ~80 km	Breckner & Sunde, 2019; Harari & La Ferrara, 2018
African Flood and Drought Monitor (AFDM)	**Description**: Precipitation and temperature data for monitoring droughts and floods in Africa. **Availability**: Public. **Update frequency**: Near real-time monitoring. **Provider**: Princeton University and UNESCO-IHP.	Africa	1971–present	0.25°; ~27.8 km	Cappelli et al., 2023; Cappelli et al., 2024
NOAA's NCEP/NCAR Reanalysis Monthly Means Dataset	**Description**: Reanalysis of temperature and precipitation data. **Availability**: Public. **Update frequency**: Monthly. **Provider**: NOAA's NCEP/NCAR.	Global	1948–present	2.5°; ~278 km	Landis, 2014
Global Surface Summary of the Day (GSOD)	**Description**: Daily summaries of global surface weather observations. **Availability**: Public. **Update frequency**: yearly. **Provider**: NCEI.	Global	1929–present	Varies by weather station	Jones et al., 2017

Composite indicators deviations					
SPEI (Standardized Precipitation-Evapotranspiration Index)	**Description**: Drought index based on precipitation and evapotranspiration data. **Availability**: Public. **Update frequency**: Monthly. **Provider**: Spanish National Research Council (CSIC)	Global	1901–present	0.5°; ~55.6 km	Almer et al., 2017; Cappelli et al., 2023; Cappelli et al., 2024; De Juan & Hänze, 2021; Harari & La; Ferrara, 2018; Vesco et al., 2021; von Uexkull et al., 2016
Palmer Drought Severity Index (PDSI)	**Description**: Drought index. **Availability**: Public. **Update frequency**: Monthly. **Provider**: National Centers for Environmental Information (NCEI).	Global	1895–present	Varies by region	Couttenier & Soubeyran, 2014; Salehyan & Hendrix, 2014; Vesco et al., 2021
Extreme events/Climatic disasters					
NatCatSERVICE	**Description**: Data on climate-related natural disasters, including economic damage estimates. **Availability**: Proprietary. **Update frequency**: Annually. **Provider**: Munich Re.	Global	1980–2010	Event-based	Schleussner et al., 2016
Climate change effects on land and vegetation					
AVHRR (Advanced Very High-Resolution Radiometer)	**Description**: Vegetation health data via NDVI and VCI. **Availability**: Public. **Update frequency**: Daily **Provider**: NOAA.	Global	1981–present	1 km – 16 km	Linke et al., 2015
Copernicus Global Land Service	**Description**: Satellite data on dry matter vegetation (phytomass). **Availability**: Public. **Update frequency**: Weekly. **Provider**: Copernicus program.	Global	1999–present	~1 km	McGuirk & Nunn, 2020

Table 3. Climatic variables.

Variables	Indicator Types	Features	Used in
Simple indicators deviations			
Temperature Deviations	Temperature	**Description**: Measures changes in temperature relative to historical baselines. **Best at:** Useful for understanding heat stress and drought conditions impacts on crop yields. **Datasets**: MODIS Terra; CRU.	Bohmelt et al., 2014; Ateba Boyomo et al., 2023; Jones et al., 2017; Landis, 2014; O'Loughlin et al., 2014; Pacillo et al., 2022; Salehyan & Hendrix, 2014; Wang et al., 2022
Precipitation Deviations	Precipitation	**Description**: Tracks deviations in precipitation from historical averages using standardized indices. **Best at:** Monitoring droughts, floods, and water availability. **Datasets**: CHIRPS, CMAP, GPCC, GPCP.	Almer et al., 2017; Bohmelt et al., 2014; Devlin and Hendrix, 2014; Ateba Boyomo et al., 2023; Jones et al., 2017; O'Loughlin et al., 2014; Pacillo et al., 2022; Raleigh et al., 2015; Salehyan & Hendrix, 2014; Wang et al., 2022
Composite indicators deviations			
Standardized Precipitation and Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI)	Precipitation and temperature	**Description**: Tracks frequency and intensity of flooding events and droughts. **Best at:** Monitoring drought and flood intensity and assessing impacts on infrastructure and populations. **Datasets**: AFDM, GPCC.	De Juan & Hänze, 2021; Harari & La Ferrara, 2018; von Uexkull et al., 2016; Couttenier & Soubeyran, 2014; Salehyan & Hendrix, 2014
Extreme events/Climatic disasters			
Flood Frequency	Extreme event	**Description**: Tracks frequency and intensity of flooding events, often linked to excess precipitation and storm surges. **Best at:** Monitoring flood risks and impacts on infrastructure and populations. **Datasets**: AFDM, GPCC.	Ghimire and Ferreira, 2015; McGuirk & Nunn, 2020; Mounirou, 2022; Nardulli et al., 2015
Storms and Hurricanes	Extreme event	**Description**: Tracks frequency of storms, hurricanes, and extreme weather events, often linked to rapid-onset climate impacts. **Best at:** Predicting immediate risk to life and property due to extreme weather. **Datasets**: NOAA's NCEP/NCAR, NatCatService.	Mounirou, 2022; Nardulli et al., 2015
El Niño/Southern Oscillation (ENSO)	Climatic pattern deviation / disasters	**Description**: Measures large-scale ocean-atmosphere climate interactions causing global temperature and precipitation variability.	Landis, 2014

		Best at: Explaining long-term variability in global weather patterns, droughts, and floods. **Datasets**: NOAA's NCEP/NCAR, ECMWF.	
Climate change effects on land and vegetation			
Vegetation Condition Index (VCI)	Vegetation health	**Description**: Measures the health of vegetation based on deviations from optimal conditions. **Best at**: Assessing short-term changes in vegetation cover and stress due to climate variations. **Datasets**: AVHRR.	Linke et al., 2015
Phytomass and Vegetation Degradation	Vegetation productivity	**Description**: Tracks the amount of dry matter vegetation (phytomass) and assesses long-term trends in land degradation. **Best at:** Monitoring biomass production and the impact of land-use changes or climate stressors. **Datasets**: Copernicus Global Land Service, AVHRR.	McGuirk & Nunn, 2020

Table 4. Conflict datasets.

Datasets	Definitions	Spatial Coverage	Temporal Coverage	Resolution	Mentioned in
Global focus					
ACLED (Armed Conflict Location & Event Data Project)	**Description:** Data on political violence (battles, protests, riots, bombings, and violence against civilians) and non-violent events (demonstrations, strategic developments). **Availability:** Public. **Update frequency:** Weekly. **Provider**: ACLED	Global	1997-present	Subnational, georeferenced by coordinates (latitude/longitude), detailed to city, village, and administrative region levels	Ateba Boyomo et al., 2023; Ayana et al., 2016; Breckner & Sunde, 2019; Cappelli et al., 2024; Freeman, 2017; George et al., 2020; Gilmore & Buhaug, 2021; Koren & Schon, 2023; Landis, 2014; Maystadt & Ecker, 2014; Maystadt et al., 2015; McGuirk & Nunn, 2020; O'Loughlin et al., 2014; Pacillo et al., 2022; Petrova, 2021; Raleigh et al., 2015; Song et al., 2023
UCDP/PRIO (Uppsala Conflict Data Program/Peace Research Institute Oslo)	**Description:** Data on organized armed conflicts, including intrastate and interstate conflicts. Includes UCDP GED for georeferenced conflict events. **Availability:** Public. **Update frequency:** annually for most datasets, while UCDP-GED is event-based and updated more frequently. **Provider**: UCDP/PRIO	Global	1946-present	Country-level for core UCDP/PRIO data; events in UCDP GED are georeferenced by coordinates (latitude/longitude)	Ang & Gupta, 2018; Ayana et al., 2016; Bazzi & Blattman, 2014; Buhaug et al., 2015; Cappelli et al., 2023; Couttenier & Soubeyran, 2014; Ecker et al., 2023; Ghimire and Ferreira, 2015; Harari & La Ferrara, 2018; Helman et al., 2020; McGuirk & Nunn, 2020; Salehyan & Hendrix, 2014; Schleussner et al., 2016; Vesco et al., 2021; von Uexkull, 2014; von Uexkull et al., 20 16; Wang et al., 2023; Wischnath & Buhaug, 2013
GDELT (Global Database of Events, Language, and Tone)	**Description:** Data on political and social conflicts (protests, revolutions, armed conflicts) in real time, with events coded from news articles worldwide. **Availability:** Public. **Update frequency**: Daily. **Provider**: the GDELT project.	Global	1979-present	Global, georeferenced by coordinates (latitude/longitude)	Ecker et al., 2023

ICEWS (Integrated Crisis Early Warning System)	**Description:** Data on political instability, including armed conflicts, protests, and social unrest globally, with a focus on event prediction. **Availability:** Public. **Update frequency:** Daily (near real-time). **Provider**: DARPA (Defense Advanced Research Projects Agency) and later maintained by Lockheed Martin and U.S. Government.	Global	1995-2018	Global, georeferenced by coordinates (latitude/longitude)	Landis, 2014
		Regional/Country focus			
SCAD (Social Conflict in Africa Database)	**Description:** Data on social conflicts such as protests, riots, strikes, and government repression. **Availability:** Public. **Update frequency:** Not specified, regularly updated with new events. **Provider**: Robert S. Strauss Center for International Security and Law at The University of Texas at Austin.	Africa (countries with over one million population)	1990-2010	Country-level,	Almer et al., 2017; Buhaug et al., 2015; Jones et al., 2017; Landis, 2014
UNSFIR (United Nations Support Facility for Indonesian Recovery)	**Description:** Violent events related to political and religious conflict, including intercommunal violence. **Availability:** Local researchers and UNSFIR. **Update frequency:** Irregular (based on field reports and local event data). **Provider**: United Nations Support Facility for Indonesian Recovery (UNSFIR).	Indonesia (14 provinces)	1993-2003	Province-level, no georeferencing	Caruso et al., 2016
Varshney-Wilkinson Dataset	**Description:** Data on Hindu-Muslim riots in India, focusing on communal violence in urban areas. **Availability:** Academic institutions and researchers. **Update frequency:** Not regularly updated; based on archival newspaper records. **Provider**: Ashutosh Varshney and Steven Wilkinson.	India	1950-1995	City-level, no georeferencing	Mary, 2022; Sarsons, 2015

Local focus					
Newspaper articles and individual records	**Description:** Data on regional or local conflicts from newspapers and case study records. **Availability:** Newspaper articles. **Update frequency:** Not regularly updated; based on archival newspaper records. **Provider**: various.	Regional/ local	Varies	Local-level, some data georeferenced	Petit et al., 2023

Table 5. Conflict variables.

Variables	Definitions	Frequency	Duration	Onset	Fatalities	Used in
Events	A single instance of politically violent or non-violent activity that occurs at a specific location and on a specific date, involving designated actors. An incident where armed force was used by an organized actor against another organized actor, or against civilians.	Daily (ACLED)	Days to weeks (ACLED)	First recorded violent engagement (ACLED)	No threshold for inclusion	George et al., 2020; Harari & La Ferrara, 2018; Pacillo et al., 2022; von Uexkull et al., 2016
		Daily (UCDP)	Days to months (UCDP/PRIO)	First organized violence (UCDP)	At least 1 direct death, with specific location and date	
Protests	Non-violent demonstrations against governments or political entities.	Daily (ACLED, ICEWS)	Hours to days (ACLED, ICEWS)	Start of demonstration (ACLED, ICEWS)	No threshold for inclusion	Ash & Obradovich, 2020; Jones et al., 2017; Landis, 2014; Nardulli et al., 2015; O'Loughlin et al., 2014; Pacillo et al., 2022; Petrova, 2021; Wang et al., 2023
		Yearly (UCDP)	Days to months (UCDP)	First violent escalation leading to deaths (UCDP)	UCDP tracks fatalities if protests turn violent	
Riots/Political or social unrest	Violent disturbances involving clashes between civilians and government forces or other groups.	Weekly (ACLED)	Hours to days (ACLED)	First significant escalation (ACLED, GDELT)	No threshold for inclusion	Jones et al., 2017; Pacillo et al., 2022; Petrova, 2021; Wang et al., 2023; Buhaug et al., 2015
		Daily (GDELT)	Days to weeks (GDELT)	Organized violence threshold reached (UCDP)	No threshold for inclusion	
		Yearly (UCDP)	Months (UCDP)	Organized violence leading to deaths (UCDP)	UCDP tracks if >25 deaths (per year)	

Explosions	Bombings or explosions targeting civilians, military, or infrastructure.	Weekly (ACLED)	Seconds to hours (ACLED)	Time of detonation or first explosion (ACLED)	No threshold for inclusion	Pacillo et al., 2022
		Monthly (ICEWS)	Seconds to hours (ICEWS)	Time of detonation or first explosion (ICEWS)	No threshold for inclusion	
		Yearly (UCDP)	Days to weeks (UCDP)	Organized violence resulting in fatalities (UCDP)	UCDP tracks if death threshold is met	
Strategic Developments	Contextually important information regarding the activities of violent groups that may trigger future events. Not systematically coded, as their significance varies by context and time.	As necessary	Variable	Context-dependent, might not directly lead to an event	No threshold for inclusion	George et al., 2020
Violence Against Civilians	Targeted killings, abductions, or assaults on civilians by armed actors.	Daily (ACLED)	Hours to days (ACLED)	First targeted attack on civilians (ACLED)	No threshold for inclusion	Koren & Schon, 2023; Pacillo et al., 2022
		Yearly (UCDP)	Days to months (UCDP)	First large-scale civilian attack (UCDP)	>25 deaths/ year (UCDP)	
State-Based Conflict	Armed conflicts between state forces and organized armed groups, e.g., civil wars or interstate conflicts (UCDP). ICEWS tracks conflicts between state and non-state actors.	Yearly (UCDP)	Months to years	Onset when the first violent event is recorded (UCDP)	>25 deaths/ year (UCDP) If >1,000 deaths/year conflict is classified as war	Vesco et al., 2021; Wischnath & Buhaug, 2014
		Daily (ICEWS)	Days to months (ICEWS)	Onset is identified when the first significant violent event is detected (ICEWS)	No specific threshold	Landis, 2014

Non-State Conflict	Conflicts involving non-state actors, such as inter-group clashes without government involvement. ACLED and UCDP track these events, with UCDP monitoring those leading to 25+ deaths annually.	Weekly (ACLED)	Days to months (ACLED)	First engagement between non-state groups (ACLED, UCDP)	No threshold for inclusion	Ayana et al., 2016; Helman et al., 2020; Landis, 2014; Vesco et al., 2021
		Yearly (UCDP))	Weeks to months (UCDP)	First engagement between non-state groups (UCDP)	>25 deaths/ year (UCDP) per year	
One-Sided Violence	Direct violence against civilians by organized armed groups or state forces (UCDP, ACLED).	Weekly (ACLED)	Days to months	First large-scale attack on civilians (ACLED)	No threshold for inclusion. Only deliberate attacks on civilians by rebel or government forces	Maystadt et al., 2015
		Yearly (UCDP)	Days to months	First large-scale attack on civilians (UCDP)	>25 deaths/ year (UCDP) per year	Martin-Shields & Stojetz, 2019

Table 6. Socioeconomic datasets.

Datasets	Definitions	Spatial Coverage	Temporal Coverage	Spatial Resolution	Mentioned in
Socio-economic datasets					
International Monetary Fund Statistics	**Description**: Economic data on GDP, government expenditures, and macroeconomic indicators. **Availability**: Public. **Update frequency**: Annually. **Provider**: IMF.	Global	1948–present	Country-level	Raleigh et al., 2015; Schleussner et al., 2016
World Development Indicators (WDI)	**Description**: Data on GDP, population, poverty, and other socioeconomic variables. **Availability**: Public. **Update frequency**: Several times per year. **Provider**: World Bank.	Global	1960–present	Country-level	Couttenier & Soubeyran, 2014; von Uexkull et al., 2016; Bazzi & Blattman, 2014
Censuses and National Statistics	**Description**: Data on socioeconomic statistics. **Availability**: Public, through national agencies. **Update frequency**: Varies by country, usually every 5 to 10 years. **Provider**: National Statistical Offices and other national agencies.	National	Varies	District-level, National	Ash & Obradovich, 2020; Ateba Boyomo et al., 2023; Bhavnani and Lacina, 2015; Harari & La Ferrara, 2018; Sarsons, 2015; Tubi and Feitelson, 2016; Caruso et al., 2016; Ecker et al., 2023; Linke et al., 2015
Gridded GDP Dataset (Kummu et al., 2018)	**Description**: High-resolution gridded GDP data. **Availability**: Public. **Update frequency**: Irregular. **Provider**: Aalto University.	Global	1990–2015	5 arc-minutes	Cappelli et al., 2023; Cappelli et al., 2024
CIESIN Gridded Population of the World	**Description**: Gridded population data. **Availability**: Public. **Update frequency**: Periodically. **Provider**: CIESIN, Columbia University.	Global	2000–present	30 arc-seconds (~1 km)	von Uexkull, 2014; von Uexkull et al., 2016
VIIRS and/or DMPS-OLS Nighttime Light Emissions	**Description**: Data on nighttime light emissions as a proxy for economic activity. **Availability**: Public. **Update frequency**: Monthly. **Provider**: National Oceanic and Atmospheric Administration (NOAA) .	Global	1992–present	500m – 1km	Cappelli et al., 2024

Afrobarometer Survey	**Description**: Data on public opinion regarding governance, economic conditions, and social issues in Africa. **Availability**: Public. **Update frequency**: Every 2-3 years. **Provider**: Afrobarometer Network.	Africa	1999–present	Country-level	De Juan & Hänze, 2021; Harari & La Ferrara, 2018
AfroGrid	**Description**: Data on GDP per capita, population, and nighttime light emissions in Africa. **Availability**: Public. **Update frequency**: Irregular. **Provider**: World Bank and Collaborating Institutions.	Africa	1989–2020	0.5° x 0.5°	Koren & Schon, 2023
LSMS	**Description**: Data on household income, consumption, education, health, and labor data. **Availability**: Public. **Update frequency**: Varies by country, typically 3-5 years. **Provider**: World Bank.	Sub-national	1980s–present	Household level	George et al., 2020
MICS	**Description**: Data on children and women well-being, including health and education indicators. **Availability**: Public. **Update frequency**: Varies, typically every 3-5 years. **Provider**: UNICEF.	National	1995–present	Household level	Mounirou, 2022
IPUMS-DHS	**Description**: Household level data on demographics, health, and nutrition. **Availability**: Public. **Update frequency**: Every 5 years. **Provider**: USAID.	National	1984–present	Household level	Munala et al., 2023
Other Household Surveys	**Description**: Data from household surveys on health, migration, food security, and agriculture. **Availability**: Public or through organizations. **Update frequency**: Varies. **Provider**: National Statistical Offices and Organizations.	National/subnational	1980s–present	Household level	Petrova, 2021; Song et al., 2024

Agrifood datasets					
FAOSTAT	**Description**: Data on agricultural production, food security, and commodity prices. **Availability**: Public. **Update frequency**: Annually. **Provider**: FAO.	Global	1961–present	Country-level	Buhaug et al., 2015; Helman et al., 2020
FAO GAEZ (Global Agro-Ecological Zones)	**Description**: Data on potential crop yields and agricultural productivity. **Availability**: Public. **Update frequency**: Irregular. **Provider**: FAO.	Global	Varies	5 arc-minutes	Ang & Gupta, 2018; Breckner & Sunde, 2019
USDA National Nutrient Database	**Description**: Data on the caloric content and nutritional value of crops. **Availability**: Public. **Update frequency**: Annually. **Provider**: USDA.	Global	Varies	Varies	Ang & Gupta, 2018
HYDE 3.2 Database	**Description**: Historical data on population and land use. **Availability**: Public. **Update frequency**: About every 5 years. **Provider**: PBL Netherlands Environmental Assessment Agency.	Global	10,000 BC–2015 AD	5 arc-minutes	Cappelli et al., 2023; Cappelli et al., 2024
Comprehensive Food Security and Vulnerability Analysis	**Description**: Data on food security and vulnerability. **Availability**: Public. **Update frequency**: Every 3-5 years. **Provider**: WFP.	Regional (Developing regions)	2009–present	Subnational (District-level)	Mounirou, 2022
Vulnerability Analysis and Mapping (WFP-VAM)	**Description**: Retail and wholesale food prices in markets across developing countries. **Availability**: Public. **Update frequency**: Monthly. **Provider**: WFP.	Primarily developing countries	Early 2000s - present	Country/subnational (where available)	
LSMS-ISA	**Description**: Provides household-level and plot agricultural data. **Availability**: Public. **Update frequency**: Every 3-5 years. **Provider**: World Bank.	Sub-Saharan Africa	2009–present	Household level	Pacillo et al., 2022

Other datasets					
Geo-Referenced Ethnic Groups (GREG)	**Description**: Data on the spatial distribution of ethnic groups. **Availability**: Public. **Update frequency**: Irregular. **Provider**: ETH Zurich.	Global	1960–present	Subnational	Cappelli et al., 2023; Cappelli et al., 2024
Ethnographic Atlas	**Description**: Data on the cultural and ethnic characteristics of societies. **Availability**: Public. **Update frequency**: Not updated since its publication in 1967. **Provider**: Murdock (1967)	Global	Ancient societies–1967	Ethnicity Level	Mcguirk & Nunn, 2020
Ethnic Power Relations Dataset (GeoEPR)	**Description**: Data on the political status and spatial distribution of ethnic groups. **Availability**: Public. **Update frequency**: Irregular. **Provider**: Swiss Federal Institute of Technology Zurich (ETH Zurich), International Conflict Research (ICR) group.	Global	1946–present	Country-level	De Juan & Hänze, 2021; Harari & La Ferrara, 2018; von Uexkull, 2014; von Uexkull et al., 2016; Wang et al., 2023

Table 7. Socioeconomic variables.

Variables	Level of analysis	Features	Used in
		Socio-economic variables	
GDP per capita / Per capita income	Country/Subnational	**Description**: Measures economic output per person. **Datasets**: WDI, IMF, Gridded GDP Dataset, AfroGrid.	Bazzi & Blattman, 2014; Bohmelt et al., 2014; Cappelli et al., 2024; Koren & Schon, 2023; Landis, 2014; Salehyan & Hendrix, 2014
Government expenditures	Country	**Description**: Tracks public spending as a percentage of GDP. **Datasets**: datasets: World Bank, IMF.	Jones et al., 2017
Population density	Country/Subnational	**Description**: Examines population distribution. **Datasets**: WDI, CIESIN Gridded Population of the World, Censuses, National Statistics, HYDE 3.2 Database.	Bohmelt et al., 2014; Breckner & Sunde, 2019; Ghimire & Ferreira, 2015; Madu & Nwankwo, 2021; Mounirou, 2022; Sarsons, 2015; Song et al., 2024; Wang et al., 2023
Nighttime light emissions	Subnational	**Description**: Proxy for economic activity and infrastructure development. **Datasets**: VIIRS Nighttime Light Emissions.	Koren & Schon, 2023
Household income / Off-farm income	Subnational/Household	**Description**: Tracks income at household level and non-agricultural income. **Datasets**: LSMS, Other Household Surveys, Afrobarometer Survey.	George et al., 2020; Iqbal et al., 2018; Madu & Nwankwo, 2021; Mounirou, 2022
Educational facilities and attainment	Subnational/Household	**Description**: Access to educational infrastructure. **Datasets**: IPUMS-DHS, MICS, Other Household Surveys.	Munala et al., 2023; Mounirou, 2022
Household consumption	Household/Individual	**Description**: Tracks expenditure on food and non-food items at the household level. **Datasets**: LSMS-ISA, IPUMS-DHS, Other Household Surveys.	Munala et al., 2023
Access to Credit	Household/Individual	**Description**: Data on financial services access. **Datasets**: LSMS-ISA, Other Household Surveys.	George et al., 2020
Market Access	Household/Individual	**Description**: Measures distance to markets and market interactions. **Datasets**: LSMS-ISA, Other Household Surveys.	Almer et al., 2017

Child nutrition, health, and mortality	Household/Individual	**Description**: Measures child nutrition and health indicators (e.g., WHZ, MUACZ). **Datasets**: MICS, IPUMS-DHS, Other Household Surveys.	Ecker et al., 2023
Migration (internal/external)	Household/Individual	**Description**: Tracks migration, including internal/external movement. **Datasets**: LSMS-ISA, IPUMS-DHS, National Census, Other Household Surveys.	Bhavnani & Lacina, 2015; Cappelli et al., 2023; Pacillo et al., 2022; Petrova, 2021; Tubi & Feitelson, 2016
Agrifood variables			
Agrifood production	Country / Subnational	**Description**: Measures agricultural production levels. **Datasets**: FAOSTAT, FAO GAEZ, WDI, HYDE 3.2 Database.	Ang & Gupta, 2018; Bohmelt et al., 2014; Bollfrass & Shaver, 2015; Breckner & Sunde, 2019; Buhaug et al., 2015
Food prices/Livestock prices	Country / Subnational	**Description**: Tracks food and livestock price changes. **Datasets**: FAOSTAT, IMF, Other National/Subnational Surveys.	Ateba Boyomo et al., 2023; Maystadt & Ecker, 2014; Raleigh et al., 2015;
Food insecurity	Country	**Description**: Measures food availability and vulnerability. **Datasets**: FAOSTAT, Comprehensive Food Security and Vulnerability Analysis, LSMS-ISA, USDA Caloric Content Data.	Buhaug et al., 2015; Mounirou, 2022; Pacillo et al., 2022
Other variables			
Ethnic groups	Subnational	**Description**: Tracks ethnic group distribution. **Datasets**: Geo-Referenced Ethnic Groups (GREG), Ethnographic Atlas (Murdock, 1967), Ethnic Power Relations Dataset (GeoEPR).	Cappelli et al., 2023; Cappelli et al., 2024; De Juan & Hänze, 2021; Harari & La Ferrara, 2018; von Uexkull et al., 2016

Table 8. Empirical strategies.

Method Group	Features	Best For	Research Questions	Strengths	Limitations	Applied in
Linear and Panel Models	**OLS FE**: Controls for unobserved heterogeneity with fixed effects. **GMM**: Uses Generalized method of moments in dynamic panels. **MLE**: Combines Maximum Likelihood Estimation with OLS. **Panel Regression**: For cross-sectional time series data. **PCSE, FGLS**: Handle fixed effects, heteroskedasticity, and autocorrelation in panels.	Estimating linear relationships across time and units	How do climate or economic changes affect conflict over time?	Simple, interpretable, controls for time-invariant effects	Assumes linearity, limited in addressing endogeneity	von Uexkull et al., 2016; Koren & Schon, 2023; Caruso et al., 2016; Buhaug et al., 2015; Mary, 2022; Sarsons, 2015; Breckner & Sunde, 2019
Binary and Count Models	**Logit Regression / Probit**: Estimates binary event probabilities. **Relogit**: For rare event data. **Conditional Logistic**: For matched/grouped data. **Negative Binomial**: Extends Poisson for over-dispersed data. **ZINB**: Handles count data with excess zeros.	Predicting binary outcomes (e.g., conflict onset) or event counts	What factors drive conflict onset or frequency?	Suitable for binary outcomes, handles overdispersion in count data	Sensitive to distributional assumptions	von Uexkull et al., 2016; Jones et al., 2017; Sarsons, 2015; Cappelli et al., 2023; Koren & Schon, 2023; Almer et al., 2017
Causal Inference Models and Advanced Statistical Models	**IV-2SLS-FE**: Combines IV, two-stage least squares, and fixed effects. **SEM**: Estimates multiple equations simultaneously. **GLM / GAM**: Extensions of GLM for non-linear and non-normal distributions. **MLM-RE**: Multilevel model with random effects. **Dependence Structure Models**: Analyzes dependence between random variables.	Modeling causal effects and complex pathways	What is the causal impact of climate shocks on conflict? How do indirect effects influence outcomes?	Mitigates endogeneity, captures indirect effects	Requires strong instruments, sensitive to model misspecification	Koren & Schon, 2023; Caruso et al., 2016; Maystadt & Ecker, 2014; Pacillo et al., 2022; Helman et al., 2020

	Event Series Interrelationship Models: Quantifies relationships between event series. **DiD**: Compares pre- and post-treatment changes between treated and control groups. **Staggered DiD**: Handles staggered treatment timing across groups.					
Spatial and Non-Linear Models	**SAR**: Spatial autoregressive model accounting for spatial dependence. **Spatial DiD**: Combines spatial econometrics with discontinuity design. **Global Moran's I / Moran's Index**: Measures spatial autocorrelation. **OHSA**: Hot spot analysis for conflict events. **GWR**: Geographically weighted regression for spatially varying relationships.	Addressing spatial dependence and non-linear relationships	How do neighboring regions influence conflict? How do climate extremes affect conflict?	Corrects for spatial autocorrelation, captures non-linear effects	Computationally intensive, requires large datasets	Song et al., 2024; Cappelli et al., 2024; Breckner & Sunde, 2019; Maystadt et al., 2015; Wang et al., 2023; Harari & La Ferrara, 2018

Table 9. Indirect coefficients of climate change on conflict outcomes.

Source	Link Studied	Impact	SD	Significance Level	Empirical Approach
Bohmelt et al., 2014	Reduced agricultural productivity - Conflict	0.03	0.009	***	Probit model
Mounirou, 2022	Rainfall deficit - Internal migration	0.125	0.012	***	Multivariate probit model
Petrova, 2021	Drought - Internal migration	0.576	0.306	*	Mixed-effect logistic regression
Bhavnani and Lacina, 2015	Inadequate and/or excess rainfall - Male migrants	0.9	0.18	***	2SLS
Bhavnani and Lacina, 2015	Male migrants - Riots	0.62	0.2	***	2SLS
Petrova, 2021	International migration - Protests	0.035	0.011	***	Negative binomial
Bazzi & Blattman, 2014	Positive price shock − Conflict onset	−0.0027	0.0014	*	Panel regression
Wischnath & Buhaug, 2014	Agricultural production growth - Conflict	−1.379	0.414	**	OLS
Ecker et al., 2023	Civil conflict - Child nutrition	−0.056	0.201	***	OLS
George et al., 2020	Boko Haram fatalities - Food consumption score	−0.037	-2.22	**	OLS
Guariso & Rogall, 2017	Between-group rainfall inequality - Ethnic conflict	0.338	0.184	*	OLS
Ateba Boyomo et al., 2024	Temperature increase - Livestock Production	−0.954	0.102	***	Panel FE

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Appendix

Table A1 – List of selected studies.

Citation	Type	Pathway	Countries/Region	Survey Years
Abdullahi et al., 2024	Literature Review	Both	East Africa	
Abid et al., 2016	Qualitative	Not Specified	Pakistan	2014
Abrahams & Carr, 2017	Conceptual	Both	Global	
Abrahams, 2020	Qualitative	Not Specified	Uganda	
Abrahms et al., 2023	Conceptual	Resource competition	Global	
Adams et al., 2023	Literature Review	Not Specified	West and Central Africa	
Ahmed et al., 2023	Conceptual	Agricultural productivity	Global	
Almer et al., 2017	Quantitative	Resource competition	SSA	1990-2011
Ang & Gupta, 2018	Quantitative	Agricultural productivity	Global	1960-2014
Ani & Uwizeyimana, 2020	Qualitative	Resource competition	Nigeria	
Ash & Obradovich, 2020	Quantitative	Not Specified	Syria	2005-2010
Ateba Boyomo et al., 2024	Quantitative	Agricultural production	Sub-Saharan Africa	2000-2021
Ateba Boyomo et al., 2023	Quantitative	Not Specified	Cameroon	2000-2021
Ayana et al., 2016	Quantitative	Resource competition	Eastern Africa	1997–2013
Balestri & Caruso, 2024	Quantitative	Both	Sub-Saharan Africa and South/South-East Asia	1995–2021
Bazzi & Blattman, 2014	Quantitative	Not Specified	Africa, the Middle East, Latin America, and Asia	1957-2007
Bedasa & Deksisa, 2024	Conceptual	Agricultural productivity	East Africa	
Berchin et al., 2017	Conceptual	Resource competition	Global	
Bhavnani and Lacina, 2015	Quantitative	Not Specified	India	1991-2001

Boege, 2023	Conceptual	Resource competition	Pacific Island Countries	
Bohmelt et al., 2014	Quantitative	Both	Middle East and Sahel	1997-2009
Bollfrass & Shaver, 2015	Quantitative	Agricultural productivity	SSA	1989-2008
Bosetti, Cattaneo, & Peri, 2021	Quantitative	Resource competition	Global	1960-2000
Breckner & Sunde, 2019	Quantitative	Agricultural productivity	Africa	1997–2015
Brzoska & Fröhlich, 2016	Conceptual	Resource competition	Global	
Buhaug & von Uexkull, 2021	Conceptual	Not Specified	Global	
Buhaug et al., 2015	Quantitative	Agricultural productivity	SSA	1960-2010
Buhaug et al., 2023	Conceptual	Resource competition	Global	
Buhaug, 2015	Conceptual	Both	Global	
Buhaug, 2016	Conceptual	Agricultural productivity	Global	
Burke et al., 2015	Literature Review	Not Specified	Global	
Busby, 2018	Conceptual	Agricultural productivity	Global	
Cappelli et al., 2023	Quantitative	Both	Africa	1990-2016
Cappelli et al., 2024	Quantitative	Resource competition	East Africa	1997-2016
Carneiro et al., 2023	Conceptual	Resource competition	Somalia	
Caruso et al., 2016	Quantitative	Agricultural productivity	Indonesia	1993-2003
Castells-Quintana et al., 2017	Conceptual	Not Specified	Global	
Clack et al., 2023	Conceptual	Resource competition	Global	
Conca, 2023	Conceptual	Resource competition	Global	
Couttenier & Soubeyran, 2014	Quantitative	Resource competition	Africa	1945-2005
Crost et al., 2018	Quantitative	Agricultural production	Philippines	2001-2009
De Juan & Hänze, 2021	Quantitative	Resource competition	Africa	2004-2005

Detges, 2016	Quantitative	Not Specified	SSA	1990-2010
Devlin and Hendrix, 2014	Quantitative	Resource competition	Global	1950–2002
Doring, 2020	Quantitative	Resource competition	Africa and the Middle East	1990–2014
Ecker et al., 2023	Quantitative	Not Specified	Yemen	2012-2013
Freeman, 2017	Conceptual	Resource competition	Global	
Froese & Schilling, 2019	Conceptual	Resource competition	Global	
George et al., 2020	Quantitative	Agricultural productivity	Nigeria	2010–2011, 2012–20113, 2015–2016
Ghimire and Ferreira, 2015	Quantitative	Resource competition	Global	1985-2009
Gilmore & Buhaug, 2021	Conceptual	Not Specified	Global	
Gómez-Álvaro & Caro-Carretero, 2024	Literature Review	Resource competition	Horn of Africa	
Guariso & Rogall, 2017	Quantitative	Not specified	Africa	1982-2001
Harari & La Ferrara, 2018	Quantitative	Not Specified	Africa	1997-2011
Helman et al., 2020	Quantitative	Not Specified	Africa and the Middle East (ME)	1992–2012
Homer-Dixon, 2023	Conceptual	Agricultural productivity	Global	
Hsiang & Burke, 2014	Conceptual	Not Specified	Global	
Huber et al., 2023	Conceptual	Not Specified	Central America	
Ibrahim-Olesin et al., 2021	Conceptual	Both	Nigeria and West Africa	
Ide, 2018	Conceptual	Not Specified	Syria	
Ikhuoso et al., 2020	Conceptual	Resource competition	Nigeria	
Iqbal et al., 2018	Qualitative	Not Specified	Afghanistan	2015
Issifu et al., 2022	Conceptual	Not Specified	Ghana	
Jones et al., 2017	Quantitative	Not Specified	Africa	1991–2011

Jun, 2017	Quantitative	Agricultural production	Sub-Saharan Africa	1970–2012
Kim & Garcia, 2023	Literature Review	Not Specified	MENA Region	
Koren & Schon, 2023	Quantitative	Agricultural productivity	Sahel Region	2006-2018
Koren et al., 2021	Qualitative	Not Specified	Kenya	
Koubi et al., 2018	Quantitative	Not Specified	Vietnam, Cambodia, Uganda, Nicaragua, Peru	2013-2014
Koubi, 2017	Conceptual	Not Specified	Global	
Koubi, 2018	Literature Review	Not Specified	Global	
Koubi, 2019	Literature Review	Not Specified	Global	
Landis, 2014	Quantitative	Resource competition	Global	1948–2011
Linke et al. (2015)	Quantitative	Resource competition	Kenya	2013
Mach et al., 2019	Conceptual	Agricultural productivity	Global	
Madu & Nwankwo, 2021	Quantitative	Not Specified	Nigeria	2017
Martin-Shields & Stojetz, 2019	Conceptual	Not Specified	Global	
Mary, 2022	Quantitative	Agricultural productivity	India	1971-1999
Maystadt & Ecker, 2014	Quantitative	Resource competition	Somalia	1997–2009
Maystadt et al., 2015	Quantitative	Resource competition	Sudan	1997-2009
McGuirk & Nunn, 2020	Quantitative	Not Specified	Africa	1989-2018
Mfon, 2023	Conceptual	Not Specified	Nigeria	
Minale et al., 2024	Qualitative	Resource competition	Ethiopia	
Mounirou, 2022	Quantitative	Not Specified	Benin	2017
Munala et al., 2023	Quantitative	Not Specified	Uganda; Zimababwe; Mozambique	2006;2010;2011
Nardulli et al., 2015	Quantitative	Agricultural productivity	Global	1981-2004
Nyiayaana & Okoh, 2023	Conceptual	Not Specified	Nigeria	

O'Loughlin et al., 2014	Quantitative	Resource competition	Sub-Saharan Africa	1980–2011
Okafor et al., 2023	Qualitative	Not Specified	Nigeria	
Okunade & Kohon, 2023	Conceptual	Resource competition	Nigeria	
Olagunju et al., 2021	Conceptual	Resource competition	Nigeria	
Pacillo et al., 2022	Quantitative	Agricultural productivity	Mali	2014-2018
Petit et al., 2023	Qualitative	Not Specified	France	1959–2020
Petrova, 2021	Quantitative	Not Specified	Bangladesh	2010-2015
Phyffer, 2024	Conceptual	Not Specified	Mozambique	
Plänitz, 2019	Literature review	Both	Sub-Saharan Africa	
Post et al., 2016	Conceptual	Both	Middle East	
Raleigh et al., 2015	Quantitative	Not Specified	Africa	1997-2010
Ray & Esteban, 2017	Literature Review	Not Specified	Global	
Roy et al., 2022	Qualitative	Resource competition	Bangladesh	
Sakaguchi et al., 2017	Literature Review	Not Specified	Global	
Salehyan & Hendrix, 2014	Quantitative	Resource competition	Global	1970–2006
Sarsons, 2015	Quantitative	Not Specified	India	1961-1991
Scheffran, 2022	Conceptual	Not Specified	Global	
Schleussner et al., 2016	Quantitative	Not Specified	Global	1980-2010
Sharifi et al., 2021	Literature Review	Not Specified	Global	
Shemyakina, 2022	Literature Review	Not Specified	Global	
Sitati et al., 2021	Conceptual	Both	Global	
Song et al., 2024	Quantitative	Not Specified	Chad, Sudan, South Sudan, DRC, Kennya, Nigeria	2010-2023
Thalheimer, 2023	Conceptual	Both	East Africa	

Tubi and Feitelson, 2016	Qualitative	Both	Israel	1957-1963
van Baalen & Mobjörk, 2018	Conceptual	Not Specified	Africa	
Vargas et al., 2021	Conceptual	Resource competition	Chile	
Vesco & Buhaug, 2020	Literature Review	Not Specified	Global	
Vesco et al., 2021	Quantitative	Resource competition	Global	1982–2015
von Uexkull & Buhaug, 2021	Conceptual	Agricultural productivity	Global	
von Uexkull et al., 2016	Quantitative	Not Specified	Africa; Asia	1989–2014
von Uexkull, 2014	Quantitative	Both	Sub-Saharan Africa	1989-2008
Wang et al., 2023	Quantitative	Both	Central Africa, including Sudan, Zaire, and Somalia	2000-2015
Wischnath & Buhaug, 2014	Quantitative	Agricultural productivity	India	1980–2011
Xie et al., 2024	Literature Review	Both	Global	

Table A.2 – List of quantitative studies.

Citation	Linkage studied	Spatial unit climate variable	Spatial unit socio-economic variables	Spatial unit conflict variables	Temporal unit	Hypotheses and variables	Qualitative effect (direct association)	Qualitative effect (indirect association)	Relationship between variables	Quantitative findings	Significance level (direct association)	Significance level (indirect association)
Almer et al., 2017	Climate Change - Conflict	Grid-based	Grid-based	Subnational (provinces, regions, and districts)	Monthly	Hypothesis: Water scarcity leads to an increase in small-scale social conflict. Dependent variable: Days with riots, Incidence, Onset. Independent variable: SPEI (precipitation balance). Control variables: Ethnic diversity, water scarcity, cropland, urbanization.	Positive		Negative water shocks increase the likelihood of riots. The relationship is stronger in areas with more water scarcity and ethnic diversity, supporting the competition-for-water hypothesis.	A one-standard-deviation decrease in SPEI increases the probability of at least one riot by 8.3% in a given cell and month. The impact increases to 14.7% in densely populated areas (top 10th percentile of population).	*	
Ang & Gupta, 2018	Agricultural yield - Conflict	Grid-based	Subnational (administrative level)	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Higher temperatures and extreme weather conditions reduce agricultural productivity, leading to increased conflict and violence. Dependent variables: Incidence of social unrest, Incidence of violence. Independent variables: Temperature anomalies, Precipitation anomalies. Control variables: Ethnic diversity, Economic development (GDP per capita), Urbanization, Institutional quality (government effectiveness).		Positive	Higher variation in potential crop yield increases conflict incidence. The relationship remains significant after controlling for geographical and socioeconomic factors.	A 1 standard deviation increase in variation in potential crop yield leads to a 0.17 standard deviation increase in conflict incidence, depending on the model.	***	
Ash & Obradovich, 2020	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (regions, districts)	Monthly	Hypothesis: Climatic stress (such as higher temperatures and decreased precipitation) increases the likelihood of anti-government protests, especially in agrarian societies. Dependent variables: Incidence of anti-government protests. Independent variables: Climatic stress (temperature and precipitation anomalies). Control variables:Population density, Agricultural reliance, Migration due to climatic stress.	Positive		There is no direct effect of climatic stress on anti-government protests, but climatic stress induces migration, leading to increased protests in receiving regions, especially Sunni Arab areas.	A one-degree increase in temperature combined with reduced precipitation significantly reduces nighttime light intensity, suggesting migration due to climatic stress. Increased migration correlates with higher protest risk.	*	
Ateba Boyomo et al., 2024	Climate Change - Livestock Production	National	National		Yearly	Hypothesis: Climate change reduces livestock productivity, exacerbating conflicts. Dependent variable: Livestock production. Independent variable: Rainfall	Negative	Temperature increases and erratic rainfall negatively affect livestock	An increase in temperature reduced livestock productivity.	***	Boyomo et al., 2024	Climate Change - Livestock Production

						patterns, temperature anomalies. Control variables: Maize prices, water access.		production, increasing pastoral conflicts.				
Ateba Boyomo et al., 2023	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Rainfall anomalies impact agricultural production and increase the risk of violent conflict. Dependent Variables: Agricultural output, Violent conflict incidence. Independent Variables: Rainfall anomalies, Crop yields. Control Variables: Local governance, Income levels.	Positive		Rising temperatures and reduced rainfall increase conflict risk, while food price volatility and deforestation amplify these effects.	The influence of climate change on conflict increases as food price volatility and deforestation rise. Regions most affected by severe conflict include the Far North, North-West, and South-West regions. The model shows a statistically significant positive correlation between climate variables and conflict in crisis regions, supported by robustness checks and alternative measures like the number of deaths and the conflict severity index.	*	
Ayana et al., 2016	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Monthly	Hypothesis: Water and forage scarcity (as measured by precipitation and NDVI anomalies) lead to an increase in pastoralist conflicts in East Africa. Dependent variables: Conflict incidence, Conflict clusters, Spatial distribution of conflict events. Independent variables: Precipitation anomalies, NDVI anomalies (vegetation stress). Seasonal failure (one, 1.5, and two-cycle stress periods). Control variables: Topography (highland vs. lowland), Livestock density, Cross-border movements of pastoralist.	Neutral		No clear spatial relationship between precipitation, NDVI, and conflict; conflict clusters form in areas with high forage and water availability, suggesting competition for resources as a driver.	Significant decline in precipitation and NDVI in the Moyale cluster; non-significant trend in the Karamoja cluster; limited precipitation stress in conflict years. NDVI stress observed in one year of the Moyale cluster (2000).	*	
Balestri & Caruso, 2024	Climate Vulnerability - Communal Conflicts	National	National	National	Yearly	Hypothesis: Climate vulnerability increases the likelihood of communal conflicts. Dependent variable: Communal violence incidents. Independent variable: ND-GAIN index. Control variables: Resource access, rainfall deviations.	Positive		Higher climate vulnerability correlates with increased communal violence, especially in resource-scarce regions.	Regions with higher ND-GAIN scores saw an increase of almost 18% in communal conflict likelihood.	***	
Bazzi & Blattman, 2014	Economic shocks - Conflict	Country	Country	Country	Yearly	Hypothesis: Commodity price shocks affect conflict incidence. Dependent variable: Civil war onset and intensity. Independent variables: Commodity price shocks (export prices), food & fuel price		Neutral	No robust positive correlation between commodity price shocks and conflict onset. Annual agricultural prices weakly reduce conflict	A 1 SD increase in prices raises GDP by 22–36%, weak association between annual crop shocks and conflict reduction, no consistent relationship for extractive commodities.		*

						shocks. Control variables: GDP, export dependence			risk; extractive prices not significant			
Bhavnani and Lacina (2015)	Climate Change - Conflict	Subational (Indian states)	Subnational (administrative level)	Subnational (districts, states)	Monthly	Hypothesis: Migration may be endogenous to rioting. Rainfall shocks affect migration, which then impacts riots. Dependent variable: Rioting incidents. Independent variables: Migration (male migrants), abnormal rainfall shocks, unemployment rates, political alignment. Control variables: Abnormal monsoon rainfall in the host state, land degradation, income per capita, trade flows, state population, urbanization rates, youth population (aged 15–24), school enrollment rates.	Positive		A 10% increase in male migration leads to a 5.5% increase in rioting. The effect of migration on riots is reduced in states politically aligned with the central government.	A 10% increase in male migration causes a 9% increase in riots. A 5.5% increase in riots with migration controlling for other variables. Political alignment weakens the effect.		***
Bosetti et al., 2018	Climate Migration - Local Conflicts	National	National	National	Yearly	Hypothesis: Migration mitigates conflict in origin areas but may transfer tensions to destination areas. Dependent variable: Conflict incidence. Independent variable: Temperature variations, migration rates. Control variables: Socioeconomic conditions, political stability.	Neutral		Higher migration propensity reduces conflict in origin regions, with limited evidence of increased conflict in destination regions.	There is no statistically significant effect of climate migrants on conflicts in countries of destination.	Bosetti et al., 2018	Climate Migration - Local Conflicts
Bohmelt et al. (2014)	Climate Change - Conflict	Country	Country	Country	Yearly	Hypothesis: Domestic water-related conflict and cooperation are driven by demand for water resources, water supply variability, and political/institutional restraint. Dependent variable: Water-related conflict and cooperation (measured by the Water Events Scale, WES). Independent variables: Population density, agricultural productivity, GDP per capita, temperature variability (30-year moving average), precipitation variability (30-year moving average), democracy (Polity IV score), political stability. Control variables: Country fixed effects, and year fixed effects.	Positive		Economic development increases the risk of low-intensity water-related conflict. Democracy decreases violent conflict but increases non-violent disputes over water.	GDP per capita increases the WES conflict score by 14%. Democracy reduces water-related violence but leads to more non-violent conflict. Climate variability (precipitation, temperature) has no significant effect.		***
Bollfrass & Shaver, 2015	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (regions, districts, provinces)	Yearly	Hypothesis: Higher temperatures lead to increased civil war incidence in sub-Saharan African states due to their heavy dependence on rainfed agriculture. Temperature also affects violence through non-agricultural channels,	Positive		Positive relationship between higher temperature and conflict incidence, with stronger effects in agricultural areas, but	A 20°F increase in mean temperature is associated with a 2% increase in the likelihood of deadly conflict.	***	

						such as labor markets, migration, food prices, and psychological effects. Dependent variable: Incidence of civil war (measured by substate conflict resulting in 25 battlefield deaths or more). Independent variables: Annual temperature, precipitation, agricultural productivity (crop yields), migration (displacement of populations), food prices, labor markets, and terrain (mountainous and forest cover). Control variables: Ethnic composition, distance to the capital, population size, GDP per capita, and governance factors (e.g., democracy).			present even in non-agricultural areas.			
Breckner & Sunde, 2019	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeference d dataset)	Monthly	Hypothesis: Economic shocks interact with climate variability to influence conflict onset. Dependent Variable: Conflict onset (binary). Independent Variables: Economic growth, temperature variability, rainfall variability. Control Variables: Governance, GDP per capita, population density.	Positive		Positive relationship between temperature extremes and conflict incidence, with higher conflict in densely populated and agriculturally vulnerable areas.	A 1-unit increase in temperature extremes leads to a 0.084 increase in conflict incidence, with stronger effects in long-run differences analysis.	***	
Buhaug et al., 2015	Climate Change - Conflict	Country	Country	Country	Yearly	Hypothesis: Climate variability (temperature and precipitation) affects food production, which in turn influences the likelihood of political violence. Dependent Variable: Incidence of political violence (from UCDP/PRIO, SCAD, and Non-State Conflict dataset). Independent Variables: Temperature variability, precipitation variability, food production. Control Variables: Non-linear climate effects, food production dynamics, socio-economic factors.	Neutral		Climate variability (rainfall and temperature) affects food production, but the relationship between food production shocks and political violence is weak and inconsistent across conflict types. The analysis suggests that social unrest is not directly linked to agricultural performance or food production shocks caused by climate variability.	Weak and statistically insignificant effect of food production on political violence. Rainfall positively affects food production, but its effect on violence is limited.	**	

Cappelli et al., 2023	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Climate shocks exacerbate violent conflict, particularly in less economically developed regions. Dependent Variables: Conflict incidence. Independent Variables: Temperature anomalies, Precipitation variability. Control Variables: Governance, Economic development.	Positive		The study finds that higher temperatures and lower rainfall (drought) increase the likelihood of conflicts, while floods and other extreme water events also increase the number of conflicts, particularly through competition for agricultural resources. Spillover effects from neighboring areas amplify local conflicts.	A one-degree increase in long-term average temperatures more than doubles the expected number of conflicts. Rainfall increases reduce conflicts but only marginally. Spillover effects from neighboring cells also significantly impact conflict probability and intensity.	No significance level reported/Coefficient of direct relationship not significant	
Cappelli et al., 2024	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Climate extremes increase the risk of conflict by exacerbating economic and social vulnerabilities. Dependent Variables: Conflict incidence. Independent Variables: Temperature and Precipitation anomalies. Control Variables: Economic vulnerability, Social factors.	Positive		Spatial inequality (nightlights), population density, and drought stress increase conflict risk. Interaction between rural population and climatic conditions decreases conflict risk, while urbanization increases it.	Positive, quadratic relationship between temperature anomalies and conflict risk; long-term drought and floods do not increase conflict directly; spatial inequalities and access to resources play a major role in mediating climate-conflict nexus.	*	
Caruso et al., 2016	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (districts, provinces)	Seasonal for rice-growing period	Hypothesis: An increase in minimum temperature during the core growing season (December) reduces rice production, leading to decreased food availability and increased violence in Indonesia. Dependent variable: Number of violent incidents. Independent variables: Minimum temperature deviations, rainfall deviations during the growing season, population size (logged), provincial GDP, income inequality (share of poor population), decentralization reform (dummy variable from 2001 , access to improved water sources, and household area per capita. Control variables: Lag of violence incidents, economic conditions, living standards.	Positive		Positive correlation between minimum temperature increases during growing season and conflict escalation.	Minimum temperature increases reduced rice availability, fueling violence. Results are robust despite limited data.	No significance level reported/Coefficient of direct relationship not significant	
Couttenier & Soubeyran, 2014	Climate Change - Conflict	Grid-based	Country	Country	Yearly	Hypothesis: Weather anomalies (rainfall, temperature, and drought) affect civil war. Dependent Variable: Civil war occurrence and intensity (dummy variable for	Positive		Positive relationship between drought (PDSI) and civil war incidence when	A one standard deviation increase in the PDSI corresponds to a 0.7% increase in the annual risk of conflict. The effect diminishes	*	

						battle deaths > 1,000). Independent Variables: Rainfall, temperature, PDSI (Palmer Drought Severity Index). Control Variables: Country fixed effects, country-specific time trends, year fixed effects.			controlling for country-fixed effects.	significantly with year-fixed effects.		
Crost et al., 2018	Climate Change - Civil Conflict	Subnational (Seasonal rainfall variation)	Subnational (Agricultural output)	Subnational (Philippine provinces)	Yearly	Hypothesis: Seasonal rainfall affects agriculture, influencing conflict. Dependent variable: Civil conflict incidents. Independent variable: Seasonal rainfall. Control variables: Agricultural productivity, infrastructure.	Positive (wet season)	Wet season rainfall increases conflicts, while dry season rainfall reduces conflicts through agricultural channels.	A increase in wet-season rainfall (10-cm) is associated with additional conflict-related incidents the following year.	**		Crost et al., 2018
De Juan & Hänze, 2021	Climate Change - Intra-ethnic and inter-ethnic trust	Grid-based	Individual-level	Grid-based	Monthly	Hypotheses: 1) Drought influences intra- and inter-ethnic trust. 2) Drought conditions worsen food security. Variables: Dependent Variables: Intra-ethnic trust, inter-ethnic trust, and food security. Independent Variable: Drought exposure (SPEI index). Control Variables: Age, gender, education, occupation, location (longitude/latitude).	Positive		Positive relationship between drought exposure and trust levels, both intra-ethnic and inter-ethnic. However, horizontal inequality weakens intergroup trust, but strengthens intra-ethnic trust.	Drought increases intra- and inter-ethnic trust in East Africa, with stronger effects among politically marginalized groups. Drought worsened food insecurity significantly across affected regions.	No significance level reported/Coefficient of direct relationship not significant	
Detges, 2016	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based and Subnational (project-level georeferenced data)	Yearly	Hypotheses: 1) Droughts in regions with poorly developed infrastructure (roads, water) increase conflict. Variables: Dependent Variables: Civil conflict and communal conflict incidence. Independent Variable: Extreme drought (SPI). Control Variables: Population size, income, conflict history, spatial lags.	Positive		Positive interaction between drought and low road density for civil conflicts. Communal violence risk increases with poor access to water and drought. No significant effect of drought alone on either civil or communal conflicts.	Civil conflict risk is 28% higher in areas with extreme drought and poor road infrastructure. In areas with limited water access, communal conflict risk rises by 59% with extreme drought within 150 km.	+	
Devlin and Hendrix, 2014	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (ethnic regions, territories)	Yearly	Hypotheses: 1) Joint acute water scarcity increases interstate conflict. 2) Higher precipitation variability increases conflict. Variables: Dependent Variable: MID (Militarized Interstate Dispute) onset. Independent Variables: Precipitation scarcity, mean precipitation, precipitation variability. Control Variables: Distance, joint democracy, economic development, population.	Neutral		Negative relationship between joint acute water scarcity and conflict. Positive relationship between precipitation variability and conflict. No effect of shared river basins or contiguity on the relationship between water scarcity and conflict behavior.	Joint acute water scarcity reduces the probability of conflict by 33.7%. A one standard deviation increase in precipitation variability raises the probability of conflict by 45.7%. Increased mean precipitation decreases conflict likelihood by 41%.	*	

Döring, 2019	Groundwater Scarcity - Communal Violence	Grid-based	Grid-based	Grid-based	Yearly	Hypothesis: Groundwater scarcity increases communal violence, especially during droughts. Dependent variable: Communal violence incidents. Independent variable: Groundwater access, drought presence. Control variables: Rainfall, major rivers, population density.	Positive		Limited groundwater access increases the likelihood of communal violence, exacerbated by population density and drought conditions.	Regions with restricted groundwater access showed a higher risk of violence, with the effect more pronounced in areas with higher drought frequency.	***	
Ecker et al., 2023	Civil Conflict - Child Nutrition	Subational (Districts across 19 governorates in Yemen)	Household-level	Grid-based (georeferenced dataset)	Quarterly	Hypotheses: 1) Armed conflict increases the risk of child malnutrition. 2) Cash transfer programs mitigate the impact of conflict on child nutrition. Dependent variable: Weight-for-height z-scores (WHZ), which measure the short-term nutritional status of children under 5 years of age. Independent variables: Conflict intensity (measured by civilian casualties in the district), household exposure to conflict, beneficiary status in the Social Welfare Fund (SWF) cash transfer program, household wealt status, ousehold size, sex and age of the household head, literacy status of the household head, child sex, child age (in months), extreme weather events (district-level temperature and precipitation anomalies), and time fixed effects (survey rounds). Control variables: District fixed effects, household fixed effects, individual fixed effects, household asset-based wealth index, economic conditions, and child characteristics known to influence nutrition outcomes.		Negative	Negative relationship between conflict intensity and child nutritional status (WHZ). Positive moderating effect of cash transfers, particularly for older beneficiaries.	A 1 SD increase in conflict intensity decreases child WHZ by 0.06, reducing the mean by 9.6%. The cash transfer program mitigates the adverse effect by 43.2% (household-level model) and 42.4% (individual-level model).		***
George et al., 2020	Conflict-Food Security	Subnational (administrative level)	Household-level	Grid-based (georeferenced dataset)	Survey waves	Hypotheses: Armed conflict, specifically Boko Haram insurgency, decreases household food security in conflict-affected regions. Increased conflict intensity (measured by fatalities) leads to higher food insecurity through price shocks, income shocks, and input shortages. Dependent variables: Various food insecurity outcomes, such as Food		Positive	Positive: Conflict intensity (measured by fatalities) negatively affects food security. Food insecurity arises through reductions in income and farm input availability.	Each additional fatality due to conflict reduces FCS by 0.037, implying a 1.73% decrease in FCS for average households. Conflict also increases days of food insecurity per week by 0.4 days.		**

						Consumption Score (FCS), reliance on less preferred foods (RLPF), limiting the variety of foods eaten (LVFE), limiting portion size at meal times (LPSM), and going a whole day without eating (WDWE). Independent variables: Fatalities due to Boko Haram insurgency, household characteristics (number of children, distance to the nearest market, female-headed household), annual mean temperature, annual rainfall, and per capita food expenditure. Control variables: Household fixed effects, survey year fixed effects, LGA-specific time trends.						
Ghimire and Ferreira (2015)	Climate Change - Conflict	Country	Country	Country	Yearly	Hypotheses: Large floods increase the likelihood of armed conflict incidence, but not conflict onset. The risk of conflict increases with flood disasters due to weakened governmental capacity to manage emergencies. Dependent Variables: Armed conflict onset, Armed conflict incidence. Independent Variables: Flood frequency (lagged), Rainfall variability (used as an instrument for floods). Control variables: GDP growth, GDP per capita, ethnic tensions, total population, youth population, polity score, infant mortality rate, conflict in neighboring countries.	Neutral		Positive correlation between floods and conflict incidence; no significant effect on conflict onset.	1 additional flood increases conflict incidence by 5.7%, with a stronger effect in conflict-prone countries (15.6%).	*	
Guariso & Rogall, 2017	Rainfall Inequality - Ethnic Conflict	Subnational (Rainfall data during plant-growing season)	Subnational (Ethnic group economic disparities)	Subnational (Ethnic regions in Africa)	Yearly	Hypothesis: Rainfall inequality increases ethnic conflict risk. Dependent variable: Ethnic conflict incidents. Independent variable: Rainfall inequality index. Control variables: Political power distribution, rainfall variability.	Positive		Rainfall inequality intensifies ethnic grievances, increasing conflict likelihood in marginalized groups.	One standard deviation increase in rainfall inequality raised ethnic conflict risk by 16%.	***	

Harari & La Ferrara, 2018	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypotheses: 1) Negative agricultural shocks (weather-related) increase conflict likelihood via lower opportunity costs of rebellion and poverty exacerbation. 2) Conflict spillovers across space and time. Dependent variable: Conflict incidence, measured as the occurrence of at least one conflict-related event in a given subnational grid cell. Independent variables: Climate indicators (e.g., precipitation, SPEI), terrain characteristics, roads, rivers, minerals, ethno-linguistic fractionalization, and spatial lags of these variables. Control variables: Time-invariant cell characteristics, year and country fixed effects, spatial and temporal lags of conflict, and interaction terms for state capacity, road infrastructure, and ethnic fractionalization.	Positive		Positive relationship between agricultural shocks and conflict incidence, with significant spatial and temporal spillovers.	A 1 standard deviation increase in favorable weather (SPEI) during the growing season reduces conflict incidence by 1.5 percentage points in the subsequent year (9% of mean conflict incidence).	***	
Helman et al., 2020	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypotheses: 1. Climate anomalies (temperature, rainfall) have direct and indirect effects on non-state conflict outbreaks. 2. Agricultural dependence, economic welfare, and proximity to borders influence climate-conflict relationships. Variables: Dependent: Conflict incidence (binary). Independent: Temperature anomalies, rainfall anomalies, yield, IMR, economic welfare, distance to borders.	Positive		Temperature anomalies increase conflict risk, especially in agriculture-dependent and low-welfare areas, while rainfall anomalies decrease it indirectly through welfare improvements.	In Africa, temperature had a positive direct effect on conflict risk (0.020), while in the Middle East, rainfall had a significant negative effect (-0.015). IMR and proximity to borders also significantly influenced conflict risk.	**	
Jones et al., 2017	Climate Change - Conflict	Country	Country	Country	Monthly	Hypothesis: State vulnerability moderates the effect of food insecurity on violent unrest. Dependent Variable: Violent unrest. Independent Variables: Food insecurity, state vulnerability, precipitation, temperature, world food prices. Control Variables: Agriculture percentage of GDP, Polity score, imports, GDP per capita, neighboring conflict.	Positive		State vulnerability and food insecurity interact to increase the likelihood of unrest. The most vulnerable states are more likely to experience conflict when facing food insecurity.	The likelihood of unrest is highest in states with low institutional capacity, greater reliance on agriculture, and higher food price volatility. State vulnerability magnifies the effect of food insecurity, increasing the probability of unrest by up to 44%. Conversely, low vulnerability can reduce the probability of unrest to a low as 9% despite rising food prices.	*	

Jun, 2017	Climate Change - Civil Conflicts	National	National	National	Yearly	Hypothesis: Rising temperatures reduce crop yields and increase civil conflicts. Dependent variable: Civil conflict incidence. Independent variable: Temperature anomalies. Control variables: Agricultural productivity, rainfall.	Positive		Temperature-induced reductions in maize yields exacerbate civil conflict risks.	An increase in growing season temperature (1°C) raises conflict incidence by 12%.	*	
Koren & Schon, 2023	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Monthly	Hypothesis: Climate variability (drought) increases the risk of ethnic conflict. Dependent Variables: Incidence of ethnic conflict. Independent Variables: Droughts, Ethnic diversity, Agricultural reliance. Control Variables: Economic development, Political exclusion.	Neutral		Nonstate actors (rebels, militias) increase VAC in response to higher agricultural productivity, whereas state actors do not. Climate stress, especially higher precipitation and temperature, also increases nonstate VAC.	Rebel VAC increases by 94% in months with higher cash crop productivity. The same applies to militia VAC, with an average increase of 0.022 events per month. State VAC remains unaffected by crop productivity, while nonstate VAC is significantly responsive to climate conditions like higher precipitation and temperature.	***	
Koubi et al., 2018	Climate Change - Conflict Perceptions	Country	Individual-level	Subnational (provinces, regions, and districts)	Retrospective perception of climate events over the past five years; Cross-sectional conflict perceptions captured via surveys (2013–2014)	Hypothesis: Climate-induced migration increases the likelihood of conflict in receiving areas. Dependent Variable: Conflict incidence. Independent Variables: Migration patterns, temperature anomalies, precipitation anomalies. Control Variables: GDP per capita, political exclusion, population density.	Positive		Migrants who experienced long-term environmental stress are more prone to perceive conflict due to accumulated grievances, while those facing short-term events are less likely to perceive conflict.	Women and younger individuals are slightly more likely to perceive conflict, but the effects are not statistically significant. Economic conditions, such as whether the migration was driven by economic reasons, have a more significant influence. Migrants exposed to gradual environmental change are more likely to perceive conflict than those exposed to sudden shocks.		
Landis, 2014	Climate Change - Conflict	Grid-based	Country	Grid-based (georeferenced dataset)	Monthly	Hypothesis: Climate variability is positively associated with conflict. Dependent Variable: Onset of civil war (including low and high intensity conflicts). Independent Variable: Temperature mean and deviations (positive and negative). Control Variable: Regime type, GDP per capita, population, and precipitation levels.	Neutral		Positive temperature deviations increase the risk of civil war onset, but no consistent effect is found for non-state conflict. Precipitation changes tend to reduce the likelihood of high-intensity civil wars but not non-state conflict.	A 2°C increase in temperature raises civil war onset probability by 4.55% and non-state conflict by 11.65%. Precipitation decreases the risk of high-intensity civil wars by 28.28%.		

Linke et al., 2015	Climate Change - Conflict	Subnational (administrative level)	Individual-level	Individual-level	Monthly	Hypotheses: Drought perception increases support for violence. Dependent Variable: Support for violence. Independent Variable: Perceived drought severity and frequency. Control Variable: Government rules, inter-community dialogue.	Negative		There is a negative relationship between drought and violence when inter-community dialogue is present, reducing support for violence by 76%. In contrast, formal government rules did not significantly moderate the impact of drought on violence.	Drought perception alone did not significantly increase violence support, but with inter-community dialogue, support for violence was reduced by 76%. In contrast, the presence of government rules had no significant effect in moderating this relationship.		
Madu & Nwankwo, 2021	Climate Change - Migration	Subnational (administrative level)	Household-level	Micro-level (individual-level, household)	Yearly	Hypotheses: Climate shocks influence migration. Dependent Variable: Migration (internal, external, short-term, long-term). Independent Variable: Rainfall deficits, storms, floods. Control Variable: Education, conflict, access to healthcare.	Neutral		Positive relationship between rainfall deficits and migration (both internal and external), as well as short- and long-term migration options. Migration is a coping mechanism for climate shocks.	Migration is more likely with increased rainfall deficits and storms, especially in regions with degraded vegetation and conflict between farmers and herders. Economic conditions also drive migration decisions.		
Mary, 2022	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (regions, states)	Yearly	Hypotheses: Rainfall shocks increase conflict in rain-fed districts. Dependent Variable: Religious conflict (Hindu-Muslim riots). Independent Variable: Rainfall shocks (positive/negative). Control Variable: Dams, district income.	Negative		Negative relationship between rainfall shocks and conflict in rain-fed districts. Dams mitigate the impact of rainfall on conflict in dam-fed districts.	Rainfall shocks increase agricultural output by 0.145 and decrease conflict by -0.081 in rain-fed districts. No significant effects of rainfall shocks in dam-fed districts.		
Maystadt & Ecker, 2014	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based (georeferenced dataset)	Monthly	Hypotheses: Droughts increase conflict via livestock price shocks. Dependent Variable: Violent conflict events. Independent Variable: Drought intensity, livestock prices. Control Variable: Precipitation anomalies.	Positive		Positive relationship between drought intensity and conflict. Negative relationship between livestock prices and conflict in Somalia.	A one-point increase in temperature anomaly increases conflict likelihood by 0.71 points. A decline in cattle prices by 6% is associated with a 72% increase in conflict.		
Maystadt et al., 2015	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Quarterly	Hypotheses: Temperature anomalies increase the likelihood of conflict. Dependent Variable: Violent conflict events. Independent Variable: Temperature anomalies. Control Variables: Precipitation anomalies, night-lights density.	Positive		Positive relationship between temperature anomalies and violent conflict, with a stronger impact in pastoralist areas.	A 1 standard deviation increase in temperature anomalies raises the likelihood of violent conflict by 32%. Temperature variations may have contributed to 26% of violent events in Sudan.		
McGuirk & Nunn, 2020	Climate Change - Conflict	Grid-based	Subnational (administrative level)	Grid-based (georeferenced dataset)	Yearly	Hypotheses: Rainfall scarcity in transhumant pastoral areas increases conflict in neighboring agricultural lands. Dependent Variable: Conflict incidence. Independent Variable: Rainfall in pastoral areas. Control Variables: Population, temperature.	Positive		Negative relationship between rainfall in transhumant pastoral areas and conflict in neighboring agricultural areas, with more conflict during adverse rainfall.	A 1 standard deviation decrease in rainfall increases conflict by up to 37.5% of the mean incidence for UCDP conflict and by 13.6% for ACLED conflict in neighboring agricultural cells.		

Mounirou, 2022	Climate Change - Migration	Subnational (administrative level)	Household-level		Yearly	Hypothesis: Climate shocks lead to migration (internal and external) in cotton zones. Dependent variables: Internal, external, short-term, and long-term migration. Independent variables: Rainfall deficit, storms, floods, global warming. Control variables: Socioeconomic factors, political access, educational facilities.	Positive		Significant positive correlation between rainfall deficits, storms, and migration decisions (internal and external).	Rainfall deficit and climatic shocks increase the probability of internal migration by 0.125 (internal) and external migration by 2.145.		
Munala et al., 2023	Climate Change - Intimate partner violence	Subnational (administrative level)	Household-level	Subnational (cities, districts)	Yearly	Hypothesis: Severe weather events increase the incidence of intimate partner violence. Dependent variables: Intimate partner violence (physical, emotional, sexual). Independent variables: Severe weather events (droughts, floods). Control variables: Partner's alcohol consumption, work in agriculture, education level.	Positive		Significant positive relationship between severe weather events and increased intimate partner violence in Uganda (OR = 1.23), Zimbabwe (OR = 1.28), and Mozambique (OR = 1.91). Alcohol consumption increases odds of IPV in all countries.	In Uganda, a 1.23 odds ratio for severe weather and intimate partner violence. In Zimbabwe, the odds ratio is 1.28, and in Mozambique, it is 1.91. Alcohol consumption by partners increases odds of violence (Uganda: OR = 2.19, Zimbabwe: OR = 1.81, Mozambique: OR = 2.64).		
Nardulli et al., 2015	Climate Change - Conflict	Country	Country	Subnational (regions, administrative units)	Daily (climate: 1981-2004); event-level (conflict: 1981-2004)	Hypotheses: 1) No increase in unrest post-climate disaster; 2) No increase in proximate areas; 3) Greater unrest among affiliated initiators. Dependent Variable: Civil unrest (mass protests, political violence). Independent Variable: Climate-related disasters (storms, floods). Control Variables: Proximity, organizational affiliation, event characteristics.	Positive		Civil unrest rises post-disaster, especially political violence initiated by organized groups. Proximate areas exhibit less unrest compared to distant areas, contrary to expectations, suggesting a complex interaction of social dynamics post-disaster.	Civil unrest increased in 15% of episodes, with mass protests involving up to 18,000 demonstrators and violent events causing over 300 injuries and 450 deaths. Proximate unrest was less significant than distant unrest in many cases.		
O'Loughlin et al., 2014	Climate Change - Conflict	Grid-based	Subnational (administrative level)	Grid-based (georeferenced dataset)	Monthly	Hypotheses: Climate variability increases conflict risk. Dependent Variable: Violent conflict (battles, riots, protests, violence against civilians). Independent Variable: Temperature and precipitation anomalies (TI6 and SPI6). Control Variables: Population, access to roads, capital city proximity, prior conflict, election periods, infant mortality rate (IMR), political rights, media trends, ethnic exclusion, proximity to borders.	Positive		Within-grid higher temperature anomalies lead to more violence, particularly against civilians. Drier conditions reduce the overall number of violent events, except in extreme cases where rioting increases. The Sahel region shows the strongest temperature-related violence increases.	Temperature anomalies of +1 SD lead to a 10.7% increase in conflict, with an estimated 0.102 additional violent events per grid cell. Droughts reduce conflict overall, but extreme dry conditions lead to more riots and violence against civilians. Violence is spatially clustered, with prior violence increasing future events.		

Pacillo et al., 2022	Climate Change - Conflict	Grid-based	Household-level	Grid-based (georeferenced dataset)	Monthly	Hypothesis: Climate variability is positively associated with conflict. Dependent Variable: Conflict events (including violence against civilians, riots, protests). Independent Variable: Climate variability (temperature and precipitation anomalies). Control Variable: Agricultural production (maize), household food security status.	Positive		Negative precipitation anomalies reduce maize production and increase household food insecurity, which sequentially increases the likelihood of conflicts.	A one standard deviation increase in temperature anomalies increases total conflicts by 0.011, while negative precipitation anomalies increase conflicts by 0.015.		
Petrova, 2021	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Natural hazard-induced migration contributes to higher protest frequency in migrant-receiving areas. Dependent Variable: Number of protests. Independent Variables: Migration flows, flood shocks, drought shocks. Control Variables: Population density, urbanization, economic conditions.	Neutral		General migration increases protest frequency, but natural hazard-induced migration does not significantly contribute to protests.	A 10% increase in total migration is associated with a 5% increase in protest frequency, but climate-related migration does not show a significant effect on protest incidence.		
Raleigh et al., 2015	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based (georeferenced dataset)	Monthly	Hypothesis: Higher food prices and conflict are in a reciprocal relationship. Dependent Variable: Number of conflict events. Independent Variable: Commodity prices. Control Variable: Rainfall anomalies, civil war presence, levels of democracy, and economic growth.	Positive		A positive feedback exists between food price and violence – higher food prices increase conflict rates within markets and conflict increases food prices. Anomalously dry conditions are associated with increased frequencies of conflict. Decreased rainfall exerts an indirect effect on conflict through its impact on food prices.	Lower rainfall by one standard deviation (based on average for previous 30-120 days) was associated with a 9.1% expected increase in food prices. Doubling food prices in a given market was associated with a 13% increase of conflict events in that market in a given month.		
Salehyan & Hendrix, 2014	Climate Change - Conflict	Country	Country	Country	Yearly	Hypothesis: Precipitation and temperature anomalies influence the occurrence and intensity of civil conflict. Dependent Variable: Annual count of conflict-related battle deaths. Independent Variables: Temperature and precipitation anomalies. Control Variables: Population, socio-economic factors.	Neutral		Short-term water abundance is associated with increases in organized political violence, especially in less-developed, more agricultural economies. Climate change may cause more regions of the world to become drought prone, but such droughts are unlikely to cause fighting to erupt. Water abundance does play countervailing	In the global sample, a precipitation anomaly that is higher by one-standard deviation is associated with a 4.3% increase in terror attacks, a 6.9% increase in associated deaths, and a 12.3% higher probability of civil conflict. For a two-standard deviation anomaly, the increases are, respectively, 8.8%, 14.2% and 26.0%.		

									effect through economic growth, but the direct effect dominates.			
Sarsons, 2015	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (cities, districts)	Monthly	Hypothesis: A negative income shock incrases the number of riots in a district. Dependent Variable: Number of riots (indicator and count). Independent Variable: Income shocks (using rainfall growth as an instrument for GDP growth). Control Variable: District characteristics, including past riot counts and socioeconomic factors	Positive		Positive rainfall shocks reduce conflict; negative rain shocks lower income, thereby spurring violence. However, the effect of rain shocks on conflict is stronger in areas downstream of dams even though irrigation makes agricultural production and thus income less sensitive to rain shocks. It appears rainfall affects conflict not only through income but also some other channel.	Substantive interpretation of results not given.		
Schleussner et al., 2016	Climate Change - Conflict	Country	Country	Country	Yearly	Hypothesis: Climate-related natural disasters enhance the risk of armed conflict. Dependent Variable: Armed conflict outbreaks (instances with more than 25 battle-related deaths). Independent Variable: Climate-related disaster events (categorized by economic damage). Control Variable: Country-specific factors including ethnic and religious fractionalization, GDP measures, and historical conflict data.	Positive		Armed-conflict risks are enhanced by climate-related disasters in ethnically fractionalized countries.	Globally, a coincidence rate of 9% between armed-conflict outbreak and disaster occurrence such as heat waves or droughts. During the period under study, about 23% of conflict outbreaks in ethnically highly fractionalized countries robustly coincide with climatic calamities.		
Song et al., 2024	Climate Change - Conflict	Subnational (administrative level)	Subnational (administrative level)	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Droughts and temperature anomalies exacerbate intercommunal violence. Dependent Variables: Number of intercommunal conflict events. Independent Variables: Droughts, Temperature anomalies, Agricultural reliance. Control Variables: Economic development, Governance quality.	Positive		Droughts and extreme temperature anomalies increase the likelihood of intercommunal violence, particularly in agrarian societies with weak governance systems.	A one-standard deviation decrease in precipitation leads to a 10% increase in intercommunal violence, particularly in regions dependent on agriculture and weak governance.		

Vesco et al., 2021	Climate Change - Conflict	Grid-based	Country	Country	Yearly	Hypothesis: Spatial concentration of crop production and climate variability influence conflict onset. Dependent Variable: Conflict onset (binary). Independent Variables: Precipitation anomalies, temperature anomalies, crop production concentration. Control Variables: GDP, population, governance indicators.	Positive		Climate variability combined with crop production concentration increases the likelihood of conflict, particularly non-state and communal conflicts.	A one-standard deviation decrease in precipitation combined with a one-standard deviation increase in crop production concentration increases the likelihood of non-state conflict by 6% and communal conflict by 5%.		
von Uexkull, 2014	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypotheses: Drought increases civil conflict risk, especially in areas reliant on rainfed agriculture. Dependent Variable: Civil conflict incidence. Independent Variable: Drought conditions. Control Variables: Population, GDP, ethnic exclusion, spatial-temporal conflict lag.	Positive		Drought has a significant positive effect on conflict incidence in regions with rainfed agriculture. Prolonged drought exposure amplifies this effect, but the same is not observed in regions with irrigation or non-agricultural livelihoods.	Significant increase in conflict risk (up to double) in rainfed agricultural regions after multiple years of drought. Conflict risk increases from 1.3% in non-drought years to 4.8% after three consecutive drought years in regions with rainfed agriculture.		
von Uexkull et al., 2016	Climate Change - Conflict	Subnational (administrative level)	Subnational (Ethnic group-level)	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Growing-season drought increases the risk of ethnic group involvement in civil conflict. Dependent Variable: Civil conflict onset and incidence (binary). Independent Variables: SPEI (Standardized Precipitation Evapotranspiration Index), agricultural dependence, economic development, ethnopolitical exclusion. Control Variables: Group size, GDP per capita, conflict spillover, group-specific time trends.	Positive		Drought increases conflict risk for agriculturally dependent groups in low-development countries but not significantly for non-agrarian groups.	For politically excluded groups, five consecutive years of growing-season drought increase the likelihood of conflict incidence from 12% to 15%. Conflict risk increases with each additional year of drought.		
Wang et al., 2023	Climate Change - Conflict	Grid-based	Grid-based	Grid-based (georeferenced dataset)	Yearly	Hypothesis: Precipitation and temperature anomalies increase the risk of conflict in Central Africa. Dependent Variables: Conflict occurrence. Independent Variables: Temperature anomalies, Precipitation variability, Agricultural output. Control Variables: Income levels, Population density.	Positive		Precipitation variability and temperature anomalies are strongly associated with increased conflict risk, particularly in densely populated agricultural regions.	A one-standard deviation increase in temperature anomalies raises the probability of conflict by 7%, particularly in densely populated regions relying on agriculture.		

Wischnath & Buhaug, 2014	Food production - Conflict	Subnational (administrative level)	Subnational (administrative level)	Subnational (administrative level)	Yearly	Hypotheses: Food production growth affects the severity of political violence. Dependent Variable: Conflict severity (fatalities from state-based violence). Independent Variable: Food production growth (wheat, rice). Control Variables: Neighboring state conflict severity, time trend, prior conflict severity, spatial dependence, and state fixed effects.		Neutral	Food production growth (lagged) negatively impacts conflict severity. Neighboring conflict has an inverse relationship with state-level conflict severity, meaning violence tends to cluster within specific states rather than spreading across borders.	Lagged food growth shows a significant negative effect on conflict severity: ISPS fatalities (-0.514), SATP fatalities (-0.473), UCDP battle deaths (-1.379). Neighboring state conflict severity has a negative impact on local conflict severity.		