UNIVERSITÀ DEGLI STUDI FIRENZE
DISEI
DIPARTIMENTO DI SCIENZE PER L'ECONOMIA E L'IMPRESA

Working Papers – Economics

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Working Paper N. 08/2026

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Via delle Pandette 9, 50127 Firenze (Italia)
www.disei.unifi.it

Climatic Shocks and Conflicts Across Agricultural Livelihoods and Agrarian Contexts: Evidence from West Africa *

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Abstract

This paper examines how climatic shocks affect conflict risk across heterogeneous livelihood systems in four rain-fed, agriculture-dependent West African economies — Burkina Faso, Niger, Nigeria, and Côte d'Ivoire — over 2010–2023. Combining geocoded household panel data with high-resolution climate anomalies and conflict events, we estimate the effect of growing-season droughts and excess rainfall on post-harvest conflict incidence. Results show strong spatial and livelihood heterogeneity driven by the interaction between household and local livelihood structures: droughts increase conflict risk in mixed-livelihood areas in Burkina Faso and Côte d'Ivoire, in pastoral-dominated areas in Nigeria irrespective of household type, and in farm-dominated systems in Niger, while wet anomalies display more context-dependent effects, reducing conflict under moderate conditions but increasing tensions under extreme rainfall in mixed and flood-prone areas. We document transmission channels consistent with the opportunity cost mechanism — through lower agricultural productivity, reduced farm revenues, and labor reallocation away from off-farm activities — showing that climate-induced income shocks erode livelihood viability. By linking micro-level climatic stress to localized conflict outcomes, the paper highlights the moderating role of agrarian structure in shaping vulnerability to climate change and underscores the need for adaptation and social-protection policies tailored to specific livelihood systems.

Keywords: Climate change; Conflict; Livelihood systems; West Africa.

JEL codes: Q54; Q15; C33; D74; O13.

*The authors acknowledge the financial support of the Italian Ministry of University and Research (MUR), PRIN-2022 project 2022RSZW83 "Climate change, violent conflicts and welfare: A multi-scale investigation of causal pathways in different institutional contexts (CLIMATE-CONFLICTS)". The authors also gratefully thank Romina Cavatassi, Alessandra Garbero, Marco Letta, Erdgin Mane, Adriana Paolantonio and Philip Randolph for valuable feedback on earlier drafts of the paper and the 14th AIEAA Conference (Pisa, June 18–20, 2025), SITES X Annual Conference in Development Economics (Rome, September 15-16, 2025), SIE Annual Conference (Naples, October 23-25, 2025), and APPLICATE Workshop (Palermo, November 6-7, 2025) participants for their comments.

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1 Introduction

Climate shocks have increasingly been recognized as major covariate risks shaping economic instability and social unrest in low-income settings (Llerena Pinto et al., 2025; Carleton and Hsiang, 2016; Dell et al., 2012), especially in agriculture-dependent regions, posing growing threats to the viability of agrarian livelihoods (Lobell et al., 2011; Burke et al., 2009). By reducing crop yields and pasture availability, threatening food security, and displacing populations, these shocks intensify existing socio-economic vulnerabilities and may eventually increase the risk of conflict (Maystadt and Ecker, 2014; Hsiang et al., 2013). As climate change increases the frequency and intensity of weather shocks, the risk of social and economic instability is expected to grow (Burke et al., 2024). Yet, despite extensive evidence linking adverse climatic conditions to conflict incidence (Vanden Eynde and Vargas, 2025), the literature provides limited insight into the underlying microeconomic mechanisms through which weather anomalies affect household behavior, local competition over resources, and, ultimately, the likelihood of conflict. In particular, the literature has paid little attention to how livelihood composition and spatial heterogeneity in production systems condition the local response to climatic shocks (Eberle et al., 2025; McGuirk and Nunn, 2025). This paper addresses this gap by integrating household-level data with spatially matched measures of climatic shocks and conflict events to estimate how droughts and excess rainfall propagate through income, employment, and resource-allocation channels across distinct livelihood systems in West Africa. Indeed, West Africa is very suitable to analyze the complex interlinkages between climatic shocks and conflicts, being characterized by diverse agroecological zones, highly climate-sensitive agricultural systems and high sociopolitical instability (IPCC, 2022).

Over the years, a growing body of literature has sought to disentangle the climate-conflict nexus, identifying two main pathways (Romano et al., 2025): (i) climate shocks exacerbate competition over natural resources (Eberle et al., 2025; McGuirk and Nunn, 2025) and (ii) climate-induced declines in agricultural productivity – such as crop failures or livestock losses – that can reduce household incomes and lower the opportunity cost of engaging in violence (Harari and La Ferrara, 2018; Buhaug et al., 2015; Wischnath and Buhaug, 2014). This study focuses on the second pathway. The setting of the analysis includes Burkina Faso, Niger, Nigeria, and Côte d'Ivoire and focuses on the period 2010–2023, during which the number of conflict events surged significantly (see Appendix A, Figure A.1). To identify climate shocks during the agricultural season, we employ the Standardized Precipitation Evapotranspiration Index (SPEI, cf. Vicente-Serrano et al., 2010), spatially matched with conflict data from the Armed Conflict Location & Event Data Project (ACLED, cf. Raleigh et al., 2010) during the post-harvest year, as well as household-level panel data from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA, cf. LSMS-ISA, 2019) and the *Enquête Harmonisée sur les Conditions de Vie des Ménages* (EHCVM, cf. EHCVM, 2022). Using fixed-effects OLS regressions, the study first assesses the relationship between climatic anomalies – both dry and wet events – and conflict incidence.[1] Furthermore, to capture heterogeneity in the climate–conflict relationship, we interact climate anomalies with livelihood structures defined at both the household and local level. This design allows the study to identify how the co-existence of similar/different household and community-level economic structures moderates exposure and adaptive capacity under climatic stress.

Our findings show a clear pattern emerging across the West African cases: drought is the dominant climate-related driver of conflict. By contrast, in arid and semi-arid settings such as Niger, Burkina Faso, and northern Nigeria, wet conditions are generally associated with lower conflict risk. Disaggregating by household livelihood type and by the predominant livelihood system in the surrounding area, we find a marked heterogeneity in the results. As for drought events, in Burkina Faso and Côte d'Ivoire, the coexistence of different livelihood systems (i.e., mixed-livelihoods) is positively associated with conflict, whereas in Nigeria, pastoral-dominated areas are more likely to experience conflict regardless of household livelihood type, and in Niger the pattern is primarily shaped by farm-dominated systems.

Overall, climate shocks operate primarily through income, agricultural productivity, and labor-market channels. Possible pathways explaining the main results in the case of dry anomalies are: large crop-yield losses (Burkina Faso and Niger) and revenue declines (Nigeria and Burkina Faso), fewer agricultural workdays (Burkina Faso and Niger), a shift away from paid and off-farm work toward unpaid farm labor and increased credit uptake (for some groups in Côte d'Ivoire). Wet conditions exhibit a more

[1] We consider as conflict events only violence against civilians, battles, riots and protests that are of primary interest for our analysis. In fact, these conflict events – i.e, mostly non-state violence episodes – appear to be particularly sensitive to climatic shocks (cf. section 3.1 for more details).

pronounced heterogeneity. In Nigeria, floods depress yields and – amid constrained mobility – heighten violence among agropastoral households in pastoral-dominated areas; likewise, mixed-livelihood areas show increased conflict, plausibly via resource competition and flood severity. In Niger, agropastoral and pastoral households in mixed-livelihood contexts experience declines in crop revenues, agricultural workdays, and off-farm jobs, channeling into higher protest activity; by contrast, farming households in farm–dominated areas benefit from expanded off-farm options, with lower violence. In Burkina Faso, in mixed-livelihood settings, wet anomalies are associated with reduced conflict risk across all household types; moderate wetness raises revenues for farming households and expands off-farm opportunities for agropastoral households. No statistically significant effects are detected in Côte d'Ivoire. Overall, flood impacts operate mainly through yield losses, reallocation between farm/off-farm work (also likely due to reduced mobility), and resource competition. All these results are robust to standard-error corrections for spatial correlation and survive several robustness checks.

The observed patterns are consistent with the opportunity cost theory (Burke et al., 2015; Hsiang et al., 2013), which posits that climate-induced economic stress undermines the viability of livelihoods, thus increasing incentives to engage in violence. Moreover, our findings reveal the mediating role of the agrifood sector in the climate–conflict nexus, underscoring the need for mitigation and adaptation strategies tailored to the diversity of local livelihood systems. Strengthening the ability of the most exposed households to cope with climate-related economic pressures is essential to reducing the risk of conflict. As climate change intensifies environmental stress and places growing pressure on rural communities, advancing our understanding of the complex, context-specific linkages between climatic shocks, agrarian systems, and violence becomes key to developing effective, locally grounded responses in fragile settings.

The study addresses several key research gaps in the climate-conflict literature. First, although climate is increasingly recognized as a "threat multiplier" (Koubi, 2019), there is limited empirical evidence on how specific climate anomalies interact with distinct household and local livelihood systems to influence conflict. Second, while the existing literature predominantly focuses on drought, it often overlooks the role of wet anomalies and the potential for non-linear effects (Cappelli et al., 2023). We specifically categorize SPEI values to highlight the different roles of wet anomalies and dry climate shocks (moderate to extreme). Third, differently from many previous studies relying on national or regional averages (Romano et al., 2025; Buhaug et al., 2015), our study adopts a more granular analytical approach by integrating household panel data with spatially disaggregated climate and conflict information, enabling a more detailed assessment of heterogeneous patterns, in line with more recent literature (Eberle et al., 2025; McGuirk and Nunn, 2025). Moreover, by disaggregating conflicts into violent (e.g., riots, battles, violence against civilians) and non-violent (e.g., protests) events, we provide a more nuanced understanding of localized unrest. Fourth, the literature usually relies on ancestral livelihood types (Eberle et al., 2025; McGuirk and Nunn, 2025) to assess how local livelihood systems shape localized conflict dynamics. Instead, this paper leverages spatial variation in current livelihood systems by incorporating indicators that classify both household-level livelihood types and the dominant systems within surrounding areas. Fifth, much of the literature emphasizes the "resource competition" pathway – conflict arising during or at the end of the growing season as a result of drought-induced migration, farmer–herder clashes, or land disputes. In contrast, this study shifts the focus to the post-harvest period, examining the relatively underexplored literature on economic strain to livelihood – i.e., the economic hardship resulting from the climate-induced decrease in agricultural yields and revenues – as an incentive to join the conflict (Harari and La Ferrara, 2018), and how the effects of climatic shocks evolve over time. Finally, by focusing on West Africa – a region highly exposed to climate risks yet underrepresented in empirical research – this study responds to growing calls in the literature to expand geographic scope and improve contextual understanding (Romano et al., 2025).

The remainder of this paper is organized as follows. Section 2 reviews the most relevant literature and provides the contextual background for the countries under study. Section 3 presents the data sources and outlines the empirical strategy. Section 4 discusses the main results, while robustness checks are presented in Section 5. Section 6 explores the underlying mechanisms. Section 7 concludes.

2 Background

2.1 Literature Review

A large and fast-growing body of empirical research has investigated the link between climatic anomalies and conflict risk, often finding a positive association between deviations in temperature or precipitation and violence (Buhaug et al., 2023; Koubi, 2019; Burke et al., 2015; Hsiang et al., 2013). Droughts and floods can be viewed as exogenous economic shocks. Within this framework, the impact of such shocks on conflict has typically been interpreted through two main theoretical mechanisms (Collier and Hoeffler, 2004). On the one hand, the *opportunity cost* effect suggests that economic downturns reduce the relative attractiveness of legal employment compared to rebellion, thereby increasing the likelihood of engaging in violence (Burke et al., 2015; Chassang and Miquel, 2009). The resulting economic hardship can heighten the risk of conflict, as individuals facing financial distress may become more susceptible to recruitment by rebel groups or involvement in violent actions (Burke et al., 2009). On the other hand, the *rapacity* effect posits that diminished economic returns reduce the value of assets available for appropriation, thus lowering the incentives for conflict, and vice versa (i.e. the higher the value of appropriable assets, the higher the risk of conflict). This raises the broader issue of whether the dominant mechanism is one of grievance and opportunity cost or of greed and rapacity – an issue the literature continues to debate. The net effect of these opposing forces depends on the nature of the sector affected – particularly whether it is labor- or capital-intensive (Eberle et al., 2025). In contexts such as Sub-Saharan Africa, where agriculture is predominantly labor-intensive, the opportunity cost mechanism is expected to prevail (Harari and La Ferrara, 2018; Jun, 2017; Wischnath and Buhaug, 2014; Dal Bo and Dal Bo, 2011), implying that adverse agricultural shocks are more likely to fuel conflict.

Much of the literature analyzing the relationship between climate shocks and conflict is characterized by reduced-form estimations that document statistical associations without clarifying the mechanisms at play (Burke et al., 2024; Hsiang et al., 2013). Meta-analytical work confirms a general positive relationship between climate anomalies and conflict risk. Romano et al. (2025) report an average 1.52% increase in conflict probability per one standard deviation change in climate variables, slightly lower than earlier estimates (Burke et al., 2024), though the magnitude and direction of effects vary by context. Frequently, studies focus on the immediate effects of climate anomalies on conflict onset (Kim and Garcia, 2023), while others examine specific intermediate mechanisms (Pacillo et al., 2022; Petrova, 2021). The result is a fragmented literature, with limited integration across the multiple pathways through which climate shocks might escalate conflict.

The agrifood system has increasingly been identified as a central mediator in the climate-conflict nexus (Romano et al., 2025). Climate shocks influence a range of decisions that bear on conflict dynamics by affecting food availability, market access, labor allocation, and income levels. In agrarian societies, climate-induced resource scarcity – particularly water and arable land – can intensify communal tensions and contribute to outbreaks of violence. Maystadt and Ecker (2014) demonstrate that agricultural shocks translate into conflict, particularly when economic alternatives are limited, while Vesco et al. (2021) highlight the role of food insecurity in fostering unrest. Furthermore, climate-induced market volatility can intensify grievances, particularly in contexts of food price inflation (Busby, 2018; Raleigh et al., 2015), and a weak institutional setup can exacerbate the effect (Ateba Boyomo et al., 2023; Helman et al., 2020).[2] Eberle et al. (2025) show that a localized 1°C temperature increase raises conflict probability by 54% in areas where herders and farmers compete over ecological boundaries. In Southern Ethiopia, conflicts often arise where loosely defined boundaries separate different livestock-raising ethnic groups, as herders are forced to migrate into contested areas during periods of drought (i.e., scarcity of grazing resources), increasing the risk of violence (Sakketa et al., 2025). McGuirk and Nunn (2025) demonstrate how rainfall scarcity in pastoralist homelands leads to earlier migration and increased conflict with sedentary farmers, highlighting the importance of cross-border spillovers.

The relationship between climate change and conflict is shaped by local social cohesion and institutional capacity. Societies with strong social ties and effective dispute resolution mechanisms are better able to absorb shocks and prevent escalation (Iyigun et al., 2017). In contrast, where ethnic or socioeconomic divisions are pronounced, such shocks can deepen existing grievances and trigger violence. Cappelli et al. (2024, 2023) argue that the climate-induced economic disruptions interact with existing structural vulnera-

[2]On the other hand, climatic shocks and the resulting economic strains may erode state capacity and weaken governance structures, creating institutional vacuums that armed groups can exploit, thereby heightening the risk of conflict (Iyigun et al., 2017).

bilities – such as weak institutions or political marginalization – to heighten the risk of conflict. Song et al. (2024) and Moscona et al. (2020) emphasize how political marginalization, ethnic fragmentation, and governance structures shape how communities respond to climate-related stress. Benjaminsen et al. (2012) and Munala et al. (2023) add that corruption, rent-seeking behavior and gender inequalities can further deepen vulnerability. The interaction between climatic shock and pre-existing social cleavages may thus turn latent grievances into open conflict (Hsiang and Burke, 2014). These structural characteristics condition both exposure and response, making it clear that climate-induced violence is not an automatic outcome but is mediated by local institutions, social configurations, and livelihood systems (Livorno and Tiberti, 2026).

The type and intensity of weather events also matter. Koubi (2019) emphasizes the need to differentiate between fast-onset shocks – such as floods – and slow-onset environmental degradation – such as drought and desertification – as their economic impact and their effects on social stability can differ significantly. The empirical literature shows that droughts are more consistently associated with violence than wet anomalies, although floods and extreme rainfall can also act as conflict triggers – or, in some cases, suppressors – depending on the context (Cappelli et al., 2023; Harari and La Ferrara, 2018). For instance, flood-induced displacement may exacerbate already existing conflicts (Ghimire et al., 2015).[3] Furthermore, floods may heighten tensions through economic losses, but they can also reduce violence by limiting mobility and disrupting coordination (Harari and La Ferrara, 2018). For this reason, we distinguish between abnormally dry and wet conditions, qualifying both of them as moderate to extreme to capture not only exceptional events.

2.2 Study Setting

In recent decades, the West African region has experienced increasing climatic variability, characterized by higher average temperatures, rainfall shortages, more erratic rainy seasons, longer dry seasons, and dry spells alternating with heavy rains and floods (Masih et al., 2014). In fact, West Africa has been identified as one of the global hotspots where climate change is already eroding livelihoods and intensifying competition over natural resources (IPCC, 2022), with severe implications for crop yields, pasture availabil-

[3] Although the current evidence about climate shocks is inconclusive, with some reporting that climate-induced migration does not influence conflict (Thalheimer et al., 2023).

ity, and access to water resources (WMO, 2022). These changes have rendered farming more unpredictable and less productive, posing serious threats to populations due to the depletion of natural resources and food and water shortages (Tefera et al., 2025; Gosset et al., 2023).

This study examines the climate-conflict nexus across four West African countries selected for their varied yet interlinked climatic, environmental, and socio-economic characteristics. Burkina Faso and Niger are landlocked Sahelian nations with predominantly arid and semi-arid climates, where agropastoralism and pastoralism are the dominant livelihood systems (UNOWAS, 2018). In contrast, Nigeria and Côte d'Ivoire are coastal countries predominantly characterized by tropical savannah and humid climates (see Figure A.2 in Appendix A). Nevertheless, significant agroecological and climatic variability exists within each country, such as pronounced aridity in Northern Nigeria.

These four countries are highly exposed to climate-induced environmental stress, contributing to climate-induced conflicts (Koren and Schon, 2023; Okafor et al., 2023; Brottem, 2016). Additionally, the population's strong reliance on rain-fed agriculture and natural resource-based livelihoods heightens their sensitivity to growing-season droughts and other climatic shocks (Sultan and Gaetani, 2016; Sylla et al., 2016). Droughts are a primary source of income loss for smallholder farmers, with immediate negative impacts on crop yields, labor, health and food security (Dessy et al., 2025; Dinkelman, 2017). Moreover, floods and storms have become increasingly frequent and intense, amplifying vulnerability and compounding the risks associated with climate variability (Mahmood, 2025; Umar and Gray, 2023). Beyond the escalating agricultural risks induced by climate change, these countries are exposed to a compounded vulnerability stemming from the growing incidence of conflict over time (see Appendix A, Figure A.1). A discussion of the climate and political features and challenges in the four countries is available in the online Appendix B.

3 Data and Empirical Strategy

This section describes the data used in the analysis,[4] the data preparation process, and the empirical strategy adopted in the study.

[4]Descriptive statistics for all variables used in the analysis are reported by household type and grid type in Appendix A, Tables A.2 to A.8

3.1 Conflict data

Conflict data are sourced from ACLED,[5] that offers detailed and disaggregated information on political violence and protest events without applying a minimum fatality threshold (Raleigh et al., 2010). This characteristic makes ACLED particularly well-suited for examining localized, low-intensity conflicts, which are central to this analysis, that focuses on socially and territorially vulnerable settings (Buhaug et al., 2023). ACLED's emphasis on intra-state violence, particularly non-state conflict, aligns further with evidence suggesting that these forms of violence are especially sensitive to climatic variability (Gleditsch and Nordås, 2014).

Conflict variables. We restrict the conflict typology to four categories particularly relevant to our context and that allow for the exploration of localized dynamics: protests, riots, violence against civilians, and battles.[6] Each category captures distinct forms of conflict intensity: protests involve non-violent demonstrations over grievances often related to economic hardship, land use disputes, or governmental policy; riots escalate to violent collective action, frequently tied to food price spikes or access to basic services, involving physical violence and property damage and reflecting heightened social tensions; violence against civilians encompasses targeted attacks on non-combatant individuals by state or non-state actors, with the definition including abductions, killings, and other forms of coercive violence aimed at intimidating or punishing the population; and lastly, battles capture armed clashes between organized groups such as military forces, rebel groups, or militias, typically occurring in areas of contested control. As an outcome variable, we use a count measure representing the number of conflict events to capture the intensity of exposure; additionally, we define a binary indicator to denote the presence or absence of at least one conflict event, thus enabling analysis along both the extensive and the intensive margins (Eberle et al., 2025).

Data preparation. Conflict events are spatially assigned to the households within a 27.5 km radius of each Enumeration Area (EA), as their geographic coordinates are collected at the EA level. This buffer size, which approximates the size of a 0.5-degree resolution

[5] The dataset is publicly available at ,

[6] Focusing on these conflict types resontaes previous research linking climatic shocks and conflict (McGuirk and Nunn, 2025; Eberle et al., 2025; Harari and La Ferrara, 2018).

climate grid cell (McGuirk and Nunn, 2025; Eberle et al., 2025), is empirically grounded in prior studies on localized conflict exposure (Bloem et al., 2025; Del Prete et al., 2023) that use buffer zones from 10 to 50 kilometers to measure localized conflict exposure. While any threshold is inherently arbitrary, the selected radius is particularly appropriate as it accounts for potential spatial uncertainty in both conflict events and household geolocation, while also reflecting a plausible distance within which conflict events may exert direct or indirect socio-economic impacts on rural communities and encompass potential recruitment zones.

The decision to construct a conflict grid around the location of each EA enables us to exploit the spatial heterogeneity in EA positions. While climatic shocks may affect large regions (in our case, the SPEI grid of approximately 55x55 km), our objective is to focus on localized conflicts, that is, those occurring in close proximity to the households. However, defining the conflict grid too narrowly would be problematic for two main reasons. First, the geographic coordinates of both the EAs and the conflict events are subject to measurement error. Second, overly restrictive spatial boundaries could lead to the omission of relevant nearby events. Therefore, the selected radius provides a reasonable balance between spatial accuracy and representativeness. An alternative approach would have been to align the conflict variable directly with the SPEI grid, thereby analyzing at the gridcell level (Eberle et al., 2025; McGuirk and Nunn, 2025; Harari and La Ferrara, 2018). However, we aim to capture the heterogeneity arising from the diverse geolocations of individual households. Therefore, our analysis is conducted at individual household level.[7]

Conflict events are aggregated over a 12-month period following the end of the harvest season,[8] in accordance with literature emphasizing the delayed effects of climatic

[7]For completeness, we also perform a robustness check aligning the conflict and SPEI grids, which yields qualitatively and quantitatively similar results. Results are discussed in Section 5.

[8]In Nigeria, we have a clear distinction between the post-planting and post-harvest phases, as this separation is embedded in the survey design. In contrast, the EHCVM surveys carried out in Burkina Faso, Côte d'Ivoire and Niger are primarily designed to monitor consumption, so households are not explicitly interviewed within a dedicated post-harvest window. Instead, interviews typically start at the beginning of the dry season (October) and continue throughout the conclusion of the harvest period, with households reporting on their agricultural activities during the recently completed rainy season. A second round of interviews takes place, on average, between April and July of the following year, still referring to the same agricultural season, which is also the most recent. To mitigate endogeneity and reverse causality concerns in the livelihood definition, conflict events in the EHCVM sample are considered from the end of the interview period onward and cover the following year, which reasonably aligns with the entire post-harvest period. As an additional robustness check, we align the conflict event window across the two interview rounds.

anomalies on conflict dynamics through agricultural shocks (Busby, 2018; Harari and La Ferrara, 2018; von Uexkull et al., 2016; Burke et al., 2015), and consistently with the opportunity cost theory of engaging in conflict. This temporal specification reflects the hypothesized mechanism by which climate-induced livelihood disruptions do not immediately affect conflict. Instead, the effects may unfold over time, mediated by agricultural cycles: climatic anomalies during the growing season increase the risk of conflict, which tends to materialize after the harvest, when economic strain hits the household. To address the prevalence of zero values and the skewed distribution of conflict event counts, we apply the inverse hyperbolic sine (IHS) transformation to the count variable that improves the regression estimates in datasets with many small or zero observations by retaining zero values while approximating a log transformation for larger values (Bellemare and Wichman, 2020).

3.2 Climate data

In line with previous studies (De Juan and Hänze, 2021; Harari and La Ferrara, 2018), our climate indicator is the Standardized Precipitation and Evapotranspiration Index (SPEI) derived from the SPEI Crop Drought Monitor,[9] a global drought monitoring system based on the ERA5 reanalysis dataset,[10] which is the most recent SPEI dataset to date (Vicente-Serrano et al., 2023; Hersbach et al., 2020). This index is particularly suitable to detect agricultural drought, which occurs when soil moisture is insufficient to offset evapotranspiration losses, adversely affecting both crops and livestock (Xing et al., 2020; Yihdego et al., 2019). While SPEI is primarily used to detect drought, it has also been applied as a proxy for flood risk – e.g., Shen et al. (2025); Ansari and Grossi (2021).[11]

Climate variable. The SPEI is calculated at a spatial resolution of 0.5° × 0.5° and at a weekly temporal resolution, covering a global scale and extending from 1979 to the

[9]The dataset is publicly available at: `https://global-drought-crops.csic.es`.

[10]Reanalysis data help address the challenges associated with the sparse distribution of weather stations across remote regions. Generating high-resolution climate data in such contexts typically relies on substantial interpolation, which can introduce artificial spatial correlations in weather shocks and potentially bias the estimates. Moreover, the availability of gauge data may itself be endogenous to conflict dynamics, further complicating the analysis (Harari and La Ferrara, 2018).

[11]However, "wet and dry events" in SPEI do not directly correspond to observed floods or droughts. At short time scales (1–3 months), SPEI > 1.5 often signals excess soil moisture, increasing flood likelihood if followed by heavy rainfall. High SPEI values in prior months frequently precede major floods, highlighting the role of soil saturation. Bischiniotis et al. (2018) report that 70% of floods were preceded by positive SPEI1, 65% by positive SPEI3, and 57% by positive SPEI6. Flood risk is 2.5 times higher when SPEI3 > 1.5 and rises 6.5 times when SPEI0 exceeds 2.

present. It is a comprehensive measure of climate variability, as it incorporates both precipitation (water supply) and potential evapotranspiration (atmospheric water demand). Unlike rainfall or temperature alone, SPEI provides a more comprehensive assessment of drought conditions, soil moisture dynamics, and water stress. Its standardized nature allows for spatial and temporal comparisons (Vicente-Serrano et al., 2010). We use October 15th SPEI at a 6-month timescale, which captures climate anomalies during the May–October growing season for rainfed agriculture in West Africa.[12] This period aligns with the key rainfed crop growth season, as over 90% of plots in our pooled sample rely solely on rainfall (INSD, 2022; NBS, 2019). As the index is measured during the agricultural growing season, it aims to isolate the effect within the agricultural sector.

Data preparation. To address non-linear effects of climatic variability, we transform the continuous SPEI-6 into a categorical variable with three classes (Ayugi et al., 2020; McKee et al., 1993):

- **0** = Normal conditions ($-1.00 < \text{SPEI6} < 1.00$)
- **1** = Moderate to extreme wet conditions ($\text{SPEI6} \geqslant 1.00$)
- **2** = Moderate to extreme dry conditions ($\text{SPEI6} \leqslant -1.00$)

We chose to maintain the ±1 standard deviation threshold to capture as much spatial and temporal variability as possible, allowing us to detect any climate deviations. These anomalies represent deviations from the long-term average and are thus considered abnormal. We adopt a relatively low SPEI threshold to capture moderate conditions, which, though less severe, can still impact livelihoods, especially in contexts of recurrent climate-related strain. Higher cutoffs (e.g., 1.5 or 2 SD) risk overlooking these relevant events and would not allow enough variability in our data/years. Leveraging GPS coordinates, each EA is linked to the centroid of the nearest corresponding SPEI grid cell. The distribution of SPEI is shown in Figures A.3 and A.4 in Appendix A.

3.3 Socioeconomic Data

This study employs georeferenced micro-level panel survey data, with the household serving as the primary unit of analysis. For Nigeria, the analysis is based on four waves

[12] This has been checked according to the MIRCA2000 crop calendar (Portmann et al., 2010). Though quite old, the MIRCA2000 is still widely used as it is considered broadly accurate (Harari and La Ferrara, 2018).

(2010–2019) of the General Household Survey (GHS), which is part of the World Bank's Living Standard Measurement Study Integrated Survey on Agriculture (LSMS-ISA) program. For Niger, Burkina Faso, and Côte d'Ivoire we rely on two waves (2018–2022) of the *Enquête Harmonisée sur les Conditions de Vie des Ménages* (EHCVM). Both surveys are nationally representative household survey providing panel datasets. Enumeration Areas (EAs) serve as the primary sampling units, with GPS coordinates[13] enabling spatial matching with weather and conflict data. To ensure cross-country comparability, household surveys have been harmonized with respect to variable selection and coding. Designed with a similar methodology, the surveys adopt a two-stage stratified cluster sampling approach, using EAs as primary sampling units and include two seasonal rounds per wave to capture household production and consumption variation. Strata are defined by the combination of region and settlement type (urban/rural). In the first stage, clusters (primary sampling units) were selected with probability proportional to the number of households. In the second stage, a fixed number of households – 12 for EHCVM and 10 for the GHS – were randomly selected within each cluster with equal probability. Migrant households are followed across waves, no matter if within or outside the EA in the case of Nigeria, while in the other countries this was done only if they moved within the original EA (Table 1).[14]

Sample restriction. Given the study's focus on climate impacts on agricultural livelihoods, our sample is restricted to households involved in farming, agropastoralism, or pastoralism. Households solely engaged in non-agricultural activities (e.g., commerce, wage labor) are excluded.[15] This approach reflects evidence that agriculturally dependent households are more directly affected by climate variability and more exposed to the climate–conflict nexus (Burke et al., 2024). Still, these households may have an off-farm income source that contributes more or less significantly to their total income. Only households surveyed in at least two waves are retained, thereby allowing for within-household variation to be exploited. This restriction does not mean we automatically

[13]While GPS coordinates do not correspond to exact locations due to confidentiality requirements, they provide a reliable approximation of the geographic position of the EAs.

[14]A detailed description of the survey design and datasets per each country is reported in C.

[15]To determine whether a household engages in agricultural activities, we relied on the agricultural modules of each survey. Therefore, for a household to be included in our sample, it must appear in the agricultural module in at least two consecutive waves (either as a farmer, a pastoralist, or both). If a household is only off-farm, it is excluded. Likewise, if a household is an agricultural household in only one wave and then permanently becomes off-farm, it is excluded.

exclude households that did not harvest any crops or abandoned their fields to temporarily engage in off-farm activities in response to the climatic shock. These households are still retained as long as they are included in the agricultural questionnaire. Moreover, because the survey waves are spaced several years apart, sample selection cannot be affected by households dropping out in later waves due to a climatic shock that occurred years earlier. This is also consistent with our view of climate-induced economic downturns as inherently temporary.

Following the sample restrictions, the final dataset includes (Table A.10 of Appendix A) 2,129 households (4,258 household-by-wave observations) in Burkina Faso, implying a reduction of 1,098 households from the original panel (equal to 34%); 4,390 households (8,780 household-wave observations) in Côte d'Ivoire, implying a reduction of 4,464 households from the originl complete panel sample (equal to 50.4%); 3,301 households (6,602 household-wave observations) in Niger, implying a reduction of 1,288 households from the original panel (equal to 28.1%); and 3,327 distinct households (9,859 household-wave observations) in Nigeria, implying a reduction of 1,649 households from the original panel (equal to 33.15%).[16]

Variable definition. The crop-growing season analyzed corresponds to the agricultural cycle immediately preceding the survey, specifically the period between the post-planting and post-harvest visits for Nigeria, as respondents report on the most recent season. Importantly, agricultural households constitute the majority of the sample in all four countries. Agropastoral households are more common in arid contexts like Niger and Burkina Faso, while farming households dominate in more humid, crop-suitable regions such as Nigeria and Côte d'Ivoire.

Specifically, each household is classified as:

1. "*Agropastoral*" if at least one household member cultivated a plot and at least one was engaged in pastoral activities during the previous 12 months;

2. "*Farming*" if engaged in crop production and not in livestock herding;

[16]The fixed effect estimator we use in the analysis automatically drops singleton observations – i.e., those that belong to a fixed effect group with only one observation – because they do not contribute to within-group variation and can bias standard errors if retained. Therefore, observations for Nigeria drop to 9,816 household-wave.

3. "*Pastoral*" if owning herding-reliant animals (e.g., sheep, goats, cattle, camels), excluding non-herding species like pigs, as in McGuirk and Nunn (2025), and none of the household members is engaged in farming activities.

This three-way classification enables a more refined analysis of how distinct agrarian livelihood systems are exposed to and affected by climate shocks, surpassing traditional binary distinctions in the literature between farmers and herders.

Key variables are constructed as follows:

1. *Livelihood variables*, defined at the household level, as a categorical variable for household type, classifying households as agropastoral, farming and pastoral, and at the grid-cell level, as categorical variable according to the prevalent livelihood (more frequent in terms of number of households) in a gridcell, distinguishing between mixed livelihood areas,[17] farmer-dominated areas and pastoral-dominated areas.

   The reference grid cell used to identify the grid type coincides with the one employed for the calculation of the SPEI, thus having a spatial resolution of 0.5 degrees. Although the dependent variable is defined over a grid with a 27.5 km radius centered on the coordinates of each EA, we preferred to define the grid type using the broader 0.5° grid in order to avoid overlaps between EA-based grids. This approach ensures a unique and consistent classification of the grid type, independent of the specific EA to which a household belongs. Conversely, if we had defined the grid type based on the predominant livelihood within each EA, we may not have captured the true livelihood predominance in the surrounding geographic area. This is because neighboring EAs might have different livelihood compositions, and focusing only on the EA-specific information could lead to misclassification when another, more dominant livelihood type lies just outside its boundary.[18] Moreover, it is reasonable to assume that the predominant livelihood in a given area does not

[17] Except for Côte d'Ivoire, where the first and second grid type categories are reversed due to the overwhelming prevalence of farming-dominated cells, which in some cases would make it impossible to estimate the effect if the reference category were mixed livelihood cells.

[18] We also verified that in urban areas EAs are located closer together due to survey representativeness requirements, while in rural areas they are more spaced out. Nevertheless, there can still be a significant overlap between the conflict grids identified for different EAs even in rural areas. Therefore, attributing a predominant livelihood type to a grid defined solely on the basis of EA boundaries could result in arbitrary or non-unique classifications. The results of this robustness assessment are available upon request.

depend on the arbitrary boundaries of the EA, but rather on the historical and current climatic conditions prevailing in that geographical context, proxied by the SPEI in our analysis.

This two-level classification, at household and gridcell level, enables us to assess a dual moderating effect: *(i)* whether households with a given personal livelihood strategy and *(ii)* located in a given grid cell dominated by a specific livelihood type – which may coincide or differ from the household's own livelihood – are differentially exposed to conflict-prone environments following climatic shocks. Both variables are time-varying across waves. Concerning the grid type variable, Category 1, labeled "Mixed" cells, is assigned to the grid type variable under three alternative conditions: (*i*) when only agropastoral households exceed a predetermined threshold (40%, 50%, or 60%)[19] of total number of households in the grid; (*ii*) when two livelihood categories exceed the threshold; or (*iii*) when no single category exceeds the threshold. Category 2, labeled "Farm-dominated" cells, is assigned when only farming households exceed the threshold. Category 3, labeled "Pastoral-dominated" cells, is assigned when only pure pastoralist households exceed the threshold. The decision to classify a grid cell as "Mixed" either when agropastoral is the only group above the threshold, or when multiple livelihood types coexist without a clear prevalence, draws on the definition of mixed settlement in Eberle et al. (2025), capturing areas where multiple livelihood strategies coexist, reflecting greater diversity and potential interaction. This classification acknowledges the unique role of agropastoralism, which integrates farming and herding, promoting resilience through reciprocal use of livestock and crop residues (Fernández-Rivera et al., 2004). However, overlapping strategies may intensify competition for scarce resources and spark tensions (Debela et al., 2019). Despite synergies, such as seasonal cooperation and input exchange between crop and livestock farming (Moritz, 2010), integrated systems still face barriers – e.g., weak land rights and institutional fragmentation – and are increasingly vulnerable to climate change (McGuirk and Nunn, 2025), exposing agropastoralists to compounded risks.

2. *Control Variables*, defined at the household level: household size, gender of the household head, annual consumption per capita as a proxy of household vulner-

[19]The standard threshold is 40%, while the 50% and 60% thresholds are used as a robustness check.

ability and at the EA level: average distance to the closest urban center or market.[20] These variables allow us to account for both socio-demographic composition, structural household characteristics and geographical positioning in the analysis of household exposure to climate shocks and conflict dynamics.

3. *Mechanism variables*, defined as:

   3.1 *Crop Yield*, as the value of crop output per GPS-measured plot area, where output is the product of quantity harvested and unit price in kg.[21] Household-level yields are averaged, adjusted using temporal and spatial price deflators, and transformed using the inverse hyperbolic sine to address skewness. Values are expressed in local currency. Having plot areas measured using GPS allows for a more accurate estimation of crop yield by reducing biases associated with self-reported plot sizes.[22]

   3.2 *On Farm Labor*, based on data availability, proxied by the occurrence of at least one hour of paid farm labor in the past 7 days by household members of working age (15 to 60 years old), measured at the individual level and aggregated to the household level as the percentage of household members who engaged in farm work for at least one hour during the past week. The same for unpaid farm work.[23] In EHCVM surveys, we need to restrict the sample to Round 1 for each wave (interviewed at the end of the harvest or shortly thereafter), as Round 2 interviews were conducted several months after the end of the growing season. As a result, reported work during the past seven days would not accurately capture the mechanisms we aim to analyze. This is why, at least for Burkina Faso and Niger, we supplement the data with the total num-

[20] Based on limited data availability, we use distance to the nearest city in Niger, Burkina Faso, and Côte d'Ivoire, and distance to the nearest market in Nigeria, assuming the two are broadly equivalent given that markets are typically located in cities.

[21] In Côte d'Ivoire, we are unable to confidently estimate crop yields, as severe and systematic data quality issues result in a high proportion of missing values and measurement errors, primarily in GPS-measured crop areas, crop prices, and the conversion factors used to translate non-standard units into kilograms. Therefore, this variable has not been used in the case of Côte d'Ivoire mechanism analysis.

[22] In Nigeria, the survey design incorporates a clear distinction between the post-planting and post-harvest phases. This is not the case for the EHCVM surveys, where interviews typically begin during the dry season, which still overlaps with the harvest and post-harvest periods. Around 90% of interviewed households in Burkina Faso and Niger report having already completed their harvests at the time of the interview, while in Côte d'Ivoire this share drops to around 50%. For those who have not yet completed the harvest, we use the available information on agricultural outcomes up to that point.

[23] Present only in EHCVM surveys.

ber of days worked on on-farm activities—including soil preparation, seeding, weeding, crop treatment and protection, harvesting, and threshing—by both household members and hired labor, specifically for agropastoral and farming households. In this case, there is no need to restrict the sample, as we can rely on both Round 1 and Round 2 for each wave. This is because the question refers retrospectively to the most recent agricultural season, making the data more reliable. Unfortunately, this information is not available for Côte d'Ivoire.

3.3 *Off Farm Labor*, as a binary indicator of individual engagement in off-farm wage employment, aggregated at the household level as the percentage of household members who engaged in off-farm work for at least one hour during the past week.[24] Here as well, in the EHCVM we restrict the sample to Round 1 only, for the reasons outlined in point 3.2.

3.4 *Crop Revenues*, as the self-reported revenues from that agricultural season, expressed in local currency units (LCU), adjusted by spatial and temporal price deflators, and transformed using the inverse hyperbolic sine.

3.4 Descriptive statistics

Detailed descriptive statistics for these variables are provided by country, wave and household type in Appendix A, Tables A.2 to A.8. To illustrate the approach we adopted, Appendix A also provides a descriptive visualization of the geographical distribution of our variables of interest by country and by wave (see Figures A.4 and A.5).

In Burkina Faso, 21.4% of households experienced moderately or extremely wet conditions during the 2018 rainy season, while in 2021, 83.6% faced dry anomalies (Table A.2). Agropastoral households were the majority in both waves (76.2% in Wave 1, 71.6% in Wave 2), followed by farming households and pastoralist households. Most observations fell in mixed cells (98.7% in Wave 1, 96.5% in Wave 2). Conflict events nearly

[24]The use of these variables as mechanisms presents both advantages and limitations. First, crop yields and crop revenues limit the analysis to households engaged in farming during the latest season, thereby excluding pure pastoralists. However, this can also enable more precise isolation of agricultural effects. Conversely, variables related to in-farm and off-farm work are not confined to the survey's agricultural modules. Yet, these variables refer to household labor behavior in the last seven days, which makes them less specific to the agricultural season. Nevertheless, since all households were surveyed during the post-harvest period, it is reasonable to assume some overlap with the relevant farming activities. In contexts where labor seasonality is critical, the timing of data collection can significantly influence the interpretation of these variables.

doubled from Wave 1 (7.33) to Wave 2 (15.48), with an overall weighted mean of 11.61 number of events per household.

In Côte d'Ivoire, 52.6% of households experienced wet events in 2018, while only 17.8% (2021) and 14.9% (2022) faced dry conditions. Pure farming households dominated (76% in Wave 1, 77.6% in Wave 2). Most were located in farm-dominated cells (96.5% in Wave 1, 93.2% in Wave 2). Conflict intensity declined from 1.67 to 0.71 (mean: 1.19).

In Niger, only 3.4% experienced wet events in 2018 and 3.9% in 2021; dry exposure increased from 0.4% to 58.6%. Agropastoralists were the largest group (66.9% in Wave 1, 64.3% in Wave 2), followed by farmers and pastoralists. Most lived in mixed cells (90.3% in Wave 1, 87.8% in Wave 2). Conflict rose from 0.99 to 3.01 (mean: 2).

In Nigeria, during Wave 1, 15.0% of households experienced wet conditions, while 1.6% faced dry events. The average number of conflict incidents during this wave was 3.10. In terms of livelihoods, households were composed of 12.9% agropastoralists, 56.5% farmers, and 30.6% pastoralists. The territorial distribution showed that 62.5% of the population lived in farm- dominated areas, 21.0% in pastoral-dominated zones, and 16.0% in mixed areas. In Wave 2, exposure to wet conditions increased substantially to 48.1%, while 9.0% of households faced dry events. The share of agropastoral households also grew, reaching 20.9%. Conflict incidents rose to an average of 9.48. In Wave 3, 35.7% of households were exposed to dry conditions, and the proportion of agropastoralists increased further to 33.9%. The average number of conflicts continued to rise, reaching 11.16. By Wave 4, 11.4% of households experienced wet conditions and 6.1% dry conditions. The share of agropastoralists climbed to 37.6%, while conflict incidents peaked at an average of 18.53. Overall, across the four waves, the average number of conflict incidents stood at 8.90.

Spatial patterns reveal that wet events in Burkina Faso occurred only in mixed cells, and in Côte d'Ivoire exclusively in farm-dominated ones. These two countries also show a moderate temporal variation within cells. In contrast, Nigeria and Niger exhibited greater spatial and temporal variation across climate, livelihood types, and grid composition.

3.5 Emprical strategy

We estimate a Linear Probability Model (LPM) using alternatively the inverse hyperbolic sine of the count-dependent variable and the binary outcome, using an OLS regression with fixed effects and following approaches used in recent literature (Eberle et al., 2025; McGuirk and Nunn, 2025).[25] All regressions include gridcell (SPEI) and year fixed effects to absorb unobserved heterogeneity at the spatial and temporal levels. Cell fixed effect capture time-invariant differences across grid cells, such as soil quality, elevation, vegetation type, long-term agroecological conditions, historical settlement patterns, and proximity to permanent natural features like rivers or mineral deposits and consequently this term control for all time-invariant structural drivers of conflict (McGuirk and Nunn, 2025; Moscona et al., 2020; Michalopoulos and Papaioannou, 2016; Besley and Reynal-Querol, 2014). Year fixed effects absorb temporal shocks and national-level events that could affect all grid cells simultaneously in a given year, such as macroeconomic shocks or country-wide policy changes.

Standard errors are clustered at the EA level, consistently with the survey design. In the robustness checks (see Section 5), we apply the arbitrary spatial clustering correction for standard errors (Conley, 1999), using the median distance between EAs per each country as distance cutoff and 10 years as lag cutoff – which is a reasonable period of time over which unobserved factors may persist and generate serial correlation in the error terms of the model – with Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors to deal with both spatial and temporal dependence between observational units.

For all estimations, starting from the panel weights provided by the respective household surveys, we adjusted them by the population size of each EA over time, in order to prevent the results from being driven solely by differences in the number of households across EAs. The survey weights are calculated at the EA level, equal for each household within the same EA and accounting for the panel structure, which helps mitigate potential bias due to attrition over survey waves and ensure representativeness.

[25] Regarding the interpretation of coefficients of interest, when dealing with *arcsinh*-linear models where the explanatory variable is a dummy, interpreting them as elasticities poses significant challenges. This issue is not unique to *arcsinh* transformations and also affects standard log-linear models (Giles, 1982; Kennedy, 1981; Halvorsen and Palmquist, 1980). In these cases, the derivative $\partial y/\partial d$ is undefined due to the discrete nature of the dummy variable. To address this, one can compute the percentage change in the dependent variable associated with a change in the dummy from 0 to 1 by applying the *sinh* transformation to the estimated *arcsinh* equation (Bellemare and Wichman, 2020). When y is large, the *arcsinh*-linear model yields interpretations approximately analogous to those of a conventional log-linear model, using the formula $\exp(\beta) - 1$. This gives the exact proportional effect of the dummy. This approximation allows researchers to interpret the coefficient as the approximate percentage change in the outcome due to the dummy variable. Coefficients of the LPM, where the dependent variable is binary, are interpreted as percentage changes by dividing them by the sample mean of the outcome and multiplying by 100 (Eberle et al., 2025).

Model 1. This model is a reduced-form regression of conflict incidence on the categorical climatic variable alone, with and without control variables:

$$\text{Conflict}^{i}_{g't} = \alpha + \beta\text{Climate}_{g''t-1} + \omega X_{it} + \phi_{g''} + \psi_t + \varepsilon_{it} \tag{1}$$

where $Conflict^{i}_{g't}$ denotes the conflict outcome for household i and that was measured at time t in g', the grid cell with a 27.5 km radius centered on EA coordinates. g'' is the grid cell with a 0.5-degree spatial resolution used to define the SPEI. t refers to the 12-month window year over which conflict incidence is measured, and $t-1$ to the most recently concluded growing season at the moment of the survey. ϕ''_g and ψ_t denote the grid cell and year fixed effects, respectively. $X_{ig't}$ is a set of time-varying control variables accounting for household socio-demographic and geographic characteristics at the EA-level where the household lives. We estimate Model 1 with and without this vector of controls for both specifications (i.e., count and binary dependent variable).

Model 2. In Model 2, we extend the analysis by introducing a triple interaction between the climate variable, the household level livelihood type (agropastoral, farming, or pastoral), and the dominant livelihood system at the gridcell level (mixed, farm-dominated, and pastoral-dominated). This specification allows us to identify context-specific heterogeneous effects, capturing how the local socio-ecological environment shapes household responses to climate shocks and how reliance on different livelihood strategies may be associated with differential conflict exposure and vulnerability. Based on the estimated coefficients, we compute conditional marginal effects to interpret these interactions and assess whether households are more likely to be exposed to localized tensions depending on both their individual livelihood strategy and the prevailing livelihood system in their area. The full specification of the second model is as follows:

$$\begin{aligned}
\text{Conflict}^{i}_{g't} = \alpha &+ \beta_1\text{Climate}_{g''t-1} + \beta_2\text{Climate}_{g''t-1} \times \text{HHtype}_{ig't} \\
&+ \beta_3\text{Climate}_{g''t-1} \times \text{GridType}_{g''t} \\
&+ \beta_4\text{Climate}_{g''t-1} \times \text{GridType}_{g''t} \times \text{HHtype}_{ig't} \\
&+ \beta_5\text{HHtype}_{ig't} \times \text{GridType}_{g''t} + \beta_6\text{HHtype}_{ig't} + \beta_7\text{GridType}_{g''t} \\
&+ \omega X_{it} + \phi''_g + \psi_t + \varepsilon_{it}
\end{aligned} \tag{2}$$

We leverage residual spatio-temporal variation in climate anomalies, net of gridcell and year fixed effects, to isolate their effect on conflict exposure. By measuring climate shocks during the growing season and conflict events after harvest, we ensure temporal ordering and mitigate reverse causality. Nevertheless, the time-varying nature of household and grid livelihood types introduces potential endogeneity, as these categories are not randomly assigned and may evolve in response to climate shocks or conflict. Indeed, households often adapt their strategies – e.g., shifting from pastoralism to agropastoralism – to manage risk, while grid-level classifications can change due to migration or displacement (Galwab et al., 2025; Ouédraogo et al., 2021). This adaptive behavior may bias estimates. Therefore, interaction terms with livelihood types are interpreted as reflecting heterogeneous vulnerability rather than causal impacts. Fixed effects help address persistent spatial heterogeneity, but time-varying unobservables remain a limitation. Empirical patterns should thus be understood as correlations shaped by local socio-ecological dynamics and adaptation processes.

4 Main results

4.1 Baseline Specification (Model 1)

The results of Model 1 are presented in Table 1. Per each country, Columns 1 and 2 report estimates using the number of conflict events as the dependent variable, with and without control variables, respectively. Columns 3 and 4 refer to a binary outcome indicating the occurrence of any conflict event, again with and without controls. Standard errors are clustered at the EA level. Columns 1 and 3 represent our preferred specifications. Disaggregated results by event type are provided in Appendix D, Table D.1.

Burkina Faso. In Burkina Faso (Table 1), dry conditions are associated with an increase in the likelihood of any conflict, which is statistically significant at 5% level, with estimated effects being about +16% relative to the sample mean (0.136/0.85, see Column 3). In contrast, wet conditions show a statistically significant negative association with conflict, reducing the probability and number of conflicts by approximately 14% (-0.118/0.85, see Column 3). The results are consistent also when using the number of conflicts as the dependent variable. Disaggregated analysis by event type (see Appendix

D, Table D.1) reveals that the positive association between drought and conflict is mainly driven by an increase in the probability that any protest occurs and an increase in the number of battles, while only violence against civilians decreases in terms of intensity under wet conditions.

These results are consistent across models with and without controls and highlight the asymmetric effect of climate shocks: while drought tends to exacerbate conflict, periods of abundant rainfall may instead contribute to a relative reduction in violent events. The spatial distribution of positive SPEI anomalies shows that in Burkina Faso the observations are left-skewed toward low positive SPEI values, with a maximum of 1.55 (see Figure A.3 in Appendix A). In this context, moderate rainfall can enhance crop productivity, thereby increasing the opportunity cost of engaging in conflict.[26]

Côte d'Ivoire. In Côte d'Ivoire, dry conditions are consistently associated with a statistically significant increase in the number of conflicts across all specifications (Table 1). Conversely, the effect of wet conditions is statistically insignificant in all specifications, indicating that rainfall abundance has a weak and unstable association with conflict incidence. These findings highlight the asymmetric impact of climate anomalies on conflict risk: droughts during the growing and rainy season substantially increase the likelihood of being in conflict-affected areas, while increased rainfall has noo significant effect. Disaggregating by event type (see Appendix D – Table D.1), drought increases the probability of events such as protests, violence against civilians and riots, whereas wet conditions are linked only to more protests.

Niger. In Niger (Table 1), dry conditions above one standard deviation are associated with a statistically significant increase in probability of conflict by +50% (0.213/0.43, see Column 3) relative to the sample mean. The results are consistent also when using the number of conflicts as the dependent variable. Unusually wet conditions also show a statistically significant positive effect on violence at the intensive margin. Particularly, drought increases the incidence of battles, protests, and violence against civilians, while wet conditions reduce riots but significantly increase protests (see Appendix D, Table D.1). Looking at the spatial distribution of SPEI values, approximately 70% of positive

[26]Conversely, excessive or poorly distributed precipitation may lead to adverse outcomes such as waterlogging, soil erosion, and disruptions to planting activities (Tefera et al., 2025).

SPEI events in Niger (i.e., 178 out of 252 posistive SPEI events) exceed +1.28, indicating that the distribution is right-skewed toward higher SPEI values (Figure A.3 in Appendix A), meaning that Niger experienced more extreme wet anomalies, which may not always yield agricultural benefits and in turn, fueling tensions.

Nigeria. In Nigeria, the probability of any conflict rises by 10% relative to the sample mean after a growing season drought (0.069/0.71, see Column 3), while the average effect of wet conditions is generally small in magnitude and statistically insignificant (Table 1). Furthermore, drought significantly raises the probability of battles (Appendix D, Table D.1). At the intensive margin, the relationship appears insignifucant in Nigeria, likely due to the country's high spatial heterogeneity in agroecological systems, socioeconomic structures, and institutional frameworks, which may dilute the aggregate climatic effects. Approximately 56% of positive SPEI events in Nigeria exceed +1.28 (i.e., more than 1.28 standard deviations above the long-term mean) (see Figure A.3. in Appendix A).

Overall, the results indicate a positive and statistically significant correlation between drought conditions (negative SPEI values) and conflict incidence across the West African countries under study. After the inclusion of household-level and geographic control variables, the positive correlation between drought and conflict remains robust, suggesting that climatic stress during the agricultural season plays a role in exacerbating local tensions, particularly in predominantly rainfed farming systems. This association is consistent with existing findings on the link between agricultural vulnerability and climate-induced conflict. In fact, the timing of SPEI measurement captured during the growing season reinforces the link between agroclimatic shocks and the agrifood sector (Harari and La Ferrara, 2018). In contrast to drought, the association of positive SPEI shocks with a conflict is more heterogenous – showing a reduction in Burkina Faso, no significant aggregate effect in Côte d'Ivoire and Nigeria, and an increase in Niger.

Indeed, the literature offers a nuanced view of positive SPEI effects. For instance, in The Gambia, positive SPEI values correlate with higher yields of key staples such as millet, sorghum, maize, and rice (Jabbi et al., 2021). Similarly, sorghum yields in Kenya are strongly linked to seasonal rainfall patterns (Philippon et al., 2016). In arid regions like the Sahel, increases in SPEI tend to produce greater yield benefits due to high baseline water stress (Jabbi et al., 2021). Precipitation increases have also modestly improved milk yields in some pastoral systems (Sagna et al., 2021). Broader evidence from the African region shows that positive SPEI values have been generally linked to lower conflict probability (Harari and La Ferrara, 2018). More specific eveidnce from the Sahel region reinforces this interpretation. Higher SPEI values during the growing season are associated with a 7.3 percentage-point reduction in conflict probability, supporting the hypothesis that improved agricultural conditions reduce violence, although spatial and institutional characteristics crucially moderate this relationship (Khan and Rodella, 2021). However, the distribution and timing of rainfall remain crucial: short-lived but intense precipitation can be detrimental, especially if poorly spread over the growing season (Mutsotso et al., 2018).

4.2 Heterogeneous Effects across Livelihood Groups (Model 2)

Model 2 aims at capturing heterogeneity in responses across different combinations of contextual and socioeconomic characteristics. For example, when climatic anomalies are interacted with household type and spatial classification, the estimated marginal effect reflects how the marginal outcome varies within each specific subgroup relative to the baseline scenario of normal climatic conditions. Table 2 reports the conditional marginal effect[27] of unusually dry and wet climatic conditions on the likelihood of being in more conflict-affected areas, based on a triple interaction between SPEI, household type, and dominant gridcell livelihood composition. For each country, results are presented using the 40% threshold (see Section 3) employed to classify the dominant livelihood type in each grid cell and margins are provided using our preferred specification (i.e., without controls and with Standard Errors clustered at EA level) for both outcomes, the counting variable (Column 1) and the binary variable (Column 2). Full regression tables for Model 2 are provided in Appendix D (Tables D.2-D.5), while in this Section we comment the marginal effects as they provide a more intuitive interpretation of the findings than the coefficients of the triple interaction.

[27] Conditional marginal effects estimate how changes in a specific explanatory variable affect the predicted outcome, while accounting for interactions between categorical factors. In the case of categorical variables, these effects represent the discrete change from a reference category, rather than a continuous slope (Wooldridge, 2010). By default, the results are computed using robust standard errors. The margins estimates reported in Table 2 reflect the marginal effects on the transformed dependent variable ($asinh(y)$) and are not directly interpretable as semi-elasticities or percentage changes in the original scale of y. Importantly, the interpretation of these effects depends on the underlying model: a statistically significant positive marginal effect indicates that the predicted outcome (number or probability of conflicts) increases, on average, when moving from the baseline level of the explanatory variable to the level of interest (such as abnormally dry or wet conditions), conditional on subgroup characteristics (Williams, 2012).

In addition to estimating conditional marginal effects, we test whether the impact of climate anomalies on conflict outcomes differs significantly across household and spatial groups.[28] For example, we can test whether the effect of a climatic shock for agropastoral households in farming-dominated areas differs significantly from that for agropastoral households in mixed areas. The null hypothesis is that the difference between these two group-specific effects is zero, and rejection of this null implies significant heterogeneity in the climate–conflict relationship across groups. The results of these tests are discussed in the text when interpreting the findings for each country and are available upon request.[29]

Burkina Faso. When disentangling by livelihood type and agrarian context, we observe that in Burkina Faso, drought (relative to normal conditions) is associated with an increased number and probability of conflict events, specifically among agropastoral households in mixed cells – by approximately 21% relative to the group's sample mean (0.81), significant at 5% level. It is worth noting, however, that this group also represents the largest share of the sample. In addition, areas dominated by farming livelihoods are especially prone to increased occurrences of riots in the aftermath of abnormally dry conditions and mixed cells to battles.[30] The overall picture suggests that resource scarcity during drought conditions may place significant strain on livelihood strategies.

Conversely, wet conditions are significantly associated with lower conflict intensity across all three livelihood categories, as indicated by a reduced number of conflict events (intensive margin). Abundant rainfall appears to partially ease tensions, likely due to improved resource availability. In particular, positive SPEI values may reduce conflict in certain contexts by mitigating resource competition and decreasing the likelihood of young people being recruited by armed groups (Khan and Rodella, 2021). The lack of significant effects on the extensive margin suggests that anomalous climatic conditions

[28] To do so, we rely on linear hypothesis testing, which allows for flexible post-estimation comparisons between any two combinations of interaction terms (Williams, 2012). This method is based on a test that evaluates whether the difference between two estimated coefficients is statistically different from zero. A statistically significant result would indicate that the climate–conflict relationship is not homogeneous across livelihood and spatial contexts, highlighting the importance of accounting for such heterogeneity in empirical models.

[29] It is important to note that merely inspecting the statistical significance of a three-way interaction term (namely, the regression tables in Appendix D) involving three categorical variables, each comprising three categories is not sufficient to fully understand the heterogeneity of the effects. This significance test merely indicates whether the interaction differs from the reference (baseline) category and does not provide information about differences between other combinations of groups.

[30] Results of Model 2 by event type are available upon request.

primarily influence conflict intensity (reflected in the number of events) rather than the likelihood of conflict occurrence.

Looking at the spatial distribution of affected households, in Burkina Faso, pastoralists located in mixed cells are scattered across the country, while agropastoral households affected by drought are more concentrated in the south-western region (Figure A.6).

Côte d'Ivoire. In Côte d'Ivoire, drought increases conflict across all household–grid combinations – particularly in mixed settings – and primarily leads to protests and riots. The results suggest that drought can more than double or even triple the number of conflicts in mixed areas with respect to normal conditions. In Farm-dominated areas, the increase in conflict probability reaches 78% for Farm households and 96% for Agropastoral households (Column 2) with respect to group mean. In this country, drought conditions are observed only in the far north, where both farming households and pastoralists are affected (Figure A.7). This region borders Burkina Faso and is characterized by porous borders and ethnically mixed communities. In such settings, drought can exacerbate pre-existing tensions related to ethnic divisions and cross-border mobility, potentially intensifying local conflict dynamics (Benjaminsen et al., 2012; Raleigh et al., 2010). In addition, we must consider that the sample mean in Côte d'Ivoire is generally much lower than in the Burkina Faso (0.45 vs. 085, respectively).

Wet conditions have a limited effect on the probability of being in a conflict-affected area, and in many cases is not significant. Lastly, while most groups have sufficient observations, some marginal effects – especially for Pastoral households in mixed areas – should be interpreted with caution due to small sample sizes (16 observations). In such cases, large percentage increases may reflect estimation instability or multicollinearity rather than robust effects.

Niger. In Niger, drought raises conflict levels for all household livelihood types in Mixed and Pure Farm-dominated areas, while wet anomalies show insignificant or negative effects. Particularly, during abnormally dry conditions, the likelihood of being located in conflict-affected areas rises by 52% relative to the group mean (0.43) for agropastoral households in mixed areas, and by over 100% for both farm households and agropastoral households in Pure Farm-dominated areas (Column 2). For pastoral households, drought is associated with a strongly significant increase in conflict only if located in mixed areas. The literature highlights that the expansion of sedentary farming into traditional grazing lands restricts herder mobility, resulting in overgrazing, land degradation, and increased vulnerability to climatic stressors. This dynamic is especially pronounced in the Sahel, where landscape fragmentation has rendered transhumance routes increasingly inaccessible (Eberle et al., 2025).

Abnormally wet conditions lead to a decrease in conflict probability for all household livelihood types when located in farm-dominated cells. Further disaggregating by event type, we observe an increase in battles following abundant rainfall in agropastoral households in mixed or farm-dominated areas, while a reduction is found in pastoral-dominated areas, which, in turn, experience a rise in protests.[31] Looking at the geographical distribution of households in Niger, we observe that they are almost entirely concentrated in the southern part of the country, as the northern region is largely desert, sparsely populated, and characterized by very limited agricultural activity. Most economic activities are clustered in the southern and, in particular, the south-western regions (see Figure A.8).

Nigeria. This country shows a marked heterogeinity of climatic conditions as well as livelihood household types and area types. Pastoralists are mainly found in the northeast, while the southern and central parts of Nigeria are predominantly inhabited by farming households (Figure A.9). This largely reflects differences in climate, with the central and northern part of the country being increasingly drier, while flood-affected areas are located in the southern coastal regions.

Nigeria exhibits greater variability across household–grid type combinations over time and space. This richer variation also allows us to obtain more informative and statistically meaningful pairwise comparisons. Indeed, the marginal effect of drought for farming households in pastoral-dominated areas is significantly higher than for the same household type in farmer-dominated areas, where the effect, although positive in magnitude, is not statistically significant. Similarly, no substantial difference is observed between pastoral and agropastoral households located in mixed cells. However, pastoral households experience significantly higher drought-related conflict in mixed or pastoral-dominated areas compared to farm-dominated ones.[32] This suggests that conflicts in

[31] Results of Model 2 by event type are available upon request.

[32] Results of pairwise comparison between groups are available upon request.

these zones may be intensified by competition over natural resources, such as grazing land and water, which become increasingly constrained during dry periods. Agropastoral households in farm-dominated areas experience a moderate increase in conflict probability (approximately +17%), while farming households in mixed areas also exhibit a positive effect on conflict incidence (+33%) under drought conditions. Notably, pastoral households in pastoral-dominated areas display a pronounced increase in response to drought shocks, with statistically significant effects also detected for the conflict count variable, suggesting heightened conflict intensity in these regions.

Wet anomalies appear more likely to fuel conflict in Nigeria's mixed livelihood zones. Specifically, this happens primarily for agropastoral and farming households in mixed areas. Interestingly, these areas are also those with the highest positive SPEI values, suggesting a greater likelihood of severe flooding that disrupts cropping cycles, damages infrastructure, or deteriorates grazing conditions. In contrast, wet anomalies tend to reduce conflict risk among pastoralists in pastoral-dominated areas and among farming households in farm-dominated areas. Taken together, these results reinforce the notion that wet conditions in ecologically or economically mismatched settings – i.e., where the household livelihood type is different from the prevailing livelihood at the area level – can exacerbate tensions. Conversely, some groups appear to benefit from wet anomalies. Pure farming households as well as pastoral households in farm-dominated areas both experience a 16% reduction in conflict probability.

Overall, climatic anomalies do not appear to exacerbate conflict per se, but rather do so primarily for households living in specific environmental contexts. This condition moderates the relationship between climate and violence (Eberle et al., 2025). Despite substantial contextual heterogeneity, the analysis reveals a consistent pattern across West African countries. Drought emerges as the primary climate-related driver of conflict, particularly in Burkina Faso, Niger, Côte d'Ivoire, and in pastoral-dominated areas of Nigeria, mainly located in the north-east. In contrast, wet conditions tend to reduce conflict risk in arid and semi-arid regions such as Niger and Burkina Faso, as well as in northern Nigeria, while increasing it in mixed settlements and in cases of extreme flooding.

We show that generally conflict is more likely to occur along livelihood frontiers – i.e., zones where communities depending on distinct agricultural or pastoral practices interact. Those are areas where competition over land and resources and communal conflict involving different ethnic and livelihood groups are more likely to emerge (van Weezel, 2019). Furthermore, we demonstrate that the above conflict dynamics can emerge not only during the growing season, but within one year after the harvest as well, as shown also by Harari and La Ferrara (2018). While the literature on resource competition suggests that farmer–herder tensions are primarily driven by drought-induced early migration of pastoralists (McGuirk and Nunn, 2025), we emphasize an alternative mechanism: the agricultural productivity pathway. We argue that climate-induced livelihood disruptions and economic strain place pressure on household subsistence strategies, thereby reducing the relative attractiveness of peaceful livelihood alternatives.

5 Robustness Checks

In this section, we conduct a series of robustness checks to validate the reliability of our main findings (sse Appendix E for details).

Correction for spatial correlation of errors. First, we replicate Model 1, correcting standard errors for both serial and spatial correlation (Colella et al., 2019; Conley, 1999), with and without controls (Appendix E, Table E.1). Then, we repeat the same check for Model 2, to ensure that inference is not biased by spatial clustering or correlation in the error terms. In both cases, the results (Tables E.2-E.5 in Appendix E) are consistent in terms of statistical significance and confirm the findings of the main analysis.[33]

Sensitivity to different gridcell thresholds. Second, we re-estimate Model 2 using alternative thresholds (60% and 50%) to define gridcell-level dominant livelihood types. In Table E.6 we report only the coefficients of conditional marginal effects for the counting dependent variable, while Tables E.7-E.8 in Appendix E provide the full set of estimates, showing that our results are robust to different definitions of this variable. Indeed,

[33]For example, the coefficient for the combination Agropastoral households–Mixed cell in the case of wet anomalies is -0.440, significant at the 5% level as in the main analysis, that matches the coefficient of the Moderately/Extremely Wet variable in Table D.2. This is also equal to the conditional marginal effects, since Agropastoral–Mixed areas are the reference category in Model 2 (Table 2). To reconstruct the marginal effects for non-reference categories, we need to combine the relevant coefficients. For instance, the coefficient for Pure Farm households in Mixed areas in the case of Dry anomalies is obtained by taking the difference between the coefficient for Dry–Pure Farm–Mixed (0.474) and that for Normal–Pure Farm–Mixed (0.184), which yields 0.29, exactly as in the main analysis.

the findings remain quantitatively and qualitatively consistent with those from the main specification, although some differences emerge, primarily due to variation in the number of observations across categories.

Gridcell-level analysis. We collapse the data at the gridcell-year level and re-estimate the models to assess whether the identified patterns persist when using aggregated data rather than household-level observations. Running the model on grid-level aggregates ensures that each grid contributes equally to identification and allows us to verify that the patterns are not an artifact of the weighting scheme used in the household-level estimates.[34] This robustness check further confirms that our household-level results also hold when aggregating at the grid level, thus ruling out potential concerns related to grid-threshold definition bias.

Particularly, we aggregated the dataset across the four countries to have a sufficient number of observations, resulting in an unbalanced panel of spatial units observed over time. The dependent variable is either the number of conflicts (*asinh*-transformed) in columns (1) and (2), and the binary indicator for the occurrence of at least one conflict in columns (3) and (4), consistently with the household-level analysis (see Table E.9. in Appendix E). Moreover, the dependent variable is defined within the same 0.5-degree grid cell on which the SPEI is computed. As a result, the grids are perfectly aligned, and the analysis is conducted entirely at the grid level, consistently with previous work in the literature. The key independent variables are the categorical SPEI classification (Normal=0, abnormally Wet=1, abnormally Dry=2) alone in columns (1) and (3) and interacted with the categorical Grid Type (Mixed cells, Pure Farm dominated and Pastoral dominated) in columns (2) and (4), which identifies the dominant livelihood in each gridcell. Standard errors are clustered at the grid cell level, and fixed effects for country-year interaction and gridcell are included to control for time-varying country-specific shocks.[35] Finally, to ensure geographic comparability with the main analysis, we collapsed the household-level dataset to the grid level; accordingly, this robustness check is carried out only for those grid cells in which households are present.

The reduced-form estimates (columns 1 and 3) broadly confirm the expected pat-

[34] It also aligns this robustness exercise with standard practice in the climate–conflict literature, where analyses are typically conducted at the grid scale, improving comparability.

[35] In this robustness check, when collapsing the variable at the grid-cell level, we weight by the panel sampling weight.

terns, reporting a positive association between drought conditions and conflict, both at the extensive and intensive margins. The effect is statistically significant at the 1% level and corresponds to a 16.5 percentage point increase in the probability of conflict under drought conditions with respect to normal conditions – approximately 27% relative to the sample mean. By contrast, the association between wet conditions and conflict is weaker and less consistent than that observed for drought, reflecting the same heterogeneity across countries observed in the household-level analysis.

Conditional marginal effects reveal that in mixed livelihood contexts, abnormally wet conditions are generally associated with a decreased probability of conflict events – statistically significant at the 1% level in column (4) – corresponding to a 17% reduction relative to the group mean. The opposite holds for farm-dominated cells during flood events, which experience an approximate 9% increase in the probability of violent events, although this effect is significant only at the extensive margin. Drought events, on the other hand, have a consistently positive effect on the likelihood of conflict in both mixed and farm-dominated areas, with effect sizes ranging from 22% to 49% relative to their respective group means. Pastoral-dominated cells – which also represent the least common cell type (6% of the sample) – do not show any statistically significant effect, likely due to lower statistical power.

Changing conflict grid definition. The results also hold when changing the definition of the conflict grid cell (Table E.10 in Appendix E). Instead of defining the dependent variable as the number of conflicts within a 27.5 km radius from the respective EA coordinates, we align the conflict grid cell with the 0.5-degree spatial resolution grid used for the SPEI (see Figure A.10). Accordingly, the dependent variable becomes the number of conflicts that occur within the SPEI grid cell associated with each household, namely, the nearest grid cell. This specification allows us to verify that no threshold effect arises from the grid definition is detected.

6 Mechanisms

The previous sections established a statistical association between climate anomalies and conflict events. This section explores the potential mechanisms through which climate variability influences the incidence and intensity of conflict. In fact, the literature highlights several key transmission mechanisms within the two broad pathways linking climate shocks to conflict via the agrifood system (Romano et al., 2025), namely resource competition (Eberle et al., 2025; McGuirk and Nunn, 2025) and reduced agricultural productivity (Caruso et al., 2016; Maystadt and Ecker, 2014; Wischnath and Buhaug, 2014). While the former has been explicitly accounted for in the previous analysis proxied by the livelihood-based classification of household and grid types, the latter can be proxied by the climate shock-induced reduction of crop yields and agricultural revenues, and the resulting broader economic strain in the agrarian setting. Indeed droughts in the growing season and erratic rainfall lower yields and incomes, increasing economic vulnerability (von Uexkull et al., 2016). In the absence of credit or insurance, reduced productivity increases the appeal of joining armed groups by lowering the opportunity cost of violence (Bloem et al., 2025; **?**; Burke et al., 2015), especially in fragile settings (Vesco et al., 2021) where alternative income opportunities are limited (Harari and La Ferrara, 2018).

A key mechanism here is represented by the shrinking and reshuffling of the labor supply. In fact, it is well known that climate shocks may contribute to rural unemployment and unmet basic needs (Kaur, 2019). In addition, labor markets play a critical role in shaping climate resilience, both *ex-ante* and *ex-post* (Rose, 2001). Adverse climate shocks can trigger labor reallocation both within the household (e.g., self-employment) and toward off-farm – both agricultural and non agricultural – employment (Bloem et al., 2025) in order to diversify income sources. Furthermore, the use of hired labor as farmer input may decrease (Gitz et al., 2012). Finally, while droughts reduce labor demand, wages do not adjust accordingly due to social norms or more formal regulations, leading to involuntary unemployment (Kaur, 2019). Notably, climate shocks – especially negative rainfalls – are associated with a greater off-farm labor supply, especially in non-agricultural sectors (Ito and Kurosaki, 2009). Indeed, households usually cope with shocks through informal safety nets, small business activities, livestock sales, and seasonal migration (Kolawole et al., 2016), with non-farm work representing an important component of household livelihoods.

We will test the hypothesis that the climate shock-induced changes in the local labor market – paid and unpaid on-farm work, off-farm work, total number of days worked during the agricultural season – can translate into a higher incentive to engage in conflict, thereby potentially increasing the incidence of violence. Along with this central hypothesis, we also test the role that access to credit plays. All of these mechanisms will be analyzed in the broader context of chenges in crop yields as well as crop revenues. Taken together, this framework aligns with the *opportunity cost* employment: in labor-intensive agricultural economies, climate shocks reduce returns to legal employment, lowering the cost of participating in violence (Eberle et al., 2025; Dal Bo and Dal Bo, 2011).

We present our empirical findings based on the same panel survey data used in the main analysis. The specifications mirror those of the main analysis, including grid and year fixed effects and clustering at the EA level, with and without the same set of control variables. We report all conditional marginal effect estimates for the various possible mechanisms, disaggregated by all combinations of livelihood strategies at both the grid and household levels, in Appendix F, namely: crop yield[36] (Table F.1), labor supply variables (Table F.2, F.4), access to credit (Table F.5) and crop revenues (Table F.6). Here, we present only two summary tables that report the sign of the climate-conflict realtionship along with that of specific potential mechanisms (where statistically significant) obtained using Model 1 (reduced form, see Table 3) and Model 2 (livelihood household type × livelihood grid type, see Table 4).[37]

Burkina Faso. In Burkina Faso, there are some evidence that moderately wetter than average conditions are associated with improved agricultural outcomes as the effect on crop yield is positive in magnitude but not statistically significant and crop revenue coefficient is positive and significant at 1% level for farming households in mixed settings, supporting the hypothesis that more abundant rainfalls can reduce conflict risk by strengthening livelihoods. Notably, this positive effect pertains to moderate increases in precipitation (with a maximum SPEI value of 1.55 standard deviations), rather than to extreme flooding events. During abnormally wet periods, there is also a reallocation toward off-farm activities for agropastoral households in mixed cells, which experience a reduction in the number of conflicts, while paid on-farm labor decreases.

Under dry conditions, farming households in farm-dominated areas experience sta-

[36]To interpret coefficients, we can rely on the $\exp(\beta) - 1$ transformation, as in a log-linear model, for our dependent variable *crop yield* even though it is IHS-transformed, when the values are relatively large-above 10 as a rule of thumb. According to Bellemare and Wichman (2020), the IHS transformation closely approximates the natural logarithm when the variable is large.

[37]Descriptive statistics of the variable used in the ananlysis of mechanisms are reported in Table A.9 in Appendix A.

tistically significant yield reductions, which, in turn, are associated with a consistent increase in riot events. These same groups also face a decline in the total number of agricultural workdays, involving both household and non-household members, across all phases of the agricultural season and a reduction in crop revenues. Agropastoral households in mixed cells, while showing a significant effect of dry conditions on conflict, do not appear to experience significant changes in crop yield, suggesting that the underlying mechanism may be different.

Côte d'Ivoire. In Côte d'Ivoire, we are unable to confidently estimate crop yields, as severe and systematic data quality issues result in a high proportion of missing values,[38] thereby compromising the reliability of the crop yield variable.

Evidence suggests that unpaid farm labor increases by around 13% on average for agropastoral and farming households in farm-dominated areas during drought, and by approximately 35% for pastoral households in mixed areas. We do not find strong evidence of an increase in off-farm labor as a source of income diversification, except for a decline among farming hoseholds in mixed cells. The increase in unpaid labor may reflect a household strategy to optimize scarce resources. Such a reallocation helps maintain control over production and mitigate potential losses (Musungu et al., 2025; Pérez-Silva et al., 2023), though not without putting additional strain on families and potentially fueling discontent. All these household groups exhibit an increased likelihood of conflict in the surrounding areas under dry conditions.

In addition, we find that the probability of contracting credit after the growing season is significantly higher (at the 5% level) for farming households in farm-dominated areas during drought than in normal climatic conditions, while it decreases for farming households in mixed areas (significant at the 10% level, see Table F.5). Access to credit can serve as a coping mechanism to mitigate the effects of drought and protect harvests, for example, by investing in fertilizers and agricultural inputs. These household groups are consistently associated with an elevated risk of conflict in surrounding areas when drought occurs.

[38] Missing values and measurement errors are primarily found in GPS-measured crop areas, crop prices, and the conversion factors used to translate non-standard units into kilograms.

Niger. In Niger, we also observe a strong negative effect of drought conditions on crop yields, suggesting that this may be one of the underlying mechanisms behind the positive relationship found between dry conditions and conflict – namely, economic strain due to poor harvests and a lower opportunity cost of engaging in conflict or protests. The heterogeneity analysis suggests that the largest negative effect (in terms of absolute magnitude) is observed among farming households in farm-dominated areas, followed by farming households in mixed areas and agropastoral households in mixed areas.[39] Pairwise comparisons reveal that farming households in mixed cells experience significantly larger yield losses than agropastoral households in the same areas. However, the former benefit from positive SPEI shocks in terms of agricultural productivity. While the yield reduction is more severe for farmers in farm-dominated zones compared to those in mixed cells, the difference is not statistically significant. These findings suggest that household livelihood type and spatial context jointly shape the degree of vulnerability to drought. In addition, we find a significant negative association between above-average wet conditions and crop revenues for agropastoral households in mixed cells, which are also affected by higher protests.

In addition, we observe that, even if there is a decline in unpaid farm labor, there is also a decrease in off-farm opportunities in the event of floods, likely due to impaired mobility, for pastoral households in mixed cells and for agropastoral in pastoral dominated cells, with both categories being associated with an increase in protest activity. The opposite occurs during drought periods, when agropastoral households reduce their engagement in paid farm labor and increase their reliance on unpaid work, fueling tensions in the surrounding areas. The same pattern is observed among farming households in mixed settings, likely leading to greater strain on household resources and internal constraints. This livelihood type is also associated with a higher probability of conflict exposure.

Being engaged in off-farm employment appears to be more common during drought than during periods of excessive rainfall. Indeed, under moderately or extremely dry conditions, off-farm work engagement increases significantly among agropastoral households in farm-dominated cells, and among farmers in mixed areas, while it decreases for farmers in farm-dominated cells. Conversely, during periods of abundant rainfall,

[39] Crop yield for the other combinations of household type and grid type is not estimable.

off-farm opportunities rise for farming households in farm-dominated settings, and this group is the only one associated with a reduction in conflict.

Lastly, in the event of drought, the total number of agricultural days worked by both household and non-household members across all phases of the agricultural season (from planting to harvest) decreases for agropastoral households in both farm-dominated and mixed cells. These groups also face a higher probability of being located in conflict-affected areas.

Nigeria. In Nigeria, floods generally exhibit a negative effect on crop yields. Notably, the study period coincides with episodes of severe flooding in the country. Such extreme events can reduce crop productivity by accelerating soil erosion and causing nutrient leaching (Sylla et al., 2016; Padi et al., 2011). When disaggregating the analysis by household type and grid composition, we find that in pastoral-dominated areas, agropastoral households experience both a decline in yields due to growing season flooding and a higher likelihood of violent events under abnormally wet conditions.

Conversely, farming households located in farm–dominated area appear to be less exposed to conflicts in surrounding areas (albeit only at the extensive margin), even though they still experience a decline in crop productivity. However, the increase in off-farm activities may offset the negative agricultural downturn, thereby easing social tensions. In addition, more homogeneous socio-economic context of these areas may show different mechanisms of social cohesion than mixed settings – such as those where agropastoral households coexist within predominantly pastoral areas. Indeed, social trust is found to be shaped by contextual factors, supporting the homogeneity hypothesis, i.e. that individuals tend to trust more in socially homogeneous settings. Broader contextual characteristics, such as income equality and ethnic homogeneity, are found to strongly explain trust levels (Öberg et al., 2011). Under dry conditions, however, it is worth noting that this latter group, together with farming households in mixed cells, experiences a decline in crop revenues following drought, which may be a channel through which higher conflict levels arise in these areas by undermining incomes and livelihoods.

Drought and wet conditions affect farm labor participation unevenly across livelihood groups. Under drought conditions, farmers in mixed cells reduce paid farm labor substantially – by approximately 43% – and are more likely to be exposed to localized tensions in surrounding areas. A similar pattern is observed for pastoral households in farm-dominated and pastoral-dominated areas, with this latter group also facing a reduction in off-farm labor opportunities. This may spark grievances and ignite violence. Likewise, the decline in off-farm labor opportunities also affects farming households in pastoral-dominated areas. However, this group simultaneously experiences an increase in farm labor of about 11% relative to normal conditions (significant at the 10% level). After drought, this latter group is also more likely to be exposed to violence in the area where they live.

7 Conclusions

This study examined the relationship between climate anomalies and conflict dynamics in Burkina Faso, Côte d'Ivoire, Niger, and Nigeria between 2010 and 2023, providing a disaggregated, micro-level analysis of how drought and excessive rainfall influence conflict risks across diverse agroecological and livelihood contexts. By integrating a standardized climate shock indicator (SPEI) with survey panel data (EHCVM and GHS) and spatially disaggregated conflict information (ACLED), the analysis reveals heterogeneous patterns shaped by household type, dominant local livelihood systems, and spatial exposure to climatic shocks. Despite substantial contextual heterogeneity, the analysis reveals a consistent pattern across the West African countries under study: drought emerges as the primary climate-related driver of conflict. In contrast, wet conditions are generally associated with a lower risk of conflict in arid and semi-arid contexts such as Niger, Burkina Faso, and northern Nigeria. However, in Nigeria's mixed livelihood areas, wet anomalies are more likely to heighten conflict risk. Notably, these areas also record the highest likelihood of severe flooding.

Overall, climatic anomalies shape conflict risk primarily through income, agricultural productivity and labor-market channels. Drought generally raises conflict risk – mostly for farming and agropastoral households in mixed or farm–dominated cells – likely via crop-yield losses (Burkina Faso, Niger), revenue declines (Nigeria, Burkina Faso), fewer agricultural workdays (Burkina Faso, Niger), and reallocation from paid/off-farm jobs to unpaid farm labor. In Côte d'Ivoire, incidence rises across all household types, especially where livelihood systems overlap. In Nigeria, drought is the primary climate driver of conflict in arid, pastoral-dominated areas, consistent with marginalization, resource scarcity, and mobility constraints limiting off-farm employment.

Effects are heterogeneous for wet conditions. In Burkina Faso, wet anomalies in mixed settings are associated with lower conflict across household types: moderate wetness raises farmer revenues and expands off-farm opportunities for agropastoral households. In Niger, agropastoral/pastoral households in mixed cells face revenue and workday losses and reduced off-farm jobs, suggestive of impaired mobility channeling into more protests. By contrast, farming households in farm-dominated cells benefit from expanded off-farm opportunities, reducing violence (as also observed in Nigeria). In Nigeria, floods depress yields and raise violence among agropastoral households in pastoral-dominated areas (especially in subhumid mixed zones), while for farmers in homogeneous areas, expanded off-farm options partially offset losses, easing tensions; mixed cells see higher conflict, plausibly from resource competition and severe flooding.

Overall, our findings are more consistent with the opportunity cost theory of conflict – i.e., economic strain by reducing the livelihood options, lowers the opportunity cost of joining violent/armed groups – as opposed to the rapacity theory of conflict. Our analysis shows that the mechanisms are driven primarily by the shrinking and restructuring of the labor supply taking place after a climate-induced shock in agrarian setting and by the market failures such as the lack of access to credit as well as governance failure such as the lack of effective social safety nets. These results have survived several robustness checks, including alternative clustering procedures, model specifications, and a grid-level analysis.

Several policy implications arise from these findings. First, climate adaptation strategies must be context-specific and account for the differential exposure and responses of distinct livelihood systems, with targeted support to buffer climate risks, such as tailored insurance schemes, input subsidies, or adaptive extension services. Where pastoral and farming systems coexist, reviving flexible land-use arrangements and mobility corridors (rather than imposing fixed tenure systems) may reduce competition and ease inter-group tensions. Given the role of yield declines and labor reallocation in exacerbating conflict, investment in small-scale irrigation, local storage, and market linkages is essential to stabilize incomes and reduce subsistence pressure, especially in drought-prone areas. Furthermore, early warning systems should incorporate both climatic anomalies and local livelihood structures, enabling timely interventions that are spatially and socially calibrated. Finally, supporting crop diversification and access to credit can enhance household resilience and improve the returns to peaceful livelihoods. Policy interventions should also aim to foster cooperation and build on potential synergies arising within mixed-livelihood settings.

The study has some limitations. A key issue lies in the spatial misalignment between household coordinates and the climate grid: conflicts were assigned within an arbitrary buffer around household locations, which may not correspond precisely with the SPEI grid cell used to measure climatic anomalies and to classify the grid type. However, robustness checks that align conflict events directly with the SPEI grid structure and conduct a grid-level analysis provide reassuring evidence. While the approach adopted in these two checks helps assess the robustness of our findings, it inherently sacrifices the fine-grained spatial variation captured by household-level data and limits our ability to exploit the heterogeneity in the geographic positioning of enumeration areas, which represents a key strength of our micro-level design.

Another limitation concerns the presence of violence perpetrated by terrorist groups within our sample, which climate-related factors may or may not not influence. For instance, Boko Haram–related violence in Nigeria escalated during the study period and may partially explain the heightened levels of battles observed in the northeastern pastoral-dominated areas of the country. Although this raises the possibility of a hidden spurious correlation between climate anomalies and conflict in these regions, it may also point to a potential recruitment base in contexts of climate-induced economic distress. Environmental pressures, such as droughts or desertification, undermine traditional livelihoods, thereby creating fertile ground for terrorist recruitment (Chukwunonso et al., 2025; Salihu, 2018). Further work could also deepen the disaggregation by actors to identify more specific climate-conflict pathways.

In addition, the 12-month time window used to measure conflict incidence is relatively broad and may capture a range of confounding factors, potentially undermining the identification of a true climate-conflict relationship. Moreover, a potential endogeneity concern arises due to the possible adaptation of livelihood systems to conflict over time, which prevents us from making any causal claims. Our findings should therefore be interpreted as robust conditional associations, shaped by the interaction between climatic stressors and local socio-ecological conditions.

Rather than arguing if favor of a deterministic link between climate variability and conflict, this study highlights the amplifying effect of climate variability as a threat multiplier across various livelihood strategies and agrarian contexts, particularly during periods of economic strain following harvest. These findings underscore the need for more granular analyses to examine how specific climate shocks shape conflict risks differently depending on local vulnerabilities. Future research should explore the temporal dynamics of post-harvest stress transmission in greater detail, the adjustment of household and local livelihood arrangements, and investigate institutional mediators, such as governance quality, land tenure security, and social cohesion, that may amplify or mitigate the impact of climate stress on conflict.

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Main Results

Table 1: *Climate Anomalies and Conflict*

	Burkina Faso				Côte d'Ivoire				Niger				Nigeria			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Moderately/Ext wet	-0.521**	-0.516**	-0.118*	-0.115*	0.046	0.051	0.051	0.054	0.343**	0.363**	0.135	0.142*	0.051	0.062	-0.040	-0.035
	(0.203)	(0.205)	(0.061)	(0.061)	(0.061)	(0.061)	(0.037)	(0.037)	(0.162)	(0.165)	(0.084)	(0.084)	(0.062)	(0.064)	(0.032)	(0.031)
Moderately/Ext dry	0.392**	0.383**	0.136**	0.132**	0.688***	0.689***	0.404***	0.404***	0.620***	0.627***	0.213***	0.215***	0.047	0.036	0.069**	0.066**
	(0.179)	(0.179)	(0.063)	(0.063)	(0.114)	(0.115)	(0.068)	(0.068)	(0.095)	(0.097)	(0.070)	(0.071)	(0.086)	(0.085)	(0.031)	(0.031)
Observations	4258	4258	4258	4258	8780	8780	8780	8780	6602	6602	6602	6602	9816	9816	9816	9816
Adj R-squared	0.691	0.692	0.399	0.399	0.423	0.427	0.335	0.338	0.657	0.679	0.423	0.436	0.845	0.847	0.645	0.647
R-squared	0.698	0.699	0.411	0.413	0.431	0.435	0.344	0.347	0.664	0.685	0.433	0.447	0.849	0.850	0.654	0.655
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Clusters (EA)	475	475	475	475	745	745	745	745	409	409	409	409	355	355	355	355
Mean DV (IHS)	2.47	2.47	0.85	0.85	0.67	0.67	0.45	0.45	0.78	0.78	0.43	0.43	2.01	2.01	0.71	0.71

Notes: *Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Standard errors clustered at EA level. Columns 1 and 3 report estimates without controls, while columns 2 and 4 include controls. The control variables are: household size, gender of household head, distance from closest city or market in km (inverse hyperbolic sine transformed), and annual consumption per capita (inverse hyperbolic sine transformed). The dependent variable is the number of conflicts up to one year after the harvest (inverse hyperbolic sine transformed) in columns 1 and 2 (intensive margin), and a binary variable for the occurrence of any conflict in columns 3 and 4 (extensive margin). The independent variable is a categorical variable equal to 0 in case of normal climatic conditions, 1 if above the long-term average by one standard deviation (wet conditions), and 2 if below average by at least one standard deviation (dry conditions).*

Table 2: *Climate Anomalies, heterogeneous livelihoods and Conflict: Conditional marginal effects (40% grid threshold)*

	Burkina Faso		Côte d'Ivoire		Niger		Nigeria	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Moderately/Ext wet								
Agropastoral HH × Mixed GC	-0.440**	-0.094	..	..	0.291	0.065	0.625***	0.155
	(0.203)	(0.065)	..	..	(0.302)	(0.153)	(0.182)	(0.118)
Agropastoral HH × Farm-dominated GC	..	..	0.081	0.073	-0.621	-0.257**	-0.235	0.030
	..	..	(0.076)	(0.049)	(0.504)	(0.115)	(0.148)	(0.061)
Agropastoral HH × Pastoral-dominated GC	..	..	..	..	-0.015	0.138	0.264	0.259*
	..	..	..	..	(0.168)	(0.155)	(0.220)	(0.147)
Farming HH × Mixed GC	-0.461**	-0.019	..	..	0.566	0.048	0.602***	0.191**
	(0.210)	(0.059)	..	..	(0.422)	(0.147)	(0.190)	(0.075)
Farming HH × Farm-dominated GC	..	..	-0.008	0.025	0.403	-0.231**	-0.089	-0.129***
	..	..	(0.063)	(0.039)	(0.295)	(0.102)	(0.072)	(0.034)
Farming HH × Pastoral-dominated GC	..	..	..	..	-0.142	-0.013	0.197	0.059
	..	..	..	..	(0.172)	(0.118)	(0.222)	(0.118)
Pastoral HH × Mixed GC	-0.710**	-0.120	..	..	0.187	0.011	0.105	0.160
	(0.330)	(0.083)	..	..	(0.460)	(0.183)	(0.281)	(0.100)
Pastoral HH × Farm-dominated GC	..	..	0.390*	0.152*	-0.097	-0.255**	-0.015	-0.127**
	..	..	(0.205)	(0.090)	(0.369)	(0.101)	(0.144)	(0.054)
Pastoral HH × Pastoral-dominated GC	..	..	..	..	-0.043	0.086	-0.310**	0.006
	..	..	..	..	(0.161)	(0.120)	(0.128)	(0.082)
Moderately/Ext dry								
Agropastoral HH × Mixed GC	0.502***	0.170**	1.493***	0.749***	0.632***	0.225***	0.065	0.108
	(0.176)	(0.067)	(0.309)	(0.198)	(0.098)	(0.072)	(0.236)	(0.096)
Agropastoral HH × Farm-dominated GC	-0.118	0.340	0.682***	0.385***	1.877***	0.746***	0.006	0.138***
	(0.496)	(0.221)	(0.119)	(0.074)	(0.598)	(0.096)	(0.111)	(0.044)
Agropastoral HH × Pastoral-dominated GC	..	..	..	..	..	..	..	..
	..	..	..	..	..	..	..	..
Farming HH × Mixed GC	0.290	0.105	1.774***	0.914***	0.517***	0.121	0.364	0.241**
	(0.232)	(0.083)	(0.309)	(0.247)	(0.136)	(0.094)	(0.299)	(0.118)
Farming HH × Farm-dominated GC	-0.098	-0.018	0.564***	0.361***	0.666***	0.754***	-0.005	0.036
	(0.555)	(0.125)	(0.128)	(0.074)	(0.122)	(0.097)	(0.089)	(0.032)
Farming HH × Pastoral-dominated GC	..	..	..	..	..	..	0.723***	0.327***
	..	..	..	..	..	..	(0.211)	(0.090)
Pastoral HH × Mixed GC	0.196	0.015	1.284***	0.663**	0.664***	0.176**	0.037	0.281***
	(0.319)	(0.065)	(0.291)	(0.267)	(0.124)	(0.075)	(0.259)	(0.091)
Pastoral HH × Farm-dominated GC	0.452	0.049	0.612***	0.360***	..	..	-0.053	0.084*
	(0.620)	(0.181)	(0.169)	(0.107)	..	..	(0.124)	(0.046)
Pastoral HH × Pastoral-dominated GC	..	..	..	..	0.145	-0.010	0.495***	0.299***
	..	..	..	..	(0.164)	(0.111)	(0.174)	(0.078)
Observations	4258	4258	8780	8780	6602	6602	9816	9816
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Clusters (EA)	475	475	745	745	409	409	355	355
Controls	N	N	N	N	N	N	N	N
Spatial correlation	N	N	N	N	N	N	N	N
Mean DV	2.47	0.85	0.67	0.45	0.78	0.43	2.01	0.71

Note: *Standard errors in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by household type (HH) and grid type (GC). Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1) and binary variable any event (2). Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). Household types: Agropastoral HH, Farming HH, Pastoral HH. Grid types (40% threshold): Mixed GC, Farm-dominated GC, Pastoral-dominated GC. Empty categories are expressed with (..). No controls. Marginal effects for factor variables express the discrete change in unit of outcome (IHS-scale or probability) that can be interpreted as change from the baseline category (normal conditions).*

Table 3: *Climate Anomalies and Conflict: Summary of Potential Mechanisms*

	Burkina Faso		Côte d'Ivoire		Niger		Nigeria	
	Main	**Mech.**	**Main**	**Mech.**	**Main**	**Mech.**	**Main**	**Mech.**
Mod./Ext. wet	–	+ CR – PW + OW	+ only protests		+	– CR		
Mod./Ext. dry	+		+	+ UW	+	– CY – PW + UW	+	– PW

Source: *Authors' elaboration based on regression results.*

Notes: *The column "Main" indicates the sign of the estimated effect of SPEI classes (wet and dry anomalies) on conflict (intensive and/or extensive margin) under the specified climate condition (+ for a positive correlation, – for a negative correlation). The column "Mechanism" indicates the sign of the estimated effect of SPEI classes on* ***PW*** *= paid work,* ***UW*** *= unpaid work,* ***OW*** *= off-farm work,* ***CY*** *= crop yield,* ***WA*** *= workdays during agricultural season,* ***AC*** *= access to credit,* ***CR*** *= crop revenues. Empty cells indicate no robust evidence (either not statistically significant or not estimable).*

Table 4: *Climate Anomalies, Heterogeneous Livelihoods and Conflict: Summary of Potential Mechanisms*

	Burkina Faso		Côte d'Ivoire		Niger		Nigeria	
	Main	**Mechanism**	**Main**	**Mechanism**	**Main**	**Mechanism**	**Main**	**Mechanism**
Moderately/Extremely wet								
Agropastoral HH × Mixed GC	–	- PW; + OW			+ (only Protest)	- WA; - CR	+	
Agropastoral HH × Farm-dominated GC			+ (only protest)		–			
Agropastoral HH × Pastoral-dominated GC					+ (only Protest)	- OW	+	- CY
Farming HH × Mixed GC	–	+ CR			+ (only Protest)	+ CY	+	
Farming HH × Farm-dominated GC			+ (only Protest)	+ CR	–	+ UW; + OW	–	- CY; + OW
Farming HH × Pastoral-dominated GC					+ (only Protest)			
Pastoral HH × Mixed GC	–	- PW			+ (only Protest)	- UW; - OW	+	
Pastoral HH × Farm-dominated GC			+	+ UW	–		–	- PW
Pastoral HH × Pastoral-dominated GC					+ (only Protest)	+ PW	–	
Moderately/Extremely dry								
Agropastoral HH × Mixed GC	+		+		+	- CY; + UW; - WA		
Agropastoral HH × Farm-dominated GC			+	+ UW	+	- PW; + UW; + OW; - WA	+	
Agropastoral HH × Pastoral-dominated GC								
Farming HH × Mixed GC			+	- OW; - AC	+	- CY; - PW; + UW; + OW	+	- PW; - CR
Farming HH × Farm-dominated GC	+ (only Riots)	- CY; - UW; - WA; - CR	+	+ UW; + AC	+	- CY; + PW; - UW; - OW		
Farming HH × Pastoral-dominated GC							+	+ PW; - OW
Pastoral HH × Mixed GC			+	+ UW; + AC	+		+	
Pastoral HH × Farm-dominated GC			+				+	- PW
Pastoral HH × Pastoral-dominated GC							+	- PW; - OW

Source: *Authors' elaboration based on regression results presented in Sections 4 and 6.*
Notes: *CC = Climate Change, proxied by the SPEI, which is the independent variable. Household types: Agropastoral HH, Farming HH, Pastoral HH. Grid types (40% threshold): Mixed GC, Farm-dominated GC, Pastoral-dominated GC. The column "Main" indicates the sign of the estimated effect of SPEI classes (wet and dry anomalies) on conflict (intensive and/or extensive margin) under the specified climate condition (+ for a positive correlation, – for a negative correlation). The column "Mechanism" indicates the sign of the estimated effect of SPEI classes on* ***PW*** *= paid work,* ***UW*** *= unpaid work,* ***OW*** *= off-farm work,* ***CY*** *= crop yield,* ***WA*** *= workdays during agricultural season,* ***AC*** *= access to credit,* ***CR*** *= crop revenues. "dom." = dominated. Empty cells indicate no robust evidence (either not statistically significant or not estimable).*

Appendix

A Descriptive statistics

Table A.1: *Descriptive statistics by HH type and Grid type - Burkina Faso*

	Agrop. HH – Mixed GC	Agrop. HH – Farm-dom. GC	Farming HH – Mixed GC	Farming HH – Pastoral-dom. GC	Pastoral HH – Mixed GC	Pastoral HH – Farm-dom
No. of Conflicts within 27.5km	11.72	6.73	11.33	16.70	33.62	17.43
IHS No. conflicts	2.12	1.75	2.16	2.93	3.88	3.08
Number of battles	3.85	2.70	3.26	5.09	13.62	9.71
Number of protests	2.54	0.08	3.45	2.70	4.55	0.20
Number of riots	0.63	0.00	0.75	1.26	0.33	0.00
Number of VAC events	4.71	3.94	3.87	7.66	15.12	7.52
anyevent	0.81	0.76	0.83	0.87	0.98	1.00
anybattle	0.54	0.76	0.54	0.87	0.95	1.00
anyprot	0.43	0.07	0.53	0.41	0.72	0.20
anyriot	0.22	0.00	0.25	0.39	0.12	0.00
anyvac	0.57	0.68	0.60	0.83	0.95	0.90
spei	-0.32	-1.05	-0.51	-1.13	-0.92	-1.21
Household Size	7.37	6.69	6.10	6.99	7.58	7.62
Female-headed household (0,1)	0.09	0.00	0.24	0.04	0.14	0.00
Distance closest city (km)	23.92	43.02	22.45	31.33	2.74	28.55
Annual cons. per adult eq. (IHS)	13.38	13.35	13.41	13.20	13.96	13.53
Observations	3118	27	786	64	252	5

Source: Authors' elaboration based on EHCVM BFA 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023). Summary statistics use
Note: 4258 household × wave observations, 2,129 distinct households. HH = Households; GC = Grid cell.

Table A.2: *Descriptive statistics of sample households — Burkina Faso (Categorical variables)*

	Wave					
	1		2		Total	
	Absolute	%	Absolute	%	Absolute	%
SPEI6 class						
Normal	1674.0	78.6	349.0	16.4	2023.0	47.5
Moderately/Ext wet	455.0	21.4	0.0	0.0	455.0	10.7
Moderately/Ext dry	0.0	0.0	1780.0	83.6	1780.0	41.8
Grid Type >40%						
Mixed cells	2101.0	98.7	2055.0	96.5	4156.0	97.6
Pure Farm-dominated	28.0	1.3	68.0	3.2	96.0	2.3
Pastoral dominated	0.0	0.0	6.0	0.3	6.0	0.1
Grid Type >50%						
Mixed cells	2105.0	98.9	2055.0	96.5	4160.0	97.7
Pure Farm-dominated	24.0	1.1	68.0	3.2	92.0	2.2
Pastoral dominated	0.0	0.0	6.0	0.3	6.0	0.1
Grid Type >60%						
Mixed cells	2116.0	99.4	2085.0	97.9	4201.0	98.7
Pure Farm-dominated	13.0	0.6	38.0	1.8	51.0	1.2
Pastoral dominated	0.0	0.0	6.0	0.3	6.0	0.1

Source: Authors' elaboration based on EHCVM BFA 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023).

Notes: The absolute and percentage frequency are expressed in number of households belonging to that specific category.

Table A.3: *Descriptive statistics by HH type and Grid type - Côte d'Ivoire*

	Agrop. HH – Mixed	**Agrop. HH – PFD**	**Pure farm HH – Mixed**	**Pure farm HH – PFD**	**Pastoral HH – Mixed**	**Pastoral HH – PFD**	**Pooled**
No. of Conflicts within 27.5km	0.68	0.91	0.78	1.37	0.19	3.55	1.33
IHS No. conflicts	0.39	0.56	0.44	0.70	0.16	0.89	0.67
Number of battles	0.03	0.12	0.07	0.15	0.00	0.23	0.15
Number of protests	0.17	0.35	0.27	0.47	0.02	1.61	0.47
Number of riots	0.22	0.33	0.20	0.62	0.04	1.32	0.58
Number of VAC events	0.26	0.12	0.23	0.13	0.14	0.38	0.14
anyevent	0.28	0.40	0.31	0.46	0.16	0.49	0.45
anybattle	0.03	0.11	0.07	0.13	0.00	0.15	0.13
anyprot	0.11	0.21	0.15	0.23	0.02	0.28	0.22
anyriot	0.11	0.22	0.10	0.31	0.04	0.35	0.29
anyvac	0.19	0.10	0.14	0.10	0.14	0.16	0.11
spei	-0.28	0.63	-0.43	0.72	-0.30	0.55	0.66
Household Size	7.00	6.24	5.91	5.07	4.95	5.48	5.30
Female-headed household (0,1)	0.02	0.06	0.03	0.14	0.05	0.09	0.12
Distance closest city (km)	29.93	21.78	20.75	20.84	37.65	17.24	21.06
Annual cons. per adult eq. (IHS)	13.61	13.78	13.67	13.78	14.19	13.96	13.78
Observations	228	1636	206	6534	16	160	8780

Source: Authors' elaboration based on EHCVM CIV 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023). Summary statistics use panel weights adjusted by EA size.

Note: 8780 household × wave observations. Agrop. HH = Agropastoral; Pure farm HH = Pure farmer; Pastoral HH = Pastoral; Mixed = Mixed Grid cell; PFD = Pure farm dominated Grid cell.

Table A.4: *Descriptive statistics of sample households — Côte d'Ivoire (Categorical variables)*

	Wave					
	1		**2**		**Total**	
	Absolute	%	Absolute	%	Absolute	%
SPEI6 class						
Normal	2082.0	47.4	2953.0	67.3	5035.0	57.3
Moderately/Ext wet	2308.0	52.6	782.0	17.8	3090.0	35.2
Moderately/Ext dry	0.0	0.0	655.0	14.9	655.0	7.5
Grid Type >40%						
Mixed cells	152.0	3.5	298.0	6.8	450.0	5.1
Pure Farm-dominated	4238.0	96.5	4092.0	93.2	8330.0	94.9
Grid Type >50%						
Mixed cells	197.0	4.5	251.0	5.7	448.0	5.1
Pure Farm-dominated	4193.0	95.5	4139.0	94.3	8332.0	94.9
Grid Type >60%						
Mixed cells	445.0	10.1	474.0	10.8	919.0	10.5
Pure Farm-dominated	3945.0	89.9	3916.0	89.2	7861.0	89.5

Source: Authors' elaboration based on EHCVM CIV 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023).

Notes: The absolute and percentage frequency are expressed in number of households belonging to that specific category.

Table A.5: *Descriptive statistics by HH type and Grid type - Niger*

	Agrop. HH – Mixed	**Agrop. HH – PFD**	**Agrop. HH – PD**	**Pure farm HH – Mixed**	**Pure farm HH – PFD**	**Pure farm HH – PD**	**Pastoral HH – Mixed**	**Pastoral HH – PFD**	**Pastoral HH – PD**	**Pooled**
No. of Conflicts within 27.5km	1.99	2.59	2.86	2.36	2.21	0.62	3.96	1.84	4.79	2.35
IHS No. conflicts	0.70	1.23	0.79	0.75	0.94	0.20	1.16	0.95	1.19	0.78
Number of battles	0.28	0.27	0.17	0.35	0.22	0.00	0.46	0.22	0.36	0.31
Number of protests	0.23	0.24	1.25	0.25	0.23	0.48	1.10	0.45	0.91	0.34
Number of riots	0.16	0.00	0.24	0.17	0.00	0.07	0.54	0.00	0.40	0.20
Number of VAC events	1.32	2.09	1.20	1.59	1.76	0.07	1.87	1.17	3.11	1.49
anyevent	0.42	0.74	0.26	0.42	0.69	0.07	0.53	0.68	0.41	0.43
anybattle	0.16	0.27	0.05	0.19	0.12	0.00	0.23	0.19	0.23	0.18
anyprot	0.11	0.24	0.18	0.13	0.23	0.07	0.32	0.45	0.23	0.14
anyriot	0.10	0.00	0.21	0.12	0.00	0.07	0.25	0.00	0.23	0.12
anyvac	0.27	0.50	0.16	0.27	0.46	0.07	0.38	0.23	0.30	0.28
spei	-0.58	-0.34	0.74	-0.59	-0.07	0.72	-0.58	0.69	0.03	-0.55
Household Size	6.64	7.37	6.74	5.39	4.83	5.01	5.18	5.80	5.35	6.20
Female-headed household (0,1)	0.13	0.05	0.01	0.21	0.27	0.22	0.31	0.21	0.18	0.16
Distance closest city (km)	30.86	24.01	51.19	31.28	37.28	57.33	21.03	21.31	51.17	30.79
Annual cons. per adult eq. (IHS)	13.25	13.88	13.52	13.24	13.56	13.31	13.75	13.62	13.58	13.31
Observations	4266	30	33	1116	39	10	495	10	603	6602

Source: Authors' elaboration based on EHCVM BFA 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023). Summary statistics use panel weights adjusted by EA size.

Note: 6602 household × wave observations. Agrop. HH = Agropastoral; Pure farm HH = Pure farmer; Pastoral HH = Pastoral; Mixed = Mixed Grid cell; PFD = farm dominated Grid cell; PD = Pastoral dominated Grid Cell.

Table A.6: *Descriptive statistics of sample households — Niger (Categorical variables)*

	Wave					
	1		2		Total	
	Absolute	%	Absolute	%	Absolute	%
SPEI6 class						
Normal	3177.0	96.2	1236.0	37.4	4413.0	66.8
Moderately/Ext wet	112.0	3.4	130.0	3.9	242.0	3.7
Moderately/Ext dry	12.0	0.4	1935.0	58.6	1947.0	29.5
Grid Type >40%						
Mixed cells	2980.0	90.3	2897.0	87.8	5877.0	89.0
farm-dominated	28.0	0.8	51.0	1.5	79.0	1.2
Pastoral dominated	293.0	8.9	353.0	10.7	646.0	9.8
Grid Type >50%						
Mixed cells	3009.0	91.2	2913.0	88.2	5922.0	89.7
Farm-dominated	0.0	0.0	18.0	0.5	18.0	0.3
Pastoral dominated	292.0	8.8	370.0	11.2	662.0	10.0
Grid Type >60%						
Mixed cells	3031.0	91.8	2949.0	89.3	5980.0	90.6
Pure Farm-dominated	0.0	0.0	8.0	0.2	8.0	0.1
Pastoral dominated	270.0	8.2	344.0	10.4	614.0	9.3

Source: Authors' elaboration based on EHCVM NER 2018/2019 and 2021/2022; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023).

Notes: The absolute and percentage frequency are expressed as number of households belonging to that specific category.

Table A.7: *Descriptive statistics by HH type and Grid type - Nigeria*

	Agrop. HH – Mixed	Agrop. HH – PFD	Agrop. HH – PD	Pure farm HH – Mixed	Pure farm HH – PFD	Pure farm HH – PD	Pastoral HH – Mixed	Pastoral HH – PFD	Pastoral HH – PD	Pooled
No. of Conflicts within 27.5km	3.08	8.13	0.52	7.34	22.90	1.36	5.91	10.07	1.01	14.35
IHS No. conflicts	1.10	1.97	0.35	1.88	2.63	0.61	1.27	2.04	0.44	2.01
Number of battles	0.65	1.19	0.15	2.09	2.68	0.63	2.02	1.73	0.48	1.91
Number of protests	0.59	3.23	0.01	1.60	13.31	0.01	1.18	4.82	0.02	7.68
Number of riots	0.34	1.57	0.00	0.87	3.15	0.04	0.50	1.50	0.02	1.96
Number of VAC events	1.50	2.13	0.36	2.78	3.76	0.68	2.21	2.02	0.49	2.79
anyevent	0.53	0.82	0.30	0.73	0.83	0.37	0.48	0.78	0.31	0.71
anybattle	0.31	0.62	0.14	0.49	0.64	0.31	0.30	0.54	0.19	0.52
anyprotest	0.19	0.50	0.01	0.41	0.68	0.01	0.27	0.60	0.02	0.49
anyriot	0.21	0.43	0.00	0.46	0.55	0.04	0.31	0.40	0.02	0.42
anyvac	0.39	0.53	0.21	0.57	0.69	0.18	0.36	0.52	0.18	0.56
spei	-0.09	0.06	0.70	0.11	-0.01	0.46	0.40	0.12	0.62	0.04
Household Size	9.81	8.55	7.76	8.45	6.11	5.27	7.22	7.13	7.74	7.38
Female-headed household (0,1)	0.06	0.17	0.01	0.13	0.23	0.06	0.12	0.17	0.02	0.16
Distance market (km)	65.41	57.22	73.73	57.16	57.54	66.66	64.28	69.88	73.48	60.92
Annual cons. per capita (IHS)	12.04	12.25	11.71	12.24	12.56	11.98	11.82	12.16	11.62	12.32
Observations	1599	678	84	721	4826	111	363	577	890	9849

Source: Authors' elaboration based on GHS NGA - Panel 2019, ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023). Summary statistics use panel weights adjusted by EA size.

Note: 9849 household × wave observations. Agrop. HH = Agropastoral; Pure farm HH = Pure farmer; Pastoral HH = Pastoral; Mixed = Mixed Grid cell; PFD = Pure farm dominated Grid cell; PD = Pastoral dominated Grid Cell. There are 10 missing values in the variable Annual cons. per capita (IHS); therefore, its mean is always computed over 9,849 household × wave observations, whereas all the other variables have 9,859 observations. Moreover, in the regressions we use only 9,816 households because the remaining ones are automatically dropped by the estimator as singletons.

Table A.8: *Descriptive statistics of sample households — Nigeria (Categorical variables)*

	Wave									
	1		**2**		**3**		**4**		**Total**	
	Absolute	%	Absolute	%	Absolute	%	Absolute	%	Absolute	%
SPEI6 class										
Normal	2572.0	83.4	1227.0	42.9	1872.0	64.2	826.0	82.5	6497.0	65.9
Moderately/Ext wet	463.0	15.0	1376.0	48.1	1.0	0.0	114.0	11.4	1954.0	19.8
Moderately/Ext dry	49.0	1.6	257.0	9.0	1041.0	35.7	61.0	6.1	1408.0	14.3
Grid Type >40%										
Mixed cells	509.0	16.5	640.0	22.4	1058.0	36.3	477.0	47.7	2684.0	27.2
Pure Farm-dominated	1926.0	62.5	1845.0	64.5	1800.0	61.8	512.0	51.1	6083.0	61.7
Pastoral dominated	649.0	21.0	375.0	13.1	56.0	1.9	12.0	1.2	1092.0	11.1
Grid Type >50%										
Mixed cells	404.0	13.1	753.0	26.3	1077.0	37.0	417.0	41.7	2651.0	26.9
Pure Farm-dominated	1936.0	62.8	1702.0	59.5	1787.0	61.3	572.0	57.1	5997.0	60.8
Pastoral dominated	744.0	24.1	405.0	14.2	50.0	1.7	12.0	1.2	1211.0	12.3
Grid Type >60%										
Mixed cells	990.0	32.1	1177.0	41.2	1321.0	45.3	537.0	53.6	4025.0	40.8
Pure Farm-dominated	1488.0	48.2	1348.0	47.1	1567.0	53.8	452.0	45.2	4855.0	49.2
Pastoral dominated	606.0	19.6	335.0	11.7	26.0	0.9	12.0	1.2	979.0	9.9

Source: Authors' elaboration based on GHS Nigeria Panel 2010–2019; ACLED and SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023).
Notes: The absolute and percentage frequency are expressed as number of households belonging to that specific category.

Table A.9: *Descriptive statistics of mechanism variables*

Country	Wave	Statistics	Crop yield (IHS) in LCU	Crop revenues (IHS) in LCU	% of In-Farm work (paid)	% of In-Farm work (unpaid)	% of Off-Farm work	Total workdays in agricultural season (IHS)
Burkina Faso	Wave 1	mean	12.19	12.44	65.17	13.35	2.59	6.18
		sd	0.89	1.62	37.06	26.60	10.85	0.93
		N	566	591	1000	1000	1000	1935
	Wave 2	mean	12.96	12.25	39.31	11.75	4.09	6.10
		sd	1.15	1.68	38.05	23.60	13.24	1.01
		N	566	591	1000	1000	1000	1935
Côte d'Ivoire	Wave 1	mean	–	13.27	58.81	12.56	4.54	–
		sd	–	1.48	35.93	24.93	16.69	–
		N	–	3200	1868	1868	1868	–
	Wave 2	mean	–	13.34	43.65	23.70	3.36	–
		sd	–	1.40	33.70	30.61	13.30	–
		N	–	3104	1868	1868	1868	–
Niger	Wave 1	mean	11.85	10.97	58.34	9.25	4.16	5.20
		sd	1.18	1.31	36.58	21.66	13.74	0.90
		N	2064	1341	1574	1574	1574	2560
	Wave 2	mean	12.19	11.39	47.58	29.07	4.95	5.18
		sd	1.54	1.31	36.85	32.42	15.38	0.84
		N	2064	1053	1574	1574	1574	2560
Nigeria	Wave 1	mean	14.07	13.08	17.46	–	8.5	–
		sd	2.00	2.62	26.6	–	18.17	–
		N	663	250	3077	–	3077	–
	Wave 2	mean	12.41	11.83	14.66	–	7.4	–
		sd	1.57	1.95	23.43	–	16.05	–
		N	999	458	2857	–	2857	–
	Wave 3	mean	11.18	10.04	14.12	–	5.4	–
		sd	2.10	3.05	21.67	–	12.67	–
		N	1255	568	2914	–	2914	–
	Wave 4	mean	12.72	7.24	20.64	–	5.3	–
		sd	2.78	5.10	27.79	–	12.69	–
		N	561	360	1000	–	1000	–

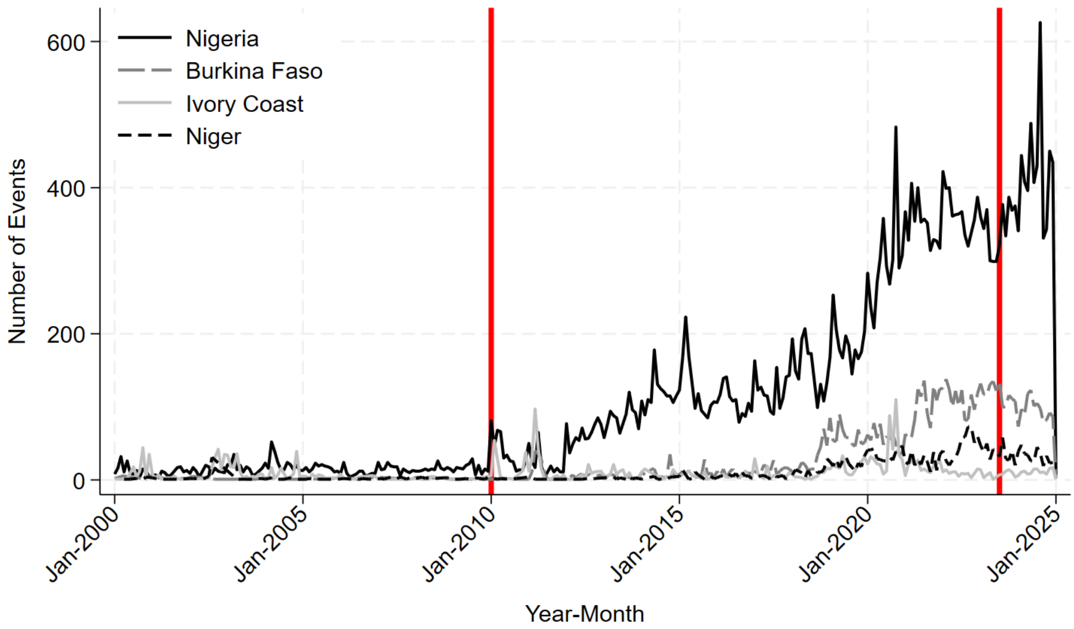
Source: Authors' elaboration based on EHCVM (CIV, NER, BFA 2018/2019 and 2021/2022) and GHS Nigeria Panel 2010–2019.
Notes: Summary statistics are presented using panel weights provided by the survey. Only observations in at least two consecutive waves are retained in the sample for each variable. For the labor supply variables from the EHCVM survey, we retained only the observations from the first round, as the interview dates are closer to the agricultural season and correspond to those used in the regressions.

Table A.10: *Sample restrictions across survey waves*

	CIV		NER		BFA		NGA			
	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2	Wave 3	Wave 4
Panel size	9211	9211	5055	5055	3227	3227	3517	3499	3244	1034
Other adjustments (missing EA coordinates, not completed survey)	8854	8854	4589	4589	3227	3227	3517	3499	3244	1034
Retained only Agricultural households (CS)	7335	5882	4539	3559	4974	2309	3190	2896	2989	1010
Retained households if at least in two consecutive waves	4390	4390	3301	3301	2129	2129	3084	2860	2914	1001
Final sample	4390	4390	3301	3301	2129	2129	3084	2860	2914	1001
Distinct hhid in total	4390		3301		2129		3327			
Final sample hh $\times$ wave	8780		6602		4258		9859			

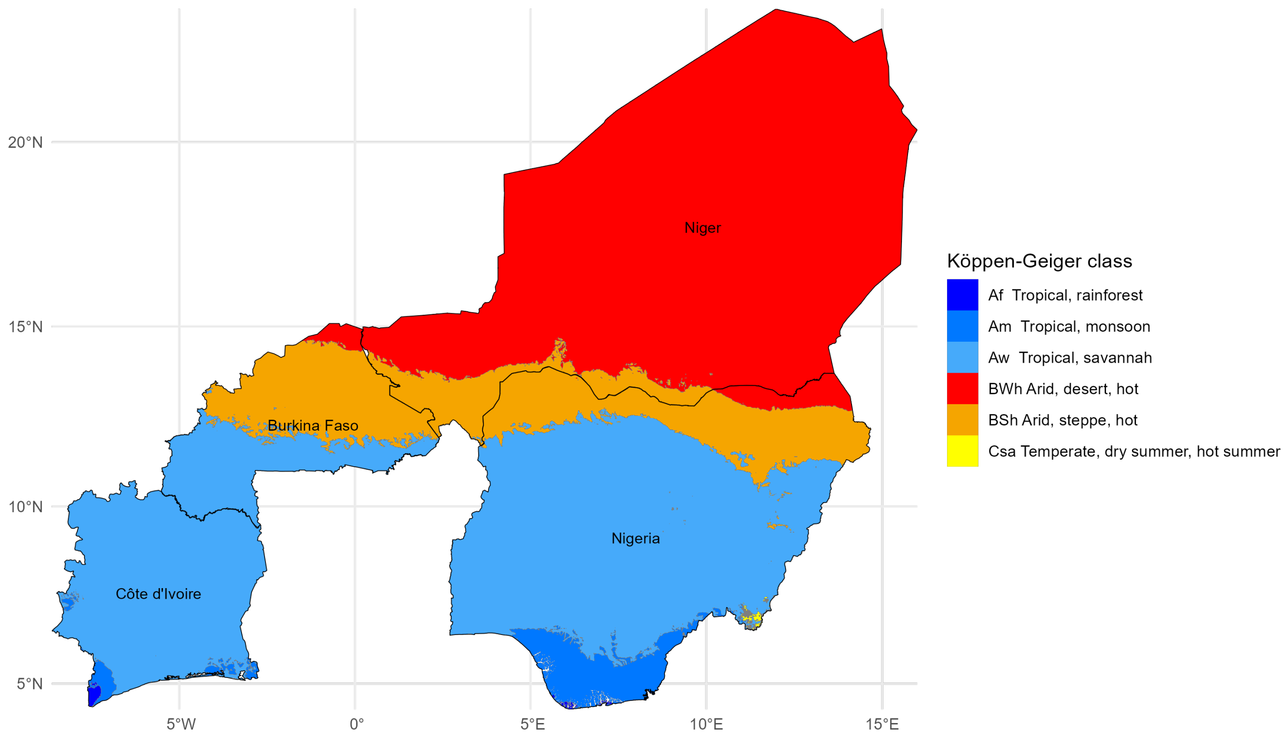
Source: *EHCVM for Burkina Faso, Niger and Côte d'Ivoire, GHS - Panel for Nigeria.*

Figure A.1: *Monthly number of conflict events by country, 2000–2025*



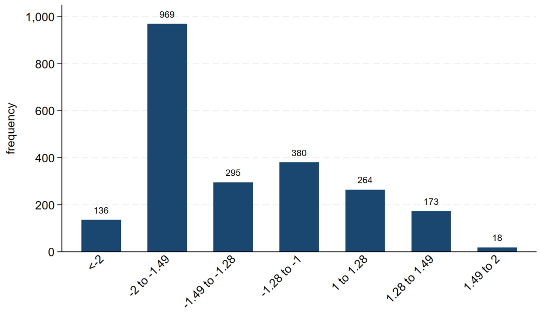
Source: *Authors' elaboration based on ACLED data (Raleigh et al., 2010). The red vertical lines identify the study period (2010–2023). Event types: violence against civilians, battles, riots and protests. Data aggregated by month.*

Figure A.2: *Köppen-Geiger climate zones (1991–2020) in the study area*

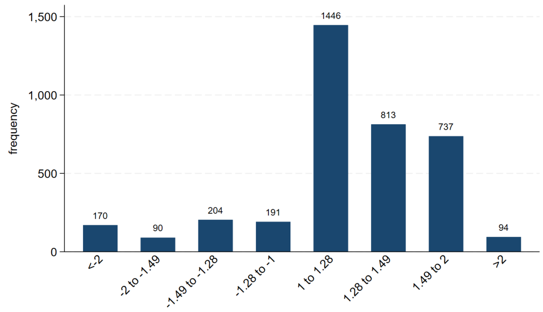


Source: Authors' elaboration based on Beck et al., 2023

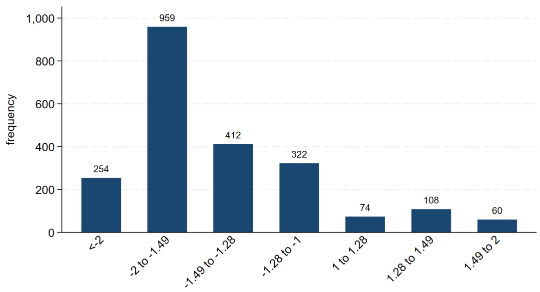
Figure A.3: *SPEI distribution by country*



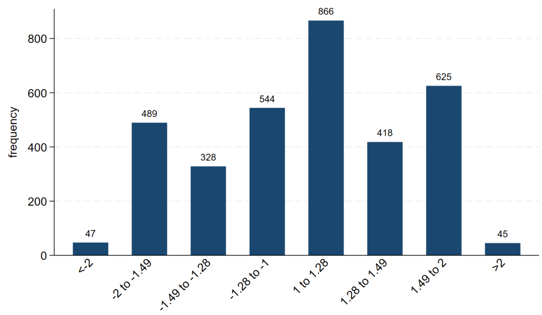
Burkina Faso



Côte d'Ivoire



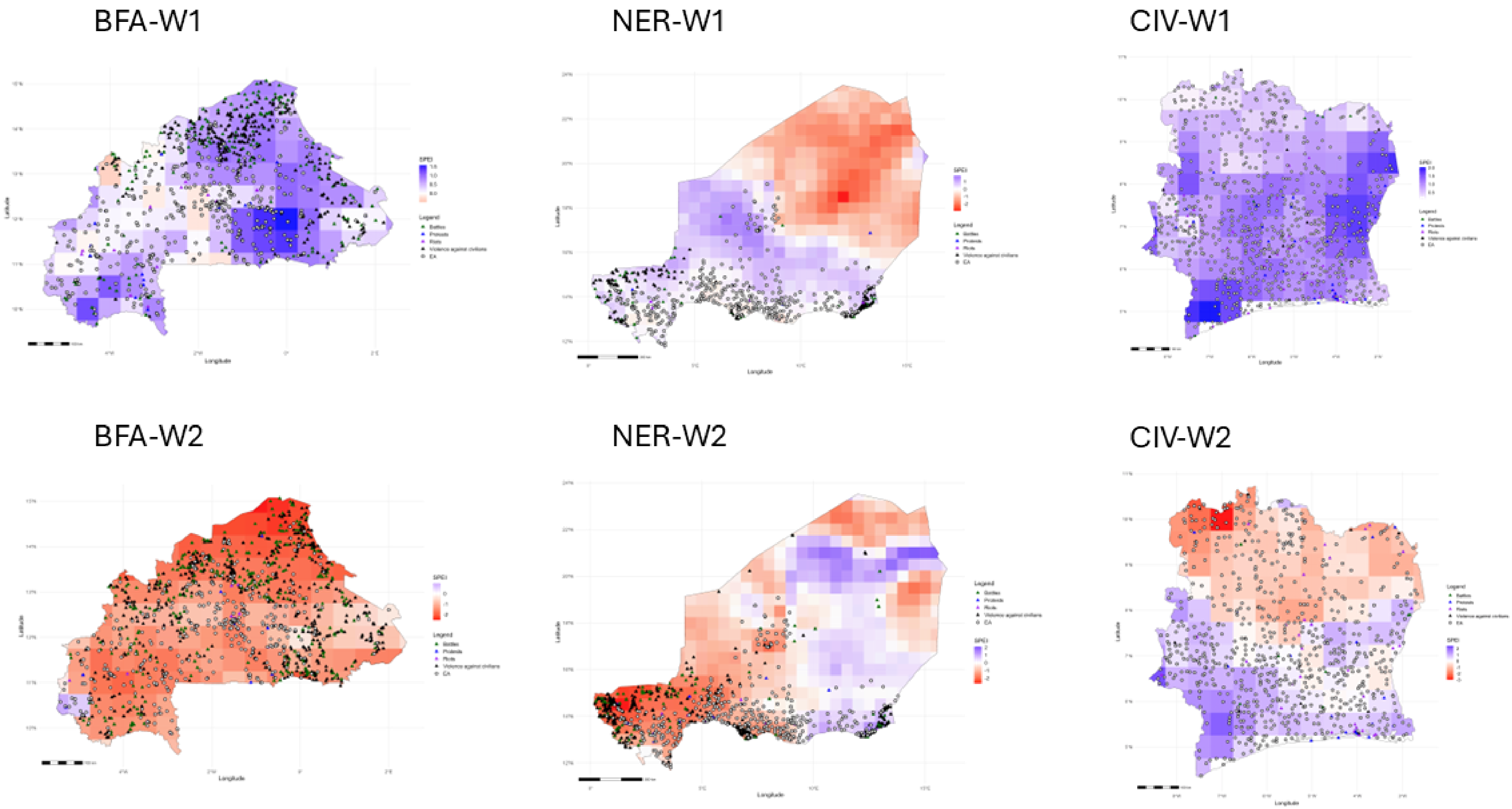
Niger



Nigeria

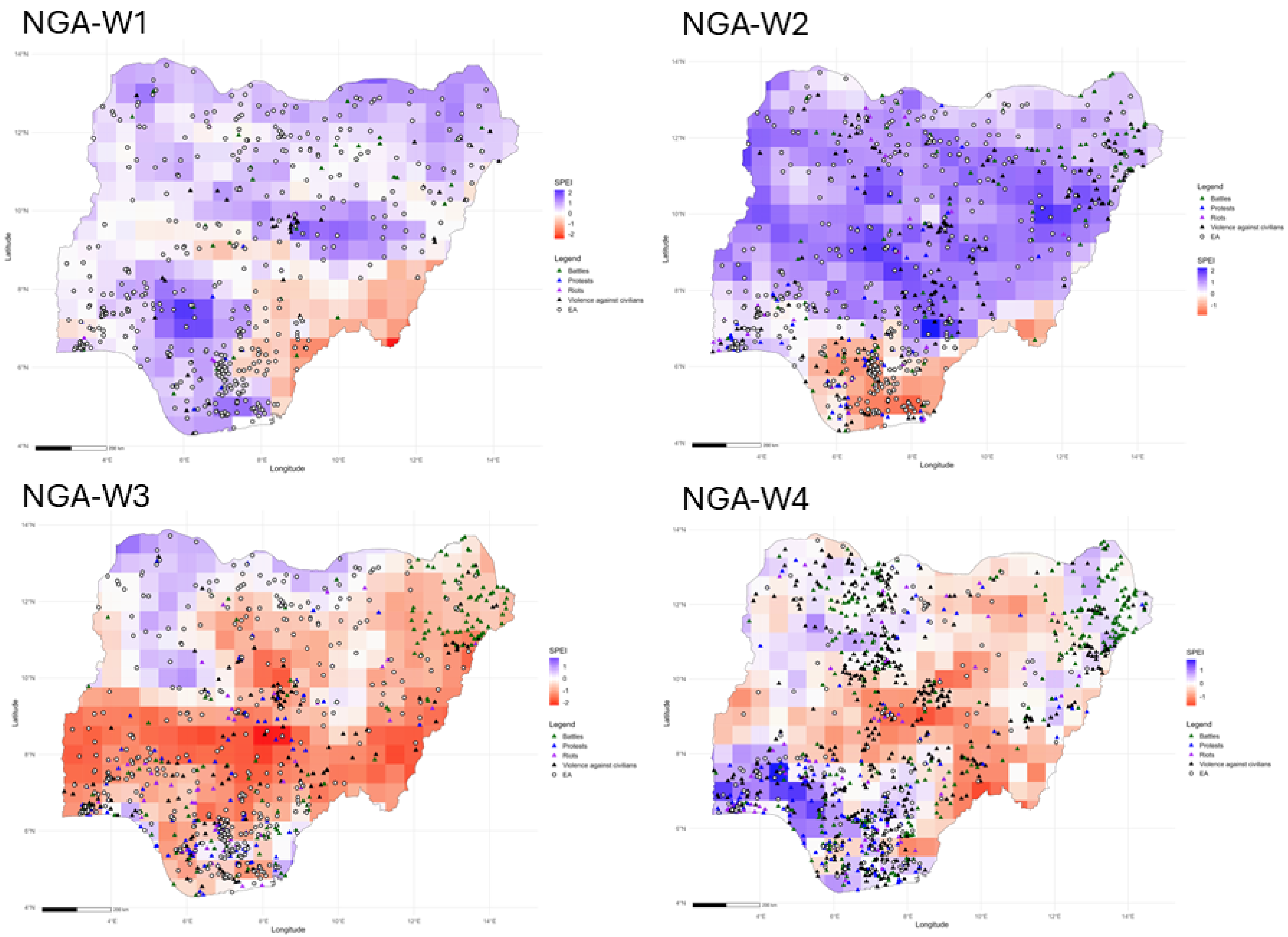
Source: Authors' elaboration based on SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023). Frequency (number of households) of SPEI at a 6-month time scale, measured on October 15 during the crop growing season, pooled across survey waves and by country. Households with normal climatic conditions ($-1 < \text{SPEI} < 1$) are not represented in these graphs.

Figure A.4: *Spatial distribution of Climate, Conflict and household data – Burkina Faso, Niger and Côte d'Ivoire*



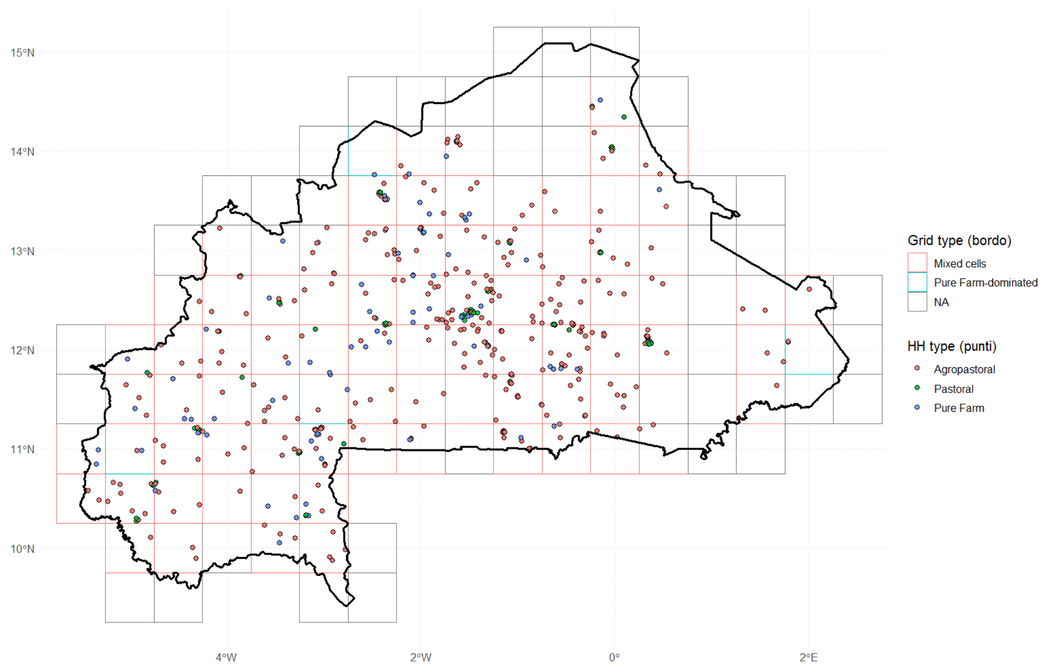
Source: Authors' elaboration based on ACLED data (Raleigh et al., 2010); SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023) and Household survey data EHCVM BFA/CIV/NER. Points identify Enumeration Areas. BFA = Burkina Faso; NER = Niger; CIV = Ivory Coast.

Figure A.5: *Spatial distribution of Climate, Conflict and Household data – Nigeria*



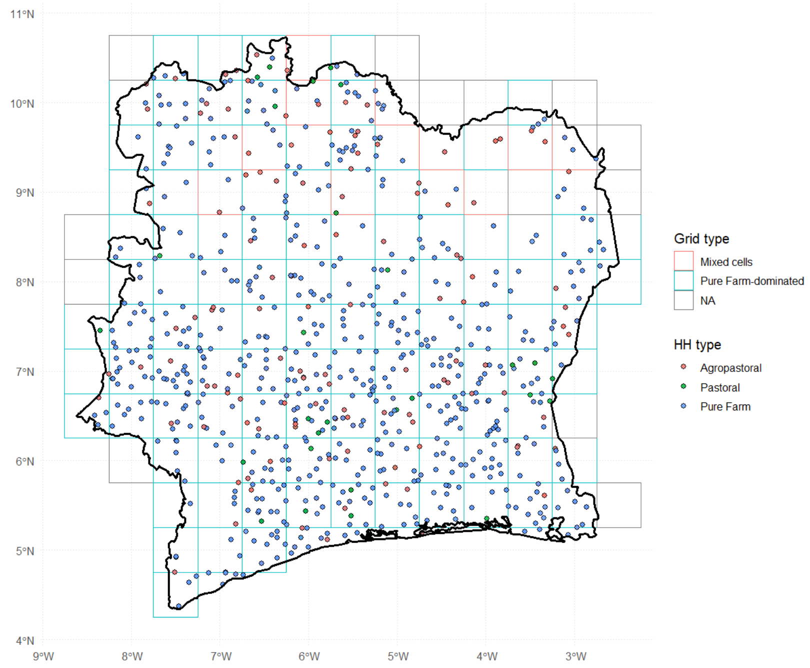
Source: Authors' elaboration based on ACLED data (Raleigh et al., 2010); SPEI Crop Drought Monitor (Vicente-Serrano et al., 2023) and Household survey data GHS Panel Nigeria 2010–2019. Points identify Enumeration Areas. NGA = Nigeria.

Figure A.6: *Spatial distribution of households by Household Type and Grid Type - Burkina Faso Wave 1*



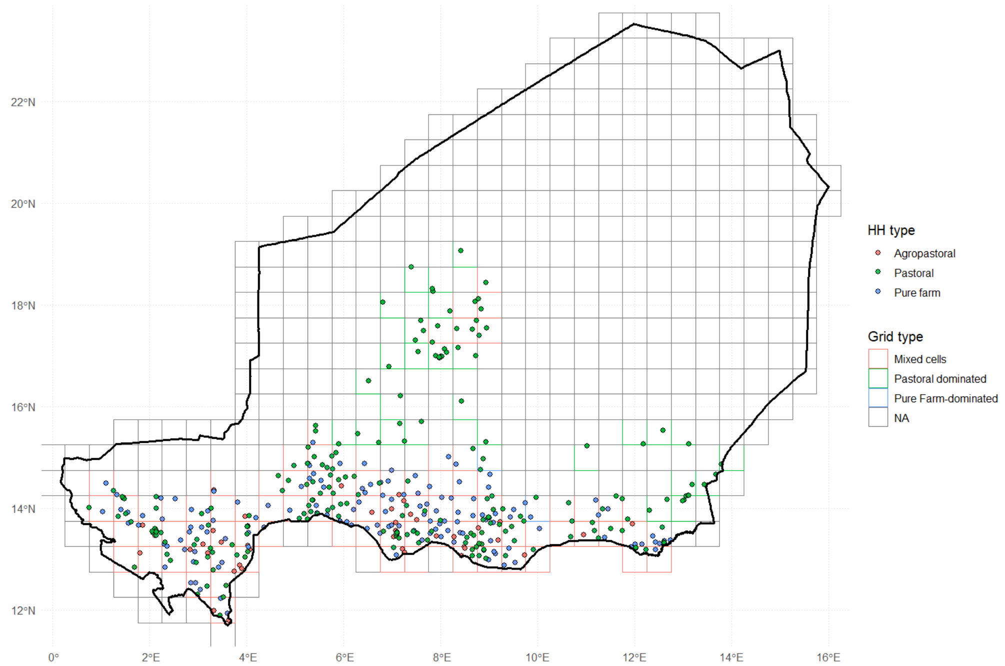
Source: Authors' elaboration based on EHCVM BFA 2018/2019

Figure A.7: *Spatial distribution of households by Household Type and Grid Type - Côte d'Ivoire Wave 1*



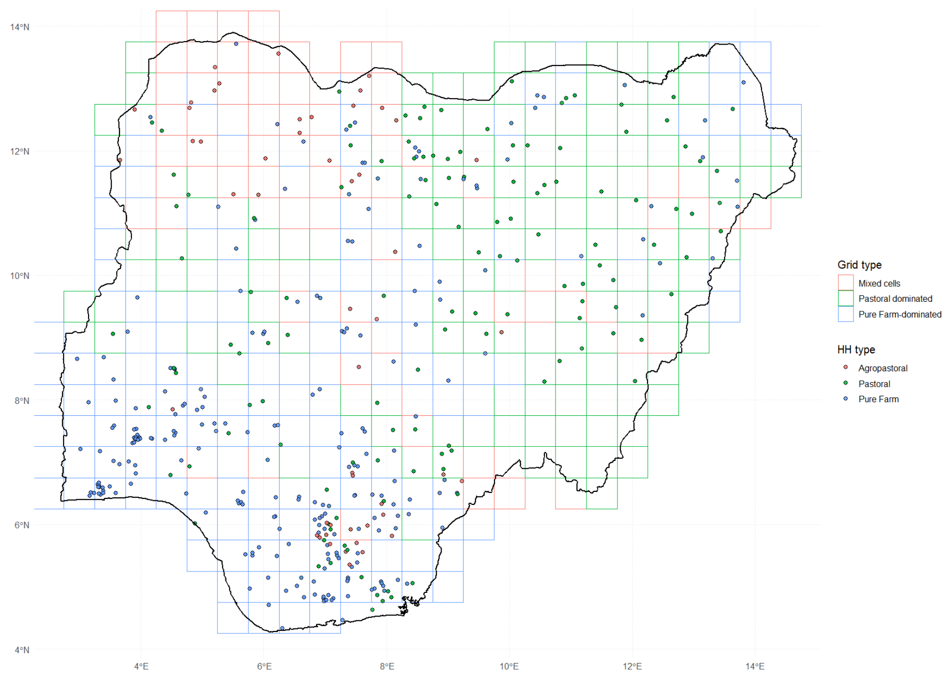
Source: Authors' elaboration based on EHCVM CIV 2018/2019

Figure A.8: *Spatial distribution of households by Household Type and Grid Type - Niger Wave 1*



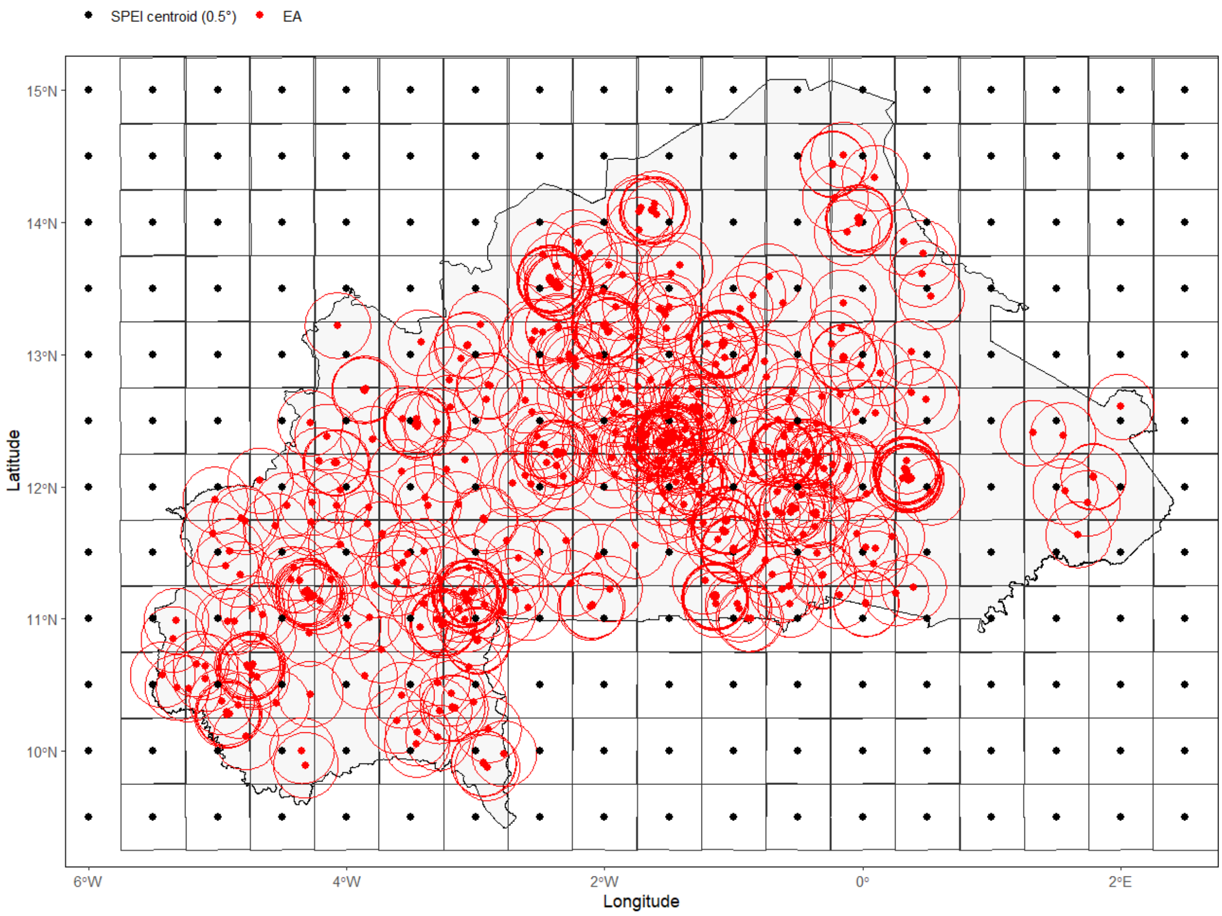
Source: Authors' elaboration based on EHCVM NER 2018/2019

Figure A.9: *Spatial distribution of households by Household Type and Grid Type - Nigeria Wave 1*



Source: Authors' elaboration based on GHS NGA - Panel 2019

Figure A.10: *Overlap between the SPEI grid and the conflict grid defined by EA coordinates - Burkina Faso*



Source: Authors' elaboration based survey data EHCVM BFA

B Climate and Political Characteristics and Challenges in the Analysed Countries

Burkina Faso. Since the 1970s, recurrent droughts have undermined Burkina Faso's crop sector and groundwater recharge (Sawadogo, 2022), increasing rural livelihoods' vulnerability to climate risks—an exposure further compounded by land tenure reforms that reduced grazing areas and intensified farmer-herder tensions (Sorgho et al., 2020). In response, pastoralists have adopted adaptive strategies such as cross-border migration, illegal grazing, and livelihood diversification, with adaptation outcomes varying by ethnicity, land access, and proximity to protected areas (Ilboudo et al., 2025).

In addition, over the past two decades, Burkina Faso has shifted from relative political stability to becoming one of the epicenters of armed conflict in the Sahel region. The ousting of President Blaise Compaoré in 2014—who had ruled the country for 27 years following a coup—left behind a power vacuum and fragile institutions that contributed to the rise of jihadist insurgencies. Since around 2015–2016, armed groups such as Jama'at Nusrat al-Islam wal-Muslimin (JNIM) and the Islamic State in the Greater Sahara (IS Sahel) have carried out increasingly frequent attacks against government institutions, schools, health centers, and villages. As of 2024, up to 50% of the country's territory is estimated to be outside state control, with more than 2 million internally displaced persons and over 5,700 schools closed (Engels, 2025).

In response, the Burkinabè government established the paramilitary "Volunteers for the Defence of the Homeland" (VDP) in 2020. While they were intended to assist in protecting local communities, VDP operations have raised serious concerns regarding human rights abuses and the erosion of social cohesion.[40] Political instability has further compounded the crisis: two military coups occurred in 2022 alone—the first led by Lieutenant Colonel Paul-Henri Sandaogo Damiba, and the second, just eight months later, by Captain Ibrahim Traoré, amid widespread frustration over continued insecurity. These events have placed Burkina Faso squarely within the so-called "coup belt" of West Africa (Engels, 2025).

[40] https://acleddata.com/profile/volunteers-defense-homeland-vdp

Côte d'Ivoire. In Côte d'Ivoire, climatic stressors and socio-political tensions intersect with land and water disputes, escalating conflicts among farmers, herders, and migrant communities—particularly following land ownership restriction reforms (Allouche et al., 2024). Meanwhile, coastal cities like Abidjan are increasingly exposed to flooding, posing growing threats to infrastructure and livelihoods (Kablan et al., 2017).

Over the past 20 years, Côte d'Ivoire has experienced two major civil conflicts rooted in political power struggles, identity tensions, and regional divides. The first civil war began in September 2002 when northern rebel groups launched an uprising, effectively splitting the country between a rebel-held north and government-controlled south. The second conflict erupted after the 2010 presidential elections, when incumbent Gbagbo refused to concede defeat to Alassane Ouattara. The structural roots of these conflicts lie in the divisive concept of *ivoirité*, which excluded northern populations and descendants of immigrants from full citizenship and political participation, fueling ethnic and regional tensions. Since 2011, under President Ouattara, the country has seen relative political stability and economic growth (Allouche et al., 2024). In our study period, Côte d'Ivoire experienced renewed political tensions rooted in constitutional ambiguity and centralized power, with political stability remaining fragile despite economic growth. Frequent leadership reshuffles revealed institutional volatility and reinforced concerns over democratic backsliding and the exclusion of opposition voices from meaningful participation. Risks remain due to institutional fragility, unresolved grievances, and political exclusion.[41]

Niger. In Niger, agriculture is the backbone of the economy, contributing significantly to GDP and employing over 85% of the active population. However, the sector is highly vulnerable to climatic risks such as droughts, floods, and land degradation, all exacerbated by climate change and rapid population growth. Niger has limited arable land (less than 4% of its territory), with permanent pastures covering about 9% and forests only 2%. Agricultural areas are restricted in the north, while the Sudanian and Sahelo-Sudanian zones are more suitable for sedentary farming, unlike the predominantly nomadic north. Climatically, two-thirds of Niger's territory is desert, with increasing aridity and highly variable rainfall that decreases from south to north. Frequent droughts, irregular rain-

[41] https://www.britannica.com/place/Cote-dIvoire/Cote-dIvoire-since-independence

fall, and extreme temperatures expose the population to recurrent risks of crop, livestock, and resource losses. These conditions expose the country to chronic food and nutritional insecurity (INS, 2023).

Over the past two decades, Niger has experienced a complex and turbulent history of political instability, armed rebellions, and jihadist violence. After a failed democratization process in the 1990s, marked by the First Tuareg Rebellion (1990–1995), the country was rocked by a series of military coups in 1996, 1999, and again in 2010. In 2007, the Second Tuareg Rebellion erupted in the north, driven by grievances over marginalization and unfair distribution of uranium revenues. Although peace was formally restored in 2009, instability persisted. From 2015 onwards, Niger faced increasing jihadist threats, particularly from Boko Haram, active in the Diffa region, and from the Islamic State in the Greater Sahara (ISGS), operating mainly in the Tillabéri region. These groups exploited ethnic tensions and porous borders to entrench themselves. The fragile democratic transition suffered a major setback with the military coup of July 2023, led by General Abdourahamane Tchiani, who ousted President Bazoum amid growing popular dissatisfaction, security failures, and political discord within the military. This series of events illustrates Niger's enduring struggle to achieve democratic stability amid regional insecurity and internal fractures (Korotayev et al., 2024).

Nigeria. Nigeria exhibits severe climate vulnerability, with northern regions facing advancing desertification and drought, key drivers of farmer-herder conflicts and internal migration (Efobi et al., 2025), with the water scarcity fueling disputes, especially in North-Central Nigeria, where the Fulani herder-farmer conflict caused over 2,500 deaths between 2012 and 2017 (Chidi and Adie, 2021). These conflicts reflect deeper issues of marginalization, weak governance, and the erosion of traditional dispute-resolution mechanisms (Shettima and Tar, 2008). In addition, the country is prone to flooding (Umar and Gray, 2023).

Over the last two decades, Nigeria has undergone one of the most intense and prolonged experiences of jihadist terrorism in Africa. Boko Haram expanded its activities beyond Nigeria's northeast, carrying out widespread attacks including the infamous 2014 Chibok schoolgirls' kidnapping. In 2015, Shekau pledged allegiance to the Islamic State, leading to the creation of the Islamic State's West Africa Province (ISWAP). Internal disputes over Shekau's extreme tactics caused further splits, with ISWAP emerging as a more structured and regionally integrated faction. Despite military operations and international pressure, ISWAP has grown stronger, expanding its influence through coercion, service provision, and taxation, while maintaining links with global jihadist networks. By 2023, Nigeria continued to face a resilient insurgency marked by adaptive tactics, regional expansion, and deep entrenchment in local political economies (Kostelyanets and Denisova, 2024).

C Surveys and Datasets Description

Burkina Faso. In Burkina Faso, 585 EAs were selected, with 12 households per EA, totaling 7,010 households in Wave 1. Round 1 (August–December 2018) covered 3,507 households, while Round 2 (April–July 2019) covered 3,503 households. The panel sample of the EHCVM 2021/22 corresponds to half of the households interviewed in EHCVM 2018/19. Households were tracked within the EA, that is EHCVM households that had left their EA of origin were not surveyed. Similarly, the household members who left the household since 2018 were not followed up physically. Therefore, in Wave 2 the panel consisted of 3,510 households, interviewed between August–December 2021 and April–July 2022. Sampling only 6 households out of the 12 surveyed in 2018/19 allowed for replacements if a previously sampled household was unavailable for the new round of surveys. The final actual size of the panel sample is 3,227 households, of which 1647 were interviewed in Round 1 and 1,580 in Round 2. The actual attrition from the theoretical panel size of 3,510 to 3,227 corresponds to an attrition rate of approximately 8%. Panel weights account for sample attrition between waves to ensure representativeness of the tracked households.

Côte d'Ivoire. In Côte d'Ivoire, 1,084 EAs were selected, with 12 households per EA, for a total sample of 13,008 households, of which 12,992 successfully completed the interview. Round 1 (August–December 2018) included 6,490 households and Round 2 (April-July 2019) included 6,502 households. In 2021/2022, the survey strategy involved revisiting the same clusters. Depending on availability, either the same 12 households from 2018/19 were re-interviewed, or a combination of relocated and replacement households was used to restore the sample to 12 households per cluster. This was done in cases where some households from the 2018/19 database were missing, or where fewer than 12 could be located during the enumeration phase. This process resulted in 8,854 panel households were reinterviewed between November 2021–February 2022 and April–July 2022. This implies an attrition of 4,138 households between waves, corresponding to an attrition rate of approximately 31.8%.

Niger. In Niger, 504 EAs were sampled with 12 households each, totaling 6622, of which 6,024 households successfully completed the interview. Round 1 (October–December

2018) covered 2,983 households and Round 2 (April–July 2019) covered 3,041 households. In 2021/22, the survey strategy was to revisit the same clusters as in 2018/19. This involved re-interviewing the original 12 households where possible, or supplementing the sample to reach 12 households per cluster when fewer were found during the enumeration phase—either because some households were missing from the final 2018/19 database or could not be located. The result is that wave 2 tracked 4,589 panel households, interviewed from November 2021–February 2022 and June–August 2022. This implies an attrition of 1,435 households between waves, corresponding to an attrition rate of approximately 23.82%.

Nigeria. Lastly, for Nigeria, the General Household Survey (GHS-Panel) includes four waves (2010–2019), each with post-planting and post-harvest visits. The household questionnaire differs slightly between the two visits, with some information collected only in one visit and some in both. Wave 1 began in 2010, Wave 2 in 2012, Wave 3 in 2015, and Wave 4 in 2018. Also in this case, the sample followed a two-stage probability design. In the first stage, 500 EAs were selected with probability proportional to size, based on the number of households listed in each EA across states and the Federal Capital Territory. In the second stage, 10 households per EA were selected using systematic random sampling, resulting in a total of 5,000 households interviewed for the panel component (GHS-Panel), with proportional allocation across states and specifically designed to be representative at the national and zonal levels. Households were not selected using replacement. Thus, the final number of households interviewed was slightly less than the 5,000 eligible for interviewing. The final number of households interviewed was 4,986 for a non-response rate of 0.3 percent. In the second, or post-harvest, visit, some households had moved; thus, the final number of households with data at both points in time is 4,851. After nearly a decade of visiting the same households, a partial refresh of the GHS-Panel sample was implemented in Wave 4. The overall attrition rate since the first wave was 8.3%, with higher rates in specific zones—reaching 19.5% in the North East. The long panel sample includes 1,425 households from 158 EAs, drawn from the original 2010 panel and tracked even if relocated. Due to conflict and security issues, some EAs were inaccessible and replaced. In total, 4,976 households across 517 EAs were successfully interviewed in both survey rounds, of which 1,425 were from the long panel sample and 3,551 from the refresh sample. Although 159 long panel and 360 refresh EAs were selected and visited in the post-planting visit; conflict events prevented interviewers from visiting 2 rural EAs in the North West during the post-harvest visit (one EA from the long panel sample and one from the refresh). Therefore, the final number of EAs visited in both post-planting and post-harvest was 158 long panel EAs and 359 refresh EAs.

Since Wave 1, significant efforts have been made to track relocated households and minimize attrition, particularly within the long panel sample. In Wave 4, households that had moved were followed up and interviewed in a separate tracking phase. Of the 1,590 households initially interviewed in Wave 1 across the 159 EAs, 1,425 were successfully reinterviewed in both visits of Wave 4, corresponding to an overall attrition rate of 10.4%. Attrition varied across zones and sectors, reaching 22.5% in rural South West and dropping to 4.7% in rural North Central. It was also higher in urban areas (14.1%) than in rural areas (8.6%). In total, 152 long-panel households (over 10%) were successfully tracked and interviewed in their new locations, with the highest mobility observed in the urban South West.

D Main results – Full Estimates

Table D.1: *Model 1 by event type*

	(1) IHS Battle	(2) IHS Protest	(3) IHS Riot	(4) IHS VAC	(5) Any Battle	(6) Any Protest	(7) Any Riot	(8) Any VAC
Burkina Faso								
Moderately/Ext wet	-0.0969	0.385**	0.0493	-0.622***	-0.0820	0.0448	-0.0474	-0.253***
	(0.209)	(0.168)	(0.0653)	(0.226)	(0.0885)	(0.0925)	(0.0623)	(0.0755)
Moderately/Ext dry	0.610***	0.403***	0.0228	0.161	0.0807	0.270***	0.0244	-0.0252
	(0.154)	(0.154)	(0.101)	(0.184)	(0.0674)	(0.0764)	(0.0859)	(0.0792)
Observations	4,258	4,258	4,258	4,258	4,258	4,258	4,258	4,258
R-squared	0.768	0.480	0.455	0.751	0.531	0.414	0.324	0.522
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	N	N
Mean DV	1.45	0.95	0.29	1.62	0.63	0.50	0.21	0.65
Côte d'Ivoire								
Moderately/Ext wet	-0.0333	0.108**	-0.0423	0.0195	-0.0275	0.142***	-0.0111	0.00699
	(0.0294)	(0.0500)	(0.0468)	(0.0261)	(0.0279)	(0.0337)	(0.0361)	(0.0272)
Moderately/Ext dry	0.0124	0.239***	0.486***	0.184***	0.00670	0.208***	0.381***	0.141***
	(0.0573)	(0.0775)	(0.0677)	(0.0602)	(0.0622)	(0.0556)	(0.0634)	(0.0511)
Observations	8,780	8,780	8,780	8,780	8,780	8,780	8,780	8,780
R-squared	0.297	0.416	0.391	0.329	0.276	0.327	0.328	0.253
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	N	N
Mean DV	0.12	0.27	0.36	0.11	0.13	0.22	0.29	0.11
Niger								
Moderately/Ext wet	-0.119	0.736***	-0.608***	-0.287	-0.220**	0.314***	-0.255***	-0.0982
	(0.0909)	(0.123)	(0.134)	(0.232)	(0.0945)	(0.0758)	(0.0832)	(0.0918)
Moderately/Ext dry	0.136**	0.154***	0.0622	0.486***	0.0786	0.120***	0.0413	0.141**
	(0.0555)	(0.0532)	(0.0437)	(0.0831)	(0.0551)	(0.0360)	(0.0433)	(0.0600)
Observations	6,602	6,602	6,602	6,602	6,602	6,602	6,602	6,602
R-squared	0.569	0.552	0.405	0.708	0.411	0.469	0.358	0.539
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	N	N
Mean DV	0.206	0.187	0.141	0.498	0.178	0.139	0.122	0.285
Nigeria								
Moderately/Ext wet	0.118**	-0.0898*	0.0487	0.0690	0.0162	-0.0677**	-0.0175	0.00255
	(0.0587)	(0.0535)	(0.0520)	(0.0642)	(0.0405)	(0.0323)	(0.0306)	(0.0348)
Moderately/Ext dry	0.131*	-0.0678	-0.109	-0.0128	0.0576	-0.0490	0.0106	-0.0106
	(0.0701)	(0.0611)	(0.0789)	(0.0772)	(0.0421)	(0.0363)	(0.0385)	(0.0394)
Observations	9,816	9,816	9,816	9,816	9,816	9,816	9,816	9,816
R-squared	0.717	0.905	0.780	0.748	0.597	0.703	0.647	0.661
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	N	N
Mean DV	0.926	1.38	0.838	1.23	0.518	0.488	0.419	0.561

Notes: *Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors clustered at Enumeration Area level. Dependent variable: inverse hyperbolic sine of number of Battles (1), Protests (2), Riots (3) and Violence Against Civilians (VAC) (4) and binary variable any event Battles (5), Protests (6), Riots (7) and Violence Against Civilians (VAC) (8) after harvest. The independent variable is the categorical SPEI6 (=0 if Normal conditions, =1 if Moderately or Extremely Wet, =2 if Moderately or Extremely Dry). No controls. Panel weights are applied.*

Table D.2: *Regression table – Model 2 – Burkina Faso*

	Number of conflicts (IHS)		Any conflict	
	(1)	(2)	(3)	(4)
Moderately/Ext wet	-0.440**	-0.431**	-0.0936	-0.0901
	(0.203)	(0.203)	(0.0652)	(0.0655)
Moderately/Ext dry	0.502***	0.500***	0.170**	0.168**
	(0.176)	(0.176)	(0.0667)	(0.0665)
Pure Farm	0.184*	0.207**	0.0277	0.0290
	(0.0979)	(0.0985)	(0.0310)	(0.0305)
Pastoral	0.0833	0.0136	0.0683**	0.0589**
	(0.209)	(0.202)	(0.0264)	(0.0279)
Wet × Pure Farm	-0.0214	-0.0342	0.0745	0.0731
	(0.149)	(0.152)	(0.0475)	(0.0485)
Wet × Pastoral	-0.271	-0.251	-0.0266	-0.0235
	(0.283)	(0.272)	(0.0672)	(0.0666)
Dry × Pure Farm	-0.212	-0.223	-0.0647	-0.0693
	(0.159)	(0.157)	(0.0562)	(0.0561)
Dry × Pastoral	-0.305	-0.293	-0.155***	-0.157***
	(0.286)	(0.281)	(0.0404)	(0.0412)
Pure Farm-dominated	-0.176	-0.150	-0.346*	-0.339*
	(0.403)	(0.398)	(0.201)	(0.203)
Pastoral dominated	0.286	0.358	-0.0645**	-0.0577*
	(0.261)	(0.254)	(0.0320)	(0.0334)
Dry × Pure Farm-dominated	-0.620	-0.631	0.170	0.162
	(0.497)	(0.495)	(0.221)	(0.225)
Pure Farm × Pure Farm-dom.	-0.0598	-0.0329	0.128	0.138
	(0.334)	(0.324)	(0.109)	(0.109)
Pastoral × Pure Farm-dom.	-0.494	-0.440	0.214	0.230
	(0.475)	(0.463)	(0.202)	(0.201)
Dry × Pure Farm × Pure Farm-dom.	0.232	0.151	-0.294	-0.314*
	(0.473)	(0.471)	(0.184)	(0.188)
Dry × Pastoral × Pure Farm-dom.	0.876	0.863	-0.136	-0.144
	(0.560)	(0.553)	(0.234)	(0.235)
Observations	4,258	4,258	4,258	4,258
Adj R-squared	0.693	0.695	0.411	0.412
R-squared	0.701	0.703	0.425	0.427
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	N	N	N	N
Controls	N	Y	N	Y
Clusters	475	475	475	475
Mean DV	2.47	2.47	0.85	0.85

Notes: *Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors clustered at Enumeration Area level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1,2) and binary variable any event (3,4). The independent variable is the triple interaction between SPEI6, HH type and Grid Type. HH type has 3 categories: Agropastoral, Pure farmers, Pastoral. Category 1 (Mixed cells): if only agropastoral_share > 40% threshold, or if two categories exceed the threshold, or none. Category 2 (Pure Farm dominated): if only pure_farm_share > 40% threshold. Category 3 (Pastoral dominated): if only pastoral_share > 40% threshold. Empty categories are omitted. Specifications (2) and (4) include control variables. Controls include: household size, gender of household head, average distance to closest city or market in km (inverse hyperbolic sine transformed) and annual consumption per adult equivalente (IHS-transformed). Panel weights adjusted for EA size are applied.*

Table D.3: *Regression table - Model 2 - Côte d'Ivoire*

	Number of conflicts (IHS)		Any conflict	
	(1)	(2)	(3)	(4)
Moderately/Ext wet	-0.00769	-0.00180	0.0251	0.0282
	(0.0632)	(0.0634)	(0.0387)	(0.0387)
Moderately/Ext dry	0.564***	0.562***	0.362***	0.360***
	(0.128)	(0.128)	(0.0738)	(0.0743)
Agropastoral	-0.102***	-0.0965***	-0.0390*	-0.0369
	(0.0319)	(0.0337)	(0.0221)	(0.0229)
Pastoral	-0.0622	-0.0820	-0.0322	-0.0419
	(0.0709)	(0.0734)	(0.0506)	(0.0525)
Wet × Agropastoral	0.0888	0.0870	0.0482	0.0472
	(0.0624)	(0.0626)	(0.0401)	(0.0400)
Wet × Pastoral	0.398*	0.360*	0.127	0.109
	(0.204)	(0.194)	(0.0877)	(0.0863)
Dry × Agropastoral	0.118	0.127	0.0231	0.0270
	(0.0825)	(0.0819)	(0.0598)	(0.0594)
Dry × Pastoral	0.0483	0.0601	-0.00177	0.00541
	(0.152)	(0.155)	(0.0942)	(0.0947)
Grid Type >40%, Mixed	-0.786***	-0.788***	-0.469***	-0.470***
	(0.165)	(0.165)	(0.0922)	(0.0918)
Dry × Mixed	1.210***	1.209***	0.552**	0.552**
	(0.342)	(0.338)	(0.260)	(0.257)
Agropastoral × Mixed	0.0671	0.0894	0.0102	0.0208
	(0.0929)	(0.0954)	(0.0527)	(0.0539)
Pastoral × Mixed	0.134	0.153	0.101	0.112
	(0.136)	(0.141)	(0.114)	(0.116)
Dry × Agropastoral × Mixed	-0.399	-0.391	-0.188	-0.184
	(0.277)	(0.269)	(0.183)	(0.177)
Dry × Pastoral × Mixed	-0.538*	-0.506*	-0.249	-0.237
	(0.290)	(0.281)	(0.250)	(0.245)
Observations	8,780	8,780	8,780	8,780
Adj R-squared	0.430	0.432	0.341	0.344
R-squared	0.439	0.443	0.351	0.354
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	N	N	N	N
Controls	N	Y	N	Y
Clusters	745	745	745	745
Mean DV	0.67	0.67	0.45	0.45

Notes: *Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors clustered at Enumeration Area level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1,2) and binary variable any event (3,4). The independent variable is the triple interaction between SPEI6, HH type and Grid Type. HH type has 3 categories: Pure farmers, Agropastoral, Pastoral. Category 1 (Pure Farm dominated): if only pure_farm_share > 40% threshold. Category 2 (Mixed cells): if only agropastoral_share > 40% threshold, or if two categories exceed the threshold, or none. Category 3 (Pastoral dominated): if only pastoral_share > 40% threshold. Empty categories are omitted. Specifications (2) and (4) include control variables. Controls include: household size, gender of household head, average distance to closest city or market in km (inverse hyperbolic sine transformed) and annual consumption per adult equivalente (IHS-transformed). Panel weights adjusted for EA size are applied.*

Table D.4: *Regression table - Model 2 - Niger*

	Number of conflicts (IHS)		Any conflict	
	(1)	(2)	(3)	(4)
Moderately/Ext wet	0.291	0.380	0.0650	0.0980
	(0.302)	(0.311)	(0.153)	(0.157)
Moderately/Ext dry	0.632***	0.643***	0.225***	0.229***
	(0.0984)	(0.101)	(0.0719)	(0.0730)
Pure Farm	0.0296	0.0254	0.00884	0.00702
	(0.0331)	(0.0327)	(0.0209)	(0.0210)
Pastoral	0.174**	0.0446	0.0599*	0.0105
	(0.0710)	(0.0633)	(0.0360)	(0.0321)
Wet × Pure Farm	0.275	0.172	-0.0167	-0.0548
	(0.223)	(0.197)	(0.0353)	(0.0385)
Wet × Pastoral	-0.104	-0.200	-0.0542	-0.0886
	(0.367)	(0.306)	(0.0847)	(0.0890)
Dry × Pure Farm	-0.115	-0.107	-0.104**	-0.101**
	(0.0922)	(0.0905)	(0.0517)	(0.0510)
Dry × Pastoral	0.0325	-0.00524	-0.0487	-0.0625
	(0.111)	(0.113)	(0.0525)	(0.0549)
Grid Type >40%, Pure Farm-dom.	0.101	-0.0132	0.103	0.0606
	(0.0818)	(0.115)	(0.0684)	(0.0740)
Grid Type >40%, Pastoral-dom.	-0.186	-0.264	-0.280**	-0.309**
	(0.153)	(0.165)	(0.116)	(0.121)
Wet × Pure Farm-dom.	-0.912	-0.745	-0.322*	-0.260
	(0.584)	(0.614)	(0.176)	(0.182)
Wet × Pastoral-dom.	-0.306	-0.0602	0.0733	0.164
	(0.337)	(0.327)	(0.215)	(0.207)
Dry × Pure Farm-dom.	1.245**	1.052*	0.521***	0.447***
	(0.597)	(0.582)	(0.0775)	(0.0834)
Dry × Pastoral-dom.	-0.519**	-0.424**	-0.186	-0.151
	(0.204)	(0.193)	(0.128)	(0.124)
Pure Farm × Pure Farm-dom.	-0.0373	0.100	-0.0165	0.0338
	(0.0354)	(0.0965)	(0.0242)	(0.0386)
Pure Farm × Pastoral-dom.	0.112	0.180**	0.131*	0.156**
	(0.0945)	(0.0905)	(0.0756)	(0.0738)
Pastoral × Pure Farm-dom.	-0.155**	-0.115	-0.0411	-0.0253
	(0.0747)	(0.0876)	(0.0413)	(0.0416)
Pastoral × Pastoral-dom.	-0.0921	0.0381	0.0299	0.0790
	(0.0894)	(0.0878)	(0.0675)	(0.0666)
Wet × Pure Farm × Pure Farm-dom.	0.750*	0.609	0.0429	-0.00858
	(0.398)	(0.487)	(0.0638)	(0.0858)
Wet × Pure Farm × Pastoral-dom.	-0.401	-0.376	-0.134	-0.123
	(0.256)	(0.245)	(0.121)	(0.132)
Wet × Pastoral × Pure Farm-dom.	0.628	0.519	0.0557	0.0136
	(0.412)	(0.401)	(0.103)	(0.114)
Wet × Pastoral × Pastoral-dom.	0.0767	-0.153	0.00179	-0.0841
	(0.375)	(0.321)	(0.122)	(0.124)
Dry × Pure Farm × Pure Farm-dom.	-1.096**	-0.765**	0.112**	0.235**
	(0.546)	(0.384)	(0.0531)	(0.0990)
Observations	6,602	6,602	6,602	6,602
Adj R-squared	0.661	0.680	0.428	0.441
R-squared	0.668	0.687	0.440	0.453
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	N	N	N	N
Controls	N	Y	N	Y
Clusters	409	409	409	409
Mean DV	0.78	0.78	0.43	0.43

Notes: *Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors clustered at Enumeration Area level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1,2) and binary variable any event (3,4). The independent variable is the triple interaction between SPEI6, HH type and Grid Type. HH type has 3 categories: Agropastoral, Pure farmers, Pastoral. Category 1 (Mixed cells): if only agropastoral_share > 40% threshold, or if two categories exceed the threshold, or none. Category 2 (Pure Farm dominated): if only pure_farm_share > 40% threshold. Category 3 (Pastoral dominated): if only pastoral_share > 40% threshold. Empty categories are omitted. Specifications (2) and (4) include control variables. Controls include: household size, gender of household head, average distance to closest city or market in km (IHS-transformed) and annual consumption per adult equivalent (IHS-transformed). Panel weights adjusted for EA size are applied.*

Table D.5: *Regression table - Model 2 - Nigeria*

	Number of conflicts (IHS)		Any conflict	
	(1)	(2)	(3)	(4)
Moderately/Ext wet	0.625***	0.622***	0.155	0.156
	(0.182)	(0.182)	(0.118)	(0.117)
Moderately/Ext dry	0.0648	0.0397	0.108	0.0992
	(0.236)	(0.244)	(0.0958)	(0.0979)
Pure Farm	0.165***	0.160**	-0.00482	-0.00605
	(0.0627)	(0.0623)	(0.0232)	(0.0234)
Pastoral	0.451**	0.473**	-0.0483	-0.0441
	(0.207)	(0.210)	(0.0583)	(0.0582)
Wet × Pure Farm	-0.0226	-0.0365	0.0362	0.0308
	(0.190)	(0.189)	(0.100)	(0.0996)
Wet × Pastoral	-0.520*	-0.523*	0.00503	0.00727
	(0.290)	(0.290)	(0.127)	(0.126)
Dry × Pure Farm	0.299	0.318	0.133	0.139
	(0.263)	(0.269)	(0.0878)	(0.0903)
Dry × Pastoral	-0.0280	-0.0301	0.173	0.176
	(0.296)	(0.303)	(0.107)	(0.109)
Grid Type >40%, Pure Farm-dom.	0.258*	0.273*	0.104	0.109*
	(0.145)	(0.148)	(0.0634)	(0.0637)
Grid Type >40%, Pastoral-dom.	0.443**	0.434**	-0.121	-0.124
	(0.208)	(0.212)	(0.122)	(0.125)
Wet × Pure Farm-dom.	-0.860***	-0.827***	-0.125	-0.117
	(0.240)	(0.242)	(0.134)	(0.134)
Wet × Pastoral-dom.	-0.361	-0.290	0.104	0.127
	(0.297)	(0.301)	(0.190)	(0.190)
Dry × Pure Farm-dom.	-0.0585	-0.0111	0.0294	0.0463
	(0.246)	(0.252)	(0.100)	(0.102)
Dry × Pastoral-dom.	0.458*	0.449	0.0176	0.0166
	(0.273)	(0.277)	(0.110)	(0.110)
Pure Farm × Pure Farm-dom.	-0.114	-0.0930	0.0245	0.0303
	(0.0871)	(0.0868)	(0.0339)	(0.0340)
Pure Farm × Pastoral-dom.	0.333	0.359	0.252**	0.262**
	(0.239)	(0.244)	(0.122)	(0.124)
Pastoral × Pure Farm-dom.	-0.431**	-0.417*	0.0561	0.0619
	(0.218)	(0.222)	(0.0670)	(0.0674)
Pastoral × Pastoral-dom.	0.206	0.213	0.307**	0.312**
	(0.285)	(0.290)	(0.125)	(0.126)
Wet × Pure Farm × Pure Farm-dom.	0.169	0.166	-0.195*	-0.195*
	(0.229)	(0.231)	(0.117)	(0.116)
Wet × Pure Farm × Pastoral-dom.	-0.0435	-0.0853	-0.236	-0.253
	(0.345)	(0.347)	(0.208)	(0.206)
Wet × Pastoral × Pure Farm-dom.	0.740**	0.742**	-0.163	-0.162
	(0.351)	(0.349)	(0.144)	(0.143)
Wet × Pastoral × Pastoral-dom.	-0.0542	-0.104	-0.258	-0.278
	(0.362)	(0.362)	(0.185)	(0.183)
Dry × Pure Farm × Pure Farm-dom.	-0.310	-0.366	-0.235**	-0.253**
	(0.282)	(0.286)	(0.0962)	(0.0985)
Dry × Pure Farm × Pastoral-dom.	-0.0992	-0.0631	0.0686	0.0691
	(0.381)	(0.389)	(0.132)	(0.134)
Dry × Pastoral × Pure Farm-dom.	-0.0318	-0.0540	-0.227**	-0.237**
	(0.324)	(0.329)	(0.115)	(0.116)
Observations	9,816	9,816	9,816	9,816
Adj R-squared	0.855	0.857	0.654	0.656
R-squared	0.859	0.861	0.663	0.665
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	N	N	N	N
Controls	N	Y	N	Y
Clusters	355	355	355	355
Mean DV	2.01	2.01	0.71	0.71

Notes: *Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors clustered at Enumeration Area level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1,2) and binary variable any event (3,4). The independent variable is the triple interaction between SPEI6, HH type and Grid Type. HH type has 3 categories: Agropastoral, Pure farmers, Pastoral. Category 1 (Mixed cells): if only agropastoral_share > 40% threshold, or if two categories exceed the threshold, or none. Category 2 (Pure Farm dominated): if only pure_farm_share > 40% threshold. Category 3 (Pastoral dominated): if only pastoral_share > 40% threshold. Empty categories are omitted. Specifications (2) and (4) include control variables. Controls include: household size, gender of household head, average distance to closest city or market in km (IHS-transformed) and annual consumption per adult equivalent (IHS-transformed). Panel weights adjusted for EA size are applied.*

E Robustness checks

Table E.1: *Correction for spatial correlation of errors – Model 1*

	Burkina Faso				Côte d'Ivoire				Niger				Nigeria			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Moderately/Ext wet	-0.521**	-0.516**	-0.118***	-0.115***	0.00699	0.00700	0.0510	0.0537	-0.0982	-0.0953	0.135*	0.142**	0.00255	0.00750	-0.0399	-0.0350
	(0.224)	(0.223)	(0.0346)	(0.0342)	(0.0184)	(0.0188)	(0.0394)	(0.0391)	(.)	(.)	(0.0760)	(0.0724)	(0.0305)	(0.0282)	(0.0332)	(0.0329)
Moderately/Ext dry	0.392*	0.383	0.136	0.133	0.141***	0.141***	0.404***	0.404***	0.141*	0.143*	0.213***	0.215***	-0.0106	-0.0138	0.0690*	0.0660*
	(0.226)	(0.236)	(0.0958)	(0.0973)	(0.0242)	(0.0237)	(0.0544)	(0.0552)	(0.0736)	(0.0736)	(0.0664)	(0.0682)	(0.0426)	(0.0429)	(0.0397)	(0.0387)
Observations	4258	4258	4258	4258	8780	8780	8780	8780	6602	6602	6602	6602	9816	9816	9816	9816
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Spatial correlation	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean DV (IHS)	2.47	2.47	0.85	0.85	0.67	0.67	0.45	0.45	0.78	0.78	0.43	0.43	2.01	2.01	0.71	0.71

Notes: *Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Standard errors are corrected for spatial and serial correlation (Conley, 1999), using the median distance between EAs as distance cutoff and 10 years as lag cutoff. Columns (2, 4) include controls. The control variables are: household size, gender of household head, distance from closest city or market in km (inverse hyperbolic sine transformed), and annual consumption per adult equivalent (inverse hyperbolic sine transformed). The dependent variable is the number of conflicts up to one year after the harvest (inverse hyperbolic sine transformed) in columns 1 and 2 (intensive margin), and a binary variable for the occurrence of any conflict in columns 3 and 4. The independent variable is a categorical variable equal to 0 in case of normal climatic conditions, 1 if above long-term average by one standard deviation (wet conditions), and 2 if below average by at least one standard deviation (dry conditions).*

Table E.2: *Model 2 correcting for spatial correlation – Burkina Faso*

	(1)	(2)	(3)	(4)
Normal – Agropastoral – Pure Farm-dominated	-0.176	-0.150	-0.346*	-0.339*
	(0.306)	(0.315)	(0.183)	(0.181)
Normal – Pure Farm – Mixed	0.184	0.207	0.0277	0.0290
	(0.180)	(0.170)	(0.0369)	(0.0358)
Normal – Pure Farm – Pure Farm-dominated	-0.0524	0.0243	-0.190	-0.172
	(0.475)	(0.455)	(0.121)	(0.112)
Normal – Pastoral – Mixed	0.0833	0.0136	0.0683**	0.0589***
	(0.0660)	(0.0727)	(0.0288)	(0.0226)
Normal – Pastoral – Pure Farm-dominated	-0.587	-0.576	-0.0638	-0.0499
	(0.389)	(0.392)	(0.134)	(0.132)
Wet – Agropastoral – Mixed	-0.440**	-0.431**	-0.0936**	-0.0901**
	(0.207)	(0.208)	(0.0455)	(0.0458)
Wet – Pure Farm – Mixed	-0.277	-0.258	0.00855	0.0120
	(0.197)	(0.193)	(0.0636)	(0.0636)
Wet – Pastoral – Mixed	-0.627*	-0.668**	-0.0520	-0.0548
	(0.344)	(0.332)	(0.0508)	(0.0449)
Dry – Agropastoral – Mixed	0.502***	0.500***	0.170**	0.168*
	(0.173)	(0.179)	(0.0862)	(0.0865)
Dry – Agropastoral – Pure Farm-dominated	-0.295	-0.282	-0.00595	-0.00855
	(0.404)	(0.410)	(0.146)	(0.146)
Dry – Pure Farm – Mixed	0.474*	0.484*	0.133	0.128
	(0.269)	(0.288)	(0.116)	(0.120)
Dry – Pure Farm – Pure Farm-dominated	-0.151	-0.179	-0.208	-0.225
	(0.510)	(0.540)	(0.191)	(0.202)
Dry – Pastoral – Mixed	0.280	0.221	0.0833	0.0704
	(0.202)	(0.211)	(0.0848)	(0.0905)
Dry – Pastoral – Pure Farm-dominated	-0.135	-0.138	-0.0144	-0.0204
	(0.281)	(0.292)	(0.130)	(0.134)
Dry – Pastoral – Pastoral dominated	0.565***	0.578***	0.0187	0.0127
	(0.190)	(0.203)	(0.0823)	(0.0806)
Observations	4,258	4,258	4,258	4,258
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	Y	Y	Y	Y
Controls	N	Y	N	Y
Mean DV	2.47	2.47	0.85	0.85

Notes: *Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors corrected for spatial and serial correlation (Conley, 1999), using the median distance between EAs as distance cutoff and 10 years as lag cutoff. Dependent variable: inverse hyperbolic sine of the number of conflicts after harvest in columns (1)–(2); binary indicator for any event in columns (3)–(4). The key regressor is the triple interaction between SPEI6, household (HH) type, and Grid Type. SPEI6 is a categorical variable equal to 0 under normal conditions, 1 if above the long-term average by at least 1 s.d. (wet), and 2 if below by at least 1 s.d. (dry). HH types: Agropastoral, Pure farmers, Pastoral. Grid Type categories: (1) Mixed (if only agropastoral_share > threshold, or ⩾2 categories exceed the threshold, or none); (2) Pure Farm-dominated (only pure_farm_share > threshold); (3) Pastoral-dominated (only pastoral_share > threshold). Columns (2) and (4) include controls. The control variables are: household size, gender of household head, distance from closest city or market in km (inverse hyperbolic sine transformed), and annual consumption per adult equivalent (inverse hyperbolic sine transformed). Coefficients are interpreted as changes in the IHS scale of conflicts (models 1–2) or in the probability that an event occurs (models 3–4), relative to the omitted baseline "Normal – Agropastoral – Mixed". Empty categories are omitted. Panel weights are applied.*

Table E.3: *Model 2 correcting for spatial correlation – Côte d'Ivoire*

	(1)	(2)	(3)	(4)
Normal – Pure Farm – Mixed	-0.0785**	-0.0785**	-0.469***	-0.470***
	(0.0309)	(0.0311)	(0.0855)	(0.0813)
Normal – Agropastoral – Farm-dominated	-0.0159*	-0.0165*	-0.0390	-0.0369
	(0.00956)	(0.00946)	(0.0248)	(0.0234)
Normal – Agropastoral – Mixed	-0.0557	-0.0567	-0.498***	-0.486***
	(0.0470)	(0.0469)	(0.0792)	(0.0736)
Normal – Pastoral – Farm-dominated	-0.00881	-0.00957	-0.0322	-0.0419
	(0.0184)	(0.0169)	(0.0489)	(0.0481)
Normal – Pastoral – Mixed	0.0532	0.0551	-0.400***	-0.400***
	(0.0744)	(0.0726)	(0.109)	(0.111)
Wet – Pure Farm – Farm-dominated	-0.00624	-0.00621	0.0251	0.0282
	(0.0159)	(0.0163)	(0.0385)	(0.0378)
Wet – Agropastoral – Farm-dominated	0.0383	0.0375	0.0344	0.0385
	(0.0314)	(0.0283)	(0.0409)	(0.0424)
Wet – Pastoral – Farm-dominated	0.0767	0.0757	0.120**	0.0954*
	(0.0472)	(0.0464)	(0.0475)	(0.0531)
Dry – Pure Farm – Farm-dominated	0.127***	0.126***	0.362***	0.360***
	(0.0295)	(0.0287)	(0.0581)	(0.0587)
Dry – Pure Farm – Mixed	0.155	0.154	0.445***	0.442***
	(.)	(.)	(0.100)	(0.0984)
Dry – Agropastoral – Farm-dominated	0.122***	0.121	0.346***	0.350***
	(0.00715)	(.)	(0.0754)	(0.0745)
Dry – Agropastoral – Mixed	0.165***	0.164***	0.251***	0.269***
	(0.0192)	(0.0194)	(0.0832)	(0.0850)
Dry – Pastoral – Farm-dominated	0.170*	0.172*	0.328***	0.324***
	(0.0919)	(0.0930)	(0.0816)	(0.0823)
Dry – Pastoral – Mixed	0.0363	0.0385	0.262*	0.281*
	(0.0545)	(0.0542)	(0.147)	(0.146)
Observations	8,780	8,780	8,780	8,780
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	Y	Y	Y	Y
Controls	N	Y	N	Y
Mean DV	0.67	0.67	0.45	0.45

Notes: *Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors corrected for spatial and serial correlation (Conley, 1999), using the median distance between EAs as distance cutoff and 10 years as lag cutoff. Dependent variable: inverse hyperbolic sine of the number of conflicts after harvest in columns (1)–(2); binary indicator for any event in columns (3)–(4). The key regressor is the triple interaction between SPEI6, household (HH) type, and Grid Type. SPEI6 is a categorical variable equal to 0 under normal conditions, 1 if above the long-term average by at least 1 s.d. (wet), and 2 if below by at least 1 s.d. (dry). HH types: Agropastoral, Pure farmers, Pastoral. Grid Type categories: (1) Mixed (if only agropastoral_share > threshold, or ⩾2 categories exceed the threshold, or none); (2) Pure Farm-dominated (only pure_farm_share > threshold); (3) Pastoral-dominated (only pastoral_share > threshold). Columns (2) and (4) include controls. The control variables are: household size, gender of household head, distance from closest city or market in km (IHS), and annual consumption per adult equivalent (IHS). Coefficients are interpreted as changes in the IHS scale of conflicts (models 1–2) or in the probability that an event occurs (models 3–4), relative to the omitted baseline "Normal – Agropastoral – Mixed". Empty categories are omitted. Panel weights are applied.*

Table E.4: *Model 2 correcting for spatial correlation – Niger*

	(1)	(2)	(3)	(4)
Normal – Agropastoral – Pure Farm-dominated	0.0791*	0.0616	0.103**	0.0606
	(0.0458)	(0.0377)	(0.0486)	(0.0420)
Normal – Agropastoral – Pastoral dominated	-0.279***	-0.291***	-0.280***	-0.309***
	(0.0693)	(0.0712)	(0.0855)	(0.0859)
Normal – Pure Farm – Mixed	-0.00532	-0.00511**	0.00884	0.00702
	(.)	(0.00260)	(0.0249)	(0.0253)
Normal – Pure Farm – Pure Farm-dominated	0.0689	0.0742*	0.0953**	0.101*
	(0.0444)	(0.0445)	(0.0478)	(0.0518)
Normal – Pure Farm – Pastoral dominated	-0.149***	-0.146**	-0.140**	-0.146**
	(0.0576)	(0.0576)	(0.0549)	(0.0650)
Normal – Pastoral – Mixed	0.0325	0.0201	0.0599***	0.0105
	(0.0227)	(0.0283)	(0.00293)	(.)
Normal – Pastoral – Pure Farm-dominated	0.104**	0.0792*	0.122**	0.0459
	(0.0501)	(0.0412)	(0.0506)	(0.0489)
Normal – Pastoral – Pastoral dominated	-0.251***	-0.259***	-0.190***	-0.220***
	(0.0533)	(0.0575)	(0.0704)	(0.0729)
Wet – Agropastoral – Mixed	-0.0296	-0.0183	0.0650	0.0980*
	(.)	(.)	(0.0454)	(0.0525)
Wet – Agropastoral – Pure Farm-dominated	-0.145**	-0.124***	-0.154**	-0.102
	(0.0576)	(0.0460)	(0.0615)	(0.0649)
Wet – Agropastoral – Pastoral dominated	-0.465***	-0.430***	-0.142**	-0.0469
	(0.0710)	(0.0695)	(0.0580)	(0.0865)
Wet – Pure Farm – Mixed	-0.00918	-0.0109	0.0571	0.0502
	(.)	(.)	(0.0415)	(0.0409)
Wet – Pure Farm – Pure Farm-dominated	-0.231***	-0.226***	-0.135***	-0.124***
	(0.0536)	(0.0531)	(0.0378)	(0.0413)
Wet – Pure Farm – Pastoral dominated	0.0513	0.0826	-0.153**	-0.0622
	(0.0650)	(0.0614)	(0.0653)	(0.0866)
Wet – Pastoral – Mixed	0.0215	0.00137	0.0707	0.0200
	(.)	(0.0264)	(0.0934)	(0.0820)
Wet – Pastoral – Pure Farm-dominated	-0.240***	-0.262***	-0.134***	-0.191***
	(0.0516)	(0.0686)	(0.0363)	(0.0251)
Wet – Pastoral – Pastoral dominated	-0.499***	-0.507***	-0.104	-0.130**
	(0.0224)	(0.0288)	(0.0635)	(0.0568)
Dry – Agropastoral – Mixed	0.137*	0.139*	0.225***	0.229***
	(0.0780)	(0.0783)	(0.0717)	(0.0749)
Dry – Agropastoral – Pure Farm-dominated	0.727***	0.692***	0.849***	0.737
	(0.0626)	(0.0910)	(0.0181)	(.)
Dry – Pure Farm – Mixed	0.0839	0.0881	0.130	0.135*
	(0.0804)	(0.0797)	(0.0793)	(0.0785)
Dry – Pure Farm – Pure Farm-dominated	0.727***	0.764***	0.849***	0.911***
	(0.0626)	(0.0598)	(0.0181)	(0.0314)
Dry – Pastoral – Mixed	0.191***	0.175***	0.236***	0.177***
	(0.0626)	(0.0611)	(0.0582)	(0.0681)
Dry – Pastoral – Pastoral dominated	-0.167***	-0.167***	-0.200***	-0.204***
	(0.0567)	(0.0602)	(0.0604)	(0.0587)
Observations	6,602	6,602	6,602	6,602
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	Y	Y	Y	Y
Controls	N	Y	N	Y
Mean DV	0.78	0.78	0.43	0.43

*Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors corrected for spatial and serial correlation (Conley, 1999), using the median distance between EAs as distance cutoff and 10 years as lag cutoff.*

Dependent variable: inverse hyperbolic sine of the number of conflicts after harvest in columns (1)–(2); binary indicator for any event in columns (3)–(4). The key regressor is the triple interaction between SPEI6, household (HH) type, and Grid Type. SPEI6 is a categorical variable equal to 0 under normal conditions, 1 if above the long-term average by at least 1 s.d. (wet), and 2 if below by at least 1 s.d. (dry). HH types: Agropastoral, Pure farmers, Pastoral. Grid Type categories: (1) Mixed; (2) Pure Farm-dominated; (3) Pastoral-dominated. Columns (2) and (4) include controls. Control variables: household size, gender of household head, distance from closest city or market (IHS), and annual consumption per adult equivalent (IHS).

Coefficients are interpreted as changes in the IHS scale of conflicts (models 1–2) or in the probability that an event occurs (models 3–4), relative to the omitted baseline "Normal – Agropastoral – Mixed". Empty categories are omitted. Panel weights are applied.

Table E.5: *Model 2 correcting for spatial correlation – Nigeria*

	(1)	(2)	(3)	(4)
Normal – Agropastoral – Pure Farm-dominated	-0.0939	-0.0910	0.104	0.109*
	(0.0688)	(0.0669)	(0.0638)	(0.0633)
Normal – Agropastoral – Pastoral dominated	0.153**	0.152*	-0.121	-0.124
	(0.0766)	(0.0789)	(0.141)	(0.143)
Normal – Pure Farm – Mixed	0.0475*	0.0474	-0.00482	-0.00605
	(0.0288)	(0.0295)	(0.0181)	(0.0189)
Normal – Pure Farm – Pure Farm-dominated	-0.0665	-0.0578	0.124**	0.134**
	(0.0663)	(0.0653)	(0.0609)	(0.0601)
Normal – Pure Farm – Pastoral dominated	0.212***	0.219***	0.126*	0.131**
	(0.0484)	(0.0530)	(0.0656)	(0.0604)
Normal – Pastoral – Mixed	0.0995**	0.105**	-0.0483	-0.0441
	(0.0458)	(0.0469)	(0.0408)	(0.0439)
Normal – Pastoral – Pure Farm-dominated	-0.0776	-0.0646	0.112**	0.127**
	(0.0866)	(0.0834)	(0.0545)	(0.0539)
Normal – Pastoral – Pastoral dominated	0.273***	0.278***	0.138***	0.144***
	(0.0139)	(0.0219)	(0.0204)	(0.0119)
Wet – Agropastoral – Mixed	0.144	0.145	0.155	0.156
	(0.0924)	(0.0918)	(0.121)	(0.120)
Wet – Agropastoral – Pure Farm-dominated	-0.177*	-0.163	0.134	0.149
	(0.104)	(0.101)	(0.0957)	(0.0964)
Wet – Agropastoral – Pastoral dominated	0.268***	0.286***	0.138**	0.159***
	(0.0286)	(0.0307)	(0.0604)	(0.0490)
Wet – Pure Farm – Mixed	0.0842	0.0814	0.186***	0.181**
	(0.0974)	(0.0978)	(0.0708)	(0.0726)
Wet – Pure Farm – Pure Farm-dominated	-0.0954	-0.0824	-0.00499	0.00958
	(0.0643)	(0.0618)	(0.0479)	(0.0494)
Wet – Pure Farm – Pastoral dominated	0.440***	0.450***	0.185**	0.193**
	(0.0660)	(0.0640)	(0.0845)	(0.0778)
Wet – Pastoral – Mixed	0.0203	0.0275	0.111	0.120
	(0.122)	(0.120)	(0.0944)	(0.0941)
Wet – Pastoral – Pure Farm-dominated	-0.115	-0.0911	-0.0156	0.0126
	(0.0881)	(0.0708)	(0.0744)	(0.0699)
Wet – Pastoral – Pastoral dominated	0.278***	0.288***	0.144***	0.157***
	(0.0379)	(0.0378)	(0.0344)	(0.0271)
Dry – Agropastoral – Mixed	-0.0812	-0.0866	0.108	0.0992
	(0.115)	(0.117)	(0.0728)	(0.0708)
Dry – Agropastoral – Pure Farm-dominated	0.0539	0.0633	0.242***	0.255***
	(0.0980)	(0.101)	(0.0778)	(0.0797)
Dry – Pure Farm – Mixed	-0.208*	-0.207	0.236**	0.232**
	(0.125)	(0.127)	(0.0938)	(0.0993)
Dry – Pure Farm – Pure Farm-dominated	-0.0792	-0.0746	0.160**	0.165**
	(0.0696)	(0.0684)	(0.0697)	(0.0701)
Dry – Pure Farm – Pastoral dominated	0.323***	0.329***	0.453***	0.455***
	(0.0962)	(0.0975)	(0.0611)	(0.0628)
Dry – Pastoral – Mixed	-0.0476	-0.0469	0.233***	0.231***
	(0.116)	(0.116)	(0.0627)	(0.0658)
Dry – Pastoral – Pure Farm-dominated	-0.108	-0.0965	0.196***	0.212***
	(0.0767)	(0.0792)	(0.0593)	(0.0596)
Dry – Pastoral – Pastoral dominated	0.320***	0.322***	0.437***	0.436***
	(0.0871)	(0.0884)	(0.0602)	(0.0599)
Observations	9,816	9,816	9,816	9,816
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Spatial correlation	Y	Y	Y	Y
Controls	N	Y	N	Y
Mean DV	2.01	2.01	0.71	0.71

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *FE = fixed effects. Y = yes, N = no. All specifications include year and gridcell fixed effects. Robust standard errors corrected for spatial and serial correlation (Conley, 1999), using the median distance between EAs as distance cutoff and 10 years as lag cutoff. Dependent variable: inverse hyperbolic sine of the number of conflicts after harvest in columns (1)–(2); binary indicator for any event in columns (3)–(4). The key regressor is the triple interaction between SPEI6, household (HH) type, and Grid Type. Columns (2) and (4) include controls (household size, gender of household head, distance to closest city/market — IHS, and annual consumption per adult equivalent — IHS). Coefficients are relative to the omitted baseline "Normal – Agropastoral – Mixed". Empty categories omitted. Panel weights applied.*

Table E.6: *Climate Anomalies, heterogeneous livelihoods and Conflict: Conditional marginal effects (with different grid thresholds)*

	Burkina Faso			Côte d'Ivoire			Niger			Nigeria		
	40%	50%	60%	40%	50%	60%	40%	50%	60%	40%	50%	60%
Moderately Extreme Wet												
Agropastoral × Mixed cells	-0.440**	-0.444**	-0.493**	0	0.896*	0.118	0.291	0.204	0.188	0.625***	0.530***	0.350**
Agropastoral × Pure Farm-dominated	0	0	0	0.081	0.104	0.0937	-0.621	0	0	-0.235	-0.186	-0.0748
Agropastoral × Pastoral dominated	0	0	0	0	0	0	-0.015	0.273	0.222	0.264	0.196	0.367
Pure Farm × Mixed cells	-0.461**	-0.456**	-0.495**	0	0.721*	0.111	0.566	0.563*	0.554*	0.602***	0.453***	0.200
Pure Farm × Pure Farm-dominated	0	0	0	-0.008	0.00854	-0.00224	0.403	0	0	-0.089	-0.101	-0.0715
Pure Farm × Pastoral dominated	0	0	0	0	0	0	-0.142	0.0212	-0.128	0.197	0.504	0.151
Pastoral × Mixed cells	-0.710**	-0.707**	-0.748**	0	0.914***	0.197	0.187	0.135	0.0871	0.105	0.453***	0.0713
Pastoral × Pure Farm-dominated	0	0	0	0.390*	0.487**	0.483**	-0.097	0	0	-0.015	-0.205	-0.138
Pastoral × Pastoral dominated	0	0	0	0	0	0	-0.043	0.221	0.0816	-0.310**	-0.364***	-0.303**
Moderately Extreme Dry												
Agropastoral × Mixed cells	0.502***	0.513***	0.536***	1.493***	0.656***	1.024***	0.632***	0.631***	0.632***	0.065	0.0662	-0.0515
Agropastoral × Pure Farm-dominated	-0.118	-0.424	0.612***	0.682***	0.799***	0.662***	1.877***	2.165***	0	0.006	-0.00896	0.0542
Agropastoral × Pastoral dominated	0	0	0	0	0	0	0	0.635***	0	0	0	0
Pure Farm × Mixed cells	0.290	0.313	0.278	1.774***	0.795***	1.189***	0.517***	0.515***	0.516***	0.364	0.469	0.0934
Pure Farm × Pure Farm-dominated	-0.098	-0.292	0.336	0.564***	0.632***	0.502***	0.666***	0.947***	0	-0.005	-0.0406	0.00571
Pure Farm × Pastoral dominated	0	0	0	0	0	0	0	0	0	0.723***	0.611***	0.537**
Pastoral × Mixed cells	0.196	0.213	0.254	1.284***	0.395**	0.775***	0.664***	0.662***	0.667***	0.037	0.180	-0.0773
Pastoral × Pure Farm-dominated	0.453	-0.727*	0	0.612***	0.758***	0.636***	0	0	0	-0.053	-0.177	-0.0363
Pastoral × Pastoral dominated	0	0	0	0	0	0	0.145	0.425**	0.260	0.495***	0.409**	0.336**

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Only coefficients are reported. Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by HH_type and Grid_type. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1). Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = farmer, 3 = pastoral. Grid_type (40%, 50%, 60% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). No controls. Marginal effects for factor variables express the discrete change in unit of outcome (IHS-scale or probability) and they can be interpreted as change from the baseline category (normal conditions).*

Table E.7: *Conditional marginal effects using grid threshold 50%*

	BFA		CIV		NER		NGA	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Moderately/Ext wet								
Agropastoral # Mixed cells	-0.440**	-0.0936	0.896*	0.528	0.204	0.0441	0.530***	0.184*
	(0.203)	(0.0652)	(0.474)	(0.360)	(0.277)	(0.137)	(0.174)	(0.101)
Agropastoral # Pure Farm-dominated	0	0	0.104	0.0887*	0	0	-0.186	-0.0298
	(.)	(.)	(0.0768)	(0.0490)	(.)	(.)	(0.162)	(0.0625)
Agropastoral # Pastoral-dominated	0	0	0	0	0.273	0.298	0.196	0.206
	(.)	(.)	(.)	(.)	(0.222)	(0.222)	(0.190)	(0.146)
Pure Farm # Mixed cells	-0.461**	-0.0192	0.721*	0.526	0.563*	0.00851	0.453***	0.174***
	(0.210)	(0.0595)	(0.437)	(0.364)	(0.329)	(0.118)	(0.168)	(0.0570)
Pure Farm # Pure Farm-dominated	0	0	0.00854	0.0347	0	0	-0.101	-0.138***
	(.)	(.)	(0.0634)	(0.0388)	(.)	(.)	(0.0718)	(0.0334)
Pure Farm # Pastoral-dominated	0	0	0	0	0.0212	0.126	0.504	0.185
	(.)	(.)	(.)	(.)	(0.219)	(0.176)	(0.376)	(0.133)
Pastoral # Mixed cells	-0.710**	-0.120	0.914***	0.394	0.135	-0.0138	0.453***	0.220***
	(0.330)	(0.0828)	(0.337)	(0.377)	(0.370)	(0.148)	(0.159)	(0.0614)
Pastoral # Pure Farm-dominated	0	0	0.487**	0.215**	0	0	-0.205	-0.232***
	(.)	(.)	(0.233)	(0.0973)	(.)	(.)	(0.154)	(0.0488)
Pastoral # Pastoral-dominated	0	0	0	0	0.221	0.295*	-0.364***	0.0109
	(.)	(.)	(.)	(.)	(0.191)	(0.163)	(0.130)	(0.0831)
Moderately/Ext dry								
Agropastoral # Mixed cells	0.502***	0.170**	0.656***	0.230	0.631***	0.227***	0.0662	0.0995
	(0.176)	(0.0667)	(0.180)	(0.156)	(0.0974)	(0.0708)	(0.241)	(0.0961)
Agropastoral # Pure Farm-dominated	-0.118	0.340	0.799***	0.465***	2.165***	1.023***	-0.00896	0.127***
	(0.496)	(0.221)	(0.134)	(0.0805)	(0.588)	(0.0221)	(0.118)	(0.0437)
Agropastoral # Pastoral-dominated	0	0	0	0	0.635***	0.705***	0	0
	(.)	(.)	(.)	(.)	(0.157)	(0.115)	(.)	(.)
Pure Farm # Mixed cells	0.290	0.105	0.795***	0.450**	0.515***	0.122	0.469	0.172
	(0.233)	(0.0827)	(0.187)	(0.219)	(0.135)	(0.0928)	(0.332)	(0.118)
Pure Farm # Pure Farm-dominated	-0.0983	-0.0182	0.632***	0.390***	0.947***	1.023***	-0.0406	0.0324
	(0.555)	(0.125)	(0.130)	(0.0725)	(0.0558)	(0.0221)	(0.0894)	(0.0328)
Pure Farm # Pastoral-dominated	0	0	0	0	0	0	0.611***	0.406***
	(.)	(.)	(.)	(.)	(.)	(.)	(0.191)	(0.0996)
Pastoral # Mixed cells	0.196	0.0150	0.395**	0.0633	0.662***	0.174**	0.180	0.188**
	(0.319)	(0.0646)	(0.192)	(0.219)	(0.124)	(0.0736)	(0.208)	(0.0750)
Pastoral # Pure Farm-dominated	0.453	0.0495	0.758***	0.489***	0	0	-0.177	0.0708
	(0.620)	(0.181)	(0.205)	(0.119)	(.)	(.)	(0.142)	(0.0462)
Pastoral # Pastoral-dominated	0	0	0	0	0.425**	0.216	0.409**	0.319***
	(.)	(.)	(.)	(.)	(0.193)	(0.156)	(0.164)	(0.0768)
Observations	4258	4258	8780	8780	6602	6602	9816	9816
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster (EA)	475	475	745	745	409	409	355	355
Controls	N	N	N	N	N	N	N	N
Spatial correlation	N	N	N	N	N	N	N	N
Mean DV	2.47	0.85	0.67	0.45	0.78	0.43	2.01	0.71

*Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by HH_type and Grid_type. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1) and binary variable any event (2). Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = farmers, 3 = pastoral. Grid_type (50% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). Panel weights are applied. Given the small sample size in farm-dominated cells in Niger (n = 8), wet coefficients are not estimated, while dry coefficients are, but they should be interpreted with caution due to high variance and potential overfitting. Moreover, in column (2), the estimated coefficients exceed one, which is inconsistent with the bounded nature of probabilities in a Linear Probability Model (LPM); as such, these estimates lack meaningful interpretation.*

Table E.8: *Conditional marginal effects using grid threshold 60%*

	Burkina Faso		Côte d'Ivoire		Niger		Nigeria	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Moderately/Ext wet								
Agropastoral × Mixed cells	-0.493**	-0.106	0.118	0.261	0.188	0.0262	0.350**	0.148*
	(0.203)	(0.0654)	(0.224)	(0.163)	(0.274)	(0.136)	(0.155)	(0.0818)
Agropastoral × Pure Farm-dominated	0	0	0.0937	0.0717	0	0	-0.0748	-0.102
	(.)	(.)	(0.0789)	(0.0501)	(.)	(.)	(0.273)	(0.105)
Agropastoral × Pastoral-dominated	0	0	0	0	0.222	0.419***	0.367	0.222
	(.)	(.)	(.)	(.)	(0.193)	(0.131)	(0.237)	(0.192)
Pure Farm × Mixed cells	-0.495**	-0.0268	0.111	0.233*	0.554*	-0.00146	0.200	0.0939**
	(0.210)	(0.0593)	(0.177)	(0.138)	(0.327)	(0.117)	(0.140)	(0.0435)
Pure Farm × Pure Farm-dominated	0	0	-0.00224	0.0241	0	0	-0.0715	-0.141***
	(.)	(.)	(0.0644)	(0.0394)	(.)	(.)	(0.0766)	(0.0346)
Pure Farm × Pastoral-dominated	0	0	0	0	-0.128	0.0627	0.151	0.0197
	(.)	(.)	(.)	(.)	(0.214)	(0.147)	(0.260)	(0.136)
Pastoral × Mixed cells	-0.748**	-0.131	0.197	0.305	0.0871	-0.0600	0.0713	0.0745
	(0.331)	(0.0832)	(0.317)	(0.263)	(0.359)	(0.153)	(0.132)	(0.0595)
Pastoral × Pure Farm-dominated	0	0	0.483**	0.194**	0	0	-0.138	-0.208***
	(.)	(.)	(0.229)	(0.0983)	(.)	(.)	(0.163)	(0.0564)
Pastoral × Pastoral-dominated	0	0	0	0	0.0816	0.236*	-0.303**	0.00490
	(.)	(.)	(.)	(.)	(0.183)	(0.125)	(0.132)	(0.0863)
Moderately/Ext dry								
Agropastoral × Mixed cells	0.536***	0.178***	1.024***	0.541***	0.632***	0.227***	-0.0515	0.0658
	(0.176)	(0.0671)	(0.181)	(0.134)	(0.0972)	(0.0707)	(0.215)	(0.0852)
Agropastoral × Pure Farm-dominated	0.611***	0.129	0.662***	0.376***	0	0	0.0542	0.186***
	(0.217)	(0.127)	(0.141)	(0.0768)	(.)	(.)	(0.127)	(0.0448)
Agropastoral × Pastoral-dominated	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Pure Farm × Mixed cells	0.278	0.0922	1.189***	0.706***	0.516***	0.123	0.0934	0.128
	(0.232)	(0.0835)	(0.146)	(0.128)	(0.135)	(0.0927)	(0.253)	(0.0974)
Pure Farm × Pure Farm-dominated	0.336	0.0426	0.502***	0.305***	0	0	0.00571	0.0361
	(0.379)	(0.0426)	(0.142)	(0.0721)	(.)	(.)	(0.0928)	(0.0335)
Pure Farm × Pastoral-dominated	0	0	0	0	0	0	0.537**	0.300***
	(.)	(.)	(.)	(.)	(.)	(.)	(0.241)	(0.0952)
Pastoral × Mixed cells	0.254	0.0268	0.775***	0.380*	0.667***	0.179**	-0.0773	0.133*
	(0.320)	(0.0655)	(0.253)	(0.204)	(0.123)	(0.0736)	(0.210)	(0.0754)
Pastoral × Pure Farm-dominated	0	0	0.636***	0.409***	0	0	-0.0363	0.127**
	(.)	(.)	(0.227)	(0.122)	(.)	(.)	(0.154)	(0.0570)
Pastoral × Pastoral-dominated	0	0	0	0	0.260	0.128	0.336**	0.276***
	(.)	(.)	(.)	(.)	(0.185)	(0.122)	(0.151)	(0.0763)
Observations	4258	4258	8780	8780	6602	6602	9816	9816
Gridcell FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster (EA)	475	475	745	745	409	409	355	355
Controls	N	N	N	N	N	N	N	N
Spatial correlation	N	N	N	N	N	N	N	N
Mean DV	2.47	0.85	0.67	0.45	0.78	0.43	2.01	0.71

*Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by HH_type and Grid_type. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1) and binary variable any event (2). Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = farmers, 3 = pastoral. Grid_type (60% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). Panel weights are applied.*

Table E.9: *Analysis by grid cell*

	Pooled sample			
	Number of conflicts (IHS)		Any conflict	
	(1)	(2)	(3)	(4)
Moderately/Ext wet	-0.0303	-0.209**	0.0142	-0.110***
	(0.0399)	(0.0954)	(0.0199)	(0.0381)
Moderately/Ext dry	0.346***	0.376***	0.165***	0.132***
	(0.0438)	(0.0663)	(0.0231)	(0.0335)
Pure Farm-dominated		-0.0150		0.0233
		(0.0756)		(0.0409)
Pastoral-dominated		0.505***		0.121**
		(0.115)		(0.0546)
Wet × Pure Farm-dominated		0.233**		0.165***
		(0.106)		(0.0456)
Wet × Pastoral-dominated		0.0847		0.101
		(0.166)		(0.0833)
Dry × Pure Farm-dominated		-0.0381		0.0753*
		(0.0872)		(0.0441)
Dry × Pastoral-dominated		-0.335**		-0.138*
		(0.143)		(0.0824)
Observations	4680	4680	4680	4680
Adj R-squared	0.744	0.747	0.431	0.436
R-squared	0.859	0.861	0.686	0.690
Clusters (Gridcellid)	2089	2089	2089	2089
Country × Year FE	Y	Y	Y	Y
Gridcell FE	Y	Y	Y	Y
Spatial correlation	N	N	N	N
Controls	N	N	N	N
Mean DV	1.464	1.464	0.614	0.614

*Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Y = yes, N = no. All specifications include country × year and gridcell fixed effects. Robust standard errors are clustered at gridcellid level. Dependent variable: inverse hyperbolic sine of number of conflicts after harvest (1,2) and binary variable any event (3,4). The independent variable is SPEI6 in (1,3) and the double interaction between SPEI6 and Grid Type (2,4). SPEI6 is a categorical variable = 0 if normal climatic conditions, =1 if above long-term average at least by 1SD (wet conditions), =2 if below average at least by 1SD (dry conditions). Grid type has 3 categories: Category 1 (Mixed cells): if only agropastoral_share > 40% threshold, or 2 categories exceed threshold, or none. Category 2 (Pure Farmer dominated): if only pure_farm_share > 40% threshold. Category 3 (Pastoral dominated): if only pastoral_share > 40% threshold. No control variables.*

Table E.10: *Number of conflict (IHS) defined on SPEI grid cell*

	Burkina Faso	**Côte d'Ivoire**	**Niger**	**Nigeria**
Moderately/Ext wet	-0.875***	0.027	0.322***	-0.026
	(0.198)	(0.065)	(0.093)	(0.067)
Moderately/Ext dry	0.515***	0.706***	0.686***	0.108
	(0.164)	(0.109)	(0.095)	(0.066)
Observations	4,258	8,780	6,602	9,816
Clusters	475	745	409	355
R-squared	0.850	0.709	0.847	0.873
Gridcell FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	N	N	N

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is the IHS-transformed number of conflict events at the SPEI grid cell level. All models include gridcell and year fixed effects. Standard errors are clustered at the EA level.

F Analysis of the Mechanisms Linking Climatic Shocks and Conflict Dynamics

Table F.1: *Conditional marginal effects of climatic anomalies on crop yield (IHS transformed)*

	Burkina Faso (1)	Niger (2)	Nigeria (3)
Moderately/Ext wet			
Agropastoral × Mixed cells	0.276	-0.468	-0.193
	(0.192)	(0.433)	(0.291)
Agropastoral × Pure Farm-dominated	0	-0.232	-0.988***
	(.)	(0.399)	(0.364)
Agropastoral × Pastoral dominated	0	0	-1.633***
	(.)	(.)	(0.401)
Pure farm × Mixed cells	0.169	0.953***	-0.183
	(0.247)	(0.326)	(0.425)
Pure farm × Pure Farm-dominated	0	0.612	-0.978**
	(.)	(0.489)	(0.447)
Pure farm × Pastoral dominated	0	0	-1.424
	(.)	(.)	(1.560)
Moderately/Ext dry			
Agropastoral × Mixed cells	0.0566	-0.908***	0.372
	(0.239)	(0.129)	(0.365)
Agropastoral × Pure Farm-dominated	-1.547***	0	-0.390
	(0.355)	(.)	(0.399)
Agropastoral × Pastoral dominated	0	0	0
	(.)	(.)	(.)
Pure farm × Mixed cells	-0.00438	-1.222***	-0.349
	(0.296)	(0.187)	(0.443)
Pure farm × Pure Farm-dominated	-1.034***	-1.457***	-0.499
	(0.298)	(0.440)	(0.319)
Pure farm × Pastoral dominated	0	0	0
	(.)	(.)	(.)
Observations	1132	4128	3459

*Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by HH_type and Grid_type. Model VCE: robust standard errors. All specifications include year and gridcell fixed effects; SE clustered at EA level. Dependent variable: inverse hyperbolic sine of crop yield. Independent variable: climatic anomalies—normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = pastoral, 3 = farmers. Grid_type: 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. No controls. Panel weights are applied.*

Table F.2: *Effects of Wet and Dry Conditions on On-Farm Work*

	Niger		Burkina Faso		Côte d'Ivoire		Nigeria
	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid	Paid
Moderately/Ext wet							
Agropastoral × Mixed cells	2.490	5.676	-12.97**	4.663	0	0	2.69
	(12.19)	(8.827)	(6.405)	(6.454)	(.)	(.)	(3.27)
Agropastoral × Pure Farm-dominated	0	0	0	0	-6.652	1.484	2.84
	(.)	(.)	(.)	(.)	(4.202)	(3.647)	(4.09)
Agropastoral × Pastoral dominated	-12.15	6.588	0	0	0	0	-0.885
	(16.39)	(6.148)	(.)	(.)	(.)	(.)	(4.42)
Pure farm × Mixed cells	12.65	-2.149	-2.752	3.598	0	0	1.83
	(8.951)	(8.993)	(8.453)	(6.882)	(.)	(.)	(3.68)
Pure farm × Pure Farm-dominated	-13.17	59.03***	0	0	0.193	-2.861	0.581
	(8.806)	(3.408)	(.)	(.)	(2.990)	(2.320)	(1.42)
Pure farm × Pastoral dominated	0	0	0	0	0	0	-5.28
	(.)	(.)	(.)	(.)	(.)	(.)	(4.31)
Pastoral × Mixed cells	16.00	-8.597*	-19.26*	4.066	0	0	1.28
	(11.59)	(4.713)	(10.04)	(4.972)	(.)	(.)	(3.30)
Pastoral × Pure Farm-dominated	0	0	0	0	2.804	11.38**	-3.81
	(.)	(.)	(.)	(.)	(9.655)	(5.407)	(2.76)
Pastoral × Pastoral dominated	33.87***	0.158	0	0	0	0	2.05
	(12.79)	(5.443)	(.)	(.)	(.)	(.)	(1.52)
Moderately/Ext dry							
Agropastoral × Mixed cells	-9.209	10.59**	-2.293	-8.584	-3.180	-1.021	-8.85***
	(5.678)	(4.615)	(9.106)	(7.701)	(11.26)	(8.528)	(3.31)
Agropastoral × Pure Farm-dominated	-35.56***	30.36***	70.51***	-59.30**	-9.362	26.05***	-4.90
	(10.31)	(5.891)	(14.51)	(25.15)	(5.948)	(5.004)	(3.48)
Agropastoral × Pastoral dominated	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Pure farm × Mixed cells	-27.25***	15.56***	1.223	-3.862	-2.574	-16.42	-0.031
	(5.890)	(5.829)	(10.85)	(8.476)	(12.60)	(14.35)	(4.95)
Pure farm × Pure Farm-dominated	28.87***	-5.893**	18.65	-34.86**	-1.973	14.26***	-3.67***
	(1.750)	(2.977)	(16.81)	(15.21)	(4.013)	(4.117)	(1.393)
Pure farm × Pastoral dominated	0	0	0	0	0	0	20.09***
	(.)	(.)	(.)	(.)	(.)	(.)	(4.57)
Pastoral × Mixed cells	3.194	9.193	0	0	7.753	69.28**	-4.94
	(9.771)	(5.814)	(.)	(.)	(18.23)	(31.37)	(8.16)
Pastoral × Pure Farm-dominated	0	0	0	0	6.247	-8.173	-7.97**
	(.)	(.)	(.)	(.)	(10.05)	(6.204)	(2.83)
Pastoral × Pastoral dominated	28.27**	0.345	0	0	0	0	3.65
	(12.30)	(5.390)	(.)	(.)	(.)	(.)	(2.341)
Observations	3148	3148	2000	2000	3736	3736	9807

*Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Conditional marginal effects (dy/dx) of `SPEI6_class` (Wet/Dry) by `HH_type` and `Grid_type`. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: percentage of household engaged in in-farm work (paid/unpaid) during the past 7 days. Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). `HH_type`: 1 = agropastoral, 2 = farmers, 3 = pastoral. `Grid_type` (40% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). No control variables. Coefficients and margins are in percentage points. For EHCVM, the sample is restricted to Round 1 of each wave (the question refers to the past 7 days; Round 2 occurs months after the agricultural season). Panel weights applied.*

Table F.3: *Effects of Wet and Dry Conditions on Off-Farm Work*

	Niger	**Burkina Faso**	**Côte d'Ivoire**	**Nigeria**
Moderately/Ext wet				
Agropastoral × Mixed cells	-2.222	2.516**	0	-0.051
	(1.929)	(1.019)	(.)	(0.853)
Agropastoral × Pure Farm-dominated	0	0	0.829	-0.491
	(.)	(.)	(1.604)	(1.356)
Agropastoral × Pastoral dominated	-20.18***	0	0	-1.02
	(4.384)	(.)	(.)	(2.08)
Pure farm × Mixed cells	1.448	15.88	0	-0.414
	(2.410)	(10.99)	(.)	(1.527)
Pure farm × Pure Farm-dominated	8.873*	0	-0.306	2.03**
	(4.609)	(.)	(0.920)	(0.910)
Pure farm × Pastoral dominated	0	0	0	4.23
	(.)	(.)	(.)	(3.32)
Pastoral × Mixed cells	-11.22***	4.444	0	0.825
	(3.162)	(9.853)	(.)	(1.51)
Pastoral × Pure Farm-dominated	0	0	3.496	-0.697
	(.)	(.)	(9.943)	(1.44)
Pastoral × Pastoral dominated	-5.902	0	0	0.871
	(5.764)	(.)	(.)	(0.789)
Moderately/Ext dry				
Agropastoral × Mixed cells	1.669	1.202	-7.306	1.48**
	(1.302)	(1.985)	(4.718)	(0.651)
Agropastoral × Pure Farm-dominated	16.14***	22.02*	0.170	3.58**
	(5.411)	(12.95)	(2.114)	(1.39)
Agropastoral × Pastoral dominated	0	0	0	0
	(.)	(.)	(.)	(.)
Pure farm × Mixed cells	3.662*	0.597	-10.91*	-1.31
	(2.197)	(2.317)	(6.066)	(1.245)
Pure farm × Pure Farm-dominated	-2.800**	-2.366	-1.968	0.141
	(1.331)	(3.318)	(2.021)	(0.901)
Pure farm × Pastoral dominated	0	0	0	-8.816***
	(.)	(.)	(.)	(2.03)
Pastoral × Mixed cells	-0.662	0	-3.057	2.68
	(4.090)	(.)	(5.561)	(1.81)
Pastoral × Pure Farm-dominated	0	0	32.05	0.287
	(.)	(.)	(19.88)	(1.367)
Pastoral × Pastoral dominated	-8.968**	0	0	-5.979***
	(4.272)	(.)	(.)	(1.03)
Observations	3148	2000	3736	9813

*Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Conditional marginal effects (dy/dx) of `SPEI6_class` (Wet/Dry) by `HH_type` and `Grid_type`. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: percentage of household engaged in off-farm work (paid) during the past 7 days. Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). `HH_type`: 1 = agropastoral, 2 = farmers, 3 = pastoral. `Grid_type` (40% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). No control variables. Coefficients and margins are already expressed in percentage points. For EHCVM survey, we restricted the sample to only Round 1 per each wave as the question refers to the past 7 days and Round 2 has been interviewed several months after the end of the agricultural season. Panel weights are applied.*

Table F.4: *Total workdays during agricultural season (IHS transformed)*

	Niger	Burkina Faso
	(1)	(2)
Moderately/Ext wet		
Agropastoral × Mixed cells	-0.308**	0.0302
	(0.146)	(0.142)
Agropastoral × Pure Farm-dominated	-0.319	0
	(0.347)	(.)
Agropastoral × Pastoral dominated	0	0
	(.)	(.)
Pure farm × Mixed cells	0.0981	0.231
	(0.189)	(0.224)
Pure farm × Pure Farm-dominated	-0.628	0
	(0.444)	(.)
Pure farm × Pastoral dominated	0	0
	(.)	(.)
Moderately/Ext dry		
Agropastoral × Mixed cells	-0.139*	0.147
	(0.0708)	(0.113)
Agropastoral × Pure Farm-dominated	-0.907***	-0.521**
	(0.334)	(0.247)
Agropastoral × Pastoral dominated	0	0
	(.)	(.)
Pure farm × Mixed cells	0.109	0.191
	(0.0858)	(0.130)
Pure farm × Pure Farm-dominated	0.203	-0.423**
	(0.299)	(0.203)
Pure farm × Pastoral dominated	0	0
	(.)	(.)
Observations	5120	3870

*Notes: Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Conditional marginal effects of SPEI6_class (Wet/Dry) by HH_type and Grid_type. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: total number of workdays in the latest agricultural season by household and non household members in all the phases (planting, growing, harvesting). Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = farmers, 3 = pastoral. Grid_type (40% threshold): 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. Empty categories are expressed with 0 and (.). No control variables. For Côte d'Ivoire and Nigeria we do not have this information available. Panel weights are applied.*

Table F.5: *Access to credit during and/or post growing season in Côte d'Ivoire*

	(1)	(2)
Moderately/Ext dry		
Pure Farm × Pure Farm-dominated	0.323**	0.319**
	(0.145)	(0.145)
Pure Farm × Mixed cells	-0.411*	-0.419*
	(0.248)	(0.248)
Pastoral × Mixed cells	0.458*	0.443*
	(0.241)	(0.261)
Observations	1044	1044
Adj. R-squared	0.210	0.216
R-squared	0.301	0.309
Gridcell FE	Y	Y
Year FE	Y	Y
Spatial correlation	N	N
Controls	N	Y
Clusters	461	461
Mean DV	0.452	0.452

*Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Conditional marginal effects (dy/dx) of SPEI6_class (Wet/Dry) by HH_type and Grid_type. Standard errors robust to estimate margins by default. All specifications include year and gridcell fixed effects. Margins from OLS with SE clustered at EA level. Dependent variable: binary indicator =1 if the household reported to have contracted a credit after the relevant growing season. Independent variable: climatic anomalies: normal (0), wet (1), or dry (2). HH_type: 1 = farmers, 2 = agropastoral, 3 = pastoral. Grid_type (40% threshold): 1 = Pure Farm-dominated, 2 = Mixed, 3 = Pastoral dominated. Empty categories or not significant are omitted for the sake of brevity. (1) No controls; (2) Controls. Controls include: household size, gender of household head, distance from closest city in km (inverse hyperbolic sine transformed), annual consumption per adult equivalent. All controls are set at their means by default. The sample is restricted to households who responded to the question: "In which year and month did you contract your credit?". Therefore, it encompasses households with a history of credit requests. Panel weights are applied.*

Table F.6: *Conditional marginal effects of climatic anomalies on crop revenues (IHS transformed)*

	Burkina Faso (1)	**Côte d'Ivoire** (2)	**Niger** (3)	**Nigeria** (4)
Moderately/Ext wet				
Agropastoral × Mixed cells	0.398	0	-0.430**	1.286
	(0.255)	(.)	(0.210)	(1.143)
Agropastoral × Pure Farm-dominated	0	0.0707	-0.614	1.299
	(.)	(0.119)	(0.409)	(1.142)
Agropastoral × Pastoral dominated			0	-0.480
			(.)	(2.047)
Pure farm × Mixed cells	1.335***	0	-0.391	-0.322
	(0.429)	(.)	(0.389)	(1.314)
Pure farm × Pure Farm-dominated	0	0.154*	-0.0656	-1.380
	(.)	(0.0864)	(0.521)	(0.871)
Pure farm × Pastoral dominated			0	0
			(.)	(.)
Moderately/Ext dry				
Agropastoral × Mixed cells	-0.213	0.122	0.00742	0.212
	(0.302)	(0.345)	(0.132)	(0.682)
Agropastoral × Pure Farm-dominated	-1.503**	-0.150	0	0.856
	(0.626)	(0.205)	(.)	(0.976)
Agropastoral × Pastoral dominated			0	0
			(.)	(.)
Pure farm × Mixed cells	-0.269	-0.416	0.0166	-2.813***
	(0.343)	(0.356)	(0.244)	(1.032)
Pure farm × Pure Farm-dominated	-1.552***	-0.0377	0	-1.102*
	(0.498)	(0.182)	(.)	(0.618)
Pure farm × Pastoral dominated			0	0
			(.)	(.)
Observations	1182	6304	2390	1623

*Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Conditional marginal effects (dy/dx) of SPEI6 class (Wet/Dry) by HH_type and Grid_type. Model VCE: robust standard errors. All specifications include year and gridcell fixed effects; SE clustered at EA level. Dependent variable: inverse hyperbolic sine of* crop revenues*. Independent variable: climatic anomalies—normal (0), wet (1), or dry (2). HH_type: 1 = agropastoral, 2 = pastoral, 3 = farmers. Grid_type: 1 = Mixed, 2 = Pure Farm-dominated, 3 = Pastoral dominated. No controls. Panel weights are applied. 13 singleton observations were automatically dropped in Nigeria and 4 in Niger during estimation.*