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Food security, shocks, resilience and fragility: Panel evidence from Sudan

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Abstract
Hundreds of millions of people around the world live in fragile situations, where shocks are highly prevalent and threaten well-being. Guided by a novel framework for measuring food system resilience in fragile situations (Serfilippi et al., 2025) and panel survey data collected during Sudan's ongoing civil war, we study the effects of climate shocks on household food security in a highly fragile setting. We find that from the lean season to the harvest season, food insecurity fell sharply, but that unusually high temperatures, the most widespread climate shock in this period, strongly reduced this improvement: one standard deviation of additional heat exposure offset about two-thirds of the average gain in food security. That reduction was about twice as large for households with lethal conflict within 25km, although the difference is not robust across all specifications. Fragility experience reported before the shock did not amplify the effect of heat, but heat losses were larger where households reported more fragile conditions at the end of the window between the rounds. Households with greater pre-shock resilience capacities were initially less food insecure, but they did not gain more over the harvest than households with the same room to improve, and we find no evidence that they lost less of the gain to heat. We discuss what these findings imply for the targeting and timing of resilience programming in conflict-affected areas, and document both the feasibility and the limits of phone-based panel monitoring in extremely fragile environments, where sample selection is itself shaped by conflict.

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1. Introduction

Hundreds of millions of people live in fragile situations: environments where weak institutions, active conflict, and environmental stress create compounding threats to lives and livelihoods (World Bank, 2024; OECD, 2022). In 2024, conflict was the primary driver of food crises affecting over 130 million people, and climate change is intensifying drought and resource scarcity in many of the same regions (FSIN, 2024). Yet these two dominant drivers of fragility are overwhelmingly studied in isolation: a recent systematic review finds that only 11 percent of household-level studies on food security published between 2020 and 2025 analyze combined climate-conflict crises (Awoke & Brück, 2026). We know very little about how conflict and climate challenges interact at the household level: whether their joint effects are additive, or whether they compound into polycrises that are qualitatively worse (Lawrence et al., 2024; Stojetz et al., 2025).

A fundamental reason for this knowledge gap is measurement. The settings where evidence on resilience is most urgently needed are precisely the settings where data collection is most difficult (Martin-Shields & Stojetz, 2019; Kayaoglu, Baliki & Brück, 2023). Acute crises destroy infrastructure, displace populations, and prevent access, among many other challenges. The result is a paradox: the populations in the most fragile situations are the least represented in the evidence base that should inform their protection.

This paper studies household food security in a highly fragile polycrisis setting: Sudan during its ongoing civil war (since April 2023). We study how climate shocks between the lean season and the harvest affect household food security, placing particular emphasis on the role of exposure to conflict and other experiences of fragility and on the role of pre-shock resilience.

Conceptually, we build on Serfilippi et al.'s (2025) analytical framework for measuring food system resilience in fragile situations, which distinguishes fragility conditions (exposure and experience) from resilience capacities (absorptive, adaptive, transformative) across economic, environmental, social, and institutional dimensions. We operationalize this framework through a Computer-Assisted Telephone Interview (CATI) panel survey across seven Sudanese states, embedded within the Sudan Sustainable Natural Resources and Livelihoods Programme (SNRLP). Targeting a pre-existing household sample surveyed between December 2022 and

January 2023 as the program baseline (PACT Consultancy, 2023), we conducted two rounds of data collection: Round 1 was collected between 5 August and 25 September 2025, before the main harvest (N=565), and Round 2 between 25 November and 20 December 2025, while the main harvest was under way (N=458), yielding a panel of 342 households observed across the baseline and both rounds (or 684 panel observations). We complement the survey with a meso-level key informant survey (N=115), conflict event data from the Armed Conflict Location & Event Data project (ACLED) and the Uppsala Conflict Data Program (UCDP), and climate data on rainfall, drought, flooding and temperature, allowing us to construct household- and locality-level shock measures independent of household self-reports. The framework measures fragility and resilience at the macro, meso and micro levels, and our data cover all three. As objective indicators of fragility exposure at the macro level, we use conflict event and climate data, which we link to each household's location, in line with the framework's micro-level notion of exposure as the direct presence of an actor in relation to a hazard. The household panel measures fragility experience and resilience capacities at the micro level.

Our analysis centers on this panel. Observing the same households before and after the shocks between the rounds allows us to compare changes within households rather than differences between them, to absorb all time-invariant household characteristics, including unobserved capacities and pre-war conditions, and to measure resilience and fragility for the same individuals at different points in time. Our main model is thus a difference-in-differences design with household and region-by-round fixed effects, which compares households in the same region that differ in their exposure to climate shocks.

Our descriptive findings document a population under severe but evolving stress. In Round 1, 45 percent of panel households are severely food insecure. Shock exposure is pervasive, with 96 percent of households reporting at least one shock in the previous 12 months, and recovery is generally limited: about three-quarters of the households that report a shock have not recovered to their pre-shock level in either round. From the lean season to the harvest, food security improves: the raw score of the Food Insecurity Experience Scale (FIES) falls from 3.3 to 1.4 and the share of severely food insecure households from 45 to 20 percent. Exposure to fragility is also widespread. Before Round 1, 69 percent of households had at least one lethal conflict event within 25 km, and 35 percent had three or more. Between the rounds, mean daily maximum

temperature exceeded the local 1991–2020 normal by more than one standard deviation for 69 percent of households. At the same time, the share of shock-affected households reporting no recovery at all rises from 9 to 24 percent, and emergency coping, that is, selling productive assets or relocating, rises from 16 to 35 percent of households. Reported crop yields per hectare for the 2025 harvest season fell by 68 percent compared with those reported in Round 1 for the 2024 season, and the share of households owning no livestock increased between the two waves.

Our regression analysis yields four main findings. First, unusually high temperatures between the two rounds, the most widespread climate shock in this period, undermined the harvest-related improvement in food security. One standard deviation of additional heat exposure reduces the improvement in the FIES raw score by 1.2 points, about two-thirds of the average improvement of 1.7 points in the analytical sample; the effect on severe food insecurity is of similar relative size. Second, the heat-related loss is about twice as large for households with lethal conflict within 25 km before the shock (2.3 versus 1.0 FIES points), although the difference is not statistically significant under small-cluster inference. Third, fragility experience reported before the shock does not amplify heat losses, whereas heat losses are larger where households report more fragile conditions during the harvest (by 2.3 FIES points per standard deviation of heat between households one standard deviation above and below the mean of the fragility index). Fourth, more resilient households are less food insecure, but we find no evidence that pre-shock resilience capacities protect food security gains against heat. It shows that higher household resilience capacities are associated with lower food insecurity, but they may not be sufficient to protect households against climate shocks. This suggests that interventions should adopt an integrated approach, combining the strengthening of economic and productive resilience, specific climate adaptation measures and social protection and food security systems: providing targeted support to the most vulnerable households through cash transfers, improved access to food, and rapid response mechanisms to climate shocks. Our study yields important methodological insights for data collection in fragile settings. Only 52-64% of the re-contacted households from baseline could be reached in subsequent rounds. Many households could not be surveyed because of intense conflict, including all households in South and West Kordofan. We focus on the panel, but in the full sample, there is also attrition due to conflict between the rounds: among Round 1 respondents, households in localities with more conflict were less likely to take part in

Round 2. Key informants, mostly office holders of village development committees, report much less worry about violent conflict and more frequent support from local institutions than households in the same localities (Section 6), which further emphasizes the importance of collecting data at both levels. Our study contributes to measurement methodology by demonstrating the feasibility of agile, CATI-based panel monitoring during active conflict, and by documenting how conflict shapes sample selection at successive stages of a phone panel.

Our paper contributes to several literatures. First, we contribute to the small but growing empirical literature on climate-conflict polycrises at the household level. This evidence consists of a handful of studies (Awoke & Brück, 2026). For example, Stojetz et al. (2024b) show, with panel data from Borno State in northeast Nigeria, that the positive effect of violence on social safety net participation reverses when households also experience drought, and Stojetz et al. (2025) find, for 21 African countries, that extreme climate events reduce labor intensity more in conflict environments, particularly among youth and women. We extend this evidence to a setting of even greater fragility and to the food security domain, and we use a panel to estimate the climate effect from changes within households. We find that heat-related food security losses are about twice as large where lethal conflict occurred nearby, although the difference is not statistically significant under small-cluster inference.

Second, we add to the growing literature on resilience in development economics (Barrett & Constas, 2014; Cissé & Barrett, 2018; Alloush & Carter, 2026; Béné et al., 2023; Lee et al., 2026). While some existing studies assess resilience in conflict-affected settings (Brück, d'Errico & Pietrelli, 2019; Stojetz et al., 2024a), the evidence base is skewed toward post-conflict or low-intensity-crisis environments. We provide one of the first panel-based analyses of household resilience dynamics and drivers during an active, high-intensity humanitarian crisis. We document that a standard capacity index predicts lower food insecurity in the cross-section but neither larger food security gains nor smaller shock losses among households with the same room to change, and that improvements in food security between rounds coincide with more frequent emergency coping. Both findings caution against assessing resilience by capacity indices or food security indicators alone (Upton et al., 2022; Alloush & Carter, 2026). In doing so, we show that comparisons of changes in food security across resilience groups must account for differences in the starting point on a bounded scale, and we adapt a normalized change

measure from the measurement of learning gains for this purpose (Hake, 1998; Marx & Cummings, 2007).

Third, our study is, to our knowledge, one of the first to operationalize the innovations by Serfilippi et al. (2025) on fragility: understanding resilience in fragile settings requires understanding fragility, but to date it often remains an abstract and theoretical concept. We build on Serfilippi et al. (2025) and Baliki et al. (2022) to measure (objective) fragility exposure and (subjective) fragility experience and to test how fragility shapes food insecurity outcomes. We find suggestive evidence that prior exposure to conflict events amplifies the negative impacts of climate shocks during the harvest, as does experienced fragility during the harvest.

Our findings have implications for programming in fragile settings. First, they point to the timing of support. The heat shock fell in the weeks before and during the harvest, when households would otherwise recover from the lean season, so monitoring temperature anomalies in this window could help identify localities where harvest-related gains are at risk. Second, they suggest caution in targeting by household resilience indices: in our data, these indices identify households that are less food insecure, but not households that are better protected against shocks. The integration of conflict and climate considerations is already embedded in the design of programs such as SNRLP, so we focus on what our results imply for the targeting of support across households and areas, and for its timing relative to the agricultural season and to climate shocks. Where our results speak to the interplay of household capacities and systemic fragility, we present them as hypotheses for program design rather than as estimated effects of interventions.

The remainder of the paper proceeds as follows. Section 2 presents the background and context, including the conceptual framework, climate-conflict polycrises, and the Sudanese crisis. Section 3 describes the data, covering survey design, sampling, response patterns, and the panel. Section 4 presents the empirical strategy. Section 5 reports the results, including descriptive findings and regression analyses. Section 6 discusses implications. Section 7 concludes.

2. Background and context

2.1 Conceptual framework

Resilience measurement: progress and unresolved challenges. The concept of resilience has gained substantial traction in development economics and policy over the past decade, reflecting a growing recognition that the ability to withstand, adapt to, and recover from shocks is central to sustained poverty reduction and food security (Barrett & Constas, 2014; Barrett et al., 2021; UN, 2020). Four broad conceptualizations have emerged: resilience as recovery ability, resilience as capacity, resilience as a normative condition (Barrett et al., 2021), and resilience as avoided losses relative to a counterfactual (Alloush & Carter, 2026). The first treats resilience as the ability to recover (IFAD, 2015). The second treats resilience as a set of capacities (absorptive, adaptive, and transformative) that enable actors to maintain or enhance well-being in the face of disturbances (Béné et al., 2012, 2015, 2023; FAO, 2016; USAID, 2018). This resilience-as-capacity view underpins the measurement frameworks most widely used by operational agencies, including FAO's Resilience Index Measurement and Analysis (RIMA) and the TANGO method adopted by USAID and Mercy Corps. The third conceptualization anchors resilience to normative well-being standards: Cissé & Barrett (2018) define resilience as a household's conditional probability of maintaining well-being above a threshold, estimated through the conditional moments of the well-being distribution. In the fourth, Alloush & Carter (2026) define resilience as the cumulative economic losses a household experiences relative to a counterfactual trajectory without the shock, linking resilience directly to shock impacts rather than to latent capacities or probabilistic thresholds. The four are related: capacities describe what a household brings to a shock, recovery and avoided losses describe what happens after it, and the normative approach summarizes the resulting distribution of well-being over time.

Despite this progress, resilience measurement remains contested. Upton, Constenla-Villoslada & Barrett (2022) compare the three most widely used measurement approaches (RIMA, TANGO, and Cissé & Barrett, 2018) using nationally representative panel data from Ethiopia and Niger. The study finds that the three measures generate significantly different distributions, rank households differently, fail basic internal consistency tests, and exhibit only modest out-of-sample predictive accuracy. Notably, none consistently outperforms the far simpler approach of using the most recent value of the relevant well-being measure to predict future well-being. This raises questions about what existing resilience measures capture and what value they add beyond more established welfare indicators. Our panel allows a simple version of this test: we ask

whether a capacity index measured before a shock predicts food security gains, and smaller losses from the shock, among households that start with the same room to improve (Section 4.3).

Lee, Abay, Barrett & Hoddinott (2026) extend this critique to the multidimensional case. They show that univariate resilience measures constructed from different well-being indicators (consumption expenditure, dietary diversity, and livestock assets) are only weakly correlated (rank correlations of 0.10–0.37), even when using the same estimation method. Their Shapley decomposition further shows that the factors driving different resilience dimensions diverge sharply: community-level attributes explain most of the variation in dietary resilience, while household productive assets dominate consumption and livestock-based resilience. These findings imply that resilience is not a single latent variable that can be captured by any one indicator but a multidimensional concept whose measurement requires explicit choices about which dimensions to include and how to aggregate them. None of these approaches accounts explicitly for the fragility conditions under which households use their capacities, which is the element that the framework we follow adds.

Alloush & Carter (2026) offer a different approach. Rather than constructing a resilience index from household characteristics and hoping it predicts future well-being, they propose measuring resilience through its consequences: the cumulative losses a household experiences in the wake of a shock, relative to a counterfactual trajectory. Their Cumulative Avoided Loss (CAL) measure requires panel data spanning a shock event, plus a credible counterfactual (typically from experimental or quasi-experimental variation). Using simulated data calibrated to a dynamic stochastic optimization model, they demonstrate that the CAL measure can evaluate resilience-building interventions and identify poverty traps. They also show that in the presence of poverty traps, consumption-based measures can be misleading in short panels because households falling into traps may temporarily boost consumption by de-accumulating productive assets, appearing more resilient by consumption metrics while becoming structurally less resilient.

The Serfilippi et al. (2025) framework: resilience and fragility as distinct, complementary dimensions. Our analysis builds on the analytical framework for measuring food system resilience in fragile situations developed in Serfilippi et al. (2025). This framework relies on the

conceptualization of resilience as recovery ability and as a set of capacities. Furthermore it integrates two bodies of theory (on resilience and on fragility) into a unified multi-level measurement system that addresses limitations of both the resilience-as-capacity and resilience-as-outcome approaches. We summarize its key elements here and refer to Serfilippi et al. (2025) for a full exposition.

Following Béné (2020), the framework distinguishes between resilience capacities, defined as the inputs and endowments available for responding to a shock, and resilience outcomes, defined as the actual recovery trajectory. Capacities are categorized as absorptive (preparedness, short-term coping), adaptive (livelihood adjustment, diversification), and transformative (fundamental restructuring of livelihood strategies). This distinction matters for measurement because it implies that both ex ante capacities and ex post recovery should be assessed.

Fragility, in the framework, is operationalized through the exposure–experience distinction proposed by Baliki et al. (2022). Exposure to fragility refers to the objective condition of being subject to potential harm: the spatial and temporal intersection of shocks and stressors with actors and systems. At the macro level, this includes conflict incidence, climate hazard severity, and institutional performance. Experience of fragility refers to how these exposures translate into actual impacts on functioning and well-being, mediated by actors' capacities and characteristics. At the household level, experience is captured through self-reported impacts, coping behaviors, and perceived vulnerabilities. The framework's indicators of household experience include the type and severity of the shocks households suffered, such as climatic shocks, violence and theft, and displacement. Shocks thus enter the framework twice: as exposure, measured objectively, for example by geocoded conflict events or climate anomalies, and as experience, measured by household reports (Serfilippi et al., 2025).

The framework treats resilience and fragility not as opposing ends of a single continuum but as conceptually distinct, complementary dimensions: fragility captures systemic conditions and constraints, while resilience captures the capacities and actions of actors operating within those conditions.

The framework organizes measurement across four core dimensions: economic (price volatility, productivity, market disruptions), environmental and climate (water and land scarcity, climate

vulnerability), security and social (social cohesion, conflict exposure, displacement), and political and institutional (governance effectiveness, infrastructure, service delivery). For each dimension, indicators are specified at macro, meso, and micro levels, with a clear classification rule: fragility indicators capture conditions and constraints in the system, while resilience indicators capture capacities, enabling factors, and actions taken by actors. Our data cover all three levels: conflict event and climate data provide objective indicators of exposure, the key informant survey covers the meso level, and the household survey measures experience and capacities at the micro level (Section 3).

Testable predictions. The framework generates three empirically testable predictions that structure our analysis. First, fragility conditions should amplify shock impacts: households operating in more fragile environments, characterized by weaker institutions, greater displacement, or more severe infrastructure disruption, should experience larger food security losses from equivalent shocks. Because conflict is a form of fragility exposure, the interaction between a climate shock and conflict exposure is one test of this prediction; the interaction with fragility experience is another. Second, resilience capacities should buffer the impact of shocks on food security: households with greater absorptive, adaptive, or transformative capacity should experience smaller declines in food security when exposed to the same shock. Several studies have tested this prediction in less fragile settings (d'Errico et al., 2018; Smith & Frankenberger, 2018). This prediction is shared with capacity-based approaches; the first and third follow from the framework's distinction between fragility and resilience. Third, the framework predicts that fragility should erode the protective effect of resilience: a household with strong social networks, for instance, may find those networks less effective when the institutional environment has collapsed. This third prediction implies a three-way interaction between shocks, resilience, and fragility, a hypothesis that has, to our knowledge, rarely been tested empirically. Because our sample excludes the most conflict-affected localities, our tests of the first and third predictions apply to a restricted range of fragility conditions, which reduces statistical power and may attenuate the estimated interactions.

We test these predictions using a moderation approach. Conceptually, this choice follows from the framework's structure: fragility conditions and resilience capacities shape how shocks translate into outcomes, so we treat them as moderators of the relationship between shocks and

food security. Both are dynamic and may themselves respond to shocks. We therefore measure resilience capacities before the shock whose effects they are hypothesized to moderate. For fragility experience, we compare reports from before the shock with reports from the end of the window between the rounds, which describe the conditions under which the shock unfolded but may also partly reflect it (Section 4.3). Moderation estimates describe how shock impacts differ across households with different conditions and capacities; they do not identify the causal effect of fragility or resilience as such. In addition, we test whether fragility experience and resilience capacities predict food security gains regardless of the shock, which separates their role as moderators from their association with the level of food security.

2.2 Climate-conflict polycrises

A polycrisis arises when several shocks and stressors occur together and interact, so that their joint impact exceeds the sum of their separate effects (Lawrence et al., 2024). Climate and conflict shocks tend to cluster in the same regions and periods (FSIN, 2024), and the framework treats their combination as a point where fragility and resilience meet: when actors face conflict exposure and environmental stress at the same time, their ability to cope with either may diminish, because environmental stress limits the resources households need to withstand conflict-related shocks, and conflict disrupts the social and economic systems that support adaptation to climate pressures (Serfilippi et al., 2025). If climate and conflict shocks compound in this way, policies that address climate adaptation and conflict response separately will leave households exposed to their joint effects.

We approach the polycrisis hypothesis as a question of effect heterogeneity. We treat the climate shock between the two survey rounds as the shock of interest and conflict exposure before it as a pre-determined condition, the component of fragility exposure that is measured before the shock. We then ask whether the same climate shock reduces food security more where conflict was present. A larger effect where conflict was present is consistent with a polycrisis; an equal effect means that the two crises add up. Because conflict is not randomly assigned, this comparison describes how the climate effect differs across conflict environments and does not identify the effect of conflict as such (Section 4.2).

Sudan offers a setting in which to examine the polycrisis hypothesis under severe stress, although our sample is concentrated in the less conflict-affected areas that remained reachable by phone (Section 3.2). With 342 panel households, our analysis is best seen as a test of the hypothesis within a specific, selected population rather than as evidence of a general pattern.

2.3 The Sudanese crisis

Sudan presents an extreme case for studying resilience under compounding fragility. After decades of recurrent civil war, including the conflicts that led to the secession of South Sudan in 2011 and the war in Darfur since 2003, the hopes raised by the transition of 2019 ended with the military coup of October 2021 and the outbreak of war between the Sudanese Armed Forces (SAF) and the Rapid Support Forces (RSF) in Khartoum on 15 April 2023.

The conflict rapidly spread from the capital to other parts of the country, with particularly intense fighting in Darfur, Kordofan, Khartoum State, and Al Jazeera (Gazira). The RSF captured El Fasher, the capital of North Darfur and the last major government-held city in Darfur, in October 2025, after an eighteen-month siege, with widespread reports of mass atrocities against civilians. In the weeks between our two survey rounds, the conflict also escalated in one of our study states: the RSF captured Bara in North Kordofan on 25 October 2025, and nearly 39,000 people were displaced across Kordofan between late October and early November (Al Jazeera, 2025). By the time the war entered its fourth year in April 2026, it had produced what multiple international organizations describe as the world's worst humanitarian crisis. Approximately 11 million people are internally displaced, the largest internal displacement crisis globally, and an additional 4 million have fled to neighboring countries as refugees (CSIS, 2026). An estimated 33.7 million people, roughly two-thirds of the population, require urgent humanitarian assistance (UNICEF, 2026).

The impact on food systems has been severe. Agriculture, the dominant livelihood for approximately 80 percent of the population, has been systematically disrupted through direct destruction of farms and livestock, displacement of farming communities, disruption of input supply chains, and the breakdown of market infrastructure. In 2016, roughly 12 percent of Sudan's population experienced crisis levels of food insecurity; by 2024, this share had risen to over half the population.

Simultaneously, Sudan faces significant and intensifying climate-related challenges. Large parts of the country are semi-arid or arid, and agriculture is predominantly rainfed, making it highly vulnerable to precipitation variability. Recurrent droughts, floods, and shifting weather patterns have been a persistent feature of Sudan's food system for decades, but climate change is increasing both the frequency and intensity of extreme weather events. In 2025, extreme weather events including heavy rains, droughts, and recurring flooding forced additional displacement alongside the conflict-driven crisis (IOM, 2026). The 2025 rainy season started late, with rains picking up only in late July or early August, and brought moderately below-average but evenly distributed rainfall; agroclimatic conditions were overall described as favorable (FEWS NET, 2025; IPC, 2025; FAO, 2026a). The most visible climate event around the time of our surveys was flooding, while the most widespread anomaly in our study areas was heat: in the two months between the rounds, maximum temperatures were more than one standard deviation above the 1991–2020 normal for 69 percent of panel households (Section 5.1). In late September and early October 2025, at the end of Round 1 fieldwork and in the weeks after, the Blue Nile and the main Nile rose well above normal levels, inundating homes and farmland in Blue Nile, Sennar, Gezira, Khartoum, White Nile, River Nile and Northern states; water releases from the Grand Ethiopian Renaissance Dam and a rainy season extending into October were cited as causes. Rivers in Kassala and Gedaref also flooded (AllAfrica, 2025; FEWS NET, 2025). National cereal production in 2025 was about 22 percent below 2024, mainly because of conflict-related disruptions to input supply and access to farmland (FAO, 2026b). Our meso-level data show that poor water management, rather than drought alone, is cited as the primary driver of water shortages by community-level respondents, suggesting that institutional and governance failures amplify the impact of climate stress, the kind of fragility-resilience interaction that the Serfilippi et al. (2025) framework is designed to capture.

Conflict disrupts the adaptive strategies and infrastructure that households would otherwise use to cope with climate variability, while climate stress exacerbates resource competition and may intensify conflict dynamics. Our survey captures this compounding vulnerability: conflict worry remains extremely high (mean of 7.2 on a 0–10 scale in Round 2), climate worry is also elevated (mean of 7.0), and the majority of households report experiencing multiple overlapping shocks.

3. Data

3.1 Survey design and data collection

Our analysis draws on a two-round adaptive resilience monitoring system embedded within the Sudan Sustainable Natural Resources and Livelihoods Programme (SNRLP). Both rounds were conducted using Computer-Assisted Telephone Interviews (CATI), targeting a pre-existing sample of 879 households reached during pre-survey sensitization from the SNRLP baseline (N=3,564). Round 1 was conducted between 5 August and 25 September 2025, before the main harvest, yielding 565 completed interviews (response rate: 64 percent of re-contacted households). Round 2 was conducted between 25 November and 20 December 2025, during the main harvest period, yielding 458 completed interviews (response rate: 52 percent of re-contacted households). The average call duration was 13 minutes in Round 1 and 11 minutes in Round 2. The roughly two months between the rounds (26 September to 24 November 2025) thus fall entirely outside both household survey periods. Interview dates are not recorded at the household level, so we define all exposure windows relative to the round fieldwork periods.

In addition, a meso-level survey of 115 key informants across 10 of the 23 baseline localities was conducted between 23 October and 30 November 2025, between the two household rounds and overlapping the start of Round 2 (average duration: 22 minutes). This provides community-level information on market conditions, institutional capacity, resource management, and service provision that complements the household-level data. Most key informants (104 of 115) are office holders of village development committees, mainly their presidents (64) and secretaries (21), who answer for their village; the other 11 answer for their locality and are officials of state agricultural, range and humanitarian agencies (7) or staff of banks and microfinance institutions (4). Key informants were sampled from an existing list of 763 actors that IFAD compiled as part of the Sudan Sustainable Natural Resources and Livelihoods Programme. The sampling was done proportionally to the number of villages in each locality. For 51 key informants, the person in the sampling frame was replaced by another respondent. Because the meso survey covers only 10 localities, we use it descriptively, comparing key informants' reports with those of households in the same localities (Section 6), rather than linking it to households in the regression analysis.

The surveys build directly on the Serfilippi et al. (2025) framework and cover four dimensions: (a) economic indicators (income sources, land use, crop and livestock production, financial services); (b) environmental and climate indicators (water availability, climate vulnerability, risk-proofing infrastructure); (c) security and social indicators (social trust, civic participation, intergroup relations, inequality perceptions); and (d) political and institutional indicators (social support access, transportation, telecommunications, energy, agricultural practices). A dedicated module captures shock exposure, severity, recovery, coping strategies, and the eight-item Food Insecurity Experience Scale (FIES), the indicator used to monitor SDG target 2.1. The FIES items refer to the 30 days before the interview, so that Round 1 captures the pre-harvest lean period (approximately July to September 2025) and Round 2 the harvest period (approximately late October to December 2025). Shock questions refer to the preceding 12 months, so their reference periods overlap across rounds.

3.2 Sampling and response patterns

Table 1 summarizes the sample across waves. Of the 3,564 baseline households, 879 (25 percent) could be reached during sensitization. The remainder could not be reached, mostly because their phones were not functioning, which is plausibly linked to conflict-related disruption of telecommunications and to displacement. From the sensitized sample, 565 (64 percent) consented in Round 1, 458 (52 percent) in Round 2, and 342 households appeared in all three waves (baseline, Round 1, Round 2), forming the panel sample. Relative to the full baseline, the Round 1 and Round 2 samples thus represent 15.9 and 12.9 percent of households, and the balanced panel 9.6 percent. Selection therefore operates at three stages (reachability at sensitization, participation in Round 1 and retention in Round 2), and we analyze each in turn. Our analysis focuses on the panel: the 342 households observed in both rounds, of which 247 have a known location and FIES in both rounds. We describe how this panel was formed and what selection implies for the interpretation of our estimates.

Table 1. Sample and conflict exposure by selection stage

Stage	Households	Localities	ACLED : mean	ACLED : p90	ACLED: above baseline p90	UCDP 25 km: mean	UCDP: above baseline p90	South and West Kordofan
Baseline roster	3,564	23	79	215	7.0%	3.6	6.2%	703
Reached at sensitization	879	16	56	113	3.9%	3.2	5.9%	0
Round 1	565	16	53	113	3.0%	3.0	5.4%	0
Round 2	458	15	49	113	2.8%	2.7	4.6%	0
Panel (both rounds)	342	15	47	113	2.9%	2.8	5.2%	0
Analytical sample	247	15	43	113	3.2%	2.8	5.3%	0

Notes: ACLED: political violence events in the household's locality, April 2023 to July 2025. UCDP: GED 26.1 events with at least one death within 25 km of the household location, 15 April 2023 to the start of Round 1; households with a location only (2,907 at baseline, 723 reached, 461 in Round 1, 390 in Round 2, 288 in the panel). Above baseline p90: share of households above the 90th percentile of the baseline roster (ACLED: 215 events; UCDP: 9 events). Analytical sample: panel households with a location and FIES in both rounds.

We analyze the determinants of being reached at sensitization, of participation in Round 1 among those reached, and of participation in Round 2 among Round 1 respondents, using probit models with baseline household characteristics and the log number of ACLED conflict events in the household's locality between April 2023 and the start of Round 1, with standard errors clustered by locality. Households in localities with more conflict were less likely to be reached at sensitization (average marginal effect of a one-unit increase in log events: −5 percentage points, $p = 0.008$), but this association disappears with region fixed effects (−1 percentage point, $p = 0.61$), which indicates that it reflects the loss of entire regions rather than selection within them. Among households reached, conflict does not predict participation in Round 1 ($p = 0.77$). Among Round 1 respondents, by contrast, households in localities with more conflict were less likely to take part in Round 2 (−6 percentage points, $p = 0.02$; −9 percentage points, $p < 0.001$, with region fixed effects). Treatment status is not associated with participation at the 5 percent level at any stage, which is encouraging for program evaluation. Older respondents, male respondents and members of larger households were more likely to take part in Round 1, and male respondents also in Round 2. Exposure to heat between the rounds also predicts attrition: among Round 1 respondents, in a linear probability model with region fixed effects, one standard deviation of heat (0.20) lowers the probability of taking part in Round 2 by 18 percentage points

(wild bootstrap p = 0.01). If the households hit hardest by heat were more likely to drop out, our panel estimates understate the effect of heat; if those who dropped out were less affected, they overstate it. We address this with inverse probability weights (Section 5.2.1).

The geographic composition differs markedly from the baseline (Table 1): all 703 households in South Kordofan and West Kordofan were lost before Round 1, while Sennar and Kassala are over-represented. The analytical sample covers 15 of the 23 baseline localities and a narrower range of conflict exposure. The mean number of ACLED events in a household's locality since the start of the war falls from 79 at baseline to 43 in the analytical sample, and the share of households in localities above the 90th percentile of the baseline distribution from 7 to 3 percent (8 households). Within 25 km of the household location, the change is smaller: the mean number of UCDP events falls from 3.6 to 2.8, and the share above the baseline 90th percentile from 6 to 5 percent. Exposure to heat between the rounds is not truncated (mean z-score of 1.03 at baseline and 1.11 in the analytical sample). The loss of entire localities means that the most conflict-affected households are absent from our sample. This limits external validity and, because conflict and fragility are also explanatory variables in our models, reduces power and may attenuate or distort the estimated moderating effects. Reweighting can address selection within covered localities but not the absence of entire localities. We therefore interpret all estimates as applying to households in localities that remained reachable.

3.3 Conflict and climate data

We complement the survey data with conflict event data and climate data, all measured independently of household reports. Our main conflict measure is based on the UCDP Georeferenced Event Dataset (GED, version 26.1), which records events of organized violence with at least one death (Sundberg & Melander, 2013). We count events within 25 km of the household location (own GPS coordinates where available, otherwise the village centroid or OCHA settlement location; 288 of the 342 panel households) between the start of the war on 15 April 2023 and the start of Round 1, and use an indicator for any such event. The 25 km radius is the smallest consistent with the location precision of UCDP events. Appendix B lists the alternative conflict measures we use as a robustness test. Conflict between the two rounds was rare in our sample: only 7 percent of analytical households, in 3 localities, had a UCDP event within 25 km between 26 September and 24 November 2025. We therefore treat conflict as a pre-

determined condition, measured before the climate shocks between the rounds, rather than as a shock in that window.

For climate shocks, we measure anomalies at the household location relative to the same calendar window in 1991–2020. Our main heat measure is the mean daily maximum temperature between 26 September and 24 November 2025 from ERA5-Land (Muñoz-Sabater et al., 2021), expressed as a z-score against the mean and standard deviation of the same window in 1991–2020. For rainfall, we use the October–November total from CHIRPS (Funk et al., 2015), again as a z-score against 1991–2020, and the two-month Standardized Precipitation Index (SPI-2) for November. Appendix B lists the alternatives. For floods, no long-term normal is available, so we measure the excess share of land flooded within 5 km in October and November 2025 relative to the same months in 2023 and 2024. Anomalies in a window common to all households provide plausibly exogenous variation in exposure; Section 5.1 describes their distribution and spatial variation.

3.4 Constructing resilience and fragility indices

We construct resilience and fragility indices from the survey data, guided by the Serfilippi et al. (2025) framework's classification rule: resilience indicators capture capacities, enabling factors, and actions taken by actors; fragility indicators capture conditions and constraints in the system. Table A1 lists the 14 resilience and 11 fragility indicators by dimension. For resilience, our main measures follow two approaches. The first is the resilience-capacity approach, for which we aggregate the 14 indicators with a one-factor polychoric factor analysis of their mixed (polychoric, polyserial and Pearson) correlation matrix, pooled over both rounds, and compute regression-method scores standardized on the pooled panel, as in RIMA (FAO, 2016). The factor explains 21 percent of the variance; agricultural, livestock and risk-proofing practices and the use of financial services load most strongly, while the social and institutional indicators load close to zero (Table A1). The second is the recovery-ability approach (IFAD, 2015), based on households' self-reported recovery from the shocks of the previous 12 months, coded from 1 (not recovered) to 4 (recovered to a better level); this measure is available only for households that report a shock. For each of the four dimensions (economic, environmental, social, institutional), we also construct additive sub-indices, averaging pooled z-scores within each dimension, and an additive overall index that averages the four sub-indices; the additive indices, which Upton et al.

(2022) find perform no worse than more complex methods, serve as robustness checks. As a further check, we construct both polychoric indices from an alternative classification of the questionnaire items (Appendix B).

In the framework, fragility comprises exposure and experience (Baliki et al., 2022). We measure exposure with the conflict and climate data described in Section 3.3, and experience with household reports of conditions and constraints, aggregated in the same way as resilience into a polychoric factor score (main measure; the factor explains 17 percent of the variance), four additive sub-indices and an additive overall index. Because the framework counts households' own experience of shocks as part of fragility experience, we construct each fragility index without and with shock experience over the previous 12 months. In Round 1, shock experience consists of the number of shock types reported and the severity of their impact. In Round 2, the shock question allowed essentially one answer, so shock experience consists of the severity of the impact alone. The versions without and with shock experience are almost identical (correlation 0.96 in Round 1 and 0.98 in Round 2). Resilience indices enter the regressions as standardized Round 1 values; fragility experience indices enter as standardized Round 1 or Round 2 values (Section 4.3). Appendix Table A2 summarizes the constructs and their main and alternative measures. Before using the indices in the regression analysis, we document their distributions and variation, their correlations with each other and with FIES, and their measurement quality (Section 5.1).

4. Empirical strategy

Our empirical strategy is built around the temporal structure of the data. Resilience capacities and fragility experience are measured in Round 1, in the lean season of 2025, and fragility experience also in Round 2; climate shocks are measured over the window between the two rounds (26 September to 24 November 2025), which is common to all households because interview dates are recorded only by round; and food security is measured in both rounds. We first estimate the effect of climate shocks on the change in food security between the rounds, then test whether this effect differs with pre-determined conflict exposure, and finally examine the role of pre-shock resilience and fragility. The panel is central to each step: all regressions compare changes within the same households between the rounds, so that time-invariant

differences between households, observed or not, cannot drive the results. Baseline indicators collected before the war serve as background and, in Section 5.3, for reweighting.

4.1 Climate shocks and food security

Our main specification is a difference-in-differences model with continuous exposure, estimated on the panel of households observed in both rounds:

$$FIES_{it} = \mu_i + \lambda_{r,t} + \beta\,(Climate_i \times Round2_t) + \varepsilon_{it} \quad (1)$$

where $FIES_{it}$ is the FIES raw score (0–8) of household i in round t, μ_i are household fixed effects, $\lambda_{r,t}$ are region-by-round fixed effects for the three program regions (Butana, Sennar and Kordofan), $Climate_i$ is the climate anomaly between the rounds at the household location, and $Round2_t$ indicates Round 2. Household fixed effects absorb all time-invariant differences between households, including their pre-war conditions, location and livelihood, and region-by-round effects absorb the seasonal change between the lean season and the harvest, which differs between regions with different agricultural calendars. With two rounds, equation (1) is identical to the first-difference regression $\Delta FIES_i = \alpha_{r(i)} + \beta\ Climate_i + \varepsilon_i$, which is how we estimate it. Because FIES increases with food insecurity and falls on average between the rounds, $\beta > 0$ means that households with larger anomalies gain less food security over the harvest. Our main shock is the heat anomaly, the most widespread climate anomaly between the rounds; we estimate the effects of the rainfall, drought and flood anomalies in the same way. We also estimate equation (1) for severe food insecurity (any of FIES items 6 to 8), and express effects as the change associated with one standard deviation of the anomaly across households, which we compare with the average improvement between the rounds.

The identifying assumption is that, in the absence of the shock, the change in food security between the rounds would not have differed systematically with the size of the anomaly within a region. Because every household is exposed to some heat anomaly, β compares households with different levels of exposure rather than exposed households with unexposed households. Its interpretation as an average causal effect per unit of exposure therefore requires a stronger version of the parallel trends assumption, under which households with different levels of exposure would have responded in the same way to the same exposure (Callaway et al., 2024). We assess the role of functional form by replacing the z-score with an indicator for exposure

above one standard deviation, and test whether the absolute temperature level, rather than the deviation from the local normal, drives the result.

We probe the identifying assumption in three ways. First, we estimate placebo effects of the locality-level heat anomaly in the same window of 2023 and 2024, which cannot have affected food security between the 2025 rounds. Second, we use alternative outcomes (moderate or severe food insecurity and a Rasch-scaled FIES score) and the locality-level anomaly. Third, we test whether the heat anomaly predicts participation in Round 2 among Round 1 respondents (Section 3.2) and reweight the panel by the inverse probability of remaining in it. These tests support the design: the placebo anomalies have no effect, the estimate holds for the alternative outcomes and the locality-level anomaly, and the reweighted estimate is slightly larger than the unweighted one (Section 5.2.1). Because the household fixed effects absorb initial levels of food security, we do not condition on Round 1 food insecurity in equation (1).

4.2 Climate-conflict polycrises

To test whether the effect of climate shocks is larger where households are also exposed to conflict, we add an interaction with the pre-determined conflict measure:

$$\Delta \text{FIES}_i = \alpha_{r(i)} + \beta_1 \, \text{Climate}_i + \beta_2 \, \text{Conflict}_i + \beta_3 \, (\text{Climate} \times \text{Conflict})_i + \varepsilon_i \quad (2)$$

where Conflict_i indicates any UCDP event within 25 km of the household between the start of the war and Round 1; as with equation (1), we also estimate it for severe food insecurity. Because conflict is measured before the shock, β_3 compares the effect of the same climate anomaly between households in more and less conflict-affected surroundings; $\beta_3 > 0$ is consistent with a polycrisis in which the joint impact exceeds the sum of the separate effects. Conflict exposure is not random, so β_3 describes how the climate effect differs with the conflict environment and does not identify the causal effect of conflict as such. Localities with more conflict may also differ in markets, livelihoods and aid, and these differences, rather than conflict itself, may shape how households respond to heat. Exposure to conflict and to heat are also correlated across households (correlation 0.51 between heat and the log number of UCDP events), so we report the climate effect separately for households with and without nearby conflict. In the framework, conflict and climate hazards are both forms of fragility exposure

(Serfilippi et al., 2025), so equation (2) tests the first prediction for the component of fragility exposure that is measured before the shock.

4.3 Fragility experience and resilience capacities

Beyond fragility exposure, measured by conflict nearby (Section 4.2), we examine fragility experience and resilience capacities in two steps, which correspond to the first two testable predictions of the framework. First, we test whether households with higher values of an index gain more food security between the rounds, or lose less, regardless of the shock:

$$\Delta FIES_i = \alpha_{r(i)} + \gamma M_i + \varepsilon_i \quad (3)$$

where M_i is a standardized index of fragility experience or of resilience capacities. Comparing changes in food insecurity across levels of resilience requires care. More resilient households start from much lower levels of food insecurity (Section 5.1, Fig. 4), and the FIES raw score is bounded at 0 and 8. A household that reports no food insecurity experience in Round 1 cannot improve and can only deteriorate, whereas a household at the top of the scale can only improve, so the room for change differs across households for reasons unrelated to their capacities. Without accounting for the starting point, γ mixes the capacity to improve with the room to improve. A linear control for Round 1 FIES does not resolve this problem in our data. Round 1 FIES is bimodal, with half of the households at 0 and a third at 6 to 8, so a linear control compares households at the floor with households far above it and extrapolates between the two groups. Conditioning on the starting value and analyzing changes can then lead to different conclusions about group differences (Lord, 1967; Allison, 1990).

We therefore compare households on the margin on which they can move, which corresponds to the distinction between resistance to a shock and recovery from it in the resilience literature (Lloret, Keeling & Sala, 2011; Barrett & Constas, 2014; Knippenberg, Jensen & Constas, 2019). The resistance margin consists of households without food insecurity in Round 1 ($FIES_{i1} = 0$). For them, we estimate the equations for the change in FIES, which equals Round 2 FIES, and for the probability of becoming food insecure. The recovery margin consists of households with $FIES_{i1} \geq 1$, for which we use the normalized change in food insecurity (Marx & Cummings, 2007):

$$NC_i = 100\,(FIES_{i2} - FIES_{i1}) / FIES_{i1} \;\text{ if } FIES_{i2} < FIES_{i1};\quad 100\,(FIES_{i2} - FIES_{i1}) / (8 - FIES_{i1}) \;\text{ if } FIES_{i2} > FIES_{i1};\quad 0 \text{ otherwise}$$

An improvement is measured as the share of the possible improvement realized and a deterioration as the share of the possible deterioration, so NC_i ranges from −100, when food insecurity is fully resolved, to +100, when the household falls to the most severe score. In our setting, it is the share of lean-season food insecurity that the harvest resolved. The measure was developed to compare learning gains between groups that start from different pre-test scores on a bounded test, where the raw gain depends mechanically on the pre-test score (Hake, 1998; Marx & Cummings, 2007), and it parallels the ecological measure of relative resilience, which scales recovery by the damage incurred (Lloret et al., 2011). Scaling by the starting point also limits regression to the mean, because the gain of a household whose Round 1 score is high by chance is divided by a larger starting value, but it does not remove it. We check the results on the recovery margin by restricting it to households with $FIES_{i1} \geq 3$, by using the proportional change without normalizing deteriorations (Hake, 1998), by reweighting the terciles of the capacity index to a common distribution of Round 1 FIES (DiNardo, Fortin & Lemieux, 1996), and by estimating the models with locality fixed effects. Second, we test whether pre-shock resilience reduces the effect of the climate shock and whether fragility exacerbates it:

$$\Delta FIES_i = \alpha_{r(i)} + \beta\, Climate_i + \theta\, M_i + \varphi\, (Climate \times M)_i + \varepsilon_i \quad (4)$$

where $\varphi < 0$ means that households with higher index values lose less of the harvest-related improvement to the shock; the framework predicts $\varphi > 0$ for fragility experience and $\varphi < 0$ for resilience capacities. For resilience capacities, we estimate both equations for all households, as observed, and separately on the recovery and resistance margins; for fragility experience, we report the comparison for all households. Because heat varies mostly between localities while the indices vary mostly within them, we also estimate equation (4) with locality fixed effects and without the heat main effect, which compares households exposed to the same anomaly. To relax the linearity of the interaction, we estimate the effect of the shock separately within the terciles of each index. We report results as the difference between households one standard deviation above and below the mean of the index; the estimates use the full variation in the index.

Moderation estimates describe how shock impacts differ across households with different capacities and conditions; they do not identify the causal effect of resilience or fragility.

The round in which each index is measured follows its role in the framework. Resilience capacities are the resources available for responding to a shock (Béné, 2020), so we use Round 1 capacities, measured before the shock; Round 2 capacities may already reflect it. Fragility experience describes how households encounter the conditions they are exposed to, including the shocks they suffer and their severity (Serfilippi et al., 2025). We therefore use the Round 1 fragility experience indices without and with households' own shock experience, which describe conditions before the shock, and the Round 2 indices, which describe the conditions at the end of the window between the rounds and so are closer in time to the shock. Because Round 2 fragility is measured after the shock, it may respond to it. We test whether heat changed it, given its Round 1 value, and interpret its interaction with heat as a conditional association.

4.4 Fragility and the protective role of resilience

The framework also predicts that fragility weakens the protective role of resilience. We test this prediction with conflict exposure, the component of fragility exposure that is measured before the shock, and with fragility experience, measured in Round 1 without and with shock experience and in Round 2. We add the triple interaction between the climate anomaly, Round 1 resilience and fragility, together with all lower-order terms, to equation (4):

$$\Delta FIES_i = \ldots + \psi\,(Climate \times R_{i1} \times F_i)_i + \ldots \quad (5)$$

where $\psi > 0$ means that the protective role of resilience is weaker where fragility is higher.

We implement this test with the composite indices to maintain statistical power. With conflict, it has low power, because only 76 analytical households in 9 localities had no conflict nearby.

4.5 Inference and threats to identification

With 15 localities in the analytical sample and a treatment that varies mostly between localities (95 percent of the variance of the heat anomaly), inference requires care. We cluster standard errors by locality and report wild cluster bootstrap p-values with Webb weights and 9,999 replications (Cameron et al., 2008; Roodman et al., 2019; Webb, 2023). For the main estimates,

we also report randomization inference, which permutes the locality-level anomaly across localities (for the polycrisis interaction, the locality share of households with conflict nearby), and Conley (1999) standard errors with cutoffs of 25, 50 and 100 km, and for the polycrisis interaction CR2 standard errors with Satterthwaite degrees of freedom (Pustejovsky & Tipton, 2018). Because a few localities account for much of the variation in exposure, we re-estimate the main models leaving out one locality at a time. The main remaining threat to identification is a shock between the rounds that is correlated with heat within regions and affects food security directly; the absence of effects of the other climate anomalies (Section 5.2.1) limits this concern for climate shocks. Sample selection is a further threat (Section 3.2): because the most conflict-affected localities are absent, the range of the conflict and fragility measures is truncated, which reduces power and may attenuate or distort interaction effects. Finally, food security is self-reported with a 30-day recall, and the respondent within a household may change between rounds; we return to these measurement issues in Section 5.1.

5. Results

5.1 Descriptive results

Food security improved sharply between the lean season and the harvest (Table 2). Among the 299 panel households with FIES in both rounds, the mean FIES raw score fell from 3.3 to 1.4 and the share of severely food insecure households from 45 to 20 percent (both $p < 0.001$). Food insecurity fell for 44 percent of households and rose for 12 percent. The improvement was concentrated in Butana, where the FIES raw score fell from 4.0 to 1.4, and in Sennar (3.1 to 1.4). In Kordofan, where average food insecurity was lower than in the other regions in Round 1, it did not change (1.2 in both rounds). Round 2 fell within the main harvest, which was completed in January 2026, so this improvement reflects the seasonal cycle at least in part.

Table 2. Food security, shocks, coping and indices by round, panel households

	Round 1: mean	Round 1: SD	Round 2: mean	Round 2: SD	Change	p (paired)	N (pairs)
FIES raw score (0–8)	3.19	3.39	1.36	2.59	−1.83***	< 0.001	299
Severely food insecure	0.43	0.50	0.20	0.40	−0.23***	< 0.001	299
Moderately or severely food insecure	0.49	0.50	0.22	0.42	−0.27***	< 0.001	299

	Round 1: mean	Round 1: SD	Round 2: mean	Round 2: SD	Change	p (paired)	N (pairs)
Reported any shock, last 12 months	0.96	0.19	0.93	0.26	−0.03**	0.034	336
Number of shock types reported	1.32	0.94	0.94	0.28	−0.38***	< 0.001	336
Not recovered to pre-shock level	0.76	0.43	0.76	0.43	0.00	0.51	215
No recovery at all	0.09	0.29	0.24	0.43	0.15***	< 0.001	215
Recovery ability (1–4)	2.19	0.67	2.04	0.78	−0.16	0.20	213
Erosive coping	0.68	0.47	0.64	0.48	−0.04	0.25	303
Emergency coping	0.16	0.37	0.35	0.48	0.19***	< 0.001	303
Sold productive assets	0.10	0.30	0.17	0.38	0.07***	0.007	303
Reduced essential expenditure	0.37	0.48	0.25	0.43	−0.13***	0.001	303
Resilience capacity index (z)	0.26	1.06	−0.25	0.87	−0.51***	< 0.001	338
Fragility experience index (z)	0.18	0.97	−0.17	1.00	−0.35***	< 0.001	337

Notes: Means and standard deviations among panel households observed in each round; change: difference between the Round 2 and Round 1 means; paired t-test among households observed in both rounds. Severe food insecurity: any of FIES items 6 to 8. Recovery questions are asked of households that report a shock. Erosive coping: sold assets or household items, relocated or reduced essential expenditure; emergency coping: sold productive assets or relocated. In Round 2 the shock question allowed essentially one answer, so the number of shock types is not comparable between rounds. Indices: polychoric factor scores standardized on the pooled panel. Change: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (paired t-test).

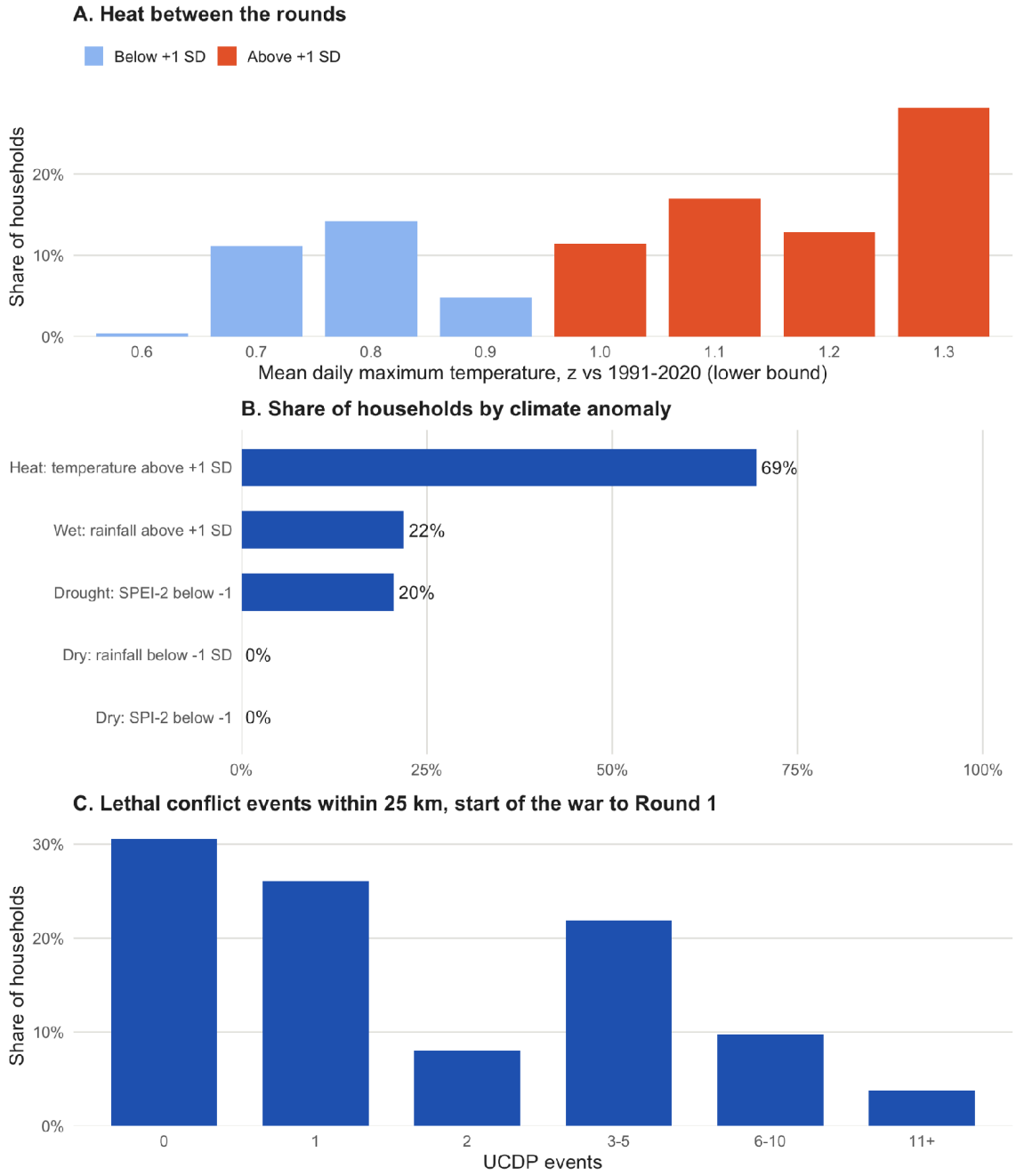
Shock experience and recovery deteriorated over the same period (Table 2). In Round 1, 96 percent of households reported at least one shock in the previous 12 months, most often high production costs and theft. About three-quarters of the households that reported a shock had not recovered to their pre-shock level in either round. In Round 1, 9 percent had not recovered at all, 68 percent had recovered to a worse level, 18 percent to the same level and 5 percent to a better level; in Round 2, the shares were 24, 53, 19 and 4 percent. Emergency coping, that is, selling productive assets or relocating, rose from 16 to 35 percent of households, and the share selling productive assets from 10 to 17 percent, whereas reducing essential expenditure became less common (37 to 25 percent). This combination of better food security and worse recovery is consistent with, but does not demonstrate, households drawing down assets to maintain food security; it may also reflect the timing of the harvest and differences in reference periods.

Unusually high temperatures were the most widespread climate anomaly between the rounds. Mean daily maximum temperature exceeded the local 1991–2020 normal for the same window by 1.1 standard deviations on average (range 0.7 to 1.4), and by more than one standard

deviation for 69 percent of households, in 11 of the 15 localities. By contrast, no household experienced rainfall more than one standard deviation below normal or SPI-2 below −1; 22 percent experienced unusually high rainfall in October and November; and 20 percent had an SPEI-2 below −1, which reflects higher evaporative demand (Fig. 1, panels A and B). The heat anomaly varies mostly between localities (95 percent of its variance) and between regions (78 percent), which motivates the region-by-round fixed effects and clustering by locality in equation (1).

Before Round 1, 69 percent of households had at least one lethal conflict event within 25 km, and 35 percent had three or more (Fig. 1, panel C). In the analytical sample, 12 of the 15 localities had at least one such event, and locality explains 42 percent of the variance in the number of UCDP events within 25 km. ACLED exposure is measured at the locality level only and therefore takes 15 distinct values. Exposure to conflict and to heat are positively correlated (0.51 for UCDP and 0.54 for ACLED events).

Figure 1. Fragility exposure: heat between the rounds and conflict before Round 1

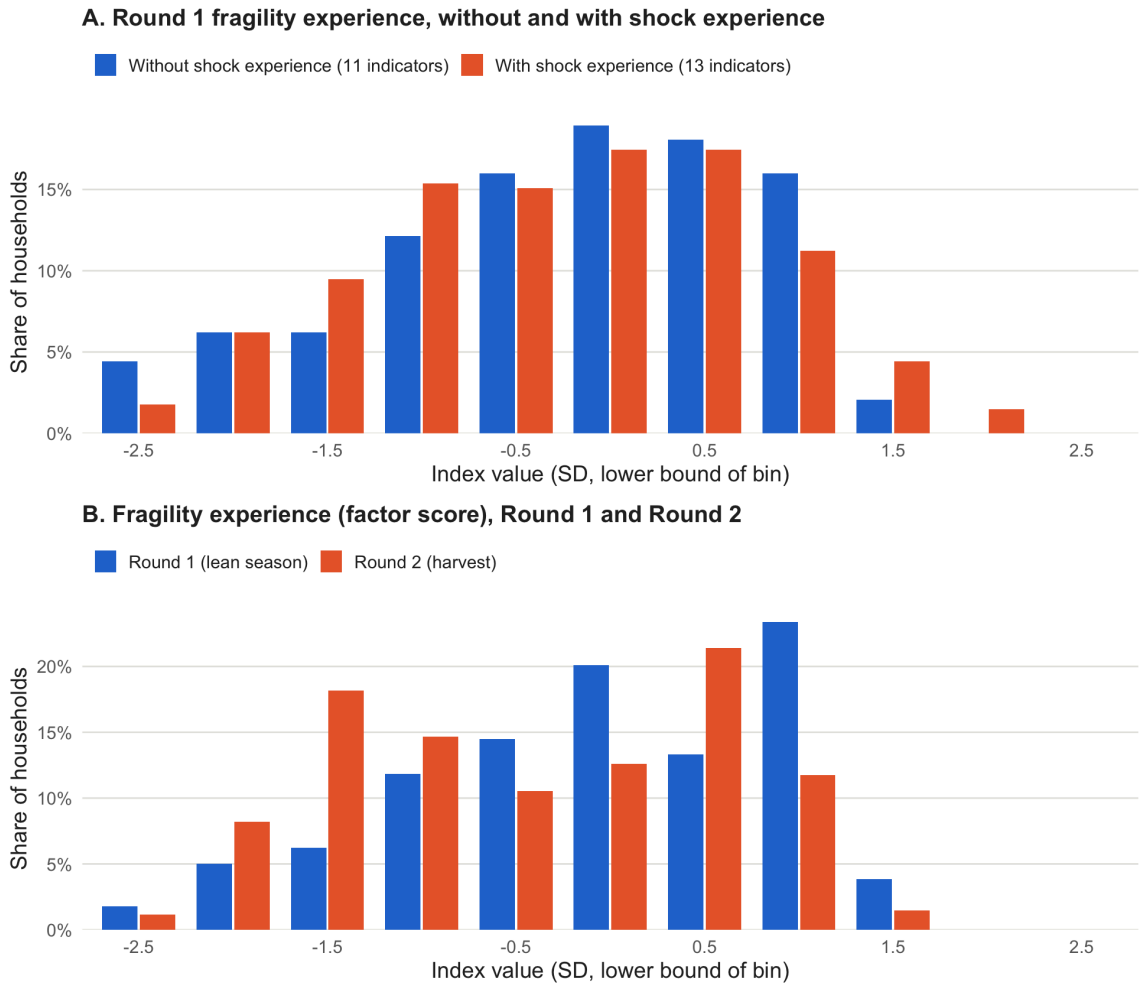


Notes: Panel households with a known location (288). Heat: mean daily maximum temperature, 26 September to 24 November 2025 (ERA5-Land), z-score against the same window in 1991–2020, at the household location; bins of 0.1, labeled by their lower bound. Rainfall: October–November total (CHIRPS), z-score against 1991–2020; SPI-2: November; SPEI-2: TerraClimate. Conflict: UCDP GED 26.1 events of organized violence with at least one death within 25 km of the household, 15 April 2023 to the start of Round 1.

The resilience and fragility indices vary considerably within both rounds, and mostly within localities: locality explains between 7 and 24 percent of the Round 1 variance of the resilience

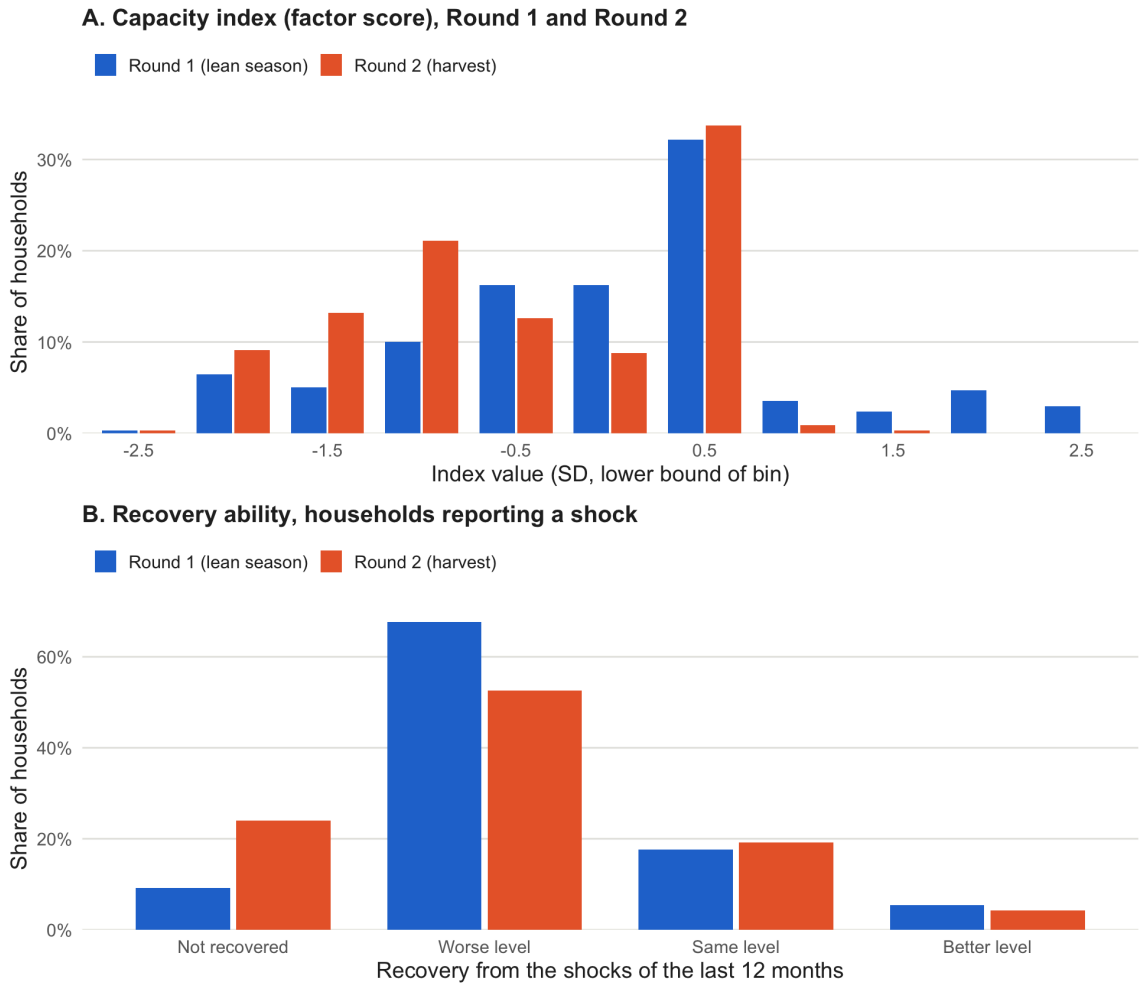
measures (economic 12, environmental 17, social 12 and institutional 9 percent) and between 14 and 23 percent of the variance of the fragility experience measures (economic 15, environmental 14, security and social 21 and institutional 17 percent). The capacity index falls by 0.5 standard deviations between the rounds (Table 2); part of this fall reflects fewer answer options recorded for agricultural and livestock practices in Round 2. Shock experience is nearly universal in Round 1, so the fragility index with shock experience varies mainly through the number of shocks (17 percent report two or more types) and their severity (61 percent report a strong or the worst-ever impact). Round 1 and Round 2 fragility experience are almost uncorrelated (0.06 in the analytical sample). Figures 2 and 3 show the distributions of the main indices, and Appendix Figures A1 to A3 those of the dimension sub-indices and of the adaptive capacity indicators.

Figure 2. Fragility experience, Round 1 and Round 2



Notes: Panel A: Round 1 panel households (338); polychoric factor scores without shock experience (11 indicators) and with shock experience (13 indicators: number of shock types and severity of the impact), both standardized among Round 1 panel households. Panel B: factor score without shock experience, standardized on the pooled panel, by round. Bins of 0.5 standard deviations, labeled by their lower bound; tails merged.

Figure 3. Resilience capacities and recovery ability, Round 1 and Round 2



Notes: Panel A: capacity index, polychoric factor score of 14 indicators, standardized on the pooled panel; bins of 0.5 standard deviations, labeled by their lower bound; tails merged. Panel B: households that report a shock in the previous 12 months (Round 1: 238; Round 2: 308). The two measures are almost unrelated (correlation 0.07 in Round 1).

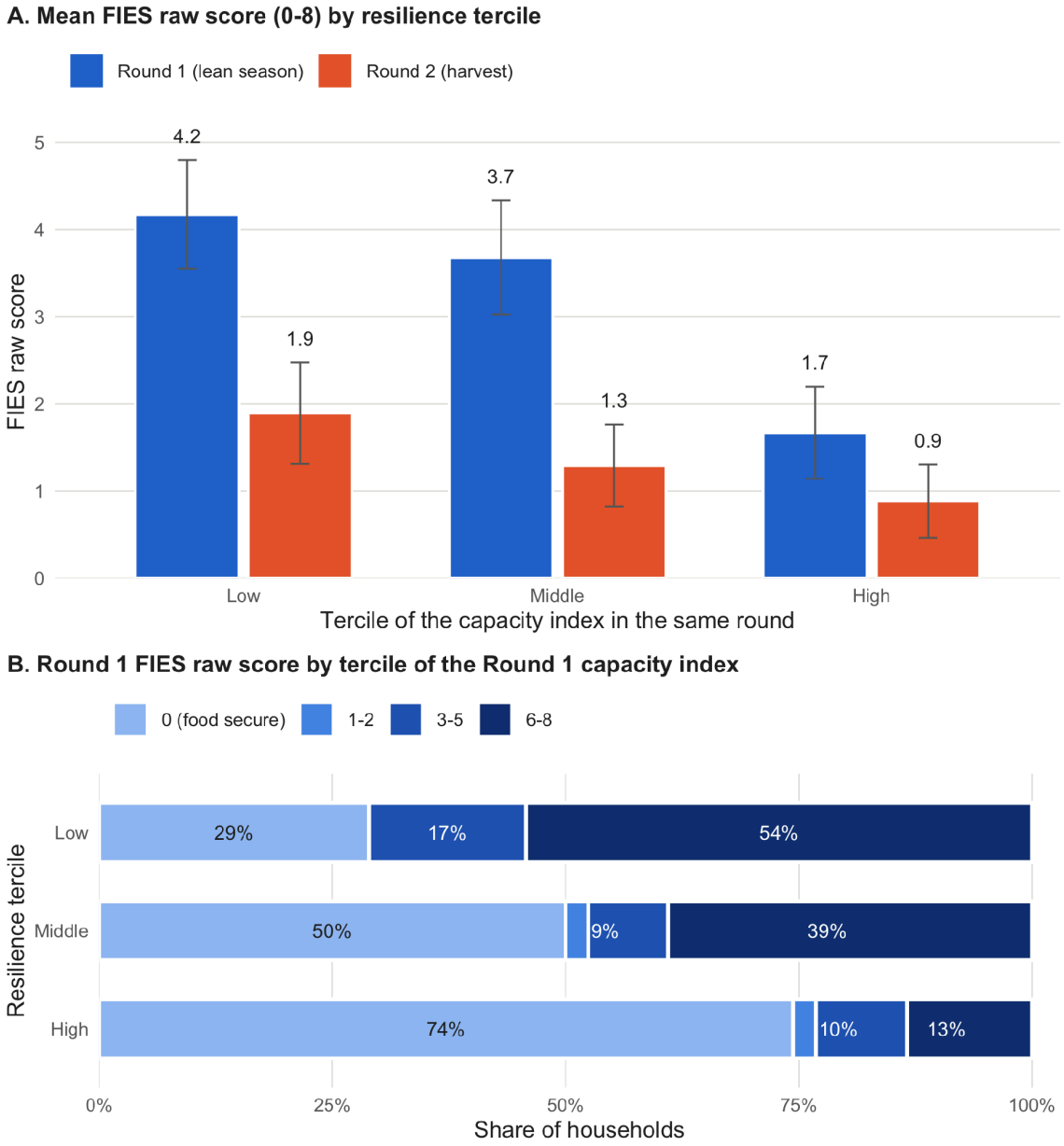
The indices are measured with considerable noise. Cronbach's alpha is 0.96 for the eight FIES items in Round 1, but only 0.51 for the resilience indicators and 0.56 for the fragility indicators. The same household's values correlate only weakly between the rounds: 0.11 for the FIES raw score, 0.16 for the capacity index, 0.32 for economic resilience and 0.04 for the fragility experience index. Low persistence mixes genuine change between the lean season and the harvest with measurement error and possibly changes in who answered: for 41 percent of panel households, the respondent age reported in Round 2 differs by more than five years from the age carried forward from the program records, although almost all Round 2 respondents are recorded as the same respondent as in Round 1. Noise in an index biases its estimated interaction with a

shock toward zero and lowers power, so the absence of significant moderation is weak evidence of no moderation.

More resilient households are less food insecure: within region, one standard deviation of the Round 1 capacity index is associated with 1.2 fewer FIES points in Round 1 (wild bootstrap $p < 0.001$) and a 15 percentage point lower probability of severe food insecurity ($p = 0.002$), and the Round 1 FIES raw score falls from 4.2 in the lowest to 3.7 in the middle and 1.7 in the highest tercile of the index (Fig. 4, panel A). The same holds in Round 2 for Round 2 resilience (1.9, 1.3 and 0.9 FIES points across terciles), although less strongly and not significantly (−0.35 FIES points per standard deviation, $p = 0.19$), and Round 1 resilience does not predict Round 2 FIES. However, the capacity index is almost unrelated to recovery ability (correlation 0.07) and positively correlated with the fragility experience index (0.55).

Because the FIES raw score is bounded, these differences in levels imply differences in the room to change. Round 1 food insecurity is bimodal: among the 247 analytical households, 51 percent report none of the eight FIES experiences, 36 percent report six to eight, and few lie in between. In the top tercile of the Round 1 capacity index, 74 percent of households start at the floor of the scale, against 50 percent in the middle and 29 percent in the bottom tercile (Fig. 4, panel B). Households at the floor cannot gain over the harvest and can only become food insecure, whereas most other households can only improve. The moderation analysis therefore compares households on these two margins separately (Section 4.3).

Figure 4. Food insecurity by tercile of the capacity index, Round 1 and Round 2



Notes: Panel A: mean FIES raw score (0–8) with 95 percent confidence intervals among panel households with FIES and the capacity index observed in the same round (Round 1: 328; Round 2: 309), by tercile of the capacity index in that round. Panel B: distribution of the Round 1 FIES raw score among the 247 analytical households, by tercile of the Round 1 capacity index; shares below 5 percent are not labeled.

5.2 Regression results

5.2.1 Shocks and food security

Heat between the rounds undermined the harvest-related improvement in food security (Table 3, column 1). One unit of the heat z-score reduces the improvement in the FIES raw score by 5.5 points (s.e. 1.7). Since the standard deviation of the heat z-score across households is 0.22, one standard deviation of additional heat exposure reduces the improvement by 1.2 points, about two-thirds of the average improvement of 1.7 points. For severe food insecurity, the corresponding reduction is 19 percentage points, compared with an average decline of 22 percentage points (column 2). The estimates are significant under the wild cluster bootstrap ($p = 0.02$ for the FIES raw score and $p = 0.03$ for severe food insecurity), under randomization inference for the locality-level anomaly ($p = 0.003$) and with Conley standard errors ($p \leq 0.02$ at cutoffs of 25, 50 and 100 km).

Table 3. Heat between the rounds and the change in food security

	(1) ΔFIES	(2) ΔSevere	(3) ΔFIES	(4) ΔFIES	(5) ΔSevere
Heat (z-score)	5.47***	0.88***	5.62***		
	(1.69)	(0.25)	(1.76)		
Temperature level (°C)			0.23		
			(0.41)		
Heat above +1 SD				1.46	0.24*
				(1.07)	(0.13)
p, clustered	0.006	0.004	0.006	0.193	0.093
p, wild cluster bootstrap	0.023	0.031	0.024	0.247	0.150
p, randomization inference	0.003	0.003			
p, Conley 25 km	0.015	0.006			
Effect of +1 SD heat	1.19	0.19	1.23		
Sample	All	All	All	All	All
Households	247	247	247	247	247
Localities	15	15	15	15	15

Notes: Difference-in-differences (equation 1), estimated in first differences: change in the FIES raw score (0–8) or in severe food insecurity from Round 1 to Round 2 on the heat anomaly, with region-by-round fixed effects. Heat: mean daily maximum temperature, 26 September to 24 November 2025 (ERA5-Land), z-score against the same window in 1991–2020, at the household location. Standard errors clustered by locality in parentheses. Wild cluster bootstrap: Webb weights, 9,999 replications. Randomization inference: regression on locality-level heat (coefficients 6.96 and 1.13), with locality-level heat permuted across

localities (1,999 permutations). Effect of +1 SD heat: coefficient × 0.22, the standard deviation of the heat z-score; average change −1.73 FIES points and −0.22 for severe food insecurity. The temperature level is the mean daily maximum temperature in the window. * p < 0.10, ** p < 0.05, *** p < 0.01 (standard errors clustered by locality; wild cluster bootstrap p-values in the table).

The effect stems from the deviation from the local normal, not from the absolute temperature level. When both enter the model, the coefficient on the deviation is unchanged (5.6) and the temperature level has no effect (0.23, p = 0.59; column 3). An indicator for heat above one standard deviation in place of the z-score has a positive but insignificant effect (1.46 FIES points, wild bootstrap p = 0.25; 0.24 for severe food insecurity, clustered p = 0.09, wild bootstrap p = 0.15). Other climate anomalies between the rounds do not significantly affect the change in food security: the coefficients on rainfall in October and November or in September and October, SPI-2, a drought indicator and the flood anomaly are all small and imprecise (wild bootstrap p ≥ 0.17).

The placebo tests support the design. Locality-level heat anomalies in the same window of 2023 and 2024 have no effect on the change in food security between the 2025 rounds (0.5, p = 0.87, and −0.6, p = 0.57). The effect holds for moderate or severe food insecurity (0.72, p = 0.04), for the Rasch-scaled FIES score (1.47 standard deviations per unit of the heat z-score, clustered p = 0.007, 279 households) and for the locality-level anomaly (7.0, p = 0.02). Because heat also predicts attrition between the rounds (Section 3.2), we reweight the panel by the inverse of each household's predicted probability of remaining in it, estimated from heat, nearby conflict, Round 1 food insecurity, baseline characteristics and region. The reweighted estimate is slightly larger (6.1, wild bootstrap p = 0.01; 0.91 for severe food insecurity, p = 0.009), so attrition on observed characteristics does not account for the effect.

The heat-related loss is larger where lethal conflict occurred nearby before the shock (Table 4). For households with no UCDP event within 25 km before Round 1, one standard deviation of heat reduces the improvement by 1.0 FIES points (wild bootstrap p = 0.02); for households with at least one such event, by 2.3 points (p = 0.01). The difference of 1.3 points corresponds to an interaction of 6.0 (s.e. 2.7), which is significant with conventional clustered (p = 0.04) and Conley standard errors (p = 0.03 at 25 km), but not under the wild cluster bootstrap (p = 0.20), with CR2 standard errors (p = 0.15) or under randomization inference for its counterpart with the locality share of exposed households (p = 0.23); the wild bootstrap 95 percent confidence

interval ranges from −2.5 to 13.0. The minimum detectable interaction with 80 percent power is 8.0, larger than the estimate, and the interaction falls to 1.0 (p = 0.62) without the locality of Reifi Khashm Elgirba in Kassala. Conflict measured by ACLED events in the locality does not interact with heat (−0.7, p = 0.67). The interaction is almost identical with conflict measured up to the start or the end of Round 2, and it has the same sign at radii of 10 to 50 km. The point estimates are consistent with prior evidence on climate-conflict polycrises (Stojetz et al., 2024b; Stojetz et al., 2025), but our sample does not allow us to distinguish the interaction from zero.

Table 4. Heat, conflict before the shock and the change in food security

	(1) ΔFIES	(2) ΔSevere
Heat (z-score), no conflict within 25 km	4.47***	0.77***
	(1.10)	(0.26)
Heat × conflict within 25 km	6.03**	0.78*
	(2.65)	(0.39)
Conflict within 25 km	−0.64	−0.10
	(0.47)	(0.10)
Heat, conflict within 25 km (sum)	10.50***	1.55***
	(2.84)	(0.42)
Effect of +1 SD heat: no conflict / conflict	0.97 / 2.29	0.17 / 0.34
Inference for the interaction (p)		
Clustered by locality	0.039	0.068
Conley, 25 / 50 / 100 km	0.03 / 0.04 / 0.05	0.06 / 0.05 / 0.08
Households / localities	247 / 15	247 / 15

Notes: Equation (2), estimated in first differences with region-by-round fixed effects: change in the FIES raw score (column 1) or in severe food insecurity (any of FIES items 6 to 8; column 2) from Round 1 to Round 2. Conflict: any UCDP GED 26.1 event with at least one death within 25 km of the household, 15 April 2023 to the start of Round 1 (171 households in 12 localities; 76 households in 9 localities without). Heat is centered at its sample mean, so the conflict coefficient is the difference at mean heat. Standard errors clustered by locality in parentheses; wild bootstrap p-values for the heat effects in the two groups: 0.016 and 0.013 (FIES), 0.035 and 0.017 (severe). Other p-values for the interaction: wild cluster bootstrap 0.20 (FIES) and 0.21 (severe); CR2 with Satterthwaite degrees of freedom 0.15 and 0.20; randomization inference 0.23 and 0.49, from a model in which heat interacts with the locality share of exposed households and this share is permuted across localities. * p < 0.10, ** p < 0.05, *** p < 0.01 (standard errors clustered by locality).

5.2.2 Fragility experience

Fragility experience reported before the shock is associated with smaller food security gains (Table 5, column 1). Households one standard deviation above the mean of the Round 1 fragility factor score improve 1.5 FIES points less than households one standard deviation below it ($p = 0.02$), and 1.4 points less with shock experience ($p = 0.04$). On the recovery and resistance margins, however, the factor score does not predict gains (2.0 percentage points, $p = 0.75$; 0.28 FIES points, $p = 0.50$), so the pooled difference may reflect differences in the starting point. The additive indices show no such difference ($p \geq 0.13$).

Fragility experience reported before the shock does not alter the effect of heat (Table 5, column 2). The difference in the improvement lost to one standard deviation of heat between households with high and low values of the Round 1 factor score is 0.48 FIES points without shock experience ($p = 0.30$) and 0.63 points with it ($p = 0.24$), and no composite Round 1 fragility index has a significant interaction ($p \geq 0.24$), although the institutional and economic sub-indices do, with opposite signs (Appendix Table A4).

Fragility experience at the end of the window between the rounds is associated with larger heat losses (Table 5, Round 2 rows). Households one standard deviation above the mean of the Round 2 factor score lose 2.3 FIES points more of the improvement to one standard deviation of heat than households one standard deviation below it (wild bootstrap $p = 0.004$). The estimate is the same with shock severity (2.2, $p = 0.005$) and similar for the additive index (1.7, $p = 0.01$) and for the change in the factor score between the rounds (1.3, $p = 0.007$). Among the dimensions, the association comes from environmental, security and social, and institutional fragility (Appendix Table A4). Heat does not appear to have changed the reported conditions: given their Round 1 values, Round 2 fragility experience is 0.14 standard deviations higher per standard deviation of heat ($p = 0.50$), and the change in the fragility index is unrelated to heat ($p = 0.54$). Pooled over all households, Round 2 fragility experience is not associated with food security gains as such (0.09 FIES points, $p = 0.92$), but it is associated with larger improvements on the recovery margin (−29.8 percentage points, $p = 0.009$) and less deterioration on the resistance margin (−2.3 FIES points, $p = 0.001$).

Table 5. Fragility experience, food security gains and heat losses

Outcome	(1) Gains ΔFIES	(2) Heat loss ΔFIES
Round 1 (before the shock)		
Factor score, without shock experience	1.46** (0.016)	0.48 (0.30)
Factor score, with shock experience	1.35** (0.038)	0.63 (0.24)
Additive index, without shock experience	−0.48 (0.38)	0.48 (0.37)
Additive index, with shock experience	−0.98 (0.13)	0.39 (0.47)
Alternative classification, factor score	2.69*** (0.000)	0.38 (0.45)
Round 2 (end of the window between the rounds)		
Factor score, without shock experience	0.09 (0.92)	2.31*** (0.004)
Factor score, with shock severity	0.12 (0.88)	2.24*** (0.005)
Additive index	0.85 (0.31)	1.66** (0.012)
Change in factor score, Round 2 − Round 1	−0.67 (0.11)	1.27*** (0.007)

Notes: Each cell is from a separate regression and reports the difference between households one standard deviation above and below the mean of the fragility index, with the wild cluster bootstrap p-value in parentheses (Webb weights, 9,999 replications; SE clustered by locality); region fixed effects; 247 households in 15 localities. Column 1: change in the FIES raw score from Round 1 to Round 2 (equation 3); positive values mean smaller gains for high index values. Column 2: difference in the change associated with one standard deviation of heat (equation 4); positive values mean larger losses to heat. Shock experience: Round 1, number of shock types and severity of the impact; Round 2, severity of the impact. Change: in standard deviations of the Round 1 index. Alternative classification: Appendix B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (wild cluster bootstrap).

5.2.3 Resilience capacities

Pre-shock resilience does not predict food security gains when we compare households on the margin on which they can move (Table 6, columns 1 to 3). As observed, households one standard deviation above the mean of the capacity index improve 2.7 FIES points less than households one standard deviation below it ($p < 0.001$). This result likely reflects their starting point: they were much less food insecure in Round 1 (Fig. 4). Among households that were food insecure in Round 1, the harvest resolved on average 70 percent of their food insecurity (a normalized change of −70), and this share does not differ with the capacity index (6.0 percentage points, $p = 0.63$; column 2). Among households without food insecurity in Round 1, 18 percent became food insecure by Round 2, and the capacity index does not predict this deterioration either (0.62 FIES points, $p = 0.37$; column 3). The same holds for the additive index, recovery ability, the index from the alternative classification and the four dimension sub-indices (all $p \geq 0.09$; Appendix Table A3). Only recovery ability is associated with a somewhat larger normalized improvement (14.0 percentage points, $p = 0.095$).

We find no evidence that resilience protects households against the heat shock (Table 6, columns 4 to 6). Pooling all households, the difference in the improvement lost to one standard deviation of heat between households with high and low values of the capacity index is 0.36 FIES points ($p = 0.59$; column 4). This pooled estimate averages two margins on which the interaction has opposite signs. Among households that were food insecure in Round 1, one standard deviation of

heat reduces the share of food insecurity resolved by 32.4 percentage points more for households one standard deviation above the mean of the capacity index than for households one standard deviation below it (wild bootstrap p = 0.006; 95 percent confidence set 17.8 to 48.1; column 5). In FIES points, the difference is 1.8 points (p = 0.02). Among households without food insecurity in Round 1, the interaction has the sign of protection but is not significant (−1.31 FIES points, p = 0.34; column 6).

The estimate on the recovery margin should not be overinterpreted. It is similar when we handle the starting point differently: among households with Round 1 FIES of at least 3 (33.0 percentage points, p = 0.01), with the terciles of the capacity index reweighted to a common distribution of Round 1 FIES (33.6, p = 0.01) and with the proportional change in place of the normalized change (29.0, p = 0.007). However, it is smaller and less precise with locality fixed effects, which compare households exposed to the same anomaly (28.2, p = 0.09), and it is close to zero without the households in Kassala State (−2.0, p = 0.96). It also rests on a few households: only 21 of the 121 households on the recovery margin are in the top tercile of the capacity index. On the resistance margin, the sign of protection is significant within localities (−1.81 FIES points, p = 0.04), but not within regions (p = 0.34). We therefore read these results as showing no protective role of resilience capacities; they do not allow us to conclude that more resilient households lost more.

Table 6. Pre-shock resilience capacities, food security gains and heat losses

Outcome	(1) Gains: all ΔFIES	(2) Gains: recovery margin NC	(3) Gains: resistance margin ΔFIES	(4) Heat loss: all ΔFIES	(5) Heat loss: recovery margin NC	(6) Heat loss: resistance margin ΔFIES
Capacity index (main)	2.71*** (0.000)	6.0 (0.63)	0.62 (0.37)	0.36 (0.59)	32.4*** (0.006)	−1.31 (0.34)
Additive index	0.87 (0.15)	−7.0 (0.52)	0.34 (0.40)	0.69 (0.20)	15.4* (0.064)	−0.19 (0.74)
Recovery ability	1.41** (0.035)	−14.0* (0.095)	0.38 (0.38)	−0.21 (0.87)	15.3 (0.19)	−1.43 (0.11)
Alternative classification, factor score	2.68*** (0.000)	4.0 (0.82)	0.63 (0.41)	0.28 (0.64)	42.0*** (0.009)	−1.38 (0.19)

Notes: Each cell is from a separate regression and reports the difference between households one standard deviation above and below the mean of the Round 1 resilience index, with the wild cluster bootstrap p-value in parentheses (Webb weights, 9,999 replications; SE clustered by locality); region fixed effects. Columns 1 to 3: equation (3). Columns 4 to 6: difference in the change associated with one standard deviation of heat (equation 4). Columns 1 and 4: change in the FIES raw score, all households (247 in 15 localities). Columns 2 and 5, recovery margin: normalized change in food insecurity NC (Section 4.3), in percentage points, households with Round 1 FIES ≥ 1 (121 in 14 localities). Columns 3 and 6, resistance margin: change in the FIES raw score, households with Round 1 FIES = 0 (126 in 15 localities). Positive values mean smaller gains for high index values (columns 1 to 3) or larger losses to heat (columns 4 to 6); negative values in columns 4 to 6 mean that high index values protect. Recovery ability: 185, 101 and 84 households. Dimension sub-indices: Appendix Table A3. * p < 0.10, ** p < 0.05, *** p < 0.01 (wild cluster bootstrap).

5.2.4 Fragility and the protective role of resilience

The capacity index may protect against heat only where there was no conflict nearby (Table 7). Among households without a UCDP event within 25 km before Round 1, households one standard deviation above the mean of the capacity index lose 1.4 FIES points less of the improvement to one standard deviation of heat than households one standard deviation below it; among households with nearby conflict, they lose 1.0 point more. The difference is not significant ($p = 0.12$ within regions; $p = 0.10$ within localities; columns 1 and 2), and there is no such pattern for economic resilience. On the recovery margin, the interaction between heat and the capacity index is positive both without and with nearby conflict (40.6 and 25.1 percentage points; $p = 0.64$ for the difference; column 3). In the general test, the role of resilience does not differ with nearby conflict ($p = 0.51$). With 76 households in 9 localities without nearby conflict, this test has little power, and we interpret the pattern as suggestive at most. With fragility experience as the measure of fragility, the three-way interaction is small and not significant, for the Round 1 index without and with shock experience and for the Round 2 index ($p \geq 0.47$ in all specifications).

Table 7. Fragility and the protective role of resilience

	(1) All households ΔFIES, region effects	(2) All households ΔFIES, locality effects	(3) Recovery margin NC, region effects
Conflict within 25 km before Round 1			
No conflict	−1.42 (0.45)	−1.34 (0.46)	40.6 (0.15)
Conflict	1.02 (0.17)	1.61 (0.23)	25.1* (0.094)
Difference (three-way interaction)	2.44 (0.12)	2.94 (0.10)	−15.4 (0.64)
Fragility experience, Round 1, without shock experience			
Low (−1 SD)	0.06 (0.92)	−0.09 (0.89)	32.3** (0.020)
High (+1 SD)	0.73 (0.52)	0.94 (0.53)	31.6** (0.039)
Difference (three-way interaction)	0.67 (0.63)	1.03 (0.47)	−0.7 (0.97)
Fragility experience, Round 1, with shock experience			
Low (−1 SD)	−0.18 (0.81)	−0.30 (0.69)	30.0** (0.013)
High (+1 SD)	0.46 (0.71)	0.84 (0.63)	32.0* (0.073)
Difference (three-way interaction)	0.64 (0.69)	1.14 (0.52)	2.0 (0.96)
Fragility experience, Round 2			
Low (−1 SD)	−0.50 (0.64)	−0.43 (0.73)	28.9* (0.088)
High (+1 SD)	−0.03 (0.97)	−0.02 (0.98)	18.7 (0.11)
Difference (three-way interaction)	0.47 (0.74)	0.41 (0.78)	−10.2 (0.68)

Notes: Each cell reports the difference between households one standard deviation above and below the mean of the Round 1 capacity index in the change associated with one standard deviation of heat, at the stated level of fragility, from a regression of the change on heat, the capacity index, the fragility measure and all their interactions (equation 5). Difference: the difference between the two levels (conflict minus no conflict; +1 SD minus −1 SD). Negative values mean that high resilience protects. Columns 1 and 2: change in the FIES raw score, all households (247 in 15 localities), with region effects or locality effects (without the main effect of heat, which varies mostly between localities). Column 3: normalized change in food insecurity NC, in percentage points, households with Round 1 FIES ≥ 1 (121 in 14 localities). Wild cluster bootstrap p-values in parentheses (Webb weights, 9,999 replications; SE clustered by locality). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (wild cluster bootstrap).

5.3 Results by program participation

Program participation does not change these conclusions (Table 8). Of the 247 analytical households, 151 are program beneficiaries (treatment households) and 96 non-beneficiaries (control households), according to the treatment status recorded in the program data. Because we do not know how the two groups were selected, and because participation is concentrated in some localities, we compare them descriptively and do not interpret differences between them as program effects. The two groups were equally food insecure in Round 1 (3.2 and 3.0 FIES points; $p = 0.73$ for the difference within regions) and improved by similar amounts over the harvest (1.8 and 1.6 points; $p = 0.72$). They faced similar heat and conflict exposure, and their capacity index does not differ ($p = 0.24$), whereas beneficiaries report more fragile conditions in Round 1 (0.34 standard deviations; $p = 0.02$). The heat effect is larger for beneficiaries than for non-beneficiaries (8.3 against 4.9 FIES points per unit of the heat z-score, or 1.8 against 1.1 points for one standard deviation of heat), but the difference is not significant ($p = 0.23$), and the same holds for severe food insecurity ($p = 0.18$). The interaction between heat and the capacity index is not significant in either group (−0.53 FIES points among non-beneficiaries, $p = 0.11$; 0.84 among beneficiaries, $p = 0.39$).

The comparison is robust to differences between the groups in pre-war characteristics (Appendix Table A10). Treatment status is assigned by village: in the program's baseline survey, all but 2 of 185 villages are either entirely treatment or entirely control villages, and status is known for all but one of the 3,564 households on the baseline roster, so it does not need to be imputed and could not be predicted validly from household characteristics. At baseline, beneficiary respondents were younger and less often male than non-beneficiary respondents (standardized differences of −0.38 and −0.27). We therefore reweight non-beneficiaries to resemble beneficiaries, with inverse probability weights from a probit of treatment status on age, sex, household size, years of schooling, literacy, durable and productive assets at baseline, and region, and re-estimate Table 8 with these weights. Propensity scores overlap (0.20 to 0.84 for non-beneficiaries and 0.23 to 0.90 for beneficiaries), and after weighting all standardized differences are 0.11 or smaller. The conclusions are unchanged. The two groups remain similar in food insecurity and in its change over the harvest (difference in the change −0.04 FIES points, $p = 0.93$; doubly robust estimate −0.10, $p = 0.84$), beneficiaries still report more fragile conditions in Round 1 (0.32 standard deviations, $p = 0.01$), and the heat effect is still larger for beneficiaries,

without a significant difference (7.5 against 4.7 FIES points per unit of the heat z-score; p = 0.33). With the weights, the interaction between heat and the capacity index becomes significant among non-beneficiaries (−0.60 FIES points, p = 0.03), but it rests on 96 households in 10 localities, and we do not interpret it. The 26 analytical households without baseline household characteristics are all beneficiaries; they keep a weight of one.

Table 8. Food security, exposure and heat effects by program participation

	(1) Non-beneficiaries	(2) Beneficiaries	(3) Difference
A. Levels and changes			
FIES raw score, Round 1	3.03	3.22	0.13 (0.73)
FIES raw score, Round 2	1.42	1.41	−0.03 (0.92)
Change in FIES raw score	−1.61	−1.81	−0.17 (0.72)
Severely food insecure, Round 1	0.42	0.45	0.03 (0.71)
Severely food insecure, Round 2	0.22	0.21	−0.01 (0.82)
Capacity index, Round 1 (z)	−0.12	0.08	0.19 (0.24)
Fragility experience, Round 1 (z)	−0.20	0.13	0.34** (0.018)
Heat between the rounds (z-score)	1.11	1.12	0.02 (0.86)
Conflict within 25 km before Round 1	0.62	0.74	0.13 (0.45)
B. Heat effects			
Heat (z-score): change in FIES	4.94** (0.034)	8.27** (0.011)	3.33 (0.23)
Heat (z-score): change in severe food insecurity	0.80** (0.016)	1.35*** (0.005)	0.55 (0.18)
Heat × capacity index (high − low)	−0.53 (0.11)	0.84 (0.39)	
Households	96	151	247

Notes: Analytical sample (247 households in 15 localities). Program participation: treatment status recorded in the program data. Panel A: means; difference: coefficient on beneficiary status from a regression with region fixed effects. Panel B: effect of the heat z-score on the change from Round 1 to Round 2 for each group, from one regression with region fixed effects in which heat is interacted with beneficiary status, and the difference between the groups; last row: difference between households one standard deviation above and below the mean of the capacity index in the change associated with one standard deviation of heat (as Table 6, column 4), estimated separately for each group. Wild cluster bootstrap p-values in parentheses (Webb weights, 9,999 replications; SE clustered by locality). * p < 0.10, ** p < 0.05, *** p < 0.01 (wild cluster bootstrap). Appendix Table A10: the same comparison with inverse probability weights based on pre-war characteristics.

6. Discussion

Our study shows that a climate shock can undermine food security in a season of improvement. One standard deviation of additional heat in the weeks before and during the harvest offset about two-thirds of the average seasonal gain in food security. One potential explanation is that high temperatures reduce the yields of crops harvested late in the season, or the availability of water and pasture for livestock, at a time when households would otherwise replenish their food stocks. The absence of effects of rainfall and drought anomalies in a season described as agroclimatically favorable (FEWS NET, 2025; FAO, 2026a) suggests caution in generalizing the size of the effect.

The heat-related losses were about twice as large where lethal conflict had occurred nearby, although the difference is not statistically significant under small-cluster inference. This pattern aligns with prior evidence that climate shocks are more harmful in conflict environments (Stojetz et al., 2024b; Stojetz et al., 2025), and extends it to food security during an active war.

We find no evidence that resilience capacities protect food security. More resilient households were less food insecure, but among households with the same room to change they did not gain more over the harvest or face a lower risk of worsening food insecurity, and they did not lose less of the gain to heat. This pattern echoes the finding of Upton et al. (2022) that resilience measures add little predictive power beyond the current value of the well-being indicator, and it differs from studies that find a buffering role of resilience capacities in less fragile settings (d'Errico et al., 2018; Smith & Frankenberger, 2018). Three features of our setting may explain the difference. First, the indices are noisy and persist little between rounds, which attenuates interactions and lowers power. Second, the shock varies mainly between localities and the capacities mainly within them, so the moderation tests rely on few localities. Third, the indices do not align well with the framework: the capacity index is dominated by agricultural practices and financial services, it is almost unrelated to recovery ability, and it correlates positively with fragility experience.

The analysis also shows how much conclusions about resilience depend on the handling of the starting point. Pooled over all households, the interaction between heat and the capacity index is close to zero, whereas it differs in sign between households that start at the floor of the FIES and the others, and neither estimate is stable across specifications and samples. A linear control for Round 1 food insecurity does not separate the two margins when the starting distribution is bimodal (Lord, 1967; Allison, 1990).

The fragility results give mixed support to the prediction that fragility amplifies shocks. The composite indices of fragility experience reported before the shock do not predict larger heat losses, with or without households' own shock experience. Fragility experience reported at the end of the window between the rounds is associated with larger heat losses, as the framework predicts, and heat does not appear to have changed these reports. Because these conditions are measured after the shock and correlate little with those reported in the lean season, the pattern

may reflect conditions that arose between the rounds, such as disrupted roads and phone networks or local disputes, and that compounded the effect of heat. It is a conditional association, however, and not an estimate of the causal effect of fragility. The suggestive pattern that resilience protects against heat only where there was no conflict nearby is consistent with the framework's third prediction that fragility erodes the protective role of resilience (Serfilippi et al., 2025), but it is far from conclusive.

Food security improved over the harvest while recovery deteriorated and emergency coping became more common. Because we observe neither consumption nor a long panel, and because the improvement coincides with the harvest, we cannot interpret this co-movement as evidence of households drawing down assets to protect consumption. It does, however, caution against assessing resilience by food security indicators alone (Alloush & Carter, 2026).

Key informant reports also diverge from household reports. In the ten localities covered by the meso survey, key informants report much less worry about violent conflict than households (2.6 against 7.5 on a scale from 0 to 10 in Round 1; lower in all ten localities), fewer disputes over natural resources (3.0 against 4.1), and more frequent support from the village-level native administration (2.7 against 1.6 on a scale from 1 to 4; higher in all ten localities), whereas nearly all key informants and households report a shock in the previous 12 months (Appendix Table A9). Most key informants hold office in village development committees, which may make them more likely to report institutional support and less likely to report insecurity. Key informant reports therefore cannot substitute for household-level data on fragility experience in this setting.

Our analysis has several limitations. First, with 247 households in 15 localities, power is limited, particularly for interactions. Second, selection at three stages truncates the conflict distribution, so our estimates apply to households in localities that remained reachable. Third, the moderation estimates are conditional associations and should not be interpreted as causal effects. Fourth, FIES is an experience-based measure with a 30-day recall, and we observe neither consumption nor interview dates, so we cannot separate seasonal from other changes at the household level. Fifth, Round 2 coincided with the harvest, so our estimates capture the effect of heat on the harvest-related improvement rather than on food security in general. Sixth, attrition between the rounds was related to conflict and to heat, so our panel estimates apply to the households that

remained in the survey; reweighting on observed characteristics leaves the heat estimate almost unchanged, but it cannot address selection on unobserved characteristics.

For programming, our results point to timing and targeting. Monitoring temperature anomalies in the weeks before and during the harvest could help identify localities where harvest-related gains are at risk. Household capacity indices identified the less food insecure, but not those better protected against shocks, which suggests that they should complement rather than replace direct measures of food insecurity in targeting. Where climate and conflict shocks overlap, bundled support, as already pursued by SNRLP, is consistent with our point estimates, although our design cannot show which combination of interventions works best.

7. Conclusion

This paper provides panel evidence on food security, shocks, resilience and fragility from Sudan during its civil war. Following the same households from the lean season to the harvest in a phone panel embedded in an IFAD program, we find that one standard deviation of additional heat exposure between the lean season and the harvest offset about two-thirds of the average seasonal improvement in food security, and that the loss was about twice as large, although imprecisely estimated, where lethal conflict had occurred nearby. Pre-shock resilience capacities, measured with an index built on the Serfilippi et al. (2025) framework, are associated with lower food insecurity but do not predict food security gains among households with the same room to change, and they do not reduce heat losses. Households that reported more fragile conditions before the shock gained less over the harvest, though not when compared with households with the same room to change, and heat losses were larger where households reported more fragile conditions at the end of the window between the rounds. Our experience also shows that phone-based monitoring is feasible during active conflict, but that selection removes the most conflict-affected areas and that resilience and fragility measures collected by phone are noisy.

Future research should extend the panel beyond the harvest to examine whether the losses persist and whether the co-movement of food security and emergency coping continues, use baseline indicators from before the war as more stable measures of capacities, increase the number of localities to improve power for interactions, and implement counterfactual-based measures of resilience such as cumulative avoided losses (Alloush & Carter, 2026).

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Appendix

Appendix A. Indicators, constructs and distributions

Table A1. Resilience and fragility indicators and factor loadings

Dimension	Indicator	Loading	Alternative classification
Resilience capacities			
Economic	Financial services used (count)	0.76	Resilience
Economic	Income sources (count)	0.50	Resilience
Economic	Livestock, log(1 + TLU)	0.23	Not used
Economic	Area cultivated with the main crop (category)	0.14	Not used
Environmental	Agricultural practices adopted (count)	0.76	Resilience
Environmental	Livestock practices adopted (count)	0.79	Not used
Environmental	Risk-proofing practices (count)	0.84	Resilience
Environmental	Water and irrigation sources available (count)	0.18	Fragility (few sources)
Social	Member of a community group	0.00	Resilience
Social	Trusts others to give a good deal (1–4)	−0.25	Fragility (low trust)
Institutional	Received any support, last 12 months	0.19	Resilience
Institutional	Felt support by local institutions (mean, 1–4)	0.22	Resilience
Institutional	Electricity or solar lighting	−0.09	Resilience
Institutional	Motorized or public transport to market	0.01	Not used
Fragility experience			
Economic	Minutes to market	0.02	Not used
Economic	Rarely gets a good market deal (1–4)	−0.35	Fragility
Environmental	Water-related crop or livestock losses	0.63	Not used
Environmental	Distance to drinking water (1–6)	−0.03	Resilience (water nearby)
Environmental	Worry about climate shocks (0–10)	0.62	Fragility
Security and social	Disputes over natural resources (0–10)	0.33	Fragility
Security and social	Relocated farming due to insecurity	0.35	Fragility
Security and social	Worry about conflict (0–10)	0.50	Fragility

Dimension	Indicator	Loading	Alternative classification
Security and social	Internally displaced	−0.12	Not used
Institutional	Road disruptions (1 never – 5 always impossible)	0.58	Fragility
Institutional	Phone or internet disruptions (1 never – 5 no service)	0.39	Fragility
Only in the alternative classification			
Social	Disputes resolved by a local, village-level mechanism	–	Resilience
Economic	Dissatisfied with financial services (1–4)	–	Fragility
Added in the version with shock experience (Round 1)			
Shock experience	Number of shock types reported, last 12 months	0.23	Not used
Shock experience	Severity of the shock impact (1 no impact – 5 worst ever)	−0.15	Not used

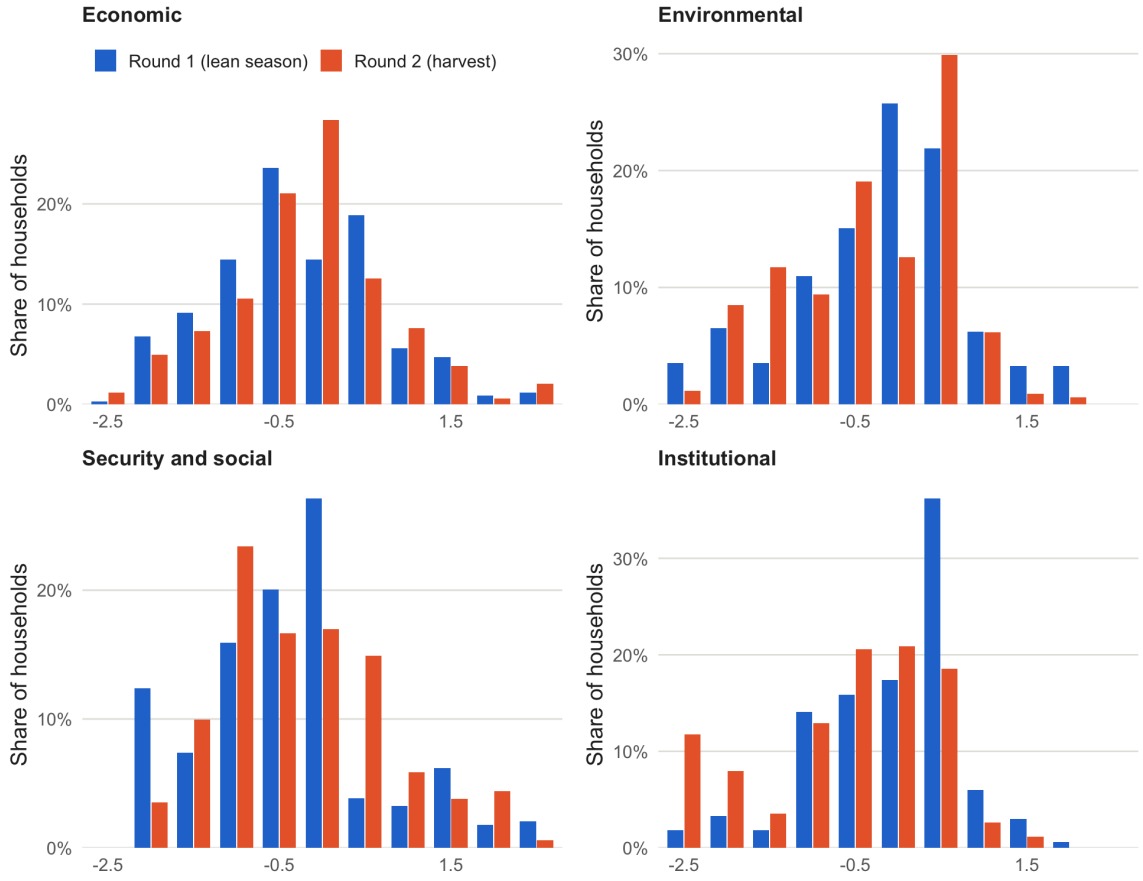
Notes: Loadings from one-factor polychoric factor analyses of the mixed correlation matrix of the indicators, panel households, both rounds pooled (version with shock experience: Round 1). The factor explains 21 percent of the variance of the resilience indicators and 17 percent of the variance of the fragility indicators. Additive sub-indices average the standardized indicators within each dimension. Alternative classification: allocation of the questionnaire items to resilience and fragility proposed for this study; coping strategies, also listed there under resilience, are treated as outcomes.

Table A2. Framework constructs and measures

Construct	Main measure	Alternatives
Fragility: exposure	UCDP events within 25 km, start of the war to Round 1; heat z-score between the rounds	UCDP within 10, 50 and 100 km; fatalities; 12 months before Round 1; ACLED events and fatalities in the locality; rainfall, SPI-2, SPEI-2, floods
Fragility: experience	Factor score of 11 reported conditions and constraints, without and with own shock experience, Round 1 and Round 2	Additive index; four dimension sub-indices; alternative classification
Resilience: absorptive	Factor score of all 14 capacity indicators, Round 1 (no separate main index by capacity)	Financial services, livestock (TLU), community group, support received, risk-proofing practices
Resilience: adaptive	As above	Income sources, agricultural and livestock practices, area cultivated, trust in market partners
Resilience: transformative	As above	Felt support by local institutions, electricity or solar lighting, motorized transport, water sources
Resilience: other	As above	Additive index; four dimension sub-indices; recovery ability (households reporting a shock); alternative classification

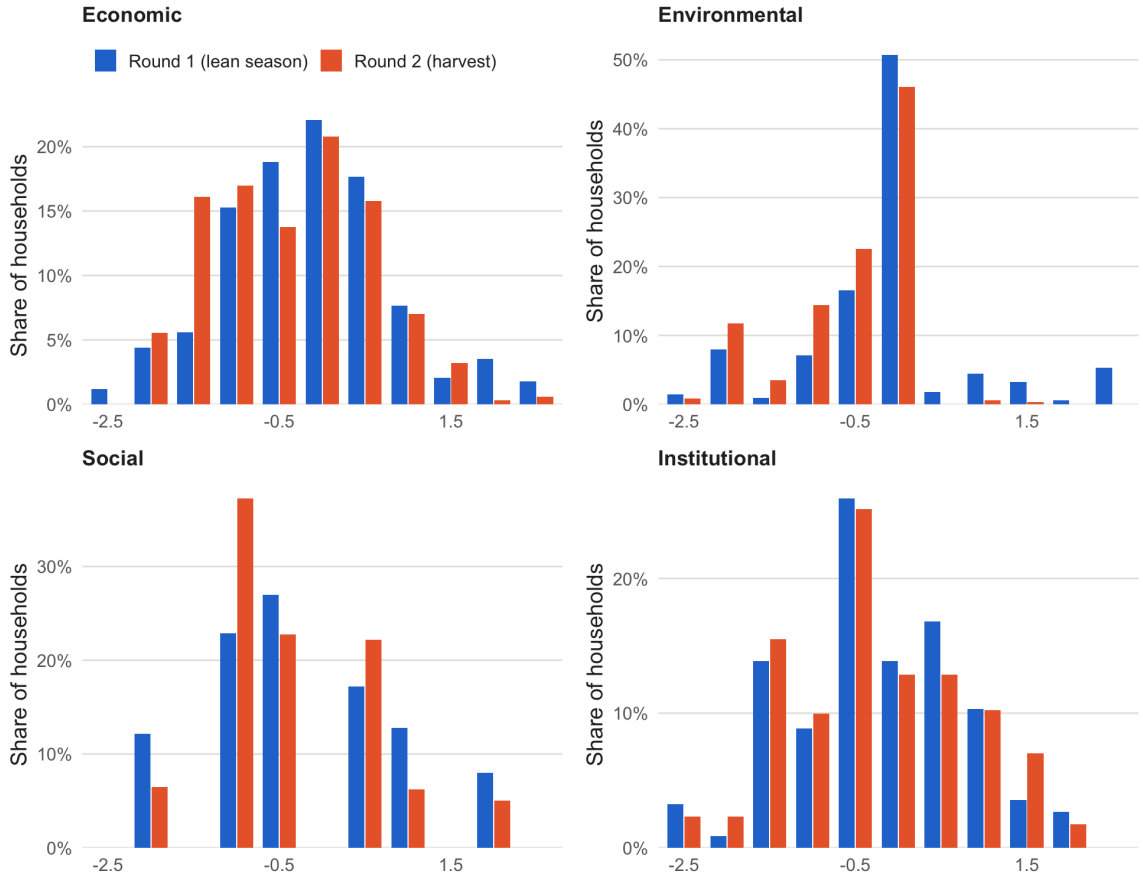
Notes: Exposure is measured with external data, experience with household reports (Serfilippi et al., 2025). The allocation of the capacity indicators to absorptive, adaptive and transformative capacities is our proposal. Additive indices: indicators z-scored on the pooled panel, averaged and re-standardized.

Figure A1. Fragility experience by dimension, Round 1 and Round 2



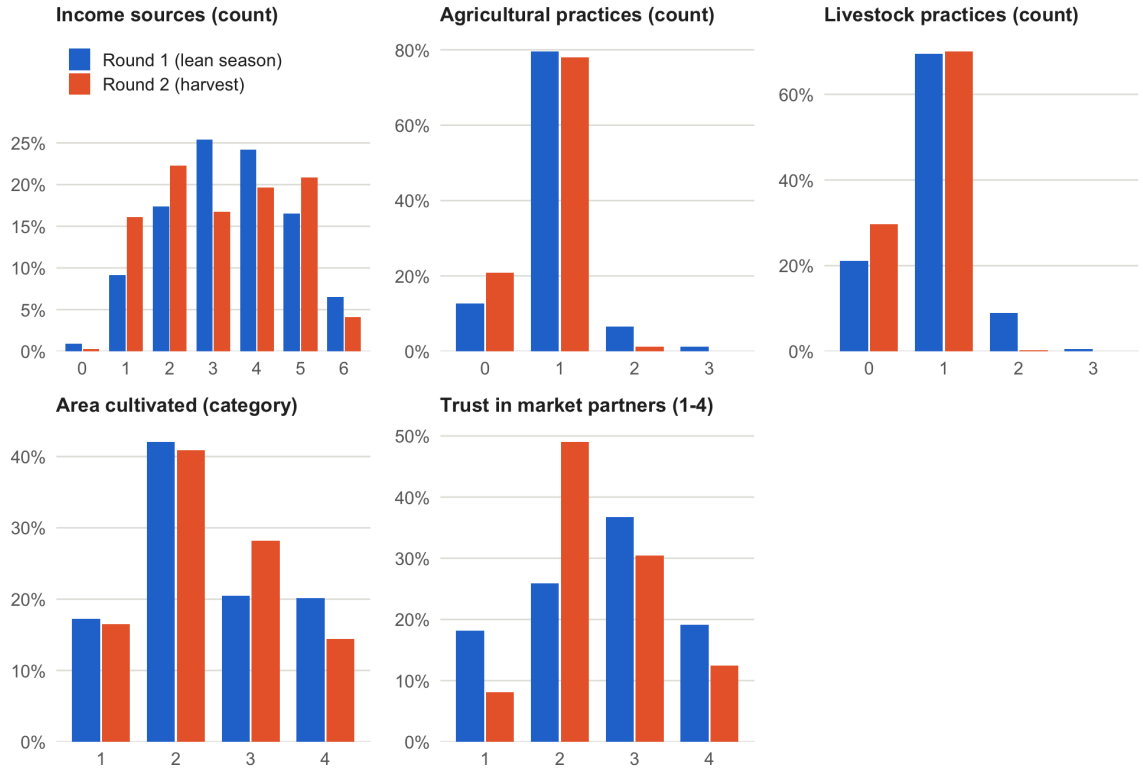
Notes: Panel households. Additive sub-indices: indicators z-scored on the pooled panel, averaged within the dimension and re-standardized. Economic: distance to market, poor market deals. Environmental: water-related losses, distance to water, climate worry. Security and social: disputes, relocated farming, conflict worry, displacement. Institutional: road and phone disruptions. Bins of 0.5 standard deviations, labeled by their lower bound; tails merged.

Figure A2. Resilience by dimension, Round 1 and Round 2



Notes: As Figure A1. Economic: financial services, income sources, livestock, area cultivated. Environmental: agricultural, livestock and risk-proofing practices, water sources. Social: community group, trust in market partners. Institutional: support received, felt support by local institutions, lighting, transport.

Figure A3. Adaptive capacity indicators, Round 1 and Round 2



Notes: Panel households. Counts: number of options reported. Fewer answer options for agricultural and livestock practices were recorded in Round 2.

Appendix B. Measurement details

As alternative conflict measures, we use radii of 10, 50 and 100 km and distance rings (0–10, 10–25, 25–50 and 50–100 km), the log number of events, fatalities, windows of 12 months before Round 1 and up to the start or the end of Round 2, ACLED counts of political violence events and fatalities in the household's locality up to January 2026, and ACLED events geocoded up to December 2024 (Raleigh et al., 2010), which are about five times denser than UCDP events and correlate with them at 0.90 within 25 km.

As alternative climate measures, we use the September–October rainfall total, the two-month SPEI from TerraClimate, which also reflects evaporative demand, and indicators for anomalies beyond one standard deviation.

The alternative classification of the questionnaire items proposed for this study (Table A1) moves water access to resilience, water sources and trust to fragility, adds local dispute

resolution and satisfaction with financial services, and leaves out livestock holdings, area cultivated, livestock practices, transport, distance to markets, water-related losses and displacement. The alternative indices correlate at 0.93 (resilience) and 0.89 (fragility) with our main indices.

Appendix C. Additional results

On the recovery margin, economic resilience (27.4 percentage points, p = 0.02), that is, assets and financial services, and environmental resilience (15.6, p = 0.04), that is, the adoption of agricultural, livestock and risk-proofing practices, have interactions with heat of the same sign as the capacity index (Table A3); the caveats in Section 5.2.3 apply. Social and institutional resilience do not interact with heat on either margin (all p ≥ 0.64). Among the fragility experience dimensions, institutional fragility in Round 1 is associated with larger heat losses (1.10, p = 0.03) and economic fragility with smaller ones (−1.09, p = 0.02) (Table A4). In Round 2, environmental, security and social, and institutional fragility are associated with larger heat losses (1.63, p = 0.001; 1.79, p = 0.02; 1.05, p = 0.03), and economic fragility with smaller ones (−0.71, p = 0.07).

Table A3. Resilience dimension sub-indices, food security gains and heat losses

Outcome	(1) Gains: all ΔFIES	(2) Gains: recovery margin NC	(3) Gains: resistance margin ΔFIES	(4) Heat loss: all ΔFIES	(5) Heat loss: recovery margin NC	(6) Heat loss: resistance margin ΔFIES
Economic	1.89*** (0.001)	−0.9 (0.95)	0.44 (0.26)	−0.15 (0.72)	27.4** (0.022)	−0.89 (0.19)
Environmental	1.86*** (0.005)	3.8 (0.65)	0.14 (0.75)	1.08*** (0.006)	15.6** (0.040)	−0.28 (0.76)
Social	−2.68*** (0.000)	−9.1 (0.33)	0.01 (0.98)	−0.43 (0.52)	−3.2 (0.69)	0.43 (0.80)
Institutional	0.81 (0.16)	−9.1 (0.39)	0.12 (0.77)	0.84 (0.24)	3.1 (0.64)	0.02 (0.95)

Notes: As Table 6, for the additive resilience sub-indices, Round 1 (Appendix A). * p < 0.10, ** p < 0.05, *** p < 0.01 (wild cluster bootstrap).

Table A4. Fragility experience dimension sub-indices, food security gains and heat losses

Outcome	(1) Gains ΔFIES	(2) Heat loss ΔFIES
Round 1 (before the shock)		
Economic	−1.43** (0.043)	−1.09** (0.017)
Environmental	−0.93* (0.055)	0.11 (0.67)
Security and social	0.05 (0.93)	0.70 (0.27)
Institutional	1.50** (0.044)	1.10** (0.031)
Round 2 (end of the window between the rounds)		
Economic	1.02* (0.062)	−0.71* (0.066)
Environmental	0.70 (0.41)	1.63*** (0.001)
Security and social	−0.66 (0.39)	1.79** (0.021)
Institutional	0.82 (0.20)	1.05** (0.030)

Notes: As Table 5, for the additive fragility experience sub-indices (Appendix A). * p < 0.10, ** p < 0.05, *** p < 0.01 (wild cluster bootstrap).

Appendix D. Descriptive statistics

Table A5. Resilience indicators, Round 1

	Mean	SD	Min	Max
Economic				
Financial services used (count)	0.79	0.64	0.00	4.00
Income sources (count)	3.47	1.42	0.00	6.00
Livestock, log(1 + TLU)	0.56	0.83	0.00	4.98
Area cultivated with the main crop (category)	2.49	1.03	1.00	4.00
Environmental				
Agricultural practices adopted (count)	0.93	0.48	0.00	3.00
Livestock practices adopted (count)	0.90	0.57	0.00	3.00
Risk-proofing practices (count)	0.86	0.61	0.00	3.00
Water and irrigation sources available (count)	1.00	0.20	0.00	2.00
Social				
Member of a community group	0.29	0.45	0.00	1.00
Trusts others to give a good deal (1–4)	2.51	0.99	1.00	4.00
Institutional				
Received any support, last 12 months	0.49	0.50	0.00	1.00
Felt support by local institutions (mean, 1–4)	1.60	0.74	1.00	4.00
Electricity or solar lighting	0.64	0.48	0.00	1.00
Motorized or public transport to market	0.78	0.41	0.00	1.00

Notes: Analytical sample (247 households; 211 to 247 with non-missing values). Indicators as in Table A1; counts are numbers of options reported; binary indicators are shares.

Table A6. Fragility experience indicators, Round 1 and Round 2

	Mean	SD	Min	Max
Round 1 (before the shock)				
Minutes to market	37.20	29.55	3.00	180.00
Rarely gets a good market deal (1–4)	2.52	0.94	1.00	4.00
Water-related crop or livestock losses	0.63	0.48	0.00	1.00
Distance to drinking water (1–6)	2.30	1.43	1.00	6.00
Worry about climate shocks (0–10)	7.83	3.97	0.00	10.00
Disputes over natural resources (0–10)	3.69	2.97	0.00	10.00
Relocated farming due to insecurity	0.09	0.28	0.00	1.00
Worry about conflict (0–10)	7.02	4.47	0.00	10.00
Internally displaced	0.07	0.26	0.00	1.00
Road disruptions (1–5)	3.13	1.25	1.00	5.00
Phone or internet disruptions (1–5)	3.52	0.91	1.00	5.00
Shock experience: number of shock types reported	1.32	0.91	0.00	6.00
Shock experience: severity of the impact (1–5)	3.49	1.00	1.00	5.00
Round 2 (end of the window between the rounds)				
Minutes to market	39.12	29.46	1.00	240.00
Rarely gets a good market deal (1–4)	2.58	0.92	1.00	4.00
Water-related crop or livestock losses	0.53	0.50	0.00	1.00
Distance to drinking water (1–6)	2.68	1.14	1.00	6.00
Worry about climate shocks (0–10)	6.69	3.92	0.00	10.00
Disputes over natural resources (0–10)	3.48	3.09	0.00	10.00
Relocated farming due to insecurity	0.15	0.36	0.00	1.00
Worry about conflict (0–10)	7.33	3.79	0.00	10.00
Internally displaced	0.11	0.32	0.00	1.00
Road disruptions (1–5)	2.41	1.24	1.00	5.00
Phone or internet disruptions (1–5)	3.12	1.12	1.00	5.00
Shock experience: number of shock types reported	0.95	0.27	0.00	3.00
Shock experience: severity of the impact (1–5)	3.47	1.11	1.00	5.00

Notes: Analytical sample (247 households; 233 to 247 with non-missing values). Indicators as in Table A1. Severity: 1 if no shock was reported. In Round 2, the shock question allowed essentially one answer, so the number of shock types is not comparable with Round 1 and is not used.

Table A7. Climate exposure between the rounds

	Mean	SD	Min	Max
Heat: mean daily maximum temperature, z-score, household location	1.11	0.22	0.73	1.38
Heat: z-score above 1 (share)	0.69	0.46	0.00	1.00
Heat: z-score, locality	1.10	0.22	0.75	1.32
Mean daily maximum temperature (°C)	37.92	0.61	34.95	38.66
Rainfall, October–November, z-score	0.39	0.57	−0.62	1.95
Rainfall, September–October, z-score	1.10	0.43	−0.14	2.06
SPI-2, November	0.48	0.52	−0.56	1.70
SPEI-2, November	−0.08	0.85	−1.36	1.58
Flooding: excess share of land flooded within 5 km (percentage points)	2.69	5.61	−4.92	46.88

Notes: Analytical sample (247 households). Window between the rounds: 26 September to 24 November 2025. Z-scores against the same window in 1991–2020. Heat: ERA5-Land; rainfall: CHIRPS; SPEI-2: TerraClimate. Flooding: October and November 2025 relative to the same months in 2023 and 2024.

Table A8. Conflict exposure

	Mean	SD	Min	Max
UCDP events with at least one death, start of the war to Round 1				
Any event within 25 km (share)	0.69	0.46	0.00	1.00
Events within 25 km	2.77	5.07	0.00	49.00
Fatalities within 25 km	32.42	51.31	0.00	375.00
Events within 10 km	0.61	1.11	0.00	8.00
Events within 50 km	8.09	12.15	0.00	64.00
Events within 100 km	25.14	42.33	0.00	386.00
UCDP events within 25 km, other windows				
12 months before Round 1	1.54	3.17	0.00	29.00
Between the rounds	0.15	0.74	0.00	7.00
ACLED political violence events in the locality				
Start of the war to Round 1	42.68	72.89	0.00	430.00
12 months before Round 1	24.38	36.73	0.00	160.00
Between the rounds	1.02	5.24	0.00	37.00

Notes: Analytical sample (247 households in 15 localities). UCDP GED 26.1, events of organized violence with at least one death, counted around the household location; start of the war: 15 April 2023. ACLED: events in the household's locality.

Table A9. Key informant and household reports in the localities of the meso survey

	Key informants	Households, Round 1	Households, Round 2	Localities with key informants below households (Round 1 / Round 2)
Worry about violent conflict (0–10)	2.55	7.55	7.04	10 / 9
Disputes over natural resources (0–10)	2.96	4.15	3.47	9 / 6
Support from the village-level native administration (1 never – 4 always)	2.74	1.55	1.70	0 / 0
Any shock, last 12 months (share)	0.99	0.97	0.92	1 / 0

Notes: Ten localities. Key informants: meso survey, 23 October to 30 November 2025 (115 respondents). Households: panel households in the same localities (270). Means over localities of the locality means, so that each locality counts once.

Table A10. Beneficiaries and non-beneficiaries: balance and results with inverse probability weights

	Unweighted	Weighted
A. Pre-war characteristics (standardized difference, beneficiaries − non-beneficiaries)		
Respondent male	−0.27	−0.05
Age of the respondent	−0.38	0.04
Household members	−0.04	0.06
Years of schooling	0.10	0.10
Literate	0.08	0.08
Durable asset index	−0.16	0.11
Productive asset index	0.01	0.02
B. Differences, beneficiaries − non-beneficiaries (as Table 8, column 3)		
FIES raw score, Round 1	0.13 (0.73)	0.34 (0.46)
FIES raw score, Round 2	−0.03 (0.92)	0.31 (0.42)
Change in FIES raw score	−0.17 (0.72)	−0.04 (0.93)
Change in severe food insecurity	−0.04 (0.50)	−0.01 (0.84)
Capacity index, Round 1 (z)	0.19 (0.24)	0.19 (0.23)
Fragility experience, Round 1 (z)	0.34** (0.018)	0.32** (0.015)
Heat between the rounds (z-score)	0.02 (0.86)	0.02 (0.86)
Conflict within 25 km before Round 1	0.13 (0.45)	0.11 (0.45)
Change in FIES raw score, doubly robust (IPWRA), ATET		−0.10 (0.84)
C. Heat effects (as Table 8, panel B)		
Heat: change in FIES, non-beneficiaries	4.94** (0.034)	4.67** (0.022)
Heat: change in FIES, beneficiaries	8.27** (0.011)	7.50** (0.029)
Heat: change in FIES, difference	3.33 (0.23)	2.82 (0.33)
Heat × capacity index, non-beneficiaries	−0.53 (0.11)	−0.60** (0.029)
Heat × capacity index, beneficiaries	0.84 (0.39)	0.84 (0.39)

Notes: Analytical sample (247 households in 15 localities; 96 non-beneficiaries, 151 beneficiaries). Weights: non-beneficiaries are weighted by $p / (1 - p)$, where p is the predicted probability of being a beneficiary from a probit of treatment status on the pre-war characteristics in panel A (SNRLP baseline survey) and region; beneficiaries have a weight of one. Missing baseline values (26 beneficiaries) are set to the sample mean, with an indicator. Panel A: difference in means divided by the unweighted pooled standard deviation. Panels B and C: as Table 8, with region fixed effects; wild cluster bootstrap p-values in parentheses (Webb weights, 9,999 replications; SE clustered by locality). IPWRA: inverse probability weighted regression adjustment for the average effect on the treated, outcome model with heat and region, robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.