The Impact of Floods on Food Insecurity and Vulnerability in Democratic Republic of the Congo *

Alzaki Alhelo

March, 2025

Abstract: I study the impacts of floods on household food insecurity and vulnerability in Democratic Republic of the Congo. I combine household-level data with two measures of exposure to floods, self-reported exposure and an objective indicator of large flood events at territory-level. I exploit territory-level variation in timing of exposure to floods combined with exposure to floods to identify causal impacts. I find that self-reported exposure to flood is associated with higher food insecurity and greater reliance on negative coping strategies. In contrast, causal estimates based on an objective measure of exposure to floods suggest that exposure to floods does not significantly change consumption frequency or dietary diversity but is associated with improved food security in Eastern DRC. I explore whether this pattern is driven by short-run economic activity or increased agricultural production and find suggestive evidence that exposure to floods in this context expand cultivated land.

I. Introduction

Natural disasters have profound impacts on economic growth and development (Dell et al. (2014)). Over the past 20 years, the big five disasters: floods, earthquakes, storms, droughts, and heatwaves accounted for over 95 percent of direct disaster damages (UN Office for Disaster Risk Reduction). Floods in particular are among the most destructive disasters (Sustainability Global Team (2025)) Between 1994 and 2013, they affected around 2.5 billion people globally and caused over US$40 billion in annual losses [1]. Sub-Saharan Africa (SSA) is among the most affected regions: in 2024, floods affected over 11 million people and caused widespread damage across the continent (Africa Center for Strategic Studies (2024)). At the same time, most of the world's food-insecure population lives in SSA, and an important explanation for rising food insecurity in the region is the growing incidence of weather shocks, including floods (Omokpariola et al. (2025)). Understanding how these shocks affect household food insecurity therefore has important policy implications. Despite recent progress in the study of extreme weather events see (Dell et al. (2014)) for a survey of literature, causal evidence on their impact on household welfare in low-income settings such as SSA remains limited, this is due to both scarce high-frequency data and the non-randomness of exposure (Baseler and Hennig (2023)).

Progress in measuring exposure to flood and the increasing availability of survey and administrative data have made it possible to study the impacts of floods more systematically. Recent work has addressed key causal identification threats including measurement error and sorting, and has estimated the causal effects of exposure to flood on a range of economic and development outcomes (e.g., Chandir et al. (2023); Chen et al. (2017); Guiteras et al. (2015); Patel (2024)). However, empirical evidence on the causal impact of floods on household welfare in SSA remains rare. In this paper, I focus on Democratic Republic of the Congo (DRC), a large fragile state that has experienced recurrent extreme weather shocks since 2022. Unprecedented rainfall and record levels of the Congo River have triggered severe floods that vary in timing and intensity across provinces and

* **Acknowledgment:** This paper is funded by the Food and Agriculture Organization of the United Nations under the DIEM 2025 Small Grants Program. I am sincerely grateful to the FAO DIEM team—Neil Marsland, Filippo Fossi, and Gauny Josselin—for their constructive feedback and technical guidance throughout this work. I am specially grateful to Amandine Poncin/FAO—DIEM for the technical support in terms of addressing data issues and providing constructive comments throughout this project. I also acknowledge the invaluable support and collaboration of Julius Ssentongo, the Eastern Africa Resilience Innovation Lab, the Resilient Africa Network (RAN), and Makerere University School of Public Health. *All errors, interpretations, and views expressed in this report are entirely my own and should not be attributed to FAO, Makerere University, or any individuals and institutions acknowledged above.*

[1] World Meteorological Organization: *https://wmo.int/topics/floods*

territories. In this context, I address two questions: (i) How have recent floods in the DRC affected households' food insecurity? (ii) How have households adjusted their coping strategies in response to these shocks?

The main challenge to identify the causal effect of exposure to floods on food insecurity is that exposure is mismeasured and endogenous: self-reported exposure to floods likely correlate with both observed and unobserved household and territory factors that also drive food insecurity, and no objective flood measure exists at household level. To address this, I use two complementary measures of floods. First, I use self-reported exposure measure, fixed effects, and set of controls. Second, I construct an external measure of major flood events from OCHA–DRC records of natural disasters. I then use household-level data from the data in emergencies (DIEM–DRC) survey rounds combined with territory-level measure of exposure to floods to estimate the impacts of exposure to floods on food insecurity and vulnerability. The DIEM–DRC data cover eight survey rounds conducted between 2022 and 2025 (Amparore et al. (2023)).

Across all DIEM–DRC survey rounds, some territories appear intermittently while others appear in every round. I therefore construct three sub samples. The full sample includes all rounds, 28,171 households in 80 territories across 14 provinces were interviewed. In sub-sample (1), I restrict to territories observed in rounds 3, 4, 6, and 7. Between April 2022 and February 2024, 8,715 households in 60 territories across 12 provinces were interviewed. Finally, the sub-sample (2) includes all rounds but only territories that included in every round. Between April 2022 and July 2025, 17,128 households were interviewed in 29 territories across four eastern provinces in DRC (Ituri, Nord-Kivu, Sud-Kivu, and Tanganyika) [2]. Across all provinces and territories, large floods started in late 2022 and 2023, generating variation in timing of exposure across territories. The household survey provides detailed information on food security, consumption, and coping, as well as basic demographic and socio-economic characteristics. The OCHA–DRC records of natural disasters include all major natural disasters and their consequences, including the number of affected and displaced persons for each event. This dataset is suitable to construct a measure of exposure to large floods.

I use the standard food security indicators developed by FAO, WFP, and other humanitarian organizations and research centers (e.g., IFPRI and USAID). The outcomes of interest are: Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS) capture diet quality and access to food. Food Insecurity Experience Scale (FIES) to capture experience of food insecurity. Reduced Coping Strategies Index (rCSI) measures the extent to which households resort to distress-driven strategies to manage food shortages. Taken together, these indicators allow me to distinguish between changes in the intensity of food insecurity, dietary patterns, and behavioral responses.

I use self-reported household exposure combined with territory and time fixed effects and set of territory–level time varying controls and household characteristics to estimate two way fixed effects regression that links exposure to floods to food security outcomes. To estimate the causal effects, I construct an external measure of major flood events from OCHA–DRC records of natural disasters, which provide the timing, location, and scale of each event in terms of affected and displaced people. This allows me to exploit temporal variation in flood occurrence and the staggered exposure to floods across territories, thus, reducing concerns about sorting and subjective reporting. I use a stacked difference in differences approach that accommodates staggered treatment over time, heterogeneous treatment effects by group, time, and covariates, and particularly developed to deal with repeated cross–sections. This approach is developed by Deb et al. (2025), they call it FLEX DiD. The identification strategy rests on two main assumptions: conditional parallel trends and no anticipation.

I find that self-reported exposure to floods is associated with a sizable deterioration in experiential food insecurity. FIES and rCSI are significantly higher for households reported exposure to floods in all specifications. Self reported exposure to floods is associated with higher FIES ranges between 0.65 to 1.15 points, this is equivalent to 10 percent to 19.2 percent compared to the mean of FIES mean of non–exposed households. Similarly, Self reported exposure to floods is associated with higher rCSI ranges between 1.39 to 2.31 points, this is equivalent to 8.6 percent to 17.5 percent compared to the mean of rCSI mean of non–exposed households. These correlations are large in magnitude and precisely estimated once I condition on territory and time fixed effects and a set of household and territory-level covariates. In contrast, I do not find significant correlations between self-reported exposure and dietary diversity, as measured by FCS and HDDS: point estimates are close to zero and statistically insignificant, suggesting that exposure floods does not immediately alter diet composition or access to different food items. In the sub sample (1), FCS is lower by 1.44 and statistically significant, this is equivalent to a difference of 2.8 percent compared to the mean of rCSI mean of non–exposed households.

Taken together, the results indicate that floods are less likely to reduce dietary diversity but instead shift households at the margins into greater hunger, insecurity, and reliance on negative coping. Modest declines

[2] The sub-sample (1) is more representative but the sample size is less that the sub-sample (2) while, the later has more households in few provinces and territories. Thus, findings from sub sample (2) should be explained as the impact of exposure to floods in specific region in DRC while sub sample (1) reflects an average effect across the country.

in food security indicators translate into sharp threshold effects. Households at the margins (the edges of classifications) could be pushed into more food insecurity as a result of exposure to floods and other natural disasters. This underscores the importance of policies that not only stabilize consumption but also address the longer-term erosive strategies households employ in response to climate shocks. Its worth noting that the validity of these findings rely heavily on the absence of measurement error of self reported exposure. I controlled for the observable characteristics that appear to be heterogeneous across households and fixed effects which could reduce the endogeneity concerns and I also controlled for characteristics that appear to be fairly exogenous to exposure to floods which could roll out the bad control issue. However, concerns are still exist on unobservable characteristics that may be correlated with the exposure to floods.

When I turn to the external treatment measure constructed from OCHA records and FLEX DiD, the evidence on dietary diversity is remarkably similar: I detect no average significant effect on FCS or HDDS, though ATT's indicate some episodes of trivial decrease in HDDS following exposure. The high positive correlation of self-reported exposure with FIES and rCSI are borne out in the causal specifications. Flood exposure identified from external records leads to a statistically significant decline in FIES. In far eastern DRC, flood exposure reduces food insecurity (measured by FIES) by 0.822 points, equivalent to 12.9 percent of the non-exposed mean; no significant effects appear in Sub-sample (1). This finding is consistent with an improvement in food security, whereas the corresponding effects on rCSI remain positive but imprecisely estimated, implying at most modest changes in distress-coping behavior.

I assess the robustness of these findings through four empirical tests. First, I use alternative food insecurity and coping measures Household Hunger Scale (HHS) and Probability of Experiencing Severe Food Insecurity (PSFI). Second, I use more household- and territory-level controls. Third, I re-estimate treatment effects using lags only specification and different sub–samples (larger number of clusters). Finally, I redefine exposure to floods using a higher displacement threshold of 20,000 people. Across these exercises, the coefficients on exposure to flood remain stable in sign and significance, thus, supporting the key conclusions. In far eastern DRC, flood exposure reduces PSFI by 0.091 (43 percent relative to the control mean of 0.21), while in the representative Sub-sample (1), PSFI increases by 0.011 (7 percent relative to the control mean).

To shed light on mechanisms, I test two competing explanations. The first is that floods may induce short-run economic booms through reconstruction, raising income and employment. The second is that, in an agrarian economy, unusually high rainfall and flooding can relax water constraints, leading to expansion of planted land, and increase in harvests. I examine household income, employment status, sector of employment, and number of jobs, as well as planted area and harvest outcomes. The evidence supports the second explanation: in treated territories, households significantly expand use of land, while increase in harvest is modest and imprecisely estimated. Income and employment effects are generally positive but statistically insignificant, offering limited support for reconstruction boom.

Recent empirical work has substantially advanced the measurement and causal estimation of exposure to floods. A recent strand of this literature exploits high-resolution satellite data and panel micro-data to identify how exposure to flood shapes economic outcomes and human development. This work has shown that traditional proxies such as rainfall and self-reported flood exposure are noisy and systematically biased, and that combining hydrological models, remote sensing, and machine learning yields more reliable objective measures of inundation intensity and timing (see, e.g., Guiteras et al. (2015) ; Chen et al. (2017) ; Patel (2024)). A growing methodological innovation has been developed in settings with frequent flooding and relatively rich data, such as Bangladesh and Pakistan, where recent studies document sizeable and persistent effects of floods on schooling, migration, sectoral reallocation, and agricultural productivity, as well as the role of prior exposure and expectations in shaping adaptation responses (Patel (2024)). Other contributions in the context of Pakistan and other South Asian contexts link satellite-derived flood maps to child health investments and vaccination schedules, highlighting the breadth of development outcomes affected by extreme weather events (Chandir et al. (2023)).

A second strand of research focuses more directly on floods and food security in fragile or conflict-affected settings. Cross-country analyses in Africa find that hydrological disasters significantly increase undernourishment and food insecurity, while country-specific studies in Afghanistan and Nigeria combine household survey data with exogenous variation in flood exposure to estimate impacts on food consumption, dietary diversity, and hunger indicators (see, e.g., Reed et al. (2022) ; Hadley (2023) ; Yolchi (2024); Omokpariola et al. (2025)). These papers typically rely on standard food security metrics such as the Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), Household Hunger Scale (HHS), and the Food Insecurity Experience Scale (FIES), and document consistent negative effects of floods on both the quantity and quality of food intake (Baseler and Hennig (2023) ; Reed et al. (2022).) Methodologically, this work employs instrumental variables, event-study designs, and flexible difference-in-differences models to distinguish short-run shocks from longer-run scarring and to probe heterogeneity by geography, assets, and pre-shock vulnerability Baseler and Hennig (2023); Patel (2024); Yolchi (2024). Despite these advances, there remains relatively little causal evidence from highly fragile environments with overlapping climatic and conflict shocks, and very few studies that jointly exploit external flood measures and rich self-reported shock data to interrogate measurement error and spillover channels in food security responses (Baseler and Hennig (2023) ; Reed et al. (2022)).

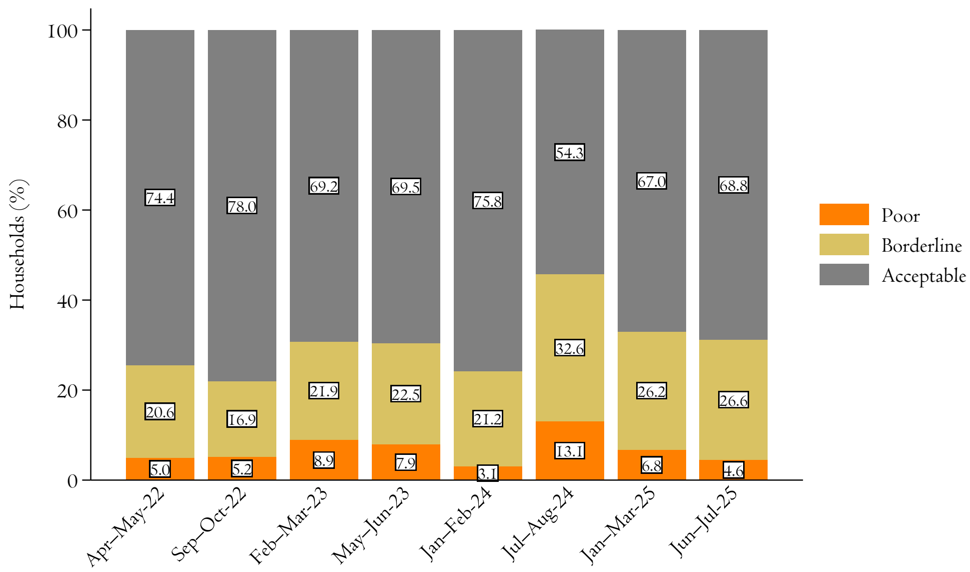
I contribute to this growing literature on climate shocks and food security in three ways. First, it provides, to the best of current knowledge, one of the first causal estimates of flood impacts on household food security in the Democratic Republic of Congo, a large fragile state where floods coexist with conflict, displacement, and economic volatility and where empirical evidence is scarce (Reed et al. (2022) ; Baseler and Hennig (2023)). Second, it combines detailed household data with both self-reported shocks and an externally constructed flood measure, allowing a direct comparison between "internal" and "external" exposure measures and clarifying when self-reported shocks can still be informative after careful econometric considerations (see, e.g., Patel (2024) for detailed discussion). Third, the analysis employs an state of the art staggered-difference in differences framework to estimate the causal effects on a rich set of food security indicators (FCS, HDDS, FIES, HHS, and severe food insecurity) and to separate direct flood impacts from territory-level spillovers. In doing so, it extends recent evidence on the link between floods and food insecurity from Bangladesh, Afghanistan, and Nigeria to a complex Sub-Saharan African context, and speaks directly to the design of climate-sensitive humanitarian and social protection policies in fragile states (Reed et al. (2022) ; (Hadley (2023) ; (Yolchi (2024) ; Patel (2024)).

The remainder of the paper is organized as follows. Section II provides brief background on food insecurity and recent floods in the DRC. Section III introduces the data and summary statistics. Section IV presents the empirical strategy and findings. Section V introduces robustness tests and mechanisms. Section VI concludes.

II. Food Security and Floods in DRC

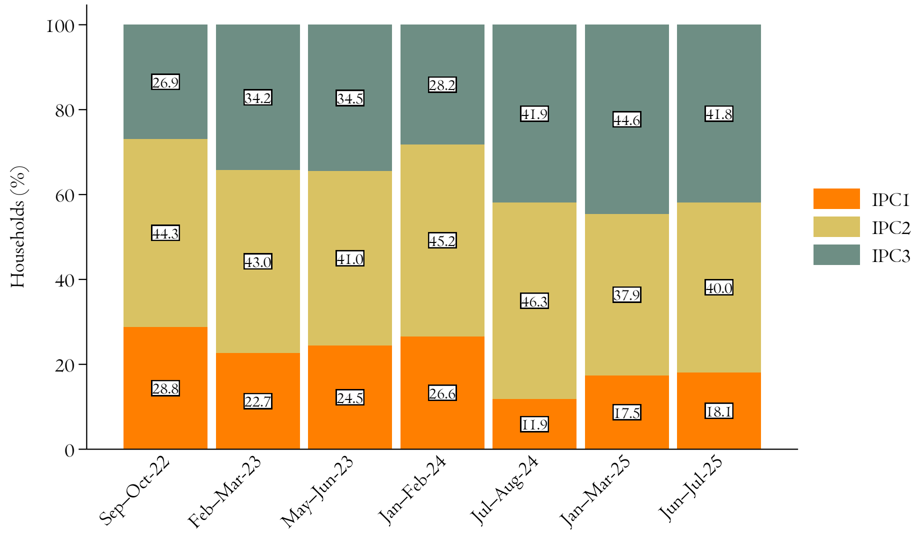
The DRC is one of Africa's largest and most populous countries, yet remains among the least developed and poorest in the world. Despite vast natural resource endowments, a legacy of colonial extraction, weak institutions, and prolonged conflict has left the country highly fragile and marked by widespread poverty; in 2024, an estimated 73.5 percent of the population lived below the international poverty line of US$2.15 per day (Insecurity Insight (2025); World Bank (2024)). In this section, I document the current food insecurity situation using household-level data from the 2022–2025 DIEM survey rounds and describe the consequences of recent natural disasters, with a particular focus on floods. Food insecurity in the DRC is severe and persistent. As of early 2025, over 28 million people (30 percent of the population) faced acute food insecurity (IPC Phase 3 or above), with 4 million in Emergency (IPC Phase 4) (World Food Programme (2025)). Conflict-related violence targeting food systems has exacerbated the crisis (Insecurity Insight (2025)). This trend confirmed by DIEM surveys (2022–2025), which reveal three patterns: persistently high food insecurity across all rounds, widespread reliance on crisis coping strategies, and pronounced variation across provinces and residency types.

Figure 1: Classification of Households' Food Consumption



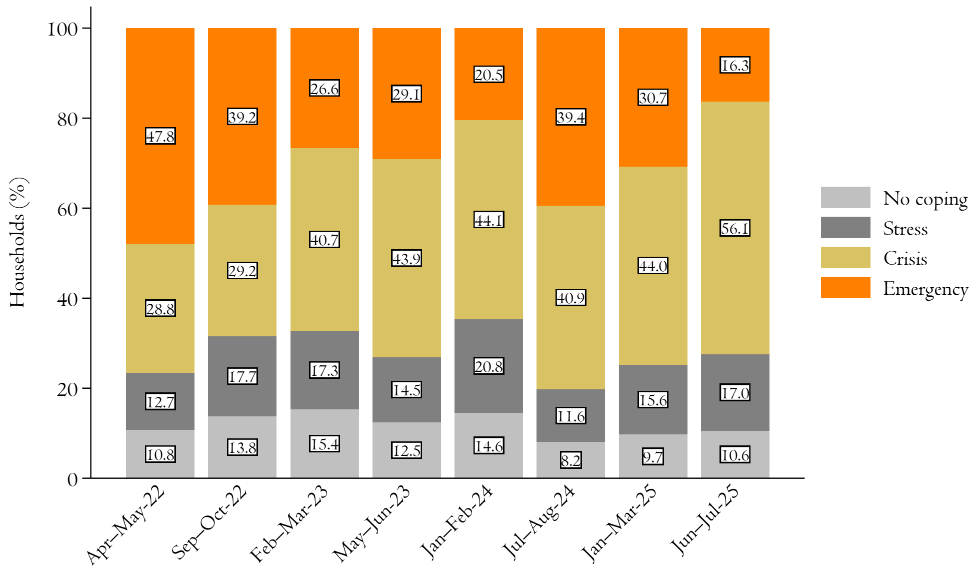
Source: Authors preparation based on Data from DIEM–DRC Survey.

Figure 2: Classification of Households' Coping Strategy



Source: Authors preparation based on Data from DIEM–DRC Survey.

Figure 3: Classification of Households' Coping Strategy



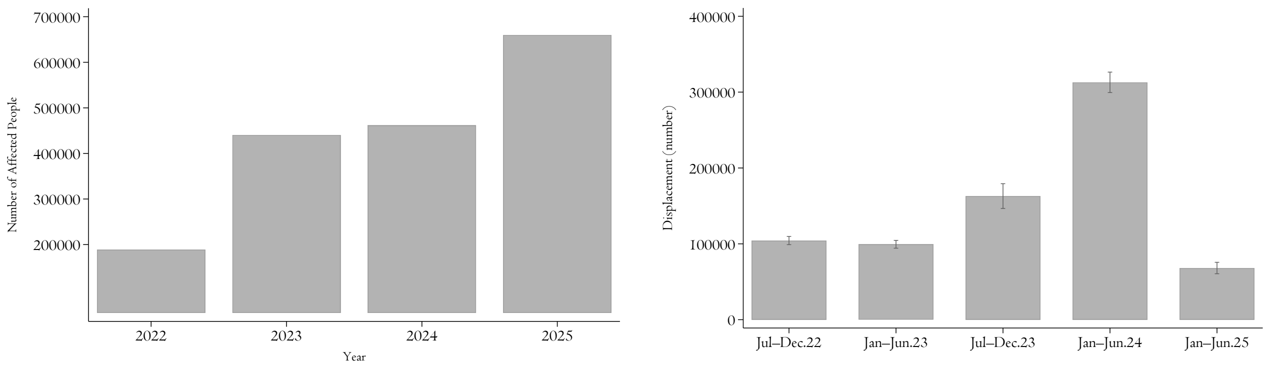
Source: Authors preparation based on Data from DIEM–DRC Survey.

DIEM data show average FCS of 45.9 and HDDS of 4.87 over 2022–2025. Forced migrants scores were substantially lower (FCS 36.7, HDDS 4.29) than residents (48.2, 5.04) and recent migrants (43.8, 4.64). Hunger (HHS 1.48 overall, 2.12 for forced migrants) and coping (rCSI 16.3 overall, 7.65 for forced migrants) indicators are similarly elevated, with FIES reaching 23.07 among forced migrants versus 15.21 for residents (Appendix (1), Tables 1-3). Item-level patterns confirm reliance on staples over nutrient-dense foods and frequent use of erosive strategies (e.g., 68–77 percent sometimes skip meals or eat less), most prevalent among displaced households. Categorical outcomes reveal widespread marginal or moderate food insecurity, with nontrivial shares severely insecure; forced migrants are disproportionately represented in worst categories across FCS, HDDS, rCSI, LCSI, and FIES (Appendix (1), Table 3). Spatial disparities are stark: North Ubangi, Kasai Central, Tanganyika, Kasai, and South Kivu show the highest insecurity (two-thirds food insecure in some rounds), while even relatively better provinces like Kasai Oriental have notable low-HDDS shares. These patterns highlight DRC households' acute vulnerability to shocks like floods, particularly among displaced populations.

In addition to this fragile situation, the DRC has recently experienced destructive floods. In early 2024, the Congo River rose to 6.20 meters—nearing the 1961 record—causing widespread inundation across nearly half of the country's provinces.(International Federation of Red Cross and Red Crescent Societies (IFRC) (2024)) Since 2019, 16 of 26 provinces have been affected, impacting nearly 2 million people in 2023 alone; in 2024, floods affected 1.8 million, damaged over 300,000 houses, and destroyed 43,000 homes and 1,300 schools.(International Federation of Red Cross and Red Crescent Societies (IFRC) (2024); OCHA (2023)) Floods exhibit significant spatial variation: Tshopo suffered extensive damage to houses, agricultural plots, and markets (affecting over 93,000 people and raising food prices), while South Kivu saw deadly landslides in Bunyakiri and Bukavu triggered by heavy rains. A dataset I constructed from OCHA records shows that between 2022 and 2024, floods affected over 2 million people, displacing 1.5 million—a sharp increase alongside conflict-driven displacement (Figure **??**, panels (a)–(b)).(International Federation of Red Cross and Red Crescent Societies (IFRC) (2024)) These events resulted in 412 deaths and 461 injuries.[3] The FAO–FloodEX DIEM dataset further documents impacts: between July 2024 and May 2025, floods affected 13.5 million people across 83 territories and 23 provinces, damaging 77,796 ha of cropland (out of 23.7 million ha total) (FAO-FloodEX). Together, this evidence underscores the DRC as a setting where climate shocks, armed conflict, and poverty interact to create a severe food security crisis, making it an ideal context for studying the consequences of flood exposure on household food security outcomes.

Figure 4: Impacts of exposure to floods (2024-2025)

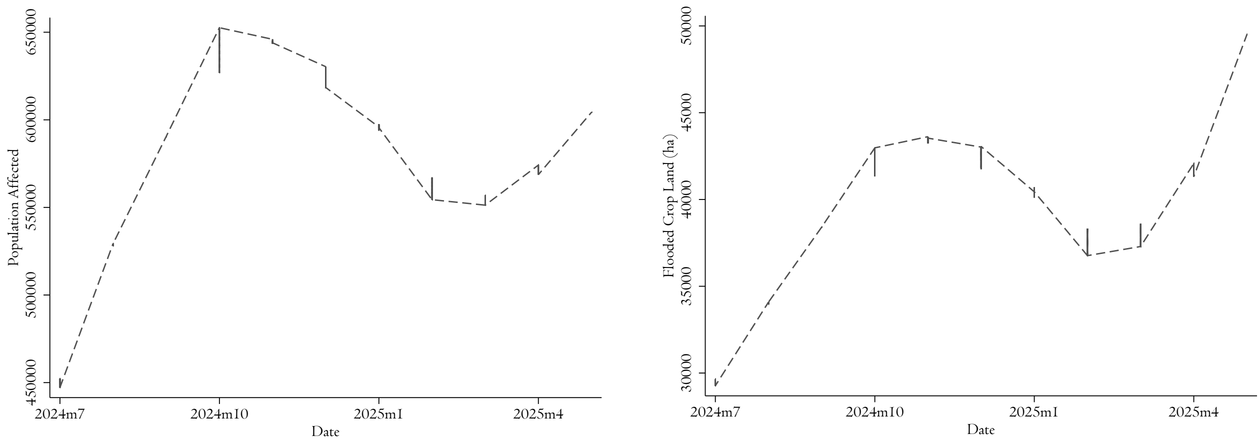
Panel (a): Number of Affected People **Panel (b):** Number of Displaced People



Source: *OCHA, DRC Natural Disasters Record*

Figure 5: Impacts of exposure to floods (2024-2025)

Panel (a): Number of Affected Population **Panel (b):** Affected Land (hectare)



Source: *The FAO, FloodEX data;* https://bit.ly/4ga9Lr7.

IV. Data and Summary Statistics

This section introduces the data, outcomes of interest, and the measures of flood exposure.

a). The DIEM–DRC Survey: This paper uses repeated household data from the Data in Emergencies Monitoring (DIEM-Monitoring) surveys. Implemented by FAO since 2020, DIEM-Monitoring follows households across 26 food-crisis countries, with repeated rounds designed to capture rapid changes in livelihoods and welfare.

[3] Data from: Democratic Republic of the Congo: Natural disaster impact. https://bit.ly/3V2G2qk.

The surveys' primary objective is to generate timely, comparable indicators of agricultural livelihoods and food security, and to track how climatic, economic, and conflict-related shocks translate into changes in household well-being (see, Amparore et al. (2023)) [4]

Table 1 shows sample sizes, dates, and geographic coverage for each round. Between April 2022 and July 2025, eight rounds of DIEM surveys were conducted in the DRC, interviewing 28,171 households across 14 provinces and 80 territories via in-person and telephone-assisted methods. Table 2 reports summary statistics for the full sample, by flood exposure status and residency type. Agricultural engagement is heterogeneous: 44 percent of households cultivate crops only, 9 percent raise livestock only, 19 percent do both, and 28 percent report no agricultural production. Household heads are predominantly male (88 percent), with educational attainment varying from 7 percent no formal schooling to 35 percent higher education. Residency is 90 percent permanent residents, 5 percent IDPs, 1.5 percent refugees, 1.1 percent returnees, and 2 percent recent migrants. Household size is 54 percent 8–14 members and 40 percent 1–7 members. Marital status shows 82 percent married household heads. Access to basic services is limited: 22 percent have electricity and 63 percent use safe water sources.

Table 1: The DIEM–DRC Survey Rounds (2022–2025)

Rounds	Households	Date	Admin (1)	Admin (2)
3	2,110	Apr–May 2022	9	62
4	2,781	Sep–Oct 2022	11	79
5	2,716	Feb–Mar 2023	11	na
6	2,745	May–Jun 2023	11	75
7	2,723	Jan–Feb 2024	11	77
8	5,782	Jul–Aug 2024	4	29
9	5,258	Jan–Mar 2025	5	35
10	4,526	Jun–Jul 2025	4	29
8	**28,171**	**2021–2025**	**14**	**80**

Notes: The data is at household, territory, and province (Admin levels 1 and 2) levels. In total, the sample includes 28,171 households for all rounds. In round 5, territories were missing, this leads to a sample size of 25,455 households with both Admin 1 and 2 over 7 time periods.
Source: Author's preparation based on the DIEM-DRC Survey rounds.

Household characteristics show that exposed and non-exposed households are broadly similar in demographics but differ in infrastructure and livelihoods. Among permanent residents, female headship, age, marital status, and education distributions are comparable across exposure status—one-third of heads attain higher education, with small fractions reporting no schooling—though non-exposed households have more respondents aged 14–42 (77 percent vs. 72 percent). Exposed households are slightly larger and have better access to safe water, public taps, and modern lighting. In agriculture, exposure correlates with greater reliance on non-agricultural activities. Among non-residents, differences are minimal except for smaller household sizes, lower electricity access, and more crop/non-agricultural livelihoods among exposed households. **b). Food Insecurity and Coping Measures:** Food security is multidimensional and cannot be captured by a single indicator (World Food Programme, Vulnerability Analysis and Mapping Branch (ODAV) (2008)). I use FCS and HDDS to measure dietary quality and diversity; FIES and HHS to capture food insecurity and hunger; and rCSI and lCSI to assess coping behaviors and access constraints. These indicators also enable categorical classifications of households by food security status, hunger severity, and coping intensity at the extensive margin Table 3 summaries food security indicators Appendix (1), Table (1), panel (a) summarizes intensive margin food security and coping indicators.

Dietary Quality (FCS and HDDS). FCS developed by the World Food Programme, assesses dietary diversity, consumption frequency, and nutritional value over the past 7 days across 9 food groups (staples, pulses, vegetables, fruit, meat/fish, dairy, oil, condiments, sugar). Frequencies (days consumed by at least half the household) are weighted by nutritional importance (staples=2, pulses=3, vegetables/fruit=1, meat/fish/dairy=4, oil/-condiments/sugar=0.5) and summed (0–112). Households are classified as poor (<22), borderline (22–35), or acceptable (≥ 36), providing an operational measure of weekly diet quality (World Food Programme, Vulnerability Analysis and Mapping Branch (ODAV) (2008)). HDDS counts the number of distinct food groups (typically 12) consumed in the past 24 hours, proxying economic access to nutrient-rich diets. Food Insecurity and Hunger (FIES and HHS). FIES measures severity of access constraints over 30 days via 8 experience-based

[4] The DIEM questionnaire covers five primary modules: (1) household roster and demographics (age, sex, education, size, migration status); (2) income sources and shocks (earnings from crops, livestock, wages, transfers; retrospective income changes; exposure to natural disasters, economic/manmade shocks, and COVID-19 restrictions); (3) crop, livestock, and fisheries production (planted/harvested areas, marketing, related shocks); (4) food security, consumption, and coping (food consumption, utilization, coping strategies); and (5) assistance and needs (received aid, priority needs, preferred support modalities), see: https://data-in-emergencies.fao.org/pages/monitoring.

questions (e.g., worry about food, skip meals, go hungry), enabling globally comparable prevalence estimates across severity levels (FAO (2014)). HHS captures household-level hunger over 30 days through 3 questions on frequency of going hungry, experiencing hunger without food, or going a whole day/night without eating. Coping Behaviors (rCSI and lCSI). rCSI quantifies frequency and severity of 5 food-based distress strategies over 7 days (e.g., skip meals, limit portions, less-preferred foods). lCSI measures 7 broader strategies (e.g., sell assets, borrow money, reduce health spending). Higher scores indicate greater food stress (World Food Programme (2023)).

Table 2: Household Characteristics by Treatment and Residency

	i). Permanent Residents						ii). Non-Residents			
	Full Sample		No Exposure		Exposure		No Exposure		Exposure	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel (a): Head of Household										
i). Gender										
Female	0.12	0.3	0.12	0.3	0.12	0.3	0.13	0.3	0.11	0.3
Male	0.88	0.3	0.88	0.3	0.88	0.3	0.87	0.3	0.89	0.3
ii). Marital Status										
Single	0.08	0.3	0.08	0.3	0.01	0.1	0.10	0.3	na	na
Married	0.82	0.4	0.83	0.4	0.74	0.4	0.74	0.4	na	na
Separated	0.10	0.3	0.09	0.3	0.25	0.4	0.12	0.3	na	na
iii). Age (Range)										
18 to 40	0.45	0.5	0.49	0.5	0.33	0.5	0.62	0.5	0.43	0.5
41 to 65	0.47	0.5	0.45	0.5	0.54	0.5	0.35	0.5	0.44	0.5
Over 65	0.08	0.3	0.06	0.2	0.13	0.3	0.04	0.2	0.13	0.3
vi). Education										
No education	0.07	0.2	0.06	0.2	0.08	0.3	0.06	0.2	0.06	0.2
Primary School	0.15	0.4	0.15	0.4	0.16	0.4	0.16	0.4	0.16	0.4
Secondary School	0.42	0.5	0.40	0.5	0.43	0.5	0.46	0.5	0.45	0.5
Higher Education	0.35	0.5	0.38	0.5	0.33	0.5	0.32	0.5	0.34	0.5
Panel (b): Respondent										
i). Respondent Gender										
Female	0.16	0.4	0.16	0.4	0.16	0.4	0.15	0.4	0.13	0.3
Male	0.84	0.4	0.84	0.4	0.84	0.4	0.85	0.4	0.87	0.3
ii). Respondent Age										
Young (14–42)	0.76	0.4	0.77	0.4	0.72	0.4	0.87	0.3	0.86	0.3
Middle (42–63)	0.20	0.4	0.19	0.4	0.24	0.4	0.12	0.3	0.13	0.3
Older (63–91)	0.03	0.2	0.03	0.2	0.04	0.2	0.01	0.1	0.01	0.1
Panel (c): Household Size										
1–7 members	0.40	0.5	0.42	0.5	0.36	0.5	0.43	0.5	0.39	0.5
8–14 members	0.54	0.5	0.53	0.5	0.57	0.5	0.53	0.5	0.55	0.5
15+ members	0.04	0.2	0.03	0.2	0.05	0.2	0.03	0.2	0.05	0.2
Panel (d): Water Sources										
Safe source	0.63	0.5	0.61	0.5	0.67	0.5	0.40	0.5	0.43	0.5
Piped water	0.18	0.4	0.17	0.4	0.19	0.4	0.16	0.4	0.15	0.4
Public tap	0.25	0.4	0.24	0.4	0.28	0.4	0.26	0.4	0.26	0.4
Protected well	0.15	0.4	0.15	0.4	0.16	0.4	0.13	0.3	0.12	0.3
Spring water	0.23	0.4	0.24	0.4	0.20	0.4	0.29	0.5	0.23	0.4
Panel (e): Lighting Source										
Electricity	0.22	0.4	0.20	0.4	0.24	0.4	0.22	0.4	0.17	0.4
Lamp with batteries	0.23	0.4	0.20	0.4	0.25	0.4	0.29	0.5	0.31	0.5
Solar panel	0.42	0.5	0.40	0.5	0.45	0.5	0.40	0.5	0.43	0.5
Panel (f): Agricultural Activity										
Crop	0.44	0.5	0.44	0.5	0.42	0.5	0.51	0.5	0.43	0.5
Livestock	0.09	0.3	0.10	0.3	0.08	0.3	0.08	0.3	0.05	0.2
Crop and Livestock	0.19	0.4	0.20	0.4	0.18	0.4	0.14	0.3	0.14	0.3
No agricultural activity	0.28	0.4	0.26	0.4	0.31	0.5	0.27	0.4	0.38	0.5
Observations	25,455		15,735		7,826		1,307		587	
Provinces (Territories)	14 (80)		14 (80)		8(23)		14 (72)		8 (23)	

Notes: An observation is a household. Part (i) report summary statistics for the full sample and resident households live in territories that not exposed to recent floods and exposed. Exposure is defined as floods (and other natural disasters) that caused a displacement of 10,000 people or more. Part (ii) report summary statistics for households that are refugees, IDPs, returnee, and recent migrants. Statistics are weighted using the DIEM sampling weights. Means are proportions, SD denotes standard deviation. Raw data from the DIEM–DRC Household Survey rounds 3 to 10, round 5 is excluded. Type of residency is not available for rounds (3 and 8), I assumed that all households in these rounds are permanent residents. Head of Household Age reported in rounds 6 to 10 (8,824 only). Marital status is available only in rounds 3,4, and 8 (for 7,141 observations). Rounds, provinces and territories are numbers in each category. Since its repeated cross sections data, the number of territories for never treated are the same as the full sample.
Source: FAO. 2025. DIEM-Monitoring. In: Data in Emergencies (DIEM) Hub. Rome. [Cited November 24, 2025]. https://data-in-emergencies.fao.org

Table 3: Summary of Food Security Indicators

Indicator	Period	Purpose and Measured Aspects
a). Quality and Dietary Diversity		
FCS	Last 7 days	Types and frequency of food consumed. Quality and dietary diversity
HDDS	Last 24 hours	Number of food groups consumed. Economic access to food
b). Food Insecurity and Hunger		
FIES	Last 30 days	Difficulty accessing food. Reflects experience-based food insecurity
HHS	Last 30 days	Hunger in the household. Good for areas with food insecurity
c). Access to Food and Behavioral Strategies		
rCSI	Last 7 days	Coping frequency and severity. Captures short-term food access
lCSI	Last 7 days	Coping strategies used. Shows household behavior under food stress

Sources: World Food Programme (2023) ; World Food Programme (2021) ; Maxwell et al. (2013) ; World Food Programme, Vulnerability Analysis and Mapping Branch (ODAV) (2008) ; Kennedy et al. (2011) ; Vhurumuku (2011) ; Swindale and Bilinsky (2006).

c). Measuring Exposure to Floods: There are several measures and data sources for floods exposure. Many international organizations provide assessments using news and government records. I measure floods in two different ways.

i). Self-reported exposure: The DIEM survey includes questions about weather households exposed to shocks or not and type of shocks. Households report exposure up to three month prior to the survey date.

Figure 6: Self-reported exposure to floods by round

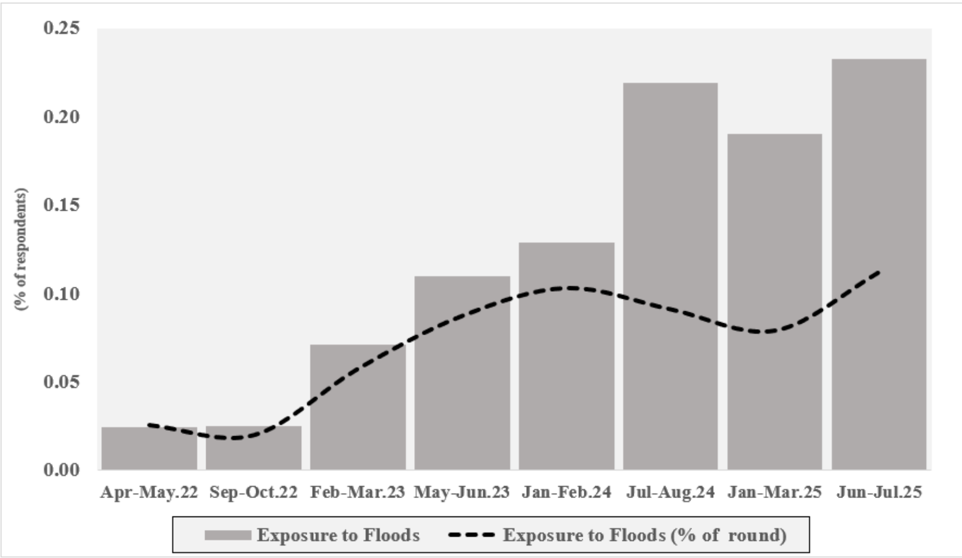


Table (4) reports self-reported household exposure to shocks. The table documents substantial exposure to shocks across all categories, with important variation in both frequency and type. Overall, 30 percent of households report at least one shock, driven primarily by intra-household events: 37 percent experienced an intra-household shock, most commonly sickness or death of a household member (32 percent), followed by loss of work and other idiosyncratic shocks. Economic shocks are reported by 16 percent of households, with higher food prices (10 percent) and other economic disruptions (9 percent) far more prevalent than higher fuel prices. Crop and livestock shocks are less frequent, affecting about 5 percent of households, mainly through plant and animal diseases or lack of pasture. Natural shocks are reported by 9 percent of households—largely floods and droughts—while man-made shocks are more common: 24 percent of households report some man-made shock, and 20 percent specifically report exposure to violence, insecurity, or conflict, with smaller shares reporting theft of productive assets, man-made fires, or other man-made hazards. Exposure to floods dominates natural disasters, 8 percent (2,180 households) of the sample reported being directly exposed to floods.

Table 4: Household Exposure to Various Shocks by Category (Self-reported)

	Intra-household		Economic		Crop & Livestock		Natural		Man-made	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Exposure	0.30	0.46								
1).Intra-household	0.37	0.48								
1.1). Sickness or death	0.32	0.47								
1.2). Loss of work	0.04	0.19								
1.3). Other Intra	0.06	0.24								
2). Economic			0.16	0.37						
2.1). Higher food prices			0.10	0.30						
2.2). Higher fuel prices			0.02	0.14						
2.3). Other economic			0.09	0.29						
3).Crop & Livestock					0.05	0.22				
3.1). Pest outbreak					0.01	0.08				
3.2). Plant disease					0.02	0.15				
3.3). Animal disease					0.01	0.12				
3.4). No pasture					0.01	0.11				
3.5). Other crp&live					0.01	0.10				
4). Natural Disasters							0.09	0.29		
4.1). Flood							0.08	0.27		
4.2). Hurricane							0.01	0.10		
4.3). Drought							0.04	0.20		
4.4). Earthquake							0.01	0.08		
4.5). Landslides							0.01	0.08		
4.6). Natural fire							0.01	0.11		
4.7). Weather							0.01	0.08		
5). Man-made									0.24	0.43
1.5). Violence/insecurity									0.20	0.40
2.5). Theft of assets									0.02	0.14
3.5). Man-made fire									0.01	0.10
4.5). Other man-made									0.04	0.19
Observations					25,455					

ii. Exposure to floods record: This raw data (collection of news) contains detailed description of floods and collects news on many variables including number of affected people, damaged households, displaced population, damage to livestock. I used the news to construct panel data across both admin 1 and 2 and time to match the DIEM surveys dates. I will use the constructed data to learn about the impact of floods as it includes the damage based on visiting to affected locations or news collected from journalists. This approach may misreport small floods as highlighted by (Patel (2024)), however, it will be a useful source to identify which territories affected most [5].

d). Other Relevant Covariates: Other datasets include: ACLED conflict data disaggregated at Admins 1, 2 and climate indicators: droughts, precipitations, and temperature.

[5] Several datasets record floods events around the world. For instance, Dartmouth Flood Observatory (DFO), currently, it is part of Global Flood Observatory at the University of Colorado, since the late 1990s, has been a leading source of satellite data on floods worldwide. However, these datasets typically report very large floods while OCHA record includes flood events that displace less than 100 persons.

V. Empirical Strategy and Results

a). Self Reported Exposure

To estimate the effects of exposure to floods on food security and coping strategies, I use the self reported exposure from the DIEM-DRC survey rounds (Section III, part c).i) as the main regressor and estimate the following specification:

$$Y_{ijr} = \beta \cdot Flood_{ijr} + X'_{ijr}\theta + +\rho \mathbf{Z}_{\ell,r} + \gamma_j + \delta_r + \varepsilon_{ijr}, \tag{1}$$

Where y_{ijr} is the outcome of interest (food security and coping) for household i in territory j, and survey round r. $Flood_{ijr}$ measures exposure in territory j, and round r. This is the treatment variable of interest. X_{ijr}: Vector of household-level controls (e.g., household size, respondent age, gender of household head, education, and other natural shocks). Z_{jr} is a vector of territory-level covariates such as other climate shocks and other measurable and observable factors that vary across space and time. γ_j is the territory fixed effects capturing time-invariant differences across territories (e.g., geography, baseline livelihood patterns and unobserved factors that differ across territories but time invarying). δ_r is the round fixed effects capturing aggregate shocks and seasonality common to all territories in round r (e.g., macroeconomic fluctuations). ε_{ijr} is an error term. β is the coefficients of interest. It captures the effect of exposure to floods. Ideally, I intend to compare between two groups, the exposed group (treated), households live in territories that exposed to floods after time t versus the non-exposed (untreated) group. Thus, the baseline specification could take a two way fixed effects in equation (1). I begin by estimating equation 1 using the self-reported floods exposure as the main treatment.

Across all survey rounds, some territories appear intermittently while others appear in every round. I therefore construct three samples. The full sample includes all five rounds: 28,171 households in 80 territories across 14 provinces (23,387 households report no flood exposure; 2,025 report exposure). In Sub-sample (1), I restrict to territories observed in rounds 3, 4, 6, and 7, yielding 8,715 households in 60 territories across 12 provinces (8,159, 93.6 percent, unexposed; 556, 6.4 percent, exposed). Sub-sample (2) includes all rounds but only territories present in every round, with 17,128 households in 29 territories across four eastern provinces (Ituri, Nord-Kivu, Sud-Kivu, and Tanganyika). I also divided the sample into two: full sample that include all households and a sub sample that include only permanent residents households [6].

Overall, conditional on household covariates and fixed effects (territory and round), the estimates suggest that exposure to flood (self reported) has a relatively negligible effect on household dietary diversity outcomes. Meanwhile, the effects on food insecurity and reliance on negative coping is considerable. FCS and HDDS signs are positive in all specifications (columns 1 and 3) except column (2). However, the coefficients are statistically insignificant for both specifications. In contrast, the signs of FIES and rCSI–food insecurity and coping measures are positive and statistically significant for both specifications (columns 5 to 8). Exposure to floods is associated with 0.10 (and -0.10) points increase/reduction in the FCS (or 0.9 percent of the control mean (no exposure)) (Table 5, columns 1 and 2), though this correlation is statistically insignificant. The magnitude is also small, the FCS thresholds distinguish between borderline and acceptable consumption, such a minor declines could shift only households at the margin into more insecure categories. Similarly, HDDS shows no meaningful correlation (Table 5, columns 3 and 4). These findings indicate that floods do not immediately alter access and types of food consumed. This correlation is robust to the inclusion of more household and territory level covariates. Findings from the two sub samples are reported in The Appendix (3), Tables (1.3) to (6.3).

Where self exposure to floods matter most is in intensifying food insecurity and reliance on least preferred coping strategies. Average FIES for households whose reported exposure to floods is 0.58–0.71 points higher than those with no reported exposure (8–11 percent compared to mean of control group: no exposure) (Table 6, columns 1 to 3). Similarly, on average, rCSI is higher by 1.21–1.59 (7.7–10 percent compared to mean of control group) (Table 6, columns 4 to 6). These findings indicate that households become more food insecure (measured by FIES) after exposure to floods within 3 month before the survey time. They also rely on negative coping strategies (measured by overall rCSI). The HHS increased by 0.12–0.18 points, this is equivalent to 8–12.5 percent of the control mean (Table 7, columns 1 to 3), pushing households closer to the "moderate hunger" category.

These findings suggest that exposure to floods did not primarily alter dietary diversity or immediate consumption but instead exacerbate stress, hunger, and food insecurity, especially among those already close to the margins (thresholds). The set of covariates incorporated indicate that vulnerability is tied to household characteristics.

[6] All households sample include other residents (refugees and IDPs) whose food insecurity is already severe due to displacement conditions thus, the results could be driven by this fact rather than an exposure to floods effect. Therefore, I use the estimates from the permanent residents sample more frequently.

Larger households consistently fare worse by all measures, with lower consumption, dietary diversity, higher hunger and rely on stress coping, reflecting the increased reliance on limited resources. Older household heads appear to have smooth consumption and further experience higher food security and coping without stress. Gender effects are mixed, female-headed households face higher vulnerability in several outcomes. Education exerts a powerful protective effect: households with more educated heads report significantly higher food consumption and dietary diversity, lower food insecurity and reduced reliance on coping strategies, underscoring the role of human capital in resilience. Households not engaged in agriculture face mixed effects, benefiting from more stable nonfarm income in some measures but simultaneously relying more heavily on negative coping in others. Finally, exposure to other natural shocks compounds these effects, further raising hunger and coping burdens and amplifying the vulnerability of already at-risk households. These other shocks appear to be quantitatively important in determining the food security.

Table 5: Self–reported Exposure to Flood and Dietary Diversity outcomes: FCS and HDDS

	(1) FCS	(2) FCS	(3) FCS	(4) HDDS	(5) HDDS	(6) HDDS
Panel (a): Exposure Effect						
Flood	0.02	-0.49	0.12	0.06	0.00	-0.00
	(0.59)	(0.57)	(0.72)	(0.04)	(0.04)	(0.07)
Panel (b)						
HoH Gender	1.79***	1.77***	0.91	0.06	0.05	-0.02
	(0.57)	(0.49)	(0.68)	(0.05)	(0.04)	(0.06)
Education	5.80***	4.57***	4.16***	0.42***	0.36***	0.29*
	(1.02)	(0.81)	(1.11)	(0.11)	(0.10)	(0.16)
Respondent Age	-0.86**	-0.87**	-0.79	-0.09**	-0.09**	-0.03
	(0.39)	(0.39)	(0.50)	(0.04)	(0.04)	(0.06)
Household Size	-2.71***	-2.11***	-2.93***	-0.18***	-0.14***	-0.16***
	(0.32)	(0.29)	(0.45)	(0.03)	(0.03)	(0.03)
Panel (c): Additional HH Covariates						
No Agriculture		-1.11**			-0.11**	
		(0.44)			(0.05)	
Access to Safe Water		4.80***			0.31***	
		(0.49)			(0.05)	
Access to Electricity		10.38***			0.57***	
		(0.62)			(0.05)	
Panel (c)						
Natural Disasters		-0.60			0.27	
		(0.70)			(0.22)	
Intra-household Shock		-3.65***			-0.30***	
		(0.42)			(0.08)	
Economic Shock		-1.13**			0.15	
		(0.54)			(0.10)	
Man-made Shock		-1.44***			0.08	
		(0.37)			(0.05)	
Panel (d): Territory–level Climate Indicators						
Precipitations			0.03			0.01
			(0.03)			(0.00)
Temperature			5.59			0.73
			(3.93)			(0.56)
Droughts			0.64			0.02
			(0.58)			(0.09)
Conflict Events			0.09**			0.02**
			(0.03)			(0.01)
Control Mean	47.23	47.23	47.23	5.09	5.09	5.09
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.13	0.19	0.16	0.06	0.08	0.08
Observations	24,874	24,871	15,240	24,876	24,873	15,242

Notes: The table reports two way fixed effects estimates (equation 1). I use all DIEM–DRC rounds. Panel (a) reports correlation between exposure to floods measured as a binary self-reported indicator and dietary diversity outcomes: FCS and HDDS. Panel (b) reports household characteristics. Panel (c) reports correlations between FCS and HDDS with additional household–level control. Panel (d) reports correlations between FCS and HDDS with territory–level climate indicators. All regressions include fixed effects (round and territory). Standard errors (in parentheses) clustered at territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Across all models (Table 7, panel c), exposure to shocks (self–reported) consistently worsen household food security outcomes, although the magnitude and significance differ by type of shock. Economic shocks significantly worsen all indicators of food insecurity: they increase hunger (HHS), raise reliance on negative coping strategies (rCSI and lCSI), and increase the probability of food insecurity (FIES). Similarly, Natural shocks were associated with a significant increases in hunger, negative coping strategies, and food insecurity, though their effect on FCS and HDDS is not statistically significant. Man-made shocks also significantly worsen hunger, coping reliance, and food insecurity. By contrast, intra-household shocks are the most harmful: these type of shocks were associated with a significant decline in the FCS, significantly increase hunger and coping mechanisms more than any other shock category. Climatic deviations, higher temperatures (LTSD) are sometimes associated with worse food security, but not consistently significant across outcomes, while precipitation anomalies show essentially no significant effects. Overall, shocks, especially intra-household and man-made were associated with worse food security, with intra-household shocks having the strongest negative association across the six indicators.

Table 6: Self–reported Exposure to Flood and Coping Outcomes: FIES and rCSI

	(1) FIES	(2) FIES	(3) FIES	(4) rCSI	(5) rCSI	(6) rCSI
Panel (a): Exposure Effect						
Flood	0.52***	0.71***	0.58***	1.23***	1.59***	1.21**
	(0.10)	(0.08)	(0.16)	(0.36)	(0.33)	(0.49)
Panel (b): HH Characteristics						
HoH Gender	-0.68***	-0.65***	-0.62***	-1.34***	-1.32***	-1.15***
	(0.09)	(0.08)	(0.11)	(0.27)	(0.25)	(0.31)
Education	-1.23***	-0.95***	-0.94***	-2.57***	-1.84***	-2.99***
	(0.15)	(0.10)	(0.15)	(0.69)	(0.54)	(0.55)
Respondent Age	0.35***	0.35***	0.34***	1.99***	1.98***	1.62***
	(0.09)	(0.07)	(0.09)	(0.24)	(0.22)	(0.26)
Household Size	0.69***	0.57***	0.70***	2.48***	2.14***	2.40***
	(0.05)	(0.05)	(0.08)	(0.16)	(0.15)	(0.24)
Panel (c): Additional HH Covariates						
No Agriculture		0.31***			0.85***	
		(0.08)			(0.26)	
Access to Safe Water		-0.76***			-2.69***	
		(0.07)			(0.23)	
Access to Electricity		-1.60***			-4.61***	
		(0.10)			(0.30)	
Natural Disasters		0.71***			1.62***	
		(0.11)			(0.37)	
Intra-household Shock		1.30***			2.58***	
		(0.09)			(0.29)	
Economic Shock		0.63***			1.80***	
		(0.08)			(0.24)	
Man-made Shock		0.64***			2.21***	
		(0.06)			(0.20)	
Panel (d): Territory–level Climate Indicators						
Precipitations			-0.01			-0.01
			(0.01)			(0.01)
Temperature			-2.06**			1.05
			(0.86)			(1.66)
Droughts			-0.25*			-0.70*
			(0.14)			(0.38)
Conflict Events			-0.02***			-0.02
			(0.01)			(0.03)
Control Mean	6.39	6.39	6.39	15.76	15.76	15.76
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.10	0.17	0.12	0.09	0.14	0.09
Observations	24,876	24,873	15,242	22,852	22,849	13,218

Notes: The table reports two way fixed effects estimates (equation 1). I use all DIEM–DRC rounds. Panel (a) reports correlation between exposure to floods measured as a binary self-reported indicator and food security (FIES) and coping (rCSI) outcomes: FCS and HDDS. Panel (b) reports household characteristics. Panel (c) reports correlations between FCS and HDDS with additional household–level control. Panel (d) reports correlations between FCS and HDDS with territory–level climate indicators. All regressions include fixed effects (round and territory). Standard errors (in parentheses) clustered at territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Taken together, the results indicate that floods are less likely to reduce dietary diversity but instead shift households at the margins into greater hunger, insecurity, and reliance on negative coping. Modest declines in food security indicators translate into sharp threshold effects. Households at the margins (the edges of classifications) could be pushed into more food insecurity as a result of exposure to floods and other natural disasters. This underscores the importance of policies that not only stabilize consumption but also address the longer-term erosive strategies households employ in response to climate shocks. Its worth noting that the validity of these findings rely heavily on the absence of measurement error of self reported exposure. I controlled for the observable characteristics that appear to be heterogeneous across households and fixed effects which could reduce the endogeneity concerns and I also controlled for characteristics that appear to be fairly exogenous to exposure to floods which could roll out the bad control issue. However, concerns are still exist on unobservable characteristics that may be correlated with the exposure to floods. This is the object of the next sections.

Table 7: Self–reported Exposure to Flood and Food Security Outcomes: HHS and PSFI

	(1) HHS	(2) HHS	(3) HHS	(4) SFI	(5) SFI	(6) SFI
Panel (a): Exposure Effect						
Flood	0.12***	0.18***	0.13**	0.01*	0.02***	0.02
	(0.03)	(0.03)	(0.06)	(0.01)	(0.01)	(0.01)
Panel (b): Household Characteristics						
HoH Gender	-0.24***	-0.23***	-0.22***	-0.06***	-0.06***	-0.06***
	(0.04)	(0.03)	(0.05)	(0.01)	(0.01)	(0.01)
Education	-0.44***	-0.35***	-0.34***	-0.12***	-0.10***	-0.09***
	(0.07)	(0.05)	(0.06)	(0.02)	(0.02)	(0.02)
Respondent Age	0.14***	0.14***	0.13***	0.01*	0.01**	0.01*
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Household Size	0.24***	0.21***	0.23***	0.05***	0.04***	0.05***
	(0.02)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
Panel (c): Additional Household Covariates						
No Agriculture		0.18***			0.04***	
		(0.03)			(0.01)	
Access to Safe Water		-0.29***			-0.06***	
		(0.02)			(0.01)	
Access to Electricity		-0.53***			-0.10***	
		(0.04)			(0.01)	
Natural Disasters		0.20***			0.05***	
		(0.04)			(0.02)	
Intra-household Shock		0.37***			0.07***	
		(0.03)			(0.01)	
Economic Shock		0.19***			0.04***	
		(0.03)			(0.01)	
Man-made Shock		0.13***			0.03***	
		(0.02)			(0.01)	
Panel (d): Territory–level Climate Indicators						
Precipitations			-0.00			-0.00
			(0.00)			(0.00)
Temperature			-0.39			-0.16**
			(0.32)			(0.07)
Droughts			-0.06			-0.00
			(0.05)			(0.01)
Conflict Events			-0.01*			-0.00***
			(0.00)			(0.00)
Control Mean	1.44	1.44	1.44	0.20	0.20	0.20
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.15	0.11	0.09	0.14	0.14
Observations	24,876	24,873	15,242	24,608	24,605	15,008

Notes: Two-way fixed effects estimates from equation (1) using all DIEM–DRC rounds. Columns (1)–(3) use the Household Hunger Scale (HHS) as the dependent variable; columns (4)–(6) use the probability of severe food insecurity (SFI). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To understand these effects, I estimated equation 1 with FIES and rCSI components as outcomes Table 8 shows the results. Exposure to flood is associated with systematically worse food security and coping outcomes across all self-reported components of FIES and rCSI. Conditional on household covariates and territory and round fixed effects, flooding significantly raises all five rCSI components, with point estimates between 0.08 and 0.21 standard deviations, indicating greater reliance on borrowing food, less preferred foods, and more severe rationing strategies. Floods also worsen experiential food insecurity as captured by FIES, increasing the likelihood of eating less, consuming fewer foods, skipping meals, and worrying about having enough food, with precisely estimated effects of roughly 0.04 to 0.06 points across items. These effects are robust to controlling for other natural disasters, which themselves display positive and significant coefficients of comparable or larger magnitude, and they remain stable after conditioning on education, household size, and respondent age, suggesting that climatic shocks independently exacerbate both coping behavior and psychological dimensions of food insecurity (see, Table 8, columns 2,3,5, and 6).

Table 8: Impact of Flood Exposure on Food Security Outcomes, FIES and rCSI components

	i). rCSI components					*ii). FIES items*				
	(1) rCSI(1)	(2) rCSI(2)	(3) rCSI(3)	(4) rCSI(4)	(5) rCSI(5)	(6) FIES(1)	(7) FIES(2)	(8) FIES(3)	(9) FIES(4)	(10) FIES(5)
Flood	0.08^{*}	0.21^{***}	0.13^{**}	0.14^{**}	0.12^{**}	0.06^{***}	0.04^{***}	0.05^{***}	0.05^{***}	0.05^{***}
	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender	-0.15^{***}	-0.23^{***}	-0.23^{***}	-0.23^{***}	-0.13^{**}	-0.04^{***}	-0.05^{***}	-0.04^{***}	-0.05^{***}	-0.05^{***}
	(0.04)	(0.06)	(0.05)	(0.05)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education	-0.41^{***}	-0.44^{***}	-0.31^{***}	-0.31^{***}	-0.20	-0.05^{***}	-0.09^{***}	-0.10^{***}	-0.08^{***}	-0.09^{***}
	(0.11)	(0.08)	(0.07)	(0.08)	(0.14)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Res Age	0.26^{***}	0.07^{*}	0.16^{***}	0.21^{***}	0.29^{***}	0.02^{**}	0.02^{**}	0.00	0.02^{*}	0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HH Size	0.19^{***}	0.31^{***}	0.30^{***}	0.30^{***}	0.34^{***}	0.04^{***}	0.04^{***}	0.06^{***}	0.04^{***}	0.06^{***}
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Natural Disasters	0.23^{***}	0.22^{***}	0.19^{***}	0.27^{***}	0.21^{***}	0.04^{**}	0.06^{***}	0.08^{***}	0.08^{***}	0.07^{***}
	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control Mean	1.23	2.96	2.37	2.32	1.74	0.76	0.70	0.65	0.67	0.66
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.05	0.05	0.05	0.06	0.06	0.04	0.04	0.06	0.04	0.06
Observations	20,987	20,987	20,987	20,987	20,987	23,000	23,004	23,001	23,008	23,005

Notes: The table reports associations between exposure to floods and food security outcomes (rCSI and FIES items), controlling for household characteristics and fixed effects. Sample is restricted to permanent residents only. Respondent age is used instead of head's age (missing in some rounds). Education is a dummy: 0 indicates no education and 1 indicates primary or higher education. Household size is grouped into dummies (small, medium, large). Self-reported shocks are included as controls where indicated. rCSI (1): borrowed food ; rCSI (2): less preferred foods ; rCSI (3): limit_portions ; rCSI (4): reduce number of meals ; rCSI (5): restrict adult consumption. FIES (1): Ate less; FIES(2): few foods ; FIES(3): healthy food; FIES(4): skipped meals ; FIES(5): worried ABOUT HAVING ENOUGH FOOD. Standard errors (in parenthesis) are clustered at the territory level (80 clusters).

b). Identification Strategy

As I compare two groups: eventually exposed households (in territories that have been exposed to floods in time t) and households in territories that did not exposed to floods during 2022-2025, on average, exposed and never exposed groups must be similar to each other and exposure to floods must be measured correctly, then β could uncover the average treatment effect on treated (ATET). However, this set up described in equation (1) poses several identification threats. First, exposure to floods would be measured with error. Measuring floods using self reported data and/or rainfall have been proven to be poor proxies for measuring exposure to floods (Patel (2024) and Guiteras et al. (2015)). Second, selection on unobservables and/or unmeasurable factors may arise from the fact that households live in flood-prone areas may be systematically different from others (e.g., being poor or more food insecure even in the absence of shocks). This might be true for most of environmental shocks (see, Baseler and Hennig (2023)). Using the DIEM-DRC survey rounds poses an additional concern, that is; using repeated cross sections data, the distribution of characteristics may change across rounds. Furthermore, the starting of flooding was not in the same calender-year, instead, the exposure was staggered. Some territories recorded high rainfall and floods by end of 2022 while others flooded beginning in 2023 and 2024.

To address these concerns and credibly estimate the causal effect of floods on food security and coping strategies, previous literature has made an important progress in addressing measurement error by using satellite data and constructing various measures of inundation using high resolution data (every 16 days as in Guiteras et al. (2015) ; every 2 days as in Chandir et al. (2023) ; every day as in Patel (2024)). Furthermore, exposure to large floods can be captured by flood records (as in Kocornik-Mina et al. (2020) among others). These papers have also used staggered DID approaches developed recently. For instance, to estimate the effect of exposure to floods and strikes, Chandir et al. (2023) used a difference in differences and Callaway and Sant'Anna (2021) approach that accounts for the possibility of stacked exposure. Patel (2024) used stacked DID constructed a comparison group based on several sample restrictions. I constructed a plausibly exogenous measure of exposure to large floods from detailed news record as described in section (III, part b). Furthermore, I used an identification strategy that that is suitable for the type of data (the DIEM-DRC survey rounds) and heterogeneous exposure.

b.1). Measuring exposure to floods

To improve the measurement of floods, I used the list of floods and other natural disasters collected by OCHA, I manually prepared variables for the territories that recorded natural disasters between 2022 and 2025. I constructed a set of variables that identify what territories exposed to floods and when. This list enabled me to create an exposure dummy where some territories exposed to natural disasters starting from July 2022. I then matched the time of exposure with the time of DIEM rounds to have a treatment by round, this set up is suitable to pursue an identification strategy where the treatment is staggered. However, the treatment captures the large floods that led to displacement, infrastructure damage and other consequences on the population and economic activities. Figure 2 shows the number of affected people due to the occurrence of natural disasters. Between 2022 and 2025, 42 territories recorded exposure to natural disasters including floods, fire, storms and other natural disasters. Floods induced by the heavy rains dominates the list of natural disasters. Around 1.7 million people were affected by these natural disasters, around 700,000 were in the sampled territories.19 territories were in the DIEM sample, this makes the treated territories. I defined treatment by the exposure to floods that caused displacement of 10,000 people or more.

b.2). Identifying the Causal Effects

To identify the causal effect, my identification strategy exploits staggered exposure to floods across territories using the FLEX difference-in-differences framework of Deb et al. (2024). let households i being unit of observation that repeatedly sampled from a stable underlying population in each time $t = 1, \dots, 7$ and are nested in territories (groups) $g = 1, \dots, G$. Floods occur at the group (territory) level. For each treated territory g, let q_g denote the first survey period in which it is exposed to a flood; territories with the same q_g form a *cohort*. Let territories that never experience floods over the sample be the never-treated group. The repeated cross-sectional structure implies that different households are observed in each round, but within each territory–round cell the sample is representative of the same underlying population [7].

Let $Y_{igt}(g')$ denote the potential outcome for household i in territory g at time t under the treatment group g', and let X_t denote observed household level covariates. According to Deb et al. (2025), estimating the ATET and identifying the causal effects rest on four assumptions. First, *a Stable Unit Treatment Value Assumption* (*SUTVA*) at the territory level: outcomes in territory g depend only on its own treatment status, so floods in one territory do not affect outcomes in other territories (no spillovers). Second, *No Bad Controls:* covariates are taken as pre-determined with respect to flood exposure, so $X_t(g) = X_t(\infty) = X_t$ for all g, which rules out including variables that are themselves affected by floods in the conditioning set. Third, *Conditional No Anticipation*: in all periods before a territory's first flood, its potential outcome paths under its eventual treatment equal potential outcome under never being treated; for $t < q_g$,

$$\mathbb{E}\left[Y_t(g) \mid R_1, \dots, R_G, X_t\right] = \mathbb{E}\left[Y_t(\infty) \mid R_1, \dots, R_G, X_t\right],$$

Thus, flood exposure does not affect outcomes before it occurs. Fourth, *Conditional Parallel Trends*: absent treatment, the evolution of outcomes in treated and never-treated territories would be the same once we condition on covariates, which allows the untreated observations to identify the pre-treatment trend parameters. Empirically, treatment is a binary indicator Flood_{gt} equal to one once territory g first experiences a flood and zero before, so territories are "treated forever" after q_g. FLEX implements a lags-and-leads regression specification, estimated by OLS, that fully parametrizes treatment dynamics at the group–time level. In event-time notation the model can be written as below:

$$Y_{igt} = X'_{igt}\zeta + \sum_{k \geq 0} \tau_k \mathbf{1}\{t - q_g = k\} + \sum_{k<0} \ell_k \mathbf{1}\{t - q_g = k\} + \mu_g + \tau_t + \varepsilon_{igt}, \tag{2}$$

where the "lags" τ_k capture the causal effect k periods after the first flood and the "leads" ℓ_k capture pre-treatment differences relative to the never-treated territories. Group fixed effects μ_g absorb time-invariant

[7] This section is a summary of Deb et al. (2025) steps with reference to the treatment of being exposed to floods. Thus, I use the same notations as in that paper.

territory characteristics, while time fixed effects τ_t capture shocks common to all territories in each round. Covariates X_{igt} enter additively or interacted with event-time dummies as deviations from group means to preserve the interpretation of the lags as Average Treatment Effects on the Treated (ATETs). In practice, some specifications set all lead coefficients to zero ("lags only"), which maximally imposes the parallel-trends restriction, whereas the lags-and-leads specification allows an explicit assessment of pre-trends at the cost of some efficiency. FLEX thus delivers a collection of heterogeneous treatment effects $\tau_{g,t}$ at the territory–time level. Rather than report all group–time coefficients, we aggregate them to an overall ATET by averaging over treated territory–time cells, with weights proportional to the number of sampled households in each cell:

$$\widehat{ATET} = \frac{1}{N_{\text{treat}}} \sum_{g} \sum_{t \geq q_g} n_{gt}\, \widehat{\tau}_{g,t}, \tag{3}$$

where n_{gt} is the number of treated observations in territory g at time t and $N_{\text{treat}} = \sum_g \sum_{t \geq q_g} n_{gt}$. Under the assumptions above, equations (2) and (3) identify the causal effect of flood exposure on household food security outcomes.

b.3). Causal Effects of Exposure to Floods

This subsection describes the estimation strategy and reports the causal estimates using FLEXDiD. I restricted the sample to sub–sample (2) and permanent residents only. This sub–sample includes 19 ever-flooded territories and 7 never-flooded territories, with treatment staggered over five exposure rounds from mid-2023 to mid-2025. Ever-treated observations are 13,718 observations (of which: 9,943 exposed to floods while 3,775 did not expose in rounds 3 and 4 when no large floods were recorded) (see, The Appendix 4, Table 1.4) [8]. I compare never treated to ever treated. Following Deb et al. (2025) the ATETs are obtained in three steps: *estimation, identification, and aggregation*. Ordinary least squares is used to estimate a flexible model that allows for heterogeneity in treatment effects over time and across groups, where groups are defined at the territory level. In line with the underlying FLEXDiD framework, treatment effects are permitted to vary by calendar time and by group, and few household--level covariates are included additively as in the main specification rather than fully interacted.

The modeling choices follow the three decisions emphasized in the FLEXDiD approach. First, heterogeneity is imposed at the group (territory) level, rather than at the cohort level, because multiple territories may start treatment in the same period but need not share identical treatment effects. Second, the baseline specification is estimated in "leads and lags" specification, so that treatment effects can differ both before and after first exposure. In robustness checks, I consider specification with lags only as well (not recommended when parallel trends are not hold). Third, I use three covariates separately as additional controls, without interacting with the treatment indicators, to avoid over-fitting while still absorbing important compositional differences; all covariates are chosen to be plausibly exogenous with respect to flood exposure. After estimating group-by-time treatment effects, results are summarized and visualized by aggregating to the event-time dimension. Event-study plots graph the estimated differences between ever-treated territories and never-treated territories in each pre-treatment period, providing a visual assessment of the parallel-trends and no-anticipation assumptions. The same plots then display post-treatment effects of the effects on food security outcomes. An overall ATET is then a weighted average of the group-time treatment effects in post-treatment periods, using as weights the number of treated observations in each group-time cell. The figures that follow report these event-study plots and the corresponding aggregated ATETs for the main food security and coping outcomes.

c). Main Findings

1). FLEXDiD ATETs–FCS and HDDS : Table 9 shows the findings from defining the treatment based on a 10k and 20k displaced people thresholds. The overall ATET for FCS is small and statistically insignificant. Figure 7 provides support to the main identification assumption, no pre trends in FCS and HDDS. The calender time ATETs are also shown in Table 10 which indicate that there is no significant difference between households FCS and HDDS in never treated and ever treated territories. At the calendar-time level, pre-exposure coefficients are imprecisely estimated and not statistically different from zero, which supports the parallel-trends assumption in the pre-treatment periods. Exposure to floods shows no statistically significant effects on either FCS or HDDS across all specifications in Table9. In eastern DRC, the Sub–Sample (2), point estimates for FCS range from 1.275 (10K threshold, panel (a), column (2)) to 3.206 (20K threshold, panel (b), column (2)). Relative to the control mean of households in never treated territories, these estimates correspond to changes of about +2.8 percent and 7.1 percent of the mean, respectively.

[8] In the robustness check, I used the full sample and 80 clusters.

In all cases, however, the confidence intervals are wide and include zero, indicating that there is no significant effect on dietary diversity. In the representative sub–sample (1), the effect of exposure to floods defined by a 10k displacement is positive but insignificant while when defining treatment at a 20k threshold, the effect becomes negative but remains statistically insignificant. The sign of the coefficient varies across specifications—switching from positive to negative when the exposure threshold increases from 10K to 20K—suggesting that the estimates are not robust to alternative treatment definitions. A similar pattern emerges for HDDS. Across specifications, the estimated effects are negative but small in magnitude. For example, the largest coefficient in absolute value is -0.467 in sub-sample 2 under the 10K threshold. Given a control mean between 4.98 and 5.37 points, this corresponds to a decline of roughly 0.5 points, or about 9 percent of the control group mean. However, these estimates are not statistically distinguishable from zero. This pattern holds across both exposure thresholds (10K and 20K) and across sub–samples, indicating that the results are not sensitive to the definition of flood exposure or the geographic scope of the analysis. The estimates suggest that flood exposure does not systematically affect overall food consumption adequacy or dietary diversity in the study sample. While point estimates for HDDS are consistently negative, their magnitudes remain modest relative to baseline consumption levels, and the lack of statistical precision precludes strong conclusions about adverse dietary effects.

In contrast, some post–treatment coefficients become positive and statistically significant in specific rounds (for example, around 6). Calender ATETs are shown in Table10. FCS FLEX DiD calender estimates suggest a temporary decline in food consumption shortly after flood exposure, followed by a significant increase. Prior to treatment, the differences between exposed and non–exposed households are small and statistically insignificant, indicating no evidence of differential pre–trends. Beginning in calendar/round 6–the first post–treatment period, the estimated effect becomes negative and statistically significant. In the specification with covariates, the ATET is (4.27) points in calendar 6 and increases to 7.75 points in calendar 8, both statistically significant. Relative to the control mean of 46.1, these estimates correspond to improvements of roughly (9) to 17 percent decrease/increase in food consumption. However, this effect appears short–lived. By calendars 9 and 10 the coefficients decline and become statistically insignificant, suggesting that the initial gains dissipate within a few periods after the shock. In contrast, HDDS exhibits a more persistent negative pattern following flood exposure. Pre–treatment estimates remain small and statistically insignificant, again supporting the absence of differential trends before the shock. After treatment begins, however, the coefficients turn consistently negative. In the specification with covariates, the estimated effect reaches (0.54) food groups in calendar 7, (0.66) in calendar 9, and (0.64) in calendar 10, with several estimates statistically significant. Given a control mean of 4.98 food groups, these coefficients correspond to declines of roughly 10–13 percent relative to baseline dietary diversity. Unlike FCS, which shows a short-run increase that fades over time, HDDS suggests a more sustained deterioration in dietary diversity in the periods following flood exposure.

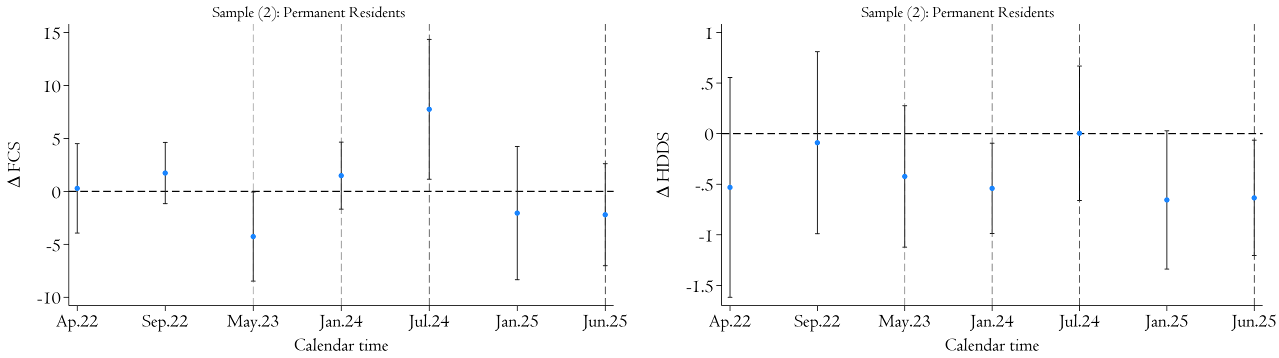
This result suggests that flood exposure may increase FCS in some rounds rather than uniformly over time. Meanwhile, Taken together with the calendar-time FCS estimates, these results suggest that while total food consumption may recover or even improve in some later periods, dietary diversity tends to deteriorate for later-treated households, pointing to potential quality-versus-quantity trade-offs in food access after floods.

Table 9: FLEX DiD Event Study: Exposure to Floods and Food Security

	FCS		HDDS		FIES		rCSI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (a): 10K threshold								
Exposure to Flood	1.192	1.275	-0.307	-0.467	-0.021	-0.822*	0.528	0.241
	(1.338)	(2.575)	(0.272)	(0.274)	(0.267)	(0.423)	(0.503)	(1.414)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Control Mean	52.0	46.1	5.33	4.98	5.97	6.44	13.2	15.9
Observations	7,788	15,519	7,789	15,519	7,789	15,519	5,932	14,898
Panel (b): 20K threshold								
Exposure to Flood	-2.454	3.206	-0.283	-0.105	0.284	-1.056**	0.085	0.117
	(1.554)	(2.451)	(0.222)	(0.249)	(0.218)	(0.360)	(0.705)	(1.339)
Control Mean	52.06	44.94	5.336	4.930	6.61	6.38	15.31	14.40
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,788	15,519	7,789	15,519	7,789	16,808	5,776	14,663

Notes: FLEX DiD ATT estimates of exposure to floods on food security outcomes. Treatment defined as territory exposed to floods leading to (a) 10K or (b) 20K displacement. Sub Sample (1): lags only; Sub Sample (2): leads and lags. Standard errors (in parentheses) clustered at territory level (60 clusters for Sub Sample 1, 26 for Sub Sample 2). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 7: FLEXDiD ATETs — FCS and HDDS



2). FLEXDiD ATETs–FIES and rCSI: The external flood-exposure measure yields effects that are opposite in sign and magnitude to those obtained with the self-reported exposure. Exposure to floods leads to statistically significant decline in FIES while effect on rCSI is statistically indistinguishable from zero. Coefficients are depicted in Figure 8 and results are shown in Tables 9 and 10 .

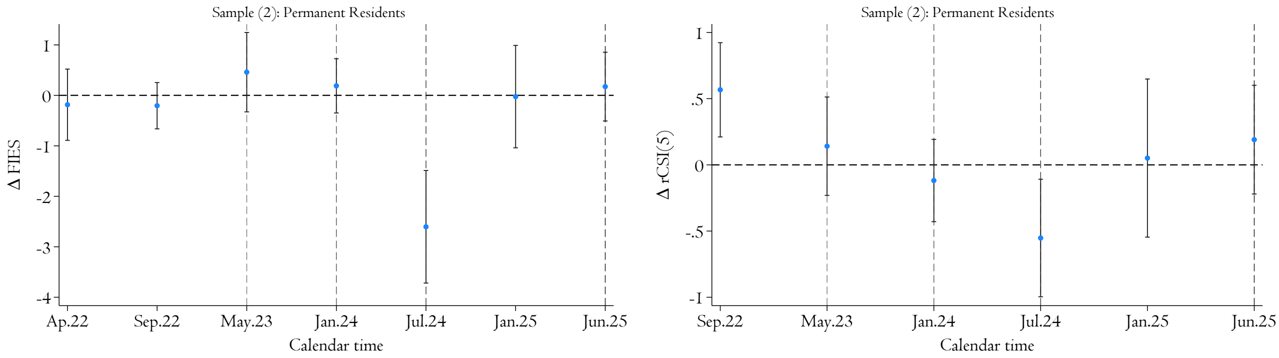
Table 10: FLEX DiD Event Study: Exposure to Floods and Food Security

	FCS		HDDS		FIES		rCSI	
	(1)		(2)		(3)		(4)	
Panel (a): Leads and Lags, no covariates								
ATET	1.668	(2.644)	-0.478	(0.284)	-0.845**	(0.447)	0.219	(1.428)
Calendar 3	0.013	(1.945)	-0.541	(0.538)	-0.043	(0.326)	–	
Calendar 4	1.480	(1.507)	-0.087	(0.420)	-0.226	(0.232)	1.113	(1.062)
Calendar 6	-4.203***	(1.898)	-0.384	(0.334)	0.506	(0.402)	1.586	(1.027)
Calendar 7	1.218	(1.468)	-0.601***	(0.210)	0.262	(0.257)	-0.992	(0.760)
Calendar 8	9.115***	(3.298)	0.100	(0.355)	-2.723***	(0.619)	-2.349	(1.400)
Calendar 9	-2.254	(3.119)	-0.721***	(0.345)	0.008	(0.519)	1.613	(1.880)
Calendar 10	2.114	(2.437)	-0.681***	(0.289)	0.173	(0.337)	1.723	(1.252)
Panel (b): Leads and Lags with covariates								
ATET	1.275	(2.575)	-0.467	(0.274)	-0.822	(0.423)	0.241	(1.414)
Calendar 3	0.281	(2.049)	-0.531	(0.527)	-0.186	(0.343)	–	
Calendar 4	1.729	(1.405)	-0.090	(0.437)	-0.205	(0.222)	1.443	(0.997)
Calendar 6	-4.268***	(2.041)	-0.423	(0.339)	0.459	(0.382)	1.257	(0.974)
Calendar 7	1.485	(1.536)	-0.541***	(0.217)	0.188	(0.261)	-1.115	(0.782)
Calendar 8	7.748***	(3.206)	0.004	(0.323)	-2.604***	(0.541)	-1.697	(1.430)
Calendar 9	-2.052	(3.056)	-0.656***	(0.332)	-0.025	(0.492)	1.282	(1.909)
Calendar 10	-2.208	(2.338)	-0.635***	(0.277)	0.173	(0.331)	1.523	(1.247)
Control Mean	46.100		4.980		6.440		15.900	
Observations (a)	15,778		15,821		15,821		14,898	
Observations (b)	15,519		15,519		15,519		14,663	
Fixed Effects	Yes		Yes		Yes		Yes	

Notes: The table reports ATETs by calendar time. Calendars 3–10 correspond to survey rounds 3–10. Panel (a) reports specifications without covariates, while Panel (b) includes household head gender and education, and household size. Round 5 is excluded because treatment is defined at the territory level while that round reports only provinces. Standard errors (in parentheses) are clustered at the territory level (26 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The FIES results from the leads-and-lags specification with covariates (10K flood threshold) reveal no pre-treatment effects and limited post-treatment impacts on moderate-to-severe food insecurity. Leads for calendar times 3 and 4 are small in magnitude and statistically insignificant, consistent with the parallel trends assumption, while post-treatment lags show small increase in FIES at calendar 6 and 7, suggesting a modest reduction in food security relative to the control mean, though calendar 8 exhibits a large negative shift in food insecurity, measured by the decline of FIES by 2.7 points (42 percent decrease relative to the control mean) ; the overall ATET of FIES is (0.82) which is a 12.7 percent of the control mean, indicating that flood exposure may be associated with slightly lower FIES on average, which indicates higher food security. For rCSI, the same leads and lags specification (10K threshold, with covariates) similarly supports parallel trends in pre-treatment periods, but post-flood dynamics are more volatile and predominantly negative in the first 6 months after exposure. However, the overall ATET remains insignificant, suggesting that there is no significant difference on how households cope with emergency.

Figure 8: FLEXDiD ATETs — HHS and PSFI



d). Robustness Check

This section summaries a set of robustness exercises that support the main causal estimates.

1). Additional Outcomes: I use two additional food security indicators, HHS and PSFI. Figure 8 provides support to parallel trends assumption. FLEXDiD ATTs estimates using treatment defined as 10k and 20k displacement are shown in Table Table 11. The findings are consistent with the main findings and confirm that flood exposure is associated with similar patterns of food security.

Table 11: Flood Exposure and Food Security Outcomes

	HHS		PSFI	
Lags and Leads	Sub Sample (1) (1)	Sub Sample (2) (2)	Sub Sample (1) (3)	Sub Sample (2) (4)
Panel (a): 10K				
Exposure to Flood	-0.010	-0.269	0.011***	-0.091***
	(0.126)	(0.137)	(0.030)	(0.036)
Control Mean	1.248	1.450	0.165	0.214
Observations	7,788	15,519	7,675	15,368
Fixed Effects	Yes	Yes	Yes	Yes
Panel (b): 20K				
Exposure to Flood	0.266	-0.279	0.047	-0.058
	(0.118)	(0.127)	(0.021)	(0.028)
Control Mean	1.52	1.42	0.24	0.21
Observations	7,789	15,519	7,675	16,649
Fixed Effects	Yes	Yes	Yes	Yes

Notes: The table reports FLEX-DiD ATET estimates of exposure to floods on food security outcomes. All specifications include household–level covariates. Treatment is defined as being located in a territory exposed to floods that led to 20,000 displacement. Sample (1) includes lags only, while Sample (2) includes both leads and lags. The number of clusters is 60 territories for Sub Sample (1) and 26 for Sub Sample (2). Standard errors (in parentheses) are clustered at the territory level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 9: FLEXDiD ATETs — HHS and PSFI

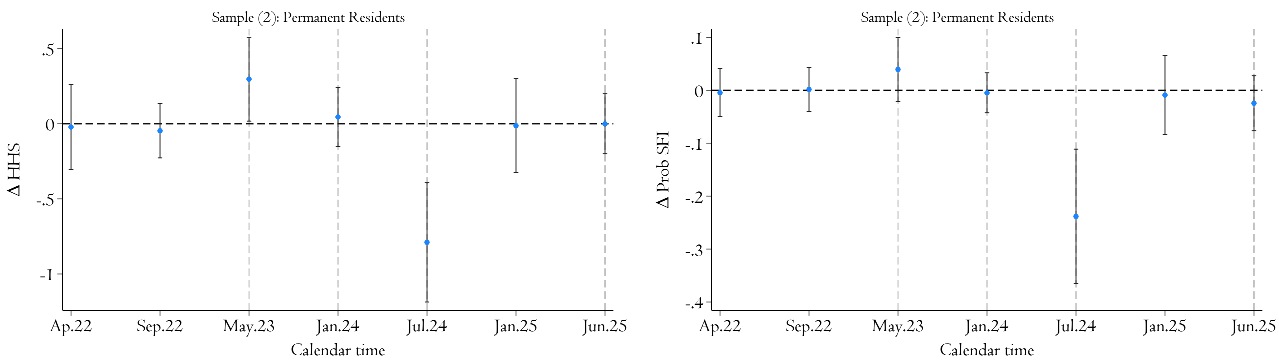


Table 12: FLEX DiD Event Study: Exposure to Floods and Food Security

	HHS		PSFI	
	(1)		(2)	
Panel (a): Lags only, no covariates				
ATET	-0.269***	(0.137)	-0.095***	(0.039)
Calendar 3	0.030	(0.127)	0.002*	(0.021)
Calendar 4	-0.062	(0.097)	-0.003	(0.020)
Calendar 6	0.309***	(0.141)	0.042	(0.032)
Calendar 7	0.075	(0.092)	-0.001	(0.020)
Calendar 8	-0.852***	(0.217)	-0.262***	(0.071)
Calendar 9	0.008	(0.165)	-0.002	(0.039)
Calendar 10	0.003	(0.107)	-0.021	(0.028)
Panel (b): Lags only with covariates				
ATET	-0.183**	(0.106)	-0.091***	(0.036)
Calendar 3	-0.021	(0.137)	-0.005	(0.022)
Calendar 4	-0.046	(0.088)	0.001	(0.020)
Calendar 6	0.298***	(0.136)	0.039	(0.029)
Calendar 7	0.046	(0.095)	-0.005	(0 .018)
Calendar 8	-0.790***	(0.193)	-0.238***	(0.062)
Calendar 9	-0.012	(0.152)	0-.009	(0.036)
Calendar 10	0.001	(0.097)	-0.025	(0.025)
Control Mean	1.450		0.214	
Observations (a)	15,821		15,622	
Observations (b)	15,519		15,368	
Fixed Effects	Yes		Yes	

Notes: The table reports ATETs of exposure to floods on HHS and PSFI by calendar time. Calendars 3–10 correspond to survey rounds 3–10. Panel (a) reports specifications without covariates, while Panel (b) includes household head gender, household head education, and household size. Round 5 is excluded because treatment is defined at the territory level while that round reports only provinces. Standard errors (in parentheses) are clustered at the territory level (26 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2). Different FLEX Specification: ATETs are re-estimated using a lags-only specification and all sub–samples. full sample has higher number of clusters 80 compared to 26 in sub–sample (2) and 60 in the sub–sample (1). Furthermore, the treatment is redefined using an alternative threshold based on displacements exceeding 20,000 people. Findings are reported in Table 13 (for the 10k threshold) and Appendix 4, Table 1.2 (for the 20k threshold). The key conclusions remain unchanged under this stricter definition of major flood events.

Table 13: Lags-Only ATETs: Food Security and HHS Outcomes

		ATET (SE)			Obs			Ctrl Mean		
Outcome	Spec	Full	S(2)	S(1)	Full	S(2)	S(1)	Full	S(2)	S(1)
FCS	No cov	0.819 (1.410)	1.344 (1.551)	0.342 (1.181)	23516	15778	8032	–	52.1	44.9
	Cov	0.744 (1.265)	1.181 (1.367)	1.192 (1.338)	23019	15519	7788			
HDDS	No cov	0.026 (0.193)	−0.022 (0.222)	−0.353* (0.242)	23561	15821	8033	–	5.3	5.0
	Cov	0.032 (0.191)	−0.018 (0.220)	−0.307 (0.272)	23021	15519	7789			
FIES	No cov	−0.442 (0.308)	−0.351 (0.338)	−0.053 (0.215)	23561	15821	8033	–	6.6	6.4
	Cov	−0.447 (0.291)	−0.339 (0.314)	−0.021 (0.267)	23021	15519	7789			
rCSI	No cov	0.619 (0.742)	0.614 (0.908)	0.742 (0.531)	21406	14898	5932	–	15.8	14.4
	Cov	0.536 (0.759)	0.481 (0.927)	–	20997	14663	–			
HHS	No cov	−0.185* (0.114)	−0.158 (0.127)	0.001 (0.110)	23561	15821	8033	–	1.52	1.42
	Cov	−0.183* (0.106)	−0.148 (0.118)	−0.010 (0.126)	23021	15519	7789			

Note: *p<0.10, **p<0.05, ***p<0.01. SE clustered at group level. S(2)=Sample 2 (residents), S(1)=Sample 1. Full sample clusters: 80; S(2): 26; S(1): 60. No-cov: lags-only without covariates; Cov: lags-only with hh gender, education, size. Ctrl means shown for no-cov S(2) and S(1).

e). Mechanisms

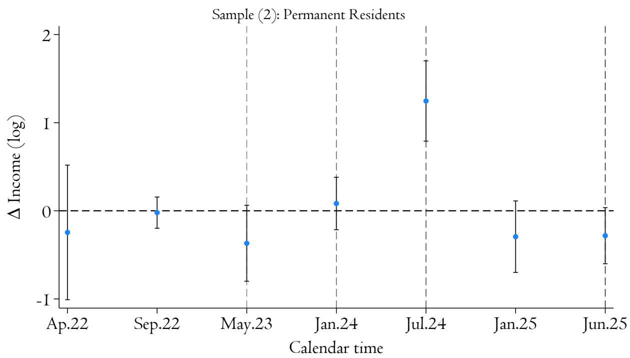
The FLEXDiD ATETs estimates suggest that flood exposure is associated with a decline in food insecurity (that is, an improvement in food security), an unexpected pattern that calls for further empirical investigation. To interrogate this conclusion, the ATETs were re-estimated for each rCSI and FIES component, yielding overall effects that are broadly consistent with the aggregate estimates but still surprising in sign. One plausible interpretation is that floods generate positive externalities through reconstruction activities, the inflow of food assistance, and related support, which may temporarily ease food constraints among affected households relative to non-exposed areas. Another explanation might be the availability of water for agriculture due to heavy precipitation that induce floods. To shed light on these mechanisms, additional outcomes such as income, employment, number of jobs, income sources, and sector of activity are analyzed, providing evidence on why households in flooded territories appear more food secure than their counterparts.

The event–study estimates using FLEXDiD show no systematic impact of flood exposure on any of the rCSI components, either in the overall ATET or across calendar-time coefficients. ATETs for borrowing food, shifting to less preferred foods, limiting portions, reducing the number of meals, and restricting adult consumption are uniformly small in magnitude, imprecisely estimated, and insignificant, suggesting that the earlier cross-sectional associations between floods and coping strategies do not survive once time-varying confounders and staggered treatment timing are controlled for. This explains why the overall rCSI response is insignificant (see, Appendix (5), Figures 5.1 to 5.5).

Turning to the income and labor-market channels, the FLEXDiD estimates indicate that floods are associated with a sizable but transitory rise in household income and modest, short-lived adjustments in employment, number of income sources, and sector of activity, with significant effects emerging primarily in the period of large-scale displacement and reconstruction and then dissipating thereafter. These dynamic patterns are mirrored, but not strongly amplified, in the FIES items: households report temporary reductions in worries about food adequacy and in episodes of eating few or unhealthy foods around the peak income shock, yet the overall ATETs remain small and statistically indistinguishable from zero, indicating that flood-related income gains and employment reallocation only partially translate into improved food security (see, Figures 10 and 11).

In contrast, I find evidence on a positive effect of exposure to floods on planted land. I examine two agricultural outcomes using lags-only specifications and the sub–sample (2). Flood exposure has no significant effect on the binary harvest indicator, coefficients is 0.050 without covariates and 0.056 with covariates, both insignificant; this suggests that floods do not systematically disrupt the extensive margin of harvest success in the post-treatment period. However, flooded territories exhibit a robust 10.3 percentage point increase in cultivated area, significant at the 1% level across both specifications, indicating an economically meaningful intensification response on the extensive margin—households appear to expand land under cultivation post-flood, potentially as a recovery strategy that could underlie the null-to-positive food security effects observed earlier (see, Figures 12 and 13).

Figure 10: FLEXDiD ATETs for Income and Employment



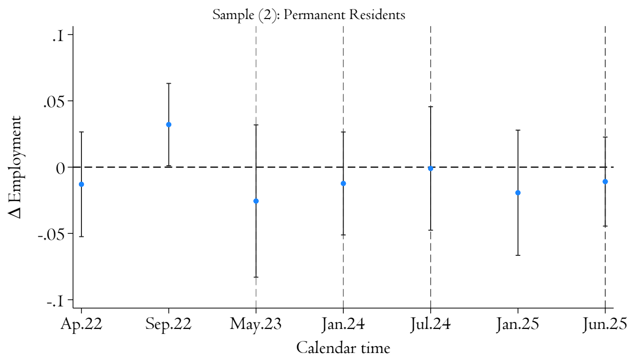
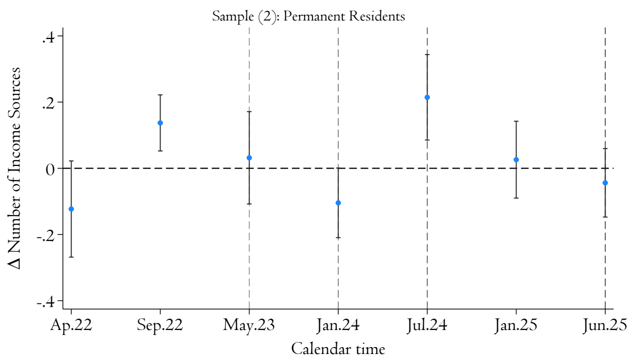


Figure 11: FLEXDiD ATETs for Number of Income Sources and Sector



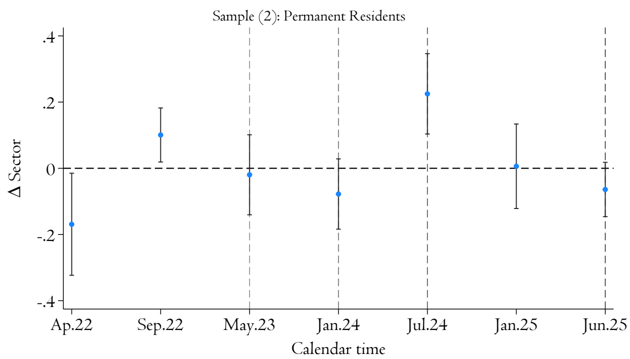


Figure 12: ATT: Change in Harvest

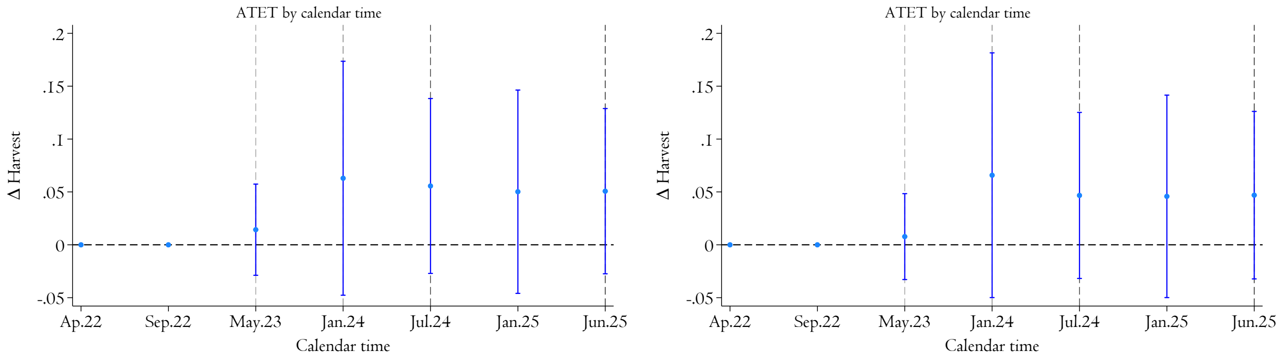
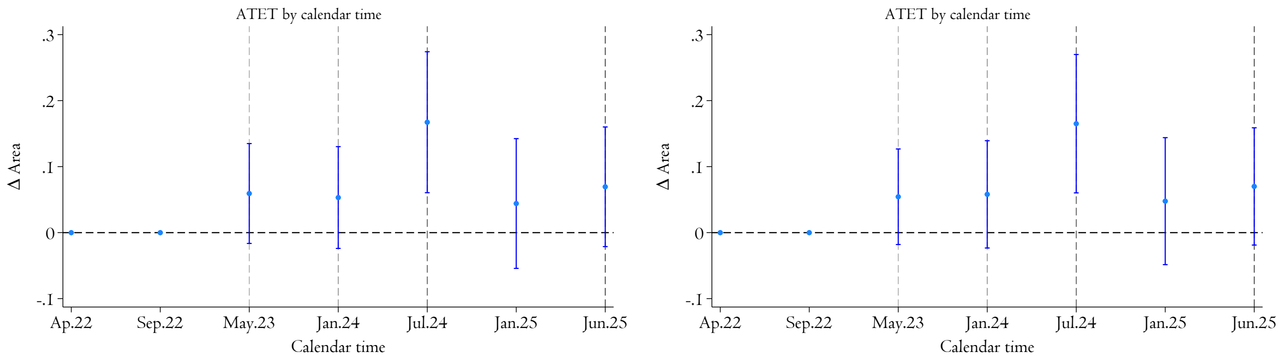


Figure 13: ATT: Change in Planted Area



VII. Conclusion

This paper provides new evidence on how exposure to floods affects household food security in a fragile context, the DRC. I use household data from the DIEM survey rounds conducted between 2021 and 2025 combined with two measures of exposure to floods; self–reported exposure and an external measure of flood exposure. I estimated the impact of self–exposure to floods on food security outcomes using two way fixed-effects and a flexible staggered difference-in-differences estimator designed to accommodate repeated cross-sections, staggered exposure, and heterogeneous treatment effects. The results show a sharp contrast between subjective and externally measured exposure to floods. Self-reported exposure is associated with higher food insecurity and greater reliance on negative coping strategies, while the causal estimates based on defining treatment at the territory–level that exposed to floods led to displaced 10k and 20k people OCHA record. The estimates show little effect on dietary diversity and food quality but indicate improvements in hunger and severe food insecurity indicators in the post-flood period. The event-study estimates from flexible staggered difference-in-differences reveal no significant impact on rCSI components once time-varying confounders and heterogeneous treatment timing are accounted for. This suggests that correlations between self–reported floods and coping behavior largely reflect measurement error, sorting, and/or anticipatory responses. To explain the finding that objective flood exposure is associated with null-to-positive food security effects rather than harm, I test two mechanisms: (i) income/labor market channels and (ii) agricultural production responses. For income/labor, I find sizable but transitory household income gains, short-lived shifts in employment, income sources, and sector composition peaking during the displacement periods, which partially translate into temporary FIES reductions (less severe hunger) but yield insignificant overall ATETs on dietary outcomes. For agriculture, flood exposure shows no significant harvest disruption but a robust expansion in cultivated area, indicating an economically meaningful post-flood intensification on the extensive margin; this recovery response—potentially amplified by precipitation benefits likely offsets direct damages and underlies the observed null-to-positive patterns across aggregate food security indicators. These findings have three main implications. First, they underscore the importance of combining objective hazard records with flexible causal estimators when assessing the welfare impacts of climate shocks in low-income, conflict-affected settings, where self-reported exposure and standard two-way fixed effects are likely to be misleading. Second, exposure to floods is not always lead to a decline in households welfare, this is consistent with some previous studies (e.g., Boustan et al. (2012) ; Gray and Mueller (2012); Kocornik-Mina et al. (2020)). In contrast, these findings are consistent with many recent studies (e.g., Institution (2023) ; Yolchi (2024) ; Asongu et al. (2025) ; Atubiga and Donkor (2022). Finally, the findings suggest that after exposure to floods, a support of agricultural land expansion could be a good coping measures in an agrarian communities. The work on impacts of floods in developing countries could be expanded in three ways. First, there is a need for high frequency micro data that could enable researchers to leverage quasi experiments and estimate causal impacts on a range of outcomes at household level. Second, the use of more objective measure for exposure to flood on both extensive and intensive margins combined with causal inference approaches could greatly support response to natural disasters, flood in particular in vulnerable countries. The third extension should focus on focus on heterogeneous treatment effects, mechanisms and coping responses. Using the more objective flood measures and the rich information on adaptation strategies in the DIEM rounds. Future research should explore and identify the mechanisms and strategies that could mediate the impact of exposure to floods.

References

Africa Center for Strategic Studies. Record levels of flooding in africa compounds stress on fragile countries. https://africacenter.org/spotlight/record-levels-of-flooding-in-africa-compounds-stress-on-fragile-countries/, December 2024. Accessed: 2025-09-02.

A. Amparore, M. A. Constas, F. Fossi, et al. The data in emergencies (diem) hub for evaluating multiple shock impacts on food security. *Nature Food*, 4:628–629, 2023. doi: 10.1038/s43016-023-00825-7. URL https://doi.org/10.1038/s43016-023-00825-7.

Simplice A Asongu et al. The effect of natural disasters on food security in sub-saharan africa. *Social Responsibility Journal*, 21(1):180–198, 2025. doi: 10.1108/SRJ-05-2024-0354. URL https://www.emerald.com/insight/content/doi/10.1108/SRJ-05-2024-0354/full/html.

John Aloba Atubiga and Eric Donkor. Exploring the impact of floods on rural communities on emerging food security challenges in ghana. *Journal of Social Sciences*, 18(4):191–200, 2022. doi: 10.3844/jssp.2022.191.200. URL https://thescipub.com/pdf/jssp.2022.191.200.pdf.

Travis Andreas Baseler and Jakob Johannes Hennig. Disastrous displacement: The long-run impacts of landslides. Technical Report 10535, The World Bank, 2023.

Leah Platt Boustan, Matthew E. Kahn, and Paul W. Rhode. Coping with economic and environmental shocks: Institutions and outcomes: Moving to higher ground: Migration response to natural disasters in the early twentieth century. *American Economic Review*, 102(3):238–244, May 2012. doi: 10.1257/aer.102.3.238.

Brantly Callaway and Pedro H. C. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021. doi: 10.1016/j.jeconom.2020.12.001.

Subhash Chandir, Rachel Glennerster, Maryiam Haroon, Edward Jee, and Danya Arif Siddiqi. Does childhood immunization rebound after extreme shocks? evidence from floods and strikes in pakistan. *AEA Papers and Proceedings*, 113:642–646, 2023. doi: 10.1257/pandp.20231110.

Joyce J. Chen, Valerie Mueller, Yuanyuan Jia, and Steven Kuo-Hsin Tseng. Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, 107(5):441–445, 2017. doi: 10.1257/aer.p20171052.

Partha Deb, Edward C. Norton, Jeffrey M. Wooldridge, and Jeffrey E. Zabel. A flexible, heterogeneous treatment effects difference-in-differences estimator for repeated cross-sections. Technical Report Working Paper No. 33026, National Bureau of Economic Research, October 2024. URL https://www.nber.org/papers/w33026. Revised May 2025.

Partha Deb, Edward C. Norton, Jeffrey M. Wooldridge, and Jeffrey E. Zabel. A flexible, heterogeneous treatment effects difference-in-differences estimator for repeated cross-sections. NBER Working Paper 33026, National Bureau of Economic Research, Cambridge, MA, 2025. URL http://www.nber.org/papers/w33026. October 2024, Revised May 2025.

Melissa Dell, Benjamin F. Jones, and Benjamin A. Olken. What do we learn from the weather? the new climate–economy literature. *Journal of Economic Literature*, 52(3):740–798, 2014. doi: 10.1257/jel.52.3.740.

FAO. The food insecurity experience scale: Measuring food insecurity through people's experiences. Technical report, FAO, 2014. URL https://www.fao.org/3/i4830e/i4830e.pdf. Voices of the Hungry Project.

Clark Gray and Valerie Mueller. Natural disasters and population mobility in bangladesh. *Proceedings of the National Academy of Sciences*, 109(16):6000–6005, 2012. doi: 10.1073/pnas.1115944109.

Raymond Guiteras, Amir Jina, and A. Mushfiq Mobarak. Satellites, self-reports, and submersion: Exposure to floods in bangladesh. *American Economic Review*, 105(5):232–236, 2015. doi: 10.1257/aer.p20151095.

K. Hadley. Mechanisms underlying food insecurity in the aftermath of floods in nigeria. *The Lancet Planetary Health*, 2023. Before-and-after comparative study.

Insecurity Insight. Chronic insecurity: How armed groups undermine food security in ituri and north kivu provinces, drc. https://insecurityinsight.org/wp-content/uploads/2025/01/Chronic-Insecurity-How-Armed-Groups-Undermine-Food-Security-in-Ituri-and-North-Kivu-Provinces-DR-January-2025.pdf, 2025. Report, January 2025. Accessed: 2025-09-02.

NSF Institution. New study details impacts on food security caused by floods. NSF news release, 2023.

International Federation of Red Cross and Red Crescent Societies (IFRC). Dref operation: Democratic republic of congo floods. Technical report, International Federation of Red Cross and Red Crescent Societies, February 2 2024.

Gina Kennedy, Terri Ballard, and Marie-Claude Dop. Guidelines for measuring household and individual dietary diversity. Technical report, Food and Agriculture Organization of the United Nations, 2011.

Adriana Kocornik-Mina, Thomas K. J. McDermott, Guy Michaels, and Ferdinand Rauch. Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66, 2020. doi: 10.1257/app.20170066.

Daniel Maxwell, Jennifer Coates, and Bapu Vaitla. How do different indicators of household food security compare? empirical evidence from tigray. Technical report, Feinstein International Center, Tufts University, Medford, MA, 2013.

OCHA. In dr congo, pooled funds helped families rebuild after floods. Technical report, United Nations Office for the Coordination of Humanitarian Affairs, 2023. URL https://www.unocha.org/publications/report/democratic-republic-congo/dr-congo-pooled-funds-helped-families-rebuild-after-floods. Accessed June 11, 2025.

D. O. Omokpariola, C. Agbanu-Kumordzi, T. Samuel, et al. Climate change, crop yield, and food security in sub-saharan africa. *Discover Sustainability*, 6:678, 2025. doi: 10.1007/s43621-025-01580-4. URL https://doi.org/10.1007/s43621-025-01580-4.

Dev Patel. Floods, January 28 2024. Unpublished.

C. Reed, S. McDermid, and W. Anderson. The impact of flooding on food security across africa. *Proceedings of the National Academy of Sciences*, 119, 2022. doi: 10.1073/pnas.2119399119.

Sustainability Global Team. Flood disasters in 2025. https://sustainabilityglobal.org/flood-disasters-in-2025/, July 2025. Accessed: 2025-09-04.

Anne Swindale and Paula Bilinsky. Household dietary diversity score (hdds) for measurement of household food access: Indicator guide (v. 2). Technical report, FHI 360/FANTA, Washington, D.C., 2006.

UN Office for Disaster Risk Reduction.

Elliot Vhurumuku. Food security indicators. Workshop presentation, WFP East and Central Africa Bureau, Nairobi, February 25–27 2011.

World Bank. The world bank in drc: Overview. https://www.worldbank.org/en/country/drc/overview, 2024. Accessed: 2025-09-02.

World Food Programme. Technical guidance for wfp's consolidated approach for reporting indicators of food security (cari). Technical report, World Food Programme, Research, Assessment and Monitoring Division, Rome, November 2021.

World Food Programme. Livelihood coping strategies indicator for food security: Guidance note. Technical report, World Food Programme, March 2023.

World Food Programme. Drc emergency response. https://www.wfp.org/emergencies/drc-emergency, 2025. Accessed: 2025-09-02.

World Food Programme, Vulnerability Analysis and Mapping Branch (ODAV). Food consumption analysis: Calculation and use of the food consumption score in food security analysis. version 1. Technical report, World Food Programme, Rome, February 2008.

J. Yolchi. Impact of floods on food security in rural afghanistan. *Undisclosed Journal*, 2024. Cited by SLIS.

Appendix

Appendix (1): Food Insecurity and Coping Strategies in DRC

Table (1.1): Household Food Security Indicators by Year and Migrant Type

	Full sample	2022	2023	2024	2025	Permanent	Temporary	FMs
Panel (a): Food security indicators								
FCS	45.9	45.2	49.2	44.9	45.2	48.2	43.8	36.7
HDDS	4.87	5.10	4.41	4.67	5.16	5.04	4.64	4.29
HHS	1.48	1.51	1.36	1.57	1.47	1.34	1.62	2.12
FIES	5.81	na	5.48	5.98	5.86	5.44	6.09	7.65
rCSI	16.3	15.9	14.9	16.1	17.4	15.21	18.31	23.07
Panel (b): FCS items								
Staples	5.8	5.7	5.4	5.7	6.2	5.94	5.73	5.73
Pulses	2.9	2.7	3.0	3.0	3.0	2.92	3.25	2.65
Vegetables	4.8	na	5.0	4.6	4.8	4.97	4.24	4.44
Fruit	2.0	2.3	2.5	1.9	1.8	2.21	1.73	1.29
Meat and fish	2.4	2.3	2.7	2.4	2.4	2.63	2.14	1.49
Dairy	1.1	1.3	1.6	1.1	0.9	1.29	1.01	0.50
Oil	6.1	6.1	6.2	6.0	6.0	6.24	5.61	5.29
Condiments	5.8	na	5.6	5.5	6.2	6.02	5.88	5.50
Panel (c): rCSI module								
Less-preferred foods	3.1	3.0	2.7	3.2	3.4	2.96	3.22	3.90
Borrowed food	1.3	1.5	1.2	1.3	1.4	1.20	1.60	2.12
Reduced number of meals	2.5	2.4	2.3	2.5	2.6	2.31	2.76	3.31
Limited portion size	2.5	2.6	2.3	2.5	2.6	2.35	2.74	3.45
Restricted adult consumption	1.9	1.7	1.8	1.8	2.0	1.73	2.13	2.73
Panel (d): FIES module								
Worried about food	0.68	0.70	0.62	0.71	0.67	0.63	0.72	0.83
Could not eat healthy food	0.66	0.67	0.61	0.70	0.66	0.62	0.70	0.77
Ate few kinds of foods	0.71	0.71	0.69	0.74	0.71	0.69	0.73	0.78
Skipped meals	0.68	0.70	0.65	0.70	0.68	0.65	0.73	0.81
Ate less than needed	0.77	0.76	0.75	0.80	0.77	0.74	0.76	0.87
Ran out of food	0.51	na	0.50	0.54	0.50	0.48	0.52	0.69
Was hungry but did not eat	0.46	na	0.43	0.49	0.46	0.42	0.50	0.66
Not eating for a whole day	0.36	na	0.33	0.40	0.35	0.31	0.42	0.57
Observations	28 ,171	4 ,8915	,4618	,0359	,784	18 ,619	717	1 ,406

Note: Each observation represents a household. Statistics are weighted using DIEM sampling weights. Statistics are means for continuous indicators and proportions for binary FIES items; "na" indicates that the indicator is not available for a given year. Panels (a)–(d) report, respectively, summary scores, FCS component items (number of days consumed in the previous 7 days), rCSI items (number of days coping strategies were used in the previous 7 days), and FIES items (binary indicators of experiences). Columns 2–6 show averages for the full sample and by survey year; columns 7–9 reproduce the same indicators by migrant type: permanent residents, temporary migrants (recent migrants and returnees), and forced migrants (IDPs and refugees).

Table (2.1): Coping Strategy Indicators by Type of Residency (Round 10)

	Full sample	**Permanent**	**Temporary**	**FMs**
Panel (a): Sold household assets				
Assets: Yes	0.37	0.34	0.57	0.59
Assets: No, not necessary	0.58	0.61	0.37	0.32
Assets: No, done before	0.03	0.03	0.04	0.05
Panel (b): Sold more animals than usual				
Sold more animals: Yes	0.16	0.15	0.19	0.16
Sold more animals: No, not necessary	0.54	0.56	0.45	0.43
Sold more animals: No, done before	0.04	0.04	0.07	0.02
Panel (c): Spent savings				
Spent savings: Yes	0.61	0.59	0.79	0.77
Spent savings: No, not necessary	0.35	0.38	0.16	0.18
Spent savings: No, done before	0.03	0.03	0.05	0.03
Panel (d): Ate elsewhere (e.g. with friends/relatives)				
Ate elsewhere: Yes	0.31	0.27	0.55	0.56
Ate elsewhere: No, not necessary	0.66	0.69	0.42	0.42
Ate elsewhere: No, done before	0.03	0.03	0.03	0.02
Panel (e): Borrowed food or received help				
Borrowed food/help: Yes	0.57	0.54	0.81	0.81
Borrowed food/help: No, not necessary	0.40	0.44	0.18	0.17
Borrowed food/help: No, done before	0.02	0.02	0.00	0.02
Panel (f): Bought food on credit				
Bought on credit: Yes	0.67	0.64	0.84	0.82
Bought on credit: No, not necessary	0.31	0.34	0.12	0.17
Bought on credit: No, done before	0.02	0.02	0.04	0.01
Panel (g): Borrowed money				
Borrowed money: Yes	0.65	0.63	0.80	0.82
Borrowed money: No, not necessary	0.32	0.35	0.18	0.14
Borrowed money: No, done before	0.02	0.02	0.02	0.04
Panel (h): Sold productive assets				
Sold productive assets: Yes	0.12	0.11	0.18	0.17
Sold productive assets: No, not necessary	0.74	0.76	0.60	0.57
Sold productive assets: No, done before	0.02	0.02	0.04	0.01
Panel (i): Reduced health expenditures				
Reduced health exp.: Yes	0.54	0.51	0.68	0.76
Reduced health exp.: No, not necessary	0.43	0.46	0.29	0.23
Reduced health exp.: No, done before	0.03	0.03	0.03	0.01
Panel (j): Harvested immature crops				
Harvested immature crops: Yes	0.29	0.29	0.41	0.32
Harvested immature crops: No, not necessary	0.54	0.56	0.40	0.47
Harvested immature crops: No, done before	0.03	0.02	0.05	0.01
Panel (k): Begged				
Begged: Yes	0.12	0.10	0.25	0.29
Begged: No, not necessary	0.87	0.89	0.72	0.68
Panel (l): Engaged in illegal activities				
Illegal activities: Yes	0.04	0.04	0.08	0.07
Illegal activities: No, not necessary	0.95	0.95	0.90	0.90
Panel (m): Household member migrated				
Household member migrated: Yes	0.04	0.03	0.09	0.10
Household member migrated: No, not necessary	0.94	0.95	0.88	0.84
Observations	4526	4002	188	336

Note: Each observation represents a household. Statistics are weighted using DIEM sampling weights. Entries report the share of households in each coping response category. Columns correspond to the full sample and residency types: permanent residents, temporary migrants, and forced migrants.

Table (3.1): Food Security Categories by Year and Residency (Rounds 4, 5, 6, 7, 9, 10)

	Full sample	Perm 2023	Perm 2024	Perm 2025	Temp 2023	Temp 2024	Temp 2025
Panel (a): FCG							
Poor	0.06	0.08	0.03	0.08	0.16	0.08	0.14
Borderline	0.21	0.21	0.19	0.29	0.22	0.33	0.37
Acceptable	0.59	0.71	0.78	0.62	0.62	0.59	0.48
Panel (b): HHG							
Little to none (IPC–1)	0.39	0.42	0.46	0.36	0.30	0.31	0.15
Slight (IPC–2)	0.19	0.18	0.18	0.17	0.17	0.17	0.16
Moderate (IPC–3)	0.36	0.35	0.30	0.39	0.44	0.42	0.53
Severe (IPC–4)	0.04	0.03	0.05	0.04	0.05	0.06	0.09
Severe (IPC–5)	0.02	0.02	0.01	0.03	0.04	0.04	0.06
Panel (c): HDDS							
Low dietary	0.15	0.27	0.07	0.11	0.30	0.21	0.15
Medium dietary	0.30	0.28	0.30	0.29	0.34	0.38	0.42
High dietary	0.56	0.44	0.63	0.61	0.36	0.41	0.43
Panel (d): rCSI							
IPC1	0.21	0.25	0.27	0.19	0.16	0.17	0.05
IPC2	0.40	0.42	0.45	0.37	0.37	0.40	0.27
IPC3	0.39	0.33	0.28	0.45	0.47	0.43	0.68
Panel (e): LCSI							
No coping	0.12	0.14	0.14	0.11	0.11	0.03	0.02
Stress	0.16	0.15	0.19	0.16	0.10	0.14	0.08
Crisis	0.44	0.43	0.46	0.43	0.35	0.41	0.40
Emergency	0.29	0.27	0.20	0.30	0.43	0.42	0.50
Panel (f): FIES (1)							
Yes	0.49	0.49	0.44	0.53	0.58	0.50	0.69
No – not necessary	0.14	0.16	0.13	0.13	0.13	0.14	0.14
No – done before	0.28	0.28	0.25	0.31	0.36	0.28	0.41
Not applicable	0.07	0.06	0.05	0.09	0.08	0.07	0.13
Panel (g): FIES (2)							
Yes	0.45	0.42	0.38	0.47	0.55	0.59	0.68
No – not necessary	0.16	0.15	0.13	0.15	0.17	0.26	0.19
No – done before	0.25	0.22	0.21	0.27	0.29	0.30	0.41
Not applicable	0.04	0.04	0.04	0.05	0.07	0.03	0.09
Panel (h): FIES (3)							
Yes	0.34	0.31	0.28	0.36	0.48	0.49	0.59
No – not necessary	0.15	0.15	0.11	0.14	0.17	0.17	0.23
No – done before	0.17	0.15	0.15	0.18	0.27	0.28	0.29
Not applicable	0.03	0.02	0.02	0.04	0.04	0.04	0.07
Observations	20 749	4965	2518	4681	490	205	577

Note: Each observation represents a household. Statistics are weighted using DIEM sampling weights. Entries are proportions of households in each category; the last row reports the number of non-missing observations for each subsample. FIES (1): ran out of food ; FIES (2) hungry; FIES (3) whole day without eating.

Appendix (2): DIEM–DRC Survey Methodology

DIEM Surveys Methodology – DRC

This paper uses repeated cross-sectional household survey data for the Democratic Republic of the Congo collected by the Food and Agriculture Organization of the United Nations (FAO) under the DIEM – Data in Emergencies Monitoring system. The analysis draws on seven rounds (Rounds 3–10, excluding Round 5 owing to the lack of territorial identifiers) implemented between April 2022 and July 2025. The DIEM surveys collect information on agricultural livelihoods and household food security among agricultural and non-agricultural households in conflict-affected areas. Each round relies primarily on a computer-assisted telephone interview (CATI) design, with households randomly selected under a stratified simple random sampling scheme. The sampling strategy aims to achieve representativeness in the eastern provinces most affected by insecurity. Rounds 3, 4, 6, and 7 cover 9–11 provinces (Ituri, the three Kasaï provinces, North and South Kivu, North and South Ubangi, Kwango, Tshopo, and Tanganyika), with sample sizes of about 2,100–2,800 households and representativeness at the second administrative level (territories). Later rounds expand both coverage and depth: Round 8 surveys 5,782 households in 29 territories across Ituri, North Kivu, South Kivu, and Tanganyika using a mixed design (3,487 CATI interviews and 2,296 face-to-face interviews based on village listing and random household selection), and Round 9 surveys 5,258 households in 35 territories across North Kivu, South Kivu, Ituri, Tanganyika, and Kasaï, with representativeness at the territorial level. Across rounds, strata are defined by province and, where sample sizes permit, by territory; households are randomly sampled within these strata from FAO phone lists or village household rosters, ensuring coverage of both agricultural and non-agricultural households. The resulting samples allow disaggregation of key outcomes – including the Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), Household Hunger Scale (HHS), reduced Coping Strategies Index (rCSI), and Food Insecurity Experience Scale (FIES) – at the provincial level (admin 1) in earlier rounds and at the territorial level (admin 2) in later rounds. High-resolution interactive dashboards on income and shocks, crop and livestock production, food security outcomes, and needs complement the survey microdata and reflect the same sampling frame.

Source: DIEM – Data in Emergencies Monitoring, FAO. Accessible at: *https://bit.ly/4oujvPq*

Appendix (3): Additional Self–reported Estimates

Table (1.3): Self–reported Exposure to Flood and Dietary Diversity outcomes: FCS and HDDS

	(1) FCS	(2) FCS	(3) FCS	(4) HDDS	(5) HDDS	(6) HDDS
Panel (a): Exposure Effect						
Flood	0.13	-0.42	0.50	0.07	0.00	0.01
	(0.81)	(0.79)	(1.16)	(0.05)	(0.06)	(0.11)
Panel (b): Household Characteristics						
HoH Gender	2.20***	2.18***	1.43*	0.10	0.08	0.02
	(0.70)	(0.58)	(0.82)	(0.06)	(0.05)	(0.06)
Education	5.69***	4.49***	3.49***	0.41***	0.35***	0.26
	(1.21)	(0.97)	(1.18)	(0.14)	(0.11)	(0.18)
Respondent Age	-0.05	-0.01	0.38	-0.02	-0.01	0.11
	(0.46)	(0.42)	(0.63)	(0.06)	(0.05)	(0.11)
Household Size	-1.83***	-1.32***	-1.95***	-0.14***	-0.11***	-0.15***
	(0.32)	(0.31)	(0.62)	(0.04)	(0.04)	(0.06)
Panel (c): Additional Household Covariates						
No Agriculture		-0.83			-0.06	
		(0.65)			(0.06)	
Access to Safe Water		3.98***			0.35***	
		(0.45)			(0.07)	
Access to Electricity		10.11***			0.64***	
		(0.71)			(0.06)	
Natural Disasters		-0.11			0.32	
		(0.84)			(0.29)	
Intra-household Shock		-3.63***			-0.33**	
		(0.52)			(0.12)	
Economic Shock		-0.70			0.26*	
		(0.72)			(0.13)	
Man-made Shock		-1.18**			0.11	
		(0.45)			(0.07)	
Panel (d): Territory–level Climate Indicators						
Precipitations			-0.05			0.00
			(0.05)			(0.01)
Temperature			8.22*			1.27**
			(4.61)			(0.56)
Droughts			0.27			0.14
			(1.28)			(0.17)
Conflict Events			0.12***			0.02**
			(0.04)			(0.01)
Control Mean	45.81	45.81	45.81	5.00	5.00	5.00
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.16	0.21	0.21	0.08	0.11	0.10
Observations	15,509	15,508	8,057	15,509	15,508	8,057

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (2), DIEM–DRC rounds. Columns (1)–(3) use the Food Consumption Score (FCS) as the dependent variable; columns (4)–(6) use the Household Dietary Diversity Score (HDDS). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table (2.3): Self–reported Exposure to Flood and Coping Outcomes: FIES and rCSI

	(1) FIES	(2) FIES	(3) FIES	(4) rCSI	(5) rCSI	(6) rCSI
Panel (a): Exposure Effect						
Flood	0.46***	0.65***	0.38**	1.01**	1.39***	0.97
	(0.11)	(0.09)	(0.18)	(0.42)	(0.40)	(0.60)
Panel (b): Household Characteristics						
HoH Gender	-0.76***	-0.72***	-0.67***	-1.62***	-1.62***	-1.35***
	(0.11)	(0.08)	(0.13)	(0.32)	(0.29)	(0.30)
Education	-1.29***	-1.01***	-0.86***	-2.64***	-1.92***	-2.78***
	(0.18)	(0.12)	(0.17)	(0.77)	(0.61)	(0.54)
Respondent Age	0.13	0.14	0.09	1.52***	1.52***	0.87**
	(0.11)	(0.09)	(0.12)	(0.31)	(0.27)	(0.32)
Household Size	0.54***	0.43***	0.51***	2.09***	1.80***	1.91***
	(0.06)	(0.05)	(0.09)	(0.17)	(0.17)	(0.26)
Panel (c): Additional Household Covariates						
No Agriculture		0.27**			0.75*	
		(0.12)			(0.40)	
Safe Water		-0.69***			-2.76***	
		(0.07)			(0.29)	
Electricity		-1.48***			-4.23***	
		(0.13)			(0.38)	
Natural Disasters		0.70***			1.47***	
		(0.12)			(0.41)	
Intra-household Shock		1.29***			2.63***	
		(0.11)			(0.41)	
Economic Shock		0.60***			1.40***	
		(0.11)			(0.25)	
Man-made Shock		0.61***			2.16***	
		(0.07)			(0.22)	
Panel (d): Territory–level Climate Indicators						
Precipitations			0.01			0.03
			(0.01)			(0.02)
Temperature			-2.94***			0.89
			(0.90)			(1.50)
Droughts			0.16			-0.73
			(0.22)			(0.65)
Conflict Events			-0.02***			-0.03
			(0.01)			(0.02)
Control Mean	6.43	6.43	6.43	16.17	16.17	16.17
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.13	0.20	0.19	0.08	0.13	0.09
Observations	15,509	15,508	8,057	14,653	14,652	7,201

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (2), DIEM–DRC rounds. Columns (1)–(3) use the Food Insecurity Experience Scale (FIES) as the dependent variable; columns (4)–(6) use the reduced Coping Strategies Index (rCSI). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table (3.3): Self–reported Exposure to Flood and Food Security Outcomes: HHS and PSFI

	(1) HHS	(2) HHS	(3) HHS	(4) SFI	(5) SFI	(6) SFI
Panel (a): Exposure Effect						
Flood	0.11***	0.17***	0.05	0.01	0.02*	-0.00
	(0.04)	(0.03)	(0.06)	(0.01)	(0.01)	(0.01)
Panel (b): Household Characteristics						
HoH Gender	-0.27***	-0.25***	-0.24***	-0.06***	-0.06***	-0.06***
	(0.04)	(0.04)	(0.07)	(0.01)	(0.01)	(0.01)
Education	-0.45***	-0.36***	-0.31***	-0.13***	-0.11***	-0.09***
	(0.08)	(0.06)	(0.07)	(0.03)	(0.02)	(0.02)
Respondent Age	0.07	0.08*	0.07	-0.00	-0.00	0.00
	(0.05)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)
Household Size	0.19***	0.16***	0.17***	0.04***	0.04***	0.04***
	(0.02)	(0.02)	(0.03)	(0.00)	(0.00)	(0.01)
Panel (c): Additional Household Covariates						
No Agriculture		0.16***			0.04***	
		(0.04)			(0.01)	
Safe Water		-0.27***			-0.06***	
		(0.03)			(0.01)	
Electricity		-0.48***			-0.08***	
		(0.05)			(0.01)	
Natural Disasters		0.20***			0.05**	
		(0.05)			(0.02)	
Intra-household Shock		0.39***			0.07***	
		(0.04)			(0.01)	
Economic Shock		0.19***			0.03***	
		(0.03)			(0.01)	
Man-made Shock		0.11***			0.02***	
		(0.03)			(0.01)	
Panel (d): Territory–level Climate Indicators						
Precipitations			0.00			0.00
			(0.00)			(0.00)
Temperature			-0.64*			-0.24**
			(0.34)			(0.09)
Droughts			0.09			0.04*
			(0.08)			(0.02)
Conflict Events			-0.01***			-0.00***
			(0.00)			(0.00)
Control Mean	1.47	1.47	1.47	0.21	0.21	0.21
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.12	0.17	0.16	0.13	0.17	0.20
Observations	15,509	15,508	8,057	15,361	15,360	7,935

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (2), DIEM–DRC rounds. Columns (1)–(3) use the Household Hunger Scale (HHS) as the dependent variable; columns (4)–(6) use the probability of severe food insecurity (SFI). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table (4.3): Self–reported Exposure to Flood and Dietary Diversity outcomes: FCS and HDDS

	(1) FCS	(2) FCS	(3) FCS	(4) HDDS	(5) HDDS	(6) HDDS
Panel (a): Exposure Effect						
Flood	-0.90	-1.44*	-0.94	0.08	-0.01	0.08
	(0.81)	(0.85)	(0.80)	(0.09)	(0.09)	(0.09)
Panel (b): Household Characteristics						
HoH Gender	0.18	0.40	0.17	-0.16	-0.17*	-0.17
	(0.92)	(0.88)	(0.92)	(0.10)	(0.09)	(0.10)
Education	6.74***	5.90***	6.74***	0.42**	0.38**	0.41**
	(1.42)	(1.52)	(1.40)	(0.16)	(0.17)	(0.16)
Respondent Age	-0.78	-0.68	-0.81	-0.04	-0.04	-0.04
	(0.88)	(0.82)	(0.88)	(0.07)	(0.07)	(0.07)
Household Size	-3.62***	-2.81***	-3.61***	-0.16***	-0.13***	-0.16***
	(0.58)	(0.49)	(0.58)	(0.03)	(0.03)	(0.03)
Panel (c): Additional Household Covariates						
No Agriculture		-1.02			-0.17***	
		(0.81)			(0.06)	
Safe Water		6.82***			0.25***	
		(0.94)			(0.08)	
Electricity		9.07***			0.41***	
		(1.05)			(0.09)	
Natural Disasters		-2.74***			0.24**	
		(0.86)			(0.11)	
Intra-household Shock		-4.19***			-0.31***	
		(0.77)			(0.05)	
Economic Shock		-2.34***			-0.27**	
		(0.87)			(0.11)	
Man-made Shock		-2.10***			-0.04	
		(0.75)			(0.08)	
Panel (d): Territory–level Climate Indicators						
Precipitations			0.01			0.00
			(0.03)			(0.00)
Temperature			-3.96			0.20
			(4.07)			(0.92)
Droughts			0.59			0.10
			(0.77)			(0.12)
Conflict Events			0.10			0.04***
			(0.10)			(0.01)
Control Mean	51.46	51.46	51.46	5.31	5.31	5.31
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.15	0.09	0.02	0.04	0.03
Observations	7,788	7,786	7,788	7,789	7,787	7,789

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (1), DIEM–DRC rounds. Columns (1)–(3) use the Food Consumption Score (FCS) as the dependent variable; columns (4)–(6) use the Household Dietary Diversity Score (HDDS). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table (5.3): Self–reported Exposure to Flood and Coping Outcomes: FIES and rCSI

	(1) FIES	(2) FIES	(3) FIES	(4) rCSI	(5) rCSI	(6) rCSI
Panel (a): Exposure Effect						
Flood	0.91***	1.15***	0.92***	1.97***	2.31***	2.00***
	(0.21)	(0.20)	(0.22)	(0.74)	(0.68)	(0.73)
Panel (b): Household Characteristics						
HoH Gender	-0.48***	-0.54***	-0.47***	-0.91	-1.07	-0.89
	(0.15)	(0.12)	(0.15)	(0.65)	(0.66)	(0.65)
Education	-0.65**	-0.50*	-0.63**	-3.20***	-2.40**	-3.23***
	(0.26)	(0.26)	(0.26)	(1.17)	(1.17)	(1.15)
Respondent Age	0.38***	0.34***	0.39***	1.12***	0.99**	1.14***
	(0.12)	(0.10)	(0.12)	(0.41)	(0.38)	(0.42)
Household Size	0.79***	0.63***	0.78***	2.78***	2.24***	2.77***
	(0.09)	(0.08)	(0.09)	(0.32)	(0.30)	(0.32)
Panel (c): Additional Household Covariates						
No Agriculture		0.14			0.00	
		(0.11)			(0.40)	
Safe Water		-0.92***			-3.14***	
		(0.15)			(0.47)	
Electricity		-1.56***			-4.64***	
		(0.18)			(0.52)	
Natural Disasters		0.67***			2.76***	
		(0.19)			(0.60)	
Intra-household Shock		1.46***			2.71***	
		(0.15)			(0.41)	
Economic Shock		0.87***			3.74***	
		(0.15)			(0.42)	
Man-made Shock		0.86***			2.21***	
		(0.13)			(0.61)	
Panel (d): Territory–level Climate Indicators						
Precipitations			-0.01*			-0.04*
			(0.01)			(0.02)
Temperature			0.67			1.57
			(0.75)			(2.06)
Droughts			-0.43***			-0.35
			(0.13)			(0.36)
Conflict Events			0.02			-0.02
			(0.01)			(0.06)
Control Mean	6.00	6.00	6.00	13.18	13.18	13.18
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.13	0.06	0.07	0.13	0.07
Observations	7,789	7,787	7,789	5,776	5,774	5,776

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (1), DIEM–DRC rounds. Columns (1)–(3) use the Food Insecurity Experience Scale (FIES) as the dependent variable; columns (4)–(6) use the reduced Coping Strategies Index (rCSI). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table (6.3): Self–reported Exposure to Flood and Food Security Outcomes: HHS and PSFI

	(1) HHS	(2) HHS	(3) HHS	(4) SFI	(5) SFI	(6) SFI
Panel (a): Exposure Effect						
Flood	0.24***	0.31***	0.24***	0.04***	0.06***	0.04***
	(0.07)	(0.06)	(0.07)	(0.02)	(0.01)	(0.02)
Panel (b): Household Characteristics						
HoH Gender	-0.16**	-0.17***	-0.16**	-0.04***	-0.04***	-0.04***
	(0.06)	(0.05)	(0.06)	(0.01)	(0.01)	(0.01)
Education	-0.26***	-0.21**	-0.25***	-0.04	-0.03	-0.04
	(0.09)	(0.09)	(0.09)	(0.02)	(0.02)	(0.02)
Respondent Age	0.11**	0.10***	0.11***	0.01	0.01	0.01
	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
Household Size	0.25***	0.20***	0.25***	0.05***	0.04***	0.05***
	(0.04)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)
Panel (c): Additional Household Covariates						
No Agriculture		0.09**			0.02*	
		(0.04)			(0.01)	
Safe Water		-0.35***			-0.07***	
		(0.05)			(0.01)	
Electricity		-0.49***			-0.09***	
		(0.06)			(0.01)	
Natural Disasters		0.12*			0.02	
		(0.06)			(0.01)	
Intra-household Shock		0.38***			0.06***	
		(0.06)			(0.01)	
Economic Shock		0.23***			0.05***	
		(0.05)			(0.01)	
Man-made Shock		0.20***			0.02*	
		(0.04)			(0.01)	
Panel (d): Territory–level Climate Indicators						
Precipitations			-0.00**			-0.00
			(0.00)			(0.00)
Temperature			0.25			0.11*
			(0.25)			(0.06)
Droughts			-0.12***			-0.01
			(0.04)			(0.01)
Conflict Events			0.01			0.00
			(0.00)			(0.00)
Control Mean	1.26	1.26	1.26	0.17	0.17	0.17
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.11	0.06	0.04	0.08	0.04
Observations	7,789	7,787	7,789	7,675	7,673	7,675

Notes: Two-way fixed effects estimates from equation (1) using Sub–Sample (1), DIEM–DRC rounds. Columns (1)–(3) use the Household Hunger Scale (HHS) as the dependent variable; columns (4)–(6) use the probability of severe food insecurity (SFI). Panel (a) reports associations between a binary self-reported flood exposure indicator and each outcome. Panel (b) adds household characteristics; Panel (c) adds additional household-level controls; Panel (d) adds territory-level climate indicators. All regressions include round and territory fixed effects. Standard errors (in parentheses) are clustered at the territory level (80 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix (4): Exposure to Natural Disasters: Average Treatment Effects

Figure (1.4): Natural Disasters Driven Displacement in DRC

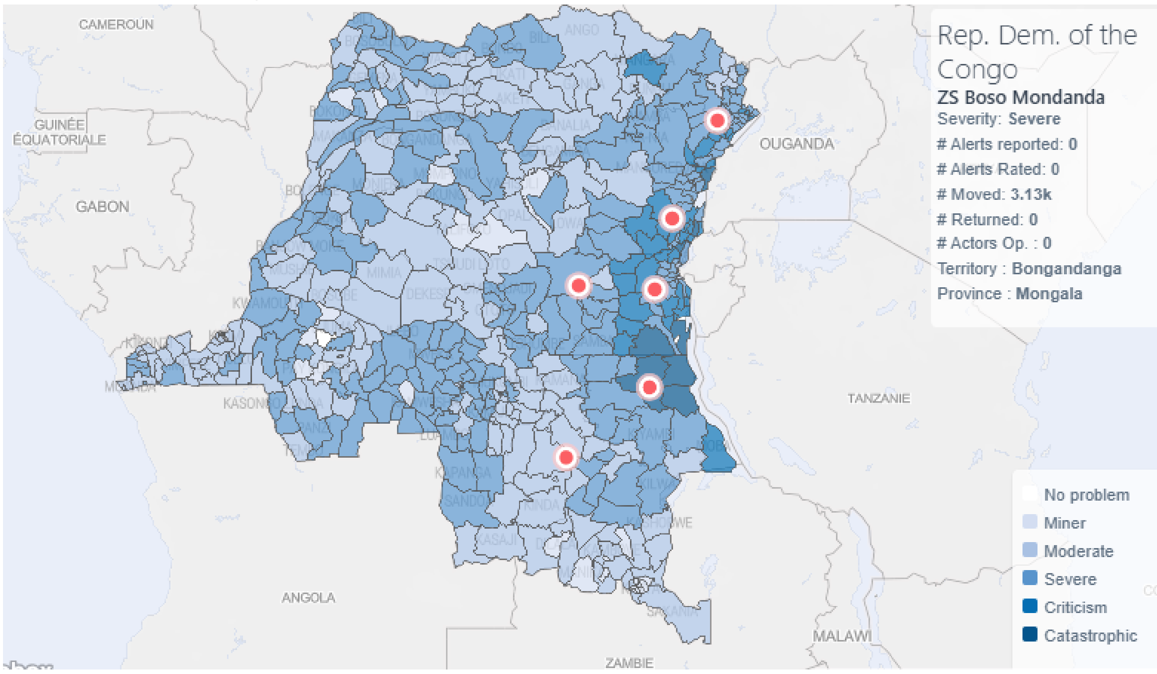


Table (1): Flood Exposure: Timing and Spatial Distribution

a). Staggered Flood Treatment

Exposure time	Control	Treated	Total
Apr–May 2022	780	0	780
Sep–Oct 2022	865	0	865
May–Jun 2023	784	166	950
Jan–Feb 2024	282	627	909
Jul–Aug 2024	465	2,676	3,141
Jan–Mar 2025	599	3,156	3,755
Jun–Jul 2025	0	3,318	3,318
Total	3,775	9,943	13,718

b). Sample Distribution by Province (adm1)

Province (adm1)	Freq.	Percent	Cum.
Ituri	5,655	33.02	33.02
Nord-Kivu	4,170	24.35	57.36
Sud-Kivu	3,870	22.59	79.96
Tanganyika	3,433	20.04	100.00
Total	17,128	100.00	

c). Flood Exposure by Territory (adm2)

Territory (adm2)	Freq.	Percent	Cum.
Ever flooded territories (19)			
Bukavu	937	5.47	11.65
Djugu	954	5.57	26.43
Goma	945	5.52	31.95
Kabalo	461	2.69	40.66
Kabare	605	3.53	44.20
Kalehe	547	3.19	47.39
Kalemie	810	4.73	52.12
Kongolo	509	2.97	55.09
Lubero	551	3.22	58.31
Manono	497	2.90	61.21
Masisi	512	2.99	64.20
Moba	556	3.25	67.45
Nyiragongo	533	3.11	70.56
Nyunzu	600	3.50	74.06
Rutshuru	556	3.25	77.31
Shabunda	461	2.69	80.00
Uvira	537	3.14	83.14
Walikale	518	3.02	86.16
Walungu	569	3.32	89.48
Never flooded territories (7)			
Aru	1,058	6.18	95.66
Bunia	1,023	5.97	101.63
Butembo	555	3.24	104.87
Idjwi	214	1.25	106.12
Irumu	818	4.78	110.90
Mahagi	972	5.67	116.57
Mambasa	830	4.85	121.42
Total	17,128	100.00	

Source: *OCHA-DRC*; https://ehtools.org/.

Table (2): Effects of shock on food security indicators–FLEXDiD

Outcome (Covariates)	Specification	Full sample		Sample (1)		Sample (2)	
		All	Residents	All	Residents	All	Residents
Panel (a): FCS and HDDS							
FCS (No covariates)	Leads–lags	0.38 (0.86)	1.49 (0.50)	-2.71 (0.04)	-2.98 (0.05)	1.99 (0.44)	3.47 (0.18)
	Lags only	1.73 (0.20)	2.06 (0.14)	-0.92 (0.30)	-1.02 (0.31)	3.26 (0.03)	3.64 (0.02)
FCS (Covariates)	Leads–lags	0.55 (0.80)	1.59 (0.45)	-2.17 (0.13)	-2.45 (0.12)	1.77 (0.49)	3.21 (0.20)
	Lags only	1.49 (0.27)	1.80 (0.18)	-0.78 (0.40)	-0.87 (0.38)	2.74 (0.08)	3.14 (0.04)
HDDS (No covariates)	Leads–lags	-0.16 (0.49)	-0.08 (0.71)	-0.25 (0.32)	-0.23 (0.41)	-0.20 (0.47)	-0.11 (0.68)
	Lags only	-0.15 (0.35)	-0.11 (0.54)	0.13 (0.52)	0.19 (0.40)	-0.17 (0.37)	-0.14 (0.50)
HDDS (Covariates)	Leads–lags	-0.15 (0.52)	-0.08 (0.73)	-0.28 (0.21)	-0.28 (0.28)	-0.19 (0.49)	-0.11 (0.68)
	Lags only	-0.14 (0.31)	-0.11 (0.42)	0.10 (0.60)	0.14 (0.49)	-0.19 (0.31)	-0.16 (0.42)
Panel (b): FIES and rCSI							
FIES (No covariates)	Leads–lags	-0.66 (0.03)	-0.78 (0.01)	0.41 (0.08)	0.44 (0.03)	-1.05 (0.01)	-1.15 (0.01)
	Lags only	-0.61 (0.01)	-0.68 (0.00)	0.29 (0.16)	0.31 (0.12)	-0.78 (0.00)	-0.81 (0.01)
FIES (Covariates)	Leads–lags	-0.72 (0.02)	-0.84 (0.01)	0.26 (0.32)	0.28 (0.20)	-1.06 (0.01)	-1.14 (0.01)
	Lags only	-0.48 (0.01)	-0.54 (0.00)	0.23 (0.32)	0.24 (0.25)	-0.73 (0.00)	-0.76 (0.00)
rCSI (No covariates)	Leads–lags	0.53 (0.62)	1.05 (0.32)	0.18 (0.81)	-0.08 (0.91)	-0.11 (0.92)	-0.14 (0.90)
	Lags only	0.31 (0.73)	0.12 (0.89)	0.79 (0.32)	0.48 (0.53)	-0.44 (0.66)	-0.49 (0.63)
rCSI (Covariates)	Leads–lags	0.92 (0.40)	0.40 (0.71)	0.37 (0.65)	0.09 (0.91)	0.41 (0.75)	0.12 (0.93)
	Lags only	0.61 (0.39)	0.20 (0.78)	0.38 (0.63)	0.14 (0.85)	-0.47 (0.67)	-0.52 (0.64)
Panel (c): P_SFI and HHS							
P_SFI (No covariates)	Leads–lags	-0.03 (0.21)	-0.04 (0.16)	0.03 (0.07)	0.04 (0.03)	-0.07 (0.04)	-0.07 (0.04)
	Lags only	-0.06 (0.05)	-0.07 (0.04)	0.05 (0.02)	0.05 (0.01)	-0.08 (0.05)	-0.08 (0.05)
P_SEV (Covariates)	Leads–lags	-0.04 (0.13)	-0.04 (0.10)	0.03 (0.12)	0.05 (0.03)	-0.06 (0.05)	-0.06 (0.07)
	Lags only	-0.02 (0.16)	-0.03 (0.12)	0.04 (0.06)	0.04 (0.03)	-0.07 (0.03)	-0.08 (0.03)
HHS (No covariates)	Leads–lags	-0.13 (0.20)	-0.17 (0.12)	0.14 (0.11)	0.18 (0.05)	-0.20 (0.06)	-0.22 (0.04)
	Lags only	-0.19 (0.05)	-0.22 (0.03)	0.18 (0.04)	0.21 (0.02)	-0.25 (0.03)	-0.27 (0.02)
HHS (Covariates)	Leads–lags	-0.15 (0.15)	-0.19 (0.09)	0.21 (0.09)	0.27 (0.03)	-0.26 (0.04)	-0.28 (0.04)
	Lags only	-0.09 (0.17)	-0.11 (0.09)	0.15 (0.09)	0.18 (0.04)	-0.23 (0.03)	-0.25 (0.02)

Notes: The table reports FLEXDiD ATETs from lags–leads and lags only specifications for the main food security outcomes. Treatment is defined by exposure to floods that displace more than 10,000 people. P_values in parenthesis. Covariates are *Household Size, Head of household education and gender*. Standard errors clustered at territory level (80 clusters in the full sample and sample (1), 26 clusters in sample (2). All FLEXDiD main fixed effects included.

Appendix (5): Average Treatment Effects for FIES and rCSI Components

Figure 14: FIES (1) and (2)

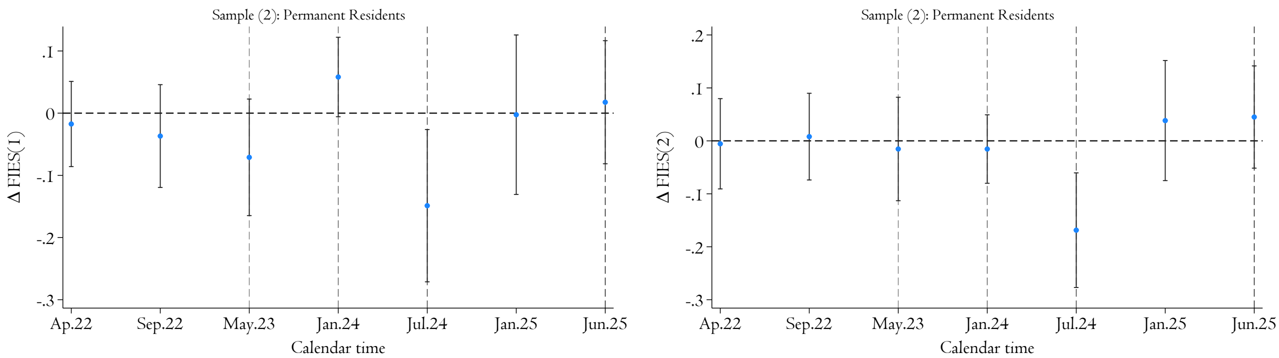


Figure 15: FIES (3) and (4)

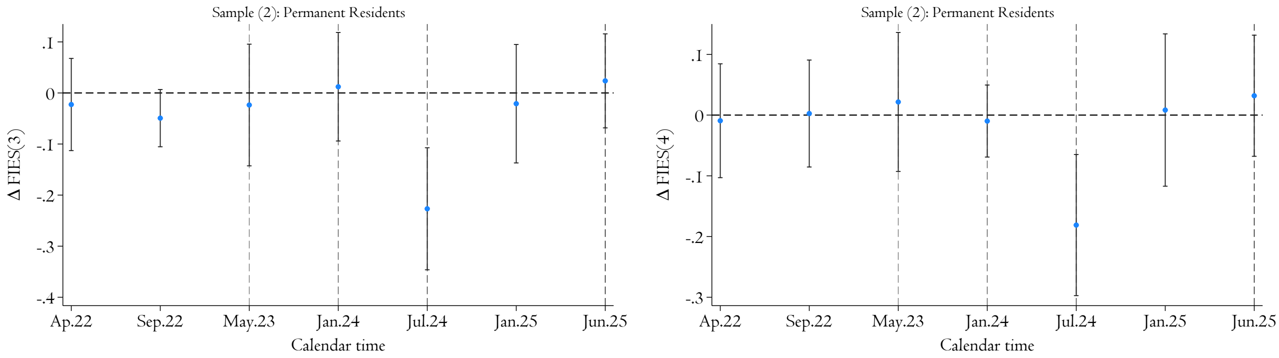


Figure 16: FIES (5) and rCSI (1)

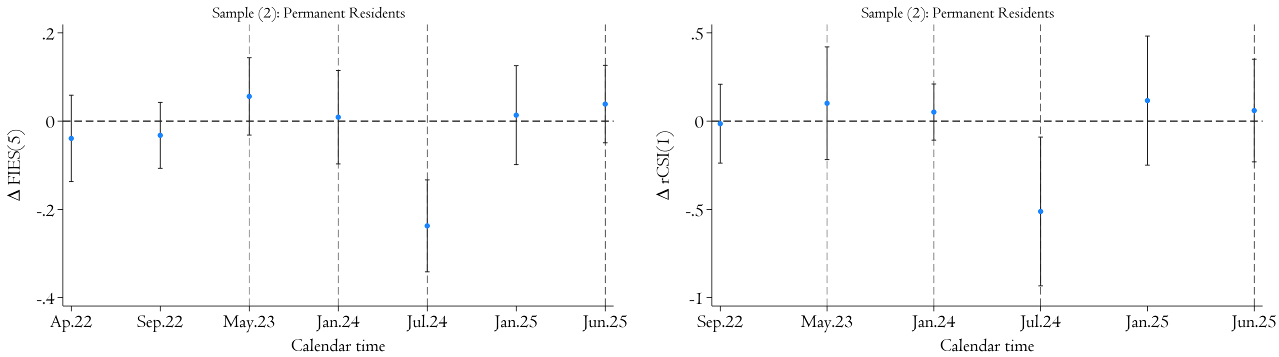


Figure 17: rCSI (2) and (3)

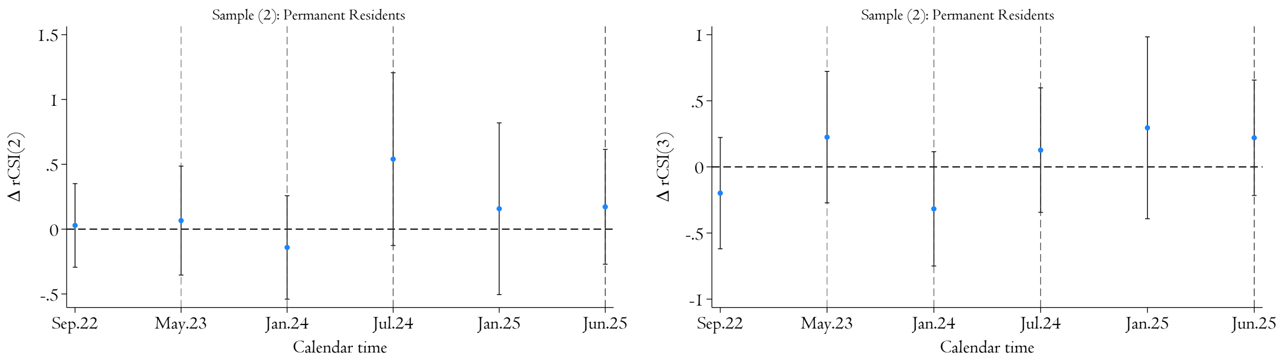


Figure 18: rCSI (4) and (5)