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Combined Effects of Weather and Health Shocks on Consumption in Rural Uganda

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Abstract

Background

Compound and cascading shocks are common in rural areas and pose significant threats to food security and household welfare. While the importance of these combined shocks for rural communities is gaining attention, there is still very limited empirical research on the topic. This paper aims to assess the combined effects of weather and health shocks on the food, non-food, and total consumption of rural households in Uganda. Our analysis uses customized high-frequency panel household survey data collected across six waves, employing fixed effects quantile regression methods.

Results

The findings indicate that a short-term increase in temperature leads to a reduction in total consumption by 12–16%, with a more pronounced lagging effect on food consumption, which can be as high as 30%. Similarly, excessive rainfall adversely affects food consumption and diet diversity. The combined effects of health and weather shocks on consumption are negative and significant for lagged interaction terms, exhibiting varied effects across different household categories. Notably, the poorest quartile experiences the most substantial negative effects. Additionally, the findings reveal considerable consumption mobility among rural households over a 12-month period. Even households in the richest quartile may find themselves in the lowest consumption categories at certain times of the year. To manage these fluctuations in consumption, the poorest quartiles tend to rely on group networks and loans, while wealthier quartiles more frequently utilize remittances.

Conclusion and policy implications

Recognizing Uganda's vulnerability to extreme weather events and epidemics, this paper suggests key policy measures. Enhancing social protection through access to credit, social networks, safety nets, and health insurance can help households cope with climate challenges. These strategies will strengthen food system resilience and promote sustainable development.

1. Introduction

Extreme weather events and health challenges present significant risks for rural farming households in low—and middle-income countries (LMICs). These risks, whether individually or in combination, can limit economic opportunities and increase costs, such as medical expenses related to illness and the depletion of assets. This can lead to substantial reductions in consumption, potentially creating vicious cycles of hunger and poverty. The effects of various shocks can differ significantly around the world. In advanced economies, socio-economic and health risks may sometimes have a more pronounced impact than environmental shocks, such as long-term climate change or acute extreme weather events (1, 2). However, the situation differs in low- and middle-income countries (LMICs). In these regions, climate-related threats are equally critical, particularly to rural households. These climate threats affect crop yields, income, water access, food availability (3–6), and overall rural poverty (7) and health (8, 9).

The vulnerability of rural households in Sub-Saharan Africa (SSA) to the adverse effects of weather and health shocks primarily stems from their heavy reliance on agricultural-based livelihoods and the lack of access to formal insurance and credit markets. Additionally, markets are often incomplete, and governments do not provide adequate public social safety nets. For example, countries in sub-Saharan Africa spend an average of only US$16 per citizen annually on safety net programs (10). The benefits of these safety nets, expressed as a share of income or consumption, are particularly low in low-income nations, estimated at just 13% (10). Similarly, the insurance industry in Africa is still in its infancy. In 2017, insurance penetration in many countries was below average, with more than half of the SSA countries, including Uganda, reporting less than 1% penetration rates (11). This situation leaves households ill-equipped to adapt to and cope with the regular seasonal variations in consumption and health (12), resulting in limited resilience to shocks.

Given the increasing frequency, intensity, and duration of weather and climate-related shocks worldwide, it is crucial to understand their impact on vulnerable populations. Recent studies highlight that while increased rainfall can enhance consumption levels, insufficient rainfall tends to have detrimental effects (13, 14). Furthermore, research indicates that greater variability in rainfall can

lead to notable reductions in both consumption and overall life satisfaction (15). Furthermore, several studies document the harmful effects of rising temperatures on consumption (13, 16).

The literature identifies several pathways in which weather variability impacts consumption. High temperatures and low rainfall can lead to food shortages due to decreased agricultural and total factor productivity (14, 16). Furthermore, droughts and other climate-related shocks can affect agricultural prices (17, 18) and income (15, 19), which in turn can have a direct effect on consumption. There is a growing body of empirical evidence examining how climate and weather shocks influence the nutritional quality of foods and dietary diversity (20–22). Some studies have focused on the effect of seasonality—indirectly capturing weather events—on food security measures. These studies have reported significant seasonality in food prices and various food security measures, including household dietary diversity, especially in rural areas (23, 24). Overall, climate-related shocks have negative effects on all four dimensions of food security (25).

A separate body of literature examines the relationship between health shocks and consumption (26–30). These studies report mixed results regarding the effects of health shocks on consumption (both food and non-food) and other economic outcomes among rural households. For example, study (29) finds significant negative effects of health shocks on food consumption, while study (28) identifies significant negative effects on food expenditures only among households that experienced income loss or substantial expenses due to illness. Interestingly, in some studies, the food expenditures of households facing short-term health shocks remained unaffected (28). Similarly, study (31) reports that adult mortality did not influence food expenditures, whereas study (30) notes that although the overall effect of illness was insignificant for total food consumption, purchased food was negatively affected by illness. In contrast, study (27) finds positive and insignificant effects of injury on food consumption before 2002 but a significant negative effect after 2002. Regarding diet quality, adult mortality decreased the variety of unique foods consumed, particularly among poorer households, although the total number of food groups remained unaffected by illness (31).

The effect of health shocks on non-food expenditures shows mixed results. For example, some studies report that rural households experience increased spending on electricity and housing items following a health shock (29). Additionally, there is evidence of a positive and significant effect of health shocks on non-food consumption in specific contexts (28). Conversely, other research consistently finds negative effects of health shocks on non-food consumption (26, 30). It is important to note, however, that significant negative effects were only observed in relation to the activities of daily living (ADL) index, rather than illness symptoms (26). Furthermore, one study reported negligible effects of mortality on non-food consumption (31). The variation in these findings can be attributed to the different categories of consumption examined, the specific health measures used, and the mechanisms explored.

The effects of weather variability on consumption and health have traditionally been studied in isolation, which can limit our understanding of their interconnectedness. This research aims to enhance the existing literature by examining the simultaneous effects of weather and health shocks on consumption patterns. While existing studies have primarily examined these factors separately with limited attention to how they interact, one notable study has looked at both shocks simultaneously (32). This study examined the financial burden of drought-related health outcomes through medical expenditures, paving the way for further exploration in this area (32).

This research utilizes innovative intra-annual & intra-seasonal high-frequency panel data collected every two to three months. This approach allows us to investigate the short-term connections between health shocks and consumption more effectively. Furthermore, the study focuses on the institutions and mechanisms households use to mitigate the effects of health shocks.

The primary objective of this study is to assess how extreme weather events and illnesses—individually and collectively—affect rural household consumption while also uncovering the mechanisms behind these effects. To achieve this, we seek to answer several critical research questions: (1) What effect do extreme weather, illness, and weather-induced illness have on total household consumption and food and non-food expenditures? (2) What underlying mechanisms drive these effects? (3) How do the effects of these shocks differ across various rural households? Additionally, the study offers insights into households' coping and risk-sharing strategies to manage these challenges. By addressing these questions, we hope to contribute valuable knowledge that can inform policy and support rural communities in navigating the complex interplay between health, weather events, and consumption.

The remainder of this paper is organized as follows: Section 1.1 introduces the theoretical frameworks. Section 2 discusses the materials and methods, including data sources, variables, descriptive statistics, and the empirical framework. The empirical results

are presented in Section 3, while Section 4 provides relevant discussions and conclusions.

1.1 Theoretical Framework

This study is guided by the theory of full insurance (also known as complete market hypothesis), which states that full insurance is Pareto efficient, i.e., households' consumption growth rate will be independent of shocks - especially idiosyncratic risks such as illness affecting household resources and income (30, 33, 34) - if households group themselves to share and manage risks (35) perfectly. This implies that risk-averse households are protected from idiosyncratic risks, and household consumption will only depend on community average consumption given that preferences do not change frequently (Islam & Maitra, 2012). However, this theory predicts that consumption is uninsured against covariate shocks that adversely affect communities or group of households within a community. Therefore only idiosyncratic shocks are insured through risk-sharing models (36).

The specification for this test, according to (33) is as follows;

$$\log\left(\frac{C_t^j + 1}{C_t^j}\right) = \sigma + \beta X_{t+1}^j + \varepsilon_{t+1}^j, \qquad j = 1, 2, 3 \ldots N$$

Where $C_t^j + 1$, C_t^j is household consumption growth for household j, and X_{t+1}^j is an idiosyncratic shock.

Most rural households, especially in LMICs, use different formal and informal risk-sharing mechanisms such as informal networks, borrowing, savings, markets, insurance contracts, and technologies either jointly or singly for consumption insurance when faced with a health burden such as major illness or other shocks that have economic consequences on the households. In general, the literature shows that the complete market hypothesis has been rejected in least-developed countries by most empirical studies (36, 37) (De Weerdt & Dercon, 2006; Nguyen et al., 2019).

Other coping mechanisms in rural areas include participation in extra income work, e.g., casual (36), and asset smoothing, which is guided by an alternative theory, Asset Smoothing Theory (AST), proposed by (38). The AST predicts that rather than consumption smoothing, households, especially those who are poor, smooth productive assets such as livestock (36) when faced with shocks. Furthermore, households' behaviors are different when faced with an income shock, and some are predicted to invest in productive assets, even if this requires a reduction in consumption (38), while others (above the Micawber threshold) are predicted to deplete assets to smooth consumption (36). AST tests are, however, restrictive to homogenous farming households where livestock are the main productive assets and farming is the main source of income, and even for studies that have considered the diversity of assets, they assume imperfect sharing constraints (36). In addition, AST is restrictive to households with no access or limited access to labor and credit markets. Yet, informal credit is popular in rural areas of LMICs (36), and gifts in the form of cash, kind, and labor as a common form of sharing the risk, achieved through networks such as local groups (37).

Consumption smoothing is a welfare enhancing mechanism practiced by risk-averse households in response to shocks, and is one of the policies to enhance resilience. Labor markets outside the agricultural sector, insurance against weather risks such as drought and floods, and government interventions related to insurance and compensation are some of the mechanisms that may help households to insure against different types of covariate shocks (36).

2. Materials and Methods

2.1 Data Sources

2.1.1 Household High-Frequency Panel Survey (HFPS)

The study employs primary data collected in collaboration with the College of Agricultural and Environmental Sciences (CAES) at Makerere University and the Center for Development Research (ZEF) at the University of Bonn. Data collection for the panel dataset occurred between June 2020 and August 2021, involving six waves of surveys administered every 2 to 3 months. The surveys took place in June/July, September, December, March, May, and August of both 2020 and 2021, as detailed in Table 1. The SARS-CoV-2 pandemic partly influenced the timing of these surveys. Given the short-term fluctuations in food availability and accessibility for

rural households in developing countries, seasonality was crucial in determining when to conduct the surveys. Additionally, seasonality significantly impacts the spread of diseases (39).

Table 1
Dates of high frequency survey rounds

Survey rounds	Survey start dates	Number of households
Round 1 (Baseline)	22 June 2020	638
Round 2	31 August 2020	637
Round 3	14 December 2020	633
Round 4	01 March 2021	631
Round 5	10 May 2021	626
Round 6	7th August 2021	623

[Table 1 **near here]**

The questionnaires were administered by trained and experienced enumerators through face-to-face interviews with the selected respondents using a computer-assisted personal interviewing (CAPI) tool. Comprehensive information was collected in each wave concerning key elements such as asset and livestock ownership, shocks, health indicators, income, family labor allocation, consumption of food and non-food items, household demographics, social participation, maternal and child diets, and food security indicators.

The sampling strategy was multi-stage sampling strategy[1]. The study was conducted in eight districts across three regions of Uganda: North, East, and West. These districts were purposefully selected due to the recent occurrence of either climate or price shocks. The selected districts include Kole, Lira, Kamwenge, Kisoro, Kotido, Moroto, Sironko, and Bududa. A comprehensive sampling frame, which included all sub-counties, parishes, and villages within each district, was obtained from the Uganda Bureau of Statistics (UBOS). Four sub-counties were then randomly selected from each district for the study.

All parishes in the selected sub-counties were eligible to participate in the study. However, only 25 percent of the villages within each parish were randomly selected, excluding those located within town councils. A sampling frame of households in these selected villages was compiled by researchers at Makerere University in collaboration with community leaders. A probability proportionate to size sampling strategy was then employed to select 80 households per district. In total, 640 households were selected from eight districts, as illustrated in Fig. 1, and were considered for data collection. After excluding duplicates, data were collected from 638 unique households during the baseline survey. Throughout the subsequent waves, attrition rates remained low, with a maximum of 2% from the first to the last wave. However, we only included a balanced dataset of 621 households for our analysis.

2.1.2 Weather Data

We use publicly available rainfall and temperature datasets. Using the georeferenced household data from the Household Panel Survey (HFPS), we matched each household with temperature and rainfall data. The rainfall datasets utilized were derived from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) version 2, covering the period from 1990 to August 2021. Temperature data was collected from the Moderate Resolution Imaging Spectroradiometer (MODIS) for the years 2000 to 2021.

Figure 2 presents the average monthly rainfall patterns along with the annual average rainfall (measured in millimeters) for the sampled districts. On average, the year the survey began (2020) was the wettest on record for the sampled areas. However, there were regional variations; notably, higher rainfall was recorded mainly in Sironko and Bududa, as illustrated in Fig. 2b. The Moroto and Kotido districts also experienced increased rainfall in 2020 compared to previous years, while rainfall amounts in Lira and Kole were nearly the same as in 2019.

Kotido and Moroto districts experience a unimodal pattern of rainfall, with relatively good precipitation occurring from April to October. In contrast, the other districts receive a bimodal type of rainfall. In these districts, harvesting typically takes place in June

and July (see Figure S1 in the supplementary materials). However, the timing of the second harvest season can vary depending on the specific district and the types of crops that are planted.

2.2 Data Variables

The primary outcome variable of the study is the total consumption per adult equivalent. This value includes the mean of all food consumed by the household, as well as non-food expenditures, excluding medical expenses, divided by the adult equivalent.

Food consumption encompasses all foods and beverages consumed from purchases made both at home and away, food sourced from personal production, and food received as gifts over the past seven days. Non-food consumption is categorized into non-durable goods, frequently purchased services, semi-durable goods, durable goods, and expenditures not related to consumption. Data on non-food expenditures are collected over a two-month recall period.

To create a total consumption variable, the value of food items consumed in the past seven days is scaled to reflect a two-month period. This approach aligns with similar methods previously used to calculate total food consumption with varying recall periods (15, 28).

The household dietary diversity indicator is computed from the household food consumption expenditure section where different food elements consumed in the previous 7 days are grouped into 12 food groups (40), and aggregated at household to compute the total count of food groups. These food groups include; cereals (1), roots and tubers, including cooking bananas (2), legumes and pulses (3), vegetables (4), fruits (5), meat and offal (6), fish and fish products (7), eggs (8), milk and milk products (9), oils and fats (10), sugar and honey (11), and others/beverages/miscellaneous (12).

The primary explanatory variables in this study include short-term health indicators and weather shocks, which correspond to the recall period for consumption. Two health shocks are derived from the health module, where household members reported their experiences with illness and injury over the past two months. The first health measure is a binary variable indicating whether any household member was sick for more than 30 days. The second measure is another binary variable that indicates whether any household member was hospitalized for at least one night due to illness or injury. Previous studies have utilized self-reported health measures to construct health variables and to define shocks based on the number of days of illness or the number of days household members were unable to carry out their usual activities due to health issues (29, 41).

The weather shock measures are derived from rainfall and temperature data, specifically z-scores of these weather variables based on two-month rolling averages. These measures are used in the main analysis. Additionally, we conduct separate regressions using shock measures defined by dummy variables created from the z-scores of temperatures and rainfall.

This study focuses on extreme rainfall events, specifically those where the z-score for rainfall is greater than 1. Thus, a dummy variable of 1 indicates that the rainfall level is at least one standard deviation above the long-term average. For temperature, we also use z-scores with a cutoff of + 1 to define extremely hot conditions.

Previous studies used different weather shock measures. For instance, (42) did not specify any cut-off for their first measure but rather defined their negative shock measure based on any negative deviation from long-term mean while the other categorical shock measure was based on the percentiles. Similarly, (43) and (44) define their rainfall shock measures (positive and negative rainfall shocks) based on any level of deviation from the long-term mean, even though the latter study computed the standardized z scores. While (16) defined temperature and precipitation shocks based on standardized z scores, (14) defined their rainfall shock measures using dummy variables based on the standardized score, i.e. if the deviation from the long-term mean was greater than + 0.5 or -0.5 for positive and negative rainfall shocks respectively. This was informed by their argument that any anomaly of weather variables from the long-term average may not necessarily capture a shock. To this end, we use both the z scores and shock measures based on z scores cutoff points. Furthermore, we consider both the shocks in the current year and their first lag in all estimations given that some shocks may have lagged effect. Previous studies that have use lagged values of their main explanatory variables include (43, 45, 46).

2.3 Empirical Framework

To address the objective of this study, which is to estimate the effect of weather shocks, health-related weather shocks, and their interactions on household consumption, we utilized fixed effects models for our main analysis. The primary outcomes of the study

are continuous variables: food consumption, non-food consumption, and total consumption per adult equivalent. Additionally, we consider household dietary diversity as a measure of diet quality. Our dataset is longitudinal and was collected over six time periods, which is why we employed panel estimators. As a starting point, we estimate the relationship between changes in outcome variables and changes in weather, illness, and the interaction between both weather and illness. This approach allows us to determine whether the hypothesized relationship exists before explaining the mechanisms through which these effects occur. The general specification of the panel data model is as follows, with 'i' indexing households and 't' representing the time.

$$C_{it} = \alpha + \beta_1 H_{it} + \beta_2 H_{it-1} + \beta_3 W_{it} + \beta_4 W_{it-1} + \beta_5 (W_{it} \times H_{it}) + \beta_6 (W_{it-1} \times H_{it-1}) + \beta_7 X_{it} + \beta_8 S_{it} + \epsilon_{it}$$

1

Where C_{it} is consumption value for household i for time t regressed against health measures (H_{it}) and extreme weather events (W_{it}) for a given household. Lagged values of different shocks (H_{it-1}), W_{it-1}) and the interactions effects are also included in the model. Our main coefficient of interests is on the interaction term β_5 and β_6 which indicates the effect of health outcomes on consumption based on weather characteristics in the current and previous waves. Additionally, coefficients β_1, β_2, β_3 and β_4 on health and weather shocks are of interest to the study. All our explanatory variables of interest are time varying. X_{it}denotes time-variant characteristics such as assets and livestock value, among others. Different self and mutual insurance consumption mechanisms are denoted by S_{it} and they include social networks (membership in groups), access to loans, remittances, and free medical services. The error term is denoted by ϵ_i which captures household-specific unobserved components. Standard errors are clustered at the district level

We fit the above estimation using fixed effects (within estimator) which strictly excludes time-invariant variables. The time-constant variables are removed through the subtraction process. Time demeaning eliminates individual-specific unobserved effects that might be correlated with other independent variables in the model. The ability to overcome omitted variable bias and obtain consistent estimators is one attractive advantage of using a fixed effects model. We repeat these estimations with household diet diversity as a dependent variable and use the fixed effect Poisson model. Both shocks in the contemporaneous period, their first lag, and all interactions are estimated in one model, for each estimation. Furthermore, wave fixed effects are included in the main estimation. The model with all these variables is treated as our base model given the lower AIC and BIC as compared to models excluding some of the variables.

There are several mechanisms through which weather-related illnesses can affect consumption. To establish this connection for the second research question, we estimate an equation with medical expenditures, labor, and earnings as the dependent variables. Since a significant number of households did not report any wage labor income or health expenditures, we employ a panel random effects Tobit model and include fixed effects for person-days in our analysis. The general equation for this estimation is as follows;

$$L_{it} = \alpha + \vartheta_1 H_{it} + \vartheta_2 H_{it-1} + \vartheta_3 W_{it} + \vartheta_4 W_{it-1} + \vartheta_5 W_{it} * H_{it} + \vartheta_6 W_{it-1} * H_{it-1} + \vartheta_7 X_{it} + \epsilon_i$$

The explanatory variables remain as earlier explained in previous equations. L_{it} represents either wage labour income, health expenditures and family agricultural labour supply in terms of person days. Coefficient of interest is on the interaction term consisting of weather and health variables (ϑ_5 & ϑ_6) as well as on health and weather covariates (ϑ_1, ϑ_2, ϑ_3 & ϑ_4).

In order to explore the effect of our main explanatory variables on the entire distribution of our main response variables (consumption), we adopt panel quantile regressions methods including individual effects. Quantile regressions ($Q_y (\tau \mid X)$ enables examination of the distributional and heterogeneous effects across different quantiles and are more suitable in presence of outliers (47). In this study, we employ fixed effects Method of Moments Quantile Regression (MMQR) proposed by (48), effective for panel data models.

3. Results and Discussion

3.1 Descriptive Statistics

The socio-demographic, economic, and weather characteristics of the sampled households across the six waves are presented in Table S1 of the supplementary materials. The findings indicate that the average household size was approximately seven members per wave. A significant proportion of households faced floods or experienced extremely high rainfall during the second and third

waves compared to the other waves. According to objective weather measurements, 44% of households reported excessive rainfall in the second wave. Additionally, in wave six, 23.8% of households experienced extreme temperatures, defined as temperatures greater than one standard deviation from the long-term mean for that month..

Sickness was a common issue, with at least 71% of households reporting that at least one member had been ill in the past two months. More households reported illnesses during wave two, while households in wave six reported fewer instances of sickness. This trend is evident in both the proportion of affected households and the total number of illness days and workdays lost due to illness. Additionally, a higher proportion of households in waves two and three reported that at least one member had been hospitalized due to illness. It is likely that extreme rainfall contributed to the high incidence of sickness in these households, as a significant number of households experiencing both extreme rainfall and illness were found in waves two and three. In contrast, wave six recorded a lower prevalence of sickness and fewer flood events.

Health expenditures were highest during wave two, followed by waves one and three. Approximately 22% of households received free medical services. Regarding labor force participation, over half of the households engaged in wage-related activities across all waves. However, participation was notably higher in waves five and two, with 65% and 63% of households, respectively, involved in wage labor markets. Similarly, income levels were greater in waves one, two, and four, while both participation and income received were lower in wave six. Total agricultural family labor was highest in wave five and lowest in wave two. The high levels of wage labour participation and family labour can be attributed to the seasonality of agricultural activities.

3.1.1 Primary outcome variables

According to Table S1, an average of 69% of total consumption expenditure was allocated to food items. The estimated average food consumption per adult equivalent was 157,829 UGX[2] (40 USD), while the value of non-food consumption (excluding medical expenditures) was 70,193 UGX (18 USD) over the past two months. Food consumption values were higher in waves one and two, whereas non-food consumption was greater in waves four and five. Wave one occurred during the harvest period, while wave two represented a transition period between harvest and planting. It is important to note that wave five had a lower food consumption value compared to other waves, as it fell during the lean season. Additionally, total and non-food consumption in both Wave One and Wave Six were low, which can be partially attributed to the COVID-19 lockdown measures.

On average, households had a dietary diversity of seven. However, there were significant regional differences in the number of food groups consumed. Households in the Kole, Lira, Bududa, and Sironko districts reported consuming eight food groups. In contrast, those in the Moroto and Kisoro districts consumed six food groups, while households in Kotido had a diet diversity of only five (as shown in Fig. 3).

3.1.2 Consumption Mobility

To assess consumption mobility and the persistence of poverty across various survey rounds, we analyze consumption matrices based on five classes (quintiles) of the total consumption distribution. The 5x5 consumption transition matrices illustrate the probabilities of households moving between different quintile classes. Each of these transition matrices is calculated using the logarithmic values of per adult equivalent total consumption, as we rely on log values for our empirical analysis. The figures on the diagonal of each matrix represent the percentage of households that remained in the same quintile, while the off-diagonal figures indicate the level of consumption mobility.

Table S2 of the supplementary materials reveals that 49% of households in poverty (quintile 1) during wave one remained in poverty by wave six, while 51% of households that were initially in the lower quintile moved out of poverty by wave six. This trend mirrors the mobility patterns observed from wave one to wave two. Most households that transitioned from the bottom quintile in wave two moved to quintile two (21%) and quintile three (14%), with only 6% advancing to the top quintile. The household diet diversity consumption matrix displays a similar pattern, indicating that a relatively higher number of households continued to remain in poorer quintiles over time. For example, 67% of households that were in the poorest quintile during wave four continued to be poor, as illustrated in Fig. 4. These findings align with observations that the lean period is the most challenging time of the year, during which the poor are at their most vulnerable and likely to fall deeper into poverty (39)Indeed, 33% of households in the second quintile and 14% from the third quintile in wave four experienced a decline in their economic status by wave five.

3.2 Empirical Results

Our primary focus is to establish the connection between extreme weather, illness, and the effect of shocks on consumption. As a starting point, we estimate this relationship without considering wave-fixed effects, with the results presented in Table S3. However, we prioritize the results in Table 2, which include wave-fixed effects, as our main estimation (the whole table, along with all other covariates, is provided in the supplementary materials, Table S4). The findings indicate that when a household member is sick for more than 30 days, there is no significant effect on total consumption, food consumption, diet diversity, or non-food consumption. Similar insignificant results were noted for the lagged effects of this shock measure on consumption. In contrast, the results for hospitalization show a positive and significant effect on both total and food consumption, while the lagged effects have a weakly significant influence on non-food consumption.

An increase in temperature and rainfall above the long-term average had negative effects on consumption, as illustrated in Table 2. Specifically, heightened rainfall led to a 5% reduction in total consumption and a 6% decrease in food consumption. However, the effect of rainfall on non-food consumption was insignificant. The lagged effects of rainfall were consistently inconsequential across all estimations. In contrast, an increase in temperature had significant negative effects on total consumption in both the current and previous periods. For food consumption, only the lagged temperature variables were significant. Interestingly, for non-food consumption, only the temperature from the current period had a significant effect, resulting in a 22% reduction.

Regarding extreme weather events, Table S5 in the supplementary materials indicates that exposure to high rainfall decreased food consumption by 14% and diet diversity by 5%. The lagged effects of extreme rainfall were insignificant, while the lagged effects of extreme temperature were consistently negative and significant across all estimations. The effect of lagged extreme temperature was notably greater than that of extreme temperature experienced in the current wave. Specifically, lagged extreme temperature reduced food consumption by 30%, non-food consumption by 27%, total consumption by 16%, and diet diversity by 6%.

Table 2: **Effect of health, weather shocks and their interactions on consumption and diet diversity**

	Total consumption		Food consumption		Nonfood consumption		HDDS	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sick more than 30 days (t)	0.018		0.043		-0.100		0.025	
	(0.039)		(0.032)		(0.066)		(0.016)	
Sick more than 30 days (t-1)	0.009		-0.001		0.052		-0.005	
	(0.030)		(0.026)		(0.031)		(0.013)	
Hospitalized (t)		0.057**		0.048**		0.058		0.009
		(0.021)		(0.016)		(0.044)		(0.012)
Hospitalized (t-1)		0.023		-0.011		0.090*		-0.016
		(0.015)		(0.015)		(0.044)		(0.011)
Rainfall z scores (t)	-0.051***	-0.052***	-0.056***	-0.057***	-0.021	-0.022	-0.014***	-0.014***
	(0.012)	(0.011)	(0.016)	(0.015)	(0.015)	(0.017)	(0.004)	(0.004)
Rainfall z scores (t-1)	-0.013	-0.013	-0.013	-0.012	0.020	0.013	0.004	0.002
	(0.010)	(0.009)	(0.018)	(0.017)	(0.014)	(0.016)	(0.004)	(0.005)
Temperature z scores (t)	-0.125**	-0.122***	-0.056	-0.056	-0.226***	-0.224***	0.022	0.022
	(0.037)	(0.033)	(0.054)	(0.051)	(0.044)	(0.043)	(0.015)	(0.015)
Temperature z scores (t-1)	-0.167***	-0.163**	-0.191**	-0.182**	-0.004	-0.011	-0.012	-0.013
	(0.047)	(0.049)	(0.066)	(0.067)	(0.066)	(0.077)	(0.015)	(0.016)
Sick 30days# rainfall (t)	-0.034		-0.034		-0.026		-0.012	
	(0.032)		(0.029)		(0.049)		(0.011)	
Sick 30days# temperature (t)	0.017		0.021		-0.104		0.000	
	(0.057)		(0.055)		(0.086)		(0.020)	
Sick 30days# rainfall (t-1)	-0.032		-0.026		-0.041*		-0.005	
	(0.023)		(0.024)		(0.019)		(0.008)	
Sick 30days# temperature (t-1)	-0.037		-0.012		-0.056**		-0.019	
	(0.045)		(0.048)		(0.023)		(0.016)	
Hospitalized #rainfall (t)		-0.012		-0.024		0.018		-0.007
		(0.035)		(0.027)		(0.066)		(0.008)
Hospitalized #temperature		0.005		0.015		-0.040		-0.005
		(0.038)		(0.036)		(0.054)		(0.015)
Hospitalized #rainfall (t-1)		-0.015		-0.024**		0.020		0.011
		(0.009)		(0.009)		(0.040)		(0.008)
Hospitalized #temperature (t-1)		-0.027		-0.056*		0.039		-0.010
		(0.030)		(0.026)		(0.101)		(0.017)

Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other variables [1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,105	3,105	3,105	3,105	3,105	3,105	3,105	3,105
R-squared	0.109	0.109	0.117	0.118	0.061	0.062	-	-
AIC	2697	2697	2548	2545	6251	6249	9033	9033
BIC	2740	2739	2590	2586.	6293	6291	9184	9184
Number of HHID	621	621	621	621	621	621	621	621

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Columns 1 -6 clustered at district level and fixed effects regression while columns 7-8 robust standard errors reported for the FE Poisson model. Columns 1 ,3, 5 & 7 are regressions with sick days used as a health measure on total, food, non-food and HDDS while columns 2, 4, 6 & 8 use hospitalization as a health measure on total, food, non-food consumptions and HDDS respectively.

[1] Coefficients of other variables reported in supplementary materials

[Table 2 **near here]**
The coefficients for the interaction terms between all health measures and weather measures in the current period showed insignificant effects on total and food consumption. In contrast, negative and significant effects were observed for the lagged interaction terms between health shocks and weather measures, particularly affecting food and non-food consumption. This indicates that the interactions of shocks experienced in the current period had a more detrimental effect on households' consumption in the subsequent period, rather than in the current period.

3.2.1 Heterogeneous Effects of Illness and Weather on Consumption

We conducted a deeper analysis of the distributional and heterogeneous effects of health and weather shocks and their interactions on various categories of consumption, utilizing panel fixed effects quantile regression estimators. The results presented in Table 3 indicate that illness (defined as a household member being sick for more than 30 days) had an insignificant effect on total consumption across all quantiles. In contrast, hospitalization was positively and significantly associated with total consumption at all percentiles except the 20th percentile.

The relationship between rainfall and total consumption was consistently negative and significant across all quantiles. However, the lagged effects of rainfall on total consumption were significant for households in the lower quantiles (20th and 40th percentiles), indicating that these households are affected by rainfall shocks not only in the current period but also from previous periods. The effect of temperature on total consumption was significant at all quantiles, except for the top quantile, while the lagged effect of temperature was significantly and consistently negative across all quantiles. The interaction terms between health and weather shocks on total consumption were found to be consistently insignificant across all quantiles. Additional covariates included in the model can be found in the supplementary materials, specifically in Table S6.

Regarding quantile regressions for food consumption, health measures were found to be insignificant across all quantiles, except for the middle quantiles. In these cases, there was a weak significant effect observed on hospitalization, as presented in Table 4. Rainfall during the current period had a consistently negative and significant effect on food consumption, while the lagged effects of rainfall were insignificant across all quantiles. Both current and previous temperature levels exhibited significant effects on the 1st and 2nd quantiles. The interaction terms between health indicators (hospitalization) and extreme temperatures showed negative effects on food consumption across all quantiles but were only significant at the second quantile. The coefficients for other covariates included in the model can be found in Table S7. Additionally, membership in financially related groups was positively and significantly associated with food consumption across all quantiles.

Table 5 and S8 present the results of quantile regression analysis examining the effects of key covariates on non-food consumption. Households with a member sick for more than 30 days experienced a negative and significant effect on non-food

consumption at the 40th percentile. In contrast, hospitalization was positively and significantly associated with non-food consumption, but this effect was observed only in the top quantiles during the current period. The lagged effect of hospitalization was significant across all quantiles except for the top quantile.

The influence of increased rainfall, both in the current and previous waves, was consistently insignificant across all quantiles. Similarly, the lagged temperature measure showed no significant effects. However, the current period's increased temperature had a consistently negative and significant effect on non-food consumption across all quantiles, with more pronounced effects noticed at the lower quantiles.

Although the interaction terms between temperature and whether a household member was sick for more than 30 days were negative, these effects were insignificant across all quantiles. In summary, the quantile regression estimates indicate that households in the lower quintiles were adversely affected by weather events occurring both in the current period and in the previous waves, in contrast to households in the higher quintiles.

Table 3
Quantile FE results on effect of health, weather shocks and interactions on total consumption

	Total consumption percentiles							
	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sick more than 30 days (t)	-0.010	0.007	0.026	0.048				
	(0.047)	(0.036)	(0.038)	(0.057)				
Sick more than 30 days (t-1)	0.048	0.025	-0.002	-0.033				
	(0.039)	(0.030)	(0.032)	(0.048)				
Hospitalized (t)					0.052	0.055**	0.058**	0.062*
					(0.033)	(0.025)	(0.025)	(0.037)
Hospitalized (t-1)					0.015	0.020	0.026	0.032
					(0.033)	(0.025)	(0.025)	(0.037)
Rainfall z scores (t)	-0.050***	-0.050***	-0.051***	-0.051***	-0.048***	-0.050***	-0.053***	-0.055***
	(0.012)	(0.009)	(0.010)	(0.015)	(0.013)	(0.009)	(0.010)	(0.014)
Rainfall z scores (t-1)	-0.024*	-0.018*	-0.010	-0.001	-0.021	-0.016	-0.011	-0.005
	(0.014)	(0.010)	(0.011)	(0.017)	(0.014)	(0.010)	(0.011)	(0.016)
Temperature z scores (t)	-0.166***	-0.142***	-0.114***	-0.083	-0.157***	-0.136***	-0.112***	-0.086*
	(0.042)	(0.032)	(0.034)	(0.051)	(0.042)	(0.031)	(0.032)	(0.047)
Temperature z scores (t-1)	-0.173***	-0.169***	-0.165***	-0.160***	-0.161***	-0.162***	-0.164***	-0.165***
	(0.044)	(0.033)	(0.036)	(0.054)	(0.045)	(0.034)	(0.034)	(0.051)
Sick 30days# rainfall (t)	-0.014	-0.026	-0.040	-0.055				
	(0.036)	(0.027)	(0.029)	(0.044)				
Sick 30days# temperature (t)	0.049	0.030	0.008	-0.017				
	(0.060)	(0.045)	(0.049)	(0.073)				
Sick 30days# rainfall (t-1)	-0.030	-0.031	-0.032	-0.034				
	(0.033)	(0.025)	(0.026)	(0.040)				
Sick 30days# temperature (t-1)	0.001	-0.022	-0.048	-0.078				
	(0.056)	(0.042)	(0.045)	(0.068)				
Hospitalized #rainfall (t)					-0.031	-0.019	-0.006	0.008

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8

	Total consumption percentiles							
					(0.026)	(0.019)	(0.020)	(0.029)
Hospitalized #temperature (t)					-0.007	0.000	0.009	0.018
					(0.044)	(0.033)	(0.033)	(0.049)
Hospitalized #rainfall (t-1)					-0.019	-0.016	-0.014	-0.011
					(0.025)	(0.018)	(0.019)	(0.028)
Hospitalized #temperature (t-1)					-0.052	-0.037	-0.020	-0.001
					(0.044)	(0.033)	(0.034)	(0.050)
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8								

[Table 3 **near here]**

Table 4
Quantile FE results on health, weather shocks and interactions on food consumption

	Food consumption percentiles							
	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sick more than 30 days (t)	0.011	0.031	0.053	0.076				
	(0.049)	(0.036)	(0.037)	(0.052)				
Sick more than 30 days (t-1)	0.042	0.015	-0.015	-0.045				
	(0.042)	(0.031)	(0.032)	(0.045)				
Hospitalized (t)					0.047	0.048*	0.048*	0.049
					(0.034)	(0.025)	(0.026)	(0.037)
Hospitalized (t-1)					-0.019	-0.014	-0.008	-0.002
					(0.034)	(0.025)	(0.026)	(0.037)
Rainfall z scores (t)	-0.058***	-0.057***	-0.056***	-0.055***	-0.056***	-0.057***	-0.057***	-0.058***
	(0.013)	(0.009)	(0.010)	(0.014)	(0.013)	(0.009)	(0.010)	(0.014)
Rainfall z scores (t-1)	-0.022	-0.017	-0.010	-0.004	-0.017	-0.013	-0.010	-0.006
	(0.014)	(0.010)	(0.010)	(0.015)	(0.014)	(0.010)	(0.010)	(0.015)
Temperature z scores (t)	-0.074*	-0.063**	-0.050	-0.037	-0.073*	-0.062**	-0.050	-0.038
	(0.042)	(0.031)	(0.032)	(0.046)	(0.042)	(0.031)	(0.032)	(0.045)
Temperature z scores (t-1)	-0.192***	-0.191***	-0.191***	-0.191***	-0.174***	-0.179***	-0.184***	-0.190***
	(0.045)	(0.033)	(0.034)	(0.048)	(0.044)	(0.033)	(0.034)	(0.048)
Sick 30days# rainfall (t)	-0.011	-0.025	-0.042	-0.058				
	(0.034)	(0.025)	(0.025)	(0.036)				
Sick 30days# temperature (t)	0.036	0.027	0.016	0.005				
	(0.060)	(0.044)	(0.045)	(0.065)				
Sick 30days# rainfall (t-1)	-0.013	-0.021	-0.030	-0.038				
	(0.031)	(0.023)	(0.024)	(0.034)				
Sick 30days# temperature (t-1)	0.010	-0.004	-0.020	-0.036				
	(0.056)	(0.042)	(0.042)	(0.061)				
Hospitalized #rainfall (t)					-0.032	-0.027	-0.021	-0.016

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8

	Food consumption percentiles							
					(0.026)	(0.019)	(0.020)	(0.028)
Hospitalized #temperature (t)					0.020	0.017	0.013	0.009
					(0.045)	(0.033)	(0.034)	(0.049)
Hospitalized #rainfall (t-1)					-0.033	-0.028	-0.022	-0.015
					(0.026)	(0.019)	(0.019)	(0.028)
Hospitalized #temperature (t-1)					-0.067	-0.060*	-0.052	-0.045
					(0.047)	(0.035)	(0.035)	(0.051)
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8								

[Table 4 **near here]**

Table 5
Quantile FE results on effect of health, weather shocks and interactions on non-food consumption

	Non-food percentile							
	0.2	0.4	0.6	0.8	0.2	0.4	0.6	0.8
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sick more than 30 days (t)	-0.122	-0.108*	-0.092	-0.076				
	(0.083)	(0.062)	(0.062)	(0.088)				
Sick more than 30 days (t-1)	0.079	0.062	0.043	0.024				
	(0.071)	(0.053)	(0.053)	(0.076)				
Hospitalized (t)					-0.001	0.035	0.077	0.119*
					(0.069)	(0.051)	(0.049)	(0.069)
Hospitalized (t-1)					0.142**	0.110**	0.073*	0.035
					(0.063)	(0.046)	(0.044)	(0.063)
Rainfall z scores (t)	-0.016	-0.019	-0.022	-0.025	-0.013	-0.019	-0.025	-0.031
	(0.023)	(0.017)	(0.017)	(0.024)	(0.025)	(0.018)	(0.018)	(0.025)
Rainfall z scores (t-1)	0.026	0.023	0.018	0.014	0.022	0.017	0.011	0.005
	(0.024)	(0.018)	(0.018)	(0.026)	(0.027)	(0.020)	(0.019)	(0.027)
Temperature z scores (t)	-0.278***	-0.246***	-0.209***	-0.171**	-0.260***	-0.238***	-0.213***	-0.187**
	(0.076)	(.057)	(0.057)	(0.081)	(0.083)	(0.061)	(0.059)	(0.083)
Temperature z scores (t-1)	-0.009	-0.006	-0.002	0.002	0.000	-0.007	-0.015	-0.022
	(0.081)	(0.061)	(0.061)	(0.086)	(0.089)	(0.066)	(0.063)	(0.089)
Sick 30days# rainfall (t)	-0.017	-0.022	-0.029	-0.036				
	(0.065)	(0.048)	(0.048)	(0.069)				
Sick 30days# temperature (t)	-0.106	-0.105	-0.103	-0.102				
	(0.113)	(0.084)	(0.084)	(0.120)				
Sick 30days# rainfall (t-1)	-0.045	-0.042	-0.040	-0.037				
	(0.062)	(0.046)	(0.046)	(0.065)				
Sick 30days# temperature (t-1)	-0.034	-0.047	-0.063	-0.079				
	(0.109)	(0.081)	(0.081)	(0.115)				
Hospitalized #rainfall (t)					-0.008	0.008	0.027	0.046

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8

	Non-food percentile							
					(0.053)	(0.039)	(0.038)	(0.053)
Hospitalized #temperature (t)					-0.140	-0.080	-0.009	0.064
					(0.089)	(0.066)	(0.063)	(0.089)
Hospitalized #rainfall (t-1)					0.026	0.022	0.018	0.014
					(0.050)	(0.037)	(0.035)	(0.050)
Hospitalized #temperature (t-1)					0.008	0.027	0.048	0.070
					(0.089)	(0.066)	(0.063)	(0.089)
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0. Columns 1–4 is quantile regressions using a health variable “if household member was sick more than 30 days while hospitalization health measure was used in columns 5–8								

[Table 5 **near here]**

3.2.2 Potential Pathways

Illness can affect consumption through several mechanisms, including out-of-pocket health expenditures, income, labor supply, or labor productivity. The results presented in Table S9, columns 1–2, illustrate how illness affects household health expenditures. As expected, all measures of illness demonstrated significant positive effects on health expenditures in both the current and previous waves. Notably, the effects of illness were larger in the current period. Additionally, an increase in rainfall was linked to higher medical expenditures, while the effect of temperature was also positive and significant in the current period; however, the lagged effects were not significant. Furthermore, access to free medical services and membership in a health-related group led to reduced household medical expenditures.

We did not observe any significant changes in wage labor earnings or family agricultural labor due to illness. However, extreme temperatures have been found to significantly decrease labor income and the family labor supply for agricultural activities. The lagged effects of these factors remained insignificant. The absence of a noticeable effect of illness on labor income may be explained by the fact that most rural households are involved in informal on-farm employment. In cases of sickness, families with affected individuals can negotiate with employers to allow other household members to fill in and continue earning income. As a result, overall household income remains stable. Additionally, rural households employ various coping strategies to manage labor shortages when sickness occurs, helping them to compensate for the lost labor.

3.2.3 Consumption Smoothing Mechanisms, Healthcare and Labour Coping Strategies

The empirical results discussed above provide some evidence of households' ability to manage the economic costs associated with illness. Generally, the findings from the consumption models (Tables S3-S8) show that membership in financial-related groups is positively linked to all consumption categories. This effect is consistently significant across all consumption quantiles, as indicated in Tables S6-S8.

Access to loans significantly increased non-food consumption for households in the bottom and middle quantiles, but not for those in the top quantile. In contrast, remittances boosted total and non-food consumption for households in the middle and top quantiles, but not for those in the bottom quantile. These results suggest that households in the lower quantiles tend to rely on loans when faced with liquidity constraints.

Access to free medical services significantly reduced healthcare expenditures and increased food consumption for households in the middle-income quantiles but not for those in the top quantile. Other key coping mechanisms used to manage health care costs

included household savings, utilized by 27% of all households and 38% of households with sick members. Additional strategies included the sale of agricultural produce, livestock sales, and borrowing or receiving assistance from friends, as illustrated in Fig. 5.

We did not find a significant effect of illness on labor supply and earned income, as shown in Table S4. These findings suggest that households employed various labor-related coping strategies to protect their income from losses associated with illnesses. Unfortunately, data on these coping strategies were only collected in Wave 6, where households indicated the methods they used to compensate for lost labor when a family member was unable to perform usual activities due to illness or injury. Therefore, we can only present descriptive statistics of the different labor coping strategies used by households, as we anticipate that these strategies may not change over time. The results in Fig. 6 show that over a third of households hired additional labor, reallocated tasks from ill members to healthy ones, and increased the working hours of healthy members. Only a small proportion of households utilized free community labor.

4. Discussion and Conclusions

Our analysis, which employed various health indicators and panel regression methods, shows that illness generally does not have a negative effect on food consumption. This suggests that households are somewhat able to protect their food intake despite health challenges. However, we found that food consumption does suffer when weather events occur. This outcome is not surprising, considering that many food-insecure households in Uganda are situated in areas vulnerable to weather shocks. Floods can diminish food consumption by reducing productivity and destroying arable land, as well as disrupting food supply channels when road infrastructure is damaged, making it harder for food to reach those in need. These results are consistent with (49) and, (50) who found negative effects of floods on consumption and decreased calorie. Our findings indicate that covariate shocks are not fully insured. Moreover, with the rising frequency of flood events in East Africa—impacting even areas that have not historically experienced floods or excessive rainfall—some households may lack effective risk-sharing institutions to counteract the negative effects of these new shocks (floods) on their consumption. As a result, they may struggle to be resilient in the face of this climatic challenge. This inability to recover quickly from hazards not only affects household consumption but also has negative implications for other developmental outcomes.

On non-food consumption, hospitalization increased consumption significantly which is consistent with (29) while illness of more than 30 days did not have significant effects. Quantile regression analysis revealed heterogeneity in the effects observed, with households at the 40th percentile significantly reducing their non-food consumption. Moreover, households at the lowest quantile were adversely affected by weather shocks both in the current and previous survey waves, indicating a low capacity for resilience.

Our findings have important policy implications. Since the main cost of illness in Uganda arises from health expenditures rather than lost wage earnings, we recommend interventions aimed at reducing out-of-pocket expenses and minimizing financial risks. This could include implementing a national health insurance scheme to promote universal health coverage. Additionally, strategies for flood protection and risk reduction, such as early warning systems for floods, will help mitigate the negative impacts of flooding on consumption and health. Furthermore, social protection measures—such as access to credit, development of social networks, remittances, and both formal and informal safety nets—are crucial for maintaining consumption in the face of climate change. These strategies are vital for strengthening food system resilience and enhancing overall household resilience against shocks.

A key limitation of this study is the lack of a comprehensive gender analysis, although we did incorporate some gender dimensions by including the gender of the asset owner in our empirical models.

Declarations

Ethics approval and consent to participate

Research ethics approval was obtained from the Makerere University School of Public Health Institutional Review Board (IRB). All respondents consented to the interviews, which were, in any case, not intrusive.

Consent for publication

Not applicable

Author Contribution

Conceptualization, EA, AM, LK and JvB; Methodology, EA, AM, LK and JvB; Data curation; EA, LK, RI and BB; data management EA, LK, BB and RI; data analysis, EA and LK; project administration, LK, BB and RI. All authors participated in the writing of the manuscript, read and approved the final manuscript

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Data Availability

The data supporting this study's findings are available from the corresponding author, [E.A], upon reasonable request and after an agreement with the project team.

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Footnotes

1. The questionnaire administered and sampling strategy was slightly modified from “Feed the Future Innovation Laboratory for Nutrition” questionnaire, previously conducted in Uganda in 2012, 2014 and 2016.
2. The average monthly exchange rate of 1 USD- 3639.5 UGX. This was computed from monthly averages of June 2020 to July 2021.

Figures

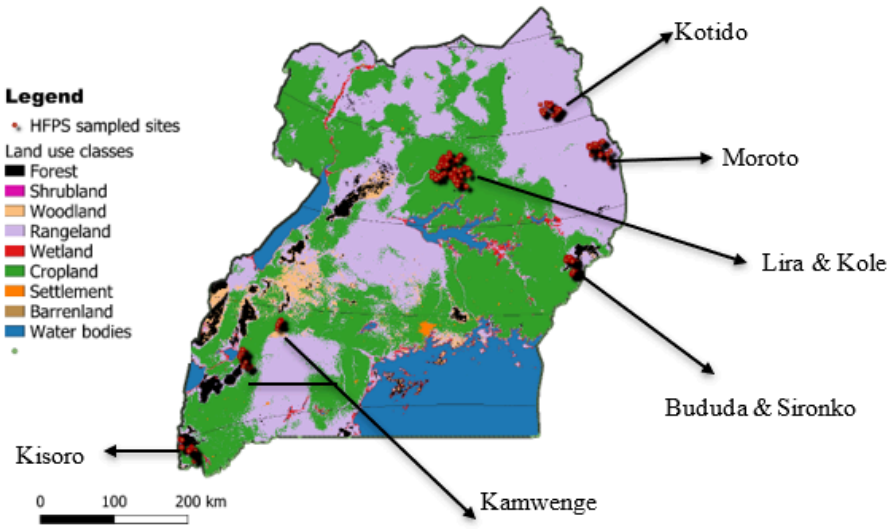


Figure 1

The location of the sampled districts and land use cover data were adapted from the Moderate Resolution Imaging Spectroradiometer (MODIS) 2018 data. Source: Own GPS data, Uganda shapefile from Hijmans et al. (2012).

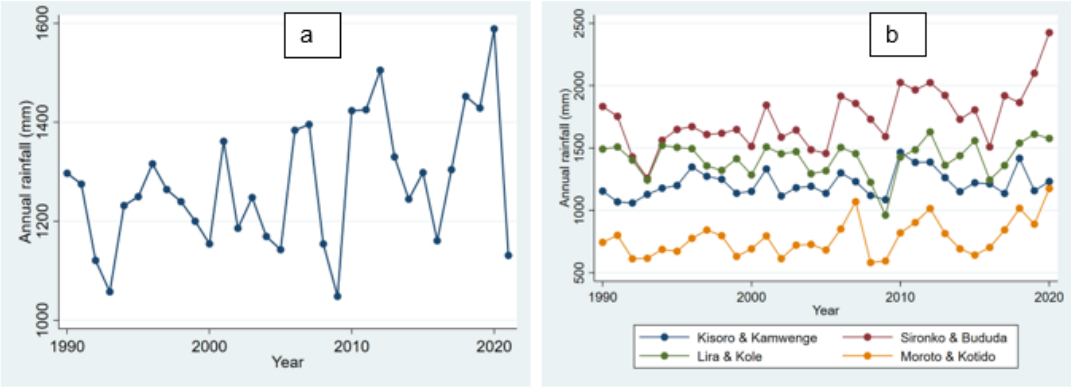


Figure 2

CHIRPS Rainfall data aggregated for all regions (A) and across HFPS districts (B). Mean range from (1990-2020).

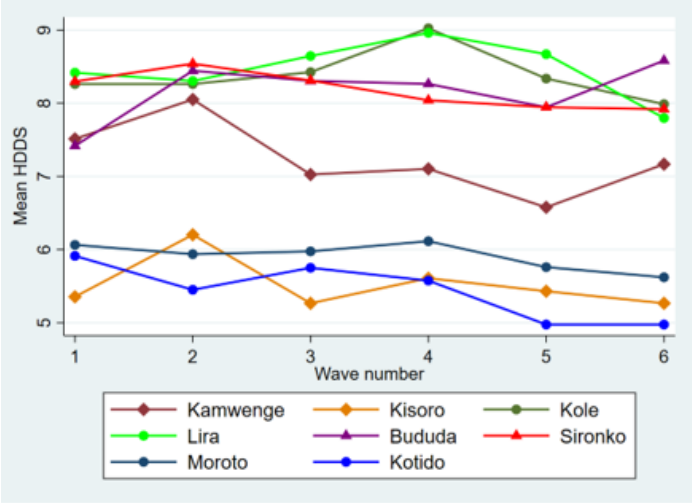


Figure 3

Household diet diversity across sampled districts for the six waves

Source: From authors data

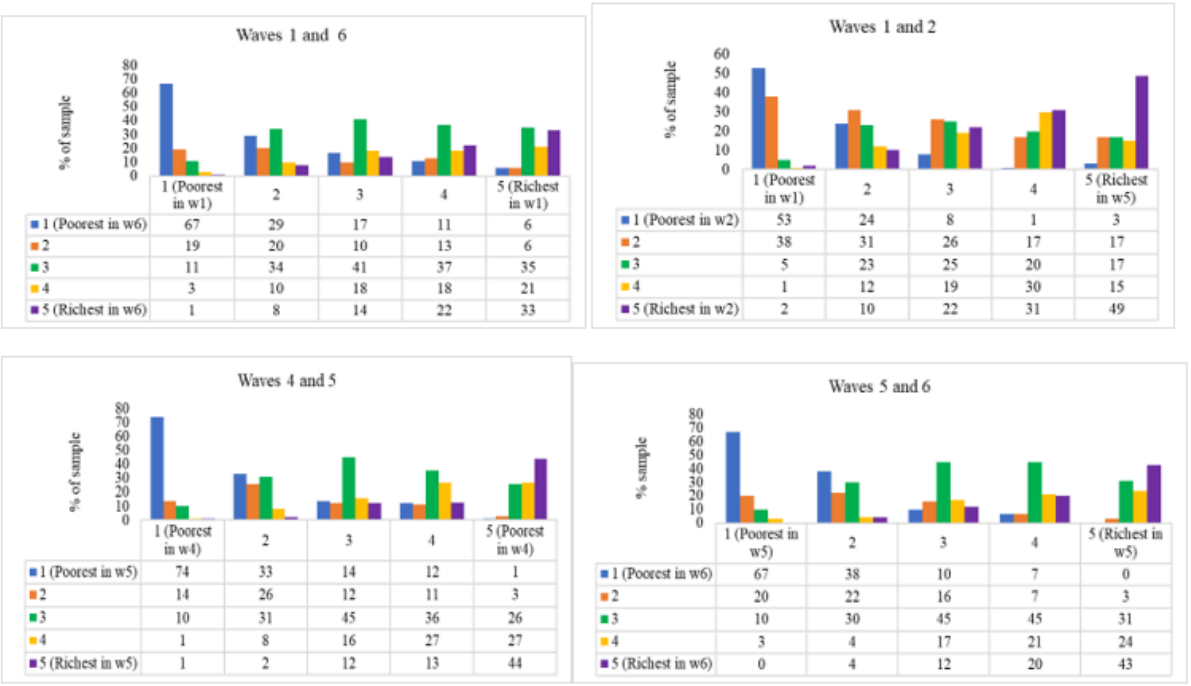


Figure 4

Resilience assessment: HDDS transition matrix (%)

Source: From authors own data

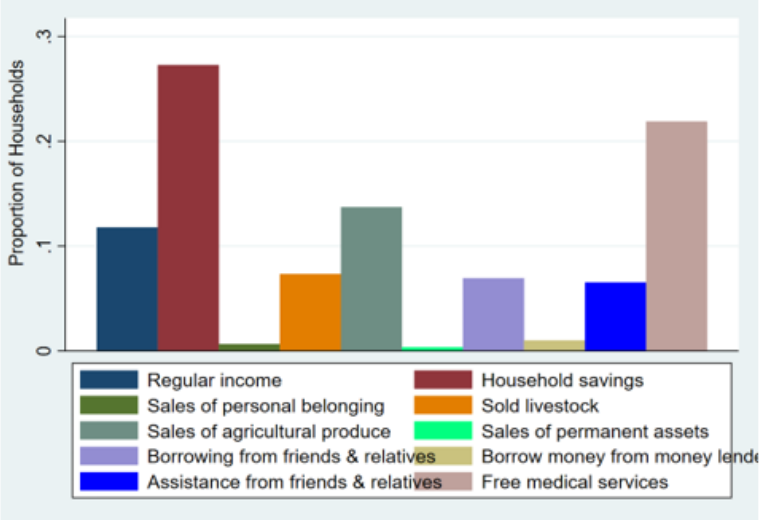


Figure 5

Households using different financial sources for medical expenditures

Source: From authors own data

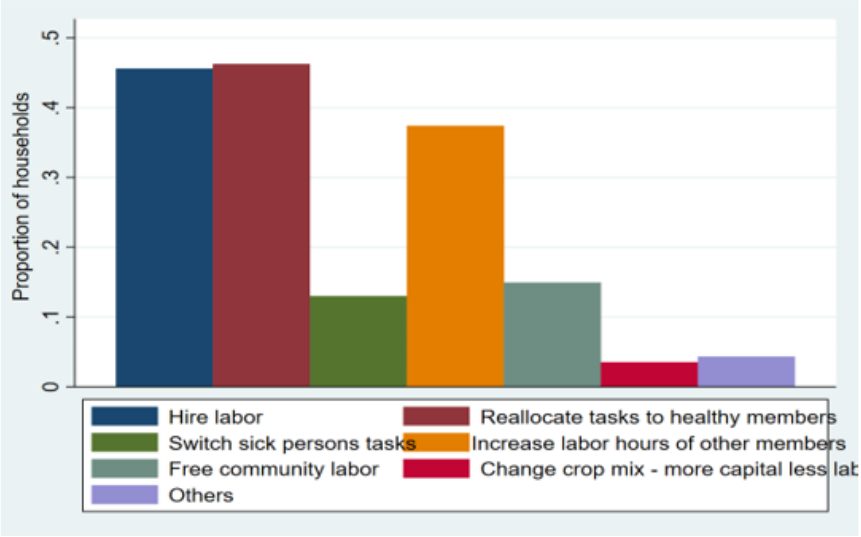


Figure 6

Proportion of households using different labour adjustment strategies

Source: From own data

Supplementary Files

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- SupplementarymaterialsJanuary2025.docx