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ORIGINAL PAPER

Household resilience to food insecurity: evidence from Tanzania and Uganda

Marco d'Errico[1] · Donato Romano[2] · Rebecca Pietrelli[1]

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Abstract
Resilience—the capacity that ensures adverse stressors and shocks do not have long-lasting adverse consequences—has become a key topic in both scholarly and policy debates. More recently some international organizations have proposed the use of resilience to analyze food and nutrition security. The objective of the paper is twofold: (i) analyze what the determinants of household resilience to food insecurity are and (ii) assess the role played by household resilience capacity on food security outcomes. The dataset employed in the analysis is a panel of three waves of household surveys recently collected in Tanzania and Uganda. First, we estimated the FAO's Resilience Capacity Index (RCI), combining factor analysis and structural equation modeling. Then probit models were estimated to test whether the resilience is positively related to future food security outcomes and recovery capacity after a shock occurs. In both countries, the most important dimension contributing to household resilience was adaptive capacity, which in turn depended on the level of education and on the proportion of income earners to total household members. Furthermore, household resilience was significantly and positively related to future household food security status. Finally, households featuring a higher resilience capacity index were better equipped to absorb and adapt to shocks.

Keywords Resilience · Food security · Structural equation model · Panel data

JEL classification D10 · Q18 · I32 · O55

1 Introduction

Natural, economic and political risks faced by households, firms, economies and even whole countries are on the rise both in terms of frequency and severity (Zseleczky and Yosef 2014). This is probably the reason why resilience has become a key topic in recent debates. For example, the World Bank's 2012 Social Protection and Labour Strategy was called "Resilience, Equity, Opportunity", the Davos World Economic Forum 2013 focused on "Resilient Dynamism" and the International Food Policy Research Institute 2020 Conference, held in Addis Ababa in 2014, focused on "Building Resilience for Food and Nutrition Security".

The concept of resilience has been used in different fields such as ecology, engineering, psychology and epidemiology (Holling 1996; Gunderson et al. 1997). Over the last decade or so, the concept of resilience has been applied in the social sciences and specifically in the analysis of complex systems, such as those of socio-ecology. These are systems in which the ecological and socioeconomic components are closely integrated (Folke 2006). This is precisely the case of agro-food systems in developing countries, where many communities and social groups gain their livelihoods using renewable natural resources through activities such as farming, agro-forestry and fishing. More recently, some international organizations (FAO, UNICEF, WFP 2012; EU Commission 2012) proposed the use of resilience in order to analyze food and nutrition security.

✉ Marco d'Errico
marco.derrico@fao.org

Donato Romano
donato.romano@unifi.it

Rebecca Pietrelli
rebecca.pietrelli@fao.org

[1] Food and Agricultural Organization of the United Nations, Rome, Italy

[2] Dipartimento di Scienze per l'Economia e l'Impresa, Florence, Italy

The use of the resilience concept in the development field is relatively new and only recently a comprehensive theoretical framework for defining and measuring resilience has been proposed (Barrett and Constas 2014). In contrast, measurement efforts aiming at assessing resilience in development, and specifically with reference to food insecurity, appeared much earlier.

Most of these efforts focused on how to overcome the fact that resilience to food insecurity is unobservable ex ante, focusing on how to estimate a proxy index of household resilience based on observable variables. However, this literature did not provide a robust theoretical framework (cf. Constas et al., 2013 and 2014; d'Errico et al. 2016). As a result, the proposed indicators are heuristic and the question remains whether or not they actually represent the construct they are intended to measure, i.e. household resilience.

Alinovi et al. (2008 and 2010) were probably the first authors who tried to define and measure household resilience to food insecurity. In their framework, the household was the entry level of analysis because it is the decision-making unit where the most important decisions are made on how to manage risks, both ex ante and ex post, including those affecting food securities. To measure resilience, Alinovi et al. estimated a resilience index as a latent variable (unobservable) through a two-stage factor analysis based on observables. The analytical framework was static because of data limitations (cross-sectional datasets) and did not explicitly measure shocks but used proxies such as index of coping mechanisms.

Vaitla et al. (2012) presented a livelihood change approach to measuring resilience, focusing on how assets held by a household or other social unit are used in various livelihood strategies to achieve certain outcomes. Although, in principle this framework should be able to analyze food security determinants, asset dynamics over time and eventually household welfare dynamics, the authors were only able to examine the determinants of well-being as their paper was based on cross-sectional data.

Smith et al. (2014) were interested in measuring community resilience based on the conceptual framework provided by Frankenberger et al. (2012) for program design in vulnerable communities with high levels of exposure to shocks and stresses. Household resilience capacity determinants were identified by regressing self-reported assessments of respondents on different indexes of capacity—absorptive, adaptive and transformative—which, in turn, have been estimated via principal/polychoric component analysis. While the hierarchical linear modeling technique they recommend does allow for multi-system-multi-level interactions, dynamics were assumed to be linear.

To measure resilience, FAO developed the so-called Resilience Index Measurement Analysis (RIMA) approach (FAO, 2015 and 2016a; d'Errico and Di Giuseppe 2016; d'Errico and Pietrelli 2017) maintaining the seminal idea of Alinovi et al. (2008) that resilience, which is not observable, can be estimated as a latent variable through a two-stage procedure on some observable variables. In more recent applications, FAO further refined the approach (FAO 2016b) by including some other variables as proxies for the natural environment and enabling institutional environment, and substituting structural equation modeling for factor analysis as a method to estimate the resilience index. Although this evolution represents an improvement vis-à-vis the original approach, it still maintains the same limits, i.e. linearity and the static nature of the analytical framework.

Alfani et al. (2015) proposed an interesting alternative to all previous approaches that, in principle, were looking for longitudinal data to estimate household resilience. They, using readily available cross-sectional data, were able to classify households as chronically poor, non-resilient, and resilient, estimating households' counterfactual welfare measures and considering shocks as treatments (Alfani et al. 2015). Though handy because less demanding in data requirement, this approach suffers from the same limitations as other applications being static.

Cissé and Barrett (2018) developed a moments-based approach to estimate stochastic and possibly nonlinear well-being dynamics. Another important feature of this paper is the derivation of a decomposable resilience measure based on the Foster, Greer and Thorbecke class of poverty measures, which makes possible the comparison of resilience of various sub-populations of interest. This is the only paper developing an empirical strategy consistent with a truly dynamic theoretical framework.

Finally, Smith and Frankenberger (2018) adopted a latent variable model for measuring resilience in Northern Bangladesh: this paper highlights the importance of taking a comprehensive approach to understanding the determinants of resilience accounting for the full range of potential capacities.

This non-exhaustive account of the evolution of discourse on resilience in development, with a focus on measurement issues, shows that the various approaches, and the related conceptual frameworks, share common elements (Constas et al. 2013). Building on these commonalities the Technical Working Group on Resilience Measurement[1] has advanced a definition of resilience as "the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences" (Constas et al. 2013: 6) that has become the reference for both scholars and practitioners in the development field. This definition implies that (Constas et al. 2014): (i) resilience is an outcome-based concept, the outcome being a measure of poverty, food security (as in this paper), or

[1] The Technical Working Group on Resilience Measurement is a group of experts set up in 2013 by FAO, IFPRI and WFP to secure consensus on a common analytical framework and guidelines for food and nutrition security resilience measurement, and to promote adoption of agreed principles and best practices on data collection and analysis, tools and methods.

any other indicator of well-being; (ii) resilience must be analyzed with regard to the experience of specific shocks and associated background stressors (which we collectively refer to as risk); (iii) unlike similar concepts (e.g. vulnerability), resilience emphasizes long-lasting effects on the outcome variable at hand and (iv) resilience explicitly requires "agency" that is the agent's capacity to absorb, adapt and transform livelihood strategies to offset the (anticipated or actual) negative impacts of shocks and stressors.

Any modeling and estimation effort should be able to capture these features. Unfortunately, none of the abovementioned conceptual frameworks, except that of Cissé and Barrett (2018) is consistent with such a theoretical framework. Even though we acknowledge the limits of measurement frameworks other than Cissé and Barrett (2018), it is worth asking what these frameworks are actually measuring. As emphasized by Hoddinott (2014: 12) "proposed measure[s] should be subjected to tests of validity and reliability; in the case of measures of resilience capacity, we are also interested in understanding their predictive power". This paper will attempt to do so, with specific reference to the oldest and most widely used measure of resilience—the FAO's Resilience Capacity Index (RCI) estimated using the so-called Resilience Index Measurement Analysis (RIMA) approach (FAO 2016a)—based on two case studies: Tanzania and Uganda. Early attempts at what is known as the RIMA approach were originally proposed by FAO during the second half of the 2000 decade (Alinovi et al., 2008 and 2010). Since then it has been widely used by FAO to perform resilience analysis in 15 Sub-Saharan countries—mostly in the Sahel and the Horn of Africa and Palestine (for the complete list of countries, cf. FAO 2016a).

Specifically, the paper first estimates the RCI and, building on this, analyzes what are the most important components of household resilience. Then it uses the estimated household RCIs to test whether or not they capture household resilience to food insecurity. It will do so by assessing if RCI positively relates to (a) high (future) food security outcomes and (b) post-shock recovery capacity.

2 Materials and methods

2.1 Data

This paper uses two panel datasets from the World Bank Living Standard Measurement Studies Integrated Survey on Agriculture (LSMS-ISA), each of them covering three rounds: the 2008–2009, 2010–2011 and 2012–2013 Tanzania National Panel Survey (TZNPS) and the 2009–2010, 2010–2011 and 2011–2012 Uganda National Household Survey (UNHS). These surveys are multi-topic household surveys that represent the most important sources for gathered information on household behavior in each country. Both datasets are nationally representative and offer a unique opportunity to study and compare household resilience across diverse contexts. The questionnaires administered in the two countries were highly consistent with each other thus guaranteeing cross-country comparability and both household and community modules were administered to the entire samples. At the household level, the questionnaire collects information on expenditure, labour market participation, socio-demographic characteristics, asset ownership, family wealth, private transfers and different types of shocks experienced by the household. Furthermore, an additional module collecting detailed agricultural information was administered to agricultural households. At the community level, the questionnaire includes the socio-economic characteristics of the community as well as infrastructure of the place where the respondent lives, such as the distance to health and educational infrastructure.

The main food security indicators employed in the analysis were:

- the daily per capita caloric intake (a quantitative measure of food security computed by converting the quantity of consumed food—purchased, self-produced and self-consumed, or received as gift—into daily calories. The last was finally divided by the household size to obtain the per capita value of the caloric intake);
- a household dietary diversity index, the Simpson index, which is a measure of diet quality that is computed by considering the contribution of various food groups—cereals, roots, vegetables, fruits, meat, legumes, dairy, fats and other—to overall food caloric intake.

These indicators were selected because they are employed by the empirical literature as the main indicators of food security at the household level. The surveys also included additional anthropometric variables that could be employed for estimating malnutrition indicators such as data on children under five.

Each observation in both datasets was also geo-referenced, additional datasets were merged with LSMS–ISA by exploiting the geographic reference of each household in each dataset. To ensure confidentiality, the actual coordinates of each sampled household have been modified by relying on random offset of cluster center-point coordinates within a specific range based on rural or urban classification. For urban areas, a smaller range was used.

We used the Normalized Difference Vegetation Index (NDVI) derived from the NOAA Climate Data Record (CDR) of Advanced Very High Resolution Radiometer (AVHRR) Surface Reflectance. The dataset spans from 1981 to 10 days from the present using data from seven NOAA polar orbiting satellites: NOAA-7, -9, -11, -14, -16, -17 and -

18. The data were projected onto a 0.05° × 0.05° global grid (Vermote et al. 2014). Additionally, we employed the global, monthly Palmer Drought Severity Index (PDSI) computed using observed or model monthly surface air temperature and precipitation, plus other surface forcing data (Dai et al. 2004 and updates). The data resolution was a 2.5° spatial grid.

Both indexes provide information on the health of vegetation in different regions across the world and were used to describe local conditions and to build natural shock variables. In order to do this, the empirical models included the long-term (25 years) average of the NDVI and PDSI, calculated taking into account the growing season according to FAO's crop calendar in each country, to control for the different climatic conditions and a set of four dummy variables aiming to capture extreme events, such as floods and droughts. In the case of NDVI, the dummy "wet NDVI anomaly" was equal to 1 if the average NDVI of the growing season was above one standard deviation from the long-term average and dummy "dry NDVI anomaly" was equal to 1 if the average NDVI of the growing season was below one standard deviation from the long-term average. The same applied to PDSI, that is the dummy "flood" was equal to 1 if the average PDSI of the growing season was above one standard deviation from the long-term average, and dummy "drought" was equal to 1 if the average PDSI of the growing season was below one standard deviation from the long-term average. Data on NDVI and PDSI covered a period of 25 years. The dummy variables were calculated as anomalies (i.e. distances from average) with respect to the overall trend.

A second dataset, providing long-term (1997–2015) data on conflict episodes in African countries (Carlsen et al. 2010), was used to build a conflict intensity index (Bozzoli et al. 2011) by aggregating the number of conflict episodes for a given year and discounting them by their distances from the location of the household.

2.2 Estimating resilience

The FAO's RIMA methodology was adopted (FAO 2016b) to estimate the RCI at household level. This approach is based on a two-stage procedure (Fig. 1). In the first step, Factor Analysis (FA) is used to identify the attributes—called "pillars" within the RIMA framework—that contribute to household resilience, starting from observed variables. In this paper, the pillars analyzed were Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN) and Adaptive Capacity (AC). All observed variables used to estimate the pillars are listed in the Annex along with definitions and summary statistics. The factors considered for each pillar were only those able to explain at least 95% of the variance.

In the second step, a Multiple Indicators Multiple Causes (MIMIC) model was used (Bollen et al. 2010). Specifically, a system of equations was constructed, specifying the relationships between an unobservable latent variable (resilience), a set of outcome indicators (food security indicators) and a set of attributes (pillars). Factor Analysis—employed in the first step—assumes that the residual errors (i.e. unique factors) are uncorrelated with each other and are uncorrelated with the common (i.e. latent) variable. In the case of food security analyses, the latter assumption cannot be accepted, as the probability of intra-dimension correlation is high. On the contrary, structural equation modelling allows correlation among residual errors.

The MIMIC model is made up of two components, namely the measurement Eq. (1)—reflecting that the observed indicators of food security are imperfect indicators of resilience capacity—and the structural Eq. (2), which correlates the estimated attributes to resilience:

$$\begin{bmatrix} \textit{Food consumption} \\ \textit{Dietary diversity} \end{bmatrix} = [\Lambda_1, \Lambda_2] \times [RCI] + [\varepsilon_1, \varepsilon_2] \tag{1}$$

$$[RCI] = [\beta_1, \beta_2, \beta_3, \beta_4] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + [\varepsilon_3]. \tag{2}$$

A word of caution is required here in interpreting the latent variable model above as a causal inference model. The reason is the risk of endogeneity that arises when the latent construct (in this case a resilience index) is jointly determined with the outcome of interest, or is correlated with the error term. If there is endogeneity, the parameter estimates will be biased. While MIMIC does not completely solve the endogeneity problem, it can nevertheless smooth it, as confirmed by the Hausman-Vu tests for the presence of endogeneity in our application. Furthermore, RIMA is very careful in using the MIMIC approach as a mere descriptive tool of the relationship between resilience and its components, while causal inference is left to subsequent regression analysis.

The estimated Resilience Capacity Index (RCI) is not anchored to any scale of measurement. Therefore, a scale has been defined setting the coefficient of the food consumption loading (Λ_1) equal to 1, meaning that one standard deviation increase in RCI implies an increase of one standard deviation in food consumption. This also defines the unit of measurement for the other outcome indicator (Λ_2) and for the variance of the two food security indicators:

$$\textit{Food consumption} = \Lambda_1 \mathrm{RCI} + \varepsilon_1 \tag{3}$$

$$\textit{Dietary diversity} = \Lambda_2 \mathrm{RCI} + \varepsilon_2. \tag{4}$$

Finally, for ease of understanding the RCI has been standardized through a Min-Max scaling transformation.[2]

[2] The Min-Max scaling is based on the following formula: $RCI_h^* = \frac{(RCI_h - RCI_{min})}{(RCI_{max} - RCI_{min})} \times 100$, where h represents the hth household.

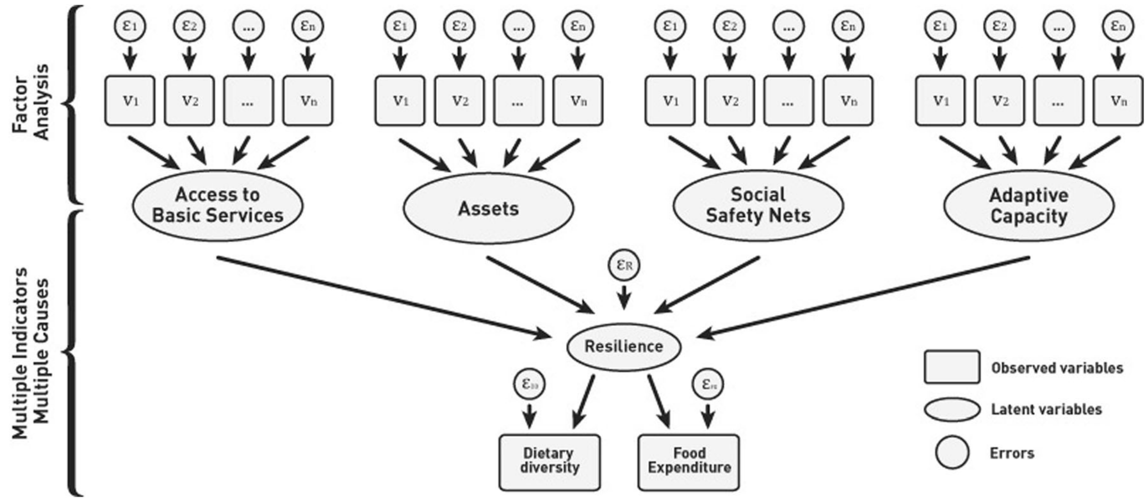

Fig. 1 Resilience Capacity Index (RCI) estimation strategy in two steps: (1) Factor Analysis (FA)—pillars (Access to Basic Services, Assets, Social Safety Nets, Adaptive Capacity), observed variables v_i, residual errors ε_i; (2) Multiple Indicators Multiple Causes (MIMIC) model—pillars, food security indicators (food expenditure, dietary diversity), residual errors ε_i

2.3 Linking resilience and food security

A very general analytical structure linking resilience and food security can be thought of as a relationship between a dependent variable, Y, indicating the status (i.e. a food security quantitative indicator that can be categorical or continuous depending on the specific variable) of the unit of analysis (the household), and some independent variables, X_i, $(i = 1, \ldots, n)$ that have an impact on this status:

$$Y = f(X_1, X_2, \cdots X_n). \tag{5}$$

Our assumption is that there are some characteristics (household or context-specific) that make a given household more resilient than others to a given shock. Hence, it is crucial to identify the attributes of this resilience "capacity":

$$Y = f[RCI(X_1, X_2, \ldots, X_m), X_{m+1}, X_{m+2}, \ldots, X_n] \tag{6}$$

where variables 1 to m are resilience correlates, which in turn impact the status Y (i.e. food security), while variables $m + 1$ to n are other variables that impact Y, though they do not influence household resilience, RCI.

The relationship between resilience and food security is expected to be positive: specifically, a higher RCI in time t should be associated with (a) a lower probability of decreasing food security between t and $t + 1$, and (b) a higher probability of recovery between time $t + 1$ and $t + 2$ for the ones who had suffered a worsening of food security status between t and $t + 1$.

To explore the relationship between resilience and food security, a probit model was estimated, where Φ represents the cumulative density function (CDF) that follows a normal distribution and the probability of suffering a negative food security (FS) outcome (i.e. a reduction in caloric intake or dietary diversity loss) between time t and $t + 1$, *loss in* $FS_{t,t+1}$, depends on the RCI and a vector of household characteristics $\mathbf{X}$ in time t:

$$Prob\left(loss\ in\ \mathrm{FS}_{t,t+1}\right) = \Phi\left(\mathrm{RCI}_{h,t}, \mathbf{X}_{h,t}\right). \tag{7}$$

Outcome variables other than the per capita caloric intake or the dietary diversity index—such as per capita food expenditure and food consumption score (Pangaribowo et al. 2013)—have been used to test the robustness of the estimates. The general pattern does not change (these results are not shown but are available upon request).

Furthermore, the probability of recovering between time $t + 1$ and $t + 2$ can be assessed estimating another probit model for the sub-sample of households that suffered a reduction in caloric intake or a dietary diversity loss between t and $t + 1$.

Model 7 captures the role of RCI and other covariates on the probability of suffering a food security loss in the first period of the analysis irrespective of the cause of such a loss. However, a resilience analysis must include shocks that may have an impact on food security outcomes, idiosyncratic (i.e. affecting specific individuals or households) as well as covariate (i.e. affecting groups of households or whole communities). In fact, the relevance of the resilience concept rests precisely on the household capacity to maintain or improve a certain level of welfare (in this case food security) in the face of man-made or natural shocks and stressors.

In order to explore the role of these variables, shocks are included in model 7 as follows:

$$Prob\left(loss\ in\ \mathrm{FS}_{t,t+1}\right) = \Phi\left(\mathrm{RCI}_{h,t}, \mathbf{X}_{h,t}, \boldsymbol{S}_{h,t}, RCI_{h,t} \times \boldsymbol{S}_{h,t}\right) \tag{8}$$

where $\boldsymbol{S}$ is a vector of covariate or idiosyncratic shocks that affect the household between t and $t + 1$. Shocks and stressors,

Table 1 Multiple Indicators Multiple Causes (MIMIC) model of Resilience Capacity Index (RCI): coefficients of structural and measurement components

	1 Tanzania	2 Uganda
Structural component		
Access to Basic Services (ABS)	0.041***	0.065***
	(0.005)	(0.016)
Assets (AST)	0.047***	0.024
	(0.012)	(0.024)
Social Safety Nets (SSN)	0.133***	0.161***
	(0.018)	(0.025)
Adaptive Capacity (AC)	0.166***	0.262***
	(0.009)	(0.016)
Measurement component		
Per capita food consumption	1	1
	(0)	(0)
Household dietary diversity	0.111***	0.075***
	(0.009)	(0.007)
Goodness-of-fit statistics		
χ^2	8.93	10.82
p value	0.030	0.013
RMSEA	0.026	0.036
Pr RMSEA	0.972	0.815
CFI	0.995	0.988
TLI	0.986	0.965
Observations	2866	2031

Standard errors in parentheses: ***$p < 0.01$

defined as short-term deviations from long-term trends, may be factored into a resilience model through either self-reported or exogenously determined indicators. Furthermore, some interaction terms between the RCI and the shock variables (represented in model 8 by the term $\mathrm{RCI}_{h,\ t} \times \boldsymbol{S}_{h,\ t}$) were included in the model, aiming to capture the marginal effect of the RCI on how a specific shock impacted household food security.

The time frame of the study was as follows: the RCI was measured in the first round of each survey, namely 2008–2009 for Tanzania and 2009–2010 for Uganda. The self-reported (idiosyncratic) shocks came from the same round of the survey. The only difference was that, in Tanzania, the reference period for the shock-related questions was the 5 years preceding the interview, while in Uganda, the reference period of the question was the past year. The covariate climatic shocks (flood and drought dummy shock) were calculated using as reference the average NDVI or PDSI of the first round of the surveys.

3 Results

3.1 Estimating resilience

The FAO-RIMA approach provides two outputs: an estimate of the RCI and an assessment of how the different attributes correlate with resilience. Table 1 reports the MIMIC estimates for the two countries at time *t*. The results of the first step (factor analysis) are available in the Appendix (Tables 10–12).

All the pillars were statistically significant, except AST in Uganda.

Table 2 analyzes what were the most relevant variables/indexes per pillar in each country. The details of the variables/indexes included in the pillars can be found in Table 9 in the Appendix. Further details on the estimation of the agricultural asset index, wealth index and household infrastructure index can be found in Winters et al. (2009). In the case of ABS, the distances to school and to market were relevant variables in Uganda, while infrastructure and distance to school were the most relevant variables in Tanzania. In terms of AST, Tropical Livestock Units and agricultural index played the most relevant roles. Education and the ratio of income earners to total household members were the most relevant variables for AC. Private transfers were the most important variable for SSN.

Table 2 Variables relevance: absolute correlation variable-pillar by country

	Tanzania	Uganda
ABS		
Infrastructural index	0.701	0.170
Distance to school	0.874	0.819
Distance to market	0.020	0.884
AST		
Agricultural asset index	0.716	0.801
Wealth index	0.070	0.138
Tropical Livestock Unit	0.812	0.982
Land	0.509	0.246
AC		
Income diversification	0.218	0.364
Education	0.830	0.725
Income earners' share	0.826	0.824
SSN		
Private transfers	0.973	0.906
Public or other transfers	0.282	0.591

Table 3 Food security patterns among Tanzanian and Ugandan households: caloric intake, dietary diversity and food consumption

Changes in food security status	Tanzania		Uganda	
	Sample size	Percent	Sample size	Percent
Per capita caloric intake				
Households suffering a decrease between time t and $t+1$	1145	39.95	1005	49.48
Households recovering the decrease between $t+1$ and $t+2$	702	61.31	727	72.34
Household dietary diversity				
Households suffering a loss between time t and $t+1$	1515	52.86	1219	60.02
Households recovering the loss between time $t+1$ and $t+2$	905	59.74	636	52.17
Per capita food consumption				
Households suffering a decline between time t and $t+1$	1440	50.24	1330	65.48
Households recovering the decline between time $t+1$ and $t+2$	869	60.35	939	70.60
Total households	2866		2031	

Note: only significant changes in households' food security status were considered, establishing a 5% allowance as a minimum threshold to consider food security fluctuations. Therefore, a decline in food consumption and dietary diversity between time t and $t+1$ is defined as such only if the household food security indicator in time $t+1$ is less than its value in time t minus 5%. Consistently, we considered that a household recovered the loss suffered between time t and $t+1$ if its food security indicator in time $t+2$ was greater than or equal to its value in time t minus 5%

3.2 Linking resilience and food security

Table 3 shows household food dynamics in the two countries. The share of households experiencing a worsening of food security between time t and $t+1$ ranged between 40 and 50% in Tanzania, while it was slightly larger in Uganda where it ranged between 50 and 65% of total households. Among the Tanzanian households that experienced a decrease in food security between time t and time $t+1$, around 60% were able to recover this decrease between time $t+1$ and $t+2$. Uganda showed more variable figures, ranging from 52% recovery in dietary diversity to 72% recovery in per capita caloric intake.

To investigate the relationship between food security and resilience two probit models of experiencing a reduction in per capita caloric intake (Table 4) and dietary diversity (Table 5) were estimated for the two countries. Endogeneity and multicollinearity were tested using the Durbin-Wu-Hausman test and variance inflation factor test, respectively. Both tests were negative for all models and all food security indicators except endogeneity in Tanzania in the case of the per capita caloric intake model that was slightly significant. This was due to the rural Tanzanian sub-sample, while in the case of the urban sub-sample the endogeneity test was negative.

As expected, a higher RCI in time t negatively affected the probability of suffering a loss between time t and $t+1$ in both countries, irrespective of the adopted food security indicator. On the contrary, the RCI positively affected the probability of recovering between time $t+1$ and $t+2$ in the case of Uganda for both indicators. In the case of Tanzania this is true for dietary diversity while for per capita caloric intake it was not statistically significant. The higher the initial level of food security the more likely a worsening of food security status between t and $t+1$ and the less likely the recovery between $t+1$ and $t+2$. This is not to say that a household becomes food insecure (i.e. it falls below the minimum food requirement threshold) but only that the per capita caloric intake or the dietary diversity was lower than in the initial state. This probably reflects the fact that if a household starts at a higher level of food security it can decrease food intake without compromising its survival, while a household that starts at a lower level of food security cannot reduce too much its food intake without putting its surviva at risk. Significantly, when the food insecurity dummy was interacted with the RCI, the latter dampened the original effect of the former. The effect of the food insecurity dummy at the mean level of RCI for Tanzania (59.745) was equal to $-1.062+(0.0188\times 59.745)=0.061$ (p value of the joint significance of the food security dummy and the interaction term was 0.0002); therefore the effect was lower compared to the food insecurity coefficient of column 1. The same was confirmed in the Uganda case, where the effect of the food insecurity dummy at the mean level of RCI (51.042) was equal to $-0.470+(0.0081\times 51.042)=-0.056$ (p value 0.0754).

Other socio-demographics were generally not statistically significant but the age of the household head, which negatively affected only the likelihood of a decrease in per capita caloric intake between t and $t+1$, and the household size (useful for controlling for measurement error and omitted variable bias) that positively affected the probability of suffering a decrease in food security between t and $t+1$ and reduced the possibility of

Table 4 Probit regression of the likelihood of suffering a decrease in per capita caloric intake between t and t+1 (assuming value 1 for decline in columns 1, 2, 4 and 5) and likelihood of recovering from the loss between t+1 and t+2 (assuming value 1 for recovery in columns 3 and 6)

	Tanzania			Uganda		
	1 Decline btw t and $t+1$	2 Decline btw t and $t+1$	3 Recovery btw $t+1$ and $t+2$	4 Decline btw t and $t+1$	5 Decline btw t and $t+1$	6 Recovery btw $t+1$ and $t+2$
RCI	−0.018***	−0.032***	0.002	−0.007***	−0.011***	0.014***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)
Caloric intake	0.001***	0.001***	−0.001***	0.001***	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caloric intake < 2100	0.169*	−1.062***	−0.013	−0.068	−0.470**	−0.274**
	(0.094)	(0.342)	(0.108)	(0.098)	(0.237)	(0.132)
RCI × caloric intake < 2100		0.019***			0.008*	
		(0.005)			(0.004)	
Female household head	0.067	0.067	0.018	−0.000	−0.004	−0.055
	(0.066)	(0.066)	(0.100)	(0.069)	(0.069)	(0.108)
Age of household head	−0.003*	−0.004*	0.004	−0.004*	−0.004*	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)
Household size	0.143***	0.133***	−0.092*	0.151***	0.146***	0.076
	(0.031)	(0.031)	(0.048)	(0.035)	(0.035)	(0.064)
Squared household size	−0.007***	−0.006***	0.003	−0.008***	−0.008***	−0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
Rural	−0.019	−0.026	−0.108	−0.346	−0.089	−0.504
	(0.072)	(0.072)	(0.110)	(0.325)	(0.354)	(0.546)
Constant	−2.418***	−1.400***	1.858***	−0.346	−0.089	−0.504
	(0.331)	(0.430)	(0.527)	(0.325)	(0.354)	(0.546)
Observations	2866	2866	1145	2031	2031	1002
Log-likelihood	−1415	−1408	−656	−1208	−1207	−487
Pseudo-R2	0.266	0.270	0.141	0.141	0.143	0.189
Pearson's χ^2	3404	3471	1262	2029	2027	1252
Prob > χ^2	0.000	0.000	0.001	0.425	0.433	0.000

All explanatory variables are at time t except per capita caloric intake in models 3 and 6, which are at time $t+1$. Regional dummies are included as control: 26 dummies in models 1 and 2 and 4 dummies in models 3 and 4. Standard errors in parentheses: ***$p<0.01$, **$p<0.05$, *$p<0.1$

recovery between $t+1$ and $t+2$. The direction of this relationship changed when using a squared measure of household size that controlled for the presence of a potential nonlinear effect of household size on food security patterns: this means that the initial increase in the number of household members had a negative effect on food security achievements but, after a certain threshold, further increases turned into a positive effect.

To test the robustness of the analysis and to take into account the role of shocks on the relationship between resilience and food security, we first estimated model 8 including the shocks self-reported by interviewees in the LSMS-ISA surveys (Table 6). The questionnaires included information about the major shocks that were self-reported by the respondent. In the Tanzania LSMS-ISA, section R ("Recent shocks to household welfare") the questionnaire asks the household whether it has been negatively affected by a list of shocks over the past 5 years. Furthermore, for the three most significant shocks, additional information on their impacts was collected: reduction in income/assets caused by the shock, dispersion of the shock, and year of occurrence of the shock. In the Uganda LSMS-ISA survey, section 16 ("Shocks and coping strategies") collects information on the shocks that occurred during the last 12 months, the length of the shock, the reduction in income, assets, food production and food purchase due to the shock, and the strategies adopted to cope with the shock.

The sign, magnitude and significance of RCI did not change when self-reported shock (dummy) variables were included in the probit model (8), but self-reported shocks were generally not

Table 5 Probit regression on the likelihood of suffering a dietary diversity loss between t and $t+1$ (dummy equal to 1 for the loss in columns 1 and 3) and recovering from the loss between $t+1$ and $t+2$ (dummy equal to 1 for the recovery in columns 2 and 4)

	Tanzania		Uganda	
	1 Loss btw t and $t+1$	2 Recovery btw $t+1$ and $t+2$	3 Loss btw t and $t+1$	4 Recovery btw $t+1$ and $t+2$
RCI	− 0.015***	0.009***	− 0.006**	0.016***
	(0.002)	(0.003)	(0.003)	(0.004)
Dietary diversity	6.396***	− 5.159***	4.562***	− 4.857***
	(0.286)	(0.347)	(0.325)	(0.326)
Female household head	0.079	0.071	0.170**	− 0.134
	(0.063)	(0.087)	(0.070)	(0.093)
Age of household head	− 0.002	0.001	0.003	− 0.000
	(0.002)	(0.002)	(0.002)	(0.003)
Household size	0.042**	− 0.043	− 0.057*	− 0.046
	(0.018)	(0.045)	(0.032)	(0.047)
Squared household size	− 0.002**	0.004	0.002	0.005
	(0.001)	(0.003)	(0.002)	(0.003)
Rural	0.165**	− 0.082	0.155*	0.062
	(0.069)	(0.094)	(0.084)	(0.115)
Constant	− 4.545***	3.776***	− 2.473***	2.142***
	(0.300)	(0.532)	(0.344)	(0.453)
Observations	2866	1515	2031	1219
Log-likelihood	− 1577	− 862	− 1189	− 663
Pseudo-R2	0.201	0.155	0.128	0.213
Pearson's χ^2	2843	1594	2545	1339
Prob > χ^2	0.438	0.021	0.000	0.004

All explanatory variables are at time t except dietary diversity in models 2 and 4, which are at time $t+1$. Regional dummies are included as control: 26 dummies in models 1 and 2 and 4 dummies in models 3 and 4. Standard errors in parentheses: ***$p<0.01$, **$p<0.05$, *$p<0.1$

statistically significant (Table 13 in Appendix shows all the variables' coefficients). Therefore, we estimated again the model introducing exogenously estimated covariate shocks that were PSDI flood, PSDI drought, wet NDVI anomaly, dry NDVI anomaly and conflict intensity indexes (Table 7 shows selected variables and Table 14 in the Appendix reports the full set of coefficients). Only the PSDI flood and the wet NDVI anomaly dummies were statistically significant showing the expected sign, i.e. both indicators increased the probability of suffering a food security loss, while the PDSI drought, dry NDVI anomaly and conflict indexes were not significant. The RCI played exactly the same role as in previous models, i.e. decreasing the probability of suffering a loss.

Finally, a more complete estimation of Eq. (8) is reported in Table 8 (short version of Table 15 in the Appendix) where exogenously estimated covariate shocks, self-reported idiosyncratic shocks and the interaction terms between RCI and specific shocks are included. The aim of including the interaction terms is to test whether the negative effect of the shocks was weakened by the household resilience capacity.

The estimates of the coefficients of the RCI are quite robust, showing the same signs and values close to the ones estimated in the models not including the shocks (cf. Tables 4 and 5).

4 Discussion

This paper provides empirical evidence on how household resilience contributes to the evolution of food security among Tanzanian and Ugandan households. It also tests the role of shocks on resilience measurement. By doing so, i.e. including both conflicts and climatic shocks within a resilience analysis framework, it contributes to filling a gap, so-far largely unexplored, in the empirical literature on resilience measurement.

The main results of the analysis are the following:

a. Adaptive capacity is the most relevant factor contributing to household resilience, and education and the proportion of income earners to total household members are the

Table 6 Probit regression of the likelihood of food security worsening (assuming value 1 for decrease in caloric intake in columns 1 and 3 and value 1 for loss in dietary diversity in columns 2 and 4) including self-reported shocks

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake	2 Loss btw t and $t+1$ in dietary diversity	3 Decrease btw t and $t+1$ in per capita caloric intake	4 Loss btw t and $t+1$ in dietary diversity
RCI	− 0.019***	− 0.015***	− 0.006**	− 0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
Caloric intake	0.001***		0.001***	
	(0.000)		(0.000)	
Dietary diversity		6.405***		4.653***
		(0.287)		(0.328)
Observations	2866	2866	2031	2031
Pseudo R2	0.271	0.206	0.146	0.134
Self-reported shocks (dummy variables)	Yes	Yes	Yes	yes
HH control characteristics	Yes	Yes	Yes	Yes

Regional dummies are included in all models. HH control characteristics (female HH head, age of HH head, HH size, squared HH size and rural) are included in all models but regression coefficients are not shown in the table (see Table 13 in the Appendix for the full set of variables' coefficients). Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 Probit regression of the likelihood of food security worsening (assuming value 1 for decrease in caloric intake in columns 1 and 3 and value 1 for loss in dietary diversity in columns 2 and 4) including covariate shocks

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake	2 Loss btw t and $t+1$ in dietary diversity	3 Decrease btw t and $t+1$ in per capita caloric intake	4 Loss btw t and $t+1$ in dietary diversity
RCI	− 0.018***	− 0.015***	− 0.007***	− 0.008***
	(0.003)	(0.002)	(0.003)	(0.003)
Caloric intake	0.001***		0.001***	
	(0.000)		(0.000)	
Dietary diversity		6.392***		4.620***
		(0.286)		(0.330)
Covariate climatic shocks				
Wet NDVI anomaly dummy	0.192**	0.091		
	(0.095)	(0.089)		
PDSI flood dummy			0.269**	− 0.019
			(0.116)	(0.118)
Observations	2866	2866	2031	2031
Pseudo R2	0.267	0.204	0.142	0.127
Self-reported shocks (dummy variables)	Yes	Yes	Yes	Yes
Covariate shocks	Yes	Yes	Yes	Yes
HH control characteristics	Yes	Yes	Yes	Yes

Regional dummies were included in all models. HH control characteristics (female HH head, age of HH head, HH size, squared HH size and rural) were included in all models but regression coefficients are not shown in the table (see Table 14 in the Appendix for the full set of variables' coefficients). Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8 Probit regression of the likelihood of food security worsening (assuming value 1 for decrease in caloric intake in columns 1 and 3 and value 1 for loss in dietary diversity in columns 2 and 4) including self-reported shocks, covariate shocks and interaction terms RCI × shocks

	Tanzania		Uganda	
	1 Decrease btw *t* and *t* + 1 in per capita caloric intake	2 Loss btw t and *t* + 1 in dietary diversity	3 Decrease btw *t* and *t* + 1 in per capita caloric intake	4 Loss btw *t* and *t* + 1 in dietary diversity
RCI	− 0.030***	− 0.015***	− 0.008*	− 0.006*
	(0.006)	(0.004)	(0.004)	(0.003)
Caloric intake	0.001***		0.000***	
	(0.000)		(0.000)	
Dietary diversity		6.425***		4.769***
		(0.288)		(0.336)
Interaction terms				
RCI × PDSI flood dummy			− 0.017***	− 0.003
			(0.006)	(0.006)
RCI × PDSI drought dummy			0.050*	0.017
			(0.029)	(0.024)
RCI × conflict intensity	− 0.000	− 0.002*	− 0.000	− 0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Observations	2866	2866	2031	2031
Pseudo R2	0.275	0.206	0.159	0.139
Self-reported shocks (dummy variables)	Yes	Yes	Yes	Yes
Covariate shocks	Yes	Yes	Yes	Yes
Interaction terms RCI × shocks	Yes	Yes	Yes	Yes
HH control characteristics	Yes	Yes	Yes	Yes

Regional dummies are included in all models. HH control characteristics (female HH head, age of HH head, HH size, squared HH size and rural) are included in all models but regression coefficients are not shown in the table (see Table 15 in the Appendix for the full set of variables' coefficients). Standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

most relevant determinants of this factor in both countries. Moreover, adaptive capacity is the pillar most strongly correlated to resilience as shown by Gallopin (2006) with SSN also contributing significantly to resilience in both countries as in Dercon (2002) and Devereux and Getu (2013);

b. Household resilience is positively related to future household food security outcomes, decreasing the probability of suffering a future food security loss and facilitating the recovery after the occurrence of a loss. These results are robust to various model specifications and valid for both countries;

c. Finally, the resilience capacity index mitigates the negative impact of shocks.

The self-reported shocks were generally not statistically significant irrespective of the adopted food security indicator. This is probably a result of the low accuracy of the self-reported information which may depend on over-/under-estimation of the shocks' perceived impact by respondents. The questionnaire collected dichotomous information—yes or no—on whether households had been affected by a list of shocks (drought, flood, loss of land, crop diseases or pests, illness of household members, loss of employment and so forth) over the past year. Furthermore, only some shocks were statistically significant, probably because of the too short period of analysis (only 4 years in the case of Tanzania and 3 years in Uganda) over which only a few shocks took place. However, the RCI remained negative and statistically significant in the case of Tanzania for both indicators, while the interaction terms were not statistically significant. On the contrary, in the case of Uganda, despite RCI showing the right sign, it was less statistically significant ($p = 0.90$). However, in this case, a few interaction terms between RCI and specific shocks were statistically significant and had a sign opposite to that of the shock alone, meaning that RCI is able to dampen the impact of such a shock.

It is therefore possible to conclude that the heuristically developed indicator—i.e. the Resilience Capacity Index developed according to the FAO's RIMA approach—is able to capture the unobservable construct it intends to measure, i.e. the capacity of a household to withstand shocks.

This is quite reassuring because it means that the operationalization of the concept of resilience as a policy objective may be feasible. However, the way to fully operationalize this concept is still long and further analyses need to be conducted before it can be properly used. For instance, from the theoretical viewpoint, any proposed index of resilience needs to be clearly linked to an underlying theoretical framework. From the empirical viewpoint, a better understanding of the role played by idiosyncratic and covariate shocks is needed. Moreover, so far no resilience measurement paper, including this, has analyzed the different mechanisms through which household resilience affects household food security. In other words, the empirical tests presented in this paper confirm the existence of a positive relationship between the RCI and household food security without investigating the specific conduit mechanism by which resilience can contribute to realizing positive food security outcomes.

Avenues for further empirical research are largely conditional on the availability of better quality data. The analysis may be extended to other African countries. An expanded sample of countries could provide more robust evidence, confirming or challenging the results presented here. Furthermore, using longer time series of household surveys, as soon as they become available, may prove useful in deepening the analysis, especially with regard to the effect of shocks and stressors on food security and on the role played by household resilience on the way shocks affect the status of household food security.

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Compliance with ethical standards

The views expressed in this article do not necessarily reflect the views of the Food and Agriculture Organization of the United Nation.

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Table 9 Summary statistics of the variables used in the estimates (pooled samples, 3 rounds)

		Uganda				Tanzania			
Variable	Definition/notes	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Food consumption per capita	Monetary value, expressed in US dollars, of per capita monthly food consumption, including expenditure on food, the monetary value of auto-produced food, received for free food (as gifts or part of a conditional project) and stored food.	14.053	17.511	0	190.358	20.116	12.377	0.43	90.029
Simpson dietary diversity	Index that takes into account the number of food group (cereals, roots, vegetables, fruits, meat, legumes, dairy, fats and other) consumed as well as their relative abundance (Simpson, 1949). The index ranges between 0 and 1, where 1 represents maximum dietary diversity and 0 represents no diversity. Specifically: $Dietary \quad diversity = 1 - \sum_{i=1}^{n} p_i^2$ where p_i is the share of consumed calories of the ith food group in a sample of n food groups.	0.611	0.187	0	1	0.608	0.123	0	0.873
Access to Basic Services (ABS)									
Infrastructural index		−0.105	0.937	−0.898	4.567	0.203	0.304	−0.038	1.024

Table 9 (continued)

Variable	Definition/notes	Uganda Mean	Std. Dev.	Min	Max	Tanzania Mean	Std. Dev.	Min	Max
	Index combining six dummies, each of them equal to one for having a home; cement roof; brick walls; non-dirty floor; running water; toilet; electricity. The index is created using principal component analysis. A higher value of the index indicates better dwelling conditions.								
Distance to school	The distance is expressed in km	22.793	14.457	0	90	0.229	0.789	0	17
Distance to market	The distance is expressed in km	35.766	35.216	0	300	7.726	11.619	0	132
Assets (AST)									
Agricultural asset index	A list of dummy variables assuming value 1 or 0 is used, depending on whether or not a household has specific agricultural tools, such as a hoe, plough, harrow, tractor, harvesting and threshing machine, water pumping set, reapers and fertilizer distributor. The index aggregates the dummy variables through factor analysis. The index has a higher value for households with a higher productive asset position.	0.016	0.768	−0.858	18.427	−0.102	0.95	−0.733	14
Wealth index	A list of dummy variables assuming value 1 or 0 is used, depending on whether or not a household has specific non-productive assets, such as a telephone, fridge, furniture, lantern, computer, utensil, television, radio, lamp, mosquito nets, iron, stove, water-heater, stereo, books, antenna, motor vehicle, motorcycle and bicycle. The index is created through factor analysis. The index is a proxy for the richness of the household. It assumes higher values for households with a higher non-productive asset position.	0.04	1.263	−1.726	11.269	0.075	0.639	−0.923	2.297
Land owned	Hectares of owned land per capita.	1.44	5.458	0	330.264	1.296	2.04	0	34.803
Tropical Livestock Unit (TLU)	TLU standardizes different types of livestock into a single unit of measurement. TLU is a weighted sum of the number of different livestock owned by the household. The conversion factor (weights) adopted is: 1 camel; 0.7 cattle; 0.55 donkeys/mules/horses; 0.1 sheep/goats; 0.01 chickens.	1.318	8.323	0	575.26	1.366	4.248	0	66.4
Adaptive Capacity (AC)									
Income diversification	Principal component index with dummies for income from (1) agriculture and fishing wages; (2) non-agriculture wages; (3) farming production; (4) livestock and fishing production; (5) non-agriculture business; (6) transfers and (7) other income sources.	0.28	0.376	−0.593	1.385	0.17	0.421	−0.463	1.299
Average education	Numbers of average years of education among HH members	4.715	3.665	0	17	5.202	3.349	0	17
Income earners' share	Number of active household members (> 15 and < 64 years old) divided by household size	0.484	0.251	0	1	0.526	0.237	0	1
Social Safety Nets (SSN)									
Private transfers (US dollars)	Received private transfers monthly per capita in US dollars (continuous variable).	1.525	5.815	0	123.607	0.728	1.466	0	12.157
Other transfers (US dollars)	Received non-private transfers monthly per capita in US dollars (continuous variable).	0.39	2.656	0	49.333	0.028	0.284	0	20.055
HH control characteristics									
Female HH	Dummy = 1 if yes	0.314	0.464	0	1	0.247	0.431	0	1
Age of HH	Numeric	47.683	14.943	0	100	48.23	15.224	17	107

Table 9 (continued)

Variable	Definition/notes	Uganda Mean	Std. Dev.	Min	Max	Tanzania Mean	Std. Dev.	Min	Max
Household size	Numeric	5.539	2.847	1	23	5.579	3.008	1	55
Squared household size	Numeric	38.784	40.381	1	529	40.179	68.261	1	3025
HH engaged in agriculture	Dummy = 1 if yes	0.839	0.367	0	1	0.766	0.423	0	1
Shocks (first round)									
Drought or flood/drought	Dummy = 1 if yes, the household has experienced the specific shock	0.508	0.500	0	1	0.224	0.417	0	1
Flood	Dummy = 1 if yes	0.020	0.141	0	1				
Erosion	Dummy = 1 if yes	0.006	0.080	0	1				
Crop disease or pests	Dummy = 1 if yes	0.053	0.223	0	1	0.168	0.374	0	1
Fall in sale price for crops	Dummy = 1 if yes	0.021	0.142	0	1	0.178	0.383	0	1
Rise in agricultural input prices	Dummy = 1 if yes	0.018	0.134	0	1	0.182	0.386	0	1
Livestock died or stolen	Dummy = 1 if yes	0.033	0.180	0	1	0.156	0.363	0	1
Large rise in price of food	Dummy = 1 if yes					0.522	0.500	0	1
Business failure	Dummy = 1 if yes					0.041	0.199	0	1
Reduction/loss of salary	Dummy = 1 if yes	0.012	0.108	0	1	0.020	0.140	0	1
Loss of employment	Dummy = 1 if yes	0.002	0.050	0	1				
Severe water shortage	Dummy = 1 if yes					0.254	0.435	0	1
Loss of land	Dummy = 1 if yes					0.031	0.174	0	1
Illness of household member	Dummy = 1 if yes	0.065	0.246	0	1	0.074	0.262	0	1
Illness of income earners	Dummy = 1 if yes	0.068	0.252	0	1				
Death of a member of household/death of income earners	Dummy = 1 if yes	0.010	0.101	0	1	0.110	0.313	0	1
Death of other family member	Dummy = 1 if yes	0.028	0.165	0	1	0.324	0.468	0	1
Break-up of the household	Dummy = 1 if yes					0.046	0.210	0	1
Jailed	Dummy = 1 if yes					0.005	0.071	0	1
Fire	Dummy = 1 if yes	0.011	0.104	0	1	0.016	0.126	0	1
Robbery	Dummy = 1 if yes					0.076	0.265	0	1
Theft non-agricultural assets	Dummy = 1 if yes	0.042	0.200	0	1				
Theft agricultural assets	Dummy = 1 if yes	0.050	0.218	0	1				
Dwelling damage	Dummy = 1 if yes					0.008	0.087	0	1
Conflict	Dummy = 1 if yes	0.014	0.117	0	1				
Other shocks	Dummy = 1 if yes	0.038	0.192	0	1	0.039	0.195	0	1
NDVI long-term average	Normalized Index Vegetation Index, long-term average	0.375	0.051	0.171	0.450	0.342	0.043	0.239	0.434
Wet NDVI anomaly dummy	Dummy = 1 if NDVI average is above 1 standard deviation from long-term average	0.236	0.425	0	1	0.100	0.300	0	1
Dry NDVI anomaly dummy	Dummy = 1 if NDVI average is below 1 standard deviation from long-term average	0.017	0.130	0	1	0.006	0.075	0	1
PDSI, long-term average	Palmer Drought Severity Index, long-term average	− 1.061	0.500	− 1.813	0.031	− 0.260	0.498	− 1.639	0.731
PDSI flood shock dummy	Dummy = 1 if PDSI average is above 1 standard deviation from long-term average	0.166	0.373	0	1	0.246	0.431	0	1
PDSI drought shock dummy	Dummy = 1 if PDSI average is below 1 standard deviation from long-term average	0.009	0.094	0	1	0.012	0.111	0	1
Conflict intensity index	Information about the exact geographic location of each event (yj) (from ACLED dataset) and the household (i) in that year are needed. Then the square of the distance (d) in degrees between the household and each of the events is estimated. The index is given as Conf = Σ (j = 1.....J) e − α(d(yj,i)), where α is a distance-discount factor. The index therefore captures the number of "geographically discounted" events for each individual. As in Bozzoli et al., α = 10.	5.096	9.340	0	35.701	1.810	4.539	0	27.640
Obs.		6093				8598			

Table 10 Factor analysis results for access to basic services (ABS) by country

ABS

	Tanzania			Uganda		
	Factor 1	Factor 2	Uniqueness	Factor 1	Factor 2	Uniqueness
Infrastructural index	0.476	− 0.042	0.772	0.156	0.220	0.927
Distance to school	0.477	0.039	0.771	0.641	− 0.126	0.574
Distance to market	0.016	0.092	0.991	0.680	0.068	0.532

The number of factors used for estimating ABS in Tanzania is 1. It explains the 97% of the variable variance. The number of factors used for estimating ABS in Uganda is 1. It explains the 92% of the variable variance

Table 11 Factor analysis results for assets (AST) by country

AST

	Tanzania				Uganda			
	Factor 1	Factor 2	Factor 3	Uniqueness	Factor 1	Factor 2	Factor 3	Uniqueness
Agricultural asset index	0.798	− 0.124	0.024	0.348	0.913	− 0.177	− 0.111	0.122
Wealth index	− 0.281	0.529	− 0.015	0.641	0.227	− 0.073	0.218	0.896
Tropical Livestock Unit	0.600	0.316	− 0.108	0.529	0.955	0.157	0.056	0.060
Land	0.230	0.252	0.178	0.852	0.067	0.417	− 0.030	0.821

The number of factors used for estimating AST in Tanzania is 2. They jointly explain the 97% of the variable variance. The number of factors used for estimating AST in Uganda is 2. They jointly explain the 96% of the variable variance

Table 12 Factor analysis results for adaptive capacity (AC) by country

AC

	Tanzania			Uganda		
	Factor 1	Factor 2	Uniqueness	Factor 1	Factor 2	Uniqueness
Income diversification	− 0.291	0.270	0.842	− 0.255	0.138	0.915
Education	0.664	− 0.047	0.557	0.583	− 0.015	0.659
Income earners' share	0.539	0.204	0.668	0.549	0.080	0.691

The number of factors used for estimating AC in Tanzania is 2. They jointly explain the 100% of the variable variance. The number of factors used for estimating AC in Uganda is 1. It explains the 96% of the variable variance

Note: Social Safety Nets (SSN) pillar is estimated as sum of private and public transfers. Factor analysis is not employed when the number of variables is less than 3

Table 13 Probit regression of the likelihood of food security worsening (decrease in caloric intake in columns 1 and 3 and loss in dietary diversity in columns 2 and 4) including self-reported shocks

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	2 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)	3 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	4 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)
RCI	− 0.019***	− 0.015***	− 0.006**	− 0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
Caloric intake	0.001***		0.001***	
	(0.000)		(0.000)	
Dietary diversity		6.405***		4.653***
		(0.287)		(0.328)
Self-reported shocks				
Drought or flood/drought	− 0.063	0.014	0.015	0.011
	(0.071)	(0.068)	(0.066)	(0.066)
Flood			0.133	0.228
			(0.224)	(0.234)
Erosion			0.481	0.220
			(0.391)	(0.364)
Crop disease or pests	− 0.006	− 0.062	− 0.108	− 0.120
	(0.075)	(0.072)	(0.147)	(0.147)
Fall in sale price for crops	− 0.002	0.033	− 0.500*	− 0.148
	(0.080)	(0.076)	(0.256)	(0.240)
Rise in agricultural input prices	− 0.010	0.045	− 0.035	− 0.262
	(0.081)	(0.077)	(0.248)	(0.236)
Livestock died or stolen	0.011	0.028	− 0.254	− 0.017
	(0.072)	(0.069)	(0.180)	(0.179)
Large rise in price of food	0.022	0.015		
	(0.065)	(0.061)		
Business failure	0.018	0.108		
	(0.126)	(0.120)		
Reduction/loss of salary	− 0.035	0.181	0.233	0.013
	(0.170)	(0.162)	(0.291)	(0.293)
Loss of employment			− 0.278	0.676
			(0.611)	(0.713)
Severe water shortage	0.022	− 0.019		
	(0.064)	(0.061)		
Loss of land	− 0.145	− 0.025		
	(0.162)	(0.151)		
Illness of household member	0.114	− 0.132	0.214*	0.053
	(0.094)	(0.090)	(0.119)	(0.122)
Illness of income earners			− 0.020	0.017
			(0.123)	(0.126)
Death of a member of household/ death of income earners	0.108	− 0.007	− 0.124	− 0.187
	(0.079)	(0.077)	(0.309)	(0.307)
Death of other family member	0.064	− 0.012	0.068	0.081
	(0.060)	(0.057)	(0.179)	(0.183)
Break-up of the household	− 0.091	− 0.111		
	(0.130)	(0.122)		

Table 13 (continued)

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	2 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)	3 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	4 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)
Jailed	0.821**	−0.038		
	(0.360)	(0.315)		
Fire	−0.321	−0.010	−0.121	−0.026
	(0.224)	(0.195)	(0.286)	(0.298)
Robbery	−0.073	0.053		
	(0.095)	(0.088)		
Theft non-agricultural assets			−0.104	−0.186
			(0.153)	(0.149)
Theft agricultural assets			0.070	0.055
			(0.144)	(0.144)
Dwelling damage	0.212	0.005		
	(0.247)	(0.248)		
Conflict			−0.077	−0.111
			(0.282)	(0.276)
Other shocks	0.422***	0.044	0.050	0.018
	(0.155)	(0.148)	(0.158)	(0.158)
HH control characteristics				
Female HH head	0.056	0.091	0.007	0.168**
	(0.067)	(0.064)	(0.070)	(0.071)
Age of HH head	−0.004*	−0.002	−0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
HH size	0.134***	0.041**	0.153***	−0.069**
	(0.031)	(0.018)	(0.035)	(0.032)
Squared HH size	−0.007***	−0.002*	−0.008***	0.003
	(0.002)	(0.001)	(0.003)	(0.002)
Rural	−0.009	0.172**	−0.132	0.131
	(0.076)	(0.073)	(0.087)	(0.087)
Constant	−2.062***	−4.584***	−0.577*	−2.498***
	(0.295)	(0.307)	(0.325)	(0.352)
Observations	2866	2866	2031	2031
Log-likelihood	−1405	−1573	−1200	−1183
Pseudo R2	0.271	0.206	0.146	0.134
Pearson's χ^2	3296	2845	2031	2632
Prob > χ^2	0.000	0.333	0.310	0.000

Regional dummies are included in all models

Standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 14 Probit regression of the likelihood of food security worsening (decrease in caloric intake in columns 1 and 3 and loss in dietary diversity in columns 2 and 4) including covariate shocks

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	2 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)	3 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	4 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)
RCI	−0.018***	−0.015***	−0.007***	−0.008***
	(0.003)	(0.002)	(0.003)	(0.003)
Caloric intake	0.001***		0.001***	
	(0.000)		(0.000)	
Dietary diversity		6.392***		4.620***
		(0.286)		(0.330)
Covariate climatic shocks				
NDVI long-term average	−0.756	0.076		
	(1.096)	(1.034)		
Wet NDVI anomaly dummy	0.192**	0.091		
	(0.095)	(0.089)		
Dry NDVI anomaly dummy	0.224	−0.070		
	(0.260)	(0.246)		
PDSI, long-term average			0.032	0.017
			(0.085)	(0.087)
PDSI flood dummy			0.269**	−0.019
			(0.116)	(0.118)
PDSI drought dummy			0.098	0.227
			(0.314)	(0.333)
Covariate conflict shocks				
Conflict intensity index	−0.020	−0.011	−0.003	−0.001
	(0.024)	(0.023)	(0.005)	(0.005)
HH control characteristics				
Female HH head	0.062	0.079	0.001	0.152**
	(0.066)	(0.063)	(0.069)	(0.069)
Age of HH head	−0.003*	−0.002	−0.005**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
HH size	0.144***	0.043**	0.155***	−0.061*
	(0.031)	(0.018)	(0.035)	(0.032)
Squared HH size	−0.007***	−0.002**	−0.008***	0.002
	(0.002)	(0.001)	(0.003)	(0.002)
Rural	−0.019	0.164**	−0.147	0.121
	(0.073)	(0.070)	(0.090)	(0.091)
Constant	−1.897***	−4.586***	−0.397	−2.362***
	(0.455)	(0.442)	(0.328)	(0.362)
Observations	2866	2866	2031	2031
Log-likelihood	−1414	−1576	−1207	−1192
Pseudo R2	0.267	0.204	0.142	0.127
Pearson's χ^2	3249	2845	2039	2534
Prob > χ^2	0.000	0.409	0.349	0.000

Regional dummies are included in all models

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15 Probit regression of the likelihood of food security worsening (decrease in caloric intake in columns 1 and 3 and loss in dietary diversity in columns 2 and 4) including self-reported shocks, covariate shocks and interaction terms RCI × shocks

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	2 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)	3 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	4 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)
RCI	− 0.030***	− 0.015***	− 0.008*	− 0.006*
	(0.006)	(0.004)	(0.004)	(0.003)
Caloric intake	0.001***		0.000***	
	(0.000)		(0.000)	
Dietary diversity		6.425***		4.769***
		(0.288)		(0.336)
Caloric intake < 2100	− 0.969***		− 0.557**	
	(0.354)		(0.248)	
RCI × caloric intake < 2100	0.017***		0.010**	
	(0.005)		(0.005)	
Covariate climatic shocks				
NDVI long-term average	− 0.758	− 0.030		
	(1.110)	(1.040)		
Wet NDVI anomaly dummy	0.205	− 0.084		
	(0.409)	(0.375)		
Dry NDVI anomaly dummy	0.603	0.210		
	(1.022)	(1.097)		
PDSI long-term average			− 0.012	− 0.059
			(0.086)	(0.088)
PDSI flood dummy			1.039***	0.093
			(0.306)	(0.323)
PDSI drought dummy			− 1.653	− 0.360
			(1.097)	(0.937)
Covariate conflict shocks				
Conflict intensity index	0.017	0.131*	0.011	− 0.001
	(0.082)	(0.077)	(0.018)	(0.019)
Self-reported shocks				
Crop disease or pests			− 0.903	0.879
			(0.681)	(0.649)
Fall in crop sale prices	− 0.109	0.366	− 0.473	− 0.561
	(0.314)	(0.291)	(1.142)	(0.983)
Rise in agricultural input prices	− 0.223	− 0.252	− 0.185	0.262
	(0.326)	(0.301)	(1.052)	(0.944)
Large rise in price of food	0.221	−0.078		
	(0.264)	(0.249)		
Illness of income earners			0.818*	0.190
			(0.431)	(0.445)
Jailed	− 0.413	0.042		
	(1.533)	(1.318)		
Other shocks	0.965	0.381		
	(0.768)	(0.807)		
Interaction terms				
RCI × wet NDVI anomaly dummy	0.000	0.003		
	(0.006)	(0.006)		

Table 15 (continued)

	Tanzania		Uganda	
	1 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	2 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)	3 Decrease btw t and $t+1$ in per capita caloric intake (dummy one for decrease)	4 Loss btw t and $t+1$ in dietary diversity (dummy one for loss)
RCI × dry NDVI anomaly dummy	− 0.007	− 0.005		
	(0.018)	(0.018)		
RCI × PDSI flood dummy			− 0.017***	− 0.003
			(0.006)	(0.006)
RCI × PDSI drought dummy			0.050*	0.017
			(0.029)	(0.024)
RCI × conflict intensity	− 0.000	− 0.002*	− 0.000	− 0.000
	(0.001)	(0.001)	(0.000)	(0.000)
RCI × crop disease or pests			0.016	− 0.017
			(0.013)	(0.012)
RCI × fall in sale price for crops	0.002	− 0.006	− 0.002	0.006
	(0.005)	(0.005)	(0.022)	(0.019)
RCI × rise in agricultural input prices	0.003	0.005	0.000	− 0.011
	(0.005)	(0.005)	(0.020)	(0.018)
RCI × large rise in price of food	− 0.003	− 0.004		
	(0.004)	(0.004)		
RCI × illness of income earners			− 0.012	− 0.002
			(0.009)	(0.009)
RCI × jailed	0.026	0.024		
	(0.025)	(0.026)		
RCI × other shocks	− 0.008	− 0.008		
	(0.011)	(0.011)		
HH control characteristics				
Female HH head	0.056	0.081	0.013	0.180**
	(0.067)	(0.063)	(0.070)	(0.071)
Age of HH head	− 0.004*	− 0.002	− 0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
HH size	0.134***	0.039**	0.161***	− 0.071**
	(0.032)	(0.018)	(0.036)	(0.033)
Squared HH size	− 0.007***	− 0.002*	− 0.008***	0.003
	(0.002)	(0.001)	(0.003)	(0.002)
Rural	− 0.030	0.162**	− 0.174*	0.126
	(0.075)	(0.072)	(0.092)	(0.092)
Constant	− 1.307**	− 4.571***	− 0.290	− 2.515***
	(0.596)	(0.480)	(0.389)	(0.378)
Observations	2866	2866	2031	2031
Log-likelihood	− 1397	− 1573	− 1183	− 1172
Pseudo R2	0.275	0.206	0.159	0.139
Pearson's χ^2	3528	2846	2038	2779
Prob > χ^2	0.000	0.340	0.280	0.000

Regional dummies are included in all models

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Marco d'Errico holds a Ph.D. in Economics and is an economist at the Food and Agriculture Organization (FAO) of the United Nations. He joined FAO in 2009 and, since then, he has participated in resilience analysis. He is currently responsible for the Resilience Analysis and Policies (RAP) team in FAO, implementing RIMA (Resilience Index Measurement and Analysis). He has been working in many African countries and in the West Bank and Gaza Strip as well as India and Thailand.

Professor Romano has a bachelor degree in Forestry and a PhD degree in Forest Economics and Management, both from the University of Florence. Professor Romano's research interests have shifted over the years from environmental resource valuation and econometric modelling of consumers' decisions concerning rural development analysis, globalization and economic growth to food security, poverty and microeconomic analysis of agriculture and rural development issues. He has published more than 100 papers in Italian and in international refereed journals as well as 15 books and monographs on these topics. Prof. Romano has been involved in and/or has been the coordinator of several EU and national research projects. He has been a consultant for the FAO, WFP, IFAD, the EU Commission (Agriculture DG and Research DG), the Instituto Nacional de Desarrollo Agropecuario (INDAP), Chile, the Italian Ministry of Scientific Research, and the Italian Ministry of Agriculture.

Rebecca Pietrelli is an economist of the Resilience Analysis and Policies (RAP) team at the Food and Agricultural Organization (FAO) of the United Nations. She holds a Ph.D. in Economics from La Sapienza University of Rome and an M.Sc. in Development Economics from Sussex University. Before joining FAO, she was a research fellow at Rome Tre University within the FOODSECURE research project. She has experience in household surveys and indicators of food security, resilience and vulnerability to poverty.