FINAL REPORT

(#1259359 – The Disaster Risk Financing Challenge Fund)

Forecast-based Financing for Food Security

IVM Institute for Environmental Studies VU

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FINAL REPORT

Dear funders, May 2021

We are very glad to provide you with the final report of our Challenge Fund Forecast-based Financing for Food Security (F4S). In this report, we outline the innovations produced by the F4S project, and their concrete application for disaster risk financing and forecast-based financing. With this final milestone, we feel that the F4S project has contributed to the development of new insights for risk financing that have been collectively researched with beneficiaries, and well-grounded in both science and practice.

If you have any questions or queries about this report, please do not hesitate to contact us.

With Kind Regards,

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LIST OF ABBREVIATION

ADASYN	Adaptive Synthetic sampling approach
CBA	Cost-Benefits Analysis
CE	Change Event
CEA	Cost-Effectiveness Analysis
CVA	Cash and Voucher Assistance
DCS	Dummy classifier
DREF	Disaster Response Emergency Fund
EAP	Early Action Protocol
F4S	Forecast-based Financing for Food Security
FEWS NET	Famine Early Warning System
FFT	Fast-and-Frugal Trees
FGD	Focus group discussion
IARP	Innovative Approaches in Response Preparedness
IBLI	Index-Based Livestock Insurance
ILRI	International Livestock Research Institute
IPC	Integrated Food Security Phase Classification
KSh	Kenyan Shillings
LD	Long Rain Long Dry season
LR	Long rain
LZ	Livelihood Zone
ML	Machine Learning
NDVI	Normalized Difference Vegetation Index
pFA	Probability of a false alarm
pHI	Probability of a hit
PSNP	Productive Social Safety Net
SD	Short Rain Short Dry season
SOPs	Standard operating procedures
SR	Short rain
T1- 4	Work Package 1 - 4
TAMSAT	Tropical Applications of Meteorology using Satellite
TLU	Tropical livestock unit
WFP	World Food Programme
Xgboost	Extreme Gradient Boosting Algorithm

EXECUTIVE SUMMARY

The Forecast-based Financing for Food Security project (F4S) aimed at developing information that enables the triggering of early actions to reduce the risk of food insecurity in Ethiopia, Kenya, and Uganda. For achieving this aim, the F4S project centred its developments around three pillars: (1) Forecasting key drivers of food insecurity, (2) Collection of local evidence and (3) Evaluation of cash transfer mechanism. All information obtained through these pillars attempted to address challenges inherent to decision-making based on forecasting information, with a special focus on the implementation of ex-ante cash transfers.
In summary, the main findings of the F4S can be summarised as follows:

1. There is a measured advantage and growing opportunity in using Machine Learning for forecasting relevant risk information to the food security system. The three models developed in alignment with the F4S project were able to provide accurate forecasts on key indicators of food security long ahead of a shock, which opens a month to annual window of opportunity for implementing anticipatory action;
2. The surveyed communities indicated to implement early action based on forecasting information of an upcoming hazard. However, such hazards often cause households to implement negative coping strategies such as to reduce the number of meals and amount of food consumed. Additionally, we have found that the communities have a large variety of local knowledge to predict threats to food security, and that this knowledge is used for guiding their decisions. Therefore, the integration of local and scientific knowledge could lead to a valuable improvement of existing disaster preparedness strategies;
3. Acting early based on forecasting information can generate both social and economic benefits. Furthermore, cash transfer programmes can potentially achieve significant reduction in costs if cash is disbursed earlier supported by forecasting information;
4. Based on a Choice Experiment, we also observed that the designing choices of a cash transfer programme such as the timing of payment and its format may affect people's expenditure behaviour. Understanding people's expenditure behavior if they are beneficiaries of ex-ante cash transfer, in combination with their existing local knowledge, are important factors for determining the suitability of disaster preparedness interventions to the local context. Therefore, it is important to further invest in co-design strategies between institutions and beneficiaries.

With this final milestone, the F4S project has contributed to the development of new insights for risk financing that have been collectively researched with beneficiaries, and well-grounded in both science and practice. It is important to highlight that this final milestone has only been feasible due to the strong collaboration and partnerships with key local partners and the communities surveyed, and due to the grant received through from Global Facility for Disaster Reduction and Recovery, the Foreign, Commonwealth & Development Office, and the Centre for Global Disaster Protection. This final report showcases the main findings of the F4S project in five chapters: (T1) Developing a forecasting model; (T2) Collecting local evidence and information; (T3) Evaluating cash transfer mechanism; (T4) Channels for operationalization; and (T5) Evaluation criteria.

OVERVIEW OF THE F4S PROJECT

Disaster risk financing has the potential to increase welfare, reduce exposure to hazards and promote mitigation prior to a shock. Therefore, timely ex-ante cash transfers can be more cost-effective than relying on ex-post disaster relief to respond to food insecurity , but only when leveraged by a credible plan, pre-agreed triggers for action, and pre-arranged financing and infrastructure to support cash transfer initiatives.To ensure adeq uate financial action one needs to have the right information to guide fast and evidence-based decision-making. Key enabling aspects are an understanding of the potential/upcoming food security impacts, the resources needed to address them, and an insight in the associated costs, beneficiaries' preferences, and lead times. Limited evidence and information exists to support the implementation of early actions that can reduce the risk of food insecurity. Through F4S, we aimed at:

1. Developing an impact-based probabilistic food insecurity forecasting model using Machine Learning algorithms and datasets of food insecurity drivers (T1);
2. Collecting local evidence on food insecurity triggers and information on individual preferences on key design elements of cash transfer mechanisms (T2);
3. Evaluating the cost-effectiveness of different cash transfer mechanisms (T3);
4. Exploring the potential channels of operationalization, including existing (government-led) social protection systems, to disseminate the knowledge gained within T1-T3 and to make a first step towards operationalization (T4).

Each of the aforementioned tasks was divided into sub-tasks and with each output a number of deliverables. Figure 1 visualizes the overall outline of the project and the linkages between the different the accomplished tasks and sub-tasks.

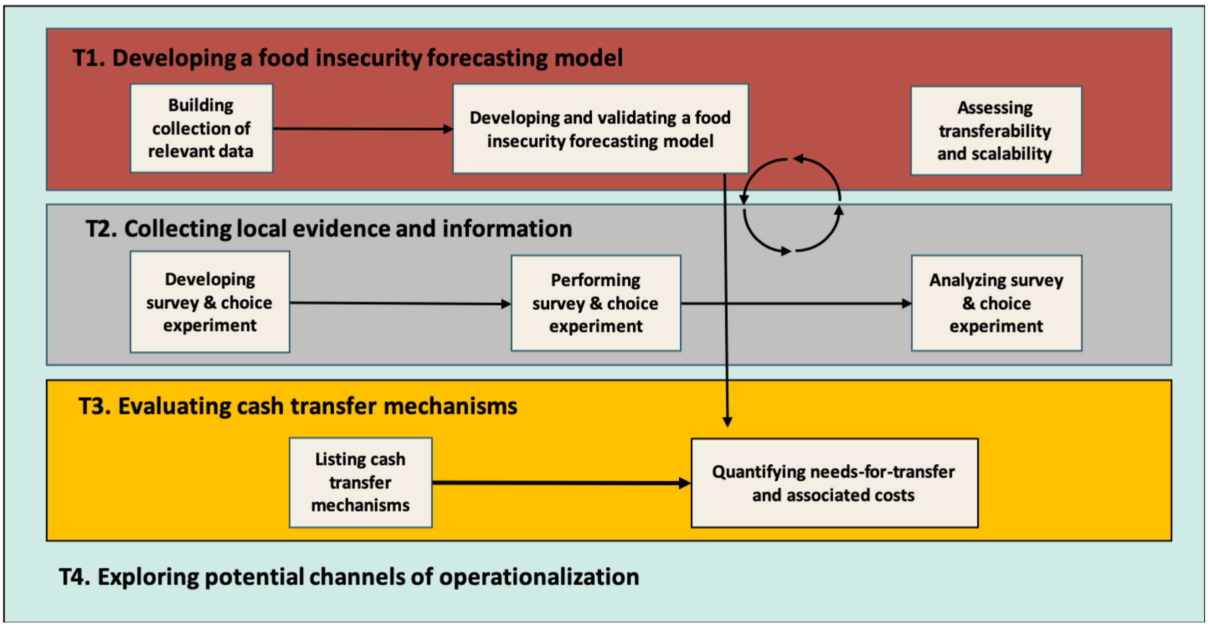


Figure 1 Flowchart of the F4S activities

T1: DEVELOPING A FOOD INSECURITY FORECASTING MODEL

For the Work Package 1 (T1), we applied Machine Learning to forecast proxies of food insecurity (details available at sections T1.2.1 – T1.2.4 of this report) at the district or livelihood zone scale of the three pilot countries. The lead time of the forecasting models range from annual to sub-seasonal scales. In Figure 1, we highlight the main activities and their interactions as part of the F4S project. In Chapter T1, a more technical overview of the forecasting models is provided.

For enabling the development of the forecasting model, we first built an inventory of datasets consisting of relevant biophysical and socioeconomic data for the three pilot countries (T1.1). Subsequently, we developed and validated the forecasting models, and for some of them, we further refined the model's development by triangulating the local knowledge emerging from the household survey (T2). Lastly, we have assessed the scalability and transferability of our models within and between the pilot countries (T1.3). As a result, we reached the following technical deliverables:

TD1.1: A collection of relevant biophysical and socioeconomic datasets for the three pilot countries;
TD1.2: A food insecurity forecasting model for the three pilot countries running at the district or livelihood level with early warning triggers and thresholds for food insecurity;
TD1.3: A report on the developing, testing, and validation of the food insecurity model for the three pilot countries, transferability of the model and its triggers, and scalability towards the rest of East Africa.

T1.1: BUILDING A COLLECTION OF RELEVANT DATA

Prior to the model's development, we focused on collecting relevant datasets which consisted mostly of open-source biophysical and socioeconomic data for the three pilot countries. The datasets and sources that were used as input for our food insecurity forecasting models are listed in Table 1. At the inception phase of the project, most of the data collection was guided by existing expertise of the F4S team's member. However, following the kick-off of the F4S project in Nairobi (October 2019), data collection efforts continued to also capture new insights emerging from the brainstorming and consultation section with the regional stakeholders. The data collection efforts and the subsequent model development phase (T1.2) has greatly benefited from the partnership with the Innovative Approaches in Response Preparedness (IARP) project, which has also been working on similar thematic and study area.

Another important activity related to data collection was the performance of a household survey, which consisted of a semi-structured questionnaire and choice experiment. With this activity (details available in section T2), we were able to collect, from 564 households[1], local knowledge on drivers of food insecurity that were incorporated in the forecasting model and information regarding their preferences and behavior that can shape design elements of ex-ante cash transfer programmes. As a result, we were able to incorporate different systems of knowledge into our forecasting models.

[1] Due to the existence of private information, the raw household survey data are not openly accessible by the public. Overall results of household survey are available in section T2.3.

Table 1. Inventory of datasets used in the different forecasting models highlighted in three different colours. Datasets used for extracting the proxies of food insecurity are named as "Predictand" whereas drivers of food insecurity as "Predictor".

Variable name	Used for extracting	Source	Model
Maize yield (subnational)	Predictand	Iizumi, T., & Sakai, T. (2020); Ministry of Agriculture Livestock, Fisheries and Cooperatives, Kenya	Shortage of calories
Maize production (subnational)	Predictand	Iizumi, T., & Sakai, T. (2020)	
Harvest Area subnational	Predictand	Iizumi, T., & Sakai, T. (2020)	
Export	Predictand	FAO	
Population count	Predictand	Gridded Population of the World, NASA	
Crop Usage	Predictand	Cassidy, Emily S., et al. (2013)	
Dietary preferences	Predictand	See footnote 4	
Maize production lag	Predictor	Iizumi, T., & Sakai, T. (2020); Kenyan Ministry of Agriculture, Livestock and Fisheries	
Water balance	Predictor	CHIRPS; Hobbins, Mike, et al. 2016	
NDVI	Predictor	Landsat	
Near surface wind speed	Predictor	FLDAS	
Travel time to markets	Predictor	Malaria Atlas Project, University of Oxford; WFP VAM; FSD Kenya	
GINI coefficient	Predictor	Kenya National Bureau of Statistics; Uganda Bureau of Statistics	
Total precipitation	Predictor	CHIRPS	Forage scarcity
Multivariate ENSO Index	Predictor	NOAA-PSL	
Potential evaporation	Predictor		
NDVI MODIS Aqua	Predictor	NASA	
Average soil moisture top two layers (0-40 cm)	Predictor	MERRA-2 atmospheric reanalysis & CHIRPS	
Net precipitation	Predictor	CHIRPS; Hobbins, Mike, et al. 2016	
Precipitation minus multi-year mean	Predictor	CHIRPS	
Potential evaporation minus multi-year mean	Predictor	Hobbins, Mike, et al. 2016	
Net precipitation minus monthly mean	Predictor	CHIRPS; Hobbins, Mike, et al. 2016	
Precipitation minus monthly mean	Predictor	CHIRPS	
Potential evaporation minus monthly mean	Predictor	Mike, et al. 2016	
Net precipitation minus monthly mean	Predictor	CHIRPS; Hobbins, Mike, et al. 2016	
Cumulative precipitation: 2-12 months	Predictor	CHIRPS	
Cumulative potential evapotranspiration: 2-12 months	Predictor	Hobbins, Mike, et al. 2016	
Cumulative NDVI MODIS Aqua: 2-12 months	Predictand/ Predictor	MODIS Aqua	
Cumulative net precipitation: 2-12 months	Predictor	CHIRPS; Hobbins, Mike, et al. 2016	
Dummy variable months falling in rainy (1) or dry (0) season	Predictor	FEWSNET	
Evapotranspiration	Predictor	FLDAS	
Downward longwave radiation flux	Predictor		
Net longwave radiation flux	Predictor		
Surface pressure	Predictor		
Specific humidity	Predictor		
Soil heat flux	Predictor		
Net sensible heat flux	Predictor		
Latent heat flux	Predictor		
Surface runoff	Predictor		
Baseflow	Predictor		
Surface radiative temperature	Predictor		
Total precipitation rate	Predictor		
Surface downward shortwave radiation	Predictor		
Net shortwave radiation flux	Predictor		
Near surface air temperature	Predictor		
Near surface wind speed	Predictor		
Soil moisture (0-10 cm underground)	Predictor		
Soil moisture (10-40 cm underground)	Predictor		
Soil moisture (40-100 cm underground)	Predictor		

Soil moisture (100-200 cm underground)	Predictor		
Soil temperature (0-10 cm underground)	Predictor		
Soil temperature (10-40 cm underground)	Predictor		
Soil temperature (40-100 cm underground)	Predictor		
Soil temperature (100-200 cm underground)	Predictor		
Livelihood zone	Predictor	FEWSNET	Transition in the state of food security
Soil moisture profile	Predictor	Bolten et al., 2010; Bolten and Crow, 2012; Kerr and Levine, 2008; Mladenova et al., 2017; Sazib et al., 2018	
Surface soil moisture	Predictor		
Surface soil moisture anomaly	Predictor		
Subsurface soil moisture	Predictor		
Subsurface soil moisture anomaly	Predictor		
Rainfall	Predictor	Adler et al., 2003; Huffman, 2014, 1997; Huffman et al., 2007, 1997, 2001, 1995	
NDVI	Predictor	Google Earth Engine	
Elevation	Predictor	Danielson and Gesch, 2011	
Accessibility	Predictor	Weiss et al., 2018	
Friction	Predictor	Weiss et al., 2018	
Population Count	Predictor	Center for International Earth Science Information Network	
Population Density	Predictor	Center for International Earth Science Information Network	
Food price	Predictor	World Food Program	
Conflict	Predictor	Uppsala University	
Agriculture profile	Predictor	FEWSNET	
Livestock	Predictor	FEWSNET	
Time context	Predictor	FEWSNET	
IPC	Predictand	FEWSNET	

T1.2: DEVELOPING AND VALIDATING A FOOD INSECURITY FORECASTING MODEL

The first step towards designing a forecasting model that predicts proxies of food insecurity is understanding the socio-economic characteristics of the three pilot countries. For detecting key socio-economic characteristics of a location, we used the generalized livelihood zone (LZ) definitions available at the FEWS NET portal. Livelihood zones highlight geographic areas of a country where people have similar options for accessing and obtaining food and income (FEWSNET 2021). This geographical overview (Figure 2) also provides the basis for identifying geographically relevant food security indicators. In Figure 2a-c, we have used the classification of livelihood zones from the years of 2011, 2018, and 2013 for Kenya (total of 24 LZs), Ethiopia (total of 187 LZ) and Uganda (total of 40 LZ), respectively. Given the large number of livelihood zones, we carried out a reclassification task to identify the most common socio-economic activities according to the following major categories (i) Pastoralism, (ii) Agro-pastoralism, (iii) Agriculture and (iv) others. It is important to notice that the aim of this reclassification is two-fold: reduce the number of livelihood zone classes, and provide the basis for identifying geographically relevant indicators of food security at the district level (except for Ethiopia in which the scale of the model is kept at the LZ scale).

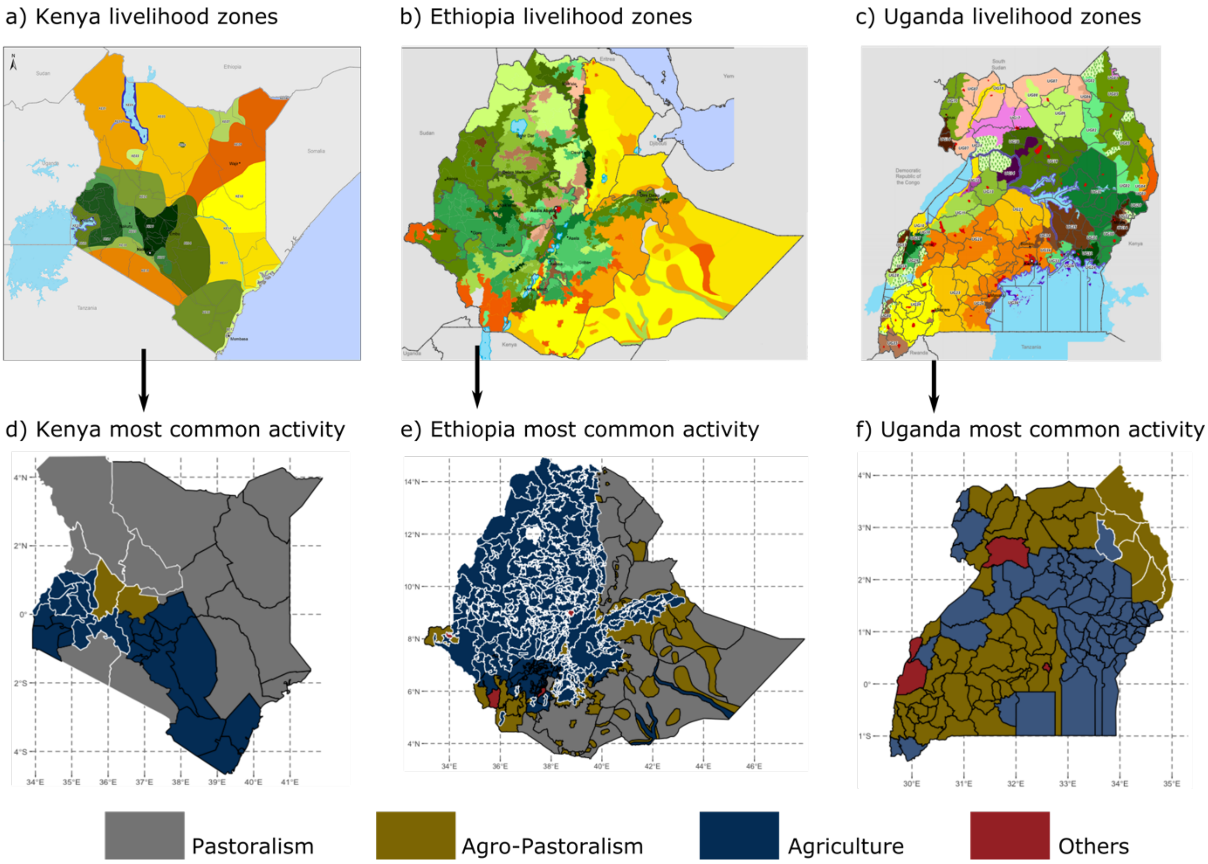


Figure 2. Plots a) to c) shows the livelihood zones in the three pilot countries. Plots d) to f) shows the outcome of our livelihood zone reclassification. Data Sources: Ethiopia: Livelihoods Integration Unit (LIU)/Ethiopian Ministry of Agriculture and Rural Development (MoARD)

AGRICULTURE AND AGRO-PASTORALISM

Agriculture and agro-pastoralist regions, and more specifically small-scale farmers, depend on a good season and harvest for sustaining their daily food calorific intake (Mohajan 2014). Therefore, increased or decreased levels of crop productivity are an important issue for the food security status in these regions. Thus, for all the districts and livelihood zones (Ethiopia) that have agriculture and agro-pastoralism as the most widespread socio-economic activity, we have developed a forecasting model to predict a shortage of calories due to low agricultural productivity (T1.2.1). The technical overview of this forecasting model is available in section T1.2.1, and a scientific article is currently under development.

PASTORALISM

In pastoral regions, productivity is directly affected by vegetation health. As a consequence, the normalized difference vegetation index (NDVI) is widely used to monitor vegetation changes. Currently, the Kenya Hunger Safety Net Programme and the Index-Based Livestock Insurance (IBLI) triggers ex-post insurance premiums based on the monitoring of an indicator derived from NDVI. Therefore, for the districts in Northern Kenya that have pastoralism as the most widespread socio-economic activity, we have developed a forecasting model to predict forage scarcity (T1.2.2)[2].

ALL LIVELIHOOD ZONE TYPES

For all livelihood zone types in Ethiopia, the Integrated Food Security Phase Classification (IPC) indicator is available at the Famine Early Warning System (FEWS NET) portal for informing about the historical state of the country's food security. The IPC classification is a commonly used index, which requires vast expertise from a wide range of disciplines including food security, livelihoods, nutrition, markets, agriculture and others. For grasping the complexity of the food security in the country, we have developed a forecasting model to predict changes in the IPC indicator (changes are defined as an improvement, deterioration and no change in the IPC class) (T1.2.3)[3].

[2] A technical overview of this forecasting model is available at the section T1.2.2, and a more in-depth description available at the master thesis of Marte Siebinga entitled "Forecasting Forage Scarcity for index-based livestock insurance in Northern Kenya" (available upon request). This thesis was developed in alignment with the F4S project, and a scientific article is under development

[3] A technical overview of this forecasting model is available at the section T1.2.3, and a more in-depth description available at the master thesis of Joris Westerveld "Modelling Food Insecurity in Ethiopia" (available upon request). This thesis was developed in alignment with the F4S and Red Cross' IARP projects. A scientific article is currently in review.

T1.2.1: FORECASTING SHORTAGE ON CALORIES

For the districts and livelihood zones where farming practices are a common mode of livelihood, we focused on forecasting seasons with shortages of maize calories. In Kenya, Ethiopia and Uganda, among other important crops, maize is considered a staple food, accounting for a large part of the population's total daily food calorific intake. In Kenya, Ethiopia and Uganda, maize consumption represents 36%, 17% and 11% of the caloric intake, respectively (Berhane et al. 2011; Haggblade and Dewina 2010; Mohajan 2014). In addition, agriculture employs the majority of the population in these areas. Thus, the cultivation of staple crops such as maize is essential for income generation, especially among smallholder farmers. Therefore, maize production is a key agricultural crop for food security.

In Kenya, maize is the most important cereal crop and the main staple food of the country. In terms of land usage, maize accounts for about 56% of cultivated land in Kenya. In addition, maize accounts for about 20% of total food expenditures among the poorest and is essentially locally produced. On average, only 3.5% of Kenya national consumption of maize is imported (Mohajan 2014). In Ethiopia, maize, sorghum and other cereals are considered an important component of the food basket of the bottom 40 percent. However, it is rarely consumed by the highest 60 percent of urban residents (Berhane et al. 2011). In Uganda maize is the most widely grown crop in the country, and nationally about 57% of farm households grow maize. Uganda is also self-sufficient in maize, with about 15% of total production exported to regional markets. Maize represents the third most consumed food crop in Uganda, preceded only by plantains and cassava. Therefore, Ugandan farmers grow maize as a staple food crop as well as a key cash crop for export (Haggblade and Dewina 2010). The agricultural sector is still a major backbone of the economy in Kenya, Ethiopia and Uganda, and local/national production of maize a key component for the food security.

T1.2.1: SUMMARY OF DATA AND METHODS

The methodology to develop the shortage on calories model consisted of four steps (Figure 3). In Step 1, the key datasets were colleced and aggregated at the district/livelihood zone scale, producing both a range of seven predictors as well as the target variable: shortage of maize calories. In Step 2, the Fast-and-Frugal Trees (FFT) model's parameters were tuned using a k-fold cross-validation scheme while simultaneously solving the class imbalance and applying two decision-making approaches. In Step 3, the model's accuracy was evaluated in a hold-out set both at the district/livelihood zone scale and at long-lead times. In addition, we also evaluated the potential cost-effectiveness of ex-ante cash transfers in comparison to ex-post.

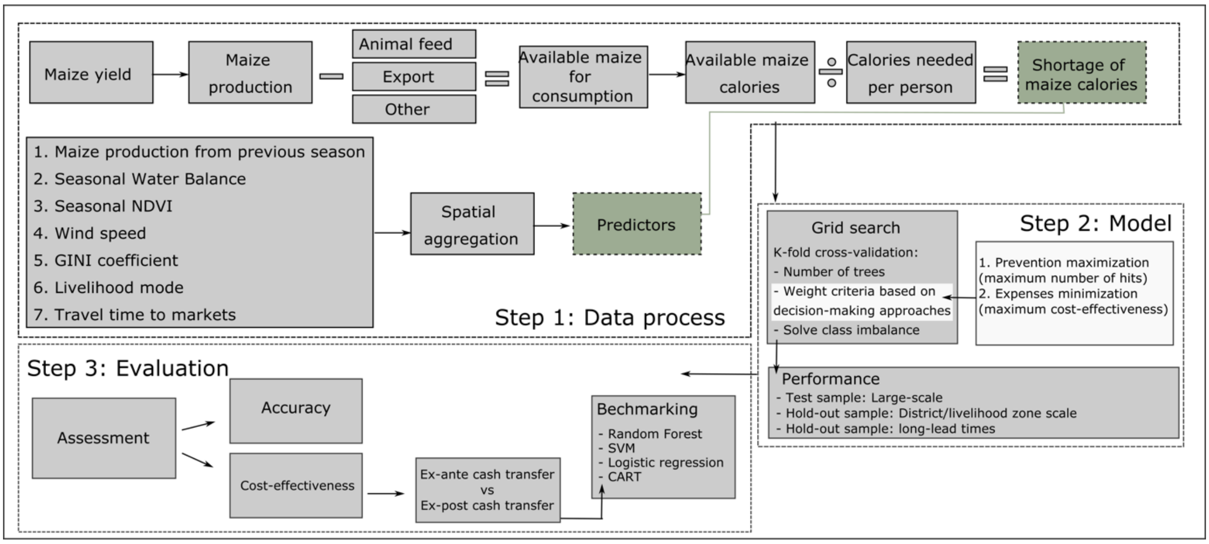


Figure 3 Overview of the methodological framework of the forecasting model for shortages of maize calories. As the flowchart indicates the methods consisted of four different steps; Step1: Data process, Step 2: Model, Step 3: Evaluation and Step 4: Interpretability.

STEP 1: DATA PROCESS

In our approach, shortage of maize calories is mainly driven by low levels of maize productivity. Therefore, this proxy for food insecurity is mostly focused on the availability and utilization components of food security. To derive the metrics of "shortages of maize calories", we analyzed the amount of maize produced in each district/livelihood zone per season during the period of 1983 to 2014 (Kenya) and 1982 to 2016 (Ethiopia and Uganda). After deducting the amount of maize exported and the ratio used for animal feed and other non-food uses, we extracted the amount of maize (in tons) available for human feed (from local production) per district/livelihood zone. After that, we transformed maize tonnes into calories, and assessed the ratio of the population that could be potentially fed[4] according to dietary preferences of each country[5]. We investigated years in which at least 25% of the population in each district did not have sufficient calories from maize[6].

As predictors, we have extracted seven variables. These variables represent a range of socio-economic and climatic factors at different time scales (from constant to monthly). From an annual to biannual time scale, we have extracted the indicator of (1) "maize production from previous season", which seeks to incorporate characteristics from the previous season that may influence the current one being investigated. At the seasonal scale, we have extracted two indicators which are often linked to agricultural risks: (2) seasonal water balance and (3) and seasonal normalized difference vegetation index (NDVI). The indicator of seasonal water balance represents the cumulative difference between

[4] In Kenya, we use an average intake of 2700 calories diet per day in which maize intake corresponds to 36% of total. In Ethiopia, we use an average intake of 2329.94 calories diet per day in which maize intake corresponds to 17% of total (Berhane et al. 2011). In Uganda, we use an average intake of 2021 calories diet per day in which maize intake corresponds to 11% of total (FAO 2010).

[5] Future investigations can benefit analyzing the caloric requirements that match the age and sex distributions of a given area.

[6] The threshold of 25% was adopted to represent a moderate high level of insufficient maize calories. This numeric threshold matches with WFP classes' boundaries of the Food Consumption score.

rainfall and evaporative demand, whereas for seasonal NDVI the cumulative monthly maxima NDVI is used. Both indicators were aggregated within the growing season of maize[7], seeking to incorporate seasonal climate variability into the forecasting model. Next, we have extracted the (4) mean wind speed value of the month previous to the start of the raining season. It is important to highlight that indicators *3* and *4* have been pointed out by the surveyed communities in T2 of the F4S project as an important early warning indicators of an upcoming unfavorable season. The fifth indicator (5) is GINI coefficient, which aimed at incorporating the impact of income inequalities on maize productivity. High levels of poverty and income inequality may undermine the potential gains from technological advances in the agriculture sector. The sixth indicator (6) is a dummy variable used to discretize districts/livelihood zones with mostly agricultural or agro-pastoral modes of livelihood. Lastly, we extracted the indicator (7) named “travel times to markets”. This indicator measures the mean travel time (in minutes) within a district/livelihood zones to key markets[8] in the region, and seeks to incorporate information on farmers’s market access to agricultural inputs. It is important to note that indicators *5* to *7* are represented mostly by a constant value across time, due to the lack of data and/or due to less frequent updates (e.g. each 5th year following the census).

STEP 2: MODEL

In this study, we used Fast-and-Frugal Trees[9] (FFT) as a forecasting tool. FFT are simple and intuitive type of classification decision trees that allow for decision making to be optimized with little information (Phillips, Woike, and Gaissmaier 2017). Even though FFT is a simple alternative for more complex Machine Learning algorithms such as Random Forest and Xgboost, there are still some parameters that needed to be tuned in order to control the learning process of the model. This process is named Grid Search. For FFT, two parameters are crucial: the number of trees to be grown in the “forest” of decision trees and the weight placed on detecting true positives (or true cases of calories shortage). For both parameters, a number of values were tested, but ultimately a decision criteria should be adopted in order to decide on a specific value that optimizes these two parameters. According to (Lopez et al. 2020), humanitarian agencies often face two dilemmas regarding a decision criteria:

1. Should one act given any arbitrary forecast probability of an extreme event? This will have high costs, but will ensure that a region will have very few damages and losses if the extreme event materializes. This is named the “Prevented event maximization”, which core values lied in detecting true positive at the expense of false alarms.
2. Alternatively, should one use the forecasts to try to minimize on spending, and only act on the forecasts that ensure a better chance of preventing disasters? This is named “Expense minimization”, which core values lied in improving the portfolio of anticipatory action in relation to the cost-effectiveness, which in turn can yield significant cost savings.

[7] Crop calendar are available at the FEWS NET website.

[8] Location of markets in Ethiopia and Uganda were derived from the WFP VAM website (https://dataviz.vam.wfp.org/economic_explorer/prices). Location of markets in Kenya were extracted from the Humanitarian Data Exchange portal (https://bit.ly/2Q5R7bL).

[9] Available at the R package FFTrees (Phillips, Woike, and Gaissmaier 2017)

For these two parameters, we looped a range of values[10] using a 3 k-fold cross-validation scheme, in which part of the dataset is used for training and testing the model. Additionally, we left the most recent four years of records (named the hold-out set), for assessing the skill of the model to forecast outside the range of values in which the model was built. The k-fold cross validation was repeated 50 times to produce a more robust estimation of the parameters. During each of these iterations, we solved the issue of class imbalance (given that there are fewer shortage than non-shortage events) using the Adaptive Synthetic sampling approach (ADASYN) by (He et al. 2008). Finally, we chose values for the parameters that maximized each of the decision-making criteria.

STEP 3: EVALUATION

In step 3, we evaluated the model's accuracy using the hold-out set. Accuracy is a measure of the number of correct decisions made by the forecasting model. We created a large-scale model by pulling together, for each country, datasets of the districts (for Ethiopia the livelihood zones) that follow similar rainfall patterns (see Figure 2), and evaluated the skill of the model to detect shortage of calories at the district (livelihood zone). This is often the scale in which early action protocols for anticipatory action are designed. Furthermore, we also tested how the model performed over different lead times by artificially re-creating the predictors of seasonal water balance and seasonal NDVI. This is done by summing the observed value of each predictor form the start of the raining season up to the lead time of interest *m* with the climatological value of the subsequent remaining months. Lastly, we evaluated the potential cost-effectiveness of ex-ante cash transfer in comparison to ex-post cash transfer. We did that by extracting the mean value of basket of goods (e.g. maize, teff, sorghum, wheat, oil, barley and others staple food items) at the month of the intervention based on price levels available at the WFP VAM repository[11]. When disbursing ex-ante cash transfer based on forecasting information, hits, false alarms and missed events can occur. As consequence, in our approach, hits and false alarms are considered to cost the mean value of the basket of goods in a month *m,* whereas missed events are considered to cost the mean value of the basket of goods in a later month *m* times an increasing factor. This should reflect common price increases experienced during shocks (Guimarães Nobre et al. 2019). On the other hand, disbursing ex-post cash transfer based on observations of shortage events does not cause false alarms to happen. However, interventions are considered to be costlier given that a higher amount would need to be disbursed to reflect price increases during shocks and other human impacts such as malnutrition. Therefore, ex-post cash transfer is considered to cost a similar amount to missed events in the scenario with ex-ante cash transfer. In order words, ex-post interventions cost the mean value of the basket of goods in a later month *m* times an increasing factor.

T1.2.1: SUMMARY OF FINDINGS

WHAT IS OVERALL SKILL OF THE MODEL TO DETECT LARGE-SCALE SHORTAGE OF MAIZE CALORIES?

In Figure 4, we display the overall accuracy of the forecasting model to predict shortages of maize calories adopting two decision-making approaches (minimization and prevention). For the districts and livelihood zones with bi-modal rainfall patterns, we show the mean accuracy value between the two seasons. Overall, the highest accuracy is observed adopting the minimization approach. This is due to

[10] Number of trees tested: 11, 31 and 51. Weight factor tested: 0.1 to 1 in 0.1 steps.

[11] Price dataset is available at https://dataviz.vam.wfp.org/economic_explorer/prices

the fact that this decision-making criterion seeks a higher balance between hits and false alarms in comparison to the prevention one. The highest accuracy is observed for the Karamoja region in Uganda (98%, minimization), and lowest for some central regions in Kenya (61%, prevention). On average, the skill of the model to detect large-scale shortage of maize calories are 81% and 74% for the minimization and prevention approach, respectively. Given that the presented results use information observed during the growing season, a very short-term lead time exists for implementing early action. Furthermore, the datasets from several districts (or livelihood zones) have been pulled for training the model, which resulted in a large-scale training and testing of the model. For assessing whether the model can be used for guiding early action with sufficient long-lead time, we also tested the skill of forecasting information at the district/livelihood zone level.

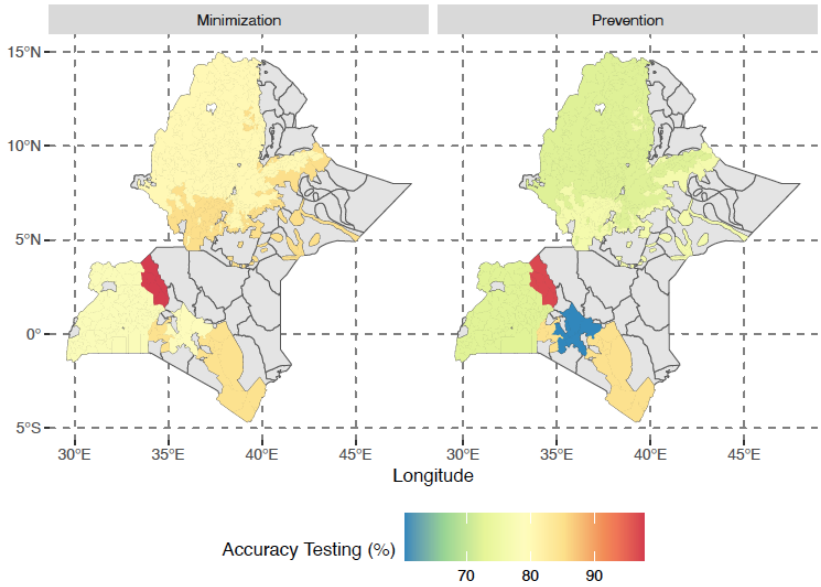


Figure 4 Overall accuracy (%) of the model in predicting shortages of maize calories using two optimization approaches for Kenya, Uganda and Ethiopia: i) Minimization and ii) Prevention. Grey areas represent areas in which agricultural and agro-pastoral activies are not widely observed.

WHAT IS OVERALL SKILL OF THE MODEL TO DETECT SHORTAGE OF CALORIES AT THE DISTRICT (LIVELIHOOD ZONE) AND MONTHS AHEAD?

In Figure 5, we display the overall accuracy of the forecasting model to predict, up to three months ahead, shortages of maize calories at the district/livelihood zone scales, adopting two decision-making approaches. This result uses the hold-out set, which is a part of the dataset unseen by the forecasting model. The mean accuracy of the model considering lead times 1 to 3 months and the two decision approaches is 74%. Districts and livelihood zones with bimodal rainfall patterns have, on average, higher accuracy rates for forecasting shortage on calories compared to the ones with unimodal rainfall patterns (75% against 70%). Districts in Kenya with unimodal and districts in Uganda with bimodal rainfall patterns (see Figure 2) have, on average, the lowest (54%) and highest (81%) accuracy values. In addition, we have found that 59% and 50% of the districts in Kenya and Uganda have an accuracy rate higher than 70%, respectively. In Ethiopia, 49% of the livelihood zones have an accuracy rate higher than 70%. On the other hand, 5%, 4% and 3% of the districts/livelihood zones in Kenya, Uganda and Ethiopia have an accuracy rate lower than 30%, respectively.

Considering a specific decision-making criteria and lead-time, for each country, the forecasting model yields the highest accuracy rate as follows:

1. For Kenya, adopting the decision-making criteria of minimization and information available at lead-time 1 yields, on average, to 82% and 75% accuracy rate for districts with bimodal and unimodal rainfall patterns, respectively. If the prevention approach is adopted at lead-time 1, the average accuracy rate would be 76% and 40% for districts with bimodal and unimodal rainfall patterns, respectively.
2. For Ethiopia, adopting the decision-making criteria of minimization and information available at lead-time 3 yields, on average, 82% and 80% accuracy rate for livelihood zones with bimodal and unimodal rainfall patterns, respectively. If the prevention approach is adopted at lead-time 2, the average accuracy rate would be 70% and 69% for districts with bimodal and unimodal rainfall patterns, respectively.
3. For Uganda, adopting the decision-making criteria of minimization and information available at lead-time 1 yields, on average, 70% and 81% accuracy rate for districts with bimodal and unimodal rainfall patterns, respectively. If the prevention approach is adopted at lead-time 2, the average accuracy rate would be 75% and 81% for districts with bimodal and unimodal rainfall patterns, respectively.

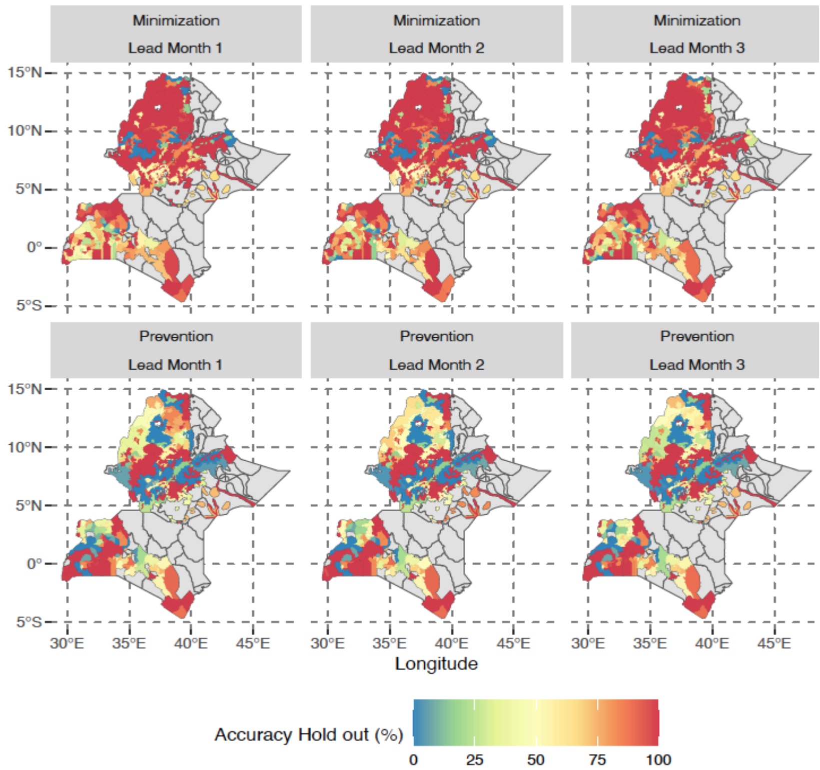


Figure 5 Overall accuracy (%) of the model in predicting shortages of maize calories in a hold-out set and at different lead-times using two optimization approaches: i) Minimization and ii) Prevention.

CAN A CASH TRANSFER PROGRAM ACHIEVE A POTENTIAL REDUCTION IN COSTS IF DISBURSED BASED ON OUR FORECASTING INFORMATION?

In Figure 6, we display the ratio in costs of disbursing ex-post cash transfers in comparison to ex-ante cash transfers (based on our forecasting system). Cost-effectiveness is achieved if the ratio of the costs of ex-post cash transfer and ex-ante cash transfer is higher than 1, and therefore cost savings could be achieved by using a forecasting model (regions in blue). Districts and livelihood zones highlighted in dark grey represent regions where no shortage of maize calories have been observed and the forecasting model predicted correctly the non-shortage events. The cost-effectiveness represents how many times ex-ante cash transfer is more or less costly than ex-post cash transfer per beneficiary. Considering the two decision-making approaches, on average, 78% and 66% of the investigated areas have a cost-effectiveness higher than 1, which means that ex-ante cash transfer is potentially less costly than ex-post in a very large share of the investigated areas. Among all lead times, lead month 3 has the highest percentage of the investigated regions with cost-effectiveness higher than one.

Considering a specific decision-making criteria and lead-time, for each country, the forecasting model yields the highest percentage of the investigated regions with cost-effectiveness higher than one as follows:

1. For Kenya, adopting the decision-making criteria of minimization, lead-time 3 yields the highest proportion of the districts (67%) with cost-effectiveness higher than 1. If the prevention approach is adopted, all lead times lead to similar proportion of districts (57%) with cost-effectiveness higher than 1.
2. For Ethiopia, adopting the decision-making criteria of minimization, lead-time 3 yields the highest proportion of the districts (82%) with cost-effectiveness higher than 1. If the prevention approach is adopted, lead-time 2 yields to highest proportion of the districts (65%) with cost-effectiveness higher than 1.
3. For Uganda, adopting the decision-making criteria of minimization, lead-time 2 yields the highest proportion of the districts (79%) with cost-effectiveness higher than 1. If the prevention approach is adopted, lead-time 3 yields to highest proportion of the districts (74%) with cost-effectiveness higher than 1.

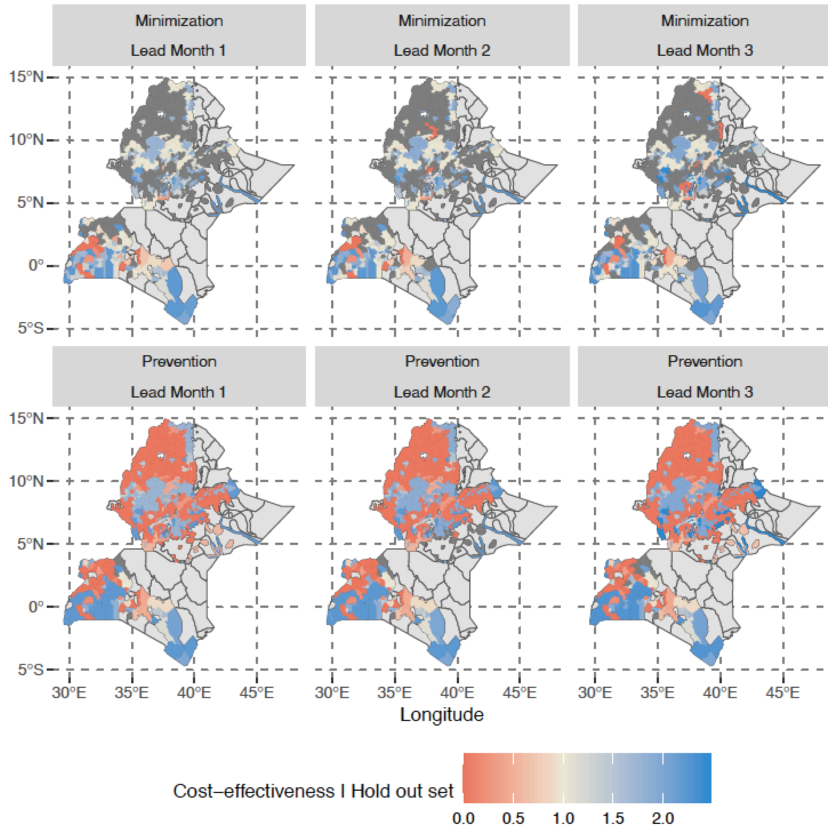


Figure 6 Ratio in costs of disbursing ex-post cash transfers in comparison to ex-ante cash transfer (based on our forecasting system). Cost-effectiveness is achieved if the ratio of the costs of ex-post cash transfer and ex-ante cash transfer is higher than 1 (regions in blue).

T.1.2.2: FORECASTING FORAGE SCARCITY[12]

Pastoral communities in northern Kenya face significant livestock losses as a consequence of recurring drought events. A program that exists to help pastoralists deal with these losses and to increase their resilience to these environmental shocks is Index-Based Livestock Insurance (IBLI). With this livestock insurance scheme, pastoralists can insure their herds against drought-related livestock mortality. Specifically, the IBLI program uses the Normalized Difference Vegetation Index (NDVI) to construct a seasonal forage scarcity index, which in turn determines if indemnity payouts are made. However, in case of drought, pastoralists only receive their payouts after the dry season as the payouts are made based on these NDVI observations (Figure 7– top figure). This means the pastoralists have already suffered their losses. As a result, the pastoralists use the allocated funds to replace their livestock, which is likely to be less cost-effective and beneficial for the households than an early payout. Therefore, we have developed a forecasting model aimed to predict forage scarcity in order to trigger early action before the start of the dry season and increase cost-effectiveness of the insurance program. Forecast models were developed for five different districts in northern Kenya by using a Machine Learning algorithm named Fast-and-Frugal Trees (FFT). In addition, a Cost-Benefit Analysis was performed to estimate the benefits associated with acting early (Figure 7 – bottom figure).

[12] This section is based on findings of master thesis from Marte Siebinga entitled "Forecasting Forage Scarcity for index-based livestock insurance in Northern Kenya"

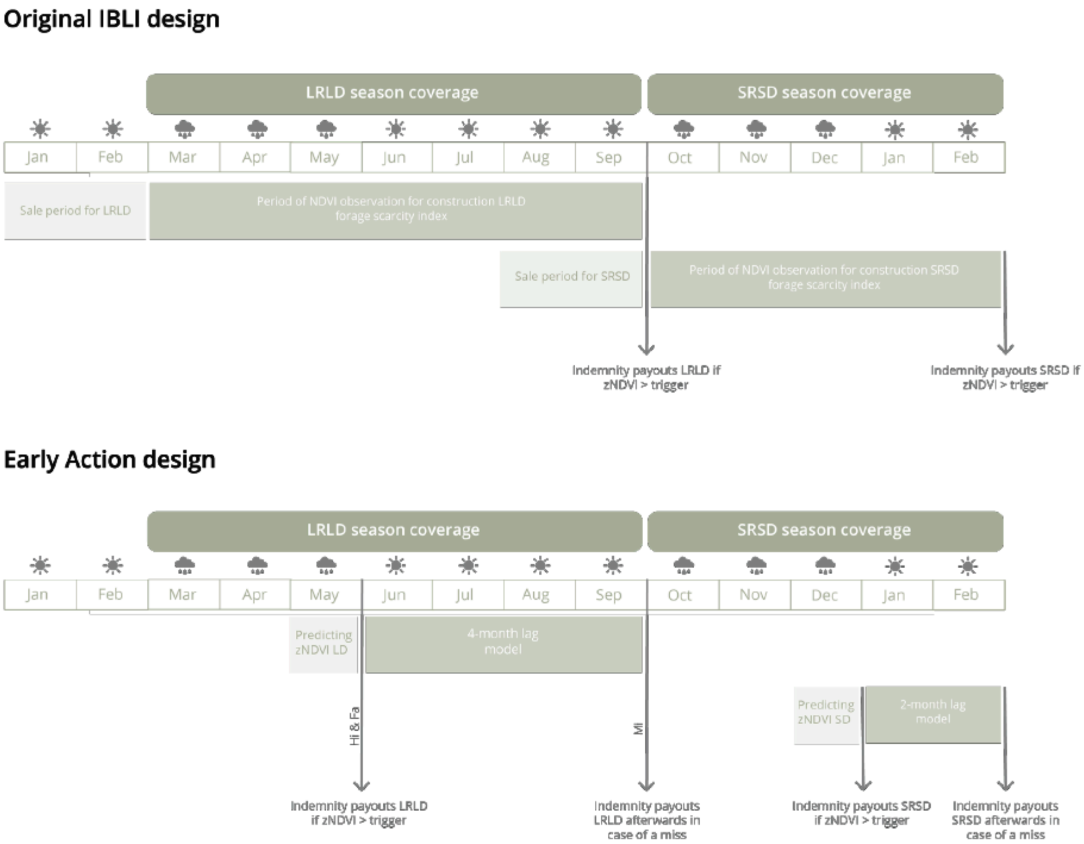


Figure 7: Designs of the current IBLI program (top) and the proposed approach (bottom). In the current design (top), potential payouts are made after the dry seasons (October and March). The Early Action design (bottom) enables the payments to be made before the dry season (May and December) by using 4- and 2-month lag models, respectively, to predict forage scarcity for the long dry (LD) and short dry seasons (SD). LR = long rain, SR = short rain When the models predict forage scarcity (hits and false alarms; Hi and Fa) payouts will be made early. In case the models falsely predict no forage scarcity (Misses; Mi), while in reality forage scarcity occurs, payouts will be made afterwards as compared to the original design.

T1.2.2: SUMMARY OF DATA AND METHODS

The methodology of this study consists of three different sections (Figure 8). In Step 1, the input data were collected and prepared. Step 2 comprised the tuning, running and evaluation of the model. The last section, involved the Cost-Benefits Analysis (CBA) and Cost-Effectiveness Analysis (CEA).

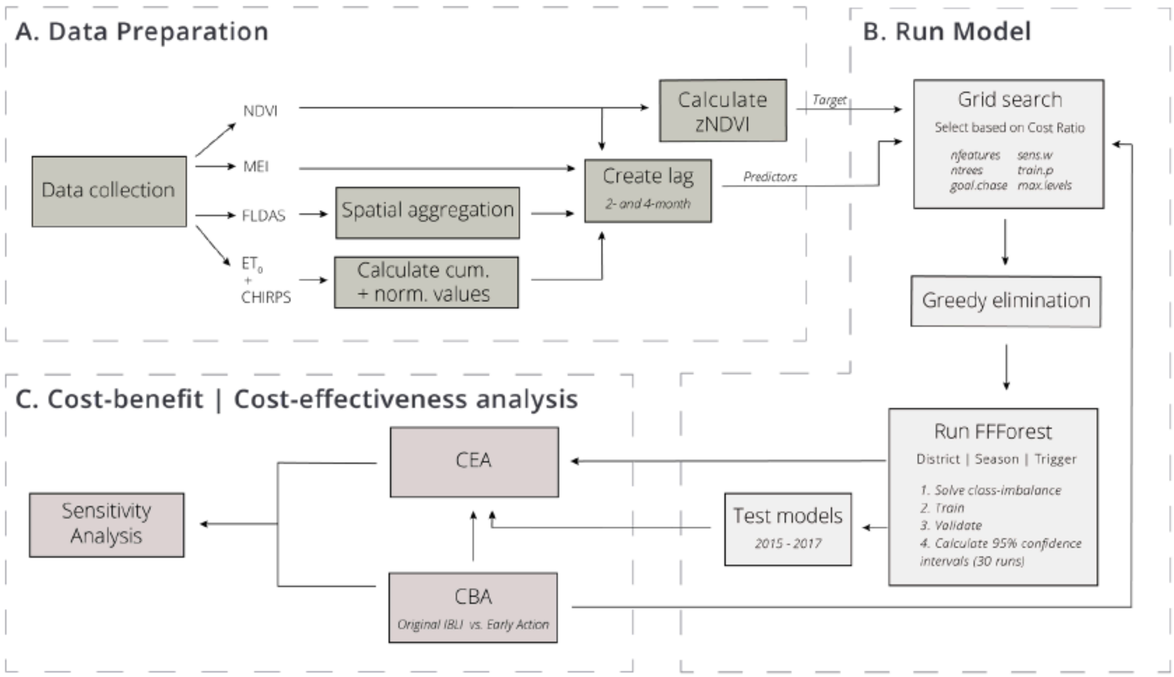


Figure 8: Overview of the methodological framework of the study. As the flowchart indicates the methods consisted of three different sections; section A: Data preparation, section B: Run model, and section C: Cost-Benefit and Cost-Effectiveness Analysis. Note that section C functioned as input for section B.

STEP 1: DATA PREPARATION

Droughts are one of the most complex natural hazards. Due to their occurrence at different spatial and temporal scales and their diverse drivers, there is no single indicator that can appropriately predict all facets of drought, and thus drought-related forage scarcity (Hao, Singh, and Xia 2018).This study included many variables originating from various sources to deal with this complexity. First, all datasets were processed at monthly time-steps. Subsequently, all predictor variables were lagged by 2 and 4 months to create two separate input datasets for the Short Rain Short Dry season (SD) and Long Rain Long Dry season (LD) seasons. A dummy variable was also included in both datasets to distinguish between months falling in the rainy season and months falling in the dry season. In total, 74 variables were extracted to be used as predictors in the forecasting model. The two datasets both had a length of 15 years, covering the period 2003-2018. Of these time series, the period of 2003-2014 was used for training and validation of the model. The last three years were used for independent testing.

STEP 2: RUN MODEL

In total four steps compose section B: (i) Grid Search; (ii) Greedy elimination; (iii) running algorithm; and (iv) testing the models. Machine learning models, like FFT, often contain multiple hyperparameters. Hyperparameters are predefined parameters that control the learning process of the model and cannot be learned directly from the data during the training process (Claesen and De Moor 2015). The right choice of these hyperparameters is crucial as the performance of a machine learning model can be highly dependent on these parameters. As machine learning models are developed to solve a specific problem, the goal of the hyperparameter optimization process is to find a specific parameter combination resulting in the optimum outcome regarding this problem. Therefore, the first step was to carry out a Grid Search. Grid search is the most straightforward approach for optimizing hyperparameters as it simply evaluates all possible combinations of a predefined set of values for each hyperparameter (Tu and Nair 2018). Here, the grid search technique was implemented by using nested for-loops, looping over all possible combinations. In parallel to the Grid Search, we carried out a Greedy elimination, which consisted of iterative elimination of variables based on their correlation with other variables. Third, after the selection of adequate hyperparameters and predictors, the best performing trees were run 30 more times for each model and 95% confidence intervals were calculated. Subsequently, the models were evaluated based on their performance by calculating the Hit rate and False Alarm rate. Besides validating the models' performance on their validation set, three years (2015-2017) were used for independent testing. It is important to notice that before running the FFT algorithm, the class imbalance was solved by using random over-sampling. By applying over-sampling, the class distribution was balanced through the random reproduction of minority class examples.

STEP 3: COST-BENEFIT AND COST-EFFECTIVENESS ANALYSES

To assess the cost-effectiveness of using the forecast model for IBLI, the benefits and costs associated with acting early and protecting livestock had to be estimated and compared to the costs and benefits of the current IBLI design. For this purpose, cost benefit analyses (CBAs) were conducted for both the current design and the Early Action design as proposed in this study. Multiple impact assessments and modelling studies have shown that acting early during drought can have a positive impact on pastoral households' livelihoods. Acting early can for example lead to avoided losses, a protected food security, strengthened resilience, faster recovery, and avoided or mitigated physical and psychological suffering (Weingärtner, Pforr, and Wilkinson 2020). For a complete evaluation of the benefits, both the direct and indirect positive effects should be considered. However, due to data limitations and the difficulty of monetizing social or human impacts such as violence or stress, this CBA only focused on the following direct benefits obtained by anticipatory action:

- **Prevention of livestock losses**: livestock mortality during the dry season was estimated from data from IBLI's impact evaluation survey that took place in Marsabit from 2009-2015. The obtained value was subsequently multiplied by the average price of one tropical livestock unit (TLU) before drought to acquire the total value of the prevented losses per TLU in Kenyan Shillings (KSh).
- **Increased milk production**: to estimate the market value of the increased milk production it was assumed that providing supplementary feeds during the dry season sustains the average milk production of the rainy season. Accordingly, the average milk productions of both the dry and rainy season (L/TLU/month) were estimated and subtracted from each other to calculate the increase in production.
- **Improved body conditions of the livestock**: To estimate the value of the improved body condition, it was assumed that the entire herd (100%) loses body mass during drought. Providing supplementary feeds during drought improves the physical state of the livestock, resulting in an increase in the value of the livestock. The increased market value of the livestock is considered beneficial to pastoral households in times of drought as selling livestock to purchase food and water for human and animal consumption is a key drought mitigation strategy

After running the FFForest algorithm, the obtained costs were used for the Cost-Effectiveness Analyses (CEA). The aim of the CEA was to compare the total costs of using the forecast model, i.e. taking early action, with the total costs of the original IBLI program. To do this, the number of Hits, False Alarms and Misses from the model output were multiplied by the associated costs. Lastly, the difference between the costs of both designs was calculated by subtracting the total costs of the Early Action design from the costs of the original IBLI.

T1.2.2: SUMMARY OF FINDINGS

In Figure 9, the performance of the forecasting model in predicting forage scarcity is presented per district, for the two different lag times (SD and LD), and for the four trigger levels (i.e. payout percentages)[13]. Figure 9 shows the model performances on the validation sets (therefore years set aside for independent testing are not included), and the error bars show the 95% confidence intervals. In general, the probability of a hit (pHI) outweighed the probability of a false alarm (pFA) and no significant contrasts in model performance could be observed between the districts. Across all models, the mean pHI was 92%, with Marsabit district having the lowest average pHI of 86%. The mean pFA across all models was 52%. Of all districts, the Mandera model had the highest average probability of predicting False Alarms (66%). Between the SD and LD models, only minor differences in performances were seen. The mean pHI across all SD models was 95%, while the pFA equaled 53%. The LD models still showed good predictive skills with a pHI of 89% and pFA of 51%. In addition, it can be observed that in most cases model performance improved at higher trigger levels, or specifically pHI increased and pFA decreased at increasing trigger levels. This might be caused by the oversampling of the data. Since the higher trigger levels, a.k.a. the more severe events, contained fewer positive cases, more cases had to be oversampled in order to solve the class imbalance problem. As a result, variable values of the few positive cases were randomly duplicated, which means the positive cases of these higher trigger levels consisted of more comparable variable values.

[13] The trigger is the standard deviation of the NDVI ($zNDVI_{U,S}$) threshold below which payouts are made. The exit is the $zNDVI_{U,S}$ value corresponding to the maximum indemnity payouts. In the current IBLI design, the trigger and exit values are set based on return periods. The trigger corresponds to a one-in-five seasons event, or in other words the 20th percentile. The exit is set as a one-in-hundred seasons event, which equals the 1st percentile.

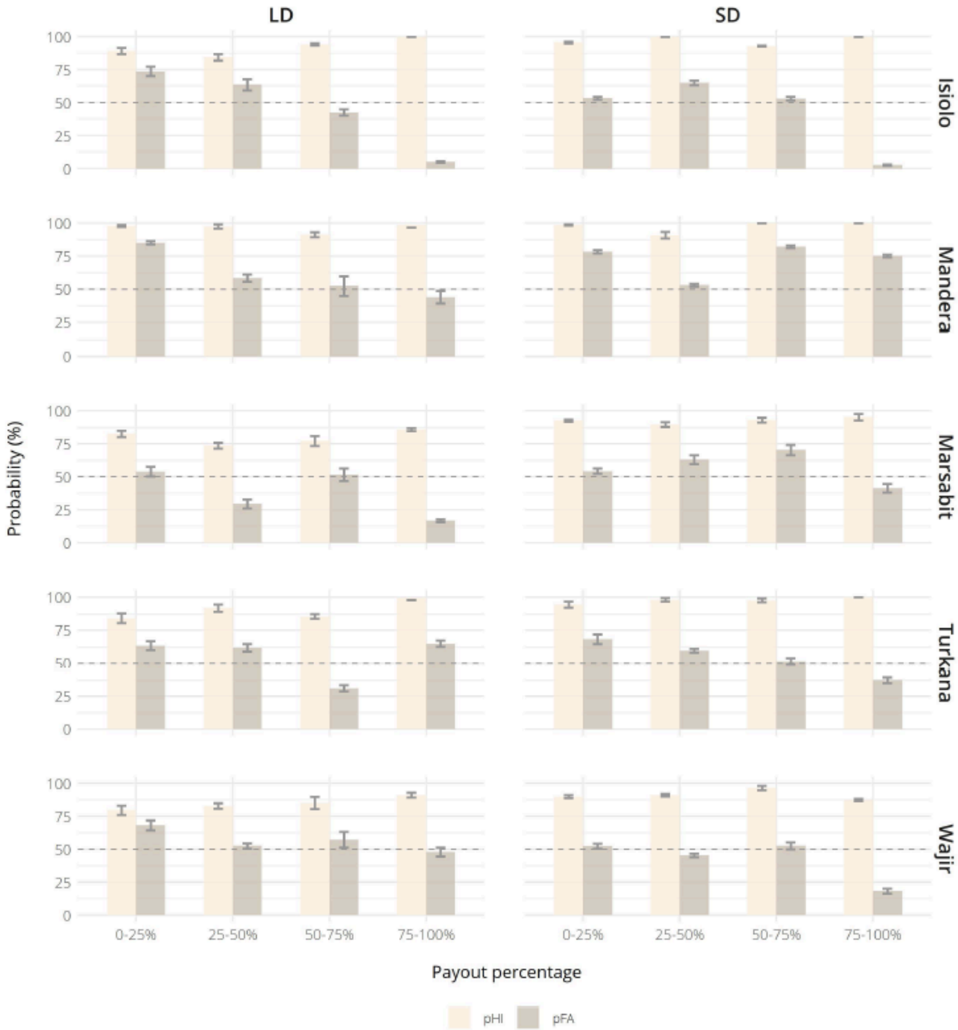


Figure 9 Plot showing the probability of Hits (pHI) and False Alarms (PFA) for the model validation per district, for the LD and SD, and the four different trigger levels. The error bars indicate the 95% confidence intervals.

The outcomes of the CEA are displayed in Figure 10. The plots show the monthly costs or benefits per insured TLU associated with the two different IBLI designs, and the difference between the two designs, per district, for all trigger levels, and both seasons. When assuming a perfect forecast model (100% Hits, 0% False Alarms), the monthly benefits would range from 637.45 KSh (first trigger level) to 4462.15 KSh (fourth trigger level) for the LD season. For the SD, the monthly benefits would range from 758.88 to 5312.15 KSh. Figure 10 displays the results of the CEA based on the validation dataset, with the error bars indicating the 95% confidence intervals. In general, taking early action by using the forecast model would be cost-effective across all districts, trigger levels, and for both seasons. The green outlines of the Early Action bars indicate that the benefits generated by the design outweigh the costs. Over all districts, the potential average monthly benefit of implementing the Early Action design would in this case be 956.21 KSh. The highest potential benefit, of 1098.30 KSh, was found for Isiolo district. Generally, the benefits associated with the Early Action design increased at higher trigger levels. This can be attributed to the fact that with the occurrence of a more extreme drought more costs can be saved by taking anticipatory action. Besides, the SD models are slightly more cost-effective than the LD models. This can be explained by the slightly higher average pHI found for the SD models.

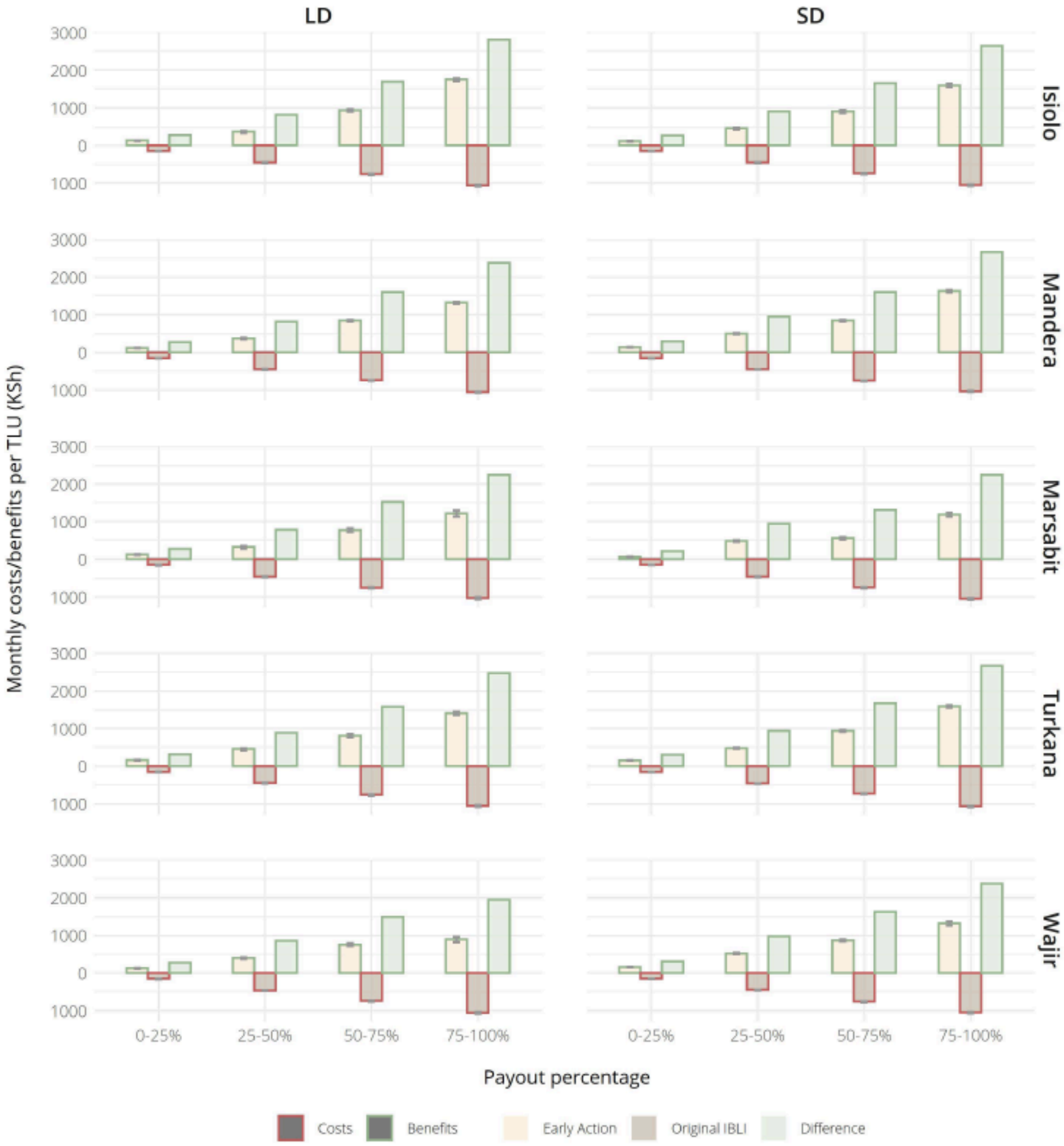


Figure 10 Plot showing results of the CEA based on the validation results per district, for the LD and SD, and the four different trigger levels. The third bar indicates if using the forecast model is cost-effective or not. In this case, using the forecast model is cost-effective in all cases.

T.1.2.3: FORECASTING TRANSITIONS IN THE STATUS OF THE FOOD SECURITY[14]

Food insecurity is a growing concern due to human-made conflicts, climate change, and economic downturns. Forecasting changes in the state of food security is essential to be able to trigger early actions, for example, by humanitarian actors. Expert and consensus-based approaches are currently used, in addition to surveys to measure the actual food insecurity state. Both require substantial human effort, time, and budget. This section introduces an extreme gradient boosting machine learning model to forecast monthly transitions in the state of food security in Ethiopia, at a spatial granularity of livelihood zones, and for lead times of 1 up to 12 months ahead based on open-source data. The transition in the state of food security, hereafter referred to as predictand, is represented by the Integrated Food Security Phase Classification Data. From 19 categories of datasets, 130 variables were derived and used as predictors of the transition in the state of food security. The predictors represent changes in climate and land, market, conflict, infrastructure, demographics and livelihood zone characteristics.

A limited number of models exist to forecast changes in the state of food security. Currently, the central system for food security monitoring and forecasting is the Famine Early Warning Systems Network (FEWS NET). The FEWS NET has been monitoring food security since 1985 (Funk et al. 2019), by providing information that stakeholders require for strategic decision-making about food security. The FEWS NET forecasts the state of the food security using the Integrated Phase Classification (IPC). Through the use of the IPC indicator, the complexity of the status of food security in a region can be translated in a generic, yet rigorous and straightforward way. For determining a certain IPC class, FEWS NET builds technical consensus regarding the classification of acute food insecurity by engaging with relevant experts in every country they operate. This early warning system has been tested in previous research (Choularton and Krishnamurthy 2019), which showed that it was remarkably accurate in Ethiopia although with mixed forecasting accuracy in situations of transition from food security to food crises. The FEWS NET forecast is not fully data-driven but relies largely on convergence of evidence, expert judgment and "most likely" scenarios. For driving the "most likely" scenarios, key assumptions based on critical factors are considered. However, the choices for key factors can increase a model's uncertainty and reduce its transparency. Therefore, producing a data-driven approach for quantifying key factors can strengthen FEWS NET's transparency, accuracy, and reproducibility, especially when using open data.

In addition to the FEWS NET, (Andrée et al. 2020) used machine learning to forecast food security crisis transitions as part of the Artemis (Famine Action Mechanism) FAM program. They have tested a range of simple to complex machine learning models such as linear regression and Random Forest. Random Forest performed best in their case. Building upon earlier research from (van der Heijden et al. 2018) and in line with previous work by Andrée et al., 2020, we used artificial intelligence in the form of machine learning and open data to forecast, for different lead times, changes in the state of food security in Ethiopia. We also seek to demonstrate the added value of using Machine Learning by extensively benchmarking our approach against other techniques. In summary, our research

[14] This section is based on findings of master thesis from Joris Westerveld entitled “Modelling Food Insecurity in Ethiopia”. A scientific article is currently in review.

hypothesized that a supervised machine learning algorithm can forecast whether the state of food security improves, remains the same or deteriorates (hereafter called "change events") within a livelihood zone from 1 to 12 months ahead of a change.

T1.2.3: SUMMARY OF DATA AND METHODS

In order to forecast transitions in food security, we developed a new approach that is depicted in Figure 11. First, we collected scalable datasets at monthly intervals to be used as predictors of change in the state of food security in Ethiopia (Figure 11, step 1) and derived the target variable for classification (change event; Figure 11, step 2). Second, we preprocessed the datasets by carrying out three sub-steps: imputation and processing (Figure 11, step 3), feature engineering (Figure 11, step 4), and class imbalance (Figure 11, step 5). Third, we applied three Machine Learning algorithms named "Extreme Gradient Boosting", "Random Forest" and "CatBoost" (Figure 11, step 6), tuned the hyperparameters and validated the best model (Figure 11, step 7). Lastly, we compared our results with several baselines (Figure 11, step 8).

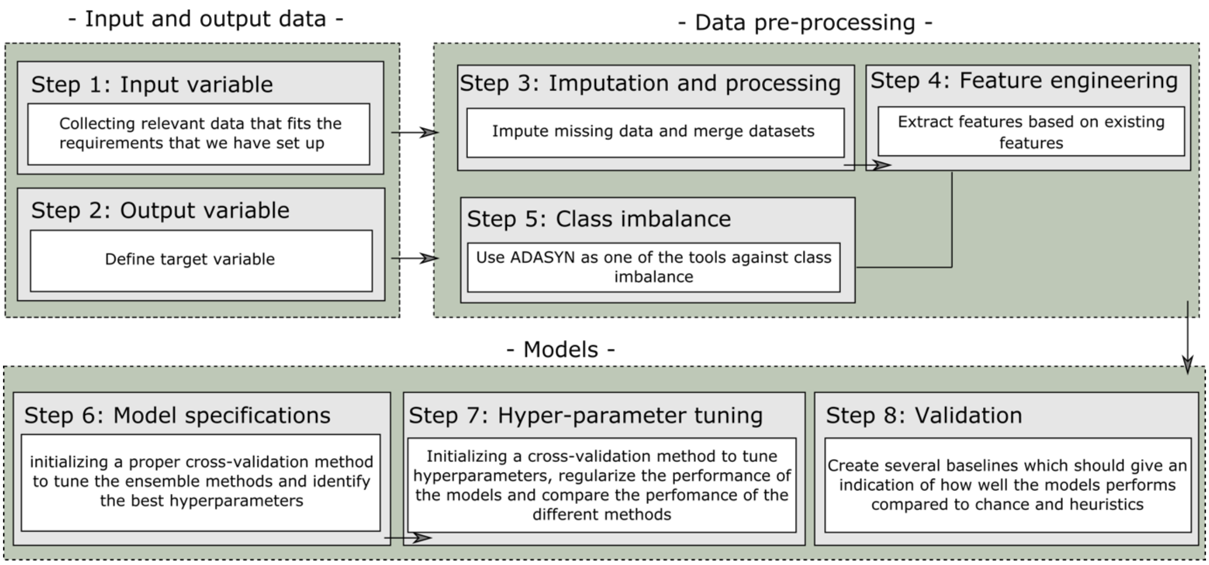


Figure 11 Flowchart of the methodological framework divided into three steps: (i) collection of input and output data; (ii) data preprocessing; and (iii) modelling. ADASYN refers to the Adaptive Synthetic sampling approach.

INPUT AND OUTPUT DATA (STEP 1& STEP 2)

In our model, we have used a range of different drivers of food security, which fall into the bigger category of markets, conflict, climate and land, infrastructure, demographical variables and livelihood zone characteristics (see Table 1). In total, 130 variables were derived and used as predictors of the transition in the state of food security. The predictors used in this study were extracted at the livelihood zone level and at the monthly scale. It is important to note that the large number of predictors used are openly available from global data repositories. This means that the methodology implemented in this case study can be transferred to other countries. For the target variable we used the current situation Integrated Phase Classification (IPC) class (or the actual observed IPC) from FEWS NET (2011) during the period of 2010 to 2018, to differentiate between three different transitions. In brief, we compared the IPC class of some months ahead (1 to 12 months), with the current IPC class to identify whether the IPC class has changed value, and thus to extract the Change Event (CE). The worsening, amelioration and no differences in the state of the food security are named “Deteriorations”, “Improvements” and “No Change”, respectively. The IPC class were obtained from the FEWS NET.

DATA PRE-PROCESSING (STEP 3, STEP 4 & STEP 5)

As missing values in both input and output datasets existed, we applied linear interpolation to fill up the gaps. The importance of this step is twofold. First, IPC values were released every January, April, July, and October from 2010 until the end of 2015. However, in 2016, the release date shifted to February, June, and October. Because of this temporal shift, we linearly interpolated to make it possible to use the IPC class data from the two different periods. Second, given that we interpolated the IPC values every month, we could use the input datasets also every month instead of only for particular periods. Furthermore, in order to increase the performance of the machine learning approach, feature engineering was used. As such, we created 50 additional variables using feature engineering. However, the above-described data collection and processing resulted in a somewhat imbalanced dataset. For instance, food security transition No Change was observed 12,266 times while Deterioration only 1995 times and Improvements 2207 times. In order to counter this imbalance, we used Adaptive Synthetic sampling approach (ADASYN) by He et al. (2008) for machine learning.

MODELS (STEP 6, STEP 7 & STEP 8)

In order to find out which machine learning algorithm performed best, we compared three different ensemble methods with each other. In our case, we compared a Random Forest, Extreme Gradient Boosting Algorithm (Xgboost), and a Catboost algorithm. To compare the different ensemble methods fairly, we performed hyper-parameter tuning. Tuning the hyper-parameters allowed us to identify the model with the best performance that generalizes well to unseen data. In order to tune the model without biasing the performance of the model, the training set have been used in a grid search time series cross-validation to find the best hyper-parameters for the three different ensemble methods. In addition, we also validated the model by looking at geographical differences to detect zones in which the forecasting works more and less accurately. For representing the goodness of the model, we calculated the F1 score per livelihood zone. Furthermore, we also tested how the model performed over different lead times. To interpret model performance, we compared the best Machine Learning method to a number of baselines. These baselines are composed of simple heuristic models or models based on chance. This way, we are able to demonstrate the added value of using a Machine Learning approach.

T1.2.3: SUMMARY OF FINDINGS

In Figure 12, we display the performance of the Xgboost (XGB) model against the baseline models based on 100 runs. We selected the Xgboost given its slightly higher performance in the validation set. However, the Random Forest also performed satisfactorily. Subsequently, we calculated the 95% confidence intervals of the F1 score for the Xgboost approach and for the first baseline (a dummy classifier or DCS). Note that confidence intervals are not applicable to the other approaches as they are deterministic by nature. We found that the overall Xgboost model performs well above all other models (Figure 12A). Moreover, the Xgboost model performs at least twice as well as the best baseline performance on Deterioration events (Figure 12B) and almost five times as good on Improvement events (Figure 12D). Only on No Change Events can the baseline performance surpass the Xgboost model (Figure 12C). This pattern is often expected given that we apply techniques to balance the data set, which in turn leads to performance increase for the minority class and performance decrease for the majority class. Since performance appears to stabilize around the 7-month interval we further explored the model in two timescales: up to 3 months and up to 7 months. These time intervals can potentially support short- and long-term planning of humanitarian interventions. However, in practice, a 7 months early warning for potential food insecurity would require additional monitoring of the food security status. On the other hand, a 3-month interval is more likely to trigger action, and therefore is important to understand the variables generating this early warning signal. It should be noted however, that the variables used to predict the transitions in the state of food security (derived from IPC scores) such as commodity prices and environmental conditions are often used when designating IPC scores themselves. Therefore, this could potentially play a role on our estimates of out-of-sample forecast accuracy.

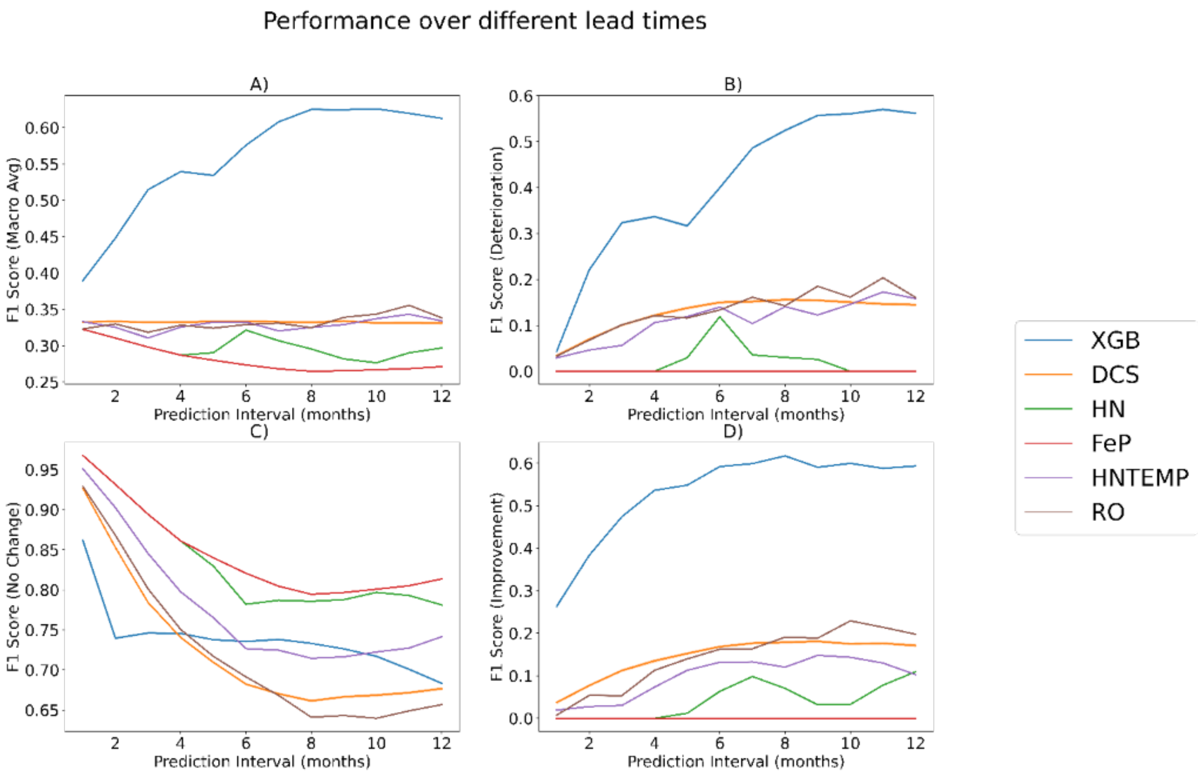


Figure 12 Average performance of the models, bootstrapped over 100 runs whenever possible, for different forecast intervals. Figure shows the overall performance expressed as the F1 Macro, including, when applicable, the 95% confidence intervals (note that the small interval size makes them hard to see). The Xgboost classifier (XGB) performs better for each forecast window when compared to the baselines. The performance increases as the forecast interval expands. Figures B-D show the performances for specific classes in more detail. Note that while the relatively uninteresting class 'No Change Event' decreases in performance for longer intervals, the classes 'Improvement' and 'Deterioration' both increases.

LONG- AND SHORT-TERM FORECASTING: 7-MONTH & 3-MONTH INTERVAL

To score the importance of each variable, and thus identify which variables are the most important for our model, we used the feature importance tool from scikit-learn, for 100 Xgboost models. Next, we aggregated the mean importance values of each variable based on these 100 models (Figure 13). Since there are many variables included in the model, we decided to only showcase the top 20 highest scoring feature importance variables. Results show that the most important variables at a 7-month lead time reflect the IPC situation descriptors at the time point from at which the forecast is made. On the other hand, for the 3-month lead time, we observe that a range of climate and biophysical predictors are being used, which demonstrate that intra-seasonal weather variability has strong links with the state of the food security in Ethiopia. Furthermore, we observe that variables that reflect soil moisture levels have most predictive value for the upcoming state of food security.

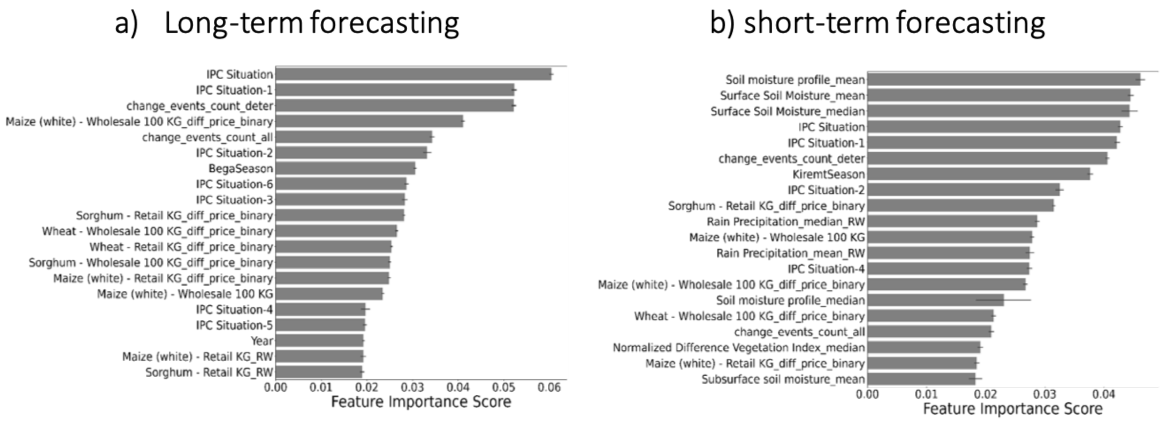


Figure 13 Top twenty features with the highest average feature importance scores over 100 runs of the model with a) a 7-month lead time and b) a 3-month lead time.

SPATIAL DIFFERENCES

In order to identify regions where the model is performing well, we assessed the F1 macro score (validation) of the Xgboost model at livelihood zones. In particular, we observed the spatial variation in performances for these different livelihood zones using the 7-month lead time model over 100 runs (Figure 14). The model identifies regions in the northwestern area more easily (thus a higher F1). These are high potential cropping highland regions with stable state food security levels, which the Xgboost forecast very accurately the No Change events of the IPC class 1. The darker regions are more difficult to forecast compared to regions that have a lighter color. The lowest performance is observed largely at the Afar Region, a predominant pastoral region with consistently high levels of food crisis with recurrent crisis condition (Choularton and Krishnamurthy, 2019). Furthermore, the model performance over large pastoral areas of the Somali and Oromia regions shows moderate to poor performance. Despite experiencing recurrent conflict and high levels of dryness, several pastoral communities in the Somali region also have to deal with declined levels of rainfall due to climate change. Overall, forecasting the status of food security in this region is a challenging task.

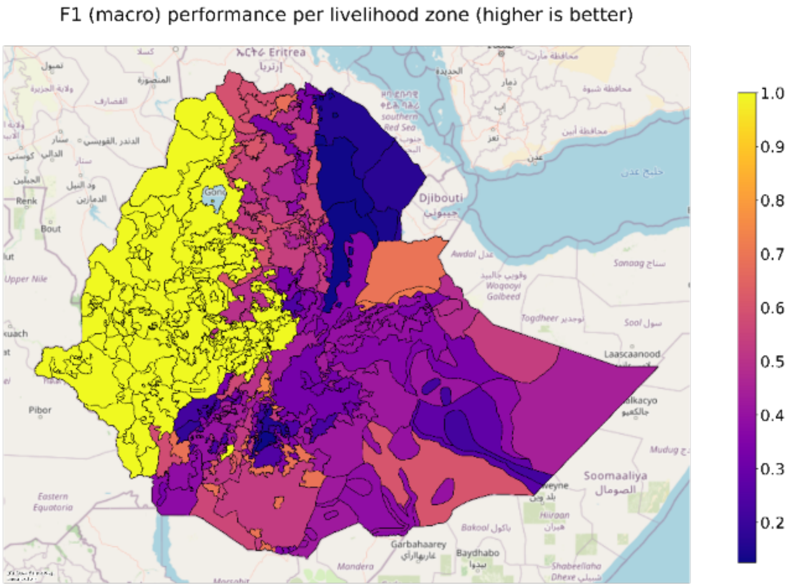


Figure 14 shows the map of Ethiopia overlaid with the Xgboost model performance per region for the 7-month lead time. The regions in the northwestern were the easiest for the model to identify (thus a higher F1). The darker regions are more difficult to identify compared to regions that have a lighter color.

T1.3: ASSESSING TRANSFERABILITY AND SCALABILITY

The forecasting models produced in alignment with the F4S project are of relevance given the transferability and scalability of the methodologies to other countries in Eastern Africa. This is because most of the data on the predictors are openly available from global repositories. Although the model is transferable and scalable, the importance given to the predictors might differ among countries given that there are different socio-economic and environmental processes at play. We used the forecasting models for forage scarcity and transitions in the state of food security as a proof-of-concept on a smaller scale given the existence of an index-based insurance programme for pastoralist communities (Kenya), and regular wide-spread food security transitions (Ethiopia). The satisfactory outcomes of these two models open up the possibility for transferring the methodology to other countries of interest.

Furthermore, we believe that there might exist room for improving model's performance if forecasting models are built at a finer spatial scale. For instance, the models of shortage of calories and transitions in the state of food security were built considering the scale adopted by humanitarian agencies to develop their anticipatory action plan. However, given the large dimensions of some districts and livelihood zones, some key biophysical and socio-economic characteristics might be better captured if adopting a smaller spatial scale. Besides, it should be mentioned that the spatial scale of the forage scarcity model does not match the scale of the IBLI program. The IBLI uses insurance units for their contract coverages, whereas the developed forage scarcity models are on district level. Implementing the Early Action design means that the input data have to be aggregated at the insurance unit scale. Nevertheless, this would cause no major problem for implementation as all datasets used in this research are available at the smaller spatial scale. In addition it should be noted that further improvements of the original forage scarcity index can be made. For example, the spatial aggregation can be adapted by masking wildlife areas where grazing of livestock is prohibited. Moreover, movement of livestock keepers may take place outside the currently used insurance units, especially during dry years (Vrieling et al. 2014). Consequently, adapting the insurance units based on the actual used rangelands during droughts might also improve the forage scarcity index. Lastly, we would like to highlight that another potential way to improve our forecasting models is by increasing the lead time of the impact-based forecasting information, especially for the models of shortage on calories and forage scarcity. One way to implement this approach is by replacing the observation of some of the biophysical indicators (e.g. seasonal rainfall) by their forecasted values using a seasonal forecasting system. We have decided not to use this approach in the F4S project given that the discussions regarding which forecasting model to use is still ongoing by humanitarian agencies implementing forecast-based financing in the region. However, we have built models that can be adaptable to accommodate this possibility, which would essentially result in a hybrid forecasting system. For instance, we have started to investigate the use of soil moisture forecasts by the Tropical Applications of Meteorology using Satellite (TAMSAT) in the model for shortage on calories, and initial results suggest an improvement in the model's skill in Ethiopia.

T2: COLLECTING LOCAL EVIDENCE AND INFORMATION

The research objective of the F4S field activities within T2 was two-fold: (1) to collect local knowledge on drivers of food insecurity that should be incorporated in the forecasting model to improve model's performance (four research questions related to this objective questions are elaborated in Table 2); (2) to collect information regarding individual's preference and behavior that shape the key design elements of ex-ante cash transfer schemes (four research questions related to this objective are elaborated in Table 3). The research questions are not posed directly to the interviewees or respondents, but rather used for steering the design of the data collection method (T2.1).

Table 2 Sub-research questions related to the collection of local knowledge information

LOCAL KNOWN DRIVERS FOR FOOD INSECURITY		RESEARCH APPROACH
1	Which local knowledge on early warning indicators do people have?	Household survey – questionnaire Focus Group Discussion
2	Which external (scientific) knowledge, that can be used to foresee food insecurity, reaches people and via which channels?	Household survey- questionnaire Focus Group Discussion
3	Which early actions do people take to lessen the impact of impending food insecurity?	Household survey- questionnaire Key informant interviews
4	How can local knowledge on food security be converted into a quantitative model input?	Key Informant Interviews

Table 3 Sub-research questions related to the cash transfer design preference

PREFERENCE FOR CASH TRANSFERS		RESEARCH APPROACH
1	What is the current experience with cash transfers?	Household survey- questionnaire Focus Group Discussion
2	What could be the impact of ex-ante cash transfers on food security?	Household survey- questionnaire Focus Group Discussion
3	Which individual precautionary actions are encouraged by such a cash transfer mechanism?	Household survey- questionnaire Key Informant Interviews
4	Under which set of core design elements of cash transfer programmes such as (1) lead time of the aid (2) predicted impact on food security and (3) the distribution of the cash transfer (lump-sum or small payments) are individual precautionary measures taken to avoid food insecurity?	Household survey - Choice experiment

T2.1: DATA COLLECTION METHOD

We have carried out three different, complementary data collection methods: key informant interviews (T2.1.1), focus group discussions (T2.1.2), and a household survey, which consisted of both a semi-structured questionnaire (T2.1.3; related to objective 1) and a discrete choice experiment (T2.1.4; related to objective 2), both conducted with the household head (if not present, the wife, husband, eldest, adult child were asked to respond).

For targeting communities, we adopted the following criteria:

- Vulnerable to food insecurity in concurrence with flood and/or drought events.
- Eligible for cash-transfers
- Communities where pastoralists, agro-pastoralism and agriculturalist modes of livelihood are predominant.
- Accessible for the research team as well as a presence of local Red Cross branches

For selecting participants (except for the interviews), we adopted the following criteria:

- Be the head of a household (a mix of child, female and male headed households)
- Have experienced food insecurity in the past
- Living in the village for most of their lives
- Following the International Federation of Red Cross and Red Crescent Societies gender mainstreaming policy will ensure a minimum 30% of respondents will be women and aim for an equal 50% split, while respecting cultural norms.
- Look at vulnerable households: make sure some of the selected respondents are female-headed households and child-headed households

Within the villages, respondents were randomly sampled as much as possible. Sampling strategies closest to the expertise from the countries' Red Cross National Society (random walk and snowballing) were adopted to allow each point within the study to have an equal chance of being sampled each time. For each of the data collection activities, an informed consent form – detailing the goal of the study, the use of the answers and an introduction of the interviewer, guaranteeing anonymous data analysis to the interviewee (except in the case of the key informants), was accepted by all respondents. The interviews were held live, recorded and transcribed later, while the focus group discussion (FGD), questionnaire and experiment were recorded using KoboToolbox, which automatically uploads completed answer forms to the cloud.

T2.1: THE KEY INFORMANT INTERVIEW

Key informant interviews were carried out in order to collect additional local knowledge. They took place in the field with a community leader, experts from the Red Cross National Societies branches or with local governmental experts on disaster risk management or food security (these experts can also be located in the capital). Other possible key informants identified were local forecasters, weather forecaster, group leaders, and local development partners. We provide an overview of the questions in ANNEX A: Key Informant interviews.

T2.2: THE FOCUS GROUP DISCUSSION

In order to tailor the household questionnaire questions to the local context (allow for participant input), to better align some items in the choice experiment such as the clarity of icons, the classes of expenditure, and to fine tune language and practice translation from English to local language, FGD activities were planned. These FGD – consisting of the same questions as the questionnaire and experiment - could serve as a pilot during the first day of field activities in each study area, based on which the questions and experiment could be adjusted before the survey started. Six FGDs, each with a maximum of six participants, were planned to be carried out, each planned to take 45-60 minutes. The participants were asked not only to answer the questions, but to discuss the clarity of the questions, evaluate the logic of the structure and identify possible gaps in the data collection material. Moreover, it also helped the enumerators/surveyors/interviewers to get familiar with the questions (in topic and in language).

T2.3: THE SEMI-STRUCTURED QUESTIONNAIRE

The semi-structured questionnaire was composed of five sections related to: (i) participants past experiences; (ii) response actions and adaptation to shocks; (iii) Early Warning System; (iv) local knowledge; and (v) socio-economic background. The semi-structured questionnaire was tailored to the local context, allowing for participant's input and to better align some items in the choice experiment (e.g. icon visualizations and expenditure basket). In addition, local experts were consulted to support the team to fine tune language, translation and reword and/or remove some questions that were not suitable given specific cultural aspects. Therefore, the number of questions slightly changed according to study area. We provide an overview of the questions in Annex B (version without local contextualization).

T2.2: MATERIALS: THE CHOICE EXPERIMENT

The choice experiment, uncovering people's preferences for cash transfer schemes and possible spending patterns, in combination with the semi-structured questionnaire, enabled us to understand people's experience with cash transfer programs, and investigate potential changes in expenditure that can potentially occur based on key design elements of a cash transfer. Such information may be valuable for actors who seek to achieve certain goals while implementing cash transfers before acute impacts are felt by the eligible community.

The choice experiment consisted of one test choice (to check understanding of the experiment with the respondent) and six recorded choices, which each were visualized through a choice card and pictures of expenditure classes (here called baskets). The choice cards (example in Figure *15*) each portray 2 different designs of ex-ante cash transfer schemes, with different lead times of the warning (short –weeks - and long – months-) and payment scheme (one payment or two sums), and different predicted severity of the upcoming hazard (moderate or severe impacts expected). Respondents were asked which ex-ante cash transfer scheme they would prefer most. Then, respondents were asked how they would spend the cash by selecting the respective expenditure baskets: one "basket" contained consumptive food source options (stacking up food; buying water, etc.) and the other "basket" mitigation-related choices (contributing to digging boreholes; vaccinating livestock; stacking up fodder; etc.); a third "basket" contained “other household expenditures” (schooling fees, for instance); and the fourth "basket" contained the option for saving the aid.

The narrative used for introducing the choice experiment to participants are available in ANNEX C: NARRATIVE FOR ENUMERATORS. Furthermore, the block of scenarios played with participants can be found in ANNEX D: BLOCK OF SCENARIOS (EXAMPLE DROUGHT & RED BLOCK).

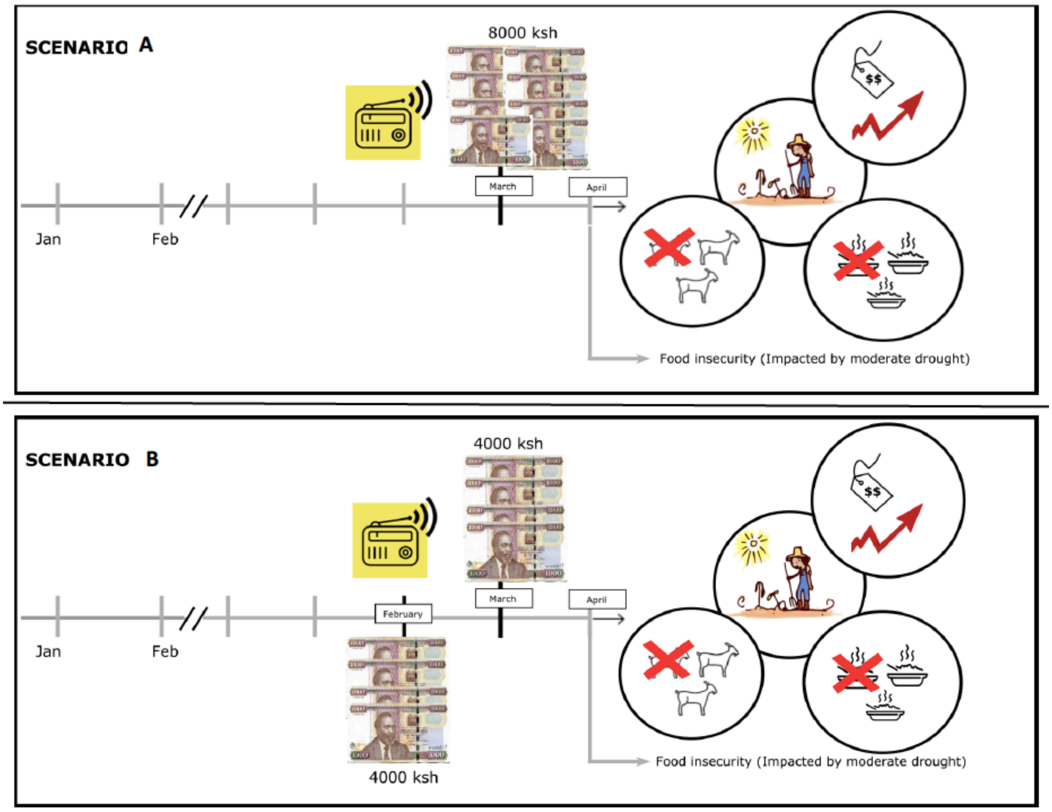


Figure 15 Example of one round played by participants of the choice experiment. In this round, participants were asked whether they would prefer to receive ex-ante cash transfer according to specifications of scenario A or B. If scenario A was chosen, participants would receive fake bills equivalent to 8000 Kenyan shillings (example of game played in Kenya) all at once. Subsequently, participants were asked how they would spend the aid and answers would be recorded. If B was chosen, participants would receive fake bills equivalent to 4000 Kenyan shillings and answers would be recorded. Subsequently, participants were asked how they would spend the aid. Furthermore, participants would be given additional fake bills equivalent to 4000 Kenyan shillings, and their expenditure recorded once again by the enumerators. An explanation of the icons displayed in the scenarios is available in the Annex C.

T2.2: PERFORMING SURVEY AND CHOICE EXPERIMENT

The field activities started and concluded in December 2020. The selected study sites were: agro-pastoralist communities in Borena (Ethiopia), agro-pastoralist communities in Sembabule and Moroto (Uganda) and agro-pastoralist communities in Isiolo (Kenya). In total, 161, 217 and 186 households were interviewed in Ethiopia, Uganda and Kenya, respectively. In addition, several focal group discussions and key informant interviews were carried out in all sites. In Figure 16, we show the coordinate points recorded during the field campaign.

In November, prior to the field activities, the F4S team carried out three online sessions, in which the teams from the Kenya, Ethiopia and Uganda Red Cross Society were briefed on the field activities materials. The field logistics, training of Red Cross volunteers and performance of all field activities were facilitated by focal points of the national societies, and therefore, all information was collected due to the support of the local team.

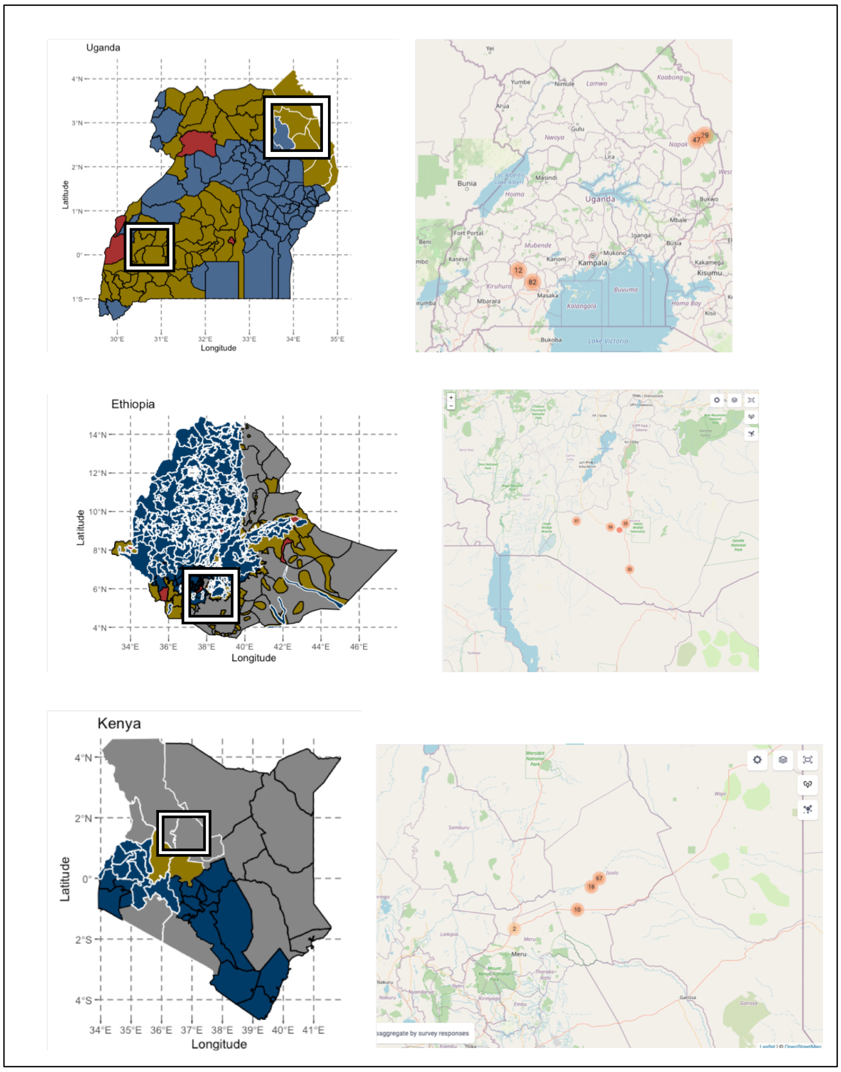


Figure 16 Overview of study areas. Blue and yellow represents regions in which agicultural and agro-pastoralism are a main compenent of livelihoods, respectively. Grey represents regions in which pastoralism is a main compenent of livelihoods.

During the field work, the surveyor's team was in charge of explaining the goals of the survey and its ground rules, as well as reading the informed consent form to the participants and making sure that all COVID-19 safety measures were taken. In order not to lose any valuable information and to comply with peer review research standards, key informant interviews were fully audio recorded, transcribed and translated 'word-by-word'. During the activities, the focal point kept into contact with the scientific team for questions and feedback from and to the field teams, and for reporting on the progress and challenges. Besides, each time the enumerators reached wifi-zones, the completed forms were sent to the cloud and accessed by the scientific team at VU to make sure questions were interpreted and filled in in a correct way. Whatsapp contact with the enumerators in the field allowed for close follow-up and handling of contingencies. After the completion of the data collection, all interviews were translated to English (if not done in English) and sent to the research team for analysis. Upon completion of the field survey, the focal point in charge compiled and sent the data to the 510 and Vrije Universiteit Amsterdam representatives. Afterwards, initial results were summarized and presented to the local teams/focal point in order to enable a better interpretation of findings.

T2.3: ANALYZING SURVEY AND CHOICE EXPERIMENT

In this section, we present the key findings obtained from the household surveys according to the relevance to each research question. In total, household data from 564 respondents was gathered and analyzed. It is important to note that we selected only key questions of the questionnaire based on their relevance to our study goals. However, an overview of all questions can be obtained at Annex B. An overview of the socio-economic background of repondents is available in Table 4.

Table 4 Descriptive statistics of the respondents of household's survey

	Kenya	Ethiopia	Uganda
Count of respondents	151 (Female) 35 (Male)	57 (Female) 104 (Male)	129 (Female) 88 (Male)
Mean size of household [Standard deviation size of household]	6.30 [2.74]	7.72 [9.96]	6.82 [6.41]
Mean age [Standard deviation age]	32.60 [11.45]	39.98 [17.65]	41.25 [15.82]
Majority income of respondents/month	More than 300 KSh	Less than 500 birr	Less than 100,000 Ugx
Majority educational background of respondents	Illitarate	Illitarate	Illitarate

WHICH LOCAL KNOWLEDGE ON EARLY WARNING INDICATORS DO PEOPLE HAVE?

Within the first section of the household questionnaire, we have designed questions in order to understand participants' past experiences with situations of food insecurity. We believe that past experiences with situations of food insecurity, and a comprehensive understanding of the causes, might shape the way people perceive early warning signs. In Figure 17, we show the responses obtained from people's perception on the causes of food security per study area. In Kenya, the majority of the responses identified seasonal rainfall deficits and excesses as an "extremely important" cause of food insecurity, followed by meager income. In Ethiopia, the three causes most remarkably considered as "very important" were: God's will; instability due to conflicts; and instability due to political changes. In Uganda, the responses were primarily mixed, however, causes related to a certain failure within the agricultural cycle (e.g. lack of farm inputs or inability to produce due to pests and weather extremes) were often considered "extremely important".

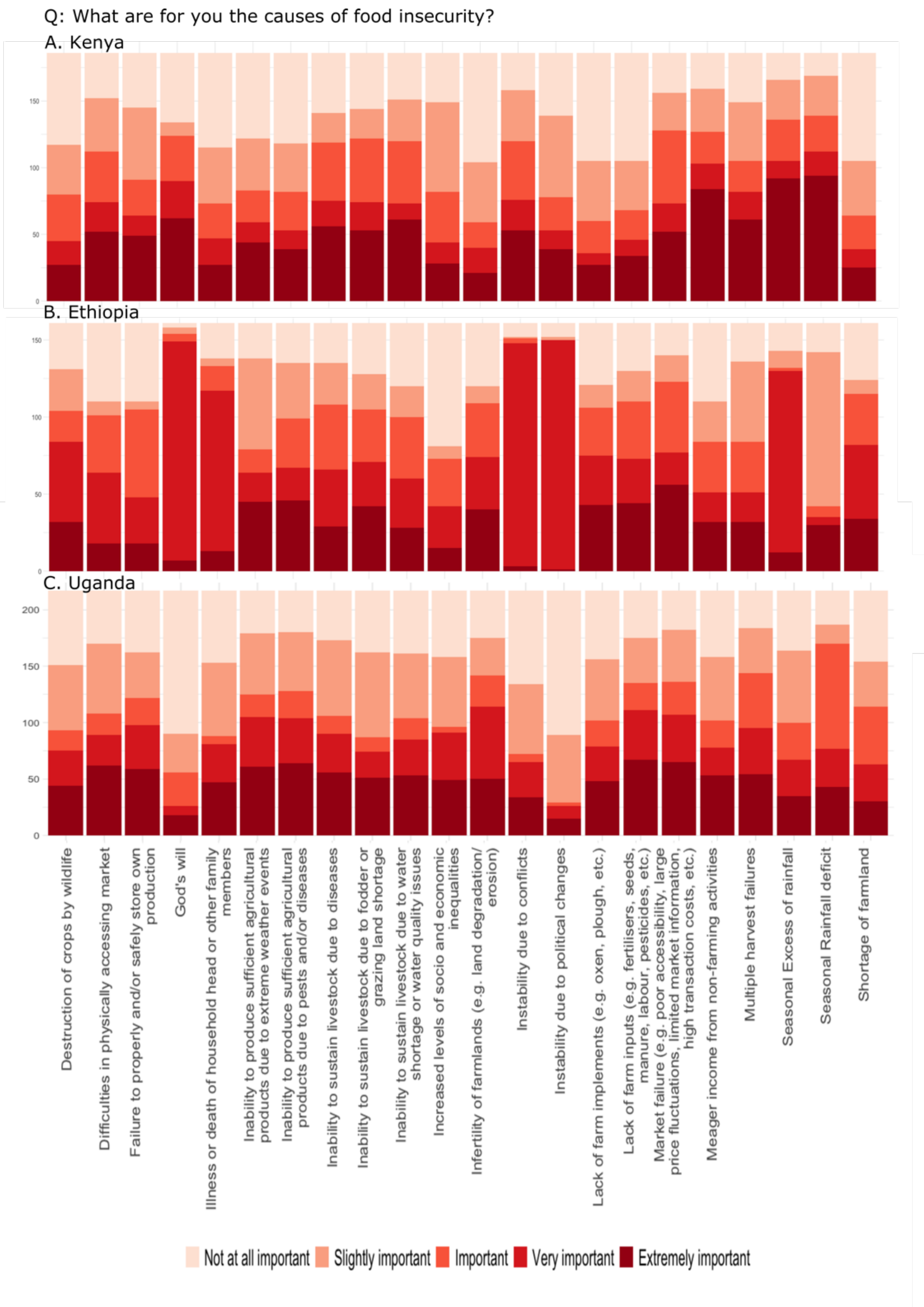


Figure 17 Causes of food insecurity identified by respondents of the household survey per study area.

Furthermore, we have also included a question in relation to early warning indicators, which aimed at better comprehending how people use their traditional knowledge to predict potential situations of food insecurity. In Figure 18, we display the responses linked to changes that people observe in the environment that are believed to have a connection to an upcoming threat to food security. In all three countries, changes observed in the wind was the most frequently answered, followed by changes in temperature, sun, animal intestines and trees.

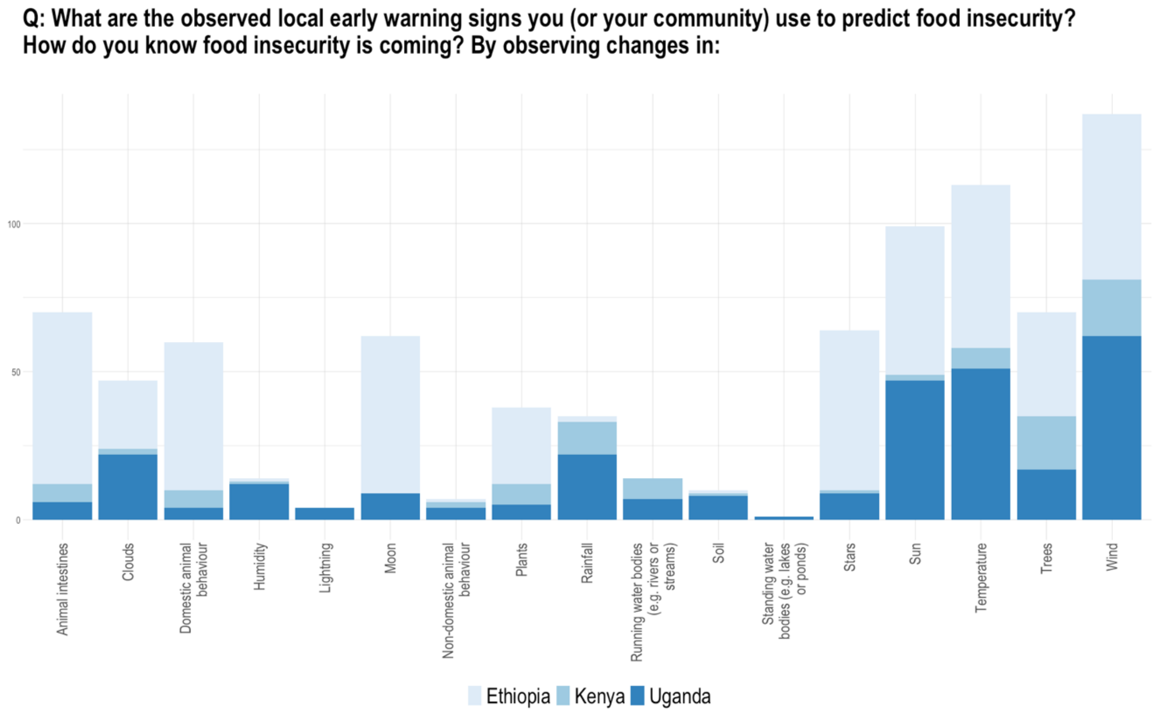


Figure 18 Changes that respondents observe in the environment that are considered to have a connection to an upcoming threat to food security. Y axis represent the number of responses.

WHICH EXTERNAL (SCIENTIFIC KNOWLEDGE), THAT CAN BE USED TO FORESEE FOOD INSECURITY, REACHES PEOPLE AND VIA WHICH CHANNELS?

Within the section of Early Warning System of the household questionnaire, we added a number of questions seeking to understand people's experience with Early Warning information, as well as to investigate how this information is disseminated, and whether it is trusted and/or used by the communities. In Figure 19, we display the answers obtained regarding early warning information dissemination. We observed that the majority of the respondents have indicated that radio is the mean of communication most used to disseminate information, followed by the local weather forecaster, especially in Ethiopia. Social media, internet and WhatsApp groups are among the means of communication least chosen.

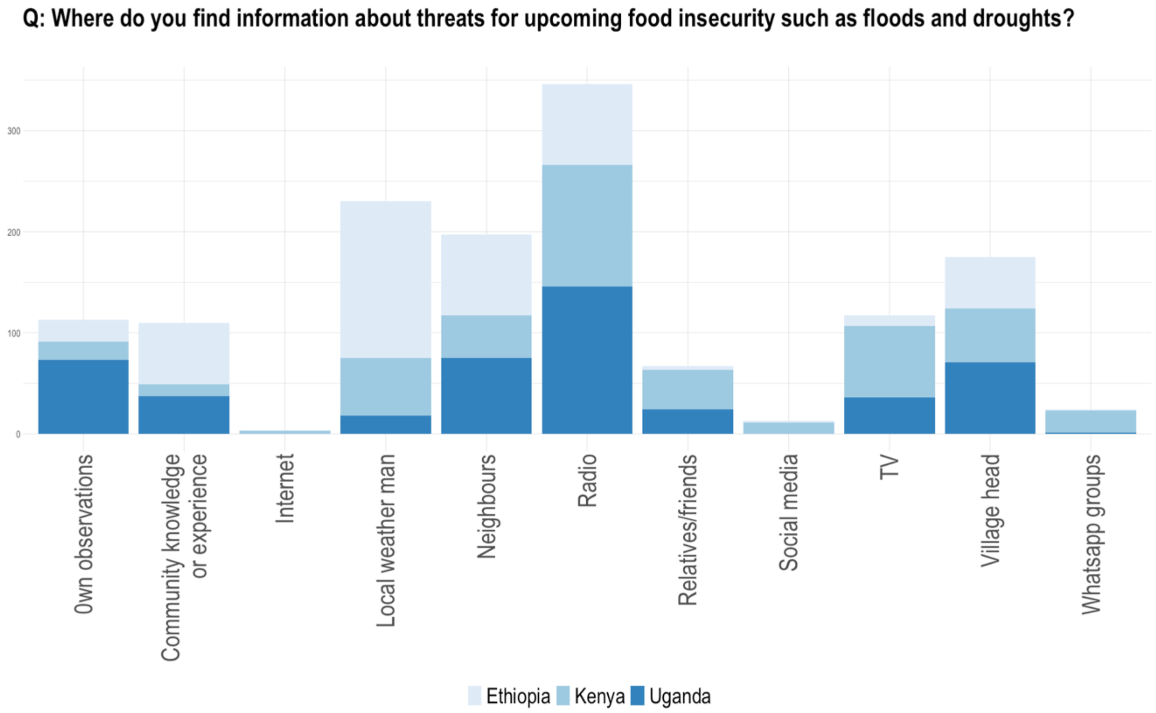


Figure 19 Means of communication utilized by the communities to receive early warning information. Y axis represent the number of responses

In Figure 20, we present the answers related to the trust and usability of the received early warning information. Most of the respondents have indicated that they agree with the statement that the received forecast information can be trusted and used for their farm practices. This statement is predominantly observed from responses obtained from the Kenyan study area (Isiolo). Overall, we note that the surveyed communities indicated to have access to trustful and useful forecast information for supporting their agricultural practices, even though the source of information is unknown by the communities.

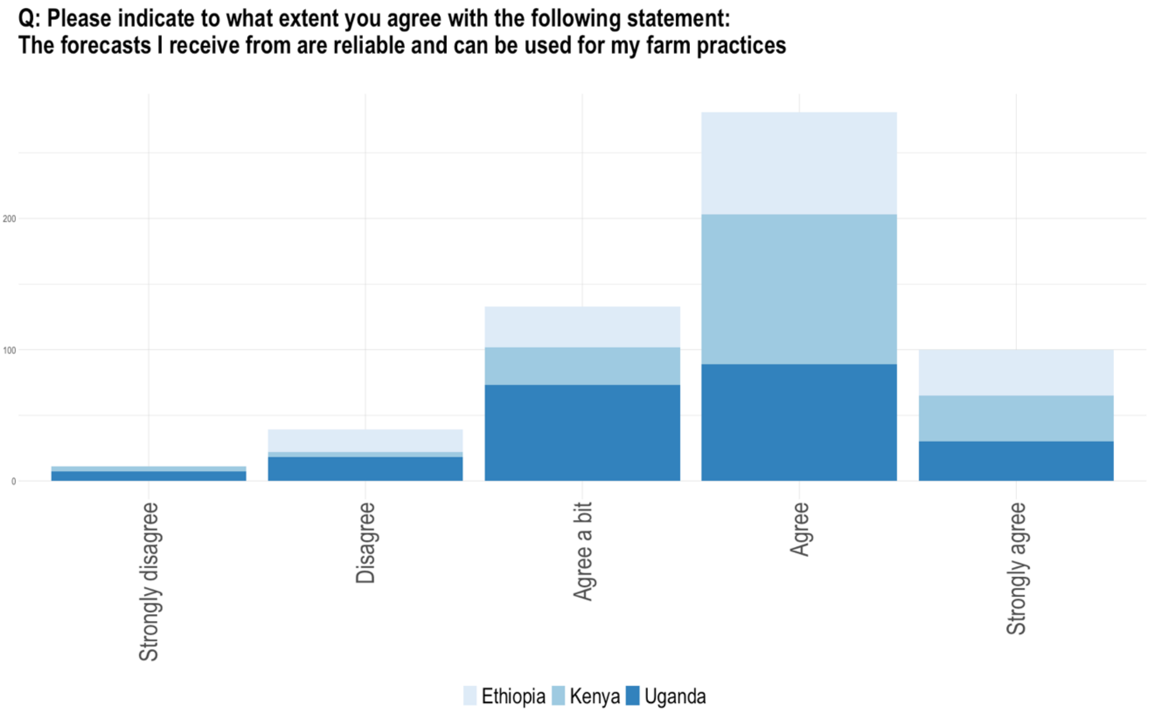


Figure 20 Trust and usage of forecast information by the communities for their farm practices. Y axis represent the number of responses.

WHICH EARLY ACTIONS DO PEOPLE TAKE TO LESSEN THE IMPACT OF IMPENDING FOOD INSECURITY?

Within the survey section "response actions and adaptation to shocks" we aimed at capturing people's adaptation and response's behavior during and before a shock. In Figure 21, we display the answers related to local action that are traditionally implemented by the communities to mitigate the impacts of droughts and increase drought preparedness once they know that are drought is coming. In all study areas, the most indicated mitigation preparedness action was "stock on food" (especially in Kenya and Uganda) followed by "increased livestock and product sales" (especially in Kenya), "savings" and "grain/fodder storage". It is important to note that this question attempted at capturing people's mitigation behavior using their own resources. In the last result section of this chapter we explore which sort of precautionary actions are encouraged if respondents would be recipients of ex-ante cash transfer.

Some of the drought mitigation actions shown in Figure 21 have a direct impact on communities' food security level during a drought. For instance, stocking on food for own consumption before the acute impact of droughts are felt, may enable people to access the markets at more stable price levels, whereas storing grain/fodder can be seen as a way to ensure that livestock are fed, and that a livestock's body health condition is maintained. Understanding people's mitigation behavior allows to support humanitarian agencies to identify a range of anticipatory action against droughts that can be implemented based on forecasting information that is also fit for purpose and imbedded on cultural norms.

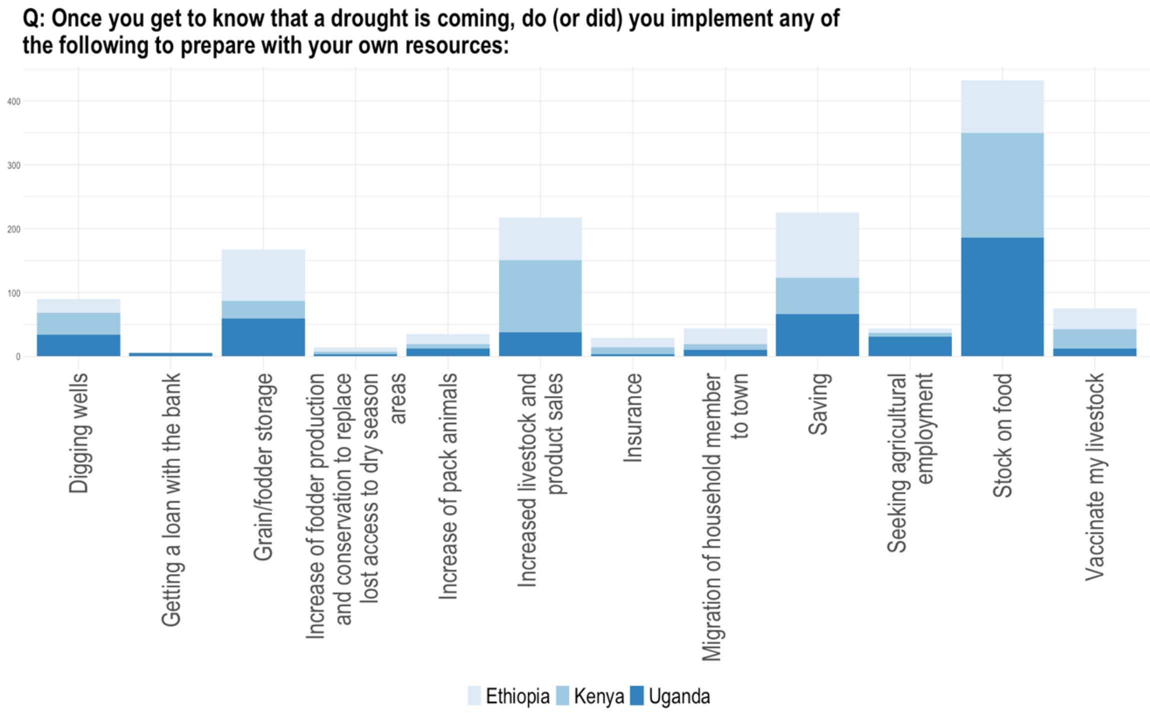


Figure 21 Preparedness measures taken by the surveyed communities before a drought. Y axis represent the number of responses

HOW CAN LOCAL KNOWLEDGE ON FOOD SECURITY BE CONVERTED INTO A QUANTITATIVE MODEL INPUT?

Following from the answers shown in Figure 18, we have asked participants to further explain how early warning signs could tell them that a food insecure time is coming and when are these changes observed. Furthermore, we asked how different these signs were from a "normal" situation? In Table 5, we display some of the open answers given by the participants per study area. In Kenya, several respondents indicated to perceive changes in the wind suggesting that wind becomes stronger than normal. In addition, others indicated to observe changes in animals (e.g. abnormally unhealthy or unusual animals been seeing) and trees (e.g. change in color or dryness). Furthermore, others have indicated a direct link between rainfall deficits and upcoming threats to food security. In Ethiopia, several respondents indicated to perceive strength in the wind (e.g. becoming stronger) and in the constellation of the stars (e.g. related to the position on the sky). In addition, respondents pointed out t changes in animals (e.g. sounds), trees (e.g. leaf color) and temperature (e.g. very hot or sunny). Lastly, in Uganda respondents mostly indicated to observe changes in animals (e.g. intestines and movements) and on temperature (e.g. sun burns crops, humidity) whereas others reported changes on trees, wind, moon and stars.

Based on these responses, we consulted with the surveys' facilitators from the Kenyan, Ugandan and Ethiopian Red Cross in order to understand how we could convert some of these information into quantitative model input for the forecasting model. Given the limited time frame remaining within the F4S project, we focused on representing the local knowledge information through proxy indicators that could be extracted from readily available data repositories. As a result, we have chosen to capture, to a certain extent, the changes that are observed in wind and trees due to two reasons: (i) the changes on these two elements were reported across all study areas and (ii) the current availability of dataset that could be used as proxy indicator. To represent changes in wind, we used a dataset of wind speed, whereas for changes in trees, we adopted the satellite-derived NDVI index. In more detail, we extracted the mean wind speed during the month prior to the start of the raining season within a district/livelihood zone, and for the NDVI, we extracted the mean maximum cumulative NDVI value during the raining season within a district/livelihood zone. For more details about these two datasets, see section T.1.2.1 of this report. As a result, we were able to generate a hybrid forecasting model that utilizes both scientific and traditional knowledge.

Table 5 Collection of answers given per study area to the following question: 4. Can you explain how these signs tell you that a food insecure time is coming and when do you observe them? How do the indicators differ from a "normal" situation?

Kenya	Ethiopia	Uganda
Animals become weak	Example at the morning very cold and in the afternoon very Sunny with no cloud sky	The animal intestines can be able to portray the real signs of famine and food insecurity
Strong winds blow	Wind it has so dust or dust full wind at the moment of the wind there is no air and cloud on the sky	The indicators happen most especially in the beginning of the year
Winds blow strongly	Example star the position on the sky is not the same in the normal condition	When people think the digging season is on and the rain is not coming the elders start to kill animals to check on the intestines
When trees are green they indicate well food secure and when they dry out they show food insecurity is to happen	Sun is so shine and the air is extremely dry	The moon comes in when it is a little brown showing signs of rain and very bright showing signs of drought
When there is rain there is food when there is no rain there will be food insecurity	Star the position of star in sky is not at fixed place or the same	Animals start to move to the east every morning
When trees dry out there will be food insecurity and when trees are well green means well food secure	Tree the leaf of the tree is neatest to yellow in a normal condition	Too much sunshine
Strong winds	Using the sound of some birds is different from in a normal condition	Wind blows facing different side
When rivers dry means there is drought thus food insecurity	(Humidity) in rain season there is no humidity or humidity is not that much	Too much sunshine which will dry the crops
In a normal situation trees and green but when stroked by drought they dry up hence indicating food insecurity	The position of star and sun at that time when sun comes back to the star there is a serious drought	If the sunshine exceeds beyond the expected month
When there is rain there will be food and when there is no rain there will be shortage of food hence food insecurity	Sun and wind	The wind with dry spell indicates a sign of drought
The intestines have abnormal glands	Sun and animals' intestine	Too much sunshine that burns crops
Lack of rainfall means there will be drought and food insecurity will be experienced	Star the position of star in sky	Too much sun
The wind blows strongly	Simply I hear that sign but what I have experienced is (wind) wind is so blows than the earlier	Trees shade off their leaves has a sign of drought
The soil gets hot and the land dry	Sun is very hot and dry weather conditions	Too much rainfall washes away all the crops
Blowing of strong winds	The position of star in sky star is moving in the sky	If the sunshine is too much it destroys all the crops
Strong winds indicating food insecurity	Sun and it's hotness	When trees shade of their leaves
Trees drying showing drought thus food insecurity unlike in normal situations trees are green	Only I hear this is indicators sign	Running water washes away all the crops in the gardens making bare
Blowing winds	In the drought time some Star is not appeared comparing to the rain time	The wind comes up than when we are in the normal situation and ants at times start drying
The elders know the secrets	I can't tell this all because I hear from the local weather forecasters and radio	Humidity mostly indicates sunshine or it also forecasts heavy and dangerous rainfall
Animal intestines indicate looming drought	Moon is so could and very small comparing to the rain season	
A cluster of weaverbirds	Weather changed from time to time	
Abnormal flock of birds	Wind falls down the tree and any other property when comparing to the normal.	
Shoats eating while lying down indicative of a looming drought	Sun hotness	
amount of rain that season	Sun is very hot at that time	
Less rainfall that season leads to drought		
Hot temperatures warn of severe drought and flowing of seasonal rives on fully capacity is a sign of flooding in my area		
Clouds: They become white in color. The trees and plants all wither		

WHAT IS THE CURRENT EXPERIENCE WITH CASH TRANSFERS?

In Figure 22, we observed that, among the surveyed communities, respondents have more traditionally received humanitarian aid by means of food aid or as food for work programme. Furthermore, we observed that the majority of the respondents who received cash transfers are located in Kenya as opposed to Ethiopia and Uganda. However, in Uganda, a small share of the respondents have participated in previous cash for work programme. Given the lack of experience by the communities with cash transfers programmes and their roll-out, and given the initial goal of investigating people's expenditure behaviour in relation to ex-ante cash transfer, we have created an illustrative narrative. In this narrative, we contextualised the hypothetical goal of such an ex-ante programme and its operation within the framework of the designed choice experiment (see Annex B) .

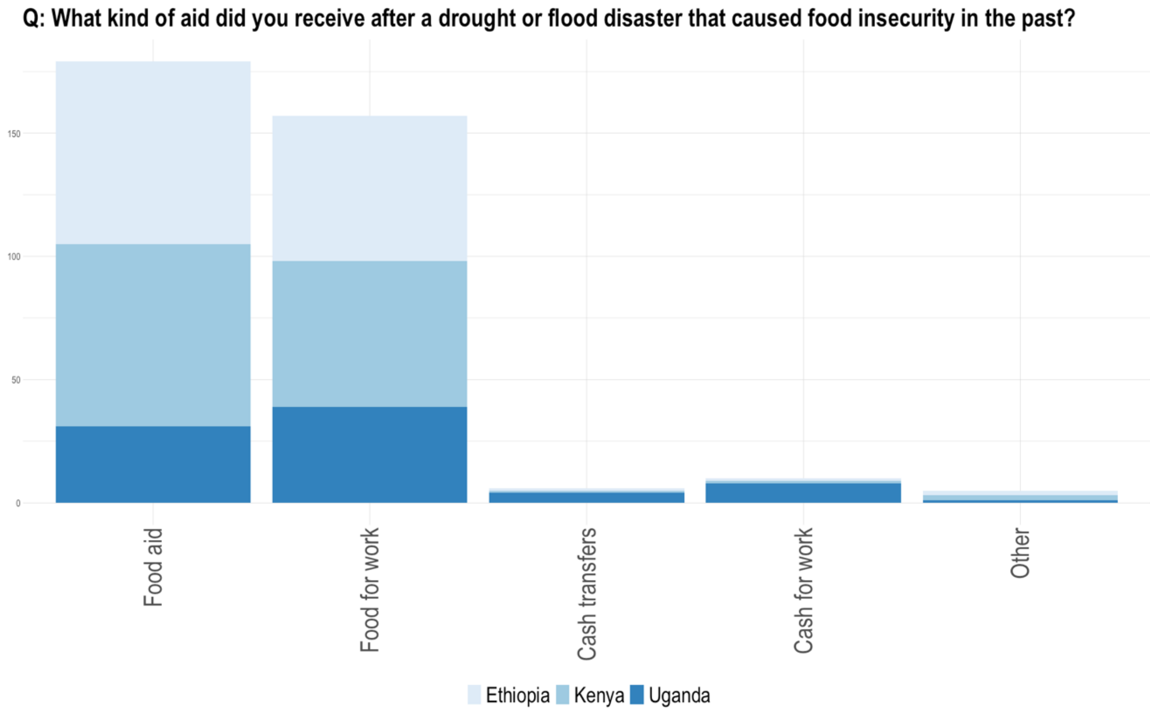


Figure 22 Figure showing people's previous experience with humanitarian aid. Y axis represent the number of responses.

WHAT COULD BE THE IMPACT OF EX-ANTE CASH TRANSFERS ON FOOD SECURITY?

In Figure 23, we display respondents' coping strategies when faced with a situation of extreme food insecurity. Most of the household indicated to implement some sort of negative coping strategies. The most commonly cited coping strategies are reduced number and amount of food consumed and relying on less preferred food. On top of limiting food intake and eating less nutritious food, which can have a long-term impact on the health of the community, respondents also reported to use savings or sell household's productive assets, which are also expected to undermine their subsequent future generation of income. Based on these past experiences, cash prior to a shock might open a window of opportunity to enable communities to put in place actions to avoid some of these detrimental coping strategies. These actions may allow beneficiaries to have access and sufficient time to execute a wider range of preventive measure that may provide them with a more dignified and prosperous coping strategy.

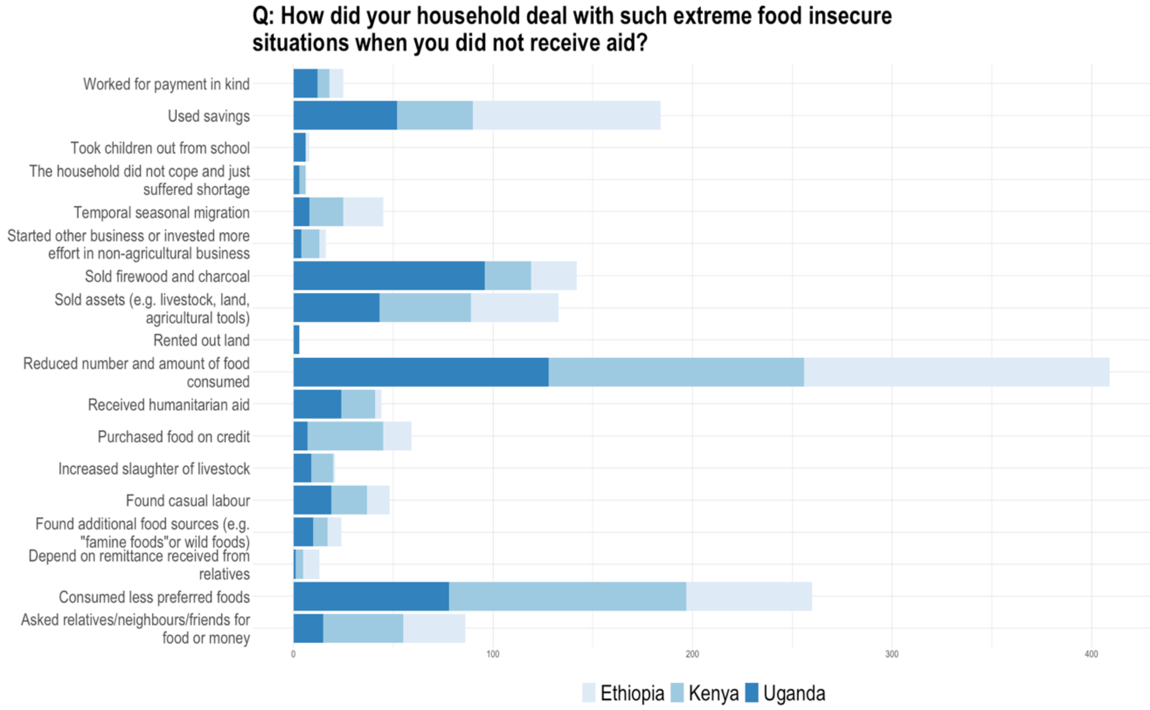


Figure 23 People's coping strategies during situations of extreme food insecurity. X axis represent the number of responses.

WHICH INDIVIDUAL PRECAUTIONARY ACTIONS ARE ENCOURAGED BY SUCH A CASH TRANSFER MECHANISM? & UNDER WHICH SET OF CORE DESIGN ELEMENTS OF CASH TRANSFER PROGRAMMES SUCH AS (1) LEAD TIME OF THE AID (2) PREDICTED IMPACT ON FOOD SECURITY AND (3) THE DISTRIBUTION OF THE CASH TRANSFER (LUMP-SUM OR SMALL PAYMENTS) ARE INDIVIDUAL PRECAUTIONARY MEASURES TAKEN TO AVOID FOOD INSECURITY?

In Figure 24, we display the proportion of the spent aid per expenditure basket and its link with the ex-ante cash transfer payment format. To achieve this result, we first divided the received answers into two categories: responses of scenarios with preference for one payment (lump sum) versus responses of responses of scenarios with preference for two payments for each of the six rounds. For each round and choice for payment format, we extracted the respondent's share of the spent aid per expenditure basket. Subsequently, we averaged the results of all rounds played. It is important to note that, among all study areas, the majority of respondents indicated that they would either spend the whole aid or part of it instead of saving the whole aid. In addition, we highlight that we have chosen to present the values in proportion of the aid spent in order to allow the easier comparability among all three study areas and to overcome challenges related to misreporting of data. Furthermore, the design elements of the choice cards were not evenly distributed among the rounds (see Annex D) and therefore they had unequal chances of being selected. As a result, it was necessary to adopt an assessment metric that captures averages rather than total values. Lastly, the results presented below should be interpreted as potential expenditures, given that the choice experiment only tries to resemble behaviour, whereas actual decision-making may differ from the played experiment.

In Kenya, respondents have chosen to spend the highest share of the hypothetical aid (refered to as "aid") on food expenditures when "aid" was received in two instalments (54%) (Figure 24A). It is interesting to notice that the expenditure behaviour can potentially change if beneficiaries would receive the aid on a lump sum format. In this case, the highest proportion of the aid is then spent on mitigation actions (40%), which is twice as large as the amount spent when a two instalments format is offered. Furthermore, the proportion spent on food expenditure also changes, decreasing from 54% (two instalment format) to 36% (lump sum). In Ethiopia (Figure 24B), respondents have chosen to spend the highest share of the hypothetical amount received on food expenditures regardless of payment format. However, when "aid" was received in two instalments, 63% of it was spent on food expenditure, 5% more than when "aid" was received in a lump sum format. The following similar characteristic can be observed as in Kenya: more is spent, proportionally, on mitigation actions if aid is received in a lump sum as opposed to two instalments (27% versus 15%). Expenditures on household items follows similar tendency as the food expenditure basket. Lastly in Uganda (Figure 24C), as opposed to Kenya and Ethiopia, mitigation actions receive the highest share of expenditure for both payment formats. However, we also observe that lump sum payments result in a higher share of the "aid" being spent on mitigation than when receiving "aid" in two instalments (43% versus 38%). In addition, a higher share of the "aid" was spent on food expenditure with the two instalments format (32% versus 26%). There is nearly no difference observed in expenditure related to household items.

An overview of the proportions per item of the expenditure basket is available in Annex E. Overall, we have observed that a higher share of the aid is potentially spent on food expenditure if beneficiaries receive the "aid" in two instalments rather than a lump sum. However, a lump sum can potentially result in a higher share of the "aid" being spent on mitigation actions.

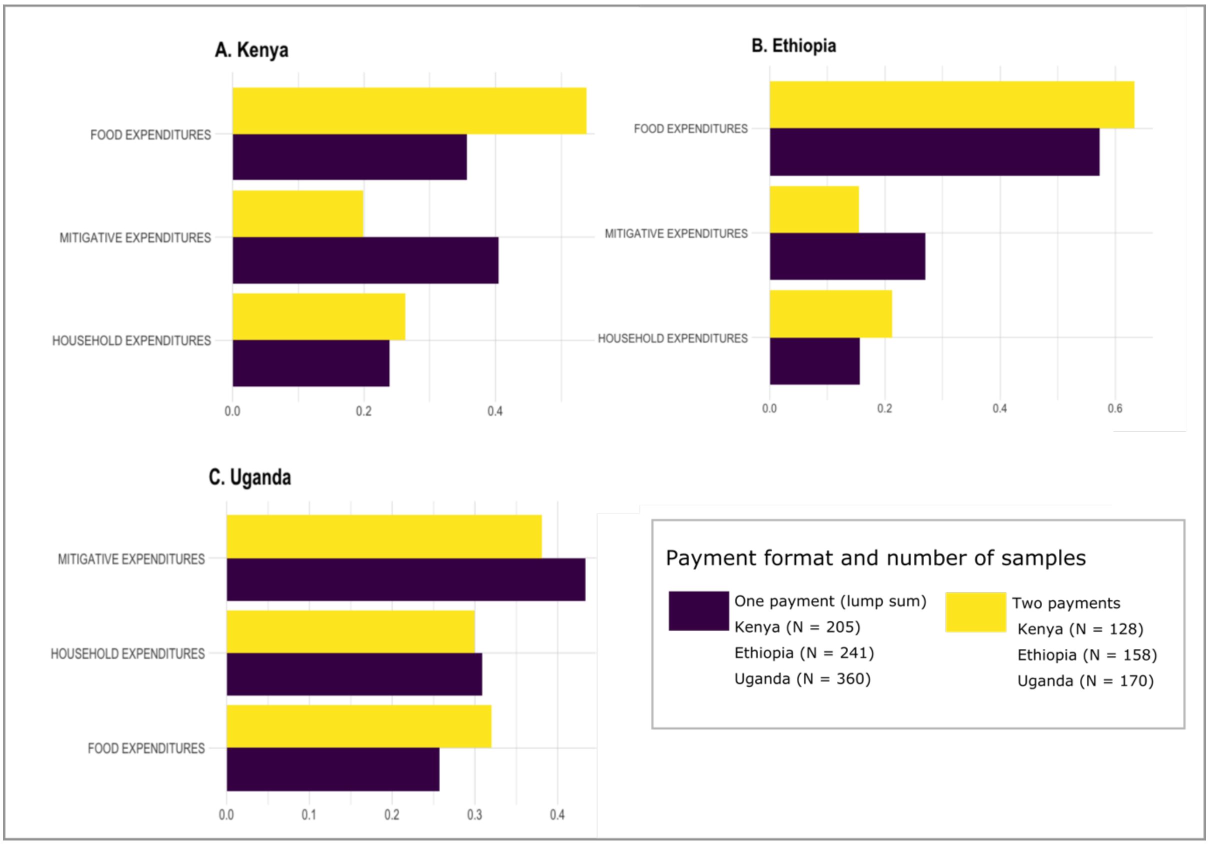


Figure 24 Share of the aid (rate, with 0 representing nothing spent and 1 being all received money spent) spent per expenditure basket, form of payment and study area. To achieve this result, we first divided the received answers into two categories: responses of scenarios with preference for one payment (lump sum) versus responses of responses of scenarios with preference for two payments for each of the six rounds. For each round and choice for payment format, we extracted the respondent's share of the spent aid per expenditure basket.N represents the number of samples, which differs across study areas depending on the amout of household data collected.

In Figure 25, we display the proportion of the spent aid per expenditure basket and its link with the timing of the ex-ante payment. To achieve this result, we first divided the received answers into two categories: responses of scenarios with preference for payments long before a shock versus responses of scenarios with preference for payments shortly before a shock for each of the six rounds. For each round and timing of payment format, we extracted the respondent's share of the spent aid per expenditure basket. Subsequently, we averaged the results of all rounds played. In Kenya and Ethiopia, among all baskets, food expenditure received the highest share of the spent "aid" regardless of timing. In Uganda, the expenditure basket that received the highest share is the one related to mitigation actions.

In all study areas, a highest share on food expenditure is observed if beneficiaries would have received payments long before a shock (Kenya: 50% ; Ethiopia: 63%; Uganda: 30%) in comparison to payments shortly before the shock (Kenya: 44%; Kenya: 60%; Uganda: 28%). For Ethiopia and Uganda, we have also observed a slight increase on expenditures related to mitigation when respondents received the "aid" shortly before the event (Ethiopia: 25%;Uganda: 44%) in comparison to long before an event (Ethiopia: 22%; Uganda: 40%). However, it is interesting to note that the differences in expenditure are not as larger as the differences observed linked to the payment format. Therefore, larger differences in expenditure behaviour could be more strongly linked to difference in payment formats rather than on timing, even though we would have expected the time element to play an important role. However, in our choice experiment, the largest time difference between “short” and “long” before a shock was on a scale of one month (see Annex B), and this relatively small window may had been perceived as indifferent for participants. In practice, timing should play an important role as several mitigation actions can be implemented if beneficiaries would be granted with ex-ante cash transfer long in advance of a shock such as purchasing of drought-resistant inputs and implementation of water harvesting infrastructure.

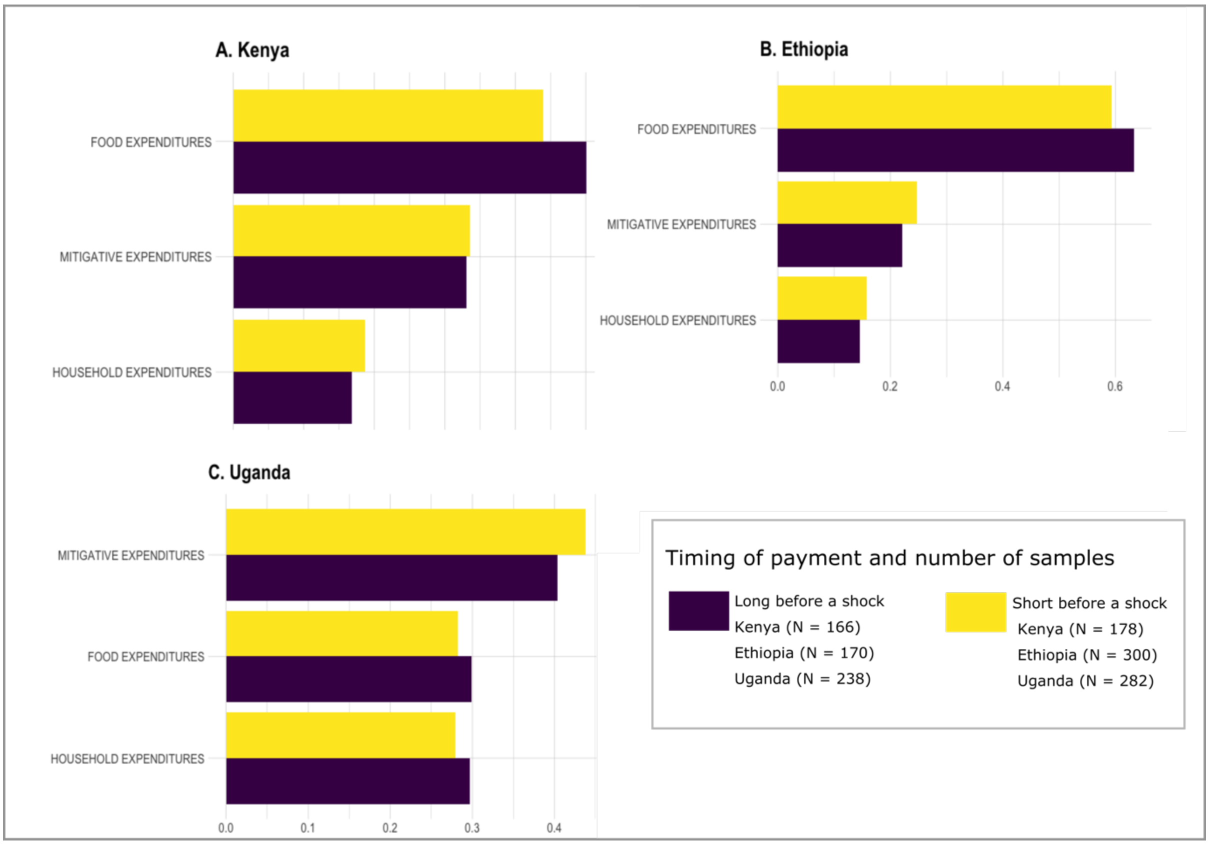


Figure 25 Share of the aid spent per expenditure basket, timing of payment and study area. To achieve this result, we first divided the received answers into two categories: responses of scenarios with preference for payments long before a shock versus responses of responses of scenarios with preference for payments short before a shock for each of the six rounds. For each round and timing of payment format, we extracted the respondent’s share of the spent aid per expenditure basket. Subsequently, we averaged the results of all rounds. N represents the number of samples, which differs across study areas depending on the amout of household data collected.

In Figure 26, we display the proportion of the spent aid per expenditure basket and intensity of event. To achieve this result, we first divided the received answers into two categories: responses of scenarios with severe impacts versus scenarios with moderate impacts. For each round, corresponding to the severity levels, we extracted the respondent’s share of the spent aid per expenditure basket. Subsequently, we averaged the results of the rounds with moderate and severe impacts. In Kenya, a higher share of the “aid” is spent on food expenditure items when the event is perceived to be of moderate impact in comparison to severe impacts (52% versus 43%). In addition, a higher share of the “aid” is also spent on the mitigation basket when the event is perceived as severe impact (35% versus 31%). In Ethiopia, a slightly higher share of the “aid” is spent on household items when the event is perceived to be of moderate impact in comparison to severe impacts (18% versus 14%), and the opposite on food expenditures (59% versus 63%). In Uganda, no large differences in expenditures are observed if impacts are perceived to be of severe or moderate magnitude. Therefore, we did not observe a coherent behaviour among the respondents in the three countries. Furthermore, in Uganda, unobserved differences between the events of different categories might be linked to risk perception. As pointed out by the surveyor team, the scenario of moderate impact is close to what is often experienced by the communities, and therefore a large difference between moderate and severe impact may not have been captured well with the designed scenarios for the study area.

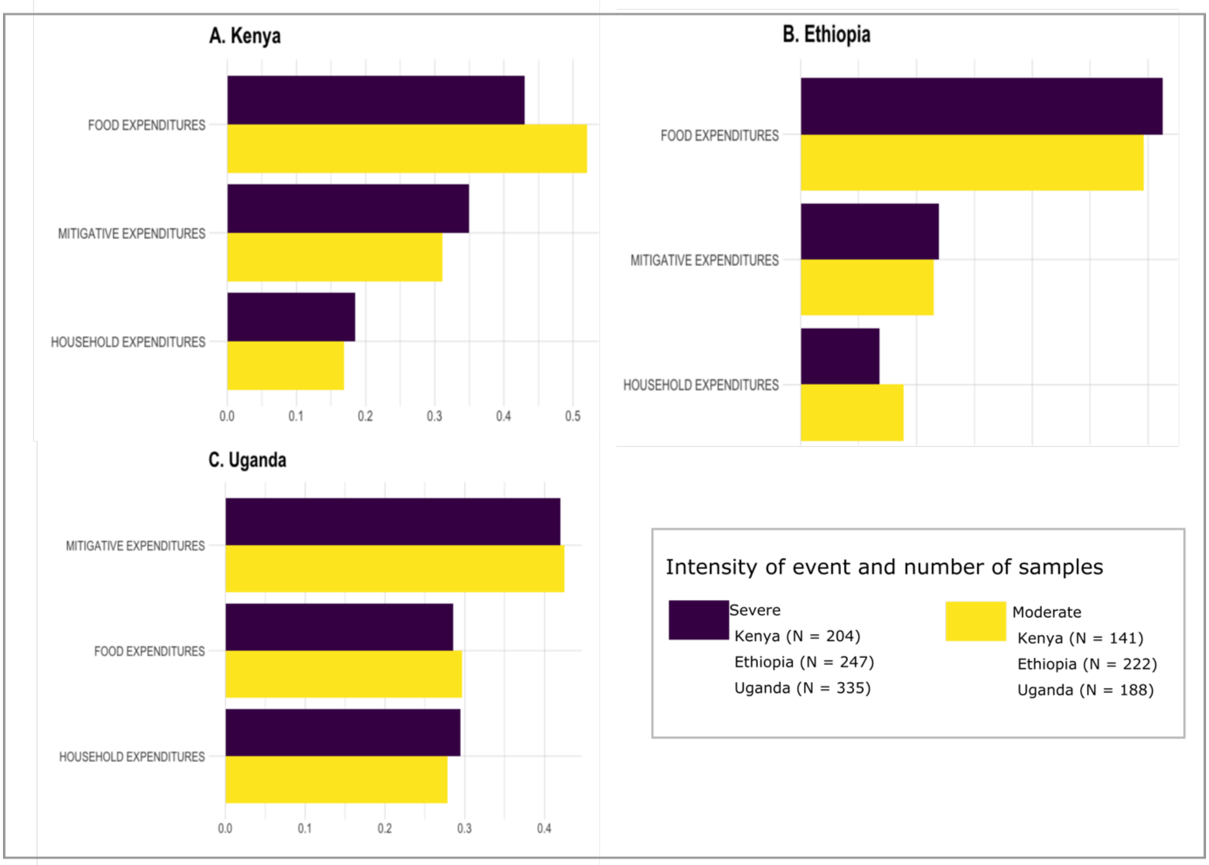


Figure 26 Share of the aid spent per expenditure basket, intensity of event and study area. To achieve this result, we first divided the received answers into two categories: responses of scenarios with severe impacts versus responses of responses of scenarios with severe impacts. For each round correspondent to the severity levels, we extracted the respondent's share of the spent aid per expenditure basket. Subsequently, we averaged the results of the rounds with moderate and severe impacts. N represents the number of samples, which differs across study areas depending on the amout of household data collected.

T3: EVALUATING CASH TRANSFER MECHANISM

T3.2: QUANTIFYING NEEDS FOR TRANSFER AND ASSOCIATED COSTS

As presented in the section above, potential beneficiaries of ex-ante cash transfers show a wide range of expenditure choices regardless of the design element being investigated. This diversification in expenditure is primarily driven by the fact that cash transfers give the purchasing power to the recipients, who are able to address their basic needs, with flexibility, speed and dignity of choice. In addition, cash transfers can be less expensive to administer than in-kind aid because they do not require logistical arrangements of storage and transportation.

The delivery of cash assistance at speed requires (humanitarian) organizations to have in place a pre-agreed activation plan, in which a number of procedures and agreements are followed once the forecasting of a shock is issued. Automatically, funds for executing this plan should be activated and populations reached within the window of opportunity between the forecast lead time and the materialization of the shock. In addition, beneficiaries should be pre-identified and registered. Oftentimes, the funds for executing this plan are limited and fixed, and therefore, the number of people assisted by the anticipatory plan bound to a budget. Therefore, the cost-effectiveness of a portfolio of anticipatory actions can determine largely the number of beneficiaries to be assisted by the anticipatory programme.

Customarily, an anticipatory action plan triggers a number of activities, which may range from activities including training and the dissemination of early warning information to ex-ante cash transfers. For each of the planned activities, a monetary cost unit is estimated, if any, and the number of targeted beneficiaries calculated depending on the total costs and available budget. For the disbursing of ex-ante cash transfer, the calculation of two components remains important: the quantification of needs and associated operationalizing costs. While the quantification of needs requires a substantial understanding of how a shock impacts a community and the amount needed to avert it, the associated operational costs can be seen as a less variable cost. Broadly speaking, the costs of a cash transfer programme can be translated into the amount that is given to the beneficiary (“the transfer value”) , and the amount spent on getting the aid to the beneficiary (“the administrative cost”) (O’Brien 2014).

The quantification of the transfer value, for food security purposes, is often linked to an economic analysis of “needs assessment”, “minimum expenditure basket” and “supply analysis”. The needs assessment aims at identifying and analysing essential needs and gaps, **estimating the number of people in need** and **profiling their main characteristics** (WFP 2020). A deep understanding of essential needs helps in the design of effective food security responses. On the other hand, the minimum expenditure basket is defined as the monetary value that households require in order to meet their essential needs. This value serves as an input for the essential needs assessment to indicate which households have the economic capacity to cover their needs (Forsen et al. 2020). Lastly the supply analysis examines the **supply of essential goods and services** to detect how well the marketplace is functioning. The thorough analysis of these three components provide a full needs analysis (Forsen et al. 2020). For the dynamic estimation of needs assessment, it is important that the analysis captures changes in wellbeing due to adverse shocks (e.g. droughts, conflicts etc.).

With the deliverables T1, T2 and T3 of the F4S project, we were able to provide information that can be useful for the analysis of needs assessment, which can support the estimation of the transfer value. In the next paragraphs, we further explain how our deliverables could feed into existing needs assessment analysis.

ESTIMATION THE NUMBER OF PEOPLE IN NEED

Through the use of impact-based Forecasting modelling within T1, we were able to forecast, with long-lead time, key components of food security, named “shortage on calories”, “forage scarcity” and “changes in the state of food security”. In addition to our models showing good skill in forecasting threats to food security months ahead of a shock, our indicators can be translated into an estimation of people affected, which serves as a first step towards geographical targeting. For instance, the forecasting model for “shortage on calories” has been designed to capture the percentage of a population within an administrative region with potential shortage on the number of required calories. Even though our model has focused on events in which at least 25% of the population could be suffering from calories shortage, this threshold can be further adapted to capture other levels. The forecasting model for “forage scarcity”, among the three produced models, is currently the one that is less representative for estimating population affected. However, there are ways in which our model could be further adapted for representing such impact. For instance, by adapting the forage scarcity index to detect the percentage of an administrative region with forage scarcity and the number of pastoralists living on the affected land. The forecasting of “changes in the state of food security” can be a useful source of information for estimating the amount of people in food insecurity given that this model uses IPC as a primary source, which in turn uses the most likely category of food security of a population living within an administrative boundary. While this forecasting model could support a wider geographical planning and targeting, other tools such as the IPC population tracking tool[15] could be used in complement with our model for refining the assessment.

CHARACTERISTICS OF THE POTENTIALLY AFFECTED PEOPLE

Within T2, we have carried out surveys with 564 households’ potential beneficiaries of cash transfers. We collected information on participants past experiences, response actions and adaptation to shocks, which is useful for the design of effective food security responses. In addition, we gathered socio-economic information on gender, age, educational status and economical activities which can be further triangulated with responses from the choice experiment. This socio-economic characteristics in combination with an analysis concerning people’s expenditure may provide institutions with valuable sources of information to support the targeting of vulnerable groups, as well as to extract information that can potentially increase the positive impact of a cash transfer. For instance, if institutions would like to have a large and direct impact on the food security levels of a community, a cash transfer programme can potentially be designed to be disbursed in two instalments given that highest share of the “aid” received was spent on food expenditures when received in two instalments instead of a lump sum. Further investigation could examine how expenditure choices could vary based on certain socio-economic characteristics.

[15] http://www.ipcinfo.org/ipc-country-analysis/population-tracking-tool/en/

THE MONETARY VALUE

In connection to the forecasting of "shortage on calories", we evaluated the potential cost-effectiveness of ex-ante cash transfer in comparison to ex-post cash transfer. We did that by extracting the mean value of basket of goods at the month of the intervention. For composing the basket of goods, we analyzed the mean price of key staple food items such as maize, teff, sorghum, wheat, oil, barley and others staple food items. One advantage of disbursing ex-ante cash transfers before a shock is that households can access markets at more stable conditions, and therefore at a lower price. Therefore, institutions operationalizing ex-ante cash transfers shall adjust the size of the transfer in in accordance with market price fluctuations. This will enable recipients to cover the needs for which they are receiving the transfer, and avoid effects of inflation (ICRC 2007). Therefore, in our analysis we considered ex-post cash transfer to be costlier given that a higher amount would need to be disbursed to reflect price increases during shocks. As a result, we were able to quantify the regions and lead time in which ex-ante cash transfer based on forecasting information could yield cost reductions in comparison to ex-post. In addition, decision-makers can extract information regarding the most cost-effective moment for action, if the "Expense minimization" approach is desired. Such estimations can be seen as a first step towards obtaining the monetary value that households require in order to meet their essential needs, if a desired nutritional level is pre-defined by the cash transfer programme (e.g. supply a transfer value that is sufficient for households to obtain 70% of the required daily calories in the local markets for a certain number of months).

Furthermore, we advanced our analysis by providing with the forecasting of "forage scarcity" a detailed cost-benefit analysis of using our forecasting model for IBLI. We did that by mapping the benefits and costs associated with acting early and protecting livestock in comparison to the costs and benefits of the current ex-post IBLI design. Acting early can lead to a range of benefits including avoided losses, a protected food security, strengthened resilience, faster recovery, and reduced physical and psychological suffering of pastoralist communities. We have found that the monthly benefits outweigh the costs in both ex-ante and -post designs. However, for the ex-ante design, every Kenya Shilling (KSh) invested would result in 3.6 KSh of benefits, whereas the original IBLI yields only 1.6 KSh of benefits per KSh of costs. This means that taking early action generates 2.0 KSh of benefits more per KSh of costs compared to the original design. Evaluation, such as the one described, provides a useful framework for policymakers for planning future cash transfer interventions. However, it is important to point out that the IBLI program is sold on a commercial basis. Since the benefits of taking early action are mainly felt at the household level, the question is whether IBLI will also benefit from implementing the Early Action design. The costs of acting in vain (based on the forecast information) have to be paid by IBLI, while the benefits are obtained by the households. As a result, implementing Early Action might not be cost-effective from IBLIs perspective, resulting in less interest in implementing the proposed design.

SUPPLY OF ESSENTIAL GOODS AND SERVICES

It should be noted that there are challenges concerning the implementation of the cash transfer programmes in some of the study areas investigated. For instance, in pastoral regions in Kenya, the main challenge is that markets to access fodder, water and veterinary drugs are often scarce, inaccessible, or even absent in the pastoral regions of northern Kenya (Lukuyu et al. 2011). This means that efforts have to be made to further develop such markets and guarantee accessibility for pastoral households in order to successfully implement the proposed design. Importing supplementary livestock feeds from, for example, Nairobi is also a possibility. However, the distribution and transport costs involved would lead to a significant increase in costs, which can be at the expense of the cost-effectiveness of taking early action. In addition, poor market integration can be a contributing factor to food insecurity in the areas investigate within the F4S project. As we have detected in the forecasting model of “shortage of calories”, some districts with long distance to main markets can show a tendency in experiencing shortage events. Therefore, cash efficiency is intrinsically interlinked with market efficiency. However, despite the fact that transferring money can be seen as a cheaper alternative to moving commodity overland, the targeting, registration and identification costs associated with starting up a cash scheme can be substantial (Audsley, Halme, and Balzer 2010). Thus, one-off start-up costs with registration and identification of registered beneficiaries can also represent sizeable costs when implementing a new cash programme.

T4: CHANNELS FOR OPERATIONALIZATION

In this section, we discuss how the knowledge gained with the F4S project can be integrated and disseminated in some of the anticipatory action activities planned by stakeholders working in the region. Some potential channels of operationalization encompass existing or planned cash transfer programmes led by governments and humanitarian organization. In addition, we discuss opportunities, challenges, and limitations to transfer and scale our models and provide recommendations of next steps towards operationalization.

HUMANITARIAN SECTOR

The Innovative Approaches to Response Preparedness (IARP) project is establishing national scale impact-based forecasting systems for both floods and droughts. Also, early warning early action or forecast-based financing (FbF) is used as terminology. The Red Cross National Societies in Kenya, Ethiopia, and Uganda are leading the development of these systems in close consultation with the communities that are flood and drought-prone and in collaboration with governmental and other key stakeholders. 510, an initiative of the Netherlands Red Cross, The British Red Cross and The Red Cross Climate Centre provide technical support. The FbF system enables access to the so-called Disaster Response Emergency Fund (DREF), an IFRC managed funding source habitually only available for humanitarian response, via an Early Action Protocol (EAP). The EAP is triggered when an impact-based forecast—i.e., the expected (humanitarian) impact as a result of the impending flood or drought—reaches a predefined danger level. An EAP outlines the potential high risk-prone areas where the FbF mechanism could be activated, the prioritized risks to be tackled by early actions, the number of households to be reached against an expected activation budget, the forecast sources of information, the expected lead time for activation, and the agencies responsible for implementation and coordination.

One of the main actions prioritised in the EAPs is ex-ante cash transfers. This type of action has been perceived by the IARP project as an effective, dignified, and a fast emergency response modality which can empower affected populations and protect their livelihood. The option of cash as a modality of undertaking anticipatory actions gives the most vulnerable communities the choice of identifying the most appropriate action that is relevant to their respective situation and further use cash to undertake that action, whether it is buying food, drought-resistant seeds or investing in other income generating activities. The emphasis of understanding people's behaviour when it comes to cash as done under the F4S project via the choice experiments will be directly beneficial to guide the use of ex-ante cash in the context of forecast-based financing. Most importantly, it will support identifying the best time to transfer cash based on the window of opportunity.

All three Red Cross National Societies have already -to a more or lesser degree- experience with ex-post Cash and Voucher Assistance (CVA). For example, The Uganda Red Cross implemented cash interventions to flood-affected populations and refugees in Western Uganda. The Ethiopian Red Cross provided cash assistance to address the food needs of drought-affected households. The Kenya Red Cross piloted already with digital cash programs. The IARP project has supported further capacity building in cash transfer programming within the National Societies. Strong leadership commitment for using cash is now also in place. This enhanced capacity and commitment will enable the rapid deployment of ex-ante cash distributions. However, as the EAPs are still in development, no actual ex-ante cash distribution has already taken place. In Ethiopia experience with financial service providers was built up through the flood EAP simulation exercise in March 2021.

In terms of developing the trigger model as part of the drought EAP, the IARP project takes the primary impacts of drought, namely (i) reduced crop yield, (ii) lack of pasture, and (iii) water scarcity, as starting point. If these primary impacts are not addressed well in advance through early action, they may cascade into other impacts such as food insecurity. The open source open data Machine Learning (ML) models as developed by the F4S project are, therefore, of direct relevance for the drought trigger model. The different ML models can be combined into a hybrid forecasting system where there is a phasing of triggers. Phasing aims to activate low-cost actions when the uncertainty of the prediction of impact is relatively high. By adding more information to the ML model over time (or by switching to a different ML model), the predictive uncertainty can reduce, and more short-term higher-cost actions can be started. Phasing also allows having a stop mechanism before continuing with uncertain actions (depending on whether one takes the Prevented event maximization or Expense minimization approach). In addition, the triggers are only for relatively extreme events with a return period of five years or more. It is therefore beneficial that the ML models have a better performance for higher trigger levels. As a next step, a detailed analysis should be carried out in order to unreveal the bias of these extreme event forecasts in relation to the methodological approach being adopted e.g. oversampling of rare events. In addition, EAPs usually have the same trigger for the whole country. So even though the F4S ML modeling will allow us to set different trigger levels per district, this will most likely not be used. This would also require a detailed return period/extreme event type of analysis per district. However, a different trigger depending on livelihood is possible to implement (e.g. one for pastoralists and another for agriculturalists), as these beneficiaries require most likely also different early action approaches.

Considering that the communities are already implementing early action based on forecast information, this provides an entry point when the EAPs will be first simulated and further implemented since the concept of taking actions before an event happened based on a forecast is not a new phenomena to the communities. IARP is also exploring how indigenous or local knowledge can be incorporated into the systems that are being developed and the wealth of knowledge collected by F4S project on the variety of local knowledge being used to predict threats to food security will be added to what has been collected so far by IARP project and integrated into the EAP in due course. Finally, the IARP project can also use the F4S CBA/CEA results to advocate for more support among a wider group of stakeholders in terms of rolling out FbF as the CBA/CEA analyses show ex-ante is more cost effective than ex-post (and that these benefits increase with higher trigger levels).

Furthermore, the World Food Programme (WFP) is currently developing their anticipatory action plan in Ethiopia and Uganda, and they have identified cash transfer as a desired activity. As a result, during the months of December 2020 and February 2021, some members of the F4S project participated in two debriefing sessions with the forecast-based financing and cash teams from WFP, who are planning pilots in the regions. There is an interest from WFP to review some of the F4S findings, and currently we are exploring how some of the lessons learnt can be applied in WFP's anticipatory action pilots in Ethiopia.

GOVERNMENT-LED SYSTEMS

In terms of existing (government-led) systems for social protection, Kenya has four national Cash Transfer programs under the National Safety Nets Programs, in which The Hunger Safety Net is the program that could more directly benefit from the F4S findings. The Hunger Safety Net is implemented through the National Drought Management Authority in four poorest and arid counties in Kenya, which are Turkana, Wajir, Mandera and Marsabit. The programme's main objective is to deliver regular and emergency cash transfers and influence the development of an integrated social protection mechanism both at the national and county levels (HSNP 2021). Currently, the program has started its 3rd phase after being signed in January 2019 a financing agreement with the World Bank to expand its geographic coverage to Garissa, Isiolo, Samburu and Tana River counties. Targeted households receive regurlarly KES 5,400 every two months delivered through Equity Bank and its agents. Monthly emergency payments of KES 2,700 are made few weeks after a drought trigger. It is important to highlight that beneficiaries on the regular programme are not eligible for emergency cash. The current drought trigger uses monthly Vegetation Condition Index to detect a "severe" or "extreme" drought. In case of a severe drought, 50% of the households are covered while in case of an extreme drought, 75% of the households are covered. Therefore, the Hunger Safety Net program can be seen as an ex-post cash transfer program that uses drought observations for triggering a response mechanism.

In addition to Hunger Safety Net program, the International Livestock Research Institute (ILRI) piloted an Index-Based Livestock Insurance Program in 2010 to decrease the vulnerability of pastoral communities in Kenya and Ethiopia. With this commercial insurance program known as IBLI, pastoralists can insure their herds against drought-related livestock losses. Due to the known correlation between forage scarcity and livestock mortality in pastoral production systems (Chantarat et al. 2013), the insurance pays out indemnities based on observations of the Normalized Difference Vegetation Index (NDVI), which is an index very similar to the one adopted by the Hunger Safety Net program. Evaluation of the impact of IBLI indicated that the program has strong positive impacts on the well-being of pastoral households. To be specific, households with IBLI coverage experienced increases in income per adult equivalent, milk production, investment in veterinary services and improvements in mid-upper arm circumference, an important predictor of acute malnutrition in children (N. D. Jensen, Barrett, and Mude 2014). The effects of IBLI were also observed from changes in coping mechanisms used by the households. During the 2011 drought for example, insured households were 25% less likely to reduce meals and 36% less likely to obligatory sell their livestock to cope with the drought (N. Jensen, Barrett, and Mude 2015). Regardless of all benefits, the insurance program still has its constraints. One of the main limitations is that the payouts can only be made after the dry season. This means the livestock may have died before the indemnities are paid out. Hence, IBLI can be seen as an asset replacement program, compensating pastoralists for their lost livestock. In February 2016, 230 million KSh was paid to 12,000 pastoralists - an average of around €150 per household - to compensate for the extreme forage scarcity during the last season. However, according to the village elderly of communities in Marsabit, they had already lost 200,000 animals since October. Also residents of the Dabele village, near the Ethiopian border, pointed out that 40% of their animals had already died (Eastaugh 2017). This raises the question of whether replacing the livestock is the most beneficial and cost-effective way of increasing the pastoralists' resilience. Furthermore, in the IBLI Marsabit Household survey, pastoralists indicated that they would rather receive cash to keep their animals alive in times of severe forage scarcity than to receive funds when it is already too late. Hence, implementing the Early Action approach proposed in chapter T1.2.2 may result in more livestock keepers buying the product which will in turn benefit IBLI. Besides, the IBLI design is also adopted by the government-sponsored Kenya Livestock Insurance Program. It is expected that the government has a higher tendency to benefit the vulnerable households and increase their resilience, which makes the Early Action design particularly suitable for the Kenya Livestock Insurance Program. Lastly, we would like to highlight that the perspective of cost-efficiency should not only be the only angle analyzed when planning for a cash transfer interventions. Even in situations in which anticipatory action may be seen as less efficient, its implementation should be still considered given that there a range of benefits (both tangible and intangible) that are difficult to measure but that can produce long-term positive outcomes. Therefore, from our point-of-view, both the Hunger Safety Net and the Index-Based Livestock Insurance could benefit in applying some of the lessons learnt with the F4S project given that our analysis indicate a potential range of social and economic benefits related to early interventions. Furthermore, the proposed Early Action approach for the index-based insurance proposed by of our project can generate various benefits for the pastoral households increasing their long-term economic viability and resilience.

In Ethiopia, the Productive Social Safety Net (PSNP) programme is the second largest in Sub-Saharan Africa. The program provides cash or food assistance to chronically food insecure woredas (districts) equivalent to an established kg of grain in order to set a nutritional value for the transfer. Under its phase 4, major droughts shocks within the program are addressed using federal-level contingency budget followed by a seasonal need's assessment conducted following the main harvest seasons *meher* and *belg*. The process from triggering the needs assessment until the formulation of final Humanitarian Response Document requires the involvement of a large number of governmental actors. Interventions through Humanitarian Response Document appeals are typically associated with time delays before funds are raised, leading to response interventions during the time where coping strategies are near their exhaustion and emergency assistance is required (eight to eleven months following the main harvesting season) (Drechsler and Soer 2016). However, the PSNP program utilizes Early Warning Systems to predict the impact of droughts and the number of beneficiaries during the harvest period. Even though the system has the potential to increase its lead time, there are currently no recorded examples of this process. The increase of the lead time window would enable faster and timelier ex-ante payment (before harvesting), and therefore one of the F4S models could be effectively aligned with on-going PSNP operations.

Furthermore, for Uganda, as of yet there is no explicit Food Security social protection scheme, however the policy aligns social protection with The National Food and Nutrition Policy (2003), which aims to promote the nutritional status of all the people of Uganda through multi-sectoral and coordinated interventions that focus on food security, improved nutrition and increased incomes (Ministry of Gender Labour and Social Development 2015). It is within this linked policy framework that the F4S model could potentially be integrated.

CHALLENGES AND RECCOMENDATIONS

Regarding the set-up and distribution of ex-ante cash transfers, there are a number of challenges that humanitarian organizations can face in the study areas investigated by the F4S project. First, one of the biggest challenges currently faced by humanitarian actions is the translation from impact metrics calculated at the district or livelihood zone to observed impacts at the household level. One of the reasons for such a challenge is the lack of impact datasets, both at the district and household scales. Oftentimes, impact datasets, such as crop yields or livestock mortality are incomplete and/or have a short length, which make statistical modelling inviable. A potential way to overcome this limitation is to couple forecasting models, such as the ones developed within the F4S, with a detailed beneficiary's targeting assessments. This way, a range of beneficiaries can be pre-identified according to established socio-economic criteria or in connection to an existing social protection program. In consequence, this requires a human dimension to support operational decision-making on beneficiares' targeting while being supported by a forecasting model with the task district/livelihood zone targeting. Furthermore, implementation of the ex-ante cash transfers requires the data used by the forecasting systems to be available in near-real time. This is already the case for most data used in this project. However, some key indicators, such as the maize production, are not available up to most recent years. Therefore, other proxy indicators, such as the Dry Matter Productivity (derived from remote sensing) could be further explored as an alternative.

Besides, the proposed models are mostly developed by using a top-down approach. This means local knowledge on predicting drivers of food insecurity are only used to a limited extent. As more and more researchers agree upon the fact that integration of local and scientific knowledge could be a valuable improvement of existing disaster preparedness strategies, the incorporation of local knowledge might be another improvement to the models (Hiwasaki et al. 2014). Integration of local knowledge is likely to improve the trustworthiness of the forecast as many pastoralists and agro-pastoralists nowadays still rely on local indicators to predict floods and drought. This, in turn, might result in more trust and agreement between the communities and the humanitarian organizations, or even result in communities being more willing to purchase a designed insurance product.

Another identified challenge might be the complexity of the models. As the models are based on Machine learning systems that are often difficult to be comprehended, it might pose a number of challenges for decision makers for making use of such innovations. For instance, Machine learning systems are not entirely fed by expert judgement, which may result on a lack of ownership and motivation to use the models by decision makers, and therefore less convenient to implement them (GFDRR 2021). However, simplifications could be made by, for example, by identifying the sequence in which the variables are being used, and the thresholds for classification. Furthermore, decision trees can be converted into storylines via a detailed analysis of the cues and thresholds. This way, the implementation of the model would be based on understanding the scenarios rather than on the technical interpretation of the machine learning model. Another recommendation is to derive supporting graphs, in which user can extract the information of which variables are contributing to the Machine Learning system decisions or graphs in which the relationships between input variables and the output variable are shown (GFDRR 2021).

Furthermore, prior to the disburse of new ex-ante or ex-post cash transfer programmes, efforts should be made to investigate whether markets are accessible, especially in some more remote pastoral regions. As pointed out previously, a successful implementation of cash transfer programmes depends on well-functioning markets and therefore, a rapid market assessment and a supply analysis examining current supply of essential goods and services is needed. Lastly, humanitarian organizations can explore ways to maximize the effectiveness of cash transfer by further investigating people's behaviour in relation to the design of a programme. As observed, differences in expenditure were observed, and organizations can benefit from a co-design and consultative process with beneficiaries in order to come up with an appropriated intervention.

T5: EVALUATION

In this section, we provide a discussion regarding the innovations produced by the F4S project, and their concrete application for disaster risk financing following the set of criteria established by the committee of evaluation (5.1 -5.5). Key recommendations are highlithed within the grey boxes.

5.1 FORMING OR STRENGTHENING LOCAL PARTNERSHIPS

The F4S project aligned with Red Cross' IARP activities, and established a partnership with local staff and volunteers, and local officers of the Red Cross Society of Kenya, Uganda and Ethiopia. This partnership has jointly supported the development and performance of the survey and choice experiment, as well as the feasibility assessment study. As the core principle of the F4S was to learn from the people who are closest to the problem, the F4S team, through this strong collaboration with the National and local branches of the Red Cross Societies, engaged with local key stakeholders such as district agricultural officers, community development officers and village elders. This engagement supported our project to achieve the goal of collaborating with local decision-makers to produce timely actionable insights and cost-effective solutions that reduces the risk of food insecurity. Moreover, during the project's development, we were able to exchange virtually with key stakeholders from the regions (FAO and IGAD) through a consultation with the Tufts University[16]. Lastly, members of the F4S team participated in a series of virtual consultations in April/2021 about Early Warning tools for pastoral regions. In these meetings we discussed some of the lessons learnt with the project.

In the grey boxed below, we detail how we have formed or strengthened local partnerships throughout all the different work packages:

- The T1 "modelling - co-design process" focused on the needs of users – both current and anticipated – and offered a space for local experts and the community to contribute to building a comprehensive food security assessment and datasets across selected case-studies. This process enabled the F4S project to deliver a set of models and triggers that are inclusive and multidisciplinary (natural, social, local knowledge), that can be made available for decision-making and early action.
    - Within T1, local knowledge on triggers and data were gathered by asking the people themselves during discussions, interviews and surveys, forming new connections.
    - Within T1, we made sure that the triggers complied with algorithmic accountability guidelines[17], which requires an established partnership. For instance, the actors using the machine learning models were co-developers of the model.
- The T2 "integrating local knowledge and local data into the modelling exercise" aimed to highlight unique aspects of a community that are relevant for forecasting important drivers of food insecurity.

[16] Consultation resulted on a series of reported available at https://sites.tufts.edu/earlywarning/

[17] Algorithmic accountability guidelines aims to provide a set of ethical and practical guidelines for humanitarian data collectors, users, and stakeholders to consider when data science and artificial intelligence for humanitarian work (Dodgson et al. 2020)

- Within T2, local evidence was collected together with our regional Red Cross and KRCS-ICHA partners, benefiting from the Red Cross' IARP project, in case-studies in the three pilot countries.
- Within T3, we compared different ex-post and ex-ante cash transfer schemes designed to provide temporary resources to mitigate food insecurity impacts at different lead times. Using the co-developed forecasting model (T1) and capitalizing the findings from the survey performed (T2), F4S provided a better understanding of lead-time and cost-effectiveness of cash transfer programmes, as well as the preferences associated with different transfer schemes. The recommendations of the F4S can be further applied in the Red Cross' IARP project, and have the potential to be disseminated via the Red Cross Societies into the Cash Working Group in the pilot countries.
- Within T4, and together with our partners and local stakeholders and the Red Cross Societies, we are exploring potential ways and benefits of operationalizing the outputs obtained from T1-T3 into ongoing cash transfer pilot initiatives from the Red Cross' IARP and WFP.

5.2 CO-DEVELOPMENT OF THE RISK FINANCING INNOVATION WITH BENEFICIARES

Within T2, we have developed and executed a household survey within the three pilot areas, which gave us the opportunity to incorporate local early warning signs of food insecurity into the Machine Learning Model. This analysis enabled us to incorporate local triggers that reflect real action on the ground, and how communities prepare for droughts and floods and other drivers for food insecurity. These helped to improve the accuracy of the model, and in consequence increase the cost-effectiveness of ex-ante cash transfers. Furthermore, we have developed a choice experiment involving individuals to investigate people's expenditure behaviour and preferences to key design elements of a cash transfer. The result of these experiments provided us with information about human behaviour that can shape the key design elements of ex-ante cash transfer schemes (payment method, time of the aid release and severity) so as to steer the people's decision towards ex-ante risk reduction rather than disaster response activities. The completion of T2, and the inclusion of its results in the other work packages, enabled us to deliver a set of recommendations on how ex-ante cash transfers can be implemented that have been co-developed with beneficiaries of the aid.

5.3 DEVELOPING OR SUPPORTING LOCAL CHAMPIONS AND TRAINING OF LOCAL BENEFICIARIES

Within T2 we developed surveys, choice experiments, Focal Group Discussions, and Key Informant Interviews. In particular, the surveys and choice experiments were developed in partnership with a team of local experts, and were conducted and facilitated at the community level by a team of local Red Cross volunteers and a designated Focal Point. The team received training on the relevance of local knowledge for risk modelling, and on the design and performance of a choice experiment, which is a methodology not yet widely explored. In addition, several Focus Group discussions were carried out. The groups we composed of both male and female participant households. Local volunteers and champions on disaster risk reduction were identified and solicited to take part in the field activities and key informant interviews, providing the scientific team with feedback while also gaining understanding about the project goal and methods. Furthermore, following up the completion of activities, the results were debriefed and put into perspective through online sessions between the F4S team and the facilitators. Following up on the F4S project, this team of local volunteers will be able to communicate the outcomes and lessons learnt to the community who contributed to the development of findings.

5.4 CASH OR IN-KIND LEVERAGE TOWARD FURTHER ACCESS OR USE OF YOUR RISK FINANCING INNOVATION

As presented in this final report, there are opportunities for implementing cash transfers as a mechanism for risk financing in the three pilot countries. This enabling environment emerges from a combination of both positive experiences of past cash transfer programmes and from the availability of the required infrastructure for implementing the programmes (details available at the mid-term report).

In the mid-term report, we highlighted key opportunities and recommendations that would guide the effective implementation of the cash transfer programing both during the preparedness and the response phases. Here, we would like to recap these recommendations putting them into perspective from the new findings from the survey and choice experiment. The opportunities and recommendations are:

- To conduct education and trainings of the community in order to allow a full understanding of the cash transfer programme goals;

  - This recommendation should be seen as one of the priority actions given the fact that most of the surveyed households (especially in Uganda and Ethiopia) do not have experience with (ex-ante) cash transfer programmes.
  - Providing cash transfer before a shock during the preparedness phase may help the community to invest in a number of mitigative alternatives in combination with expenditure choices that directly improve their food security levels. This aid may avert some of the impacts and prevent that negative coping strategies are adopted during a crisis such as reduced food consumption or selling assets.
  - Current dissemination about early warnings for food insecurity mainly uses radio, which could be a relevant medium for such trainings.
  - Understanding of the ex-ante cash transfer programme goals can also generalize or contextualize the choice experiment results: Do lump sums cash transfers steer people towards mitigation actions for any livelihood zone? Does the timing influence the amount of money spend on food stocking both close and far from central markets?

- The Government and the techinical working groups on cash transfers should work together during their interventions as this will help in building the Disaster Risk Reduction community of the country;

  - For a successful implementation of a Cash Transfer programme, adequate security and supply of essential goods and services in markets are needed.
  - Institutions operationalizing ex-ante cash transfers shall adjust the size of the transfer in accordance with market price fluctuations (as food items are found to be the largest

source of expenditure, and also indicated to be the most important preparedness measure even without getting ex-ante cash aid). This will enable recipients to cover the needs for which they are receiving the transfer, and avoid effects of inflation.

- Humanitarian actors should make cash transfer top of the list when preparing for shocks, as it has proved to be efficient and effective in past programmes.
    - Pastoralist communities can largely benefit from early payouts. For instance, earlier payouts can enable them to allocate funds to protect livestock instead of replacing them, which we proved to have much more benefits than costs.
    - Despite saving lives and creating a range of additional benefits, early cash transfers – initiated based on predictions with lead times of 3 (Kenya, Ethiopia) or 2 (Uganda) months from the collaboratively produced Machine Learning model, can also be a cost-effective solution.
- Timely cash transfers require timely targeting and registration of beneficiaries.
- One-off start-up costs with registration and identification of registered beneficiaries can also represent sizeable costs when implementing a new cash programme.
- Private sector needs to innovate to solve the various cash transfer challenges such as distance to markets and security of the funds.

5.5 USING INFORMATION ON GENDER GAPS RELEVANT TO YOUR RISK FINANCING INNOVATION TO TRY TO CLOSE THOSE GAPS

By applying the Kenya Red Cross Society gender mainstreaming policy in all three countries, we ensured a minimum of 30% of female respondents of the survey and choice experiment, while respecting cultural norms. The survey and choice experiment were post-processed in a way that information on local knowledge and preferences can be identified across genders. We have also gathered socio-economic information on gender, age, educational status and economic activities that can be further triangulated with responses from the choice experiment. These socio-economic characteristics, in combination with an analysis concerning people's expenditure, may provide institutions with valuable sources of information to support the targeting of vulnerable groups, as well as to extract information that can potentially increase the positive impact of a cash transfer. We also selected participants from special groups such elderly, female-headed and child-led households.

OUTREACH AND SCIENTIFIC DELIVERABLES

Through the F4S project, we were able to collaborate with more than 560 households, a large team of local staff, researchers and students, as well as to present our scientific findings in several forums. Some of the deliverables include:

- Six master theses, in which one has received the prize of the best Hydrology thesis of the year and was among the top 3 theses of the Vrije Universiteit Amsterdam. The theses are:

    - Mathijs van Eeuwijk, VU Amsterdam, July 2020. "How accurate is the Famine Early Warning System Network? A Kenyan and Ugandan case study".

- Marte Siebinga, VU Amsterdam, July 2020. “Forecasting forage scarcity for index-based livestock insurance in northern Kenya”. *Cum laude.*
- Willemijn van Vuure, VU Amsterdam, September 2020. “Forecasting Drivers of Food Insecurity in Kenya Using the Random Forest Algorithm”.
- Amber Emeis, VU Amsterdam, *in progress*. “Analysing the cost-effectiveness of early action through forecasting shortages in maize calories; a case study for Ethiopia”.
- Joep Hoeijmakers*, TU Delft in progress*. “Cash transfer policies as a response to Food insecurity”.
- Joris Westerveld, Utrecht University, May 2019. *“*Modelling Food Insecurity in Ethiopia Towards a machine learning model that predicts the transitions in food security using scalable features”.

o Three scientific articles:

- Westerveld, Joris JL, et al. "Forecasting transitions in the state of food security with machine learning using transferable features." *Science of The Total Environment (2021): 147366.*
- Siebinga et al. *in progress*. Forecasting forage scarcity for index-based livestock insurance in northern Kenya.
- Guimarães Nobre et al. *in progress.* Forecasting shortage on calories for anticipatory action.

o Presentation and dissemination:

- EGU 2021, press conference, “Improving food security: new techniques”.
- EGU 2021, presentation, “forecast based Financing for Food Security : from early warning to early action in Eastern Africa”.
- EGU 2021, presentation, “analysing the cost-effectiveness of early action for food security through forecasting shortages in maize calories; a case study for Ethiopia”.
- EGU 2020, presentation, “forecast based action: developing triggers for preventing food insecurity in Eastern Africa”.
- EGU 2019, Forecast based financing for food security, https://meetingorganizer.copernicus.org/EGU2019/EGU2019-12573.pdf
- Global Dialogue Platform on Anticipatory Humanitarian Action 2020, presentation, “how can research contribute towards the development of protocols for early action?”.

o Technical Reports:

- An inception report, submitted in October 2018
- A mid-term report, submitted in April, 2020
- A final report, submitted in May 2021

REFERENCES

Andrée, Bo Pieter Johannes, Andres Chamorro, Aart Kraay, Phoebe Spencer, and Dieter Wang. 2020. “Predicting Food Crises.” www.worldbank.org/prwp.

Audsley, Blake, Riikka Halme, and Niels Balzer. 2010. “Comparing Cash and Food Transfers: A Cost-Benefit Analysis from Rural Malawi.” In *Revolution: From Food Aid to Food Assistance, Innovations in Overcoming Hunger*.

Berhane, Guush, Zelekawork Paulos, Kibrom Tafere, and Seneshaw Tamiru. 2011. “Foodgrain Consumption and Calorie Intake Patterns in Ethiopia Ethiopia Strategy Support Program II (ESSP II).” www.ifpri.org.

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Michael R. Carter. 2013. “Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya.” *Journal of Risk and Insurance* 80 (1): 205–37. https://doi.org/10.1111/j.1539-6975.2012.01463.x.

Choularton, Richard J., and P. Krishna Krishnamurthy. 2019. “How Accurate Is Food Security Early Warning? Evaluation of FEWS Net Accuracy in Ethiopia.” *Food Security*. https://doi.org/10.1007/s12571-019-00909-y.

Claesen, Marc, and Bart De Moor. 2015. “Hyperparameter Search in Machine Learning.” *ArXiv Preprint ArXiv:1502.02127*, February. http://arxiv.org/abs/1502.02127.

Dodgson, Kate, Prithvi Hirani, Rob Trigwell, and Gretchen Bueermann. 2020. “A Framework for the Ethical Use of Advanced Data Science Methods in the Humanitarian Sector.” https://www.hum-dseg.org/.

Drechsler, Mareile, and Wolter Soer. 2016. “Early Warning, Early Action The Use of Predictive Tools in Drought Response through Ethiopia’s Productive Safety Net Programme.” http://econ.worldbank.org.

Eastaugh, Sophie. 2017. “Satellite Images Trigger Payouts for Kenyan Farmers in Grip of Drought | Hunger.” The Guardian. 2017. https://www.theguardian.com/global-development/2017/apr/25/satellite-images-trigger-payouts-for-kenya-farmers-in-grip-of-drought.

FAO. 2010. “Nutrition Country Profile the Republic of Uganda 2010.” http://www.fao.org/3/bc643e/bc643e.pdf.

FEWSNET. 2021. “FEWS NET Data Center | Famine Early Warning Systems Network.” 2021. https://fews.net/fews-data/335.

Forsen, Yvonne, Susanna Sandstrom, Lena Hohfeld, and Nynne Warring. 2020. “Minimum Expenditure Baskets.”

Funk, Chris, Shraddhanand Shukla, Wassila Mamadou Thiaw, James Rowland, Andrew Hoell, Amy McNally, Gregory Husak, et al. 2019. “Recognizing the Famine Early Warning Systems Network (FEWS NET): Over 30 Years of Drought Early Warning Science Advances and Partnerships Promoting Global Food Security.” *Bulletin of the American Meteorological Society*, no. 2019.

https://doi.org/https://doi.org/10.1175/BAMS-D-17-0233.1.

GFDRR. 2021. "Responsible AI for Disaster Risk Management." www.gfdrr.org.

Guimarães Nobre, G., Frank Davenport, Konstantinos Bischiniotis, Ted Veldkamp, Brenden Jongman, Christopher C Funk, Gregory Husak, Philip J Ward, and Jeroen C J H Aerts. 2019. "Financing Agricultural Drought Risk through Ex-Ante Cash Transfers." *Science of the Total Environment* 653: 523–35. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.10.406.

Haggblade, Steve, and Reno Dewina. 2010. "Staple Food Prices in Uganda Food Prices in Uganda." https://doi.org/10.22004/AG.ECON.58553.

Hao, Zengchao, Vijay P. Singh, and Youlong Xia. 2018. "Seasonal Drought Prediction: Advances, Challenges, and Future Prospects." *Reviews of Geophysics* 56 (1): 108–41. https://doi.org/10.1002/2016RG000549.

He, Haibo, Yang Bai, Edwardo A Garcia, and Shutao Li. 2008. "ADASYN: Adaptive Synthetic Sampling Approach for Imbalanced Learning." In *Ieeexplore.Ieee.Org*. https://ieeexplore.ieee.org/abstract/document/4633969/.

Heijden, Wesley van der, Marc van den Homberg, Martijn Marijnis, Marijke de Graaff, and Hennie Daniels. 2018. "Combining Open Data and Machine Learning to Predict Food Security in Ethiopia." In *Conference: UNESCO Chair in Technologies for Development: Voices of the Global South*. https://www.researchgate.net/publication/326096566_Combining_Open_Data_and_Machine_Learning_to_predict_Food_Security_in_Ethiopia.

Hiwasaki, Lisa, Emmanuel Luna, Syamsidik, and Rajib Shaw. 2014. "Process for Integrating Local and Indigenous Knowledge with Science for Hydro-Meteorological Disaster Risk Reduction and Climate Change Adaptation in Coastal and Small Island Communities." *International Journal of Disaster Risk Reduction* 10 (December): 15–27. https://doi.org/10.1016/j.ijdrr.2014.07.007.

HSNP. 2021. "About HSNP." 2021. https://www.hsnp.or.ke/index.php/as/objectives.

ICRC. 2007. "Guidelines for Cash Transfer Programming."

Jensen, Nathan, Christopher Barrett, and Andrew Mude. 2015. "The Favourable Impacts of Index-Based Livestock Insurance: Evaluation Results from Ethiopia and Kenya Key Points."

Jensen, Nathaniel D., Christopher B. Barrett, and Andrew G. Mude. 2014. "Basis Risk and the Welfare Gains from Index Insurance: Evidence from Northern Kenya."

Lopez, Ana, Erin Coughlan de Perez, Juan Bazo, Pablo Suarez, Bart van den Hurk, and Marteen van Aalst. 2020. "Bridging Forecast Verification and Humanitarian Decisions: A Valuation Approach for Setting up Action-Oriented Early Warnings." *Weather and Climate Extremes*. https://doi.org/10.1016/j.wace.2018.03.006.

Lukuyu, Ben, Steven Franzel, Patrick Ongadi Mudavadi, and Alan J Duncan. 2011. "Livestock Feed Resources: Current Production and Management Practices in Central and Northern Rift Valley Provinces of Kenya." https://www.researchgate.net/publication/287168075.

Ministry of Gender Labour and Social Development. 2015. “The National Social Protection Policy Income Security and Dignifi Ed Lives for All.” http://www.mglsd.go.ug.

Mohajan, Haradhan Kumar. 2014. “Food and Nutrition Scenario of Kenya.” *American Journal of Food and Nutrition* 2 (2): 28–38. https://doi.org/10.12691/ajfn-2-2-3.

O’Brien, Clare. 2014. “A Guide to Calculating the Cost of Delivering Cash Transfers in Humanitarian Emergencies with Reference to Case Studies in Kenya and Somalia.” https://reliefweb.int/report/world/guide-calculating-cost-delivering-cash-transfers-humanitarian-emergencies-reference.

Phillips, Nathaniel D, Jan K Woike, and Wolfgang Gaissmaier. 2017. “FFTrees : A Toolbox to Create , Visualize , and Evaluate Fast-and-Frugal Decision Trees.” *Judgment and Decision Making* 12 (4): 344–68.

Tu, Huy, and Vivek Nair. 2018. “Is One Hyperparameter Optimizer Enough.” In *Proceedings of the 4th ACM SIGSOFT International Workshop on Software Analytics*. New York, NY, USA: ACM. https://doi.org/10.1145/3278142.3278145.

Vrieling, Anton, Michele Meroni, Apurba Shee, Andrew G. Mude, Joshua Woodard, C. A.J.M. de Bie, and Felix Rembold. 2014. “Historical Extension of Operational NDVI Products for Livestock Insurance in Kenya.” *International Journal of Applied Earth Observation and Geoinformation* 28 (1): 238–51. https://doi.org/10.1016/j.jag.2013.12.010.

Weingärtner, Lena, Tobias Pforr, and Emily Wilkinson. 2020. “The Evidence Base on Anticipatory Action.”

WFP. 2020. “Essential Needs Assessment Guidance Note.” https://www.wfp.org/publications/essential-needs-guidelines-july-2018.

ANNEX A: Key Informant interviews

Hello,

My name is (insert name) I am a (insert position) for the Red Cross. Before we begin, I would like to take a minute to explain why I am inviting you to participate and what I will be doing with the information you provide to me. Please stop me at any time if you have any questions. After I've told you a bit more about my project, you can decide whether or not you would like to participate.

The questionnaire I am about to ask you to participate in, is part of research that is being carried out by the Uganda Red Cross in villages in the Karamoja region. We work with national and international researchers and want to investigate the food security situation and evaluate methods to decrease shocks in food security. The research will be used for academic and humanitarian purposes, it will support the Red Cross on designing humanitarian operations.
You will be asked a series of questions about your access to climate and weather information and to financial aid in times of food insecurity. We will also ask about your choices and your household situation. This research will help us better understand the needs of the community in order to improve future food security interventions directed toward this region.

Participation should take about 1,5 hours. Participation is on a purely voluntary basis and is not rewarded. There are no costs of participation. The information we collect today is private and confidential. We will not share any personal details from the survey with anyone besides the research team. No names will be stored nor published. Your responses will be numbered. Confidentiality Disclaimer: "Researchers will keep your information confidential to the extent possible and allowable by law."

If you experience distress over the nature of some of the questions, you are free to skip any question that makes you feel uncomfortable. If at any time you would like to stop participating, please tell me. We can take a break, stop and continue a bit later, or stop altogether. You will not be penalized in any way for deciding to stop participation at any time. Declining nor participating will affect chances of receiving an intervention or change your status with organizations. There are no correct or incorrect responses, so please express your opinions freely.

If you have questions, you are free to ask them now. Do you agree to participate in this interview?

→ adapt to who to interview

GUIDING QUESIONS

- For how long have you been living in this area?
- What is your role within the community?
- Does your community receive any kind of official forecasting information regarding food insecurity?
  - What type of information does your community receive?
    (e.g. seasonal forecasts, monthly forecasts etc.)
  - From what sources do you receive the information?
  - Does everybody of the community receive the forecast information? Why not?

    - How would you like to adapt or what would you like to add to the existing forecast to improve it for your community?
- Does your community use local knowledge to predict weather and/or natural hazards?
    - Does your community have a weather man who makes predictions based on local knowledge?
    - What types of local knowledge or early warning signs are used by your community and how are they used?
    - When are the local early warning signs observed by your community members?
    - Can you tell based on the local early warning sign how severe the predicted event will be?
    - What are the ways in which local knowledge is shared in your community?
    - In your opinion, is there a difference in the use of local knowledge for food security now compared to in the past?
    - What are the main benefits of your local knowledge?
    - What are the main limitations of your local knowledge?
    - How important is local knowledge in your community compared to official forecast information (e.g. national forecasts)?
- What are the most common threats to the communities caused by natural hazard?
    - Does it affect the food security of the community?
    - For floods, what are the most common coping strategies and for droughts, what are the most common coping strategies?
    - Which of the coping strategies require the most communal, or individual investment? How is this usually arranged in your community?
    - What are the main barriers to implementing these coping strategies by the community?
- Do you often experience an increase in prices followed by droughts and floods?
    - Which items do you mostly observe an increase in price?
    - Is food insecurity in your village closely linked to fluctuation in prices?
    - What are the main causes of food insecurity in your community?
- Humanitarian aid:
    - To what extent has your community relied on aid in the past?
    - What type of aid?
    - What was your impression on what most of the aid was spent on?
    - Do you think that there is a potential for cash-based aid in this community?
    - Do you think that people in your community would change any of the existing coping strategies if you would receive cash before severe weather events ? If so, what do you think you would change?

ANNEX B: SEMI-STRUCTURED QUESTIONNNAIRE

Local Knowledge Part 1: Past Experiences (11 questions)

1. What does food security mean to you?
(open ended question)

2. In general, before you experience a situation of food insecurity, what of the following items do you observe? (adapt to local context)

a. Meager income from non-farm activities
b. Seasonal Rainfall deficit
c. Seasonal Excess of rainfall
d. Multiple harvest failures
e. Instability due to conflicts
f. Instability due to political changes
g. Failure to properly and/or safely store own production
h. Difficulties in physically accessing market
i. Increased levels of socio and economic inequalities
j. Market failure (e.g. poor accessibility, large price fluctuations, limited market information, high transaction costs, etc.)
k. Shortage of farmland
l. Infertility of farmlands (e.g. land degradation/erosion)
m. Illness or death of household head or other family members
n. Inability to produce sufficient agricultural products due to extreme weather events
o. Inability to produce sufficient agricultural products due to pests and/or diseases
p. Inability to sustain livestock due to diseases
q. Inability to sustain livestock due to fodder or grazing land shortage
r. Inability to sustain livestock due to water shortage or water quality issues
s. Destruction of crops by wildlife
t. Lack of farm inputs (e.g. fertilizers, seeds, manure, labor, pesticides, etc.)
u. Lack of farm implements (e.g. oxen, plough, etc.)
v. God's will
w. Other, please specify

3. Where does your food come from in a "normal" (not bad, not good) situation?

a. Own crop production
b. Own livestock products
c. Purchase
d. Payment in kind
e. Gifts
f. Fish and wild foods
g. Other, please specify
(multiple answers possible)

4. Of these sources, what are your top 3 sources of calories/energy intake? Please rank them from largest (most amount) (1) to less (3).

5. In a "normal" (not bad, not good) month, how often does your household have to:

a. Rely on less preferred or less expensive food?
b. Borrow food, or rely on help from a relative?
c. Limit portion size at mealtimes?
d. Restrict consumption by adults in order for small children to eat?
e. Reduce the number of meals eaten in a day?

0. Never
1. Hardly at all (<1 time/week)
2. Once in a while (1-2 times/week)
3. Pretty often (3-6 times/week)
4. Always (every day)

6. In a "normal" (not bad, not good) YEAR, in which months do you experience a situation that there is less food than needed (so you have to borrow it, limit tie portions, restrict consumption by adults or reduce number of meals per day)

a. January
b. February
c. March
d. April
e. May
f. June
g. July
h. August
i. September
j. October
k. November
l. December

7. **Are you worried about the following shocks in relation to your household food security? [check all that apply]**

a. Droughts
b. Human diseases
c. Livestock diseases
d. Floods
e. Crop pests and diseases
f. Conflict
g. Water scarcity
h. COVID

8. **Of the mentioned shocks, which one are you most worried about / will threaten your food security the most?** *[choose one]*

a. Droughts
b. Human diseases
c. Livestock diseases
d. Floods
e. Crop pests and diseases
f. Conflict
g. Water scarcity

h. COVID

9. When in the past have you experienced severe food insecurity (less than normal - less than discussed before)?

a. 2020
b. 2019
c. 2018
d. 2017
e. 2016
f. 2015
g. 2014
h. 2013
i. 2012
j. 2011
k. 2010
l. 2009
m. 2008
n. 2007
o. 2006
p. 2005
q. 2004
r. 2003
s. 2002
t. 2001
u. 2000
v. 1999
w. 1998
x. 1997
y. 1996
z. 1995
aa. 1994
bb. 1993
cc. 1992
dd. 1991
ee. 1990
ff. 1989
gg. 1988
hh. 1987
ii. 1986
jj. 1985
kk. 1984
ll. 1983
mm. 1982
nn. 1981
oo. 1980
pp. Before 1980

10. For each of the selected years, what were the main causes (e.g. no rain, conflict) for the (extreme) food insecurity in that particular year in your experience (if you can still remember)?

11. In the last extreme food insecure year you experienced, in which months did you experience a situation where there was much less food than needed?

a. January
b. February
c. March
d. April
e. May
f. June
g. July
h. August
i. September
j. October
k. November
l. December
m. No clear trend

Part 2: response actions and adaptation to shocks (12 questions)

1. How often did you receive aid after or during a drought or flood disaster that caused food insecurity?

1. Never (go to 2.A & skip Question 3 and 4)
2. Sometimes (go to 2.A)
3. Always (go to 2.B)

2. A: How did your household deal with such extreme food insecure situations when you did not receive aid? (adapt to local context)

OR

B: How did your household deal with such extreme food insecure situations if your household would NOT have received aid?

a. Reduced number and amount of food consumed
b. Consumed less preferred foods
c. Sold firewood and charcoal
d. Found additional food sources (e.g. "famine foods"or wild foods)
e. Asked relatives/neighbours/friends for food or money
f. Temporal seasonal migration
g. Sold assets (e.g. livestock, land, agricultural tools)
h. Used savings
i. Worked for payment in kind
j. Received humanitarian aid
k. Depend on remittance received from relatives
l. Purchased food on credit
m. Increased slaughter of livestock
n. Found casual labour
o. By migrating to work elsewhere
p. Took children from school
q. Started other business or invested more effort in non-agricultural business
r. Rented out land

s. The household did not cope and just suffered shortage
t. Other, please specify

3. What kind of aid did you receive after a drought or flood disaster that caused food insecurity in the past?
a. Never received aid (skip 4-6)
b. Cash transfers (go to 4)
c. Food aid
d. Food for work
e. Cash for work
f. Other, please specify

4. When you receive cash, how long does it take you to travel to receive the cash from the agent?

5. When you receive cash, are there perceived costs involved in getting this cash transfer?

6. When you receive cash, usually, how long do you have to wait at the cash agent (if at all):

7. Please rate the statements (1= disagree, 2= partially disagree, 3= neutral, 4= partially agree, 5= agree):
a. I feel like in the past the distribution of cash-transfers has been fair
b. If I would have gotten the cash earlier, I would have spent it on other measures

8. If you would be beneficiary of humanitarian aid in the future, in which format would you prefer to receive it?
a. Cash (lump sum during phase of food insecurity)
b. Cash (multiple small sums during phase of food insecurity)
c. Cash (lump sum before phase of food insecurity)
d. Cash (multiple small sums before phase of food insecurity)
e. Food aid (bags during phase of food insecurity)
f. Food aid (bags before phase of food insecurity)
g. Voucher (voucher during phase of food insecurity)
h. Voucher (voucher before phase of food insecurity)
i. Food for work
j. Cash for work
k. Other, please specify

9. Of the following options, what method of receiving the cash transfer would you prefer if you would be beneficiary of cash transfer in the future?
I would prefer to get cash from…
a. M-pesa agent
b. Direct M-pesa transfer
c. Red Cross volunteer
d. Other

10. Once you get to know that a drought is coming, do (or did) you implement any of the following to prepare with your own resources (not relying on aid) (check all that apply) (adapt to local context):
a. Increased livestock and product sales
b. Stock on food

c. Migration of household member to town
d. household splitting
e. seeking agricultural employment
f. Grain/fodder storage
g. Increase of pack animals
h. Increase of fodder production and conservation to replace lost access to dry season areas
i. Digging wells
j. Saving
k. Insurance
l. vaccinate my livestock
m. getting a loan with the bank
n. other/n/a

11. Once you get to know that a flood is coming, do (or did) you implement any of the following to prepare with your own resources (not relying on aid) (check all that apply) (adapt to local context):

o. Increased livestock and product sales
p. Stock on food
q. Migration of household member to town
r. household splitting
s. seeking agricultural employment
t. Grain/fodder storage
u. Increase of pack animals
v. Increase of fodder production and conservation to replace lost access to dry season areas
w. Digging wells
x. Saving
y. Insurance
z. vaccinate my livestock
aa. getting a loan with the bank
bb. other/n/a

12. Of the following statements, please indicate y/n to what extent you are able to, compared to your neighbors

My assets are sufficient to feed my family, compared to other community members that I know	Y/N
I am sufficiently warned about hazards, compared to other community members that I know	Y/N
If I would know that a drought was coming in advance, I would be better able to protect myself better	Y/N
If I would know that a flood was coming in advance, I would be better able to protect myself better	Y/N
I can feed my household, compared to other community members that I know	Y/N
I have control of drought risks	Y/N
I have control of flood risks	Y/N
I take more risk than other community members that I know	Y/N
Me and my community share the risks of floods and droughts	Y/N
I feel like the incomes in my community is very equal	Y/N
It is the responsibility of the government to sufficiently prepare me against droughts and floods	Y/N
It is the responsibility of NGOs to sufficiently prepare me against droughts and floods	Y/N

Part 3: Early Warning System (7 questions)

1. **Where do you find information about threats for upcoming food insecurity such as floods and droughts?**
    1. Local weather man
    2. Village head
    3. Own knowledge or experience
    4. Relatives/friends
    5. Radio
    6. TV
    7. Internet
    8. Neighbours
    9. Whatsapp groups
    10. Social media
    11. Other, please specify ...
    12. If I follow my own knowledge, explain...

2. **Do you know what the source of this information is?**

a. Governmental
b. NGOs
c. Local knowledge
d. Unknown source

1. **If governmental or NGOs: What type of information do you receive?**

a. Daily weather forecasts
b. Weekly weather forecasts
c. Agro-meteorological forecasts
d. Dekadal (10-day) climate outlooks
e. Monthly climate outlooks
f. Seasonal climate forecasts
g. Climate change projections
h. Early warnings (e.g. pest outbreaks, natural hazards)
i. Rainfall onset and cessation date
j. Other, please specify

4. **Do you use the received information for your farming practices?**

a. Yes
b. No, because…

5. **Is there any information missing that you would like to add to these existing forecasts to better adapt to the local context? How could they be improved?**

a. No
b. Yes, please specify

6. **Please indicate for each source to what extent you agree with the following statement: "The forecasts I receive from this information source are reliable and can be used for my farm practices"?**

a. Strongly disagree
b. Disagree
c. Agree a bit
d. Agree
e. Strongly agree

7. Please indicate for each source to what extent you agree with the following statement: "The forecasts I receive from this information source contain sufficient information and can be used for my farm practices"?

a. Strongly disagree
b. Disagree
c. Agree a bit
d. Agree
e. Strongly agree

Part 4: Local Knowledge (4 questions)

1. **Could you please specify how local knowledge (which signs were used to predict what?) was used to anticipate a situation of food insecurity in the past? (If you can still remember)**
   (open ended question; leave empty if not aware of any local knowledge)

2. If local knowledge is used to predict food insecurity: Where do you use local knowledge for? To make predictions on:

a. Drought
b. Flood
c. Conflict
d. Animal diseases
e. Crop diseases
f. Pests (e.g. locusts)
g. Other, please specify

3. What are the local early warning signs you use to predict food insecurity? How do you know food insecurity is coming? By observing changes in:

a. Wind
b. Temperature
c. Clouds
d. Lightning
e. Rainfall
f. Humidity
g. Running water bodies (e.g. rivers or streams)
h. Standing water bodies (e.g. lakes or ponds)
i. Domestic animal behaviour
j. Non-domestic animal behaviour
k. Trees
l. Plants
m. Moon
n. Stars
o. Sun
p. Soil

q. Animal intestines
r. Other, please specify

4. Can you explain how these signs tell you that a food insecure time is coming and when do you observe them? How do the indicators differ from a "normal" situation?

Socio economic background (16 questions)

1. What is your gender?
a. Male
b. Female

2. What is your age?

3. What is the size of your household?

4. How many members of your household contribute to the family income?

5. Are you head of the household?

6. Marital status
a. single
b. married monogamous
c. married polygamous
d. divorced/ separated
e. widowed

7. What is your educational status?
a. Illiterate
b. I had no formal education, but I can read and/or write
c. Primary (incomplete) - started elementary school
d. Primary (completed) - elementary school degree
e. Secondary (incomplete) - started high school
f. Secondary (completed) - high school degree
g. Tertiary (incomplete) - started university
h. Tertiary (completed) - university degree

8. If you received emergency cash aid in the past, in which of the following did you spend your aid?:
a. Food
b. Water
c. Education
d. Vaccinations for livestock
e. Household member migration
f. Grain/fodder storage
g. Pesticides

h. Repaying loans
i. Remittances
j. Other, please specify

9. What are your household's main sources of income? (adapt to local context)

i. Agriculture (own farm)
j. Agriculture (someone else's farm)
k. Livestock keeping
l. Brick making
m. Household work
n. Private business
o. Bee keeping
p. Paid labour for private sector
q. Paid labour for government
r. Casual labour
s. Basket weaving
t. Tree nursery
u. Charcoal burning
v. Mining
w. Other, please specify

10. How much do you earn per month? (approximately) (adapt to local context)

a. Less than 50 KSh
b. 50 - 100 KSh
c. 100 - 200 KSh
d. 200 - 300 KSh
e. More than 300 KSh

11. How much land do you own? (in acres)

12. How much land do you use for cultivation? (in acres)(rented and own)

13. Which crops do you cultivate? (adapt to local context)

a. None
b. Greengrams
c. Maize
d. Onion
e. Kale
f. Avocado
g. Banana
h. Beans
i. Cabbage
j. Cassava
k. Coffee
l. Cowpeas
m. Fodder
n. Guava
o. Lemon
p. Mango

q. Millet
r. Oranges
s. Passionfruit
t. Pawpaws
u. Pepper
v. Pineapples
w. Potatoes
x. Pumpkin
y. Sorghum
z. Sugarcane
aa. Tomatoes
bb. Wheat
cc. Barley
dd. Sesame
ee. Lentil
ff. Other, please specify

14. Which animals do you own?

a. None
b. Bees
c. Camel
d. Cow
e. Ox
f. Chicken / poultry
g. Donkey
h. Sheep
i. Goat
j. Other, please specify

15. How many of each animal do you have?

16. Where does your livestock graze?

a. Own land
b. Communal land
c. Group owned land
d. Protected areas
e. Other, please specify

ANNEX C: NARRATIVE FOR ENUMERATORS

Explanation for the enumerators:

WHAT IT IS
The choice experiment will consist of a set of choice cards, baskets and rocks.

- The choice cards each portray 2 different designs (scenarios) of ex-ante cash transfer schemes, with different lead times of the warning and payment (2 weeks, 1 month or 2 months before the impact of droughts; 3 days, 1 weeks and 2 weeks before floods), and different predicted impact to food security (moderate or severe).
- The figure of "baskets" portraying different options to spend the ex-ante cash; one "basket" will contain more consumptive food source options (stacking up food; buying water, etc.) and the other basket more mitigation choices (contributing to digging boreholes; vaccinating livestock; stacking up fodder; etc.); a third basket will contain “other expenditures” (schooling fees, for instance); and the fourth basket will contain the option for saving the money.
- rocks are a proxy for money (eg 1 rock is 800KSh) and are a way of visualizing the cash transfer and the actions that can be done with the cash.

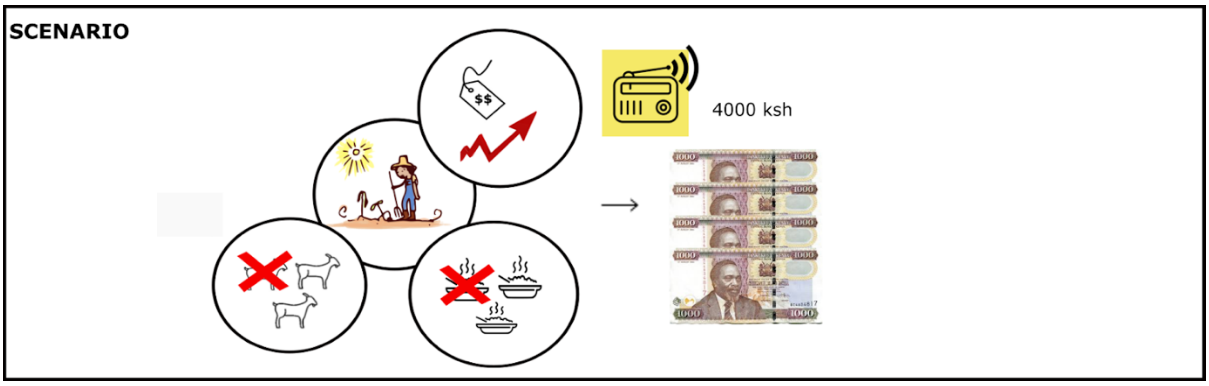
Enumerators will randomly get assigned the choice experiment related to either drought or flood.

HOW IT GOES
For each respondent, after the questionnaire is completed, the enumerator explains the experiment (see enumerator narrative) and then plays a test round. This is to see if the respondent understands it, and has one very obvious best choice and one very obvious bad choice. Whilst explaining the scenarios to the respondents, it should be really clear that it considers a hypothetical scenario. If the respondent picks the wrong answer during the test round, the enumerator asks why to identify where the respondent misunderstood it. Then she/he explains the experiment again and asks again to point to the preferred choice. If the respondent picks the right one, the enumerator also asks why to identify if the respondent really did understand it, then the enumerator gives the amount of rocks related to the scenario and asks very openly: “What would you do with the money?”; then explains the existence and meaning of the baskets and helps the respondent distribute the rocks over the baskets following the answer the respondent just gave. Enumerator should also clarify how much one rock is worth.

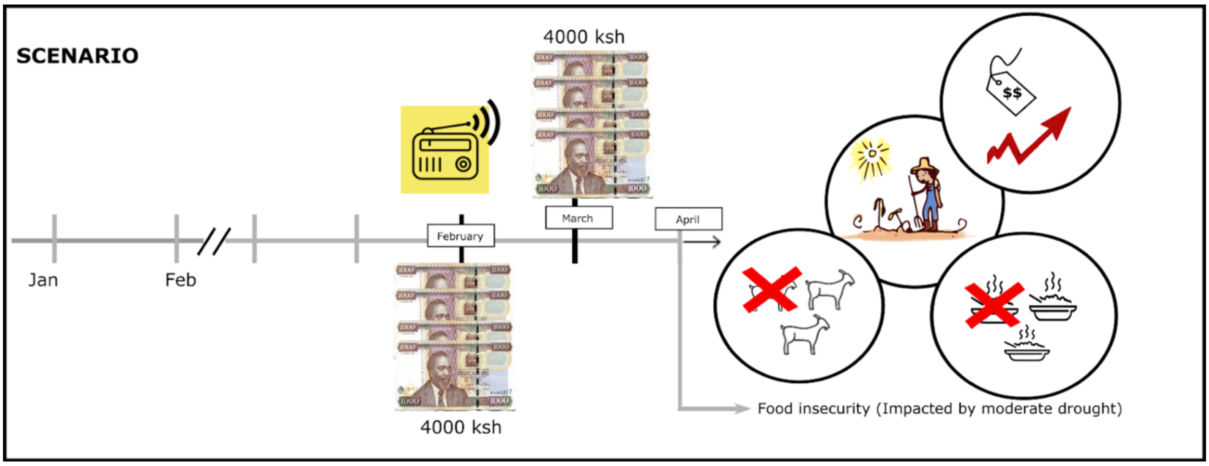
Then, per respondent, the enumerators randomly pick one choice set (set of six cards) and write down the set number and the card number. They play the six (6) rounds of the choice experiment with that respondents, each round doing the following actions:

- First, the enumerator shows a choice card (such as shown below) to the respondent and asks the respondent what is their preferred ex-ante cash transfer design. The enumerator writes down the answer/choice.
- Second, the enumerator gives the respondent the rocks representative of the scheme they choose (e.g. 2x 4000KSH or 1x8000KSH) .
- Third, the enumerator asks the respondent where they would invest the money in; the answer can be specific, so the enumerator writes down the exact answer (list of exact things on which cash was spend)
- Fourth, the enumerator helps the respondent physically distribute the rocks over the baskets of which the answers were part of (e.g. “I would use 800Ksh to vaccinate my animals”--> 1 rock go to basket B). The enumerator then also writes down the final distribution (6 in basket A, 2 in basket B…).

Test scenario



Scenario A



Scenario B

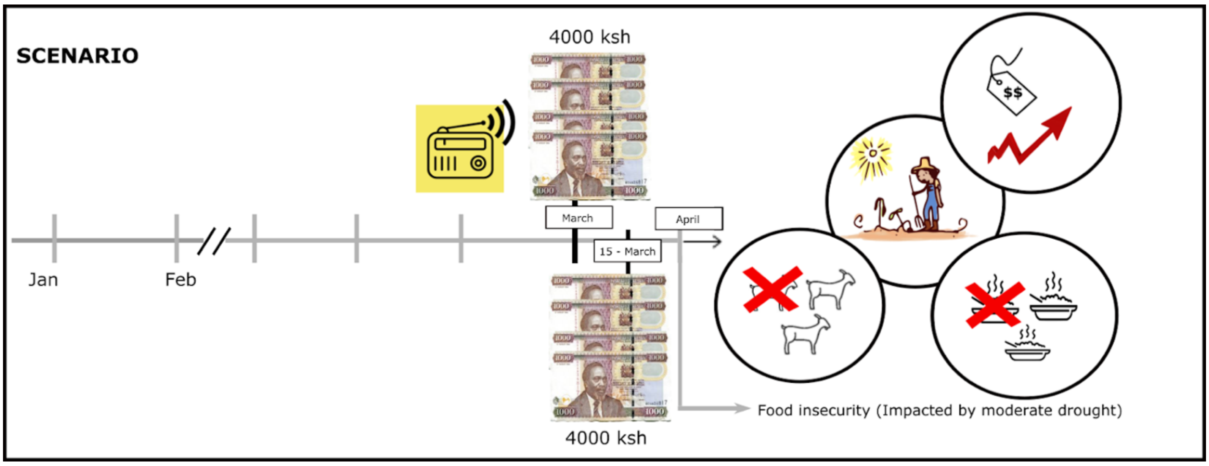


Figure 27 top card will be played during the test round to check whether participants understand the choice experiment. Middle and bottom cards represent the choice set, in which participants will indicate their preference.

Table 6: Expenditure options (baskets) for droughts

Basket A	Food sources	• Stacking up on cereals • Stacking up on other food • Buy drinking water • Other consumption
Basket B	Mitigative choices	• Vaccinations for livestock • Buy a crop or livestock insurance • Stock grains or fodder for livestock • Migration of livestock • Migration of household members to urban areas • Pesticides • Buy additional livestock • Digging boreholes or wells • Buy better quality seeds • Leaving land fallow • Fertilizers • Water harvestings (rooftop / roadside) • Build pond • Planting pits • Other Mitigative
Basket C	Household expenditures	• Fuel • School fees • Repaying loans • Clothing • Other expenditure
Basket D	Saving	• I would not spend it • I would save it for

Table 7: Expenditure options (baskets) for floods

Basket A	Food sources	• Stacking up on cereals • Stacking up on other food • Buy drinking water • Buy water tanks • Other consumption
Basket B	Mitigative choices	• Vaccinations for livestock • Buy a crop or livestock insurance • Stock grains or fodder for livestock • Migrating livestock • Migrating family • Buy additional livestock • Buy better quality seeds • Build shelter for livestock • Invest in household shelter • Make trenches in front of house • Water harvestings (rooftop / roadside)

		• Digging boreholes or wells • Other land/livestock mitigation management
Basket C	Household expenditures	• Fuel • School fees • Repaying loans • Clothing • Other expenditure
Basket E	Saving	• I would not spend it • I would save it for

Enumerator narrative (example for droughts)

In this part, we will be asking you to imagine a situation in the future. It is not the situation at present **[clearly stress this]** It is also not an exam. There is no right or wrong. We just want to get an idea of what would be your ideal/utopian future design of cash transfers in relation to drought disasters. We will ask you four times to choose between two cash designs, ask you what you would prefer hypothetically, and ask you how you prefer to spend the money in these cases. If at any point you have any questions, please interfere.

Explanation of the situation: In your community a drought is forecasted to happen.

Explanation of impact on food security: The situation will have different impacts on your food security. [show scenario 1] in this moderate situation - dry condition is already happening and the rainfall for the next xx month is forecasted to be low . As a result, some of your crop yield is expected to be below normal, the price of staple foods such as maize is expected to be above normal and it will be moderately difficult to find sources of water. This is also expected to have moderate impact on the health of your livestock. Overall, this can moderately affect your capacity to provide nutritious and safe food to feed your family.

In the second scenario [show scenario 2], it is predicted that the impact will be even higher than in the first situation - the rainfall for the next xx month is forecasted to be very low , most of your crop yield is expected to be very low, the price of staple foods such as maize prices is expected to rise sharply and it will be a lot harder to find sources of water. This is also expected to have a large impact on the health of your livestock. Overall, this will very likely affect your capacity to provide nutritious and safe food to feed your family.

Explain lead time cards: The Red Cross will provide you with cash to help you to alleviate the negative consequences. The cash will be released [show card 1 below] 2 months before the drought starts impacting your food security (or 1 month and 2 weeks).

Explanation of the cash design: To assist you, the Red Cross has different options of giving the cash, either 2x4000 KSH [show card 1] or 1x8000 [show card 2]

Explain the baskets and rocks: The different baskets pertain different options you could spend the money on [explain options]. For some of these measures, you might need all your cash. For some, it might be in addition to your own resources. These rocks represent the cash transfers (each rock representing 800KSh).

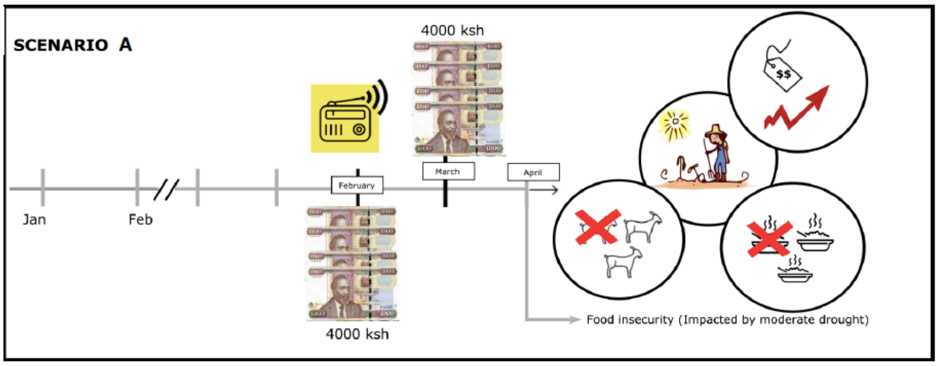
I will now give you different scenarios by showing you a combination of different cards. I will ask you which one of the hypothetical scenarios you would prefer receiving your cash transfer, and on what you would most likely spend your money on. There is no right or wrong option, your answers will not make you more or less likely to receive any cash transfer in the future, this information is anonymous and just used for science, for the development of good ex-ante cash transfer schemes.

ANNEX D: BLOCK OF SCENARIOS (EXAMPLE DROUGHT & RED BLOCK)

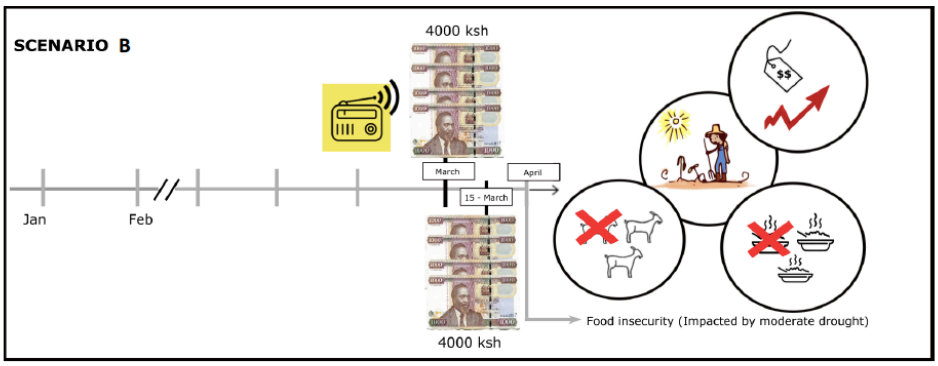
RED BLOCK

MODERATE

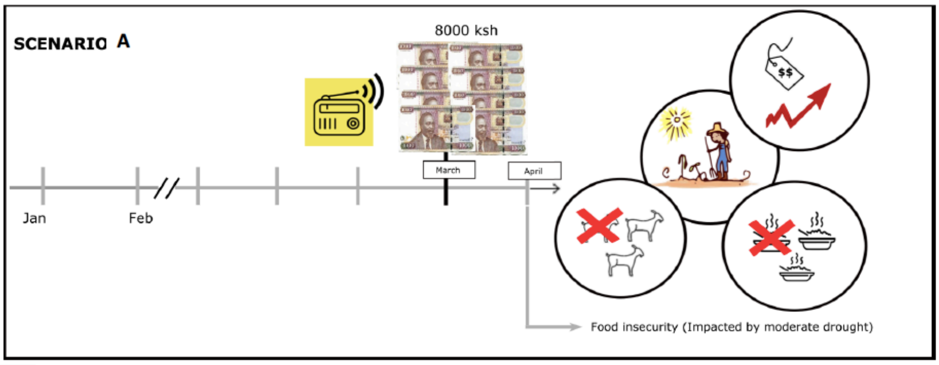
Round1



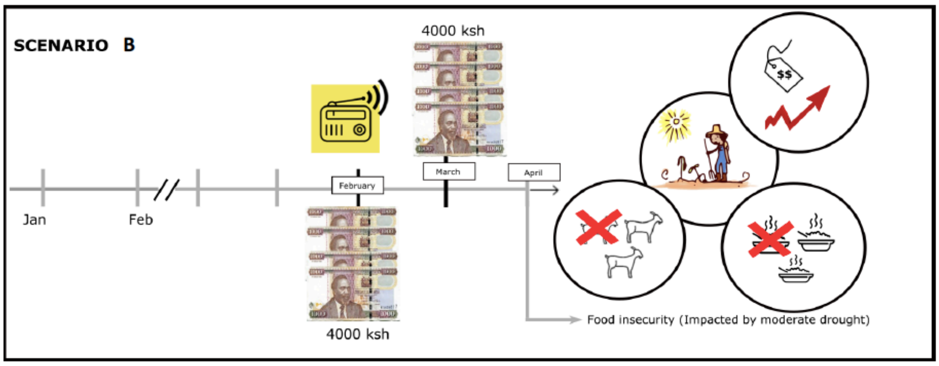
Round1



Round2

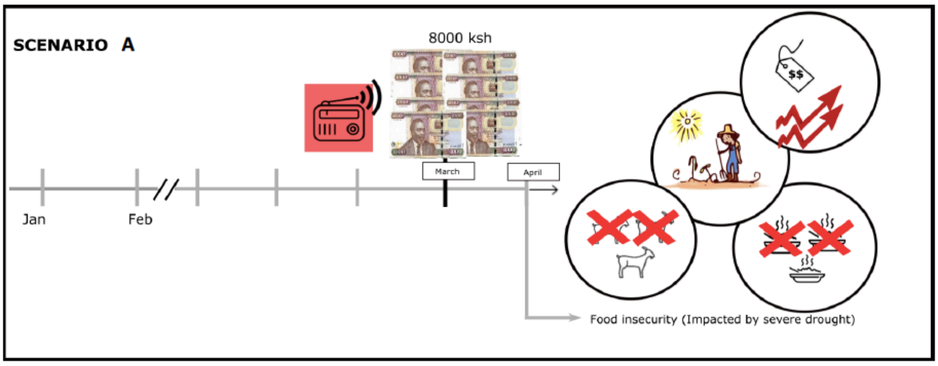


Round2

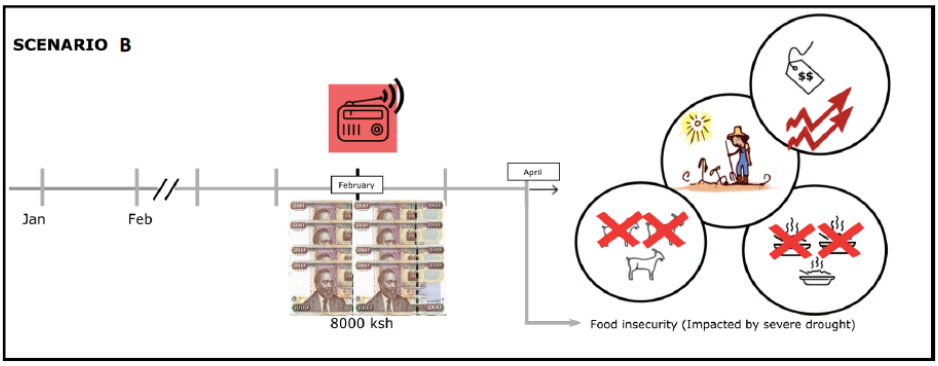


SEVERE

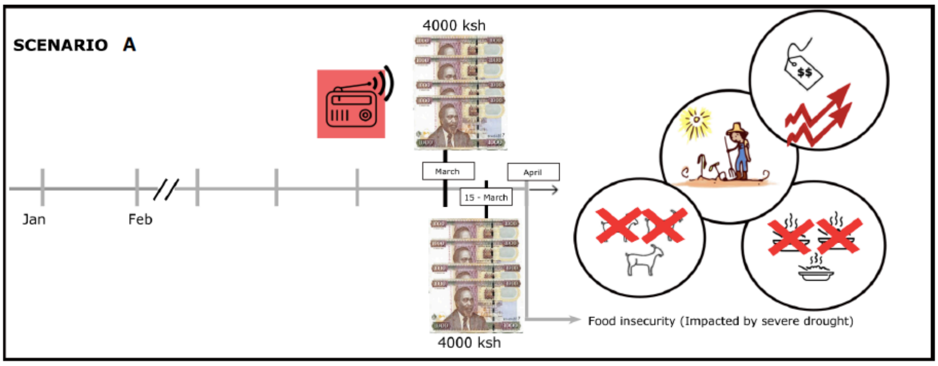
Round3



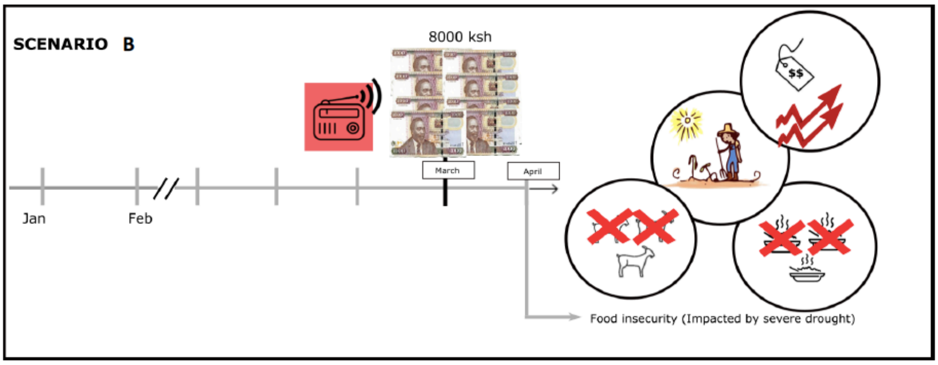
Round3



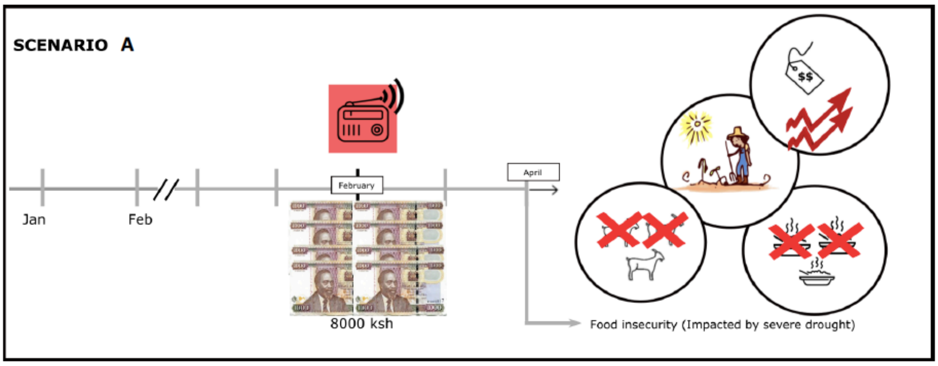
Round4



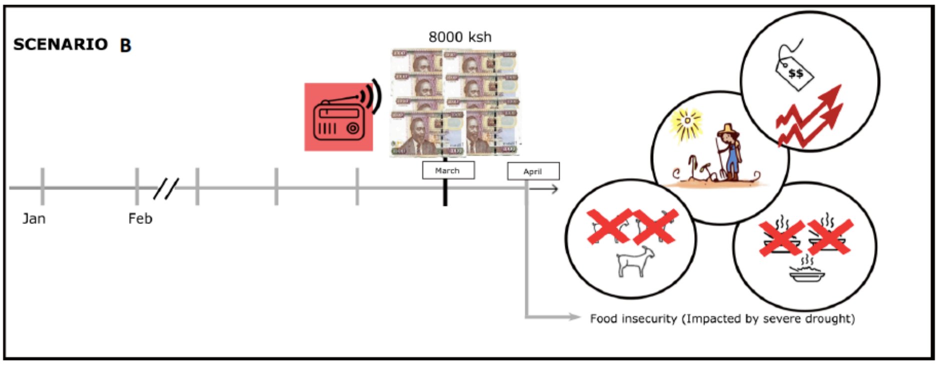
Round4



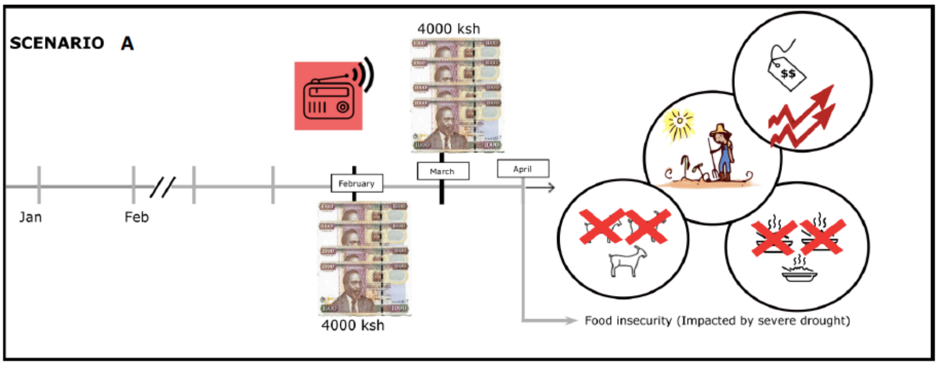
Round5



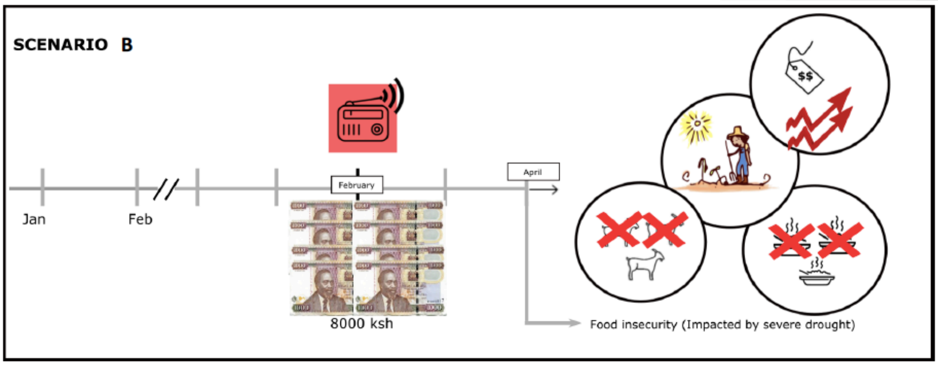
Round5



Round6



Round6



ANNEX E: SHARE OF THE AID PER ITEM OF THE EXPENDITURE BASKET

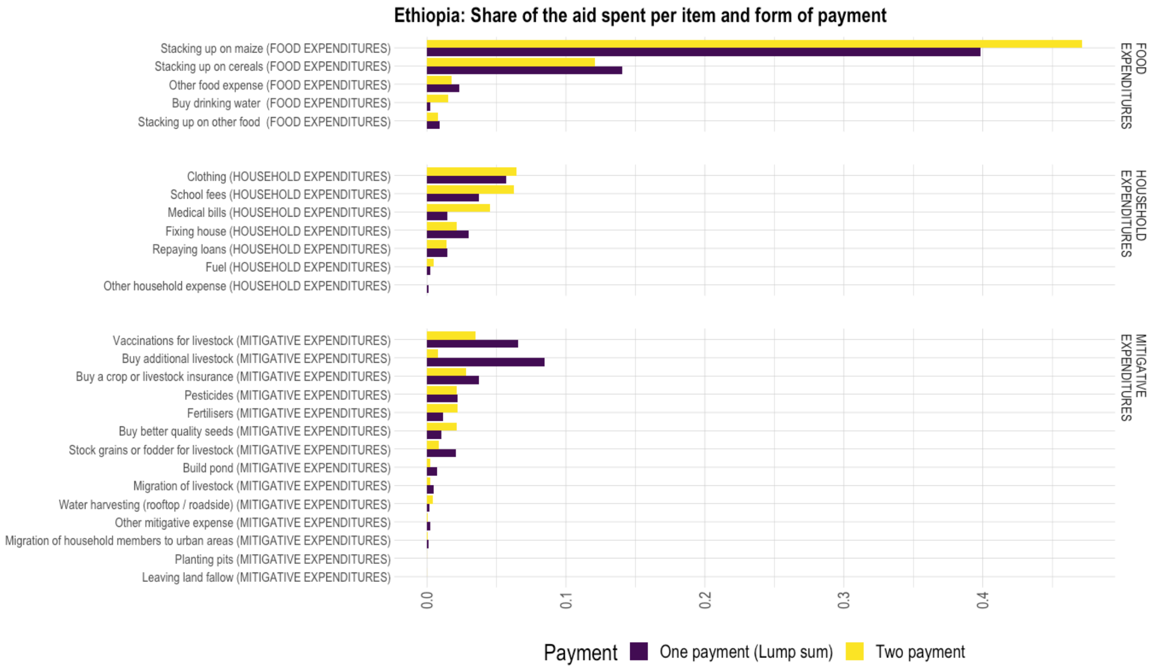


Figure 28 Share of the aid spent per item of the expenditure basket and form of payment in Ethiopia.

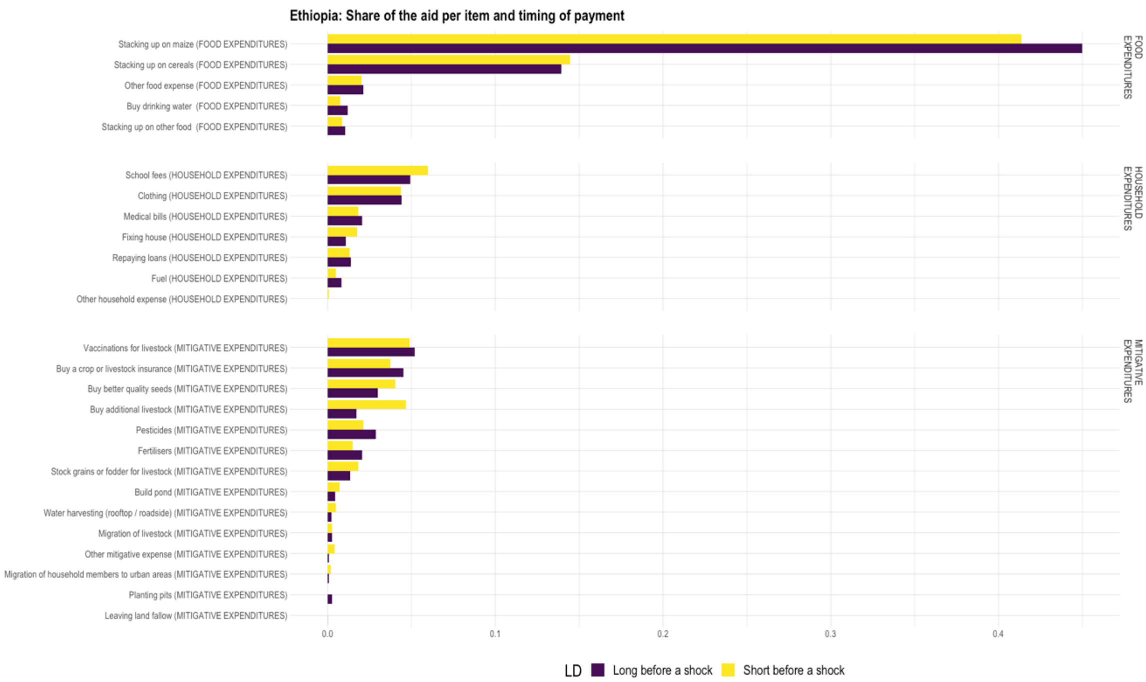


Figure 29 Share of the aid spent per item of the expenditure basket and time of payment in Ethiopia.

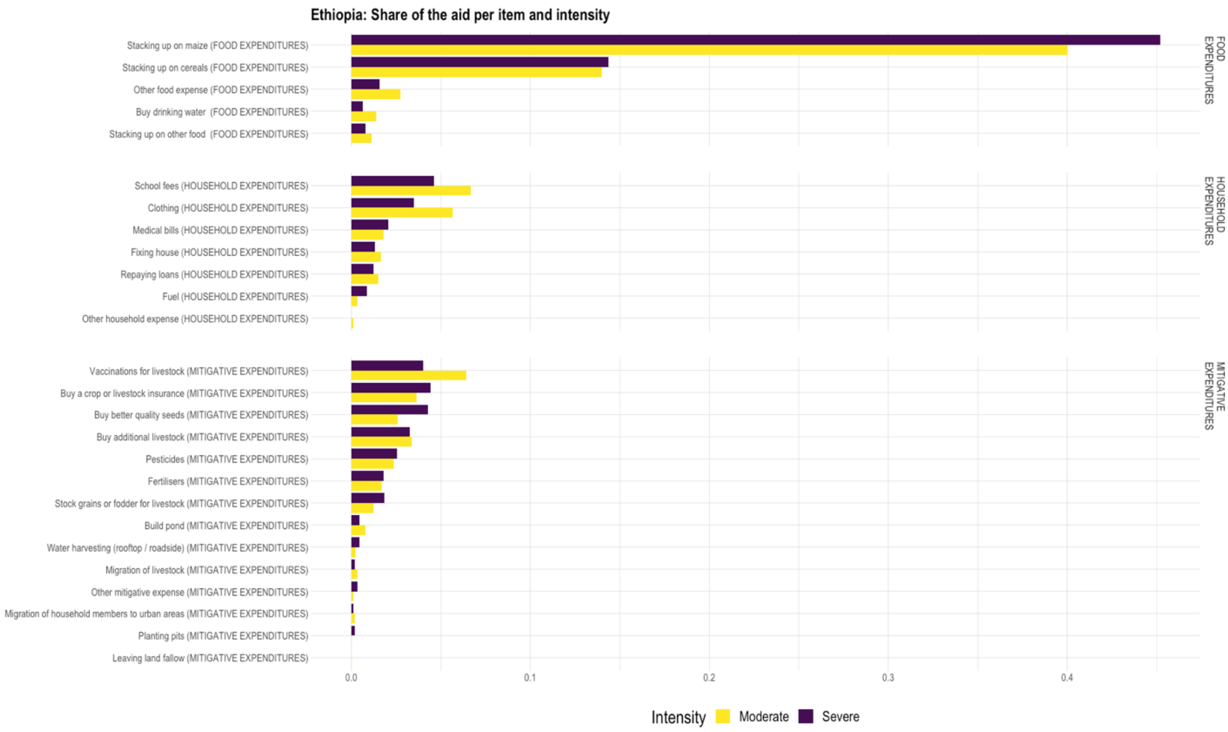


Figure 30 Share of the aid spent per item of the expenditure basket and intensity in Ethiopia.

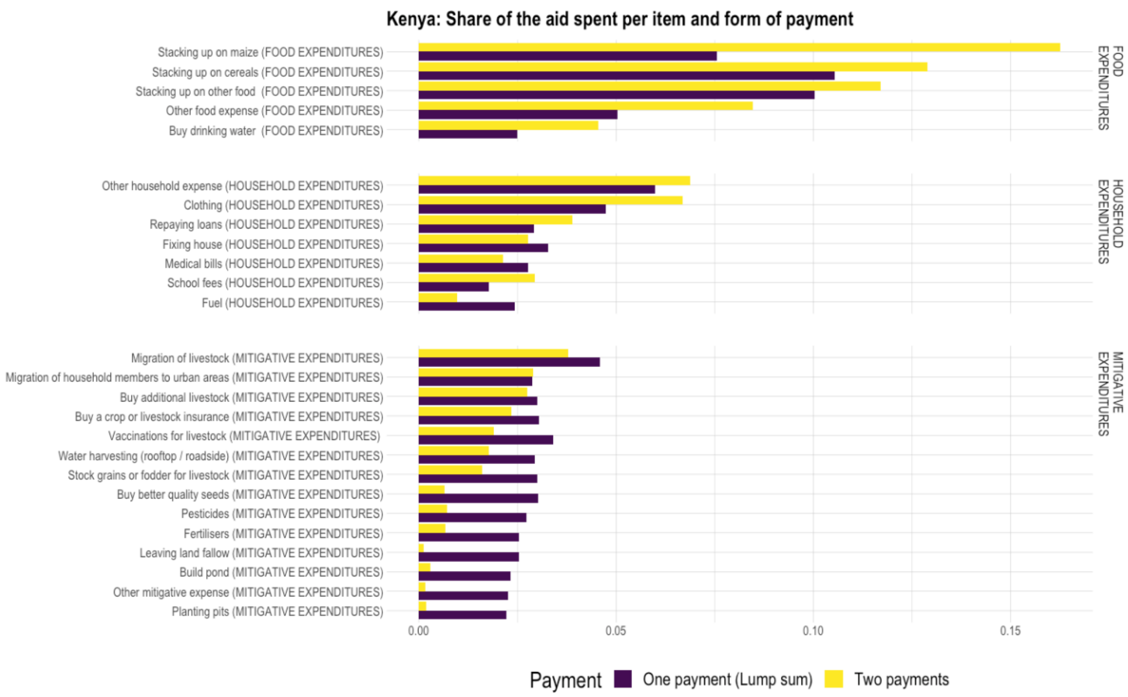


Figure 31 Share of the aid spent per item of the expenditure basket and form of payment in Kenya.

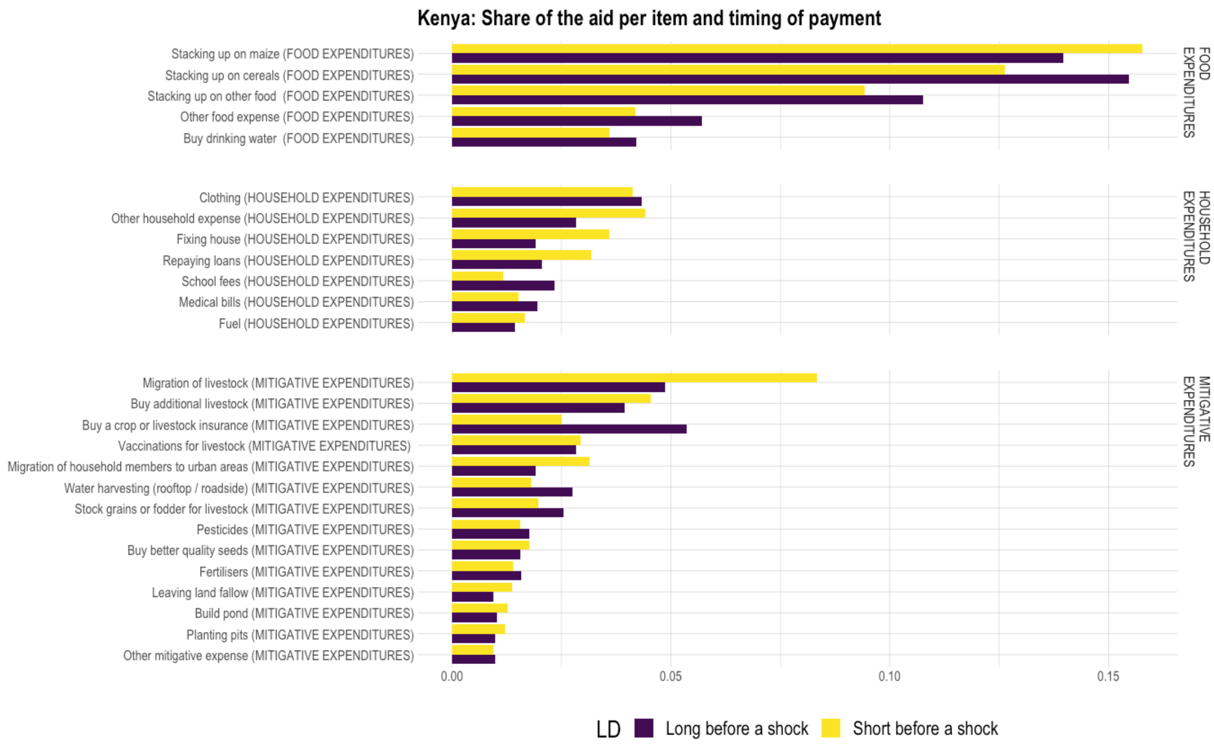


Figure 32 Share of the aid spent per item of the expenditure basket and time of payment in Kenya.

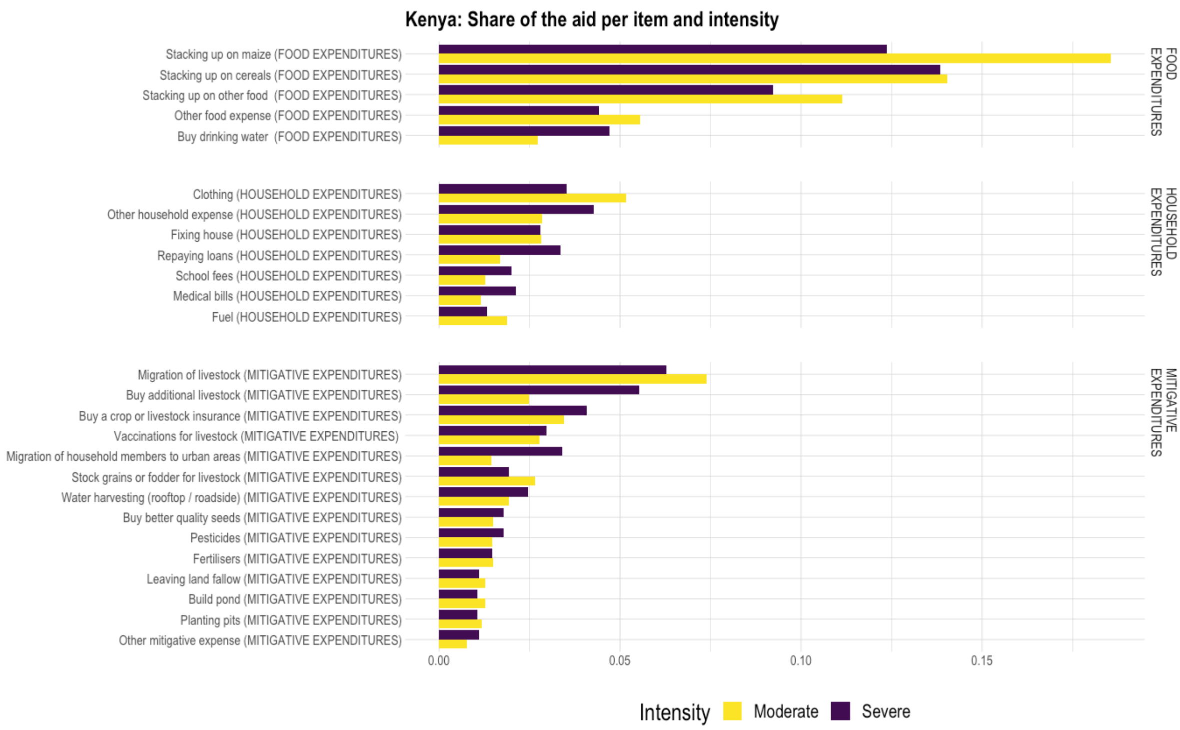


Figure 33 Share of the aid spent per item of the expenditure basket and intensity in Kenya.

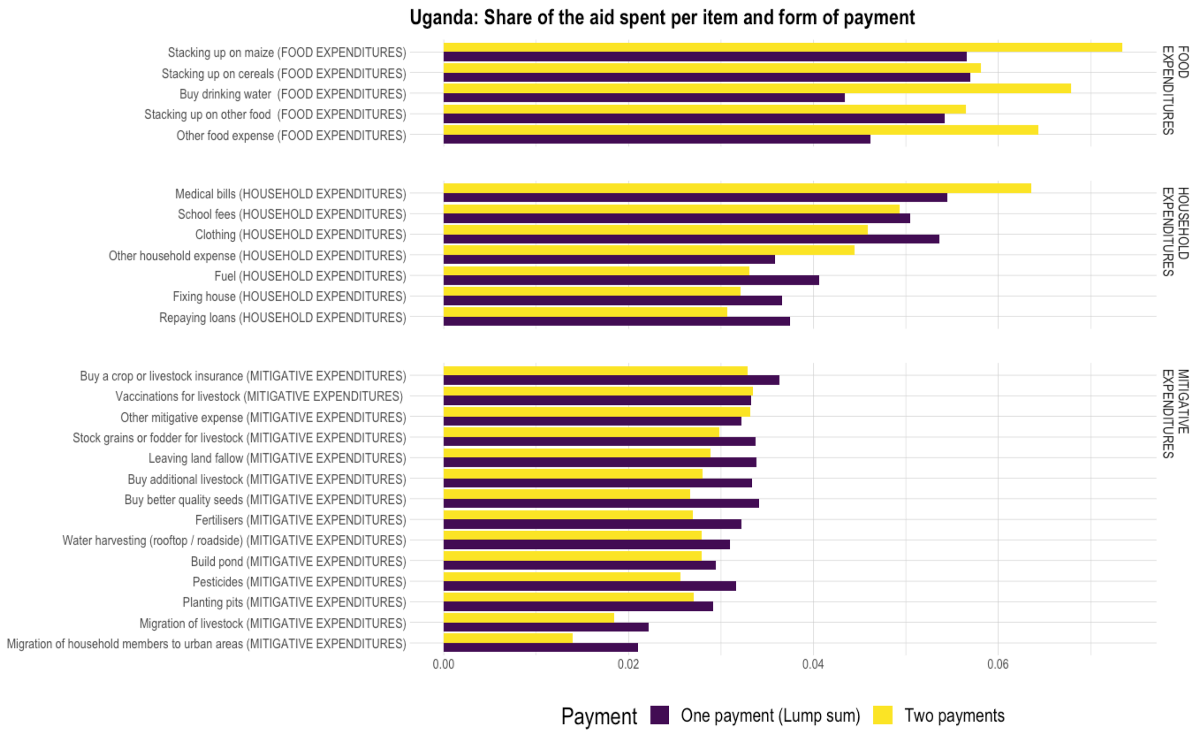


Figure 34 Share of the aid spent per item of the expenditure basket and form of payment in Uganda.

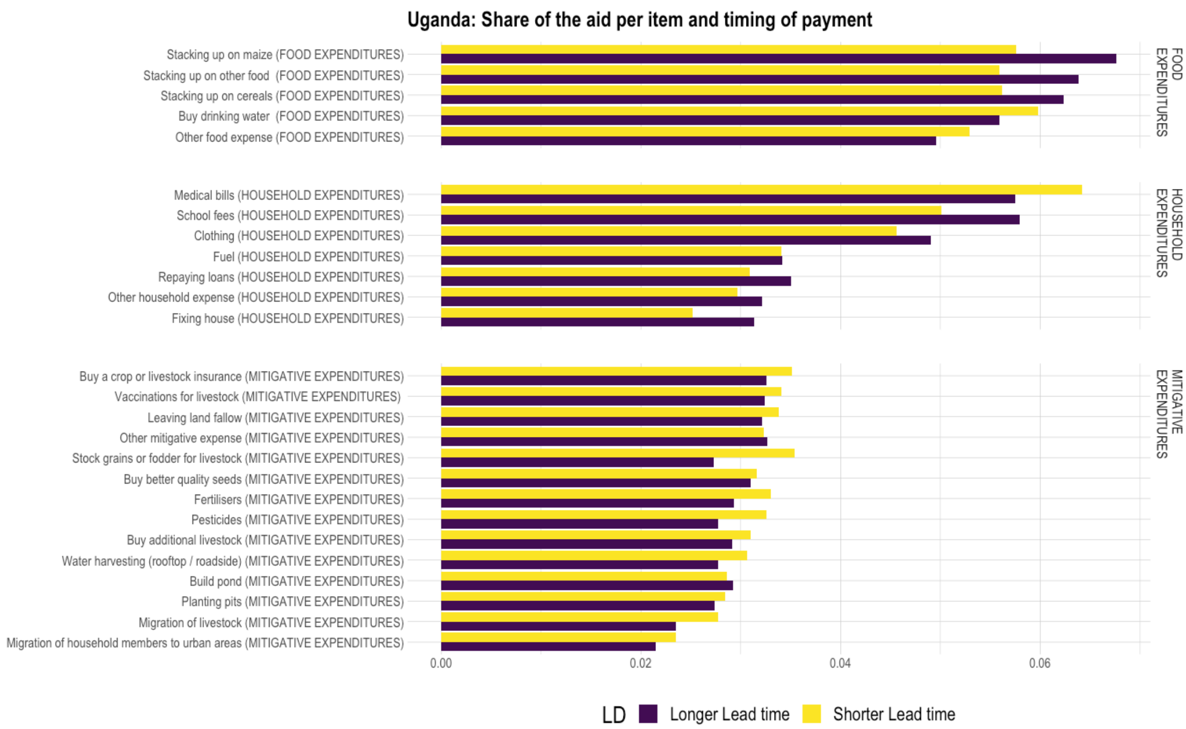


Figure 35 Share of the aid spent per item of the expenditure basket and time of payment in Uganda.

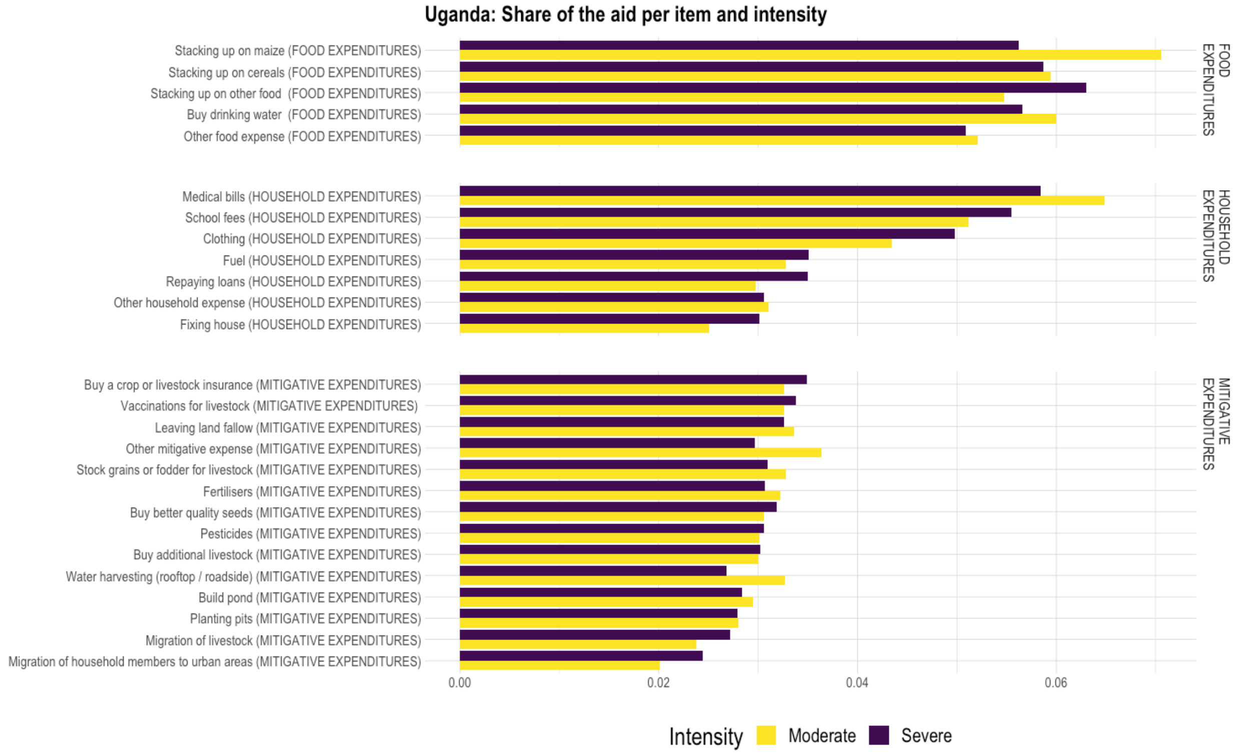


Figure 36 Share of the aid spent per item of the expenditure basket and intensity in Uganda.