MEASUREMENT INDICATORS FOR RESILIENCE ANALYSIS, PHASE II (MIRA II)

Final Report

September 2017

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Acknowledgements

The core idea of MIRA came from James Campbell, Catholic Relief Services (CRS) Southern Africa Regional Office. It was James' initial thoughts about the need to measure resilience following the 2015 flood in Malawi and his ability to garner the needed resources that moved MIRA from an abstract ambition to an operational reality. We also owe a great thanks to CRS staff in Malawi. Dane Fredenburg, UBALE Chief of Part, ensured the project had the support it needed and spearheaded in country dissemination. Jenny Haddle, the UBALE Meal coordinator, helped ensure the timely implementation of the project and provided important advice related to on the ground data collection. Owen Sopo provided vital guidance related to site visits, enumerator training, and helped establish and manage field relations. Berian Chaiwa provided valuable support on the CommCare back-end, designing and beta testing the endline survey. Kazunguza Trovehey, the field supervisor responsible for MIRA data collection, occupied a key position by supporting enumerators and helping to manage data flows. Individuals who served as village level enumerators in Chikwawa for the monthly surveys were highly effective; they were the key link in the chain of events that allowed us transform measurement objectives into actual data. Finally, and most central to what motivated the work of MIRA, we of course need to express our deepest gratitude to study participants across Chikwawa, Nsanje and Blantyre Rural. Individuals selected to participant in the study willingly shared, and continue to share, their experiences of shock exposure and recovery. Without their cooperation none of this work would be possible.

I. Overview of the Project and Organization of the Final Report

With the increasing severity of weather related shocks threatening food security, there is demand for a comprehensive protocol to monitor and evaluate resilience in the context of development. Launched as a collaboration jointly conceptualized by the monitoring, evaluation and learning unit (MEAL) within the Southern African Regional Office (SARO) of Catholic Relief Services (CRS) and the Charles H. Dyson School of Applied Economics and Management at Cornell University, the goal of the Measurement Indicators for Resilience Analysis (MIRA) project was to conduct a proof of concept study for resilience measurement that would make progress toward meeting this need.[1]

The MIRA project was developed and implemented in the context of the United in Building and Advancing Life Expectations (UBALE) program, a program that serves three of the poorest and disaster-prone districts in Malawi—Chikwawa, Nsanje, and Rural Blantyre. The purpose of MIRA is to provide timely, high frequency data offering a snapshot of the shocks and stresses experienced by UBALE beneficiaries and non-beneficiaries in these districts.

As a capstone event to the MIRA Phase I project, the result of MIRA were presented and discussed during a day-long meeting at Catholic Relief headquarters (September 23, 2016). Having completed the proof of concept study for MIRA, consensus was established to continue the project as a consultancy with Erwin Knippenberg, named MIRA Phase II. This consultancy ran from February 2017 to September 2017. The purposes of the Phase II consultancy were as follows:

- **Continued data collection -** continue to support ongoing high frequency data collection for the current sample until June 2017, as-well as administering an end-line.
- **UBALE Expansion –** expansion of the data collection to encompass all three districts currently served by UBALE
- **Resilience analytics** - produce additional analysis in terms of resilience capacities
- **MIRA implementation protocol** - develop protocols and guidelines to inform subsequent scaling up of MIRA to other countries and contexts
- **Data Dashboard –** develop the dashboard into a platform that facilitates the access and use of MIRA data flows - by program staff and related monitoring and evaluation specialists
- **Dissemination** - lead and participate in selected dissemination activities that serve the CRS-Malawi office, support CRS global community whose work is focused on resilience programming and/or on the need to measure resilience.

[1] MIRA was initially supported as a short-term project scheduled to last seven and half months, starting on January 19, 2016 and completed by the August 31, 2016. The details of the MIRA Phase I, as-well as relevant background information, are available in the Final Report provided as supplementary material to this submission.

II. Continued Data Collection

Data collection

In Chikwawa, a baseline survey containing demographic, livelihood, economic, and shock history data was collected between May 18th and June 30th 2016. The same households received monthly follow-up visits every month for a year to administer a 5-15 minute survey tracking the continued and newly experience effects shocks and related well-being outcomes. Importantly, the surveys retain respondents' prior information, allowing for follow-up questions that focused on the continued effects of previously reported shocks. The ability to have questions in one period linked to questions in a previous period is one of the distinctive features of the MIRA data collection approach.

In June 2017 the initial data collection exercise in Chikwawa was capped with an end-line. This 45 min survey collected the same set of questions as the baseline in order to construct a panel dataset (see supplementary materials). Because of the noted importance of social networks, it also included a module on family and community ties the household had with other members of the community. It also included a final round of high frequency data.

Attrition

The baseline sample consisted of 580 households from 34 villages. Each of the survey village was assigned to one of the 22 enumerators and, in some cases, an enumerator was assigned more than one village. Overall, enumerators were assigned between 15 and 39 households to survey.

A recurring concern with high frequency data is respondent fatigue, leading to attrition. As a team we tackled this issue in a twofold manner:
a) We minimized the burden on households by restricting the questionnaire to 10-15 mins
b) We worked to engage directly with the communities, including village chiefs, in disseminating the results of our data collection efforts. They in turn encouraged households to consistently respond to the administered high frequency survey.

Table 1. Observed Attrition in High Frequency Sample

Flood Plain	June	July	August	September	October	November
No	290	278	290	289	290	265
Yes	281	279	281	277	276	277
Total	571	557	571	566	566	542

Flood Plain	December	January	February	March	April	May
No	206	264	263	243	249	241
Yes	214	162	200	246	214	201
Total	420	426	463	489	463	442

We had allowed for up to 5% monthly attrition, but as a result of our efforts our attrition rate remains reasonable around 1-2%. As the June baseline and subsequent high frequency data were collected by different enumerators on different platforms, a village was missed, leading to a loss of 16 observations. These households were interviewed in the next round. Subsequent rounds show very low attrition rates, up to November.

In December and January a series of logistical challenges meant several enumerators were unable to collect data, leading to missing observations. However follow-up on the ground allowed us to recuperate a number of those households in subsequent rounds.

Summary Statistics

Table 2. Demographic summary statistics.

Characteristic	Observations	Mean	Std. Dev.	Min	Max
Age	2,948	19.93	17.99	0	116
Gender (1=male)	2,941	0.49	0.50	0	1
Education	2,948	4.75	3.69	0	15
Chronically ill or disabled	2,953	0.10	0.30	0	1
Female and pregnant/nursing (1=Yes)	1,497	0.21	0.40	0	1
Household size	580	5.13	1.95	1	13
Head of Household:					
Age	580	42.71	16.20	0	97
Gender (1=male)	580	0.76	0.43	0	1
Education	580	6.26	4.21	0	15
Chronically ill or disabled	580	0.16	0.37	0	1
Female and pregnant/nursing (1=Yes)	138	0.17	0.37	0	1

Livelihoods

Across different households, the responses indicate a lack of diversity in income sources. In terms of primary income, a few responses dominated (Figures 1 and 2).

The primary sources of income across all households in the baseline, where three sources accounted for over 95% of responses, were crop farming (64%), ganyu (22%), and business (9%). Similarly, regarding secondary sources of income, over 90% of the responses were ganyu (50%), crop farming (22%), and business (20%). Approximately 65% of households that chose crop farming as their primary source of income selected ganyu as their secondary source of income. In the end-line the dominance of crop farming is even more stark, suggesting a shift in livelihoods away from business and ganyu.

Figure 1. Primary Source of Income (baseline)

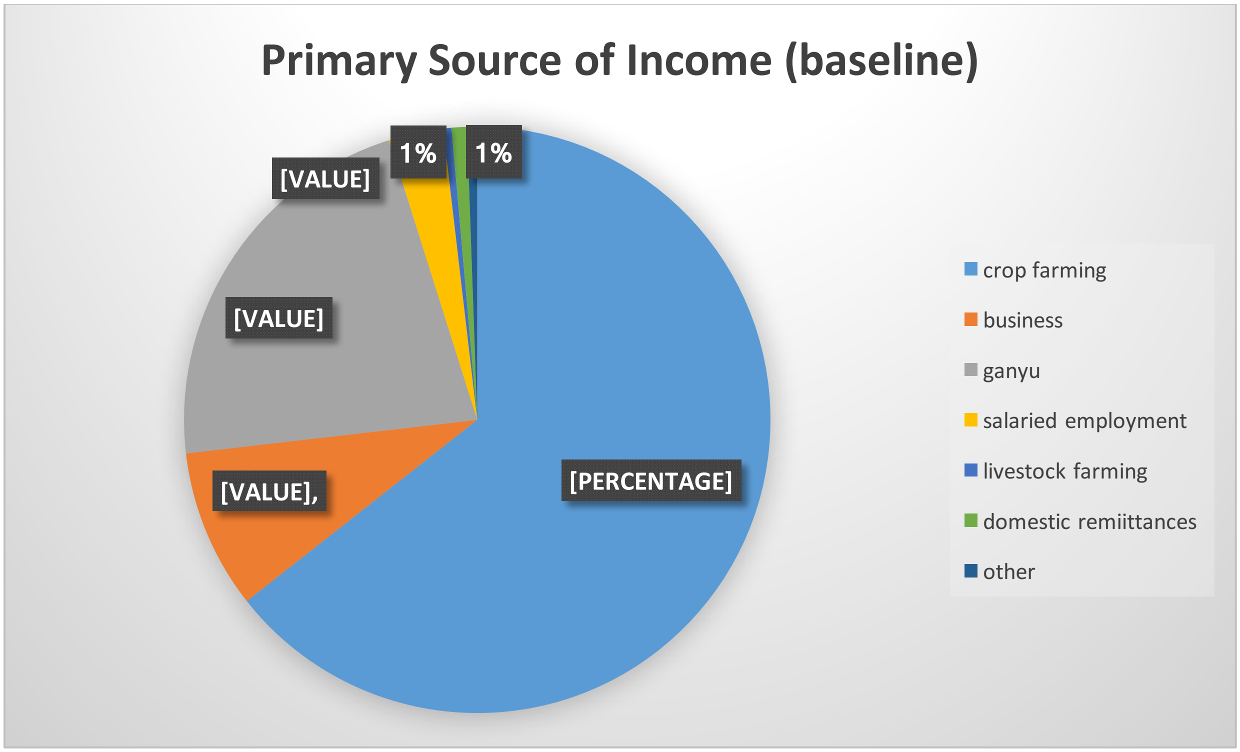
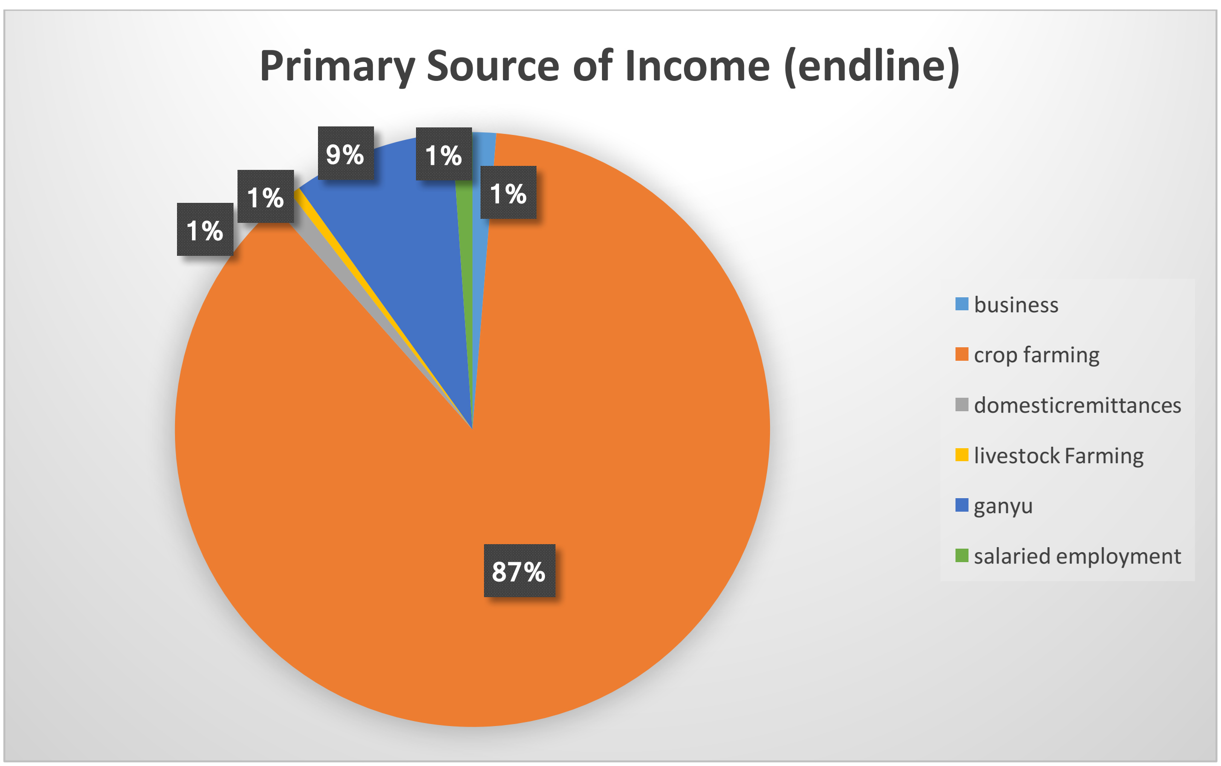


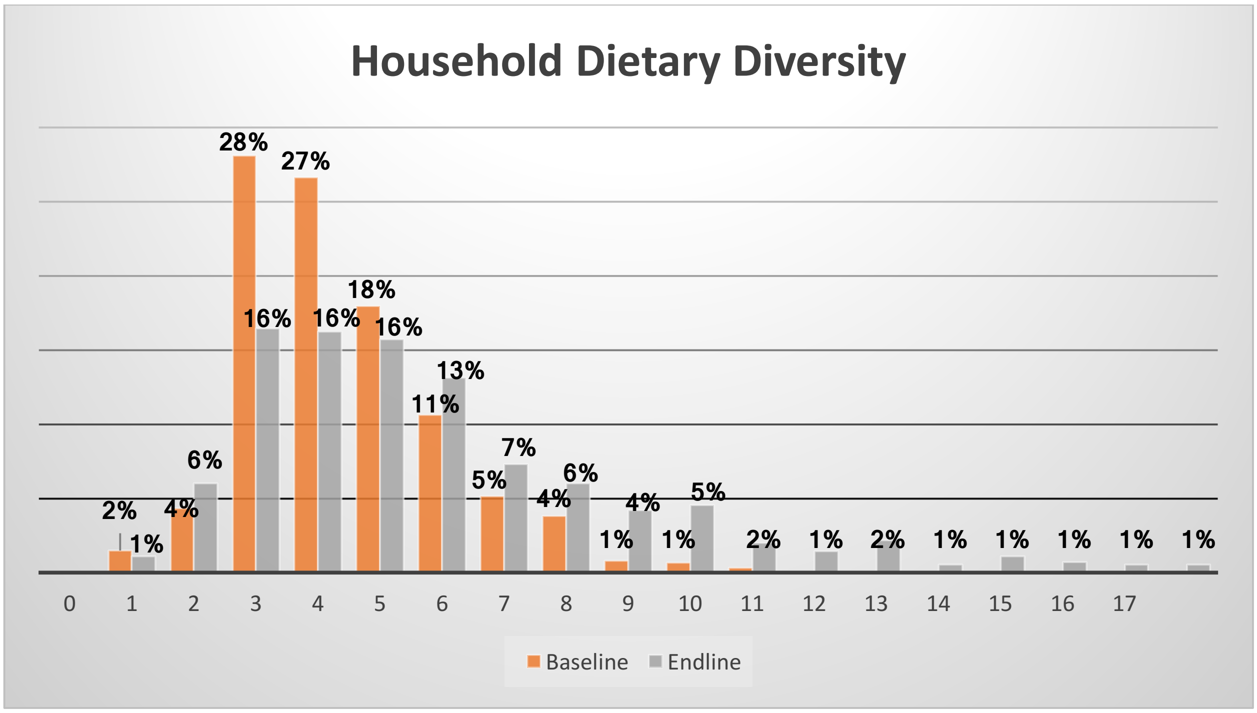
Figure 2. Primary Source of Income (Endline)



Dietary Diversity

A count based score of household's dietary diversity (DDS)[2] found it to be very low overall, suggesting that even households who do not suffer from acute hunger are subject to chronic malnutrition and over-reliance on a handful of staple crops, notably maize. However this distribution has improved significantly between the base-line and end-line. Possible explanations include the end of the drought emergency and the additional livelihoods assistance provided.

Figure 3. Dietary Diversity (Percentage)



UBALE participation

Across all HHs surveyed, 35.6 % (207 HHs) reported participating in one or more components of UBALE. Among those who reported participating in UBALE, the largest percentage of participation was in savings and internal lending community group at a participation level of 27%. The second highest level of participation was in the UBALE farmer group at a rate of 16%. The lowest level of participation was for the UBALE Care group at rate of 4%. An analysis of participation in more than one component of the UBALE program showed that SILC and Farmer was reported as the most frequent combination at a rate of 8%. An analysis of UBALE participation by traditional authority is shown in Table 3.

[2] DDS is computed as the sum of food groups a household reports consuming at least once in the past week, see FAO guidelines for further details.

Table 3. Participation rates by UBALE component across Traditional Authority (baseline)

Traditional Authority	UBALE Program Component			
	SILC Group 27% (N=155)	**Farmer Group 16% (N=93)**	**Care Group 4% (N=24)**	**SILC & Farm Group 8% (N=46)**
Mikhwira	22%	8%	2%	5%
Lundu	28%	18%	3%	7%
Ngabu	29%	23%	8%	12%
Maseya	38%	14%	0%	10%

Comparing baseline and endline data, we find that Silc, Farm and Care group participation ticked up slightly, by 6%, 3% and 6% respectively. However this increase is unevenly distributed across Traditional areas, with some experiencing a net decrease in participation.

Table 4. Participation rates by UBALE component across Traditional Authority (endline)

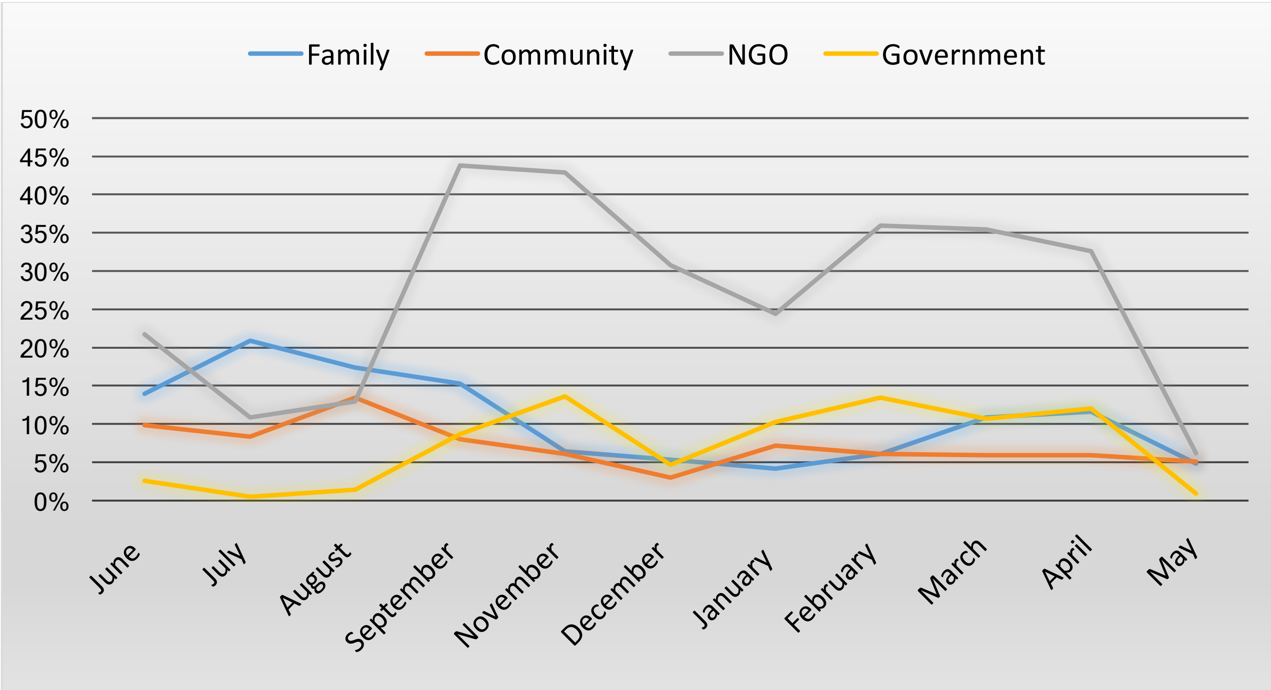
Traditional Authority	UBALE Program Component			
	SILC Group 33% (N=181)	**Farmer Group 19% (N=106)**	**Care Group 10% (N=53)**	**SILC & Farm Group 4% (N=23)**
Mikhwira	26%	12%	4%	2%
Lundu	48%	37%	22%	10%
Ngabu	27%	14%	6%	3%
Maseya	48%	14%	0%	0%

Assistance:

The high frequency survey asked questions about the forms of assistance received. As the food emergency increased during the El Nino driven drought, we see a spike in NGO assistance, which ramps up during the hunger season and winds down as the next harvest comes in, putting an end to the food emergency.

Conversely family assistance seems to drop as the crisis kicks in, perhaps due to an exhaustion in coping capacity.

Figure 4. Assistance Type Over Time



Social Networks

The end-line gave us the opportunity to interview respondents regarding their social networks. We found that the number and type of relationships varied immensely across locations. Makhuwira and Ngabu have a large number of kinship ties, as-well as self-defined friends. Interestingly though this does not necessarily translate into a denser financial network, expressed in either reciprocal gifts or loans.

Maseya seems to have a particularly low level of social density, with sub-average indicators in all categories except for the exchange of gifts.

Table 5. Average number of reported relationships per category, across Traditional Authorities

Traditional Authority	Community Relatives	Community Friends	Asked Help on Farming	Received Gift From	Given Gift	Received Loan From	Given Loan To
Lundu	6.5	5.69	1.3	0.59	0.84	0.95	0.56
Makhuwira	13.69	14.81	1.56	0.71	0.87	0.39	0.49
Maseya	2.29	2.52	0.71	0.52	0.95	0.29	0.24
Ngabu	15.96	9.49	1.54	0.59	1.08	0.5	0.56
Total	12.15	9.95	1.45	0.63	0.94	0.57	0.52

III. UBALE Expansion

The second key deliverable was expanding the survey to encompass all UBALE districts: Chikwawa, Nsanje and Blantyre Rural. With the sampling frame in place, the baseline is due for roll-out in September 2017.

Expanded Baseline/Endline Survey

The Consultant CRS teams work together to develop an appropriate base-line and end-line for the expanded sample. The end-line was designed with the intent to remain consistent with the original baseline, keeping the same phrasing and structure of questions to facilitate comparisons across datasets. However, based on lessons learned from the baseline the survey was updated. Questions that proved redundant or did not contain substantive information were dropped. For the purpose of simplicity and time efficiency, the demographic component was condensed. Given the observed importance of social capital, we also added a Social Network component.

The open source CommCare survey application was selected for the high frequency survey because of its case-management functionality, which allows for a dynamic survey based on previsions response. To ensure continuity, the MIRA baseline and end-line were incorporated into the same CommCare platform, with in-house technical assistance.

Sampling

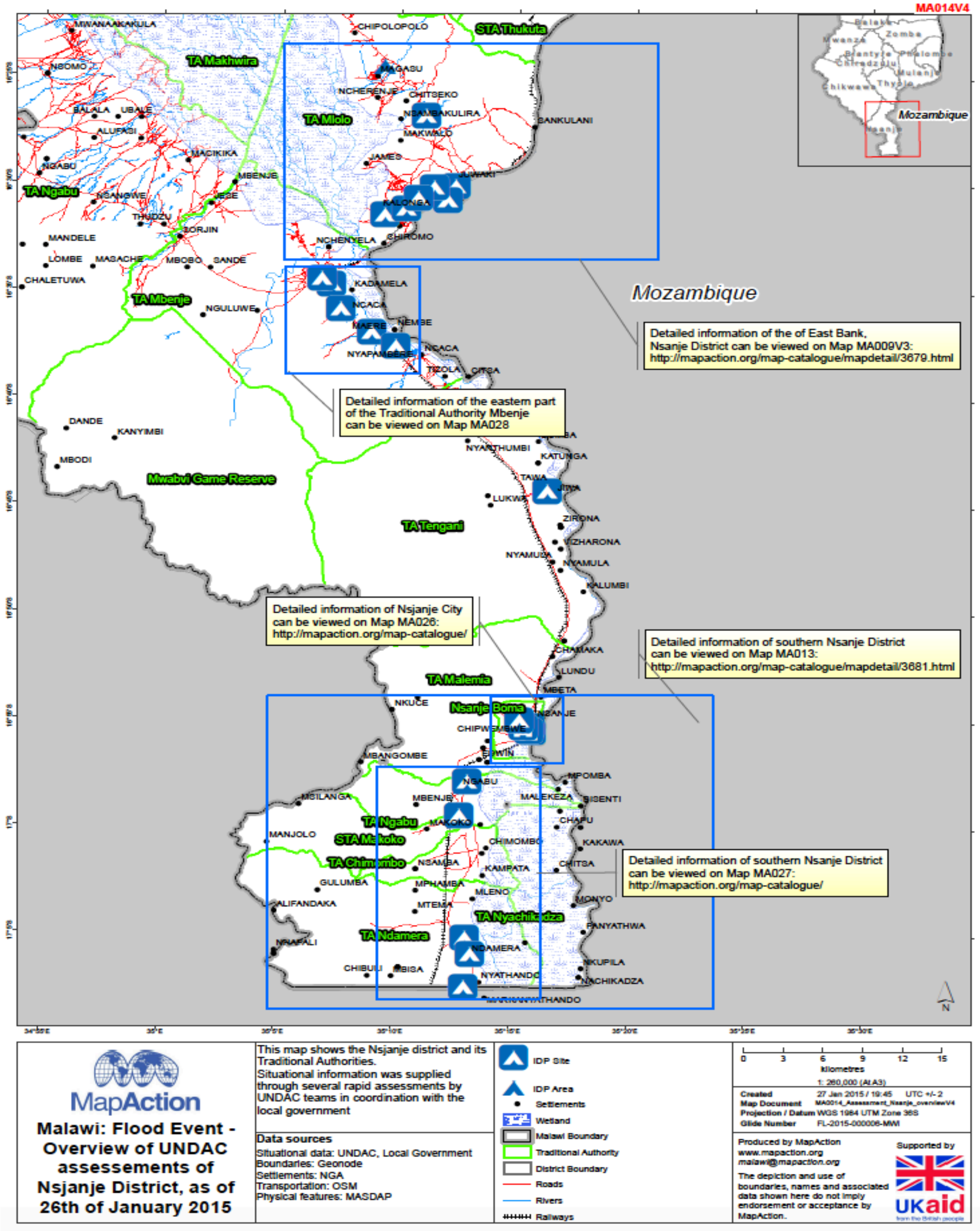
Sampling was performed using combination of purposive and random sampling. The purpose sampling was used to ensure variation in flooding history and risk. To do this, we used flood-risk data from the Dartmouth Flood Observatory (http://floodobservatory.colorado.edu/) to select 3 traditional authorities (TAs) in each district. These were intended to be spatially representative of the district as a whole, while allowing for sufficient proximity to enable a single supervisor to oversee the data collection process.

Each TA was intended to obtain GVHs that are frequently hit by droughts and GVHs that are in the floodplain. This offered us that opportunity to have within TA, between GVH heterogeneity in likelihood of floods and drought, since the two are inversely correlated. For Nsanje and Chikwawa, which are both in the Shire river basin, this was based on flood exposure maps, as illustrated in Figure 5 for Nsanje.

After stratifying the GVHs in each TA into high and low flood risk categories, three GHVs were randomly selected from each TA-strata. Two villages were then selected from each GVH based on proximity to the hired enumerator, and 16-20 households were randomly selected from each village. Due to various logistical constraints in the field, and the desire to add more households in case attrition levels were high, We oversampled in each village and allowed for an additional GVH in each TA.

The final selected sample was 2292 households, from 3 districts with 10 Traditional authorities and 64 GVHs. We sample 788 households in Nsanje, with 23 GVHs, 775 households in Chikwawa in 19 GVHs, and 729 households in Blantyre rural with 22 GVHs. With random selection carried out the HH level, the household is used as the unit of analysis. Households will, however, be grouped by flood risk and other variables to support resilience analysis.

Figure 5. 2015 Flood incidence and displacement for Nsanje, from UKAID



IV. Resilience Analytics [3]

Resilience Indicators

In empirical terms, resilience can be defined as the dynamic recovery trajectory of some well-being outcome (e.g., food security, health, and economic welfare) observed over time in the face of shocks.[4] Elements within this definition highlight the value of organizing data collection and analysis around three sets of variables:

1. *Well-being outcomes,*
2. *Shocks experienced* that have adverse effects,
3. *Capacities and characteristics that* may prevent adverse effects and/or enable recovery.

From a measurement perspective, these three variables represent the minimum set of resilience indicators needed to model resilience.

Well-being outcomes

We use three measures of welfare to measure well-being over rounds. All three of these indicators are structured so that a *decrease* in the calculated value of the indicator reflects an *increase* in wellbeing. In terms of resilience, lower reported values of a given welfare measure implies a lower vulnerability to shocks. Higher reported values of given welfare measures implies a higher vulnerability to shocks. Details associated with each of the three welfare measures is shown below:

1. *Coping Strategies Index (CSI)*
    - A composite score weighing various coping mechanisms by severity, as established in the existing literature.[5]
        - Borrow food: 2
        - Ganyu: 1
        - Eat Less Preferred Foods: 1
        - Reduce Meals: 1
        - Children beg: 4
        - Reduce Size of meals:1
2. Hunger Score
    - Households were asked three questions related to the extent of time they experienced hunger over the past month.
    - This continuous variable was divided into three bins with assigned scores
        - (0 no days, 1 <10 days, 2>=10)
    - These scores were then summed across all three questions,

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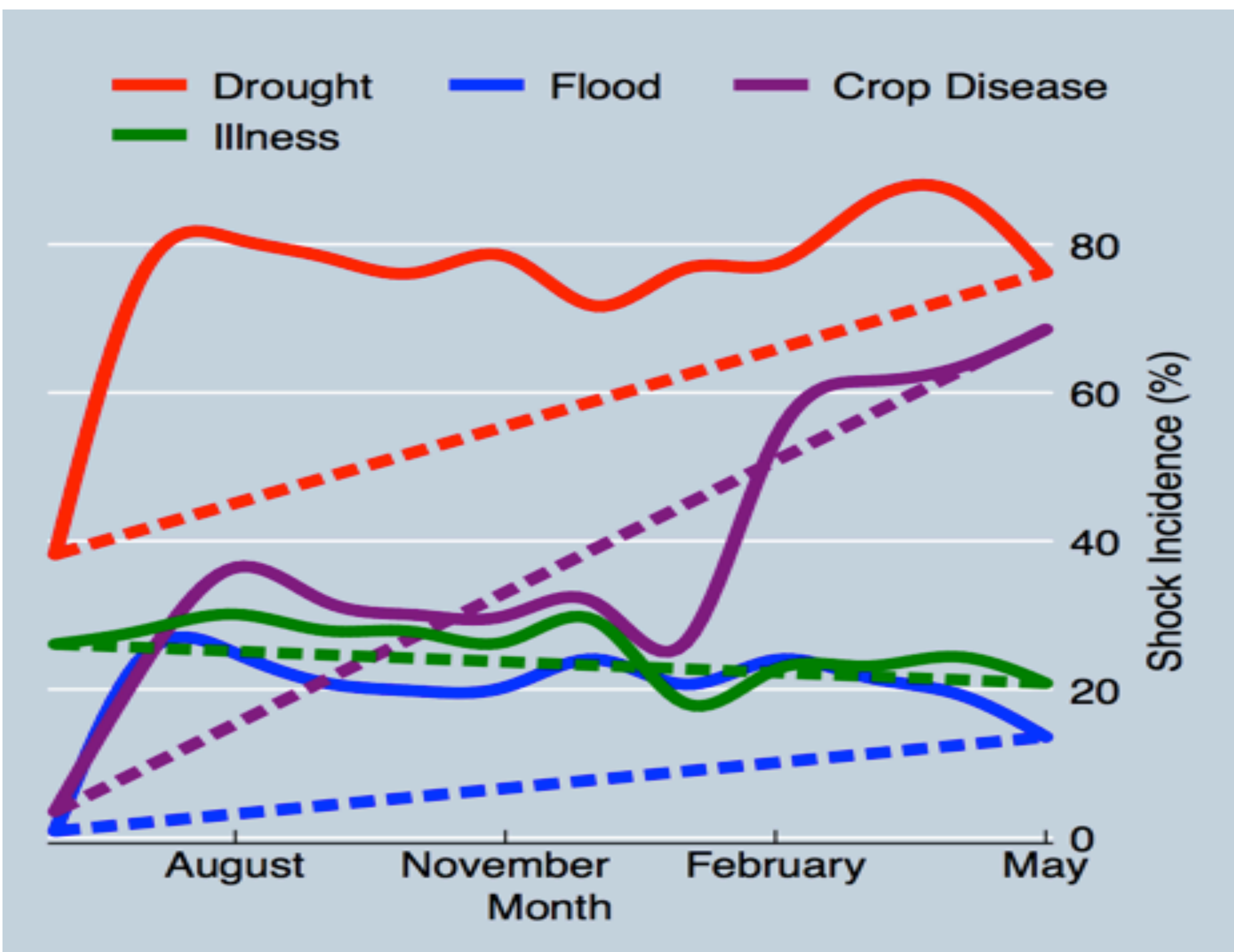
[3] This analysis was carried out on the first round (Chikwawa) dataset, for which data is available.
[4] Constas, M., T. Frankenberger, & J. Hoddinott. 2014. *Resilience measurement principles: Toward an agenda for measurement design*. Published by the Food and Agriculture Organization and the World Food Program
[5] Maxwell, Daniel, and Richard Caldwell. *The Coping Strategies Index: Field Methods Manual*. 2nd ed..: CARE. USAID, WFP, TANGO, Jan. 2008. Web. 30 Sept. 2016.

Shocks Experienced

The case-management functionality allowed us to track the incidence of shocks over time. Every month, households were prompted about the previous shocks experienced. If they reported still experiencing the adverse effects of this shock, having not yet recovered, the shock is reported as persisting. In this way we track not only the incidence of shocks but also their persistence, more relevant for long lasting shocks like drought or flood.

Tracking these over time, we find that drought is by far the most frequent shock, and is also very persistent. Other common shocks included crop illness, which follow-up field work found to be the incidence of corn worm which attacked the crops already fragilized by the drought. In this way one shock leads to another. The incidence of illness is driven by outbreaks of cholera and malaria. We also note that taking a simple linear baseline-endline projection, as is common in man evaluation frameworks, would lead to us heavily underestimating the incidence of both drought and flood, which are heavily seasonal.

Figure 6. Incidence and persistence of most common shocks per month, compared with a linear baseline-endline projection.



Capacities and Characteristics

A primary goal of any resilience measuring exercise is to identify whether proposed characteristics affects household's probability of experiencing and recovering from shocks. These characteristics include indicators of a household's assets holding, such as land and livestock, as-well as demographic indicators that speak to the head of household's human capital and social status.

Table 6. Proposed Resilience Capacities, summary statistics

Characteristic	Observations	Mean	Std. Dev.	Min	Max
Land (Ha)	580	2.59	1.91	0.2	20
Tropical Livestock Units	580	0.63	2.66	0	38
Lives in Flood Plain (1=Yes)	580	0.5	0.5	0	1
Secondary House (1=Yes)	580	0.19	0.39	0	1
Head of Household:					
Age (Years)	580	42.71	16.2	0	97
Gender (1=male)	580	0.76	0.43	0	1
Education (Years)	580	6.26	4.21	0	15
Chronically ill or disabled	580	0.16	0.37	0	1

Resilience Capacities

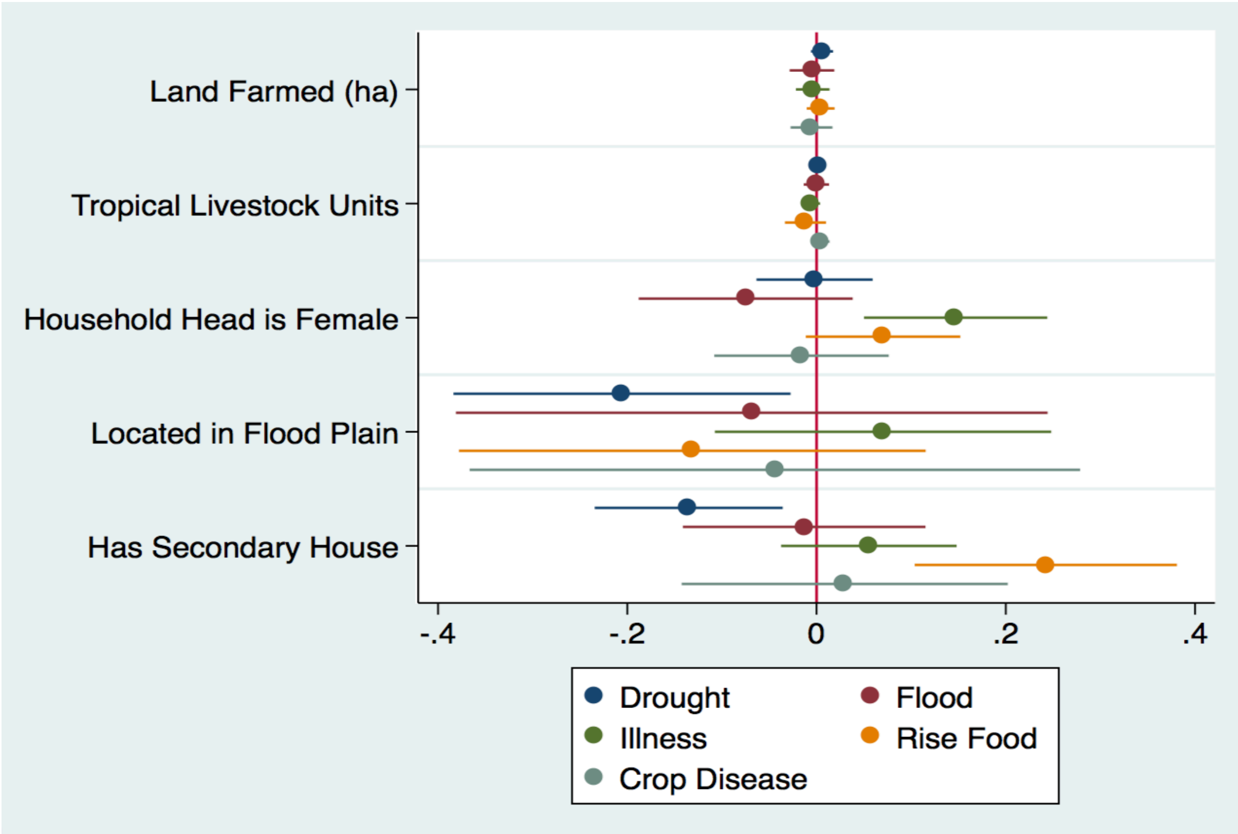
In order to investigate these resilience capacities, we first estimate each household's probability of experiencing a shock.[6] We then regress this against proposed resilience capacities to test whether they shift the observed probability. Household's with a negative change in probability are less likely to experience a shock than the mean household, making them 'positive deviants' . The illustrated results are presented in Figure 7.

Living in a flood-plain seems to decrease the probability of experiencing drought, as does having a secondary home. Since the secondary home is a coping mechanisms for seasonal floods, this makes sense. However it also seems to be correlated with an increased exposure to increased food prices. This suggests that though the households are more mobile, they might also be leading a more precarious existence.

Female headed headed households have a higher probability of experiencing illness and rise in food-prices. This suggests that when it comes to idiosyncratic shocks, these potentially more marginal households are more vulnerable.

[6] This is done by estimating a simple autho-regressive model, $S_{it} = \gamma_0 + \gamma_1 S_{it-1} + \varepsilon_{it}$ and predicting $\hat{S}_{it}$

Figure 7. Change in shock probability correlated with resilience capacity



Welfare Trajectories

Household Characteristics

Next, we look at the evolution of household welfare, disaggregated by characteristics of interest. We do this by plotting the CSI and Hunger Score across time and comparing trajectories. This gives us a richer image of how different types of households evolve over time.

Since we stratified our sample using the flood plain, our first step is to investigate whether these households truly have different trajectories. In figure 8, we find that they do. Households in the flood-plain have a lower level of food insecurity on average, as measured using the CIS. In addition, as the drought emergency abates towards the end of our sample period they seem to recover much faster. This may be because, having access to the best arable land, they can take advantage of the next growing season.

Figure 9 shows us the trajectories for households with and without a secondary home they can relocate to. As was suggested earlier, this secondary home may be a proxy indicator for living in the floodplains and having the means to relocate when necessary. These households have a lower but much for variable level of CSI, suggesting that while they're better off on average, their situation is much more precarious.

Figure 8. Welfare trajectory measured using CSI, disaggregated by flood plain

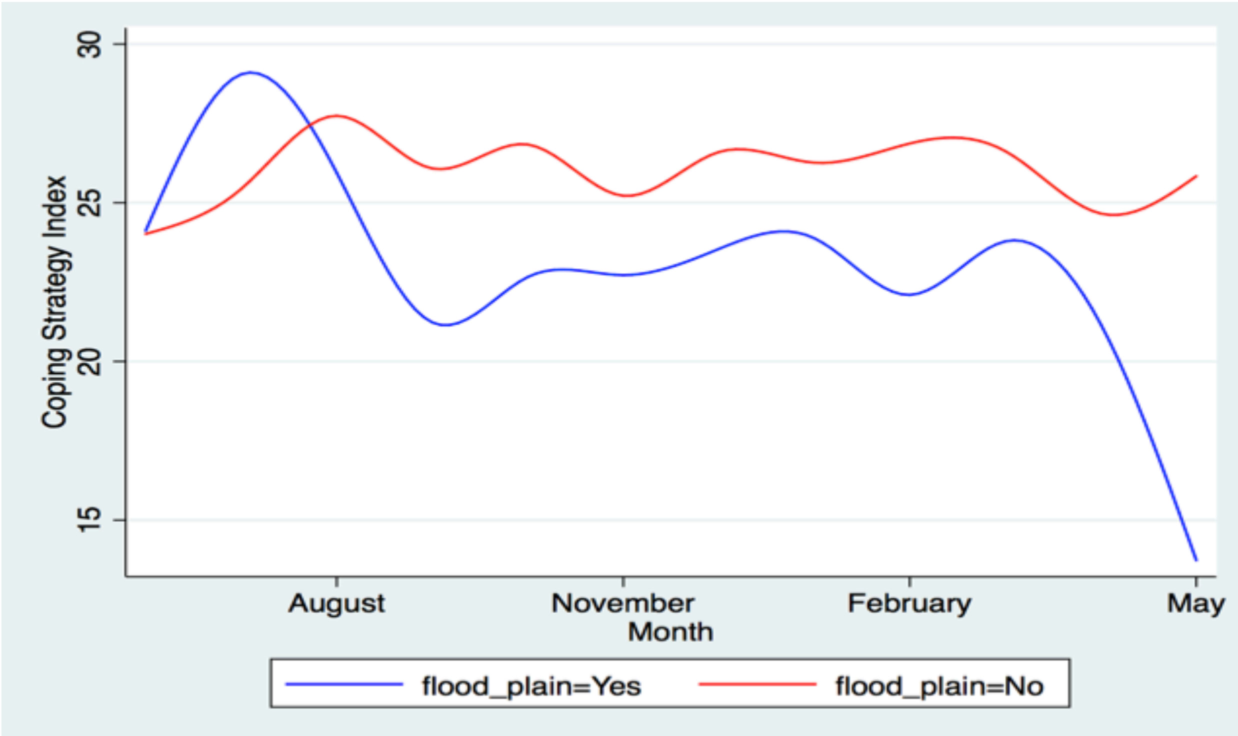
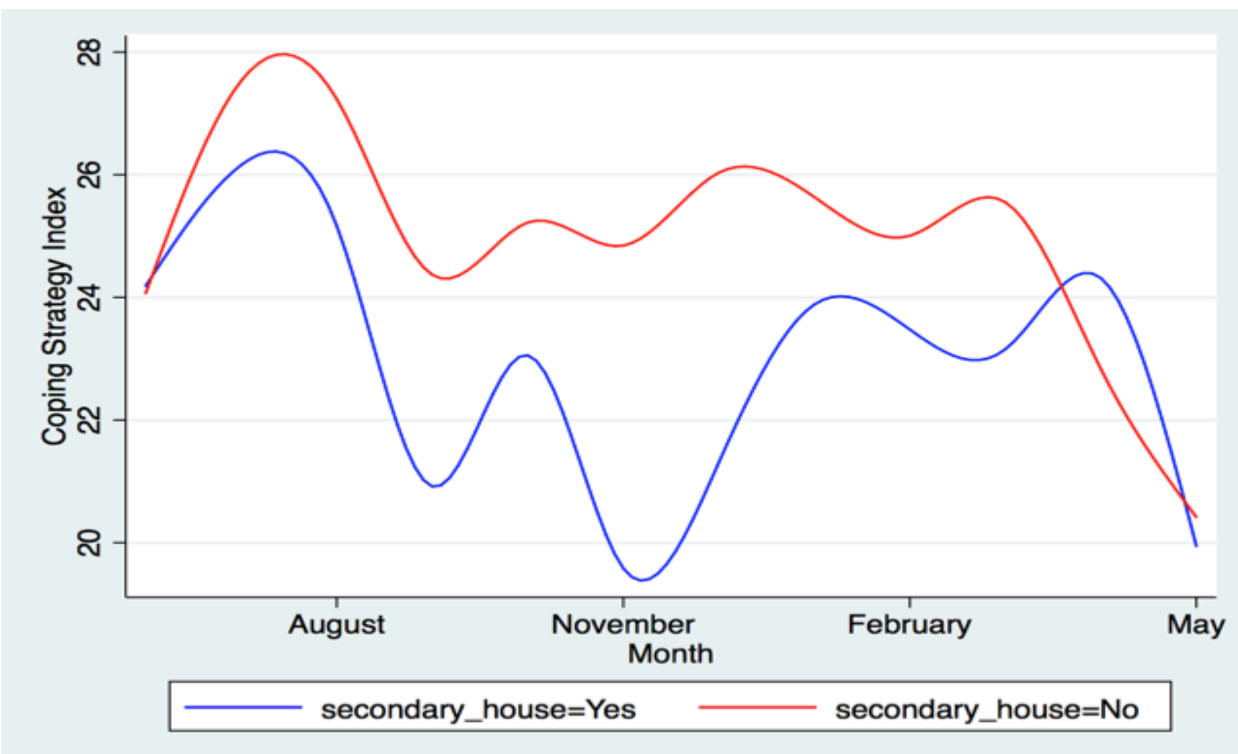


Figure 9. Welfare trajectory measured using CSI, disaggregated by owning a secondary home



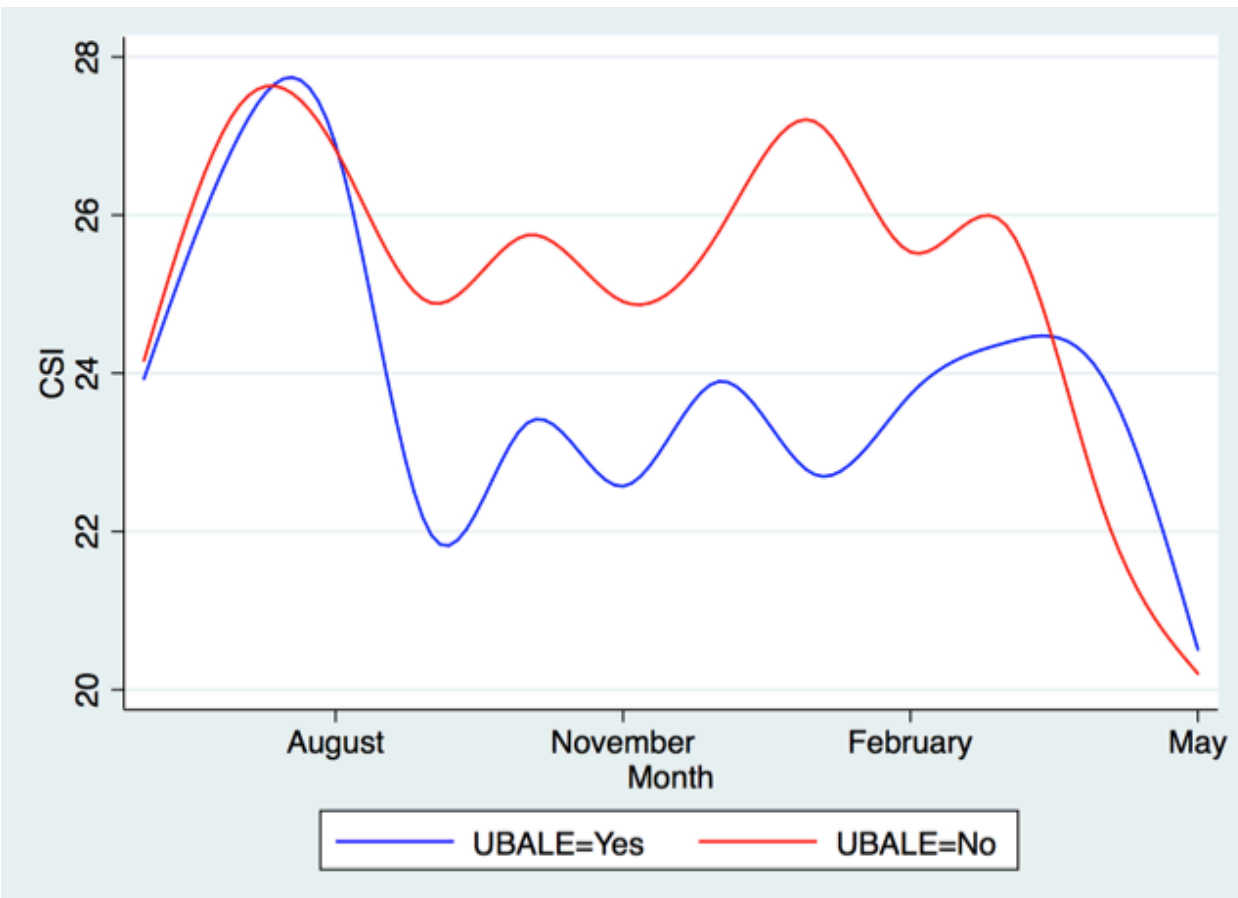
UBALE Assistance

Of particular interest to CRS, we looked at whether the receipt of UBALE assistance led to different welfare trajectories. We defined UBALE beneficiaries as the participants in any one of the three main components of UBALE: the SILC group's, farmers groups and care groups.

We see that initially both groups of household experience similar increases in food stress, as measured using CSI. However, UBALE beneficiaries recover much faster, and their level of food stress dropped significantly lower relative to non-beneficiaries. This lasted throughout the course of the food-emergency. Only when the rains came and the food emergency abated did the non-beneficiaries see a drop in their level of food stress, with the two groups converging in May.

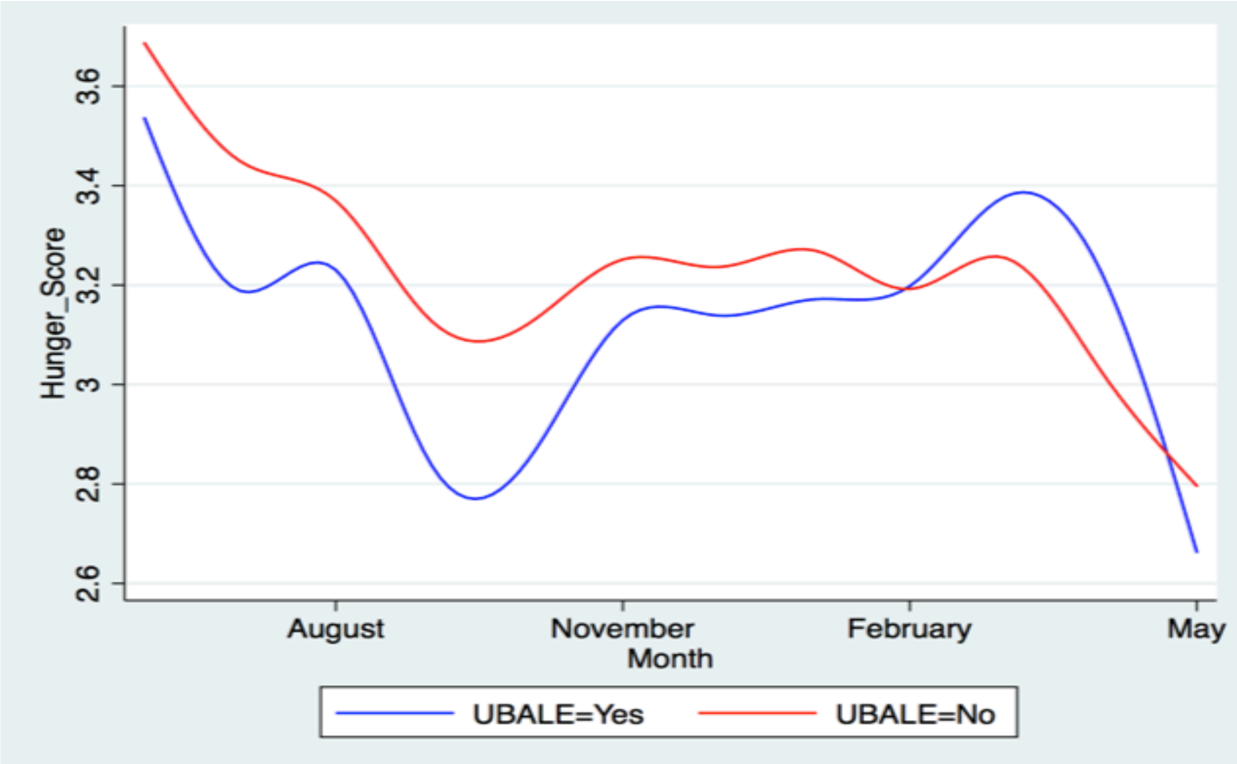
Though these are observational rather than causal, UBALE beneficiaries experienced a far lower level of food stress across this period relative to their peers.

Figure 10. Welfare trajectory measured using CSI, disaggregated by UBALE recipient



Using hunger score instead of CSI in figure 11, we see a marginally lower level of hunger among beneficiaries, but the different trajectories aren't as clear. This may be because the hunger score, being on a 6 point scale, offers a lower resolution of the households food stress level.

Figure 10. Welfare trajectory measured using Hunger Score, disaggregated by UBALE recipient

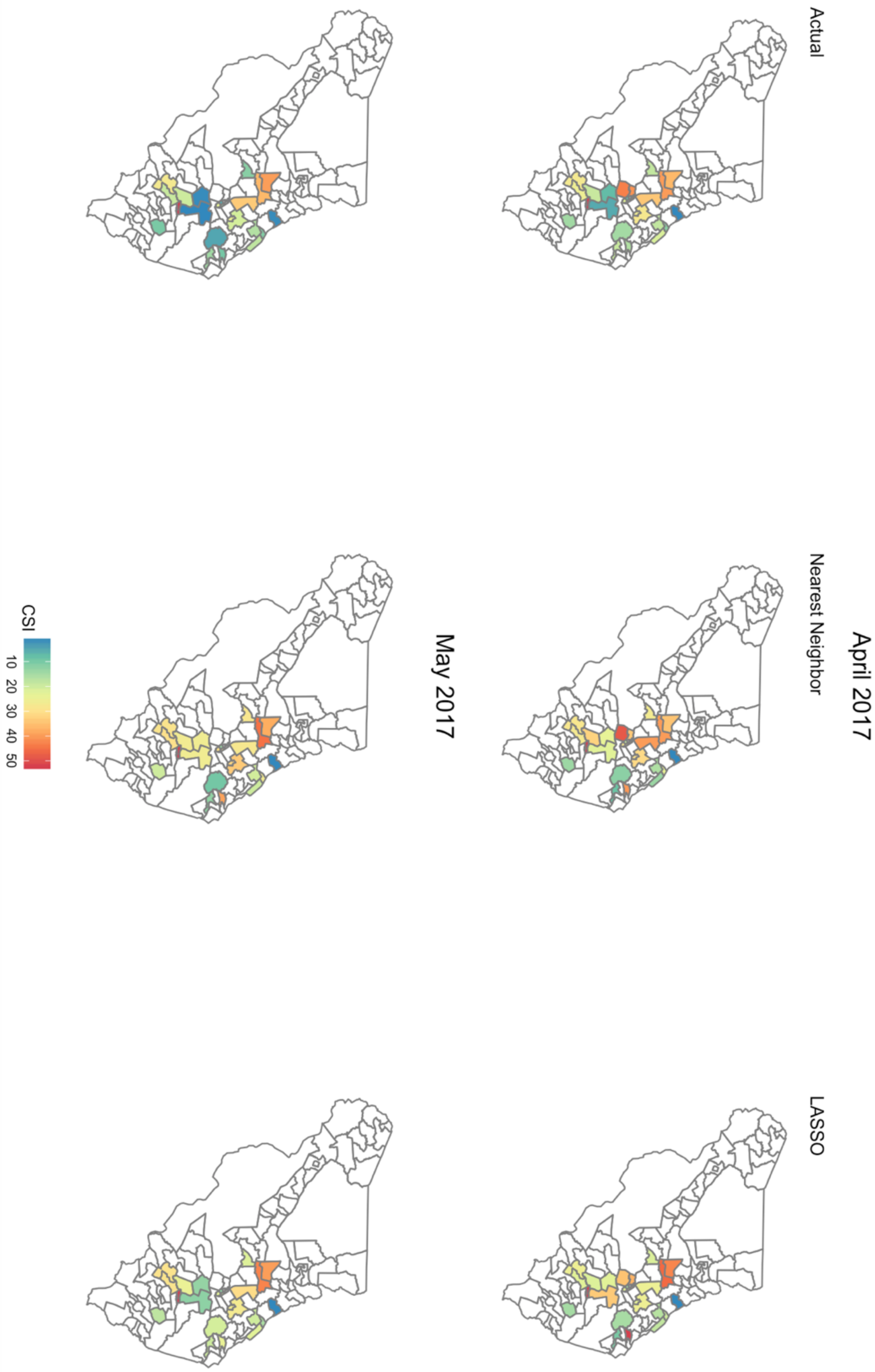


Prediction using Machine Learning

The rich, timely data available allows us to predict the future level of food stress using machine learning algorithms. Based on the observable indicators from the baseline, as well as the previous round of high frequency observation, we sought to predict the next months' incidence of food stress, as measured using CSI.

The result, presented in figure 11, compares the actual CSI measured with the predicted levels using our algorithms. Its close correspondence demonstrates that we can predict food insecurity over a future time horizon with a high level of precision, allowing for timely targeting of assistance and other interventions.

Figure 11. Actual and predicted CSI in April and May 2017, using machine learning



V. MIRA Implementation Protocol

A well-focused, rigorously constructed and easily deployed measurement protocol for resilience in development settings stands as an unmet need. Accordingly, a key deliverable was developing and disseminating a protocol allowing other CRS offices and partner organizations to adapt the methodology to their own needs.

This **MIRA Protocol** outlines how a program office can collect such data for the explicit purpose of resilience analysis, creating a feedback loop to inform their operations.

Based on data collected and lessons learned from this proof of concept, we have worked to develop and implement a process to guide the collection and analysis of high frequency, resilience-focused data from a sample of households that have suffered the effects of widespread (covariate) shocks such as floods, drought or epidemics, as-well as individual-level (idiosyncratic) level shocks such as chronic illness or loss of a family member.

The survey has two components:

1) A baseline/endline survey containing demographic, livelihood, economic, and shock history data to be administered annually or every two years.
2) A high frequency follow-up survey administers monthly to the same households, tracking continued and newly experienced effects shock, to be administered monthly.

The surveys retain respondents' prior information, allowing for follow-up questions. This dynamic nature is one of the distinctive features of the MIRA data collection approach.

It contains the following:

- Resource and Staffing Requirements
- Suggestions for the sampling frame
- Key considerations for survey design and platform
- Guidelines for analysis
- Proposed feedback mechanisms

Supporting documents include:

- A training manual for enumerators
- Sample baseline survey
- Sample high-frequency survey

The protocol and supporting documents are included as supplementary materials to this report.

VI. Data Dashboard

Requests from Malawi based field staff highlighted the importance of generating findings that could be readily accessed by program staff and monitoring and evaluation staff. The consultant responded to this need and worked with the program staff to develop and field test a user-friendly interface allowing for data visualization in real time. The excel based dashboard allows CRS and other stakeholders to monitor shocks incidence and subjective welfare perception at the sub-district (GVH) level, facilitating targeted interventions. It is uplinked to the CommCare dashboard, allowing live updates of ongoing shocks. An example of the Dashboard including only a subset of shocks is included as Figure 12:

Figure 12. A subset of shocks reported in the July, 2016 HFS and coalated in the dashboard[7].

		Shocks Recorded in Monthly Survey								
Level	**Location**	**Crop disease or pest**	**Drought**	**Assistance ending**	**Fall in crop prices**	**Flood**	**Death**	**Illness**	**Increase in food prices**	**Other**
District	Chikwawa	24%	71%	4%	5%	27%	8%	24%	33%	7%
TA	Ngabu	30%	72%	2%	4%	19%	4%	22%	22%	8%
	Lundu	17%	74%	3%	5%	39%	15%	20%	24%	4%
	Makhuwira	24%	65%	6%	3%	17%	6%	33%	62%	12%
	Maseya	28%	96%	4%	12%	16%	0%	28%	24%	12%
GVH	Kalulu	23%	74%	3%	0%	36%	8%	21%	18%	3%
	Nyambalo	2%	74%	2%	14%	10%	5%	43%	93%	5%
	Champhanda	36%	79%	11%	4%	14%	0%	18%	21%	50%
	Mpama	39%	41%	4%	0%	22%	0%	28%	37%	17%
	Jombo	69%	85%	0%	2%	4%	4%	25%	21%	17%
	Bestala	61%	89%	5%	11%	95%	18%	13%	34%	3%
	Chagambatuka	16%	89%	0%	0%	0%	0%	3%	82%	0%
	Kanyimbiri	3%	78%	0%	3%	33%	6%	33%	33%	3%
	Sabvala	53%	38%	24%	3%	50%	24%	62%	79%	0%
	Malikopo	10%	73%	2%	2%	2%	2%	27%	27%	2%
	Biyasi	22%	83%	9%	4%	26%	4%	52%	43%	17%
	Biliati	0%	85%	3%	0%	85%	0%	13%	13%	3%
	Chapomoko	19%	64%	2%	2%	2%	2%	29%	24%	21%
	Mafale	6%	68%	1%	6%	11%	21%	21%	24%	3%
	M'bande	24%	100%	5%	10%	5%	0%	33%	29%	14%
	Sekeni	25%	69%	0%	0%	38%	6%	13%	6%	6%

As part of the community outreach efforts, up to date color copies of this dashboard were disseminated to community leaders, including traditional chiefs and heads of Village Development Committees (VDCs). They proved very receptive to the data, confirming its validity for their community. Follow-up visits confirmed that in some cases the VDCs used this data as an advocacy tool, working with local government officials and NGOs to highlight the ongoing issues.

[7] The full MIRA dashboard also includes the following shocks: business failure, fire damage, household breakup, livestock disease/death, strong wind, and theft.

VII. Dissemination

External dissemination of the MIRA findings intended to share the innovative methodology pioneered by the CRS team, as-well as highlight the insights that could be gained. As part of this deliverable, various aspects of the project were presented to audiences in three different venues:

ICT4D, Hyderabad

The first dissemination event was a presentation held at the ICT4D conference in Hyderabad, India on May 18th, 2017.

The 20 min presentation focused on the technical aspect, including the use of smartphones to collect high frequency data and upload them to the cloud. It highlighted how this allowed for real-time updating of the information available, information that could be disseminated using tools like the dashboard. Finally, it gave a preview of how machine learning algorithms could be used for predictive purposes.

The audience was a mix of practitioners in both development and humanitarian relief, as-well as technical people interested in the underlying methodology.

AAEA Conference, Chicago

The 2nd dissemination even was held in Chicago as part of the Agricultural and Applied Economist Association Annual Meeting, held on July 31st .

This 15 min presentation focuse on the underlying economics behind the paper, notably how high frequency data could be used to measure resilience in innovative ways. It included three components:

a) A descriptive component, looking at shock incidence and their correlation with resilience capacities.
b) An inferential component, seeking to identify whether there was a causal link between assistance received and reduced drought persistence.
c) A predictive component, using Machine learning algorithms to calculate the future incidence of drought and compare it to the actual incidence.

The audience was largely composed of economists, who asked questions related to the concept of resilience and various potential measurement frameworks.

MIRA Workshop and Seminar, Malawi

The 3rd dissemination was a two day event held in Lilongwe, Malawi, from August 7th to 8th.

The first day was a half-day technical workshop geared towards implementing staff from the Governemnt of Malawi and partner organization . After a brief introduction to the resilience framework, it helped them work through the protocol, discussing ways in which it might be adapted to their organization's needs. The 2nd day was a shorter seminar aimed at senior activity and policy managers, highlighting results and insights gained.

The most valuable feedback from the audience was to focus on food security outcomes.

Appendices:

Appendix A: Supplementary Materials

A folder of supplementary materials were submitted with this report. A brief description of those materials follows and the file names are in quotes.

Survey Items

- “MIRA Baseline Paper Survey.docx”
- “Mira _codebook.xlsx”
- “MIRA High Frequency Survey
- “HF BL codebook.xlsx”

Dashboard

- “MIRA Dashboard (anonymized).xlsx”

MIRA Protocol

- “MIRA Study Protocol.docx”
- “MIRA Training Manual.docx”

MIRA Dissemination

- “MIRA Workshop Agenda.docx”
- “MIRA Workshop Presentation Part 1.pdf”
- “MIRA Workshop Presentation Part 2.pdf”
- “ICT4D_Conference_Collecting_High_Frequency_Data_for_Improved_Interventions.pdf”
- “Measuring_Resilience_in_Malawi (AAEA_Presentation).pdf”

Cleaned Datasets

- “MIRA_HF_Labeled.dta”
- “baseline.zip”
- “endline.zip”