MIRA – Measuring Resilience in Malawi

UBALE (Unite in Building and Advancing Life Expectations) Project - Malawi

WHY MIRA?

The Measuring Resilience in Malawi Project (MIRA) has devised a data collection and analysis scheme to measure and predict resilience among households prone to food insecurity one to two months out. Data prediction is achieved with machine learning. The goal is to be more proactive in identifying who is the most food insecure and respond in advance. **Machine learning** is a form of artificial intelligence (AI) that automatically learns and improves from experience. MIRA was implemented as part of UBALE, a USAID funded project that serves disaster-prone districts in Malawi in order to better measure the shocks and stresses for program beneficiaries. Through measuring indicators of resilience, CRS and partner, Cornell University, are able to know the greatest shocks to food security. By surveying households on a consistent basis, CRS receives robust data to predict which households would be at the greatest risk using machine learning. Identified shocks include drought, flood, illness, and crop disease. Resilience capacitation lies with characteristics such as land and livestock assets and social status.

QUICKFACTS	
Project Type	**Resilience Measurement**
Data Collection Software	**CommCare**
Project location	**Chikwawa, Nsanje, Blantyre- Malawi**
# of households surveyed	**2,292**
Timeframe	**2016 - 2017**
Partners	**Charles H. Dyson School of Applied Economics and Management at Cornell University**

HOW DOES MIRA WORK?

In order to effectively capture large scale household and individual data for resilience analysis, CRS has devised the MIRA Protocol. To start, household data is collected through two stages. First, a baseline survey is administered with a follow up survey on an annual or bi-annual basis, collecting demographic, livelihood, economic, program participation, and shock data. Second, a different follow up survey that focuses on shocks is administered to the same survey recipients on a monthly basis. The dynamics of the constant follow up survey allows MIRA to receive accurate and high frequency results for resilience analysis. The collected data is linked to a live CommCare database for constant and easy visualization.

WHO AND WHAT IS SURVEYED?

Surveyed households were selected based on their location on flood exposure maps. Relative to flood-risk data available from the Dartmouth Flood Observatory, houses were selected depending upon proximity to hired enumerators and randomized selection. Enumerators are community members located in the field and paid per survey, substantially cutting traditional monitoring costs to less than the cost of fuel. Once surveyed, the results are organized according to flood risk groups and three resilience variables:

1. Well-being outcomes

A measurement of welfare through a coping strategies index (a measurement of coping mechanisms such as borrowing food, ganyu (informal off-farm labor), eating less preferred food, reducing meals, and begging) and hunger score. A lower welfare value implies lower vulnerability to shocks and vice versa.

2. Shocks experienced (with adverse effects)

Monthly follow ups allow households to report new and continued shocks to measure persistence, with drought being the most frequent shock.

3. Capacities and characteristics (that may prevent adverse effects)

Characteristics that increase the probability of recovering from a shock include land assets, livestock, flood plain location, secondary houses, age, gender, education, and disability recordings of the head of house. The MIRA study is also able to determine whether UBALE interventions may contribute to increased resilience to shocks.

After this data is collected, each household is provided with a quantified estimation of their probability of experiencing a shock. This number is then regressed against the resilience characteristics to provide a vulnerability and resilience approximation for future decision making.

DATA ANALYSIS FOR RESULTS

The figure below (Figure 1) reveals an example of monthly recorded data from 2016. This dashboard provides easy visualization for stakeholders to perceive shocks according to region and time period. This snapshot is just a subset of a larger dataset linked to CommCare which provides ongoing, live updates of shock information. CommCare is the platform of choice as it allows for dynamic survey functionalities and Data is analyzed through a series of machine learning algorithms. These algorithms take into account baseline indicators captured from the first survey and the continuous indicators observed from monthly follow ups. Using this information, the algorithm is able to predict the following month's probability of food insecurity for more targeted preparations and intervention included as part of the United in Building and Advancing Life Expectations (UBALE) program.

The households that are resilient are not always the ones that you would expect. The ones that can bounce back from drought have land both inside and outside the floodplain. The households that are least resilient to falling ill and domestic shocks are households that are headed by women.

New shocks can be identified and added to surveys almost real-time allowing the program to adapt quickly to new shocks. Predicting food insecurity with machine learning was launched in one district in Malawi and is being expanded to two more districts

		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%

Figure 1: A subset of shocks reported in the July 2016 HFS and collated in the dashboard. TA = traditional authorities. GVH = village area.