Evaluating the Impact of Humanitarian Aid on Food Security

Jordi Cerdà-Bautista[1], José María Tárraga[1], Vasileios Sitokonstantinou[1] and Gustau Camps-Valls[1]

1. Image Processing Laboratory, Universitat de València, València, Spain

Motivation

Situation in Somalia:

*"A total of **6.5 million** people face acute food insecurity amid the driest conditions in 40 years (...) A total of **1.84 million** children under 5 face acute malnutrition. (...) over **1.5 million** drought-driven displacements since the start of the climate crisis."*

- World Food Programme, Jan 2023

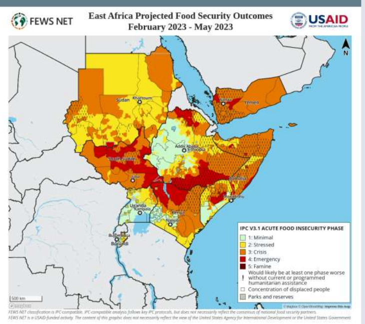

Fig. 1: Image credits to: FEWS NET, https://fews.net

Main Goal

- Quantify the effect of cash interventions on food insecurity.
- We need causal inference to answer this question.
- We rely on observational data.
- Potential Outcomes Framework:
  - Average Treatment Effect (ATE)

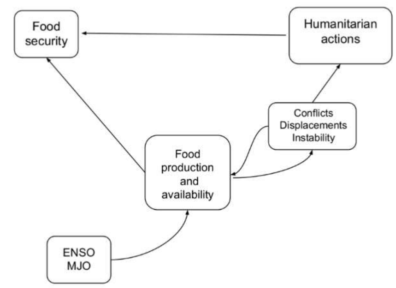

Fig. 2: Assumed graph of the food security dynamic system.

Data and Methods

We focus on Somalia

- Monthly data (2016 - 2022) at a district level.
- Available data for 57 districts.
- Data aggregated per district per year.

	Variables	Data Sources
Target	Global Acute Malnutrition (GAM)	FSNAU
Treatment	Cash Interventions	FSNAU
Climate	ENSO	WMO
	Standardized Precipitation Index (SPI)	CHIRPS
Socio - Economic	Food Prices	FSNAU
	Water Prices	FSNAU
	Livestock Prices	FSNAU
	Sorghum Production	FSNAU
	Drought IDPs	UNHCR PRMN
	Fatalities (Conflict)	ACLED
	Somalia Districts	UNDP
	Population	UNFPA

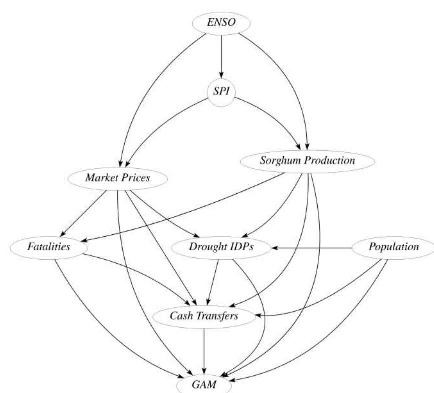

Fig. 3: DAG representing the food security system in Somalia.

- **Approach**: ATE Estimation

$$\text{ATE} = \mathbb{E}[Y|do(T=1)] - \mathbb{E}[Y|do(T=0)]$$

- Adjustment Set (back-door criterion):

Z = {Market Prices, Sorghum Production, Fatalities, Drought IDPs, Population}

- Estimations are statistically significant if p-values < 0.05
- Refutation Tests:
  - Placebo Treatment
  - Random Common Cause (RCC)
  - Random Subset Removal (RSR)

Cause-Effect Estimation

ATE Estimation Methods:

- Linear Regression
- Distance Matching
- Inverse Propensity Score Weighting
- T-Learner
- X-Learner

arXiv Link

- Treatment binarization:

Threshold	Control	Treated	Total
35 percentile	162	205	367
50 percentile	162	112	274
75 percentile	162	75	237
90 percentile	186	38	224

None of the results are statistically significant:

- Data scarcity.
- Complexity of the real problem.
- Need for enhanced and broader data collection.
- Country-level DAG may not capture localized impacts.

Open Questions

- Expert knowledge is needed. Can we define a better causal graph?
- Data quantity is very limited. Are there additional data sources available?
- Is there an alternative way to define the treatment?

Next Steps

- Identifying more suitable treatment variables.
- Refining the causal graph with domain experts.
- Conditional Average Treatment Effect (CATE): Insights on the spatio-temporal heterogeneity of impact of interventions.

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 Contact: jordi.cerda@uv.es Twitter: @isp_uv_es