Periodic Variations in Malnutrition Indicators

Evidence from SMART Surveys in the Sahel

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BACKGROUND | Malnutrition data are essential to assess the severity of a humanitarian crisis and guide decision-making for aid assistance. However, in low-income countries, data is frequently missing or inconsistent, limiting the ability to establish spatiotemporal variations both between and within years. Improved understanding of these trends can contribute to our knowledge of the drivers of malnutrition and how those drivers might vary over time and space.

Fig 1: Sahel Belt and Study Countries

METHODOLOGY | SMART survey records from 1995-2015 were abstracted from 13 countries across the Sahel (*Fig 1*). Average Z scores for height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height (WHZ) were compiled. External data on conflict, natural disasters, and environmental drivers (temperature, precipitation, and vegetation) were aggregated to spatially and temporally match SMART data. These data sources are summarized in *Table 1*, and key properties are described by country in *Table 2*.

Table 1: Data Sources & Properties

Data Source	Variables	Spatial Resolution
SMART	HAZ, WAZ, WHZ	Up to 2nd level administrative division
EM-DAT[1]	Natural Disasters	Up to 2nd level administrative division
ACLED[2]	Conflict Events	City, Town, Village or Locality
CHIRPS v2.0[3]	Precipitation	0.05° x 0.05°
MERRA-2[4]	Surface Temperature	0.625° x 0.5°
MODIS[5]	Surface Temperature	0.05° x 0.05°
NASA VIP30 Vegetation Index[5]	NDVI	0.05° x 0.05°

1: "EM-DAT: The Emergency Events Database – Université catholique de Louvain (UCL) – CRED, – www.emdat.be, Brussels, Belgium .
2: Raleigh, C. et al. 2010. Introducing ACLED-Armed Conflict Location and Event Data. Journal of Peace Research 47(5) 651-660.
3: Funk, C. et al. "The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes". Scientific Data 2, 150066. doi:10.1038/sdata.2015.66 2015.
4: Global Modeling and Assimilation Office (GMAO)(2015), MERRA-2 tavgM_2d_lnd_Nx: 2d,Monthly mean,Time-Averaged,Single-Level,Assimilation,Land Surface Diagnostics V5.12.4,Greenbelt, MD, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC). 10.5067/8S35XF81C28F
5: Wan, Z., Hook, S., Hulley, G. (2015). MOD11C3 MODIS/Terra Land Surface Temperature/Emissivity Monthly L3 Global 0.05Deg CMG V006 [MOD11C3]. NASA EOSDIS LP DAAC. doi: 10.5067/MODIS/MOD11C3.006
6: Didan, K., Barreto, A. (2016). NASA MEaSUREs Vegetation Index and Phenology (VIP) Vegetation Indices Monthly Global 0.05Deg CMG [VIP30]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MEaSUREs/VIP/VIP30.004

VALUE | Standardized Monitoring and Assessment of Relief and Transitions (SMART) surveys provide a methodologically consistent source for anthropometric measurements in nutrition emergencies. However, these data and their relationship with conflict, natural disasters, and environmental drivers (temperature, precipitation, and vegetation), have not yet been examined. A better understanding of this relationship is imperative to establish spatiotemporal patterns in malnutrition, and study the predictive capacity of external indicators in characterizing crisis severity.

Table 2: Summary of Nutrition Indicators (HAZ, WAZ, WHZ) from SMART Surveys

Country	Number of Surveys	Number of Children	Average			Trend		
			HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Burkina Faso	45	38,874	-1.70	-1.45	-0.69	0.04*	0.00	-0.03*
Cameroon	8	5,417	-1.85	-1.32	-0.35	0.06***	0.00	-0.05***
Central Afr. Republic	58	36,443	-1.69	-1.21	-0.34	-0.01	0.01	0.02***
Chad	148	97,511	-1.55	-1.53	-0.94	0.06***	0.06***	0.04***
Eritrea	2	1,622	-1.56	-1.37	-0.69	2.26	-0.64	-2.86**
Ethiopia	190	135,276	-1.50	-1.34	-0.73	0.07***	0.05***	-0.00
Mali	14	10,968	-1.20	-1.22	-0.76	-0.00	0.18***	0.26***
Mauritania	53	34,484	-1.14	-1.08	-0.63	-0.04**	-0.06***	-0.05***
Niger	30	24,904	-1.86	-1.65	-0.86	-0.07***	0.01	0.07***
Nigeria	105	64,539	-1.76	-1.40	-0.55	0.64***	0.41***	0.04***
Senegal	7	8,445	-1.12	-1.22	-0.85	1.92*	2.18**	1.57*
South Sudan	124	87,578	-0.57	-1.09	-1.12	-0.04***	-0.03***	-0.01*
Sudan	113	94,721	-1.25	-1.38	-0.97	-0.06***	-0.02***	0.02***

Significance: p < 0.001: ***, p < 0.01: **, p < 0.05: *

PERIODICITY & CORRELATION | Environmental variables display seasonal periodicity and trends; however, SMART surveys are only conducted intermittently, often during humanitarian emergencies. In the absence of regular data, correlations between nutrition outcomes and environmental, conflict, and natural disaster covariates, is considered evidence of periodicity. Preliminary findings indicate large spatial variations across and within the Sahel Region in prevalence of key malnutrition indicators: underweight, wasting, and stunting (of 20-36%, 8-19%, and 18-47%, respectively). On the regional scale, relationship between climatic variables and nutritional indicators varies drastically. Comparing Chad with South Sudan (*Table 3*) indicates the varying effects of environment on nutrition outcomes.

Table 3: Spearman Correlations of Environmental and Nutrition Indicators

	Underweight		*Wasting*		*Stunting*	
	CHAD	SOUTH SUDAN	CHAD	SOUTH SUDAN	CHAD	SOUTH SUDAN
NDVI	0.06***	-0.07***	0.05**	-0.05***	0.01	0.05***
Precipitation	0.02**	-0.08***	0.01	-0.07***	0.05**	0.06***
Temperature	0.02***	0.09***	-0.04*	0.02**	-0.01	-0.03**

Significance: p < 0.001: ***, p < 0.01: **, p < 0.05: *

CASE STUDY: CHAD | To develop the analytical framework for the full Sahel dataset, we have started by first looking more in depth into the Chad data. A seasonal analysis of wasting (aggregating wasting on month over the total sample: 1994-2014). The data shows that the peak of wasting is in May which is the end of the dry season/beginning of the rains (*Fig 2*). More so, wasting declines during the rain season. This goes against the common assumption that the prevalence of wasting increases throughout the rainy season, peaking right before harvest and thus corresponding to trends in food insecurity.

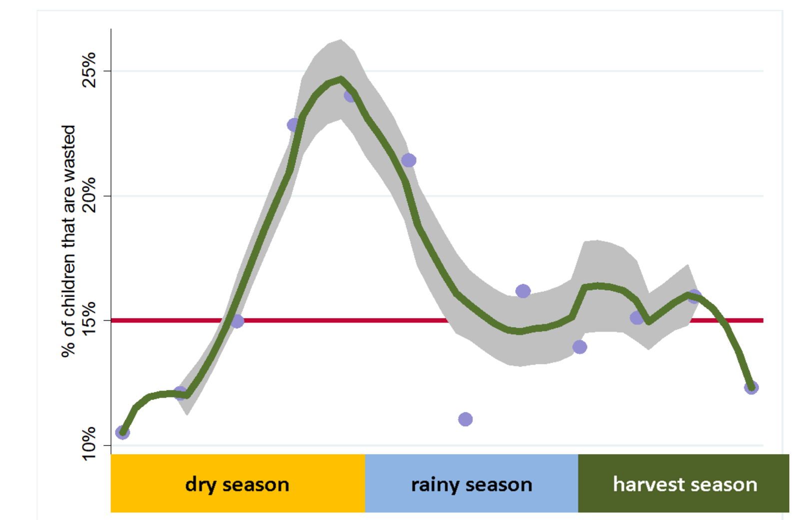

Fig 2: Percentage of Children Wasted by Season, Chad

The influence of environmental and sociopolitical hazards on nutrition indicators in this study can be modeled as:

Nutrition Indicators = *f*(age, sex, — *individual factors*
conflict, IDP camp, town, — *sociopolitical factors*
natural disasters, temperature, NDVI, rainfall) — *environmental factors*

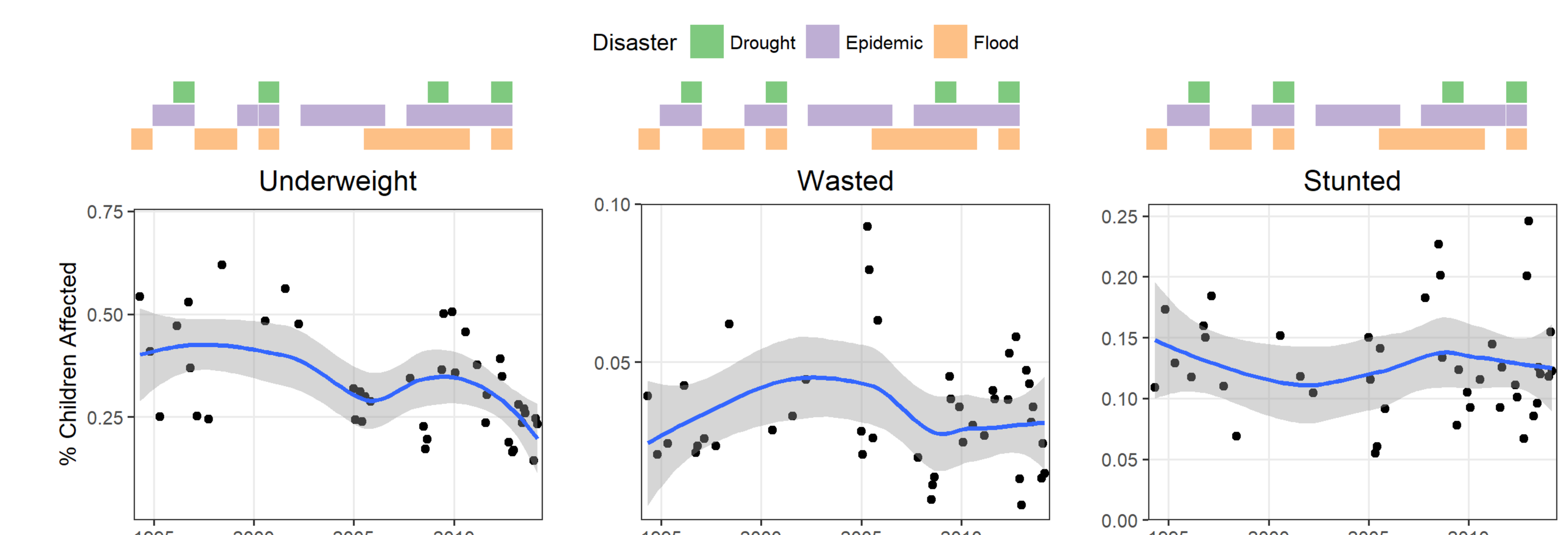

Fig 3: Natural Disasters & Percentage of Affected Children by Nutrition Status, Chad

NEXT STEPS

- Model periodicity and lagged behavior of environmental variables and conflict events through harmonic regression
- Include additional publicly available datasets, such as infrastructure and population density
- Disaggregate data by sex and age due to differential pathways to malnutrition across gender and age group (6-23 vs 24-59 months)

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