

Drought in Brazil, 2023



Flooding in Libya, 2023



Hurricane Ian in USA, 2022



(top row)

Edmar Barras / AP

Jamal Alkomaty / AP Photo

Ricardo Arduengo / AFP/Getty Images

(bottom row)

Nicolas Economou / Reuters

Abdul Majeed / AFP/Getty

Thoko Chikondi / Associated Press



Heatwave-driven wildfires in Greece, 2023



Flooding in Pakistan, 2022



Cyclone Freddy in Malawi, 2023

Effects of Extreme Weather on Global Food Security and Nutrition

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Dissertation Defense
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Thesis Committee



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Objectives

Quantify how extreme weather affects food systems

- Aim 1: Food Prices
- Aim 2: Child Wasting
- Aim 3: Famine Phase Prediction

Dissertation overview

Five types of extreme weather events:



Aim 1: Food Prices

- Changes in global retail food prices (FEWS, GIEWS, VAM)
- Changes to price seasonality



Inform policies to make nutritious foods affordable and improve supply chain resilience to climate change

Aim 2: Child Wasting

- Baseline seasonal wasting (SMART, DHS, MICS)
- Changes to seasonal wasting pattern



Improve understanding of seasonal wasting and expectations around seasonal extreme weather

Aim 3: Famine Phase Prediction

- Probability of underpredicting critical phase transitions (FEWSNET, IPC, CH)
- Changes to underprediction probabilities



Improved prediction accuracy and decision-making during / following extreme events

Key findings and policy relevance

- Retail food prices are resilient to extreme weather
 - Prioritize provision of Fruits and Vegetables during storm months
 - Demand reduction of breads and cereals across several extreme events can point to multidimensional intervention opportunities
- Wasting is seasonal and spatially heterogeneous
 - Establish baseline seasonality from available data
 - Need climatological representativeness in survey design and nutrition surveillance
- Mixed preliminary evidence around extreme weather famine phase prediction accuracy
 - Probabilistic findings can be incorporated in famine forecasting to quantify uncertainty



Motivation and Background

Current knowledge and gaps

- Retail food prices
 - Focus on staples (maize, rice, wheat) and crisis periods: 2008 and 2011 (Headey & Fan, 2008; Bellemare, 2014), Covid-19 (Narayanan & Saha, 2021; Akter, 2020; Wallingford et al, 2023)
 - Main pathways: production losses (Aker, 2008); physical barriers (Thapa and Shively, 2016)
 - Retail price seasonality (Bai et al, 2019) and weather shocks (Brown & Kshirsagar, 2015; Cedrez et al., 2020)
- Child wasting
 - Rapid response of weight and WHZ to shocks (Chotard et al., 2010; Kinyoki et al., 2017; Isanaka 2021)
 - Precipitation shocks and vegetation anomalies associated with greater wasting and stunting (Cooper et al, 2019; Phalkey et al., 2015; Shively et al., 2015; Mulmi et al., 2016; Darrouzet-Nardi & Masters, 2017)
 - Reexamination of hypothesis that greatest hunger occurs pre-harvest (Grellety et al, 2013; Saville, 2021)
 - Two peaks of wasting in arid unimodal drylands of sub-Saharan Africa (Venkat et al, 2023)
- Food security and famine early warning
 - Prediction accuracy, skill, missed transitions (Choularton & Krishnamurthy, 2019; Krishnamurthy et al, 2020; Backer & Billing, 2021)
 - Probabilistic framework evolving due to short time series

Measuring extreme weather

- Plurality of measures of events, shocks, and dimensions of extreme weather
- Relevant criteria: remotely sensed, long time series available, high spatial resolution
- Operational definitions
 - **Heatwave:** values exceeding 95th percentile of monthly maximum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
 - **Coldwave:** values below 5th percentile of monthly minimum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
 - **Flood:** values exceeding 95th percentile of 1-month SPI time series, calculated from CHIRPS (Funk et al, 2015)
 - **Drought:** values below 5th percentile of 6-month Standardized Precipitation and Evapotranspiration Index (Dalezios et al, 2017; Vicente-Serrano et al, 2010), calculated from CHIRPS monthly precipitation (Funk et al, 2015) and MOD11C3 v061 monthly temperature (Wan et al, 2021)
 - **Storm:** average radius of storm-force winds or higher, from IBTrACS (Knapp et al, 2010)



Aim 1: How are **food prices**
related to extreme events?

Specific Aim 1: Sub-aims

Aim 1.1: Global evidence
from early warning systems

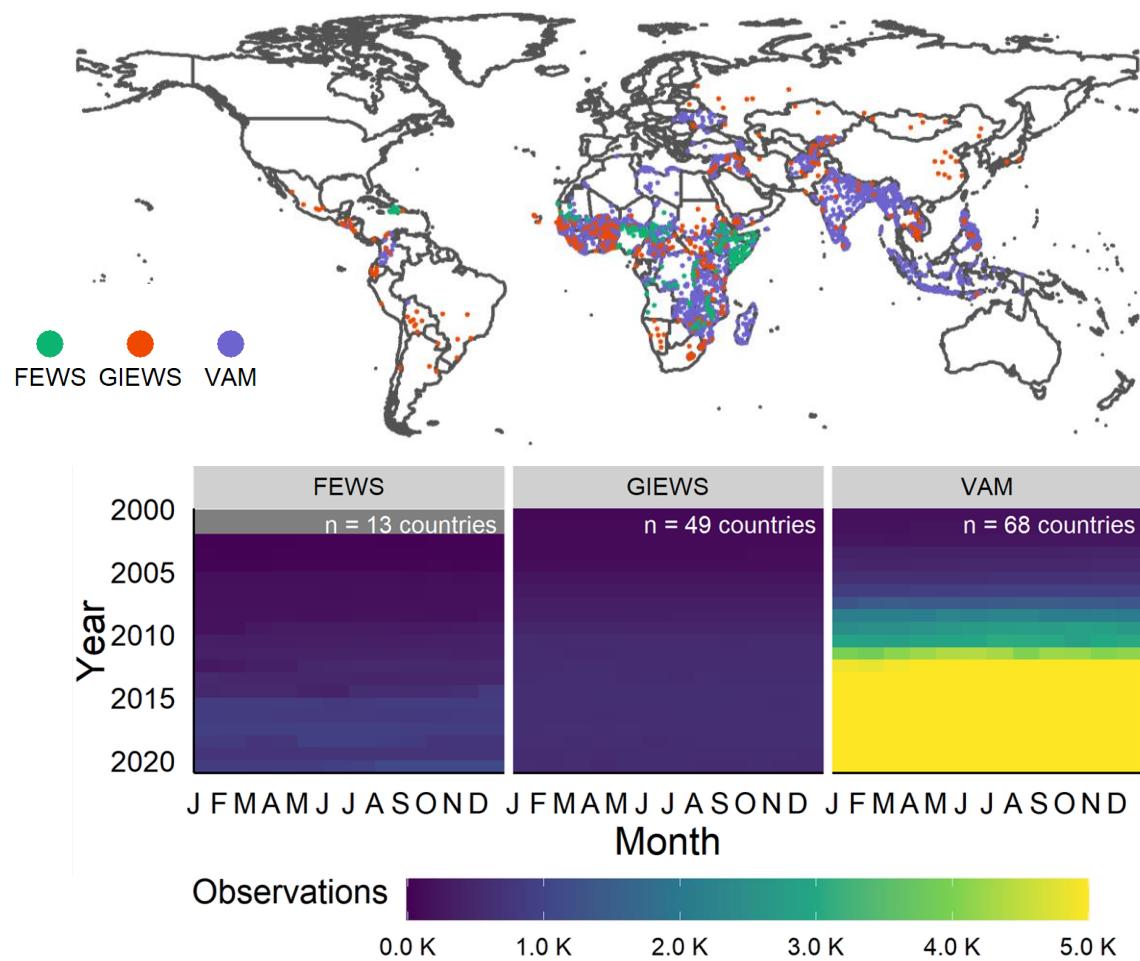
Aim 1.2: Differences across
markets and subregions

Research design

$$P_{ijmy} = \beta_0 + \boldsymbol{\beta_1} Extreme\ Event_{jmy} + \beta_2 FG_i + \\ \boldsymbol{\beta_3} (FG_i * Extreme\ Event_{jmy}) + \\ \beta_4 F_{imy} + \gamma_{jy} + \lambda_{my} + \theta_{jy} + \tau_i + \varepsilon$$

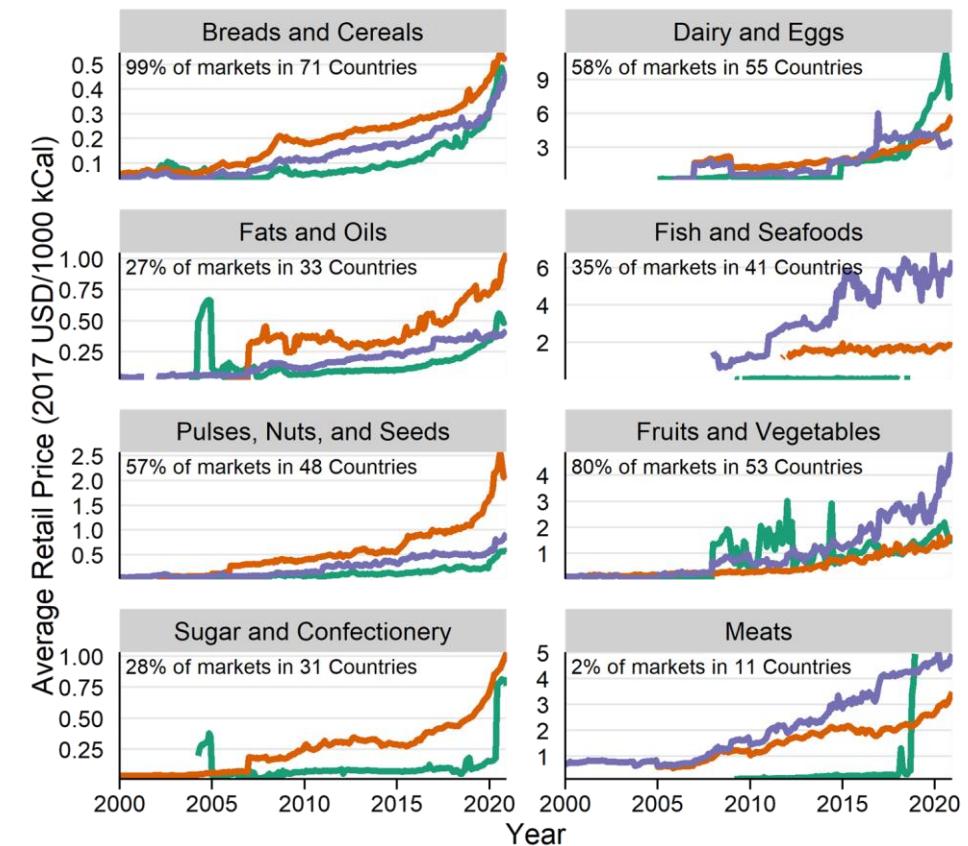
- P_{ijmy} : ln(Price per kg), ln(Price per 1000 kCal)
 - Derived from three global food security early warning systems (FAO GIEWS, USAID FEWSNET, WFP VAM)
- Extreme Event: five types of extreme weather events with independent definitions
- FG_i : one of eight food groups
 - *Non-Perishables*: Breads and Cereals; Fats and Oils; Pulses, Nuts, and Seeds; Sugar and Confectionery
 - *Perishables*: Dairy and Eggs; Fish and Seafood; Fruits and Vegetables; Meats
- Unit of analysis: food item i in market j refers in month m and year y of price observation
- F_{imy} : FAO commodity group price index for food group corresponding to i
- Fixed Effects: market location (γ_j), market-month (δ_{jm}), market-year (θ_{jy}), item (τ_i)

Dataset summary



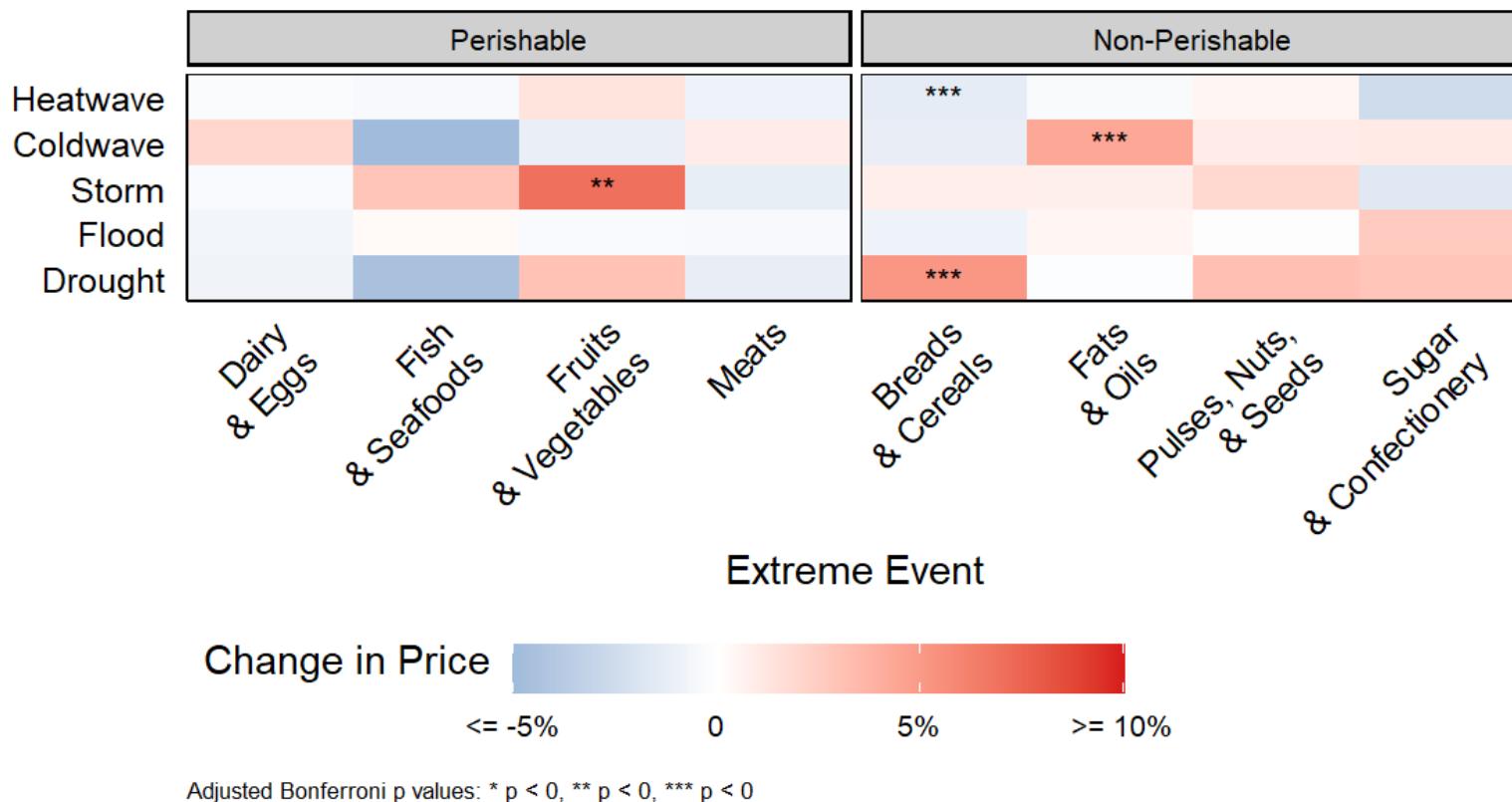
Data Sources: [FAO GIEWS](#), [USAID FEWS](#), and [WFP VAM](#)

Total $n = 1,346,513$
in 2,321 markets in 71 countries



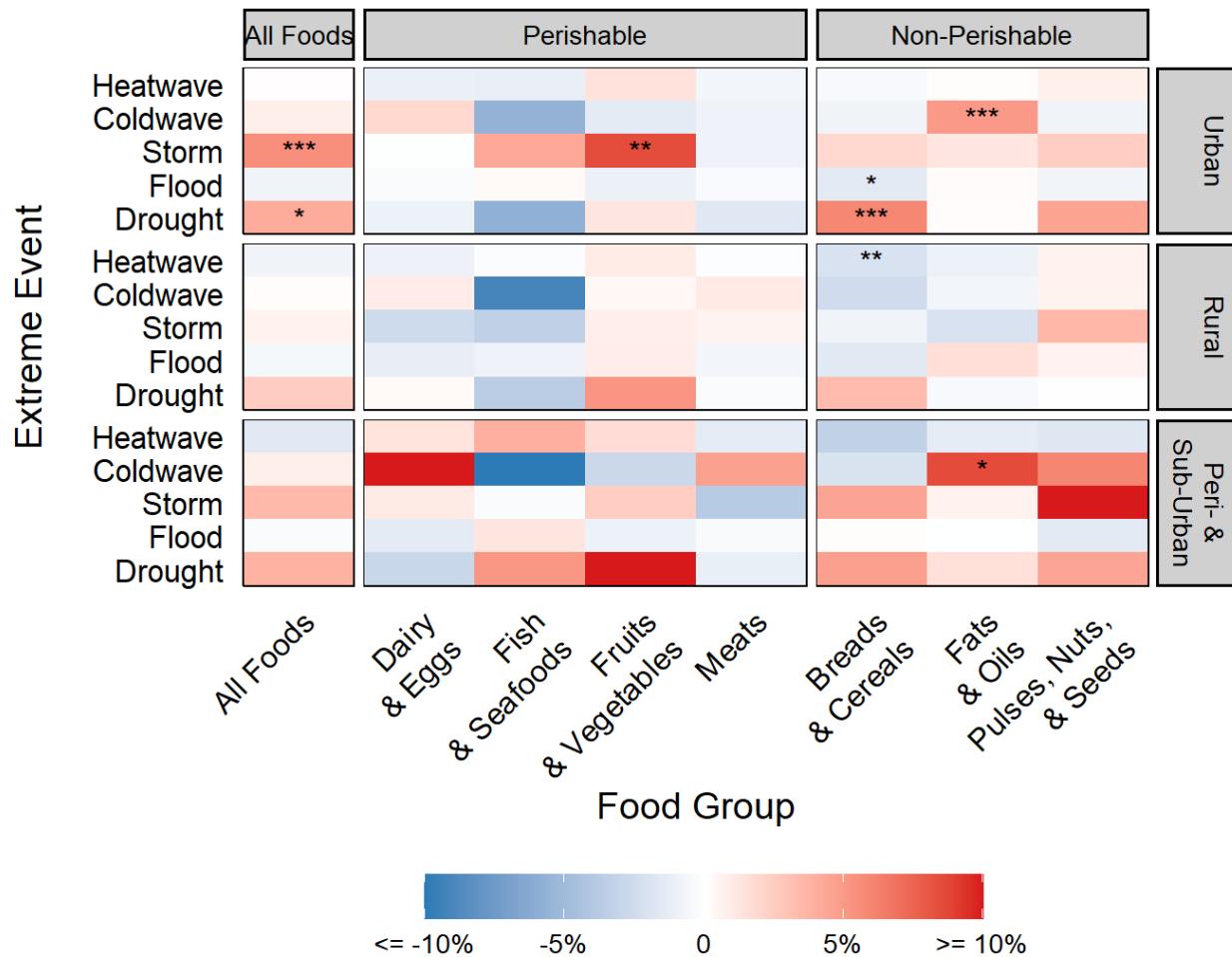
Dataset — FEWS — GIEWS — VAM

Retail prices and extreme weather



- Resilience!
- 7% \uparrow of F&V prices during Storm months
- 5.2% \uparrow in prices of Breads and Cereals during seasonal droughts
- 7% \uparrow in prices of Fats and Oils during coldwaves: residual calendar effects?

Retail prices and extreme weather



- Resilience
- Breads and Cereals
 - 1.9% ↓ during Heatwave months in Rural markets
 - 6.2% ↑ during seasonal drought months in Urban markets
- Fruits and Vegetables
 - 14.2% ↑ during Storm in Urban markets

Results: Retail Price Seasonality



- South Asia
 - Storm response concentrated in rural markets
 - Supply constriction of F&V, demand reduction of Fats and Oils during storms
- Sub-Saharan Africa
 - Demand reduction of Breads and Cereals is dominant response
 - Joint supply constriction of Breads and Cereals and Pulses, Nuts, and Seeds during seasonal droughts

Aim 2: How is **child wasting**
related to extreme weather?

Aim 2: Sub-aims

Aim 2.1: Identify the seasonal baseline pattern of wasting in diverse settings (SMART, DHS, MICS)

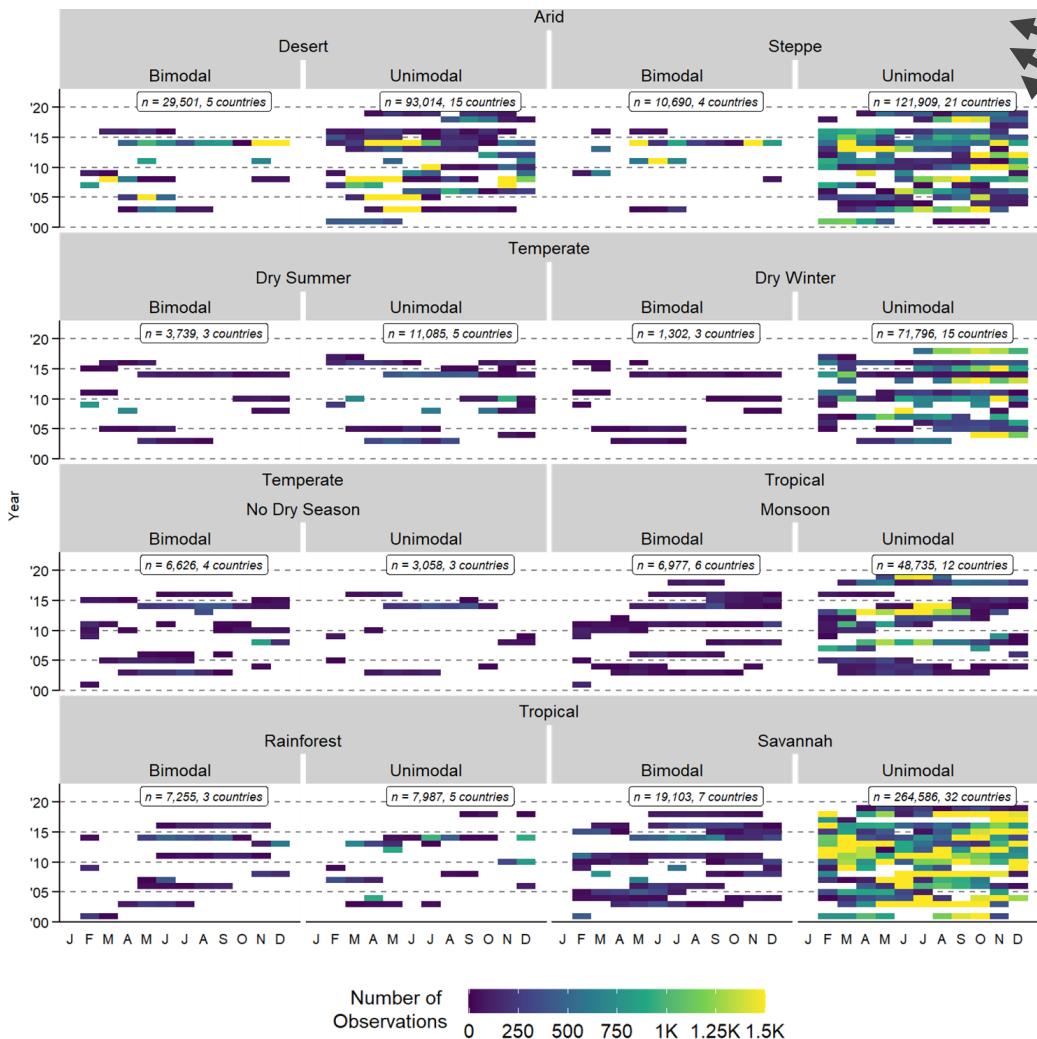
Aim 2.2: Quantify the effects of extreme events on wasting seasonality

Research design

$$\text{Logit}(W_{ijtPK}) = \beta_0 + \boldsymbol{\beta}_1 \text{Seasonality}_{jtPK} + \boldsymbol{\beta}_2 \text{Extreme Event}_{jt} + \varepsilon$$

- W : Wasting, WHZ <= -2
 - Databases of anthropometry in emergency (SMART) and non-emergency settings (DHS, MICS)
- Extreme Event: five types of extreme weather events with independent definitions
 - Limited overlap between survey months and months with extreme weather
- Subgroups
 - K : Dominant Koppen climate class of survey boundary (Beck et al, 2018)
 - P : Dominant precipitation type (unimodal or bimodal) for survey extent (Knoben, 2019)
- Unit of analysis: child i in location j (cluster / administrative boundary) at time t (month and year of survey)
- Seasonality : vector of multiple harmonic terms including linear, quadratic, and cubic trends based on continuous time series of months
 - $\beta_{S1} \sin(2\pi\omega t) + \beta_{C1} \cos(2\pi\omega t) + \beta_{S2} \sin(4\pi\omega t) + \beta_{C2} \sin(4\pi\omega t) + \beta_5 T(t)$
 - Used to extract seasonal characteristics (peak timing, peak value)

Dataset summary

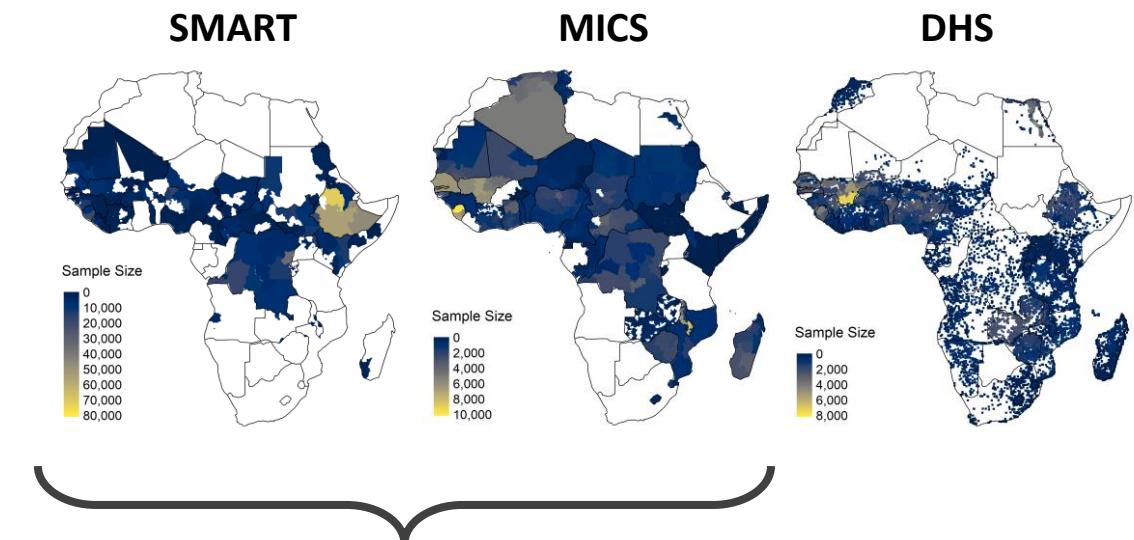


Total $n = 2,591,633$ children
in 49 countries

Level 1 Köppen climate class

Level 2 Köppen climate class:
seasonal precipitation subgroup

Precipitation mode



*Survey boundaries identified via text matching,
adjusted to remove extremely rural areas*

Distribution of significant harmonics

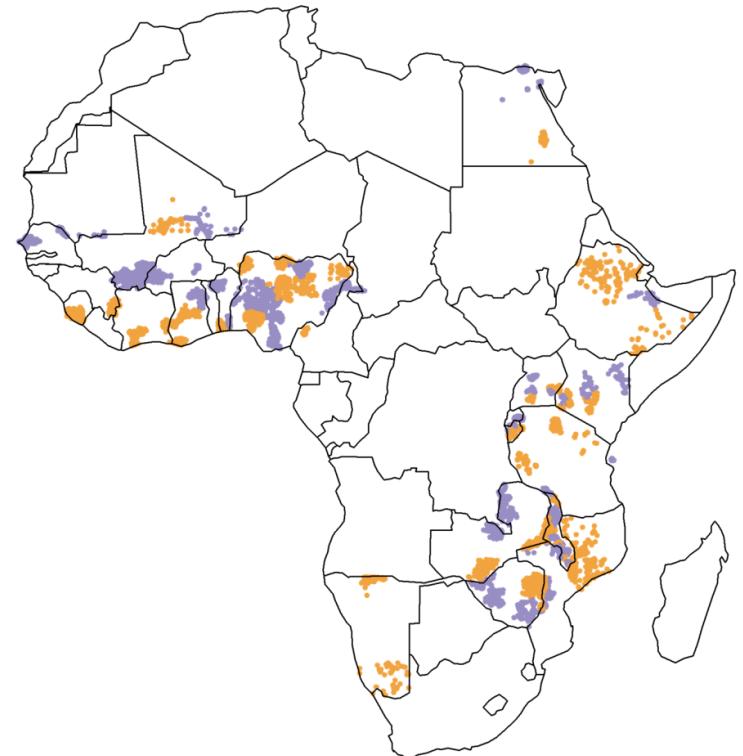
SMART



MICS



DHS



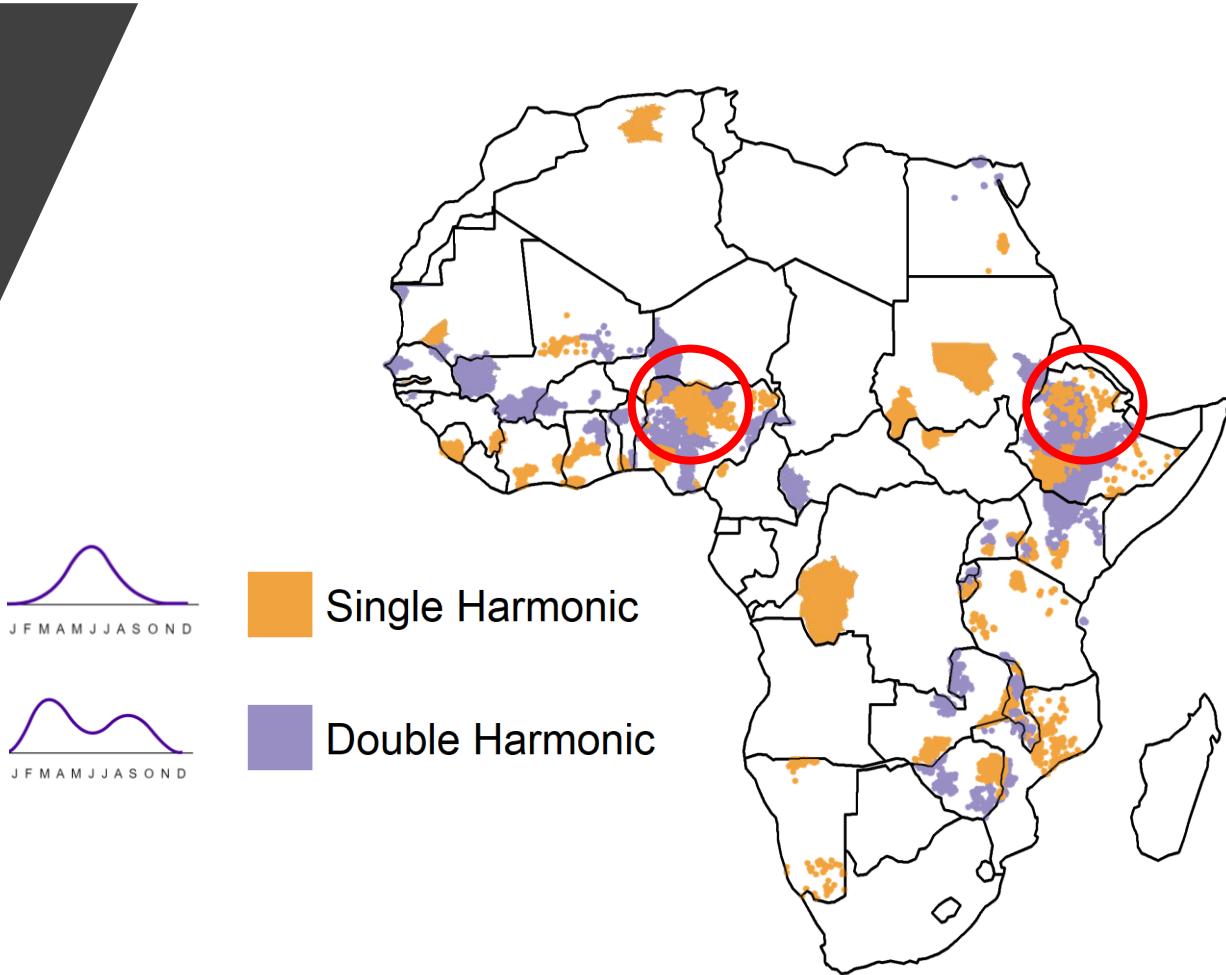
Single Harmonic



Double Harmonic



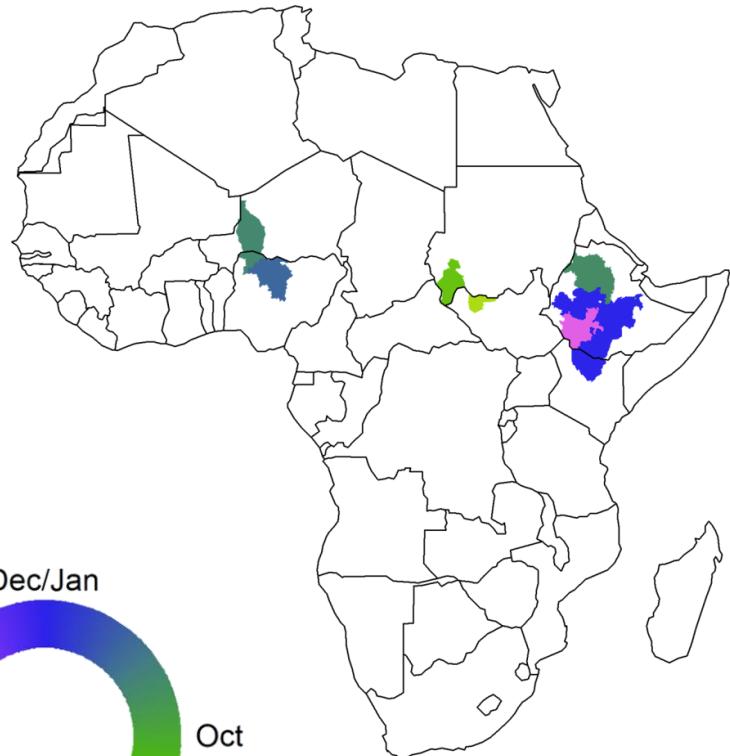
Distribution of significant harmonics



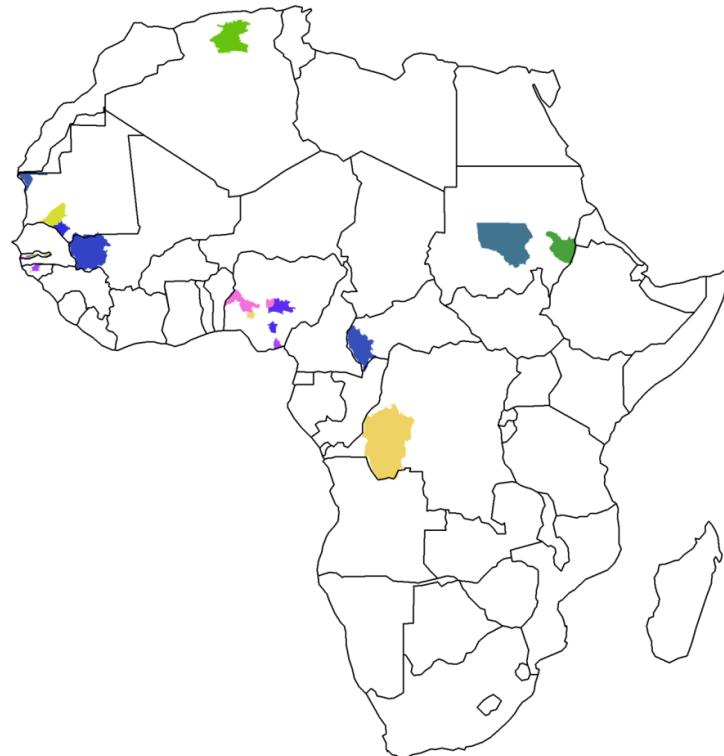
- Mix of significant single and double harmonics indicates heterogeneity
- Datasets can be utilized to validate or refute calculated harmonic patterns
 - E.g. Northern Nigeria and Ethiopian highlands
- Baseline map for other regions to contribute own analyses to fill in the gap

Distribution of peak timings

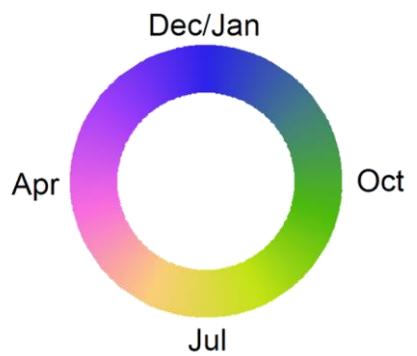
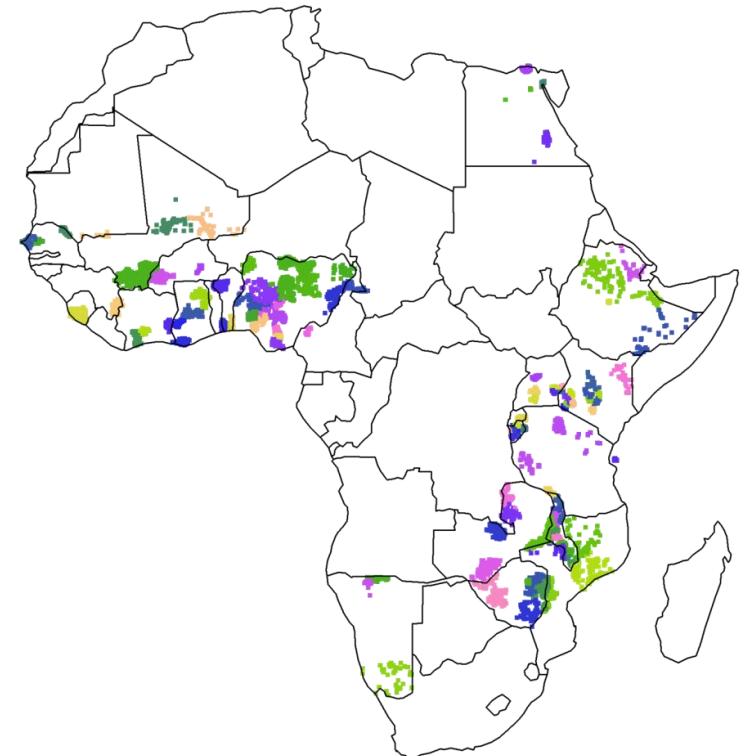
SMART



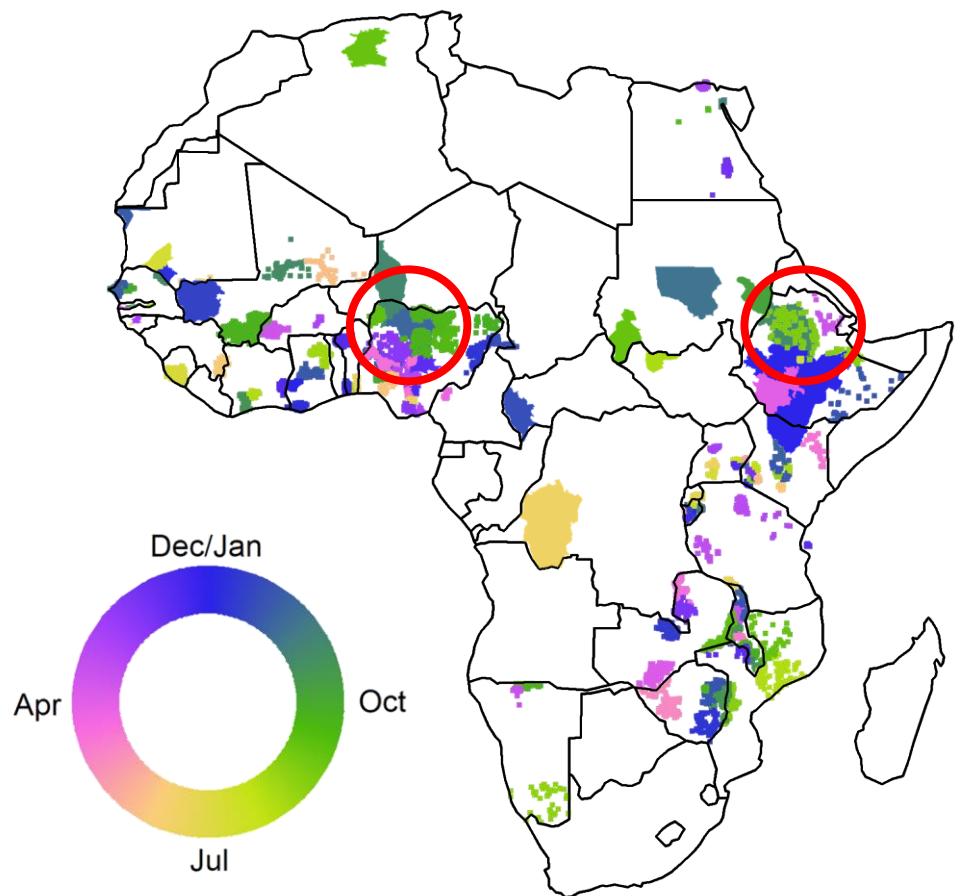
MICS



DHS



Distribution of peak timings



- Heterogeneity in peak timing
- Estimated peak values can help prioritize particular regions for nutrition surveillance
- Magnitudes of wasting may be different, not necessarily actionable

Aim 3: How are **famine phase predictions** associated with extreme weather?

Specific Aim 3: Sub-aims

Aim 3.1: Describe the quality of predictions generated by famine early warning systems

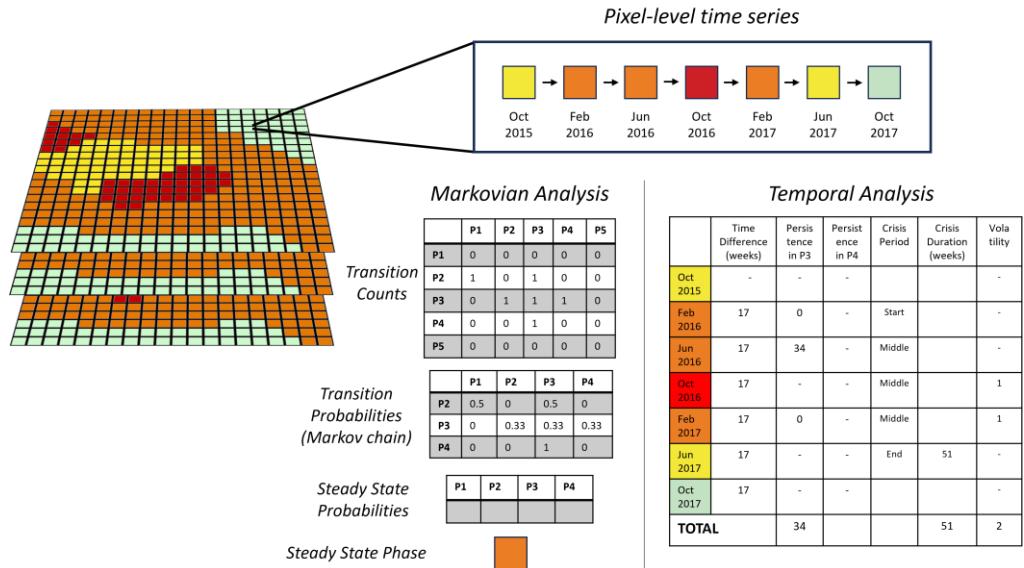
Aim 3.2: Quantify the effect of extreme events on accuracy of predictions generated by famine early warning systems

Research design

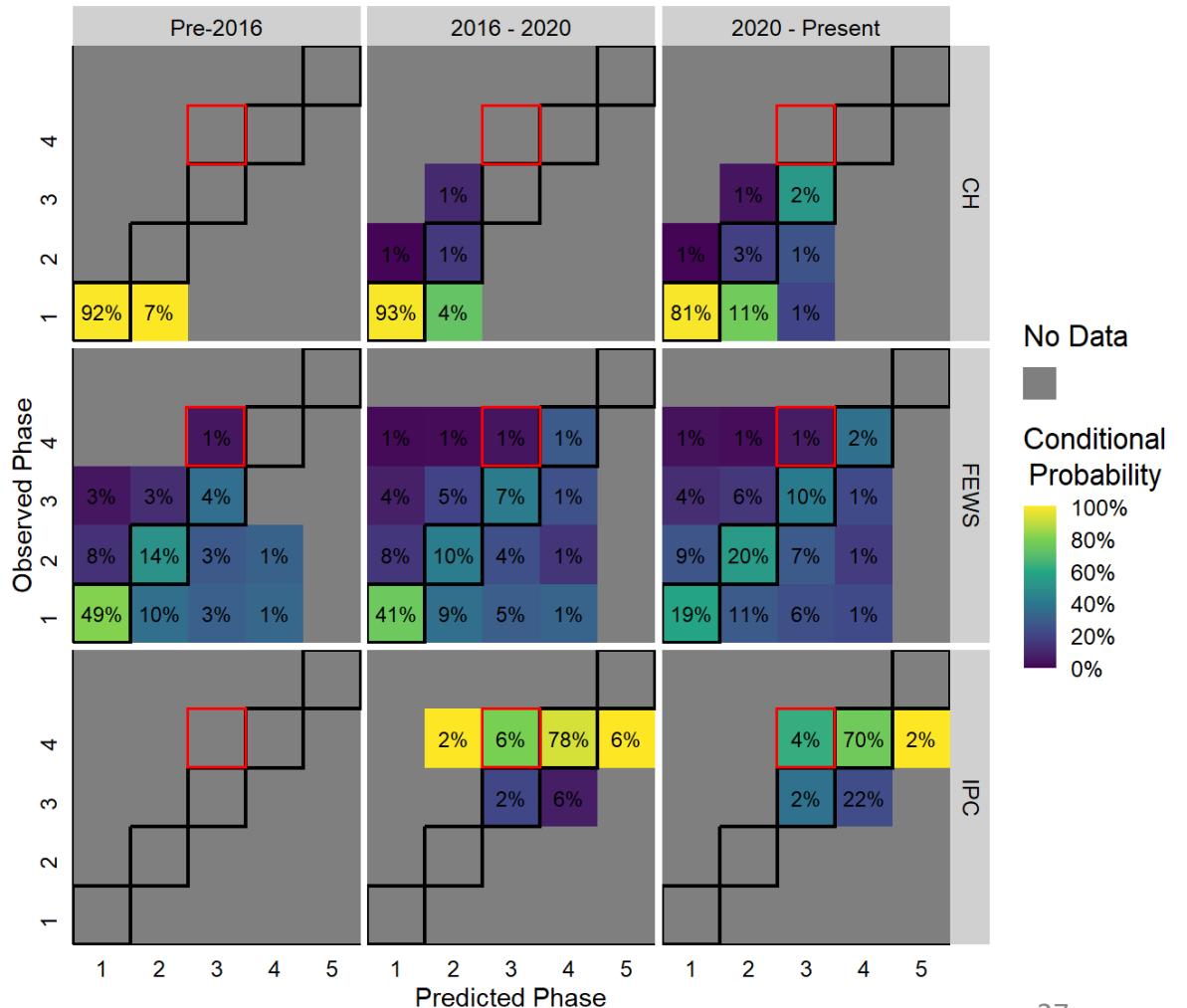
$$P(ST_{j,d,q+1} \perp CS_{j,d,q}) = \beta_0 + \boldsymbol{\beta}_1 Extreme\ Event_{j,t} + \gamma_j + \varepsilon$$

- ST_{q+1} : Short-term phase prediction
 - FEWS: four observations per year before 2016, three after 2016 (Feb, Jun, Oct)
 - CH: three observations per year (Jan, Jun, Sept), West Africa only
 - IPC: limited cyclical observations
- CS_q : Current phase classification
- Extreme Event: five types of extreme weather events with independent definitions
- Fixed Effects: country (γ_j)
- Unit of analysis: pixel j in dataset d observed at time t (month and year comprising quarter q)

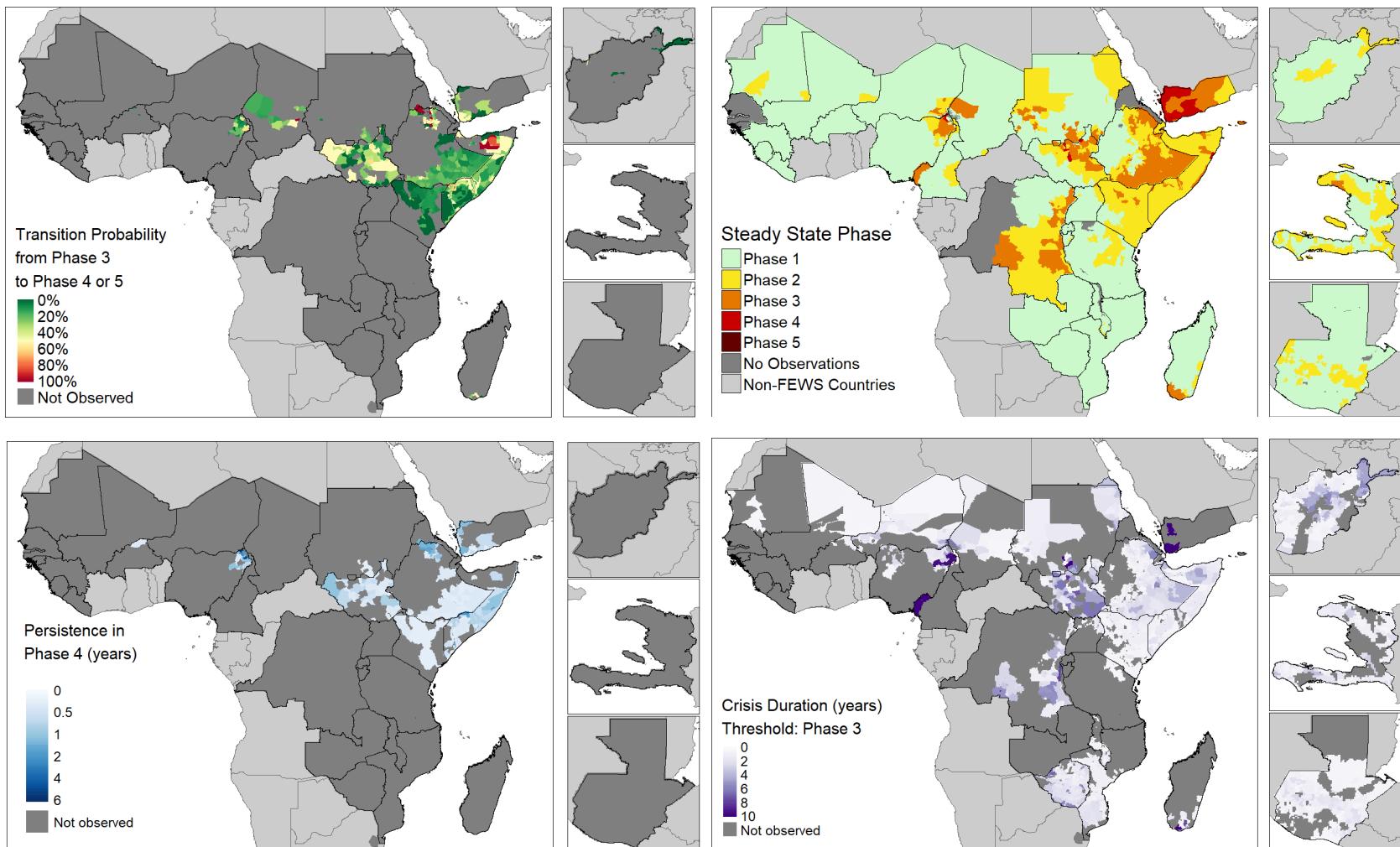
Probability summary



Preliminary result: floods associated with 2.5-12x (CH), 2.6 – 19.1 (IPC) greater odds of Phase 4 underprediction



Transition probability



Key findings and policy relevance

- Retail food prices are resilient to extreme weather
 - Prioritize provision of Fruits and Vegetables during storm months
 - Demand reduction of breads and cereals across several extreme events can point to multidimensional intervention opportunities
- Wasting is seasonal and spatially heterogeneous
 - Establish baseline seasonality from available data
 - Need climatological representativeness in survey design and nutrition surveillance
- Mixed preliminary evidence around extreme weather famine phase prediction accuracy
 - Probabilistic findings can be incorporated in famine forecasting to quantify uncertainty



Limitations

- Data availability and resolution
 - Errors in spatial matching and temporal alignment – difficult to validate retroactively
 - Spatiotemporal aggregation may obscure extremes (Alarcon et al, 2020)
 - Internal variability among datasets measuring similar phenomena (de Perez et al, 2023)
 - Non-public data in source databases may add further context or modify conclusions
- Endogeneity and exposure misclassification
 - Key assumptions: climate not affected by human activities, equal experience of climate and extreme weather in sample
 - Cascading effects, sequences, interactions among extremes (e.g. flood and storm)
- Causal inference and predictive modeling not feasible at chosen scale
- Alternate pathways beyond climate: conflict, mobility, demographics

Future directions

- Aim 1: Food prices
 - Validation at localized scales with higher resolution datasets
 - Markups in supply chain with producer, wholesale, and retail prices
 - Road distance, nighttime lights, protective effects
- Aim 2: Wasting
 - Validation at localized scales with nutrition surveillance datasets
 - Comparison of wasting vs. stunting (Cliffer et al, 2024 on growth faltering)
 - Validate climate sensitivity of GAM as binary indicator vs. z-scores, raw anthropometry
- Aim 3: Famine Early Warning Systems
 - Probabilistic inputs into scenario development, real-time uncertainty estimates
 - Advanced methods: Markovian models and Markov Chain Monte-Carlo methods, dynamic neural networks, anticipatory action pipelines

Key Messages

- **Data matters**
 - Available data is sparse, coarser resolutions than ideal
 - Creative data fusion can help generate new hypothesis and reexamine established ones
 - Scalable methods more valuable than global insights
- **Mechanism matters**
 - Food systems do not respond in same direction and/or magnitude across extreme events
 - Interventions should be sensitive to mechanism and scale
- **Uncertainty matters**
 - Need to evaluate sparsity and quality to estimate



Thank you!

- Dissertation committee
- Family and friends
- Funding support
 - Food Prices for Nutrition project at Tufts University funded by the Bill & Melinda Gates Foundation and the UK FCDO (INV-016158)
 - USAID Feed the Future Innovation Lab for Sustainable Intensification (Cooperative Agreement No. AID-OAA-L-14-00006)
 - Contracts with World Bank and Micronutrient Forum
- Mentors & collaborators
 - Ilana Cliffer
 - Anastasia Marshak
 - Helen Young
 - Daniel Maxwell
 - Paul Howe
 - Felipe Dizon
 - Kalyani Raghunathan
 - Derek Headey
- Feinstein International Center
- TTS and Data Lab
- InForMID team
 - Ryan Simpson
 - Tanya Alarcon Falconi
 - Bingjie Zhou
 - Emily Sanchez
 - Bree Langlois
- Food Prices for Nutrition team
 - Yan Bai
 - Anna Herforth
 - Rachel Gilbert
 - Kristina Sokourenko



Gerald J. and Dorothy R.
Friedman School of
Nutrition Science and Policy

InForMID
*Initiative for the Forecasting and
Modeling of Infectious Diseases*

Food Prices for
NutritionA graphic element consisting of a row of stylized human figures in various colors (blue, orange, green, purple) of different heights and shapes, representing a diverse population.

Questions?

Annex

Multiple Harmonic Regression

$$O = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(4\pi\omega t) + \beta_4 \sin(4\pi\omega t) + \beta_5 T(t)$$

Characteristic	Unimodal (2π)	Bimodal (4π)	
Regression Model	Gaussian Linear Model $Y_t = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 T(t)$	Log-Linear Model $\ln(E[Y_t]) = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 T(t)$	Gaussian Linear or Log-Linear $Y_t \text{ or } \ln(E[Y_t]) = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t) + \beta_4 \cos(2\pi\omega t) + \beta_5 T(t)$
Amplitude (γ)	$\gamma = \sqrt{\beta_1^2 + \beta_2^2}$	$\gamma = e^{\sqrt{\beta_1^2 + \beta_2^2}}$	$A = P_G - N_G$
95% Confidence Interval of Amplitude ($CI(\gamma)$)	$Var(\gamma) = \frac{\beta_1^2 \sigma_1^2 + \beta_2^2 \sigma_2^2 + 2\sigma_{\beta_1\beta_2}\beta_1\beta_2}{\beta_1^2 + \beta_2^2}$ $CI(\gamma) = \gamma \pm 1.96 \sqrt{Var(\gamma)}$	$Var(\gamma) = \gamma^2 \left(\frac{\beta_1^2 \sigma_1^2 + \beta_2^2 \sigma_2^2 + 2\sigma_{\beta_1\beta_2}\beta_1\beta_2}{\beta_1^2 + \beta_2^2} \right)$ $CI(\gamma) = \gamma \pm 1.96 \sqrt{Var(\gamma)}$	Estimated arithmetically from 999 simulations which randomly drop up to 50% of dataset $CI(\hat{\gamma}) = \sum_{n=1}^{n=999} P_G - N_G$
Peak (P)	$P = \beta_0 + \gamma$	$P = e^{\beta_0} + \gamma$	Estimated arithmetically from first, second, and third differences of the predicted seasonal curve. P_L = local maximum where $C' = 0$ and $C'' < 0$ P_G = global maximum, largest value of all P_L s
Nadir (N)	$N = \beta_0 - \gamma$	$N = e^{\beta_0} - \gamma$	Estimated arithmetically from first, second, and third differences of the predicted seasonal curve. N_L = local minimum where $C' = 0$ and $C'' > 0$ N_G = global minimum, smallest value of all N_L s
Peak Timing (P_T)	Phase shift $\Theta = \arctan\left(\frac{\beta_1}{\beta_2}\right)$ If $\beta_1 > 0$ and $\beta_2 > 0$, $P_T = (\Theta) \frac{M}{2\pi}$ If $\beta_2 < 0$, $P_T = (\Theta + \pi) \frac{M}{2\pi}$ If $\beta_1 < 0$ and $\beta_2 > 0$, $P_T = (\Theta + 2\pi) \frac{M}{2\pi}$	Estimated arithmetically from first, second, and third differences of the predicted seasonal curve. $P_{T,L}$ = Timing of P_L , $P_{T,G}$ = Timing of P_G	
95% Confidence Interval of Peak Timing ($CI(\Theta)$)	$Var(\Theta) = \frac{\beta_1^2 \sigma_2^2 + \beta_2^2 \sigma_1^2 - 2\sigma_{\beta_1\beta_2}\beta_1\beta_2}{(\beta_1^2 + \beta_2^2)^2}$ $CI(\Theta) = \Theta \pm 1.96 \sqrt{Var(\Theta)}$	Estimated arithmetically from 999 simulations which randomly drop up to 50% of dataset $CI(\widehat{P_T}) = \sum_{n=1}^{n=999} P_{T,G}$	

If neither harmonic terms are statistically significant, conclude no detectable seasonality

Complete code available on [Github!](#)

Text matching

SURVEY DATA

Step 1: Create location vocabulary

province, territory, district, village,

Step 2: Extract survey fields matching vocabulary

Respondent ID	District	Village	Survey Date
1	D.G.Khan	Muzaffargarh	20 January 2020

Step 3: Make corrections based on known survey location and concatenate into one target string

Pakistan - Dera Ghazi Khan - Muzaffargarh

REFERENCE DATA

Step 1: Compile database of reference locations

Dataset	Feature ID	ADM0	ADM1	ADM2	ADM3
DHS	DHS2017_4	Pakistan	Punjab	-	-
GAUL	2276	Pakistan	Punjab	-	-
GADM	PAK.7_1	Pakistan	Punjab	-	-
GADM	PAK.7.2_1	Pakistan	Punjab	Dera Ghazi Khan	-
GADM	PAK.7.2.3_1	Pakistan	Punjab	Dera Ghazi Khan	Muzaffargarh
GADM	PAK.7.2.4_1	Pakistan	Punjab	Dera Ghazi Khan	Rajan Pur

Step 2: Concatenate locations into one reference string per feature

Feature ID	REF_STRING
DHS2017_4 2276 PAK.7_1	Pakistan - Punjab
PAK.7.2_1	Pakistan - Punjab - Dera Ghazi Khan
PAK.7.2.3_1	Pakistan - Punjab - Dera Ghazi Khan - Muzaffargarh
PAK.7.2.4_1	Pakistan - Punjab - Dera Ghazi Khan - Rajan Pur

Step 4: Run Fuzzy String Matching

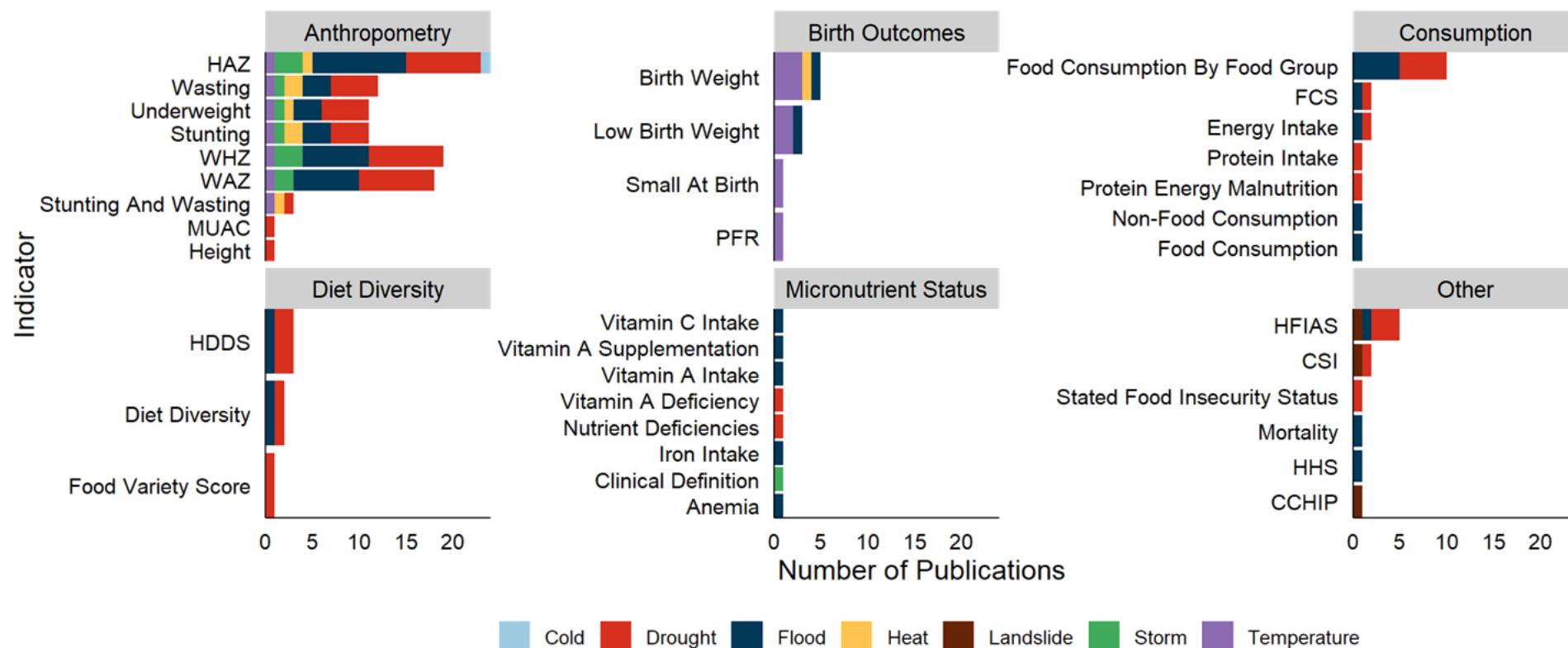
Pakistan -
Dera Ghazi Khan -
Muzaffargarh

Feature ID	REF_STRING	SCORE
DHS2017_4 2276 PAK.7_1	Pakistan - Punjab	60
PAK.7.2_1	Pakistan - Punjab - Dera Ghazi Khan	80
PAK.7.2.3_1	Pakistan - Punjab - Dera Ghazi Khan - Muzaffargarh	97
PAK.7.2.4_1	Pakistan - Punjab - Dera Ghazi Khan - Rajan Pur	82

Step 5: Extract best match and retain the spatial feature ID

Pakistan -
Dera Ghazi Khan -
Muzaffargarh is matched to PAK.7.2.3_1

Nutritional outcomes in prior work related to extreme weather



N = 238 studies containing extreme weather keywords reviewed in Chapter 2

IPC Reference Table

IPC Acute Food Insecurity (First Level Outcomes) Reference Table																														
Phase name and description	Phase 1 None/Minimal	Phase 2 Stressed	Phase 3 Crisis	Phase 4 Emergency	Phase 5 Catastrophe/ Famine																									
Food security first-level level outcomes (household level)	<p>First-level outcomes refer to characteristics of food consumption and livelihood change. Thresholds that correspond as closely as possible to the Phase description are included for each indicator. Although cut-offs are based on applied research and presented as a global reference, correlation between indicators is often somewhat limited and findings need to be contextualized. The area is classified in the most severe Phase that affects at least 20% of the population.</p> <table> <tr> <td>Quantity: Adequate energy intake</td> <td>Quantity: Minimally adequate</td> <td>Quantity: Moderately inadequate – Moderate deficits</td> <td>Quantity: Very inadequate – Large deficits</td> <td>Quantity: Extremely inadequate – Very large deficits</td> </tr> <tr> <td>Dietary energy intake:^a Adequate (avg. 2,350 Kilocalories (kcal) pp/day) and stable</td> <td>Dietary energy intake: Minimally adequate (avg. 2,100 kcal pp/day)</td> <td>Dietary energy intake: Food gap (below avg. 2,100 kcal pp/day)</td> <td>Dietary energy intake: Large food gap (well below 2,100 kcal pp/day)</td> <td>Dietary Energy Intake: Extreme food gap</td> </tr> <tr> <td>Household Dietary Diversity Score (HDDS): 5–12 food groups and stable</td> <td>HDDS: 5 FG but deterioration ≥1 FG from typical</td> <td>HDDS: 3–4 FG</td> <td>HDDS: 0–2 FG (NDC to differentiate P4 and 5)</td> <td>HDDS 0–2 FG (NDC)</td> </tr> </table>	Quantity: Adequate energy intake	Quantity: Minimally adequate	Quantity: Moderately inadequate – Moderate deficits	Quantity: Very inadequate – Large deficits	Quantity: Extremely inadequate – Very large deficits	Dietary energy intake: ^a Adequate (avg. 2,350 Kilocalories (kcal) pp/day) and stable	Dietary energy intake: Minimally adequate (avg. 2,100 kcal pp/day)	Dietary energy intake: Food gap (below avg. 2,100 kcal pp/day)	Dietary energy intake: Large food gap (well below 2,100 kcal pp/day)	Dietary Energy Intake: Extreme food gap	Household Dietary Diversity Score (HDDS): 5–12 food groups and stable	HDDS: 5 FG but deterioration ≥1 FG from typical	HDDS: 3–4 FG	HDDS: 0–2 FG (NDC to differentiate P4 and 5)	HDDS 0–2 FG (NDC)														
Quantity: Adequate energy intake	Quantity: Minimally adequate	Quantity: Moderately inadequate – Moderate deficits	Quantity: Very inadequate – Large deficits	Quantity: Extremely inadequate – Very large deficits																										
Dietary energy intake: ^a Adequate (avg. 2,350 Kilocalories (kcal) pp/day) and stable	Dietary energy intake: Minimally adequate (avg. 2,100 kcal pp/day)	Dietary energy intake: Food gap (below avg. 2,100 kcal pp/day)	Dietary energy intake: Large food gap (well below 2,100 kcal pp/day)	Dietary Energy Intake: Extreme food gap																										
Household Dietary Diversity Score (HDDS): 5–12 food groups and stable	HDDS: 5 FG but deterioration ≥1 FG from typical	HDDS: 3–4 FG	HDDS: 0–2 FG (NDC to differentiate P4 and 5)	HDDS 0–2 FG (NDC)																										
Food consumption (focus on energy intake)	<table> <tr> <td>Food Consumption Score (FCS):^c Acceptable and stable</td> <td>FCS: Acceptable but deterioration from typical</td> <td>FCS: Borderline</td> <td>FCS: Poor (NDC to differentiate P4 and 5)</td> <td>FCS: Poor (NDC to differentiate P4 and 5)</td> </tr> <tr> <td>Household Hunger Scale (HHS):^d 0 (none)</td> <td>HHS: 1 (slight)</td> <td>HHS: 2–3 (moderate)</td> <td>HHS: 4 (severe)</td> <td>HHS: 5–6 (severe)</td> </tr> <tr> <td>Reduced Coping Strategies Index (rCSI):^e 0–3</td> <td>rCSI: 4–18</td> <td>rCSI: ≥ 19 (non-defining characteristics—NDC—to differentiate P3, 4 and 5)</td> <td>rCSI: ≥ 19 (NDC to differentiate P3, 4 and 5)</td> <td>rCSI: ≥ 19 (NDC to differentiate P3, 4 and 5)</td> </tr> <tr> <td>Household Economy Analysis (HEA):^f No livelihood protection deficit.</td> <td>HEA: Small or moderate livelihood protection deficit <80%</td> <td>HEA: Livelihood protection deficit ≥20% but ≥80%; or survival deficit <20% <50%</td> <td>HEA: Survival Deficit ≥20% but <50%</td> <td>HEA: Survival deficit ≥50%</td> </tr> <tr> <td>Food Insecurity Experience Scale (FIES):^g Between -0.58 and 0.36 (30 days recall): < -0.58</td> <td>FIES: Between -0.58 and 0.36</td> <td>FIES: > 0.36 (NDC to differentiate between Phases 3, 4 and 5)</td> <td>FIES: > 0.36 (NDC to differentiate between Phases 3, 4 and 5)</td> <td>FIES: > 0.36 (NDC)</td> </tr> </table>	Food Consumption Score (FCS): ^c Acceptable and stable	FCS: Acceptable but deterioration from typical	FCS: Borderline	FCS: Poor (NDC to differentiate P4 and 5)	FCS: Poor (NDC to differentiate P4 and 5)	Household Hunger Scale (HHS): ^d 0 (none)	HHS: 1 (slight)	HHS: 2–3 (moderate)	HHS: 4 (severe)	HHS: 5–6 (severe)	Reduced Coping Strategies Index (rCSI): ^e 0–3	rCSI: 4–18	rCSI: ≥ 19 (non-defining characteristics—NDC—to differentiate P3, 4 and 5)	rCSI: ≥ 19 (NDC to differentiate P3, 4 and 5)	rCSI: ≥ 19 (NDC to differentiate P3, 4 and 5)	Household Economy Analysis (HEA): ^f No livelihood protection deficit.	HEA: Small or moderate livelihood protection deficit <80%	HEA: Livelihood protection deficit ≥20% but ≥80%; or survival deficit <20% <50%	HEA: Survival Deficit ≥20% but <50%	HEA: Survival deficit ≥50%	Food Insecurity Experience Scale (FIES): ^g Between -0.58 and 0.36 (30 days recall): < -0.58	FIES: Between -0.58 and 0.36	FIES: > 0.36 (NDC to differentiate between Phases 3, 4 and 5)	FIES: > 0.36 (NDC to differentiate between Phases 3, 4 and 5)	FIES: > 0.36 (NDC)				
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Livelihood change (assets and strategies)	<p>Livelihood change: Sustainable livelihood strategies and assets</p> <p>Livelihood coping strategies (LCSs):^h No stress, crisis or emergency coping observed.</p>	<p>Livelihood change: Stressed strategies and/or assets; reduced ability to invest in livelihoods</p> <p>LCS: Stress strategies are the most severe strategies used by the household in the past 30 days.</p>	<p>Livelihood change: Accelerated depletion/erosion of strategies and/or assets</p> <p>LCSs: Crisis strategies are the most severe strategies used by the household in the past 30 days.</p>	<p>Livelihood change: Extreme depletion/ liquidation of strategies and assets</p> <p>LCSs: Emergency strategies are the most severe strategies used by the household in the past 30 days.</p>	<p>Livelihood change: Near complete collapse of strategies and assets</p> <p>LCSs: Near exhaustion of coping capacity.</p>																									

Source: IPC Global Partners (2021) p. 37.