

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

# Climate and Health: Extreme Weather, Food Systems, 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 95<sup>th</sup> percentile of monthly maximum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
  - **Coldwave:** values below 5<sup>th</sup> percentile of monthly minimum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
  - **Flood:** values exceeding 95<sup>th</sup> percentile of 1-month SPI time series, calculated from CHIRPS (Funk et al, 2015)
  - **Drought:** values below 5<sup>th</sup> 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

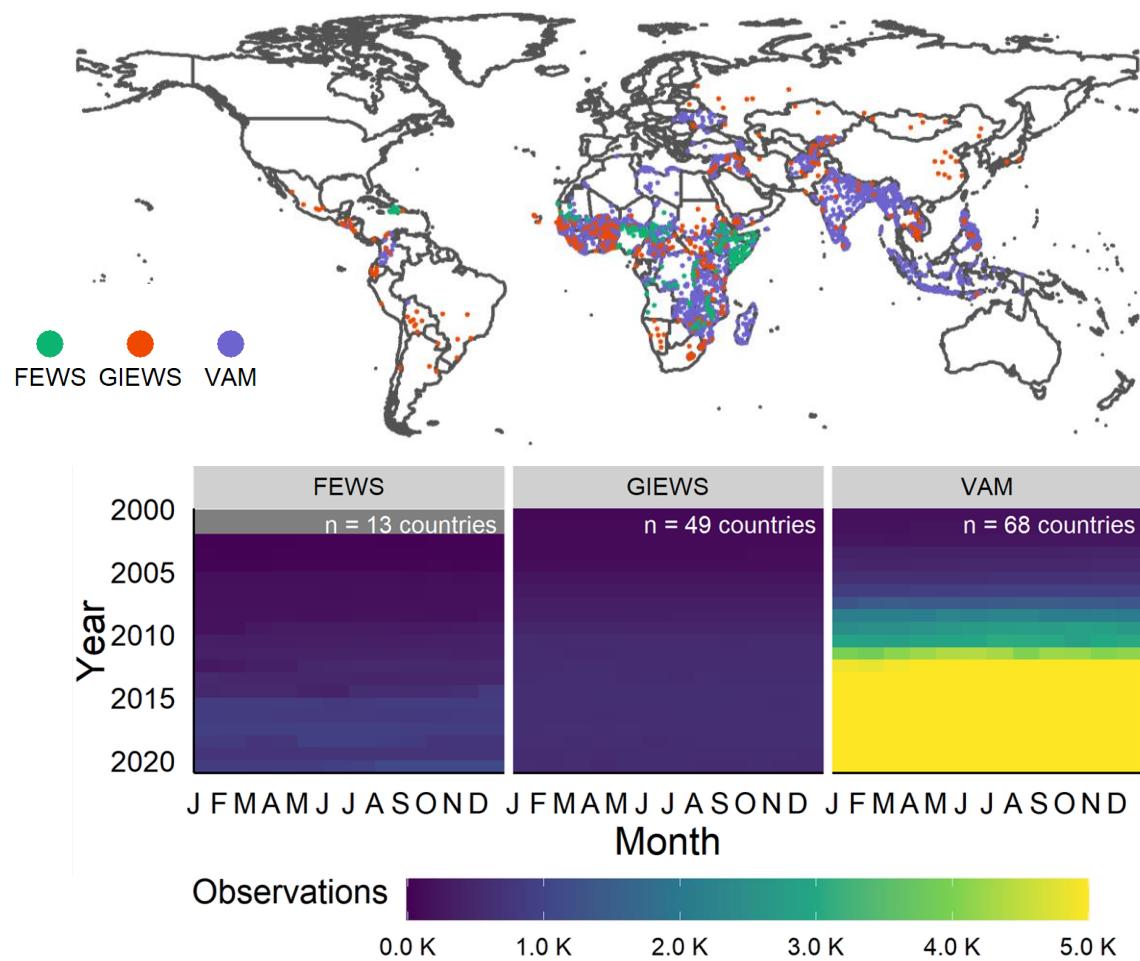
Aim 1.2: Differences across  
markets and subregions

# Research design

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

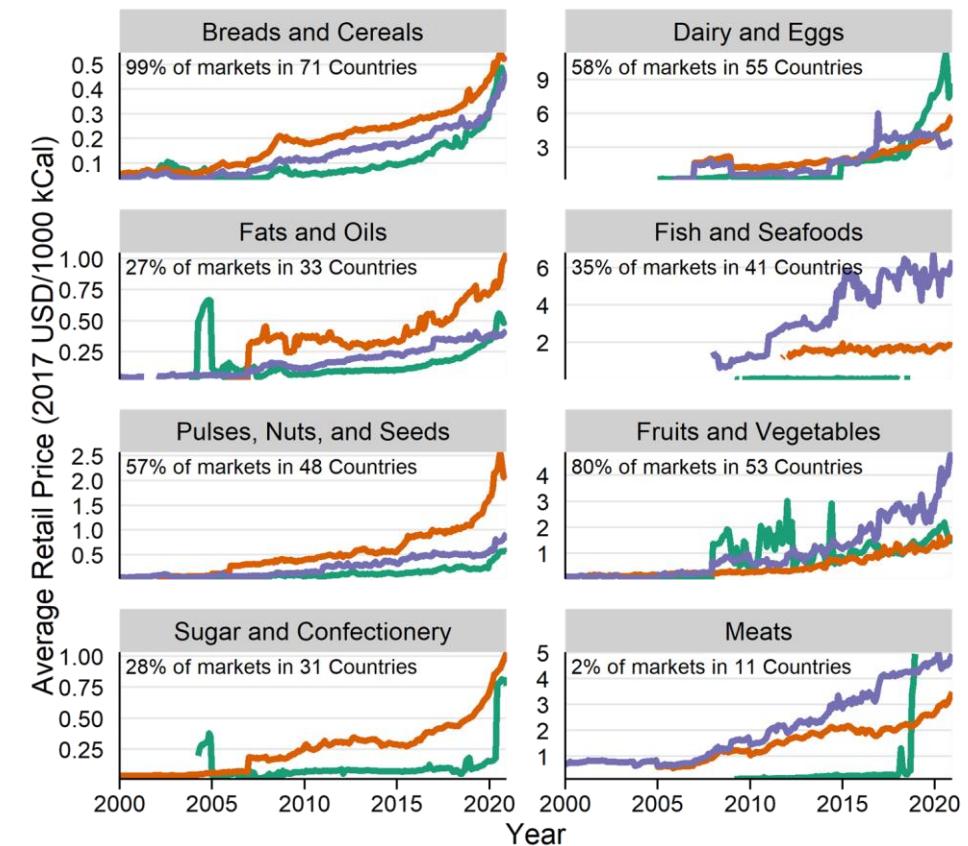
- $P_{ijmy}$ : ln(Price per kg), ln(Price per 1000 kCal)
  - Derived from three global food security early warning systems (FAO GIEWS, USAID FEWSNET, WFP VAM)
- Extreme Event: five types of extreme weather events with independent definitions
- $FG_i$ : one of eight food groups
  - *Non-Perishables*: 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 ( $\gamma_j$ ), market-month ( $\delta_{jm}$ ), market-year ( $\theta_{jy}$ ), item ( $\tau_i$ )

# Dataset summary



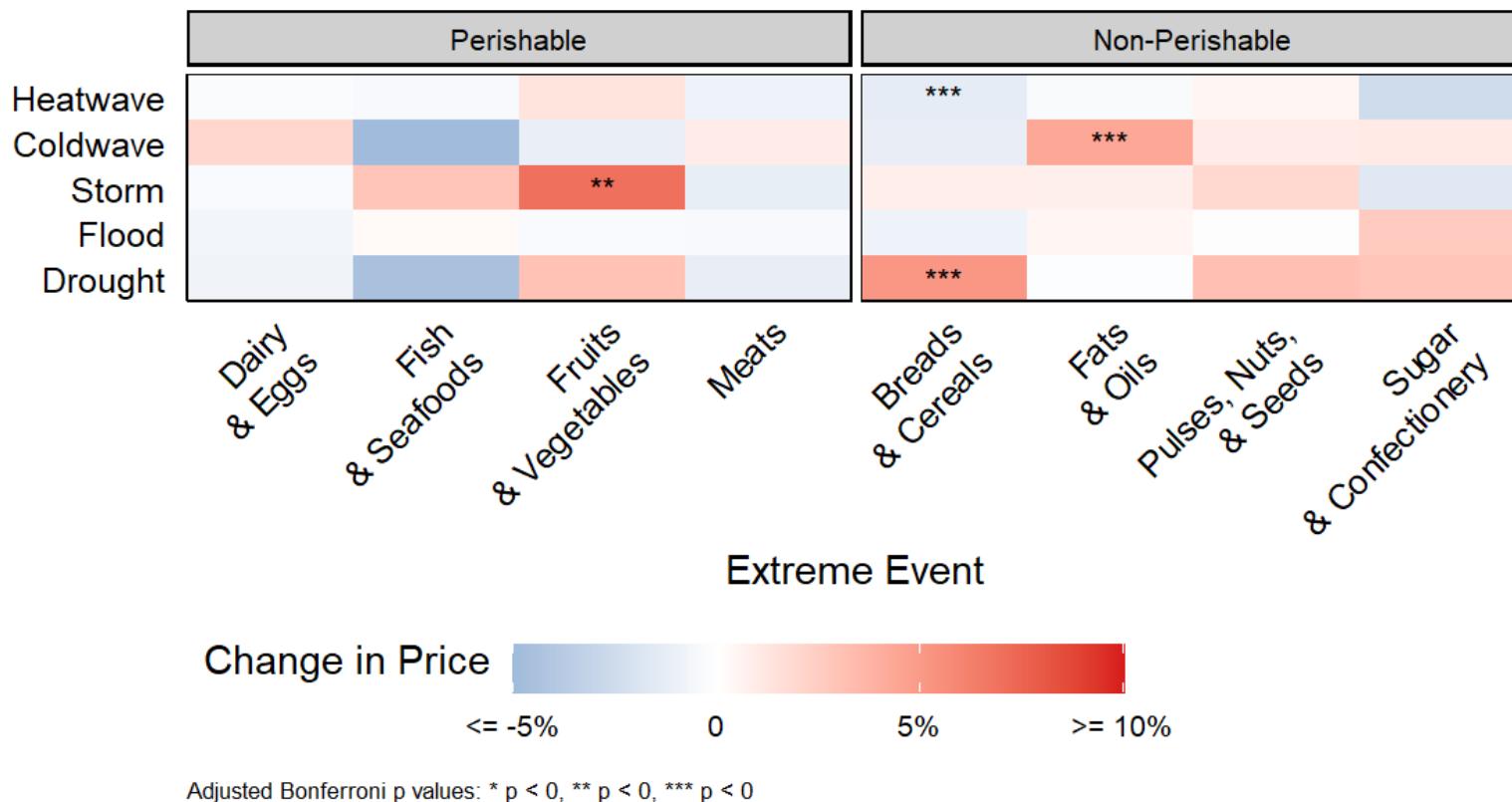
Data Sources: [FAO GIEWS](#), [USAID FEWS](#), and [WFP VAM](#)

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



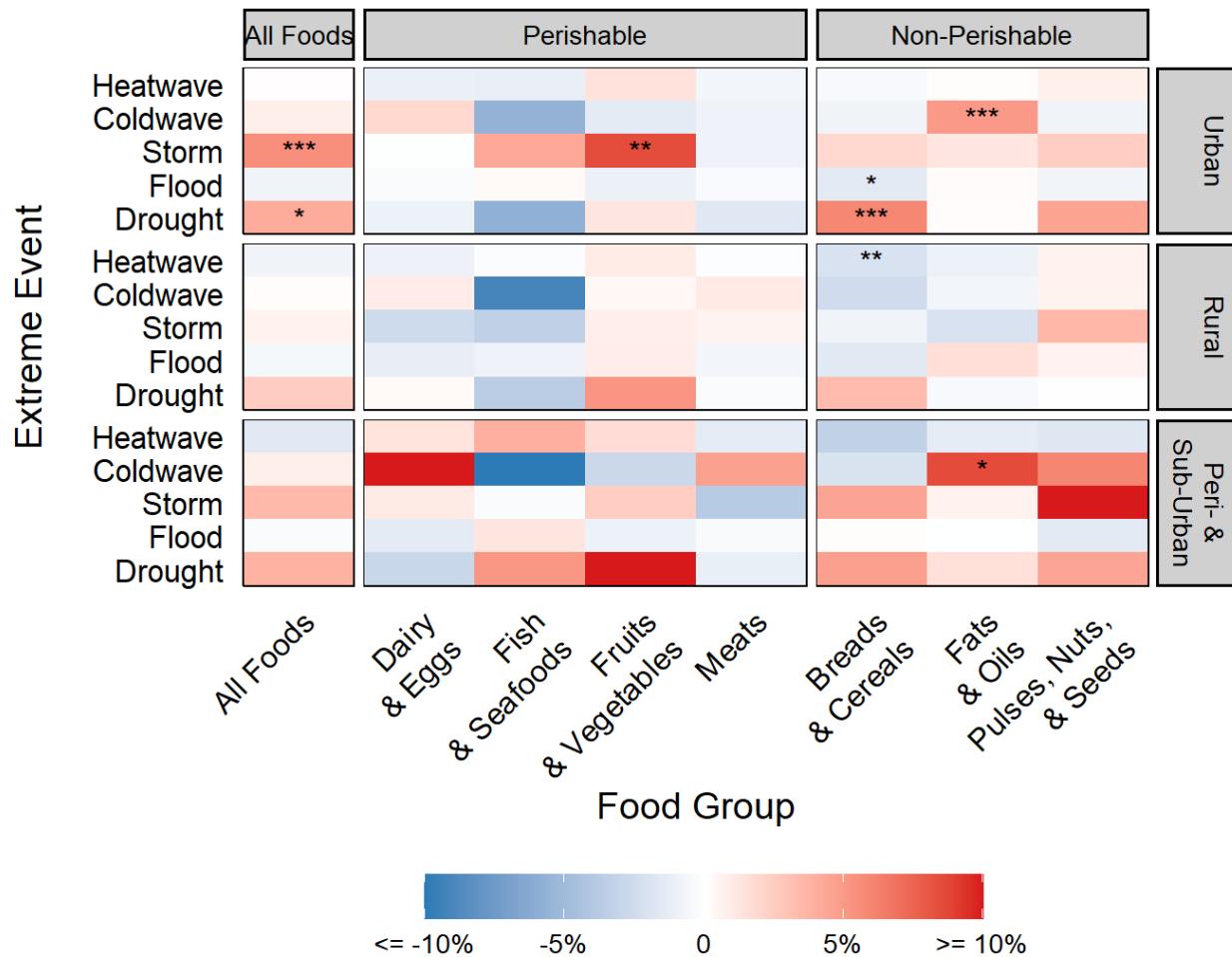
Dataset FEWS GIEWS VAM

# 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)

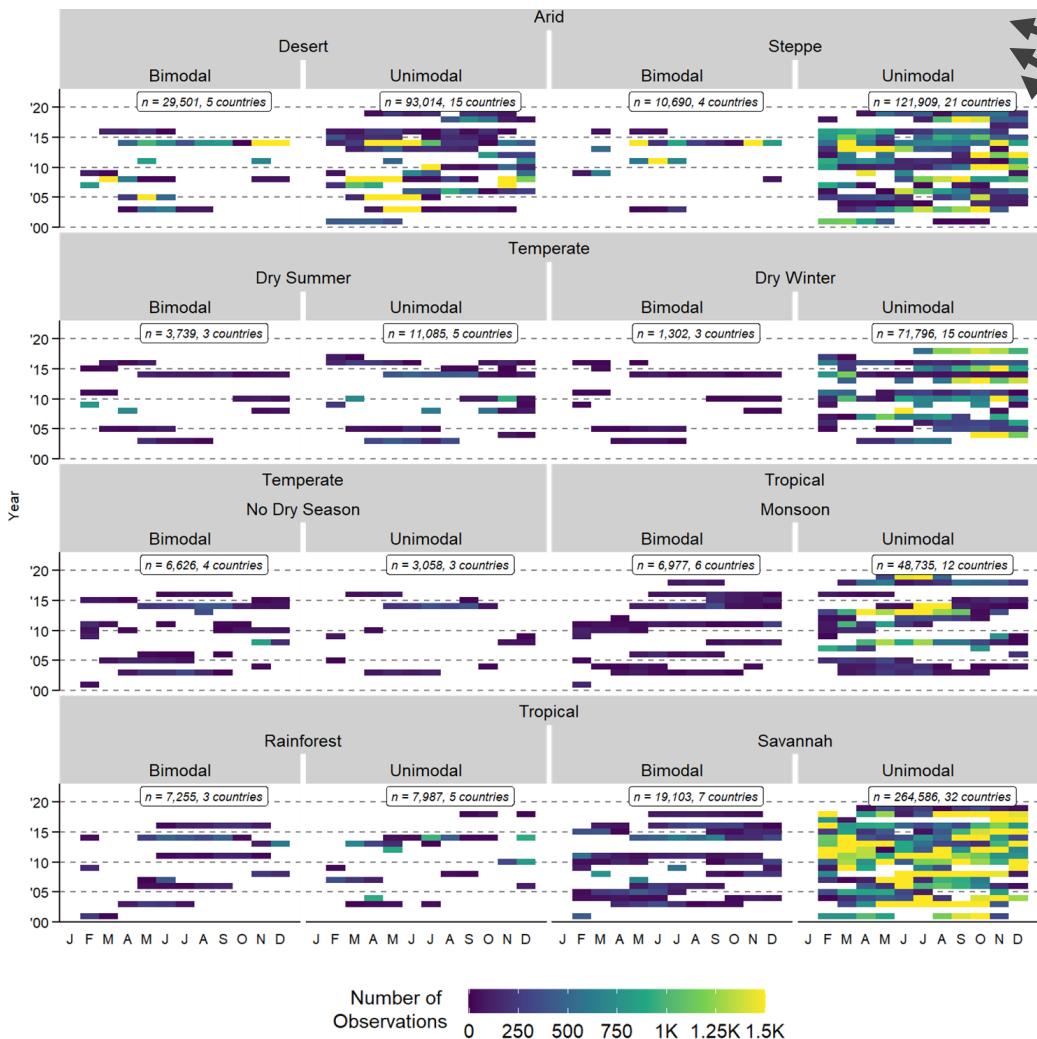
Aim 2.2: Quantify the effects of extreme events on wasting seasonality

# 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

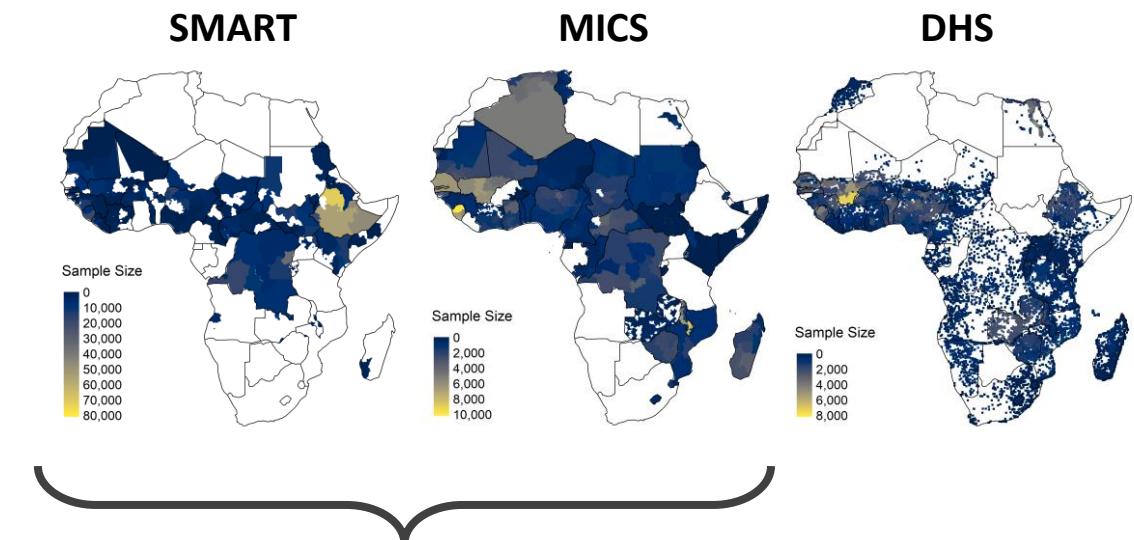


Total  $n = 2,591,633$  children  
in 49 countries

Level 1 Köppen climate class

Level 2 Köppen climate class:  
seasonal precipitation subgroup

Precipitation mode



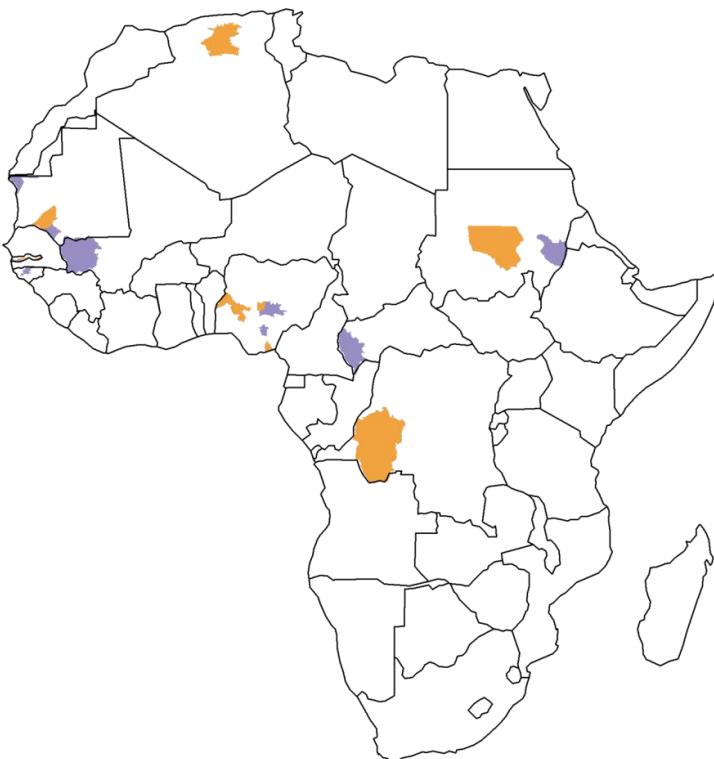
*Survey boundaries identified via text matching,  
adjusted to remove extremely rural areas*

# Distribution of significant harmonics

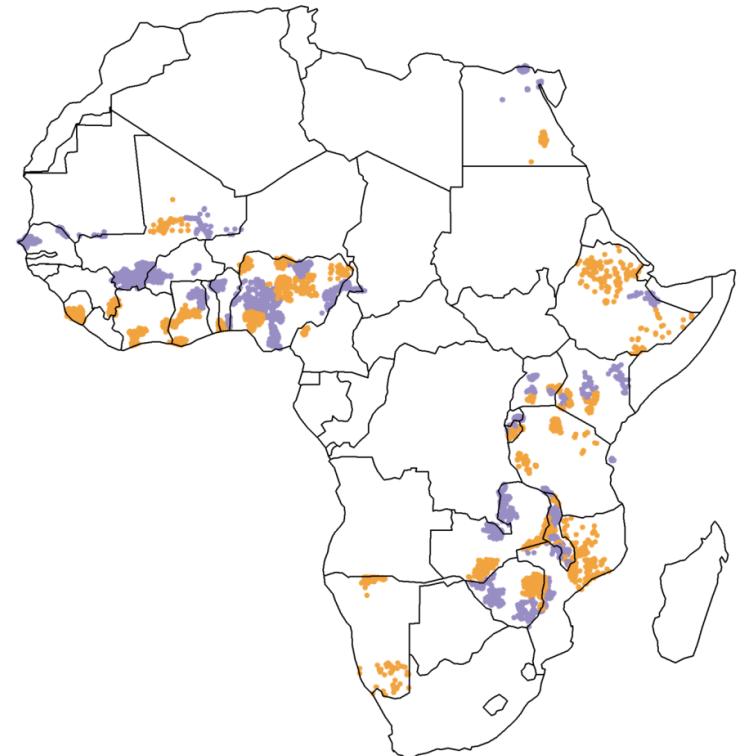
SMART



MICS



DHS



Single Harmonic



J F M A M J J A S O N D

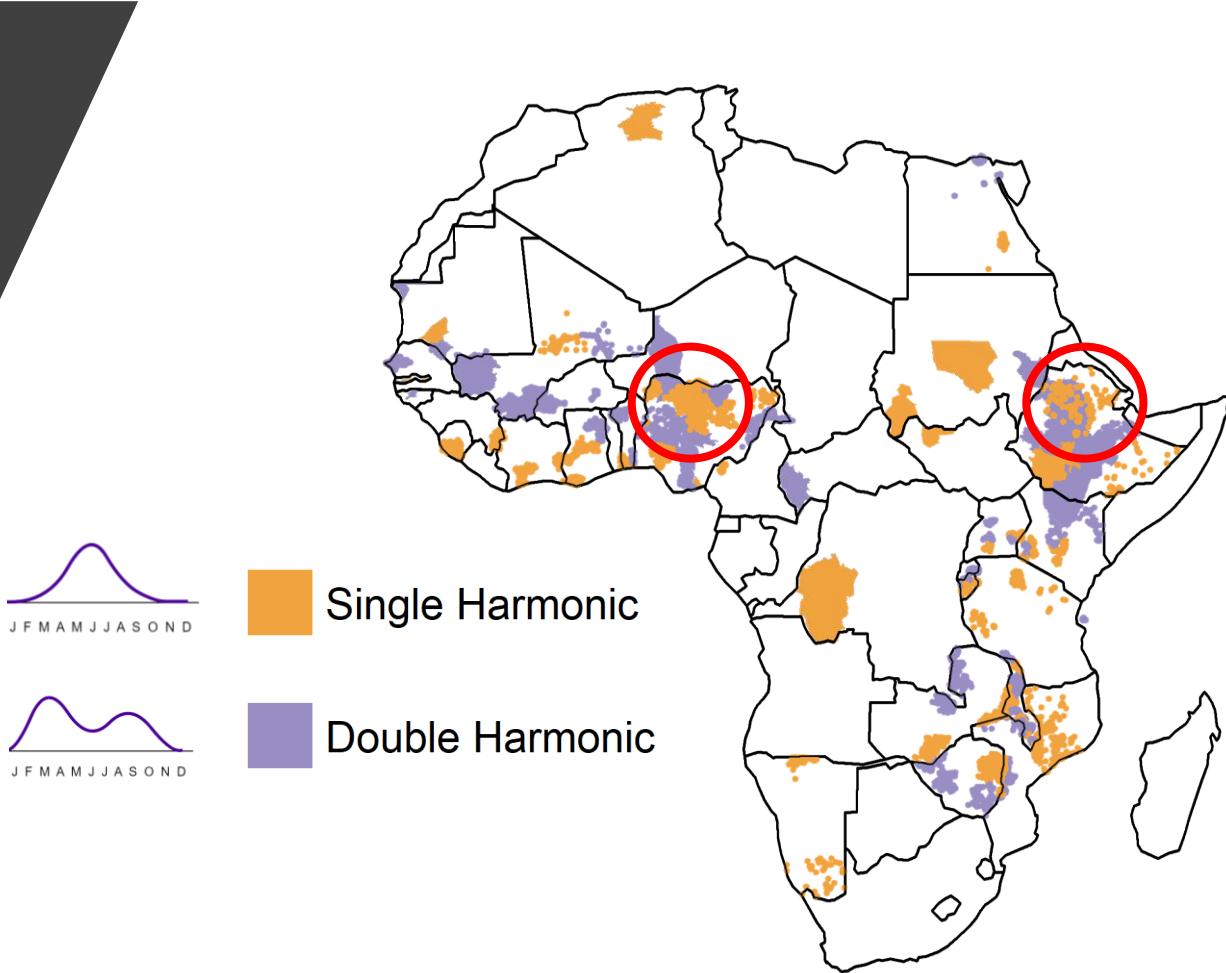


Double Harmonic



J F M A M J J A S O N D

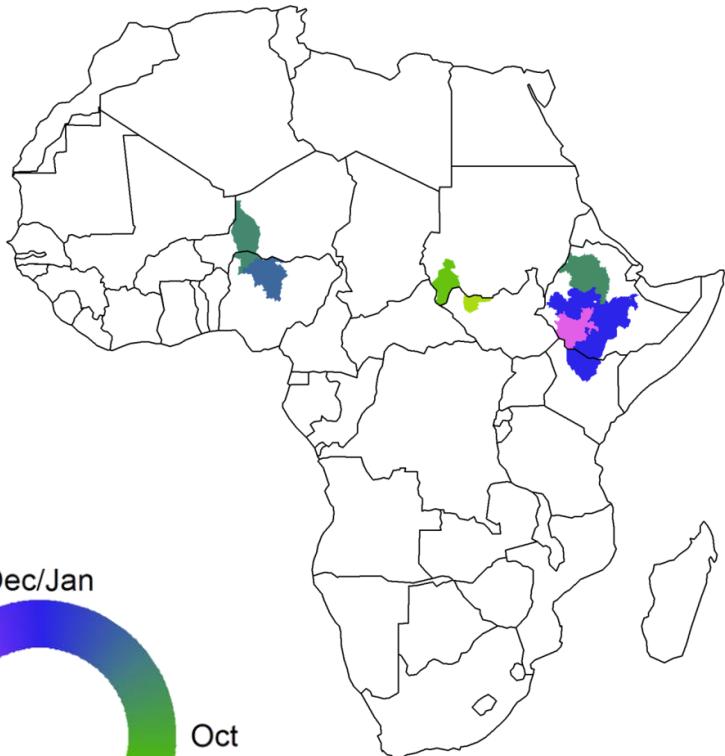
# Distribution of significant harmonics



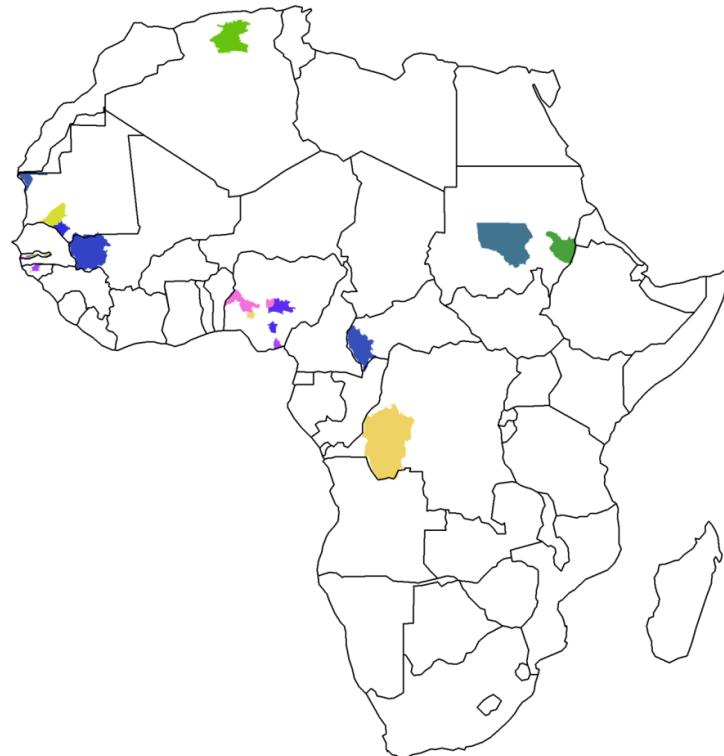
- Mix of significant single and double harmonics indicates heterogeneity
- Datasets can be utilized to validate or refute calculated harmonic patterns
  - E.g. Northern Nigeria and Ethiopian highlands
- Baseline map for other regions to contribute own analyses to fill in the gap

# Distribution of peak timings

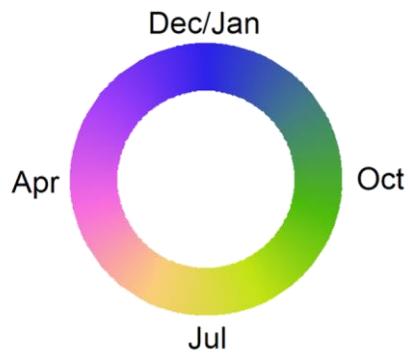
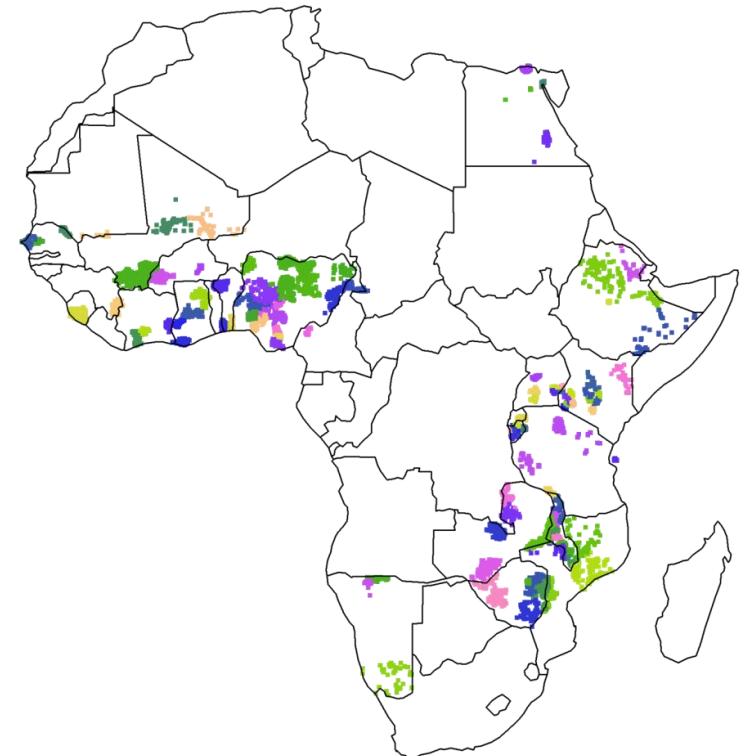
**SMART**



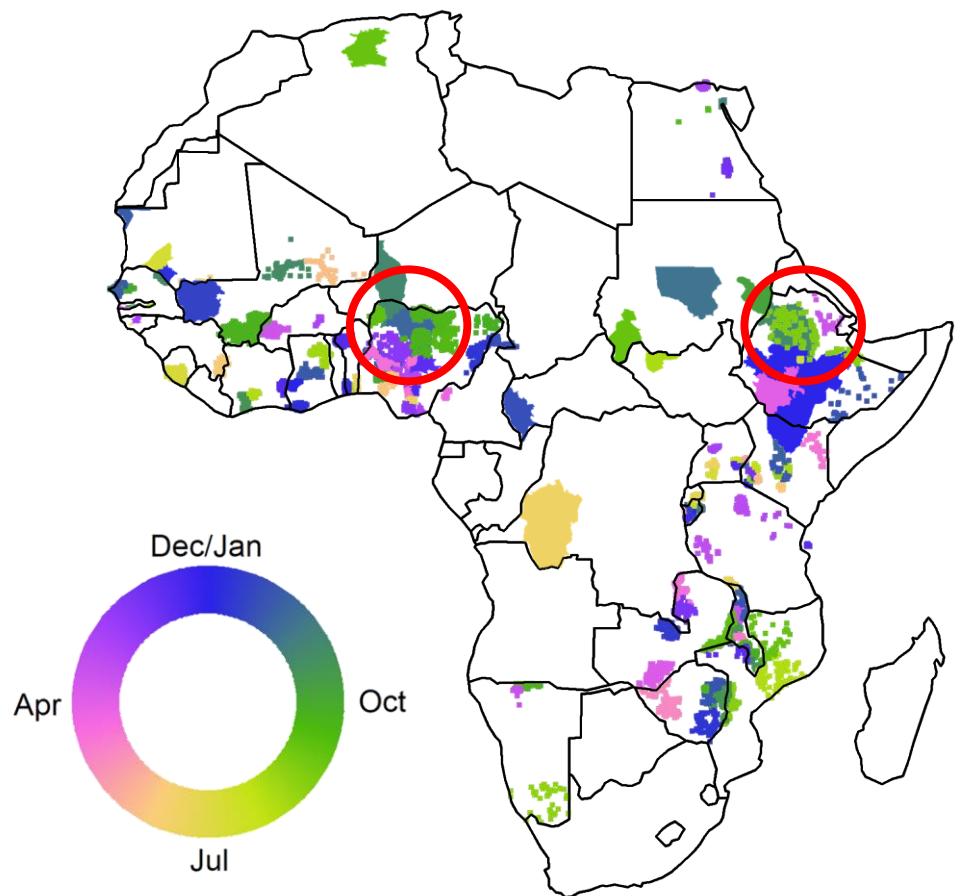
**MICS**



**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

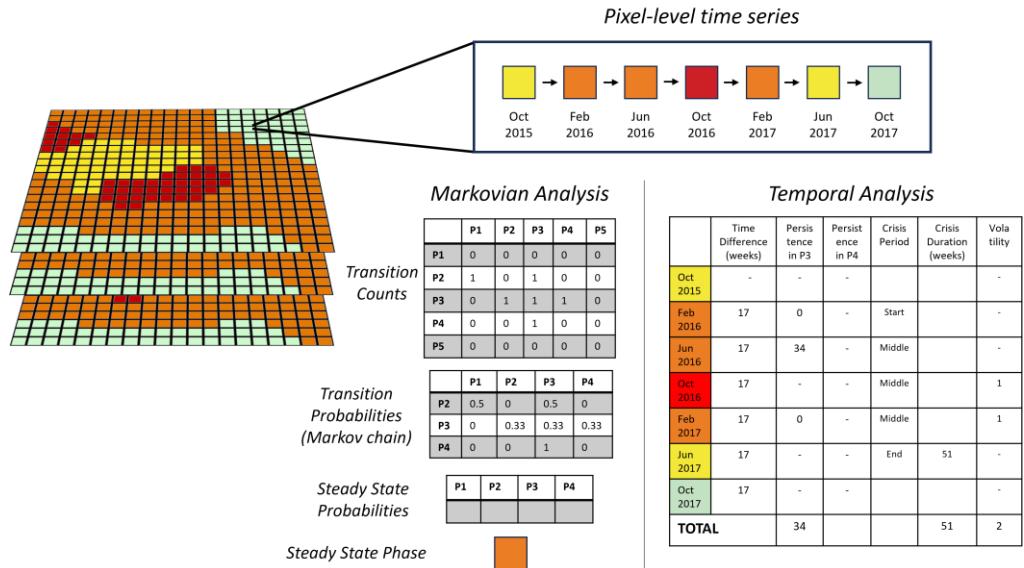
Aim 3.2: Quantify the effect of extreme events on accuracy of predictions generated by famine early warning systems

# Research design

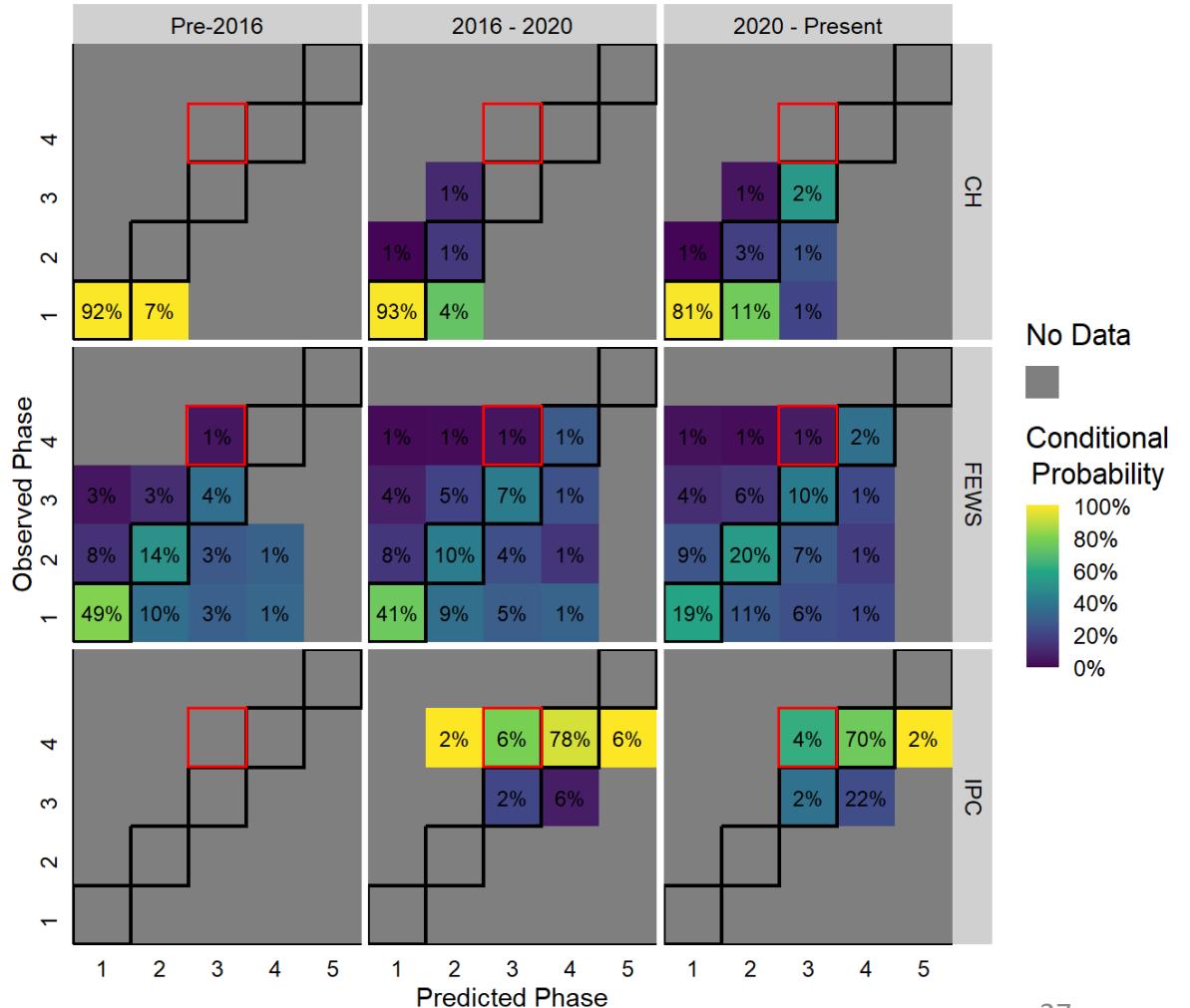
$$P(ST_{j,d,q+1} \perp CS_{j,d,q}) = \beta_0 + \boldsymbol{\beta}_1 Extreme\ Event_{j,t} + \gamma_j + \varepsilon$$

- $ST_{q+1}$ : 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 ( $\gamma_j$ )
- Unit of analysis: pixel  $j$  in dataset  $d$  observed at time  $t$  (month and year comprising quarter  $q$ )

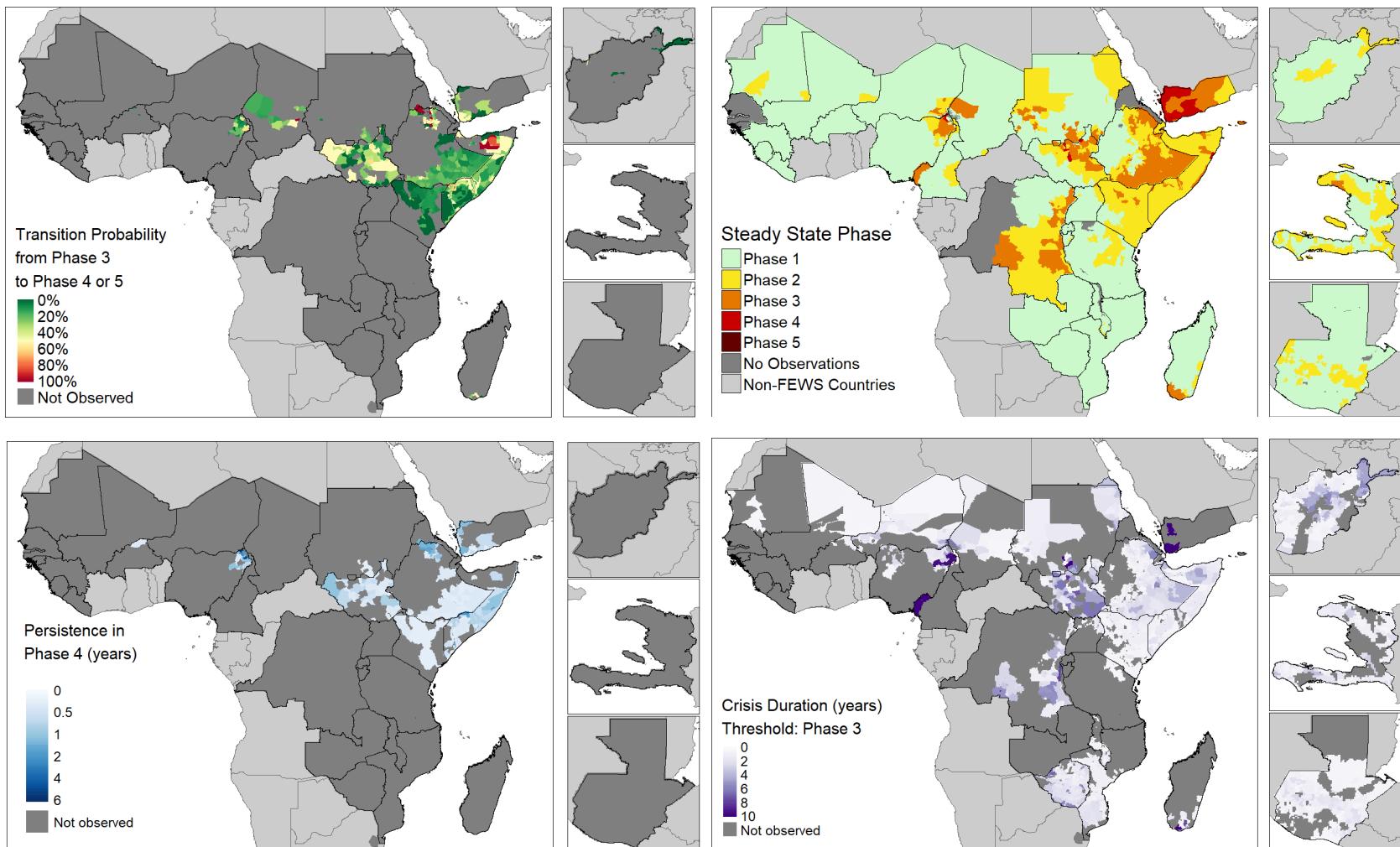
# Probability summary



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  
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**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 ( $\gamma$ )	$\gamma = \sqrt{\beta_1^2 + \beta_2^2}$	$\gamma = e^{\sqrt{\beta_1^2 + \beta_2^2}}$	$A = P_G - N_G$
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

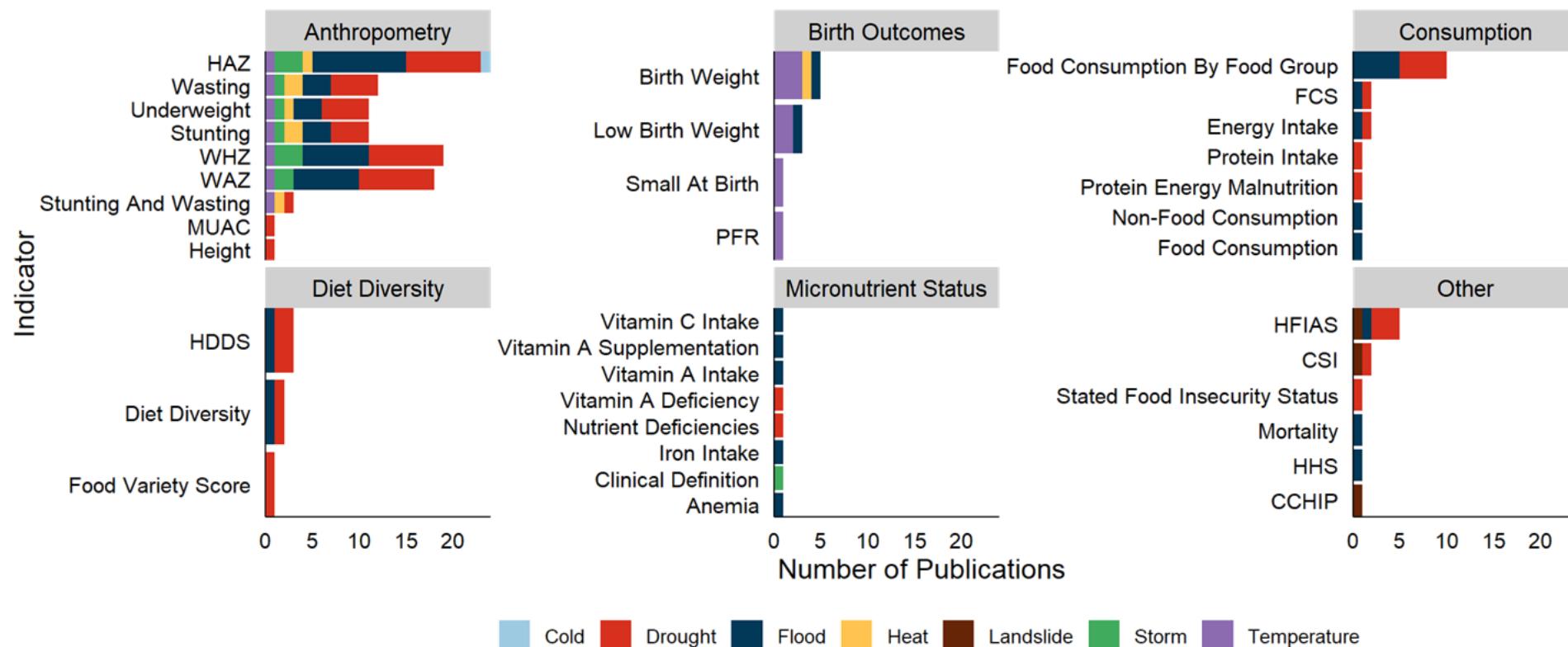
Pakistan -  
Dera Ghazi Khan -  
Muzaffargarh

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																									
<b>Food security first-level level outcomes (household level)</b>	<p><b>First-level outcomes</b> 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:<sup>a</sup> 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: <sup>a</sup> 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)														
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<b>Livelihood change (assets and strategies)</b>	<p><b>Livelihood change:</b> Sustainable livelihood strategies and assets</p> <p><b>Livelihood coping strategies (LCSs):<sup>h</sup></b> No stress, crisis or emergency coping observed.</p>	<p><b>Livelihood change:</b> Stressed strategies and/or assets; reduced ability to invest in livelihoods</p> <p><b>LCS:</b> Stress strategies are the most severe strategies used by the household in the past 30 days.</p>	<p><b>Livelihood change:</b> Accelerated depletion/erosion of strategies and/or assets</p> <p><b>LCSs:</b> Crisis strategies are the most severe strategies used by the household in the past 30 days.</p>	<p><b>Livelihood change:</b> Extreme depletion/ liquidation of strategies and assets</p> <p><b>LCSs:</b> Emergency strategies are the most severe strategies used by the household in the past 30 days.</p>	<p><b>Livelihood change:</b> Near complete collapse of strategies and assets</p> <p><b>LCSs:</b> Near exhaustion of coping capacity.</p>																									

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