Drought in Brazil, 2023

Flooding in Libya, 2023

Hurricane Ian in USA, 2022

(top row)
Edmar Barros / 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
April 24, 2024

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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 heterogenous
  - 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^{th} percentile of monthly maximum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
  - **Coldwave:** values below 5^{th} percentile of monthly minimum temperature, calculated from Terraclimate (Abatzoglou et al, 2018)
  - **Flood**: values exceeding 95^{th} percentile of 1-month SPI time series, calculated from CHIRPS (Funk et al, 2015)
  - **Drought**: values below 5^{th} 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

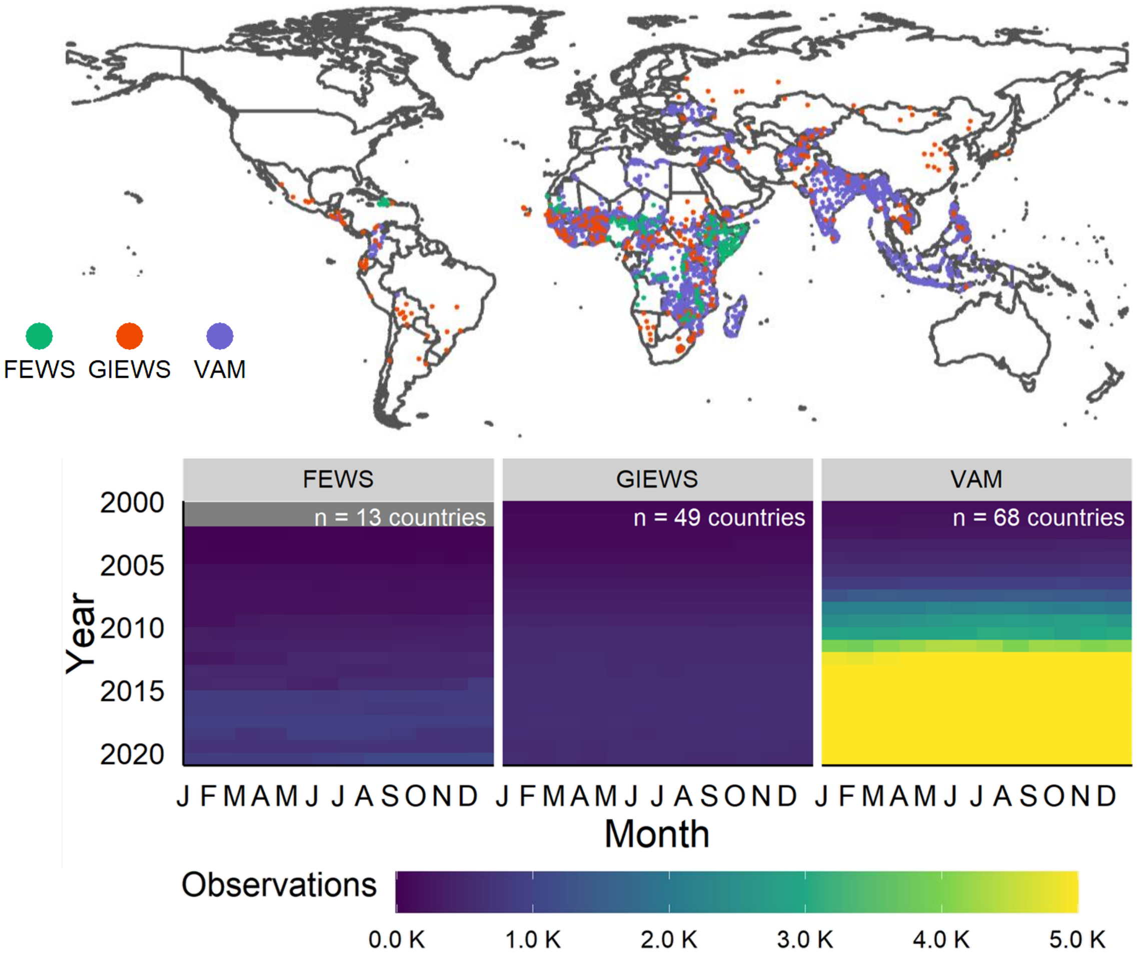
Aim 1.2: Differences across markets and subregions

Research design

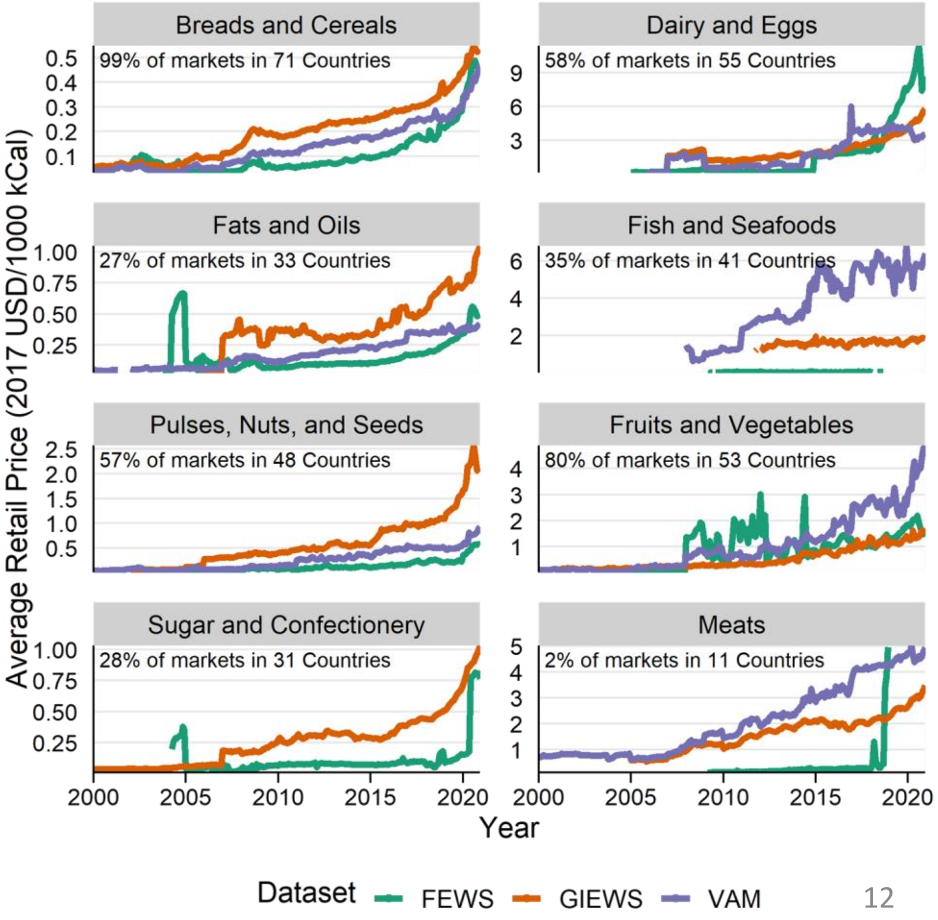
$$P_{ijmy} = \beta_0 + \boldsymbol{\beta_1} Extreme\ Event_{jmy} + \beta_2 FG_i + \boldsymbol{\beta_3}(FG_i * Extreme\ Event_{jmy}) + \beta_4 F_{imy} + \gamma_{jy} + \lambda_{my} + \theta_{jy} + \tau_i + \varepsilon$$

- 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

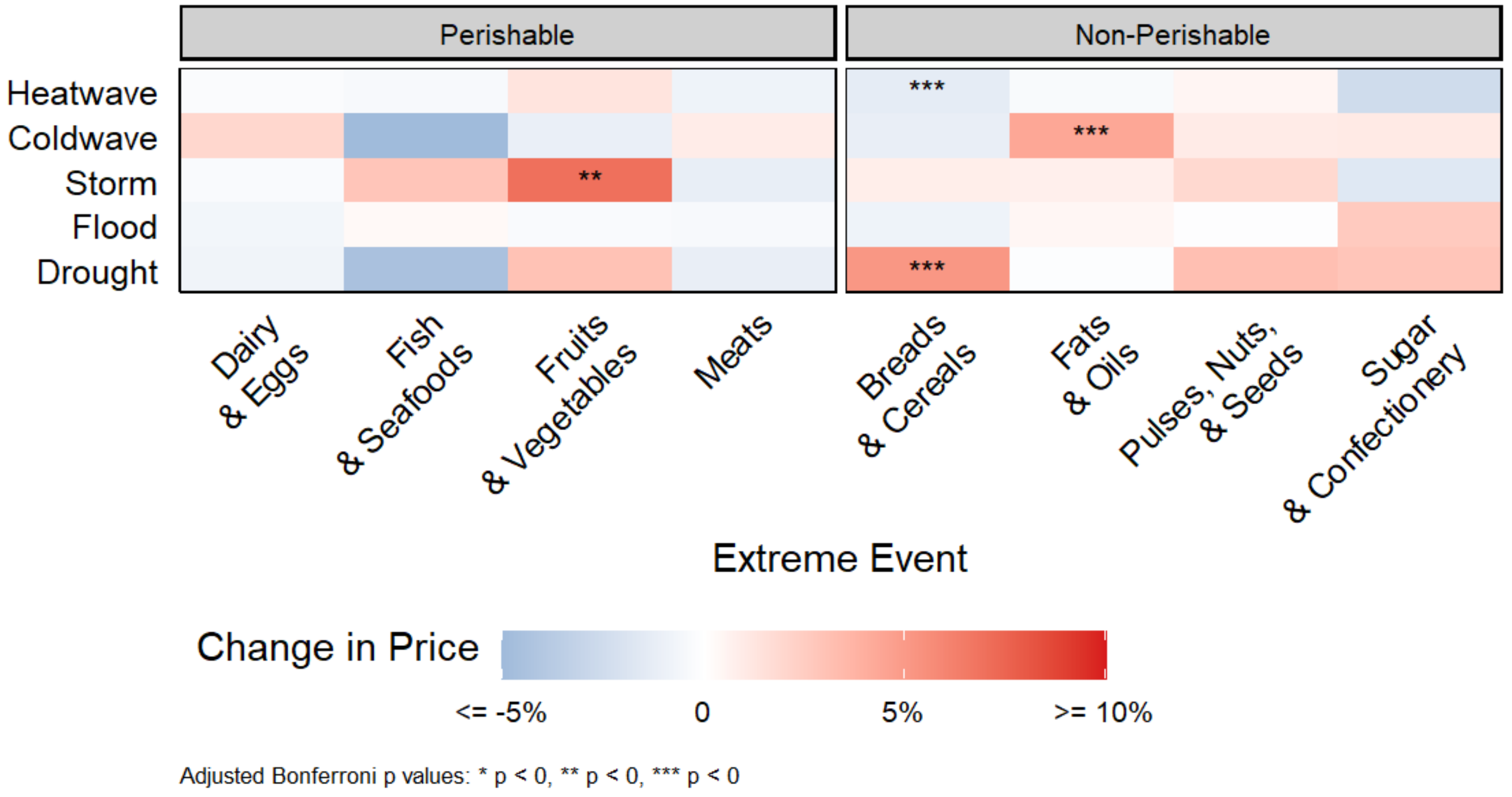


Total n = 1,346,513
in 2,321 markets in 71 countries



Data Sources: FAO GIEWS, USAID FEWS, and WFP VAM

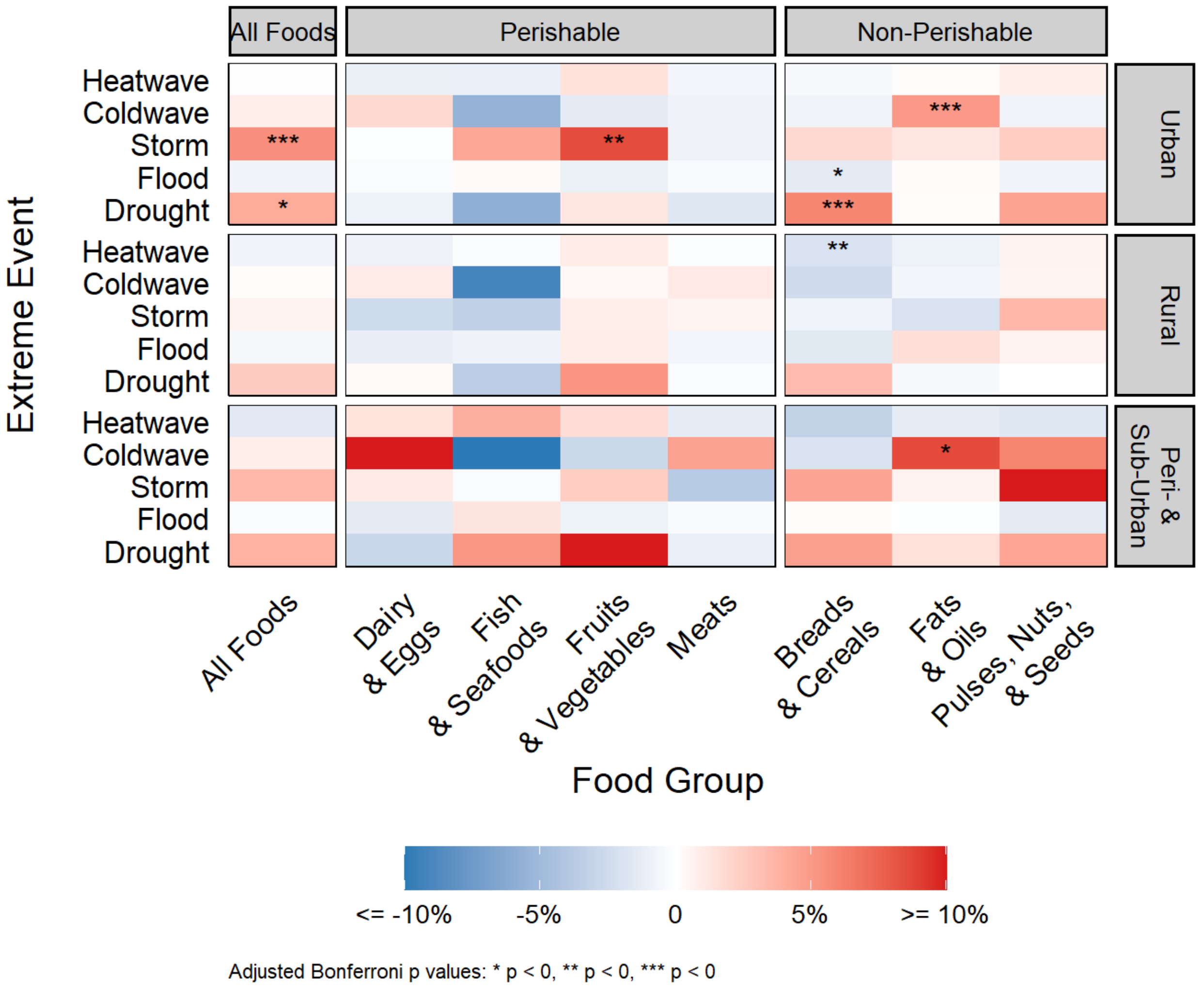
Retail prices and extreme weather



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

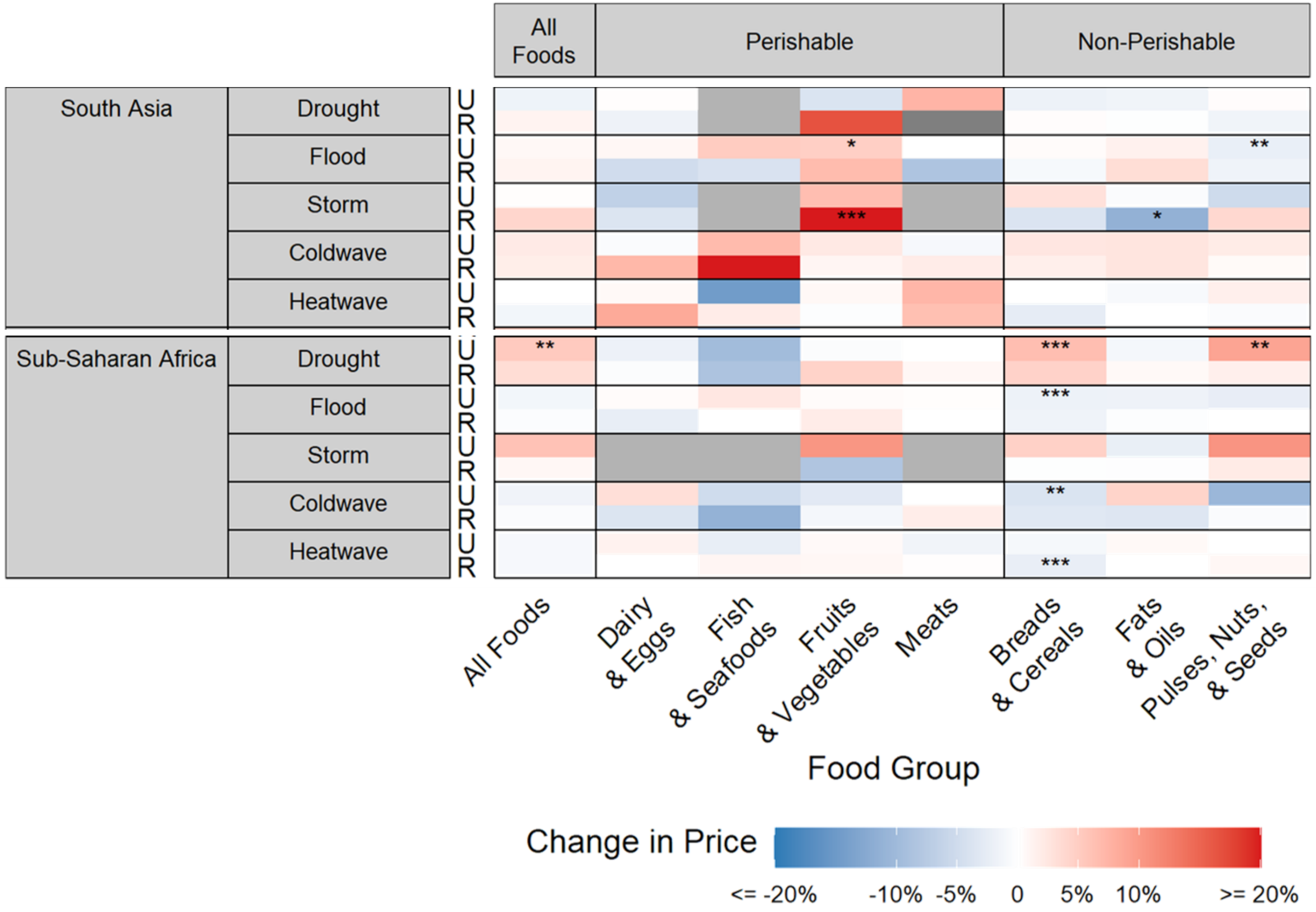
Data Sources: FAO GIEWS, USAID FEWS, and WFP VAM

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

Retail prices and extreme weather



- 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

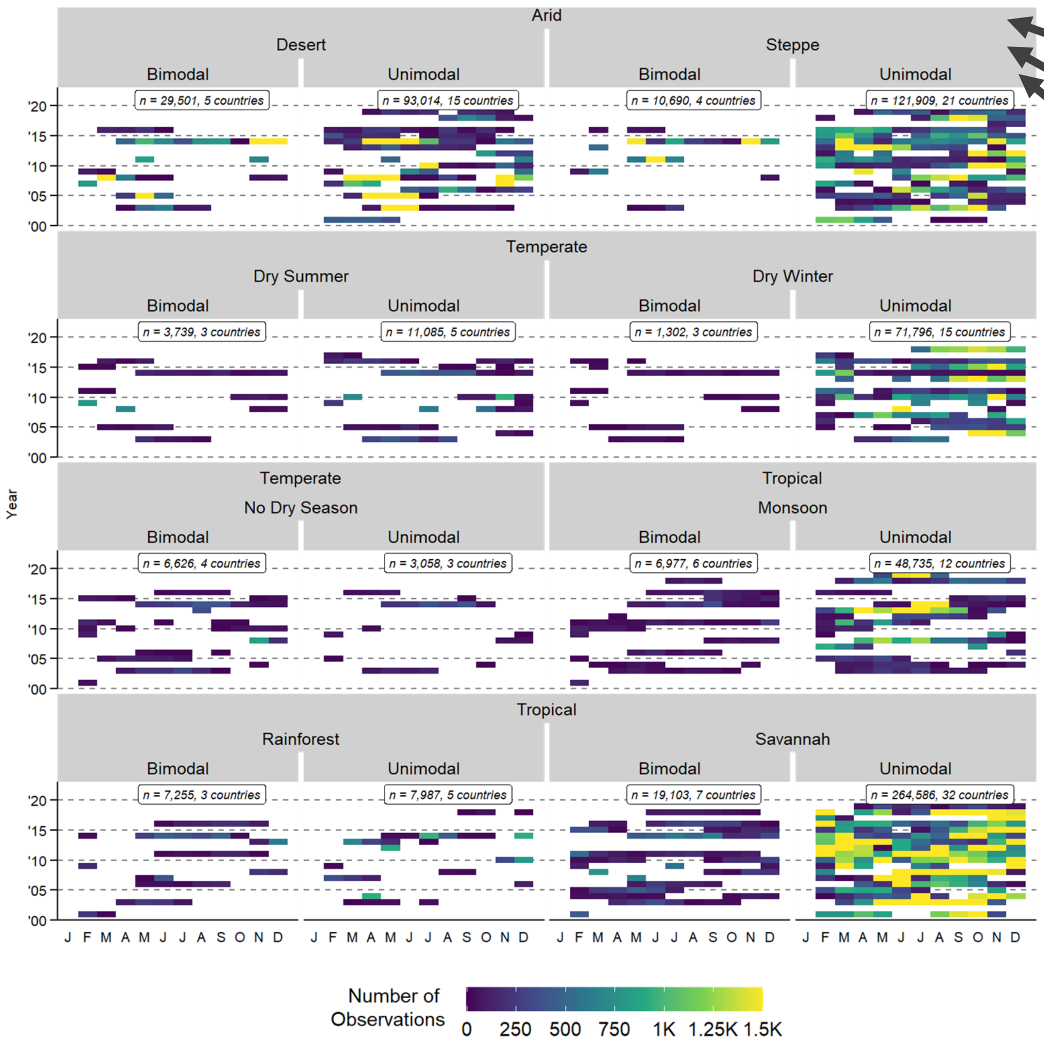
Research design

$$Logit(W_{ijtPK}) = \beta_0 + \boldsymbol{\beta_1} Seasonality_{jtPK} + \boldsymbol{\beta_2} Extreme\ Event_{jt} + \varepsilon$$

- *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

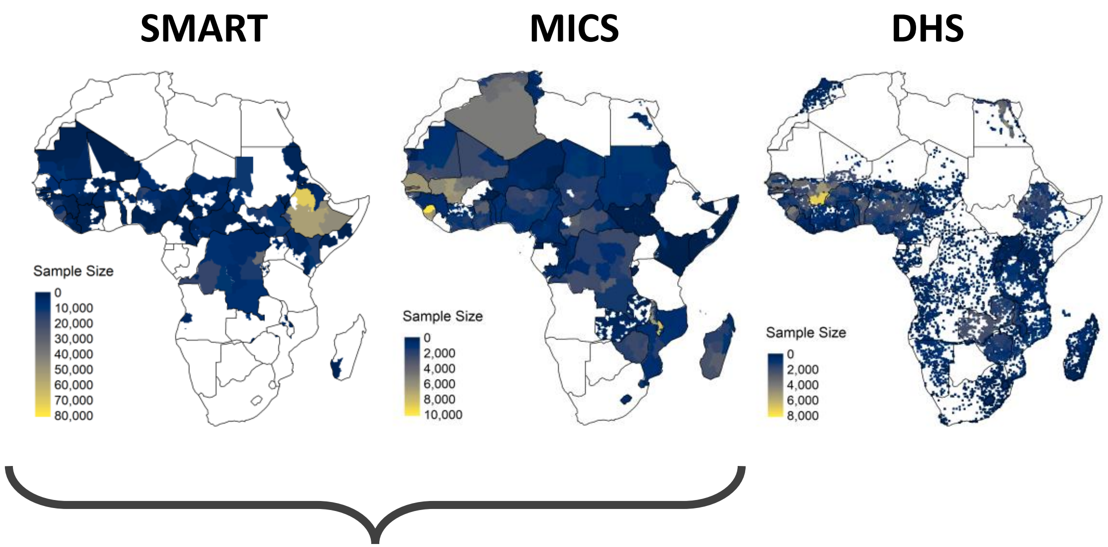
Total n = 2,591,633 children
in 49 countries



Level 1 Köppen climate class

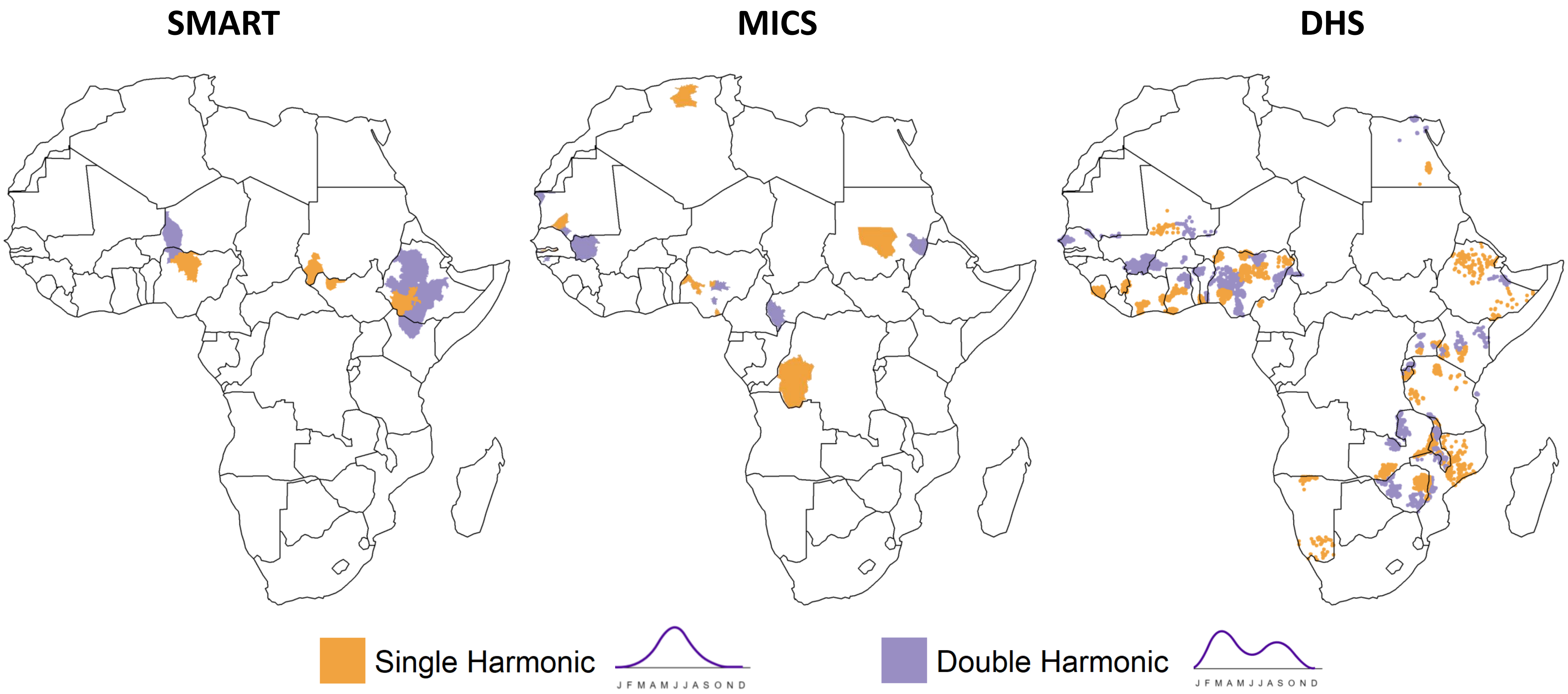
Level 2 Köppen climate class: seasonal precipitation subgroup

Precipitation mode

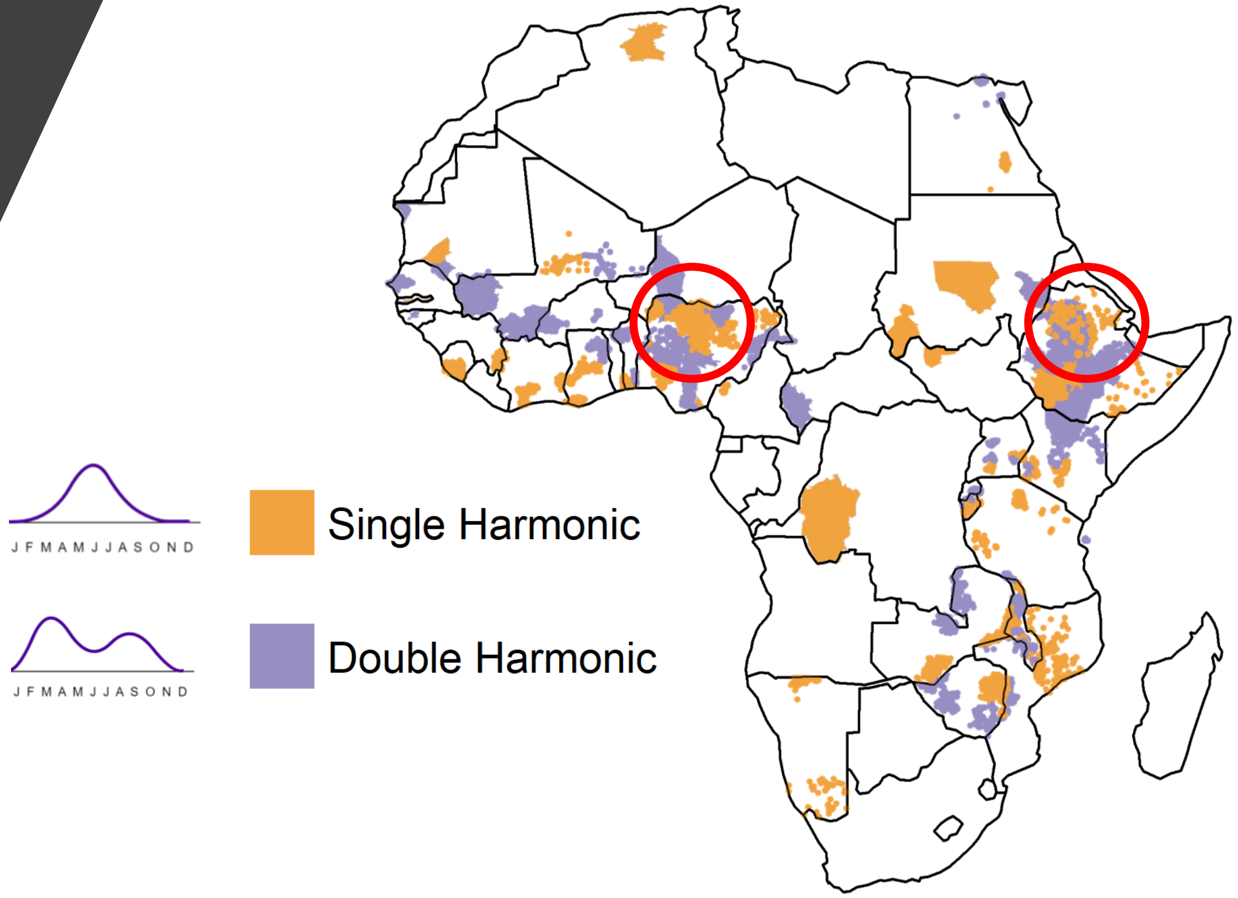


Survey boundaries identified via text matching, adjusted to remove extremely rural areas

Distribution of significant harmonics

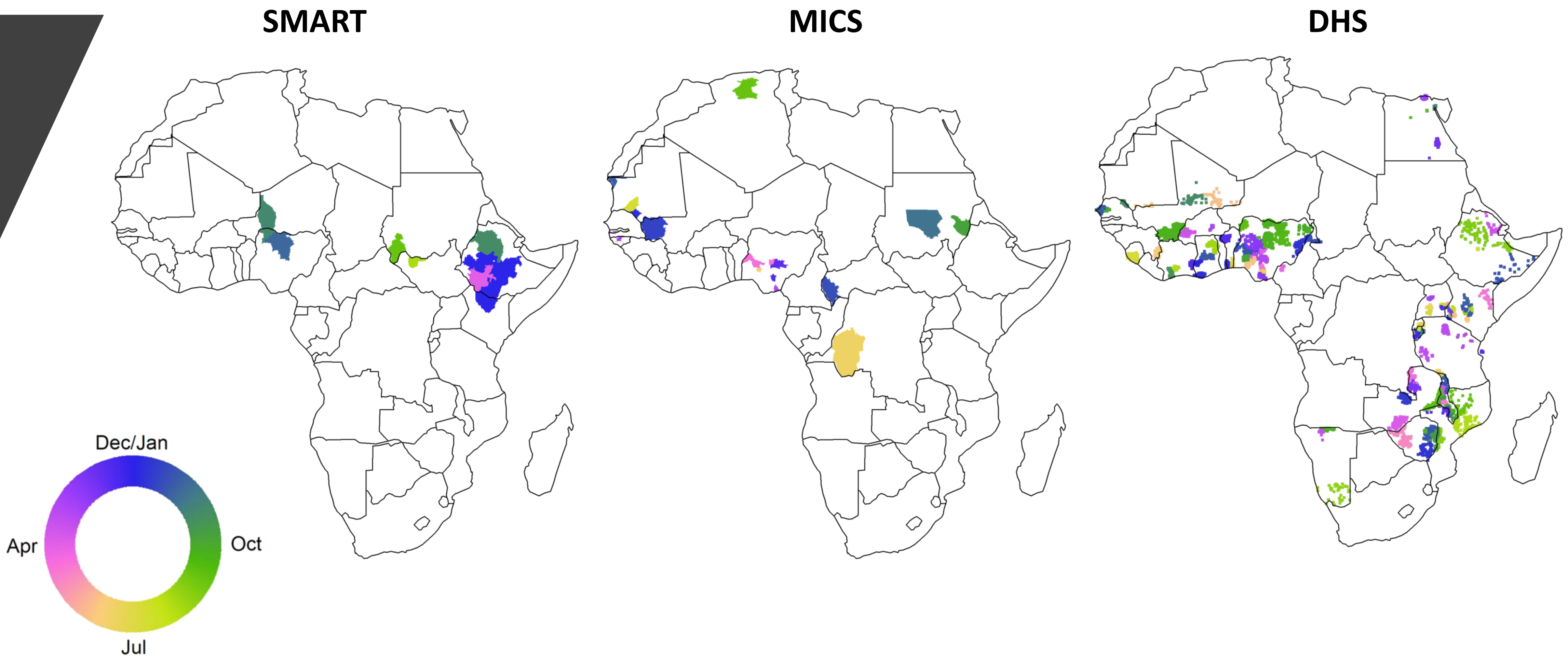


Distribution of significant harmonics

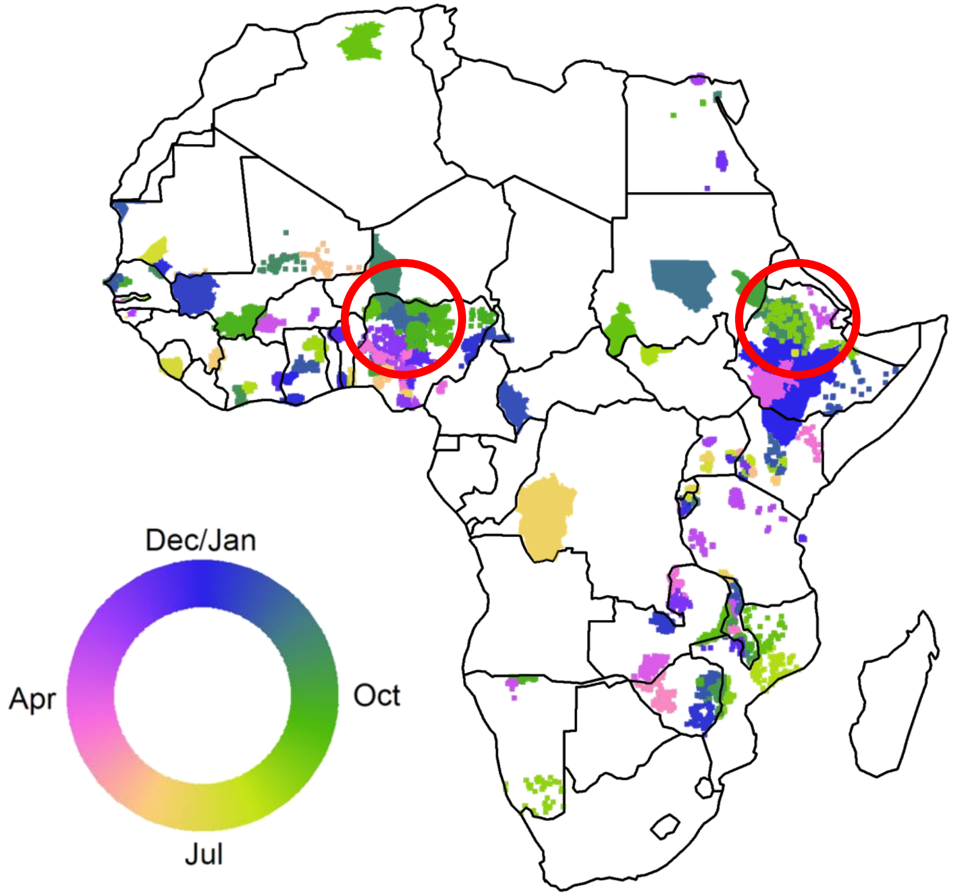


- Mix of significant single and double harmonics indicates heterogeneity
- Datasets can be utilized to validate or refute calculated harmonic patterns
  - E.g. Northern Nigeria and Ethiopian highlands
- Baseline map for other regions to contribute own analyses to fill in the gap

Distribution of peak timings



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

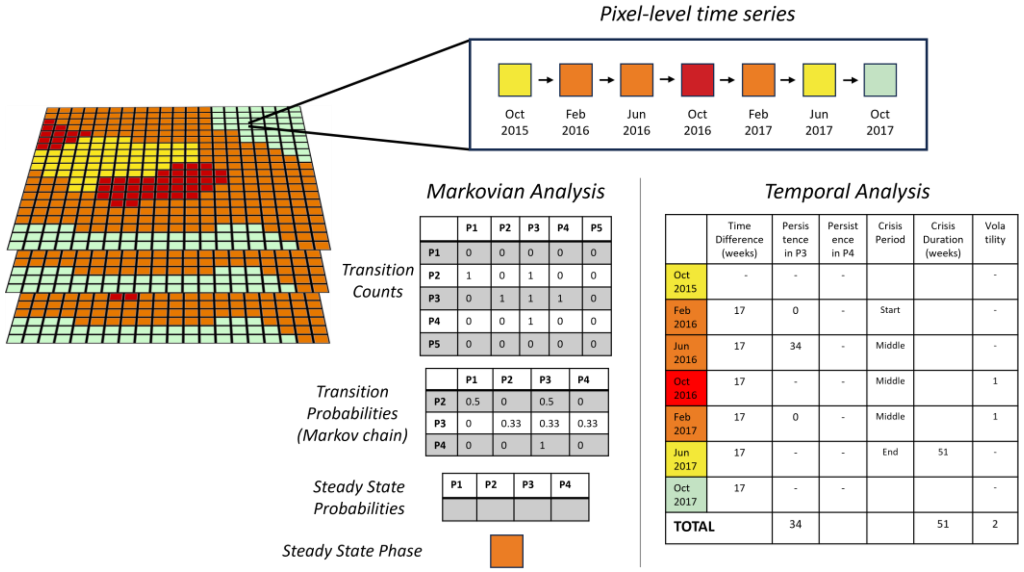
Aim 3.2: Quantify the effect of extreme events on accuracy of predictions generated by famine early warning systems

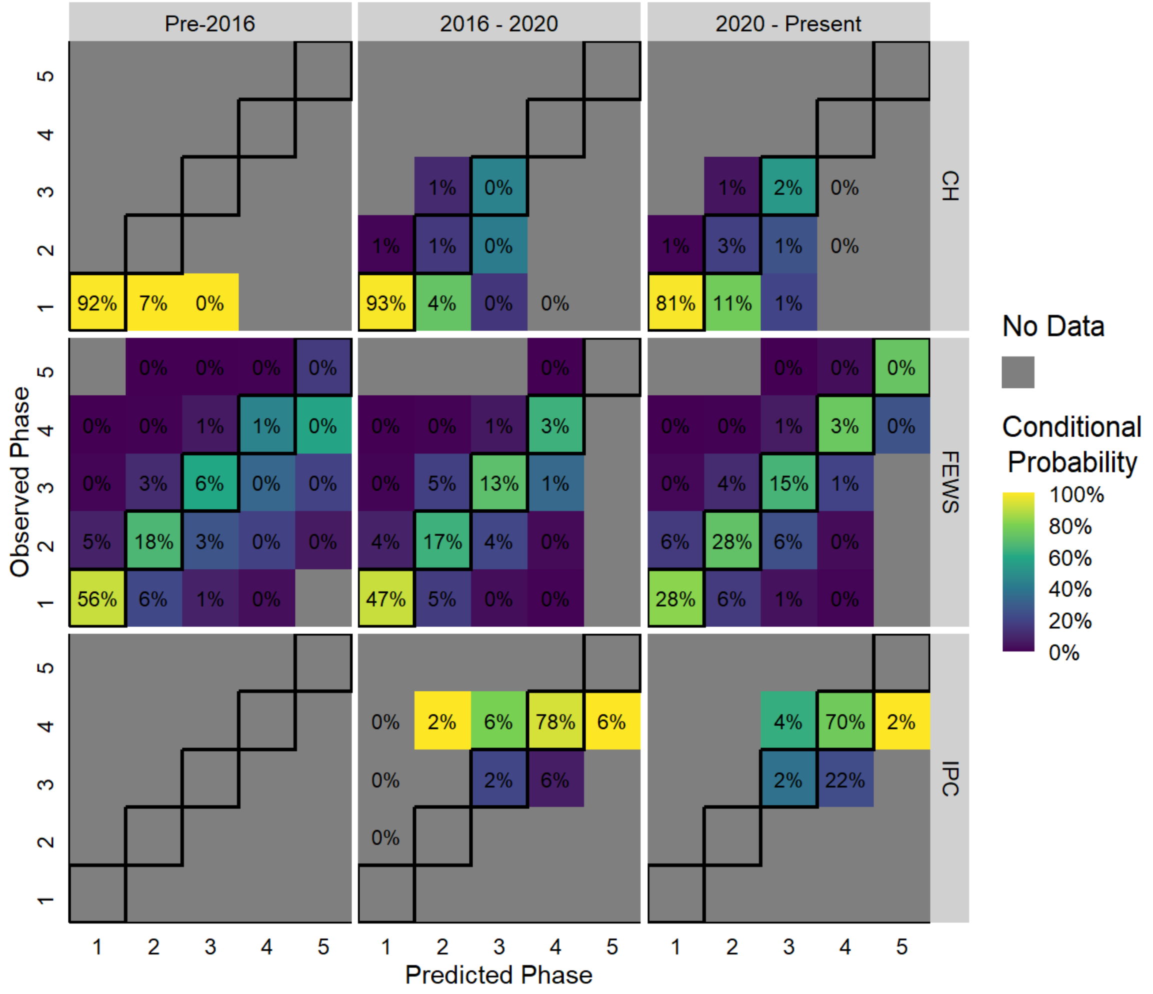
Research design

$$P(ST_{j,d,q+1} \perp CS_{j,d,q}) = \beta_0 + \boldsymbol{\beta_1} Extreme\ Event_{j,t} + \gamma_j + \varepsilon$$

- 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*)

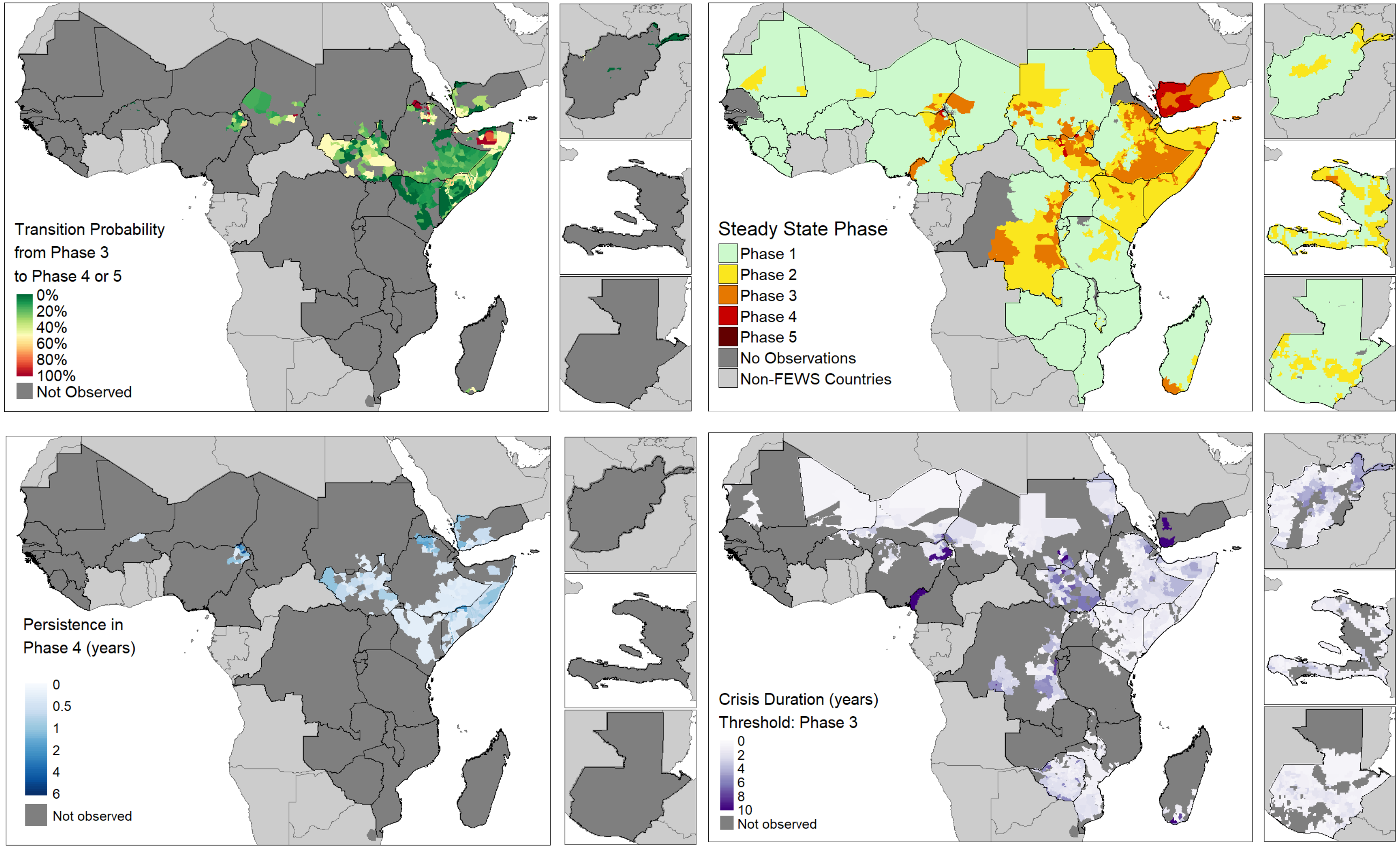
Probability summary





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 heterogenous
  - 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 data completeness and quality in spatial, temporal, and climatological domains

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

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  - 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

Tufts UNIVERSITY | 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 Nutrition

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)**
	Gaussian Linear Model	*Log-Linear Model*	*Gaussian Linear or Log-Linear*
Regression Model	$Y_t = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 T(t)$	$\ln(E[Y_t]) = \beta_0 + \beta_1 \sin(2\pi\omega t) + \beta_2 \cos(2\pi\omega t) + \beta_3 T(t)$	Y_t *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_Ls
Nadir (P)	$N = \beta_0 - \gamma$	$N = e^{\beta_0} - \gamma$	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_Ls
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

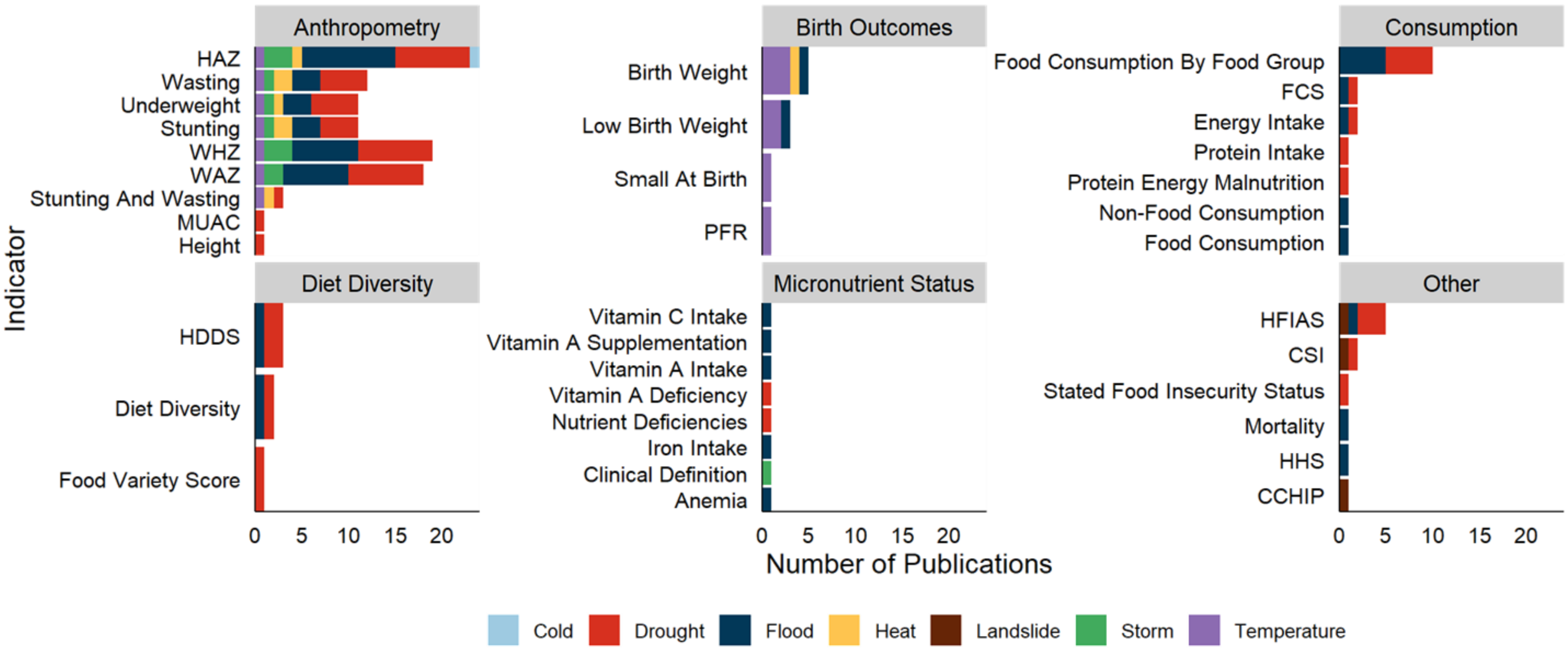
Pakistan - Dera Ghazi Khan - Muzaffargarh

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)	**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.					
	Food consumption (focus on energy intake)	**Quantity**: Adequate energy intake **Dietary energy intake**:[a] Adequate (avg. 2,350 Kilocalories (kcal) pp/day) and stable	**Quantity: Minimally adequate** **Dietary energy intake**: Minimally adequate (avg. 2,100 kcal pp/day)	**Quantity: Moderately inadequate** – Moderate deficits **Dietary energy intake**: Food gap (below avg. 2,100 kcal pp/day)	**Quantity: Very inadequate** – Large deficits **Dietary energy intake**: Large food gap (well below 2,100 kcal pp/day)	**Quantity: Extremely inadequate** – Very large deficits **Dietary Energy Intake**: Extreme food gap
		Household Dietary Diversity Score (HDDS):[a] 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 Score (FCS):[a] 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):[a] 0 (none)	**HHS**: 1 (slight)	**HHS**: 2-3 (moderate)	**HHS**: 4 (severe)	**HHS**: 5-6 (severe)
		Reduced Coping Strategies Index (rCSI):[a] 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):[a] No livelihood protection deficit.	**HEA**: Small or moderate livelihood protection deficit <80%	**HEA**: Livelihood protection deficit ≥80%; or survival deficit <20%	**HEA**: Survival Deficit ≥20% but <50%	**HEA**: Survival deficit ≥50%
		Food Insecurity Experience Scale (FIES 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)
	Livelihood change (assets and strategies)	**Livelihood change**: Sustainable livelihood strategies and assets **Livelihood coping strategies (LCSs)**:[a] No stress, crisis or emergency coping observed.	**Livelihood change**: Stressed strategies and/or assets; reduced ability to invest in livelihoods **LCS**: Stress strategies are the most severe strategies used by the household in the past 30 days.	**Livelihood change**: Accelerated depletion/erosion of strategies and/or assets **LCSs**: Crisis strategies are the most severe strategies used by the household in the past 30 days.	**Livelihood change**: Extreme depletion/ liquidation of strategies and assets **LCSs**: Emergency strategies are the most severe strategies used by the household in the past 30 days.	**Livelihood change**: Near complete collapse of strategies and assets **LCSs**: Near exhaustion of coping capacity.

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