Dynamic News Signals as Early-Warning Indicators of Food Insecurity: A Two-Stage Residual Modelling Framework

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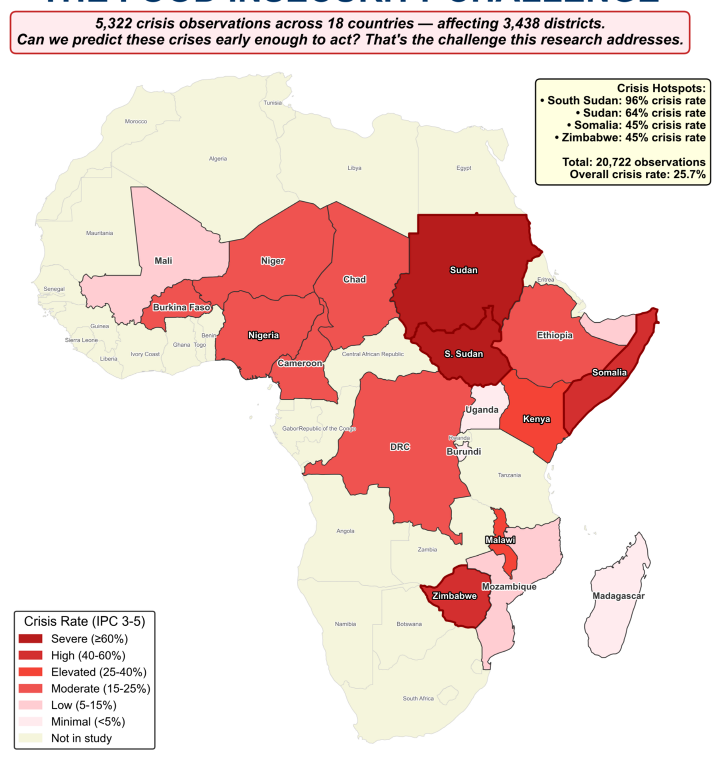
DATA FOUNDATION

7.6M	55,129	18	8 months
News Articles	IPC Assessments	African Countries	Forecast Horizon
GDELT Corpus	Food Security Data	3,438 Districts	Early Warning

THE CHALLENGE: 5,322 food crisis observations across 18 African countries. Can we predict these crises early enough to enable humanitarian intervention?

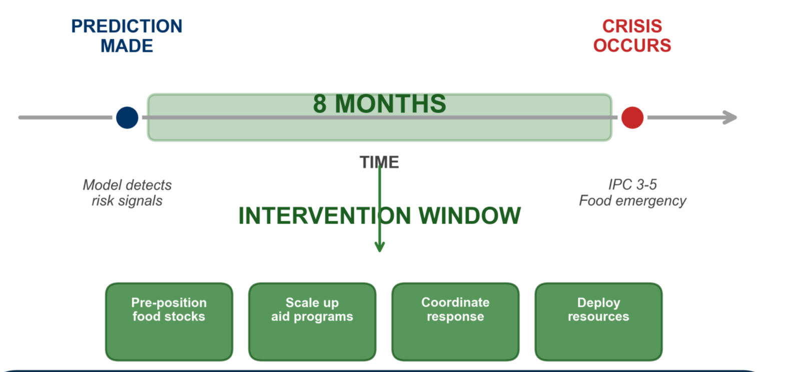
THE FOOD INSECURITY CHALLENGE

5,322 crisis observations across 18 countries — affecting 3,438 districts.
Can we predict these crises early enough to act? That's the challenge this research addresses.



THE EARLY WARNING VALUE

8-month forecast horizon enables humanitarian intervention

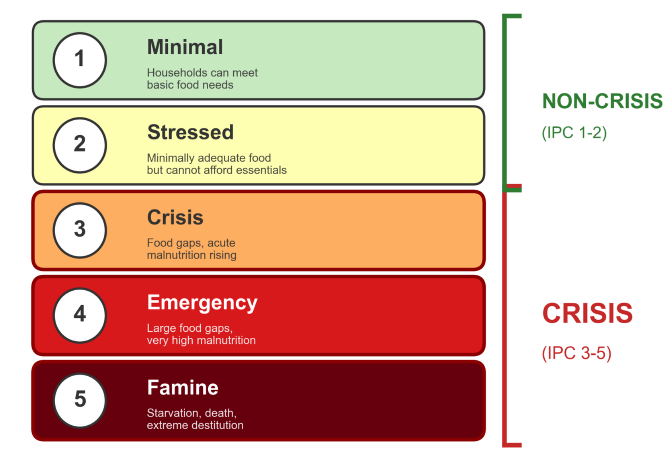


WHY EARLY WARNING MATTERS

249 crises predicted 8 months early = 249 opportunities for life-saving intervention

WHAT ARE WE PREDICTING?

The IPC Food Security Classification



OUR PREDICTION TASK

Predict which districts will transition to CRISIS (IPC 3-5)

8 months before it happens — enabling early humanitarian response

THE AUTOCORRELATION TRAP

Why food crisis prediction appears easy

TEMPORAL L_t — Past IPC values predict future

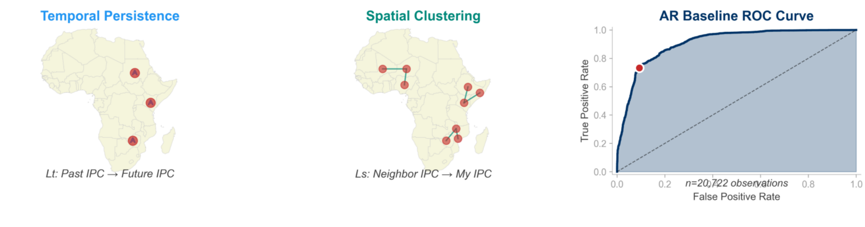
0.907 ROC-AUC

vs Balashankar et al. (PR-AUC): Ours: 0.765 vs SOTA: 0.816

94% of SOTA — 0 news features

SPATIAL L_s — Neighbor IPC values predict mine

BUT 1,427 CRISES STILL MISSED

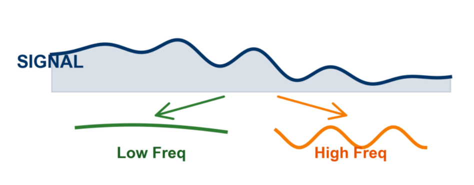


THE GAP: AR captures low-frequency persistence but misses high-frequency shocks — conflict escalations, economic collapses, displacement surges. These 1,427 missed crises are where early warning matters MOST.

TWO SIGNAL COMPONENTS: Theory vs Real Data

Crisis signals decompose into persistence (AR handles) and shocks (AR misses)

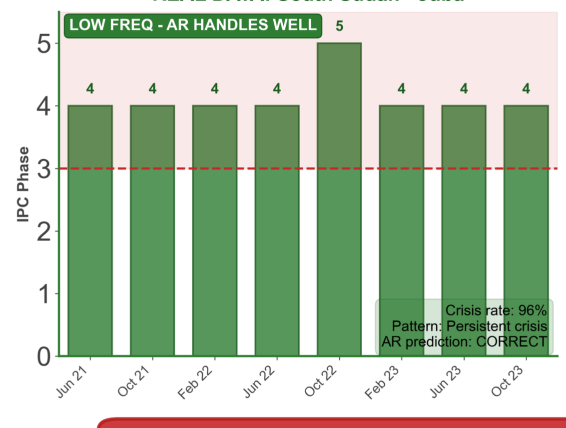
CONCEPTUAL: Signal Decomposition



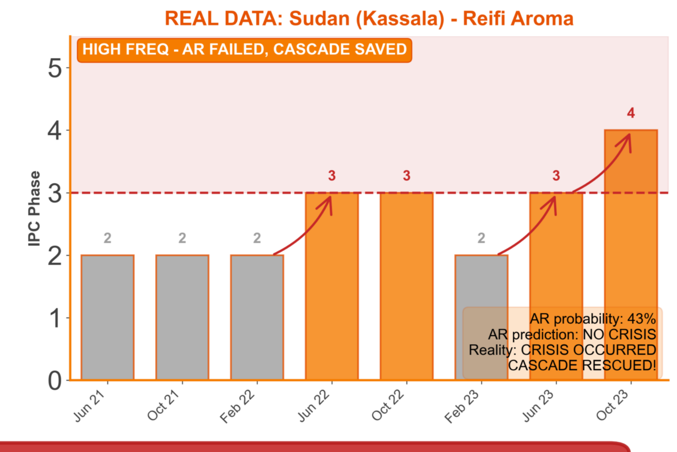
MEANING: Why AR Has Gaps

LOW FREQUENCY	HIGH FREQUENCY
Persistent patterns	Rapid-onset shocks
Chronic insecurity	Conflict escalation
Seasonal cycles	Economic collapse
Structural factors	Displacement surge
AR HANDLES	AR MISSES

REAL DATA: South Sudan - Juba



REAL DATA: Sudan (Kassala) - Reifi Aroma

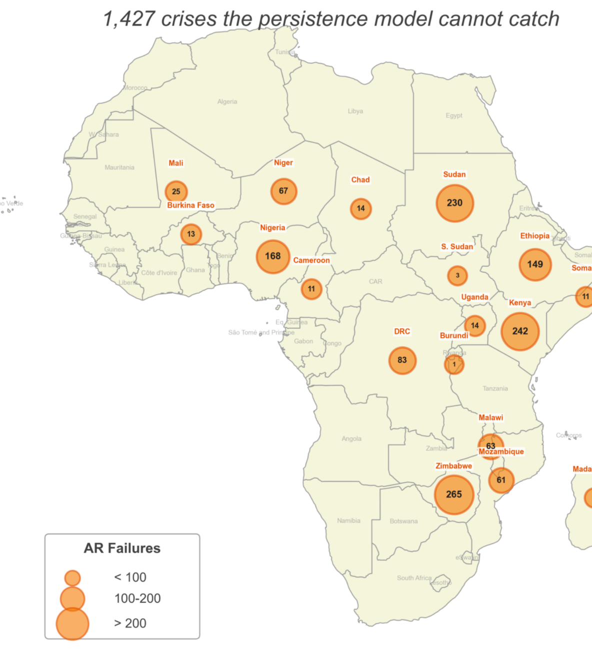


THE KEY INSIGHT

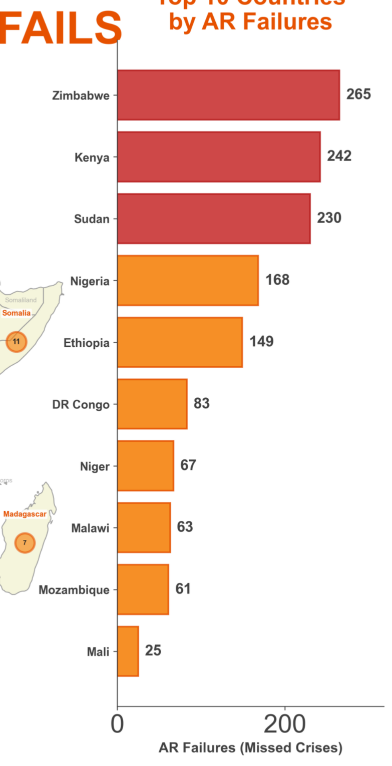
High-frequency shocks (like Sudan above) account for 1,427 AR failures.
These are HARDER to predict but WHERE EARLY WARNINGS MATTER MOST

WHERE THE AR BASELINE FAILS

1,427 crises the persistence model cannot catch



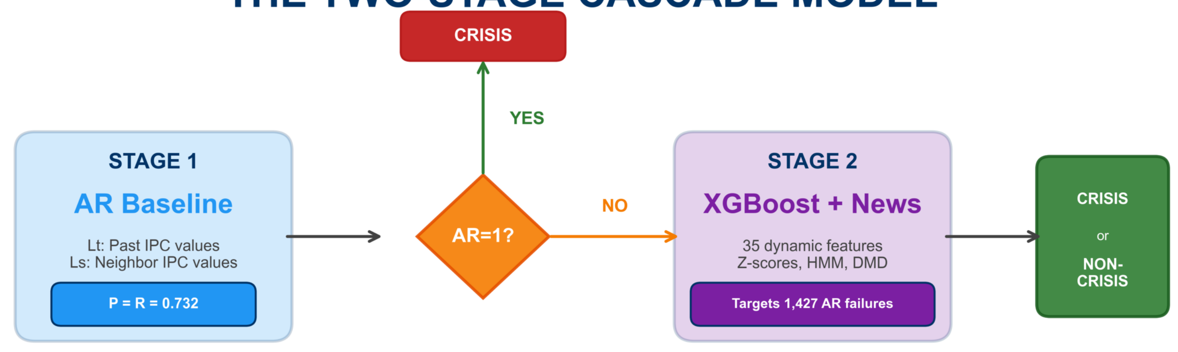
Top 10 Countries by AR Failures



These rapid-onset shocks break the temporal pattern:
Conflict (Sudan) · Economic collapse (Zimbabwe) · Displacement (DRC)

THE SOLUTION: Two-stage cascade — if AR predicts crisis, trust it. If AR predicts non-crisis, check news features. News captures the rapid-onset shocks AR misses.

THE TWO-STAGE CASCADE MODEL



LOGIC: "If AR predicts crisis, trust it. If AR predicts non-crisis, check news features."

BENEFIT 1: Improved accuracy for the difficult cases AR misses
BENEFIT 2: News features used ONLY when they matter — better interpretability

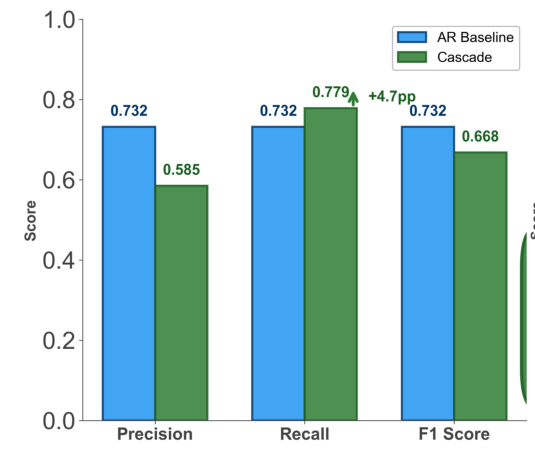
DYNAMIC FEATURE ENGINEERING: How We Extract Crisis Signals from News

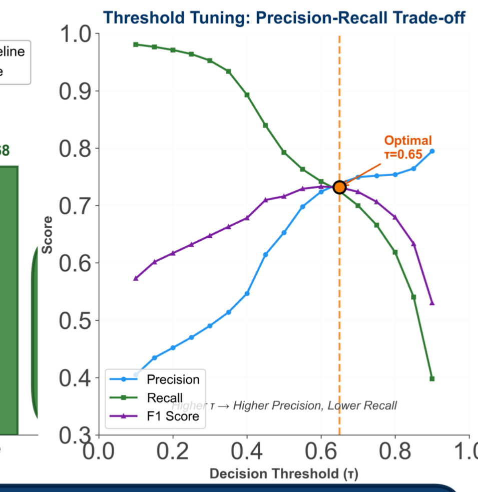
35 features engineered from 7.6M GDELT articles to detect rapid-onset shocks AR misses

	Z-SCORES	HMM	DMD	ML MODELS
	Temporal Anomaly Detection	*Hidden Regime Detection*	*Crisis Escalation Patterns*	*XGBoost + Mixed Effects*
	12-month rolling standardization	2-state Gaussian HMM with 85% persistence	SVD-based mode decomposition	Gradient boosting + random intercepts
WHY	Different districts have different news baselines	Crises have latent states not visible in raw counts	Crisis escalation has characteristic growth modes	Need nonlinear power AND interpretability
WHAT IT CAPTURES	Detects UNUSUAL spikes above historical norm	Detects Pre-Crisis → Crisis-Prone transitions	Identifies GROWING modes vs stable background	XGBoost: complex patterns Mixed: country heterogeneity
REAL EXAMPLE	*Sudan conflict +3σ before April 2023 escalation*	*8 regime shifts detected in Sudan 2022-2023*	*Growth rate λ>0.01 flags 21 escalation events*	*Zimbabwe responds to weather, Sudan to conflict*
	9 features	6 features · +0.007 AUC	8 features · +0.002 AUC	35 total · 249 saves

PERFORMANCE COMPARISON

AR Baseline vs Cascade Model





THE CRITICAL INSIGHT

The improvement from 0.732 to 0.779 recall is NOT just a better metric.

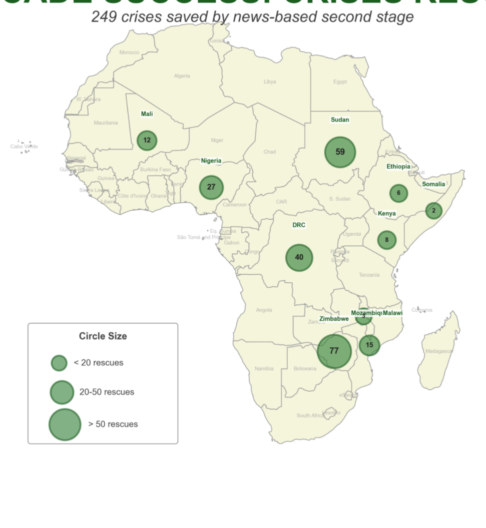
The cases that MATTER MOST are now predicted.

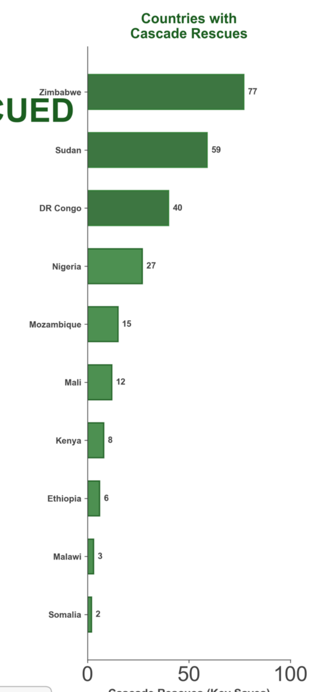
249 district-level crises predicted 8 months early — potential humanitarian interventions.

THE RESULTS: Cascade rescues 249 crises (17.4% of AR failures). Two complementary views: DOMINANT themes drive predictions (governance, humanitarian); ELEVATED themes show country-specific anomalies (weather, conflict).

CASCADE SUCCESS: CRISES RESCUED

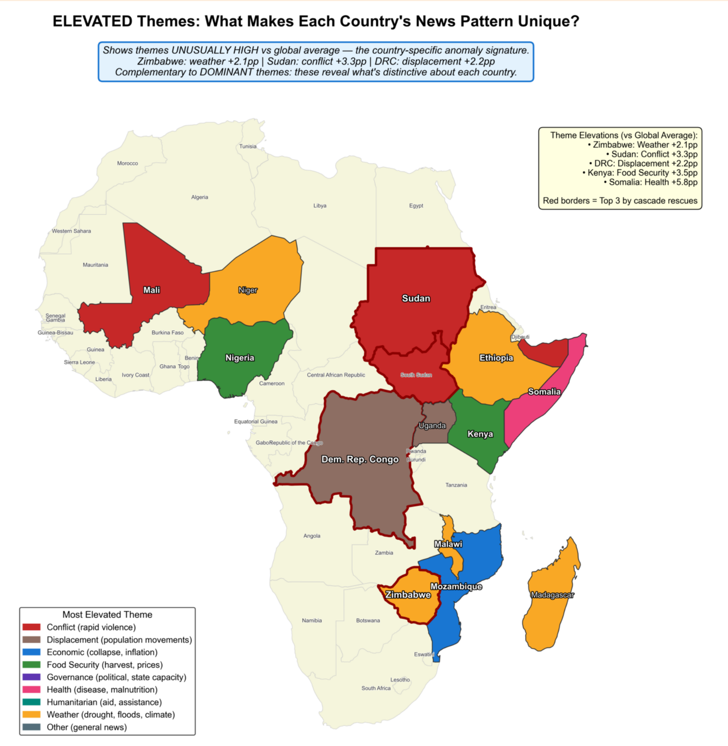
249 crises saved by news-based second stage



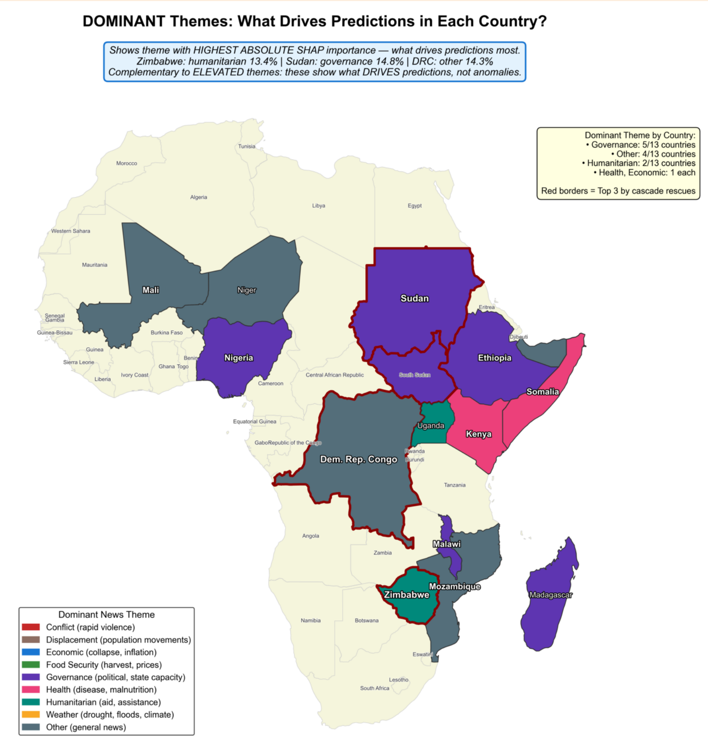


Top 3 countries = 70.7% of all rescues
News features most valuable where AR baseline fails

ELEVATED Themes: What Makes Each Country's News Pattern Unique?



DOMINANT Themes: What Drives Predictions in Each Country?

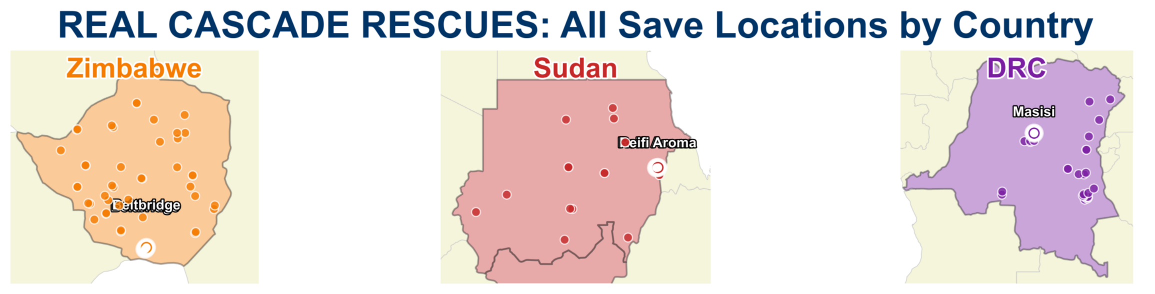


RESEARCH QUESTIONS ANSWERED

Key Findings from the Dissertation

	RQ1	RQ2	RQ3	RQ4	RQ5
	The Autocorrelation Trap	When Does News Matter?	HMM & DMD Contribution	Does Cascade Work?	Geographic Heterogeneity
	Can AR baselines replicate news model performance?	*Which features predict beyond AR baseline?*	*Do latent methods detect hidden crisis dynamics?*	*Can two-stage approach rescue AR failures?*	*Are news features equally valuable everywhere?*
	0.907 AUC	74.7% Z-score SHAP	#5 HMM rank	249 rescues	SELECTIVE deployment
FINDING	93.8% of literature performance with 0 news features	Anomaly detection crucial: Z-scores dominate SHAP, theme heterogeneity varies	HMM detects regime shifts, DMD captures escalation modes	17.4% of AR failures rescued 8 months in advance	70.7% of saves in just 3 countries: ZWE, SDN, DRC (high coverage)
EVIDENCE	AR PR-AUC=0.765 vs Balashankar PR-AUC=0.816	Weather/conflict z-scores top features; governance dominates 5/13 countries	HMM +0.007 AUC DMD coef +352.38	Recall: 0.732 → 0.779 (+4.7pp, +6.4%)	Best: SDN 0.68, UGA 0.68 Worst: Niger 0.07 (sparse)
IMPLICATION	Persistence dominates crisis prediction	Shocks + context-specific themes drive value	Interpretability for crisis dynamics	Catches hardest crises AR misses	Target high-coverage regions for max impact

REAL CASCADE RESCUES: All Save Locations by Country



77 rescues	59 rescues	40 rescues
Economic & Drought	**Conflict & Displacement**	**Conflict & Displacement**
Example: Beitbridge	Example: Reifi Aroma	Example: Masisi
Matabeleland South • October 2023	Kassala State • June 2021	North Kivu • October 2022
Currency collapse + drought detected via news signals	*Displacement crisis detected via humanitarian reporting*	*M23 resurgence detected via conflict news surge*

KEY CONTRIBUTIONS

	Contribution		Outcome	
1	**METHODOLOGICAL CRITIQUE** First systematic AR vs news comparison in food security	FIRST	**BENCHMARK** New standard for field	PROVEN
2	**TWO-STAGE ARCHITECTURE** Novel WITH_AR_FILTER strategy separates persistence from shocks	NOVEL	**FRAMEWORK** Stage 1 + Stage 2 cascade	PROVEN
3	**DYNAMIC FEATURE GROUPS** Beyond article counts: Ratio, Z-score, Location, HMM/DMD	4	**GROUPS** 35 engineered features	PROVEN
4	**TRIANGULATED INTERPRETATION** XGBoost + Mixed-Effects + SHAP reveals split ≠ prediction	3	**METHODS** Tree vs SHAP vs Coefficients	PROVEN
5	**OPERATIONAL DEPLOYMENT** Tier-based resource allocation for humanitarian agencies	3	**TIERS** AR-only vs Cascade zones	PROVEN

First AR benchmark • Novel cascade architecture • Operational deployment framework

KEY REFERENCES

1. Balashankar et al. (2023). Predicting Food Crises Using News Streams. Science Adv. doi.org/10.1126/sciadv.abm3449

2. Roberts et al. (2017). Cross-Validation Strategies for Spatial Data. Ecography. doi.org/10.1111/ecog.02881

3. Lundberg & Lee (2017). SHAP Model Interpretability. NIPS 2017.