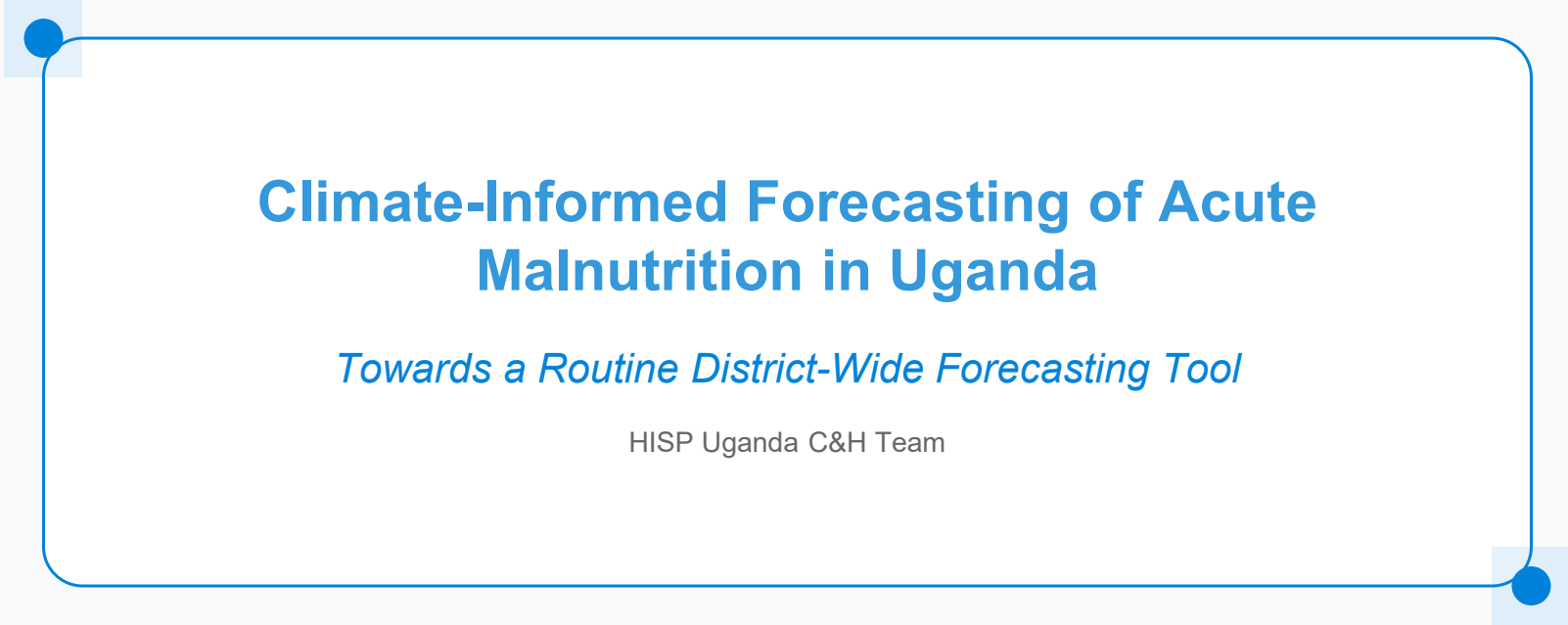




Climate-Informed Forecasting of Acute Malnutrition in Uganda

Towards a Routine District-Wide Forecasting Tool

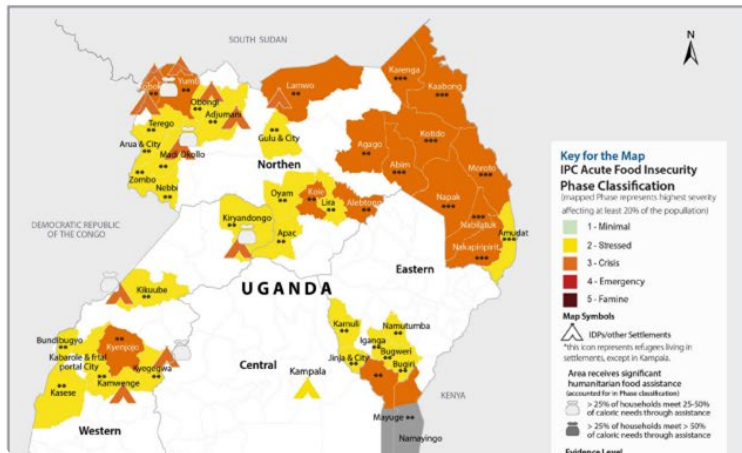
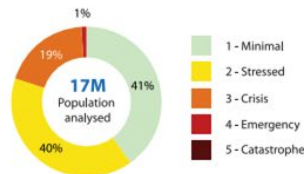
HISP Uganda C&H Team

Uganda context



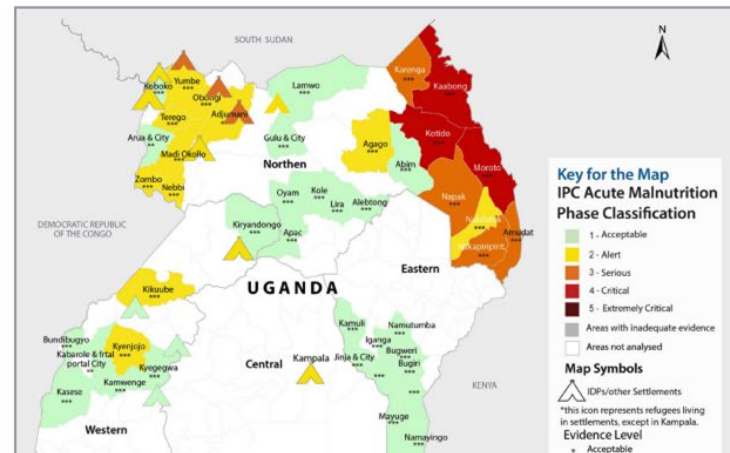
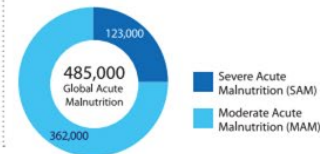
About 3.4 million people in Uganda and its refugee hosting districts experienced high levels of acute food insecurity, classified in IPC Phase 3 or above (Crisis or worse) between April and July 2025.

20 percent of the analysed population experienced high levels of acute food insecurity (IPC Phase 3 or above).



About 485,000 children aged 6-59 months in Uganda and its refugee hosting districts are suffering or expected to suffer acute malnutrition through March 2026. About 90,736 pregnant or breastfeeding women will likely suffer acute malnutrition in the same period.

123,000 children aged 6-59 months are suffering or expected to suffer severe acute malnutrition.



Key drivers

Key Drivers | Acute Food Insecurity

Low purchasing power

Most rural households rely on agriculture and casual labour. Poor yields and reduced opportunities have weakened limited ability to purchase food.

Conflict and displacement

Conflict and displacement linked to limited livestock theft have deepened vulnerabilities in Karamoja. In West Nile, refugees continue to arrive from neighbouring countries.

Climatic shocks

Poor rainfall and prolonged dry spells continue to negatively affect cereal and pulse crop production, contributing to household food deficits.

High food prices

Prices of key staples such as maize, beans, and cassava have increased due to depleted stocks, reducing food access for market-dependent households.

Contributing Factors | Acute Malnutrition

Poor feeding practices

Inadequate food intake in both meal frequency and dietary diversity among children under five years in all the four surveyed regions.

High disease burden

High cases of malaria, diarrhoea, and cholera among children aged 6–59 months pose a high risk of acute malnutrition.

Poor access to WASH services

Limited access to safe water and inadequate sanitation increase the risk of waterborne and vector-borne diseases.

Food insecurity

Limited availability and access to nutritious food at household level in Karamoja and West Nile contribute to malnutrition.

Low IMAM/ICMAM coverage

Limited access to health and nutrition services and low community health capacity has hindered treatment of acute malnutrition.

Pathway could look like this...

Climate and contextual shock

Poor rainfall, floods, drought, displacement, high prices, reduced aid



Livelihood and food system

Lower food production, reduced income, higher food prices, reduced food access



Household-level

Poor diet, reduced meal frequency, low dietary diversity

Health service

More disease, poor WASH, reduced screening and treatment coverage



Nutrition outcome

Increased acute malnutrition among children and pregnant/breastfeeding women

Our approach

1) Integrate multiple data sources

Combine data on nutrition burden, climate and environmental conditions, food security and livelihoods, disease and WASH, health services and access, and population vulnerability.

1) Develop ML tool, test and evaluate

Review and validate ML models, develop ML tool to predict three months in advance, and co-evaluate its performance and usefulness with health and nutrition programmes

2) Deploy on CHAP for operational use

Deploy the ML tool through CHAP and operationalize it within the DHIS2 Climate and Health Platform using dashboards, maps, and other visualizations.

3) Enable proactive intervention

Integrate forecasts into routine planning and decision-making processes, including IPC, to support earlier action, targeted surveillance, and timely resource allocation.

RESEARCH ARTICLE

Forecasting acute childhood malnutrition in Kenya using machine learning and diverse sets of indicators

Girmaw Abebe Tadesse^{1*}, Laura Ferguson^{2,3}, Caleb Robinson⁴, Shiphrah Kuria⁵, Herbert Wanyonyi⁶, Samuel Murage⁶, Samuel Mburu⁷, Rahul Doodhia⁸, Juan M. Lavieja Ferres⁹, Bietra Dikina¹⁰

1 Microsoft AI for Good Research Lab, Nairobi, Kenya, **2** University of Southern California, Institute on Inequalities in Global Health, Los Angeles, California, United States of America, **3** Amel International University, Nairobi, Kenya, **4** Microsoft AI for Good Research Lab, Redmond, Washington, United States of America, **5** Amel Health Africa, Nairobi, Kenya, **6** Division of Nutrition and Dietetics, Ministry of Health, Nairobi, Kenya, **7** University of Southern California, Center for AI in Society, Los Angeles, California, United States of America

* gtadesse@microsoft.com



Abstract

OPEN ACCESS

Citation: Tadesse GA, Ferguson L, Robinson C, Kuria S, Wanyonyi H, Murage S, et al. (2025) Forecasting acute childhood malnutrition in Kenya using machine learning and diverse sets of indicators. PLoS One 20(5): e0229590. <https://doi.org/10.1371/journal.pone.0229590>

Editor: Yitagesu Habtu Awelke, Addis Ababa University, ETHIOPIA

Accepted: August 11, 2025

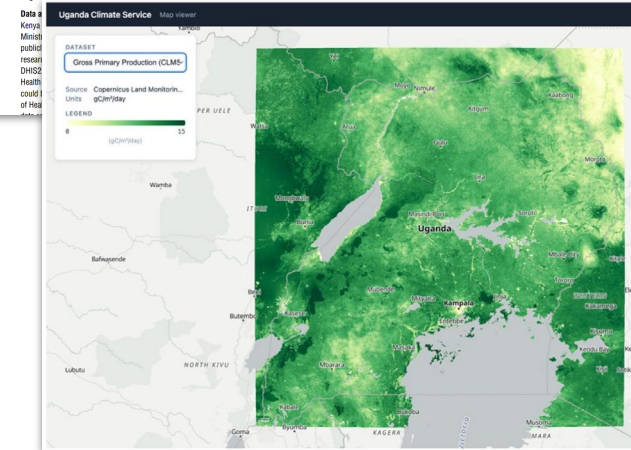
Published: March 31, 2025

Copyright: © 2025 Tadesse et al. This is an open access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Copyright: © 2025 Tadesse et al. This is an open access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Objectives: Malnutrition is a leading cause of morbidity and mortality for children under-5 globally. Low- and middle-income countries, such as Kenya, bear the greatest burden of malnutrition. The Kenyan government has been collecting clinical indicators, including on malnutrition, using District Health Information Software-2 (DHIS2) for over a decade. We aim to address the existing gap in decision-makers' ability to develop and utilize malnutrition forecasting capabilities for timely interventions. Specifically, our objectives include: develop a spatio-temporal machine learning model to forecast acute malnutrition among children in Kenya using DHIS2 data, enhance forecasting capability by integrating external complementary indicators, such as publicly available satellite imagery-driven signals, and forecast acute malnutrition at various stages and time horizons, including moderate, severe, and aggregated cases.

Methods: We propose a framework to forecast malnutrition risk for each sub-county in Kenya based on clinical indicators and remote sensory data. To achieve this, we first aggregate clinical indicators and remotely sensed satellite data, specifically gross primary productivity measurements, to the sub-county level. We then label the rate of children diagnosed with acute malnutrition at the sub-county level using the standard Inte-



Guiding questions

- 1) Which **factors are associated** with acute malnutrition in Uganda?
- 2) Which **machine-learning models** most accurately forecast burden of acute malnutrition and classify district-level?
- 3) Which **predictor time lags and forecast horizons** provide the most accurate forecasts of acute malnutrition burden?
- 4) How can the forecasting tool be **operationalized** through CHAP to complement IPC and other routine planning and decision-making processes?

Covariates/data inputs

Variable group	Variables
Nutrition burden	Global Acute Malnutrition (SAM and MAM)
Climate & environment	Rainfall, rainfall anomaly, temperature, flooding, seasonality, vegetation index, Gross/Net primary productivity, drought(standardized precipitation index)
Food security & livelihoods	IPC phase, crop yields, food prices, market access, income/livelihoods, humanitarian assistance, conflict/displacement
Disease & WASH	Malaria, diarrhoea, measles/cholera, safe water, sanitation
Services & access	Screening, treatment coverage, stock-outs, distance to services, facility density
Population vulnerability	General population, children 6–59 months, pregnant/breastfeeding women, displaced population

Modelling approach

Regression modelling

Machine learning regression is used to forecast the expected burden of acute malnutrition cases, including severe acute malnutrition (SAM) and moderate acute malnutrition (MAM).

Algorithm

- **Random Forest Regressor:** forecasts the expected number of acute malnutrition cases.
- **Percentile-based classification:** converts forecast values into **Low**, **Moderate**, **High**, or **Extreme** anomaly levels.

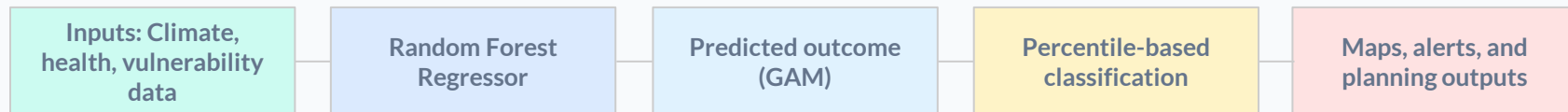
Anomaly Analysis

- **Within-district anomaly:** identifies when the forecast burden is unusually high compared with the district's own historical pattern.
- **Between-district anomaly:** identifies districts with an unusually high forecast burden relative to other districts during the same period.

Operational alert classification

The within-district and between-district anomaly levels are combined to generate the operational alert level: **Monitor**, **Alert**, or **Respond**. Greater priority is given to the within-district anomaly.

Forecasting pipeline



Thresholds (In discussions)

Anomaly levels: within/between district analysis

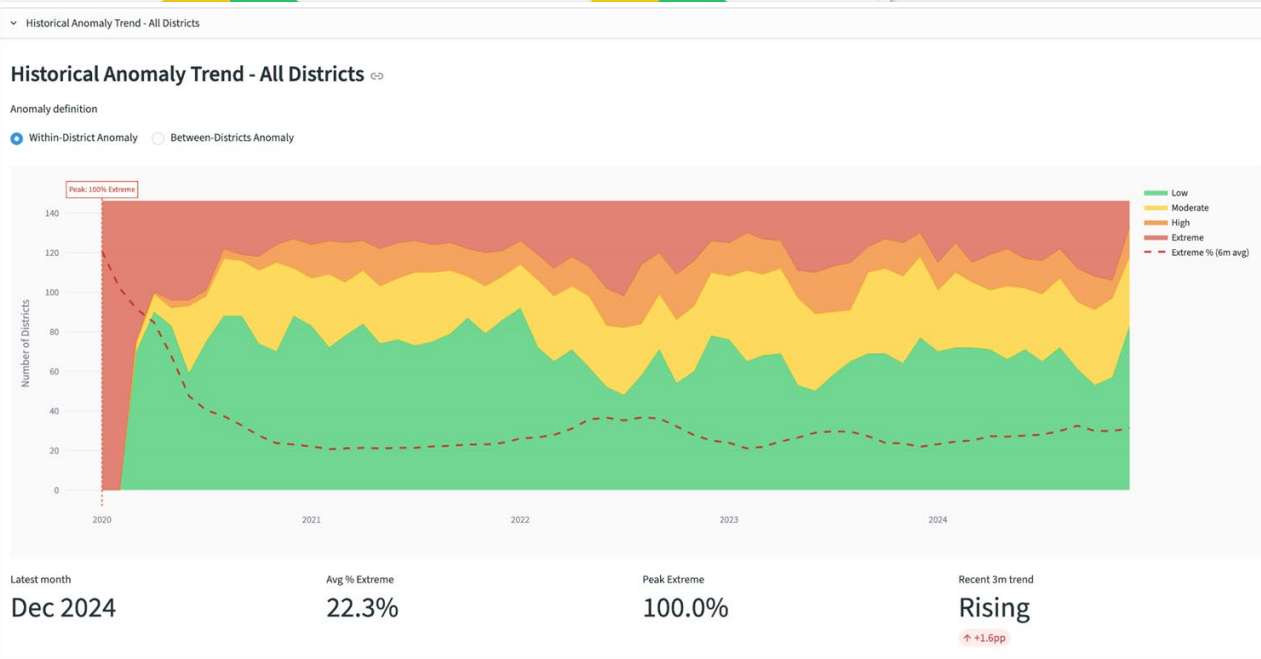
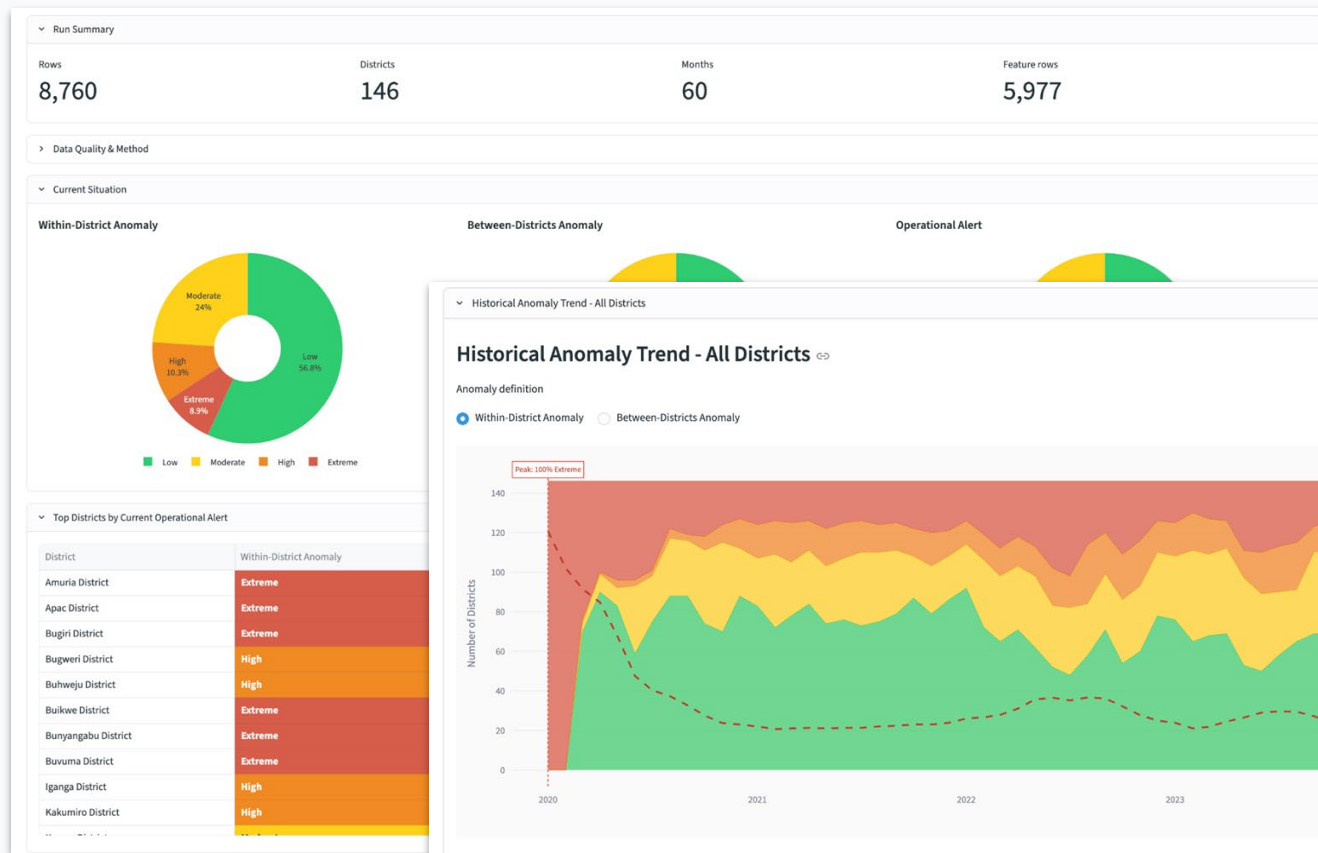
Anomaly Level	Percentile	Interpretation
Low	<75th percentile	Within the usual range
Moderate	75th-<90th percentile	Higher than usual
High	90th-<95th percentile	Unusually high
Extreme	>=95th percentile	Exceptionally high

Operational alert levels

Operational Alert Rules

Operational Alert	Combination Rule	Action
Monitor	Within = Low AND Between = (Low OR Moderate)	Routine monitoring
Alert	Within = Low AND Between = (High OR Extreme), OR Within = Moderate AND Between = (Low OR Moderate)	Heightened surveillance
Respond	Within = High OR Extreme, OR Within = Moderate AND Between = (High OR Extreme)	Immediate response

Tool features: Descriptive and exploratory analysis



Tool features: 3-horizon forecast



January 2025

7,402

↑ +38.8% vs last actual

February 2025

7,690

↑ +44.2% vs last actual

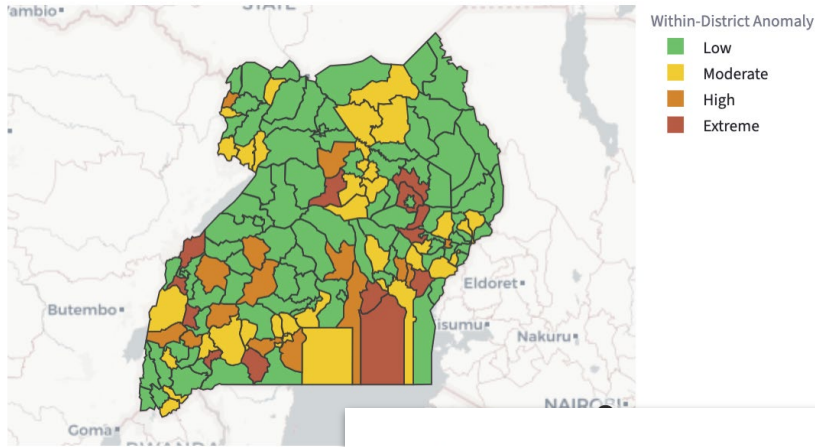
March 2025

8,013

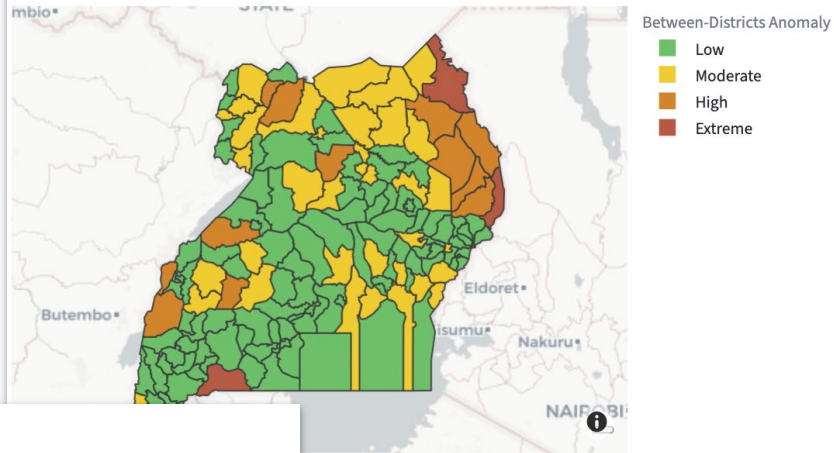
↑ +50.2% vs last actual

Tool features: Anomaly and operational alert maps

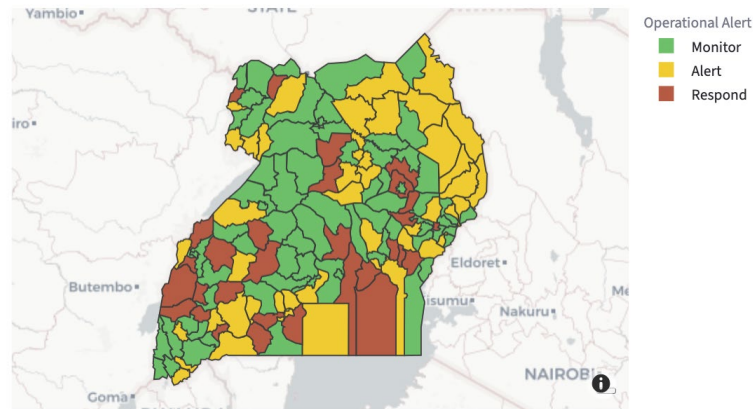
Within-District Anomaly - December 2024



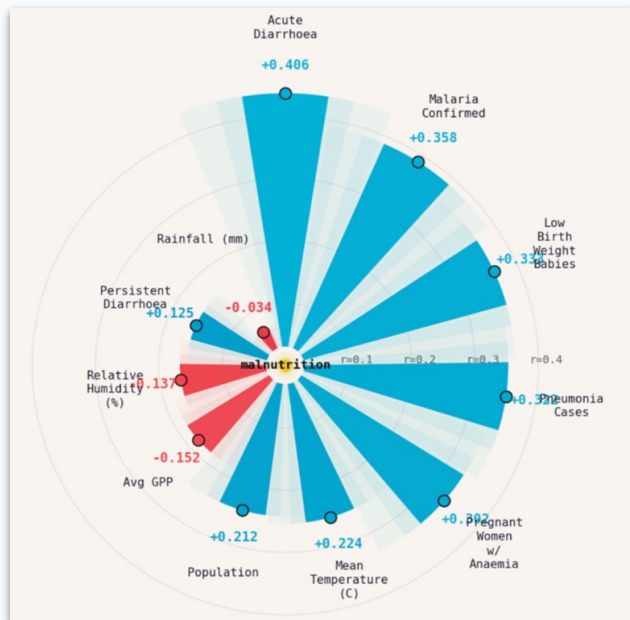
Between-Districts Anomaly - December 2024



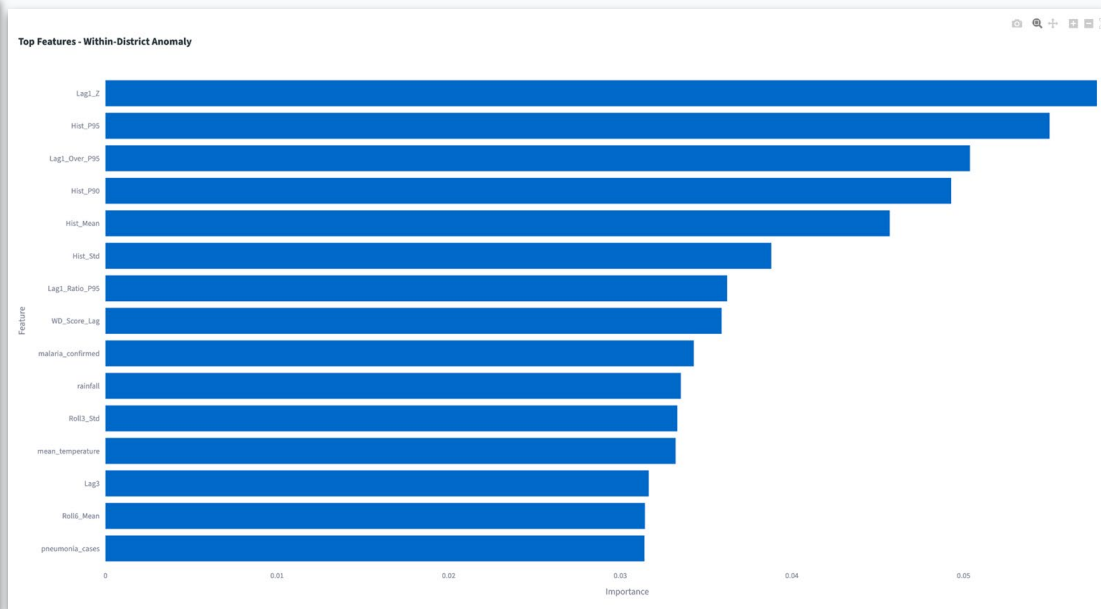
Operational Alert - December 2024



Tool features: Correlation and feature importance



What covariates are most related to the target variable?



What are the most important features the model is relying to the do the predict?

Tool features: Model evaluation

MAE (cases)

22.6

↑ +4.1

RMSE (cases)

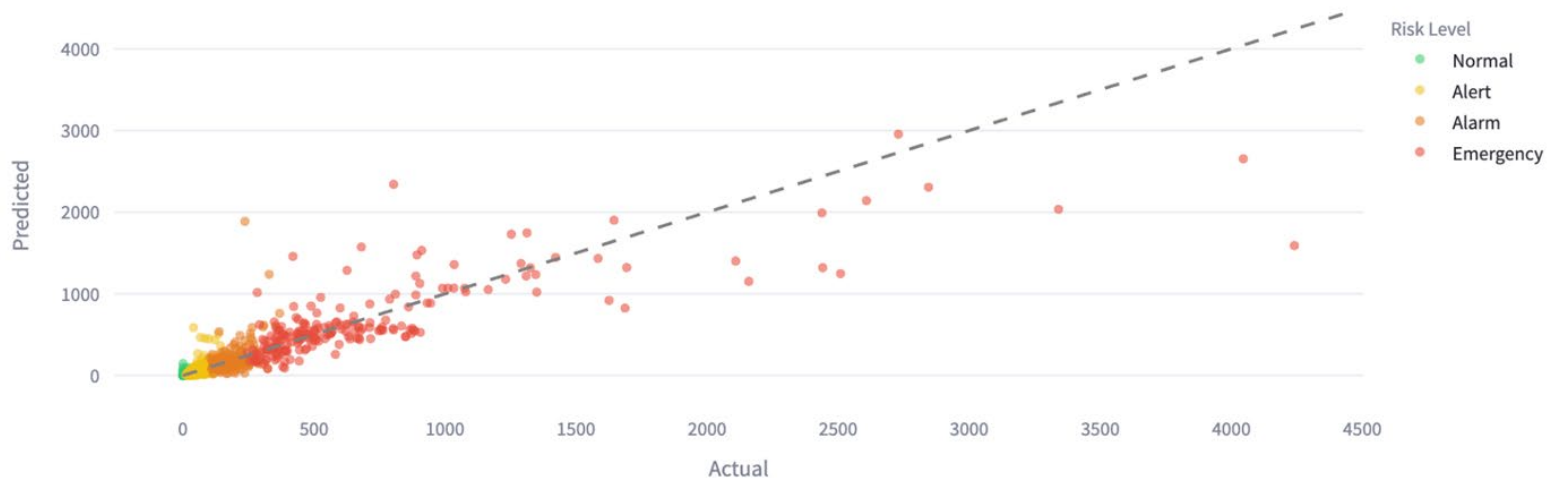
87.0

CV Folds

6



Predicted vs Actual — Walk-Forward CV



Limitations

Data

- Food prices
- Poverty and income data
- Disaster data (floods, crop destruction)
- Food security & post-harvest losses
- Interventions data (only supplementation)
- Conflicts & displaced persons

Domain knowledge validation

- Thresholds and classification decisions
- Lag specifications to apply
- Covariates

How should this align with IPC?

- **IPC remains the authoritative framework** for current and projected acute malnutrition analysis.
- **Complements IPC** with routine, district-wide forecasting burden between IPC analysis cycles.
- **Machine-learning forecasts drawing on multiple data sources** to identify emerging malnutrition risk up to three months in advance.
- **Operationalizes the forecasts** through routine dashboards, maps, alerts, and classifications within the DHIS2.
- **Outputs support routine planning and operations** including intensified surveillance, screening, preparedness, and targeted resource allocation.

Next steps

1) Finalize data sourcing, featuring engineering and model fitting

Complete data sources through deployment of climate service tools, additional data points, and model development.

2) Validate the modelling approach with nutrition experts

Review covariates, thresholds, lag periods, forecast horizon, and interpretation of outputs.

3) Align with IPC methods and outputs

Compare model risk categories with IPC phases, use IPC results for validation and inputs, and ensure the tool complements rather than duplicates IPC analysis.

1) Deploy and test the tool in CHAP

Configure the model, dashboards, risk maps, alerts, and user workflows.

2) Roll out and deepen district-level use

Scale implementation, then support practical use and refinement in selected districts.



Acknowledgement

District team, Ministry of health, Meteorological Services, HISP Uganda, HISP Centre UiO, and Wellcome Trust