Title: Forecasting Caseloads of Global Acute Malnutrition in Kenya to Support Anticipatory Action: The Role of Spatial Variation

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Short abstract

This study develops various strategies for early warning systems for child malnutrition in Kenya using patterns in climate and conflict, and facility- and community-level data. We use spatial generalized additive models with a spline fit for the spatial component of the model, as well as the climate/conflict predictors, to model Kenya ministry of health caseloads of children aged 6-49 months for global acute malnutrition (GAM) from 2012-2024.We evaluate the associations between GAM caseloads at various temporal lags up to a year prior to a month of caseloads. We also evaluate model performance at different spatial levels, building a country-wide model, and models for specific counties. We find that the country-wide model is heavily driven by the spatial component of the model, with an overall performance of a 37% explanation in the deviance of caseloads. We find that a model for Isiolo and Marsabit counties performs even better at about a 44% explanation in the deviance of caseloads, while other models for specific counties perform even worse than the country-wide model. We use this information to generate facility-level forecasts of GAM caseloads in the year of 2025.

Introduction

Food production in the Sahel region of Africa is being adversely impacted by climate change (IPCC 2022), which is disrupting local food systems and exacerbating child malnutrition. UNICEF reports that 11% of Kenya's population of children are underweight, while 4% are wasted (UNICEF Kenya). Well-timed interventions that use climate and conflict trends are needed to reduce the negative consequences of extreme hunger amongst children living in Kenya.Anticipatory action is a framework that involves acting ahead of predicted hazards to reduce the overall impact. Forecasting is a statistical method that pairs well with this framework, as it involves making future estimates with a form of accuracy embedded within it.

Research has already shown that forecasting can be used for anticipatory action against child malnutrition (Reusken et al, 2025). Other forecasting research usually operates at higher levels of analysis, such as a country's administrative unit level-1, which in Kenya's case is the county-level. Working at higher levels of analysis comes with some drawbacks. For example, Turkana county, Kenya's largest county covers up to 77,000 square kilometers. Summarizing finite climate patterns within Turkana county may lead researchers to miss out on the impact of concentrated extreme weather. Thus, other methods of forecasting at more finite levels are needed. This project seeks to fill this gap by creating forecasts at the health facility-level in Kenya.

Aim

The goal of this project is to create monthly facility-level forecasts of caseloads of acute malnutrition for the year of 2025 using climate and conflict data.

Data/Methods

We source rainfall and temperature data from UCSB's Climate Hazards Center. (https://www.chc.ucsb.edu/). We spatially aggregate the ~5km rainfall and temperature data using a 20-kilometer buffer zone around each healthcare facility. We source healthcare facility data from Kenya's Ministry of Health. We calculate the monthly average maximum temperature in Celsius and the monthly sum of rainfall in millimeters for each buffer zone around a given health care facility. We then aggregate the climate measures into three month averages for up to 1-3 months before a given month of caseloads, 4-6 months, 7-9 months, and 10-12 months. We source information on conflict from The Armed Conflict Location & Event Data Project (https://acleddata.com/). We sum all conflict events (whether lethal or non-lethal) for 1-6 months and 7-12 months before a month of caseloads. We also use livelihood zone data from the Famine Early Warning System Network (FEWSnet) (https://fews.net/east-africa/kenya).

The data for our outcome, GAM caseloads, spans from January 2012- November 2024. The Climate Hazards Center regularly updates its temperature and precipitation data. We download climate data up to March 2025.

Analytical Strategy & Controls

These measures are included in separate spatial generalized additive model that include the following control variables: month as a factor variable, year as a spline, livelihood zone as a factor variable and latitude as a spline.

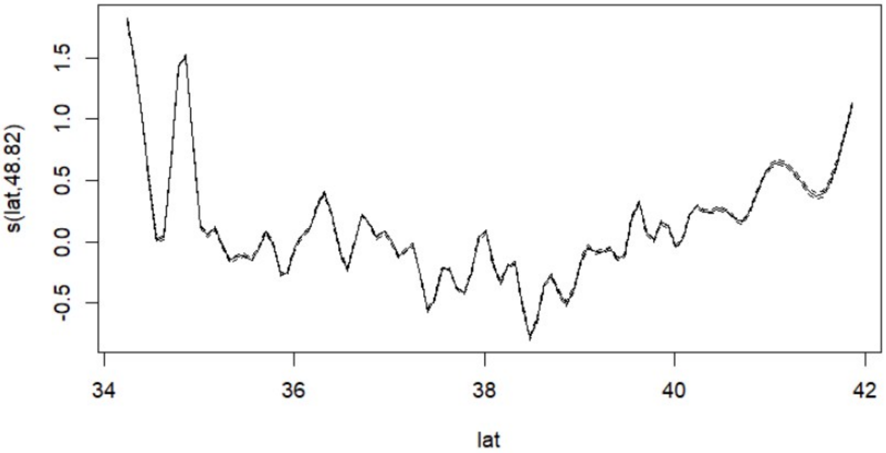
Temporal dimension of the model

First, we estimate generalized additive models to see which temporal lag between a month of caseloads and a given climate or conflict predictor has the most explanatory power. All models include the same control variables, listed above. First, we assess whether the estimates of the models have practical and statistical significance. Then we compare the Akaike Information Criterion (AIC) of each model to choose which climate and conflict predictors should be used in the final model. For the country-wide model, the average maximum temperature from the 4-6 months lag, the average monthly sum of rainfall from the 7-9 months lag had the strongest predictive power and the sum of conflict events from the 7-12 month lag.

Spatial dimension of the model

The country-wide model was shown to be heavily influenced by the model's spatial component, measured through a spline fit of latitude. This is illustrated by Figure 2, which displays a plot of the component smooth functions for latitude on the y-axis and latitude itself on the x-axis.

Figure 2. Component smooth functions by range of latitude values, k=50

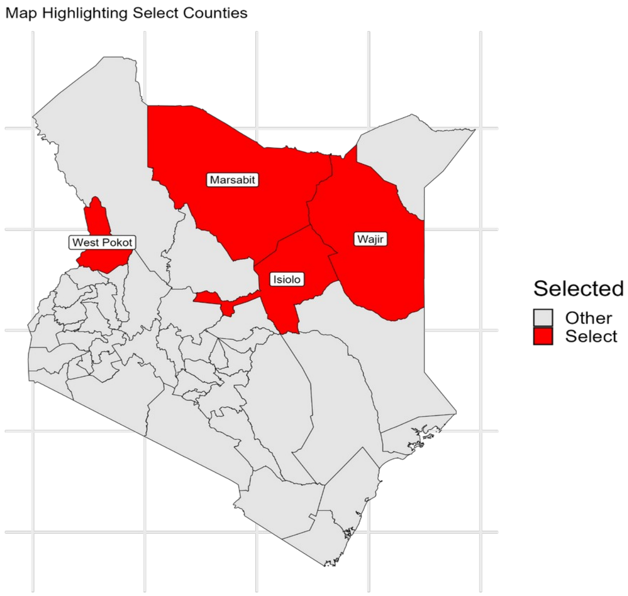


Modeling with Select Counties

The spatial variation in the country-wide model, led us to pursue models concentrated to specific counties. Four counties shown to be at high risk for child malnutrition were considered: Marsabit, Isiolo, West Pokot and Wajir (UNICEF 2021).

Two additional control variables were added at this level of modeling: facility type as a factor variable, and ward as a factor variable.

Figure 3.



Preliminary Results

Model evaluation

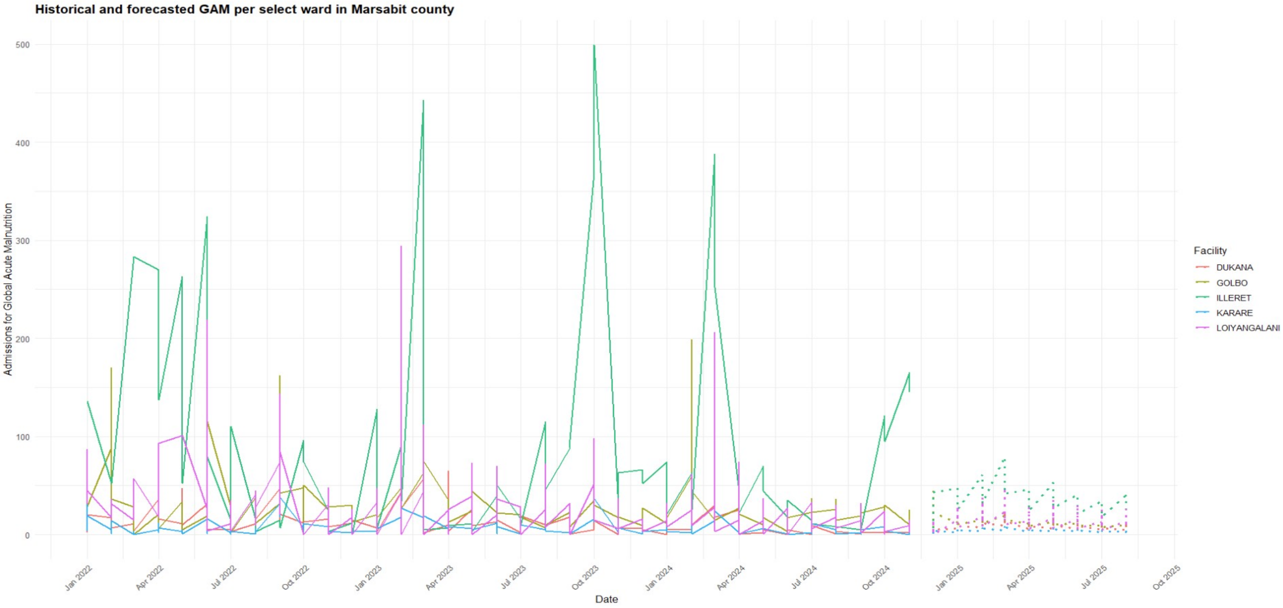
The model for these four counties had 25% explanatory power, which is nearly 8% lower than the country-wide model itself. The two counties with the strongest performing models were Marsabit and Isiolo. One model for both of these counties was selected to generate forecasts, which has an explanatory capacity of 44%

Forecasts

For the sake of illustration, we present forecasts from one of the best performing models, which was created with data from Marsabit and Isiolo counties. The best suited temporal lag for climate measures was 1-3 months before, while for conflict it was 7-12 months before, however, the further back the lag period of the climate variables the further the model can predict into the future. Therefore, we present results for a model using data 7-9 months before.

Figure 4 presents one difference to Figure 4. This model uses the 7-9 month climate lags, and thus it forecasts up to 8 months into the future.

Figure 4.



Discussion

Our study shows proof of concept for a facility-level forecasting strategy using generalized additive models. This system adds to the literature on early warning systems for child malnutrition because it evaluates both the temporal and spatial components of early warning system models. This study is also unique because it focuses on the facility-level.Other studies have sought to forecast levels of global acute malnutrition have done so at higher levels (Constenla-Villoslada et al. 2025; Reusken et al. 2025).

Children aged 6 months to under five years of age are at a heightened risk of experiencing malnutrition given prevalent violent conflict, decreasing rainfall, and rising temperatures in Kenya (Grace et al. 2022; Grace et al. 2012). This project illustrates and evaluates forecasting strategies that can be used to inform humanitarian intervention. Forecasts of global acute malnutrition have shown varied levels of performance (Bulti et al 2017; Constenla-Villoslada et al. 2025; Reusken et al. 2025), and ours sits among this research.

Although our forecasts include a substantial margin of error, our forecasts are very informative about the relationship between GAM caseloads and climate, conflict and spatial factors. Stakeholders involved in humanitarian interventions can utilize this information to act accordingly when specific conflict or climate events happen, in various spatial contexts.

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