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Forecasting the prevalence of child acute malnutrition using environmental and conflict conditions as leading indicators

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ABSTRACT

Millions of children worldwide experience acute malnutrition. Forecasts of prevalence that afford sufficient reliability, precision, and advance warning are valuable to facilitate anticipatory action capable of mitigating the extent and downsides of crises. Existing research and resources lack prediction based on statistical analysis with broad cross-national scope and a focus on identifying leading indicators. We model the prevalence of child acute malnutrition at the level of subnational geographic regions (generally first-order administrative divisions), highlighting environmental conditions (precipitation, temperature, vegetation) and lethal and non-lethal conflict activity as main predictors, alongside demographic and geographic characteristics, and involving a temporal vantage point framework that reflects requirements of practical application. Estimations are performed using the random forest machine-learning algorithm, trained on data from 36 countries across mainland Sub-Saharan Africa spanning 2003–2019, including a novel compilation of measurements of prevalence rates drawn from DHS, MICS, and SMART surveys. Our results show strong predictive performance that remains consistent with lead times extending out from one month to 12 months. All the environmental and conflict factors register as important leading indicators. The findings reinforce the potential of relying on model-based approaches to bolster the foundations for humanitarian measures that are better positioned to reduce negative repercussions of food insecurity.

1. Introduction

Since the mid-1980s, after a devastating famine in Ethiopia, the international community has devoted extensive resources to improve monitoring of food security, early warning of crises, and humanitarian preparedness. Key advances include the advent of the Famine Early Warning Systems Network (FEWS NET) sponsored by the US Agency for International Development in 1985, the Cadre Harmonisé (CH) organized by the Permanent Interstate Committee for Drought Control in the Sahel starting in 1999, and the Integrated Food Security Phase Classification (IPC) devised by the Food Security and Nutrition Analysis Unit (FSNAU) of the Food and Agricultural Organization (FAO) of the United Nations (UN) in 2004. These initiatives project food security – IPC has also projected acute malnutrition since 2014 – using a convergence-of-evidence approach whereby experts arrive at consensus judgments about expected status via a structured process of consulting pertinent data (FEWS NET, 2018; Cadre Harmonisé, 2019; IPC Global Partners, 2019). A strength of the approach is participatory engagement with these specialists and other stakeholders, down to local levels. Many humanitarian actors utilize the projections to appraise ongoing situations, to identify hotspot areas, and to guide interventions in dozens of at-risk countries around the world.

The methodology is critiqued, however, for being overly complex and opaque, digesting information that is at once elaborate and uneven, and lacking formalized statistical analysis. Those facets diminish transparency, replicability, and objectivity (Lentz et al., 2019). In fact, important concerns have been raised about the politicization of projections and underlying data (Maxwell and Hailey, 2021). Releases of projections can be infrequent, if not irregular, which constrains utilization in rapidly evolving settings (Lentz et al., 2019). Projections reflect periods of multiple months – less granular than may be most optimal for stakeholders to pinpoint needs. IPC projections can already be outdated upon release. The accuracy of FEWS NET projections is excellent overall, but tails off at higher degrees of food insecurity and can be affected by

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impacts of climate and conflict conditions (Choularton and Krishnamurthy, 2019; Krishnamurthy et al., 2020; Backer and Billing, 2021a; Backer and Billing, 2021b). Analogous validation of IPC and CH projections is lacking, leaving open questions about their reliability as resources on which stakeholders can depend.

An emergent alternative is predictive modeling, which has pros and cons relative to existing early warning systems. Modeling relies on rigorous statistical methodology conducive to transparency, replicability, and objectivity. A trade-off can be a lack of the same deep contextualization and human element of deliberative engagement. Due to the appeal, on balance, important examples of studies featuring predictive modeling have proliferated since 2019.

In one set of these studies, outcomes are defined in terms of FEWS NET assessments of food security, which also face the issues described above. Andreé et al. (2020) employ machine-learning techniques to forecast food crises with up to 12 months lead time as a function of geography, demography, land usage, climate, conflict, and food prices at the second-order administrative division (ADM2) level in 21 countries, concentrated in Sub-Saharan Africa. Westerveld et al. (2021) employ similar techniques to forecast transitions in food security with up to 12 months lead time as a function of over 100 factors spanning 19 different categories for a proof-of-concept analysis focusing on Ethiopia. Krishnamurthy et al. (2022) employ autocorrelation techniques to model transitions in food security with up to 6 months lead time as a function of soil moisture and food prices in 11 countries around the world. Wang et al. (2022) employ multiple techniques to forecast transitions in food security with up to 6 months lead time as a function of 29 agronomic, weather, conflict and economic factors (out of 1,670 candidates) across 15 countries around the world.

Another set of studies defines outcomes derived from survey data. Lentz et al. (2019) employ multiple techniques, including machine learning, to model three food security indicators as a function of geography, demography, land usage, climate, food prices, and economic assets down to the level of survey clusters in Malawi, with predictions generated from models trained on 2010 data validated out of sample against outcomes observed in 2013 data. Zhou et al. (2022) likewise employ multiple machine-learning techniques to model two measures of food security as a function of precipitation, temperature, market price, soil quality, and geographic factors at the village level in Malawi, Tanzania and Uganda, with predictions generated from models trained on earlier sources data validated out of sample against outcomes observed in the last source of available data in the series. The Hunger Map$^{\text{LIVE}}$ project of the World Food Program (WFP) also employs machine-learning techniques to model two food security indicators as a function of demography, climate, conflict, food prices, and macroeconomic indicators at the first-order administrative division (ADM1) level across more than 70 countries. These three studies rely on contemporaneous measures of the factors, thereby lacking a temporal dimension of true forecasting – though the WFP plans to add this dimension.

A further set of studies have ventured into the forecasting of outcomes derived from survey data. Foini et al. (2022) employ machine-learning techniques to model evolving trends of insufficient food consumption with up to 30 days lead time as a function of past food consumption as well as conflict, extreme weather events and economic shocks, in 6 countries across Sub-Saharan Africa and the Middle East. Gholami et al. (2022) employ multiple techniques, including machine learning, to model food security outcome indicators at the household level in Malawi with up to 18 months lead time as a function of 126 factors. Grace et al. (2022) employ multilevel techniques to model individual-level risk of acute malnutrition with up to 6 months lead time as a function of household-, community-, and subnational regional-level factors in Kenya, Nigeria, and Uganda. Checchi et al. (2022a) employ multiple techniques, including machine learning, to model the prevalence of acute malnutrition with up to 6 months lead time as a function of demography, climate, conflict, food prices, and health and macroeconomic indicators, with separate analyses conducted for Somalia and South Sudan.[1]

Building on the state of the art, we adopt the distinctive focus of aiming to forecast prevalence rates of child acute malnutrition. Often used as a major indicator of food insecurity, acute malnutrition stands out as a consequence of heightened interest. Affected children are susceptible to elevated morbidity and mortality (Blossner & De Onis, 2005; McDonald et al., 2013; Pelletier et al., 1994; Victora et al., 2008). Implementation of appropriate interventions can render acute malnutrition temporary and reversible (WHO et al., 2009; Leroy et al., 2014; Akparibo et al., 2017), with prospects boosted by well-informed anticipatory action. Knowing when, where, and why children are vulnerable is vital for targeting interventions (Collins et al., 2006). Thus, forecasts should be tailored to the specific outcome of acute malnutrition, not merely to broader concepts of food security. Despite the merits, predictive modeling of acute malnutrition has been uncommon and even empirical research concerning related risk factors is underrepresented in the field (Brown et al., 2020; Brown et al., 2021).

We favor parsimony in model specification. Limiting the list of predictors makes the analysis more straightforward to accomplish, interpret, and sustain. Models with many factors hinge on access to data not always readily available across countries, over time, or with requisite coverage, granularity, and quality. Any relative gains in predictive performance and practical utility as a function of high dimensionality may be modest and not worth the added complexity, which can equate to increased costs of analysis. Instead, we investigate whether a lot can be accomplished with a little – in keeping with most of the other predictive modeling projects cited above.

In particular, we spotlight indicators of environmental and conflict conditions as potential leading indicators. From the perspectives of both analytical validity and practical applications, success of forecasting entails factors that serve as signals to warn of expected future outcomes. For this purpose, the analysis requires factors that vary in the short to medium term and are not necessarily proximate causes. The environment and conflict – independently and interactively – operate through more direct drivers of food security and health to affect nutrition (Raleigh & Kniveton, 2012; von Uexkull, 2014; Brown et al., 2021). Environmental and conflict conditions can fluctuate frequently and sharply, an appropriate match for an outcome that is acute (vs. chronic) in nature. Suitable data on these conditions exist with worthwhile geographic and temporal granularity and a relatively low latency of availability. The distinctive utility of leading indicators contrasts with other factors that influence malnutrition risks on a cross-sectional basis, while remaining static except over longer terms. On timescales during which the factors are static, they cannot induce changes by themselves. We account for such factors alongside our candidate leading indicators.

Another pillar of our approach is capitalizing on existing data. Statistical models using publicly accessible data can greatly improve upon expert-based analyses of food insecurity (Lentz et al., 2019). We assembled a novel dataset integrating measurements of prevalence rates derived from data collected in Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), and Standardized Monitoring and Assessment of Relief and Transitions (SMART) surveys, together with corresponding spatio-temporal data on indicators of rainfall, temperature, and vegetation (derived from remote-sensing) and conflict (derived from media and NGO reporting). Most of the data we utilize are easily downloaded from online sources and do not require inside connections with providers to obtain or formal permissions to use. All the data are reasonably straightforward to employ off the shelf in analysis,

[1] See also Okori and Obua (2011).

with modest technical capabilities. No special infrastructure or tools are needed beyond computational horsepower that is widely available and inexpensive. Processing of data follows established, accepted conventions. These aspects speed work, enhance efficiency, and improve chances of uptake, sustainability, and extensions.

Our analysis is confined to countries in mainland Sub-Saharan Africa from 2003 to 2019. The choice of geographic scope is spurred by the mandates of a donor-funded research and the advantages of greater comparability of settings; extension to additional countries and parts of the world is conceivable. The temporal scope reflects considerations of data availability at the time when the analysis was undertaken, as well as data quality; updates to include more recent data, once available, are a logical, viable prospect.

The unit of analysis is a given wave of a survey within a constituent subnational region of a country. Most regions are ADM1s, such as counties in Kenya and states in Nigeria. Regions in select countries (e.g., Uganda) are more aggregate geographic areas defined by the DHS for purposes of sampling, analysis, and reporting. Our study design is oriented to meet needs of stakeholders who regularly undertake assessments, formulate strategies, and make decisions about activities at the level of these regions. Predictive modeling of outcomes for more spatially granular units presents a useful path worth pursuing that would be complementary to analysis at higher levels of spatial aggregation (subnational, national) – as is raised in the Discussion.

To conduct the modeling in a manner sensitive to stakeholders' priorities, we deploy advanced machine learning techniques with an eye toward maximizing predictive performance while also achieving interpretability of results necessary to understand the relationships that produce expected outcomes, to trust the analysis as credible, and to translate results to practice. The model estimations use a random forest algorithm to automate selection of the optimal subset of factors and their functional forms that best predict outcomes given the available data. Following the latest methods for interpretable machine learning (Molnar, 2019), we break into the "black box" of our models to convey which variables are most important and to characterize their relationship with outcomes.

Our results demonstrate the capacity of parsimonious, low-cost statistical modeling to anticipate prevalence rates of child acute malnutrition at the subnational regional level in countries across Sub-Saharan Africa. Forecasts with a strong, consistent degree of accuracy are generated with lead times up to 12 months, exhibiting remarkably little drop-off in predictive performance. Environmental and conflict conditions register as notable leading indicators, each associated with variation in prevalence of 1–2 percentage points across the observed ranges of factor. Appreciating such effects, especially when compounded, is vital to preparedness for humanitarian anticipatory action.

2. Materials and methods

Our dataset consists of 1,501 observations at the subnational region level, drawing on 122 waves of either DHS, MICS, or SMART surveys conducted among 485 regions spanning 36 countries across mainland Sub-Saharan Africa from 2003 to 2020. Over 80 percent of these regions have multiple observations. Fig. 1 displays a map of the countries and regions represented in the dataset. Appendix A supplies background on the design of the analysis and details about the assembly and contents of the dataset. Table A1 delineates observations by country and survey source. Table A2 itemizes the survey waves. Table A3 has an overview of key variables in the analysis, their measurement, and sources of data. Table A4 presents summary statistics of all variables.

2.1. Variables and data

The dependent variable in our analysis is the ***prevalence rate of gross acute malnutrition*** (GAM) among children 6–59 months of age, measured at the level of subnational regions. GAM encompasses moderate acute malnutrition (MAM) and severe acute malnutrition (SAM). The main criterion for MAM is that a child's weight-for-height z-score (WHZ) falls at least two standard deviations below expected levels, while SAM is at least three standard deviations below expected levels, assessed according to international reference standards. The term "wasted" is also applied to children with GAM. The age range is conventional in assessments (WHO, 2020). To calculate rates, we aggregate individual-level measures of the nutritional status of children based on the data from DHS, MICS, and SMART surveys. These surveys use multi-stage random sampling within subnational regions; we rely on sampling weights when aggregating to prevalence rates. Therefore, the rates are meant to be representative for the households and populations in those regions.

As an example, Fig. 2 displays variation in prevalence rates over time across the states of Nigeria. This illustration indicates that rates are hardly uniform or static, but nor do they exhibit clear seasonal or other cyclical patterns. In some states, the measured rate remained stable regardless of the survey source and timing. Other states exhibit wide variation in rates over time. Most notable, Bauchi, Jigawa, Kaduna, Kano, and Kebbi – all in Northern Nigeria – each have rates that range from below 10 % to over 30 %. Our modeling aims to anticipate such differences in rates.

Ideally, we might model changes in acute malnutrition prevalence rates as an outcome. Humanitarian stakeholders want to be aware of when evolving conditions affect expectations of future shifts, which warrant attention and intervention. Observing changes in prevalence rates over relatively short timescales (e.g., month to month) can also open up better possibilities to examine relationships to fluctuations and shocks in major factors such as environmental and conflict conditions. Unfortunately, the data we use do not permit the regular calculation of changes in prevalence rates over relevant timescales. For the most part, the data reflect sporadic measurement – far from a complete longitudinal time series with observations in many consecutive months for each country and subnational region represented. In fact, only select sources in the field afford such desirable coverage, typically limited to a single country (e.g., Kenya's National Drought Management Authority [NDMA]), or a subnational context subject to persistent crisis. Analysis using these sorts of data, with narrower bounds, falls outside the scope of this manuscript, but is on our ongoing research agenda.[2]

To each observation, we assign the month-year corresponding to the first month during which any data collection was conducted within the region for the given wave of a survey. Collection can span a period of up to 4–6 months, especially for the DHS, occurring at different times among constituent survey clusters within a region. The assignment rule defines the timing of the malnutrition outcomes that are the dependent variable in our analysis, which is necessary to establish corresponding timings for each observation of the measurement of the associated independent variables. An essential criterion is that our choice of assignment rule must be apt for forecasting, which fundamentally requires that the timings reflected in the measurement of all independent variables must be prior to and have no overlap with the timing reflected in the measurement of the dependent variable. Our particular assignment rule is the only option that meets this criterion. The approach also errs in the direction of lengthening the amount of lead time,[3] which is

[2] The lack of extensive longitudinal data on prevalence rates of acute malnutrition measured with regular monthly frequency also precludes using standard time-series modeling techniques and model specifications that include lagged dependent variables as predictors.

[3] The first month within a data collection period for a given observation tends to be earlier than the average timing of collection of measurements of acute malnutrition across the children reflected in the prevalence rate for the observation. Thus, a forecast of a prevalence rate as of the first month of the period allows greater lead time when anticipating outcomes for the children from whom data were collected later within the period.

Fig. 1. Countries and Subnational Regions Represented in Sample.

advantageous for practical applications. Other assignment rules (e.g., mean or median month, last month) are possible that we considered, but deemed inferior given the primary purpose of forecasting. For these reasons, we present results using the single assignment rule.[4]

One category of independent variables comprises several indicators that track variation in environmental conditions, derived from remotely sensed satellite imagery. The first indicator measures total *rainfall* (mm), based on the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset. A second indicator measures maximum *temperature* (°C), based on the MODIS Land Surface Temperature and Emissivity (MOD11) dataset. A third indicator measures mean *vegetation*, based on normalized difference vegetation index (NDVI) data. The source data is already pre-processed as monthly means in a 0.05° (roughly 5.5 km^2 meters at the Equator) latitude/longitude Climate Modeling Grid (CMG). We extract the relevant source data for each measure and then aggregate to monthly means across the CMG gridcells falling within each subnational region represented in our sample. For a given observation, we then identify the period of three consecutive months that ends during the 12 months prior to the vantage point of a model (see below) with the highest mean of the monthly values from the previous processing step (Thiede and Strube, 2020). In Appendix A, we provide further details about the calculations of these indicators.

The indicators together afford a profile of the environmental context that is expected to affect outcomes of interest in the future – for better or worse. Low rainfall, high temperatures, and less vegetation are each prone to be associated with higher rates of acute malnutrition. Abnormally dry rainy seasons exacerbate food insecurity (Niles and Brown, 2017). Studies have linked both extreme drought and hot temperatures to worse nutritional outcomes in Ethiopia (De Waal et al., 2006), Kenya (Grace et al., 2012), Nepal (Shively et al., 2012; Shively et al., 2015; Jacoby et al., 2017), Nigeria (Rabassa et al., 2014), and Uganda (Shively, 2017; Amegbor et al., 2020), as well as West Africa (Johnson and Brown, 2014) and Sub-Saharan Africa (Wang et al., 2009; Baker and Anttila-Hughes, 2020; Thiede and Strube, 2020). Severe, multi-year droughts can cause complex emergencies, during which acute malnutrition becomes widespread (Salama et al., 2001). A main mechanism is

[4] Other potential assignment rules are the average month or last month of data collection within a given subnational region for a given survey wave. With both these assignment rules, the timing reflected in the independent variables for models at certain vantage points can overlap with the timing of when some of the survey data were collected that serve as the basis for measuring the dependent variable. Such an overlap violates an essential criterion for forecasting.

the outputs from the latest growing season. Rainfall and temperatures are crucial inputs driving output, while vegetation is a proxy for output. Among the important outputs are agricultural products as well as livestock that rely on these products and access to vegetation and water. Agricultural products, livestock, and potable water are vital to the human food security equation, including food production. Environmental disasters also affect hygiene and other health vectors that magnify issues of resource availability. For example, floods create situations ripe for the spread of waterborne illness such as cholera, destroy crops, and damage infrastructure (Alderman et al., 2012). Meanwhile, changes in land cover (e.g., deforestation) increase the prevalence of diarrhea, while lowering consumption of nutritious foods (Johnson et al., 2013). Climate-related reductions in food production are often exacerbated by increases in local food prices (Brown et al., 2006), which further diminish access to food and amplify the risk of malnutrition in children (Grace et al., 2014).

Another category of leading indicators tracks variation in conflict activity over time, through separate sets of measures we derived of counts of *lethal events* and *non-lethal events*. These event counts are a gauge of the intensity of activity that can be consistently captured across both types of conflict, while lethality is a gauge of severity. Using a simple indicator for the presence or absence of conflict instead would mask variation in intensity. We define an event as lethal if resulting in at least one fatality, which is a conventional delineation of severity employed in analysis of conflict event data (Croicu and Eck, 2022).[5]

Our measurement of conflict activity relies on integrating three sources: (1) the Armed Conflict Location & Event Data Project (ACLED), which captures an array of contentious activity (Raleigh et al., 2010), (2) the Global Terrorism Database (GTD), which focuses on terrorist attacks (LaFree and Dugan, 2007), and (3) the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP-GED), which focuses on organized armed violence (Sundberg and Melander, 2013; Pettersson et al., 2021). These publicly available datasets are used widely in research on conflict and offer the extent of geographic and temporal coverage necessary for our analysis, unlike certain other sources. An objective of the integration is more comprehensive measurement of diverse types of conflict events. To perform the integration and correct against redundancies in measurement across datasets, we use the Matching Events by Location, Time and Type (MELTT) package (Donnay et al., 2019), developed for the R statistical software. Parameters for the integration include spatial fuzziness of 50 km, temporal fuzziness of 1 day, and taxonomies of event types, actor types, and precision codes.[6]

Using the integrated data, we calculate counts of conflict events for each observation in our dataset in the corresponding subnational region during four mutually exclusive 6-month periods encompassing the 24 months before a given vantage point. As an example, the indicators generated for the 1-month vantage point measure events during intervals 2–7 months, 8–13 months, 14–19 months, and 20–25 months before the month assigned to the outcome. Using indicators for multiple time intervals avoids specifying a single lag for conflict activity, when we do not know a priori which lag may function as an early warning signal. The intervals smooth out month-to-month fluctuations in conflict activity. Our choice of the length of intervals is designed to keep the set of indicators to a modest number, in the interest of the tractability of the models given the size of the sample. Indicators are transformed into natural logs of counts, after adding 1 to each value, following standard practice, to enable computation for observations with zero events, which is a common occurrence for conflict (Wang et al., 1993). This operationalization produces an order-of-magnitude scale that takes account of skewed distributions of event counts and spatio-temporal clustering of events.[7]

Greater conflict activity is expected to be associated with higher rates of acute malnutrition (Rowhani et al., 2012; Delbiso et al., 2017; Dunn, 2018; George et al., 2020; Howell et al., 2020). Conflict contributes to underlying and proximate causes of malnutrition, including poverty, reduced access to food, shortcomings in care and feeding practices, and an unhealthy household context (UNICEF, 1998; Biset et al., 2023; Muriuki et al., 2023), as well as outbreaks exacerbating susceptibility to disease (Akresh et al., 2012). Populations displaced due to conflict are vulnerable – even when relocating outside affected zones (Toole and Waldman, 1997; Bundervoet et al., 2009; Doocy et al., 2011; Heudtlass et al., 2016). Poor sanitary and hygiene practices and inadequate access to clean water tend to lead to ingestion of pathogens and proliferation of vector-borne diseases (Dangour et al., 2013), which induce cycles of malabsorption of nutrients and reduced resistance to further infections (Rodriguez et al., 2011; Kang et al., 2013; Dodos et al., 2017). Furthermore, conflict affects many factors integral to resource availability and allocation (Raleigh et al., 2015). Combatants may engage in theft of crops and livestock (Akresh et al., 2011), or misappropriate, block or destroy food aid and other assistance (Young, 2006). Conflict can also disrupt production and commerce, including by inhibiting free flow of trade in food (Ihle et al., 2011), restricting access to food markets (D'Souza and Jolliffe, 2013), reducing food inventories (Roseboom et al., 2006), and increasing food prices (Ali and Lin, 2010). In addition, conflict can weaken economic capital (Collier, 1999), social networks and institutions (Wood, 2008), and health systems (Ghobarah et al., 2004), raising risks of malnutrition (Niles and Brown, 2017). In the extreme, war is a major recurring cause of famines (Macrae and Zwi, 1992; De Waal, 1991; Devereaux, 2000; Teodosejevic, 2003).[8]

In the model specifications, we include additional independent variables that always remain fixed or at least tend to be slow-moving, especially within the timeframes of the observations. These variables cannot be considered leading indicators, but are expected to be associated with cross-sectional variation in the risk of child acute malnutrition

[5] Although vegetation is an output that tends to be correlated with rainfall and precipitation (Zhang et al., 2018), including the greenness variable within our models still makes sense in a forecasting context. Our top priority is minimizing out-of-sample prediction errors, rather than producing completely unbiased estimates of the influence of individual predictors. That said, NDVI is not simply a function of rainfall and temperature. Therefore, we are comfortable that the greenness variable has the potential to pick up variation in environmental conditions that would not be captured by the rainfall and temperature variables alone.

[6] While we discuss various mechanisms that plausibly connect the basic environmental variables to acute malnutrition outcomes, statistically assessing the role of such mechanisms is outside of the scope of our analysis, which focuses on the prediction task, with an emphasis on simplicity and practicality. The intent of discussing the mechanisms is to establish broad theoretical validity as a foundation for the predictive analysis, not to set the stage for studying specific pathways of influence to yield theoretical findings about causal associations.

[7] Processes linking conflict to malnutrition are complex, with potentially several mediating steps, even in the relatively short term. In addition, conflict events tend to be less common and more haphazard in nature and exhibit fewer spatio-temporal patterns relative to fluctuations in environmental conditions. The 24-month lookback period allows greater flexibility in capturing temporal relationships between conflict activity and acute malnutrition outcomes (Azanaw et al., 2023). While the relationship between the environment and nutrition is also potentially complex, a norm is to view acute malnutrition as being closely tied to conditions during the most recent growing season (e.g., Rustad et al., 2020; Grace et al., 2022). Our operationalization of environmental indicators to reflect the three highest months within the 12 months prior to the vantage point approximates the most recent growing season. We also view this approach as reasonable because our sample covers subnational regions of 36 countries. A study limited to a specific context might define these variables in a more tailored way. Such tailoring is beyond the scope of our analysis, which aims to illustrate a modelling approach that generalizes across numerous contexts.

[8] Our results are not sensitive to this transformation when operationalizing the conflict variables. Alternatives like the inverse hyperbolic sine would yield nearly identical estimates.

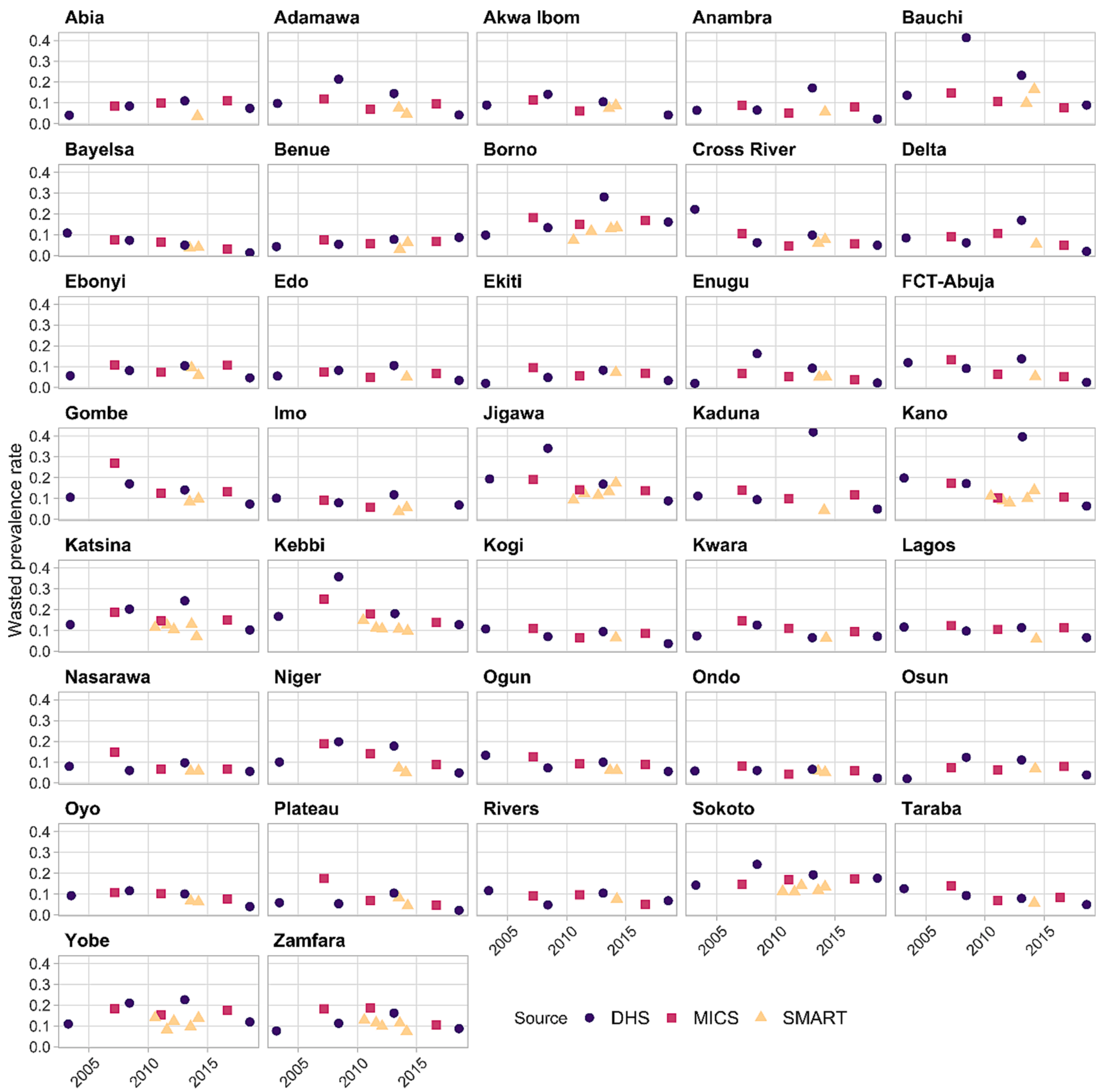


Fig. 2. Variation in Child Acute Malnutrition Prevalence Rates for States in Nigeria.

and thus to improve predictive performance. The *intensity of nighttime lights* is a proxy for the level of economic activity and human development (Bruederle and Hodler, 2018), as well as displacement (Witmer, 2015), within a geographic area. Those areas that face worse circumstances are prone to elevated rates of child acute malnutrition. We create an indicator of annual mean intensity for each region, relying on pre-processed data from PRIO-GRID (Tollefsen et al., 2012), derived from the DMSP-PLS Nighttime Lights Time Series (version 4). Observations for 2015–2020 are assigned the value from the latest available year (2014). The *population* of a region is a proxy for pressure on resources and infrastructure, as well as the degree of urbanization. Our indicator again relies on data housed by PRIO-GRID, obtained from Gridded Population of the World project, which provides estimates at 5-year intervals (2000, 2005, 2010, and 2015). We employ the most recent prior estimate, relative to the assigned timing of the observed outcome. The *distance to the capital city* (in kilometers) at the centroid of a subnational region, also from PRIO-GRID, is a proxy for the likelihood of receiving attention from the national government, international actors and the media, as well as having infrastructure conducive to the mitigation of food insecurity (Gershman and Rivera, 2018). The *longitude* and *latitude* at the centroid of a subnational region serve as proxies for persistent and emergent vulnerabilities inherent to geographic locations that affect food security, including because of patterns of agricultural production and the role of climate change (IPCC, 2019). All model specifications include indicators as well for *survey source*, *survey year*, *first month of survey wave*, and *country*, which should capture variation in observed prevalence rates arising as a function of unmeasured, intrinsic differences among the data collection initiatives, the timings of data collection, and the national contexts.

An optimal model specification might include other factors (e.g., health facilities, humanitarian aid) likely to affect variation in risks of child acute malnutrition across regions, whose addition could help improve model performance. Data on candidate indicators with the necessary coverage, geographic granularity, and temporal precision are unavailable. To reiterate, our aim is to ascertain capabilities of forecasting with a parsimonious model that highlights select factors as potential leading indicators.

We fit four separate batches of models. The multiple sets serve as robustness checks to probe the sensitivity of results to variants in operationalizations of the environmental variables.

The main results, as reported in Section 3, reflect a batch of models that employ two types of environmental variables in tandem. One type captures the levels of rainfall, temperature, and vegetation, while the other type is designed to capture localized anomalies in these variables. For the latter type, we calculate the deviation of a given observation relative to the historical mean over the 5 years prior to the relevant peak period (as described above), during the corresponding months for the corresponding subnational region. Regions with low rainfall, high temperatures and less vegetation in an absolute sense will be expected to exhibit greater vulnerabilities to acute malnutrition, compared to other regions with higher rainfall, lower temperatures and more vegetation, even if the levels of those variables are not unusual relative to historical patterns for a given region. In turn, localized anomalies can exacerbate or offset conditions. For example, a region that is normally susceptible to elevated rates of acute malnutrition, due to low levels of rainfall, could experience the unfavorable anomaly of a drought, worsening risks. Alternatively, the same region could experience better-than-normal rainfall, which mitigates risks to an extent. The two types of environmental variables are thereby designed to pick up both comparative (across settings) and longitudinal (within setting, over time) elements of risks.

Conducting analysis using the particular operationalization of environmental anomalies entails restricting the extent of the sample. We require data on environmental variables for a period of up to 7 years prior to the earliest observation of nutritional outcomes included in the analysis. First, the vantage points of the analysis extend back in time by 12 months. Second, the windows for identifying peak periods of the environmental variables extend back in time by another 12 months. Third, the operationalization of anomalies based on historical means requires a further 5 years of data. The source data for both temperature (MOD11) and vegetation (NDVI) are available only from February 2000 onwards, whereas the earliest coverage of the source data for rainfall (CHIRPS) is January 1996. Although the earliest collection of data on childhood malnutrition within our sample was in 2003, we restrict the analysis sample to observations from 2007 onwards, thereby accommodating the generation of the environmental anomaly variables that rely on data beginning in 2000. Fortunately, we retain a large majority of our sample, leaving out 260 cases (17 %) from 2003 to 2006; the training and test sets used for the purposes of the modeling are proportionally smaller.[9]

When interpreting the results for the first batch of models, we standardize each environmental level variable relative to the full sample. In other words, we calculate the difference for a given observation from the mean across the sample, then rescale the mean-centered value in units of standard deviations. Likewise, we rescale each environmental anomaly variable in units of standard deviations. These steps do not affect the model estimation. The intent is to facilitate the interpretation of results by providing a basis of comparability among variables. Values expressed in units of standard deviations more readily translate to understanding the relationship between the prevalence rate of child acute malnutrition and scenarios of factors being at, above or below mean levels.

The other batches of models capitalize on the full sample of data. The second batch substitutes environmental level variables that are standardized by country, relative to the entire time period reflected across the full sample; the 5-year anomaly variables are excluded. Such standardization represents another way to capture anomalies, via the deviations from country-specific means. The third batch substitutes environmental variables that are "globally" standardized relative to the entire time period and across all the countries reflected in the sample; the anomaly variables are again excluded. The fourth batch uses environmental level variables, with no transformations.

In all four batches of models, each of the remaining variables used in the estimations is standardized "globally", relative to all the countries across the entire time period of the sample. Here too, the rationales are to orient the operationalization of variables around identifying anomalies and to facilitate the interpretation of results in a manner that illuminates the relationship between the prevalence rate of child acute malnutrition and scenarios of factors at, above or below mean levels.

2.2. Vantage point framework

Our modeling framework was crafted with an eye toward real-world applications, addressing needs of use cases faced by stakeholders. We mimic the circumstances of an analyst tasked with forecasting prevalence rates of acute malnutrition at the subnational regional level some months ahead of time. Formally, the analyst situated at the vantage point of month *t-a* wants to forecast outcomes in month *t*. To do so, the analyst relies on historical data for relevant factors measured through *t-a-1*. This knowledge set assumes latency in data availability, to allow for an interval between occurrence and measurement leading to subsequent release of data. The assumption can be adjusted to reflect different extents of latency; certain data are released with a longer delay.

The vantage point of *t* yields the most favorable knowledge set. Yet this timing forecloses forewarning, undermining prospects of anticipatory action. Analysis might take place on the fly, about the current situation in progress, or occur after the fact once complete data are available. Pushing the vantage point back in time involves a tradeoff. An upside is greater forewarning. A month of advance notice may be too late to initiate anticipatory measures. Instead, measures will be largely responsive to advancing or imminent issues. Multiple months of advance notice provides a significant window of opportunity for organizing and implementing timely, effective anticipatory action. A downside is the knowledge set becomes less favorable at earlier vantage points, since what the analyst can know reliably is reduced. Subsequent changes in factors (e.g., emergent climate extremes, unfolding conflict events, evolving characteristics of the population), occurring up through month *t*, will likely affect malnutrition outcomes. Those changes are only observable in the future, relative to the vantage point. (Forecasts of certain factors could be obtained from other sources, but incorporating these estimates into the analysis would add to uncertainty.) Our presumption is that the forecasts made at vantage points that are less proximate to the outcome should be prone to greater error, given the intervening unknowns, than forecasts at more proximate vantage points.

2.3. Modeling strategy

We prioritize accurate predictions, while also aiming for the interpretability of factors included as leading indicators. Tradeoffs between predictive accuracy – the maximization of which can amplify model complexity – and interpretability of factors are well known (e.g., Hastie et al., 2009). "Black box" machine learning techniques facilitate automated discovery of non-linear effects and intricate interactions of factors that are potentially better at capturing underlying data-generating processes – and predicting outcomes. With these techniques, however, relationships between factors and outcomes are often unwieldy to interpret. In contrast, regression approaches that assume linear relationships between factors and outcomes offer results with straightforward interpretations, but are liable to map inadequately onto complex real-world phenomena – and thus to predict outcomes poorly. Our modeling strategy falls between these ends of the spectrum.

All the model estimations are performed with the random forest algorithm, a common, powerful machine-learning approach for prediction (Hastie et al., 2009). Beforehand, we randomly split the data into two sets. A training set of ~75 percent of the observations (930 for the main

[9] We explored sourcing data on indicators of environmental factors from AfroGrid (Schon and Koren, 2022). This new compilation resource does not provide superior historical coverage that would enable us to extend the period of the sample back in time.

batch of models with the reduced sample; 1126 for the three alternative batches of models with the full sample) is used to fit the model, estimating relationships between acute malnutrition prevalence rates (target) and the factors included in the model (features). The remaining ~25 percent of the observations (311 for the main analysis; 375 for the alternative analyses) comprises a test set that is used to assess out-of-sample predictive performance, based on the application of the results of the estimated model. The estimation involves bootstrap aggregation (bagging), which repeatedly samples at random from the data, with replacement (i.e., the same observation can be included multiple times within a sample). Bagging offers a means to address the sensitivity of results to the data on which the model is trained. A regression is fit to each sample, comprising a "tree" in the random forest. When fitting a given tree, the algorithm samples at random only a subset of the available independent variables. To optimize the models, we also use k-fold cross-validation. A given sample of training data is randomly partitioned into three "folds". Through an iterative process, the model is fit three times, each time training on two folds and evaluating performance on the third fold. This iterative process is repeated with varying configurations of tuning hyperparameters (minimum observations for node to split, maximum variables for node to split, maximum depth of tree). Tuning helps to reduce the extent of overfitting and thereby to improve the viability of out-of-sample applications. Ultimately, the results are averaged across the individual trees to create the final ensemble tree, from which predictions are derived.[10]

The analysis is run with the *ranger* implementation of the random forest algorithm in R (Wright and Ziegler, 2017). We present results for both base models and bias-corrected models. The base models exhibit tendencies toward overprediction at lower prevalence rates and underprediction at higher rates. Such rotational biases are common with the random forest algorithm. Methods developed to correct the biases help to optimize predictive performance (Zhang and Lu, 2012; Song, 2015; Malhotra and Karanicolas, 2020). We use the simple linear regression bias-correction method (Song, 2015). The benefits are better overall performance, especially at higher prevalence rates – desirable properties of the modeling when considering applications to practice, where higher rates represent humanitarian crises for which accuracy of forecasts is vital.

3. Results

Fig. 3 reports metrics of predictive performance for both the base and bias-corrected models at vantage points ranging from 0 to 12 months. The *coefficient of determination* (R^2) shown in the top panel indicates the share of the variance in the prevalence rate of child acute malnutrition explained by the factors in these models. The *root mean squared error* (RMSE) in the bottom panels reflects the typical disparity – in absolute value terms – between predicted and observed prevalence rates.

According to those two metrics, all the models yield strong predictive performance, with striking stability across vantage points. Before examining the results in detail, the findings about stability warrant reflection. An implication is that the vantage point can be moved back in time by up to 12 months with no appreciable loss of predictive performance. The stability of results may prompt skepticism about the credibility of the results: How can similar predictive performance be achieved with longer lead times? Would we not expect predictive performance to decline as the amount of lead time increases?

The answers to these questions hinge on the nature of the empirical data used in the analysis, in conjunction with our modeling framework and operationalization of indicators. For each environmental indicator, the peak months during the preceding 12-month windows can be identical for series of vantage points, even as the window progressively shifts back in time.[11] Once the vantage point moves back far enough in time, the window picks up peak months during an earlier year. In so far as environmental conditions exhibit tendencies toward consistency from year to year, including seasonal patterns, the values for the indicators used in the analysis will reflect this consistency. The conflict indicators will similarly exhibit consistency in values across series of vantage points because events are relatively infrequent in most regions during most intervals of time. Thus, values for those indicators will not necessarily change a lot as the vantage point and corresponding intervals shift back in time. Nevertheless, the modeling framework ensures that the specific data about potential predictors on which analysis relies at vantage points proximate to outcomes differs from the data at more distant vantage points – and indicator values indeed vary across vantage points. Our justification is that the framework mimics the information about predictors to which an analyst has access at each vantage point.[12]

Base models estimated on the training data account for around 95 percent of the variance in prevalence rates, and predictions fall within +/- 1.6 percentage points of observed values on average. As a reference, the standard deviation of prevalence rates in the entire dataset is 6 percentage points. When applying the results obtained from training model estimations to predict prevalence rates in the test data, performance declines. The disparities suggest some overfitting of models to the training data, which is expected when assessing out-of-sample performance. Still, the risk factors included in models account for nearly 60 percent of the variance in prevalence rates when deployed in a context akin to pure forecasting. Such a share is relatively high for an outcome like acute malnutrition, which is a complex by-product of numerous

[10] To address concerns about potential effects of spatial correlations in the data, we also conduct cross-validation grouping by country. Section 6 of the Appendix shows results of this procedure, which suggest our results are not biased by spatial correlations. Equivalent cross-validation grouping by time is infeasible given the limited longitudinal coverage of the data.

[11] We have been asked about conducting model runs for earlier vantage points. Extending the vantage point back in time – for example, by another year, to t-24 – is possible in principle. The climate variables would then cover the time period extending back to t-36 and the conflict variables would cover the time period extending back to t-48. Such analysis has a number of limitations. First, we do not see a strong theoretical rationale for environmental and conflict conditions up to 3–4 years prior to be associated with acute malnutrition (whereas chronic malnutrition is more prone to be affected by conditions persisting over longer periods). Modelling that extends the vantage point back to t-12 and examines prior conditions already seeks to capture the potential lag between when those conditions occur and the subsequent point when the conditions have a downstream impact on malnutrition. Second, we expect that humanitarian actors are less interested in practical applications of model-based forecasting with up to 2 years of early warning, which falls outside of normal time scales of anticipatory action, especially for operational purposes. Third, we would lose observations to use in the modelling, needing 8 years of lagged data on environmental factors to calculate the anomaly indicators for each observation (vs. 7 years), amid being restricted to the post-2000 period with high-quality data on environmental variables from consistent sources. Finally, the extension doubles the number of model runs, which would significantly add to the time required to undertake our analysis, since processing the environmental variables is computationally intensive.

[12] A suggestion we received is to use the mean average percentage error (MAPE) instead as the metric of predictive performance. We prefer RMSE for several reasons. Our models optimize for RMSE. Convention dictates that the metric of predictive performance should reflect the metric for which the model optimizes (Kolassa, 2020). Also, MAPE is problematic to compute when a predicted variable takes on values of zero. In our analysis, select cases are calculated as having prevalence rates of zero based on the survey data, which represents a meaningful value in the distribution. Finally, a known issue is that MAPE is susceptible to moving in directions relative to RMSE that are unexpected and appear illogical. For example, a given model could exhibit a higher RMSE, but a lower MAPE, than a comparable model (Kolassa, 2020). We found that RMSE is lower in our main results than in the grouped cross-validation results, whereas MAPE is considerably higher in the main results relative to the grouped cross-validation results – using an approach to calculating MAPE that drops zero values (Hoover, 2006).

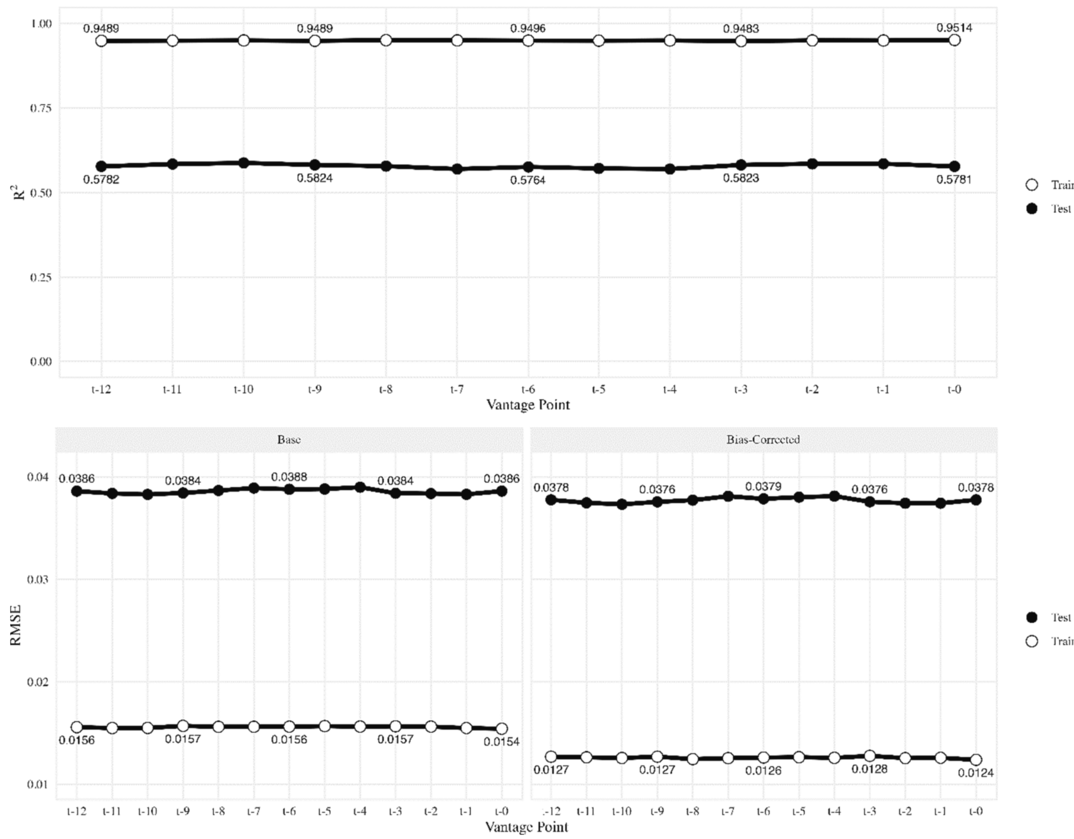


Fig. 3. Predictive Performance of Models.

factors. In addition, out-of-sample predictions fall within +/- 3.8–3.9 percentage points of observed values on average.

Bias correction improves the fit of predictions to +/- 1.3 percentage points of observed values on average within the training data. Gains in out-of-sample performance are far smaller, with predictions falling within +/- 3.8 percentage points of observed values on average. In the rest of this section, we report results from the bias-corrected analysis; comparable results for the base analysis are included in Appendix A. Results for the second, third and fourth batches of models, using variants in operationalizations of the environmental variables, are included in Section 5 of Appendix A. The conclusions from the results with these alternative operationalizations are substantively consistent with the insights from our main analysis.

Fig. 4 presents scatterplots of observed relative to predicted prevalence rates in both the training and test data for vantage points of 0, 3, 6, and 12 months (see Appendix A for plots at other vantage points). The plots also display the fit of predictions with respect to the IPC Acute Malnutrition scale, on which IPC 1 (acceptable) corresponds to WHZ-based rates below 5 %, IPC 2 (alert) to rates from 5.00 to 9.99 %, IPC 3 (serious) to rates from 10.00 to 14.99 %, IPC 4 (critical) to rates from 15.00 to 29.99 %, and lastly IPC 5 (extremely critical) to rates equal to or greater than 30 %. In the plots, the color of each point differentiates whether the predicted and observed classifications match (black) or not (orange).

Fig. 5 presents metrics of the predictive performance of our models with respect to classification along the IPC scale. All these metrics are widely used in evaluation of analyses of classification problems, including those employing machine learning techniques. *Accuracy* is the share of cases for which predicted and observed classifications match. *Precision* is the share of predictions of a given classification for which observed classifications match. *Recall* is the share of observations of a given classification that were correctly predicted. R_K is an overall gauge of the classification performance that summarizes information about true and false positives and negatives from a contingency table (Gorodkin, 2004). This metric is a generalization of the Matthews correlation coefficient (MCC) for binary classification (Matthews, 1975), which is preferred to the F1 score (the harmonic mean of precision and recall) when observations are imbalanced among classifications. In our analysis, observed prevalence rates are skewed, with outcomes corresponding to IPC 1 and IPC 2 far more common than those corresponding to IPC 3, IPC 4, and IPC 5. To emphasize, we did not specifically design the analysis to optimize predictive performance in regard to classification. Regardless, examination of the classification metrics elaborates the insight into the potential practical utility of our models and facilitates comparison of the results to an existing benchmark.[13]

The overall accuracy of our models using the training data is nearly 85 percent. By definition, the overall values for precision and recall are identical to overall accuracy in the context of multi-class classification. Values for these metrics drop to the range of 0.590–0.630 in the out-of-sample application to the test data; the highest values happen to be realized at a vantage point of 8 months. R_K values range from 0.765−0.781 in the training data and 0.397–0.465 in the test data.

Our results vary by classification in noteworthy, unexpected, nonlinear ways. Accuracy within the training data is actually highest for IPC 5, followed by IPC 4 and IPC 1, then is lower for IPC 3 and IPC 2. (The accuracy for individual classifications, which evaluates fit in binary

[13] The spikes evident in the values for recall and R_k/MCC are likely a by-product of the relatively small number of cases of prevalence rates of acute malnutrition for certain IPC levels within the data used for the analysis. Given the small number, spikes can arise from the random partitioning of the data into training and test sets (which remains consistent across model runs for the different vantage points), followed by additional random splits that are unique to each lead time during the cross-validation procedure. These spikes are unlikely to be substantively important.

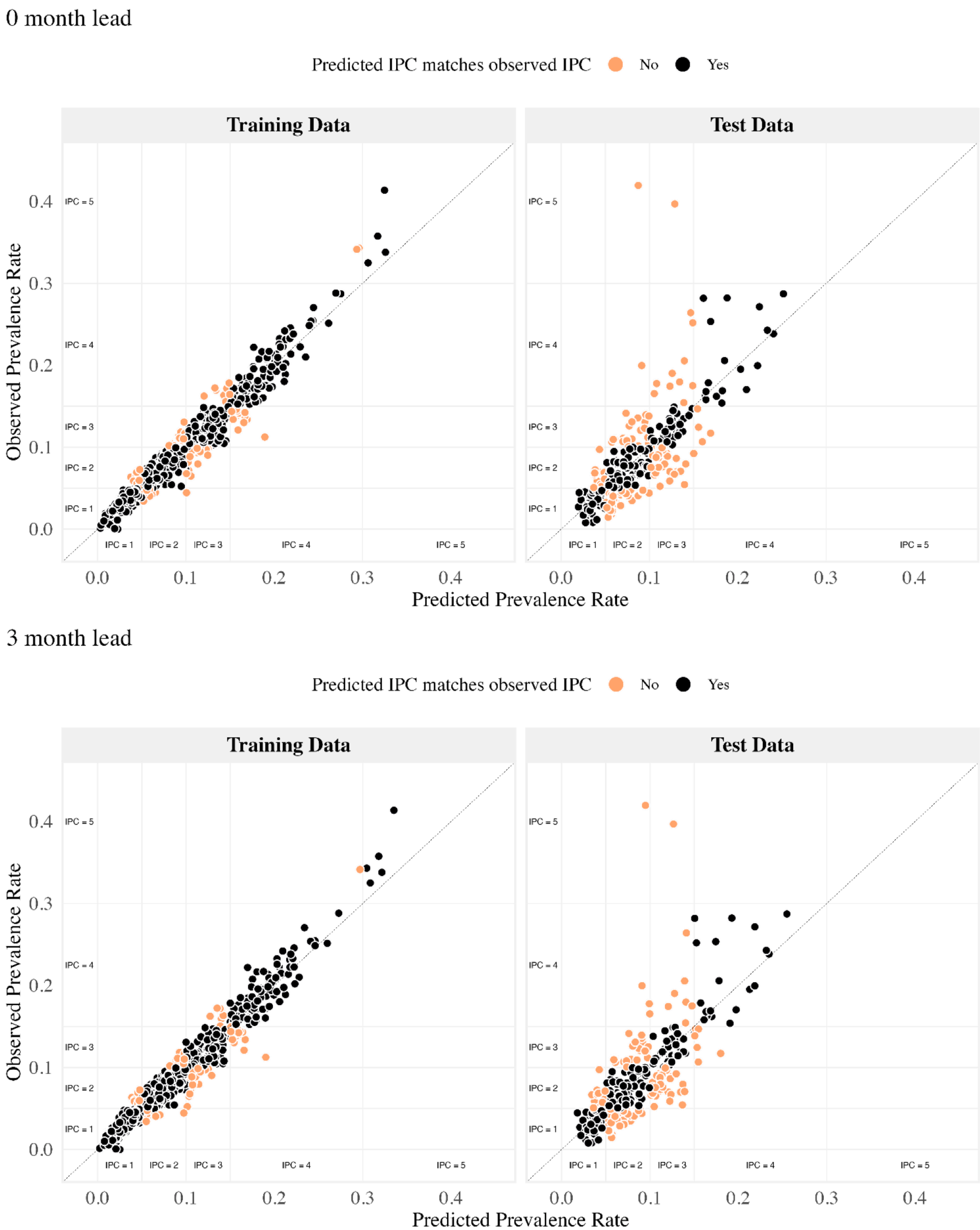
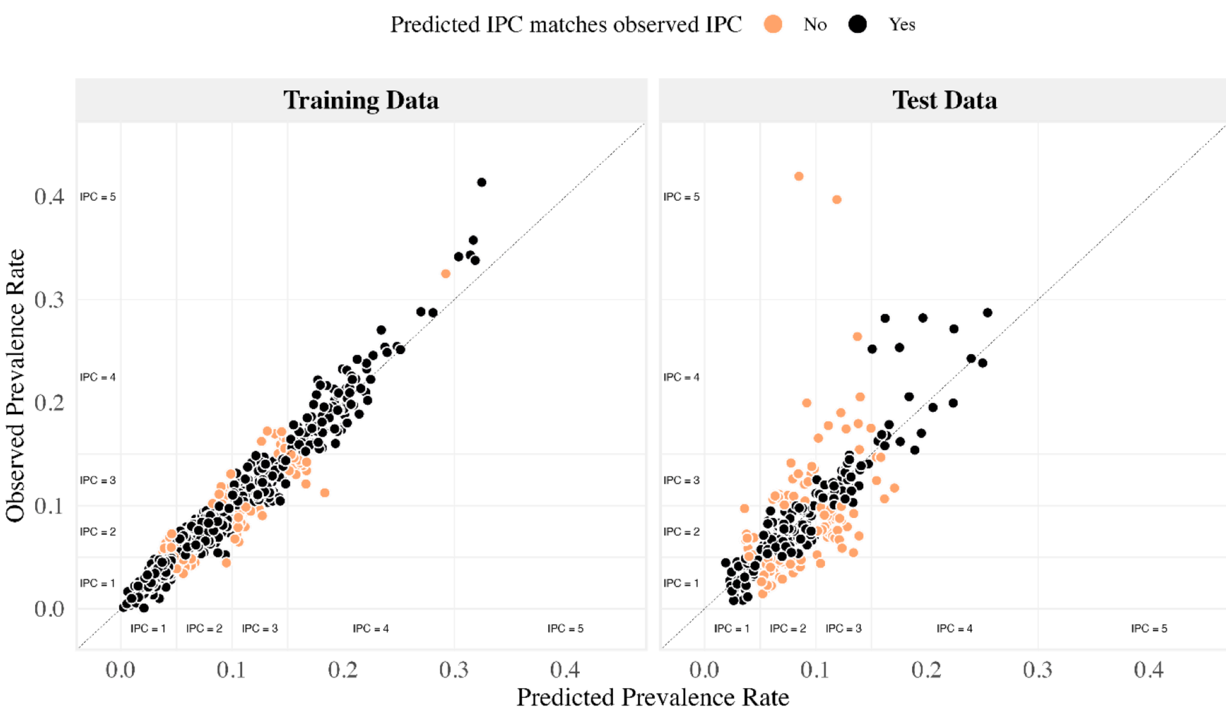


Fig. 4. Observed vs. Predicted Prevalence Rates, with IPC Acute Malnutrition Scale.

terms of each classification versus all other classifications, exceeds overall accuracy, which evaluates the exact multiclassification fit.) Perfect precision is achieved for IPC 5, but recall is mixed. Thus, predictions of prevalence rates corresponding to this classification are never wrong, but the models underpredict a majority of observations actually classified as IPC 5. Otherwise, precision ranges from 0.70 (IPC 3) to 0.90 (IPC 1), while recall ranges from 0.70 (IPC 3) to 0.93 (IPC 4). The highest MCC values are achieved with IPC 5, while the lowest values are for IPC 3. Patterns of results for the test data are similar, though performance drops to an extent. Accuracy is again highest for IPC 5 and lowest for IPC 2. Precision is highest for IPC 4 and lowest for IPC 3; no predictions are made in the test data at IPC 5. The highest recall is achieved with IPC 4, 6 month lead



12 month lead

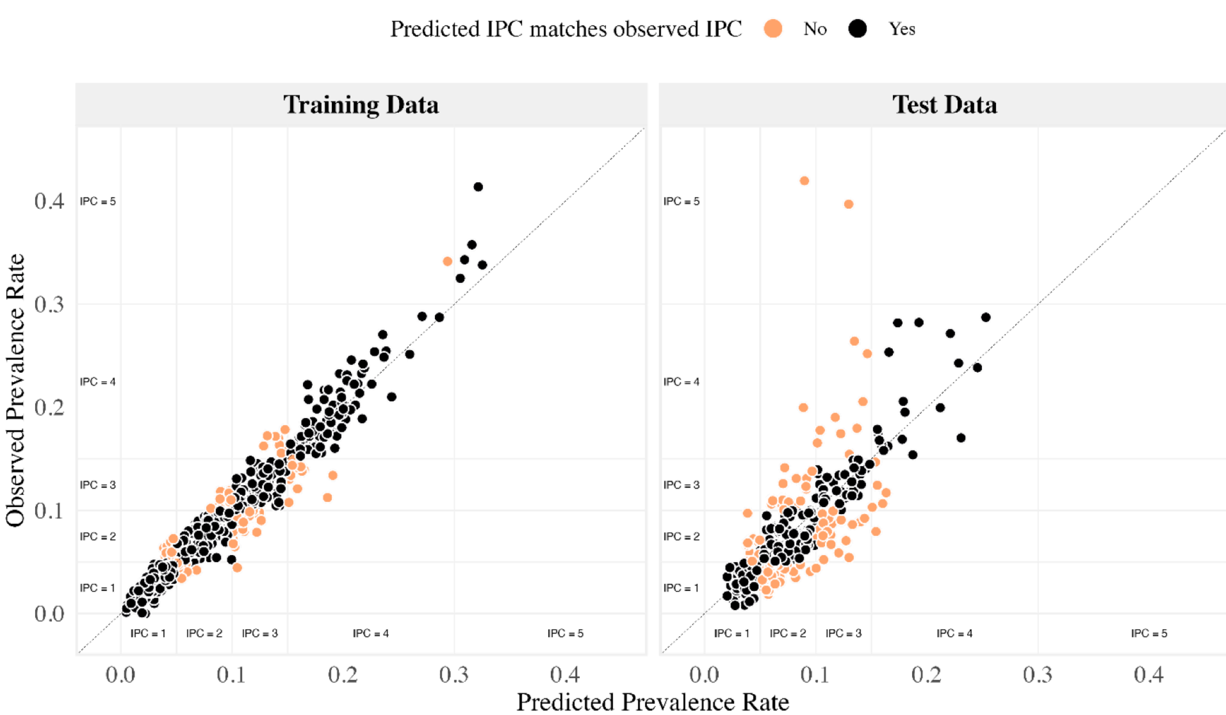


Fig. 4. (*continued*).

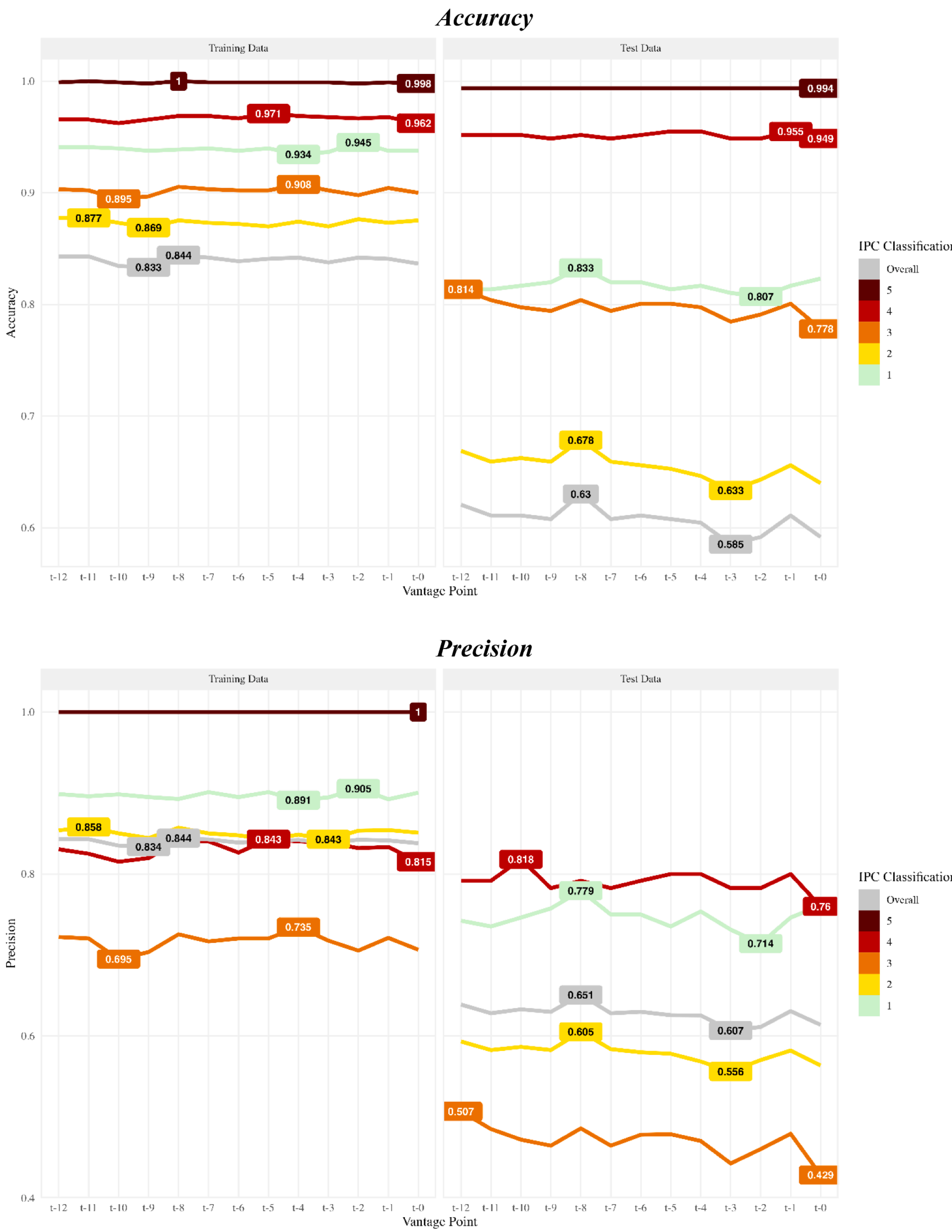
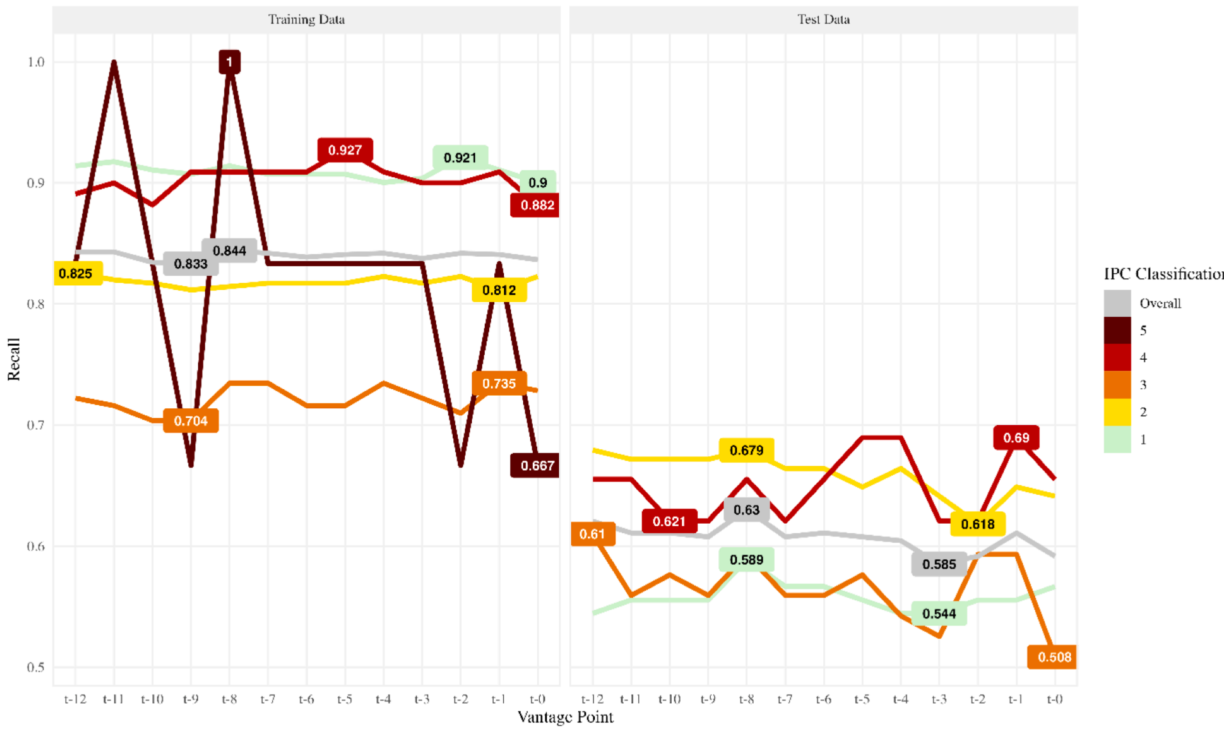


Fig. 5. Classification Performance on IPC Acute Malnutrition Scale.

Recall



MCC / R_K

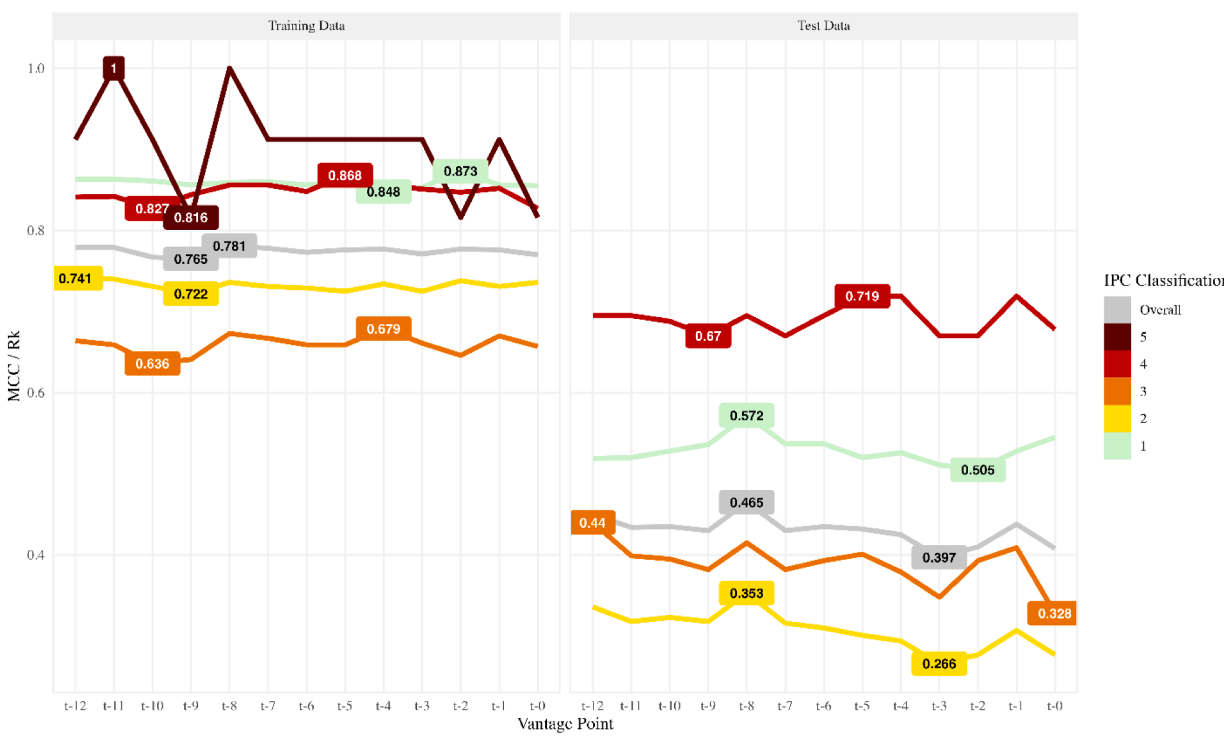


Fig. 5. (*continued*).

the lowest with IPC 5. IPC 4 exhibits the highest MCC values and IPC 2 the lowest values; no scores are calculated for IPC 5 due to the lack of predictions.

Contingency tables, which summarize the distributions of observed classifications by predicted classifications, reveal that disparities of multiple classifications are rare ($\leq$0.1 % in the training data, 2.4 % in the test data). Instead, most of the inaccurate predictions of classifications (>99 % in the training data, 96–98 % in the test data) are off by a single classification. Thus, even when the models do not exactly predict classifications, big surprises are usually avoided. Under-predictions of classifications outweigh over-predictions (~10–25 % more likely in the training data and ~40–80 % more likely in the test data), despite the use of the bias-correction approach. These asymmetries are sub-optimal in terms of the implications for humanitarian practice. Under-predictions have more serious fallout than over-predictions. Failing to anticipate a crisis – or at least the precise severity of a crisis – may mean that humanitarian actors are underprepared and do not proceed with implementing the right measures to avoid or mitigate the impact of the crisis. In contrast, raising alarm bells about crises that turn out to be not as serious as anticipated can impose costs of activating humanitarian measures, which might be viewed as a waste in retrospect, although the actions were arguably warranted given the early warning signals.

3.1. Interpreting indicators

Fig. 6 presents feature importance plots for the most predictive features in the models at illustrative vantage points of 1, 3, 6, and 12 months. From a technical perspective, these plots capture how influential each feature was, on average, when splitting nodes during the process of building the regression trees comprising the final ensemble of a model. A more intuitive understanding is that importance offers a guide for feature selection. A high degree of importance means that a feature contributes valuable information and should always be measured and used in the model, whereas a low degree of importance means that a feature does not contribute much information and might be dropped from the model without a meaningful reduction in predictive performance.

Across the vantage points, latitude is most important predictor of child acute malnutrition prevalence rates for subnational regions. Other predictors that remain fixed over time (longitude, distance to the capital city) or are usually slow-moving (nighttime light intensity, population) also register as important predictors. The upshot is that persistent vulnerabilities inherent to regions matter considerably. Yet focusing on those vulnerabilities alone is insufficient to achieve the best predictive performance. Instead, variable factors are also consequential.

Of note, the environmental and conflict factors make the list of important predictors, substantiating the merits of these variables as leading indicators. The environmental factors are among the top-ranked predictors, led by vegetation levels, with temperature levels generally not far behind, followed by rainfall levels, with temperature, vegetation, and rainfall anomalies further down the list. The fact that each of these environmental factors registers as important reinforces the value of taking all of them into account, including because of how these relationships can accumulate when conditions are unfavorable across the board. The indicators for lethal conflict also make the list, but are well below the environmental factors in terms of importance, while the indicators for non-lethal conflict are lower on the list. More recent conflict events generally have greater importance than less recent events, as might be expected, but the difference is slight – and importance is not monotonic with respect to temporal proximity to outcomes. Thus, even conflict events that occur a long while ago can serve as signals of risks of higher prevalence of child acute malnutrition in the future, with potential for these risks to ratchet up in the event that a region exhibits recurring conflict activity over time.

Section 7 of Appendix A provides further analysis of the impact of factors in the model on the accuracy of predictions. This analysis reinforces the insight that variable factors such as environmental and conflict conditions contribute substantially to improving accuracy. Relying on fixed factors alone is less effective in generating accurate predictions. Section 8 of Appendix A discusses the implementation of country and temporal indicators in applications to forecasting.

Unlike standard regression approaches, models estimated with a random forest algorithm do not produce interpretable coefficients that directly capture relationships between independent and dependent variables. The algorithm allows for highly complex functional relationships that cannot be summarized by a single number. Instead, a partial dependence plot (PDP) conveys the marginal effect of a factor on the predicted outcome across the observed range of values of the factor (Molnar, 2019).

Fig. 7 displays illustrative PDPs for environmental and conflict indicators based on the models with the 1-, 3-, 6- and 12-month vantage points. The plots are interpreted as the predicted prevalence rate for a given extent of standard deviation in an indicator from the long-run mean, marginalized over the values of all other variables in the model. Using standard deviations as units of the x-axis calibrates a sense of the spectrum of normal and extreme conditions.

Each indicator exhibits non-linear relationships with expected prevalence rates of child acute malnutrition. At the lowest observed levels of vegetation and rainfall, and the highest observed levels of temperature, expected rates approach 10 percent. Those rates are more than 1.5 percentage points above expectations under average conditions for those variables. The relationships for the environmental anomaly variables are less straightforward, obvious and intuitive; this can happen due to the complex collinearities and interactions of factors. Deviations in vegetation both below and above the 5-year historical average are associated with prevalence rates about 0.5 percentage points higher. Lower-than-average temperatures are associated with prevalence rates up to about 0.75 percentage points higher. The relationship for rainfall is generally flatter, with some indications that deviations from average conditions are associated with differences in prevalence rates up to about 0.25 percentage points. Likewise, the expected rates at the highest observed levels of lethal conflict are about 0.25 percentage points above what would be anticipated under average levels of conflict. These changes in the prevalence rate are modest, yet can equate to a consequential enlargement of the caseload of children with acute malnutrition, especially if the risks and consequent elevated rates affect more heavily populated regions and communities. Higher levels of vegetation and rainfall and lower levels of temperature and lethal conflict are associated with substantially lower expected prevalence rates.

The full range for temperature is associated with variation in expected rates of 2.0–2.5 percentage points, the ranges for both vegetation and rainfall with variation of 1.5–2.0 percentage points, and the range for lethal conflict with variation of 1.0 percentage point. Thus, differences between favorable and unfavorable environmental extremes are predicted to have a greater impact on child acute malnutrition prevalence than equivalent differences for conflict. The plots indicate that predicted rates plateau past certain levels for each of the variables. A plausible interpretation is that the most favorable conditions have diminishing returns to food security, while exceptionally unfavorable conditions may stimulate coping mechanisms and humanitarian interventions that moderate the repercussions of hazards.

4. Discussion

Food security improved globally over recent decades, but too many places remain susceptible to worrisome levels of malnutrition. In particular, over 45 million children under five years of age were estimated to be acutely malnourished around the world as of 2020 (UNICEF et al., 2022). These circumstances continue to hamper survival and opportunities to flourish. Reliable early warning that underpins functional, constructive anticipatory action is preferable to responses based on monitoring prevalence, which is often situated to detect a crisis only

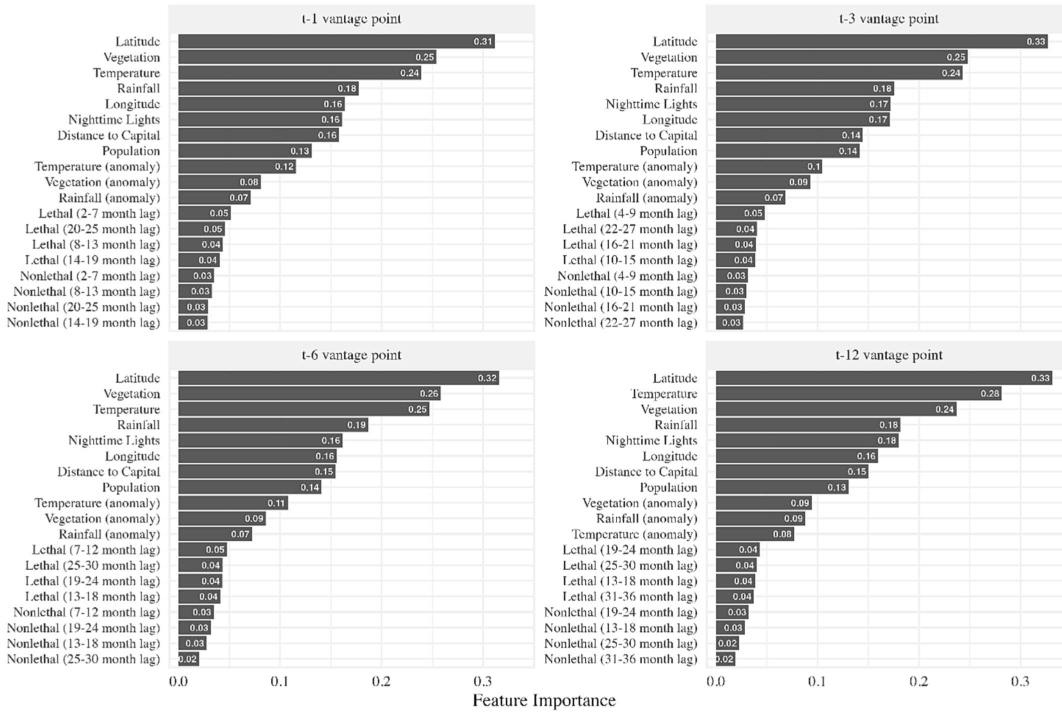


Fig. 6. Importance of Variables in Predicting Child Acute Malnutrition.

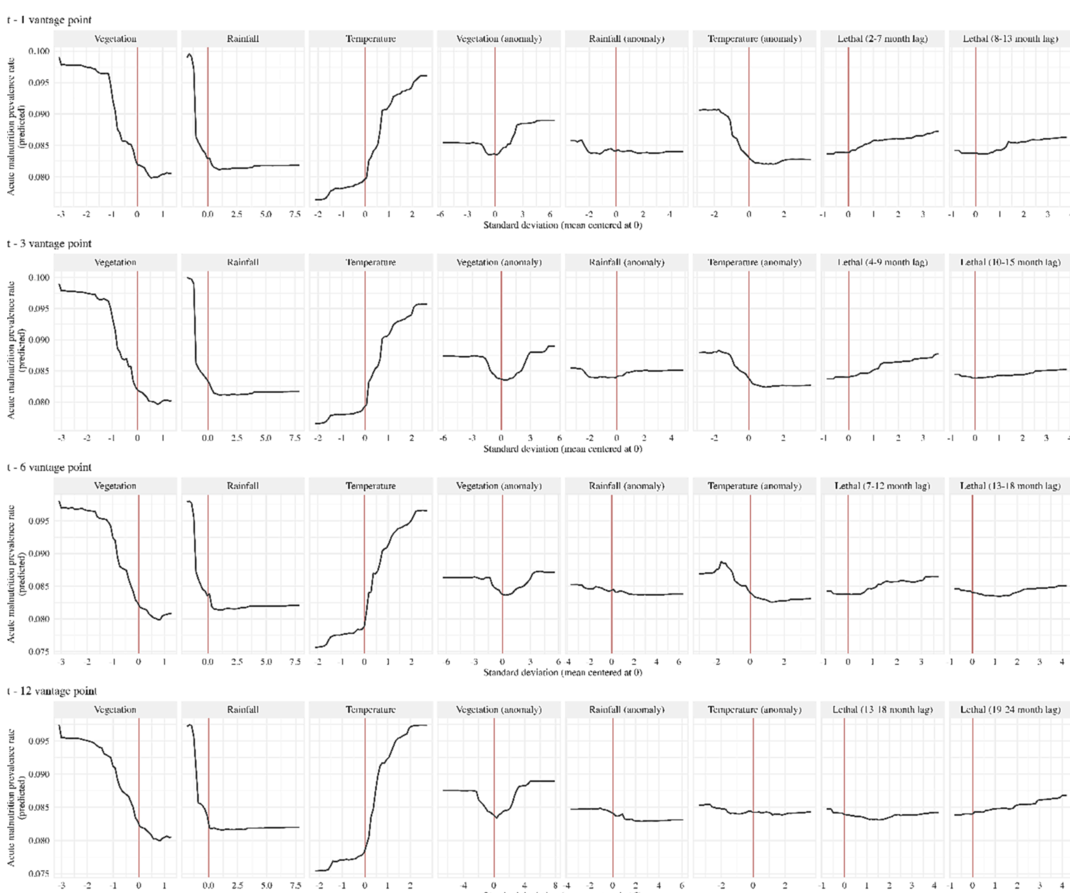


Fig. 7. Partial Dependence Plots for Environmental and Conflict Variables.

after it emerges (Maxwell et al., 2020). Accurately projecting where problems are likely to arise is integral to promoting efforts by stakeholders to reduce the extent of acute malnutrition and forestall negative impacts. With dependable forecasts that are detailed and afford enough lead time, humanitarian and development stakeholders can be better positioned to adopt strategies and direct measures that proactively address risks, working in a timely, effective, and economical manner. Existing approaches to early warning in the domain tend to exhibit shortcomings, including a lack of systematic empirical analysis and validation using statistical methodology, inadequate lead times, and inattention to predicting acute malnutrition.

In this study, we advance capabilities in these respects through rigorous statistical modeling to forecast acute malnutrition prevalence rates at a subnational regional level in dozens of countries across Sub-Saharan Africa.

4.1. Statistical forecasting is a promising tool for early warning of child acute malnutrition

A headline of our results is that the statistical models exhibit strong degrees of in-sample and out-of-sample predictive performance, which remain stable across the vantage points ranging from 0 months up to 12 months. The implication is that an analyst looking far into the future, with access to less information on risk factors – some of which might appear outdated – can be as effective at forecasting child acute malnutrition outcomes as an analyst using more complete, up-to-date information. Our forecasting models consistently yield R^2 values and classification accuracy with respect to the IPC scale of around 0.6, and R_K values of 0.4–0.5 (with F1 values computed as around 0.6), in out-of-sample validation using the test set of data. Among the conclusions is that precise prediction of the entire spectrum of outcomes is difficult. Predicting the extreme outcomes of malnutrition crises is never easy, since these cases are rare and complicated. In some ways, however, the models perform better with cases toward the extremes, whereas nailing cases in the middle of the spectrum poses certain challenges. These latter cases reflect the uncertainties of outcomes when particular risks are neither at severe levels nor coincide to magnify the dangers in ways that can make crises more of a foregone conclusion.

The performance we achieve is generally on par with other recent state-of-the art statistical models of food security and acute malnutrition, though direct juxtapositions are not straightforward since the analytical designs – especially the nature of outcome variables – and the reporting of results differ appreciably from our study. Andreé et al. (2020) report F1 scores for classification in terms of a binary crisis indicator based on the IPC scale that are around 0.3, with predictive performance declining across the range from 4-month to 8-month and 12-month lead times. Westerveld et al. (2021) report F1 scores for classification on a 3-level IPC phase transition scale that ascend from around 0.4 at a 1-month prediction interval to over 0.6 at intervals from 7 to 12 months in a subset of models that employ an extreme gradient boosting machine-learning algorithm; F1 scores for the remaining models are around 0.3 or below at all intervals. Krishnamurthy et al. (2022) report R^2 values around 0.8 for both transitions into and out of food security crises. Lentz et al. (2019) report R^2 values around 0.6 and categorical accuracy with respect to 3-level scales of 0.7–0.9 in models of two outcome variables, as well as R^2 values of 0.1 or below and categorical accuracy rates of 0.5–0.6 for a third outcome variable. Hunger Map^{LIVE} reports R^2 values of 0.6–0.8 for models of two outcome variables. Zhou et al. (2022) report categorical accuracy that ranged from 0.26 to 0.84 depending on which of the two outcome variables was modeled and which of the three countries was the setting. To reiterate, Lentz et al. (2019), Zhou et al. (2022), and Hunger Map^{LIVE} lack a forecasting dimension. Foini et al. (2022) report R^2 values exceeding 0.7 for all time horizons, ranging up to 30 days. Gholami et al. (2022) report F1 scores of around 0.7 and accuracy of nearly 0.8 in models of food insecure households. Checchi et al. (2022a) report recall maxing out in the range of 0.6–0.7, depending on the indicator of acute malnutrition, country setting, and model assumptions. Wang et al. (2022) only report RMSE as a metric of model fit, while Grace et al. (2022) do not report any such metrics. Meanwhile, the classification accuracy of FEWS NET's medium-term projections on the 5-level IPC scale for 25 countries across Sub-Saharan Africa from 2009 to 2020 was found to be 0.84 overall (Backer and Billing 2021).

Other important aspects of our research enhance the value of the contribution. This study is rare in developing statistical forecasting models specific to acute malnutrition, on an extensive scale. To our knowledge, the only other published examples are Grace et al. (2022) and Checchi et al. (2022a). IPC does generate the projections for acute malnutrition, but without a reliance on statistical modeling. Unlike IPC – and FEWS NET and CH – our methodology is fully transparent and the results are fully replicable (and empirically validated, unlike IPC and CH). The comparative scope of our analysis, though hardly exceptional in the domain, goes well beyond the single-country studies of Lentz et al. (2019) and Westerveld et al. (2021) and reinforces the viability of cross-national designs – including analysis that pools data among substantial numbers of countries – that have become more commonplace. Our approach should also be feasible to scale to additional countries and to sustain over time while making worthwhile updates, refinements, and enhancements, as well as engaging in ongoing validation – all at a low marginal cost. The modest number of indicators, drawing on existing sources of data, means that the modeling has relatively simple requirements to conduct, in line with Lentz et al. (2019), Andreé et al. (2020), and Hunger Map^{LIVE}. Most of the other predictive modeling studies we cite rely on far more extensive data. Our process certainly entails fewer inputs of information and far less infrastructure, personnel, time, and financial support to implement than IPC, FEWS NET, and CH.

4.2. Environmental and conflict factors are effective leading indicators

Another headline is that environmental and conflict conditions register as important predictors in the models. The findings are not too surprising given these factors are central to the long-standing conventional wisdom about equations affecting food security and malnutrition (UNICEF, 1998). Our analysis offers compelling evidence that the factors can be employed as leading indicators of acute malnutrition prevalence rates, which is vital to forecasting applications. Relevant research on acute malnutrition is limited (Brown et al., 2020). Studies of food security outcomes that simultaneously evaluate both types of factors are rare (Brown et al., 2021). Existing studies more often examine either environmental factors (e.g., Niles and Brown, 2017; Amegbor et al., 2020; Baker and Anttila-Hughes, 2020; Thiede and Strube, 2020) or conflict factors (e.g., Dunn, 2018; George et al., 2020), rather than considering these factors together (Rowhani et al., 2012; Delbiso et al., 2017; Njatang et al., 2023). A majority of the predictive modeling studies we cite above deviate from the pattern, including both environmental and conflict factors; Lentz et al. (2019), Gholami et al. (2022) and Zhou et al. (2022) are exceptions in omitting conflict factors. Westerveld et al. (2021), Grace et al. (2022), and Wang et al. (2022) provide points of comparison in reporting results for both types of factors, with consistent findings that environmental indicators are more influential than conflict indicators. None of these studies translates the results into substantive magnitudes of variation in acute malnutrition outcomes associated with those factors.

In contrast, we show that prevalence rates are expected to vary by roughly 1–2 percentage points over the ranges of observed values for the environmental factors, and to a lesser extent over the ranges for the conflict factors. At first glance, the extent of variation may seem small and inconsequential. Yet elevating a prevalence rate by such an amount can be significant in a vulnerable setting and tip an existing situation over a threshold into a crisis. The difference may translate to sizeable increases in caseloads of children forecast to suffer acute malnutrition within a subnational region. Furthermore, the PDPs present averages across all countries within the timeframe reflected in the sample of data. Differences are larger for certain countries and points in time. Also, as with any statistical model including multiple predictors, effects of factors can compound. In our models, the compounding is additive. Differences of several percentage points are possible when comparing the scenario of multiple environmental and/or conflict factors being at unfavorable extremes to a baseline scenario of those same factors being at normal levels. The differences widen further in comparison to scenarios of the most favorable levels of factors.

A further element bears mentioning: our analysis is the first in the domain to distinguish between and assess indicators of lethal and non-lethal conflict as predictors, in the process integrating multiple sources of event data that capture diverse manifestations of conflict activity. The results affirm the importance of events exhibiting lethal violence, but indicate that non-lethal events matter on the margin as well. Other existing studies have considered violent (i.e., lethal) conflict, without probing whether or not non-lethal conflict matters too for predicting acute malnutrition outcomes.

4.3. Practical applications

The framework of our study can bolster the foundations for anticipatory action to tackle and mitigate the potential negative impacts of food security crises in several ways. First, model-based forecasts represent expectations about prevalence rates of acute malnutrition at a subnational regional level. These expectations can be inputs to protocols that trigger responses by humanitarian actors. Being able to anticipate prevalence – and thereby to infer caseloads of at-risk populations – in different areas of vulnerable countries empowers humanitarian actors to make appropriate, tailored decisions about interventions. Second, the modeling framework exhibits potential of generating reliable forecasts of prevalence rates with substantial lead times, enhancing capabilities of early warning. Humanitarian actors are therefore positioned to be alerted to impending crises and make decisions sooner, which should facilitate anticipatory action. Third, the forecasts leverage the signals provided by environmental and conflict conditions as leading indicators, quantifying crucial relationships. Those insights can reinforce the preparedness of humanitarian actors to monitor and respond to evolving conditions. Ultimately, these and other features of model-based forecasting provide a compelling argument for integration of the resource into humanitarian planning.

4.4. Strengths & limitations

Our study is distinguished by rigorous, innovative statistical modeling of acute malnutrition that relies on novel compilation of empirical data with exceptional geographical and temporal scope, spanning several dozen countries across nearly two decades. Generating forecasts by employing methods of predictive analytics can help to address concerns of objectivity, transparency, and replicability that are raised about existing early warning systems. In the process, we encountered skepticism from certain experts in the field, premised on claims that prevalence rates of acute malnutrition can be readily anticipated based on recent trends or using static factors (e.g., location, time of year). Our examination of the historical record suggests that such anticipation is hard to achieve with consistently high fidelity. The basic spatio-temporal patterns and trajectories are not necessarily routine distributions of outcomes, regular cycles, and smooth lines. Consequently, a more sophisticated approach is required to progress from outcomes that are unpredictable to outcomes anticipated with appropriate accuracy – and forecasts that are actionable. Until recently, prediction of acute malnutrition (and food security) has rarely been formalized through statistical analysis, especially in a manner pitched toward practical applications that require anticipating future outcomes. Our study showcases formalized analysis with a forecasting orientation, conducted on a wider geographic scope than other existing work.

Among the constraints of our study is the intrinsic dependency of predictive analytics on available empirical data. Even assuming full access to data (which is difficult to accomplish), they are not always as plentiful and rich as would be ideal to elaborate and pinpoint key details of model specifications, to add analytical features most advantageous in guiding humanitarian action, and to boost predictive performance. Our choices are steered by what is realistic to accomplish with the data at hand. Where possible, different choices could be made, which have clear value.

In particular, we endorse the merits of a modeling framework with an outcome variable operationalized in terms of the change to the prevalence rate of acute malnutrition over time. Being able to anticipate whether rates are expected to change is of considerable utility to stakeholders, especially to spur action to prepare for – and avoid or at least mitigate – increases in caseloads and stave off crises. A preferable way to forecast changes is to conduct analysis that directly examines changes as the outcome. Instead, the results of our analysis generate forecasts of prevalence rates at discrete time points, which can then be assembled into a trajectory of expected outcomes, allowing inferences about month-by-month or year-over-year changes in rates.

Unfortunately, the data on which we rely in our analysis do not enable implementation of a modeling framework in which the outcome variable measures changes in prevalence rates. The DHS, MICS, and SMART surveys represent a patchwork, lacking frequent data collection with a consistent cadence and coverage. Our compilation of these sources permits the calculation of only select instances of month-to-month changes, even for a case like Nigeria that exhibits a greater density of data (motivating the illustrative example in Fig. 2). Calculation of changes with any periodicity (month-to-month, quarter-to-quarter, year-over-year for corresponding months) on an extensive let alone comprehensive scale is impossible with the compiled data.

Therefore, our analysis is largely restricted to assessing between-case variation, with some attention to timing, rather than fully probing within-case variation. The data we use has predominantly cross-sectional properties (i.e., outcomes measured for different geographic units at sporadic points in time). To go further, we require data with definite longitudinal properties (i.e., outcomes measured for the same geographic units regularly over time).

As mentioned in Section 2, data sources exist for single countries that permit the assembly of longitudinal time series with a monthly (e.g., Kenya) or biannual (e.g., Somalia) frequency and extensive coverage of sub-national regions. These sources do not support the sort of analysis with wide geographic scope that we undertake here. In separate work, we rely on those sources to conduct country-specific analyses. Others have also used those sources or similar sources in analysis, which is worthwhile and ought to be extended.

Admittedly, predictive analytics can also fall short in capturing the fuller context, dynamics, and complex natural and social processes – and their interaction – in the best of circumstances. Data tend to be a partial abstraction of conditions on the ground in countries of interest facing food security challenges. The modeling process may also shortchange the human element that can be productive to optimize the design of analysis and to enhance the interpretation of results. These potential shortcomings mean that statistical modeling should not be viewed as a substitute for early warning systems or the expertise of stakeholders. All the components should work harmoniously to complement one another and thereby to reinforce capabilities.

4.5. Extensions

Our modeling framework offers a template for ongoing research. The analysis should be updated as additional historical and contemporary data become available, thereby increasing the depth of coverage and broadening the spatio-temporal scope, with the predictive performance continually revalidated. Doing so helps to improve the prospects of practical applications in forecasting future outcomes (see Section 8 of

Appendix A). Our model specifications could be augmented with more factors, again subject to the availability of data that provide the requisite level of detail. Performance could also be explored in certain settings with sources of rich longitudinal data, where repeated measurements of acute malnutrition enable calculation of changes in prevalence rates and direct analysis of within-case variation over time. The results of this analysis ought to be compared to the results from our study, which focuses on between-case variation and merely approximates within-case variation through means such as feature importance. The relative performance of different machine-learning techniques is worth testing as well.

Another avenue is forecasting outcomes on a more disaggregated basis. Some existing research is already geared in this direction, including three recent studies produced via separate analytical workstreams of the same project in which we were involved. One of these studies uses multilevel modeling to relate nutritional status to other health, demographic, and socio-economic attributes of individual children, nested within families and households who are situated within communities and regions of Kenya, Nigeria, and Uganda (Grace et al., 2022). Another study uses computational modeling to relate nutritional outcomes to coping strategies and other factors at the family, household and community level in Kenya (Bhavnani et al., 2023a). A third study uses latent class mixed modeling and time-to-event analysis to predict a measure of resilience to acute malnutrition at the level of wards (third-order administrative division) in Kenya as a function of household and community characteristics (Bhavnani et al., 2023b). These studies, together with our own, demonstrate the exciting potential to produce forecasts across a multiple levels and units of analysis, meeting varying needs of stakeholders for information to improve anticipation and direct action. In general, analysis with greater spatial granularity is compelling (Amusa et al., 2023).

An ultimate goal should be to connect the design of the modeling and the elaboration of forecasting functionality more substantially to tangible requirements of decision-making support. Approaches proposed above contribute toward those aims. Possible advances could include factoring in loss functions, along the lines of Andreé et al. (2020), and estimating the cost and efficacy of anticipatory action and humanitarian emergency measures implemented to confront risks of acute malnutrition. Fulfilling the requirements is likely to entail systems analysis that links forecasting of acute malnutrition outcomes to decisions about allocations of resources, the operational deployment of humanitarian assistance, and downstream consequences for morbidity and mortality suffered among affected populations (Checchi et al., 2022b; Warsame et al., 2023). The success of the agenda will benefit from close consultation with relevant stakeholders to understand their perspectives and needs, as well as to evaluate the uptake, utilization, and impact of model-based forecasts as information tools (Lentz & Maxwell, 2022).

CRediT authorship contribution statement

David Backer: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing, Data curation, Resources. **Trey Billing:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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