Abstract

This paper presents the first global picture of food security at a subnational level based on the Food Insecurity Experience Scale, the indicator for the Sustainable Development Goal of "Zero Hunger" that is most indicative of the individual's lived experience of food insecurity and hunger. Using microdata from 75 countries and filling gaps using machine learning, we find significant heterogeneity in levels of food insecurity around the world. Examining global temporal trends and accounting for the effects of the COVID-19 pandemic, we find that rates of severe food insecurity are declining, resulting in global decreases in the total number of severely food insecure people. However, the total number of moderately food insecure people has been increasing and, after recovering from the shock of the COVID-19 pandemic, we predict it will continue to increase through the end of the 2020s. Overall, we conclude that current trends in development and demographic change will still leave a large share of the world's population still experiencing hunger by 2030.

1 Main

Food security is a critical component of human flourishing and its importance as a global policy objective is reflected in the second Sustainable Development Goal (SDG 2), "Zero Hunger." One of the indicators to track progress on the first target of this goal, to ensure access by everyone to safe, nutritious and sufficient food (SDG2.1), is the prevalence of moderate and severe food insecurity in the population based on the Food Insecurity Experience Scale, or FIES. The FIES was developed by FAO in 2013 as a global extension of pioneering work started in the US in the 1990's to develop a metric of food insecurity based on data gathered by interviewing the people who experience hunger and conditions that produce hunger. Other indicators of food insecurity, such as FAO's more commonly used estimate of undernourishment, are based on macro models of the mean and distribution of calories available per capita in a population, developed on the basis of infrequent and heterogeneous data on food production and consumption. These do not directly capture the actual lived exposure of individuals to food shortages.

Currently, the data used to generate the estimates that are reported at the UN SDG indicators database come primarily from the 75 countries where surveys have been commissioned, vetted, and released by FAO. To compile global and regional aggregates, the current practice at FAO is to use the prevalence rate for the countries that do have FIES data as the regional rate. Moreover, since the FIES is a relatively new metric, a sufficiently long time series to assess time trends with a reasonable degree of precision is still lacking. Thus, to fill these spatial and temporal data gaps and understand whether SDG 2 is being met, modeled estimates of food insecurity outcomes are thus required.

This paper contributes to shifting the research frontier by filling these two gaps in terms of spatial coverage and forecasts by developing a machine learning model of FIES-based food insecurity rates based on covariates that are available for territories where actual survey data are not available. This model is then employed to obtain forecasts to 2030 and assess likely future trends in food insecurity. We take advantage of individual-level characteristics collected in FAO's FIES surveys to push the analysis beyond the country level to a subnational level. To our knowledge, this is the first effort to model FIES-based food insecurity at that scale.

Food security has traditionally been difficult to measure, and this has arguably led to an incomplete or possibly inaccurate assessment of global hunger. Metrics of macro-health, such as anthropometric measures and mortality rates are correlated broadly with food insecurity and have been used for many years to monitor human well-being **Puffer1973**; **Habicht1974**. However, these metrics are affected by other determinants of health such as the occurrence of infectious diseases, and are not meaningful at the scale of individuals or households **Perumal2018**. Other proxies for food security, such as food availability estimated from crop yields **Maxwell1992**, are also inadequate because they only make rough estimates of how accessible food is to the general population, and can elide populations that are food insecure due to poor access, even when aggregate food availability is high **Sen1983**. Moreover, these metrics are very sensitive to incorrect estimates of crop yields and food reserves at a national scale. Thus, global estimates of hunger and food insecurity based on these metrics carry forward similar flaws.

As researchers began to focus on food insecurity at the individual and household level, microdata from household surveys collecting information on household finances and consumption became a basis to compute a common proxy for food security **Haddad1994**. However, these efforts were criticized for being onerous, insufficiently comparable, as well as for ignoring subjective and experiential aspects of food security **Maxwell1996**. This led to the emergence of several indicators designed to be rapidly deployable, and based on the lived experience of food security **Jones2013**. These metrics include the Household Food Security Survey Module (HFSSM) **kennedy2005keynote**, originally developed for use in the US; the Latin American and Caribbean Food Security Scale (ELCSA); and the Household Food Insecurity and Access Scale (HFIAS) **Coates2007**.

Drawing on the insights derived in designing and implementing these novel food security metrics, the FIES was developed by the Food and Agricultural Organization (FAO) of the United Nations (UN) **Ballard2013** and is now recognized as a rapidly deployable and cross-culturally valid tool for understanding individual and household-level food insecurity **wambogo2018validity**; **smith2017world**. The FIES is based on a survey of eight behaviors indicative of food insecurity and hunger over the previous year, such as skipping meals or worrying about having enough to eat. Processing the responses given to the FIES questions through the Rasch model, each individual in the survey is assigned a score that allows them to be ranked on a scale of food insecurity severity. Once the severity measures are calibrated against a common reference (the global FIES reference scale) **Cafiero2018** and individuals are ranked in this fashion, conventional thresholds for "moderate" and "severe" food insecurity are set and the prevalence of such food insecurity conditions can be computed. Thresholds are set in such a way that a moderately food insecure respondent is one who likely has compromised on food quality and variety as a result of lack of resources, has been unsure about their ability to obtain food and has skipped meals or run out of food occasionally. A severely food insecure one is likely to have run out of food and has gone an entire day without eating at times during the year. The percentage of people estimated to be over the threshold set for moderate food insecurity includes people that are also over the threshold for severe food insecurity and represents the SDG indicator 2.1.2.

Since 2014, FAO contracted the Gallup World Poll to administer the FIES survey module in as many countries as possible around the world and uses this data to estimate the prevalence of food insecurity at region and global levels. For a number of those countries for which it has been authorized to release the national-level estimates, FAO also reports the percentage of the national population that is estimated to be over the thresholds for moderate and severe food insecurity and publicly releases the microdata.

Drawing on individual-level data from these publicly available microdatasets from 75 countries, we use machine learning methods to model food insecurity based on covariates and estimate levels of food insecurity globally, at the subnational level. The model is then used to forecast food insecurity to the year 2030 under a reasonable scenario on the possible evolution of the covariates.

2 Methods

This analysis had three steps. First, in countries where FIES microdata was available at the national level, we generate subnational weights to disaggregate the microdata and estimate food insecurity rates at the first administrative level for each survey year. Second, we gather data on covariates related to food insecurity from previously published datasets that include future predictions under the Shared Socio-Economic Pathways framework. These covariates are processed to be at the same yearly, administrative area level, for all years from 2010 to 2030. Finally, we fit a machine learning model using the covariates in administrative areas where microdata is available, and use that model to make predictions for all years and all administrative areas.

2.1 Disaggregation

The data on the FIES collected by Gallup on behalf of FAO also records many individual-level attributes from the respondents, including age, gender, wealth quintile, and whether they live in an urban or rural area. Using national data on these variables, a standard weighting scheme is created for each individual, based on the ratio of population probabilities to sample probabilities of an individual with those characteristics being selected **bethlehem2009applied**. This ensures that the results are representative at a national level. We use a similar methodology, except that we calculate post-stratification weights at a subnational level. We use year-specific subnational estimates of population shares by gender, age, urbanization, and, where available, wealth, and create a separate set of weights for each subnational area across all individuals. For age and gender, we used gridded data from WorldPop **Tatem2017**; for urbanization, we used spatially explicit estimates of population in urban and rural pixels published by Jones and O'Neill and deriving from night-time lights and buffered settlement centroids **Jones2016**; and for wealth we used data on household wealth quintiles from Demographic and Health Surveys **dhsall**. This methodology rests on the mild assumption that, within a given country, two individuals of the same age, gender, urbanization level and wealth quintile will have a similar food security status, an assumption that underlies much of survey weighting methodology **bethlehem2009applied**.

2.2 Covariates

We model subnational rates of moderate and severe food insecurity as a function of several covariates related to human development, nutrition, health, infrastructure, income levels and distribution, and the environment (See Table 1). We employ covariates for which projections are available up to year 2030 and, in most cases, also have subnational spatial resolution. For projections based on the Shared Socioeconomic Pathways (SSP) framework **oneill2014new**, we use the middle-of-the-road pathway, SSP2, and for climatological variables, we use forecasts based on the Representative Concentration Pathway (RCP) 6.0 **van2011representative**.

Many of the variables require the harmonization of subnational historical data with projections at the national level. These include mean years of schooling, GDP per capita, as well as population. We use observed trajectories in the historical distribution of variables among subnational areas within a country to predict the future distribution of GDP, population, and schooling among subnational areas and disaggregate national-level future projections.

For health variables that have historically shown long-term trends and represent a rate of occurrence in a population, including stunting, wasting, and malaria mortality rate, we estimate the Annualized Rate of Change (AROC) for each subnational area to model these and to obtain predictions for variables up to 2030. We calculate the rate of change between each pair of years in the dataset, and then use the mean rate of change over the period for which data are available, giving greater weight to more recent years, and applying that mean rate of change to estimate future levels. This method is used to obtain forecasts of the rates of stunting and wasting up to the year 2030.

For the climatic variables, mean annual temperature and total annual precipitation, we combine historical observations with an ensemble of four bias-corrected simulations of the future climate from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) **warszawski2014inter**. These variables cannot speak to sudden shocks but do capture the climatic baselines relevant to agro-ecological conditions that constrain food production.

Finally, we adjust several variables to account for the effects of the COVID-19 pandemic. These include June 2020 GDP predictions from the World Bank **prospects2020**, August 2020 estimates of impacts on anthropometry from *The Lancet* **headey2020impacts**, as well as the Poverty Headcount Index **Cuaresma2018**.

Name	Source	Scale
Urban Percentage	**Jones2016**	Subnational
Stunting	**Local2020**	Subnational
Wasting	**Local2020**	Subnational
Mean Years of Schooling	**Smits2019** **KC2017**	Subnational
GDP Per Capita	**Smits2019** **Dellink2017**	Subnational
Gini Coefficient	**Rao2019a**	National
Poverty Headcount Index	**Cuaresma2018**	National
Water Scarcity	**greve2018global**	Subnational
Total Annual Precipitation (Current and Previous Year)	**abatzoglou2018terraclimate** **warszawski2014inter**	Subnational
Topographic Ruggedness	**USGS1996** **Riley1999**	Subnational
Mean Temperature (Current and Previous Year)	**abatzoglou2018terraclimate** **warszawski2014inter**	Subnational
Malaria (*P. falciparum*) Mortality Rate	**Weiss2019**	Subnational

Table 1: Covariates Included in the Analysis

2.3 Modeling

We fit two models for all subnational areas globally from 2010 to 2030: one for the percent of the population over the threshold for moderate food insecurity, and one for the percent of the population over the threshold for severe food insecurity. We assessed several different modeling strategies and found that a random forest machine learning approach performed the best. A comparison of random forest and LASSO (Least Absolute Shrinkage and Selection Operator) regressions are presented in the supplement, and additional approaches are presented in a graduate thesis by one of the authors **muller2021**. A random forest regression involves generating a large number of decision trees, each using different sub-samples of the data, and then aggregating the predictions of the decision trees. This approach performs well in the presence of non-linearities and interaction effects among predictor variables **hastie2009elements**. By taking an ensemble of decision tree models, random forests introduce more variance and balance out the bias that is common to methods based on single decision trees **friedman2001elements**. Given the bounded nature of our variables of interest, the random forest regression are applied to the logistically transformed rates. We create our models using the `randomForestSRC` package in R **ishwaran2019randomforestsrc**.

To get the best possible model performance, it is necessary to tune the hyperparamters, which control the process in which the random forest algorithm is run. These include the average number of observations in a leaf node, the number of variables randomly selected as candidates for splitting a node, and the maximum depth of each tree. We use the combination of hyperparameters that perform best under leave-one-out validation based on R^2 and mean average error (MAE).

When performing cross validation, it is typical to select observations at random. However, in our training data we have multiple highly similar observations from each country across years and subnational areas, and we extend our model predictions to countries that were not found at all in our training data. Thus, we perform a type of leave-one-out cross validation, where we leave out all of the data from one country for each iteration. Thus, the model error after cross validation gives us a sense of how the model is performing in countries where FIES data was not collected. By this validation metric, we find that our models perform well, with an R^2 of 0.787 and mean average error (MAE) of 0.07 for moderate food insecurity and an R^2 of 0.756 and a MAE of 0.037 for severe food insecurity. After fitting models on the entire dataset, we observe a within-sample R^2 of 0.936 and an MAE of 0.038 for moderate food insecurity and an R^2 of 0.99 and a MAE of 0.007 for severe food insecurity.

After fitting the models, we examine the importance of the individual covariates in explaining rates of moderate and severe food insecurity. We use a common method of permutating each individual variable and re-running the regressions, and then determining the difference in MAE between the regression **ishwaran2007variable**; **breiman2001random**. This metric can provide some interpretability to model predictions.

The Supplementary Materials provide a detailed description of the data processing for the covariates, as well as implementation and validation of the random forest models.

3 Results

3.1 Food Insecurity over Time

Globally, in the year 2020, we estimate that 820 million people are above the threshold for severe food insecurity, and 2.5 billion people are above the threshold for moderate food insecurity (See Fig. 1). These numbers are higher than the estimates in the 2020 FAO State of Food Insecurity (SOFI) report, which reports about 746 million severely food insecure people and 2 billion people experiencing at least moderate food insecurity in 2019 **sofi2020**.

Under realistic scenario assumptions, we find recent increases in the number of moderate and severely food insecure people around the world, yet expect overall decreases from 2010 to 2030. These changes are more slight for people who are at least moderately food insecure: in 2030, the number of moderately food insecure people will have decreased by 2.6% since 2010, and the number of severely food insecure people will have decreased by 12.4%. While the number of moderately and severely food insecure people are modeled to decrease overall, they are projected to increase in lower income countries through 2030.

Figure 1: Number of people over the thresholds for moderate and severe food insecurity, by World Bank income groups as of 2020. Panel (A) shows the number of food insecure people with region totals stacked, to show global trends and totals over time. Panel (B) shows regional totals compared against each other over time.

Examining the rate of food insecurity in a population, rather than the total number of food insecure people (See Fig. 2), we find clear improvements in all except high income countries. Countries that are currently upper-middle income, like China and Brazil, saw large gains in improving food insecurity rates throughout the 2010s, and will continue to see somewhat diminished gains in improving food security throughout the 2020s. Lower and lower-middle income countries, on the other hand, saw more modest gains in the 2010s but are forecasted to see greater gains in reducing the rate of food insecurity in the 2020s. In spite of this progress in the bottom three income quartiles, in high-income countries, the rates of people in moderate and severe food insecurity have been flat and are expected even to increase slightly. Overall, the world has made steady but slow progress on reducing the rate of food insecurity.

Figure 2: Percentage of the population over the threshold for moderate and severe food insecurity, by World Bank income groups as of 2020.

3.2 Food Insecurity Across Space

We find substantial heterogeneity in the global distribution of severe food insecurity across countries and subnational regions (See Fig. 3). For the year 2020, mainland sub-Saharan Africa is the continent with the highest rates of severe food insecurity, with 20% of people over the corresponding threshold in at least one subnational area in every country except Gabon, Djibouti and Equatorial Guinea. Outside of Africa, serious pockets of severe food insecurity also occur in Venezuela, Syria, Papua New Guinea, Yemen, and Afghanistan. In many large middle-income countries, severe food insecurity is also quite prevalent, with rates between 10% and 15% in parts of Latin America, many central Asian and middle-eastern countries, as well as India and Indonesia.

The experience of at least moderate food insecurity is quite common in many parts of the world. In 2020, much of Africa, south and southeast Asia, and parts of Latin America had over 50% of the population living with moderate food insecurity. Even in highly developed economies, such as the United States and parts of eastern and southern Europe, over 10% of the population is above the threshold for moderate food insecurity.

Some countries show persistent subnational gaps in rates of food insecurity, typically in areas that are more remote. For example, the Somali province of Ethiopia, Sahelo-Saharan Mali, and Amazonian Brazil are all generally more food insecure subnational areas than the more populous and accessible parts of their respective countries.

Figure 3: Spatial distribution of moderate and severe food insecurity for the years 2010, 2020, and 2030.

3.3 Important Predictors of Food Insecurity

Overall, our model was able to predict food insecurity with high accuracy in the countries for which training data was available ($R^2 = 0.936$ and $R^2 = 0.99$ for moderate and severe food insecurity, respectively), and excluding entire countries from the training data to evaluate out-of-country model error still showed overall good results ($R^2 = 0.787$ and $R^2 = 0.756$ for moderate and severe food insecurity, respectively). The relative importance of different variables as predictors of food insecurity can be assessed by examining the loss in forecast accuracy resulting from the exclusion of particular covariates.

For severe food insecurity, the most important variable for predicting food security levels is the Poverty Headcount Index (See Fig. 4), followed by the Gini coefficient and the rate of stunting. For predicting the rate of people with at least moderate food insecurity, GDP per capita is the most important, followed closely by the Poverty Headcount Index. The country's Gini coefficient is also important, more so for predicting the rate of severe food insecurity compared to moderate food insecurity. Across both outcomes, economic variables were the most relevant predictors.

Figure 4: Importance of each variable in predicting the percent of a population over thresholds for moderate and severe food insecurity. This is determined by the increase in the error when the variable is permuted before fitting the model.

The results of this analysis can be further explored in more detail on the World Hunger Clock (worldhunger.io), including statistics for each subnational administrative area.

4 Discussion

This paper presents the first global estimates of the experience of food insecurity at a subnational level, with forecasts until the year 2030. We find that, while food insecurity has been increasing and has likely worsened in 2020 due to the economic downturn associated with the COVID-19 pandemic, our models predict that the percent of people who experience food insecurity globally will decrease throughout the 2020s, largely because of economic growth in developing countries. Nevertheless, lower and lower-middle income countries are expected to see overall increases in the number of moderately food insecure people.

Our analysis of the relative importance of different predictors for future food insecurity dynamics shows that economic conditions are the largest driver of global variation in rates of food insecurity. For both moderate and severe food insecurity, the Poverty Headcount Index, the Gini coefficient, and GDP per capita appear as highly relevant predictors of the rate of food insecurity. The rate of stunting, an indicator of both sanitary conditions and chronic, long-term under-nutrition is also an important predictor of food insecurity. However, other indicators of nutrition and sanitary conditions, such as the rates of wasting and malaria mortality are less important as explanatory factors of changes in food insecurity. Geographic and climate factors, such as the percentage of urban population, topographic ruggedness and mean annual temperature or precipitation do not appear to be robust predictors of food insecurity at a global scale.

While economic conditions, and especially GDP per capita, are important predictors of food insecurity at a global scale, there is an upper limit to the extent to which increasing economic development alone can improve food security outcomes. High income countries have seen little improvement in food insecurity outcomes over twenty years, and upper-middle income countries are expected to see diminishing gains as they continue to develop economically throughout the 2020s. Among the high-income countries in our dataset, those with the lowest rates of moderate and severe food insecurity also had lower inequality and poverty. This suggests that our model's forecasted marginal increases in food insecurity in high income countries is due to trends of increasing income inequality, and that economic development alone cannot ensure that everyone is well-fed.

It should be noted that our model was using covariates and making predictions a coarser scale - the administrative area - than much of the food security literature, which, since the 1990s, has increasing focused at the scale of the household **Cooper2020**. Thus, this analysis cannot speak to the localized impact of factors like climate, urbanization, or topography at the finer spatio-temporal scales at which these variables may operate **Shukla2021**; **Blekking2020**; **Cockx2018**; **Tuholske2020**. For example, our predictor variables for temperature and precipitation, derived from future simulations of the climate, can only model the effects of shifting baselines as data is smoothed over the course of the year - our model cannot anticipate the effects of short-term and extreme climate events on food insecurity. Additionally, our model can only capture coarse, administrative area metrics of urbanization and cannot address household-level differences in food security between urban and rural households. Nevertheless, the fact that these variables explained some of the variation in food security outcomes, even at administrative area scale, underscores their importance for food security.

Our results anticipating decreases in the number of people over the threshold for moderate food insecurity conflict with the FAO's predictions of increased rates of undernourishment, the other indicator for the SDG 2 target of ending hunger **sofi2020**. However, severe food insecurity may be a more apt indicator to compare with undernourishment, as the global totals are more similar **sofi2020**. In this case, our predictions still diverge: the FAO estimates a 24% increase, from 687 to 841 million undernourished people, from 2019 to 2030, whereas we predict a 9.4% decrease, from 790 to 715 million severely food insecure people over the same period.

These discrepancies are in part due to our differing modeling approaches. Food insecurity was worsening slightly in the latter half of the 2010s, a trend noted elsewhere **Voosen2020**, and reflected in our own analysis (Fig. 1), and the SOFI report extrapolated these recent trends in undernourishment and stunting. Our approach, on the other hand, modeled food insecurity based on interactions between projections in underlying drivers like GDP per capita and population change. Additionally, our diverging predictions for different hunger indicators are not necessarily mutually exclusive, as we are using different indicators: it is theoretically possible for undernourishment to increase while severe food insecurity, as measured by the FIES, decreases. The discrepancies between our projections and those of the FAO illustrate both the complexity of hunger as a social phenomenon, as well as the challenges in predicting future socioeconomic developments, where different modeling approaches may yield different forecasts.

When making predictions in countries where we do not have primary data, we assume that the relationships among variables like poverty, stunting, inequality, and food insecurity are the same across all locations. We test the accuracy of these cases by using leave-one-out cross validation at the country level, and we find good accuracy, with our models making estimates that are only off by 4-7 percentage points on average when applied to countries outside of the training set.

Additionally, when making predictions into the future, we assume that the long-term patterns of demographic change, urbanization, and development will maintain their trajectories for the next decade. At a global scale, this is almost certainly the case: it is highly unlikely that rates of fertility or economic growth will shift suddenly and globally. Nevertheless, at more local scales, sudden crises can lead to severe and unforeseeable increases in food insecurity, as crises in the previous decade in Yemen, Syria and Venezuela have shown.

While we find that rates of food insecurity are expected to decrease overall by 2030, our model, which relies on middle-of-the-road assumptions, still expects the number of people experiencing moderate or severe food insecurity to increase in low income countries and the overall number of people experiencing moderate or severe food insecurity to fall only slightly between 2010 and 2030. This still leaves billions of people eating less than they should and three-quarters of a billion people going entire days without eating a decade from now, falling far short of the SDG 2 goal of ending hunger. Moreover, decreases in food insecurity as measured by the FIES do not necessarily mean there will be improvements in other significant challenges such as poor dietary quality, micronutrient deficiencies, sustainable diets, or obesity. Thus, while expected trends in correlates of food security give cause for optimism, there is still significant work to be done at the political level in pursuit of SDG 2.

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6 Author Contributions

MC, BM, and HK conceptualized the analysis; CC, JCC, and HK provided methodological oversight; MC, BM, and JCL processed the data; MC and BM ran the models and conducted model validation; All authors contributed to writing and reviewing the manuscript.

7 Competing Interests

We have no competing interests to disclose.

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