Modeling the Food Insecurity Experience Scale (FIES) in the Present and Future

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June 3, 2020

Abstract

The Food Insecurity Experience Scale (FIES) measures the experiential aspects of food insecurity, and has been selected as a target for the second Sustainable Development Goal (SDG) of Zero Hunger. Here, we present the preliminary results of our work modeling this indicator globally for the years 2020-2030.

1 Introduction

1.1 Measuring Food Security and the Genesis of the FIES

Food security is a key part of human development, but has traditionally been difficult to measure. Metrics of macro-health, such as anthropometry and mortality rates are correlated broadly with food insecurity [Puffer and Serrano, 1973, Habicht et al., 1974], but are confounded with other determinants of health such as infectious disease. Other proxies for food security, such as food availability estimated from crop yields [Maxwell and Frankenberger, 1992], are inadequate because they do not indicate how accessible food is to the general population, and food insecurity can certainly occur in the absence of food availability decline [Sen, 1983].

As researchers began to focus on food insecurity at the individual and household level, household microdata collecting information on household finances and consumption became a common proxy for food security [Haddad et al., 1994]. However, these efforts were criticized for being onerous, insufficiently comparable, as well as for ignoring subjective and experiential aspects of food security [Maxwell, 1996]. This led to the emergence of several indicators designed to be rapidly deployable, culturally cross-comparable, and based on the lived experience of food security. These metrics include the Household Food Insecurity and Access Scale (HFIAS) [Coates et al., 2007]; the Coping Strategies Index (CSI) [Maxwell et al., 1999]; the Household Hunger Scale (HHS) [Ballard, 2011]; the Food Consumption Score (FCS); and the Household Dietary Diversity Scale (HDDS) [Kennedy et al., 2010].

Drawing on the insights derived in designing and implementing these food security metrics, the Food Insecurity Experience Scale (FIES) was developed by the Food and Agricultural Organization (FAO) of the UN.

1.2 The FIES

The FIES asks participants eight questions about their experience of food insecurity during the previous year [Cafiero et al., 2018], collected in countries around the world both in person and over the telephone with the assistance of Gallup World Poll. These questions are:

1. During the last 12 MONTHS, was there a time when you were worried you would not have enough food to eat because of a lack of money or other resources?

2. Still thinking about the last 12 MONTHS, was there a time when you were unable to eat healthy and nutritious food because of a lack of money or other resources?
3. Was there a time when you ate only a few kinds of foods because of a lack of money or other resources?
4. Was there a time when you had to skip a meal because there was not enough money or other resources to get food?
5. Still thinking about the last 12 MONTHS, was there a time when you ate less than you thought you should because of a lack of money or other resources?
6. Was there a time when your household ran out of food because of a lack of money or other resources?
7. Was there a time when you were hungry but did not eat because there was not enough money or other resources for food?
8. During the last 12 MONTHS, was there a time when you went without eating for a whole day because of a lack of money or other resources?

Based on the responses to these questions, a Rasch model is used to generate the score for the population [Engelhard, 2013].

2 Data

For our analysis, we draw on several datasets. First, we use the individual responses from 335,139 individuals from 331 surveys across 77 countries, downloaded from the FAO microdata catalogue. Additionally, we use country-level FIES scores downloaded from FAOSTAT.

To disaggregate the FIES by urban-rural areas, we used data on urbanization from [Jiang and O'Neill, 2017].

2.1 Covariates Available in the Present

We use a large stack of covariates available for the present or the near-present, reflective of factors related to many aspects of food systems. Datasets that were originally gridded were aggregated to the Admin-1 level taking the mean value. A full table of datasets is given in Table 1.

Name	Availability	Scale	Source
Agriculture As A Percentage Of GDP	Annual	National	[The World Bank, 2016]
Net Oda Per Capita	Annual	National	[The World Bank, 2016]
Percent of Area Bare Ground	Annual	Admin-1	[Song et al., 2018]
Percent Of Area With Built Up Land Cover	2000 & 2014	Admin-1	[Pesaresi et al., 2015]
Staple Crop Proction Per Capita	Annual	National	[FAOSTAT, 2018]
Elevation	Static	Admin-1	[USGS, 1996]
Net School Enrollment	Annual	National	[The World Bank, 2016]
Forest Cover	Annual	Admin-1	[Song et al., 2018]
Government Effectiveness Indicator	Annual	National	[Kaufmann et al., 2011]
GDP PPP Per Capita	Annual	Admin-1	[Kummu et al., 2018]
HDI	Annual	Admin-1	[Kummu et al., 2018]
Value Of All Imports Per Capita	Annual	National	[The World Bank, 2016]
Irrigated Area	2000	Admin-1	[Siebert et al., 2013]
Time To Travel To A City	2015	Admin-1	[Uchida and Nelson, 2008]
Mean Annual Precipitation	Static	Admin-1	[Funk et al., 2015]
NDVIi	Annual	Admin-1	[Song et al., 2018]
People Per Pixel	2010, 2015, 2020	Admin-1	[Doxsey-Whitfield et al., 2015]
Topographic Roughness Index	Static	Admin-1	[USGS, 1996, Riley et al., 1999]
Political Stability Index	Annual	Admin-1	[Kaufmann et al., 2011]
Number Of Conflict Deaths Within 50Km	Annual	Admin-1	[Eriksson, 2015]
Nutritional Diversity Of Agriculture	2015	Admin-1	[Herrero et al., 2017]
Average Maximum Temperature	Roughly Static	Admin-1	[Sheffield et al., 2006]
Number Of Buffaloes Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Cattle Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Chickens Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Ducks Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Horses Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Pigs Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Number Of Sheep Per Square Km	2010	Admin-1	[Robinson et al., 2014]
Incidence *P. falciparum* Malaria	Annual	Admin-1	[Weiss et al., 2019]
Incidence *P. vivax* Malaria	Annual	Admin-1	[Weiss et al., 2019]

Table 1: Co-Variates Included in Present-Day Analysis

2.2 Covariates Available in the Present and Future

To model the FIES in the future, we use projections derived in line with the Shared Socio-Economic Pathways (SSPs). The SSPs are a framework to estimate what the future might look like in terms of human development and climate-change mitigation, based on a number of scenarios. We use projections of GDP [Dellink et al., 2017], education [KC and Lutz, 2017], and urbanization [Jiang and O'Neill, 2017] for SSP2, the middle-of the road pathway.

3 Methods & Results

3.1 Disaggregating the FIES Subnationally

We begin by using the probability an individual has moderate-to-severe food insecurity for the individual-level survey data derive the FIES at the country level. Using the sampling weights reported by the FAO, we found the percentage of people in each country with a greater than 50% chance of being moderate or severely food insecure. We then checked our own results against those reported by FAOSTAT and found similar, but not identical, estimates (See Figure 1).

The FIES surveys include information on whether respondents were located in urban or rural areas. However, due to the small numbers of individuals in urban areas within each coun-

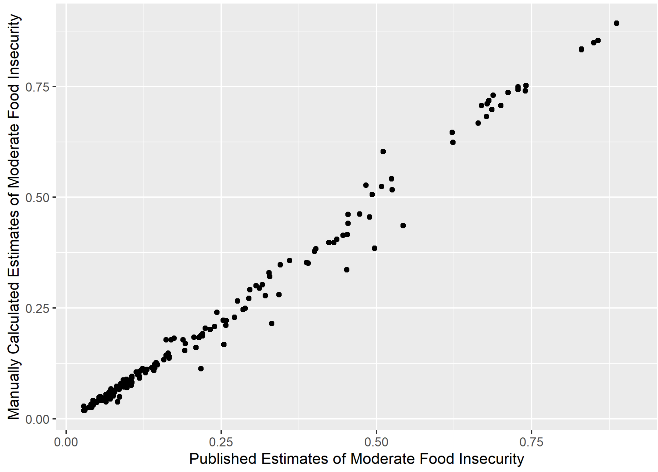

Figure 1: Comparison of derived and FAO reported estimates of food insecurity by FIES Score

try (about 200 observations), we group countries into regions and estimate regional prevalences of food insecurity for both rural and urban areas. In our grouping, we use the following regions: Eastern Europe, Latin American and the Caribbean (LAC), Southeast Asia, West Africa, Southern Africa, the Mideast and Central Asia, and High-Income Countries (HICs) (See Figure 2).

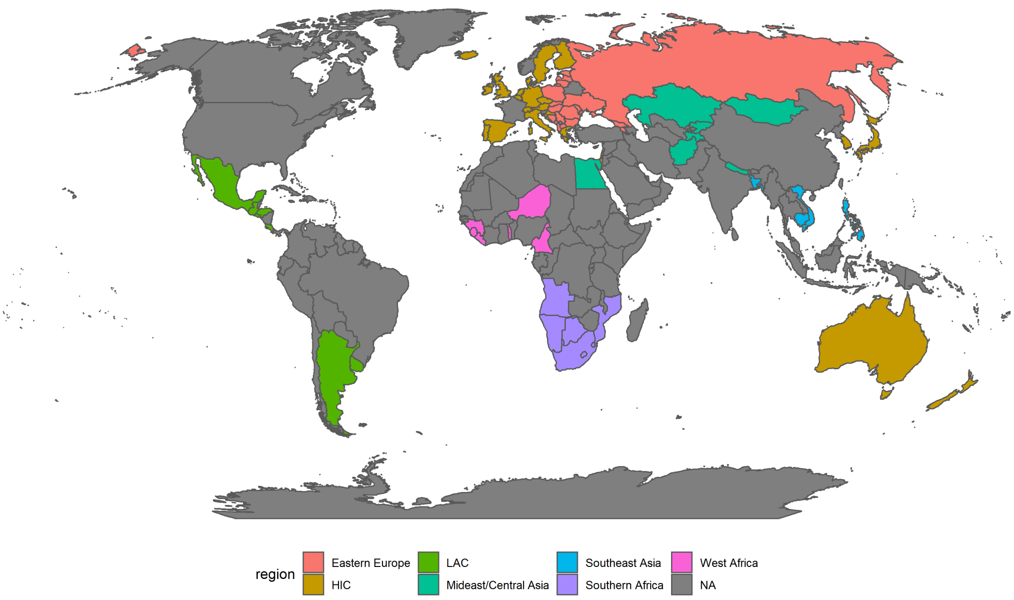

Figure 2: Grouping used to estimate regional rates of food insecurity in urban and rural areas.

Examining rates of food insecurity by both urban and rural areas shows that, in nearly every world region, food insecurity is worse in rural areas, with the largest gap in Southern Africa. High-income countries area the only exception, and food insecurity is actually worse in urban parts of these countries than in rural areas.

Given the overall rate of food insecurity in each country, the disparities in rates of urban and rural food insecurity in each world region, and the percentage of the population and urban and rural areas within each admin-1 area of each country, it is possible to derive a rate of food insecurity specific to each admin-1 area.

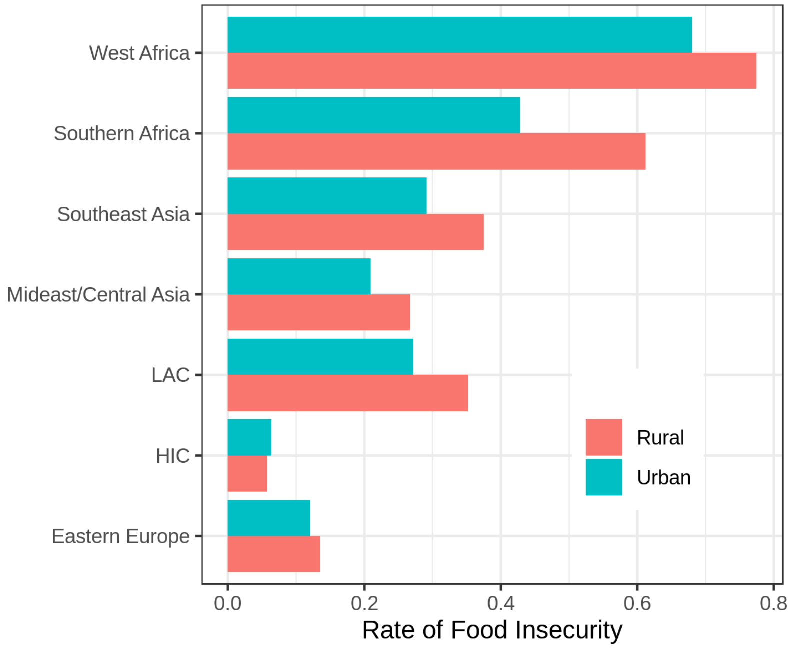

Figure 3: Rates of food insecurity in urban and rural areas by world region.

Formally, given the following two assumptions:

$$\omega/\rho = ratio \tag{1}$$

$$\omega * URB + \rho * RUR = t * TOT \tag{2}$$

Where:

- ω: The percentage of households in urban areas in a country with food insecurity (UNKNOWN)
- ρ: The percentage of households in rural areas in a country with food insecurity (UNKNOWN)
- t: The overall percentage of households in a country with food insecurity (KNOWN)
- RUR: The total population in rural areas (KNOWN)
- URB: The total population in urban areas (KNOWN)
- TOT: The total population (KNOWN)
- $ratio$: The ratio of the rates of urban food insecurity to rural food insecurity. This is known at a regional level, and it is estimated that the same ratio holds at the individual country level.

We can solve for the two unknown parameters, ω and ρ to get country-level estimates of urban and rural rates of food insecurity and derive subnational prevalences.

Thus, we derive the following map of disaggregated rates of food insecurity in countries where we have direct FIES data (See Figure 4).

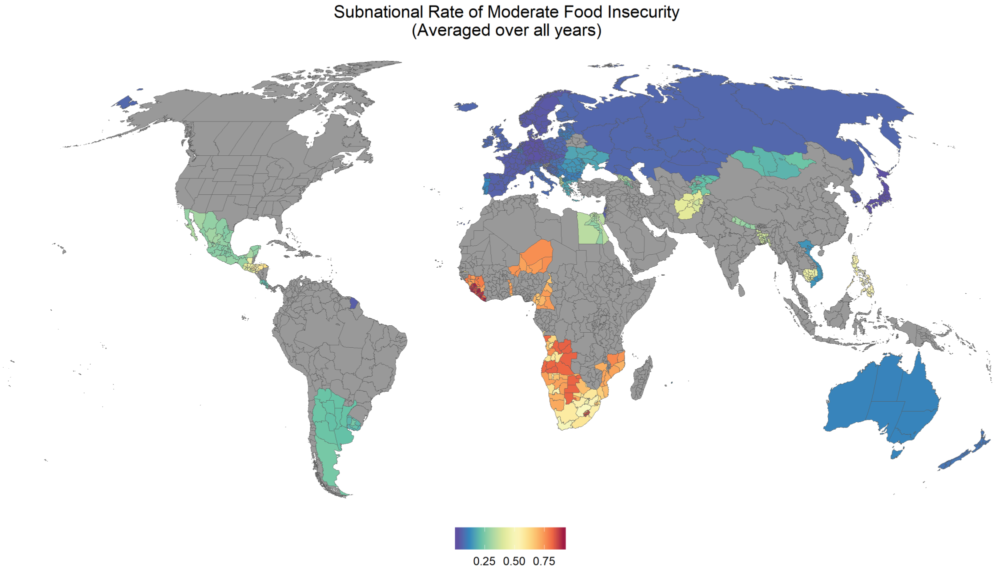

Figure 4: Rates of food insecurity in urban and rural areas by world region, averaged across all years for which survey data is available

3.2 Modeling the FIES in the Present

We then used these Admin-1 estimates, in combination with a large stack of covariates in the present, to model the prevalence of food insecurity globally for the year 2020, based on covariates for as close to the year 2020 as possible. We used a LASSO regression approach, where the size of the regression coefficients are penalized, which is most appropriate for making predictions based on a large number of covariates [Tibshirani, 2011].

For our in-sample data, the LASSO performed well (see Figure 5). The coefficients for each variable are given in Figure 6. Note that some coefficients are penalized to 0, which effectively removes them from the model. The map is the results is given in Figure 7.

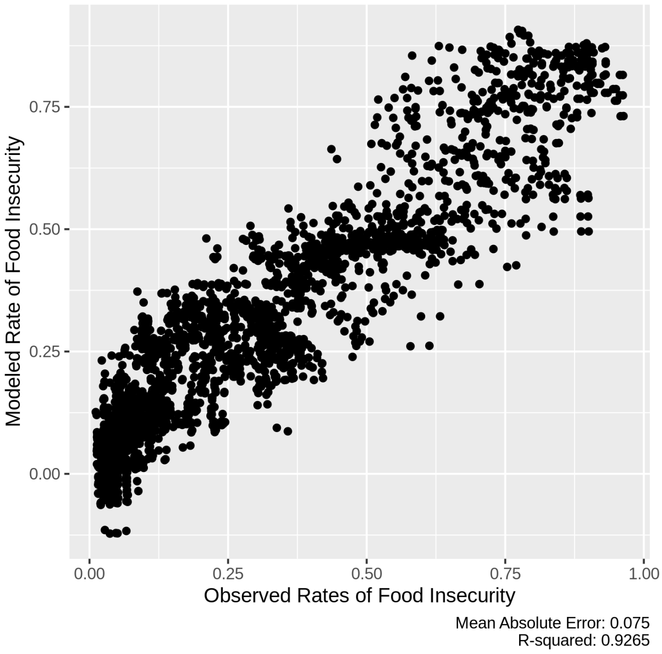

Figure 5: Correlation between observed disaggregated rates of food insecurity and modeled rates of food insecurity.

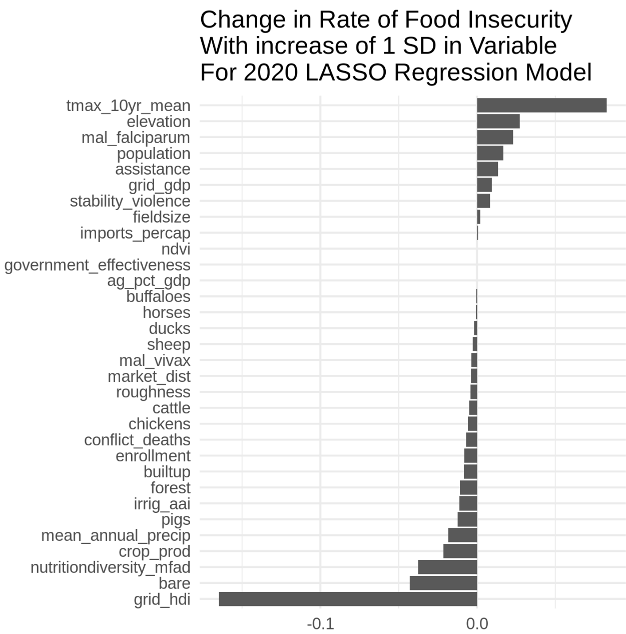

Figure 6: Change in rate of food insecurity with a 1 standard deviation increase in each variable. NOTE: IN A FUTURE EDITION THE LABELS WILL BE BETTER.

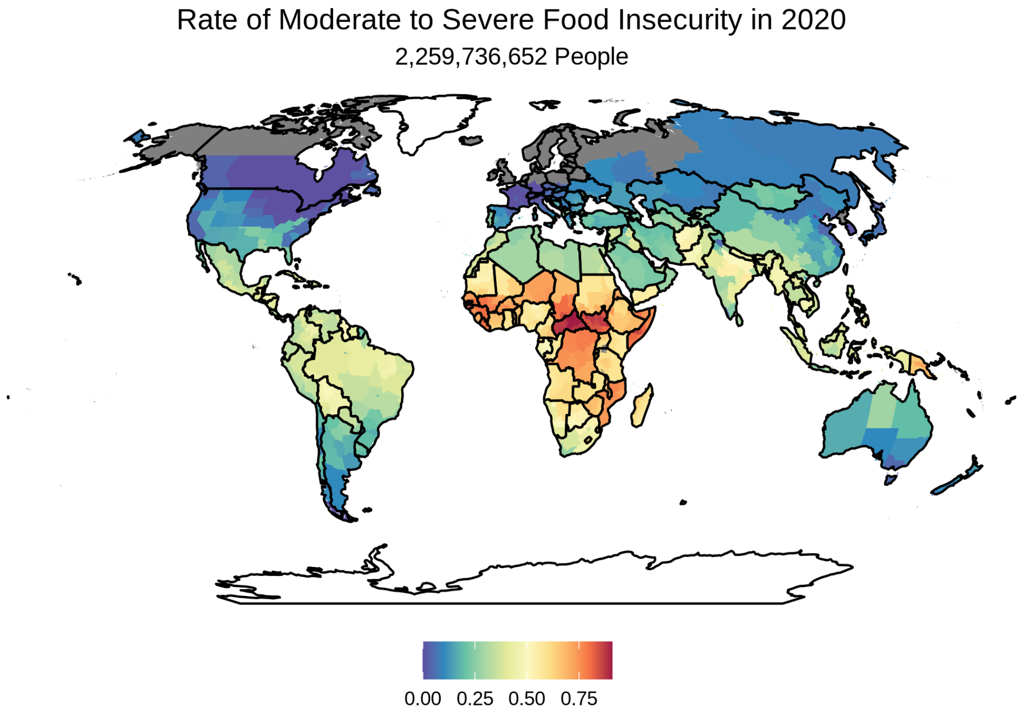

Figure 7: Estimated rates of food insecurity in 2020. NOTE: SOME COVARIATES ARE MISSING AT HIGH LATITUDES, THIS WILL BE FIXED IN A FUTURE EDITION.

3.3 Modeling the FIES in the Future

In addition to modeling the FIES in the present, we also modeled the FIES for the years 2020, 2025, and 2030, based covariates that were already extrapolated to the year 2030 in peer-reviewed literature. NOTE: MANY MORE COVARIATES ARE BEING ADDED. Similar to the previous model, we below show the correlation between the observed and predicted values (Figure 8), the estimated coefficients (Figure 9), and the mapped results (Figure 10).

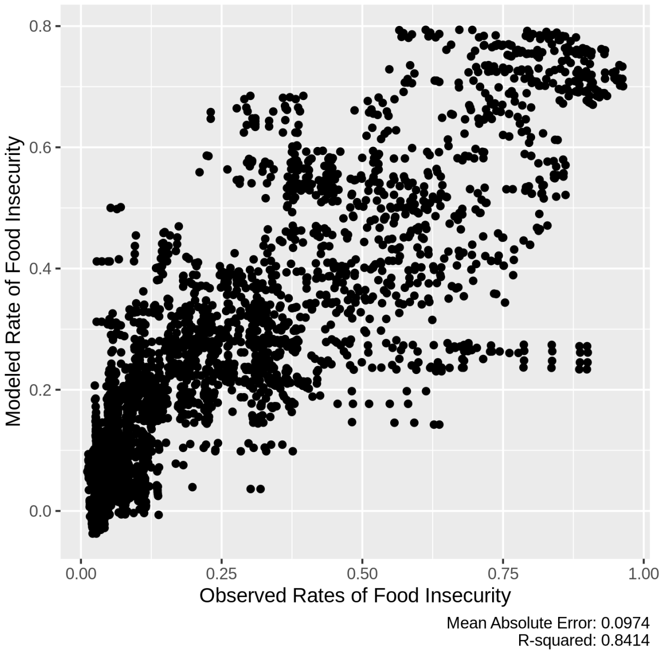

Figure 8: Correlation between observed disaggregated rates of food insecurity and modeled rates of food insecurity.

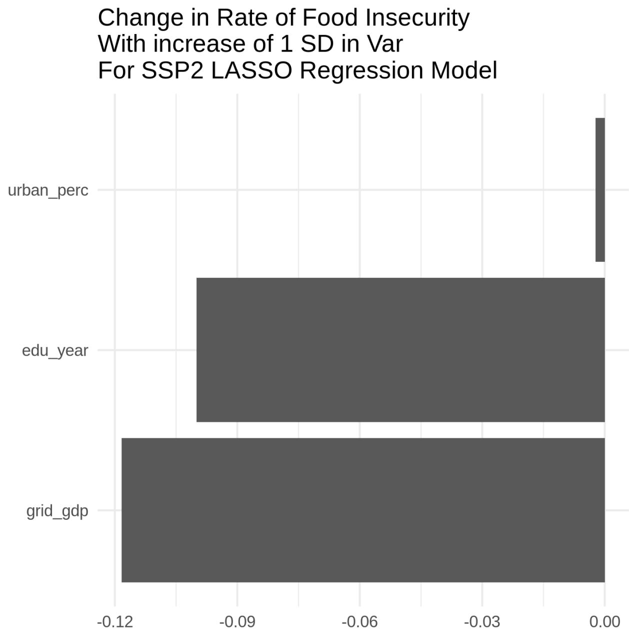

Figure 9: Change in rate of food insecurity with a 1 standard deviation increase in each variable. NOTE: IN A FUTURE EDITION THE LABELS WILL BE BETTER AND MORE COVARIATES WILL BE INCLUDED.

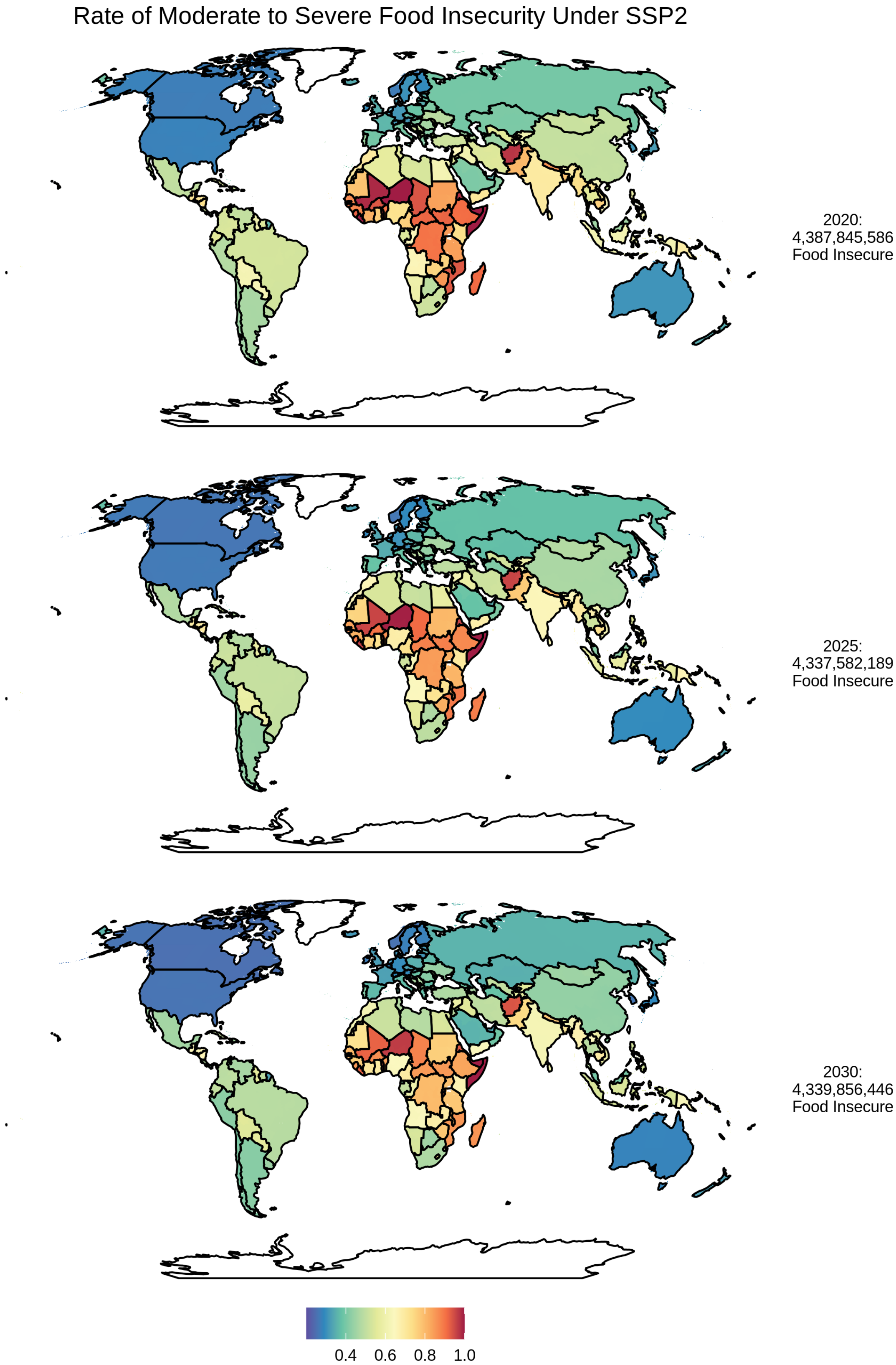

Figure 10: Estimated rates of food insecurity in 2020, 2025, and 2030.

4 Discussion

There is still a wide gap between the predictions of the 2020 model based on the large stack of covariates and the 2020 model based on just the SSP covariates.

5 Conclusion

References

[Ballard, 2011] Ballard, T. (2011). Household Hunger Scale. *Measurement*, page 23.

[Cafiero et al., 2018] Cafiero, C., Viviani, S., and Nord, M. (2018). Food security measurement in a global context: The food insecurity experience scale. *Measurement: Journal of the International Measurement Confederation.*

[Coates et al., 2007] Coates, J., Swindale, a., and Bilinsky, P. (2007). Household Food Insecurity Access Scale (HFIAS) for measurement of food access: indicator guide. *Washington, DC: Food and Nutrition Technical ...*, (August):Version 3.

[Dellink et al., 2017] Dellink, R., Chateau, J., Lanzi, E., and Magné, B. (2017). Long-term economic growth projections in the Shared Socioeconomic Pathways. *Global Environmental Change.*

[Doxsey-Whitfield et al., 2015] Doxsey-Whitfield, E., MacManus, K., Adamo, S. B., Pistolesi, L., Squires, J., Borkovska, O., and Baptista, S. R. (2015). Taking Advantage of the Improved Availability of Census Data: A First Look at the Gridded Population of the World, Version 4. *Papers in Applied Geography*, 1(3):226–234.

[Engelhard, 2013] Engelhard, G. (2013). *Invariant measurement: Using Rasch models in the social, behavioral, and health sciences.*

[Eriksson, 2015] Eriksson, M. (2015). UCDP/PRIO Armed Conflict Dataset Codebook. *Upsala Conflict Data Programs (UCDP).*

[FAOSTAT, 2018] FAOSTAT (2018). FAOSTAT.

[Funk et al., 2015] Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2:150066.

[Habicht et al., 1974] Habicht, J. P., Martorell, R., Yarbrough, C., Malina, R. M., and Klein, R. E. (1974). Height and weight standards for preschool children. How relevant are ethnic differences in growth potential? *Lancet*, 1(7858):611.

[Haddad et al., 1994] Haddad, L., Kennedy, E., and Sullivan, J. (1994). Choice of indicators for food security and nutrition monitoring. *Food Policy*, 19(3):329–343.

[Herrero et al., 2017] Herrero, M., Thornton, P. K., Power, B., Bogard, J. R., Remans, R., Fritz, S., Gerber, J. S., Nelson, G., See, L., Waha, K., Watson, R. A., West, P. C., Samberg, L. H., van de Steeg, J., Stephenson, E., van Wijk, M., and Havlík, P. (2017). Farming and the geography of nutrient production for human use: a transdisciplinary analysis. *The Lancet Planetary Health*, 1(1):e33–e42.

[Jiang and O'Neill, 2017] Jiang, L. and O'Neill, B. C. (2017). Global urbanization projections for the Shared Socioeconomic Pathways. *Global Environmental Change.*

[Kaufmann et al., 2011] Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague Journal on the Rule of Law.*

[KC and Lutz, 2017] KC, S. and Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change.*

[Kennedy et al., 2010] Kennedy, G., Berardo, A., Papavero, C., Horjus, P., Ballard, T., Dop, M., Delbaere, J., and Brouwer, I. D. (2010). Proxy measures of household food consumption for food security assessment and surveillance: Comparison of the household dietary diversity and food consumption scores. *Public Health Nutrition.*

[Kummu et al., 2018] Kummu, M., Taka, M., and Guillaume, J. H. A. (2018). Data from: Gridded global datasets for Gross Domestic Product and Human Development Index over 1990-2015.

[Maxwell et al., 1999] Maxwell, D., Ahiadeke, C., Levin, C., Armar-Klemesu, M., Zakariah, S., and Lamptey, G. M. (1999). Alternative food-security indicators: Revisiting the frequency and severity of 'coping strategies'. *Food Policy*.

[Maxwell, 1996] Maxwell, S. (1996). Food security: A post-modern perspective. *Food Policy*, 21(2):155–170.

[Maxwell and Frankenberger, 1992] Maxwell, S. and Frankenberger, T. R. (1992). Household Food Security: Concepts, Indicators, Measurements: A technical revies.

[Pesaresi et al., 2015] Pesaresi, M., Ehrilch, D., Florczyk, A., Freire, S., Julea, A., Kemper, T., Soille, P., and Syrris, V. (2015). GHS Built-up Grid, Derived from Landsat, Multitemporal (1975, 1990, 2000, 2014) European Commission, Joint Research Centre (JRC).

[Puffer and Serrano, 1973] Puffer, R. R. and Serrano, C. V. (1973). *Patterns of Mortality in Childhood*. World Heath Organization, Washington, DC.

[Riley et al., 1999] Riley, S. J., DeGloria, S. D., and Elliot, R. (1999). A Terrain Ruggedness Index that Quantifies Topographic Heterogeneity. *Intermountain Journal of Sciences*.

[Robinson et al., 2014] Robinson, T. P., William Wint, G. R., Conchedda, G., Van Boeckel, T. P., Ercoli, V., Palamara, E., Cinardi, G., D'Aietti, L., Hay, S. I., and Gilbert, M. (2014). Mapping the global distribution of livestock. *PLoS ONE*.

[Sen, 1983] Sen, A. (1983). *Poverty and famine: An essay on entitlement and deprivation*.

[Sheffield et al., 2006] Sheffield, J., Goteti, G., and Wood, E. F. (2006). Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *Journal of Climate*, 19(13):3088–3111.

[Siebert et al., 2013] Siebert, S., Döll, P., Feick, S., Frenken, K., and Hoogeveen, J. (2013). Global Map of Irrigation Areas version 5. *University of Frankfurt (Main), Germany, and FAO, Rome, Italy*.

[Song et al., 2018] Song, X.-P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., and Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*.

[The World Bank, 2016] The World Bank (2016). World Bank Open Data.

[Tibshirani, 2011] Tibshirani, R. (2011). Regression shrinkage and selection via the lasso: A retrospective. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*.

[Uchida and Nelson, 2008] Uchida, H. and Nelson, A. (2008). Agglomeration Index : Towards a New Measure of Urban. *World Development Report: Reshaping Economic Geography*, page 19.

[USGS, 1996] USGS (1996). *Global 30 Arc-Second Elevation (GTOPO30)*.

[Weiss et al., 2019] Weiss, D. J., Lucas, T. C., Nguyen, M., Nandi, A. K., Bisanzio, D., Battle, K. E., Cameron, E., Twohig, K. A., Pfeffer, D. A., Rozier, J. A., Gibson, H. S., Rao, P. C., Casey, D., Bertozzi-Villa, A., Collins, E. L., Dalrymple, U., Gray, N., Harris, J. R., Howes, R. E., Kang, S. Y., Keddie, S. H., May, D., Rumisha, S., Thorn, M. P., Barber, R., Fullman, N., Huynh, C. K., Kulikoff, X., Kutz, M. J., Lopez, A. D., Mokdad, A. H., Naghavi, M., Nguyen, G., Shackelford, K. A., Vos, T., Wang, H., Smith, D. L., Lim, S. S., Murray, C. J., Bhatt, S., Hay, S. I., and Gething, P. W. (2019). Mapping the global prevalence, incidence, and mortality of Plasmodium falciparum, 2000–17: a spatial and temporal modelling study. *The Lancet*.

Supplemental Info