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A Global-Level Model of the Potential Impacts of Climate Change on Child Stunting via Income and Food Price in 2030

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Background: In 2016, 23% of children (155 million) aged <5 were stunted. Global-level modeling has consistently found climate change impacts on food production are likely to impair progress on reducing undernutrition.

Objectives: We adopt a new perspective, assessing how climate change may affect child stunting via its impacts on two interacting socioeconomic drivers: incomes of the poorest 20% of populations (due to climate impacts on crop production, health, labor productivity, and disasters) and food prices.

Methods: We developed a statistical model to project moderate and severe stunting in children aged <5 at the national level in 2030 under low and high climate change scenarios combined with poverty and prosperity scenarios in 44 countries.

Results: We estimated that in the absence of climate change, 110 million children aged <5 would be stunted in 2030 under the poverty scenario in comparison with 83 million under the prosperity scenario. Estimates of climate change–attributable stunting ranged from 570,000 under the prosperity/low climate change scenario to >1 million under the poverty/high climate change scenario. The projected impact of climate change on stunting was greater in rural vs. urban areas under both socioeconomic scenarios. In countries with lower incomes and relatively high food prices, we projected that rising prices would tend to increase stunting, whereas in countries with higher incomes and relatively low food prices, rising prices would tend to decrease stunting. These findings suggest that food prices that provide decent incomes to farmers alongside high employment with living wages will reduce undernutrition and vulnerability to climate change.

Conclusions: Shifting the focus from food production to interactions between incomes and food price provides new insights. Futures that protect health should consider not just availability, accessibility, and quality of food, but also the incomes generated by those producing the food. https://doi.org/10.1289/EHP2916

Introduction

Despite being a focus of health and global development policy for decades, and notwithstanding significant progress in many countries, child undernutrition remains a major contributor to the global burden of disease (GBD). An estimated 23% (155 million) of children aged <5 were stunted (low height-for-age) in 2016 (UNICEF et al. 2017), which has major health implications. In comparison with not being stunted, moderate stunting has an all-cause mortality odds ratio (OR) of 1.6; for severe stunting, it increases to 4.1 (Black et al. 2008). Morbidity risk increases for diseases, including pneumonia and diarrheal disease (Prendergast and Humphrey 2014). In the longer term, a reduction in neurodevelopmental and cognitive function may lead to reduced learning and earning capacity, and the risk of chronic disease is increased (de Onis and Branca 2016; Victora et al. 2008).

Global-level modeling studies have consistently found that climate change is likely to impair progress on reducing undernutrition (e.g., Hasegawa et al. 2015; Ishida et al. 2014; Nelson et al. 2010). For instance, Lloyd et al. (2011) found that that high climate change may result in a relative increase in severe stunting of 23% in Sub-Saharan Africa and 62% in South Asia in the 2050s. In such global-level studies, the mechanism via which climate change affects undernutrition is through changed crop productivity, which affects post-trade national calorie availability. Projected calorie availability is combined with fixed (i.e., not affected by climate change) scenario-specific socioeconomic variables, such as population size and per capita Gross Domestic Product (GDPpc), to estimate undernutrition. These fixed socioeconomic variables have a major influence: A consistent finding is that the differences in undernutrition between plausible socioeconomic futures is considerably larger than that between plausible climate change futures (e.g., Lloyd et al. 2014; Schmidhuber and Tubiello 2007).

This finding raises three related issues. First, given the complexity of the causation of undernutrition, the large influence of socioeconomic conditions is expected. For example, Smith and Haddad (2015) found that between 1970 and 2012, 67% of the reduction in stunting was due to improvements in women's education, gender equality, and access to adequate water and sanitation services. Rayner and Lang (2012) state that measures of height (including stunting) are "less an indicator of nutritional status and more a comment on the 'nutrition-environment interaction,'" where "environment" refers to context rather than just the natural environment. That is, at the population level, stunting is about more than food. Second, as well as affecting food production, climate change may affect undernutrition via socioeconomic routes. For instance, recent work shows that climate change may affect the income of the poorest population groups disproportionately (Hallegatte et al. 2016), and this impact may in turn influence undernutrition risk. Third, interactions between routes from climate to undernutrition may mean the combined impacts are not simply additive and are

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thus not easily predictable. However, to our knowledge, no previous global-level climate–undernutrition models have considered impacts operating through routes other than food production or more than one climate entry point at a time.

In this paper, we take a first step toward examining how climate change entering through two interacting socioeconomic drivers—incomes of the poorest 20% of a country and food price—may affect child stunting at the national level and in rural and urban areas. Both drivers may significantly influence undernutrition. Climate change may influence incomes via its impacts on crop production, health, labor productivity, and disasters (Hallegatte and Rozenberg 2017). In turn, low income and poverty manifest in a constellation of forms, including lack of access to water and sanitation, essential medicines, education, and adequate shelter and food; these forms combine to increase the risk of undernutrition (Pogge 2010). Food prices have a more complex relation to undernutrition: As well as directly influencing ability to purchase food, prices may influence incomes and wages. For instance, sustained high prices may increase risks for low-income net food consumers while reducing the risk for net food producers (Hertel 2016; Ivanic and Martin 2008). Thus, interactions between food price and incomes, and how they are each affected by climate change, may have unexpected aggregate effects.

To investigate this, we used multilevel statistical modeling to develop a global-level model that could be driven by projection data provided by "poverty" and "food price" models. We then projected moderate and severe stunting in children aged <5 at the national level and in rural and urban areas in 2030 under low and high climate change scenarios combined with poverty and prosperity socioeconomic scenarios.

Methods

In this section, we describe: *a*) the historical data and indicators used when fitting the stunting model, *b*) the forms of the equations and the process of fitting the stunting model, and *c*) the poverty and food-price models and the scenario-specific projection data used to make the estimates of future stunting. For the latter, a full set of projection data was available only out to 2030, and this limited the temporal horizon of our stunting estimates.

Historical Data and Indicator Development

Stunting data for children <5 y of age were from the Global Database on Child Growth and Malnutrition, which is based on survey data using consistent growth standards to identify moderate stunting (height-for-age Z-scores of -3 to -2) and severe stunting (height-for-age Z-scores <-3) (WHO 2017). Data for individual countries during a given year were available for moderate stunting and severe stunting, both at the national level and separately for rural and urban areas in each country. Individual countries were included in our analysis if they met three criteria. First, data were available on the prevalence of moderate and severe stunting from surveys performed on at least three occasions from 1990 onward. Second, they had sufficient data to derive estimates of food prices at the national level and of incomes of the poorest 20% of the population in rural and urban areas, respectively, for the majority of the years with stunting data. Third, these estimates of food price and incomes of the poorest populations could also be calculated for future years using output from poverty and food price models (described below.)

To develop an indicator of rural and urban incomes for each country, we obtained historical data on the average GDPpc of the population in the lowest 20% of the income distribution in each country (*GDPpc20*), in Purchasing Power Parity 2005 dollars (PPP\$2005) (World Bank 2017) for each year with stunting data (matched as closely as possible, within a maximum of 5 y). Next, we used the ratio of rural to urban income or consumption to derive area-level income indicators for the rural and urban populations in the lowest 20% of the income distribution ($inc20_{ij}^{R}$ and $inc20_{ij}^{U}$, respectively) for each country *j* on occasion *i* when stunting was measured:

$$inc20_{ij}^{(R)} = GDPpc20_{ij} \times \left(\frac{income_{ij}^{(R)}}{income_{ij}^{(R)} + income_{ij}^{(U)}} \right) \quad \text{and}$$

$$inc20_{ij}^{(U)} = GDPpc20_{ij} \times \left(\frac{income_{ij}^{(U)}}{income_{ij}^{(R)} + income_{ij}^{(U)}} \right) \tag{1}$$

where $GDPpc20_{ij}$ is the national-level average GDPpc of the lowest 20% of the population of country *j* on occasion *i* (in PPP\$ 2005) ["i" is a sequential index of measurement occasion; this is used because it corresponds to indexing commonly used in longitudinal multilevel models (see below)], and $income_{ij}^{(R)}$ and $income_{ij}^{(U)}$ represent the average values for income or consumption in rural and urban areas of country *j* during year *i*. This metric can be derived using data on either income or consumption, as long as the same units are used for rural and urban areas in each country and year. The indicator does not give an estimate of actual income; rather, it provides a measure of the size of rural and urban incomes that is comparable over time and across countries. An increase in the income indicator for a given rural or urban area indicates an increase in the average income of the population in the lowest 20% of the income distribution for the area.

There are two key assumptions in this indicator. First, projection data from the poverty model are for agricultural and nonagricultural incomes. We assumed these corresponded to rural and urban areas, respectively, because stunting data and historical income data were split rural–urban. Second, historical data for rural and urban incomes of the bottom 20% were not available; we thus assume that average incomes are roughly proportional to incomes of the bottom 20%.

In addition, we derived the ratio of the rural-to-urban income indicator for country *j* on occasion *i* as:

$$D_{ij} = \frac{inc20_{ij}^{(R)}}{inc20_{ij}^{(U)}} \tag{2}$$

We next developed an indicator of the affordability of food for the poorest 20% of the population in a given country. The model used to project future food prices (described below) estimated within-country changes in average national-level food prices relative to the year 2000 with the effects of inflation removed, such that the projected value is set to 1 for the year 2000 in all countries, and a 10% increase in price in a given country and year would result in an indicator = 1.1. We produced equivalent historical price data by dividing the national-level Consumer Price Index (CPI) for food ($fCPI_{ij}$) by the general CPI ($gCPI_{ij}$) (both set to 100 for the year 2000) (ILO 2017) to get an indicator of change in "real" food prices for country *j* on occasion *i*. Next, to develop an indicator of food price relative to incomes of the population in lowest 20% of the income distribution that is comparable across countries, we multiplied this by the domestic food price index (DFPI, an indicator of average food price in a given country relative to other countries) for county *j* in the year 2000 (FAO 2017b) and then divided it by $GDPpc20_{ij}/460$, in which "460" represents an annual income of \$1.25 PPP2005, equal to the World Bank poverty line (Chen and Ravallion 2008). The full equation for the food price indicator ($price_{ij}$) is:

$$price_{ij} = \frac{\left(\frac{fCPI_{ij}}{gCPI_{ij}}\right) \times DFPI_j}{\left(\frac{GDPpc20_{ij}}{460}\right)} \tag{3}$$

Due to a lack of data, we could not derive separate indicators for rural and urban areas; hence, $price_{ij}$ is a national-level indicator of average prices across rural and urban areas in each country on each occasion relative to incomes in the lowest 20% of the income distribution. Additionally, a lack of data meant we were unable to account for differing expenditure patterns in low-income populations; in effect, it is assumed that expenditure patterns are similar in this population group in the study countries. As the food-price indicator increases, food becomes less affordable (on average) for the poorest part of the population. If data required to derive $price_{ij}$ for a specific year were missing, we interpolated or extrapolated the existing series or used data from the country's nearest neighbor to derive a value.

Forms of the Model Equations and Model Fitting

As we had a mix of national-level and area-level predictors, we used a two-stage approach, first modeling national-level moderate or severe stunting longitudinally, and then modeling area-level (i.e., rural and urban) moderate or severe stunting as a function of national-level stunting. We used random-effects models to account for unmeasured influences on stunting, and to allow us to make general inferences for all countries at risk of stunting, rather than limiting inferences only to the countries used to fit the model.

In the first stage, we used "growth-curve" modeling (Rabe-Hesketh and Skrondal 2012; Steele 2014) to estimate national-level trajectories of moderate stunting and severe stunting, using longitudinal national-level predictors while allowing for autocorrelation, and to assess time-varying and fixed predictors and unexplained differences (Rabe-Hesketh and Skrondal 2012). We used separate binomial logistic regression models (with the number stunted being calculated using prevalence and sample size from the survey data for stunting) to derive estimates for the prevalence of moderate stunting or severe stunting, respectively.

We initially fit "null" growth-curve models that included random effects and year only. The approach provides a formal test of whether a multilevel model gives a better fit than an equivalent single-level model and provides an initial assessment of stunting trajectories in recent decades. Following this we fit "full" models containing the predictor variables for each outcome.

Separate first-stage models for the log odds of moderate or severe stunting vs. no stunting (respectively) at the national level for each country j on occasion i for degree of stunting k ($Y_{ijk}^{(N)}$) (where the superscript N refers to national level) had the following form:

$$\begin{aligned} log\left(\frac{Y_{ijk}^{(N)}}{1-Y_{ijk}^{(N)}}\right) &= \beta_{0jk}^{(N)} + \beta_{1jk}^{(N)}(t_{ij}) + \beta_{2k}^{(N)}(G_{ij}) + \beta_{3k}^{(N)}(P_{ij}) \\ &+ \beta_{4k}^{(N)}(G_{ij} \times P_{ij}) + \mathbf{B} \cdot \mathbf{R} \end{aligned} \tag{4}$$

$$\beta_{0jk}^{(N)} = \beta_{0k}^{(N)} + u_{0jk}^{(N)} \tag{5}$$

$$\beta_{1jk}^{(N)} = \beta_{1k}^{(N)} + u_{1jk}^{(N)} \tag{6}$$

where t_{ij} is the year of measurement of stunting, centered on the year 2010; G_{ij} is $\log(GDPpc20_{ij})$; P_{ij} is mean centered log ($price_{ij}$); $\mathbf{R}$ is a column vector of 11 indicator variables for GBD regions (as a contextual variable) (IHME 2015), and $\mathbf{B}$ is the corresponding row vector of fixed parameters for each region. The subscript k is degree of stunting (0 for moderate, and 1 for severe). The coefficients $\beta_{2k}^{(N)}$, $\beta_{3k}^{(N)}$, and $\beta_{4k}^{(N)}$ are fixed global parameters; $\beta_{0jk}^{(N)}$ and $\beta_{1jk}^{(N)}$ are country-specific parameters. The random effects, representing unmeasured time-invariant country-specific effects, capture (given the covariates) country-level differences, where $u_{0j}^{(N)}$ is the random intercept, and $u_{1j}^{(N)}$ is the random slope for year. The u terms are assumed to be normally distributed with a mean of zero and collectively follow a multivariate normal distribution with a mean of zero and a specified covariance (Steele 2014):

$$\begin{pmatrix} u_{0jk}^{(N)} \\ u_{1jk}^{(N)} \end{pmatrix} \sim N(0,\Omega_u) \text{ where } \Omega_u = \begin{pmatrix} \sigma_{u_0}^2 & \\ \sigma_{u_0u_1} & \sigma_{u_1}^2 \end{pmatrix} \tag{7}$$

where σ_{u0k}^2 is the variance of $u_{0jk}^{(N)}$, σ_{u1k}^2 is the variance of $u_{1jk}^{(N)}$, and σ_{u0u1} is the covariance of $u_{0jk}^{(N)}$ and $u_{1jk}^{(N)}$.

In the second stage, we used multilevel binomial logistic regression and area-level variables to estimate the log odds of moderate stunting or severe stunting in rural areas and urban areas, respectively ($Y_{ijk}^{(A)}$), where the superscript A refers to rural or urban area, as a function of national-level stunting:

$$\begin{aligned} log\left(\frac{Y_{ijk}^{(A)}}{1-Y_{ijk}^{(A)}}\right) &= \gamma_{0jk}^{(A)} + \gamma_{1jk}^{(A)}\left(Y_{ijk}^{(N)}\right) + \gamma_{2k}^{(A)}\left(I_{ij}^{(A)}\right) \\ &+ \gamma_{3k}^{(A)}\left(Y_{ijk}^{(N)} \times I_{ij}^{(A)}\right) + \gamma_{4k}^{(A)}(D_{ij}) + \gamma_{5k}^{(A)}\left(I_{ij}^{(A)} \times D_{ij}\right) \end{aligned} \tag{8}$$

$$\gamma_{0jk}^{(A)} = \gamma_{0k}^{(A)} + w_{0jk}^{(A)} \tag{9}$$

$$\gamma_{1jk}^{(A)} = \gamma_{1k}^{(A)} + w_{1jk}^{(A)} \tag{10}$$

$Y_{ijk}^{(N)}$ is national-level stunting on occasion i in country j of degree k (i.e., moderate or severe); $I_{ij}^{(A)}$ represents area-level income as $\log(inc20_{ij}^{(R)})$ or $\log(inc20_{ij}^{(U)})$ (from Equation 1) centered just below its historical minimum; and D_{ij} represents rural–urban inequalities (from Equation 2). The coefficients $\gamma_{2k}^{(A)}$, $\gamma_{3k}^{(A)}$, $\gamma_{4k}^{(A)}$, and $\gamma_{5k}^{(A)}$ are fixed area-level global parameters; $\gamma_{0jk}^{(A)}$ and $\gamma_{1jk}^{(A)}$ are country-specific area-level parameters. The random effects $w_{0jk}^{(A)}$ and $w_{1jk}^{(A)}$ capture unmeasured time-invariant country-specific area effects (country-specific random intercepts and random slopes, respectively) for national-level stunting, which are assumed to be normally distributed (as in Equation 7).

When making projections of rural and urban stunting, to ensure consistency with the national-level projections, we proportionally rescaled the rural and urban estimates for moderate and severe stunting so that they summed to the national-level estimates.

All equations were fitted in Stata 13.0 (StataCorp LLC) using the "meqrlogit" command, which fits random-effects models for binomial responses using QR decomposition.

Upstream Models and Scenario-specific Projection Data

Two streams of modeled scenario-specific projection data were used to drive the stunting model. The first, for incomes, was from a "poverty model" (Hallegatte and Rozenberg 2017), which is a microsimulation model based on household surveys from 92 countries, thus representing individual households from across the income spectrum. The second, for food prices, was from the Global Biosphere Management Model (GLOBIOM) (Havlík et al. 2014; Havlík et al. 2015) (Figure 1). Both models were initially driven by standard climate and socioeconomic scenarios. Climate data were from five General Circulation Models (GCMs) under two emissions scenarios (Representative Concentration Pathways (RCPs) (Moss et al. 2010)). RCP 2.6 represents a low emissions future and RCP8.5 represents a high emissions future. Socioeconomic data were from two Shared Socioeconomic Pathways (SSPs) (O'Neill et al. 2017). SSP4 represents a world of rapid population growth, low economic growth, and high inequalities. SSP5 is scenario with low population growth, high economic growth, and large environmental pressures.

For the poverty model, based on the above scenarios, a set of tailored scenarios were developed to account for both socioeconomic and climate uncertainties in 2030. Firstly, socioeconomic futures were developed. A total of 300 subscenarios for each SSP were generated to capture the various ways that the macrolevel conditions specified in the SSPs may be reached by 2030. This included differences in factors such as: *a*) structural change, as share of labor force in each sector (i.e., agriculture, manufacturing, services) by skill level (i.e., low, high) and participation rates; *b*) productivity growth of skilled and unskilled labor and in each sector; *c*) demographic change, and *d*) policies (e.g., pensions and social transfers). The scenarios based on SSP4 represent "poverty" futures, with a global stability in the fraction of people living in poverty. Those based on SSP5 represent "prosperity" futures, which are broadly consistent with the achievement of the Sustainable Development Goals (SDGs) (United Nations 2018).

Following this, climate was introduced into the model: first, as a counterfactual future without climate change and then as low- and high-impact climate change scenarios. Because the magnitude of climate change in 2030 is only minimally affected by future emissions and climate policies, the difference between the low- and high-impact scenarios is related to the magnitude of expected impacts, rather than emissions. Impacts in a set of sectors were assessed across all the initial climate scenarios. These sectors included: *a*) food prices and food production (as impacts of food price on households' available income, and changes in farmers' incomes); *b*) health and labor productivity (stunting, as lost income over a lifetime; malaria and diarrheal disease, as treatment costs and days of work lost; *c*) labor productivity losses, as proportion of labor time lost; and, *d*) disasters, as income losses due to exposure to cyclones, storm surge, floods, and drought). The smallest impacts were taken to represent "low climate change" and the highest to represent "high climate change."

Of note, when accounting for uncertainty on how high food prices translate into higher revenues and for the difference between landowners and laborers, different assumptions were made in the poverty and prosperity scenarios: in the prosperity scenario, a 1% increase in food price translates into a 1% increase in farmers' income; in the poverty scenario, a larger fraction of the gain is captured by landowners at the expense of laborers, and a 1% increase in food price translates into a 0.5% increase in farmers' income.

Finally, the three climate-change scenarios (no change, low, and high) were combined with the two sets of socioeconomic scenarios to give six sets of climate-socioeconomic scenarios under which the poverty model was run. The data outputs from the poverty model used to drive the stunting model were national-level average GDPpc of the lowest 20% of the population ($GDPpc20_{ij}$) and average incomes in rural and urban areas ($income_{ij}^{R}$ and $income_{ij}^{U}$, respectively), as well as population (split into agricultural and nonagricultural for all ages and children <15). (See the original paper for a full description of the poverty model (Hallegatte and Rozenberg 2017)).

For food prices, GLOBIOM accounted for (among other things) future changes in crop productivity and global food trade, and estimated relative changes in national-level food prices based on results from Havlík et al. (2015). This provided data for the national-level deflated food CPI (i.e., $fCPI_{ij}/gCPI_{ij}$). Following the method used for poverty model, we used the lowest prices in 2030 under SSP4 and SSP5 from any RCP-GCM combination for "low climate change" in the "poverty" and "prosperity" scenarios, respectively; similarly, we used the highest prices for "high climate change." Prices in futures without climate change were used for the "no climate change" scenarios.

Additionally, SSP-specific population projections for children <5 y of age were taken from the Wittgenstein Centre for Demography and Global Human Capital (2017). The poverty model provided population data for children <15 y in agricultural and nonagricultural families; we assumed that the agricultural-to-nonagricultural ratio in children <5 y of age was the same as that for children <15 y of age. Further we assumed that agricultural populations lived in rural areas, and nonagricultural families lived in urban areas.

In the stunting model, we combine the above projection data to estimate patterns of undernutrition in children <5 y of age given climate change–impacted incomes and food prices under the climate and socioeconomic scenarios developed for the poverty model.

Two issues arise in relation to the stunting model input data. First, food-price estimates from GLOBIOM are one of the inputs into the poverty model. That is, food prices influence incomes. Second, in the poverty model, stunting affects incomes. However, as stunting-related income losses are seen in adults who were stunted when children—i.e., 10 to 20 y previously—we assume this is independent of stunted children <5 y of age in the time period of interest (Figure 1). Combining these issues, we assume that following the initial impacts of food prices and adult stunting on income (along with impacts on income due to other factors), children <5 y old are "exposed" to particular levels of income and food prices relative to income, which together influence their risk of stunting: this risk is quantified by the stunting model.

Results

Historical Data Holdings

We began with a dataset for all countries with stunting data from 1990 onwards (WHO 2017). We then dropped observations where stunting data were not split into moderate and severe (15 observations) and countries with measurements on less than three occasions (39 countries). We then obtained income and price data to match the stunting data.

The final dataset was unbalanced (the number and years of observation differed by country). It included 3–6 (mean = 4) observations from 49 countries (Table 1) for a total of 194 country-year observations. Countries from 12 of the 21 GBD regions (IHME 2015) were included (Table 1, Table S1). We did not include countries from high-income regions (Asia Pacific, High Income; Australasia; Europe, Western; Latin America, Southern; North America, High Income), where the prevalence of child stunting is very low, nor did we include data from any countries in four of the low- and middle-income GBD regions, specifically: Europe, Eastern; Latin America, Tropical; Oceania; Sub-Saharan Africa, Central.

For the national-level stunting data in the final dataset, moderate stunting ranged from 2.9% (The Former Yugoslav Republic of Macedonia in 2011) to 32.8% (Nepal in 1998), with a mean of 18.6% and a median of 19.5%. Severe stunting ranged from 1.3% (Jamaica in 1999) to 34.6% (India in 1993), with a mean of 14.6% and a median of 13.4%. For the data underlying the income indicator (Equation 1), 82 estimates were based on consumption (i.e., household spending) and 112 on income (i.e., household total income). A total of 29% of observations were matched to the same year as the stunting estimate, an additional 46% within 2 y, and the remaining 25% within 5 y. For the data underlying the food price indicator (Equation 2), 17% of values for the food CPI ($fCPI_{ij}$) and

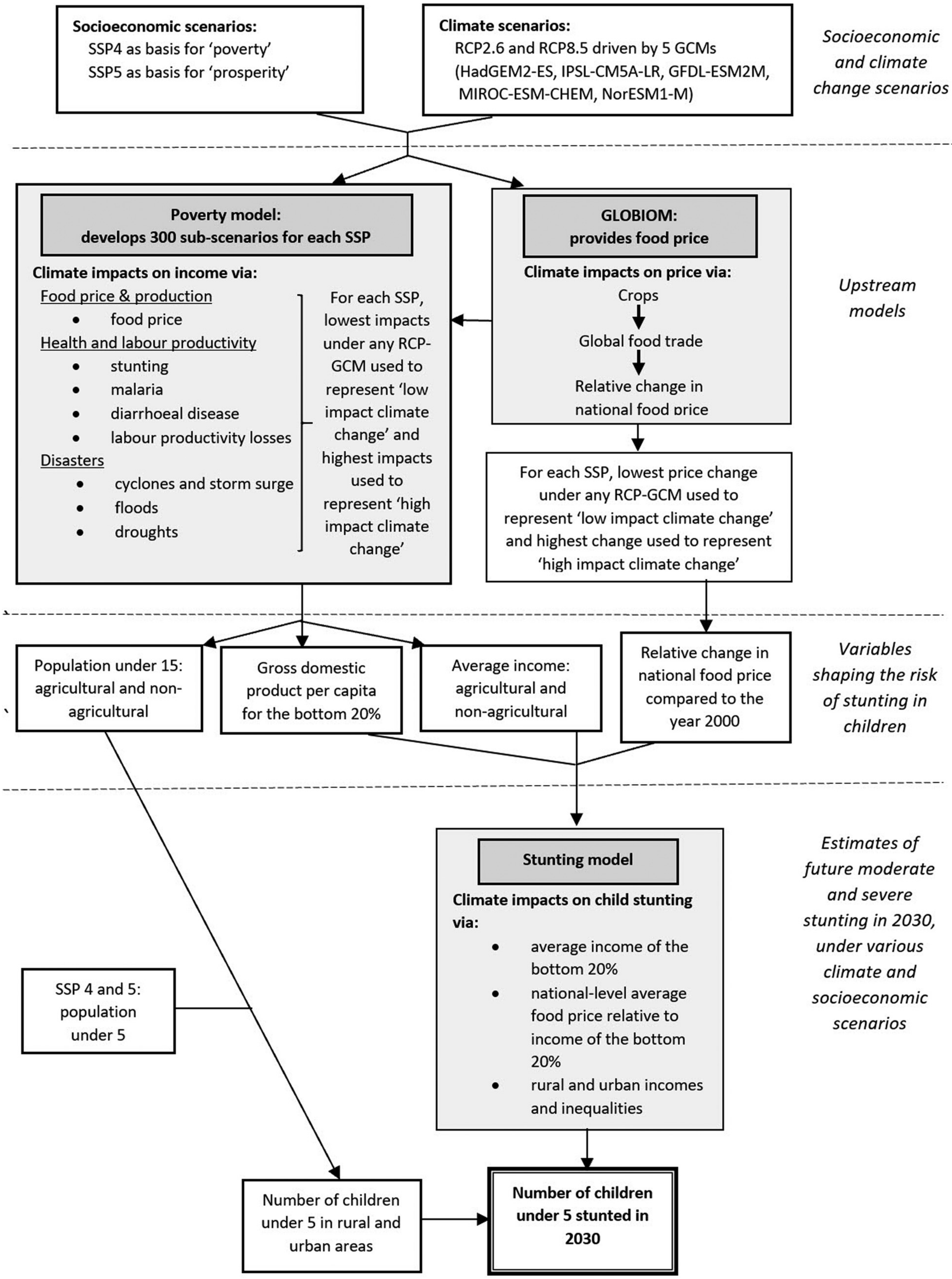


Figure 1. Conceptual diagram of the relations among climate and socioeconomic projection data, upstream models, and the stunting model. Abbreviations: SSP, Shared Socioeconomic Pathways; RCP, Representative Concentration Pathways; GCM, General Circulation Model; GLOBIOM, Global Biosphere Management Model. In the "Upstream models" food price is one of the drivers of the impacts of climate change on income (shown by the link between GLOBIOM and the poverty model), and, stunting is one of the drivers of income loss in the poverty model (due to income losses in adults who were stunted as children 10 to 20 y previously). It is assumed that "agricultural" corresponds to rural populations and "nonagricultural" to urban populations and that the proportions of children <5 y of age in rural and urban areas were the same as the estimated proportions of children <15 y of age in agricultural and nonagricultural families outputted from the poverty model.

Table 1. Estimated parameters for national-level models of moderate and severe stunting (odds ratios and 95% confidence intervals (CI) for fixed parameters; coefficients and standard errors for random variables).

	Moderate		Severe	
Parameters[a]	Null model	Full model	Null model	Full model
Fixed part				
Year	0.986 (0.980, 0.992)	0.99 (0.984, 0.996)	0.962 (0.953, 0.972)	0.97 (0.96, 0.98)
log(GDP per capita of the bottom 20%)		0.912 (0.851, 0.977)		0.6 (0.553, 0.652)
log(food price indicator)		0.814 (0.727, 0.911)		1.229 (1.072, 1.409)
Interaction of GDP and food price terms		1.03 (1.011, 1.05)		0.928 (0.907, 0.949)
Constant	0.193 (0.164, 0.227)	0.346 (0.215, 0.557)	0.109 (0.086, 0.138)	3.192 (1.729, 5.894)
Region:				
Asia, Central		1 (reference)		1 (reference)
Asia, East		0.531 (0.327, 0.862)		0.308 (0.12, 0.795)
Asia, South		1.693 (1.341, 2.138)		2.227 (1.318, 3.762)
Asia, South East		1.325 (1.065, 1.648)		1.29 (0.796, 2.091)
Caribbean		0.357 (0.253, 0.505)		0.183 (0.087, 0.385)
Europe, Central		0.501 (0.382, 0.659)		0.512 (0.298, 0.88)
Latin America, Andean		1.33 (0.981, 1.804)		0.752 (0.374, 1.509)
Latin America, Central		1.057 (0.856, 1.306)		0.6 (0.371, 0.968)
North Africa and Middle East		0.785 (0.571, 1.079)		0.592 (0.294, 1.192)
Sub-Saharan Africa, Eastern		1.569 (1.284, 1.916)		1.605 (1.043, 2.47)
Sub-Saharan Africa, Southern		1.405 (1.075, 1.835)		1.076 (0.598, 1.936)
Sub-Saharan Africa, West		1.093 (0.995, 1.201)		1.147 (1.03, 1.278)
Random part				
Variance in country-specific intercepts	0.332 (0.0699)	0.046 (0.0122)	0.702 (.147)	0.2706 (0.0597)
Variance in country-specific slopes	0.0004 (0.0001)	0.0004 (0.0001)	.0012 (0.0003)	0.0013 (0.0003)
Covariance of intercepts and slopes	0.00853 (0.0024)	0.0016 (0.001)	0.01 (0.0048)	0.0086 (0.0034)

Note: Countries included are Albania, Armenia, Bangladesh, Bolivia, Bosnia & Herzegovina, Burkina Faso, Cambodia, Cameroon, China, Columbia, Cote d'Ivoire, Dominican Republic, Egypt, El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jamaica, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Madagascar, Malawi, Mauritania, Mexico, Mongolia, Mozambique, Namibia, Nepal, Nicaragua, Niger, Pakistan, Peru, Romania, Rwanda, Senegal, Sierra Leone, Sri Lanka, Swaziland, Tajikistan, Tanzania, TFYR of Macedonia, Turkey, Uzbekistan, Vietnam, Zambia.

[a]The corresponding symbols used in Equations 4 to 6 are "Year": $\beta_{1k}^{(N)}$, "log(GDP per capita of the bottom 20%)": $\beta_{2k}^{(N)}$, "log(food price indicator)": $\beta_{3k}^{(N)}$, "Interaction of GDP and food price terms": $\beta_{4k}^{(N)}$, "Constant": $\beta_{0k}^{(N)}$, "Region": vector B, "Variance in country-specific intercepts": var($\beta_{0jk}^{(N)}$), "Variance in country-specific slopes": var($\beta_{1jk}^{(N)}$), "Covariance of intercepts and slopes": cov($\beta_{0jk}^{(N)}$, $\beta_{1jk}^{(N)}$).

16% for general CPI ($gCPI_{ij}$) were interpolated or extrapolated, and 5% of estimates for both were from nearest-neighbor countries. Screening for outliers showed that the food CPI (which was set equal to 100 in the year 2000) in Angola was 251 in the year 2001 and 2,618 in the year 2007. This apparent rapid rise to an extreme level (the next-highest estimate in the dataset is 422) appears, if assumed to be correct, to represent an outlier case in the dataset so all observations were dropped. (Note that Angola is not included in the summary data above.)

For full country-year level details of the data described above, see Excel Table S1.

Model Fitting

We first fit national-level models (Equation 4) for moderate and severe stunting, initially as null growth curve models (i.e., with random effects but no predictors other than year) and then as full models (i.e., including all predictors) (Table 1). Null models for both moderate and severe stunting had a good fit and better explained stunting trajectories than equivalent single-level models (i.e., the same models without random effects) (Likelihood ratio tests: $p < 0.0001$). That is, as expected, there are substantial between-country differences in stunting prevalence in the year 2010 as well as in trajectories of stunting over time. Using the random parts of the null models, we estimated 95% coverage intervals (the range over which 95% of country-specific values would be expected to lie) for percent stunted in 2010 (based on $\beta_{0jk}^{(N)}$) and absolute change in percent stunted from 2000 to 2010 (based on $\beta_{1jk}^{(N)}$). This involved conversion between log odds, odds ratios, and predicted probabilities, and using the standard formula for 95% coverage intervals (Rabe-Hesketh and Skrondal 2012) (See Appendix S1 for a full explanation of the calculations). For moderate stunting, predicted prevalence in 2010 across all countries (as mean (fifth centile, 95th centile)) was 16% (6% to 37%). For severe stunting, prevalence in 2010 was predicted to be 10% (2% to 36%). The estimated absolute change in percent stunting over the decade from 2000 to 2010 was −2.0% (−8.8% to 3.3%) for moderate, and −4.0% (−14.1% to 2.3%) for severe stunting (positive numbers indicate stunting increased). Additionally, the covariances for the random intercept and slope [covariance($\beta_{0jk}^{(N)}$, $\beta_{1jk}^{(N)}$); 0.00853 and 0.01 for moderate and severe stunting, respectively] indicate that when the random intercept for stunting in the year 2010 increases, the slope for year also tends to increase (i.e., the rate of decline of stunting decreases). This suggests that, in general, countries with more stunting in 2010 experienced slower rates of decline, and this relationship is stronger for severe stunting than for moderate stunting. (The correlation between the estimated random effects for slope ($u_{1jk}^{(N)}$) and intercept ($u_{0jk}^{(N)}$) is 0.37 for moderate stunting and 0.50 for severe stunting.) In line with this, between-country variance in stunting [calculated as: variance($\beta_{0jk}^{(N)}$) + 2 [covariance($\beta_{0jk}^{(N)}$, $\beta_{1jk}^{(N)}$) $\times t_{ij}$] + variance($\beta_{1jk}^{(N)}$) $\times t_{ij}^2$ (Rabe-Hesketh and Skrondal 2012; Steele 2014)] has been increasing with time (i.e., as all variance terms are positive, the value of the previous equation becomes more positive as time increases); that is, although stunting has generally been declining, some countries are being left behind. If it is assumed that the countries included in the analysis represent a random sample of all countries at risk of stunting, the above ranges and patterns may be interpreted as reflecting those seen globally.

Both full models for moderate and severe stunting had better fits than their counterpart null models (Likelihood ratio tests: $p < 0.0001$). After adding the main predictors to the model (i.e., G_{ij}, P_{ij}, $G_{ij} \times P_{ij}$), adding the contextual region variable had little influence of the predictor coefficients but the intercept random variance [var($\beta_{0jk}^{(N)}$)] decreased from 0.2716 to 0.046 (i.e., more than quartered) and from 0.6856 to 0.2706 (i.e., more than halved) in the moderate and severe stunting models, respectively. This suggests unexplained between-country differences tend to cluster by region, with stronger clustering for moderate than severe stunting.

We checked the model for multicollinearity of the main predictors (the income and food-price indicators) as well as year and concluded it was unlikely to influence model predictions. First, when adding predictors to the models, there were no large increases in standard errors, and these remained small (i.e., the 95% confidence intervals of the odds did not cross one) in the final equations (Table 1) (Goldberger 1991). Second, to assess this more formally, we used a two-step approach suggested by Hill and Adkins (2003). In step one, Variance Inflations Factors (VIFs) are used to check for the presence of multicollinearity. A commonly used rule of thumb is that values greater than 10 suggest "serious" multicollinearity. VIFs for the main predictors (excluding interaction terms) were all less than 10 [1.1, 8.7, 8.9, for year, the log of the food-price indicator (P_{ij}), and the log of *GDP20pc* (G_{ij}), respectively]. As may be expected, however, the addition of the interaction terms resulted in large VIFs (1.1, 61.7, 8.9, 54.6, for year, the log of food-price indicator (P_{ij}), the log of *GDP20c* (G_{ij}), and the price–income interaction ($P_{ij} \times G_{ij}$), respectively). In step two, we derived signal-to-noise ratios (log(odds)/SE) for each predictor to assess whether multicollinearity is likely to bias model coefficients. If the ratios are judged to be sufficiently high, multicollinearity is not likely to bias estimates (Hill and Adkins 2003). For instance, a ratio $>|1.96|$ would indicate that the 95% confidence interval would not cross the null (Kirkwood and Sterne 2003). Signal-to-noise ratios were within acceptable levels. For instance, for moderate stunting, these were −2.6, −3.6, and 3.1 for the log of *GDP20pc* (G_{ij}), the log of the food-price indicator (P_{ij}), and their interaction, respectively (Table S2). Third, in situations where multicollinearity is judged to be potentially harmful, parameters for individual coefficients may be biased (making it difficult to separate the effects of individual predictors), whereas predictions made by the model as a whole tend to remain reliable (Goldberger 1991; Hill and Adkins 2003). In our results, we do not attempt to separate the effects of income on stunting from those of price; in fact, we argue they are inseparable. All our results are based on predictions made by the model as a whole. In sum, although multicollinearity appears to be present due to the inclusion of the interaction term, it is unlikely to affect the predictions made by the model.

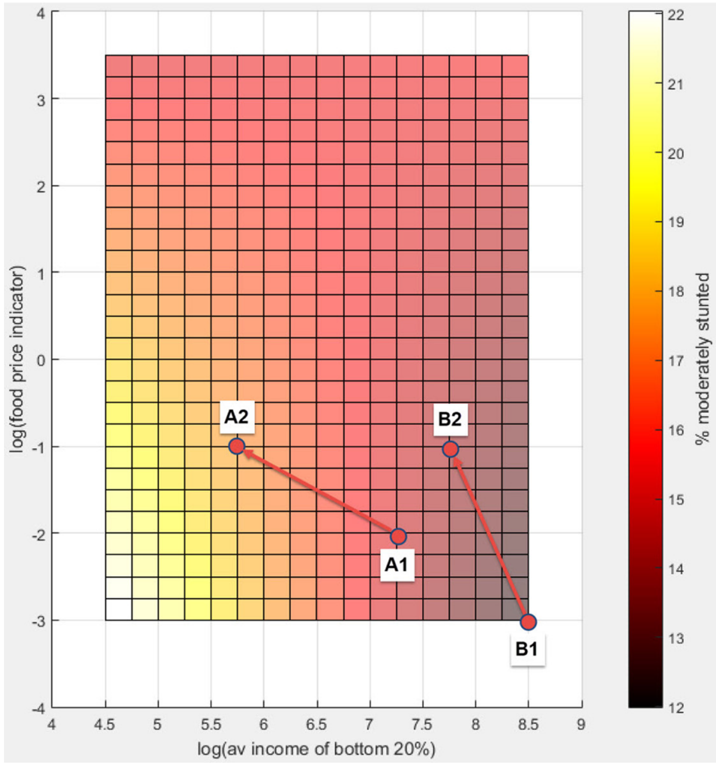
To illustrate the change in stunting when income and food price change together, we plot estimated percent stunted for average countries (i.e., random effects equal 0) in the reference region, with year held constant at 2010, over a slightly larger range of GDP20pc and the food-price indicator seen in the historical data (Figure 2). Both moderate and severe stunting are at their predicted maximums (~22% and 32%, respectively) when average income and food price relative to income are at their lowest levels. This corresponds to an average income level well below the \$1.25 per day poverty line. At this income, stunting declines as relative food prices rise. However, at this income, even at the highest relative prices in the plots, moderate and severe stunting remain high (~15% and 20% respectively). The lowest level of moderate stunting (~12%) is seen when incomes are highest (~10 times the poverty line) and relative prices are lowest. In contrast, the lowest level of severe stunting (~1%) is seen when incomes are highest but relative prices are highest; this is also when total stunting (moderate plus severe) is at its lowest.

The vectors in the plots in Figure 2 give a hypothetical example of the possible impacts of climate change on stunting if incomes were to fall and prices were to rise. In the movement from A1 to A2, as income falls and the price indicators rises, moderate stunting increases from 15% to 18% and severe stunting increases from 13% to 21%; total stunting rises by 11%. In contrast, at a higher income, when going from B1 to B2, moderate stunting increases from 12% to 14%, but severe stunting falls from 13% to 8%; total stunting decreases by 4%. This shows there is an important interaction between these two routes from climate to stunting.

Due to the limited availability of historical data we were unable to validate the model using independent data. However, based on the data used to fit the models, the correlation between observed and predicted stunting was high ($r = 0.98$, for both models) and within-countries trajectories appeared to be well reproduced. Model diagnostics also suggested the models fit well (Figures S1 and S2).

We next fit the within-country models for distributing national-level stunting between rural and urban areas (Table 2). We fit models with the full set of predictors of interest, and then used backwards stepwise regression to remove nonsignificant predictors (i.e., with 95% confidence intervals that included the null). Again, no independent data were available to validate the models, but correlations between observed and predicted stunting were consistently high (between 0.97 and 0.99) (Figure S3). Likelihood ratio tests suggest the multilevel models have a better fit than equivalent single level models. However, model residuals for the random effects for all models (moderate and severe stunting, rural and urban) show that the 95% confidence intervals are wide and frequently include zero. Further, residual plots for predicted stunting show that the pattern of errors differs by level of stunting and tend to be greatest at lower prevalences (Figures S4 and S5). This suggests that national-level stunting projections made using the equations, particularly when prevalence is low, should be interpreted cautiously. We assessed the model for multicollinearity using the same procedure we employed for Equation 5 and again found it was not likely to affect model predictions. (We note that standard errors were wide for the inequalities predictor in the rural severe

A



B

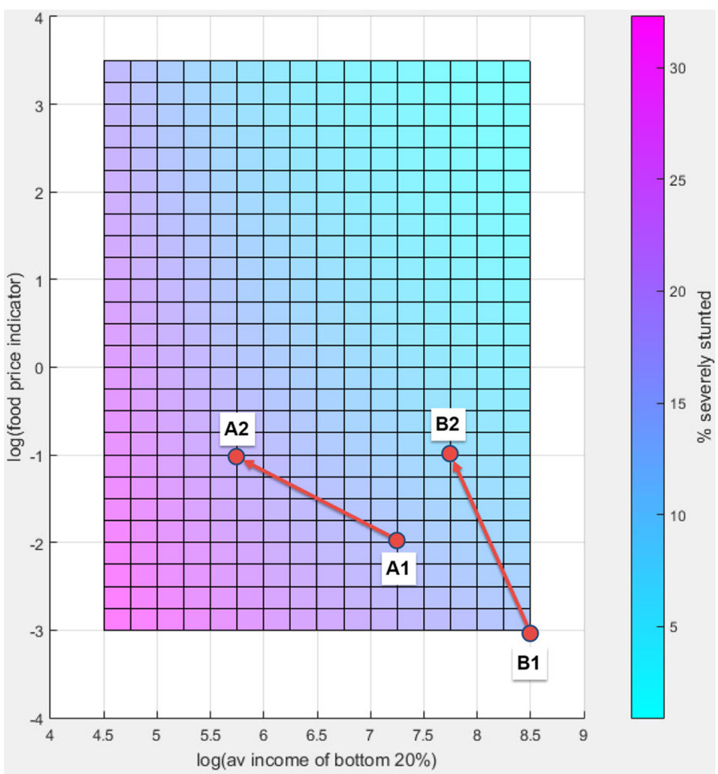


Figure 2. Plots for the full national-level (I) moderate and (II) severe stunting models showing the predicted prevalence of stunting as a function of log of the average income of the bottom 20% of the income distribution and the log of the food-price indicator, in average countries (i.e., random effects equal 0) in the reference region in the year 2010. Note that the z-axis scale differs for the moderate and severe stunting plots. Ranges of the average income and food-price indicator axes are slightly larger than those in the historical data. Note that because the food-price indicator represents price relative to income, it is partly a function of income; that is, the x- and y-axes are not independent. The vectors show examples of how the combined effects of a fall in income and a rise in price relative to income (i.e., moving from A1 to A2, and, from B1 to B2) can lead to either an increase or decrease in stunting. See the model fitting subsection of the results section for details.

Table 2. Estimated parameters for the area-level models of moderate and severe stunting (odds ratios an 95% CI for fixed parameters; coefficients and standard error for random variables).

Parameters[a]	Rural		Urban	
	Moderate	Severe	Moderate	Severe
Fixed part:				
National-level stunting	1.026	1.069	1.071	1.044
	(1.014, 1.039)	(1.051, 1.087)	(1.062, 1.08)	(1.017, 1.073)
log(income indicator)	0.744	0.873	0.861	0.878
	(0.682, 0.813)	(0.786, 0.97)	(0.776, 0.954)	(0.77, 1.001)
Interaction of national-level stunting and income indicator terms	1.015	1.011		1.017
	(1.011, 1.019)	(1.007, 1.015)		(1.01, 1.025)
Rural-urban inequalities	0.9	0.992	0.865	
	(0.845, 0.959)	(0.845, 1.164)	(0.68, 1.101)	
Interaction of income indicator and inequalities terms		0.934	1.131	
		(0.861, 1.013)	(1.007, 1.27)	
Constant	0.179	0.09	0.066	0.041
	(0.136, 0.237)	(0.07, 0.116)	(0.049, 0.089)	(0.026, 0.066)
Random part:				
Variance in intercepts	0.0803	0.152	0.2722	0.3936
	(0.0295)	(0.0389)	(0.0843)	(0.094)
Variance in slopes	0.0001	0.0015	0.0005	0.0014
	(0.0001)	(0.0005)	(0.0002)	(0.0004)
Covariance of intercepts and slopes	−0.003	−0.0134	−0.0114	−0.0219
	(0.0012)	(0.0043)	(0.0038)	(0.0057)

[a]The corresponding symbols used in Equation 8 to 10 are "National-level stunting": $\gamma_{1k}^{(A)}$, "log(income indicator)": $\gamma_{2k}^{(A)}$. "Interaction of national-level stunting and income indicator terms": $\gamma_{3k}^{(A)}$, "Rural-urban inequalities": $\gamma_{4k}^{(A)}$, "Interaction of income indicator and inequalities terms": $\gamma_{5k}^{(A)}$, "Constant": $\gamma_{0k}^{(A)}$, "Variance in intercepts": $\mathrm{var}(\gamma_{0jk}^{(A)})$, "Variance in slopes": $\mathrm{var}(\gamma_{1jk}^{(A)})$, "Covariance of intercepts and slopes": $\mathrm{cov}(\gamma_{0jk}^{(A)}, \gamma_{1jk}^{(A)})$.

and urban moderate models; however, these were included in the model as the standard errors for their interaction terms were small.) (Table S3).

Estimates of Future Stunting

Projection data to drive the stunting model were available for 44 of the 49 countries used to fit the model. Figure 3 shows the aggregated estimates of the number of children <5 y of age stunted in the study countries in 2030 under the six scenarios (as means and 5th and 95th centiles across the 300 socioeconomic subscenarios). The plot suggests, first, within any socioeconomic scenario, the impact of climate change in 2030 is relatively small (although not negligible, as discussed ahead). This finding is consistent with previous work (e.g., Lloyd et al. 2014). Second, projected differences between the two socioeconomic scenarios are large, with mean estimates of 110 million stunted children in the poverty scenario and 83 million in the prosperity scenario. Third, however, within-socioeconomic scenario uncertainty in the magnitude of the estimates is large: Estimates of total stunting range from 80 to 140 million in the poverty scenario, and from 57 to 108 million in the prosperity scenario. That is, although there is generally less stunting in the prosperity scenario, allowing for uncertainties shows there is significant across-socioeconomic scenario overlap.

Table 3 shows aggregated climate change–attributable stunting by scenario. These indicate, first, in all scenarios, that there is more stunting in 2030 in futures with climate change than without. Across the scenarios, mean climate-change attributable stunting is estimated to be between 570,000 (prosperity/low climate change) and 1 million (poverty/high climate change). Second, in the poverty scenarios, a large proportion of climate change–attributable stunting is severe, whereas under the prosperity scenarios, the moderate/severe balance tends to be more even. For example, under poverty/high climate change, the mean estimate of the ratio of moderate to severe climate change–attributable stunting is 0.39, whereas under prosperity/high climate change it is 0.95. Third, in both socioeconomic scenarios, as climate change increases, rural areas bear a greater proportion of the burden than urban areas, but less so in the prosperity than in the poverty scenarios. For the mean estimates, the ratio of climate change–attributable number of people stunted in rural versus urban areas rises from 1.06 to 1.22 under poverty, and from 1.05 to 1.12 under prosperity. Fourth, within-socioeconomic scenario uncertainty matters considerably more under poverty/high climate change than in other scenarios, with a difference of 550,000 stunted between the 5th and 95th centiles, mostly due to differences in severe stunting. In general, this within-socioeconomic scenario uncertainty in how macro conditions specified by the SSPs are met matters more for severe than moderate stunting in all scenarios.

Finally, aggregate results conceal underlying patterns in country-level climate change–attributable stunting. We developed a typology based on whether high climate change is expected to increase or decrease the mean estimates of country-level total stunting relative to low climate change in the poverty and prosperity scenarios (Table 4). The typology is intended to indicate general tendencies in stunting patterns in groups of countries sharing similar characteristics rather than rigidly separate countries and expectations regarding stunting based on statistical criteria. Type I includes 64% of countries (28 of 44) in which high climate change is expected to bring more stunting than low climate change in both socioeconomic scenarios. In 36% of countries, however, there was less climate change–attributable stunting under the high than under the low climate change scenario. In type II countries (11), this occurred in both the poverty and prosperity scenarios; in type III countries (5), this was only in the poverty scenario; and in type IV countries (2), this was only in the prosperity scenario.

Table 4 shows the patterns of incomes and food prices as countries move from low to high climate change, by country type. In type I countries, under low climate change, average incomes of the bottom 20% are relatively low (2 to 2.5 times the poverty line) and the food-price indicator (which indicates food prices relative to income) is relatively high. Under both poverty and prosperity scenarios, high climate change reduces incomes by a relative amount that is fairly typical across all study countries ($\sim 4\%$) but increases in the food-price indicator are relatively high. The combination of low incomes and large increases in price results in increased stunting as climate change increases under both socioeconomic scenarios. In type II countries under low climate change, incomes are relatively high (4 to 5 times the poverty line), and the food-price indicator is

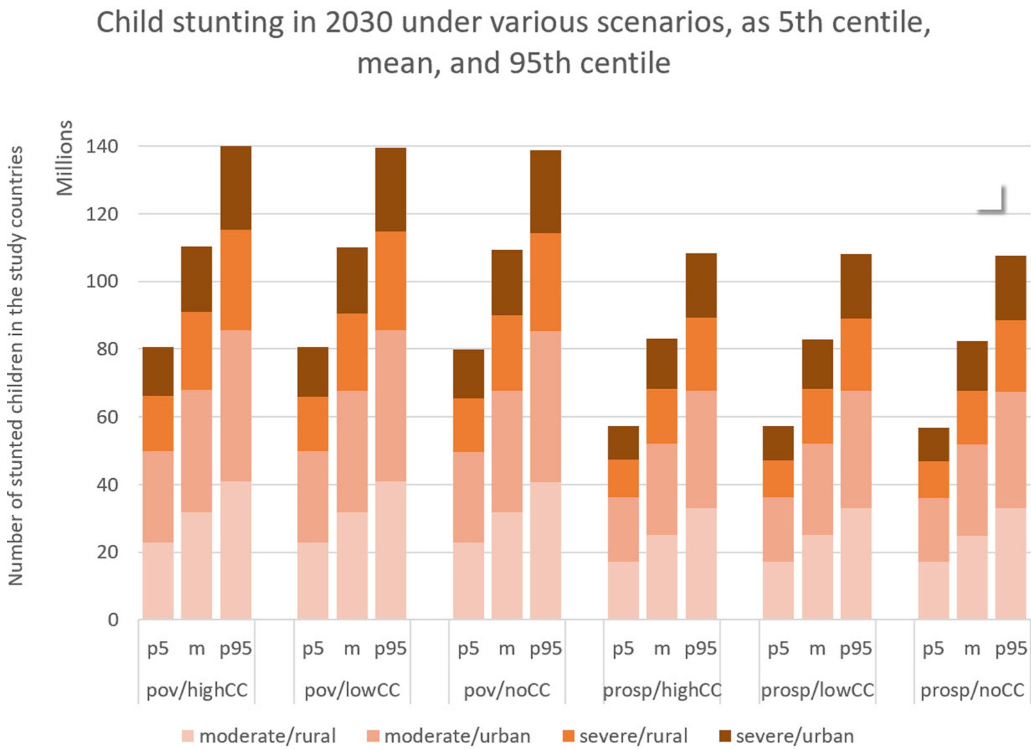


Figure 3. Projected numbers of stunted children (age <5 years) in the 49 study countries in 2030 under combined socioeconomic (poverty or prosperity) and climate change scenarios (high climate change or low climate change), according to the degree of stunting (moderate or severe) and rural or urban area. Values shown for each socioeconomic/climate change combination represent the distribution of estimates for 300 subscenarios for poverty and property projections, respectively. Abbreviations: p5, 5th percentile; m, mean; p95, 95th percentile; pov, poverty scenario; prosp, prosperity scenario; CC, climate change.

relatively low. High climate change brings typical (relative) drops in incomes, but increases in the food-price indicator are relatively small. This combination of higher average incomes and rising relative prices leads to decreases in stunting as climate change increases under both socioeconomic scenarios.

In type III countries under low climate change, incomes (3 times the poverty line) and relative prices are at an intermediate level (Table 4). High climate change brings typical relative decreases in income in both socioeconomic scenarios. In the poverty scenario, the rise in relative price is relatively high, and—at these intermediate incomes—the combination of income loss and high price increases reduces overall stunting as climate change increases. In the prosperity scenarios, the rise in relative price is relatively small and does not appear to offset the loss of income, resulting in an increase in stunting as climate change increases. Thus, type III countries appear to be at incomes where the overall effects of increases in relative food prices tend to be either harmful or beneficial.

Table 3. Estimated numbers of children (means, 5th and 95th percentiles) with climate change–attributable stunting in 2030 according to socioeconomic and climate change scenarios in the 49 study countries.

	Stunting Severity			Rural vs. Urban Areas			
Scenario	Moderate	Severe	Moderate: Severe[a]	Rural	Urban	Rural: Urban[b]	Total stunted
Poverty / high climate change							
5th centile	269,800	489,100	0.55	409,700	349,200	1.17	758,900
Mean	288,400	736,500	0.39	563,300	461,700	1.22	1,025,000
95th centile	323,200	981,300	0.33	773,400	531,100	1.46	1,304,600
Poverty / low climate change							
5th centile	181,600	432,100	0.42	328,900	284,700	1.16	613,600
Mean	199,200	569,300	0.35	396,100	372,400	1.06	768,500
95th centile	225,000	650,000	0.35	468,400	406,600	1.15	875,000
Prosperity / high climate change							
5th centile	306,100	246,700	1.24	277,700	275,000	1.01	552,800
Mean	348,400	366,700	0.95	377,700	337,400	1.12	715,100
95th centile	385,900	493,500	0.78	490,600	388,800	1.26	879,500
Prosperity / low climate change							
5th centile	207,000	256,100	0.81	232,100	231,000	1.00	463,100
Mean	222,300	347,600	0.64	291,800	278,100	1.05	569,900
95th centile	231,400	395,800	0.58	330,200	297,100	1.11	627,200

Note: Estimated numbers of children with climate change–attributable stunting are calculated for each combined scenarios as the number with stunting under high or low climate change vs. no climate change with the socioeconomic scenario (poverty or prosperity) held constant. Study countries are listed below Table 1. Values for the 5th and 95th percentiles represent distributions over the 300 subscenarios for each socioeconomic scenario (i.e., poverty or prosperity).
[a]Ratio of the projected numbers of children with moderate vs. severe stunting due to climate change.
[b]Ratio of the projected numbers of children with stunting due to climate change (regardless of severity) in rural vs. urban areas.

Table 4. Projected average income of the bottom 20%, deflated food-price index, and food-price indicator for countries grouped by the pattern of the estimated impact of high vs. low climate change on stunting under socioeconomic scenarios of poverty and prosperity.

	Low climate change			High climate change			Relative difference between high vs. low climate change		
Country type	GDP20pc mean (range)	Deflated fCPI mean (range)	log(Food price indicator) mean (range)	GDP20pc mean (range)	Deflated fCPI mean (range)	log(Food price indicator) mean (range)	GDP20pc	Deflated fCPI	log(Food price indicator)
Type I[a]									
Poverty	869 (161 to 2157)	116 (91 to 171)	0.2 (−1.86 to 2.25)	832 (149 to 2094)	122 (94 to 182)	0.3 (−1.82 to 2.36)	−4%	5%	50%
Prosperity	1142 (255 to 2867)	105 (90 to 137)	−0.24 (−1.95 to 1.69)	1101 (243 to 2799)	108 (95 to 139)	−0.17 (−1.91 to 1.64)	−4%	3%	29%
Type II[b]									
Poverty	1839 (244 to 4957)	111 (96 to 129)	−0.42 (−2.18 to 1.41)	1764 (226 to 4792)	119 (98 to 149)	−0.31 (−2.12 to 1.67)	−4%	7%	26%
Prosperity	2174 (481 to 5327)	104 (96 to 117)	−0.79 (−2.24 to 0.64)	2082 (459 to 5065)	110 (99 to 125)	−0.69 (−2.17 to 0.67)	−4%	6%	13%
Type III[c]									
Poverty	1262 (380 to 1938)	102 (88 to 120)	−0.37 (−1.92 to 1.06)	1211 (364 to 1867)	110 (93 to 135)	−0.25 (−1.83 to 1.22)	−4%	8%	32%
Prosperity	1603 (697 to 2207)	97 (90 to 106)	−0.76 (−2.07 to 0.38)	1531 (676 to 2101)	102 (94 to 113)	−0.68 (−2.00 to 0.44)	−4%	5%	11%
Type IV[d]									
Poverty	703 (601 to 805)	123 (118 to 128)	0.09 (−0.58 to 0.75)	649 (556 to 742)	134 (131 to 138)	0.25 (−0.42 to 0.93)	−8%	9%	178%
Prosperity	1045 (916 to 1174)	108 (107 to 109)	−0.43 (−1.12 to 0.26)	999 (878 to 1119)	115 (113 to 117)	−0.32 (−1.01 to 0.27)	−4%	6%	26%

Note: *GDPpc20*: per capita Gross Domestic Product of the bottom 20% in PPP 2005 (~\$460 is on the World Bank poverty line of \$1.25 per day); Deflated *fCPI* = national food consumer price index/national general consumer price index, an indication of the difference in within-country average food prices for 2030 relative to the year 2000 (i.e., it equals 1 in the year 2000; a value of 1.1, for example, indicates a 10% rise in price); log(Food price indicator): mean-centered natural log of the food price indicator ($price_{ij}$) (Equation 3), higher values indicate that food is less affordable for the poorest part of the population.

[a]Type I countries: Stunting increases more with high climate change than low climate change under both poverty and prosperity scenarios (Bangladesh, Bolivia, Cambodia, Cameroon, Cote d'Ivoire, Dominican Republic, El Salvador, Ghana, Honduras, India, Jamaica, Kenya, Madagascar, Malawi, Mexico, Mongolia, Mozambique, Nicaragua, Pakistan, Peru, Romania, Rwanda, Sierra Leone, Sri Lanka, Swaziland, Tanzania, Vietnam, Zambia).

[b]Type II countries: Stunting increases more with low climate change than high climate change under both poverty and prosperity scenarios (Albania, Bosnia and Herzegovina, Burkina Faso, Egypt, Guatemala, Indonesia, Lao PDR, Niger, TFYR of Macedonia).

[c]Type III countries: Stunting increases more with low climate change than high climate change under poverty scenarios, but not under prosperity scenarios (China, Kyrgyzstan, Nepal, Senegal, Tajikistan).

[d]Type IV countries: Stunting increases more with low climate change than high climate change under prosperity scenarios, but not under poverty scenarios (Mauritania, Namibia).

There are just two type IV countries, so interpretation should be cautious (Table 4). Under low climate change, these countries have the lowest average income (1.5 to 2 times the poverty line) and high relative prices. In the poverty scenario, as climate change increases, both the average decrease in incomes and increase in relative prices are at their highest. Together, these factors increase stunting. In the prosperity scenario, climate change brings typical reductions in incomes and a much lower increase in price; in this case, stunting is reduced.

In sum, this research suggests that when average incomes of the poorest are low and food prices are relatively high, losses of income and further increases in price tend to increase stunting at the national level. When incomes are higher and prices relative to income are relatively low (note: this does not suggest absolute food prices are low), losses of income may be offset by price increases, and overall stunting tends to decrease. This is presumably due to gains made by low-income food producers and perhaps by nonskilled wage earners. At intermediate incomes (i.e., around 3 times the poverty line) and relative prices, the overall impact of higher relative prices tends to change from increasing stunting to decreasing stunting as incomes of poorest rise further.

Discussion

To our knowledge, we have developed the first global-level model for estimating future climate change–attributable stunting in which climate change acts through two interacting socioeconomic drivers: incomes of the bottom 20% of a population and food price relative to incomes. Previous global-level undernutrition models have focused on changed food production and calorie availability in fixed socioeconomic conditions (e.g., Lloyd et al. 2011; Nelson et al. 2010). Such models provide insights into a key influence on future undernutrition while placing other influences in the background. Previous work has also suggested that socioeconomic conditions play a major role in shaping future undernutrition (e.g., Lloyd et al. 2014; Schmidhuber and Tubiello 2007): our model attempts to offer new insights by focusing on two of these conditions while placing other influences in the background. Incomes of the poorest groups and food prices are likely to play a central role in shaping future undernutrition (Mazoyer and Roudart 2006; Pogge 2010). In rural areas, smallholder farms (i.e., farms <2 hectares) are "home to about two billion people, including half the world's undernourished people and the majority of people living in absolute poverty" (IFAD 2011). The urban poor are also at high risk of undernutrition and to the impacts of price and financial shocks (Ruel et al. 2010).

Our null model suggests that the historical rate of decline in stunting has generally been slow, even during the period in which hunger was a focus of the Millennium Development Goals (United Nations 2017). The average absolute annual decline over the period 2000 to 2010 was estimated to be 0.2% for moderate stunting and 0.4% for severe stunting, although larger declines were seen in some countries (5th centiles of 0.88% for moderate and 1.41% for severe). This estimate is similar to previous estimates (Rieff 2016). Additionally, between-country differences widened as the biggest improvements tended to be in countries with lower levels of stunting. This widening suggests child stunting is likely to remain a major contributor to the global burden of disease in the coming decades, even without the additional threats posed by climate change. In the full model, when incomes and relative food price were added, we found that their interaction was critical: In some instances, a decline in income and increase in relative prices increased stunting, whereas in others they reduced it (Figure 2).

Adding regions to the model led to large reductions in unexplained between-country differences, with a much larger reduction in the moderate than in the severe stunting model. This addition suggests that, although moderate and severe stunting are distinguished using a quantitative scale, there may be qualitative differences in their causes: Moderate stunting may tend to be influenced more by regional structural factors operating both within and between countries, whereas severe stunting may tend to be more influenced by within-country processes (for example, civil conflict). Given that severe stunting brings considerably worse morbidity and mortality risks than moderate stunting does (Black et al. 2008; Victora et al. 2008), further investigation of this aspect in future work may provide useful insights.

Consistent with previous work (Lloyd et al. 2014), our projections suggest that climate change will have a relatively small—but not insignificant—impact on stunting in 2030, whereas estimated between-socioeconomic scenario differences are large. Mean estimates of child stunting in the study countries in the poverty and prosperity scenarios are 110 million and 83 million, respectively (Figure 3). Of note, the wide variation in these estimates across the 300 subscenarios for each SSP (which differed by demographic characteristics, economic policies, the distribution and participation of labor, productivity growth by sector, and labor skill levels), suggests that the particular mechanisms that produce poverty or prosperity futures could have substantial influences on patterns of health.

Our projections suggest that, in aggregate, stunting will increase as climate change increases, with larger impacts under the poverty scenario: We estimate that >1 million additional children would be stunted under poverty/high climate change, in comparison with 570,00 under prosperity/low climate change (Table 3). Further, our estimates suggests that severe stunting would account for a greater proportion of climate change–attributable stunting under the poverty scenarios than in the prosperity scenarios, and that the potential impact of climate change on stunting would be greater in rural areas in comparison with urban areas under both socioeconomic scenarios (Table 3). Previous analyses have suggested that the impact of rising food prices on poverty is, in general, greater in urban areas than in rural areas (Hertel et al. 2010; Ivanic and Martin 2008). These results, however, are not directly comparable to our findings. First, the causal pathways and outcome differ: Our model looks at the combined impacts of changes in food prices and incomes of the poorest populations on child stunting, rather than how food prices may affect the number of people below a fixed poverty line. Second, the poverty model driving the stunting model assesses how climate change may affect incomes via multiple routes rather than through food prices alone (Figure 1). Third, our estimates are based on scenario-specific projections of future socioeconomic conditions, whereas Hertel et al. (2010) hold future socioeconomic conditions constant at present level and Ivanic and Martin (2008) analyze historical data. Although this different approach may explain the differences in the results, below we briefly discuss further differences in the modeling approaches and how the stunting model may be improved by drawing on this food price–poverty literature.

We developed a typology based on country-level changes in stunting in response to increasing climate change (Table 4). In type I countries, incomes of the poorest are relatively low and relative prices tend to be high; in this situation, our projections suggest that increasing climate change is likely to increase stunting. In type II countries, incomes are higher and relative prices are lower; there, increasing climate change is likely to decrease stunting. Type III countries have intermediate incomes and relative food prices, and in these cases, increasing climate change might increase or decrease stunting. That is, type III countries appear to be at income levels where they may transition to type I countries if incomes of the poorest fall, or to type II countries if incomes of the poorest rise.

These patterns suggest that the impact of climate change will be an increase in aggregate country-level stunting for countries in which average incomes of the poorest are low and food is generally less affordable, even though rising food prices may benefit some population subgroups. However, when incomes of the poorest are higher, sustained higher food prices (relative to incomes) tend to lower country-level stunting (although some groups may be harmed). This suggests that it is not continually falling food prices that will eliminate undernutrition (see also: Hertel 2016); rather, food prices that provide a decent income to farmers alongside high levels of employment with wages that adequately cover the costs of living is required (among other things) (Holt-Giménez and Patel 2009; Mazoyer and Roudart 2006; Weis 2007). In sum, the reduction and then elimination of poverty and inequality are required. If these conditions were generally met, our estimates suggest that—at least out to the 2030s—the potential harms of climate change on stunting via the pathways considered would be significantly reduced. We stress that this does not suggest that climate change may improve population health if incomes increase. Rather, it suggests that higher incomes combined with "fair" food prices may reduce stunting and vulnerability to the impacts of climate change.

Our model has a number of limitations. The first relates to data availability. For the historical stunting data, we found 49 countries with at least three observations covering rural and urban areas and split as moderate and severe since 1990 (WHO 2017) (Table S1). We used random-effects modeling which, by assuming these countries represent a random sample of all countries at risk of stunting, allows us to make general statements about all affected countries. However, although the data covered many countries at greatest risk of stunting (including 18 in Sub-Saharan Africa and 9 in South and Southeast Asia), and countries with a wide range of stunting (2.9% to 32.8% for moderate stunting; 1.3% to 34.6% for severe stunting), we cannot rule out the potential for bias. Further, we included data for China, a country whose size and particular patterns of development can have a large influence on global-level trends of various factors. For instance, an estimated one third of global farms are in China (Lowder et al. 2016), and the inclusion or exclusion of China from global trends in poverty reduction can reverse trajectories (Pogge 2010). Given this, we assessed the potential influence of China on our model by excluding it and found only very small changes in the parameters for the main predictors. Despite these limitations, model diagnostics for the national-level model show the random effects and residuals follow the expected distributions (Figure S2), suggesting that general inferences may be both reasonable and useful.

For the predictor variables, finding data that matched the available projections for incomes and prices, and that were comparable across countries and over time, was difficult. Consequently, it was necessary to develop indicators using available data. However, as the income indicator was split by area but the price indicator was at the national level, we took a two stage-approach to modeling, first modeling the national level longitudinally and then modeling stunting by area (i.e., rural and urban). Of note, we did not model area as a distinct level as it not a random sample of area categories; rather it is a dichotomous fixed category within a country.

Second, we modeled moderate and severe stunting using independent equations. This separation is unable to capture the dynamics of changes in nutritional status and within-country migration. For example, a severely stunted child in a rural area may leave this category by becoming moderately stunted or well nourished, or by dying; additionally, the child's family may migrate to an urban area, thus reducing rural stunting but increasing urban stunting. Given the available data, it was not possible to include these dynamics in our model.

Third, again due to limited data availability, we were not able to formally validate the model. The national-level equations appear to have a reasonably good fit and show strong correlations between observed and predicted stunting; however, the diagnostics for the area-level models show the fit is not as good (Figures S3 and S4). This was further evident when rescaling rural and urban moderate and severe stunting projections so they summed to the national-level projections. For the poverty/high climate change scenarios, for example, the ratio of estimated rural and urban moderate stunting to estimated national-level stunting had a median of 1.02, meaning the magnitude of rescaling was small. The 95th centile was 1.15, requiring modest rescaling. However, the 5th centile was 0.63, which necessitated significant rescaling. For severe stunting, the ratio had a median of 0.95, 5th centile of 0.28, and 95th centile of 1.35. That is, significant rescaling was often required. Thus, the projected patterns of rural and urban stunting should be interpreted with some caution. This does not, however, affect the national-level projections, which are the basis of our core findings.

Fourth, due to the limits of the projection data, our stunting estimates do not go beyond 2030. Further into the future, it would be expected that increasing climate change would have greater impacts on poverty and food prices due to, for example, increased crop productivity losses, labor losses, infectious diseases, and disasters (Smith et al. 2014). Our findings suggest that moderate price increases in the context of reasonable incomes may bring aggregate reductions in stunting. However, increased climate change beyond 2030 may drive incomes of the poorest to low levels and food prices steeply upwards, in turn bringing increased child stunting. This possibility suggests the importance of near-term changes that increase incomes and protect the livelihoods of the poorest (in both rural and urban areas), alongside actions to improve the resilience of food crops to climate change.

A related issue is that our model assumes that an adequate food supply is available. This is arguably reasonable for the 2030s as estimates suggest there is currently sufficient food to adequately feed about 1.5 times the current population (Moore Lappé 2013), meaning we have historically moved from "hunger amidst scarcity" to "hunger amidst abundance" (Araghi 2000). However, further into the future, increasing climate change and growing populations may make food production an increasingly important cause of stunting (e.g., Lloyd et al. 2011; Nelson et al. 2010). If our model were to be used to make projections beyond 2030, it may need to be modified to include food availability (and perhaps food quality).

Fifth, our model is driven by income projections that consider shifts between general labor sectors (Hallegatte and Rozenberg 2017), represented as agricultural and nonagricultural incomes (taken to represent rural and urban incomes, respectively) in our model. However, previous studies looking at how food prices affect poverty have shown the importance of more detailed patterns of income sources, as well as ratios of net buyers to net consumers of food, in shaping the aggregate impacts of food prices on poverty (Hertel et al. 2010; Hertel 2016; Ivanic and Martin 2008). These impacts of food prices on poverty would be expected to influence patterns of undernutrition. Future undernutrition models could attempt to represent this explicitly, perhaps by closer integration with the poverty model. However, obtaining the required historical and projection data from a large number of countries is likely to be difficult. (For example, Hertel et al. (2010) included 15 countries and Ivanic and Martin (2008) included 9 countries.)

Sixth, despite the complexity of the causation of undernutrition, we include explicit predictors related only to incomes and food prices in our model. However, as our aim is to represent the total effects of incomes and food prices on stunting, we follow the general logic outlined by Biggs et al. (2010). Although other factors, such as education and access to water and sanitation, affect stunting, they are also likely to be strongly influenced by incomes. This influence means that: *a*) if such factors were added to a regression model, they would absorb some of the effects of income on stunting; and *b*) such factors are likely to be highly collinear with income and may cause model fitting problems. Thus, by including just income and price, we attempt to capture their full effects regardless of the specific causal pathway from the predictors to the outcomes.

Conclusions

Previous global-level models have shown that climate change–attributable changes in food production and distribution may affect undernutrition and have highlighted the importance of socioeconomic conditions. Our model shifts the focus to how climate change may affect two key socioeconomic drivers—incomes of the poorest and food price—and assesses how their interaction may influence stunting in the 2030s. The patterns in our aggregate results suggest that stunting will increase as climate change increases, with a greater proportion of the burden falling on rural areas, and larger increases in severe stunting in comparison with moderate stunting in the poverty scenarios.

The disaggregated country-level patterns offer a different insight: In situations when incomes of the poorest are relatively high, modest and sustained increases in food prices relative to incomes may reduce overall stunting. This finding suggests, along with ensuring that adequate quantities of food are produced in the future, a key means of reducing the impacts of climate change on stunting may be—rather than seeking ever-lower food prices—to ensure food prices are high enough to sustain farming households and that decent work with adequate incomes is available for all. Views on how this, particularly the former, might be best achieved are contested (e.g., FAO 2017a; McIntyre et al. 2009; Patel 2009), but the results of our model suggest that agricultural futures that protect health must consider not just availability, accessibility (e.g., Hasegawa et al. 2016; Lloyd et al. 2011), and quality of food (Myers et al. 2015), but also the incomes generated by those producing the food. This aspect is perhaps particularly urgent as, counterintuitively, food producers currently comprise around half of the world's undernourished people (IFAD 2011).

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