Estimated Effects of Future Atmospheric CO₂ Concentrations on Protein Intake and the Risk of Protein Deficiency by Country and Region

Danielle E. Medek,1,2 Joel Schwartz,1 and Samuel S. Myers1,3

1Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, Massachusetts, USA
2Waitemata District Health Board, Takapuna, Auckland, New Zealand
3Harvard University Center for the Environment, Cambridge, Massachusetts, USA

BACKGROUND: Crops grown under elevated atmospheric CO₂ concentrations (eCO₂) contain less protein. Crops particularly affected include rice and wheat, which are primary sources of dietary protein for many countries.

OBJECTIVES: We aimed to estimate global and country-specific risks of protein deficiency attributable to anthropogenic CO₂ emissions by 2050.

METHODS: To model per capita protein intake in countries around the world under eCO₂, we first established the effect size of eCO₂ on the protein concentration of edible portions of crops by performing a meta-analysis of published literature. We then estimated per-country protein intake under current and anticipated future eCO₂ using global food balance sheets (FBS). We modeled protein intake distributions within countries using Gini coefficients, and we estimated those at risk of deficiency from estimated average protein requirements (EAR) weighted by population age structure.

RESULTS: Under eCO₂, rice, wheat, barley, and potato protein contents decreased by 7.6%, 7.8%, 14.1%, and 6.4%, respectively. Consequently, 18 countries may lose >5% of their dietary protein, including India (5.3%). By 2050, assuming today’s diets and levels of income inequality, an additional 1.6% or 148.4 million of the world’s population may be placed at risk of protein deficiency because of eCO₂. In India, an additional 53 million people may become at risk.

CONCLUSIONS: Anthropogenic CO₂ emissions threaten the adequacy of protein intake worldwide. Elevated atmospheric CO₂ may widen the disparity in protein intake within countries, with plant-based diets being the most vulnerable.

Methods

Systematic Review and Raw Data

We conducted ISI Web of Knowledge (https://www.webofknowledge.com/) literature searches in July–September 2014 and in January 2016 for the effects of eCO₂ on the protein content of all plants listed in the FAO FBS. This study supplements the meta-analysis of common European/U.S. staples conducted by Myers et al. (2014). Because estimates of plant protein are commonly derived by multiplying measured plant nitrogen (N) by a conversion factor, we considered published changes in N and protein to be equivalent (Taub et al. 2008). For the full search string and exclusions, see “Part 1” and “Part 2” in the Supplemental Material.
Material. A total of 119 citations were used. For references, see “Part 3” in the Supplemental Material.

We included raw data from free-air CO2 enrichment (FACE) and open-top chamber studies, with data from European wheat, barley, and potato Changing Climate and Potential Impacts on Potato Yield and Quality (CHIP) and the European Stress Physiology and Climate Experiment (ESPACE) studies (A. Fangmeier, unpublished data, 1994–1999) and Australian wheat and pea Australian Grains Free Air CO2 Enrichment (AGFACE), Japanese rice, American soy, corn, and sorghum Soybean Free Air Concentration Enrichment (SoyFACE) and Arizona FACE (data from Myers et al. 2014). Raw data included free-to-air carbon dioxide elevation (FACE) and open-top chamber studies, with randomifers being the difference between ambient (aCO2) and eCO2 treatments as a modifier. We used multivariate linear mixed-effects models (the function rma.mv) with outcomes being percent decrease in protein, and modifiers being the difference between aCO2 and eCO2 in parts per million. Models included variance and were weighted by replicate facilities (e.g., number of FACE rings or growth cabinets) with random effects being year within site, and each cultivar (and untested as a modifier, each watering and nitrogen fertilizer treatment) was treated as a separate experiment. We performed Q tests to assess heterogeneity.

**Metaregression**

Metaregression was performed individually for each commodity where data were available from four or more experiments and for commodity groups listed in the FAO FBS (Table 1). We used the statistical package Metafor (version 1.9-4 Wolfgang Viechtbauer) in R (version 3.0.3; R Development Core Team). For each commodity or group, the difference between ambient (aCO2) and eCO2 treatments was tested as a modifier. We used multivariate linear mixed-effects models (the function rma.mv) with outcomes being percent decrease in protein, and modifiers being the difference between aCO2 and eCO2 in parts per million. Models included variance and were weighted by replicate facilities (e.g., number of FACE rings or growth cabinets) with random effects being year within site, and each cultivar (and untested as a modifier, each watering and nitrogen fertilizer treatment) was treated as a separate experiment. We performed Q tests to assess heterogeneity.

**Meta-Analysis**

Because there was no reliable dose-dependent decrease in protein content with degree of CO2 elevation, we used meta-analysis to derive average response ratios comparing plants grown in aCO2 with plants grown in eCO2, where eCO2 was in the range of 500–700 ppm. We used the rma.mv function as for metaregression, but without the modifier term. Both meta-analysis and metaregression tested fixed effects of pot-versus field-grown plants and a qualitative measure of nitrogen fertilizer treatment, categorized as low, adequate, or high, based on descriptions in each study’s experimental design. Neither modifier changed the magnitude of the CO2 response, and neither was used in subsequent analyses.

We minimized publication bias by including unpublished data. Furthermore, we tested sensitivity to publication bias. For each commodity, we incrementally added experiments with no effect of eCO2 on protein content (RR 1, variance 0.5) until confidence intervals for RR crossed 1. Some commodities, including rice, were sensitive to null results, but wheat was insensitive to null results (see Table S3).

**Food Balance Sheets**

The FAO FBS estimate per capita availability of each food-based commodity (including energy and protein contents). We averaged data over 2009–2013 FAO FBS. We assumed that protein availability equals protein intake, corrected for digestibility (FAO 2014a). Per convention, we assumed that plant-based protein was 80% digestible and that animal-based protein was 95% digestible (Millward and Jackson 2004).

The “Vegetables, other” and “Cereals, other” categories were large contributors to protein intake in some countries, and contained both C3 and C4 plants, and for vegetables, nitrogen fixers. We produced weighted estimates of the contributions of each these categories, using re-calculated 2009 FBS from the FAOstat classic platform (described fully by Smith et al. 2015). We converted from total grams to grams protein, using food composition tables (Abdel-Aal et al. 1997; USDA 2011; FAO 2012; Ballogu et al. 2013; New Zealand Ministry of Health 2014). We assumed that the “Cereals, other, not elsewhere specified” category within the “Cereals, other” category was derived from C4 grains in sub-Saharan Africa, but from C3 grains elsewhere.

To estimate the effect of eCO2 on protein intake in each country, we assumed constant mass-based consumption of each commodity over time, with declining protein content predicted by our meta-analyses. We used commodity-based averages when available, and otherwise applied the averages from the commodity group to each commodity (Table 1). We found no studies on eCO2 response of tree nuts, thus conservatively assumed no change in their protein content. Likewise, we assumed no eCO2 effect on animal protein.

**Plant-Based Diets**

Within a population, the lowest protein consumers also frequently consume the least meat (see World Food Programme household surveys; e.g., Santacroce 2008). For an extreme scenario, we reran the models, removing all animal-sourced foods (including eggs and dairy) from the diet, assuming no other changes in dietary fractional composition.

**Intake Distribution**

We assumed a lognormal distribution of protein intake within countries (FAO 2014b), a cumulative distribution function, with the mean,

\[ \mu = \ln \bar{x} - \frac{\sigma^2}{2} \]

and the standard deviation,
\[ \sigma = \sqrt{\ln(1 + CV^2)} \]

where \( \bar{x} \) is the national mean protein intake, as estimated above, and \( CV \) is its coefficient of variation. Because protein intake is likely to be related to household income, we estimated the CV of protein intake (\( CV_{\text{protein}} \)) from the Gini coefficient of national household income inequality. The national Gini coefficient for household income describes a Lorenz curve plotting the cumulative percentages of total income against the cumulative number of households from poorest to richest. Using linear regression, we compared per-household \( CV_{\text{protein}} \) from household surveys across 36 countries (FAO 2014a) with contemporaneous national Gini coefficients (Arneberg and Pedersen 2001; Garcia et al. 2001; Kim and Kim 2007; OECD 2009; Liberati 2013; USAID 2012; CIA 2014; Solt 2014; World Bank 2014). The FAO uses Gini coefficients, gross domestic product (GDP), and food prices to estimate CV for caloric intake (FAO 2015). We then estimated the national \( CV_{\text{protein}} \) from the country’s Gini coefficient in the year closest to 2011. Owing to high uncertainty among future economic projections, we assumed each country’s future \( CV_{\text{protein}} \) would remain constant.

**Estimated Average Requirements**

We calculated a weighted estimated average requirement (EAR) (grams per day) for absorbed protein from the published EAR for adults (0.66 g/kg/d) and for children by age and sex, using current and mid-range 2050 demographic projections (IOM 2005; UN 2013). For adults, the minimum safe protein intake in grams per day is based on the minimum healthy body weight calculated from the lowest 5th percentile of body mass index (BMI), this being 18.5 kg/m² (WHO 1995). We calculated average height from national surveys (OECD 2009; Hatton and Bray 2010; USAID 2012). Where male height was unavailable, it was calculated as 1.08 x female height, based on the median male-to-female height ratio across all countries. For child weight, the ideal body mass was the 50th percentile by age from growth tables (WHO 2006). We adjusted EAR to include the increased protein requirements of pregnant and lactating women (IOM 2005) with demographics estimated from projected birth rates, 2009 stillbirth rates and infant mortality, and breastfeeding prevalence and duration (McDowell et al. 2008; AIHW 2011; CDC 2011; UN 2013; USAID 2012; Liu et al. 2013).

**Risk of Protein Deficiency**

From each country’s 2050 population, we calculated the proportion and the number of people whose intake fell below the EAR under current and eCO2 scenarios, with the difference between these populations being our measure of impact.

We used Monte Carlo methods to propagate error from the SE of the meta-analysis results, and for modeled \( CV_{\text{protein}} \), through the model, using 10,000 random draws from normal distributions of mean national protein intakes, and again for error around linear regression of \( CV_{\text{protein}} \) on Gini coefficient. From these two parameters, we calculated the means (\( \mu \)) and standard deviations (\( \sigma \)) of 10,000 lognormal distributions. These were used to estimate the probability for each country of protein intake being below the calculated EAR.

We summarize data based on regional classifications from the reporting regions of the Global Burden of Disease Study 2010 (Lim et al. 2012), but we present India and the greater China region separately because of their large population sizes.

At each stage of analysis, where country-specific data were unavailable, data were derived from regional estimates, which were in turn derived from weighted means by population size of each available country represented within the region (see Table S4 for regions).

**Protein–Energy Ratio**

Assuming all calories lost from declines in food protein contents were replaced as carbohydrates (as supported by the stoichiometry of Løladze 2014), we calculated the ratio of protein to total energy in current diets and projected diets under eCO2. Because commodity-based digestibility of energy is less easily estimated, digestibility was not included in these estimates.

**Results**

Our analysis was based on 99 high-CO2 experiments and 48 crops, and it included 54 field experiments. Of the 64 experimental sites, 37 were elsewhere than Europe or North America (see Table S1).

In maize, peas, and mustard seed, we found a linear dose response when the RR of protein content was compared with the degree of CO2 elevation above ambient (see Tables S1 and S2). Metaregression for other crops was not significant, partly because of insufficient statistical power. Maize protein content under eCO2 was not significantly below that under aCO2 when considered overall from meta-analyses or when predicted for an atmospheric CO2 increase of 150 ppm from metaregression. Metaregression predicted a decrease in pea protein content of 4.1% (1.6–6.7%) with an atmospheric CO2 increase of 150 ppm, and overall, meta-analyses showed no significant declines in pea protein. National changes in dietary protein content were on average 0.04% less when modeled for a 150 ppm increase in atmospheric CO2 based on metaregression results compared with meta-analyses. This difference was small enough to warrant the use of meta-analyses rather than metaregression. Comparisons between field and pot-based experiments, and between nitrogen fertilizer treatments were largely nonsignificant (p > 0.05; see Table S2).

Meta-analyses confirmed lower protein content of C3 grains (including barley, 14.1% lower), tubers (including potato, 6.4% lower), fruit (23.0% lower), and vegetables (17.3% lower) under eCO2, with no significant change in the protein content of C4 grains, nitrogen-fixing pulses, or oil crops (Table 1).

When these effect sizes were translated to FBS-standardized commodity intakes, the mean protein intake decreased under eCO2 by >5% in 18 countries, including India, Bangladesh, Turkey, Egypt, Iran, and Iraq. Particularly large declines are expected through the Middle East and India, where a 5.3% decrease in dietary protein is predicted (Table 2, Figure 1).

Globally, >7% decreases in protein intake are predicted for plant-based diets under eCO2, with countries dependent on C3 staples particularly affected (Table 2), including Central Asia, North Africa and the Middle East (7.9%), Central and Eastern Europe (8.2%), and China (8.9%).

A significant positive linear relationship existed between the natural log of \( CV_{\text{protein}} \) and income-based Gini coefficients (slope 0.026, p < 0.0001; Figure 2). Income inequality explained half of within-country variation in protein intake (\( r^2 = 0.49 \)).

Estimates indicated a 12.2% current risk of protein deficiency globally. With constant atmospheric CO2 concentrations, we predict that globally, 15.1% or 1.4 billion people will be at risk of protein deficiency by 2050 because of demographic changes. This estimate includes 613.6 million people at risk in sub-Saharan Africa, 276.4 million in India, 131.7 million in Eastern and Southeast Asia and the Pacific, 84.4 million in Central Latin America and the Caribbean, and 77.8 million elsewhere in South Asia (Figure 3, Table 3).
With predicted atmospheric CO2 concentrations >500 ppm by 2050, we estimate an additional 1.57% of the world’s population (148.4 million) will be at risk of protein deficiency, compared with 2050 aCO2 scenarios. In particular, an additional 53.4 million people in India, 15.9 million elsewhere in South Asia and 24.6 million in sub-Saharan Africa are estimated to become newly at risk (Table 3, Figure 3). An additional 15.9 million people in the China region and 12.0 million in Central Asia, North Africa, and the Middle East are expected to become at risk with eCO2. The greatest increases in percent at risk of protein deficiency are expected in Tajikistan, Bangladesh, Burundi, Liberia, Occupied Palestinian Territory, Iraq, and Afghanistan (Figure 3B).

Globally, we predict the protein-energy ratio (protein caloric contribution as a percent of total calories) to decrease under eCO2 by 0.41%; in individual countries and regions, we predict this ratio to decrease by 0.6% in 17 counties including China, Iran, Iraq, Morocco, and Turkey. We expect decreases in China of 0.57% (Table 2).

Discussion
Our study highlights the potential impact of eCO2 on dietary protein intake globally. Wheat and rice, among the most sensitive crops to eCO2, are primary protein sources for 71% of the world’s population (FAO 2014a). By 2050, 148.4 million people worldwide may become at risk of protein deficiency from rising CO2.

In India, expected to be the world’s most populous country (UN 2013), and a country that is highly dependent on rice, 53.4 million people may be newly at risk of protein deficiency. Additionally, the protein deficiency in roughly 1.4 billion people globally (predicted under aCO2 in 2050) is anticipated to become more severe under eCO2 scenarios. Although estimates of current protein intake and income inequality highlight the current risk of deficiency in sub-Saharan Africa and South America, their dependence on less-sensitive C4 crops make these diets less sensitive to eCO2.

Importantly, we incorporated into the risk assessment different distributions of protein intake in countries based on income inequality from the association of income-based Gini coefficients with variability in protein intake from national dietary surveys. We find it equally plausible that CVprotein would decrease or increase by 2050. We therefore provide the most conservative estimate of future protein intake distributions, namely that CVprotein within countries will remain unchanged. We also assume unchanged duration and prevalence of breastfeeding, and unchanged adult height.

Although our calculations assume no change in the shape of the intake distribution, we anticipate a worsening of inequality in protein intake within populations because a larger decrease in protein content is observed in plant-based than in omnivore diets under eCO2 (Table 2). Some changes in meat quality are anticipated owing to increased fat content under lower-protein diets.

Note: Figures represent population-weighted averages (and 95% confidence intervals) globally and for each region (2050 population). Protein-energy ratio is the percentage of dietary energy (calories) that is derived from protein. CALACA, Central and Andean Latin America and the Caribbean; CANAME, Central Asia, North Africa and the Middle East; CEEAEU, Central and Eastern Europe; CHINAR, Greater China; ESEASP, East and Southeast Asia and the Pacific excluding China; HIGHIN, high income countries; SOASIA, South Asia excluding India; SOTRLA, Southern and Tropical Latin America; SUSAAF, sub-Saharan Africa. See Table S4 for country grouping.

Table 2. Change in dietary protein.

<table>
<thead>
<tr>
<th>Region</th>
<th>Mean change in protein intake (%)</th>
<th>Mean change in protein intake (%), plant-based diet</th>
<th>Difference in protein–energy ratio (aCO2 minus eCO2, %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CALACA</td>
<td>−1.99 (−3.61, −0.36)</td>
<td>−4.03 (−6.64, −1.42)</td>
<td>−0.20 (−0.37, −0.04)</td>
</tr>
<tr>
<td>CANAME</td>
<td>−5.04 (−7.29, −2.79)</td>
<td>−7.87 (−10.88, −4.85)</td>
<td>−0.52 (−0.75, −0.29)</td>
</tr>
<tr>
<td>CEEAEU</td>
<td>−3.43 (−4.90, −1.97)</td>
<td>−8.19 (−10.6, −5.77)</td>
<td>−0.39 (−0.55, −0.22)</td>
</tr>
<tr>
<td>CHINAR</td>
<td>−4.91 (−6.06, −3.75)</td>
<td>−8.86 (−10.4, −7.32)</td>
<td>−0.57 (−0.71, −0.44)</td>
</tr>
<tr>
<td>ESEASP</td>
<td>−4.01 (−5.51, −2.52)</td>
<td>−6.78 (−8.96, −4.59)</td>
<td>−0.36 (−0.50, −0.23)</td>
</tr>
<tr>
<td>HIGHIN</td>
<td>−2.67 (−3.65, −1.68)</td>
<td>−7.95 (−9.91, −5.98)</td>
<td>−0.32 (−0.43, −0.20)</td>
</tr>
<tr>
<td>India</td>
<td>−5.34 (−7.02, −3.66)</td>
<td>−7.04 (−9.02, −5.05)</td>
<td>−0.47 (−0.61, −0.32)</td>
</tr>
<tr>
<td>SOASIA</td>
<td>−4.69 (−6.44, −2.94)</td>
<td>−7.11 (−9.40, −4.82)</td>
<td>−0.43 (−0.59, −0.27)</td>
</tr>
<tr>
<td>SOTRLA</td>
<td>−2.40 (−3.46, −1.34)</td>
<td>−6.18 (−8.14, −4.22)</td>
<td>−0.27 (−0.38, −0.15)</td>
</tr>
<tr>
<td>SUSAAF</td>
<td>−2.03 (−4.05, −0.01)</td>
<td>−2.74 (−5.13, −0.30)</td>
<td>−0.18 (−0.36, 0.00)</td>
</tr>
<tr>
<td>World</td>
<td>−3.93 (−5.15, −2.70)</td>
<td>−7.14 (−8.91, −5.37)</td>
<td>−0.41 (−0.53, −0.28)</td>
</tr>
</tbody>
</table>

Figure 1. Per-country change in dietary protein intake under elevated carbon dioxide [eCO2 (%)]. Baseline intake is based on Food and Agriculture Organisation of the United Nations Food Balance Sheets (FAO FBS) estimates, and changes are calculated from decreases in protein content in the edible portions of crops when grown under eCO2. Data were plotted using the Rworldmap package in R (version 3.2.4; R Development Core Team).
(Blome et al. 2003), but this is likely to be negligible compared with the effects on plant-based protein sources. Those who consume the least protein have diets more dependent on plant protein, and these people are more vulnerable to eCO2 effects on plant protein. This is likely to extend the lower tail of the intake distribution, increasing the severity and prevalence of protein inadequacy. Our estimates are worst-case scenarios where no substitution of animal-sourced protein sources for other high-protein foods is allowed. In particular, the predicted large decreases in protein content of plant-based diets in high income countries may be overestimates, where plant-based diets are likely to be supplemented with other protein sources.

The countries that we estimated to be currently most at risk of protein deficiency are also those with the greatest estimated prevalence of undernourishment (FAO 2014b), increasing confidence in our estimates; however, energy balance and nitrogen balance interact (Garza et al. 1976). For simplicity, we modeled overall protein intake and risk of deficiency based on the EAR, which assumes adequate energy intake. Published EARs are defined for zero protein balance, which is a conservative estimate of protein requirements (IOM 2005). Older, sedentary people and those suffering from or recovering from illness are likely to be at greater risk of deficiency in any population (Ghosh 2013). We have not accounted for current or future patterns of illness in our estimates of EAR. Furthermore, we have not considered changes in protein quality; however, several studies have shown that essential amino acids tend to be relatively preserved at the expense of nonessential amino acids under eCO2, and degradability may decrease (Högy et al. 2009; Wroblewitz et al. 2013). Bioavailability may change, for example, if meal composition and thus digestibility changes. Furthermore, levels of secondary metabolites, including toxins, tend to increase under elevated CO2 (Cavagnaro et al. 2011), which could decrease protein bioavailability.

In addition to increasing the risk of protein deficiency, there may be other nutritional consequences of changing the stoichiometry of carbohydrate-to-protein ratios in staple food crops. For example, replacing dietary carbohydrate with protein has been shown in interventional trials and observational studies to 15-y duration, and in diverse countries including Japan, China, the United States, and Chile, to improve cardiovascular disease risk through lowering blood pressure and changing lipid profiles (Hu et al. 1999; Obarzanek et al. 1996; Appel et al. 2005; Altorf-van der Kuil et al. 2010; Rebholz et al. 2012). Improvements are often greatest with plant-rather than animal-sourced protein (Altorf-van der Kuil et al. 2010). These experiments underscore the need for additional investigation into whether replacing plant-sourced protein with plant-sourced carbohydrate could exacerbate the already concerning pandemic of metabolic disease driving increased cardiovascular morbidity and mortality globally.

It is unclear how trends in dietary quality will be counterbalanced by the effects of population growth and climate change. That is why, for our analysis, we assume no future change to food composition of diets or to per capita food intake and no dietary substitution to compensate for deficits. Agricultural production will need to roughly double to match increasing demand by 2050 (Alexandratos 1999). Climate change may pose the greatest challenge to this need. Climate change-induced reductions in crop yield are expected to be greatest in lower-latitude regions, including developing countries and those dependent on C4 crops (Rosenzweig et al. 2014). Resulting economic changes may shape future diets, and changes to water, soils, and weather in these areas may affect crops in ways that may overwhelm, or exacerbate, the effects of eCO2. For example, decreases in yield...
requirement based on 2050 demographic projections; eCO2 elevated atmospheric carbon dioxide; ESEASP, East and Southeast Asia and the Pacific excluding China; HIGHIN, the Caribbean; CANAME, Central Asia, North Africa and the Middle East; CEEAEU, Central and Eastern Europe; CHINAR, Greater China; EAR, estimated average protein grouping.

under drought and warming temperatures may counteract the effects of rising CO2 on protein concentrations (Kimball et al. 2001). Only 37 of 99 study sites in our meta-analysis were in countries outside of Europe and North America, and only just over half of the studies were performed in the field, with only 10% involving waterering experiments (see Table S1). Most experiments were undertaken over 1 y only, and effects on crop nutrient content may not match those under the next 50 y of gradual atmospheric CO2 increase. The consistent decreases in protein contents across C3 crop cultivars, including 47 wheat cultivars and 27 rice cultivars, reassure us that our results are generalizable to other cultivars. Nevertheless, to better predict the dietary impacts of eCO2, we need more long-term field-based eCO2 experiments involving plants and cultivars grown under the climates and farming practices applicable to the developing world.

We also assumed that global population growth and future demographic trends will match UN projections, which include declining fertility rates, and migration from developing to developed countries (UN 2013). However, the greatest population growth is projected to occur in areas most vulnerable to climate change (Watts et al. 2015). Climate, economic, and demographic changes will likely interact, producing a global population distribution that we are not yet able to fully comprehend. In the absence of conclusive projections of future food production, we believe it is the most conservative, albeit perhaps optimistic, assumption that per capita food intake will remain constant despite sharp increases in global demand.

In predicting the nutritional consequences of eCO2, other nutrients must be considered. Zinc and iron concentrations are greatly decreased in C3 plants grown under eCO2 (Myers et al. 2014). Zinc is a cofactor for protein synthesis, and protein inadequacy decreases uptake and availability of other nutrients (Gropper and Smith 2008). A recent analysis predicts strong increases in the risk of global zinc deficiency with eCO2 (Myers et al. 2015). Identifying the countries most vulnerable to future malnutrition requires a targeted synthesis of crop research on climate and CO2 responses. This information can then be applied to global climate and atmospheric models.

To our knowledge, this is the first global comparison of dietary protein that estimates a country-specific CV. Like energy consumption, the variability of protein consumption in a population relates to the Gini coefficient (Raubenheimer et al. 2015). Our use of this metric would be expected to produce more accurate estimates than the previously used 25% CV (Ghosh 2013). The WHO continues to refine its models of energy intake variability based on gross domestic product (GDP), Gini, and food prices, using skew log rather than lognormal distributions. As this methodology becomes available, future work could incorporate these considerations to produce better estimates of protein consumption.

Because added fertilizer did not predictably mitigate the effects of CO2 on crop protein, and with the production and application of fertilizer being a principal contributor to agricultural greenhouse gas emissions (Vermeulen et al. 2012), we cannot simply add more fertilizer to reduce the protein deficit. As populations increase, and with livestock production being resource-intensive (Vermeulen et al. 2012), eating more meat is not a practical solution. Cultivars could be selected or bred based on their nutritional content under eCO2. In addition to efforts to mitigate CO2 emissions, nutritious and resilient crops should be promoted, for example legumes, which will withstand the effects of eCO2 on protein content. Because eCO2 may have the greatest effect on the protein intake of those with the poorest diets, more equitable food distribution, and poverty reduction measures should be a focus for minimizing risk of deficiency.

Conclusions

Anthropogenic CO2 emissions, via their impact on the protein content of C3 staples, may threaten the adequacy of protein intake for many populations. Although quantifying protein deficiency is notoriously difficult, we have estimated current and future risk of protein deficiency by country and region, suggesting enduring challenges for sub-Saharan Africa and growing challenges for South Asia, including India. For nutritionally sensitive agriculture, the high CO2 effects on crop nutrient contents must be incorporated into future food security policies.

Acknowledgments

We thank A. Fangmeier for additional data generously shared, M. Smith for valuable comments and data, M. Stefan and R. Wessells for statistical advice, W. Willett for help with project conception, the Harvard University Center for the Environment for hosting D.E.M., and C. Hotz for her insights into the literature on protein deficiency.

Financial support was provided by the Bill & Melinda Gates Foundation and by the Winslow Foundation. Funding sources had no input into study design, data collection, analysis, data interpretation, report writing, or decision to submit the manuscript for publication.


