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Impacts of land use, population, and climate change on global food security

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Abstract

In recent years, global hunger has begun to rise, returning to levels from a decade ago. Climate change is a key driver behind these recent rises and is one of the leading causes of severe food crises. When coupled with population growth and land use change, future climate variability is predicted to have profound impacts on global food security. We examine future global impacts of climate variability, population, and land use change on food security to 2050, using the modeling framework FEEDME (Food Estimation and Export for Diet and Malnutrition Evaluation). The model uses national food balance sheets (FBS) to determine mean per capita calories, hence incorporating an assumption that minimum dietary energy requirements (MDER) remain constant. To account for climate variability, we use two Representative Concentration Pathway (RCP) scenarios from the Intergovernmental Panel on Climate Change (IPCC), alongside three Shared Socio-economic Pathway (SSP) scenarios incorporating land use and population change within the model. Our results indicate that SSP scenarios have a larger impact on future food insecurity, in particular because of projected changes in population. Countries with a projected decrease in population growth had higher food security, while those with a projected rapid population growth tended to experience the worst impacts on food security. Although climate change scenarios had an effect on future crop yields, population growth appeared to be the dominant driver of change in undernourishment prevalence. Therefore, strategies to mitigate the consequences of projected population growth, including improved maternal health care, increasing equality of access to food at the national level, closing the yield gap, and changes in trade patterns, are essential to ensuring severe future food insecurity is avoided.

KEYWORDS

FEEDME model, food security, undernourishment

1 | INTRODUCTION

Global hunger is currently rising and has been since 2014, after years of decline (FAO et al., 2018). The proportion of undernourished people worldwide increased to 10.6% in 2015 and then to 11% in 2016 (UN, 2018). According to the Food and Agricultural Organisation (FAO) of the United Nations, the number of undernourished people in the world reached an estimated 821 million in 2017, which is around one in nine people (FAO et al., 2018). This rise in food insecurity indicates a significant risk of falling short of achieving the Sustainable Development Goal (SDG) target of hunger eradication by 2030 (FAO et al., 2018).

Food security was defined at the 1996 World Food summit as "existing when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2008). It is determined by four main factors: (1) availability, for example, access to productive land and agricultural production, (2) access, physically, socially and economically, (3) utilization, for example, food preparation and diversity of diet, and (4) stability across the first three dimensions. Major disasters, for example, would affect the stability of a countries' food security, of which 80% of those internationally reported are climate related (FAO et al., 2018).

Climate variability and extremes are a significant driver of increases in global hunger (FAO et al., 2018). The changing nature of climate variability and extremes negatively affects all four dimensions of food security (FAO et al., 2018). It has direct impacts on crop production, with an estimated 3.1%–7.4% reduction in global yields of major crops for each degree-Celsius increase in global mean temperature (Zhao et al., 2017). Using a 2005 baseline, projections forecast an increase in global crop demand of 100%–110% by 2050 (Tilman et al., 2011), which is propelled by population growth and greater per capita income (Godfray et al., 2010). Even more recent projections which use 2014 as a baseline estimate an increase in production of 25%–70% is necessary for meeting crop demand in 2050 (Hunter et al., 2017).

The world's population is currently growing by approximately 1.1% per year, and if current trends continue, according to the medium-variant projection, the world's population is projected to reach 9.7 billion by 2050 (UN, 2019). Despite inherent uncertainty in population projections, with recent years overestimating population growth (Keilman, 1998), it is with 95% certainty that by 2050, the global population will stand between 9.4 and 10.1 billion (UN, 2019). More than half of this anticipated growth is expected to occur in sub-Saharan Africa, adding 1.05 billion people between 2019 and 2050 (UN, 2019). Two-thirds of the projected growth is projected to be attributed to current age structures, hence even if fertility levels declined, population growth would continue (UN, 2019). The majority of the increase in global population, however, can be attributed to a small number of countries. From 2019–2050, more than half of the world's population growth will be concentrated in just nine countries: India, Nigeria, Democratic Republic of the Congo, Pakistan, Ethiopia, Tanzania, the United States of America, Egypt, and Indonesia (UN, 2019).

The majority of these are low-income countries (LIC); hence, it is expected that there will be limited resources and access to technology to sustainably produce more food for growing populations. Although investment of agricultural GDP in technology is increasing worldwide, it is uneven, with spending equivalent to 3.25% in high-income countries (HIC). For LICs, where the vast majority of increased food demand will occur and the greatest impact could be seen from closing the yield gap, only 0.52% of agricultural GDP is spent on investing in research and development, despite strong evidence that this investment effectively alleviates poverty (Fuglie et al., 2020; Tilman et al., 2002). A lack of investment in technology coupled with increased fluctuations in crop yields due to climate change could lead to an accelerated cropland expansion into unsuitable lands, including conversion of natural forests (Lambin & Meyfroidt, 2011). Matching the rapidly increasing and changing demand for food, in ways which are environmentally and socially sustainable, while making sure no one goes hungry is one of the worlds' biggest challenges (Godfray et al., 2010). However, future projections of population, land use, and crop yield changes vary with different socioeconomic and climate conditions. Therefore, in this study we aim to compare future effects on global food security across a range of scenarios, building on the Dawson et al. (2016) study, which examined the impacts of changes in crop yields on global food security under the SRES A1B climate scenario.

In this study, we use two representative concentration pathways (RCPs) to demonstrate climate change impacts on future crop yields. We also examine three Shared Socioeconomic Pathways (SSPs) projecting different population change and cropland expansion scenarios to 2050. By altering the parameters of the Food Estimation and Export for Diet and Malnutrition Evaluation (FEEDME) model according to these scenarios, we have three main objectives: firstly to compare impacts of different scenarios on national food security; secondly to indicate the key drivers of undernourishment prevalence from making these comparisons; and thirdly to demonstrate which areas on a global scale are most likely to be at risk of undernourishment in the future across all scenarios considered. This is in order to direct climate change mitigation and adaptation, and food security strategies.

2 | METHODS

The FEEDME model as described in Dawson et al. (2016) was used to analyze undernourishment prevalence at a national

level. This modeling framework, as detailed in Figure 1, uses the dietary energy provision-based methodology adopted by the FAO (FAO, 2004) to allow for comparability between current, historical, and future levels of food insecurity at a national or global scale. This approach has become the standard for rapid assessment of undernourishment as an indicator of food security. The FAO indicator of the Prevalence of Undernourishment (*PoU*) is defined as "the percentage of a population whose food intake in terms of dietary energy in kilocalories is insufficient to meet requirements on a continual basis" (Hall et al., 2017). It is an internationally recognized indicator routinely used by international agencies, governments, and NGOs alike since 1998 and is evaluated with reference to a mean daily calorie threshold. This is described as a Minimum Dietary Energy Requirement (MDER) as established by nutritionists, and a probability distribution of habitual Dietary Energy Consumption of a representative individual in a population. Each country has a mean per capita MDER threshold based upon their demographic structure; therefore, the proportion of the population with food consumption below the MDER is considered by the model as undernourished.

The relatively simple parametric methodology used to calculate *PoU* for a population is able to account for two of the important aspects of food insecurity, specifically; *availability*, using mean calories (kcal person^{-1} year^{-1}) estimated from Food Balance Sheets (FBS), and differential *access*, estimated from a measure of the inequality of access to food across a population. The latter, drawing upon extensive household surveys, uses a two-parameter lognormal or three-parameter skew-normal and skew-lognormal curves to define a stylized relationship between household income and food consumption whose shape is characterized by a coefficient of variation (CV) as a parameter accounting for inequality in food consumption and a skewness (SK) parameter accounting for asymmetry in the distribution. Further information on the equations and assumptions used to derive CV and SK directly from available household survey data are described in Wanner et al. (2014). Likewise indirect methods through using macroeconomic relationships between CV and national-level Gini coefficient of income inequality (Gini), GDP, and infant mortality data are also described (Wanner et al., 2014).

FEEDME integrates the FAO methodology with country level statistics from the FAOSTAT database for use in future scenarios of climate, population, and socioeconomic changes. Within this database, food balance sheets (FBS) are compiled for each country annually, which are assumed to be the best available data despite their limitations for LICs. They specify estimates of national-level food production, imports, exports, and food availability on a per capita basis as well as in calorific values for all food commodities. The FBS for 175 countries were downloaded from the FAOSTAT website and subsequently reformatted to standardize spreadsheets for automatic manipulation of the data using the FEEDME model. Specifically, three aspects were altered manually: (a) changes in crop yields, and hence crop production, as a result of climate change, (b) land use change in terms of total area under cultivation, and (c) population changes under each scenario.

The first aspect manually altered was changes in crop yields under climate scenarios. This analysis covers two Representative Concentration Pathways which are the latest atmospheric concentration scenarios adopted by the Intergovernmental Panel on Climate Change (IPCC) for its fifth Assessment Report in 2014. We use RCP2.6 and RCP6.0 which were elected for their representativeness at the end of the 21st century (van Vuuren et al., 2011; Van Meijl

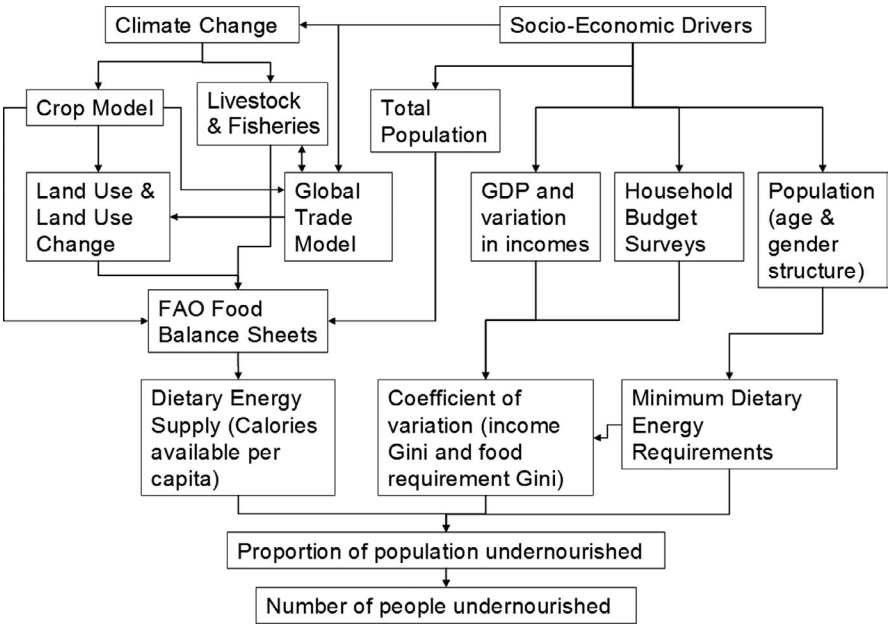

FIGURE 1 Systematic diagram of FEEDME model (Dawson et al., 2016)

et al., 2017). RCP2.6 represents the range of lowest greenhouse gas emissions, requiring strict climate policies to limit emissions and is also the lowest in terms of energy intensity (van Vuuren et al., 2011). RCP6.0 has a heavy reliance on fossil fuels, while RCP2.6 sees declines in use of oil as a result of depletion and climate policy (van Vuuren et al., 2011). Climate change effects on crop yields from these two scenarios were incorporated into the FEEDME model using regionally aggregated annual growth rates for three reference crops: wheat, maize, and soybean (Van Meijl et al., 2017). The relative change in production from the baseline year (2000) for the three reference crops were mapped to a wider list of food items (Table 1) in the countries FBS as outlined in Dawson et al. (2016).

The three reference crops were chosen due to their global significance, as well as reasons of data availability and modeling complexity. Although this approach has limitations, the individual crops chosen represent three large crop categories. All crops follow a C3 or C4 photosynthetic pathway; hence, it is assumed that changes in productivity will be similar for crops categorized into monocot C3 (wheat), monocot C4 (maize), or dicot C3 (soy) when grown in optimal conditions with no constraint on resources. It is important to note there are a range of factors which have not been considered which

TABLE 1 Assignment of FBS commodities to reference crops for projection of production changes

Group	Reference Crop	FBS commodities: summary	FBS commodities: individual
C4 (cf maize)	Maize crop yield data	Cereals, sugar crops, Vegetable Oils	Maize, millet, sorghum, sugarcane, maize germ oil
C3 (cf wheat)	Wheat crop yield data	Cereals, Alcoholic Beverages	Wheat, rice, barley, rye, oats, other cereals, beer
C3 (cf soy)	Soybean crop yield data	Pulses, Oil crops, Vegetable Oils	Soybeans, groundnuts, sunflower seed, rape and mustard seed, cottonseed, sesame seed, other oil crops, soybean oil, groundnut oil, sunflower seed oil, rape and mustard oil, cottonseed oil, sesame seed oil
Other	No change	Starchy roots, sugar crops, tree nuts, vegetables, fruits stimulants, spices, miscellaneous	Sugar beet, honey, coconuts, palm kernels, olives, palm kernel oil, palm oil, coconut oil, olive oil, wine, beverages (fermented and alcoholic)
Meat/dairy	Currently assume no change	Meat, offals—edible, animal fats (inc milk), eggs	
Aquatic	Currently assume no change	Fish, seafood; fish oils; aquatic products, other	
Sugars & Sweeteners	Based on dominant production from either sugarcane (C4) or beet (no change) above		

would produce variation between different crops and are outside the scope of this study. However for some, for example, differences due to light-use efficiency (LUE) of individual crops (the ratio of net primary productivity to absorbed photosynthetically active radiation) the difference is minimal (1%–2%). The chosen reference crops vary in their LUE from high to low (Slattery & Ort, 2015), hence can represent a wide range of crops, but the differences in LUE have a much smaller effect on productivity in comparison with climate change effects incorporated within the crop model data used for this study.

For each region, we calculated total change in crop yields over the 50 year period 2000–2050 based on estimated annual growth rates for each of the reference crops from biophysical crop modeling data produced under AgMIP (Agricultural Model Intercomparison and Improvement Project, Van Meijl et al., 2017), which were regionally aggregated into thirteen coherent spatial regions. This was used to revise the crop production values in the FBS for each country based on the region within which it was located.

Three Shared Socio-economic Pathways; SSP1, 2, and 3 were also used to provide the model with population and land use change projections, which were the other two aspects manually altered in the model. The SSP scenarios are defined as "reference pathways describing plausible alternative trends in the evolution of society and ecosystems over a century timescale" (O'Neill et al., 2014). SSP1 is the "greenest" scenario, representing low challenges for mitigation and adaptation to climate change. Sustainable development proceeds at a high pace, lessening global inequalities, and there is rapid technological change toward low carbon energy sources. SSP2 is an intermediate scenario representing moderate challenges and a future where development trends follow a "middle of the road" pathway consistent with typical patterns observed over the last century. SSP3 represents significant challenges for mitigation and adaptation to climate change, with slow technological change and a rapidly growing population. Emissions are unmitigated, there are reduced trade flows and, due to a lack of investment in human capital, large numbers of people are left vulnerable to climate change impacts with low adaptive capacity. (O'Neill et al., 2017). This scenario, when coupled with RCP6.0 (RCP6.0 SSP3), is what we describe as the scenario with the highest global impact (HGI), while SSP1 with RCP2.6 (RCP2.6 SSP1) is described as the scenario with the lowest global impact (LGI).

In this study, we look specifically at change in total area of cropland under each SSP scenario, using land use change data from the IMAGE 3.0 model. The change in total cropland area from 2010–2050 was extracted per country and percentage increase calculated over the specified time frame. Although country FBS existed for 175 countries as examined in Dawson et al. (2016), we examine only 159 here, due to a lack of availability of either land use change or population data for the excluded countries. These countries were often small islands for which the land use change data were not available due to the coarseness of the data.

The FEEDME model was run for each of the 159 countries both for the baseline period (2000–2002) and for projections to the year 2050, using population projections taken from each SSP scenario a well as modifying the crop yield and land use changes as described above. Although the baseline is 2000, the FBS were based on the mean of years 2000–2002 to reduce effects of any anomalous change in production in any one year. Both the total number of people undernourished and the undernourishment prevalence (probability of undernourishment) were produced as results, yet we present only the latter in this study. This is to enable comparison with previous studies (Dawson et al., 2016; Hall et al., 2017) as well as official FAO publications. The model adopts the following assumptions:-

1. national-level population demographic structures (age and gender) remain the same as the year 2000;
2. income and food inequality Gini coefficients remain the same as the year 2000 values;
3. minimum dietary energy requirements (MDER) for a country remain constant throughout the 21st century;
4. food trade (imports and exports) are held constant through the 21st century for each country;
5. dietary patterns remain constant until 2050.

These assumptions pose a limitation to the model, particularly the assumption of no change to food imports and exports, as this leads to a projected increase in undernourishment even without climate change effects, due to population growth projections if the country cannot meet population requirements through national production. While the assumption of no change in international trade is unrealistic, the results highlight the potential shortfall in imports which are needed to address national food needs. Hence, undernourishment prevalence should be interpreted as an indicator of exposure to undernourishment in the absence of no adaptation or mitigation responses. When faced with an increased proportion of people who are undernourished, responses often consist of increasing national food production or changing international food trade agreements, which are difficult to predict.

3 | RESULTS

Undernourishment for the baseline period 2000–2002 is shown in Figure 2 for which the prevalence of undernourishment scale was adopted from the FAO Hunger Map 2015. To validate model results, we compare baseline figures produced by FEEDME for each country to published FAO figures for the period 2000–2002 (FAO, 2004). This showed

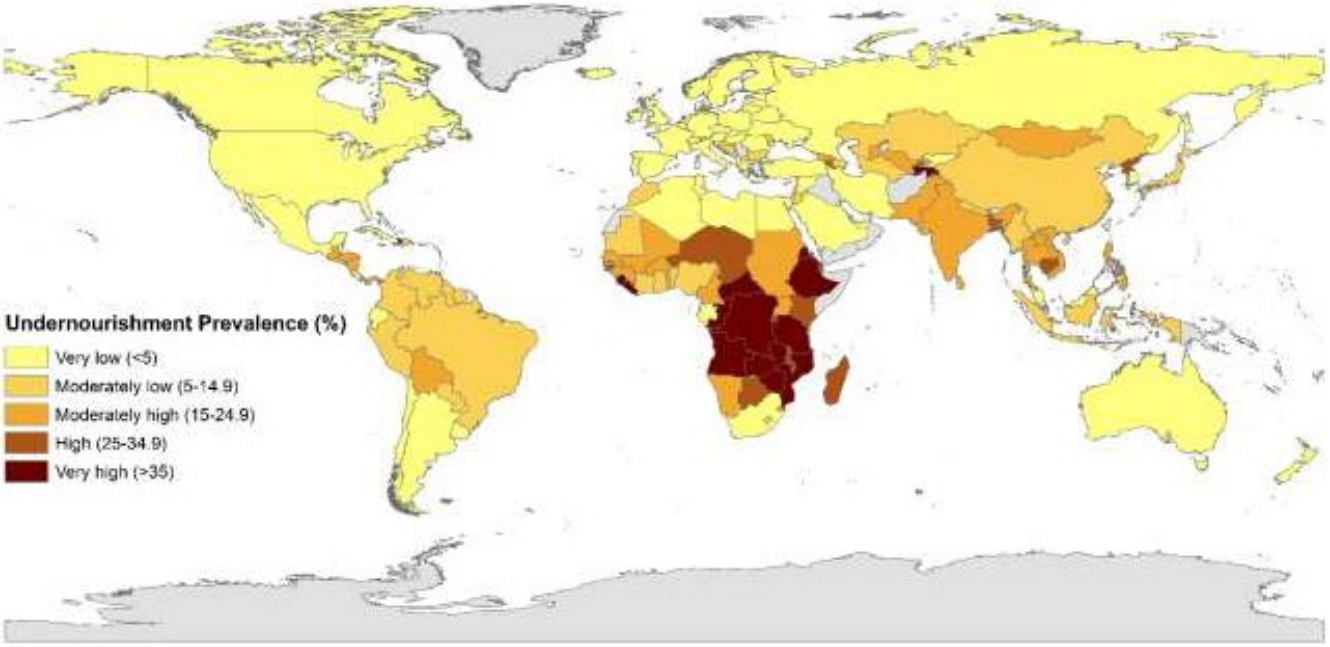

FIGURE 2 Global map showing the proportion of the population undernourished in each country for the baseline period 2000–2002 as simulated by the FEEDME model

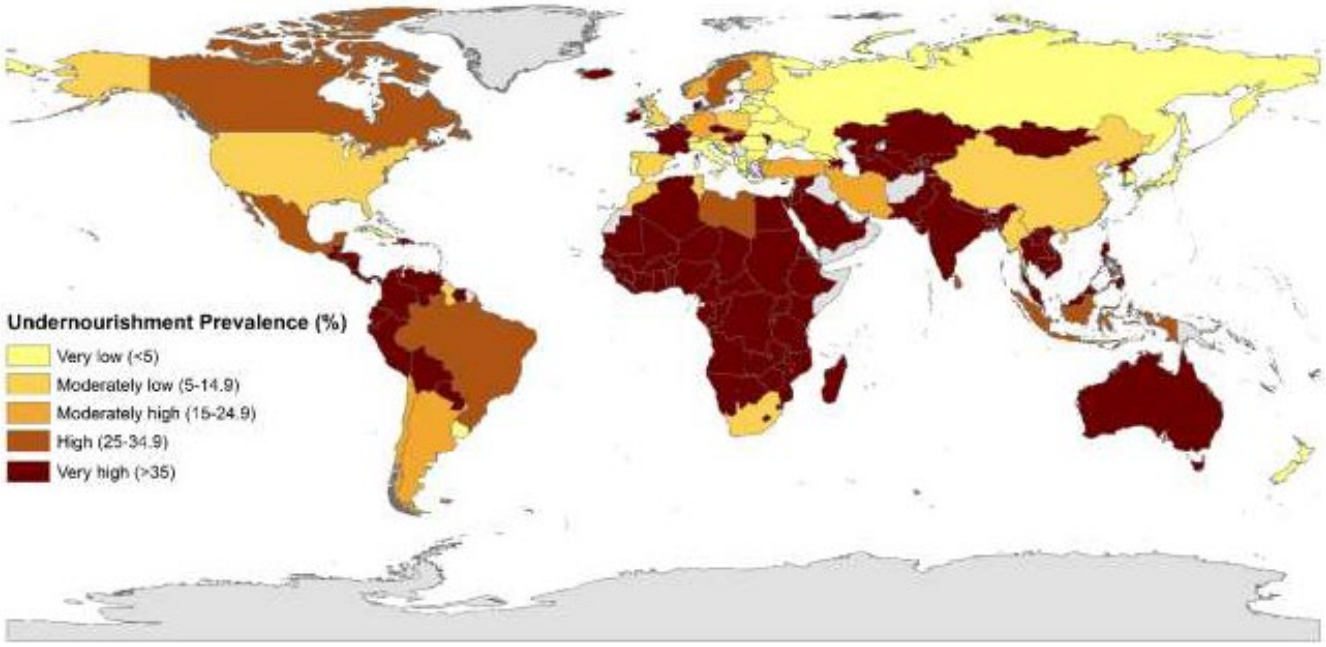

FIGURE 3 Global map showing the proportion of the population undernourished in each country for the lowest global impact (LGI) scenario, RCP2.6 SSP1

that 88% of listed "developing" and "in transition" countries were within 5% of FEEDME results, with a Person's correlation coefficient of 0.98. It is worth noting that FAO does not differentiate below 2.5% undernourishment prevalence; hence, countries with less undernourishment prevalence were listed as 2.5%. The vast majority of countries not listed in this report in North America and Europe were shown to have <2.5% undernourished according to web-based data. When these countries are also incorporated, 90% of countries are shown to be within 5% difference, with a Pearson's correlation coefficient of 0.99 (Table A1). Minor differences are explained by FEEDME using population values from the year 2000, while the FAO results are based on an average of three years of undernourishment calculations (2000–2002).

Undernourishment prevalence for RCP2.6 SSP1 and RCP6.0 SSP3 are presented (Figures 3 and 4), which incorporate land use change. These scenarios are the lowest and highest impact on global food security, with RCP2.6 SSP1

having the lowest average prevalence of undernourishment globally and RCP6.0 SSP3 having the highest (Figure 5).

In both the lowest and highest global impact scenarios, there is a considerable increase in the number of countries with a very high prevalence of undernourishment (Figures 2–4), particularly in the HGI scenario (Figure 4). In this scenario, almost the whole of Latin America, Africa, and parts of South East Asia are projected to have a very high prevalence of undernourishment (Figure 4). This scenario shows significant polarization between HICs and LICs, with most countries either being in the top or bottom category of the undernourishment prevalence scale (Figure 4). In contrast, for the LGI scenario, although the majority of Africa is still projected to have a very high prevalence of undernourishment, there is considerably more variation across Latin America and South East Asia (Figure 3).

Figure 5 shows the global average undernourishment prevalence for the baseline as well as each of the scenarios. In every scenario, undernourishment prevalence more than triples. The baseline shows less than 15% undernourishment, while every scenario shows an average of over 50% being undernourished. This graph also shows RCP2.6 SSP1 being the LGI scenario and RCP6.0 SSP3 being the HGI, with the highest prevalence of undernourishment globally, reaching almost 60% (Figure 5).

For the vast majority of regions, scenarios all show higher mean prevalence of undernourishment than the baseline, with the exception of China for which two scenarios show a lower undernourishment prevalence (Figure 6). There is variation in the patterns shown compared to the scenarios observed on the global scale. For example, in LICs such as in sub-Saharan Africa (SSA), Brazil (BRA), and Other South America (OSA), the same pattern is shown across the scenarios, with RCP2.6 SSP1 being the lowest impact and RCP6.0 SSP3, the highest, with impacts increasing across SSPs 1–3 (Figure 6). The opposite effect, however, is seen in HICs, for example in Europe (EUR), Canada (CAN), and America (USA), with the lowest impact seen in RCP6.0 SSP3 and the highest in RCP2.6 SSP1 (Figure 6).

4 | DISCUSSION

Agricultural production is very vulnerable to climate change (Osborne et al., 2013). Climate change will affect temperature, precipitation, and wind speed which all have an effect on water availability and other ecosystem services on which agriculture relies, hence consequentially on crop yields (Calvin et al., 2013). Therefore, understanding the impact of these changes on food production is essential to ensure future global food security (Zhao et al., 2017). There are limited positive impacts of climate change, for example, longer growing season in northerly latitudes. However, the vast majority of results are homogeneous across major food crops and geographical areas, with decreases in yield projected for each climate scenario (Wiebe et al., 2015; Zhao et al., 2017). Adverse impacts of climate change are particularly strong for oilseeds (Wiebe et al., 2015) which could contribute to regional variation in undernourishment prevalence. However, for all crops considered in this study, there are only a small

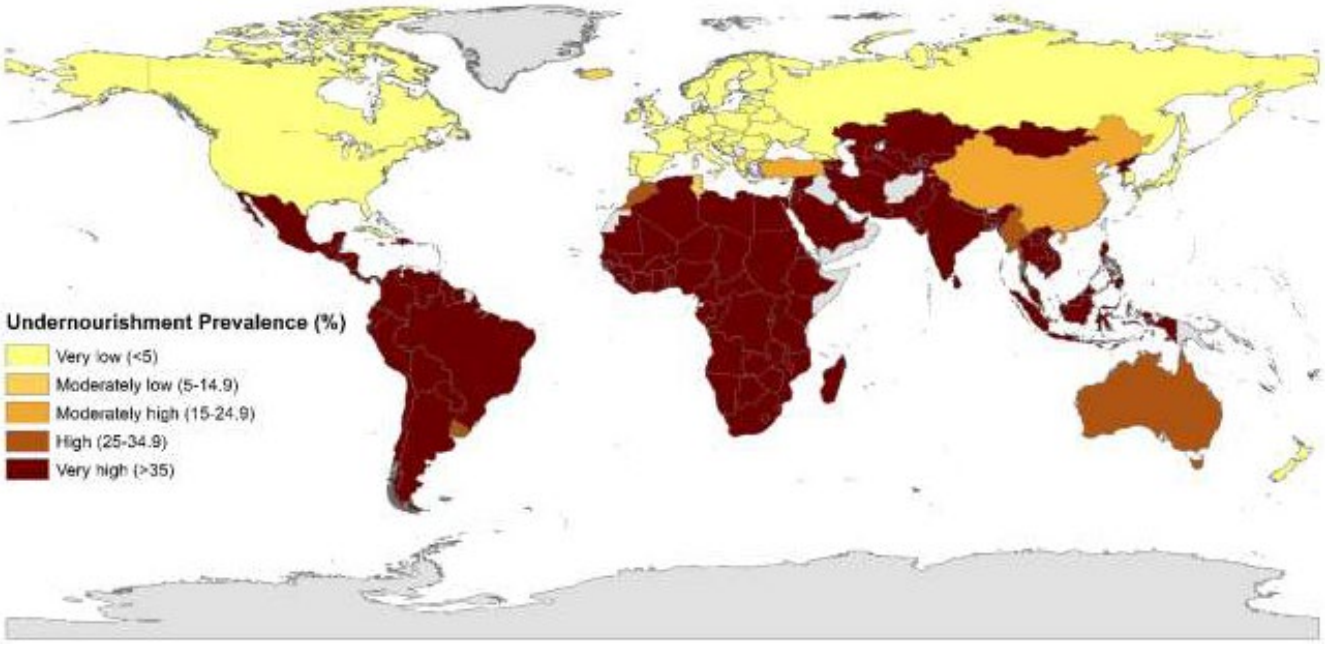

FIGURE 4 Global map showing the proportion of the population undernourished in each country for highest global impact (HGI) scenario, RCP6.0 SSP3

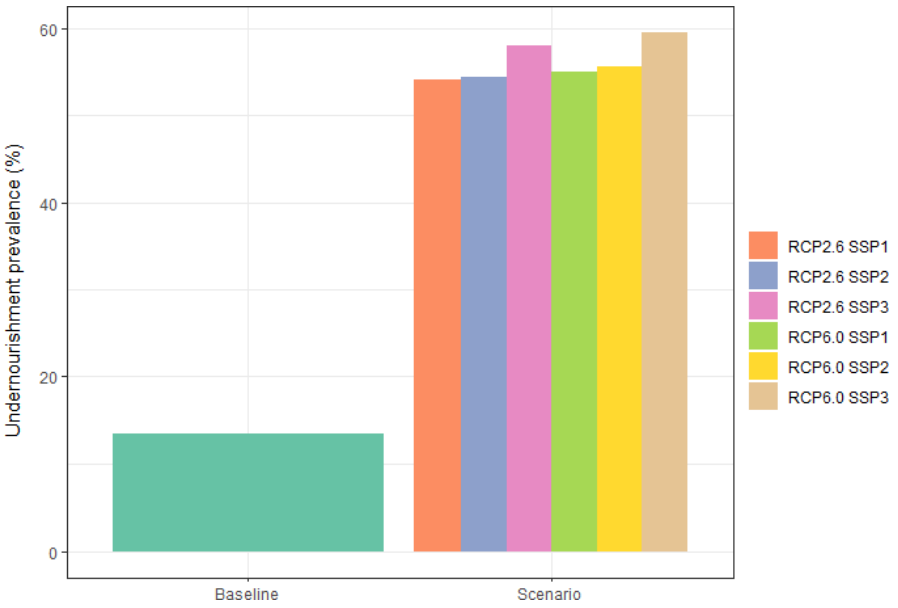

FIGURE 5 Graph showing the mean global undernourishment prevalence across all scenarios compared to the 2000–2002 baseline

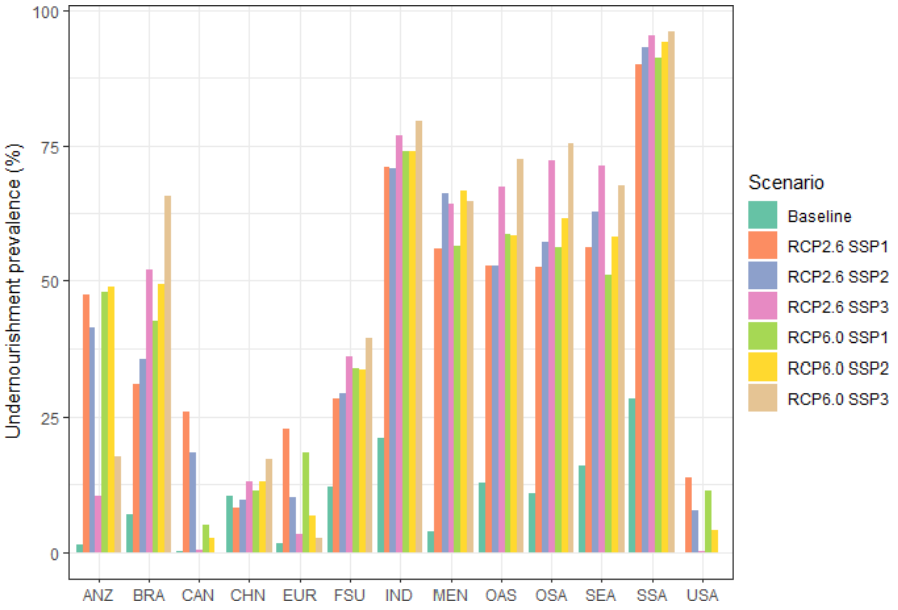

FIGURE 6 Graph showing the mean undernourishment prevalence across all scenarios within each region defined by (Van Meijl et al., 2017)

handful of regions under each climate scenario which are projected to see small increases in annual growth rates from 2000–2050 (Van Meijl et al., 2017). Hence when coupled with projected population growth, land use change, that is, cropland expansion is not shown to contribute significantly to food security. Results from this study show both globally (Figure 5), and in the vast majority of regions (Figure 6) and countries (Figure A1), there is a higher risk of undernourishment in every scenario examined (Figure 5).

For every scenario, undernourishment prevalence dramatically increases compared with the baseline, which averages 13% (Figure 5). This is also the case on a regional scale, with one exception (Figure 6). For China, two scenarios show a lower prevalence of undernourishment: RCP2.6 SSP1 and SSP2. The reason for this is both a reduction in population in SSP1 and 2, and higher crop yields in RCP2.6 as opposed to RCP6.0. Higher crop yields, combined with lower population projections, results in lower prevalence of undernourishment. This is despite decreases in total cropland area in these scenarios, showing that climate and population changes have a larger effect in this region. Previous studies in China also show projected decreases in cropland area, yet these climate scenarios show climate change to have a largely positive effect on crop yields, which combined with a plateauing population, exert a great impact on future trends of food security (Ye et al., 2013).

Although at the global scale the scenario with the largest impacts on the prevalence of undernourishment is RCP6.0 SSP3 (Figure 5), patterns vary considerably between regions (Figure 6). A clear difference is seen between low- and

high-income regions, with sub-Saharan Africa (SSA) and Latin America showing the same patterns as the global mean (Figures 5 and 6). In contrast, high-income regions including North America and Europe (EUR) show the opposite pattern, where the largest projected prevalence of undernourishment is seen in what we describe as the "lowest global impact" scenario (Figure 6). This is also shown when the difference between the LGI and HGI scenarios are examined. As expected, the majority of regions show an increase in percentage of undernourished, however for Australasia, Canada, Europe, and the United States of America, there is a decrease (Figure A2).

There are several reasons for this, one being that the effects on crop yields tend to be less severe at higher latitudes which tend to be more developed (Calvin et al., 2013). In one study, the largest negative changes in crop yield as a result of climate change, with no adaptation occurs in LICs, averaging −9 to −11%, while in the majority of scenarios, production in HICs is estimated to increase by up to 11% (Parry et al., 2005). In RCP6.0 in particular, the annual growth rates of major crops are higher in high-income regions compared with tropical areas (Van Meijl et al., 2017). Furthermore, population growth is projected to be significantly lower for HICs (UN, 2019) and even decreases in SSP3 for some countries such as Canada. Therefore, smaller populations combined with increased crop yields results in undernourishment being less prevalent.

For low-income regions however, population growth is projected to be the most extreme, with the majority occurring in sub-Saharan Africa (UN, 2019). Projections predict that Africa's population will double from one to two billion by 2050 (Foresight, 2011) and rapid population growth is expected even when assuming a substantial reduction of fertility levels (UN, 2019). This is due to"replacement-level fertility" which means that even if the number of births per woman falls instantly to levels which will stabilize the population growth, it will continue to increase in future decades because of the young age structure of the population (UN, 2019). The concentration of population growth in the poorest countries will make it more difficult for governments to combat food insecurity and eradicate poverty (UN, 2019).

Across every scenario examined, almost the whole of the continent of Africa is in the "Very high" category of undernourishment prevalence (Figure A1). There are a couple of exceptions across all six scenarios, which are Morocco and Tunisia (Figure A1). For SSP1, Libya is also an exception yet is still in the "High" category of undernourishment prevalence (Figure 2, Figure A1). South Africa however shows the most extreme difference between the LGI and HGI scenarios, moving from "Moderately low" to "Very high," an increase of over 30% of its population projected to be undernourished. For the majority of scenarios, it is not in the highest category of undernourishment (Figure A1), a pattern also shown in (Hall et al., 2017). Without the impacts of climate change, Tunisia and Morocco are also shown as exceptions (Hall et al., 2017); however, this study shows more severe impacts with the most recent climate change scenarios.

Although not shown in the scale used, the vast majority of countries in sub-Saharan Africa project over 95% of the population to be undernourished in the HGI and over 70% in LGI, excluding only South Africa, Lesotho, and Mauritius. Furthermore, when compared to the baseline scenario, there is an astonishing average across all scenarios of a 91% increase of the population projected to become undernourished by 2050 (Figure A3). Sub-Saharan Africa not only shows the largest increase in undernourishment but also shows the smallest difference between LGI and HGI scenarios (Figures 3 and 4, Figure A2). Therefore, regardless of the future pathway taken, future undernourishment prevalence is projected to be severe for this region.

These extreme rates of undernourishment prevalence have previously been attributed to an increase in food demand driven by population growth, overshadowing the effects of climate change (Hall et al., 2017). This is also the case in this study, with a larger effect shown between socioeconomic scenarios than climate scenarios. The climate scenarios used however do not include the higher emissions pathways (RCP 8.5); hence, this finding is potentially a result of there being similar climate change impacts across low to moderate emissions pathways (Wiebe et al., 2015). This is seen in the example of sub-Saharan Africa, where undernourishment prevalence increases by 5% in sub-Saharan Africa between SSP1 and 3, yet only increases by 1% between RCP2.6 and 6.0. The impact of land use is even smaller, although on a global scale land use change will decrease undernourishment prevalence in SSP2 and 3. This is largely due to cropland expansion, of which there is less in SSP1; hence in this scenario, land use change increases undernourishment prevalence. However, there is less than a 1% difference for SSA when excluded, suggesting that the main driver of undernourishment prevalence will be driven by population growth.

The largest difference between the LGI and HGI scenarios is seen in South America, with an average increase in undernourishment of almost 30%, including Brazil (Figure A2). This is also reflected in Figures 2–4. There are no countries above the "Moderately high" category in the baseline scenario (Figure 2); however, several are projected to have "Very High" undernourishment prevalence in the LGI scenario, with all countries excluding Guyana being" Very high" in the HGI scenario (Figure 4). Therefore, unlike sub-Saharan Africa, future prevalence of undernourishment in South America will be highly reliant on the pathway society and climate change take. Climate change has a larger impact on this region with an average increase of 4% of the population becoming undernourished in RCP6.0 compared to RCP2.6. However, the biggest difference again is seen between SSP

pathways, with a 20% increase in undernourishment prevalence between SSP1 and SSP3.

Like with sub-Saharan Africa, if populations continue to increase while climate change reduces food production, there is likely to be increased undernourishment in the future. Although not shown in this study, the country with the highest numbers of people projected to be undernourished by 2050 as opposed to proportion of the population, across every scenario including the baseline, is India. It also has some of the highest proportions of its population projected to be undernourished (Figure 6) as well as the largest increase in proportion of its population undernourished when compared to the baseline scenario (Figure A3), after sub-Saharan Africa. Future projections with the lowest population growth in LICs have been shown to have the largest reduction in risk of hunger (Parry et al., 2005). However even within SSP1 where population growth is the lowest, there is still severe undernourishment prevalence (Figure A1).

This indicates that even in best case scenarios like SSP1, efforts still result in undernourishment being very high purely because of the assumption of no adaptation response. Population growth and demographic change are some of the biggest challenges for the food system in the next few decades (Godfray & Garnett, 2014). Drivers of fertility are a complex topic and it is beyond the scope of this paper to engage fully on this topic, but adaptations could include supporting continued increase in access to reproductive health care, including family planning, especially in LICs (UN, 2019). This, as well as improvements to education, can have positive effects on reducing fertility while also improving women's well-being and livelihoods (Lutz et al., 2008; Nargund, 2009; UN, 2019). In LICs, fertility rates tend to be higher; however, there is often a reduction in birth rates due to high maternal and perinatal mortality (Nargund, 2009). Therefore, improved health care to reduce mortality rates would, according to conventional demographic theory, lead to natural declines in fertility (Bongaarts & Casterline, 2012).

As well as a lack of access to contraceptives and generally lower levels of female education, high fertility rates in LICs are often ascribed to the need for a labor force and to provide care for parents in old age (Nargund, 2009). Fertility preferences however tend to change as a country develops and there is a strong inverse correlation between development indicators and fertility (Bongaarts & Casterline, 2012). Countries with declining population growth rates often see benefits in their economy and reductions in poverty (Lutz et al., 2008). Increased levels of income and education can then potentially in turn lead to fertility rates naturally declining (Nargund, 2009).

Other mitigation strategies include greater global investment in appropriate technology improvement as this is crucial for reducing environmental impacts of meeting future increased crop demand (Tilman et al., 2011; Willett et al., 2019). This is largely due to strategic, sustainable intensification, which has the potential to elevate yields of existing croplands of under-yielding nations and can meet the majority of 2050 global crop demand with limited land clearing and GHG emissions (Tilman et al., 2011). Africa in particular continues to have large yield gaps (Luan et al., 2018) and seeing as this is the region with the highest undernourishment prevalence projected, closing the yield gap could make a significant difference. However, the maximum attainable yield will shift with climate change effects, therefore maintaining or increasing productivity to close yield gaps will require continued innovation (Godfray et al., 2010). Improvements in fertilizer and water use efficiency as well as enhancing biodiversity and closing nutrient loops are also essential for sustainably intensifying food production and closing yield gaps (Willett et al., 2019). Substantial increases in public and private investment in technology and human resources are needed internationally, especially in low-income countries to ensure agricultural systems are sustainable, but there are few incentives for the private sector (Godfray & Garnett, 2014). Hence, it is important to note that although technological change could have a significant impact on food security, the sociopolitical will to ensure it becomes a reality is essential, and our results emphasize how crucial it is that we act quickly and effectively to avoid alarming rates of global food insecurity in the future.

There are a number of limitations to this study. In the undernourishment scale used to create the hunger maps, any countries with an undernourishment prevalence of over 35% were shown in the same category. Thus, variation in undernourishment above this threshold is not shown. Yet when the scale is altered to “equal intervals,” there is little difference, with almost the whole of sub-Saharan Africa still in the highest category of undernourishment prevalence. There are also limitations of using only three reference crops, which were used due to global importance and availability of climate change impacts on yields. Despite being representative of a large proportion of commodities (Slattery & Ort, 2015), undernourishment prevalence for countries that rely heavily on, for example roots and tubers, is likely to be over-estimated. Hence, results should be seen as indicative, not absolute. Inclusion of other globally important crops such as rice as the data become available would also be a significant contribution to future research, although it is important to note that production differences for individual crops will show a similar order of magnitude of change from climate change impacts, due to the similar but limited mechanisms of the photosynthetic pathways for all crop types.

Projected changes in meat or fish production are not included in the modelled scenarios. While meat and fish are important sources of dietary protein, they only contribute a relatively small percentage of the total mean energy budget per capita (Dawson et al., 2016). In countries that consume

higher proportions of meat and fish, for example the USA, it still only accounts for 12% and in LICs, this percentage is insignificant. Meat products in LICs contribute about 5% to per capita calorie consumption and consumption levels have changed relatively little over the last 30 years. Livestock production is also expected to show very low growth rates under future projections, with less than 1.6% annual growth rate on a global basis to 2030, with some HICs currently showing a decline in meat production (Alexandratos & Bruinsma, 2012). Yet it is still important to note that inclusion of climate change impacts on livestock could alter the results. For example, the quality and quantity of crops used as feed for livestock, as well as changes in species composition in grassland systems impacting livestock productivity (Thornton et al., 2009). Hence, it is recommended future research incorporate pasture as well as area under cropland within land use change variables. Although comprising of relatively few calories, these food sources are essential for delivering certain micronutrients, for example, zinc, iron, and B14 (Herrero et al., 2013; Nelson et al., 2018), which global studies often neglect. There is an important role therefore for animal source foods in achieving nutrition security, as opposed to food security (Nelson et al., 2018) and even small levels of consumption can substantially reduce undernutrition (Neuman et al., 2003; Randolph et al., 2007). Although incorporation into global modeling is unlikely, it could be possible to model on smaller scales, dependent on local data availability. Yet for both inclusion of meat production and more reference crops, it is highly likely that these changes will be minimal when compared to the extreme rise in projections of undernourishment from population growth and continued inequality of access to food, which remains a challenge.

Hidden hunger in the form of micronutrient deficiency is of particular concern in LICs and in some cases, climate change noticeably lowers adequacy ratios (Nelson et al., 2018). This is not captured using FAO methodology; hence, it is important to note that results of this study do not represent a comprehensive assessment of food security. In recognizing the complexity of monitoring food insecurity, the FAO (2001) stated "no direct measure of the state of food insecurity in the world will ever be possible" due to the inability to measure all of the dimensions that constitute food security at the level of individuals in a population. This methodology does cover two of the important aspects of food insecurity specifically availability of food, and differential access, and remains the de facto standard for reporting on the outcomes of policy interventions. However, a number of assumptions and limitations exist relating to both theoretical foundation and the methodological principles of a parametric approach. The methodology uses few parameters and variables that are used to characterize undernourishment. But these have been calculated from extensive household survey data and national agricultural census data to estimate the distribution of access to food across a population and Food Balance Sheets (FBS), respectively.

Concerning the FEEDME model, there are three main areas of uncertainty: firstly, the use of the curve fit to characterize the variability of distribution of food consumption across the whole population; secondly, estimates of the cutoff point for intake inadequacy defined on the basis of Minimum Dietary Energy Requirements (MDER) referring to the specification of the basic metabolic rates of individuals, which vary with sex, age, and the level of physical activity (Anand & Harris, 1992; de Haen et al., 2011); and thirdly, the utility and accuracy of FBS, which accounts for food availability, as a proxy for food consumption. While there have been criticisms (Naiken, 2007), the lognormal (skewed curve) model was initially adopted due its simplicity, requiring only two parameters to characterize it, specifically the mean calories and a coefficient of variation of dietary energy consumption (kcal Person^{-1} Day^{-1}) owing to income inequalities, expressed in terms of the well-known Gini coefficient. In 2012, the more flexible three-parameter skew-normal and skew-lognormal curves were adopted to account for more varying degrees of asymmetry and where more information from household surveys were available. Yet in defense of the methodology, the FAO has demonstrated it delivers an appropriate inference on the individual state of undernourishment through appropriate statistical treatment of available data, even if that datum is poor or inadequate (Cafiero, 2014).

The assumption of no changes to trade is also a limitation as there would be a projected increase in undernourishment based only on population growth (Dawson et al., 2016). This assumption produces a few unexpected results. Australia, for example, is quite unexpectedly predicted to incur very high rates of undernourishment prevalence in the majority of scenarios compared to other HICs (Figure A1). It is also projected to have the largest decrease of undernourishment when comparing the LGI to the HGI scenario (Figure A2). This is because there is reduction in crop yields as a result of climate change, as well as a decrease in cropland and an increase in population. Therefore by assuming current trade levels stay the same, for example, the country exports two-thirds of all grain produced, it is less surprising that Australia is projected an increase in undernourishment prevalence. However, the results of this study should therefore be treated as the proportion of the population potentially at risk of undernourishment, which trade could at least partly ameliorate.

Countries with high GDP have the capacity to reduce their food insecurity in times of crisis by altering their trade patterns. For example, Russia in 2010 banned all exports after drought and wildfires devastated domestic crops (Wegren, 2011). However, changes in trade do not improve food availability for all (Porkka et al., 2013). An increasing dependency on trade may lead to improved food availability for example, but mainly in regions with strong economies

(Porkka et al., 2013). It is therefore a significant challenge for regions such as sub-Saharan Africa which often rely heavily on food aid due to the lack the purchasing power needed to improve their own food security.

5 | CONCLUSION

Although climate change is predicted to have a large impact on future food security, this paper shows that population growth and land use change could have the largest impact. This study highlights the severity of potential hunger prevalence in the near future, especially in sub-Saharan Africa, across all scenarios if rapid mitigation measures are not taken. Some of these mitigation measures will be location specific; however, increased access to health care, closing the yield gap, and reforming trade in LICs are three options that could help to reduce the threat of future undernourishment, reverse current trends of increasing food insecurity, and help to meet the Sustainable Development Goal to eradicate global hunger by 2030.

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CONFLICT OF INTERESTS

The authors have no competing interests.

AUTHORS' CONTRIBUTIONS

All authors contributed to the study conception and design. AM lead the analysis, and all authors have revised the article and approved the final manuscript.

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APPENDIX A

TABLE A1 Undernourishment values for 159 countries generated by the FEEDME model compared to FAO values for baseline period 2000–2002

Countries	FEEDME	FAO	Difference
Albania	4.92692029	6	−1.07308
Algeria	4.558194472	5	−0.44181
Angola	35.36696135	40	−4.63304
Argentina	2.5	2.5	0
Armenia	29.18609593	34	−4.8139
Australia	2.5	2.5	0
Austria	2.5	2.5	0
Azerbaijan	11.1865929	15	−3.81341
Bahamas	4.719992272	n/a	n/a
Bangladesh	27.99151082	30	−2.00849
Barbados	2.5	n/a	n/a
Belarus	2.5	2.5	0
Belgium	2.5	2.5	0
Belize	3.196159453	n/a	n/a
Benin	11.84184776	15	−3.15815
Bolivia	19.97775643	21	−1.02224
Bosnia and Herzegovina	7.5172141	8	−0.48279
Botswana	26.56453455	32	−5.43547
Brazil	7.08846407	9	−1.91154
Brunei Darussalam	2.702363241	n/a	n/a
Bulgaria	8.195257235	11	−2.80474
Burkina Faso	15.41258966	19	−3.58741
Burundi	61.73783628	68	−6.26216
Cambodia	30.07121959	33	−2.92878
Cameroon	21.8979724	25	−3.10203
Canada	2.5	2.5	0
Central African Republic	39.4130695	43	−3.58693
Chad	29.49745539	34	−4.50254
Chile	2.902785759	4	−1.09721
China	10.35675725	11	−0.64324
Colombia	11.20459899	13	−1.7954
Comoros	55.50843873	n/a	n/a
Congo	35.33573298	37	−1.66427
Congo (Democratic Republic of the)	65.41766187	71	−5.58234
Costa Rica	3.333620646	4	−0.66638
Côte d'Ivoire	11.21776147	14	−2.78224
Croatia	7.745260943	7	0.745261
Cuba	2.5	3	−0.5
Cyprus	2.5	n/a	n/a
Czech Republic	2.5	2.5	0
Denmark	2.5	2.5	0

(Continues)

TABLE A1 (Continued)

Countries	FEEDME	FAO	Difference
Djibouti	30.26559251	n/a	n/a
Dominican Republic	13.98294329	25	−11.0171
Ecuador	3.461978333	4	−0.53802
Egypt	2.524953702	3	−0.47505
El Salvador	9.188097375	11	−1.8119
Eritrea	81.99778217	73	8.997782
Estonia	3.647903156	5	−1.3521
Ethiopia	42.92373864	46	−3.07626
Fiji	3.287198284	n/a	n/a
Finland	2.5	2.5	0
France	2.5	2.5	0
Gabon	4.714235516	6	−1.28576
Gambia	22.25377495	27	−4.74623
Georgia	16.02238544	27	−10.9776
Germany	2.5	2.5	0
Ghana	9.646012157	13	−3.35399
Greece	2.5	2.5	0
Guatemala	19.42379303	24	−4.57621
Guinea	21.73795078	26	−4.26205
Guinea-Bissau	28.60509262	n/a	n/a
Guyana	7.816673672	9	−1.18333
Haiti	41.87429285	47	−5.12571
Honduras	19.19689161	22	−2.80311
Hungary	2.5	2.5	0
Iceland	2.5	2.5	0
India	21.13894213	21	0.138942
Indonesia	5.788677351	6	−0.21132
Iran	3.381848349	4	−0.61815
Ireland	2.5	2.5	0
Israel	2.5	2.5	0
Italy	2.5	2.5	0
Jamaica	8.183848351	10	−1.81615
Japan	5.580568675	2.5	3.080569
Jordan	6.023338221	7	−0.97666
Kazakhstan	10.65960058	13	−2.3404
Kenya	25.20931401	33	−7.79069
Kuwait	4.081377008	5	−0.91862
Kyrgyzstan	4.491279816	6	−1.50872
Laos	18.60873975	22	−3.39126
Latvia	2.871976043	4	−1.12802
Lebanon	2.5	3	−0.5
Lesotho	8.733541219	12	−3.26646
Liberia	39.13000269	46	−6.87
Libya	2.5	n/a	n/a

(Continues)

TABLE A1 (Continued)

Countries	FEEDME	FAO	Difference
Lithuania	2.5	2.5	0
Luxembourg	2.5	2.5	0
Macedonia	7.106513796	11	−3.89349
Madagascar	32.32749937	37	−4.6725
Malawi	29.50697331	33	−3.49303
Malaysia	2.5	2.5	0
Maldives	7.696831716	n/a	n/a
Mali	22.72044215	29	−6.27956
Malta	2.5	2.5	0
Mauritania	7.841008233	10	−2.15899
Mauritius	4.835172592	6	−1.16483
Mexico	4.339675161	5	−0.66032
Moldova	9.5000397	11	−1.49996
Mongolia	24.78515327	28	−3.21485
Morocco	5.26899591	7	−1.731
Mozambique	39.82991832	47	−7.17008
Myanmar	5.641057205	6	−0.35894
Namibia	20.16442232	22	−1.83558
Nepal	14.67329809	17	−2.3267
Netherlands	2.5	2.5	0
New Caledonia	8.714828017	n/a	n/a
New Zealand	2.5	2.5	0
Nicaragua	23.91910969	27	−3.08089
Niger	32.31433274	34	−1.68567
Nigeria	7.246550297	9	−1.75345
North Korea	31.67641263	36	−4.32359
Norway	2.5	2.5	0
Pakistan	19.81990822	20	−0.18009
Panama	23.9682199	26	−2.03178
Paraguay	12.53283239	14	−1.46717
Peru	10.56307966	13	−2.43692
Philippines	16.90889025	22	−5.09111
Poland	2.5	2.5	0
Portugal	2.5	2.5	0
Romania	2.5	2.5	0
Russia	2.801075768	4	−1.19892
Rwanda	32.11087489	37	−4.88913
Samoa	2.857288265	n/a	n/a
Saudi Arabia	3.044817229	3	0.044817
Senegal	19.51257471	24	−4.48743
Sierra Leone	46.15498126	50	−3.84502
Slovakia	4.013357024	5	−0.98664
Slovenia	2.5	2.5	0
Solomon Islands	17.02734588	n/a	n/a

(Continues)

TABLE A1 (Continued)

Countries	FEEDME	FAO	Difference
South Africa	2.5	n/a	n/a
South Korea	2.5	2.5	0
Spain	2.5	2.5	0
Sri Lanka	19.94639808	22	−2.0536
Sudan	21.06486007	27	−5.93514
Suriname	8.352073668	11	−2.64793
Swaziland	15.27755375	19	−3.72245
Sweden	2.5	2.5	0
Switzerland	2.5	2.5	0
Syria	2.854235917	4	−1.14576
Tajikistan	56.22063434	61	−4.77937
Tanzania	39.17990627	44	−4.82009
Thailand	20.37395063	20	0.373951
Togo	22.98879711	26	−3.0112
Trinidad and Tobago	9.496585346	12	−2.50341
Tunisia	2.5	2.5	0
Turkey	2.5	3	−0.5
Turkmenistan	7.358152696	9	−1.64185
Uganda	15.39792118	19	−3.60208
Ukraine	2.506402122	3	−0.4936
United Arab Emirates	2.5	2.5	0
United Kingdom	2.5	2.5	0
United States	2.5	2.5	0
Uruguay	2.948816474	4	−1.05118
Uzbekistan	21.31693034	26	−4.68307
Vanuatu	8.651361117	n/a	n/a
Venezuela	14.012229	17	−2.98777
Vietnam	16.70161024	19	−2.29839
Zambia	43.71487828	49	−5.28512
Zimbabwe	39.097322	44	−4.90268

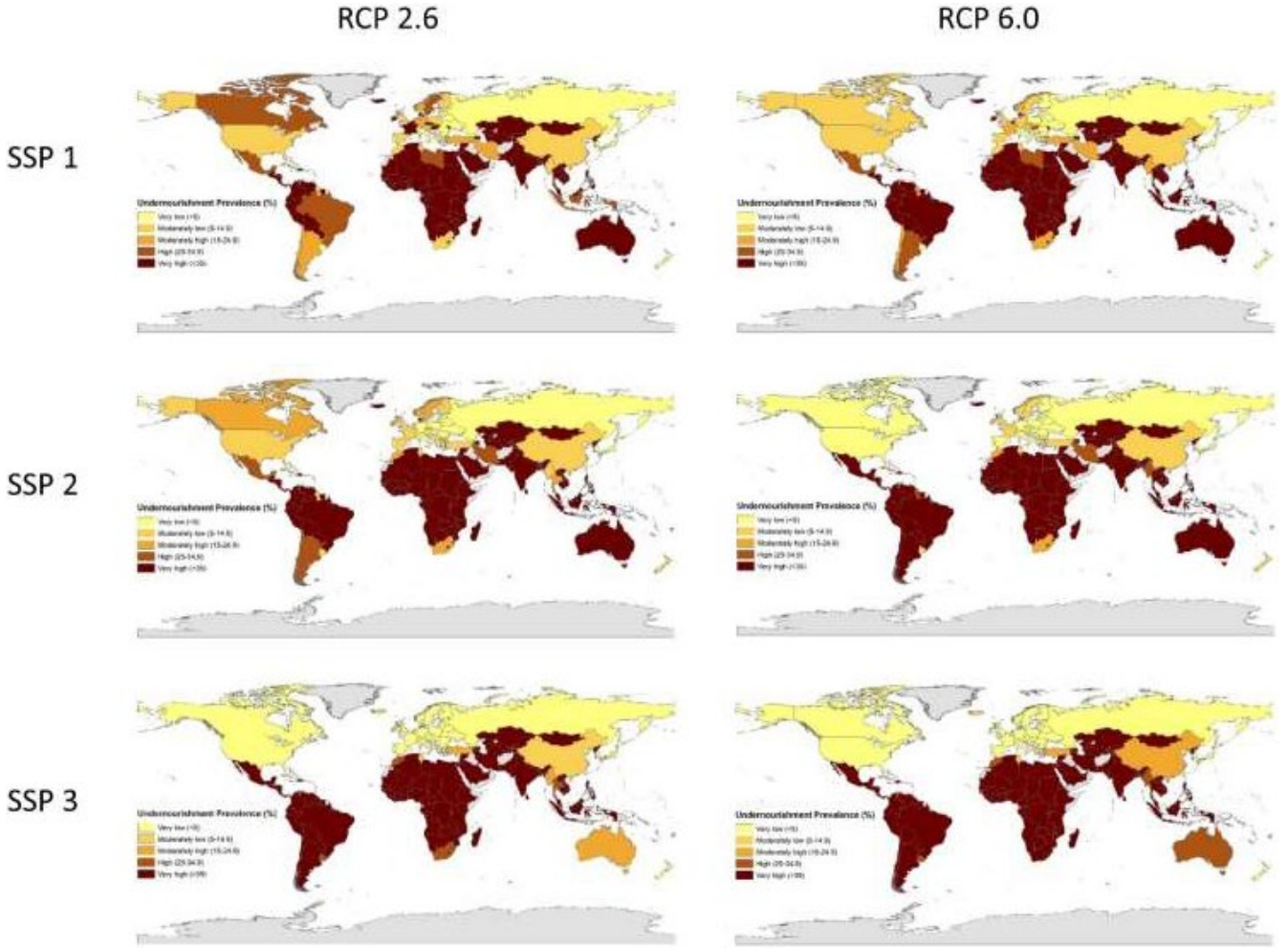
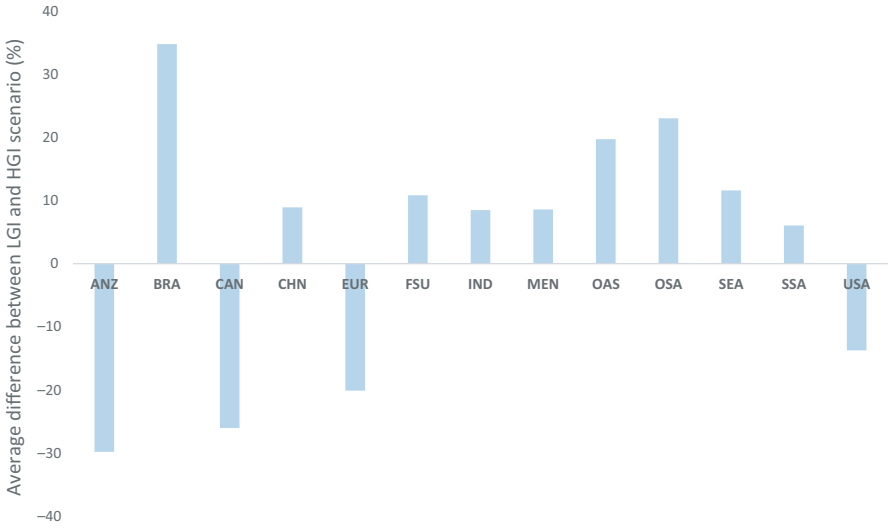


FIGURE A1 Panel of global maps showing prevalence of undernourishment under each of the six scenarios for RCP2.6 and 6.0, SSPs 1–3, including land use and population change but excluding feed and export compensation measures

FIGURE A2 Graph showing average percentage change in undernourishment prevalence per region between lowest global impact (LGI) and highest global impact (HGI) scenario



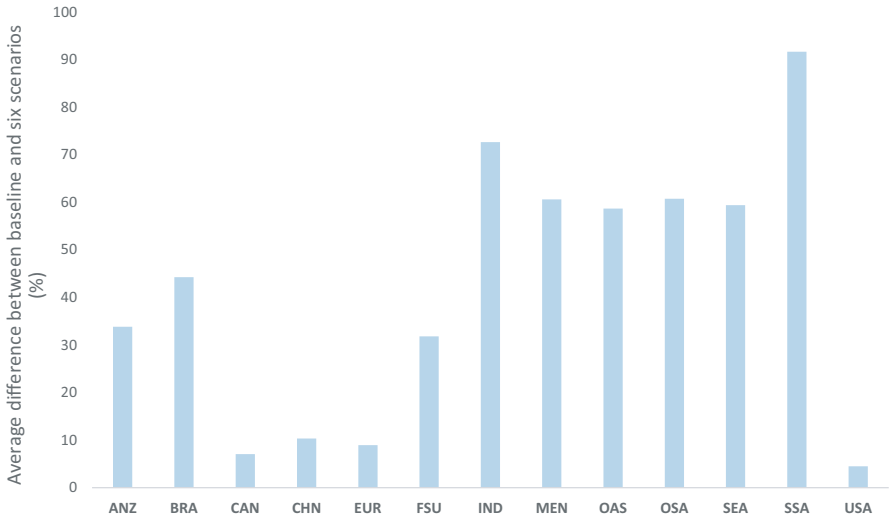


FIGURE A3 Graph showing average difference in undernourishment prevalence per region between the baseline and six scenarios examined