Global impacts of heat and water stress on food production and severe food security

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Abstract

Using a unique large-dimensional computational global intertemporal climate and trade model, GTAP-DynW, we projected the possible impacts of heat stress and water stress on global food supply and food security to 2050. The GTAP-DynW model uses GTAP data for 141 countries and regions, with varying water and heat stress baselines, and results are aggregated into 30 countries/regions and 30 commodity sectors. Findings are presented for three representative concentration pathways (RCPs); RCP4.5-SSP2, RCP8.5-SPP2, and RCP8.5-SSP3. Model results for RCP4.5-SSP2, RCP8.5-SPP2, and RCP8.5-SSP3, respectively, project: (a) substantial declines, as measured by GCal, in global food production of some 6%, 10%, and 14% to 2050 and (b) the number of additional people with severe food insecurity by 2050, correspondingly, increases by 556 million, 935 million, and 1.36 billion compared to the 2020 model baseline.

Keywords: GTAP-DynW; climate change; agricultural productivity; nutritional supply; irrigation; Computable General Equilibrium (CGE)

Model code and data sources available at: https://doi.org/10.5281/zenodo.8248417

Climate change is a serious threat to food production systems that are highly dependent on water resources and ecosystems, at multiple scales (Bellie, 2011). Various regions already suffer from water cycle disruptions due to climate change which include intensification of extreme weather events (droughts, floods) and groundwater depletion (Fecht, 2019, Scanlon et al., 2023, Yao et al., 2023). Critical future risks include heat stress and water stress on global food production and, thus, food security (Zolin & Rodrigues, 2020). Climate change risks are magnified by increasing water withdrawals for household and industry to 2050 (Luck et al., 2022), especially for irrigated agriculture that accounts for about 70% of total water withdrawals and up to 40% of the global food supply (OECD, 2017).

How these risks are realized, when and where, is determined by domestic and international input-output interactions across commodity sectors and regions, and endowments such as capital, labor, land, natural resources, and water, and the interlinkages of international trade. To quantitatively assess these risks for global food production and food security requires a Computable General Equilibrium (CGE) model, connected to a climate change model, to capture price, trade, and income effects in relation to both food supply and demand.

We used a unique intertemporal CGE model, GTAP-DynW, that extends the GTAP-AEZ, Version 10 (Plevin et al., 2014) platform, and includes the GTAP-Water dataset (Iman et al., 2016) to project global food production and food security to 2050. GTAP-DynW incorporates dynamic changes in water resources and their availability in agricultural production, international trade, and includes a food security component with climate change damages (Kompas et al., 2018; Kompas and Van Ha, 2019; Piontek et al., 2021). Model results are aggregated from 141 countries in GTAP-DynW to 30 countries and/or regions and for 30 commodities, to provide global projections.

The impacts of water stress from climate change on agricultural production and food security to 2050 were quantified using GTAP-DynW for three Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) climate change scenarios; RCP4.5-SSP2, RCP8.5-SSP2, and RCP8.5- SSP3 for decadal projections to 2050. Impacts on individual agricultural commodities (e.g., paddy rice, wheat, etc.) were summarized as GCal measures of global food production by country/region (FAO, 2022) relative to 2020. Estimates of the additional people by 2050 relative to 2020 who could be classified with severe food insecurity, as per the Food Insecurity Experience Scale (FAO, 2017), were calculated by dividing the projected global food supply in GCal by the average per person dietary requirements per year.

Results

The GTAP_DynW model was run with annual resolution to 2050 from a base year of 2020 for three global warming scenarios, RCP4.5-SSP2, RCP8.5-SSP2, and RCP8.5-SSP3. An emissions pathway between RCP4.5 and RCP8.5 is consistent with IEA scenarios and RCP8.5 is plausible to 2050 given tipping points (Lenton et al., 2013) and possible missing biotic feedbacks (Schwalm et al., 2020).

Food Production. Food production is aggregated as total nutrition by thousand Giga-calories (thous. GCal) by region and million Gcal for the world total using nutritional conversion factors for the total production of food across all food commodity sectors. A decrease in agricultural output causes a reduction in global food production (measured in total energy for nutrition) that, in turn, increases the number of people (millions) with severe food insecurity. GTAP-DynW provides these measures as model output for all climate change scenarios.

Figures 1-3 show a decreasing trend of food production as % reduction in 2050 from 2020 for each climate change scenario. Global food production falls by 5.8%, 9.7%, and 14.2%, on average, for the scenarios RCP4.5-SSP2, RCP8.5-SSP2, and RCP8.5-SSP3, respectively. Globally, for scenarios RCP4.5-SSP2, RCP8.5-SPP2 and RCP8.5-SSP3, food production decreases from 9.75 million to 9.2, 8.8, and 8.4 million GCal, respectively by 2050.

For RCP4.5, the best-case scenario, the food production by 5.1–6.6% in Africa, 5.8% in Australia, and 6.4% for some parts of South America. In 2050, food production would fall by 4.8% for the USA, 9.0% for China, and 6.5% for India. For RCP8.5-SSP3, the worst-case scenario, food production decreases by 8.2–11.8% in Africa, 14.7% for Australia, and 19.4% for some parts of Central America. For RCP8.5-SSP3, in 2050, the global food production would fall by 12.6% for the USA, 22.4% for China, and 16.1% for India.

Fig. 1 | Best-case scenario: Regional food production reduction from irrigated agriculture due to heat stress and water stress, RCP4.5 in 2050 (% ranges)

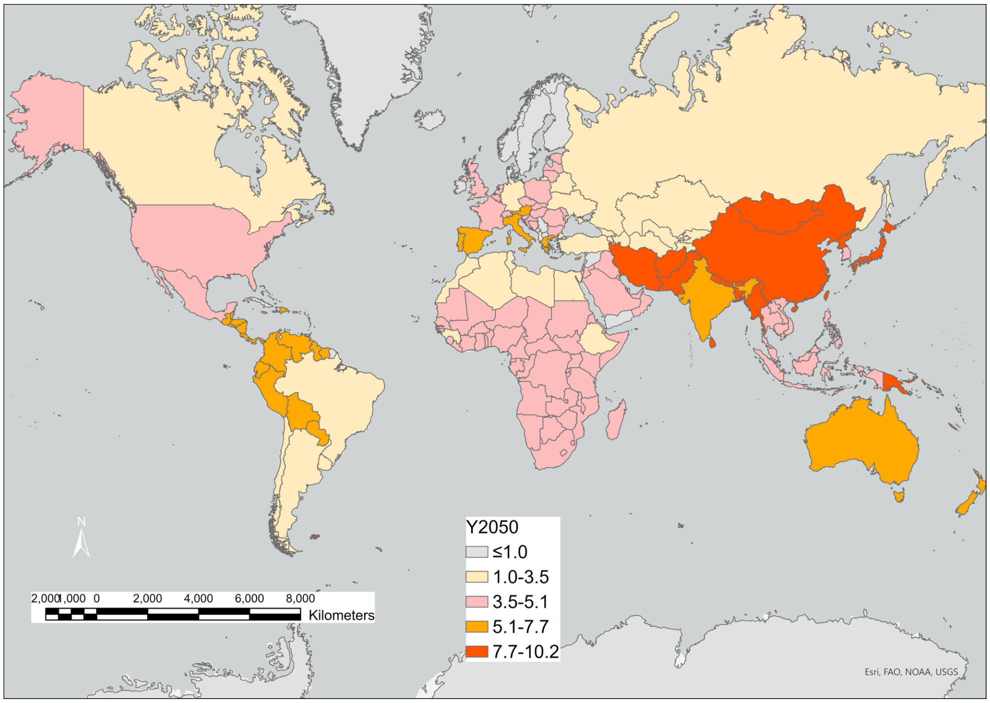


Fig. 2 | Middle-case scenario: Regional food production reduction from irrigated agriculture due to heat stress and water stress, RCP8.5- SSP2 in 2050 (% ranges)

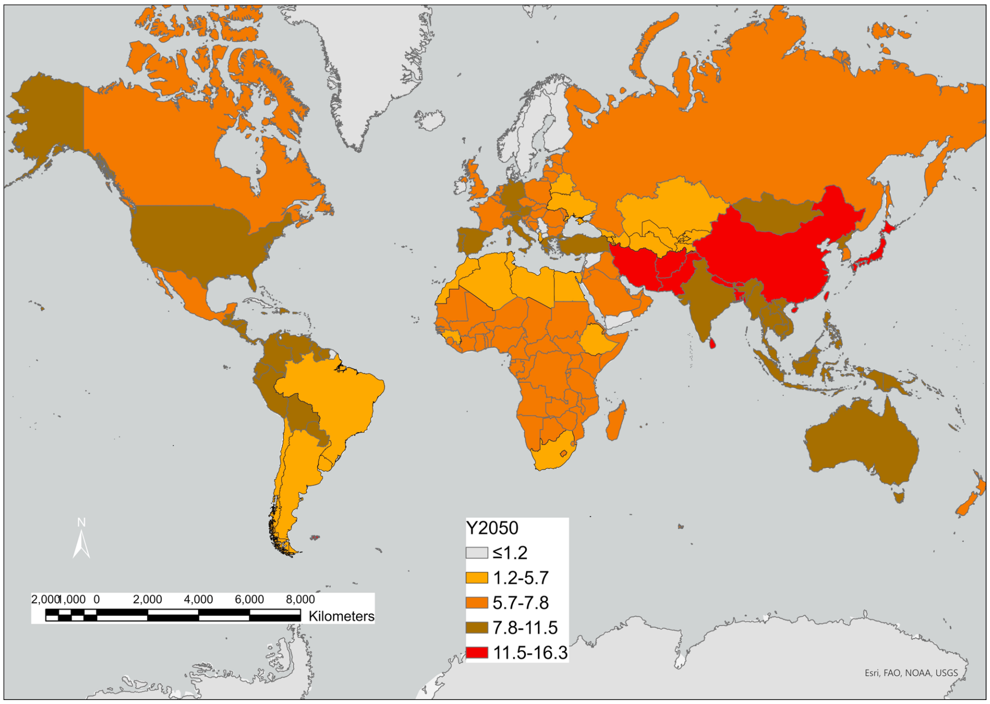
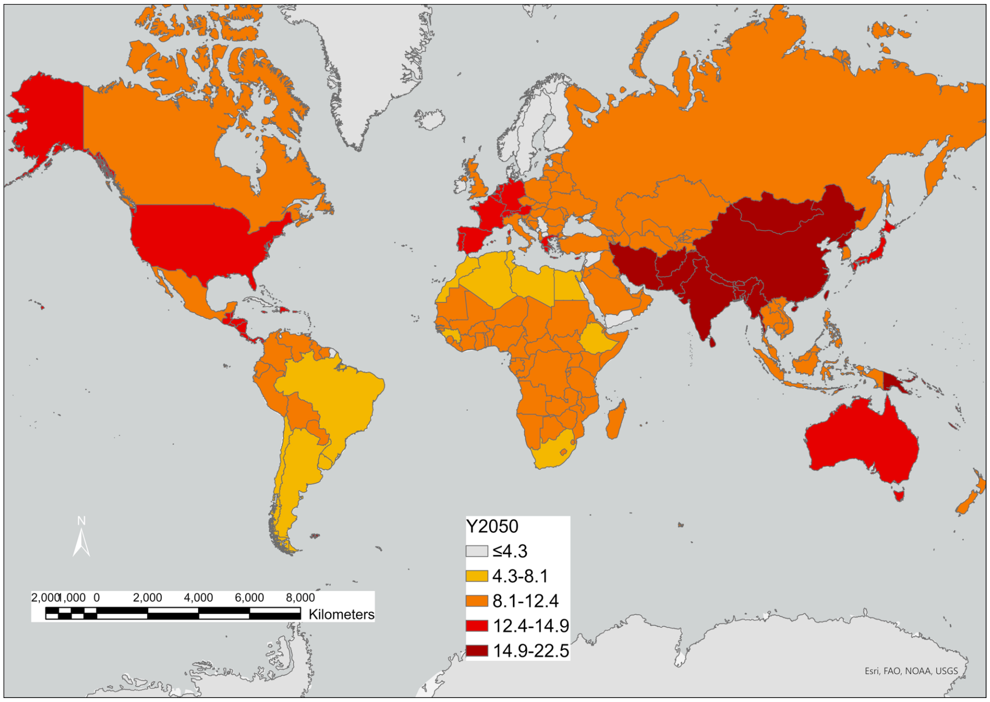


Fig. 3 | Worst-case scenario: Regional food production from irrigated agriculture due to heat stress and water stress, RCP8.5- SSP3 in 2050 (% ranges)



Food security. The number of persons (millions) with severe food insecurity caused by a decrease in global food production (or aggregated nutritional supply) is calculated as the reduction in food production relative to base nutritional supply. All outputs are trade-adjusted, noting that for net food exporting countries/regions a fall in their domestically produced food production does not necessarily increase their domestic food insecurity (e.g., Australia, the USA, Germany, France, and Russia).

Heat stress and water stress from climate change both increase global food insecurity (Figures 4–6). Overall, Africa is the most threatened in terms of severe food insecurity because of reductions in the continent's food production due to heat stress and because of the increase in Africa's population by 2050. Other regions with substantial increases in severe food insecurity include the Middle East, South Asia, and Central America.

In 2050, for RCP8.5-SSP3, the domestic food production in many African countries provides less than half of their domestic food demand (Figure 6). Some regions, such as China and ASEAN countries, switch from being net food exporters to food importers by 2050. Globally, the number of additional people with severe food insecurity by 2050, relative to 2020, for scenarios RCP4.5-SSP2, RCP8.5-SPP2 and RCP8.5-SSP3 are 556 million, 935 million and 1.36 billion, respectively.

Fig. 4 | Best-case scenario: Persons with severe food insecurity by region, RCP4.5 in 2050 (% population range)

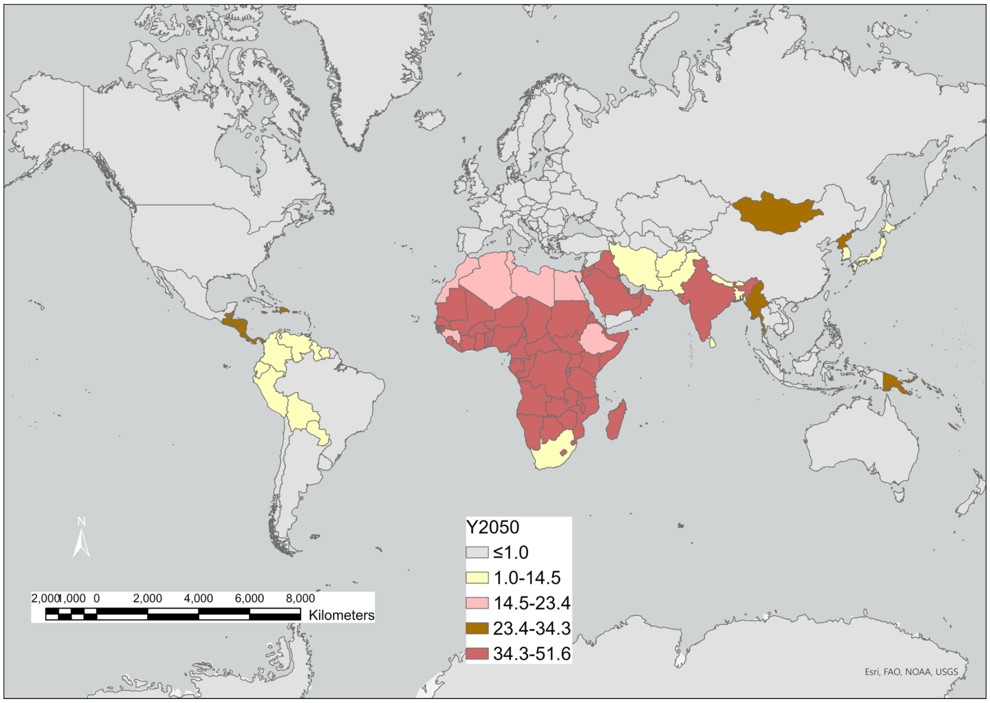


Fig. 5 | Middle-case scenario: Persons with severe food insecurity by region, RCP8.5-SSP2 in 2050 (% population range)

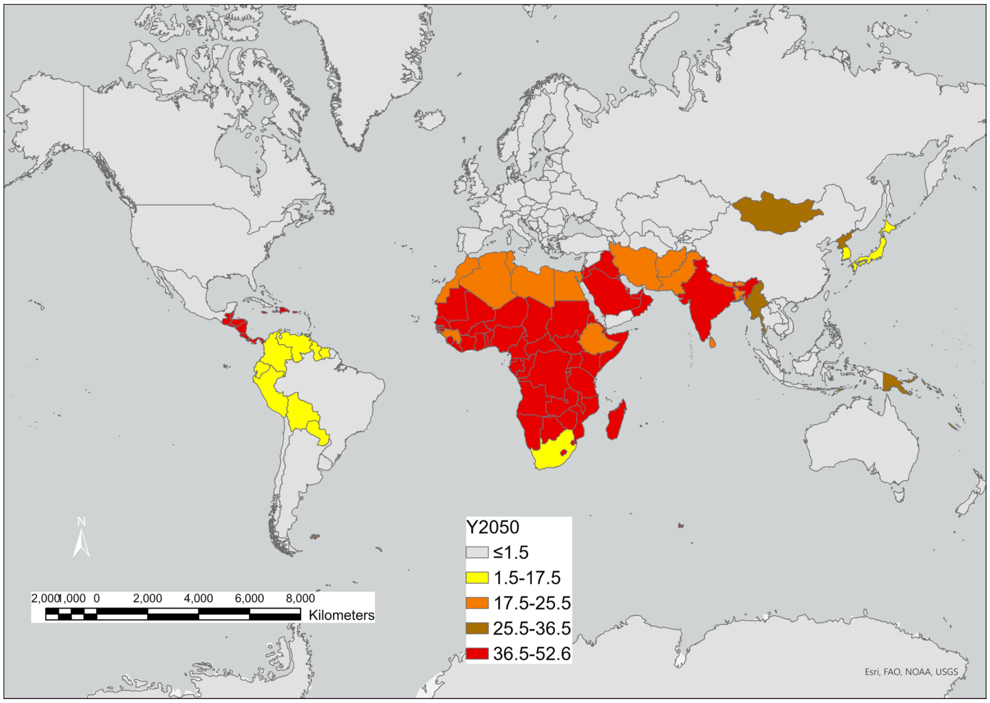
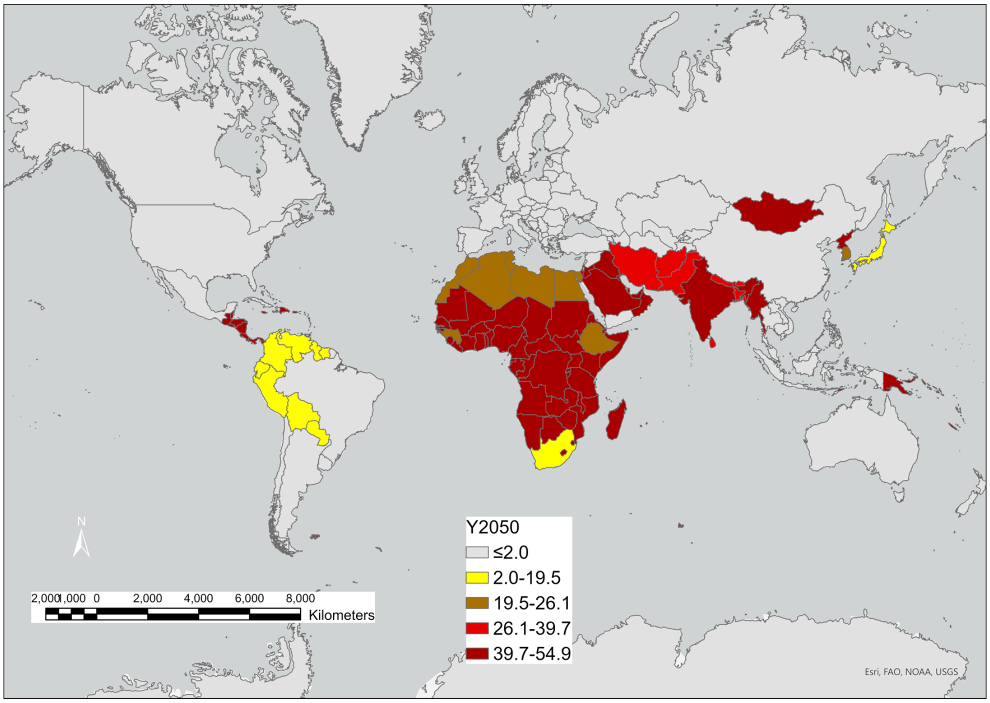


Fig. 6 | Worst-case scenario: Persons with severe food insecurity by region, RCP8.5-SSP3 in 2050 (% population range)



Discussion

The results highlight the regional and global magnitude of both heat stress and water stress on global food production. Our value add is that we: (1) quantify both heat and water stress on global food production; (b) account for global commodity price changes (30 commodities) and the reallocation of resources across 30 countries/regions; (3) incorporate trade effects noting that climate change and water withdrawals, especially groundwater depletion, can transmit risks from water stressed regions to regions without water stress via food trade (Dolan et al. 2021); and (4) allow producers and households to be forward looking.

Climate change has already had a substantial and negative impact on global agricultural productivity, reducing a global measure of agricultural productivity by about 20% since 1970, with larger negative impacts in the Near East and North Africa (Ortiz-Bobea et al., 2021). Adverse impacts on productivity and yields will magnify with future climate change given longer duration, higher magnitude, and more frequent heat extremes (Moore et al., 2017) and droughts (Santini et al., 2022; Vicente-Serrano et al., 2022). To what extent technological change can offset yield decline from climate change is uncertain (Asseng et al., 2014; Iizumi and Sakai, 2020; Lobell et al., 2007; McLachlan et al., 2020).

Global studies of decline in terrestrial water storage (Pokhrel et al., 2021; Wada et al., 2010) show statistically significant declines in global storages over the period 1992-2020 in about half of all 1058 natural lakes and 922 global reservoirs. Over half of the decline in the storages is attributable to water withdrawals, increasing temperatures and potential evapotranspiration (Yao et al. 2023). The OECD (2017) highlights that water stress, in the absence of effective policy actions in terms of water management, will significantly and negatively impact agricultural production in Northeast China, Northwest India and Southwest United States. These locations are in the world's three largest food producing countries, all of which are currently net food exporters and have the biggest cumulative food footprints (Halpern et al., 2022). Other modeling highlights that crop yield failures with climate change could be up to 25 times higher for key cereal crops (rice, soybean, maize, and wheat) that account for about two-thirds of food calorie consumption (Kim et al., 2019) for China, India, and the USA over the period 2041-2060 (Caparas et al., 2021).

A shift from blue (irrigation) to green water (rain-fed) crops can partially offset food production losses from heat and water stress in irrigated agriculture (HLPE, 2015). Nevertheless, both blue water (Rosa et al. 2020) and green water (Schyns et al., 2019), globally, are overused, especially in South Asia, East Asia, and the Middle East. Consequently, increases in agricultural production in either irrigated or rainfed agriculture in water-stressed regions will be at the expense of further groundwater depletion, inadequate stream flows and/or biodiversity loss. Agricultural extensification and increased rainfed cropping also pose other sustainability challenges; over the period 2003-2019, about half of the 9% global increase in the cropland area removed natural vegetation and tree cover (Potapov et al., 2022).

Our results highlight the critical importance of quantifying the trade-offs in relation to water and food (Grafton et al. 2017) and climate change (Grafton et al., 2013). Food systems already contribute about one-third of anthropogenic greenhouse gas emissions (Crippa et al., 2020) and emissions from food production and consumption alone could contribute, under business as usual, to almost a 1^0C increase in the global surface temperature by 2100 (Ivanovich et al., 2023). Food systems are also major contributors to biodiversity loss in Central and South America, and Africa (Marques et al., 2019).

The challenge is to increase regional and global food production but without contributing to further climate change or increased water stress (Grafton et al., 2014), while ensuring sustainability (Béné et al., 2019; Prutzer et al., 2023). This requires nothing less than a transformation in the world food systems (FAO, 2015; Fischer et al., 2014; Ringler et al., 2022) simultaneous with much greater reductions in greenhouse gas emissions from all sources, including agriculture.

Methods

The GTAP-DynW model is a large dimensional CGE model that uses the extensive GTAP (Global Trade Analysis Project) data set Version (Hertel, 1997; GTAP, 2021) in which countries or regions interact, importing goods and services from each other. GTAP-DynW is a (forward looking) intertemporal rather than a recursive CGE model and includes 18 Agro-Economic Zones (AEZ) (Ahmed et al. 2016) to characterize climate, soil, and terrain conditions pertinent to agricultural production (Lee, 2004). Following Kompas and Van Ha (2019) and Kompas et al. (2018), the model also includes climate change damage functions.

In GTAP-DynW, within each country or region, a producer combines inputs (land, labor, capital, intermediate good and natural resources) to produce a single good or service, which is consumed domestically by regional households (i.e. final consumption) and producers (i.e. intermediate demand for products as inputs in the production of other commodities) or is exported to other international or regional households and producers. Producers account for future impacts and policy settings as per the following system of motion equations:

$$\dot{k}_{r,t} = \varphi_{r,t-}\delta_r k_{r,t} \quad (1)$$

$$\dot{\mu}_{r,t} = \mu_{r,t}[i_t + \delta_r] - \frac{\phi_r}{2}\left(\frac{\psi_r}{k_{r,t}}\right)^2 p^I_{r,t} - p^K_{r,t} \quad (2)$$

where $p^K_{r,t}$ and $k_{r,t}$ are the rental price of capital and the capital stock in region r at time t; $p^I_{r,t}$ is price of an investment good; δ_r is the depreciation rate; ψ_r is the capital increment from the (gross) investment activity; i_t is the global interest rate; ϕ_r is an investment increment coefficient; and $\mu_{r,t}$ is the shadow price of capital.

Water stress effects. The production of agriculture output ($Q_{j,t}$) is approximated by a constant elasticity substitution (*CES*) production function that includes the demand for commodity i for use by j ($QF_{i,j,t}$) from both domestic and imported sources, and the value added in the industry j ($QVA_{j,t}$). The demand of endowments ($QSE_{i,j,t}$) that includes the 18 AEZ land use categories and natural resources for the value added in the industry j ($QVA_{j,t}$) is given by:

$$QSE_{i,j,t} = \left[\frac{QVA_{j,t}}{afe_{i,j,t}}\right]\left(afe_{i,j,t}\frac{PVA_{j,t}}{PSE_{i,j,t}}\right)^{\gamma_{j,t}} \quad (3)$$

where $afe_{i,j,t}$ is augmenting technological change of the endowments i by j; $PSE_{i,j,t}$ is the market price of sluggish endowment i used by industry j; $PVA_{j,t}$ is the firm's price of value added in industry j; and $\gamma_{j,t}$ is the elasticity of transformation for sluggish primary factor endowments in the production of value-added in j.

Under the effect of water stress, the deviation from the baseline resulting from climate change, the effectiveness of land use for agriculture or AEZ land decreases, where the relative reduction in the efficiency of land endowments is directly proportional to the relative increase in water stress. In GTAP-DynW, water stresses are derived from WRI (2022). This global GIS water data of 15,006 basins was spatially merged with the global GIS layers Esri-USGS (2022) to generate a geographical water stress projection for 174 countries, and then mapped to accord with GTAP-DynW's 30 aggregate countries/regions. Water stress at a time by a region i is estimated from the projection of water stress in all basins j located in the region i with a weighted coefficient of j that is measured as the area or share of

j in the total basin area in i, or

$$ws(i) = \sum_{i=1}^{J} wsb(i,j) \frac{B(i,j)}{\sum_{i=1}^{J} B(i,j)} \tag{4}$$

where $wsb(i, j)$ is the water stress of a basin j (in the set of J basins located in region i), i belongs to the GTAP-DynW's 30 regions (I); and $B(i, j)$ is the area of basin j located in i.

Water stress affects land use by AEZ by region and time in $QFE_{i,j,t}$ and changes $QVA_{j,t}$ and, thus, agricultural production ($Q_{j,t}$). The water stress indicators are deviations (too much and too little) from the 2020 baseline under the effect of climate change, following WRI (2022), and are quantified only for irrigated agriculture. The magnitudes of the water stress shock by AEZ depends on the share of irrigated land in total land use in the region's AEZ ($w_{c,irr}$) and the change of irrigated water volume in that AEZ in a region ($dIW_{c,t}$), is given by:

$$QSE_{i,j,t} = \frac{\overbrace{L(c,irr)}^{w_{c,irr}}}{L(c)} dIW_{c,t} \tag{5}$$

where c, j, t represents 18 AEZ land types, agricultural commodity, and time.

To calibrate the impact of water stress on agricultural outputs, we assumed a constant elasticity of substitution (CES) production function and defined demands for intermediate inputs ($QF_{i,j,t}$) by:

$$QF_{i,j,t} = \left[A_{i,j,t} \frac{Q_{j,t}}{afw2_{j,t} \left(\frac{pf_{i,j,t}}{afw1_{i,t}} \frac{1}{ps_{j,t}} \right)^{\gamma_{j,t}}} \right] \tag{6}$$

where $Q_{j,t}$ is the agricultural output of commodity j; $pf_{i,j,t}$ is the firm's price for input commodity i for use by j; $ps_{j,t}$ is the supply price of commodity j; $A_{i,j,t}$ is the composite regional variable of augmenting technology change; and $\gamma_{j,t}$ is the elasticity of substitution among composite intermediate inputs in the agricultural sector j. Two specific augmenting technology change variables include a water stress factor ($afw1_{i,t}$) for intermediate inputs and endowments used for production, and a region-specific average rate of intermediates augmenting technology change of j ($afw2_{j,t}$).

The shock $afw1_{c,j,t}$ depends on the weighted coefficient of irrigated land in total land use for an agricultural crop $w_{irr,j}$, the change of irrigated water by time ($dIW_{c,t}$), and the water stress coefficient to crop yields, or

$$dafw1_{c,j,t} = \frac{\overbrace{L(c,j,irr)}^{w_{irr,j}}}{L(c,j)} \frac{1}{dIW_{c,t}} ws_{c,j,t} \quad (7)$$

where *c, j, t* presents 18 AEZ land types, agricultural commodity, and time. Water prices from water resources paid by water user industries are added to regional income, but also increase costs in these sectors that may cause a shift or reallocation of water use among water using industries. For a water price *pwater*(*t*) in a region *r*, the price index for purchases of *k* commodity by *j* sector in region *r* ($PFE_{j,k,r,t}$) is given by:

$$PFE_{k,j,r,t} = \left[p_{k,j,r,t} + taxF_{k,j,t}\right] + \left(\frac{pwater_{r,t} * WIN_{j,k,r,t}}{VFA_{k,j,r,t}}\right) \quad (8)$$

where $VFA_{j,k,r,t}$ is the purchase and firm's tax of *k* inputs for use by sector *j*; $p_{j,k,r,t}$ is the market price of *k* to *j*; $taxF_{j,k,r,t}$ is the tax on firm's purchases of *k* by production *j*; $pwater_{r,t}$ is water price at *t*; and $WIN_{j,k,r,t}$ is the water intensity of *j* on *k*. Thus, a water stress shock causes a change in $PFE_{j,k,r,t}$ and a shift in water withdrawals from domestic and imported sources depends on the domestic and import commodity mix.

Heat stress effects. Damage functions provide the relationships between climate variables (such as average temperature, humidity, or extreme heat days) on productivity, income, and resource endowments (Roson & Sartori, 2016). Roson and Sartori (2016) provide the estimated parameters of damage functions for 120 GTAP countries and regions using GTAP9 with six climate impacts: sea level rise, variation in crop yields, heat stress effects on labor productivity, human health, tourism, and household energy demand. Projections from GTAP-DynW only include damage functions related to heat stress and their impacts on agricultural outputs and labor productivity in the agricultural sector using GTAP10a. The heat stress shocks from global warming (e.g. losses in agricultural and labor productivity) are based on Kompas et al. (2018), Kompas and Van Ha (2019), and Roson and Sartori (2016).

Food security effects. In GTAP-DynW, each food commodity contains nutritional components with different energy intake (calories). The aggregated nutritional supply in the region *r* (*S*(*r, t*)) (measured as Giga-calories (GCal)) is aggregated as a sum of nutritional supply from food production *i* or

$$S(r,t) = \sum_{i=1}^{I} \frac{S(i,r,t)z(i)*1000}{10^9} \quad (9)$$

where *S*(*i, r, t*) is food production *i* (thousand tons); and *z*(*i*) is the nutrition conversion factors of food *i* for calculating that food's energy content from one ton of food *i* to calories. The average daily nutrition intake *a* required for human food security is taken as given, and varies by country and region (source data: FAO (2020c), FAO (2020b), and FAO (2020a)) and is given by:

$$F(r,t) = \frac{S(r,t)*10^9}{a*365*10^6} \quad (10)$$

where a is average daily nutrition in calories. Global food production (GCal) is the sum of all regional food supply and the total population across regions is $F(r,t)$.

The number of persons with severe food insecurity, in millions, is determined by the gap in the minimum calorie demand and the available production and is given by:

$$IF(r,t) = \frac{\overbrace{[S(r,0)-S(r,t)]}^{ds(r,t)}10^9}{a*365*10^6} \quad (11)$$

where $dS(r, t)$ is the reduction of food production in region r at t to the base nutritional supply ($S(r, 0)$).

The food insecurity rate ($RIF(r, t)$) is the ratio of the number of persons with severe food insecurity over the total population of that country or $POP\ (r, t)$:

$$RIF(r,t) = \frac{IF(r,t)}{POP(r,t)} \quad (12)$$

The global reduction of food production ($dS(t)$) is the sum of the reduction of food supply ($dS(r, t)$) across all regions. The global number of persons with severe food insecurity ($IF\ (t)$) is the sum of all regions' persons with severe food insecurity resulting from the reduction of food supply (or $IF\ (r, t)$).

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