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Quantifying food security and mitigation risks consequential to climate change impacts on crop yields

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Abstract

Climate change is expected to impact crop yields globally, with some regions benefiting from favorable conditions and CO_2 fertilization, while others face adverse effects from altered precipitation and higher temperatures. Changes in crop yields can destabilize the global food system and pose challenges to food security. Moreover, crop production is crucial, as biofuels are becoming increasingly important contributors to climate change mitigation measures aimed at limiting global warming. This study uses the Integrated Model to Assess the Global Environment integrated assessment model framework to analyze different indicators related to food security and climate change mitigation under varying climate change impacts on crop yields. Twelve spatially explicit crop productivity projections were taken from the full archive of the Global Gridded Crop Model Intercomparison of 120 climate-crop model combinations, forced by CMIP6-based climate scenarios. The selection includes two average-performing climate-crop model combinations, two pessimistic combinations that perform one standard deviation below the mean, and two optimistic model combinations that perform one standard deviation above the mean. To single out the effect of climate change on productivity changes, we drew samples from two representative concentration pathways (RCP2.6 and RCP8.5). These productivity projections were applied within an otherwise uniform scenario (SSP2) and analyzed for their effect on total calorie demand, crop prices, and number of people at risk of undernourishment to quantify food security. Risks to climate change mitigation targets were explored by modeling the total bioenergy supply, emissions, and global mean temperature. The results revealed significant differences in the risk of food security and mitigation potential between different regions and climate change scenarios. Across scenarios, the crop area extent can vary up to 2 million km^2 due to changing crop yields. The projected change in global hunger ranges from 60 to 160 million undernourished people, indicating uncertainty between climate and crop model combinations. Low-income regions are especially impacted because of their high sensitivity to changes in food prices. Global climate change mitigation ambitions can also deviate by the latter part of the 21st century, as changes in yields will impact biofuel production as well as agriculture, forestry and other land use emissions. The quantitative insights generated by this study highlight the need for global policy efforts to make the agricultural system more adaptive to climate change to handle potential negative impacts.

1. Introduction

Global crop production is likely to be impacted by climate change due to CO_2 fertilization, changes in temperature and precipitation patterns, and extreme weather events (Kerr *et al* 2022). Large uncertainties exist in global crop yield projections across different climate and crop models (Jägermeyr *et al* 2021, Müller *et al* 2021). It is important to consider these uncertainties, as they can influence the sustainable development goals (SDGs) on hunger (SDG2), climate (SDG13), and biodiversity (SDG15). The 'zero hunger' target (SDG2) aims to eradicate global hunger by 2030. However, in recent years, the number of people suffering from hunger has been increasing as a result of increasing food prices, global conflicts, and more frequent extreme weather events (Sachs *et al* 2022). Most of these people live in low-income regions, such as Sub-Saharan Africa and Southern Asia (FAO *et al* 2024), which are also the regions projected to be most severely impacted by climate change (Mbow *et al* 2019). In addition, an increasing population poses additional challenges to food security in these regions (Ray *et al* 2022). The use of bioenergy can play a crucial role in climate change mitigation strategies (SDG13) to limit global warming (Rogelj *et al* 2018, Hanssen *et al* 2020), but poses an additional demand for land resources. This means that food security targets and climate mitigation can be interlinked because of (1) the competition for land, and (2) future climate impacts on yields (Hasegawa *et al* 2018, Fujimori *et al* 2019).

Projections of crop yields play an important role in determining the effectiveness of food security and mitigation targets (Xu *et al* 2022). Global gridded crop models (GGCMs) are widely used to study the impacts of climate change on crop yields (Rosenzweig *et al* 2013). GGCMs are typically driven by climate data from general circulation models (GCMs), using emission trajectories from different representative concentration pathways (RCPs). A recent multi-model intercomparison of 120 climate-crop model ensembles by Jägermeyr *et al* (2021) revealed significant uncertainties in crop yield responses for the four major food crops, which can be primarily attributed to crop models, and to a lesser extent, climate models. This large variation between models may arise because of the variety in model types, structures, and inputs (Kerr *et al* 2022). As a result, crop model projections can behave differently when exposed to driving climatic variables, such as CO_2, temperature, water, and nitrogen supply (Müller *et al* 2024). Researchers generally use an ensemble of multiple models to obtain more robust simulation results (Asseng *et al* 2015).

Most studies examining climate impacts on crops have focused on yield impacts and compared different model ensembles (e.g. Zhao *et al* (2017) or Jägermeyr *et al* (2021)). These different crop yield projections can impact food security and climate mitigation targets, yet they are often not integrated into broader impact assessments. While Molina Bacca *et al* (2023) already provide valuable insights into the costs and effectiveness of different land-use adaptation measures, the authors do not explore the consequences of these yield uncertainties on food security and mitigation targets. This study adds to the literature by integrating spatially explicit crop yield projections under climate change in the Integrated Model to Assess the Global Environment (IMAGE) 3.3 framework (PBL 2023). This way we can analyze their impacts on food security and climate change mitigation targets.

2. Data and methodology

2.1. IMAGE integrated assessment model (IAM)

IAMs combine knowledge from different disciplines to provide insights into long-term global change and impacts on social and environmental systems. The IMAGE (Stehfest *et al* 2014) was used in this study to simulate the role of crop yield uncertainty in food and energy systems. IMAGE consists of multiple interacting models that can capture the interactions between human and natural processes (SI figure 1) (PBL 2023). The agricultural economy was simulated using the Modular Applied GeNeral Equilibrium Tool (MAGNET) (Woltjer *et al* 2014). This model represents various food system processes, including crop and livestock demand and production, bilateral trade, and land rents. A decrease in agricultural productivity may lead to the conversion of new land to be taken into agricultural production. In MAGNET, this may result in higher land rents and, consequently, higher crop prices (Woltjer *et al* 2014). The energy system is represented by the energy system model TIMER, which projects the supply and demand of different energy carriers, including bioenergy from dedicated energy crops (both with and without bioenergy with carbon capture and storage (BECCS)) and residues (Van Vuuren *et al* 2007). The IMAGE-land module captures both regional and spatially explicit land-use dynamics (Doelman *et al* 2018). Using the resulting per capita food availability, total undernourishment rates are calculated following (van Meijl *et al* 2020b).

IMAGE has been used extensively to project greenhouse gas (GHG) emissions using different scenarios, and to analyze climate change mitigation pathways (see e.g. van Vuuren *et al* 2017, Doelman *et al* 2018, van Vuuren *et al* 2018, Edelenbosch *et al* 2024.

In the latest multi-model calibration (CMIP6), IMAGE performed best among other IAMs in representing GHG emissions, requiring only a 5.1% correction for baseline emission trajectories (Gidden *et al* 2019). These corrections primarily occur in sectors with smaller emission sources. IMAGE is also the only IAM that includes all key GHGs across energy, industry, land-use and waste sectors (Yan *et al* 2024). Changes in crop productivity will impact how much energy can be produced from biomass. This can happen in two ways: (1) increased energy crop production, and (2) increased agricultural production, which can lead to higher crop residues for certain crops modeled in IMAGE (Daioglou *et al* 2016). This will, in turn, influence emissions from the energy and industry sectors. IMAGE also accounts for land-use emissions. CO_2 emissions are calculated from grid-level changes in land use, such as deforestation. Activity data from the agricultural sector are combined with historically calibrated emission factors, to calculate non-CO_2 emissions (Doelman *et al* 2018). Livestock CH_4 emissions result from enteric fermentation and manure management, depending on the demand for animal products and production efficiency parameters. Other important sources for CH_4 include rice cultivation and biomass burning. N_2O emissions primarily stem from the application of synthetic fertilizers and livestock manure. The global vegetation model Lund-Potsdam-Jena managed Land (LPJmL) is coupled to the land-use system and simulates vegetation dynamics, hydrology, and crop productivity (Müller *et al* 2016). In this study, we excluded the crop-climate feedbacks between the IMAGE-land model and LPJmL, and instead used productivity responses based on the process-based climate-crop model combinations described by Jägermeyr *et al* (2021). This way we can look at the isolated impacts of crop yield impacts on food security indicators and climate mitigation targets. The GHG emissions from land-use, energy and industry sectors are aggregated in the climate emulator Model for the Assessment of GHG Induced Climate Change to estimate the global mean temperature change (Meinshausen *et al* 2011).

3. Climate change impacts on crop yields

The Global Gridded Crop Model Intercomparison (GGCMI) phase 3 ensemble (Jägermeyr *et al* (2021) consists of 12 global process-based crop models forced with five CMIP6 GCMs for different RCPs to evaluate potential future climate change impacts on wheat, maize, rice, and soybeans between 1980 and 2100. Under a high-mitigation scenario, the uncertainty associated with climate and crop models is fairly balanced; however, under a high-emission scenario, the uncertainty is dominated by large differences across crop models for all four crops (Jägermeyr *et al* 2021). Different crop model sensitivities cause a wide range of crop yield responses, especially to atmospheric CO_2 concentrations, phenological responses to warming, extreme temperatures, and changes in precipitation (Jägermeyr *et al* 2021, Müller *et al* 2024). In general, adverse climate change impacts are most severe for C4 crop maize, which can benefit less from increases in atmospheric CO_2 concentrations than C3 crops, such as wheat, rice, and soybean (Kimball 2016). Wheat, on the other hand, shows the largest increases in most models, mainly due to its high sensitivity to CO_2 changes and moderate warming at higher latitudes (Jägermeyr *et al* 2021).

We used a representative subset of all possible yield responses from the GGCMI data repository described by Jägermeyr *et al* (2021) to reduce the number of simulations. We calculated the global average yields for four crops combined between 2070 and 2100, accounting for both spatial and temporal dimensions, across all climate-crop model ensembles, then determined the mean and standard deviation (figures S2 and S3). From this, we take two optimistic climate-crop model combinations, where the crop yields are approximately one standard deviation above the mean, two pessimistic model combinations that deviate about one standard deviation below the mean, and two average-performing model combinations (close to the mean). This was done for productivity responses under a low and high climate impact scenario, represented by RCP2.6 and RCP8.5, totaling 12 projections. The projections are implemented in the IMAGE framework by applying the changes to crop productivity in the base year (2020), as modeled by LPJmL. Additionally, a baseline without climate change impact on crop yield was evaluated. In this baseline, yields are driven by socio-economic assumptions, such as technological change and GDP. The resulting spatially explicit projections show annual crop productivity changes for wheat, maize, rice, and soybean from 2020 to 2100.

Table 1 shows the final sample of the climate-crop model combinations. In this study, we aim to look only at the isolated impacts of changes in crop yields; therefore, the socio-economics for all simulations are based on SSP2: the middle of the road scenario (Riahi *et al* 2017). This approach ensures that factors like GDP, technology, and population remain constant across all scenarios, allowing us to focus on the effects of crop yield changes only. It should be noted that using only SSP2 does not fully explore the potential impacts on more extreme societal developments. All simulations implement the same price for GHG emissions to evaluate the impact of crop yield changes on climate change mitigation. This GHG price aligns with the target set by the Paris Agreement to limit global warming to well below 2 °C under SSP2.

IMAGE simulates 16 different crop types, whereas the GGCMI ensemble provides only data for four crops. To represent all the crops used in IMAGE, a mapping procedure was applied following Janssens *et al* (2020), as shown in table 2. Four main crops

Table 1. Climate-crop model combination selection.

Scenario name	Crop productivity deviation	Climate model impacts	Climate model (*GCM*)	Crop model (*GGCM*)
OPT1-low	Optimistic	RCP2.6	MRI-ESM2-0	PROMET
OPT2-low	Optimistic	RCP2.6	IPSL-CM6A-LR	PROMET
AVG1-low	Average	RCP2.6	GFDL-ESM4	LPJmL
AVG2-low	Average	RCP2.6	MRI-ESM2-0	EPIC-IIASA
PES1-low	Pessimistic	RCP2.6	UKESM1-0-LL	CROVER
PES2-low	Pessimistic	RCP2.6	MRI-ESM2-0	CYGMA (1p74)
OPT1-high	Optimistic	RCP8.5	UKESM1-0-LL	ACEA
OPT2-high	Optimistic	RCP8.5	MRI-ESM2-0	ACEA
AVG1-high	Average	RCP8.5	GFDL-ESM4	EPIC-IIASA
AVG2-high	Average	RCP8.5	MRI-ESM2-0	CYGMA (1p74)
PES1-high	Pessimistic	RCP8.5	IPSL-CM6A-LR	PEPIC
PES2-high	Pessimistic	RCP8.5	IPSL-CM6A-LR	pDSSAT
BASE	Baseline	No climate impacts	—	—

Table 2. Mapping of GGCMI crop yield projections to IMAGE crop categories.

IMAGE crop categories	GGCMI crop yield data used (wheat, rice, maize, soybean)
Wheat	Wheat productivity changes directly applied
Rice	Rice productivity changes directly applied
Maize, grains biofuel	Maize productivity changes directly applied
Tropical cereals (millet, sorghum)	Modified corn yields where only half of the negative effects are applied due to better drought tolerance
Other temperate cereals (rye, barley)	Modified wheat yields where only half of the negative effects are applied due to better drought tolerance
Soybeans, biofuel oil crops	Soybean productivity changes directly applied
Pulses (field peas), temperate oil crops (rapeseed, sunflower), tropical oil crops (groundnuts), temperate roots & tubers, tropical roots & tubers, sugar crops, oil & palm fruit, vegetable fruit, other non-food, plant based fibers, sugar crops biofuel, woody biofuel, non woody biofuel	C_3 crops are represented by the regional weighted average of three modeled C_3 crops (wheat, rice and soybean)
Grass	No changes in crop productivity

(wheat, rice, maize, and soybean) were directly available. Tropical cereals consist of sorghum and millet and are categorized as C4 crops. For these crops, yield changes are based on maize (also a C4 crop); but only with half of the negative effects due to better tolerance to drought (Müller and Robertson 2014). Similarly, yields for other temperate cereals are based on wheat but also have only half of the negative effects. All remaining crop groups were C3 crops; therefore, we used the regional average of wheat, rice, and soybean yield. In some grid cells, the GGCMI data had very low starting values and showed a strong relative increase due to climate change. To avoid unrealistic effects when applying changes to the initial yield maps, but at the same time to allow for future improvements in potential yields due to technological change, we cap the yields at twice the highest globally reported potential yield of a specific crop (van Zeist *et al* 2020). From the resulting yield projection maps, the changes over time were derived and applied to IMAGE's gridded crop yield using a running average over 10 yr intervals.

3.1. Indicators

In this study, cereal yield and total cropland area were used as indicators of agricultural productivity. Additionally, we considered crop prices, caloric demand, and the number of people at risk of undernourishment as metrics for food security, representing the food availability and accessibility dimensions of food security (Van Meijl *et al* 2020a). High food prices can impact calorie availability, especially in low-income regions. As an additional metric, the risk of undernourishment was assessed following FAO (Naiken 2003). This approach uses the minimum dietary energy requirements, calorie consumption, and a variation coefficient of food distribution within a country. Both calorie demand and risk of undernourishment are measures of food availability.

Biomass energy is an important component in scenario studies for limiting global warming (Rogelj *et al* 2018) and was used as a mitigation indicator in this study. In IMAGE, bioenergy is directly impacted by changes in crop yields, but also indirectly through residue streams from both agriculture and forestry.

Biomass can be used to produce electricity or hydrogen, and can optionally be combined with BECCS for these carriers. Biomass can only be produced on lands that are no longer needed or suitable for agricultural production or natural land that is non-forested, such as shrubland, grassland or savannah (Daioglou *et al* 2019). Food production is always prioritized over biomass. We include three types of GHG emissions (CO_2, CH_4, and N_2O) and changes in the global mean temperature as indicators for mitigation. CO_2 emissions originate primarily from the energy sector and land-use changes such as deforestation and agricultural burning. CH_4 emissions originate from enteric fermentation in livestock, animal manure, and rice production. Additionally, landfills and domestic sewage emit CH_4, which is linked through population and GDP. N_2O emissions stem from the application of nitrogen-based fertilizers as well as from land-use change.

4. Results

4.1. Impacts on cereal yields and crop area

Without climate impacts, dry matter cereal yields are expected to increase (figure 1(a)). In 2020, cereal yields are 4.1 t/ha. By 2100, cereal yield is expected to increase to around 5 t/ha in the BASE scenario, driven by technological advancements (Doelman *et al* 2018). This initial increase is lower than historical trends, but fall in the line of studies who argue that yields will reach a maximum (plateau), most notably in high-income regions (Grassini *et al* 2013, van Zeist *et al* 2020). Despite an increase in yield, crop area is expected to grow as growth in food demand outpaces growth in agricultural productivity. Total crop area is projected to increase from 16.2 million km^2 in the historical reference period (2020) to 19.9 million km^2 by 2100 (figure 1(b)) This increase can be attributed to a growing population and higher per capita income, leading to an increase in food demand. At the end of this century with high yield impact projections, optimistic yield estimates indicate global cereal yields range from 4.2 t/ha (PES2-high) to 5.9 t/ha (OPT2-high) between different scenarios (figure 1(a)). Low impact scenarios range between 4.9 t/ha (PES2-low) to 5.4 t/ha (OPT1-low) in 2100. At a regional level, cereal yields show a larger range across scenarios in medium- and high-income regions compared to low-income regions (figure 2(a)). Driven by high yield impact projections, crop area ranges from 17.4 million km^2 (OPT2-high) to 20.9 million km^2 (PES1-high) in 2100 (figure 1(b)). Low impact scenarios show a range of 18.9 million km^2 (OPT1-low) to 20.1 million km^2 (PES2-low) in 2100. Middle-income regions show again the largest variations in crop area across scenarios as yield impacts are greatest (figure 2(b)).

4.2. Food security indicators

Global mean food prices are represented as an index relative to 2020. BASE food prices depend on demand developments for crop- and animal-based food, driven by SSP2 assumptions on, for instance, population growth and GDP. When excluding climate impacts, food prices increase by around 2% in 2100 (figure 1(c)). Under high impacts, indexed food prices range from −16% (OPT2-high) to +41% (PES1-high) in 2100 (compared to 2020) across climate-crop model combinations. For low impact scenarios, prices range from −3% (OPT2-low) to +8% (PES1-low). Figure 2(c) shows the percentage change in food prices in 2100 compared to the baseline scenario without climate change impacts for three different world regions. Regional food prices can be different due to economic conditions represented by elasticities, tariffs or transport costs in MAGNET (Woltjer *et al* 2014). Low-income food prices respond relatively strong (up to +60%) to productivity changes, resulting from an increased dependency on food imports. When prices are lower than those with no climate impacts, this might indicate that food will become more accessible. On the other hand, rising food prices can put pressure on livelihoods and social stability in vulnerable regions. Combined with the developments in GDP and population, food prices influence caloric demand. Baseline global average calorie demand is 3288 kcal cap d^{-1}. The caloric demand changes between high yield impact estimates, ranging from 3133 kcal cap d^{-1} (PES1-high) to 3430 kcal cap d^{-1} (OPT2-high) in 2100 (figure 1(d)). Low yield impact scenarios show less variability, with caloric demand between 3262 (PES1-low) and 3333 kcal cap d^{-1} (OPT2-low). Food availability is most sensitive to yield impacts in high-income regions (figure 2(d)), mainly driven by changes in livestock-based food consumption.

Alongside food prices and per capita food demand, the number of undernourished people is another key indicator of food security. Low food prices and increased supply can reduce undernourishment and global hunger. Baseline projections show a decrease in the number of people suffering from hunger, from 668 million in 2020 to 88 million in 2100. This initial decrease under SSP2 can be explained by a higher GDP and more equitable distribution of food (Hasegawa *et al* 2015). In the high impact yield projections, it is estimated that the number of undernourished people range from 55 million in the optimistic (OPT2-high) climate-crop model combinations, to 166 million (PES1-high) in 2100 (figure 1(e)). Low impact yield projections show less variability across climate-crop models, ranging from 82 million (OPT2-low) to 98 million (PES1-low). High food prices place a greater burden on the poorest regions, where low GDP per capita constrains their

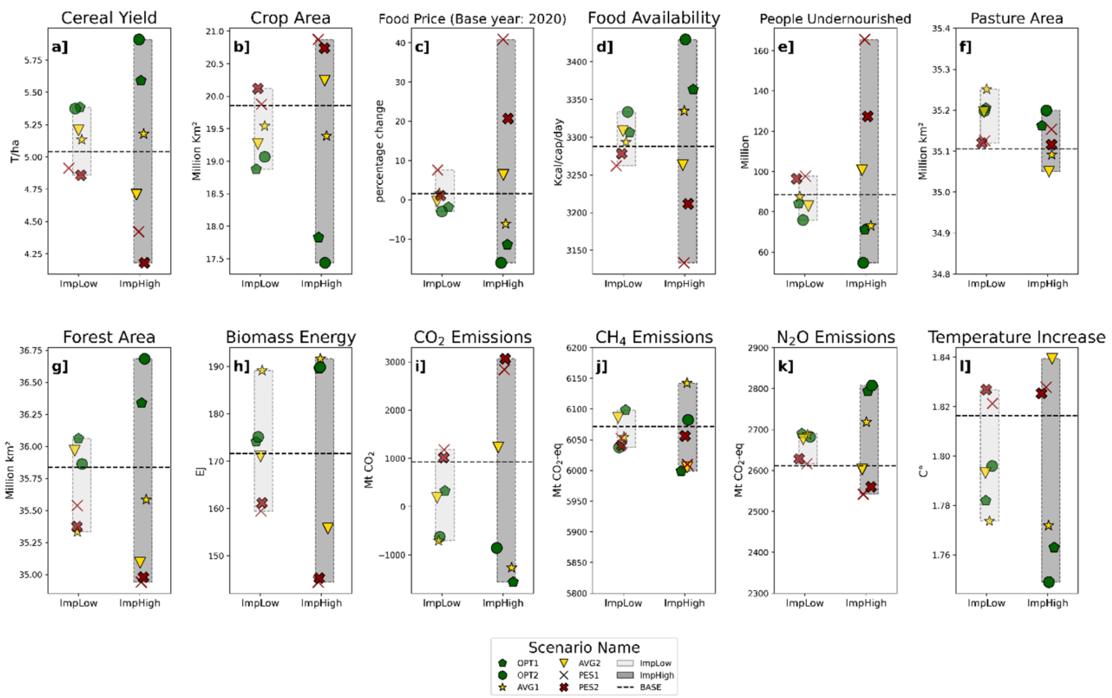

Figure 1. Global cereal yield (a), crop area (b), food security indicators (c)–(e), land use (f)–(g), and climate change mitigation (h)–(l) indicators for the optimistic, average and pessimistic climate-crop model combinations in 2100. The grey boxes represent the range of the indicator across scenarios for low and high crop productivity impacts, while the dashed line represents the indicator value for the BASE scenario.

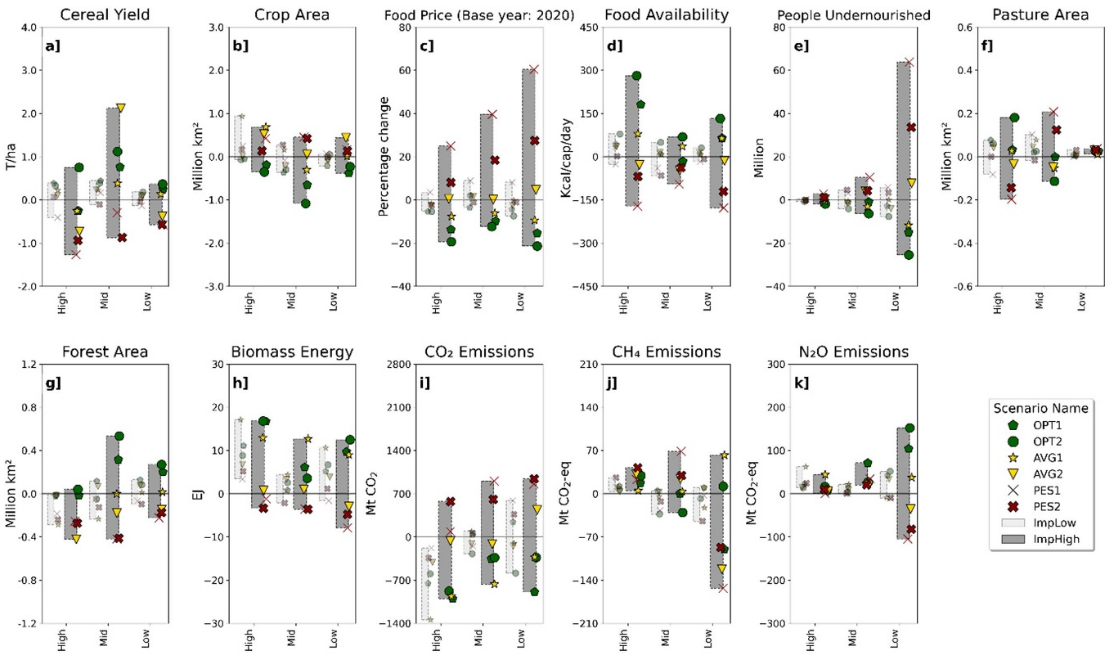

Figure 2. Regional changes (in 2100) in food security (a)–(e), land-use (f)–(g), and climate change mitigation (h)–(k) indicators compared to the baseline with no climate change impacts on crop yields for high-, middle- and low income countries under SSP2 assumptions. The grey boxes represent the range of the indicator across scenarios, for both high and low crop productivity impacts. All scenarios are compared to the baseline, where a value of 0 indicates no change compared to the baseline.

ability to afford food compared to wealthier regions (figure 2(e)).

4.3. Land use change

Global changes in pasture area (figure 1(f)) are minor, especially compared to changes in crop area (figure 1(a)). Regionally, pasture area changes differently in medium-income regions compared to high-income regions (figure 2(f)). Forest area shows higher changes (figure 1(g)). Without climate impacts forest area is projected to be 35.8 million km^2 (BASE) in 2100. Under high climate impact scenarios, forest area ranges from 36.7 million km^2 (OPT2-high) to 34.9 million km^2 (PES2-high). Low climate impact scenarios range from 36.1 million km^2 (OPT1-low) to 35.3 (AVG1-low). Forest area in middle-income regions are more directly tied to agricultural expansion and are most sensitive to changes in crop yields (figure 2(g)). Forest area in high-income regions does not increase compared to BASE, even under optimistic yield projections. In these regions, agricultural land is converted to pasture areas instead.

4.4. Mitigation indicators

IMAGE captures climate change impacts on crop productivity in the energy system via biofuels, influencing climate change mitigation targets. Biomass energy comprises crop residues and energy crops. Crop residues depend on the total agricultural production, and energy crop production is constrained by the availability of natural non-forested and agricultural land that is no longer in use (Daioglou *et al* 2019). In the baseline, primary energy from biomass is projected to be 172 EJ yr^{-1} in 2100. Under high climate impacted crop yields, with the same climate policies compared to the baseline, biomass energy production ranges from 192 EJ yr^{-1} (AVG1-high) to 144 EJ yr^{-1} (PES1-high) due to yield impacts (figure 1(h)). Under low impact scenarios, energy from biomass is projected to range between 189 EJ yr^{-1} (AVG1-low) and 159 EJ yr^{-1} (PES1-low) across optimistic and pessimistic climate-crop model combinations. In both high and low impact AVG1 scenarios, high biomass energy can be attributed to relatively high soybean yields, which are mapped to biofuel oil crops in this study.

Impacts on biofuel production can increase fossil fuel dependency, raising GHG emissions. Yield changes also impact land-use and CO_2 emissions via, for example, de- or reforestation. Due to the uniform carbon price (across all scenarios), global projected CO_2 emissions decrease sharply to 928 Mt CO_2 in 2100 (from 40 582 Mt CO_2 in 2020) in the baseline (figure 1(i)). The carbon price drives this initial reduction by incentivizing lower-carbon practices and discouraging deforestation for the expansion of agricultural land. High yield impact scenarios range from 3063 Mt CO_2 (PES2-high) to −1564 Mt CO_2 (OPT1-high). Low impact scenarios range from to 1179 Mt CO_2 (PES1-low) to −707 Mt CO_2 (AVG1-low).

Small changes in CH_4 emissions are linked to direct effects on rice cultivation and indirect impacts through livestock. Without climate impacts, global CH_4 emissions are 6071 Mt CO_2-eq in 2100 (figure 1(j)). Under high yield impacts, emissions range from 6142 Mt CO_2-eq (AVG1-high) to 5999 Mt CO_2-eq (OPT1-high), while low yield impact scenarios are ranging between 6037 Mt CO_2-eq (OPT1-low) and 6098 Mt CO_2-eq (OPT2-low). Similarly, minor changes occur in N_2O emissions. Baseline N_2O emissions are 2612 Mt CO_2-eq by 2100 (figure 1(k)). High yield impact scenarios range from 2808 Mt CO_2-eq (OPT2-high) to 2542 Mt CO_2-eq (PES1-high) and low yield impact scenarios from 2690 Mt CO_2-eq (OPT1-low) to 2616 Mt CO_2-eq (PES1-low). Interestingly, more optimistic yield projections lead to higher N_2O emissions compared to pessimistic projections. In IMAGE, fertilizer use is linked to crop production, leading to increased N_2O emissions in optimistic climate-crop model combinations.

With IMAGE, we can explore the impacts of the different yield impacts under a 2.6 W m^{-2} long-term climate mitigation target, corresponding to limiting global warming to well below 2 °C (Van Vuuren *et al* 2011). This mitigation target is applied in all scenarios. In the BASE scenario, we assume no direct climate impacts on crop yields despite global temperatures being projected to increase by 1.82 °C in 2100 compared to the pre-industrial historic reference period (1850). This assumption allows us to use the BASE scenario as a reference point to isolate and compare the effects of climate change on yields in the other scenarios. This BASE temperature increase is in line with the Paris Agreement, which limits global warming to well below 2 °C. Figure 1(l) shows the global mean temperatures when exposed to the different productivity projections. Land-use patterns can change dynamically due to changes in crop yields. This includes adjusting the land required to grow crops and potentially abandoning excess agricultural land. This land can potentially be used for bioenergy crops and impact global temperatures directly, as well as through re- or deforestation (figure 2(g)). Temperatures deviate from the BASE by 0.07 and 0.04 under high and low impact scenarios, respectively. AVG2-high shows the largest temperature increase across scenarios, driven by higher CO_2 emissions earlier in the century, resulting in larger cumulative emissions by 2100. While the scenarios were selected based on average yield impacts between 2070 and 2100, earlier-century impacts and regional differences lead to different expected temperature projections.

5. Discussion and conclusion

Uncertainty in crop productivity projections from the GGCMI archive can affect global assessments of food and energy systems. Large changes in both yields and crop area were observed under an RCP8.5 climate towards the end of the century, consistent with similar studies, such as Molina Bacca *et al* (2023). This large spread can substantially impact developments in food security and affect mitigation efforts linked to SDG2 and SDG13. In particular, low-income regions show high sensitivity to food security indicators such as prices and undernourishment. Other studies follow a similar pattern, where a decrease in global crop yields leads to high crop prices in low-income regions, such as SSA, India, and Southeast Asia (Nelson *et al* 2014). Molina Bacca *et al* (2023) use the self-sufficiency ratio (SSR): an indicator to measure a region's ability to meet its food needs through domestic production. They show that some low-income regions, such as India, are very sensitive to changes in yields. A low SSR, coupled with a sharp increase in food prices, may put a large number of people at risk of undernourishment. This modeling study focused on two main dimensions of food security: food accessibility (prices) and food availability (calorie demand and risk of undernourishment). There are also other dimensions of food security, such as the utilization (i.e. quality) and stability of food production over time (Van Meijl *et al* 2020a). IMAGE captures only the caloric content of the crops. Food nutrition and quality, including lowered protein concentrations or micronutrients, can also be impacted by climatic variables, such as elevated levels of CO_2, posing additional challenges in reaching food security targets (Taub *et al* 2008, Semba *et al* 2022). Indicators representing food stability over time are also not well captured in long-term models such as IAMs (yet) (Van Meijl *et al* 2020a).

Crop yields impact bioenergy directly via energy crop land-use and indirectly through forestry and agricultural residues, with the latter influenced by total agricultural production. Net-zero technologies linked to crop production, such as BECCS, can play a vital role in climate change mitigation scenarios (Hanssen *et al* 2020). Declining crop yields can threaten the effectiveness of these technologies (Xu *et al* 2022). Across climate-crop model combinations, global bioenergy production ranges from −10% to +10% in 2100. This aligns with another study showing an 8% increase under RCP6.0 (Zapata *et al* 2022). There still remains a lot of uncertainty on the impacts of climate change on yields and bioenergy production, mainly caused by the strength of the CO_2 fertilization effect (Gernaat *et al* 2021). This is also reflected by Zapata *et al* (2022), who show that modeled regional bioenergy production projections are almost always positive when CO_2 fertilization is included. Across climate-crop model combinations, temperature impacts from changes in GHG emissions are minimal. Adjusting carbon prices to account for changes in yields is likely to mitigate these effects.

The scope of this research was on two SDGs, but the changes in crop yields can potentially spill over to other SDG targets (Fujimori *et al* 2020). For instance, an increase in agricultural area and reduced forest lands can be harmful to biodiversity, especially in low-income regions where the sensitivity to crop variability is high (Betts *et al* 2017, Marques *et al* 2019). In addition to crop yields, there are many other factors that are impacted by climate change that can influence the agricultural sector. For instance, increased and extreme temperatures can induce heat stress in livestock (Thornton *et al* 2021) or the agricultural workforce (De Lima *et al* 2021). In addition, irrigation water shortages can pose risks to crop production (Elliott *et al* 2014). Renewable energy sources, such as hydropower or wind energy, may also be directly impacted by climate change, especially at the regional level (Gernaat *et al* 2021). Furthermore, this study used only IMAGE. Using different models can lead to different effects on food security and mitigation indicators (Bauer *et al* 2020). Crop models themselves also have limitations and do not always capture weather extremes such as floods or decreased yields as a result of pests and diseases (Rötter *et al* 2018). A study by Müller *et al* (2024) showed that crop models can have high sensitivities to different driving variables and suggested the need for better model testing and evaluation to reduce the uncertainties between models. Wang *et al* (2017) also suggested updating model response functions to reduce uncertainties between different crop models.

Food security and climate mitigation indicators, as estimated using state-of-the-art climate-crop model projections, show substantial uncertainty. There are large impacts on global food security, especially under high-emission scenarios. Low-income regions are the most vulnerable, as crop prices, undernutrition, and deforestation respond strongly to changes in crop yields. Although smaller, the impacts of climate mitigation are non-negligible. Different adaptation strategies could partially elevate the impacts on both food security and climate change mitigation indicators (Janssens *et al* 2020, Molina Bacca *et al* 2023). Global policy efforts are needed to make agricultural systems adaptive to climate change and make food systems robust to potential impacts.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing interests.

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