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Key Points:
- Climate change response patterns show regional farming systems where initial positive changes give way to long-term detrimental impacts
- Regional and species-dependent patterns of agricultural impacts on benchmark global warming levels prioritize risk management strategies
- Climate models with high climate sensitivity have less CO_2 benefit on a given global warming level (GWL) and are over-represented in ensembles of higher GWLs

Supporting Information:
Supporting Information may be found in the online version of this article.

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Non-Linear Climate Change Impacts on Crop Yields May Mislead Stakeholders

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Abstract We utilize a global warming level (GWL) lens to evaluate global and regional patterns of agricultural impacts as global surface temperature increases, providing a unique perspective on the experience of stakeholders with continued warming in the 21st century. We analyze crop productivity outputs from 11 crop models simulating 5 climate models under 3 emissions scenarios across 4 crops within the AgMIP/ISIMIP Phase 3 ensemble. We categorize regional productivity changes (without adaptation) into 9 characteristic climate change response patterns, identifying consistent increases and decreases as well as non-linear (peak or dip) responses indicative of inflection points reversing trends as GWLs increase. Many maize regions and pockets of wheat, rice and soybean show peak decrease patterns where initial increases may lull stakeholders into complacency or maladaptation before productivity shifts to losses at higher GWLs. Although the GWL perspective has proven useful in connecting diverse climate models and emissions scenarios, we identify multiple pitfalls that recommend proceeding with caution when applying this approach to climate impacts. Chief among these is that carbon dioxide (CO_2) concentrations at any GWL depend on a climate model's transient climate response (TCR). Higher CO_2 concentrations generally benefit crop productivity, so this leads to more pessimistic agricultural projections for so-called "hot" models and can skew multi-model ensemble results as models with high TCR are disproportionately likely to reach higher GWLs. While there are strong connections between many climatic impact-drivers and GWLs, vulnerability and exposure components of food system risk are strongly dependent on development pathways.

Plain Language Summary This study uses the latest ensemble of crop and climate models with a framework to identify cropping systems and regions where non-linear aspects of agricultural system response to climate change could lead to complacency or maladaptation. Results will help readers understand the different experiences and contextual adaptation needs for food systems in the coming decades. This framework could be widely applied across all impacts sectors. Analysis also highlights that climate models with particularly strong climate sensitivity lead more pessimistic projections by crop impacts, underscoring the need for special care in the use of climate model ensembles for impact assessments.

1. Motivation

Future agricultural systems are challenged to balance (a) sustainable increases in productivity and efficiency to ensure food security for growing and developing populations, (b) adaptation to current extremes and future climate change, (c) mitigation of greenhouse gas emissions and other environmental impacts, and (d) incentives for the economic engine that keeps the agricultural sector running (Mbow et al., 2019; Nabuurs et al., 2023). Each of these individual challenges is substantial and addressing them simultaneously requires foresight, systems thinking and coordinated planning of proactive solutions (Kerr et al., 2022; Mbow et al., 2019; Ruane & Rosenzweig, 2018; Sillmann et al., 2022). If farmers and stakeholders throughout the agricultural value chain take a wait-and-see approach they may find themselves without necessary capabilities that could have been possible with early investment in long-term and transformational adaptation solutions (Rickards & Howden, 2012). Impacts may be particularly severe in places where productivity trends are currently flat or increasing (lowering the concern of stakeholders) but may turn sharply negative in the future leading to a larger gap between adaptation needs and capacity (Ebi et al., 2016; Kerr et al., 2022; Sillmann et al., 2022).

Global mitigation policymaking is largely oriented around benchmark global warming levels (GWLs) such as the 1.5°C and 2.0°C targets that are designated as upper limits in the Paris Agreement (IPCC, 2018; UNFCCC, 2015).

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At a finer scale, adaptation, risk management and the implementation of specific mitigation strategies have a distinct temporal component within dynamic natural and human systems (IPCC, 2022a), often utilizing information drawn from climate models simulating Shared Socioeconomic Pathways and Representative Concentration Pathways (SSP-RCPs; IPCC, 2022b; O'Neill et al., 2016). This set of intertwined perspectives on future climate change motivated special guidance on translating between scenario/time and GWLs in the IPCC (Fischer et al., 2021).

The evolution of climate risks across time and global warming levels shapes our ability to recognize and plan climate resilient systems as we shift development pathways toward sustainability (Winkler et al., 2022). Planning processes are more easily motivated in areas where projections of future risks match current impact trends (adverse or beneficial) but are less clear in regions and systems where projections indicate a substantial acceleration, deceleration, or reversal from current trends (Ebi et al., 2016). Here we propose a simple framework to identify decision contexts where projected shifts align with present experience and those where climate risk trends may catch stakeholders by surprise.

GWLs are appealing for their potential to transcend model uncertainties and scenario differences, simplifying analysis of climate changes and corresponding impacts and risks to better draw out key messages amidst societal pathway uncertainty. Hausfather et al. (2022) recently underscored the importance of uncertainties related to climate model sensitivity to greenhouse gas forcing, suggesting that the GWL perspective may allow for ensemble analysis including models beyond the very likely climate sensitivity ranges assessed by the IPCC (Forster et al., 2021). The GWL perspective relies on a pattern scaling assumption that regional climatic impact-drivers (CIDs) look similar at a given GWL whether that GWL is reached early or late in the 21st century and independent of emissions pathway (Ranasinghe et al., 2021; Ruane et al., 2022). From a climate information perspective this approach is supported by a recognition that many CIDs scale closely with GWLs, indicating a short lag in shifts to regional circulation patterns and extreme characteristics (Tebaldi et al., 2021). GWLs are less appealing for CIDs related to the ocean and cryosphere, which commonly have a substantial lag due to large ocean heat capacity and complex ice dynamics which take more time to equilibrate to global temperature changes (Fox-Kemper et al., 2021).

The use of GWLs for impacts, adaptation and risk assessment poses additional challenges, as reflected in the Intergovernmental Panel on Climate Change finding fewer studies with GWLs for Working Group II applications (IPCC, 2023). Bloch-Johnson et al. (2022) argued for further evaluation of the impacts utility of so-called "hot models," recognizing that climate sensitivity is important information for sectoral stakeholders making decisions under uncertainty. Strong connections between CIDs and GWL relate to the hazard component of risk and thus reduce the problematic nature of "hot models," but vulnerability and exposure are distinct and not easily collapsible to GWL levels. These instead follow 21st century trajectories shaped by socioeconomic development, population growth, ecological response and the implementation of adaptation and mitigation technologies that would discourage a GWL approach (Reisinger et al., 2020; Simpson et al., 2021; Tebaldi et al., 2023).

Here, we develop and apply a climate change response pattern framework that captures the evolution of fundamental regional agricultural responses within a large climate-crop model ensemble projecting multiple emissions scenarios. This stands in contrast to agricultural impacts studies that typically examine productivity shifts within fixed future time slices (e.g., 2071–2100) and present uncertainty among models and between scenarios (Asseng et al., 2015; Jägermeyr et al., 2021; Rosenzweig et al., 2014). Our primary interest is the crop productivity impacts of benchmark GWLs, as well as the emergent patterns of climate change response by region and farming system, which may indicate the likely experiences of affected stakeholders considering climate action as the world warms (not always linearly; Ebi et al., 2016). We also examine uncertainties related to crop productivity changes at each GWL and the ability of the GWL lens to bypass uncertainties in climate model sensitivity.

2. Methods

2.1. Global Gridded Crop Models (GGCMs)

This study examines the latest output from a community ensemble featuring 11 process-based crop models running 4 crops (maize, wheat, rice and soybean) driven by 5 bias-adjusted climate models under 3 socioeconomic scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5 representing relatively low, high and very high greenhouse gas emissions, respectively) (Table S1 in Supporting Information S1). Simulations without adaptation from 1850 to 2100 were conducted as a collaboration between the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2013) Global Gridded Crop Model Intercomparison (GGCMI; Müller et al., 2017) and the Inter-Sectoral Impacts Model Intercomparison Project (ISIMIP; Warszawski et al., 2014). An overview of these simulations was provided by Jägermeyr et al. (2021), who noted ensemble projections of substantial regional and global productivity changes while also calculating the time of emergence for the climate impacts signal moving beyond the range of historical variance by region and farming system. GGCMs were run at 0.5° resolution, representing crops' genotype, environment (including weather), and management conditions to simulate their day-by-day growth and final season yields. Models simulate both rainfed and irrigated conditions and distinguish between multiple seasons of wheat and rice (unless noted in Table S1 in Supporting Information S1).

AgMIP GGCMs were used in previous ISIMIP assessments using CMIP5 outputs (Rosenzweig et al., 2014), but the crop modeling protocol has substantially improved since. All crop models have been updated and advanced, additional models participated, model inputs such as the crop calendar were improved, and the bias-adjustment of GCM data was developed further (see Jägermeyr et al., 2021, for details). These GGCMs have been evaluated against sub-national and national historical productivity statistics (Müller et al., 2017; Ruane et al., 2021) and are used as the basis for crop yield emulators that provide quick sampling of regional responses within a broad climatic change space (Franke et al., 2020). By using multiple crop models, we benefit from ensemble statistics that have proven beneficial for crop model applications (Ruane et al., 2017; Wallach et al., 2018).

Each of the GGCMs was configured to harmonize growing seasons for each region and farming system as described in Jägermeyr et al. (2021) (Figure S1 in Supporting Information S1). Outputs were quality controlled to identify and account for common output formatting issues such as short years, harvest failures, multiple harvests in same year, and reporting year offsets (Jägermeyr et al., 2021). Simulations included carbon dioxide (CO_2) responses, which remain a substantial source of uncertainty (Toreti et al., 2020), assuming negligible regional or seasonal variation in global surface concentrations compared to the long-term changes explored in this study. These GGCMI simulations do not include additional impact factors addressed elsewhere in AgMIP studies including pests and diseases (Savary et al., 2018) and ozone and air pollution (Emberson et al., 2018). Simulations are conducted with fixed farm management at the year 2015 level in order to capture the direct climate signal on agricultural systems even as farmers are likely to adapt to the extent possible given biophysical, socioeconomic and technological limitations (Franke et al., 2022; Kerr et al., 2022; Minoli et al., 2022; Zabel et al., 2021).

2.2. Regional and Global Productivity

Percentage yield changes were scaled against the SPAM observational yield reference data set (You et al., 2014) and subsequently area-weighted against MIRCA2000 area to obtain average productivity values (Portmann et al., 2010). Global productivity includes rainfed and irrigated crop productivity for all grid cells and seasons. As in Jägermeyr et al. (2021), grid cells with missing SPAM yield data but with >10 ha MIRCA2000 area were filled with yield values from Ray et al. (2012). Global productivity values are area-weighted using MIRCA2000, with map displays masking out areas that currently have less than 10 ha cultivated area for any given crop.

2.3. Climate Scenarios and Models

GGCM simulations were driven with ISIMIP bias-adjusted and downscaled projections (Lange, 2019) from 5 global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016). These GCMs are the most prominently used in ISIMIP Phase 3 projections owing in part to their availability early in the IPCC cycle. Simulations were conducted for low (SSP1-2.6), high (SSP3-7.0) and very high (SSP5-8.5) emissions scenarios (IPCC, 2021b; O'Neill et al., 2016). SSP1-2.6 represents a high mitigation scenario consistent with Paris Agreement aims to limit global warming, SSP3-7.0 represents a low mitigation scenario, and SSP5-8.5 represents a development pathway with heavy fossil fuel use. Recent reductions in coal usage have reduced the likelihood of society following an emissions pathway as high as SSP5-8.5, but this scenario provides useful insight on a global warming level analysis. Agroclimatic analysis focuses on seasonal exposure to climate according to the average historical growing seasons for each region and cropping system, as described in Jägermeyr et al. (2021).

2.4. Determination of Global Warming Levels

GWLs for each GCM/SSP-RCP were determined following the methods employed by the IPCC AR6 Working Group I (Fischer et al., 2021). We draw global surface air temperatures for each climate model simulation from the KNMI Climate Explorer (https://climexp.knmi.nl/) and represent the period whose 20-year average first exceeds the GWL in question (e.g., 2010 represents the average of 2000–2019). Observations assessed by the IPCC AR6 show that 1986–2005 was 0.69°C above 1850–1900 pre-industrial conditions and reached 0.99°C in the 2001–2020 period, 1.09°C in the 2011–2020 decade and 1.26°C in the single 2020 year (Chen et al., 2021, Figure 1.12 therein). We examine the 1986–2005 GWL of 0.69°C as a "recent climate" similar to the reference period in Jägermeyr et al. and use GWLs of 1°C, 1.5°C, 2.0°C, 2.5°C, 3.0°C, 3.5°C, and 4.0°C as benchmarks relevant to policymaking even as every increment of climate change increases global impacts and risks (IPCC, 2021b, 2022a).

We did not examine GWLs beyond 4°C given that there are fewer GCMs that reach higher GWLs by the year 2100 end of GGCMI simulations (Table S2 in Supporting Information S1). We also limit our examination of higher GWLs recognizing that IPCC Working Group III indicated that current policies place us on a pathway for 3.2 [2.2–3.5]°C GWL by 2100 (IPCC, 2022b). Internal variability in the GCMs, particularly in the 1986–2015 period targeted for ISIMIP bias-adjustment, may affect calculated GWLs and is an intriguing area of further study. The ISIMIP bias-adjustment likely affected average temperatures over land, but this is likely reduced given spatial heterogeneity in biases and thus we expect that the net global warming level effect is small compared to the overall levels of 21st century warming.

2.5. Model Projection Ensembles

Throughout this study we select the largest ensemble of crop and climate models available for any given analysis, although this leads to slightly different ensembles for each crop species and scenario (Table S1 in Supporting Information S1). Models that did not run the second season of wheat or rice were excluded from those species productivity ensembles.

3. Agricultural Perspectives on Global Warming Levels

The agricultural sector is sensitive to a large number of CIDs that cannot be assessed only on the global scale. It is therefore critical to link global temperature responses to more agriculturally-prominent hazards such as regional heat waves, seasonal temperature and precipitation changes, droughts, river and pluvial flooding and severe storms (Kerr et al., 2022; Ranasinghe et al., 2021; Tebaldi et al., 2023). Impacts from climate change are not expected to always be detrimental—in some regions and farming systems, agriculture benefits from reductions in cold waves and frost or shifts toward more suitable seasonal temperatures and rainfall patterns. Crop growth also benefits from higher CO_2 concentrations at the surface, which increases productivity by stimulating photosynthesis and improving water retention while also reducing the nutritional value of many crops (Myers et al., 2014; Toreti et al., 2020). In this section we show how agricultural impacts are determined on each GWL, key farm system impacts on benchmark GWLs, and the underlying climate information and uncertainties they reflect.

3.1. Climate Model Influences on Global Warming Level Impacts

An important attribute of each climate model is its equilibrium climate sensitivity (ECS), which is the equilibrium (steady state) change in the surface temperature following a doubling of the atmospheric carbon dioxide (CO_2) concentration from pre-industrial conditions (IPCC, 2021a, 2021b). Given continuing emissions a more relevant quantity is the transient climate response (TCR), which is defined as the surface temperature response for the hypothetical scenario in which atmospheric CO_2 increases at 1% yr^{-1} from pre-industrial to the time of a doubling of atmospheric CO_2 concentration (year 70) (IPCC, 2021a). Table 1 reports the TCR and ECS for climate models examined in this study, including the UKESM which falls outside of the IPCC *very likely* assessed range for both ECS (2–5°C) and TCR (1.2–2.4°C) (Forster et al., 2021). A GCM with high ECS generally has a high TCR, but rankings between CMIP6 models differ as TCR is further differentiated by a model's cryosphere and ocean dynamics.

Figure 1 shows global mean surface temperature observations and projections over the 21st century, presenting two perspectives to highlight global warming levels and crossing times for running 20-year averages under each

Table 1
Equilibrium Climate Sensitivity (ECS) and Transient Climate Response (TCR) for Climate Models Used in This Study (From Table 7.SM.5 in Forster et al. (2021); With Added Values for GFDL-ESM4)

Climate model	Country	Equilibrium climate sensitivity	Transient climate response
GFDL-ESM4	United States	2.6°C	1.63°C
IPSL-CM6A-LR	France	4.56°C	2.32°C
MPI-ESM1-2-HR	Germany	2.98°C	1.66°C
MRI-ESM2-0	Japan	3.15°C	1.64°C
UKESM1-0-LL	United Kingdom	5.34°C[a]	2.79°C[b]

[a]Exceeds IPCC WGI AR6 assessed ECS very likely range (2–5°C; Forster et al., 2021). [b]Exceeds IPCC WGI AR6 assessed TCR very likely range (1.2–2.4°C; Forster et al., 2021).

climate model and emissions scenario. GCMs with high TCR warm more and warm faster than others in the same emissions scenario (Meehl et al., 2020). GCMs with higher TCR reach a given GWL earlier (within the same SSP-RCP), and only high TCR models reach a 4°C GWL before 2100 under SSP3-7.0 and SSP5-8.5. This also leads to uncertainties in arrival times for each GWL, ranging from 1985 to 2006 for 0.5°C, 2002 to 2022 for 1.0°C, 2018 to 2041 for 1.5°C, 2030 to 2058 for 2.0°C, and 2046 to 2082 for 3.0°C. The range for 4.0°C was 2061–2082, but this under-represents the true range given that simulations for GCMs with lower TCR reach 4.0°C after 2100 (in SSP3-7.0 and SSP5-8.5) but those years were not simulated by crop models in this study. Uncertainties related to the arrival time for each GWL are important for proactive planning activities that aim to ensure that adaptation capabilities are suited to the strain of future hazards.

Figure 2 reveals that differences between GCMs' TCR drives substantial uncertainty in the CO_2 concentrations associated with each GWL. The clusters of symbols with the same color for each GWL indicates that each GCM reaches a given GWL at approximately the same CO_2 concentration regardless of SSP-RCP. This is consistent with TCR being a fundamental characteristic of GCM greenhouse gas response, although values for a single GCM are not identical given that each SSP-RCP has a unique pathway for short-lived climate forcers, land use and greenhouse gases beyond CO_2 (O'Neill et al., 2016; Szopa et al., 2021). CO_2 uncertainty at each GWL is therefore attributable to the GCMs themselves, leading to CO_2 concentration ranges of 340–380 ppm for 0.5°C, 370–425 ppm for 1.0°C, 405–505 ppm for 1.5°C, 430–580 ppm for 2.0°C, and 525–745 ppm for 3.0°C. The range

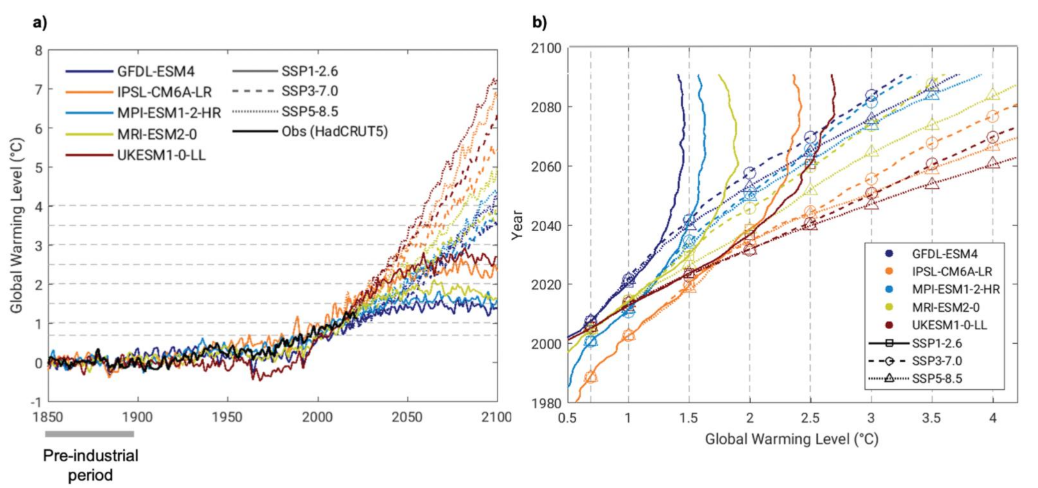

Figure 1. 5 GCM projections of global mean surface air temperature (at 2 m height) (a) from the pre-industrial period to the end of the 21st century using historical emissions and three future scenarios (raw GCM outputs from KNMI Climate Explorer: https://climexp.knmi.nl/) and (b) from 1980 to 2100 with 20-year smoothing and the axes transposed to emphasize global warming levels 0.5–4°C. Note that some model/scenario combinations exceed 4°C and others do not reach higher GWLs; 2091–2100 is omitted in panel (b) because smoothing is not possible without 2100–2109 outputs. HadCRUT5 global surface temperature observations shown in (a) for reference, and 1850–1900 pre-industrial period noted given that it is defined as the period for GWL = 0°C.

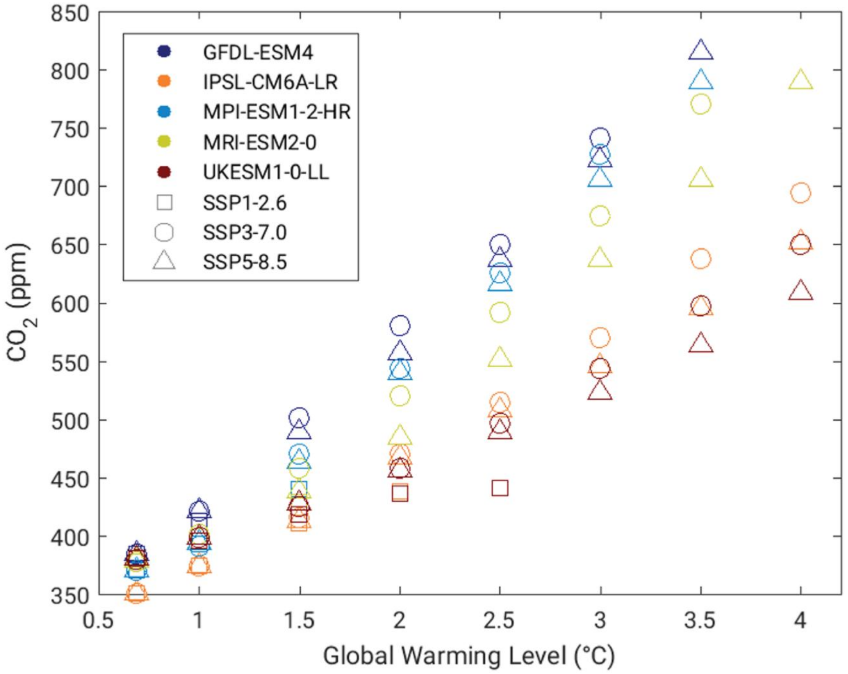

Figure 2. Climate model and scenario CO_2 concentration for each global warming level (GWL). Note that not all scenarios reach the higher global warming levels by 2100 (recall Figure 1).

for the subset of climate simulations that reached 4.0°C by 2100 was 610–790 ppm and would extend higher if simulations beyond 2100 were included. Crop model simulations show that productivity sensitivity to CO_2 is on the same order of magnitude as the sum of all other climatic impact-drivers with strong dependence on region (climate, soils) and farming system (crop species, cultivar choice, farm management) as well as substantial uncertainty across crop models (Durand et al., 2016; Franke et al., 2020; Jägermeyr et al., 2021; McDermid et al., 2015; Toreti et al., 2020). CO_2 uncertainty on crop production at lower GWLs, which is related to the range of potential TCRs, may be comparable or larger than the temperature impacts (Ruane et al., 2018a, 2018b; Schleussner et al., 2018).

3.2. Regional Agricultural Seasons by Global Warming Level

Figure 3 shows that regional temperature changes for the rainfed maize growing season rarely match the global mean surface temperature change that defines a GWL (this is consistent with additional crops and seasons shown in Figures S2–S6 in Supporting Information S1). Local temperature changes are generally similar whether drawn from all SSP-RCPs or only a single SSP-RCP, reinforcing the IPCC finding that many CIDs are consistent on a given GWL even across emissions scenarios (Ranasinghe et al., 2021; Seneviratne et al., 2021).

Changes in growing season mean temperature and precipitation generally follow a consistent regional pattern that becomes more pronounced with increasing GWL. Regional farmland temperature changes are generally above the global temperature change with some exceptions (e.g., India). Crops are grown on land and thus benefit from land amplification of the warming signal, with regional differences due to factors such as land/sea heat capacity, unique growing seasons, land cover, circulation patterns (such as the South Asian monsoon), aerosols, and corresponding shifts to the water cycle that affect surface energy balances (Gutiérrez et al., 2021; Ruane et al., 2018a, 2018b). Regions prominently differ in their projected changes in growing season precipitation, which also varies substantially across GCMs (Douville et al., 2021; Gutiérrez et al., 2021). Agriculture is particularly tied to precipitation changes in the warm seasons, which tend to have a broader drying signal and higher propensity for drought than the cool seasons (Ruane et al., 2018a, 2018b; Seneviratne et al., 2021).

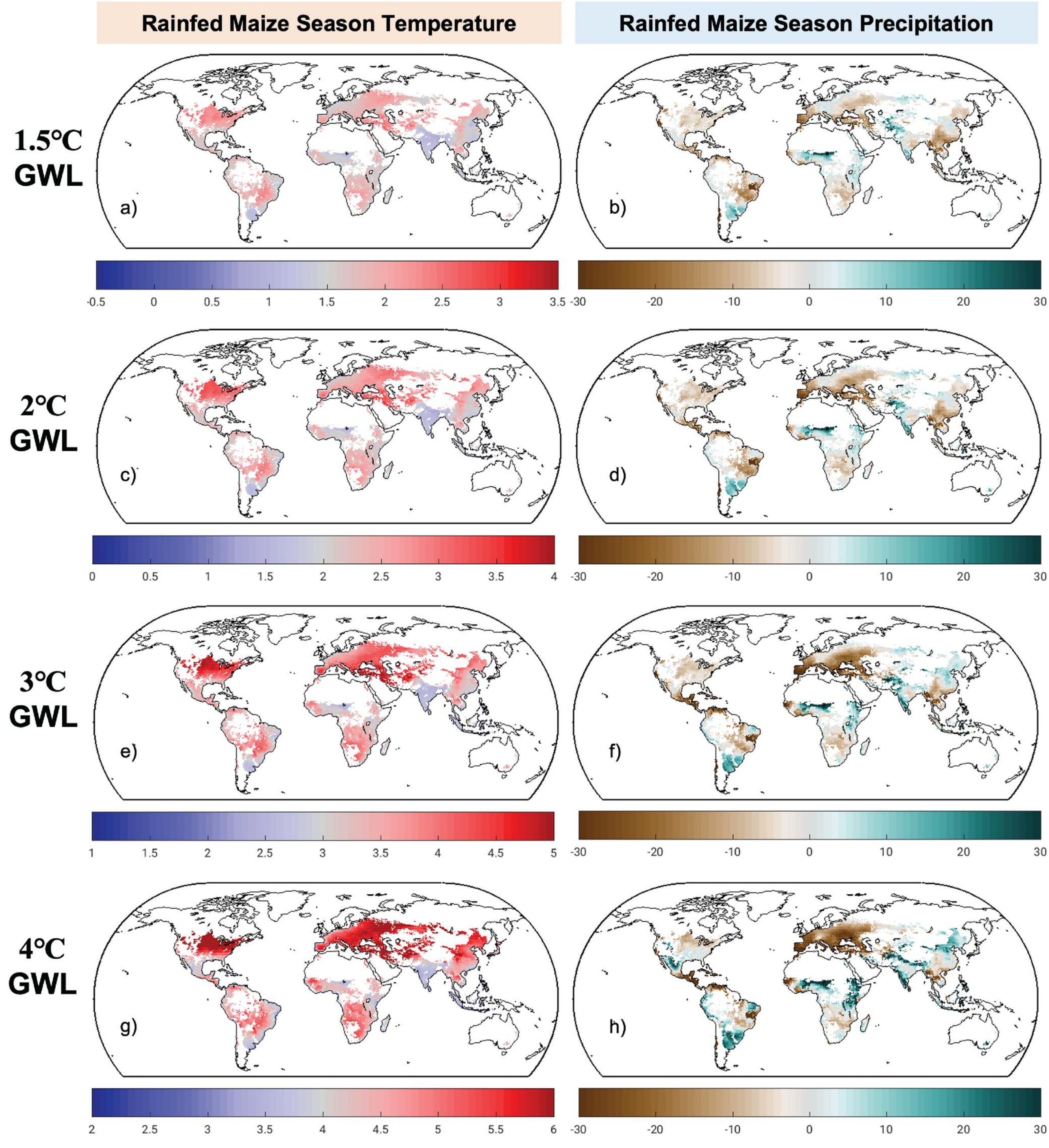

Figure 3. Ensemble projections of local rainfed maize growing season temperature (left) and precipitation (right) changes at a given GWL (compared to 1850–1900 pre-industrial) drawn from all SSP-RCP scenarios in the rainfed maize growing season for all ISIMIP model projections that reach GWL of (a) 1.5°C (14 GCM/scenario combinations), (a) 2°C (12 combinations), (a) 3°C (10 combinations) and (a) 4°C (5 combinations). All regions are warming—note that the gray portion of the temperature change color bars is aligned with the respective global warming level, such that areas that are blue warm less than the global average and areas that are red warm more than the global average. Comparisons with analyses drawing from only SSP5-85 and maps for other growing seasons are shown in Figures S2–S6 in Supporting Information S1.

3.3. Global Productivity Response by Global Warming Level

A key ensemble result reported by Jägermeyr et al. (2021) was that global productivity for maize declines by 24% under end-of-century (2069–2099) SSP5-8.5 conditions, while wheat increases by 18%. The more pessimistic projection for maize (relative to wheat) is driven largely by maize benefiting less from higher CO_2 levels owing to it being a C4 crop, while wheat, rice and soy are C3 crops with a stronger CO_2 benefit (Toreti et al., 2020). Wheat is also generally grown in cooler regions and seasons that are further from adverse extreme heat thresholds. Figure S7 in Supporting Information S1 shows a spaghetti diagram of global productivity changes for each GCM/SSP-RCP simulation across time, and we note here that the large range of productivity changes across simulations is not straight-forward to interpret given these confounding uncertainties. For example, analysis of the SSP5-8.5 end-of-century time slice blends GWLs from 2.8 to 4.3°C in 2069 to 4.15 to 7.25°C in 2099 across the driving GCMs, which begs the question of whether a GWL perspective would be more useful.

Figure 4 provides the same ensemble crop model projections via a GWL lens isolating uncertainties from SSP-RCP (left) and GCM selection (right) from 0.69°C to 4°C GWL. Productivity changes are largely consistent with the overall messages of the Jägermeyr et al. study's temporal analysis given that GWLs progressively increase with time in most SSP-RCPs. Maize productivity declines with warmer GWLs in all SSP-RCPs, reaching ∼−16% at the 3.5°C GWL. Wheat, rice and soybean productivity generally increase with higher GWLs, with soy peaking at 2.5°C (+10%), rice peaking at 3°C (9%), and wheat peaking at 3.5°C (+12%). Differences between SSP-RCP productivity responses are best explained after first examining productivity responses by GCM.

Crop model simulations driven by different GCMs (right side of Figure 4) show that GCM TCR has the potential to skew productivity responses when viewed as GWLs. Crop models driven by GCMs with lower TCR (Table 1) experience each GWL at a higher CO_2 concentration (Figure 2), resulting in a more positive CO_2 response and therefore more positive productivity changes compared to crop models driven by GCMs with higher TCR. UKESM1's high TCR is therefore a primary cause for it being the most pessimistic set of projections for each crop at each GWL. The IPSL model (with the second highest TCR) is the next most pessimistic model at higher GWL for all but the maize projections, while the lower TCR models (GFDL, MPI, MRI) generally project higher levels of productivity. Crop simulations do not perfectly follow TCR because they are also affected by unique regional patterns of climate change. For example, GCMs with increasing dry CIDs over major rainfed production regions will reflect those stronger negative impacts (Ruane et al., 2018a, 2018b).

Returning to the apparent productivity response differences across the SSP-RCP pathways, we may now attribute much of these differences to the extent of warming across each ensemble of GCM simulations. Stars in the left panels of Figure 4 indicate the highest GWL reached by all 5 GCMs in each SSP-RCP, with productivity values at higher GWLs drawn from a diminishing ensemble subset of GCMs that reached higher GWLs (depending on their TCR; see Table 1 and Table S2 in Supporting Information S1). As the models that reach the highest GWLs have disproportionately high TCRs and therefore more pessimistic responses (given lower CO_2 concentrations at each GWL), productivity responses in these diminishing ensemble subsets are more pessimistic than you would expect from the full ensemble. This is apparent in the downward divergence of each SSP-RCP productivity projection at GWLs beyond Figure 4 panel stars.

Although the left panels of Figure 4 appear to indicate substantial reversals of gains projected for wheat, rice and soybean by the 4°C GWL, the extent of these reversals is not present in any of the individual GCM simulations. Rather, these high GWL SSP-RCP changes reflect the increasing prominence of the UKESM1 and IPSL projections within the remaining ensemble. We therefore avoid GCM dependence by containing our analysis to the portion of each SSP-RCP that includes all 5 GCMs (up to Figure 4 stars). The largest sampling of GWLs is therefore drawn from the SSP5-8.5 simulations where all GCMs reached 3.5°C GWL by 2100 (for reference we provide growing season climate changes at 3.5°C for all rainfed crops in Figure S8 in Supporting Information S1).

Productivity changes for SSP3-7.0 wheat, rice and soybean under are generally more pessimistic than SSP5-8.5 at higher GWLs where the full ensemble is available for both scenarios. CO_2 levels at each of these GWLs are comparable regardless of scenario (Figure 2). This difference may be due to the later arrival time of each GWL under the lower emissions scenario which allows more time for long-term aridity trends to affect soil moisture conditions (Douville et al., 2021), although this merits further study.

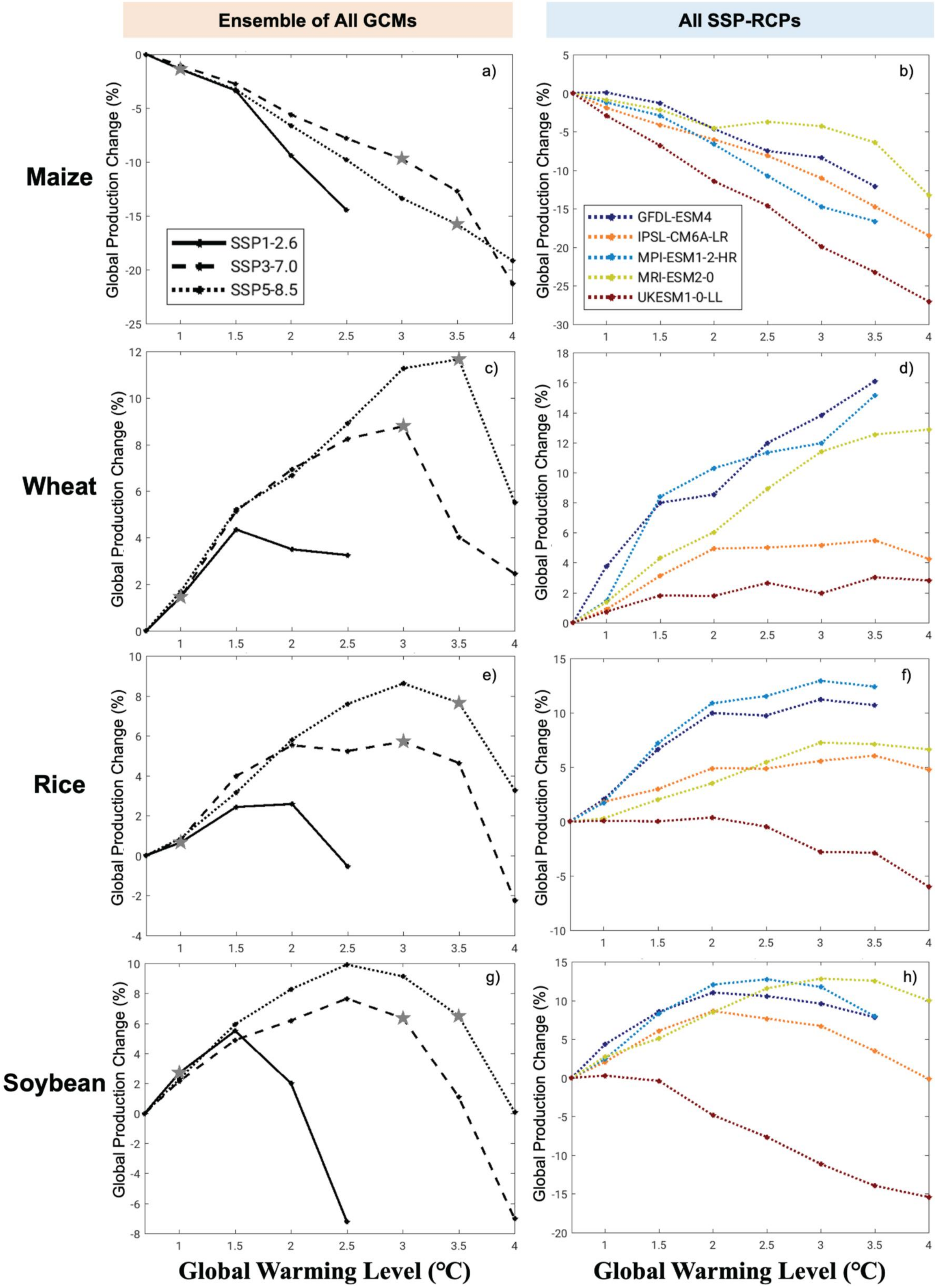

Figure 4. Global production changes of (a, b) maize, (c, d) wheat, (e, f) rice and (g, h) soybean by GWL (compared to 0.69°C GWL) for (left) GCM ensemble mean for each SSP-RCP and (right) each GCM running all SSP-RCPs that reached any given GWL. Gray stars in left panel indicate the last GWL that all GCMs reach in a given scenario in the 21st century, with higher GWL results for that SSP-RCP calculated from a decreasing subset of GCMs that increasingly sample GCMs with higher climate sensitivity (and thus lower CO_2 at each GWL).

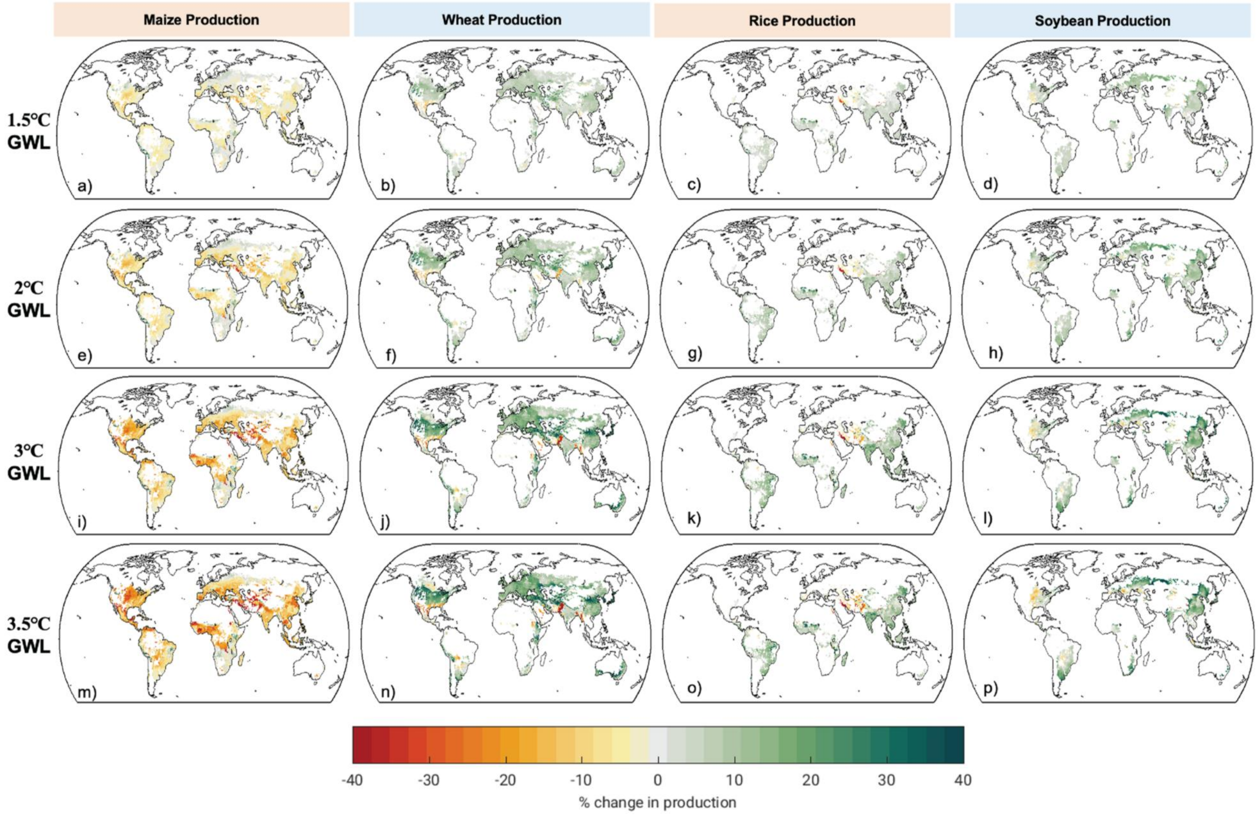

Figure 5. Mean production change compared to 0.69°C GWL for maize, wheat, rice and soybean under SSP5-8.5 (5 GCMs) at 1.5°C, 2.0°C, 3°C, and 3.5°C global warming levels (GWL).

3.4. Regional Productivity Response by Global Warming Level

Figure 5 presents maps of median global productivity changes at prominent GWLs compared to the 0.69°C GWL (corresponding to observed 1980–2005 period; see methods). The 3.5°C GWL maps are similar to those shown by Jägermeyr et al. for SSP5-8.5 end-of-the-century (2069–2099; that study used a 1983–2013 reference period), which corresponds to GWLs of 3.4–5.9°C across the ISIMIP climate models. Maize productivity decreases in nearly all regions of the world given that it has a smaller CO_2 benefit as a C4 crop and is generally planted in warm seasons closer to damaging heat thresholds. Productivity losses are particularly large in breadbaskets of the US Midwest, NE China, Southern Europe and West Africa, although reductions in non-exporting regions can have huge ramifications for local food security. Wheat productivity increases in most mid-latitude regions given that wheat has a high CO_2 benefit as a C3 crop and is often planted in cooler regions and seasons. Tropical and subtropical wheat (e.g., Mexico, the Indo-Gangetic Basin, Southern Brazil, portions of Eastern Africa and the Middle East) shows large productivity declines, as do some northern latitudes (e.g., Southern Canada). Rice productivity changes are smaller and highly regional, with losses in Central Asia appearing by 2°C GWL. Soybean productivity changes are also more modest than maize or wheat, with losses at 3.5°C GWL in portions of Southwestern Brazil, Eastern Asia, Eastern Europe and the western extent of the US Midwest.

At broad glance the patterns of these changes are visible in the lower (1.5 and 2°C) GWL maps, with impact patterns generally becoming more pronounced with higher GWLs. The GWL view makes it difficult to identify areas of acceleration, deceleration, or reversal of productivity trends as the climate system warms, which motivates the GWL evolution pattern analysis below. It is also important to contextualize these results given that observations indicate GWLs have already risen from 0.69°C (1986–2005 period) to ~1.1°C (2011–2020 period) (IPCC, 2021b). Figure S9 in Supporting Information S1 shows regional GWL impacts for all GCM/SSP-RCP combinations that reached each GWL, again showing that including GCMs from a diminishing subset at high GWLs leads to a more pessimistic outlook. Figure S10 in Supporting Information S1 shows productivity changes for each crop at the 3°C GWL broken down by climate model. This breakdown

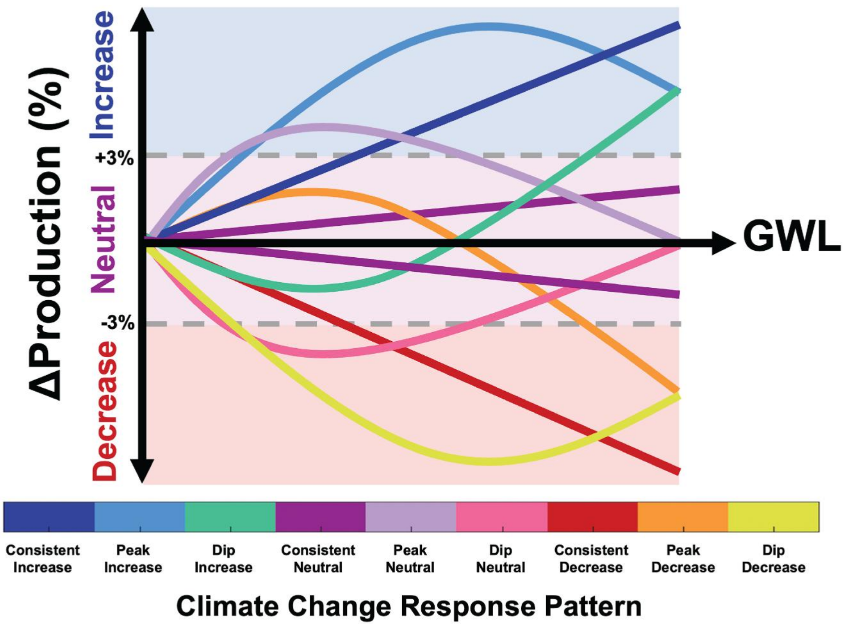

Figure 6. Schematic illustrating representative climate change response pattern, categorized by their shape as lgobal warming levels increase and their direction of change at the highest GWL evaluated. In this study we compare responses from 0.69°C to 3.5°C GWLs that were reached by all GCMs in the SSP5-8.5 scenario.

reveals distinct regional patterns associated with model-dependent shifts in the water cycle and underscores the more pessimistic nature of the "hot" UKESM model (particularly for soybean) that has lower CO_2 concentrations at each GWL.

4. Climate Change Response Patterns

4.1. Defining Global Response Patterns

We define characteristic climate change response patterns (Figure 6) distinguished by overall trends (*increase*, *neutral*, or *decrease*) and shape of productivity change (*consistent*, *peak*, *dip*) across successive GWLs up to the highest GWL seen in all 5 SSP5-8.5 GCMs (3.5°C). Trends are defined by comparing productivity at the highest GWL to the productivity at the historical 0.69°C GWL. We define increases and decreases as exceeding positive or negative 3% change in mean productivity (respectively) and neutral indicating less than 3% absolute productivity change. The ±3% threshold was selected to represent changes large enough to overcome noise in the patterns while avoiding washing out evidence of near-zero inflection points. Peaks and dips occur when the largest productivity change at an intermediate GWL (1°C, 1.5°C, 2°C, 2.5°C, or 3°C) moves in the opposite direction to the trend exhibited by the highest GWL (i.e., peaks above or dips below). When the highest GWL exhibits an absolute productivity change less than 3% (*neutral*), peaks and dips are only characterized when earlier GWL productivity changes exceeded the 3% threshold to avoid attributing shapes to small variations about 0%. Characterizing each grid cell's response according to three overall trends (*increase*, *neutral*, *decrease*) and three shapes of productivity change (*consistent*, *peak*, *dip*) results in the nine potential climate change response patterns illustrated in Figure 6.

Revisiting the global productivity changes within the SSP5-8.5 scenario (dotted line in the left panels of Figure 4 up to the star indicating the 3.5°C GWL reached by all GCMs considered here) allows us to characterize each crop species' climate change response pattern. Global maize productivity shows a *consistent decrease*, while wheat follows a *consistent increase* pattern. Rice and soybean show a *peak increase* pattern given that global rice productivity is higher at 3°C than 3.5°C and soybean peaks at 2.5°C.

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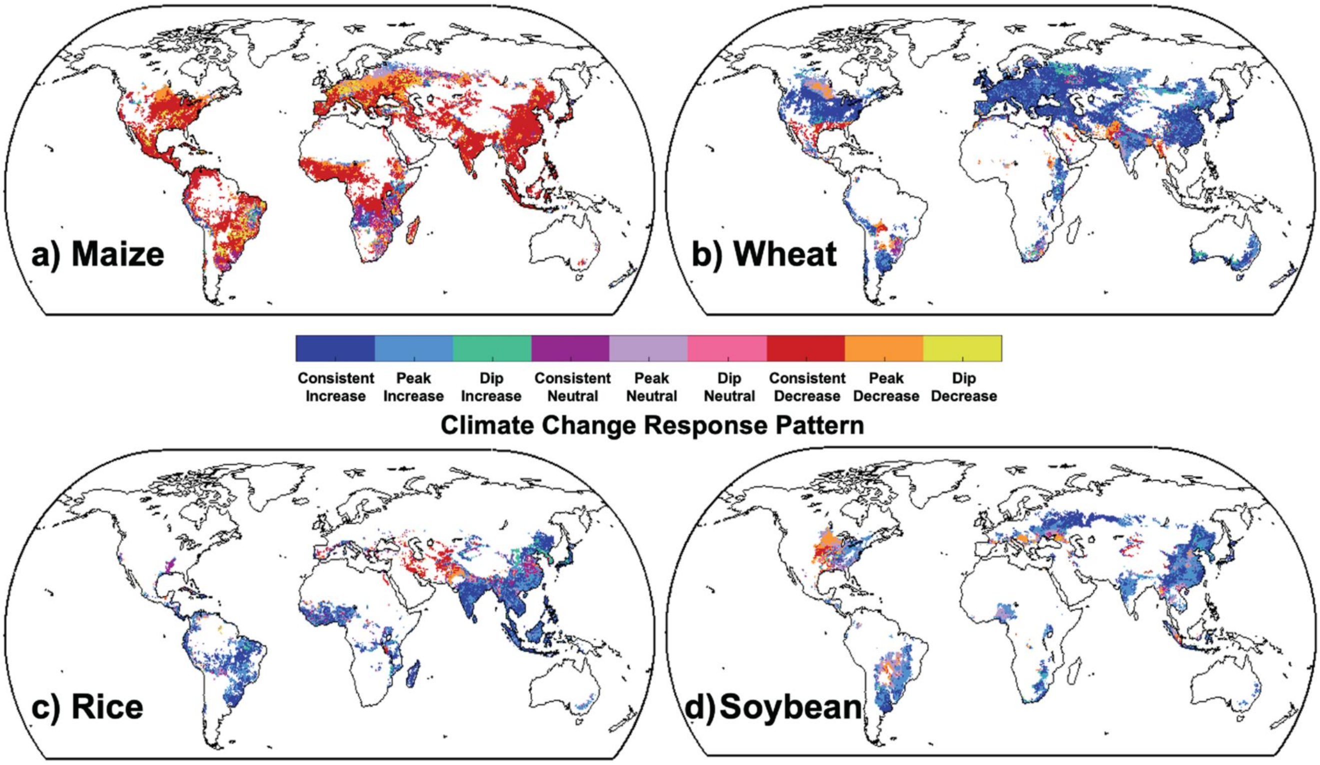

Figure 7. Regional climate change response patterns for maize, wheat, rice, and soybean from the ensemble of all SSP5-8.5 GCMs and GGCMs. Patters at each grid cell were derived from mean production changes over 0.69–3.5°C GWLs as all GCMs reached these GWLs between the historical and SSP5-8.5 simulations. Colors correspond to the climate change response pattern categories illustrated in Figure 7. Only grid cells with >10 ha cultivated areas are shown.

4.2. Regional Climate Change Response Patterns

Figure 7 characterizes the climate change response pattern for each crop type for each growing region of the world, with Table 2 showing the percentage of each crop's global productivity characterized by each response type.

Crop responses in most areas demonstrate either *consistent increase* or *consistent decrease* patterns, indicating that climate pressures are moving in a continuous direction. Areas that are currently near high temperature or water resource limitations tend to show *consistent decreases*. Maize is predominantly characterized by this pattern (78% of total productivity), including many major export food baskets (the US Midwest, Southern Europe, Eastern China, India) as well many maize regions that are vital for local food security (e.g., West Africa, Mexico and Central America, Southeast Asia). Consistent decreases are also seen for wheat in Mexico, rice in Western Asia, and soybean in the southwest US Midwest. *Consistent increases* are generally associated with cooler mean temperatures (e.g., higher latitudes or high elevations), crops grown in cool seasons (e.g., wheat, with 55% of total

Table 2
Percent Production for Maize, Wheat, Rice and Soybean Characterized by Each Climate Change Response Pattern in the SSP5-8.5 Ensemble (Corresponding to Figures 6 and 7)

	Climate change response pattern								
	Consistent increase	Peak increase	Dip increase	Consistent neutral	Peak neutral	Dip neutral	Consistent decrease	Peak decrease	Dip decrease
Maize	<1%	<1%	<1%	2%	1%	1%	78%	8%	7%
Wheat	55%	26%	2%	3%	5%	<1%	3%	6%	<1%
Rice	33.%	33%	4%	13%	7%	3%	2%	5%	<1%
Soy	13%	39%	1%	3%	20%	1%	4%	17%	2%

Note. The top three most representative patterns for each commodity are highlighted.

productivity), and C3 crops (wheat, rice and soy) where strong CO_2 benefits can overwhelm adverse temperature and drought hazards (Figure S1 in Supporting Information S1 shows growing seasons).

Fewer regional crop responses are *consistent neutral*, indicating that most regions will be substantially affected by climate change. The main exception is rice systems where consistent neutral is the third most common pattern (Table 2). Notable regions classified as *consistent neutral* include maize in southern growing regions in South America and portions of interior southern Africa extending from Lake Victoria to Zimbabwe, wheat in Southern Brazil, and rice along the Southern Mississippi River and across a zone stretching from the Southern Himalayas of India to parts of Northeastern China.

Regions whose climate change responses feature *peak* or *dip* characteristics feature substantively non-linear responses that alter the sign of productivity change trend at higher GWLs. While the causes of this shift require further analysis for any given region, this reversal is often the result of a tipping-point phenomena, such as: (a) the emergence of a new agroclimatic hazard (negative inflection; e.g., elevated probability of drought at higher GWL; Seneviratne et al., 2021); (b) a consistent trend causing conditions to surpass a biophysical tolerance level (negative inflection; e.g., extreme temperatures surpassing critical limits; Grotjahn, 2021); (c) a boon condition overwhelming competing adverse hazards (positive inflection; e.g., the beneficial effects of CO_2 for growth and water retention; Toreti et al., 2020); or (d) a positive response having diminishing benefits as GWL increases continue (negative inflection; e.g., CO_2 benefits per ppm are reduced at higher concentration levels; Franke et al., 2019). Regions where wheat or rice crops are grown in multiple seasons may also show a reversal when productivity changes in one season surpass changes in the other.

Areas categorized as *peak decrease* are concerning given that these indicate initial productivity increases followed by a substantial reversal toward negative productivity changes as global temperatures warm. Farmers and other planners in *peak decrease* regions may be less concerned with climate change given initial productivity gains, however this lack of concern is not merited given that projections suggest a sharp downturn is to come at higher GWLs. *Peak decrease* areas include the US Upper Midwest, Central and Northeastern Europe, and portions of East Africa for maize; Southern Canada, Pakistan and Bangladesh for wheat; Pakistan for rice; and the US Upper Midwest, Balkans and Caucuses for soybean (17% of total soybean productivity is characterized as *peak decrease*). *Peak neutral* conditions are similar but erase low GWL gains rather than reversing into substantial negative productivity changes. *Peak neutral* classifications are relatively common for soybean (20% of total productivity) but include maize in far Northeastern Europe and eastern South Africa, wheat in Western India, and soybeans in the Eastern US Midwest, Nigeria and Eastern Ukraine.

Dip increase regional patterns reverse low GWL losses into high GWL gains. In these regions, adaptation efforts meant to maintain current productivity levels may prove less necessary as warming continues. Additional analysis of model outputs is merited in *dip increase* regions to determine whether continued warming reduces a current hazard or whether the emergence of a countering boon condition is driving high GWL benefits even as the low GWL hazard continues. Early adaptations in that latter case would have continuing benefits and opportunities for higher productivity at high GWLs. *Dip increase* areas include maize in Inland Northeast Brazil; wheat in portions of Northwest Russia, South Africa and inland Western Australia; and rice in Southern Japan, the Korean Peninsula, and Northern China. *Dip neutral* conditions are similar but erase low GWL losses at higher GWLs without shifting into substantial productivity benefits. *Dip neutral* is the least common classification, found only in a few grid cells for maize (e.g., in northern Central Brazil and Southern Africa).

Many regional crops show *peak increase* patterns, indicating that initial increases will level off or return toward present day productivity levels before the 3.5°C GWL. *Peak increase* response patterns are seen for wheat (26% of productivity) in much of Argentina and India, Southern Mexico, East Africa and Eastern Australia; for rice (33% of productivity) in Central Brazil, Northern South America, Indonesia, Southern China, and the Murray-Darling Basin in Australia; and for soybean (39% of productivity) in Brazil, Central Europe, India, China and the Eastern US.

Maize is the only crop where the *dip decrease* response patterns characterizes substantial productivity (7%), indicating that losses rarely turn around or level off with higher GWLs. *Dip decrease* patterns are only found for maize in portions of the Southern US, Northern Mexico, Central Europe and Central Brazil. Further study is warranted to identify the drivers that reverse these regions' negative productivity trends at higher GWLs, although we caution that this classification could also be an artifact of increasing yield failures indicating a lower floor to productivity changes.

The association of climate change response patterns show how climate impacts depend on current climate zones. In many cases, classifications indicate that farmers in one region will experience productivity changes that lag or lead nearby regions, often in a predictable way across temperature or precipitation gradients. For example, maize shows *peak increase* in the coldest regions of northeast Europe, with *peak neutral* in warmer portions of northern Europe, *peak decrease* in northern Central Europe, *dip decrease* in southern Central Europe, and *consistent decrease* patterns in the hottest portions of Southern Europe. While the colder climates can benefit from initial warming, the geographical progression toward hotter current climates effectively pulls the downward inflection point from higher GWLs to lower GWLs. This means farmers in Southern Europe will face these climate challenges first, allowing them to potentially share their experiences and adaptation approaches with farmers in cooler climates as global warming increases. Similar progressions are visible for soybean in Central Brazil. Other strong geographical gradients are associated with differences in growing season (see Figure S1 in Supporting Information S1), for example, between spring and winter wheat in Northern Mexico (*consistent decrease*) and the Southern United States (*consistent increase*) or for different wheat seasons in Pakistan (*peak decrease*) and India (*peak increase*). These stark border gradients would likely be reduced with the incorporation of better management information into the crop models.

5. Implications of Main Findings

5.1. Potential for Complacency and Maladaptation

Many of the areas where previous studies noted long-term crop productivity trends show consistent changes across GWLs (e.g., *consistent decreases* for maize, *consistent increases* for many wheat and rice regions). Regions showing non-linear effects (dip or peak responses) indicate cropping systems where stakeholders will not be well-served by assuming initial trends will continue. Projections for *peak* regions indicate a downturn in productivity (with growing adaptation needs) and *dip* regions are projected to experience an upturn as global warming levels increase (with decreasing adaptation needs).

We highlight *peak decrease* regions (including many mid-latitude maize areas and pockets of wheat and soybean) as areas where stakeholders experiencing some productivity increases at low GWLs may be reluctant to adapt despite projections indicating losses at higher GWLs (see Ebi et al., 2016). Complacency to climate risks in these regions may shorten the time available to develop and implement proactive solutions for coming declines and may lead to maladaptive development that further intrenches threatened systems. *Peak increase* regions (including many soybean areas and pockets of rice and wheat) may lull stakeholders into discounting climate concerns given increasing productivity despite projections of reversing returns at higher GWLs. Few regions show *dip* behaviors, indicating that productivity losses rarely turn around with higher GWLs once they start. Nearly all regions are substantially affected by climate change. For example, *peak neutral* and *dip neutral* regions are projected to experience a range of impacts at lower GWLs even as they would appear to have low productivity impacts when examined only at higher GWLs.

5.2. Framework Can Be Used in All Impacts Sectors

We recommend applying a similar categorization to understand fundamental GWL and/or time-evolution responses for climatic impact-drivers, compound hazards, and impacts for other sectors (e.g., livestock, agroforestry, fisheries, ecosystems, human health, water resources, tourism, energy, transportation, conflict). It is likely that other aspects of human and natural ecosystems will experience *peak decrease* responses that will need extra attention given the potential for complacency and maladaptation as short-term gains obscure the projection of long-term losses.

5.3. Pessimistic “Hot Models” Due To CO_2

Efforts to combine climate projections from different climate modeling groups and emissions scenario along GWLs have proven helpful in synthesizing common responses in climatic impact-drivers, but we recommend caution in analyzing climate impacts by GWL. Hausfather et al. (2022) indicated that the appeal of GWLs is that “despite some differences related to the rate of warming and aerosol forcing, the world largely looks the same at

2°C, no matter how we get there." While that study was focused on physical climate conditions, our analysis of the AgMIP/ISIMIP ensemble shows that this is not the case for agricultural impacts owing largely to interactions between transient climate response (TCR) and CO_2 concentrations. The result is that "hot models" (with high TCR) tend to be more pessimistic given that they have lower CO_2 at a given GWL. With the appropriate caveats, these models may still be useful to explore tail risks for resilience planning. A similar CO_2 bias likely affects land ecosystem and pasture/rangeland impacts projections. The utility of GWLs for ocean ecosystems also merits urgent attention given that ocean acidification may reflect TCR uncertainties in earth system models in a similar manner.

5.4. Global Warming Level (GWL) Methods for Impacts Require Particular Care

In the course of this study we encountered numerous methodological pitfalls that are instructive for others looking to identify GWL impacts responses.

- *Dwindling ensemble members*: Models with lower TCR do not reach the higher GWLs, meaning the set of ensemble members reaching high GWLs over-represents the high TCR models (which have lower CO_2 at a given GWL) and therefore would be biased toward more pessimistic productivity changes. We therefore recommend that climate impact responses to rising GWLs be conducted on a consistent set of GCM ensemble members. Future GWL assessments could also simulate lower TCR GCMs past 2100 to ensure that all GCMs may be included at higher GWLs.
- *Time dependence*: GWL analysis trades scenario uncertainty for temporal uncertainty and a range of CO_2 concentrations that can strongly influence agriculture or ecosystems along with slow-onset changes such as growing aridity. Indicators of mitigation, adaptation and food system risk must also factor in vulnerability and exposure that do not align along GWLs given their connection to socioeconomic pathways with strong time dependence.
- *Decoupled scenarios*: Applications of a GWL approach for geoengineering scenarios (such as solar-radiation modification) are not practical given that global temperatures would decouple from important CIDs like CO_2 concentration and ocean acidification (Szopa et al., 2021).

5.5. Model Improvement

Model intercomparison and improvement within the AgMIP Community continues to increase simulations' ability to capture key biophysical processes driving future productivity changes. Continued investment is needed to improve process understanding for these major staple crops, to capture further responses to CIDs (Ruane et al., 2022), and to incorporate pressures from pests, diseases and air pollution (Emberson et al., 2018; Savary et al., 2018). There is also tremendous potential for the development of models of non-staple crops that are critical for food security and rural development. Model projections will also benefit from more accurate data on the farm environment, cultivar characteristics and farmer management.

5.6. New Simulation Designs

New simulation designs are also enabling exploration of adaptation strategies that may recover some regional yield losses or take advantage of opportunities provided by changing climate conditions (Minoli et al., 2019, 2022; Zabel et al., 2021). Simulations of representative agricultural pathways (RAPs; Valdivia et al., 2015) are also needed to understand how adaptation efforts could alter climate change response patterns. It is likely that inclusion of RAPs could identify conditions in which socioeconomic development and adaptation technologies increase upward productivity trends or reduce downward productivity trends, potentially even driving *dip*-like reversals toward higher productivity.

5.7. Final Remarks

Taken together, this study shows the urgent need to fill in gaps in our understanding of how impacts will proceed in the coming decades. Model improvement and assessment designs need to be coherent from physical conditions through system impacts, broader socioeconomic policies and emissions and adaptation actions in order to support targeted, proactive interventions that reduce future risks.

Data Availability Statement

Climate data used in this manuscript are available through ISIMIP (Lange, 2019). Crop model projections are available via AgMIP (see Jägermeyr et al., 2021). Analysis scripts and instructions for data access are available via Phillips and Ruane (2023).

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