Global economic responses to heat stress impacts on worker productivity in crop production

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Abstract

The impacts of climate change on the food system are a key concern for societies and policy makers globally. Assessments of the biophysical impacts of crop productivity show modest but uncertain impacts. But crop growth is not the only factor that matters for the food production. Climate impacts on the labour force through increased heat stress also need to be considered. Here, we provide projections for the integrated climate-induced impacts on crop yields and worker productivity on the agro-economy in a global multi-sector economic model. Biophysical impacts are derived from a multi-model ensemble, which is based on a combination of climate and crop models, and the economic analysis is conducted for different socio-economic pathways. This framework allows for a comprehensive assessment of biophysical and socio-economic risks, and outlines rapid risk increases for high-warming scenarios. Considering heat effects on labour productivity, regional production costs could increase by up to 10 percentage points or more in vulnerable tropical regions such as South and South-East Asia, and Africa. Heat stress effects on labour might offset potential benefits through productivity gains due to the carbon dioxide fertilisation effect. Agricultural adaptation through increased mechanisation might allow to alleviate some of the negative heat stress effects under optimistic scenarios of socio-economic development. Our results highlight the vulnerability of the food system to climate change impacts through multiple impact channels. Overall, we find a consistently negative impact of future climate change on crop production when accounting for worker productivity next to crop yields.

Keywords: climate change, crop yield, heat stress, CGE model

1. Introduction

The Sustainable Development Goals (SDGs) aim at, among other goals, ensuring healthy lives, achieving food security, and promoting inclusive and sustainable economic growth. They are therefore highly related to how sectors such as agriculture will evolve in the future and react to climate change. There are numerous studies using statistical and process-based crop models to assess climate-induced impacts on crop yields (e.g., Hurlbert et al., 2019; Roberts et al., 2017; White et al., 2011). Depending on the parameters and configurations chosen for the models, the results can be very different. Zhao et al. (2017) find a global decrease in wheat, rice, maize and soybean for a global increase in temperature based on four analytical methods. Deryng et al. (2011), Lobell and Field (2007), and Lobell et al. (2008) confirm the previous results, as they find a global crop yield reduction. On the other hand, Wilcox and Makowski (2014) show that the effect of high CO_2 concentrations (>640 ppm) would outweigh the effect of increasing temperature (up to +2°C) and a moderate decline in precipitation (up to -20%), leading to increasing yields globally. While atmospheric CO_2 concentrations may enhance crop production via the fertilisation effect, additional warming has a consistent negative effect and increases the risk of extremely low yields, especially in the tropics (Schleussner et al., 2018). Rosenzweig et al. (2018) find positive impacts on yield changes for wheat but negative for maize under projected climate change using an ensemble of crop models driven by projections from climate models from the fifth phase of the Coupled Model Intercomparison Project (CMIP5). Leemans and Solomon (1993) find that mostly high-latitude regions benefit from climate change, with projected longer growing periods and an increased crop productivity while tropical regions do not benefit or even lose productivity in response to projected changes in climate conditions. Overall, future climate-induced impacts on crop yields are still very uncertain, especially when accounting for the CO_2 fertilisation effect.

The economic impacts of changes in agriculture and food production are often analysed using either bottom-up partial equilibrium (PE) or top-down computable general equilibrium (CGE) models. However, most economic impact assessments focus on specific regions (Chalise and Naranpanawa, 2016; Siddig et al., 2020), and only a limited number of studies use global economic models (Fujimori et al., 2018; Moore et al., 2017; Ren et al., 2018). Compared to economic PE models, CGE models are typically spatially coarser and simpler with respect to the modelling of agricultural systems but more consistent and comprehensive from a macroeconomic point of view. The framework of CGE models can consistently capture cross-regional and cross-sectoral dependencies. Neglecting cross-sectoral interactions could lead to biased results (Harrison et al., 2016). Due to the presence of cross-regional and cross-sectoral dependencies, integrating the agricultural impacts into multi-regional multi-sectoral macroeconomic models is needed to provide a comprehensive assessment of climate impacts and social cost of carbon.

Results of previous CGE-based studies show that global economic consequences of climate-induced impacts on agriculture tend to be modest but uncertain (Fujimori et al., 2018; Moore et al., 2017). However, these studies usually only investigate the impacts on crop yields from changes in temperature and precipitation as well as CO_2 fertilisation, while other relevant factors affecting agricultural productivity, such as the impact of heat stress on worker productivity, are not considered. A large body of literature finds that heat stress could lead to substantial global productivity losses, especially in labour-intensive production sectors like agriculture where many jobs take place outdoors (Bröde et al., 2018; Kjellstrom et al., 2018, 2009). Economic costs of reduced worker productivity due to heat stress are found to be considerably high and could compensate a large part of mitigation costs (Orlov et al., 2020; Takakura et al., 2017). Even in Europe, the cost of heat stress impacts on worker productivity could be nonnegligible (Orlov et al., 2019). Hertel and de Lima (2020) suggest taking a broader view of climate-related impacts on agriculture and food production by including other important drivers of agricultural outputs, such as worker productivity. The authors find that a limited coverage of climate impacts could lead to a substantial underestimation of the consequences for food security and economic productivity. Lima et al. (2021) find that heat stress on agricultural workers could exacerbate adverse impacts of climate change on crop yields.

Here we build on previous work related to heat stress impacts on worker productivity to extend current economic impact assessments related to agriculture and food production. Specifically, we incorporate both heat-induced impacts on worker productivity and climate-induced impacts on crop productivity into a macroeconomic modelling framework. Applying an interdisciplinary approach, we conduct a global economic impact assessment using two different heat assessment metrics and show the economic response for several global regions. Moreover, we investigate the relevance of different types of scenario and modelling uncertainties.

2. Data and methodology

2.1 Economic model

To assess economic implications of climate change impacts, we use a recursive dynamic, multi-regional, multi-sectoral CGE model: Global Responses to Anthropogenic Changes in the Environment (GRACE) (Aaheim et al., 2018). The model is formulated as a mixed complementarity problem, which is written in the Mathematical Programming System for General Equilibrium (MPSGE) for the General Algebraic Modeling Language (GAMS) (Bussieck and Meeraus, 2004; Rutherford, 1999) and solved using the PATH solver (Ferris and Munson, 2000). The model features great flexibility and consistency as it can incorporate information from different impact models and consistently capture cross-sectoral (i.e., intermediate consumption) and cross-regional (i.e., trade and capital flows) dependencies. In the model, behavioural responses of producers and consumers are described as a non-linear optimization problem, where agents are assumed to optimise their production and consumption decisions to maximise profits and wealth. The overall concept underlying the model is illustrated in Fig. 1 and briefly explained below. A more detailed description of the model can be obtained in Aaheim et al. (2018).

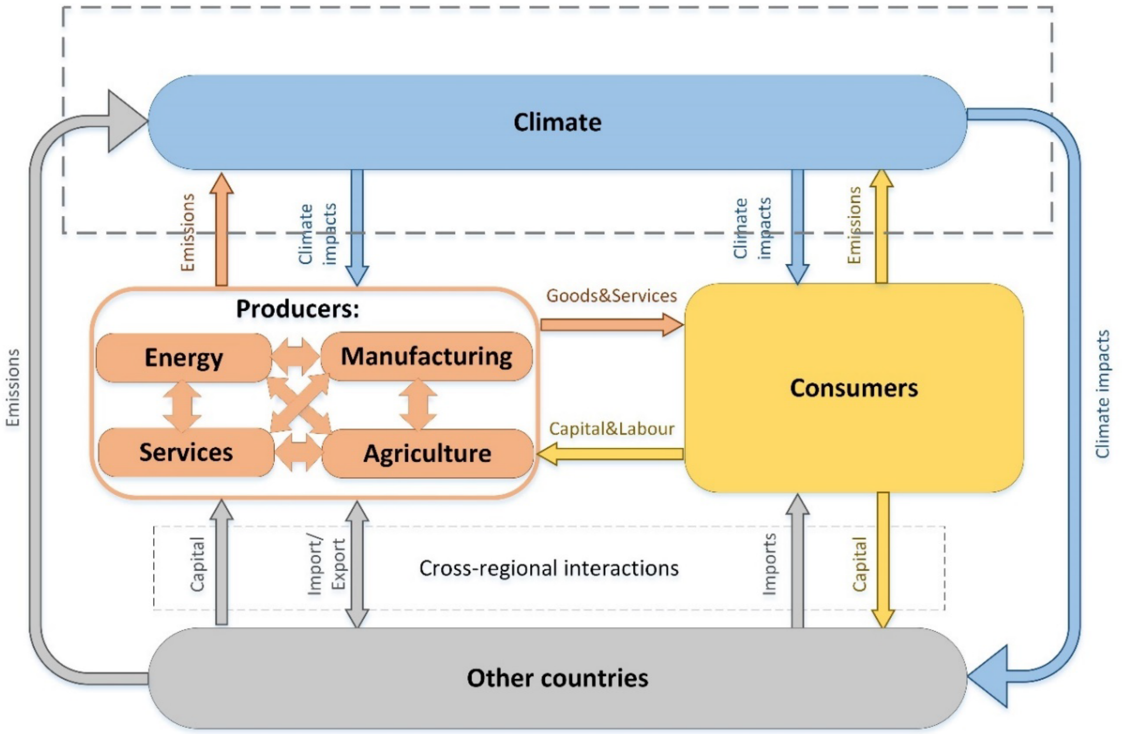

Fig. 1: Circular flows of economic activities and climate-economic interactions within a region (country) in GRACE. The climate component is not an endogenous part of GRACE's economic optimisation. Biophysical climate-induced shocks are derived from climate and impact models and exogenously incorporated into GRACE, meaning that feedbacks of the economy on climate are not accounted for.

In GRACE, goods and services are produced using intermediates and primary factors (i.e., labour, capital, and natural resources). Representative producers are assumed to maximize their profits by choosing an optimal level of production and combination of inputs subject to resources and technological constraints. Goods and services are supplied to domestic and export markets (if tradeable). Production technologies are depicted by nested constant elasticities of substitution (CES) functions, which is a standard functional form used in CGE models. A CES function allows introducing substitution possibilities among primary factors as well as substitution between primary factors and intermediates (e.g., energy inputs). Representative consumers spend their income received from supplying primary factors (i.e., wages and return to capital) on consumption of imported and domestically produced commodities, and savings. Imported and domestically produced commodities are treated as imperfect substitutes, which implies that commodities are heterogenous (i.e., different by their characteristics). Furthermore, different types of commodities (e.g., energy vs. non-energy) are also modelled as imperfect substitutes in consumption. Consumers are assumed to maximise their utility (wealth) by choosing an optimal level of consumption and combination of goods and services subject to budget constraints. Consumers' preferences are modelled using a linear expenditure demand system depicted by nested CES functions. As all producer as well as consumer groups are aggregated and modelled by representative agents, their responses should be interpreted as aggregated responses of groups. Labour is assumed to be perfectly mobile among sectors but immobile across regions (i.e., no migration). Capital is mobile among sectors and across regions (i.e., foreign direct investments). Domestic and foreign savings are spent on investment goods, which form the capital stock in the next period. In the model, apart from capital accumulation, population growth and technological change are the main drivers of economic growth.

The initial values in GRACE are calibrated using Version 9 of the Global Trade Analysis Project (GTAPv9) database (Angel et al., 2016), which depicts global economic transactions for three reference years (2004, 2007, and 2011) for 140 world regions and 57 sectors. All values in GTAPv9 are annual and measured in millions of US dollars depending on the reference year. We aggregate all countries and regions into 10 regions (Fig. 2 and Table S2.1.1, supplementary material). All production sectors are aggregated into 18 sectors, including seven sectors that constitute the broad agricultural system: rice, wheat, maize, soy, other crops, livestock, and food (Table S2.1.2, supplementary material). In the dynamic version of GRACE, to calibrate reference scenarios from 2011 to 2099, we use the Shared Socioeconomic Pathways (SSP) projections on the gross domestic product (GDP) and population growth. For the calibration of the SSP-based reference scenarios, a differentiated sectoral productivity growth is implemented following Britz and Roson (2019). Furthermore, to better depict a structural change in the economy, the income elasticities of demand for agricultural products (i.e., the responsiveness of demand to a change in income) are empirically estimated using the FAO and World Bank databases. Income elasticities of non-agricultural goods and services are obtained from Chapter 14 of the GTAP database (Hertel and Mensbrugghe, 2016).

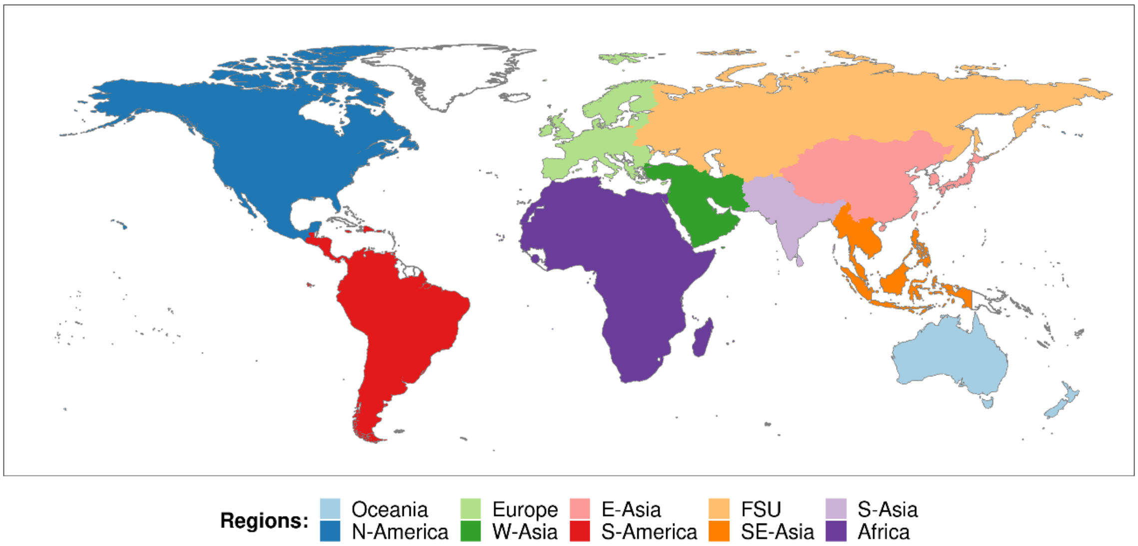

Fig. 2: Regional aggregation in GRACE.

Irrigated and rainfed growing methods are introduced as two separate production sectors, which are disaggregated using the datasets from IFPRI (2020). For irrigated crops, nested CES functions are used to incorporate substitution between capital, labour, water, and land. This depicts the possibility to adapt to water stress experienced by crops via irrigation deployment. Imperfect allocation of land among sectors, which implies conversion costs and land heterogeneity, is modelled using a nested constant elasticity of transformation (CET) functions (see Fig. S2.1.1, supplementary material).

2.2 Climate inputs and scenarios

Economic consequences of climate-induced impacts on crop yields and heat-induced impacts on worker productivity are calculated for the Radiative Concentration Pathways RCP2.6 and RCP6.0, two scenarios for changes in radiative forcing over the 21st century that attain 2.6 W/m^2 and 6.0 W/m^2 in 2100, respectively, hence reflecting different implications in terms of global warming. RCP2.6 describes an aggressive climate mitigation scenario that limits the increase in global mean temperature below 2°C compared to the pre-industrial levels (van Vuuren et al., 2011), whereas RCP6.0 implies some mitigation policies but a higher increase in global mean temperature, in a range of 1.4 to 3.1°C by the end of the century (IPCC, 2013; Masui et al., 2011). For each RCP, we use the bias-adjusted results from the phase 2b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b) (Frieler et al., 2017) forced with four Global Climate Models (GCMs): HadGEM2-ES (Collins et al., 2008) and GFDL-ESM2M (Dunne et al., 2012, 2013a), MIROC5, and IPSL-CM5A-LR. These four climate models are at the higher and lower ends of range of equilibrium climate sensitivity from the GCMs that participated in the fifth phase of the Coupled Model Intercomparison Project (CMIP5), allowing us to capture uncertainties in the global mean temperature response in each RCP (Andrews et al., 2012). The climate projections and crop model simulations for the ISIMIP2b are used to derive scaling factors, which are implemented in the GRACE model. Fig. 3 illustrates the analysis procedure, which is described in detail in Section 2.3 and 2.4.

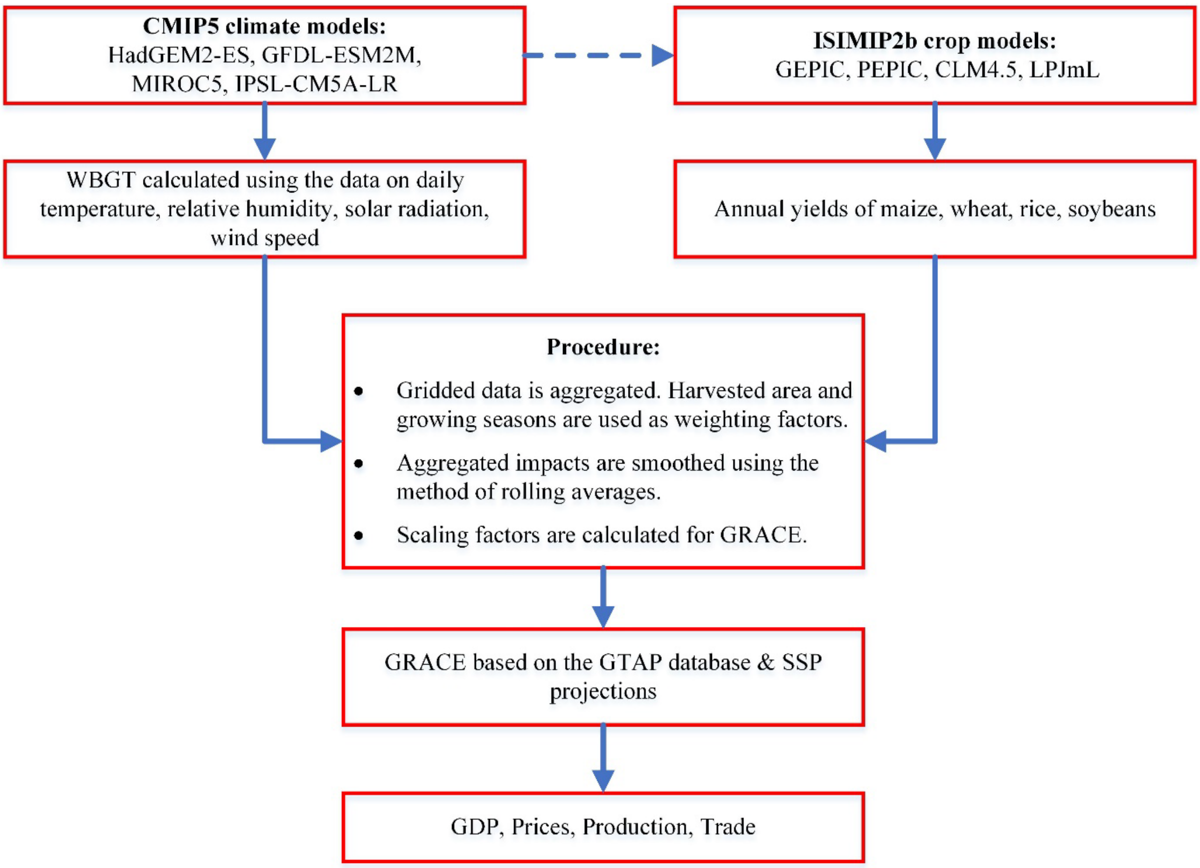

Fig. 3: Illustration of the analysis procedure. WBGT stands for the wet bulb globe temperature.

Future socioeconomic scenarios are modelled based on SSP1 and SSP4, which are compatible with the chosen RCPs. SSPs describe different possible socio-economic pathways (i.e., economic development and population growth), which describe long-term consequences of near-term decisions (Riahi et al., 2017). SSP1 (Sustainability) implies low challenges to mitigation and adaptation, while SSP4 (Inequality) describes a world with low challenges to mitigation but high challenges to adaptation (i.e., increasing inequalities and stratification both across and within countries) (Riahi et al., 2017). Thus, SSP1 and SSP4 are two contrasting scenarios (i.e., optimistic vs. pessimistic) regarding the regional adaptive capacity. For example, the SSP1 projections on GDP per capita for Oceania, North America, and Europe are very similar to SSP4, whereas in other regions and especially in Asia and Africa, economic growth is substantially higher under SSP1 compared to SSP4 (Fig. S2.2.1, supplementary material). Only inter-country (between countries) inequality is implemented in GRACE through different projections of GDP per capita. Intra-country (within country) inequality is not incorporated because GRACE is based on the GTAP database, which only provides aggregated economic data on consumption expenditures and income over all household groups within a region/country. In GRACE, the SSP projections on GDP per capita determine the autonomous mechanisation in crop production described in Section 2.4; A higher economic growth (SSP1 vs. SSP4) in developing regions implies a faster mechanisation.

2.3 Deriving climate-induced impacts on crop yields for the economic analysis

To include the climate-induced impacts on crop yields into the economic model, we calculate scaling factors for crop yields (i.e., so-called climate shifters), which quantify the weighted average changes of simulated future crop yields relative to those in a historical reference period (Villoria et al., 2016). We use spatially explicit (i.e., 0.5°×0.5° geographic grid resolution) global historical and future annual yields of main staple crops (i.e., maize, wheat, rice, and soy) from four crop models: PEPIC (Williams et al., 1989), GEPIC (Liu et al., 2007), CLM4.5 (Lawrence et al., 2011), and LPJmL (Bondeau et al., 2007). Crop model simulations are available from ISIMIP2b (Frieler et al., 2017). Bias-adjusted GCM outputs were used to force the crop model simulations (Hempel et al., 2013a). Crop model simulations for both rainfed and fully irrigated crops are used in our analysis (Figs. S2.3.1 and S2.3.2, supplementary material). In all selected crop model simulations, land management is fixed at 2005 levels throughout the 21st century. In spite of the uncertainty surrounding the effect of the CO_2 fertilisation effect next to direct climate effects on future crop yields (Gray et al., 2016; Wang et al., 2018), we use results of the simulations including the CO_2 fertilisation effect (i.e., forced with varying CO_2 concentration) because we assume that uncertainties associated with these effects are captured by using different crop and climate models. Because GRACE is not spatially explicit, we aggregate the gridded data on crop yields by calculating weighted averages for the regions of interest. The Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 2.0 (SPAM) for crop-specific harvested area (IFPRI, 2020) is used as a weighting factor for regional aggregation. In addition, to avoid extremely small/large values of scaling factors, we remove grid cells containing yields whose values are less than 0.01 tonne per hectare. Then, we calculate the harvested-area-weighted average yield for each region, crop type, growing method, crop model, climate model, and RCP scenario. As annual crop yields are very volatile, which is probably due to inter-annual variability in the precipitation data, we use the method of moving (rolling) averages to detect the long-term trends induced by anthropogenic climate change by smoothing out the noise in the data. Centred-aligned moving averages are computed from 1981 to 2099 with a window size of 30 years. For example, a moving average of 1995 is an average value of crop yield in the period of 1981-2010, a moving average of 1996 is an average value for 1982-2011, and so forth. In our analysis, the reference period, which aims to describe current climate conditions, is the period of 1981-2010. Finally, to compute the scaling factors for crop yields, moving averages of subsequent years are divided by the moving average of 1995. Note that CLM4.5 does not provide simulations for rice and therefore, we use the multi-model mean of the scaling factor for rice for CLM4.5. The global regions of interest are described in Section 2.1 (see Fig. 2). The calculated scaling factors are used to implement a biophysical yield shock on the total factor productivity in crop production in GRACE.

2.4 Deriving heat-induced impacts on worker productivity in crop production for the economic analysis

Heat-induced impacts on worker productivity are computed using the epidemiological exposure-response function, which was synthesised by Kjellstrom et al. (2018), based on field studies for the "high occupational temperature health and productivity suppression" programme (Hothaps) (hereafter: the Hothaps function) (Bröde et al., 2018). The Hothaps function describes the relationship between workability and the wet bulb globe temperature (WBGT) for three levels of work intensity (see Eq. 4 in Bröde et al. (2018)). WBGT is a heat index that measures heat stress impacts of temperature, humidity, wind speed, and solar radiation (Budd, 2008).

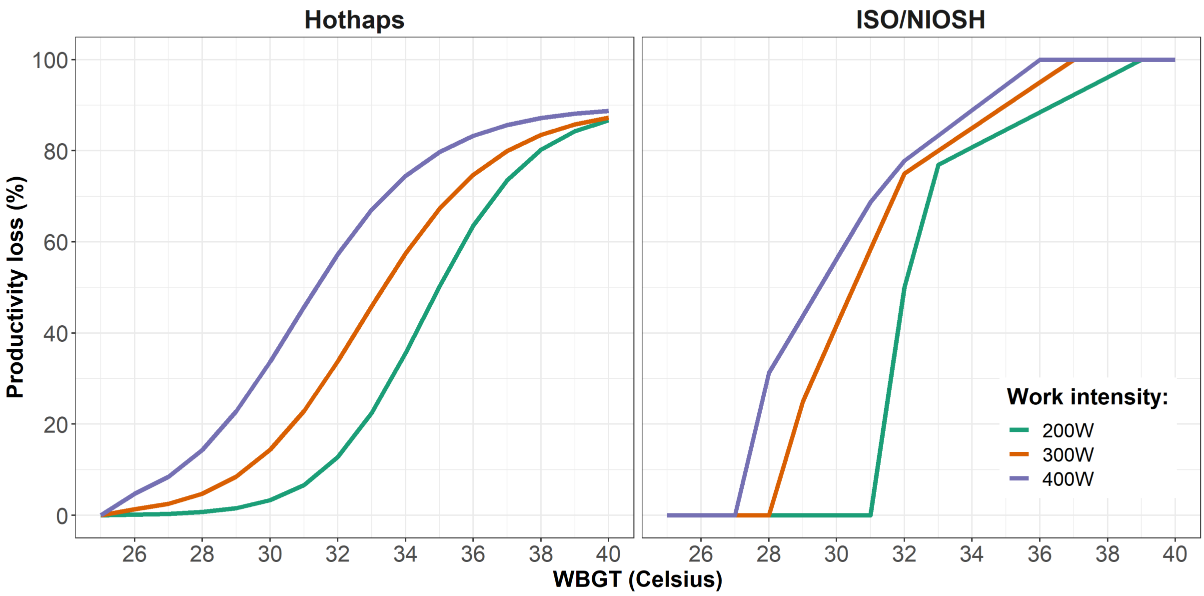

Fig. 4: Heat-induced impacts on worker productivity under two heat assessment metrics. Work intensity is measured in Watts (W); 200W is associated with a low-intensity work, 300W is for a moderate-intensity works, and 400W is for a high-intensity work. 1 kcal/min = 69.78W.

The choice of heat assessment metrics substantially affects the cost of heat stress (Orlov et al., 2020). The Hothaps function provides an assessment of the actual costs of reduced worker productivity due to heat stress (Fig. 4). It was calibrated based on the results of a few field studies, whose representativeness thereof constitutes a source of uncertainty. The ISO/NIOSH standards (ISO, 1989; NIOSH, 1986) are another widely used heat assessment metric to assess heat related impacts. For our analysis, we use both metrics (Hothaps and ISO/NIOSH), and show the range of outcomes from these two approaches.

There are two variations of WBGT indices, WBGTshade and WBGTsun, that are often used in impact studies for occupational health (Kjellstrom et al., 2016). The WBGTshade measures heat stress for working indoors, while the WBGTsun is applied for outdoor activities. In some studies (e.g., Takakura et al., 2017), the WBGTsun was used to assess heat-induced impacts on worker productivity in agriculture and construction. However, in practice, workers try to avoid heat exposure as much as possible by working when it is less hot (Kjellstrom et al., 2019). Moreover, in tropical countries, approximately 40% of days are cloudy, and therefore WBGTsun and WBGTshade should be considered as upper- and lower-bound estimates of worker productivity loss (Kjellstrom et al., 2019). We calculate both WBGT indices at each model grid point using historical and future bias-adjusted data on daily near-surface maximum and mean temperatures, relative humidity, wind speed, and solar radiation at a resolution of 0.5°×0.5° geographic grid (approximately 50 km×50 km at the equator) (Hempel et al., 2013b). Similar to the crop yield data, the climate data inputs are available through ISIMIP2b. To compute the WBGTshade index, we use the Bernard approach (Bernard and Pourmoghani, 1999; Lemke and Kjellstrom, 2012), and the WBGTsun is calculated using the Liljegren approach (Liljegren et al., 2008) approximated by a second-order polynomial. In our analysis, we use the mean values of calculated impacts on worker productivity under WBGTsun and WBGTshade.

Heat-induced impacts on worker productivity are computed for both historical and future projections at a grid cell level and daily resolution for four GCMs and three levels of work intensity (i.e., 200W, 300W, and 400W). Most of the work in agriculture is done during growing seasons. To obtain aggregated annual values for the economic analysis, the calculated impacts at a daily level are weighted by growing season days (Karstens et al., 2020; Müller and Robertson, 2014). Because the GRACE model is resolved at a regional level, we aggregate the spatially explicit impacts on worker productivity to the regions of interest using the SPAM data on harvested area as a weighting factor (i.e., the same data as for aggregating crop yields). The climate-induced changes in worker productivity in future projections relative to a historical reference period are computed using a similar procedure as for crop yields. For consistency, we choose the same reference period, 1981-2010. We also apply the method of moving averages to capture the trends in the harvested-area-weighted average changes in worker productivity. Moving averages of worker productivity in subsequent years are then divided by the moving average of 1995.

As mentioned above, the scaling factors for worker productivity are computed for three levels of work intensity. In previous studies, agriculture is assumed to require high-intensity work, which is uniform and constant across regions (Dunne et al., 2013b; Orlov et al., 2019; Roson and van der Mensbrugghe, 2010; Takakura et al., 2017). Following Orlov et al. (2020), we introduce an SSP-dependent autonomous mechanisation in crop production, which is empirically estimated using the time-series data on tractors per hectare and GDP per capita provided by the World Bank (World Bank, 2019). Mechanisation of agriculture implies a lower labour intensity, which makes agricultural productivity less vulnerable to heat stress. We use the estimated regression model to interpolate the quantified heat-induced impacts on worker productivity for three levels of work intensity (i.e., a continuous form of exposure-response functions with respect to changes in work intensity driven by mechanisation) (Fig. 5).

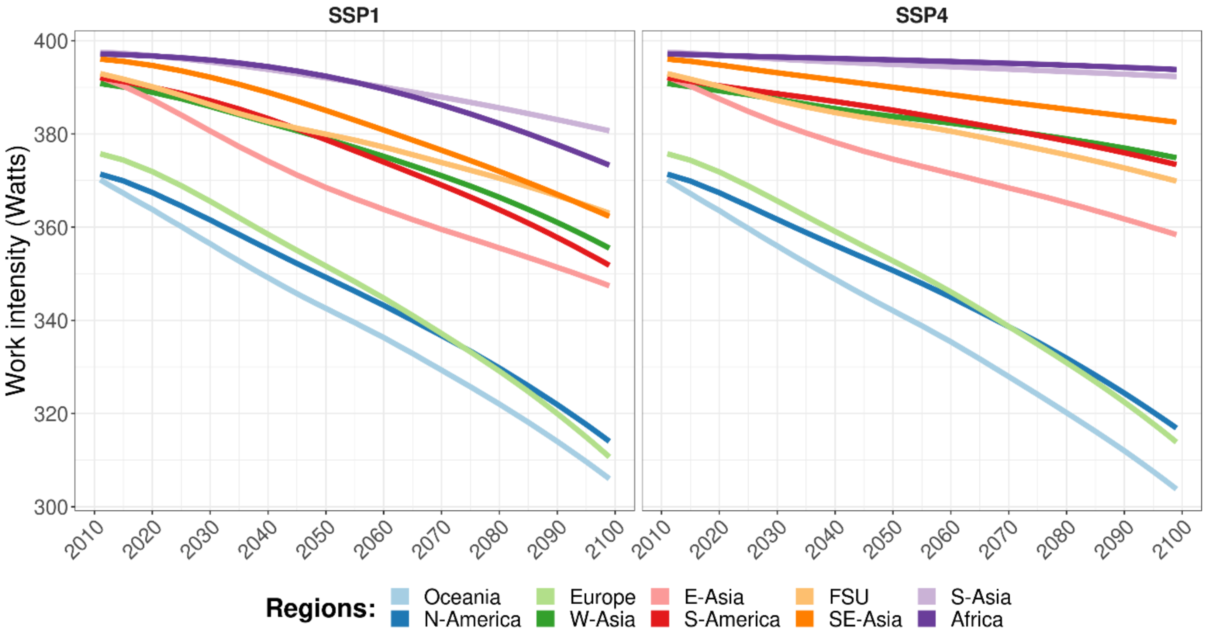

Fig. 5: Projected evolution of work intensity in agriculture in a world of sustainability-focused growth and equality (SSP1) and a world of increasing inequality (SSP4), following Orlov et al. (2020). Mechanisation of the agricultural sector was found to be positively correlated with GDP per capita, hence its deployment in regions and scenarios characterised by higher incomes leads to decreasing work intensity. 1 kcal/min = 69.78W.

Crops are assumed to have the same level of work intensity, which however differs by region due to mechanisation of agriculture. Moreover, the total impact of heat stress on agricultural productivity differs by crop type and region due to differences in value shares of labour in total production cost. In Section 3.3, in addition to the main staple crops (i.e., maize, rice, wheat, and rice), the calculated heat-induced impacts on worker productivity are also implemented in production of other agricultural crops, which are aggregated in the GRACE model. Fig. S2.4.1 (in supplementary material) reveals global hotspot areas exposed to heat stress under the RCP2.6 and RCP6.0 scenarios by the end of 21st century. Global economic responses to heat stress impacts are discussed in Section 3.2.

3. Results and discussion

Three simulation scenarios are conducted. In the first scenario, we incorporate only climate-induced impacts on yields of major crops (maize, wheat, rice, soybeans) for different GCM-CropModel-SSP combinations (Section 3.1). The second scenario is built upon the first scenario with including heat-induced impacts on worker productivity in production of these four crops (Section 3.2). In the third scenario, heat stress impacts on worker productivity are implemented in production of all crops (Section 3.3). These three scenarios are implemented in the dynamic version of the GRACE model. Below, we present and discuss global economy-wide responses to climate-induced impacts on crop production. Results from the economic analysis are presented as percentage changes relative to the GRACE reference scenarios, which are calibrated based on SSP1 and SSP4 (i.e., no climate change (NoCC) scenarios). The economic responses are presented for the middle (mid-21st) and end (end-21st) of the 21st century, which reveals average values of 2041-2070 and 2071-2100, respectively. The results from the GRACE model simulations are available from the corresponding author on request.

3.1 Climate-induced impacts on production of four major crops

Climate change-induced impacts on crop production are very uncertain and heterogeneous among regions, depending on the crop type, GCM, RCP, growing method, and crop model (Fig. 6a,b). To a large extent, relative changes in regional production of crops correspond to the changes in weighted yields within a region, which are derived from crop model simulations for ISIMIP2b. However, it is important to note that, in the applied economic model, the regional production responses in a region are also indirectly affected by changes in the agricultural productivity in other regions through trade (i.e., cross-regional interactions). Furthermore, in the applied economic model, crop-interaction effects associated with land competition and growing methods (rainfed vs. fully irrigated) are subject to an economic optimisation. At the global scale, the climate-induced impacts on crop production are relatively small because the largest producers of crops (e.g., rice in East Asia and maize in USA) are only moderately affected by projected climate change. Moreover, potential decreases in crop production in some regions could be compensated by a higher production in other regions.

Under both RCPs, by the mid-21st century, climate-induced impacts on global production of maize are moderate and uncertain (Fig. 6a). By the end-21st century, global production of maize tends to decline under both RCPs because of a lower maize production in North America, South and South-East Asia, and Africa (Fig. 6b). Maize (C4 plant) is less sensitive to changes in CO_2 compared to C3 plants, such as wheat, rice, and soybeans because C4 plants have a lower photosynthetic rate (Degener, 2015; Hamim, 2005). Moreover, in some regions like USA, maize is already growing at an optimal threshold of temperatures, and therefore increasing temperatures will likely lead to lower yields (Schlenker and Roberts, 2009). However, some other regions, such as the Former Soviet Union (FSU), East Asia, and Oceania (under RCP6.0), could experience a strong increase in maize production. Since crops are tradable goods, climate-induced impacts on yields lead to changes in the pattern of comparative advantage in crop production across regions. For example, the FSU, East Asia, and Oceania will likely become more competitive in maize production, which is indicated by a higher export supply and a lower import demand relative to the NoCC scenarios (Figs. S3.1.1 and S3.1.2, supplementary material). In contrast, North America, Africa, and South-East Asia could become less competitive on the international market of maize due to decreased crop productivity, thereby leading to a lower (higher) in export supply (import demand). Similar to maize, global production of wheat is also moderately affected under both RCPs by the mid-21st century, whereas by the end-21st century, it tends to decline under RCP6.0. At the regional level, there is a high probability that wheat production will increase in the FSU, Europe, and East and West Asia. One of the main reasons for a potential decline global production of wheat is lower wheat yields in Africa, South and South-East Asia. As the economies of these regions are growing, the yield gap is closing and these regions become more competitive in the international wheat market, thereby taking a larger share in global production of wheat. In contrast, when imposing future climate-induced impacts on wheat yields in the present-day economic setting, global wheat production will likely increase.

In contrast to maize and wheat, global production of both rice and soybeans tends to increase under both RCPs by the mid-21st and end-21st century, with the increases being more pronounced under RCP6.0. By the end-21st century, rice production tends to increase in most of the regions, especially in Europe, West Asia, and the FSU. In contrast, North America experiences a relatively strong and robust decline in rice production under both RCPs. As for soybeans, there is a high probability of a strong increase in soybean production in East Asia and the FSU, while it is likely to fall in North America. The main driver behind an increase in the global production of rice and soybeans is a higher concentration of CO_2 in the atmosphere. Our analysis includes the CO_2 fertilisation effect. Note, however, that without the CO_2 fertilisation effect, yields of four major crops fall in most regions, especially under RCP6.0 (Fig. S2.3.3, supplementary material). Moreover, a warmer climate leads to a higher crop production in high latitude regions (e.g., FSU).

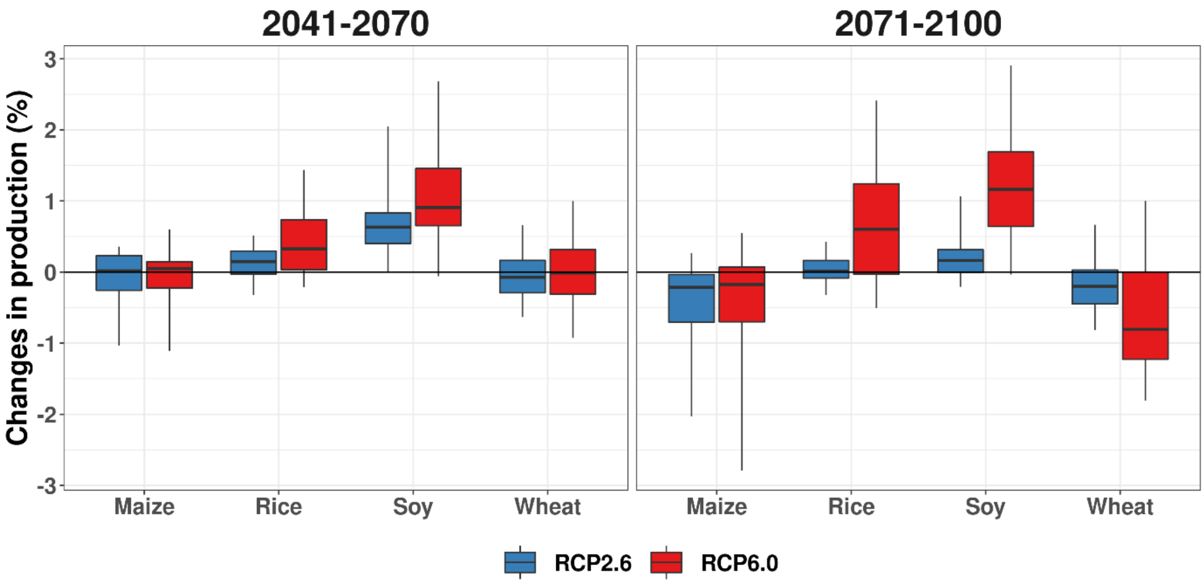

Fig. 6a: Changes in global production of crops (not accounting for heat stress-related changes in worker productivity) under the RCP2.6 and RCP6.0 scenarios by the mid-21st and end-21st century. The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The CO_2 fertilisation effect is included. The box plots reveal the uncertainties associated with GCMs, crop models, and SSPs. The whiskers are extended to capture outliers.

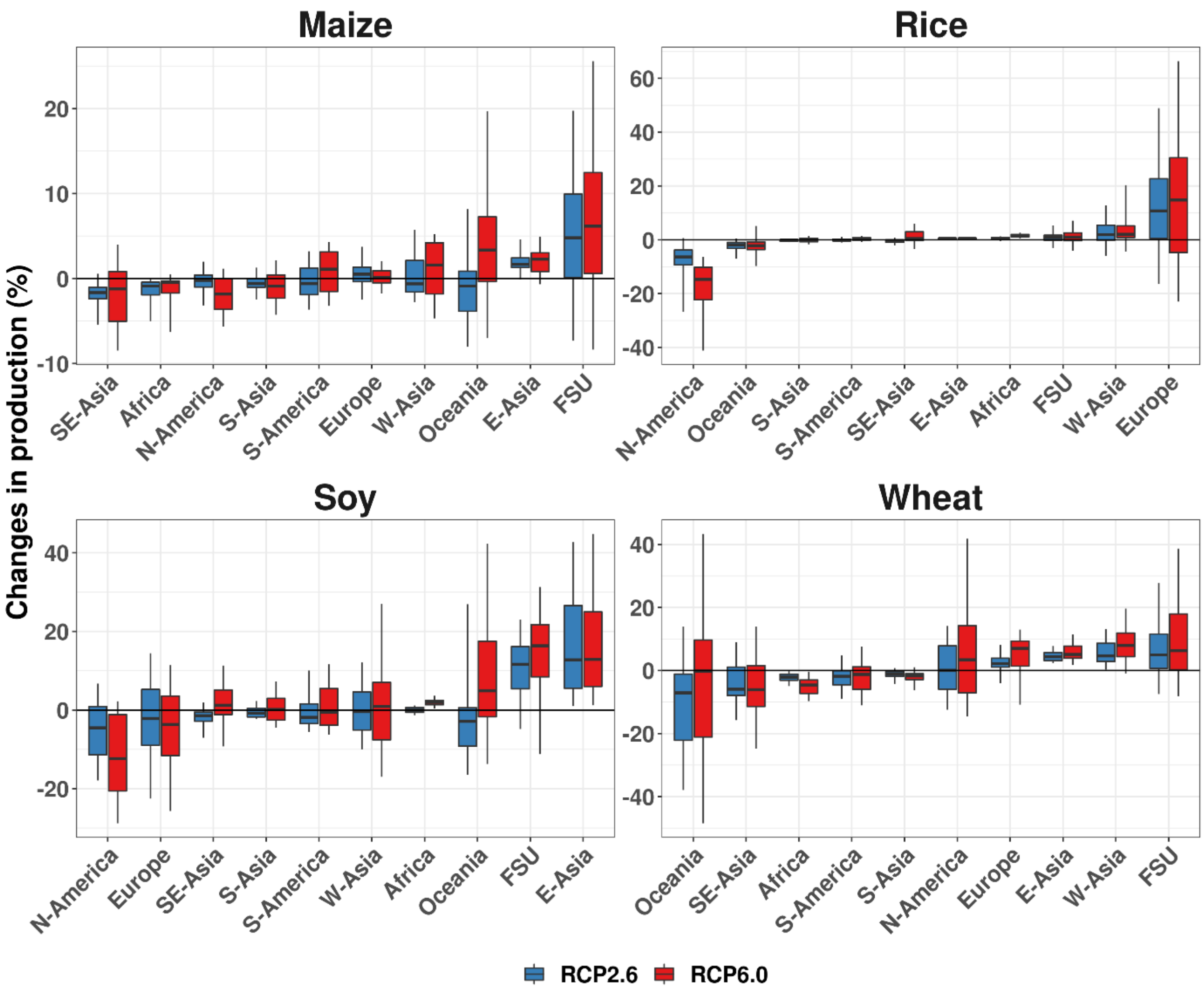

Fig. 6b: Changes in the regional production of crops (not accounting for heat stress-related changes in worker productivity) under the RCP2.6 and RCP6.0 scenarios by the end-21st century (2071-2100). The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The CO_2 fertilisation effect is included. The box plots reveal the uncertainties associated with GCMs, crop models, and SSPs. The whiskers are extended to capture outliers. Different ranges for production changes are applied on the y-axis.

Due to cross-sectoral dependencies, climate-induced impacts on crop yields affect the production of other sectors, such as livestock and food, which are large sectorial consumers of crops (Fig. 7). At a global scale, for both RCPs by the end-21st century, global production of livestock and food tends to increase relative the NoCC scenarios because of a higher production of crops in many regions. There is a high probability of a reduction in production of livestock and food in North America, which results from a decrease in the domestic production of a major feed grain, maize. Furthermore, South-East Asia appears as a big outlier in terms of the impact and uncertainties. It is important to note that heat stress impacts on livestock are not implemented in this analysis. Adverse heat stress impacts on livestock, which will be exacerbated by global warming, could lead to a higher cost of milk and meat production.

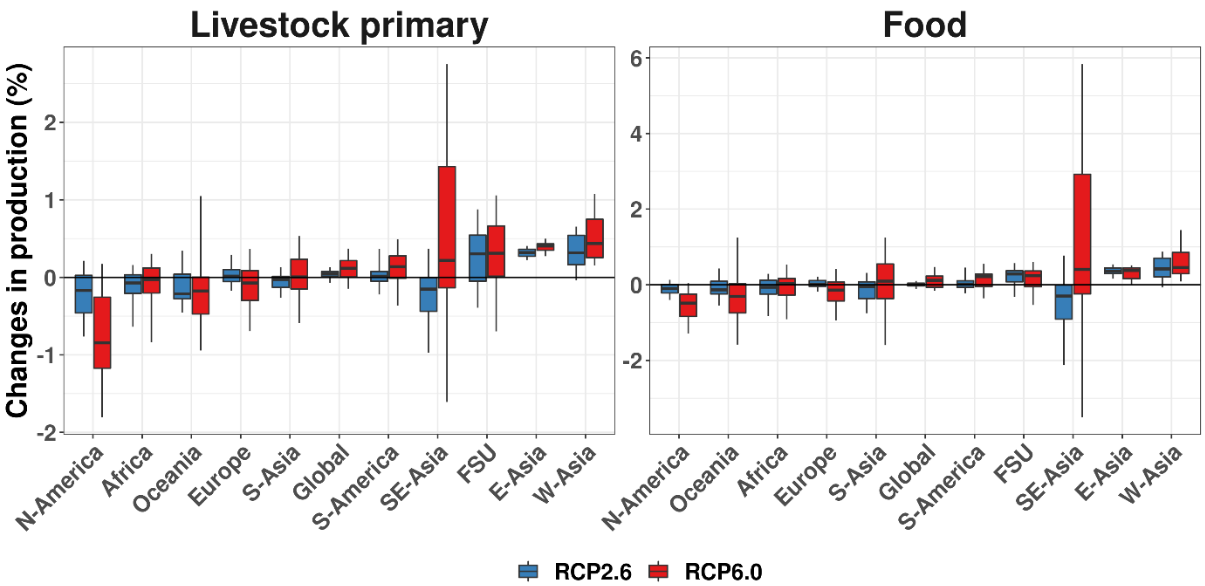

Fig. 7: Changes in the production of livestock and food under the RCP2.6 and RCP6.0 scenarios by the end-21st century (2071-2100). The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The box plots reveal the uncertainties associated with GCMs, crop models, and SSPs. The whiskers are extended to capture outliers. Different ranges for production changes are applied on the y-axis. The production of livestock and food are driven by changes in crop production. Heat stress impacts on livestock productivity are not implemented in this analysis.

Overall, the macroeconomic consequences of climate-induced impacts on crop productivity are moderate because agriculture contributes a relatively small share of national income in most regions (Fig. 8). Moreover, the share of agricultural value added to GDP is expected to decline due to (post-) industrialisation of economies, which is apparent from historical trends (World Bank, 2018). At the global scale, under both RCPs and especially under RCP6.0, the increased productivity of soybeans and rice, leads to an increase in global GDP (Fig. 8). These results are in line with those of Nechifor and Winning (2019) and Ren et al. (2018), who also find that the inclusion of the CO_2 fertilisation effect could have a strong positive impact on crop production. Even under RCP8.5, a large ensemble of crop model simulations based on CMIP5 projections reveals a relatively high probability of an increase in global crop productivity (Müller et al., 2021). Note, however, that in our analysis we investigate the long-term impacts of climate change, while climate-induced changes in climate variability could increase the frequency and intensity of drought, thereby increasing the risk of multiple-breadbasket failures (Gaupp et al., 2019).

At the regional level, under both RCPs, most regions will likely experience economic benefits as indicated by an increased GDP, which is an inflation-adjusted index measuring the value of all produced goods and services within an economy. Under RCP2.6, the economic responses by the mid-21st century are approximately of the same order of magnitude as at the end-21st century, because the radiative forcing is stabilised by the mid-21st century. Consistently, by the mid-21st century, for most regions, the increases in GDP are similar under both RCPs, whereas the differences in the results become more pronounced at the end-21st century.

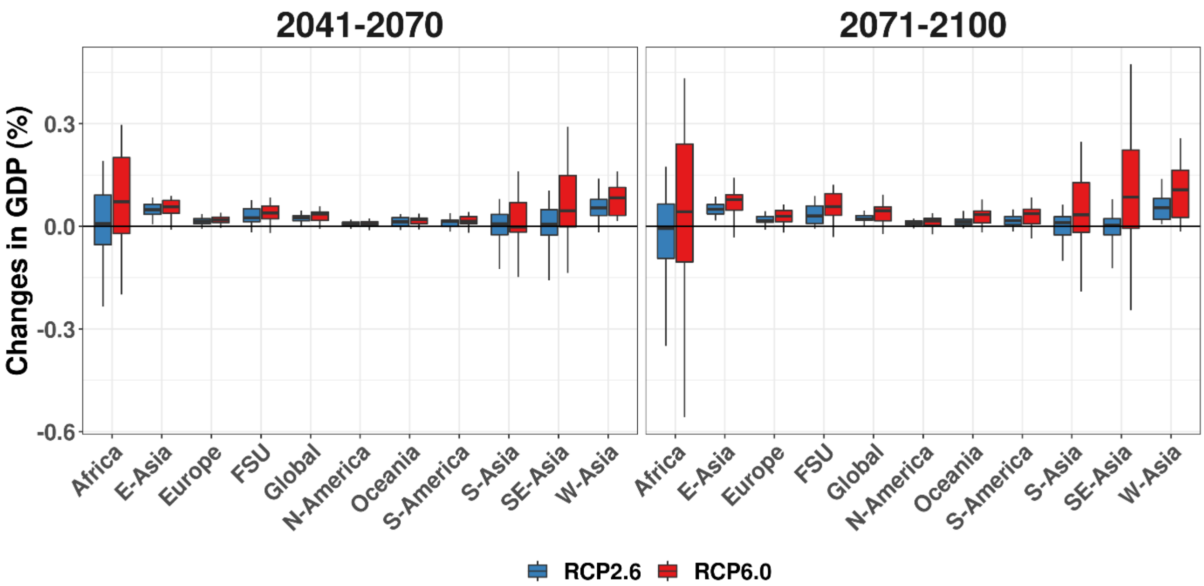

Fig. 8: Changes in regional GDP under the RCP2.6 and RCP6.0 scenarios. The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The box plots reveal the uncertainties associated with GCMs, crop models, and SSPs. The whiskers are extended to capture outliers.

As for the uncertainty attribution, the results from an analysis of variance (ANOVA) reveal that a large part of uncertainties, especially under RCP6.0, is attributed to the crop models, followed by uncertainties of the GCMs (Fig. S3.1.4, supplementary material).

Note that in our economic model, the biophysical shock on crop yields is implemented as a change in total factor productivity of crops. Alternatively, crop yield changes can be implemented as a change in land productivity (Ren et al., 2018). In most studies, crop yield changes are implemented as scaling parameters for total factor productivity. We follow this approach for comparability purposes; however, the economic impacts are substantially different between these two approaches. When climate-induced changes in yields are implemented to land productivity, economic responses to climate-induced changes in crop yields are much less pronounced.

3.2 Heat-induced impacts on worker productivity in production of four major crops

Apart from climate-induced impacts on crop yields, heat stress on agricultural workers is another important factor that could substantially affect agricultural productivity. South-East and South Asia as well as Africa are projected to be the three most adversely affected regions by heat stress (Fig. 9). While climate-induced impacts on yields could potentially enhance global crop production, including the heat-induced impacts on worker productivity leads to a higher production cost. In many regions, the impacts of heat stress result in higher producer prices; for example, South-East Asia experiences a substantial increase in the producer prices of maize and rice relative to the NoCC scenarios (Fig. 10). Price responses resulting from heat stress impacts differ by crop type because of the differences in labour intensity of crops, which is reflected by the shares of labour costs in total production costs. Although the work intensity is assumed the same for all crops, it differs by region and changes over time due to different stages in economic development. Crop production in least developed regions is associated with a high work intensity (i.e., mostly comprising manual work) and therefore is more vulnerable to heat stress. The increases in maize prices are substantial compared to other crop types. For example, in South and South-East Asia, and Africa, the increase in maize prices could exceed 30%. As explained above, crop model simulations reveal a robust decline in maize yields in many regions, which results in a lower production and higher prices. The adverse impacts of heat stress on agricultural workers further exacerbate the price increases. On the contrary, the average producer prices of wheat, rice, and soybeans tend to decline in many regions due to increased yields; however, heat stress impacts substantially diminish the reductions in producer prices.

In the most heat-exposed and vulnerable regions, the increases in producer prices of crops lead to a decline in the production of livestock and food. As a result, the impacts of heat stress could cause considerable aggregated economic losses, especially in South Asia, South-East Asia, and Africa (Fig. 11). Under RCP2.6, by the end-21st century, the adverse impacts of heat stress could offset the economic benefit from elevated yields in most regions. For RCP2.6, the economic responses by the mid-21st century are very similar to those by the end-21st century. Under RCP6.0, the economic cost of heat stress impacts on agricultural workers is substantially greater than under RCP2.6, especially by the end-21st century. For example, in Africa, a potential reduction in GDP could be up to 1.5% compared to the NoCC scenario (Fig. 11). By the mid-21st century, the macro-economic responses are of the same order of magnitude under both RCPs.

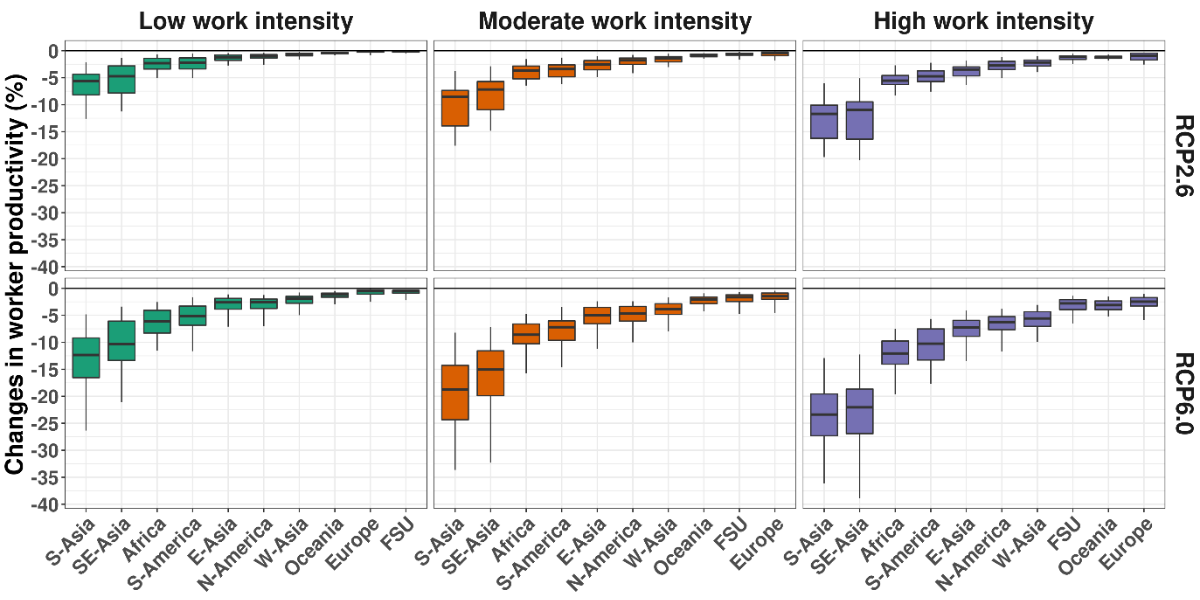

Fig. 9: Aggregated harvested-area-weighted changes in worker productivity for three levels of work intensity and RCP scenarios by the end-21st century (2071-2100) relative to the reference period (1981-2010). The Hothaps function and the NIOSH standards are used to estimate the heat impacts on worker productivity. The error bars indicate the uncertainties enveloping the minimum and maximum values estimated based on four GCMs, two heat assessment metrics (Hothaps vs. NIOSH), and two WBGT indexes. Adaptation measures, such as mechanisation, are not considered at this stage.

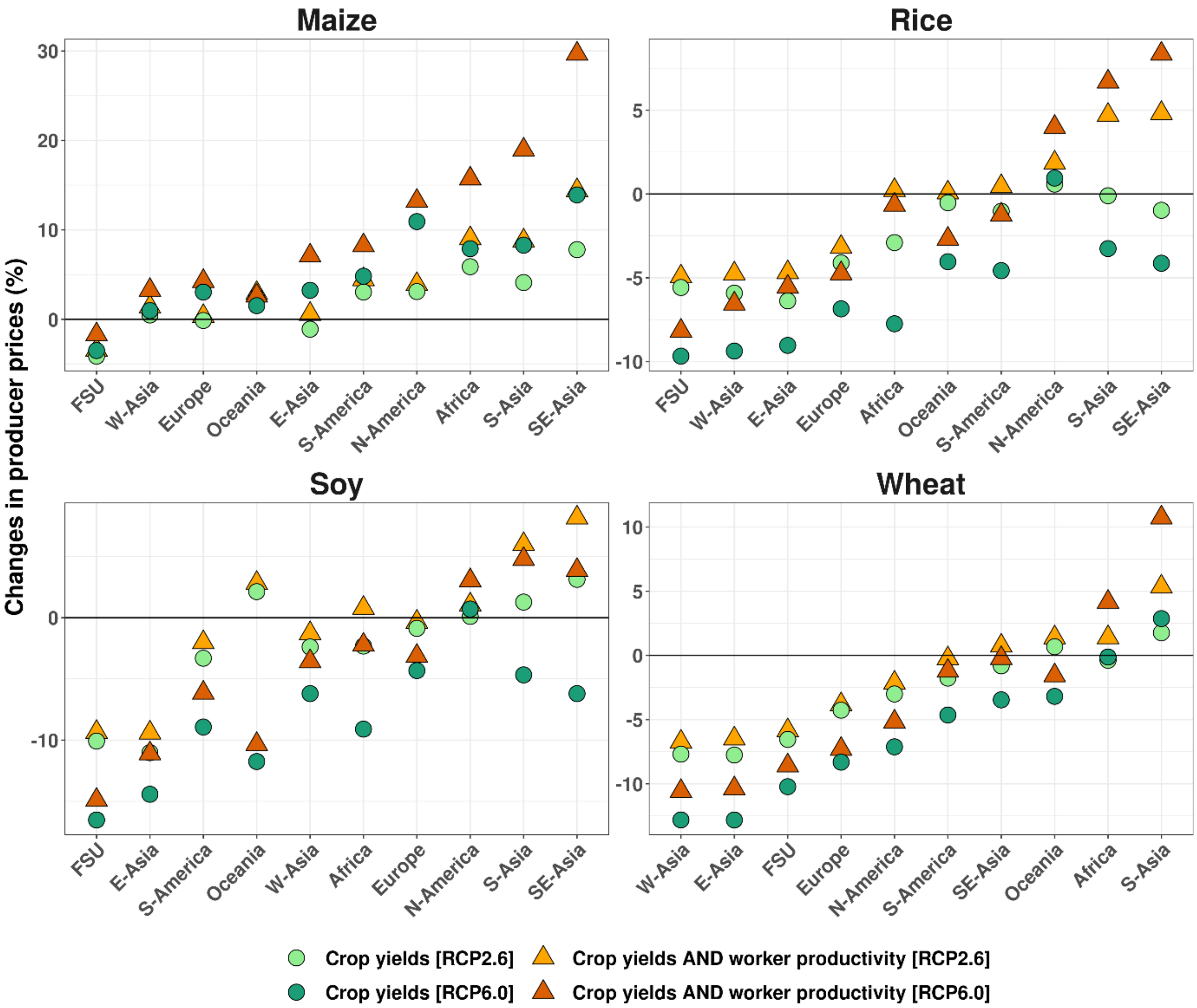

Fig. 10: Average changes in the producer prices of crops under the RCP2.6 and RCP6.0 scenarios by the end-21st century (2071-2100). The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The price responses are averaged over GCMs, crop models, and heat assessment metrics. Different ranges for production changes are applied on the y-axis.

At the global scale, even under RCP2.6, the heat-induced impacts on worker productivity could offset the benefit of enhanced yields, thereby leading to economic losses (Fig. 12). Developing countries are growing faster (i.e., the catch-up effect) and therefore, their relative contribution to global GDP increases over time, depending on the SSP scenario. Thus, global economy becomes more vulnerable to adverse climate impacts in the regions, such as Africa. Under RCP6.0, there are reductions in global GDP for many simulations, especially when using the climate projections from HadGEM2-ES. When using the climate data from GDFL-ESM2M or MIROC5, less pronounced reductions in global GDP are observed because these two climate models have almost half of the equilibrium climate sensitivity of HadGEM2-ES (Andrews et al., 2012). This highlights the relevance of the transient climate response uncertainty. A higher (lower) climate sensitivity implies more (less) warming for the same CO_2 trajectory (i.e., a more (less) pronounced negative impact of warming on worker productivity compared to a positive effect of CO_2 fertilisation).

Regarding the uncertainty attribution, for each RCP, when the heat stress impacts on workers are introduced, the largest source of uncertainties comes from GCMs, especially for the second half of the century (Fig. S3.1.4). It should be noted that when pooling the results, the scenario uncertainty (i.e., RCP) emerge as the largest source of uncertainty for heat stress impacts by the end-21st century. The choice of heat assessment metric substantially affects the cost of heat stress (Orlov et al., 2020). Both the Hothaps function and ISO/NIOSH standards are used for the core simulation runs. When using the ISO/NIOSH standards, the cost of heat stress is considerably larger due to higher labour productivity losses. In comparison to the Hothaps function, the cost estimated using the ISO/NIOSH heat assessment metric should be interpreted as the cost of preventing heat-related illness, which implies that all workers would follow these cautious recommendations. As empirically estimated region-specific exposure-response functions for heat stress are not available, we consider the Hothaps function and ISO/NIOSH standards as a lower and upper bound of estimated costs. Moreover, the uncertainties related to socioeconomic development pathways depicted by SSPs becomes more relevant compared to when only climate-induced impacts on crop yields are implemented. Under SSP4-RCP6.0, for the GCM-CropModel combinations with a high equilibrium climate sensitivity, the reduction in global GDP is larger than under SSP1. As explained in Section 2.2, we associate SSP1 with a faster mechanisation in agriculture, which diminishes the adverse impacts of heat stress. Interestingly, for some GCM-CropModel combinations with a low equilibrium climate sensitivity, the increases in global GDP under SSP4 could be slightly more pronounced than under SSP1. This is because the contribution of agricultural sector in global GDP is higher under SSP4 compared to SSP1, so a positive climate-induced impact on crop yields would lead to a stronger increase of global GDP.

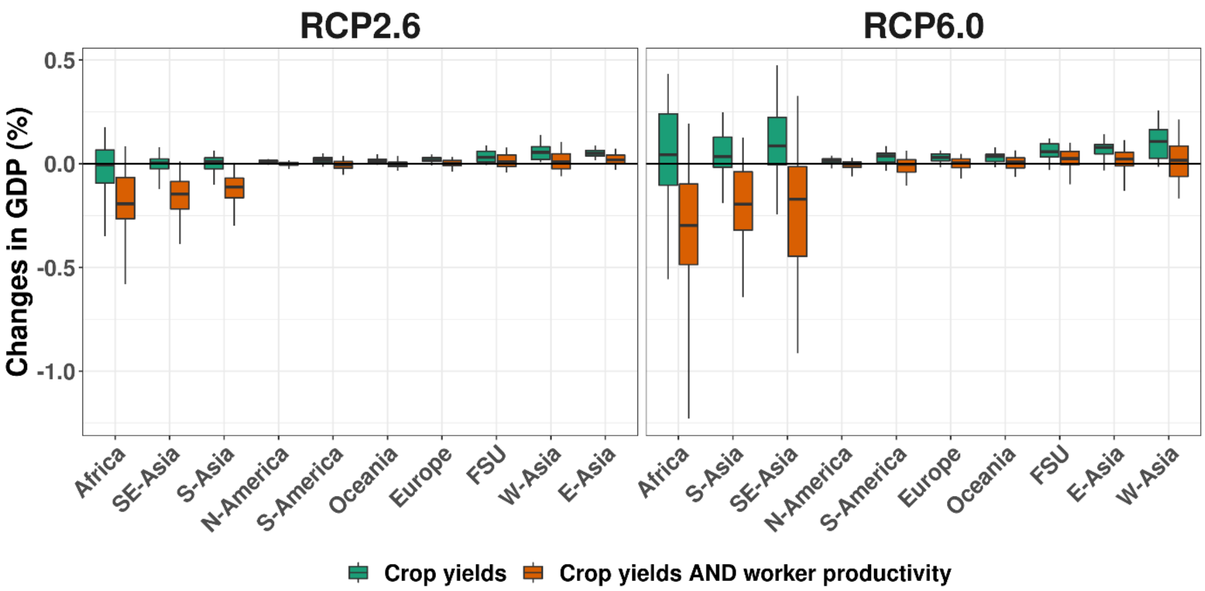

Fig. 11: Changes in regional GDP under the RCP2.6 and RCP6.0 scenarios by the end-21st century (2071-2100). The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. Under RCP2.6, the economic responses by the mid-21st century are similar to those by the end-21st century.

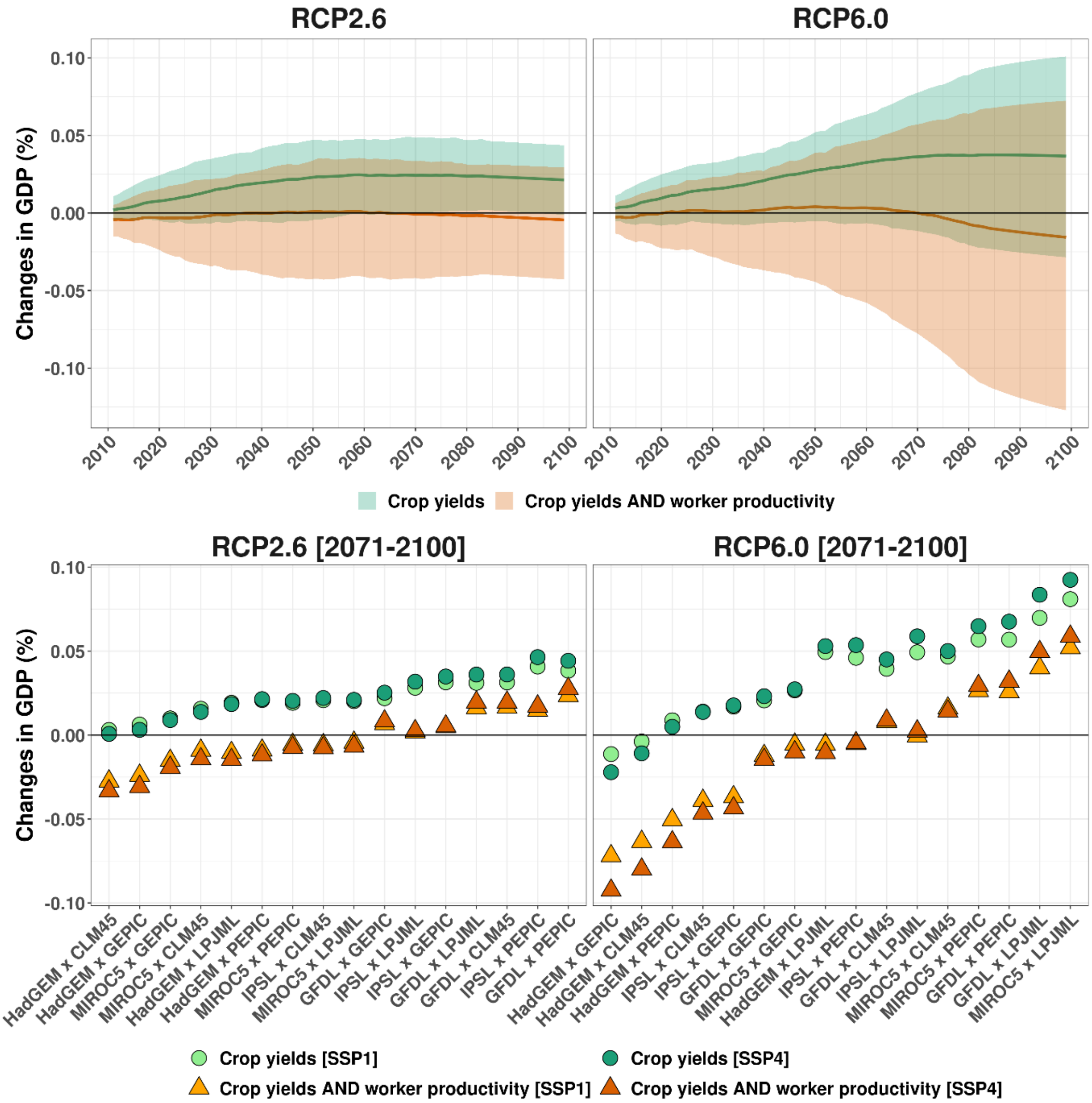

Fig. 12: Changes in global GDP under the RCP2.6 and RCP6.0 scenarios. The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. The upper panels reveal the annual evolution of global GDP, where the solid lines show the mean values and shaded areas capture the uncertainties. The lower panels show the impacts on global GDP per model combination (climate model and crop model). In the lower panels, the impacts on global GDP are averaged over two metrics (i.e., Hothaps and ISO/NIOSH).

3.3 Heat-induced impacts on worker productivity in production of all crops

In the core simulations, for consistency and comparability, we implement the heat stress impacts only on workers evolved in the production of four major crops (i.e., maize, wheat, rice, and soybeans). However, economic costs could be substantially larger when assuming that workers involved in production of other crop types are also affected by heat stress (Fig. 13). On that regard, our results are robust and reveal a potential threat to agricultural and food production especially in Africa, and South and South-East Asia.

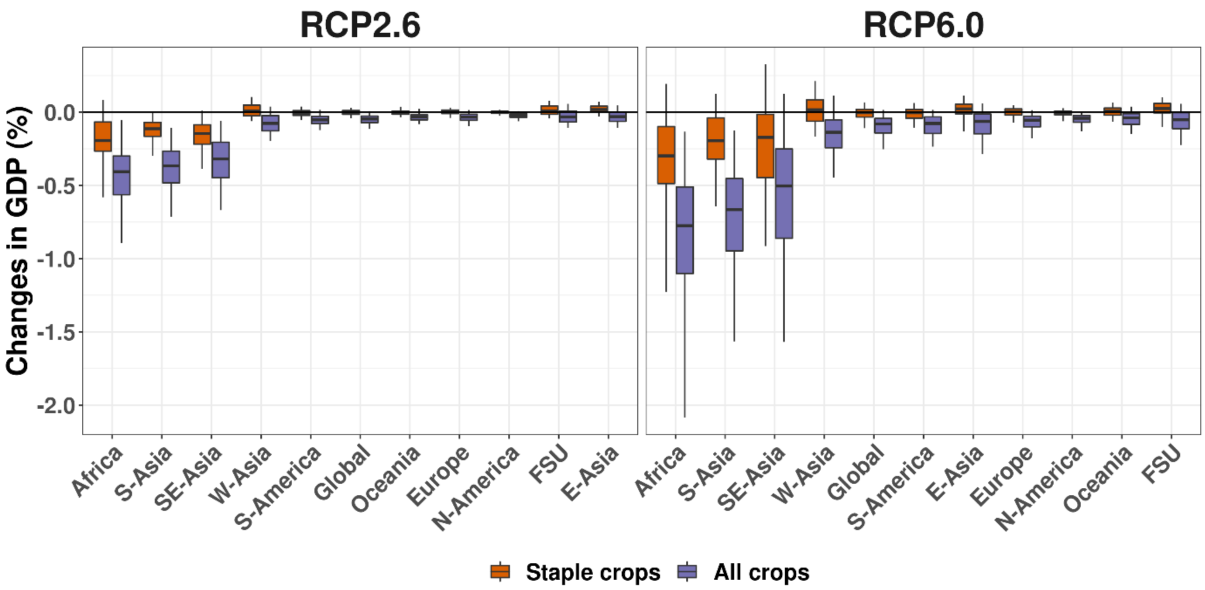

Fig. 13: Changes in region GDP due to climate-induced impacts on crop yields and heat-induced impacts on worker productivity under the RCP2.6 and RCP6.0 scenarios by the end-21st century. The changes are relative to the reference scenarios, which are simulated by GRACE based on SSPs. *"Staple crops"* implies that the biophysical shocks on crop yields and worker productivity are implemented only for four staple crops, which is the scenario setting in the core simulations. *"All crops"* means that heat stress impacts on worker productivity are implemented in production of all types of crops.

4. Conclusions

Using climate projections from the CMIP5, crop model simulations from the ISIMIP2b, and a global multi-sector CGE model, we assess the global economic responses to climate change impacts on crop production, including the heat stress impacts on workers. We consider a high mitigation (RCP2.6) and a low mitigation (RCP6.0) scenario combined with two different socio-economic scenarios (SSP1 and SSP4) reflecting different vulnerabilities of agricultural workers to heat stress via their differential implications for mechanisation in this sector. We find that under both RCP2.6 and RCP6.0, climate-induced impacts on crop yields could lead to an increase in crop production in many regions mainly due to a higher concentration of CO_2. As a result, many regions and the world as a whole could experience moderate welfare gains. For South-East Asia and Africa, the economic impacts are strong but also very uncertain. However, the impacts of heat stress on worker productivity could offset the economic benefit of increased yields in most regions, and in the regions, such as South and South-East Asia, and Africa, it could even lead to substantial economic losses. In other words, the adverse economic response to heat stress could be larger than the anticipated positive effect of elevated CO_2. When comparing the relevance of different types of modelling uncertainties, we find that the largest part of uncertainties is attributed to GCMs, followed by crop models, exposure-response functions, and socio-economic uncertainties. The uncertainty in the transient climate response to cumulative CO_2 emissions is especially important. Assuming a higher equilibrium climate sensitivity (i.e., more warming for the same CO_2 emissions) results in more pronounced welfare losses due to heat stress.

There are several limitations to this analysis. This study solely considers climate impacts on yields for four crops, while other agricultural crops could also be affected by climate change. Further work should thus consider other crop types as climate-induced impacts on other crops could have potentially equally significant macro-economic implications. Moreover, climate-induced impacts on crop yields are very uncertain, as indicated by significant differences in the results from crop model simulations. In our analysis, we use outputs from only four crop models and four global climate models, which are available from the ISIMIP2b, therefore uncertainties related to the climate and crop system responses to future greenhouse gas emissions might not be fully captured. Incorporating results from other climate and crop model simulations would be of added value. Also, the implications of potential shifts in diets, which could significantly differ by SSP scenarios, are not explored in this study. Although an autonomous SSP-dependent mechanisation as well as endogenous mechanisation via substitution between labour and capital are incorporated into the economic model, proactive investments in mechanisation and R&D (i.e., robotisation) could further diminish the adverse impacts of heat stress. The effectiveness of shifting working hours has not been investigated since we use daily levels of climate variables, while sub-daily data would be required. However, the potential of shifting working hours could already be limited in the most heat-exposed regions. The epidemiological exposure-response relationship used in this study is also very uncertain since this is calibrated based on a limited number of filed studies. More research is needed to derive region- and sector-specific exposure-response functions for heat stress impacts. Furthermore, we assess the economic response to long-term trends in climate variables, while focusing on single extreme events and compound events could be an avenue for future research. Crop yield losses tend to occur in the same period across different regions due to large scale teleconnections (Kornhuber et al., 2020; Zscheischler et al., 2018). An increase in climate volatility may lead to a sudden production loss across many regions, which could coincide with severe worker productivity losses due to heat stress.

Acknowledgement

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