chapter 2

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chapter 2

The Global Gridded Crop Model Intercomparison: Approaches, insights and caveats for modelling climate change impacts on agriculture at the global scale

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main chapter messages

- With international market integration and the global extent of climate change, future agricultural productivity and climate change impacts need to be assessed in consistent frameworks at the global level.
- The diversity of global gridded crop models is brought together in AgMIP and ISI-MIP model intercomparisons to record, evaluate and improve uncertainties and skills in global scale agricultural modeling.
- Central to the challenge are significant uncertainties not only in future climate change projections, but also in current and future management patterns and the effectiveness of carbon dioxide fertilization.
- The agricultural sector is strongly interlinked with other sectors and biophysical cycles (water, carbon). Interactions and co-limitations (e.g. bioenergy, irrigation water) need to be considered explicitly (and carefully).
- The diversity of agricultural practices around the world as well as the high level of management in agricultural systems are a central challenge for modeling efforts but also constitute a strong and varied basis for climate change adaptation measures.

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1. Rationale

Agriculture is a diverse economic sector that produces food, fibre, material and energy commodities. In most regions, agricultural productivity is directly dependent on weather and climate conditions – more so than any other major economic sector. The agriculture sector also serves a variety of purposes beyond primary production, including nature and resource conservation, recreation, greenhouse gas (GHG) mitigation and various other so-called ecosystem services [Power, 2010]. Agriculture is of central importance to society, and climate change is a major concern for agricultural systems and food security. Due to the rapid expansion of international markets, agriculture has become an increasingly globalized sector over the course of the 20th century. Shocks to production in individual countries resulting from policy or climate change can affect prices across the globe, as demonstrated, for example, during the food price spikes in 2008 and 2010 [Blandford *et al.*, 2010; Piesse and Thirtle, 2009].

Given the importance of the agricultural sector on a global scale, it is crucial to assess impacts of climate change on agricultural productivity with analysis tools that allow sufficient detail to account for interregional differences in climate and management systems, while retaining global coverage to ensure consistency. Biophysical crop models, applied globally, can provide such consistent multi-scale climate change impact assessments. Under the umbrella of the Agricultural Model Intercomparison and Improvement Project (AgMIP)[3] [Rosenzweig *et al.*, 2014] and as part of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP)[4] [Warszawski *et al.*, 2014], a coordinated climate impact analysis at the global scale was recently conducted using a group of seven Global Gridded Crop Models (GGCMs).

[3] See http://www.agmip.org

[4] See http://www.isimip.org

Following completion of this fast-track project, designed to provide rapid global analysis for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5), the project has expanded rapidly. The resulting Global Gridded Crop Model Intercomparison (GGCMI), which is the flagship project of the new AgMIP GRIDded crop modelling initiative (Ag-GRID, see http://www.agmip.org/ag-grid/), includes more than 20 modelling groups conducting hundreds of coordinated historical and projected future simulations for model intercomparison and improvement and climate impact assessment.

2. Biophysical models to assess climate change impacts on agricultural productivity

2.1 Crops and weather

Agricultural production is directly dependent on weather conditions, which – together with soil conditions – determine the conditions for plant growth. Weather conditions can be managed to some extent by, for example, using irrigation to compensate for deficient rainfall or timing the cropping season to avoid adverse weather conditions (dry, hot, cold). Greenhouses provide environments in which weather conditions can be managed with precision – including temperature and radiation inputs – but these are only economically feasible at small scales and for high-value crops. Weather extremes that cannot be managed can lead to severe damage, such as from strong winds, hail [e.g. Saa Requejo *et al.*, 2011] or frost events.

All agricultural production, including livestock production, is dependent on suitable weather conditions for plant growth. The central process of plant growth is photosynthesis, in which carbon dioxide (CO_2) is assimilated with sunlight energy to form primary sugars. These sugars are the energy source as well as the building blocks for all biomass generation. About half of the energy stored in the sugars generated by photosynthesis is used to satisfy the plant's own energy demands for the formation of complex molecules, growth and maintenance. Photosynthesis takes place in green leaves and the process is strongly affected by ambient temperature, the availability of CO_2 in the air, and availability of sufficient water and nutrient supplies in both soil and plant. Along with a number of micro-nutrients that are necessary in small amounts, nitrogen, phosphorus and potassium (in that order) are the most important plant nutrients and are often applied to fields as artificial fertilizers or manure.

The same pores that plants use to transpire water are also responsible for taking up CO_2 for photosynthesis. When these pores close to reduce water transpiration, as happens under dry conditions, the uptake of CO_2 is also reduced.

The plants in which photosynthesis is directly stimulated under elevated atmospheric CO_2 concentrations are referred to as the C_3 plants, because the primary product of their photosynthetic pathway is a sugar with three carbon atoms. Wheat, rice and soybean are the most prominent representatives of this group. Other plants have developed different mechanisms for fixing CO_2, in which atmospheric CO_2 is intermediately stored in oxaloacetic acid, a four-carbon organic acid. This group of plants is thus referred to as C_4 plants. C_4 plants are less limited by ambient CO_2 concentrations because primary fixation is achieved via a more efficient enzyme and the Rubisco enzyme is isolated from the ambient air. Some important agricultural crops belong to the group of C_4 plants, such as maize, sugar cane, millet and sorghum.

Plants with C_4 carbon fixation have developed mechanisms to partially decouple the uptake of CO_2 from transpiration by concentrating it from the atmosphere and passing this bound CO_2 on to where it is needed for photosynthesis. Due to this ability to decouple the CO_2 concentration for photosynthesis from ambient atmospheric CO_2 concentrations, this group of crops is less sensitive to elevated atmospheric CO_2 concentrations.

Many other processes relevant to plant growth and yields are affected by weather conditions: root growth affects access to soil water and nutrients; leaf formation affects a plant's ability to absorb sunlight energy; flowering is threatened by sterility under high temperatures; frost does direct damage to a plant; etc. Indirect effects of weather conditions include the mineralization of organic matter (e.g. humus or applied manure) in soils. Organic matter supplies nutrients to plants and is controlled by soil water content and temperatures. The spread of plant diseases (such as fungi) and insects can also be affected by weather and climate conditions [Gregory *et al.*, 2009] or by elevated atmospheric CO_2 concentrations [Dermody *et al.*, 2008; Zavala *et al.*, 2008].

Many of these processes can be accurately modelled as functions of local weather conditions (temperatures, precipitation, incident solar energy, and sometimes wind speeds and humidity), environmental conditions, and management conditions. Crop growth models are constructed to combine such functional representations and are designed with appropriate levels of complexity for various applications at a range of spatial scales.

2.2 Model types

Biophysical crop growth models can be categorized into two general types: empirical and process-based models. The distinction is not always completely clear, since most process-based models also include empirical relationships; however, purely empirical models, such as regression models, are quite distinct. The represented processes, data requirements (e.g. number of variables, spatial and temporal resolutions) and model outputs vary greatly among models, depending largely on the research questions and applications that motivated the model's development. At global scale, at least three types of models can be distinguished, each with a broad set of representatives.

- **Gridded versions of site-based process models**
  These models are based on field-scale models that are applied globally by simply running the model repeatedly for each locale in the (usually gridded) input dataset. These models tend to be the most complex with respect to processes represented in the model, which typically implies high requirements for input data. Field-scale models are often strongly calibrated for the variety and environmental conditions in a single field. This is especially important for central empirical processes, such as radiation use efficiency [Adam *et al.*, 2011]. This calibration is generally not performed in gridded global applications due to a lack of available reference data and the computation required. Instead, cultivar parameters in gridded process models are typically calibrated at a finite set of points, either within the researchers' realm of expertise or more broadly, and then key parameters are extrapolated globally with relatively simple algorithms. For management and soil inputs, models are usually driven with compiled and/or extrapolated observational data [e.g. FAO/IIASA/ISRIC/ISSCAS/JRC, 2012; Mueller *et al.*, 2012; Potter *et al.*, 2010; Sacks *et al.*, 2010]. Examples of this type of model that are participating in the Ag-GRID GGCMI include: pAPSIM; CropSyst [Confalonieri *et al.*, 2006; Stöckle *et al.*, 2003]; DAYCENT [Stehfest *et al.*, 2007]; pDSSAT [Elliott *et al.*, 2014b; Jones *et al.*, 2003]; and four models based on EPIC [e.g. Liu *et al.*, 2007; Xiong *et al.*, 2014].

- **Dynamic global vegetation models**
  The second major group consists of GGCMs that have been implemented into existing land surface schemes (LSMs) or dynamic global vegetation models (DGVMs). LSMs are used in climate models to simulate the energy, water, and sometimes carbon and nitrogen exchange between the terrestrial biosphere and the atmosphere. Typically, crops have been introduced into these models to improve the representation of seasonal variations in energy and matter exchanges. DGVMs are developed to study the response of natural ecosystems to climate change and the associated implications for carbon and water cycles. These models have been directly developed for global-scale application and so the exchange mechanisms between vegetation and atmosphere are generally implemented in particular detail (e.g. stomatal conductance and photosynthesis). LSM-type models require weather data at sub-daily resolution (which come from the coupled climate model). However, because their focus has typically been on global applications with relatively low spatial resolutions, these models have few data requirements otherwise. Crop yields are not the primary focus of these models, but have become of increasing interest in the applications of models such as those participating in GGCMI: CLM-Ag [Gueneau *et al.*, 2012]; CLM-Crop [Drewniak *et al.*, 2013]; ISAM; JULES-Crop [Van den Hoof *et al.*, 2011]; LPJmL [Bondeau *et al.*, 2007; Müller and Robertson, 2014; Waha *et al.*, 2012a]; LPJ-GUESS [Lindeskog *et al.*, 2013]; and ORCHIDEE [Berg *et al.*, 2011].

- **Large-area crop models or empirical/process model hybrids**
  Finally, the third group consists of crop models developed explicitly to simulate agricultural production systems at continental or global scales. These models typically include key process-based representations but eschew some of the complexities of process models (most notably in terms of management and other inputs) in favour of calibrated empirical functions. This provides more flexibility to represent complex systems with hidden variables and provides the kind of computational tractability that is often required in order to do large-scale calibration of historical datasets. Examples of these

models include CGMS [de Wit and van Diepen, 2008], GLAM [Challinor *et al.*, 2004], MCWLA [Tao *et al.*, 2009a; Tao *et al.*, 2009b], PEGASUS [Deryng *et al.*, 2011] and PRYSBI-2.

3. Challenges for global-scale modelling

3.1 Global consistency vs. data scarcity

The global scale is especially challenging for agricultural assessment because crop models depend on having good-quality, high-resolution data on weather, soils and farm management that are generally not available in much of the world. This is true for historical and projected future data inputs as well as for reference data against which crop models could be tested and improved. The fundamental processes implemented in crop models have been demonstrated to replicate controlled laboratory or field trials. The hypothesis in global modelling is that these models are valid within the range of parameters necessary for global-scale analyses and future projections.

Reference data are available for individual sites. Some examples include: the results of the free air CO_2 enrichment (FACE) experiments on the effects of elevated atmospheric CO_2 concentrations [Ainsworth and Long, 2005; Leakey *et al.*, 2009]; the eddy-flux tower measurements on CO_2 and water exchange fluxes between the land surface and the atmosphere [Baldocchi *et al.*, 2001]; and a multitude of field trials on management practices or weather modification experiments [Kimball *et al.*, 2012]. Data from these field experiments are not always easily accessible or complete, however, and they certainly do not cover the full range of environmental conditions under which crops are grown globally. Comprehensive global reference data, such as the FAOSTAT archive [FAOSTAT data, 2013], are aggregated in larger spatial units (typically national scale), focus only on productivity (production per area harvested) and have substantial uncertainties with respect to the underlying land-use patterns and the mix of management practices (e.g. share of irrigated production, share of winter varieties, fertilizer use).

Model drivers from projected future scenarios, such as daily weather data from climate model outputs, are subject to large uncertainties, which increase with spatial and temporal resolution [Hawkins and Sutton, 2009; 2011]. As most crop models require bias-corrected weather data at daily resolution, this uncertainty is compounded by the variety of datasets and algorithms used in necessary down-scaling and bias-correction methods [Roudier *et al.*, 2011].

Scenarios for future changes in management practices, including fertilizer application, planting dates, crop mixes, rotation cycles and varieties used must be developed by the crop-modelling community to evaluate potential pathways for adaptation. Scenarios on future socio-economic development, such as the Shared Socioeconomic Pathways (SSPs) [Kriegler *et al.*, 2012], can provide some guidance here, but substantial extensions are required to capture the diversity of agricultural components and, given the important role that agriculture plays for GHG budgets, reference must be made to assumptions on emissions in the Representative Concentration Pathways (RCPs) as well [Rosenzweig *et al.*, 2013].

Despite the substantial uncertainty in reference data and regarding future drivers, global-scale analyses are necessary and inevitable for the assessment of global change and climate change impacts. To be useful in economic models or assessments, for example, these analyses require crop model results that are driven with globally consistent assumptions, modelling details and input datasets. Given the international nature of agricultural markets, the effects of climate change on agricultural production and food security cannot be assessed for individual regions but require globally consistent analyses, in which regional and national analyses can be embedded. A consistent global biophysical perspective is thus essential to enable understanding of how markets will respond to altered productivity and patterns of productivity [Nelson *et al.*, 2014a; Nelson *et al.*, 2014b].

4. Recent advances in global-scale crop modelling

4.1 Global-scale impacts

The extent of future climate change itself is highly uncertain, due in large part to the inherent difficulty in predicting future energy consumption or climate policies. In the latest IPCC report, the upper end of projections for global mean temperature change is 4.1+/-0.5°C by 2100 [IPCC, in press]. The increase in global mean temperature, however, does not translate directly to temperature change in agricultural areas. Temperatures are generally expected to increase more rapidly over land, for example, since ocean temperatures – and thus air temperatures above oceans – rise more slowly. There is also the so-called "polar amplification" phenomenon, in which warming proceeds more rapidly at higher latitudes. Finally, mean annual changes may be distributed asymmetrically across seasons (summer vs. winter, spring vs. summer, etc.) and relatively small seasonal shifts may include significant increases in extreme weather events that may last only a few days but are often extremely costly.

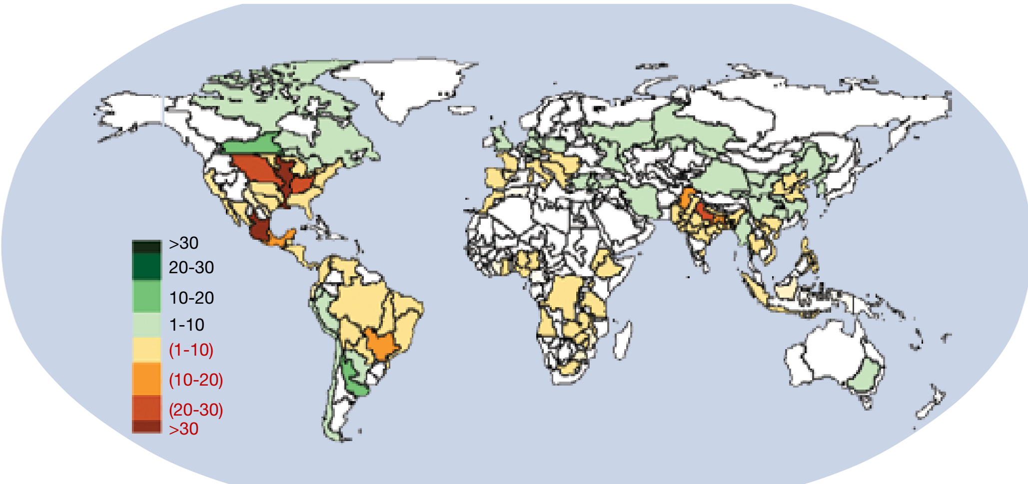
Current agricultural areas are likely to be subjected to significant temperature increases, even if effective climate policies are enforced in the near future. Precipitation patterns, incident solar energy (affected by changes in cloudiness), and the prevalence and intensity of extreme events (e.g. heat waves, floods, droughts), are expected to be strongly affected by climate change, as well. These changes are much more difficult to project reliably than are changes in temperatures, and uncertainty is thus considerably higher [Hawkins and Sutton, 2009; 2011]. This is especially true at temporal and spatial resolutions relevant to agriculture [Hawkins and Sutton, 2009; 2011]. Finally, there are additional biophysical uncertainties (such as the effectiveness of carbon dioxide "fertilization"[5] under various real-world conditions), socio-economic unknowns (such as the distribution of management and expected future changes over the coming decades) and uncertain resource constraints (such as the availability of freshwater for irrigation). Forecasts of agricultural productivity, whether under a changed climate or not, should therefore not be expected to have any reliability beyond seasonal lead times. Even so, these assessments are a necessary and invaluable tool for understanding the risks and opportunities and for identifying suitable and sustainable adaptation measures.

Despite the uncertainties, our current understanding allows for some robust conclusions that also facilitate policy-making and planning. Broadly speaking, no large-scale impact study has excluded the possibility that the overall effect of climate change and CO_2 on agricultural productivity may be negative. Climate change is clearly a risk for agricultural production and it has the potential to pose a sizeable risk that would affect production patterns, the extents of cultivated areas, and food security and prices [Nelson *et al.*, 2014b]. The recent consolidated study on the impact of global climate change on agriculture, conducted in the framework of the AgMIP and ISI-MIP projects, finds that by 2100 the impact of climate change on crop yields for high-emission climate scenarios ranges between -20 and -45 percent for maize, between -5 and -50 percent for wheat, between -20 and -30 percent for rice, and between -30 and -60 percent for soybean [Rosenzweig *et al.*, 2013a]. These impacts are likely to be at least partially offset by the beneficial effects of CO_2 fertilization, especially since carbon fertilization effects are most pronounced in high-emission scenarios. Assuming full effectiveness in large-scale production, climate change impacts would then range between -10 and -35 percent for maize, between +5 and -15 percent for wheat, between -5 and -20 percent for rice, and between

[5] The term 'carbon dioxide fertilization' is defined as the enhancement of the growth of plants as a result of increased atmospheric CO_2 concentration.

figure 1

Spatial patterns of food supply impacts. Average annual change in caloric production of maize, soy, wheat and rice by end-of-century for RCP 8.5. Median of six global crop models, driven by outputs of five global climate models from CMIP5. Results are averaged to 309 Food Producing Units (FPUs), assuming no change in farm management and including the effects on crops of increased atmospheric CO_2



0 and -30 percent for soybean. When viewed in terms of absolute changes in the expected annual caloric production of existing agricultural areas that are attributable to climate (Figure 1), implications for trade patterns become especially clear. Major current global breadbaskets (e.g. in North America and South Asia) are expected to see significant reductions in agricultural production that will reduce their export shares and may require increased imports, as in South Asia, for example.

In models that assume nitrogen is not a limiting factor, climate change impacts are generally somewhat less severe and CO_2 fertilization effects are generally more positive, meaning that yields in many areas are projected to increase [Rosenzweig *et al.*, 2013a]. This is especially true in semi-arid regions [Deryng *et al.*, in prep.].

The wealth of global, regional, and site-based studies provides a basis for conclusions that are robust across a broad selection of climate scenarios, management assumptions, locations and scales. Broadly speaking, climate change impacts on agriculture become worse with increasing temperatures. Associated changes in precipitation can cause considerable variation as well, but do not challenge the general relationship.

There are important differences between tropical and temperate/boreal regions that will affect the global patterns of agricultural production and thus affect trade. Tropical regions, including many developing countries, have climates that are already at the upper end of optimal temperature ranges for many agricultural plants and are projected to experience decreasing agricultural productivity even with small increases in temperature. In higher latitudes or at higher altitudes, agricultural production is often constrained by cold temperatures and therefore small increases in temperature of 1 to 2°C are projected to be beneficial to agricultural productivity. At higher temperature increases, climate change impacts in these regions are projected to become negative as well, although at a slower pace. Agricultural management is a crucial determinant in any projection of future agricultural productivity. Management systems do not only affect the actual strength of climate change impacts on agricultural productivity, their level of flexibility also allows for broad adaptation measures to changing environmental conditions. These measures include some that can be easily implemented at farm level, e.g. adjustments in planting dates [Liu *et al.*, 2013; Waha *et al.*, 2012a], while others may require targeted research (e.g. breeding new varieties) or intensive economic investment (e.g. large-scale expansion of irrigation infrastructure). Tropical regions, which include many developing countries, are assumed to have considerable development potential to increase agricultural productivity through improved management and technology [Deryng *et al.*, 2011; Licker *et al.*, 2010; Neumann *et al.*, 2010; van Ittersum *et al.*, 2013].

Many key aspects of the impact of climate change on agricultural production will require additional research, including the ability of plants to acquire nutrients under different conditions, such as greatly elevated atmospheric CO_2 concentrations [Boote *et al.*, 2013; Taub *et al.*, 2008], which is especially important for issues of food quality and nutrition security. The prevalence and propagation of pests and diseases are also likely to change in a warmer climate [Bebber *et al.*, 2013], posing another major management and adaptation challenge for future agricultural production.

Broadly speaking, global-scale climate change impact assessments have not evolved significantly since the first global climate change impact assessment in 1994 [Rosenzweig and Parry, 1994]. Climate change has the potential to damage productivity across all agricultural areas. Tropical areas are likely to experience detrimental impacts even at low levels of global warming and potentially catastrophic impacts at higher levels, while high-latitude and high-altitude areas could profit from small or medium increases in temperatures. There are large uncertainties with respect to the beneficial effects of CO_2 fertilization (increased photosynthetic action and reduced water requirements for plant growth under elevated atmospheric CO_2 concentrations). The first study of agricultural impacts was conducted by extrapolating just over 100 field-scale assessments [Rosenzweig and Parry, 1994], while models today cover the entirety of current global cropland area and even potentially cropped areas.

Until recently, global-scale climate impact assessments have been relatively scarce and have analysed only a single or small number of assessment models, climate forcings or climate scenarios [e.g. Fischer *et al.*, 2005; Liu *et al.*, 2007; Müller *et al.*, 2009; Nelson *et al.*, 2009; Nelson *et al.*, 2010; Parry *et al.*, 2004; Stehfes *et al.*, 2007]. However, the selection of climate scenarios, even for the same GHG emission scenario, can greatly affect the assessment of climate change impacts [Osborne *et al.*, 2013]. Depending on projected patterns of climate change, which can vary strongly between implementations of GHG emission scenarios in different climate models, projected impacts on agricultural productivity can be very different [Müller and Robertson, 2014; Osborne *et al.*, 2013].

A recently conducted first-of-its-kind intercomparison of GGCMs within AgMIP [Rosenzweig *et al.*, 2014] and for the agricultural sector in ISI-MIP [Warszawski *et al.*, 2014] allowed for a globally consistent analysis across seven different GGCMs. The project included projections for 20 different climate scenarios (four RCPs [Moss *et al.*, 2010; van Vuuren *et al.*, 2011] implemented by five different climate models as part of the Coupled Model Intercomparison Project CMIP5 [Taylor *et al.*, 2012]: HadGEM2-ES [Jones *et al.*, 2011]; IPSL-CM5A-LR [Dufresne *et al.*, 2013]; MIROC-ESM-CHEM [Watanabe *et al.*, 2011]; GFDL-ESM2M [Dunne *et al.*, 2013a; Dunne *et al.*, 2013b]; and NorESM1-M [Bentsen *et al.*, 2013; Iversen *et al.*, 2013]) and were bias-corrected against historical weather data [Hempel *et al.*, 2013]). Model groups considered fully irrigated and rain-fed systems [Rosenzweig *et al.*, 2014], using two assumptions on the effectiveness of CO_2 fertilization (i.e. none and full).

table 1

Global Gridded Crop Models and references for the AgMIP-led ISI-MIP fast-track simulation exercise

Model	Version	References for model description and applications	Institution
EPIC	EPIC0810	[Izaurralde *et al*., 2006; Williams and Singh, 1995]	BOKU, University of Natural Resources and Life Sciences, Vienna
GEPIC	EAWAG	[Liu *et al*., 2007; Williams *et al*., 1990]	EAWAG (Swiss Federal Institute of Aquatic Science and Technology)
GAEZ in IMAGE	2.4	[Bouwman *et al*., 2006; Leemans and Solomon, 1993]	Netherland Environmental Assessment Agency (PBL)
LPJmL	-	[Bondeau *et al*., 2007; Fader *et al*., 2010; Schaphoff *et al*., 2013; Waha *et al*., 2012]	Potsdam Institute for Climate Impact Research
LPJ-GUESS	2.1 with crop module	[Bondeau *et al*., 2007; Lindeskog *et al*., 2013; Smith *et al*., 2001]	Lund University, Department for Physical Geography and Ecosystem Science, IMK-IFU, Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany
pDSSAT	pDSSAT v0.5 (DSSAT 4.0 and 4.5)	[Elliott *et al*., 2013b; Jones *et al*., 2003]	University of Chicago and Argonne National Laboratory Computation Institute
PEGASUS	V. 1.1	[Deryng *et al*., 2011]	Tyndall Centre University of East Anglia, UK/ McGill University, Canada

Results from the participating models (Table 1) are directly comparable with respect to climate and CO_2 forcings[6], but their assumptions and input data on management differed in some important ways. Many of these differences are fundamental to the ways that different groups have chosen to represent management decisions such as planting, irrigation and fertilizer application. These differences in assumptions and input data contribute substantial uncertainty in addition to that caused by differences in underlying functional representations of key processes and other model implementation choices. The joint uncertainties of management assumptions and model implementations are often larger than the uncertainty represented by the five climate models selected here, although this depends on the region and scale of analysis.

A compilation of site-based climate change impact studies for the 4th Assessment Report of the IPCC showed that crop yields decline with increasing local temperature changes and associated atmospheric CO_2 concentrations and

[6] The term CO_2 forcing is short hand expression that links increased CO_2 concentration with a given rise of average temperature. The so-called "radiative forcing" is linked to CO_2 concentration and the extent of its deviation from an initial state (typically chosen as the pre-industrial CO_2 concentration level of 280 part per million value or ppmv). The higher the CO_2 concentration, the higher the radiative forcing which in turn raises the radiative energy reaching the earth's surface and cause the average earth temperature to increase.

precipitation changes [Easterling *et al.*, 2007]. In temperate regions, crops can profit from low to medium increases in local temperatures – e.g. if cold temperature limitations are alleviated or if the associated changes in precipitation and CO_2 fertilization lead to higher productivity. In the tropical regions, however, yields typically decline even with small increases in local temperatures.

With the GCCMI, these impact patterns were confirmed for a more comprehensive coverage of regions and climate scenarios, and a response to local temperature rise was documented for soybean, which had not been covered by Easterling *et al.* [2007]. This modelling exercise could also demonstrate the importance of nitrogen limitation in the assessment of climate change impacts, which indicates the general importance of management constraints for the assessment of climate change impacts on agriculture. If nitrogen limitations are explicitly considered, crops show less profit from CO_2 fertilization [Leakey *et al.*, 2009] and amplified negative climate impacts.

Accounting for nitrogen dynamics reduces the inter-model uncertainty associated with the effectiveness of CO_2 fertilization on agricultural yields, yet this factor still remains one of the largest single sources of uncertainty. While it is clear that elevated CO_2 concentrations stimulate increased photosynthesis in C_3 plants, significant questions remain as to how this translates into increases in harvested biomass (e.g. grain mass) [Leakey *et al.*, 2009], especially in real-world field conditions, and to what extent this can lead to unwanted side effects such as declining protein content and quality [Erbs *et al.*, 2010] or higher susceptibility to insect damage [Zavala *et al.*, 2008].

4.2 Focus regions of climate change impacts

There are two key types of focus regions for climate change impact assessments: those that are subject to large relative changes in agricultural productivity under climate change; and those that are currently major producers and run some risk of being negatively affected by climate change. Both types have implications for trade patterns but they may require very different assessment and response strategies.

The most substantial relative changes in crop productivity are expected in the low latitudes, across all major crops. Since agriculture is a relatively high share of national gross domestic product (GDP) in many tropical regions, these impacts combine with increasingly globalized agricultural markets to jeopardize food security in a dual way: farmers face decreasing local productivity and income, while food availability is increasingly determined by market access and global food prices. On the other hand, these countries often have average crop productivity that is considerably lower than what environmental conditions should allow (this is the so-called yield gap) [Licker *et al.*, 2010; Neumann *et al.*, 2010]. Better market access, infrastructure, fertilizers, pesticides, machinery and alternative crop varieties may be able to contribute substantially to closing these gaps [Markelova *et al.*, 2009], with implications for development, food security, poverty, climate impacts and potential climate adaptations. A notable exception to this expectation is Egypt, where the yield gap is small [Neumann *et al.*, 2010], irrigation is used extensively, and water resources are strongly limiting. Here, a shift from staple to high-value crops, which would require improved market structures, could increase farm incomes.

India is a key region for study for many reasons. It is likely to experience strong relative impacts of climate change and it is a top global producer of many crops [FAOSTAT data, 2013]. Changes in agricultural productivity in this region are thus extremely critical for both local and global food security. India's comprehensive infrastructure for irrigation [Döll and Siebert, 2000] may render adaptation to more erratic rainfall under climate change relatively easy, yet the overexploitation of groundwater reservoirs [Rodell *et al.*, 2009] and the dependence of surface water reservoirs on monsoon rainfall [Maity and Kumar, 2009] may lead to decreasing freshwater availability for agriculture under climate change and could further reduce productivity [Elliott *et al.*, 2014a].

Current yield trends in India are mixed, and largely stagnating for wheat [Ray *et al.*, 2012]. New management practices may help to improve yields [Stoop *et al.*, 2002] and have even led to a recent world record harvest [Kassam and Brammer, 2013]; however, the feasibility and applicability of these techniques at larger scales have been contested [Sumberg *et al.*, 2013]. The preponderance of sequential cropping systems – i.e. producing crops in several seasons of the year – in India will complicate simple adaptations, such as changes in planting dates or selection of fast- or slow-maturing varieties, because the implications for adjacent growing periods must be taken into account as well.

Major agricultural producers in temperate zones, such as the European Union for wheat or the United States of America for maize, can also be subject to strong negative impacts under climate change. These include: reduced water availability during the growing season; more frequent and intense heat events, which are most damaging during flowering [Asseng *et al.*, 2011; Edreira *et al.*, 2011; Hawkins *et al.*, 2013a; Teixeira *et al.*, 2013]; and accelerated phenology, which can lead to reduced biomass production [Liu *et al.*, 2013]. However, these regions also tend to have more flexibility for adaptation. Cropping periods tend to become longer in warmer climates as cold temperature limitations in spring and autumn are alleviated. Further, given the dominance of single cropping systems in these regions (i.e. only one cropping cycle per year) farmers have significant flexibility to adjust varieties (e.g. spring vs. winter varieties) or planting dates, to respond to changing conditions [Liu *et al.*, 2013]. Adjustments in planting dates can help to avoid periods with high temperature stress, exploit longer growing periods with varieties that mature more slowly and so have more time for biomass accumulation and grain filling, and target periods with improved water availability. In some temperate regions, multiple cropping systems could even become feasible in future climates, which could strongly increase agricultural productivity per area and year [Zhang *et al.*, 2013].

4.3 Inter-sectoral interaction

Agricultural production is highly integrated with other sectors and biogeochemical cycles. The most obvious of these factors are the availability of freshwater and of fertile land, which constitute direct constraints to agricultural production. Irrigation agriculture directly competes with other consumers of freshwater, such as households, industry and energy production. Along with impacts from climate change, socio-economic and environmental factors can thus have a major effect on agricultural productivity and on the potential for climate adaptation through irrigation [Elliott *et al.*, 2014a]. Indirect impacts of global climate change on agricultural productivity, such as those caused by changes in the availability of freshwater for irrigation, tend to follow similar patterns as direct impacts. As a result of climate change, freshwater availability increases in regions in the temperate zones but decreases in regions in the low latitudes, including prominent agricultural and heavily irrigated areas in India, China and Egypt. Increased availability in regions that already have ample freshwater supplies is likely to have only minimal potential to increase production, since small increases in average yield and decreased interannual variability are unlikely to justify large expenditures on irrigation infrastructure [Elliott *et al.*, 2014a]. Constraints on freshwater availability in heavily irrigated areas, however, may lead to large reductions in the irrigated share of overall agricultural production, amplifying direct climate change impacts and increasing weather-induced variability in these regions.

Freshwater rationing in the form of deficit irrigation has the potential to increase system-level water-use efficiency (i.e. agricultural production per unit of water) by applying sufficient irrigation amounts to reduce, but not eliminate, water stress. This approach of focusing on water productivity rather than land productivity (i.e.

agricultural production per unit of land) [Fereres and Soriano, 2007] is especially important in dry areas, where availability of water is usually more limiting to agricultural production than land [Geerts and Raes, 2009]. To date, there has been little research conducted on deficit irrigation at the global scale. A recent paper by Liu *et al.* (2014) tackled this issue using a global general model and may have opened the door for more research on the topic.

Availability of freshwater is also affected by increased competition from socio-economic development [Alcamo *et al.*, 2007]. Economic growth may increase withdrawal of water for industry, even if accompanied by increases in water-use efficiency. Increased energy production, whether from fossil fuels or low-carbon alternatives, generally requires substantial additional water withdrawal for cooling or cleaning.

Many assessments of likely future climate mitigation pathways project strong increases in biofuel production, which will compete directly for land and water resources with food, feed and fibre producers. Biofuels are a renewable energy source generated from re-growing plant biomass or from other biological sources (e.g. manure). Biofuels are often classified into two categories: first-generation biofuels made from sugar, starch and vegetable oils, which are typically derived from products suitable for human consumption and thus compete directly with food production; and second-generation biofuels made from cellulosic material unfit for human consumption. The conversion of cellulose into an energy source compatible with current technologies, especially in the transport sector, is still a major challenge, but its use is increasing as a feedstock for heat and electricity generation. Cellulose-based biofuels, however, compete with food production for resources, most importantly fertile land and water, as well as with many other ecosystem services. While proponents of second-generation biofuels point to the potential for using marginal lands for the production of biomass, the idea of existing "unused land" has been challenged [Searchinger *et al.*, 2008; Elbehri, Segerstedt, and Liu, 2013].

The competition for land and water leads to deforestation of primary and secondary forests, producing direct and indirect land-use change [Melillo *et al.*, 2009], which typically diminishes natural resources and ecosystem services [Metzger *et al.*, 2006] and increases emissions of GHGs [Popp *et al.*, 2010]. Under liberalized global trade regimes, increased demand for agricultural food, feed, fuel and fibre crops can thus lead to significant land-use change, with severe environmental consequences that are often difficult to account for and thus to regulate [Schmitz *et al.*, 2012; Schmitz *et al.*, 2013].

The interaction of agricultural production with other sectors and biogeochemical cycles can also diminish the ability of societies to cope with climate change, by compounding the pressures. Besides reduced response options and secondary impacts, as with the example of the reduced availability of freshwater constraining irrigation [Elliott *et al.* 2014a], multiple stressors can also reduce the adaptive capacity of societies [Quinn *et al.* 2011]. As a consequence, agricultural regions that are simultaneously subjected to detrimental impacts in other sectors may experience amplified biophysical impacts, socio-economic consequences, and/or a reduced capacity to respond to change. These "hotspots" should be focal regions for adaptation research [Piontek *et al.* 2014].

5. The Global Gridded Crop Model intercomparison

There are a variety of future climate scenarios: combinations of potential emissions pathways [e.g. Moss *et al.*, 2010; Nakicenovic and Swart, 2000]; their implementation in a general circulation or earth system model; and statistical processing for bias correction [e.g. Hempel *et al.*, 2013; Piani *et al.*, 2010] or downscaling [e.g. Pierce *et al.*, 2009] . However, despite this diversity of scenarios, it is clear that climate change poses a significant threat to agricultural production throughout the cultivated areas of the world. Even so, some regions and crops are confronted by challenges both more immediate and more severe than others. There is strong agreement among GGCM simulations that tropical regions will experience substantial negative impacts on agricultural productivity from climate change, given current management practices. While small increases in global mean temperature may be beneficial in cooler regions, climate change impacts are likely to be negative at moderate or high levels of global warming. These findings are largely in agreement with previous site-scale assessments, as summarized by the IPCC's Fourth Assessment Report [Easterling *et al.*, 2007] and earlier global-scale assessments [Rosenzweig and Parry, 1994].

Beyond broad-scale patterns the picture is more opaque, as was recently demonstrated by the first intercomparison of GGCMs within the ISI-MIP and AgMIP frameworks. This is best highlighted by the range of possible assessment outcomes based on the impact model chosen. Indeed, in the ISI-MIP and AgMIP assessments, the differences among impact models were found to dominate the ensemble spread for most measures.

In order to begin to resolve these issues, Ag-GRID has recently undertaken the GGCMI project. This project consists of a set of highly structured, protocol-based global simulation experiments designed by climate and agro-environmental scientists from around the world. The project will proceed in three overlapping phases, each building on the inputs, outputs, and lessons of the ones preceding it. In Phase 1, models will be driven by harmonized management inputs and nine historical climate-forcing datasets (spanning 1948-2012), focusing on model comparison, validation, and historical extremes. In Phase 2, historical data products will be varied to generate a structured input ensemble designed to evaluate model sensitivity and develop high-resolution multi-dimensional response surfaces for the space of possible future values of carbon, temperature, water and nitrogen. In Phase 3, a new comprehensive multi-model climate impact assessment will be conducted within the AgMIP and ISI-MIP frameworks, with climate drivers from CMIP5 and CORDEX as well as detailed adaptation scenarios and a focus on the effects of increased frequency and severity of extreme weather events.

Harmonization of assumed growing periods and nitrogen fertilization is a key feature of the GGCMI Phase I protocols, and greatly improves comparability of results between models.
New metrics for model performance are being developed in concordance with metrics developed for general circulation models [Gleckler *et al.*, 2008]. Due to the huge differences in the types and purposes of GGCMs, robust model evaluation will require much more than just the reproduction of yields. Interannual variability, the effects of historic extreme weather events on food production, and crop and region-specific analyses will also be of special interest.

6. Open questions

The uncertainty inherent in modelling global-scale climate change impacts on agriculture has several underlying reasons that carry implications for future research. Most important among these is the lack of suitable reference data for model testing, calibration and improvement – an aspect of the modelling challenge that is not likely to see great improvement in the near future. The vulnerability of a particular farm or region to climate change or to climate extremes depends strongly on the dominant management systems employed. In recent decades, much progress has been made in identifying dominant cover classes and some measures of irrigation infrastructure distribution, using remote sensing. However, little information is available regarding management practices (e.g. fertilizer application rates, planting densities, sowing dates) at the high spatial and temporal resolutions and global extent required to enable accurate representations of current management systems in GGCM simulations.

Uncertainty regarding the effectiveness of CO_2 fertilization effects, the combination of stimulated photosynthesis in C_3 plants and reduced water consumption in all plants under elevated atmospheric CO_2 concentrations, is especially large in global-scale simulations. These studies include the full range of uncertainties in field-scale modelling, and involve combinations of environmental conditions (e.g. extremely dry, low fertilizer inputs) that are not sufficiently evaluated in laboratory, open-top chamber, or FACE experiments [Ainsworth and Long, 2005; Leakey *et al.*, 2009]. Finally, national and even sub-national yield statistics are often too aggregated to provide a good evaluation of model performance or determination of the responsible underlying mechanisms, due to the large amount of spatial variability in environmental, climate and management conditions. These points are discussed in more detail in the following section.

6.1 Model evaluation and validation

For a comprehensive evaluation of GGCMs, long-time series of high-quality global data are required for many crops. National and even sub-national statistics are often at too low a resolution to capture the relevant weather-induced variability of crop productivity, which instead is smoothed out by spatial aggregation over larger regions. Changes in production area and management practices are also typically not well documented in these statistics. The only reference yield data available for comparison with sufficient spatial and temporal coverage are national yield statistics, and the absence of high-quality management data is thus a strong constraint on model evaluation. Climate change impacts also differ significantly between irrigated and rain-fed systems, yet their contribution to overall production and average yields in a given region is often unclear, especially with respect to interannual variation, because installed irrigation capacity is not always used to the same extent.

The resolution of national statistics can be improved by assimilating sub-national statistics from a variety of sources [Iizumi *et al.*, 2014; Ray *et al.*, 2012], or by incorporating satellite-based observations of productivity [Iizumi *et al.*, 2014; Ray *et al.*, 2012]. These products should greatly improve the scope of possible model evaluations, but care must be taken as these are not direct observations, but combinations of census data, remote sensing and modelling rules. Site-based reference data from FACE experiments [Ainsworth and Long, 2005; Leakey *et al.*, 2009] and eddy-flux measurements [Baldocchi *et al.*, 2001] can also provide valuable insights, but are limited with respect to coverage of agroclimatic regions, management systems and crops.

Phase I of the Ag-GRID GGCMI will use these and other reference datasets to evaluate models over more than six decades.

6.2 Management

The only datasets available for crop-specific irrigation shares are based on "installed irrigation equipment" in about the year 2000 but contain no information on the temporal variations or actual irrigation water amounts applied [Portmann *et al.*, 2010] anything on actually irrigated areas [You *et al.*, 2010] or these data are not crop-specific [Thenkabail *et al.*, 2009]. Similarly, there is large uncertainty with respect to growing seasons. Again, national census data may not reflect the sub-national variability or diversity of systems. The data compilations for global-scale applications [Monfreda *et al.*, 2008; Portmann *et al.*, 2010] fail to distinguish between spring and winter varieties or between major differences in management (e.g. rain-fed vs. irrigated systems).

Nitrogen is the most important plant nutrient, which is applied to fields in the form of organic (manure) and inorganic (artificially synthesized ammonium) compounds as well as by atmospheric deposition. Input levels vary greatly across space and time but also across crops and management systems. Observational data are generally available only for artificial fertilizer consumption at national level, with little information about its use for specific regions, crops or cropping systems. Stimulated plant growth, whether due to warmer temperatures in high latitude locations or to elevated CO_2 levels, can be inhibited by a deficit in nutrient supply, following Liebig's minimum law[7]. Nutrient deficits can also mask negative climate change impacts by reducing plants' susceptibility to changes in climate. National fertilizer data have been downscaled and assigned to specific crops [Mueller *et al.*, 2012] and will be used in combination with estimates of national manure availability [Potter *et al.*, 2010] for harmonized management data inputs in Ag-GRID's GGCMI model evaluation.

6.3 Effects of elevated atmospheric carbon dioxide concentrations

Besides global warming, increased atmospheric CO_2 concentrations also stimulate photosynthesis in C3 plants and reduce water requirements for all plants. Plant photosynthesis is constrained by available energy (sunlight being intercepted by leaves), the plant's capacity for photosynthesis (mainly determined by the abundance of the Rubisco enzyme) and the availability of CO_2 as a primary input to photosynthesis. In agricultural systems, where nutrient availability and thus nitrogen limitation of Rubisco activity can be managed to some extent, atmospheric CO_2 concentrations often limit photosynthetic rates for the majority of plant species. Under such conditions, rising CO_2 concentrations in the atmosphere due to anthropogenic emissions can stimulate photosynthesis. This effect is robust and confirmed by long-term field trials, such as the FACE experiments. Elevated atmospheric CO_2 concentrations can lead to down-regulation of Rubisco activity in the long run; however, this does not challenge the overall stimulating effect of elevated atmospheric CO_2 concentrations on photosynthesis [Leakey *et al.*, 2009].

All plants, independent of their photosynthetic pathways (C_3 or C_4), profit from elevated atmospheric CO_2 concentrations in semi-arid and arid environments because of the direct coupling of the carbon and water fluxes between plants and the atmosphere. The pores through which CO_2 enters the plant – the stomata – are also the pores through which water vapor leaves the plant during plant transpiration. The opening of the stomata is controlled by the plant's cell pressure, which decreases when the plant dries. As a consequence, plants close their stomata under dry conditions to avoid wilting and this reduces their ability to take up CO_2. Under elevated atmospheric CO_2 concentrations, stomata can be closed more often to save water without reducing the influx of carbon for photosynthesis, leading to higher crop-water productivity (unit of output per unit of water) [Manzoni *et al.*, 2011; Polley, 2002]. A large body of research, including laboratory work, open-chamber field trials and FACE experiments, has documented the beneficial effects of elevated atmospheric CO_2 concentrations on photosynthesis and plant growth [Ainsworth and Long, 2005; Leakey *et al.*, 2009; Polley, 2002].

However, there is still large degree of uncertainty regarding the general effects of elevated atmospheric CO_2 concentrations at larger scales and for longer time horizons. To harness increased plant growth under elevated atmospheric CO_2 concentrations, farmers will have to adjust fertilization and possibly other management practices, such as the selection of cultivars [Ribeiro *et al.*, 2012]. There are some indications that gains in photosynthesis and total biomass may not lead to proportional gains in yields (e.g. for grains) [Leakey *et al.*, 2009]. Increases in biomass and yield may also lead to decreases in protein concentration and thus in nutrient quality and economic profitability [Pleijel and Uddling, 2012; Taub *et al.*, 2008]. Elevated atmospheric CO_2 concentrations have the potential not only to reduce protein concentrations but also to generally alter the chemical composition of plant tissues. These changes have also been shown to change the plants' susceptibility to insect damage

7 This law, popularized by Justus von Liebig, states that states that growth is controlled not by the total amount of resources available, but by the scarcest resource (limiting factor).

[Dermody *et al.*, 2008] and may require intensified crop management to avoid losses [Zavala *et al.*, 2008].

6.4 Future challenges: Representative agricultural pathways

Agricultural production is strongly dependent on weather conditions and thus susceptible to climate change impacts. However, management is also a central aspect in agricultural production, and mismanagement can lead to substantial reductions in production. The effects of mismanagement on agricultural production are often described using the concept of "yield gap analysis", which describes the difference between yields actually achieved and potential yields – i.e. yields theoretically achievable under given environmental conditions, where no nutrient and water limitations constrain plant growth [van Ittersum and Cassman, 2013; van Ittersum *et al.*, 2013]. Global analyses have shown that there are substantial yield gaps, i.e. management-driven reductions in agricultural productivity, especially in many developing countries [Licker *et al.*, 2010; Neumann *et al.*, 2010], and limited market access was identified as one of the major reasons for this phenomenon [Neumann *et al.*, 2010]. Besides identifying managerial deficits that can lower agricultural productivity, agricultural research can greatly improve agricultural productivity, e.g. by developing novel crop varieties that are more productive or less susceptible to drought phases, heat, insect damage or pests, or new soil and water management techniques. Such targeted agricultural research has led to substantial improvements in agricultural productivity in the past, as, for example, during the so-called "green revolution" [Evenson and Gollin, 2003; Pingali, 2012]. Agricultural research is effective over longer time periods, as research and development typically have multi-annual cycles, and their effects are typically not captured by yield gap analyses because they do not necessarily affect the difference between actual and potential yields, but can move the potential yield level upwards [Dietrich *et al.*, 2012].

Historically, yield increases have resulted from a combination of closing the yield gap and shifting potential yield levels upwards and, in the past, these yield increases have sustained the increases in global population. Recently, yield increases have stalled for many important crops and countries [Lin and Huybers, 2012; Ray *et al.*, 2012] and yield improvements at historic rates have been found to be insufficient to sustain projected future demand for agricultural products [Ray *et al.*, 2013].

Current research on climate change impacts often assumes static management systems [Rosenzweig *et al.*, 2014] or addresses simple on-farm adaptation measures such as soil and water management or the adaptation of sowing dates [Folberth *et al.*, 2012; Laux *et al.*, 2010; Liu *et al.*, 2013; Waha *et al.*, 2012a], which can be assumed to be determined mostly by climatic and weather conditions [Waha *et al.*, 2012b]. Adaptation to climate change can be complex and involve targeted research [Challinor *et al.*, 2009; Challinor *et al.*, 2007; Reidsma *et al.*, 2009; Smith and Olesen 2010] but often can be achieved via simple and inexpensive technologies [Ebi *et al.*, 2011]. The assumption of static management systems in climate change impact assessments is thus not designed to provide assessments of future agricultural productivity but to explore the isolated effect of climate change only. This helps to reduce inconsistencies between biophysical models and economic models that take biophysical climate change impact projections as an input to their economic response [Müller and Robertson, 2014; Nelson *et al.*, 2014a; Nelson *et al.*, 2014b]. However, assumptions regarding management systems can also greatly affect the projected strength of climate change impacts on agricultural productivity [Rosenzweig *et al.*, 2014].

In light of its significance for the assessment of future agricultural productivity and for the assessment of future climate change impacts on agricultural productivity, consideration of various scenarios on future agricultural management is crucial. Such scenarios need to reflect plausible possible future circumstances for all socio-economic and biophysical dimensions that are important for agricultural production. At the global scale these comprise assumptions on future trade patterns, affecting global production patterns, market access for selling agricultural products and buying inputs (fertilizers, pest control, machinery, seeds) and price levels that will determine the profitability of different management options. National and economic unions (e.g. the European Union) may enforce agricultural policies or environmental regulations – including the mitigation of GHG emissions – that affect agricultural management and labour markets. Population growth [Lutz and Samir, 2010], migration [Aaheim *et al.*, 2012; Kniveton *et al.*, 2012; McLeman and Smit, 2006] and urbanization, as well as future educational systems, may affect labour availability for agricultural production as well as production costs [e.g. Martin and Calvin, 2010]. Finally, one central input for agricultural production, namely phosphorus, is in short supply globally and in the hands of very few actors; even though stocks may not be depleted this century [Van Vuuren *et al.*, 2010], this has the potential to affect productivity levels, production costs and production patterns globally [Bouwman *et al.*, 2009; Carpenter and Bennett, 2011; MacDonald *et al.*, 2011].

In global scale assessments, agricultural systems are not represented in much detail so far, but typically involve assumptions on sowing dates, varieties grown and fertilizer inputs [Rosenzweig *et al.*, 2014]. Future scenarios regarding agricultural system change thus only need to address these dimensions if models do not take up the challenge to better integrate different management systems [e.g. Del Grosso *et al.*, 2009]. This challenge can be more complex for assessments at regional scale [Antle *et al.*, under review].

The most promising approach for developing scenarios of future agricultural production systems, often referred to as Representative Agricultural Pathways (RAPs), is to expand existing (or currently under development) socio-economic scenarios, such as the so-called SSPs [Kriegler *et al.*, 2012]. These typically address some of the relevant dimensions for agricultural productions (e.g. trade liberalization scenarios) but need to be filled out with more explicit assumptions on others (e.g. fertilizer rates, speed of dissemination of better-adapted crop varieties) that just need to be consistent with the general storylines of the SSPs and the more explicit assumptions therein.

6.5 Future challenges: Drought and climate extremes

Agricultural production is directly dependent on weather conditions, especially in non-irrigated production systems. The effects of weather variability produce variations in national yield statistics; in many cases, changes in yield variability can be attributed to weather variability [Osborne and Wheeler, 2013]. As variability changes under global warming, this will affect agricultural production [Hawkins *et al.*, 2013b], especially during heat-sensitive phases [e.g. Asseng *et al.*, 2011; Edreira *et al.*, 2011; Teixeira *et al.*, 2013].

Drought affects millions of people globally each year, and warming temperatures and shifting precipitation patterns are likely to exacerbate the problem, increasing both the frequency and severity of large-scale droughts in globally important and agriculturally sensitive regions [Sheffield and Wood, 2008; Solomon *et al.*, 2007; Wehner *et al.*, 2011]. Recent work suggests that extended drought will harm more people in the future than any other climate-related impact, specifically in the area of food security [Romm, 2011]. Therefore, the extent to which climate impact models can reproduce the effects of large-scale drought and heat events is likely to be one of the most important measures of model effectiveness, for determining whether these models are able to represent future impacts successfully. Dozens of specific large-scale extreme hydrological drought and heat events from the historical record (1948-present) have been catalogued by Sheffield and Wood [2011].

Many of these events had major agricultural, food security and economic implications, and these can be evaluated using GGCMs in order to test these models under such extreme conditions. This will also result in a standardized, comprehensive multi-model analysis of agricultural drought over the last 6+ decades, comparable among regions and decades, that will improve both the understanding of drought and its effects on crops and food production and the ability of models to represent the consequences of increased drought and heat in the future.

6.6 Future challenges: Connecting with field-scale assessments

Crop growth models have been applied to multiple purposes for several decades. Given that models applied to climate change impact assessment do not always employ the most up-to-date formulations, Rötter *et al.* [2011] called for a general re-assessment of model effectiveness, as a first step towards improving model formulations. This effort has been undertaken by AgMIP [Rosenzweig *et al.*, 2013], focusing first on the major cereal crops – wheat [Asseng *et al.*, 2013], maize [Bassu *et al.*, 2014] and rice – while building communities and establishing research teams for other crops, pastures and livestock (see http://www.agmip.org). The projects focus initially on reproducing observations across different environmental gradients and management systems, followed by exploration of model sensitivities to changes in temperature, precipitation and atmospheric CO_2 concentrations.

As GGCMs are often based on field-scale models to varying degrees, field-scale model improvements can provide the basis for global-scale improvements. Processes that have been identified as important for future crop productivity, such as temperature extremes [Asseng *et al.*, 2011], tropospheric ozone concentrations [Bender and Weigel, 2011; Leisner and Ainsworth, 2012; Pleijel and Uddling, 2012] and pests and diseases [Bebber *et al.*, 2013; Mediene *et al.*, 2011], will have to be implemented and tested in field-scale models, before they can be implemented in global-scale assessments. The high quality of data available at some individual field sites greatly facilitates the development and evaluation of process formulations in crop models. Global-scale models can inform field-scale model development as well – for example, by characterizing expected ranges of growing conditions across large areas, as well as their implications for agricultural productivity and modelled sensitivities.

6.7 Future challenges: Informing economic assessment with biophysical climate change impact studies

Biophysical climate change impact assessments are a central precondition for understanding climate change impacts on future trade patterns in agricultural markets. There are a number of challenges to making these assessments useful to current agricultural economic assessments. The uncertainty with respect to climate change patterns [Christensen *et al.*, 2007] and impact models [Rosenzweig *et al.*, 2014] needs to be accounted for. A broad variety of issues exist in modelling consistency between economic and biophysical models. One important aspect is the difference between market commodities such as sugar, assumed to be homogeneous by economic models, which can be supplied by very different biophysical crops (here: sugar cane and sugar beet) that differ in their photosynthetic pathways (C_4 for sugar cane, C_3 for sugar beet), phenology, and plant organs of interest (stalks or beets). The ability to model these different crop types or assumptions about their mixture in the supply of the commodity sugar can greatly affect the assessment of climate change impacts on the commodity's market shares and production [Müller and Robertson, 2014; Nelson *et al.*, 2014a; Nelson *et al.*, 2014b].

7. Conclusions

Assessments of climate change impacts on global-scale agricultural productivity have been conducted for the last several decades [Rosenzweig and Parry, 1994]. However, quantification of the uncertainties related to different climate scenarios, impact model implementations, assumptions on management systems and CO_2 fertilization has been supplied only recently. The general global pattern of more negative impacts being experienced in the tropical regions than in the higher latitudes has been shown to be reliable across the significant uncertainty embedded in different climate scenarios and impact models used [Rosenzweig *et al.*, 2014]. Available computational power to conduct global-scale climate change impact assessments on agricultural productivity has increased since the study of Rosenzweig and Parry [1994], and models have been adjusted for gridded global simulations [e.g. Elliott *et al.*, 2014b; Liu *et al.*, 2007] and extended to cover agricultural vegetation [e.g. Berg *et al.*, 2011; Bondeau *et al.*, 2007; Deryng *et al.*, 2011; Lindeskog *et al.*, 2013] or developed explicitly for large-scale applications [e.g. Challinor *et al.*, 2004]. Input data on management aspects beyond national fertilizer rates [Liu *et al.*, 2010; Mueller *et al.*, 2012] and some estimates of growing seasons [Portmann *et al.*, 2010; Sacks *et al.*, 2010], as well as good reference data, are scarce, and products have only recently been available [Iizumi, *et al.*, 2014; Ray, *et al.*, 2012]. Therefore, evaluation of the performance of GGCMs has been very limited, mainly demonstrating that measurements of specific sites [e.g. Bondeau *et al.*, 2007] or national yield statistics [e.g. Liu *et al.*, 2007] can be reproduced.

The first GGCMI conducted within AgMIP [Rosenzweig *et al.*, 2013], as the agricultural biophysical sector assessment in the ISI-MIP, has shed some initial light on uncertainties across different GGCMs, management assumptions, climate scenarios and assumptions about the effectiveness of CO_2 fertilization [Rosenzweig *et al.*, 2014]. This study confirms general patterns of climate change impact found in previous global-scale assessments [e.g. Müller *et al.*, 2009; Rosenzweig and Parry, 1994] and site-specific studies [e.g. as compiled in Easterling *et al.*, 2007].

Future activities to improve our understanding of possible future climate change impacts on biophysical agricultural productivity will be further coordinated by Ag-GRID and its GGCMI and will cover better model evaluation and understanding of key uncertainties (management, CO_2 fertilization, temperature extremes) and model improvements (e.g. nutrient dynamics, management options). The project will foster interaction with the crop-specific activities as well as with the Global Economic group in AgMIP to address these challenges.

The role of adaptation to climate change and the biophysical options to increase productivity, especially in regions with strong managerial deficiencies, have not yet been fully explored and will require improved representation of management options in GGCMs. Current analyses of climate change impacts on agricultural productivity are thus not complete projections of future productivity but of the isolated effect of climate change only. Changes in management have the potential to mediate climate change impacts as well as to improve agricultural productivity beyond simply compensating for negative climate change impacts.

Despite considerable uncertainties in terms of climate drivers and biophysical responses of agricultural systems, it is clear that climate change will have significant impacts on agricultural trade. Given the robust pattern of less severe, or even positive, impacts in temperate zones compared to tropical regions, economic measures and trade policies will have to be developed to ensure sufficient income in developing regions to allow them to participate in trade even under declining agricultural yields.

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