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Are scenario projections overly optimistic about future yield progress?

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Are scenario projections overly optimistic about future yield progress?

Abstract

Historical increases in agricultural production were achieved predominantly by large increases in agricultural productivity. Intensification of crop and livestock production also plays a key role in future projections of agricultural land use. Here, we assess and discuss projections of crop yields by global agricultural land-use and integrated assessment models. To evaluate these crop yield projections, we compare them to empirical data on attainable yields by employing a linear and plateauing continuation of observed attainable yield trends. While keeping in mind the uncertainties of attainable yields projections and future climate change impacts, we find that, on average for all cereals on the global level, global projected yields by 2050 remain below the attainable yields. This is also true for future pathways with high technological progress and mitigation efforts, indicating that projected yield increases are not overly optimistic, even under systemic transformations. On a regional scale, we find that for developing regions, specifically for sub-Saharan Africa, projected yields stay well below attainable yields, indicating that the large yield gaps which could be closed through improved crop management, may also persist in the future. In OECD countries, in contrast, current yields are already close to attainable yields, and the projections approach or, for some models, even exceed attainable yields by 2050. This observation parallels research suggesting that future progress in attainable yields in developed regions will mainly have to be achieved through new crop varieties or genetic improvements. The models included in this study vary widely in their implementation of yield progress, which are often split into endogenous (crop management) improvements and exogenous (technological) trends. More detail and transparency are needed in these important elements of global yields and land use projections, and this paper discusses possibilities of better aligning agronomic understanding of yield gaps and yield potentials with modelling approaches.

Keywords

Shared Socio-economic Pathways (SSPs); Integrated assessment; Land use; Crop yield projections; Potential yield; Attainable yield

1 Introduction

Historically, agricultural intensification has played a key role in the increase in agricultural production (Burney et al., 2010; Foley et al., 2011; Ramankutty et al., 2018; Rudel et al., 2009). For the most recent decades (1961-2007), the Food and Agriculture Organization of the United Nations (FAO) attributes 86% of historical growth in crop production to increases in yield and cropping intensities (Alexandratos and Bruinsma, 2012; FAO). Further intensification of production on existing agricultural land can limit future expansion of agricultural land, thereby alleviating a major driver of land-use change emissions (Overmars et al., 2014; Popp et al., 2017a) and global biodiversity loss (Newbold et al., 2015; Phalan et al., 2011). However, some have argued that a continuation of historical trends in crop intensification is not sufficient to provide the necessary increase in food demand (Ray et al., 2013), and several studies have suggested that crop yield progress, mainly in developed regions, is starting to show signs of stagnation (Grassini et al., 2013; Lin and Huybers, 2012). A key question in describing the future of food production is therefore to what extent agricultural productivity will continue to increase.

Scenario projections of agricultural production and land use are at the core of agricultural land-use and integrated assessment models which aim to provide insights into the dynamics between socio-economic developments and the environment (Popp et al., 2017a; Rosenzweig et al., 2013). These models include projections of agricultural intensification with linkages to climate and other environmental factors. A range of assumptions on technical change were implemented within the Shared Socioeconomic Pathways (SSPs) framework (O'Neill et al., 2017; van Vuuren et al., 2017). A possible issue with these model projections is that they lack biophysical foundations as to crop yields, possibly leading to overoptimistic estimates of future yield increase (Schmitz et al., 2014). This is specifically true for models with a strong focus on economic relations and a limited representation of physical mechanisms, such as biophysical potential crop productivity or other empirical information (van Dijk et al., 2017). Earlier comparisons of model results within the SSPs context did not provide an evaluation of yield projections against empirical data (Hertel et al., 2016; Robinson et al., 2014).

In this study, we aim to address this shortcoming by comparing model results to empirical data on current potential crop yields (Mueller et al., 2012; van Ittersum et al., 2016) in order to evaluate whether scenario projections for agricultural productivity are overly optimistic. We compare yield projections towards 2050 for cereal crops (wheat, rice, and maize and other grains) in the SSPs to potential yields from three sources (Fischer et al., 2014; GYGA, 2018; Mueller et al., 2012). In this comparison, we have to be cognizant of the fact that potential yields have increased in the past due to improvements in cultivation techniques and crop varieties and likely will continue to do so in the future (Fischer et al., 2014; Rijk et al., 2013). Because the progress of potential yields is vital for the comparison with model projections, we use extrapolations of observed trends in potential yields from field trials (Fischer et al., 2014). Using these historical trends, we estimated the potential yields by 2050 under continuing linear trends and, alternatively, under the assumption that progress in potential yield will have stagnated by 2050. While our understanding on the future developments of potential yields is limited, these two approaches reflect two main notions where 1) there is no evidence that observed potential yield progress is slowing down (Fischer et al., 2014; Rijk et al., 2013) and 2) recognize that stagnations in yield trends have been observed due to yields reaching a plateau (Grassini et al., 2013). This analysis is augmented with insights from FAO historical data and linear extrapolations thereof.

The paper starts with an overview of the global land-use and agriculture models and mechanisms behind the yield projections (section 2.1), followed by an overview of the potential yield data used (2.2). The results, in which these two data sets are compared on a global and regional scale, first focus on the SSP2 'Middle of the Road' scenario (Section 3.1). This is followed by an analysis of the other SSPs, with varying degrees of technological progress and mitigation efforts, as well as identification of hot spots for specific crops and regions (3.2). Finally, the conclusions, limitations, and potential model improvements are discussed (Section 4).

2 Methods

2.1 Model projections

We evaluated scenario projections towards 2050 from six agricultural land-use and integrated assessment models: IMAGE-MAGNET (Doelman et al., 2018; Stehfest et al., 2014), AIM (Fujimori et al., 2014; Fujimori et al., 2017), GLOBIOM (Havlik et al., 2014; Havlik et al., 2012), MAgPIE (Dietrich et al., 2014; Popp et al., 2011; Popp et al., 2014), GCAM (Wise et al., 2014), and IMPACT (Robinson et al., 2015). The first five of these have contributed to the land-use quantification of the SSPs (Popp et al., 2017b), and all of these have participated in recent studies within the AgMIP (Agricultural Model Inter-comparison Project) consortium (Hasegawa et al., 2018; Meijl et al., 2018; Stehfest et al., 2019). We assessed five baseline SSP scenarios (See Table 1), as well as three climate change mitigation scenarios in line with RCP2.6 and the 2°C target (Meijl et al., 2018). The scenario data used in this study is based on recent work from the AgMIP consortium (Hasegawa et al., 2018; Stehfest et al., 2019). All scenarios presented here are without climate change impacts (future CO_2-fertilization, temperature and precipitation changes are excluded). Likewise, also projections of attainable yields do not account for impacts of climate change.

In the context of the AgMIP collaboration, the modelling teams have put effort into harmonizing their outputs both in terms of regional aggregation (13 regions) and crop categories. In this study, we apply an aggregation to 6 regions (see SI Supplementary Table 1), while the crop categories are retained: wheat, rice, and maize plus other cereal grains (denoted as ‘coarse grains’). Besides these crops, we also report weighted average yields (based on harvested areas) of all cereals. The alignment between these crop categories and the models’ crop categories are reported in Supplementary Table 2).

Table 1 Overview of the SSP scenarios and their characteristics of land productivity. All scenarios exclude climate change impacts.

Scenario name	Scenario label	Implementation of land productivity (Popp et al., 2017a)
Sustainability	SSP1	High improvements in agricultural productivity; rapid diffusion of best practices
	SSP1_m	SSP1 plus mitigation measures for 2°C stabilization
Middle of the road	SSP2	Medium pace of technological change
	SSP2_m	SSP2 plus mitigation measures for 2°C stabilization
Regional rivalry	SSP3	Low technology development
	SSP3_m	SSP3 plus mitigation measures for 2°C stabilization
Inequality	SSP4	Productivity high for large scale industrial farming, low for small-scale farming
Fossil-fuelled development	SSP5	Highly managed, resource intensive; rapid increase in productivity

Scenario projections by the models included in this study represent the agricultural economy either via partial equilibrium (PE) or computable general equilibrium (CGE) approaches (Table 2). These models generally address future yield developments as a combination of long-term technological change-driven improvements (continuous genetic crop improvement and new technologies), and based on changes in management (management, fertilizers, labour, capital) in response to price and market dynamics (Schmitz et al., 2014, Robinson et al., 2014). The definition and implementation of exogenous and endogenous is different for each model (Table 2), and exogenous yield trends are calibrated based on various sources. The models used in this study were part of an earlier AgMIP effort to compare and harmonize models, and in that context used one harmonized exogenous yield trend. Differences in model set-up and definitions (Table 2) suggest, however, that these exogenous trends should not necessarily be based on one single source, and yield trend assumptions for the different models have since diverged to varying degrees. For developing the SSPs, modelling teams translated the rather general scenario storylines into their specific methodologies and parameters.

Additional changes in average projected yields are the result of developments in the allocation of crop production (both within and between regions). The allocation of crop production is determined by regional economic differences, as well as local variation in environmental factors on yields (e.g., temperature, water, soil). Some teams also use global gridded crop models (GGCMs) to derive spatially explicit yield distribution. Although the environmental factors can vary over time, these crop models do not incorporate the technological progress (i.e., breeding varieties) or agro-economic management options that are included to various degrees in the full agricultural model frameworks. The extent of irrigation and changes in cropping intensity (either from multiple harvests or changes in fallow land) are also important factors related to intensification. However, these elements are not consistently part of the drivers in the models, as for example cropping intensity is often kept constant (Table 2). Changes in the extent of irrigation, which influence the average yield due to the higher yields associated with irrigated crops, are addressed in different ways in each of the models and are not explicitly addressed in this study.

Table 2 Overview of agricultural land-use and integrated assessment models and their approaches to agricultural intensification.

Model	Type*	Exogenous yield trends	Endogenous yield trends	Irrigation	Cropping intensity	Yield constraints/ ceiling/plateau	Crop model
IMAGE-MAGNET	CGE	Autonomous technological changes as exogenous assumption.	Price-driven intensifications (MAGNET) and grid-based allocation within regions between grid cells of different productivity (IMAGE).	Expansion of total irrigated area as exogenous driver.	Crop intensity is fixed at base-year level.	No. Exogenous yield trends based on FAO scenario show diminishing yield growth. Endogenous part depends on scarcity of land.	LPJmL (coupled with IMAGE gridded land use allocation module)
GLOBIOM	PE	Crop yields shifter based on econometric estimates of relationship between yields and GDP per capita (Herrero et al., 2014).	Shift between management (low and high input, rainfed and irrigated), and relocation within regions between grid cells of different productivity.	Expansion into irrigation possible depending on water resource availability. (Palazzo et al., 2019)	Crop intensity is consistently one for the global model version.	Not explicitly in exogenous trends yet diminishing rates of growth as the underlying GDP growth tends also to level off over time.	EPIC gridded data on yields by management system and climate scenarios available for each model gridcell.
AIM	CGE	Autonomous technological changes as exogenous assumption.	Market-based intensifications.	Irrigation expansion was considered exogenously in yield shifter so incorporated into the yield progress	Crop intensity is fixed at base-year level.	Diminishing yield growth based on historical observations ((Fujimori et al., 2017)	CYGMA: Crop Yield Growth Model with Assumptions on climate and socioeconomics.
GCAM	PE	Yield shifter as exogenous assumption.	Inter-regional shifting in production.	Price driven expansion.	Crop intensity is fixed at base-year level.	None considered.	None by default; can use outputs from any GGCM.
MAgPIE	PE	None (fully endogenous).	Fully endogenous via	Market-based decisions to	Crop intensity	Not explicitly but endogenous	LPJmL: used as an input

			R&D module based on production costs and the effectiveness of R&D investments.	deploy additional irrigation.	part of endogenous changes.	results are subject to diminishing rates of return from investments in technology.	for crop yields, water flows, carbon content.
IMPACT	PE	Technological progress and productivity growth based on historical trends and expert opinion.	Market-based intensifications and share-based allocation according to land availability, crop prices, water constraints, and crop yields.	Price driven expansion of irrigated croplands.	Crop intensity varies across geographies and adjusts endogenously, at the margin, to crop prices.	Yield trends calibrated to biological yield limits, along with diminishing returns on investments in R&D and productivity.	DSSAT for climate impacts on yields & suite of hydrology models for impact of water availability on yields.

* CGE: Computable General Equilibrium model, PE: Partial Equilibrium model.

2.2 Reference yield data and potential yield progress

We compare the model estimates with two widely used metrics of maximum yield expected in different regions: potential yields and attainable yields.

Potential yields (PY) can be used to assess the opportunities for the future increase in food production through increased productivity (Mueller et al., 2012; van Ittersum et al., 2016). The PY is defined as the crop yield expected with the best crop variety, under optimal (i.e., yield-maximizing) management conditions and without manageable abiotic and biotic stresses (Fischer, 2015; Lobell et al., 2009). It is an indicator of how much yield improvement is still possible by yield-maximizing crop management practices (e.g., improved sowing dates, fertilizer application, pest control) while using the latest available crop varieties. The data sources for potential yields used in this study are: 1) the global yield gap atlas (GYGA, 2018), which represents a collection of results from crop growth simulation models with detailed local information (van Ittersum et al. 2013, van Bussel et al 2015); 2) a systematic review and aggregation of many case studies on potential yields based on field trials, including trends from 1990 to 2010 (Fischer et al., 2014); and 3) the yield data from Mueller et al. 2012, which applies a frontier analysis on maximum observed yields for similar climate and soil conditions and thus refers to attainable yields rather than potential yields.

Attainable yields (AY) are yields that can be attained by farmers when economically optimal practices and levels of inputs have been adopted (FAO, 2016). They are, by definition, lower than the potential yields and imply that a minimum yield gap always exists as higher yields are not economically viable. The attainable yield gap (i.e. the gap between actual yields and attainable yields, AY gap, see Figure 1), is also often referred to as the economically exploitable yield gap (van Ittersum et al., 2013). In this study, we translate the PY datasets (Fischer et al. and GYGA) to attainable yields to make all values comparable. Maximum attainable yields are suggested to be 23% below PY (Fischer et al., 2014) and this value is applied in this study to convert all potential yields to attainable yields. It should be noted that this conversion factor is difficult to determine, as well as highly heterogenous across regions and crops, and other estimates of the attainable yield range from 15 to 25% below PY (van Ittersum et al., 2013). Furthermore, although in the current analysis we keep this factor constant at a global level, it can conceivably be influenced in the future by various scenario drivers.

Figure 1 depicts conceptually how the historical and future yield progress can be broken down into contributions from progress in potential yields (improved cultivars) and yield gap closing via improvements in soil and crop management. The PY progress can be conceptually linked to the exogenous trends as used in the model scenarios, while yield gap closing can be linked to changes of endogenous intensification in the models. The split between these two sources of yield progress differs across models, see also Table 2, and cannot be disentangled in a consistent way. The connection of technological progress of potential yields to the exogenous drivers of the model projections is thus not an exact definition but is a generalized link between the concepts.

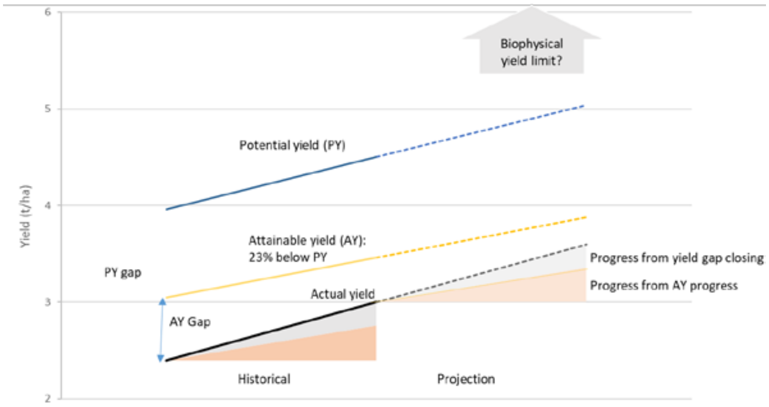


Figure 1 Conceptual depiction of historic and future yield progress. The increase in yield can be decomposed into progress in attainable and potential yield and yield gap closing.

The data sources used for our comparison of the scenario results with potential yields and attainable yields are reported in Table 3. To extrapolate the PYs to give a useful comparison with model results in 2050, we use the potential yield progress (1990-2010) from Fischer et al. We apply this trend to the average of the AY data points across the 1990-2010 period. This trend is then extended into the future in two ways: 1) linear extrapolation, where potential (and thus attainable) yields will be able to continue linearly and 2) plateauing trends, where potential yield increases are levelling off towards 2050, indicating an impending stagnation of yield progress (Grassini et al., 2013). Thus, for a plateau trend, we implement a linear decrease of the growth rate of the AY from 1990-2010 until the slope reaches zero in the 2040-2050 period. These two approaches, which we will denote as the "linear" and "plateau" AY trend, will serve as a useful range to check the projected yields against. In all cases, the yields presented here represents a weighted average irrigated and rainfed yields. Although some of the potential yield data sources make the distinction between rainfed and irrigated yields, it was not possible to make this comparison as not all models report this level of detail in their crop yield projections. The model projections contain changes in irrigated areas, whereas the attainable yield trends implicitly assume a static share of irrigated and rainfed crop areas based on the share in the reference year for the data source (Table 3).

Additionally, the scenario results were compared to historical yield trends to check whether trends deviate unrealistically far from recent observations. Historical yield data from the FAO was extended to 2050 as a linear projection based on a linear regression per crop and region of 1990-2010 data.

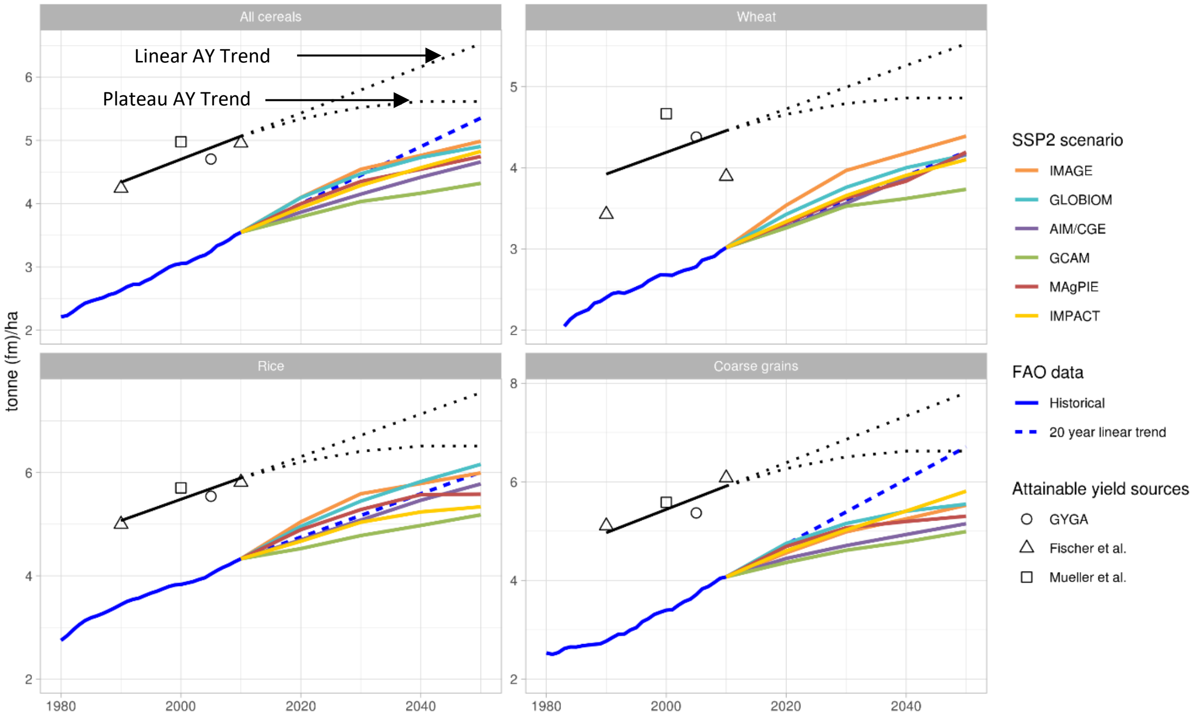
Table 3 Overview of yield data and projections used in the evaluation.

Yield data	Description of sources
Yield projections, by model and scenario	Yield projections from **agricultural land-use and integrated assessment scenarios** for the SSP scenarios referring to modelled farm yield levels. These projections (2010 – 2050) were based on recent versions of scenario results within the AgMIP project (Hasegawa et al., 2018).
FAO Historical yields	FAO historical farm yield (FAO), for 1970 – 2010 using a 5-year moving average
FAO 20 year linear yield trends	Linear extrapolation of FAO historical farm yield data towards 2050, based on the trend of 1990-2010.
Attainable yield GYGA**,** Fischer et al., and Mueller et al.	**GYGA.** Potential yields based on crop growth simulation models with detailed local information (GYGA, 2018, van Ittersum 2013, van Bussel 2015). Reported PY scaled to AY (see text). The year on which data is based varies by country, and 2005 was assigned as a common base year. Data spans 46 countries. Cereal crops covered are wheat, rice, maize, barley, sorghum, and millet. Irrigated and rainfed yield gaps are reported separately and a weighted average of these points was applied.
	Fischer et al. Potential yield and trends thereof from aggregated field trial data, based on time periods of 1990-2010. (Fischer et al., 2014). Reported PY scaled to AY (see text). Data is reported based on representative crop mega environments, which were assigned to the regions as used in this paper (see supporting information for more detail). Cereal crops covered are wheat, rice, maize and, in although in less detail, barley, sorghum and millet. Data are reported for representative crop 'Mega Environments' which represent typical rainfed or irrigated systems. The weighted average of the reported areas was applied.
	Mueller et al. Attainable yields from Mueller et al., 2012. Attainable yields based on a frontier analysis (maximum observed yield approach). Base year is 2000. Coverage Is global and the reporting on country level was used. Cereal crops covered are wheat, rice, maize, barley, rye, sorghum, and millet. The attainable yield data is reported as a combination of rainfed and irrigated yields.
Average linear and plateau AY trends	Average of the three data sources for attainable yield, with the PY trend as reported by Fischer et al. applied in linear and plateau fashion (see text). Denoted as **linear AY** and **plateau AY**. The attainable yields are extrapolated towards 2050, in which the share of rainfed and irrigated crops is kept constant.

Attainable and potential yield data are not available for all crops and regions. The gaps in the data are filled by applying values from similar regions (see the Supporting Information for more detail per data source). The datasets cover various years, and also differences in crop definitions exist. Thus, in order to make data comparable, the relative yield gaps (i.e. the difference between potential and currently realized yield) as reported in the datasets were applied to the FAO yield of the relevant year. In the same manner, the model yield projections were scaled to the 2010 FAO farm yield so that we effectively compare the relative yield trends (i.e. harmonize the starting point). This scaling is required to make the data comparable as some models report yields in dry matter instead of fresh matter or include cropping intensities (see the supporting information for details). Results presented in the next section therefore depict yield trends rather than absolute yields for most data sources.

3 Results

Figure 2 shows the global yield projections for the SSP2 scenario as implemented by agricultural land-use and integrated assessment models. The yields of all cereals combined increase on average across models from 2010 to 2050 by +34% (from +22% for GCAM to +41% for IMAGE-MAGNET). Wheat yield is projected to increase the most (by +37% on average) and coarse grains the least (+31% on average). On average across models, the share of coarse grains crop area comprises 43% of all cereals and increases to almost half of all cereals which has a minor impact on the average yield for all cereals. For all cereal types, GCAM consistently shows the lowest yield projections across models, while in contrast GLOBIOM and IMAGE-MAGNET consistently show higher yields. Across all models and crop categories, the rate of yield growth (in absolute as well as percentage terms) decreases from the period 2010-2030 to 2030-2050 (see Supplementary Table 4), with the second period on average displaying around half of the relative yield progress of the first. This general model behaviour is partially rooted in the aforementioned harmonization within AgMIP, but is also an expected result of economic process, where declining economic and population growth reduce demand and thus endogenous intensification processes.



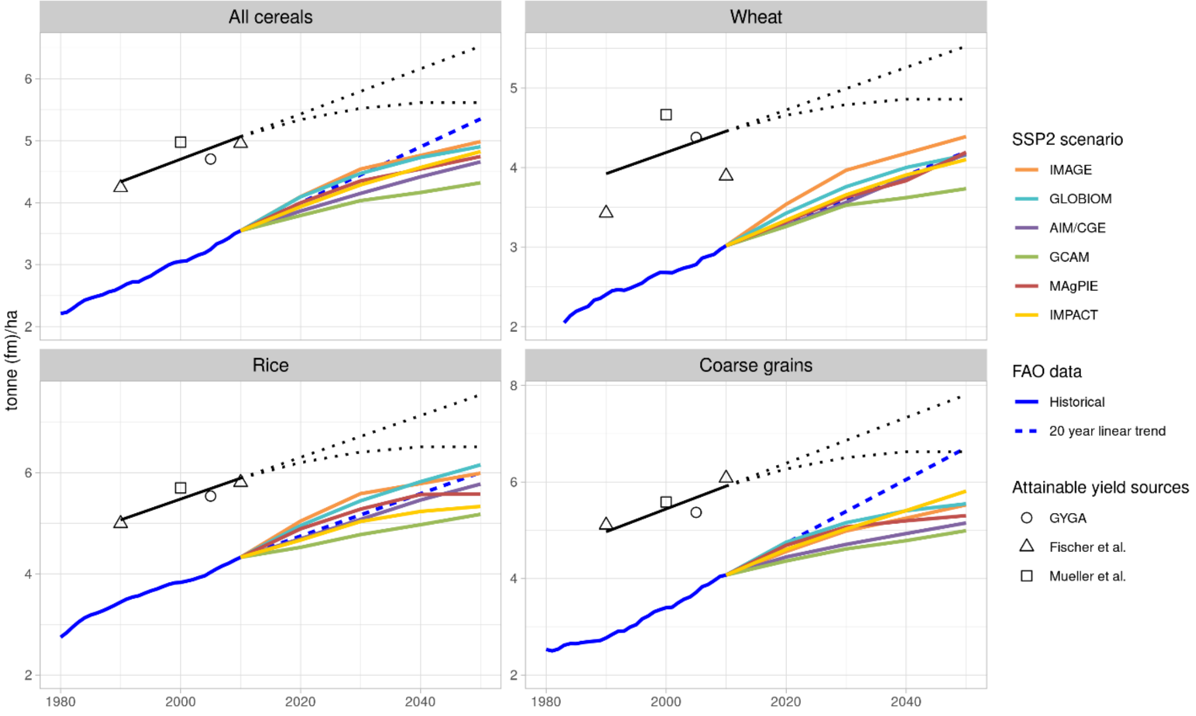


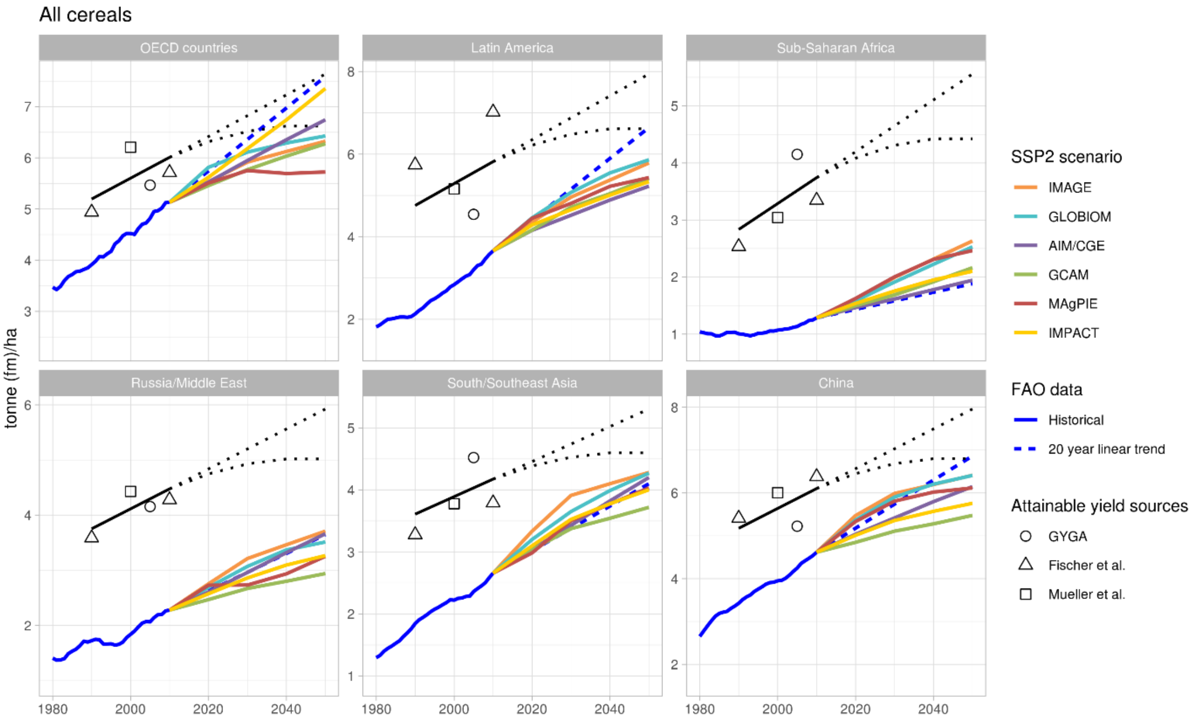
Figure 2 Global yields for SSP2 for various crops, compared to historical FAO trends and FAO-based projections, and attainable yields (three sources, average is black line) extended with a linear (upper dotted line) and plateau (lower dotted line) trend. All scenario and potential yield data were scaled so that the yields in 2010 match the 2010 FAO yields.

Comparing the model yield projections to the historical FAO trends shows that coarse grains is consistently projected with a smaller yield progress than the FAO linear trend. In contrast, we observe that for wheat and rice, the yield progress from GLOBIOM and IMAGE-MAGNET exceeds the linear trends of FAO in 2010 to 2030. However, the growth rate decreases again in 2030-2050 and the projected yields are closer to the linear extrapolation for 2050.

Figure 2 also shows the attainable yield data points (converted from the potential yield by a fixed factor, see methods). The three AY sources are in good agreement with each other on the global aggregate level. The largest range of AY data points is found for wheat, which is likely due to the definition of winter versus spring wheat, as it is not always clear which is used as a reference for potential yield (see also SI). The historical trends in the increase of potential yields were 0.7% per year for all cereals (relative to 2010, not compounded). Of the cereals, wheat shows the lowest rate of increase at 0.6% and coarse grains the highest at 0.8%. Observed actual cereal yields (FAO data) increased by slightly more than 1% per year, i.e. at a higher rate, which means that globally the yields have been slowly moving towards the attainable yields. In other words, the yield gap, i.e. the distance between actual yields and attainable yields, has been decreasing.

In comparing the model SSP2 projected yields with the attainable yields, we observe that in 2050 the scenario projections remain below the average attainable yields in both AY yield trends (linear and plateau) on a global aggregation level. The global yield gap in 2050 is largest for coarse grains, where a relatively low yield progress in the model projections is contrasted with a relatively high attainable yield growth. Furthermore, despite the faster than historical yield progress observed for some models for wheat and rice, model projections stay below the plateau AY trends in 2050.

Figure 3 shows the results for six regions for all cereals aggregated. While global data indicated that the cereal yield projections in 2050 are lower than the AY trends, zooming in on the regional data reveals regions where yield projections closely approach levels of attainable yields. Especially in the OECD countries, yield gaps are already relatively small in 2010 and for two models the cereal yields exceed the plateau AY trend in 2050. In China and South/Southeast Asia, in a number of instances for particular crops the plateau AY trend is surpassed by some models (see SI Figure 1). In the other regions, none of the models exceed the plateau AY trend in 2050. In sub-Saharan Africa, the biggest yield gaps are observed, and there is much potential for increasing yields towards 2050, even without considering the trend of the attainable yields. The same is true, to a somewhat lesser extent, of the high yield gaps in Russia/Middle East.



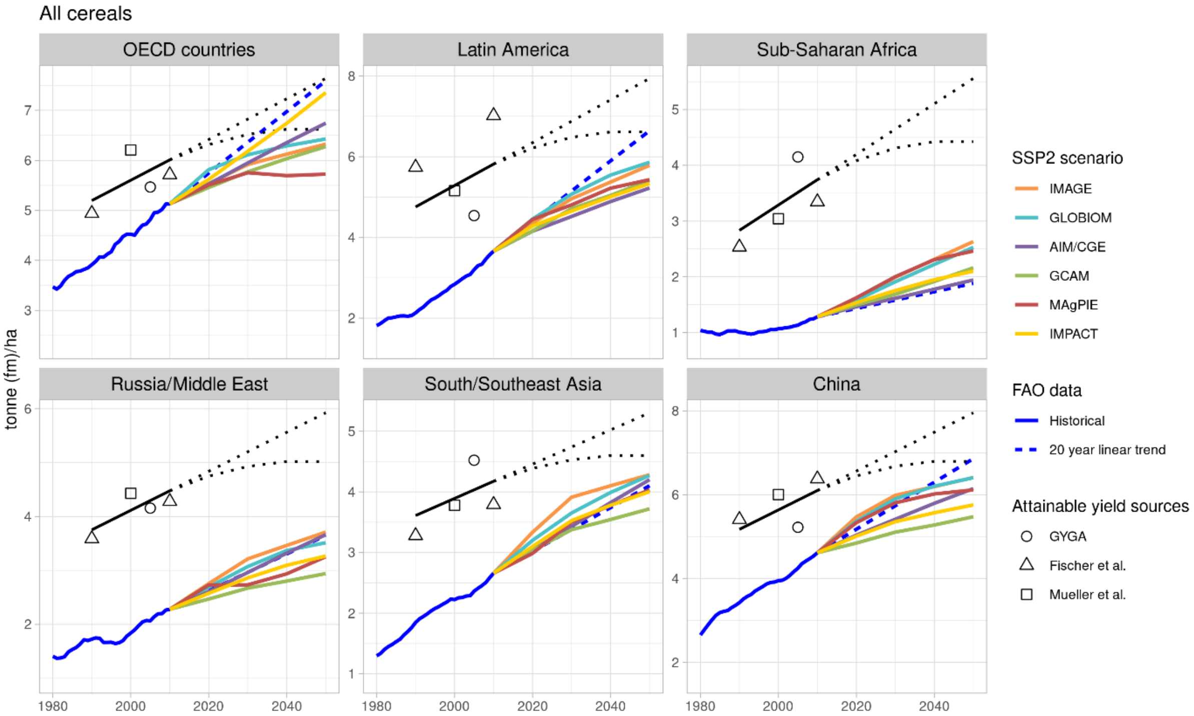


Figure 3 Regional yields for all cereals for SSP2, compared to historical FAO trends and FAO-based projections, and the attainable yields (three sources, average is black line) extended with a linear (upper dotted line) and plateau (lower dotted line) trend. All scenario and attainable yield data were scaled so that the yields in 2010 match the 2010 FAO yields.

We now expand the analysis to a larger set of scenarios (SSP1 through 5 and climate mitigation scenarios for SSP1 through 3), to cover a wider range of yield projections, including those with more optimistic assumptions about technological progress. The global average cereal yield across all models and scenarios increases from 2010 to 2050 by +36% on average (ranging from +25% for SSP3 to +45% for SSP5 and SSP1 with mitigation). To present this larger dataset (6 models, 8 scenarios, 6 regions, and 3 crop types) as concise as possible, in this section we compare only the yields projected in 2050 with the attainable yields in 2050. We can then count how often the projected yields surpass the linear or plateau AY trend. An overview of outcomes for all individual combinations is shown in the supporting figures. In summary, 141 (18%) of the 768 combinations possible in this set exceed the plateau AY trend in 2050. For the linear AY trend only 33 (4%) instances exceed this AY in 2050.

Figure 4 shows how often the projected yield exceed the plateau or linear AY in 2050 for all 8 scenarios, summarized over the 6 models. Additionally, the average level of exceeding the AY trends are shown as a colour gradient, whereas green indicates that all models stayed below the AY in 2050 for that particular combination. For all scenarios there are instances of projected yield exceeding the plateau AY trend. As is to be expected, the values are lower for the linear AY trend, where SSP4 is the only scenario staying below the AY linear trend in all cases. For both AY trends, wheat yield trends exceed the AY in slightly more cases than the other crops. Within the range of SSPs, SSP1 and SSP5 show the most instances of exceeding attainable yields in 2050, whereas SSP3 and SSP4 exceed the AY the least number of times. This is in line with the assumptions of high technological progress in the underlying storylines (high technological progress in SSP1 and SSP5, low progress in SSP3). Furthermore, yields in mitigation scenarios are higher than in the scenarios without mitigation. The effect of mitigation measures on yields is most apparent in the projections for rice. For rice in the SSP1 scenarios, the average level of exceeding the AY is higher than any other crop.

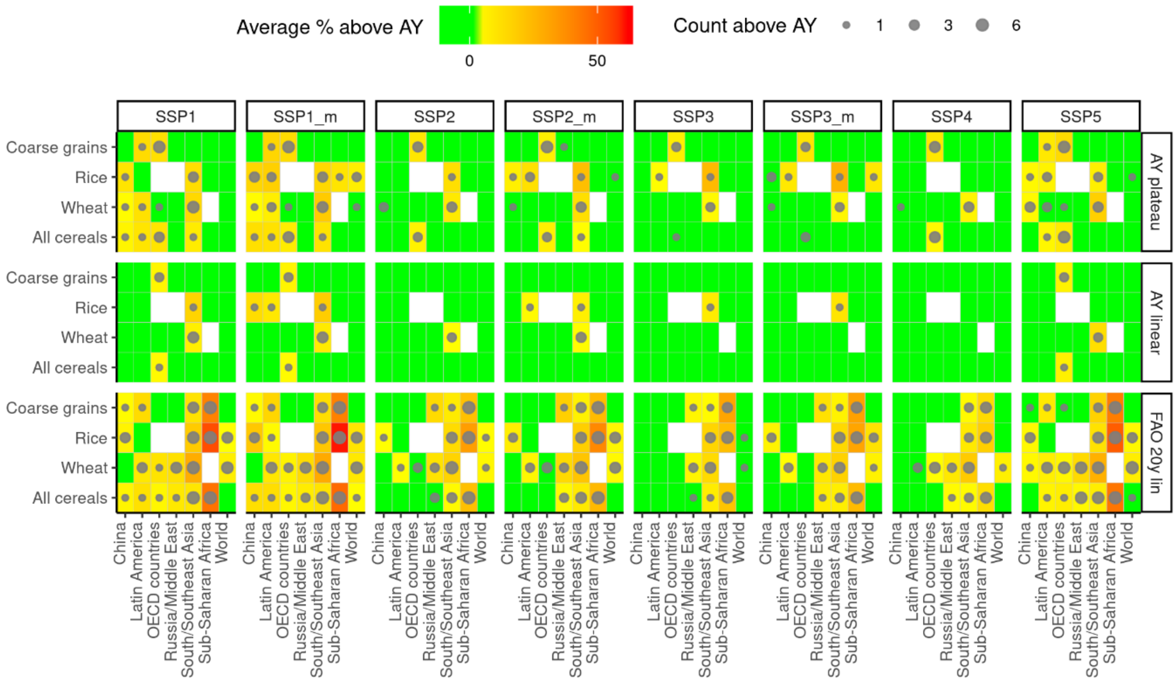


Figure 4 Number of modelled yield projections in 2050 (from a total of 6 models) that surpass the FAO linear trend (bottom), AY linear trend (middle) and AY plateau trend (top), by scenario, crop and regions. The colour scheme indicates the average difference of projected yields with the AY, for the instances where the yields exceeds the AY in 2050.

Figure 5 shows how often the individual models, for all scenarios and regions, exceed the AY trends. In comparing the models overall, MAgPIE most often exceeds the plateau AY trend, and AIM/CGE the least. The amount of times the linear AY trend is exceeded is relatively limited, yet still two models exceed the linear AY trend for the aggregated regions in the SSP1 scenarios in some regions (IMPACT due to coarse grains in OECD countries and MAgPIE due to rice in South/South-East Asia). The highest relative yields, i.e. the projected compared to AY trends are observed for rice in South/Southeast Asia. When comparing the projected yields to the linear FAO trend, there are many instances where models exceed this trend. This is not unexpected as, especially for the ‘business as usual’ SSP2, the scenario can be expected to reflect recent trends. However, the yields in sub-Saharan Africa are significantly higher than the FAO linear trend, and this effect is most pronounced in MAgPIE and least in AIM/CGE.

On the regional level, yields of coarse grains (which includes Sorghum & Millet) in sub-Saharan Africa never exceed the plateau AY trend as the yield gaps there are very high. Also, for the Russia/Middle East region, the yield projections stay below the plateau AY trend in almost all cases. Hotspots can be identified mainly for Coarse grains in OECD countries, where yield gaps are generally low, and rice in China & South/Southeast Asia. Except for MAgPIE, coarse grains in OECD countries exceeds the plateau AY in all models in at least one of the scenarios (either SSP1, SSP5 or more). Wheat in China (and to a lesser extent in South/Southeast Asia) is characterized by a particularly low yield gap, while some models (particularly IMAGE-MAGNET & GLOBIOM) project very strong increases in yield for these regions. Rice yields exceed the both linear and plateau AY trends mainly in China in the case of AIM/CGE and South/Southeast Asia in MAgPIE, and both Latin America and China for GLOBIOM.

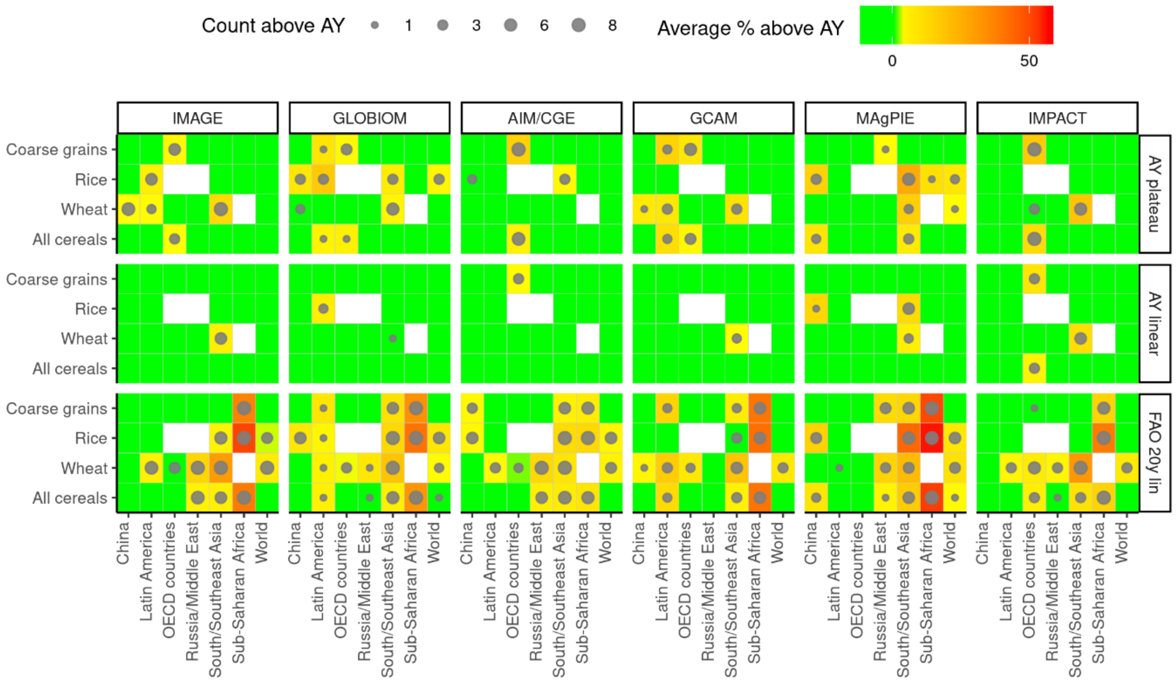


Figure 5 Number of modelled yield projections in 2050 (from a total of 8 scenarios) that surpass the FAO linear trend (bottom), AY linear trend (middle) and AY plateau trend (top), by model, crop and regions. The colour scheme indicates the average difference of projected yields with the AY, for the instances where the yields exceeds the AY in 2050.

4 Discussion and Conclusions

In this study, we compared cereal yield projections of SSP scenario results from six agricultural land-use and integrated assessment models with empirical data on attainable yields. Based on this comparison**,** we observe that the projected global averages of cereal yields in 2050 do not exceed projected attainable yields. Models show yield growth rates gradually decreasing in many regions (except for sub-Saharan Africa), most notably in OECD countries, which is consistent with literature describing limited yield growths in developed regions. In sub-Saharan Africa, on the contrary, yield gaps are large, and models project continuously high growth rates and remain below attainable yield levels. For individual crops and regions, the scenario yield projections more often overestimate future potentials. This is true for the three crop categories and six regions presented here, and likely true for even finer resolutions. There are, however, severe challenges to yield gap closure, as shown by slow progress in recent FAO trends of observed yields. Overall, despite the large differences between the model's structures, the results seem rather robust across models and mostly stay below the AY trends.

The models included in this study vary widely in their implementation of yield progress and how they differ between scenarios. Some first improvements in representing yield trends were certainly made due to the earlier AgMIP activities (Nelson et al., 2014b; von Lampe et al., 2014), though the specific yield trends used for harmonization there are no longer used in the models. Most models distinguish between exogenous yield trends and endogenous improvements (e.g. management improvements), simply reflecting that some progress comes from outside the model (exogenous), and some yield change occurs due to model-endogenous dynamics (e.g. substitution between labour and land). While it may seem most logical to associate an increase in potential yields with the exogenous factor, and management progress as endogenous, the models differ in which elements of yield progress they cover endogenously (Table 2). However, some technological improvements (e.g. new fertilizers) are difficult to assign, and probably are exogenous to the models, but do not affect potential yields. This model-specific distinction between exogenous and endogenous processes can be observed in Sub-Saharan Africa, for example, where the fast increase in projected yields is also caused by a strong exogenous intensification, and agronomic processes e.g. in IMAGE-MAGNET seem to have a smaller contribution than could be expected from the large yield gaps. A recent analysis of drivers for global land-use projections, which stresses the role of agricultural productivity in future land use, also finds that the underlying driver of crop yield increase is mostly the exogenous agricultural productivity driver on the global scale (Stehfest et al., 2019). Therefore, we need to conclude that the "exogenous" intensification used as model input is – at least for most participating models – much larger and broader than the progress in yields due to novel technologies and breeding. It covers essentially all yield progress, region- and scenario-specific – that the model currently is not representing endogenously (Table 2). Given the differences in what models define as exogenous and what is included endogenously, harmonization of the exogenous yield trend across models should not even be aimed for, as also discussed below. In that context, MAgPIE is a very specific type of model, which handles all yield progress endogenously as technological improvement based on investments in Research and Development.

An important question is whether the models implement a form of a yield limit. While the levelling-off of yield growth in several models might suggest a limit to yields that is approached, none of the models actually has such a limit implemented. Establishing a reasonable yield limit, however, is no straightforward task, and theoretically much higher productivity levels than in the SSP projections are possible (Franck et al., 2011). To increase transparency and reliability of global-scale scenarios of future land use, the various components of yield progress need to be more closely scrutinized and their future developments should be explicitly addressed in the implementation of the productivity growth changes as described in scenario storylines.

Finally, it needs to be acknowledged that the data sources used to construct the attainable yield trends show substantial uncertainties and differences in methodologies, with varying definitions of potential yield or attainable yields. For the trend extrapolation for the attainable yield only a single data source was available (Fischer et al., 2014). The quality of the comparison would greatly improve if more such trends would become available in the future.

4.1 Limitations

In this analysis, we compiled model-based yield projections and best available data on current and future attainable and potential yields. With respect to methodology and data, some limitations remain. The comparisons presented in this paper have not explicitly addressed cropping intensities. Models have various ways of addressing cropping intensity, ranging from being explicitly kept constant, to price induced changes as part of the endogenous intensifications. Because of this, as well as due to limitations to how cropping intensity was reported on the crop level, an in-depth comparison including cropping intensities was not feasible in this study. However, 'cropping intensity gaps' (or 'harvest gaps'), similar to yield gaps exist where transition from single to multiple cropping systems is possible and can increase crop production substantially (Ray and Foley, 2013; Wu et al., 2018). Because crop yield is based on harvested area, cropping intensity does not influence harvested yield directly. The effect on total production, however, can be substantial, and the cropping intensity has increased historically through more multiple cropping or less fallow periods. Potential increases of crop production via the optimization of cropping intensity are estimated to be as high as 36% (Mauser et al., 2015), while in the FAO BAU scenario, cropping intensity for cereals is projected to increase by 8% between 2012 and 2050 (FAO, 2018).

Another source of intensification is an increase in irrigated areas, the impact of which is addressed in various ways by the models (Table 2). Yields from irrigated crops are substantially higher than those of rainfed crops, and historically much of the net increase in global arable land is related to an increase in the area equipped for irrigation (Alexandratos and Bruinsma, 2012). Additionally, yield gaps can differ between irrigated and rainfed systems, which could impact the analysis presented here if more detail were available. Irrigation is thus an important option for increasing crop production. The attainable yields used in this analysis were, just as the FAO yields, a combination of rainfed and irrigated yields, and their future trends as used in this study implicitly assume that the underlying composition remains constant, whereas the reported yields in the scenarios included changes in irrigation for all models. Expanding irrigated areas, however, would mean possible increase in average rain-fed and irrigated attainable yield faster than shown here. To better disentangle the processes in irrigated and rainfed production, separate reporting on all levels would be necessary. However, changes of irrigated area have not been addressed in detail in earlier model comparisons, and global projections are scarce. Not all the models report irrigated area, or not on the crop-level as needed for this analysis. Therefore, it was not possible to treat this explicitly in the current study.

There are vivid discussions about the intensification of agriculture and its side-effects. Impacts of intensification on climate and biodiversity strongly depend on how agricultural land is intensified in the future (Beckmann et al., 2019; Silva, 2017; Tilman et al., 2011). Increased production on the same amount of land will also bear risks of environmental pollution, with both nutrients and agro-chemicals. Some of the models are equipped to address some of the effects, by explicitly including e.g. nitrogen balances (Bodirsky et al., 2014; Seitzinger et al., 2010).

Structural changes in location and crop composition were not explicitly considered here, as they are part of the regionally aggregated projected yield by the models and in most models an endogenous result. Yield changes can originate from a combination of production mix and trade changes (Popp et al., 2017a), but also from gridded land-use allocation. Recent work (Mauser et al., 2015) estimate a significant increase of production of 30% can potentially be achieved via a spatial reallocation of crops to their profit-maximizing locations. However, these opportunities will usually be constrained by local economic conditions. While these structural changes are usually endogenous parts of the models covered here, not all models include this process. Furthermore, the selected crops analysed in this study may not be representative of other crops, and future analysis should be extended to other crop groups.

The effects of climate change were not considered in this study, following the experimental design of the SSP scenarios (Riahi et al., 2017). The SSP scenarios do not include climate change impacts, in order to provide a meaningful starting point for the impact analysis based on these scenarios (O'Neill et al., 2017; van Vuuren et al., 2017). Furthermore, the trends of attainable yields were based on an extrapolation of the 1990-2010 period, and thus excluded future change in potential yields due to climate change impacts as well. Nevertheless, it is crucial that further research must expand this analysis with climate change impacts, including the effects on crop productivity. While temperature and precipitation changes are considered in most crop models and are expected to impact yields negatively in many regions and crops (Nelson et al., 2014a; Ruane et al., 2018; Wiebe et al., 2015), increased CO_2 fertilisation effects are expected to bring yield benefits, which for a number of regions bring uncertainty on the direction of the net effects. n (IPCC, 2013). Furthermore, many parameters that affect yield are not explicitly addressed in many gridded crop models, examples being land degradation (historic and future) and pest control.

To evaluate model projections of yields, we tried to compile information on potential and attainable yields from both empirical and modelling approaches. Gridded crop models (GGCMs) in principle can contribute valuable information for estimating current potential yields, but their strength lies in evaluating the impact of environmental conditions, rather than producing realistic future potential yields related to breeding. The current range and uncertainty in model results and their deviation from reported yields (Müller et al., 2018) did not allow to include these in the comparison.

4.2 Improvement options for models

This study concludes that scenario yield projections do not overestimate future potentials on a global scale. Still, many underlying mechanisms behind technology-induced progress and other factors (e.g. increased fertilizer inputs, labour productivity) that influence yields should be made more transparent to allow for better comparison between models, and – more importantly – between models and knowledge from other scientific disciplines. Thus, first steps for improvements would be to transparently include more drivers with a more direct link to storylines and assumptions as well as improving the interaction between agro-economic and biophysical components in global land models.

An implication of the results presented here is that the models' projections should more explicitly explore the heterogeneity of yield developments between regions and crop types. In implementing a more detailed split-up of the components of yield progress, focus should lie on improving descriptions of genetic improvements in yield varieties in developed regions, while in developing regions, the use of inputs (e.g. fertilizer) and more efficient management should be explicitly linked to yield levels. There is a wide range of interpretations and implementations of what constitutes the exogenous yield trends and a closer coordination between models could be beneficial. Due to the structural differences between the models, the exogenous trends as such will necessarily differ across models, and a complete harmonization of yield trends is neither practical nor desired for all aspects, so that differences in model behaviour are useful and can still be further explored (Popp et al., 2017b). However, a calibration of a suite of model inputs to arrive at a comparable long-term overall yield progress is conceivable. Additionally, harmonized climate change impacts have also been used as exogenous impacts on crop yields (Meijl et al., 2018), and the impact of both climate change and CO_2 fertilization on crop yields should be part of such an exercise.

Finally, yield gap analyses, which were used in this study, are an important source of information on the potential to increase yields through crop management. As increasingly more information, covering more crops and regions, is becoming available (e.g. (GYGA, 2018), this should be used to explicitly represent current potential (or attainable) yield levels in land-use models. However, yield gap analysis reflects the current situation (Mueller et al., 2012; Neumann et al., 2010; van Ittersum et al., 2013) and needs to be complemented by estimates on future yield potentials. Representing the entities and processes know from the plant sciences and agronomy (potential and attainable yield, progress in potential yields, and yield gap closure through improved management) explicitly in agricultural land-models will improve yield projections, allow to scrutinize them, and create more credibility and transparency in this central element in food and agricultural scenarios.

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