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Land-use change trajectories up to 2050: insights from a global agro-economic model comparison

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Abstract

Changes in agricultural land use have important implications for environmental services. Previous studies of agricultural land-use futures have been published indicating large uncertainty due to different model assumptions and methodologies. In this article we present a first comprehensive comparison of global agro-economic models that have harmonized drivers of population, GDP, and biophysical yields. The comparison allows us to ask two research questions: (1) How much cropland will be used under different socioeconomic and climate change scenarios? (2) How can differences in model results be explained? The comparison includes four partial and six general equilibrium models that differ in how they model land supply and amount of potentially available land. We analyze results of two different socioeconomic scenarios and three climate scenarios (one with constant climate). Most models (7 out of 10) project an increase of cropland of 10–25% by 2050 compared to 2005 (under constant climate), but one model projects a decrease. Pasture land expands in some models, which increase the treat on natural vegetation further. Across all models most of the cropland expansion takes place in South America and sub-Saharan Africa. In general, the strongest differences in model results are related to differences in the costs of land expansion, the endogenous productivity responses, and the assumptions about potential cropland.

JEL classifications: C61, C68, Q11, Q54

Keywords: Land-use change; Model intercomparison; Land-use models; Land expansion

1. Introduction

Land use and surface cover is determined to a large extent by human intervention, primarily through conversion for crop cultivation (Vitousek et al., 1997). Cropland expansion was the main source of growth of agricultural production throughout pre-industrial history. However, since the middle of the

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

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20th century, intensification with land-saving technologies has been the main engine of growth globally (van Meijl and van Tongeren, 1999; Wik et al., 2008). Between 1955 and 2005, arable land increased by around 15% (HYDE; Klein Goldewijk et al., 2011) whereas agricultural production rose by more than 200% (FAO, 2013). In the future, it is unclear how total cropland will respond to the anticipated increase in demand for agricultural products. The question has implications not only for food security, but also for biodiversity, terrestrial carbon stocks, and other ecosystem services (Gorenflo and Brandon, 2005; Houghton, 2003).

Land use was traditionally not a focal area for research in global economic modeling. In the last couple of decades, however, it has evolved as a new research field. New spatially explicit models of land use have been developed, with a focus on the agricultural and forestry sectors as the main users of land, and modeling teams have explicitly introduced global land use into existing computable general equilibrium (CGE) and partial equilibrium (PE) models. These efforts are still in their infancy with large uncertainty about future land use. Models used in the IPCC fourth assessment report (AR4) project cropland changes from −18 to +69% by 2050 relative to 2000 (−123 to +1158 million hectares [ha]) and forest land changes range from −18 to +3% (−680 to +94 million ha) by 2050 (Metz et al., 2007). Much of this huge range among models is related to the uncertainties in economic and demographic development. FAO projects an increase of cropland between 2005 and 2050 of 69 million ha (Alexandratos and Bruinsma, 2012) and the International Assessment of Agricultural Knowledge, Science and Technology for Development (IAASTD) around 180 million ha (van Vuuren et al., 2009). Within the U.K. Foresight Project, Smith et al. (2010) provided a review of studies on land-use projections of the past two decades, indicating a range between 90 and 470 million ha. They concluded that uncertainty about future land use is large and mainly associated with the use of different input data and assumptions about future economic and demographic development. Popp et al. (2013) show that the land-use modules of three Integrated Assessment Models project very different global land cover conversion futures due to strong differences in their assumptions and definitions of land cover distribution in 2005 and structural features of the models.

In this article, we go a step further by harmonizing key input data and assumptions across different models. Up to now, this has only been done on a small scale with a few models (e.g., Stehfest et al., 2013). For our purpose, we used the first comprehensive model intercomparison in the field of agro-economic models organized within the AgMIP consortium.[1] It includes four partial and six general equilibrium models, all of which differ in the amount of potential land and in the way how they model land supply. In this article we use the model scenarios to answer two research questions. One, how much cropland will be used in 2050 under different socioeconomic and climate change scenarios? And two, how do methods to model land supply and land expansion differ across models and how do methods differences explain differences in results?

[1] AgMIP: Agricultural Model Inter-comparison Project (www.agmip.org).

2. Models and scenarios

2.1. Model approaches and differences

The comparison includes four partial (PE) and six general equilibrium models (GE). Two PE models, MAgPIE (Lotze-Campen et al., 2008; Popp et al., 2010; Schmitz et al., 2012) and GLOBIOM (Havlik et al., 2011, 2013) incorporate spatially explicit land use as part of the model solution. The other two PE models, GCAM (Thompson et al., 2011; Wise and Calvin, 2011) and IMPACT (Rosegrant et al., 2012), link to grid-based models. The six CGE models are all based on the GTAP database. The AIM (Fujimori et al., 2012), FARM (Sands et al., 2013, 2014), and GTEM (Pant, 2007) models determine land use based on agro-ecological zones (AEZs; FAO, 1996). ENVISAGE (van der Mensbrugghe, 2013) and MAGNET (van Meijl et al., 2006) model land use at the national level with inputs from the grid-specific IMAGE model (Bouwman et al., 2006). EPPA (Melillo et al., 2009) is coupled with TEM (Felzer et al., 2004) to model future land use. The models differ substantially in how they model land supply and the amount of potential land. Table 1 gives an overview of key parameters for the modeling of land use and especially cropland expansion and how they are implemented in the different models. Table 2 provides information on the land types and how they are implemented. More details on the models can be found in the Data Appendix and in von Lampe et al. (2014).

Although the models are classified into two broad types (general or PE), there is still considerable heterogeneity within the two groups (more so within PE than within GE models). In the following, those differences are presented along with several key features (see also Hertel et al., 2009). Those include:

- Spatial dimension and data sources
- Mobility of land across uses
- Accessing new lands
- Forest and bioenergy sector
- Technological change

2.1.1. Spatial dimension and data sources

The spatial dimension is crucial in agro-economic modeling of land use. Several global land data bases have become available recently. For instance, Klein Goldewijk et al. (2011) provide data on historical land use with a 5 arc minute resolution, Ramankutty et al. (2008) do so for the year 2000. Monfreda et al. (2008) provide harvested area and yields. The SPAM (Spatial Production Allocation Model) data set uses an entropy approach to allocate national and regional production statistics over higher resolution space based on various suitability measures (You and Wood, 2006). The PE models

Table 1
Key parameters for modeling land use

Model	Model type	Land-use types†	Spatial dimension (number of units)	Data: Land use	Data: Potential cropland expansion	Method: Crop allocation	Method: Cropland expansion	Bioenergy assumptions
AIM	CGE	6	AEZ	GTAP, FAO, IMAGE	GTAP AEZ	nested logit	Within nested logit	1st + 2nd generation
ENVISAGE	CGE	2	National (114)	GTAP	FAO	CET function	Land supply curve††	No
EPPA	CGE	5	National (114)	GTAP / TEM§	TEM	–	Conversion costs	1st generation
FARM	CGE	3	AEZ	GTAP	GTAP AEZ	landrent/ market clearing	competition with pasture + forest	No
GCAM	PE	8	AEZ	GTAP, FAO, HYDE	GTAP AEZ	nested logit	Within nested logit	1st + 2nd generation
GLOBIOM	PE	7	SimU‡ (200,000)	GLC2000, FAO, SPAM	EPIC	Land rent /profitability	Conversion costs + land rent	1st + 2nd generation
GTEM	CGE	2	National (114)	GTAP	Based on historic expansion	CET function	Within CET	No
IMPACT	PE	2	FPU's¶(251)	FAO, SPAM	Expert opinion‡‡	Price elast.	Exogenously given	1st generation
MAGNET	CGE	3	National (114)	GTAP, FAO, IMAGE	IMAGE	CET function	Land supply curve††	1st generation
MAgPIE	PE	3 (5)	0.5°-grid (59,199)	Own data base	Own data base	Land rent	Conversion costs	1st generation

Notes: †Only land types that are able to change over time (please see also Table 2).
‡Clusters of 5 arc minute pixels belonging to the same slope, soil, and altitude class, to the same country, and to the same 30 arc minute pixel.
§Terrestrial Ecosystem Model (Felzer et al., 2004).
¶FPU (food production unit) is a river basin with the political boundary of a region.
††Total agricultural land (crop and pasture land).
‡‡Through Delphi methods.

Table 2
Land types represented in the different models (dynamic means that the land can change over time, static means the amount of land stays constant and "-" means that the land category is not existent in the model)

Model	Cropland	Pasture	Managed forest	Un-managed forest	Other natural vegetation	Urban
AIM	dynamic	dynamic	dynamic	dynamic	dynamic	–
ENVISAGE	dynamic	dynamic	–	–	–	–
EPPA	dynamic	dynamic	dynamic	dynamic	dynamic	–
FARM	dynamic	dynamic	dynamic	static	–	–
GCAM	dynamic	dynamic	dynamic	dynamic	dynamic	static
GLOBIOM†	dynamic	dynamic	dynamic	dynamic	dynamic	static
GTEM	dynamic	dynamic	–	–	–	–
IMPACT¶	dynamic	–	–	–	–	–
MAGNET	dynamic	dynamic	static‡	static‡	static‡	static‡
MAgPIE	dynamic	static§	static§	dynamic	dynamic	static

Notes: †Short rotation plantations as a separate land category.
‡These land-use types can be defined within or outside the land supply curve dependent on whether they can be transformed into agricultural land. Shifts are determined within IMAGE model.
§These dynamic land types in MAgPIE have been under revision for the time of the comparison and, therefore, have been put to static for this exercise.
¶IMPACT differentiate between agricultural and nonagricultural land.

GLOBIOM and MAgPIE, are constructed as grid-specific optimization models and can make use of those disaggregated data. The data for MAgPIE are taken from a consistent land-use database developed by Krause et al. (2009), which is based on Erb et al. (2007) and integrates crop suitability indicators (van Velthuizen et al., 2007), intact and frontier forest types (Bryant et al., 1997; Potapov et al., 2008), and protected areas (UNEP-WCMC, 2006). The GLOBIOM spatial modeling is based on the concept of Homogeneous Response Units (HRU) delineated by geographically clustering 5 arc minute pixels according to only those parameters of the landscape—elevation, slope, and soil—that generally do not change over time and are thus invariant with respect to land use and management or climate change. At the global scale, GLOBIOM includes five altitude classes, seven slope classes, and five soil classes. In a second step, the HRU layer is intersected with a $0.5^\circ \times 0.5^\circ$ grid and country boundaries to delineate simulation units (SimU; Skalský et al., 2008). For each SimU a number of cropland management options are simulated using the biophysical process model EPIC (Environmental Policy Integrated Climate Model; Izaurralde et al., 2006). Initial land cover and land-use distribution is based mainly on GLC2000 and harmonized when necessary to match with FAO and the crop distribution map of SPAM (You and Wood, 2006).

In contrast, other PE models and the CGE models adopt a more aggregate level of resolution, which is more in line with the spatial resolution of economic statistics. IMPACT runs on 271 food production units (FPUs), but its climate-induced shock originating from crop models are based on the 5 arc minute resolution of the SPAM data. MAGNET, GTEM, and ENVISAGE operate on a regional crop allocation; EPPA does so as well but runs in connection with the Terrestrial Ecosystem Model—TEM (Felzer et al., 2004), which distributes EPPA's land-use predictions by 0.5° grid cell level based on climate, soil, and economic information. FARM, GCAM, and AIM use the GTAP AEZ data, and land use is aggregated to the level of AEZs within countries (Monfreda et al., 2009). As most economic data are also available at the country level, FARM and AIM assume a single, national production function in which land types from different AEZs substitute for one another. In GCAM, each AEZ within a region has its own land allocation tree.

2.1.2. Mobility of land across uses and diversification of production

Some of the CGE models (ENVISAGE, FARM, GTEM, and MAGNET) assume land heterogeneity and employ a constant elasticity of transformation (CET) function by which an aggregate endowment of land is transformed across alternate uses, subject to a transformation parameter that governs the responsiveness of land supply to changes in relative yields and prices. Other models like AIM and GCAM use logit functions rather than constant elasticities to model the competition between different land types. Exponents of these functions, which determine the degree of substitutability, are usually derived from literature-based estimates of elasticities, or assumed, and in the base year they are used for calibration. In the AIM model, these substitution elasticities vary over time; they are constant over time in GCAM (Wise and Calvin, 2011). Both the CET and logit approaches have one important limitation; they are symmetric to all changes. For example, the ease of conversion from agricultural land to forest land is the same as from forest to agriculture (see Hertel et al., 2009 for a more detailed discussion).

CGE models typically "nest" the land allocation functions (EPPA is an exception to this and is explained later). Producers first determine the allocation of crop land among crops. Then based on the average return to cropland, an allocation is made between crops and livestock or crops and forestland. All models use a different nesting structure and there is little evidence that favors one structure over another. An example for a basic nested logit structure of land used is presented for the AIM model in the Data Appendix (Fig. S1). In the first step agricultural, forest and other land types are differentiated. The agricultural land is then further divided between cropland and grassland. Grassland is then divided among primary grassland and pasture actively used for livestock production. Under the cropland node land is allocated to different crops. The individual design within each model is usually more detailed and differs from this example, but the basic structure is similar across the CGE models and GCAM. Identifying transformation elasticities remains a challenge in CGE modeling as good conclusive empirical evidence does not exist. They are based on econometric studies and expert knowledge. In MAGNET, for instance, transformation elasticities are based on the more detailed OECD's Policy Evaluation Model (PEM) structure (Huang et al., 2004; OECD, 2003)

The IMPACT model specifies harvested area for each crop based on given own- and cross-price elasticities of supply. The problem with this and the CET approach is that the "transformation" of land from one use to another does not make it possible to track the allocation of hectares across agricultural activities. This can be done with the spatially explicit land rent methodology of GLOBIOM and MAgPIE. Here, the allocation of land to the different crops is based on the relative profitability of the crops, based on grid-specific biophysical characteristics. The location of the crop area across calculation units can be clearly determined. MAgPIE differs slightly from GLOBIOM and GCAM, minimizing production costs instead of maximizing profitability.

EPPA assumes that farmers can transform one land category to other if they are able to cover explicitly the costs of conversion. This approach allows tracking land area in a consistent way and implies that intensively managed land can be "produced" from less intensively or unmanaged land, as well as that farmland can be abandoned. Compared with the CET, this land transformation approach allows for longer term analysis where demand for some uses could expand substantially (as the case of biofuels in some countries), since the share-preserving nature of the CET functions limits radical land-use change.

2.1.3. Accessing new lands

A critical issue in modeling the long-run supply of land to different activities in agriculture and forestry is the availability of new lands that might be brought into production. The simplest way to handle this problem is to construct a land supply schedule in which rising land rents cause additional land to be brought under cultivation. This is the approach adopted by van Meijl et al. (2006) and Eickhout et al. (2009) in their specification of the MAGNET model, which is also used in the ENVISAGE model (for more details on this, see Hertel et al., 2009). The disadvantage is the missing spatial component to the supply decision. These models exaggerate the competition for land between very different uses—for example, orange groves and sugar beet fields in the United States, which are clearly in different biophysical zones. An improved approach is the inclusion of AEZs. This is done by AIM and GCAM, which use the 18 different AEZs specified in the GTAP database (Golub and Hertel, 2012; Monfreda et al., 2009). FARM does the same but aggregates the 18 AEZs into six land classes of each world region. The expansion of crop or other agricultural activities into forest and other land types is done within the CET or logit structure (see the AIM model example in Fig. S1). The conversion of natural vegetation in EPPA is limited by the observed land supply response in the last two decades. It mimics the increasing costs associated with larger deforestation in a single period. It also represents additional institutional costs, like environmental legislation and consumer pressures for conservation, contributing to slow down intense transformation of natural ecosystems.

The PE models GLOBIOM and MAgPIE simulate the expansion of cropland into other land types at a high spatial resolution. GLOBIOM uses nonlinear conversion costs in each region to convert nonagricultural land to agricultural land or to short rotation plantations, as well as to switch between cropland and grassland. The conversion costs are exogenously determined and used for calibration. MAgPIE uses a similar approach. The conversion costs of nonagricultural land into cropland are for preparation of new land and investments into basic infrastructure. The values are determined by different case studies and range between 600 and 7500 US$/ha depending on topography, forest type, soil conditions, applied technology, and the governmental system (Schmitz, 2012). In the version of MAgPIE used in this study, it is only possible to expand cropland into intact and frontier forest and natural vegetation not defined as grazing land or forest (globally around 734 million ha). Pasture and other land categories are kept constant over time. In GCAM, land allocation between different land types is modeled at the level of each AEZ within each geopolitical region, and is responsive to changes in land profit rates. While the specific characteristics of any technology (e.g., yield, cost) within any subregional AEZ are exogenous, endogenous yield increases may nevertheless occur at larger spatial scales due to inter-regional shifting in production. In contrast to all other models, IMPACT focuses only on cropland changes. It bases its expansion potential on exogenous area growth rates, which have been determined by a combination of historical changes in land use and expert judgment on potential future regional dynamics (Delphi method).[2] It also includes the possibility of agricultural area lost through processes not modeled, such as conversion to other land uses via government fiat or expansion of urban area.

2.1.4. Incorporation of forestry and bioenergy

Most models assume that forest area trends are driven almost exclusively by changes in agricultural area, and only deal superficially with driving forces such as global production, consumption, and trade in forest products and conservation demands. A key problem is that it takes decades to grow a new forest and that the forest stock, as well as sequestration potential, depends critically on the type of forest and its vintage. The PE models, GLOBIOM and MAgPIE, have or are about to incorporate explicit forest modules to capture the effects. The AIM, FARM, and GCAM models treat forestry within the CET or logit structure. In ENVISAGE and MAGNET forest land is not modeled explicitly but it is part of the potential agricultural land within the land supply curve. In EPPA, natural vegetation is incorporated explicitly as part of their "nonuse" value in the utility function. More details on the challenges of incorporating the forest sector in CGE models can be found in Sohngen et al. (2009)

The forestry sector is of particular importance in the study in the context of second generation bioenergy as an additional demand of land in the future. Second generation bioenergy feedstocks typically include crop and forest products grown in short-rotation plantations, and also residues from crop production or forestry. In this exercise, GLOBIOM, GCAM, and AIM account for second generation bioenergy and account for an additional threat on cropland.[3] Additionally, all models (except ENVISAGE, FARM, and GTEM) treat various first generation biofuels such as ethanol and biodiesel, which are made from sugar, wheat, coarse grains, and oilseeds, the demand figures differ quite substantially between models. The future demand of this category in all models in this study is based on policy mandates. For simplicity they are kept constant after 2030.

2.1.5. Production technology and technological change

Technological change (TC) is a critical driver of land use, and a critical assumption in the projection of land use. For example, Sands and Leimbach (2003) suggest that globally 800 million ha of cropland expansion could be avoided with a 1.0% annual growth in crop yields. Popp et al. (2011) show that protecting natural forests does not decrease biomass availability for energy production, if the reduction in available agricultural land is compensated by higher rates of TC. The Millennium Ecosystem Assessment (MEA, 2005) scenarios project positive but declining crop productivity growth over time due primarily to diminishing marginal technical productivity gains and environmental degradation. For this study, most models have harmonized their exogenous TC rates to the assumed rates from the IMPACT model. The only exception is MAgPIE as the only model, which generates endogenous TC rates (Dietrich et al., 2012, 2014). However, in addition to the exogenous given TC rates, the models have individual endogenous adjustments related to an improved allocation of crops or substituting capital and labor for land (see more details on the different implementations in Robinson et al., 2014).

Robinson et al. (2014) describe the specifications of the various production technologies used in the various models. They conclude that the elasticity of substitution between land and other production factors is crucial with regard to land use. The greater the substitutability, the easier it is to replace land by labor and capital if land prices increase as land gets scarcer.

[2] There is no constraint on land availability in IMPACT. The area equations have been calibrated with low price elasticities of land supply. We did not observe any dramatic changes in land expansion at the FPU level that occurred and did not find any unrealistic cases where land used exceeded available arable land at the FPU level. In fact, the endogenous changes in aggregated land use were dominated by the exogenous trends in supply (by FPU and land type) rather than any endogenous effects.

[3] The land for second generation bioenergy is not reported under cropland in contrast to first generation bioenergy, which usually comes from cropped feedstocks.

Table 3
Scenario overview

Scenario	Socioeconomic pathway	Climate change
Reference (S1)	SSP2	Constant climate
Fragmentation (S2)	SSP3	Constant climate
CC-LPJmL (S4)	SSP2	HadGEM 8.5 with LPJmL
CC-DSSAT (S6)	SSP2	HadGEM 8.5 with DSSAT

In this way the same production can be produced with less land inducing an endogenous yield effect. A concern is that in theory crops could be produced without an adequate amount of land, as the substitution between the various inputs (land, capital, and labor) is not bounded by physical constraints. In practice AIM assumes low substitutability between land and other factors and most yield changes are from the exogenous yield assumptions. In MAGNET, the elasticity of substitution is also low (0.05 for crops and 0.1 for livestock, based on Salhofer, 2000). ENVISAGE and GTEM assume a much higher elasticity of substitution between land and other factors of 0.5, while this elasticity in FARM is 0.3.

2.2. Scenario description

For this article, we selected four out of eight scenarios, which have been run for the AgMIP model comparison. The detailed description of the scenarios is provided in von Lampe et al. (2014). Table 3 gives an overview about the four scenarios.

We differentiate between two influencing factors—socioeconomic developments and climate change affecting agricultural yields. The socioeconomic scenarios consist of population and income projections from the shared socioeconomic pathways (SSP) scenarios—SSP2 and SSP3—developed for the IPCC 5th Assessment Report (Kriegler et al., 2012). Climate change is considered by using the HadGEM2-ES global circulation model using the representative greenhouse concentration pathway (RCP) with the highest radiative forcing among the four RCPs, of 8.5 W/m^2 (Meinshausen et al., 2011). The reference scenario (S1) assumes no climate change and a medium pathway of economic growth and population development (SSP2). The S2 scenario (“Fragmentation Scenario”), based on SSP3 generally assumes lower population growth in developed countries, but higher growth in developing countries. While growth in total GDP is assumed lower for all parts of the world, per capita GDP is higher in some countries, such as Canada. S4 and S6 use the SSP2 population and GDP growth rates and include the impacts of climate change on crop yields. They differ according to the crop model used to project the yield changes. We use the vegetation and hydrology model LPJmL (Bondeau et al., 2007) and the crop growth model DSSAT (Jones et al., 2003).[4] The productivity shocks are implemented as land-embodied technical change. In all scenarios trade and forest protection policies remain the same. However, as Table 1 shows, the models differ according to the implemented bioenergy demand.

The main intention of the scenarios presented here is to shed light on the behavior of the different models regarding land-use change and to support the learning process of this comparison exercise. Hence, the chosen scenarios are rather extreme than plausible. On the one hand, S1 and S2 are optimistic in terms of climate change, since perfect mitigation is assumed with no climate shocks on crop yields. S4 and S6 represent pessimistic scenarios with the climate change effect on yield based on a high growth rate in GHG concentrations and no additional CO_2 fertilization effects (see Müller and Robertson (2014) for a discussion).

3. Projected development of cropland

Figure 1 shows the development of global and regional cropland area in the different models compared to historic development based on the HYDE data set (Klein Goldewijk et al., 2011). The projected growth rates of cropped area of the different models are used with the HYDE data of the year 2005.[5] The boxplots indicate the cropland expansion in the year 2050 compared to 2005 (HYDE data) in the four different scenarios. This is done in order to account for the different land-use modeling in the two model types. The key results are summarized in Table 4.

In Fig. 1, showing the development of global cropland area, most models indicate that the growth in global cropland continues in all scenarios. FARM is the exception with decreasing cropland use at the global level. For GTEM, IMPACT, EPPA, GLOBIOM, and GCAM the rate of change is less than in the past 50 years as reported by HYDE.[6] MAgPIE and ENVISAGE indicate a continued trend of the historic growth while AIM and MAGNET project a slightly increasing trend in global land use. Compared to S1, the fragmentation scenario (S2) has lower global cropland area growth rates in most models. Strongest decreases can be observed for AIM, GTEM, and MAGNET, whereas FARM has higher cropland reduction rates than in S1. For the climate change scenarios (S4 and S6), all models have increasing cropland compared to S1; however, the differences between the models are large. AIM, GCAM, and MAGNET expect a relatively large increase in area. Other models indicate no huge cropland changes due to climate change.

[4] For a detailed presentation and discussion on the results of the crop model runs, please see Müller and Robertson (2014).

[5] All models have different base-year quantities of cropland due to different definitions and crops covered in the models. We use the HYDE database to harmonize the base-year values and make the model results comparable, thereby assuming that the growth rates are independent of the base-year values. Since HYDE reports physical area while IMPACT and GLOBIOM report harvested area, the results of these models are slightly overestimated in Figs. 1 and 2.

[6] Due to the large uncertainty about the historic expansion of cropland among the various sources, the projected range of possible future developments of cropland is very much in line with the uncertainty range of the estimation of historical rates.

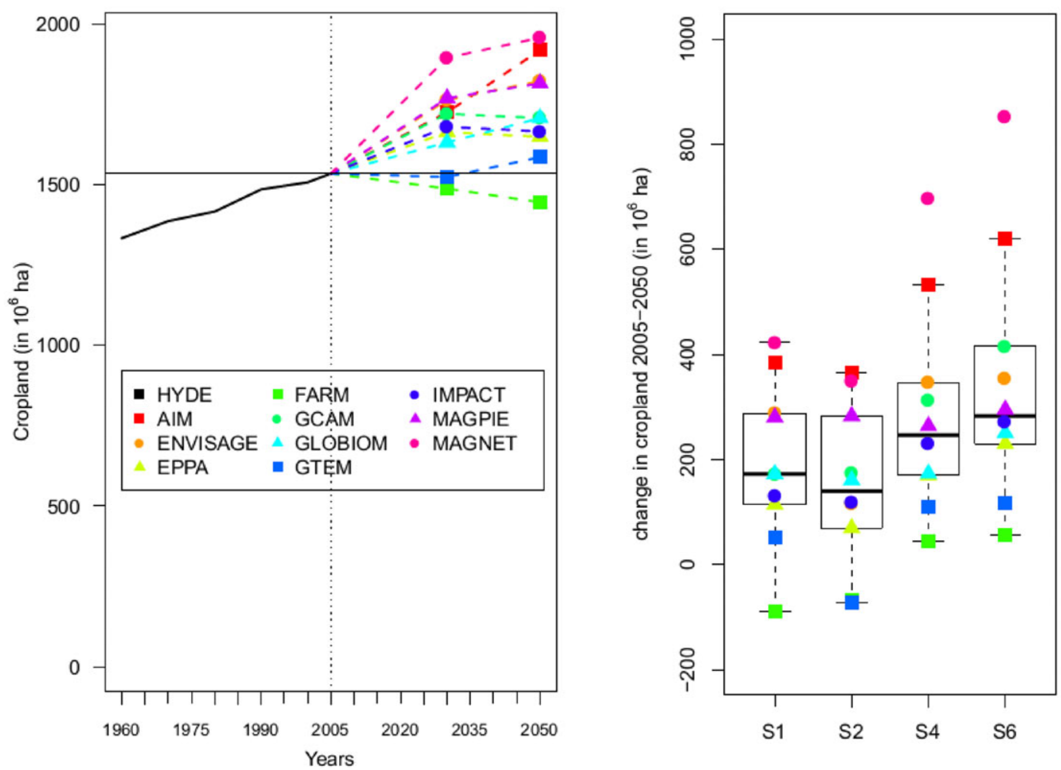

Fig. 1. Development of global cropland in S1 (cropland from the models is normalized to HYDE data from 2005; left graph) and change in cropland between 2005 and 2050 in S1, S2, S4, and S6 (mean and standard deviation; right graph). The boxplots display the median (black line), the upper and lower quartile (box), the minimum and maximum of the distribution (whiskers), and the outlier (dots; Fig. S5 in color).

Table 4
Change in cropland over time in S1 (“2050”) and across scenarios compared to S1 (“SSP3” and “CC”; in %)

Region	Scenario	AIM	ENVISAGE	EPPA	FARM	GCAM	GLOBIOM	GTEM	IMPACT	MAgPIE	MAGNET
AME	2050	+95	+54	+120	+	+26	+51	+44	+25	+19	+51
	SSP3	+	–	−27	+	o^{-}	+	−16	+	o^{+}	+
	CC	+	+	+	+17	+	–	+	+	o^{+}	+
ANZ	2050	+65	–	–	−18	–	−14	−35	–	n.a.	+
	SSP3	+	+	o^{+}	+	o^{+}	–	−11	–	n.a.	+
	CC	+	+	o^{-}	+	+	+	+	+	n.a.	+14
EUR	2050	−11	–	−54	−15	–	–	−23	−15	–	−20
	SSP3	−12	–	+19	o^{+}	–	–	o^{+}	–	–	–
	CC	+13	+	+	+	+	+	+	+	+	+10
FSU	2050	−12	–	+	−36	+23	−23	−19	+	+	–
	SSP3	+	−11	–	+	–	–	–	–	o^{+}	−14
	CC	+	+	+	+	+16	+	+	+	o^{+}	+21
NAM	2050	+14	+17	−16	–	o^{+}	+	−13	–	+	+30
	SSP3	−21	−18	+13	+	–	–	+	–	o^{+}	–
	CC	+27	+	+	+14	+15	+	+	+10	–	+43
OAM	2050	+24	+45	+15	+	+23	+37	+	+44	+78	+65
	SSP3	+	−13	+	–	–	–	–	–	+	–
	CC	+16	+	+	+12	+17	+14	+	+10	+	+25
SAS	2050	+40	+19	–	–	+	o^{-}	+	+	+11	+24
	SSP3	–	–	+	o^{-}	+	o^{+}	–	o^{-}	–	–
	CC	+	+	+	+	+	+	+	+	+	+
WLD	2050	+25	+19	+	–	+11	+11	+	+	+18	+26
	SSP3	–	–	–	+	o^{+}	o^{-}	–	o^{-}	o^{+}	–
	CC	+10	+	+	+	+11	+	+	+	+	+18

Notes: 2050: cropland change in S1 between 2005 and 2050; SSP3: cropland change in S2 compared to S1 in 2050; CC: cropland change in S4 + S6 (average) compared to S1 in 2050; **+:** cropland change between +1% and +9%; **o^{+}**: cropland change between 0% and +1%; **o^{-}**: cropland change between −1% and 0%; **-:** cropland change between −9% and −1%.

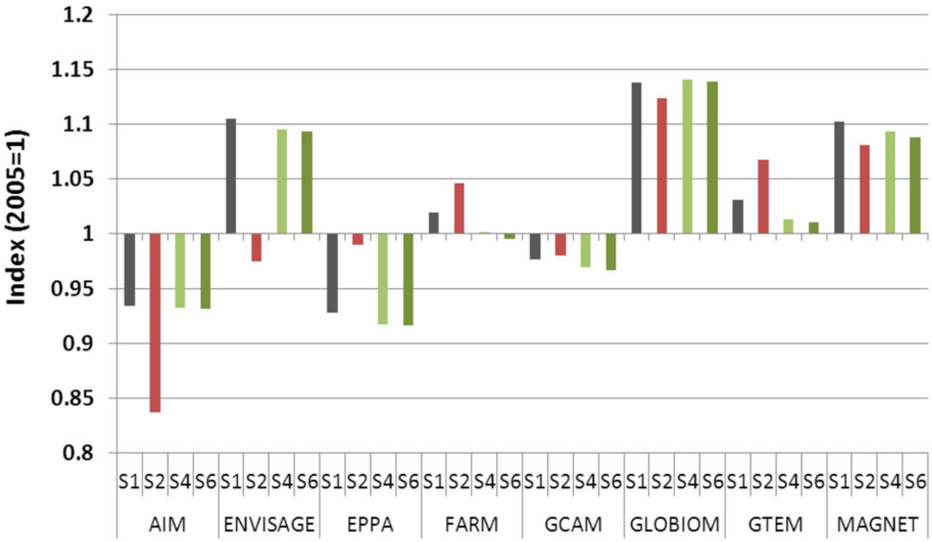

Fig. 2. Growth of global pasture area in 2050 (compared to 2005) for AIM, ENVISAGE, EPPA, FARM, GCAM, GLOBIOM, GTEM, and MAGNET (Fig. S6 in color).

In ENVISAGE, FARM, GTEM, MAGNET, and GLOBIOM, both pasture and crop area increase (Fig. 2). AIM, EPPA, and GCAM have decreasing global pasture areas in 2050; in MAgPIE pasture is constant.

Figure 3 highlights the results for the seven different regions considered in this analysis. Starting with the region Africa and Middle East (AME), cropland in EPPA increases by 120% and in AIM by almost 100%. In contrast, the area in FARM increases only marginally. AIM, ENVISAGE, GLOBIOM, and GTEM show an increased growth rate in the second half of the projected period (2030–2050), whereas the growth rates in GCAM, IMPACT, MAgPIE, and MAGNET are reduced. The fragmentation scenario influences EPPA and GTEM results, where cropland decreases by 27% and 16%, respectively (Table 4). The influence of climate change is consistently low. In GLOBIOM, cropland area decreases slightly and in FARM in average around 17% more land is used for agriculture under climate change.

The range of future cropland use in Australia and New Zealand (ANZ) is relatively large. AIM projects an increase by almost 60% while GTEM and GLOBIOM see a decrease of around 35% and 14%, respectively. The difference between AIM and GTEM in 2050 amounts to more than 40 million ha compared to total area of 53 million ha in 2005. The influence of fragmentation (decrease by 11% in GTEM) and climate change (average increase by 14% in MAGNET) is rather low.

For Europe, the models indicate that the decline in cropland will continue, although MAgPIE and GCAM show some slight increase to 2030. The largest reductions are projected by EPPA with cropland area more than halved by 2050. GTEM, MAGNET, and IMPACT follow largely the trend of the past decades. All models project an increase in 2050 cropland in scenarios with climate change, with AIM (+13%) and MAGNET (+10%) at highest.

The Former Soviet Union (FSU) saw dramatic declines in cropland after the collapse of the USSR in the 1990s. This trend has generally stabilized in the last decade, and in the future, the models have especially divergent trends for cropland in this region. The changes vary between a −36% decline (almost 125 million ha) for FARM and a 23% increase (almost 250 million ha) in GCAM. Six of the ten models project a decrease of cropland in this region. ENVISAGE, MAGNET, and IMPACT show increases till 2030 but decreases after that. The influence of increasing population and decreasing income (S2) generally has a negative impact on cropland use, with AIM, FARM, and MAgPIE as exceptions. Climate change puts new pressures on cropland. The largest mean changes in 2050 compared to S1 are from GCAM (+16%) and MAGNET (+21%).

While cropland was fairly stable in North America in the last 50 years at about 230 million ha, MAGNET, ENVISAGE, and AIM see an increase in 2050 to between 270 and 300 million ha. Only GTEM, EPPA, and IMPACT project lower cropped area in 2050 compared to 2005. Fragmentation and climate change seem to have huge impacts on cropland in North America. Under SSP3, cropland is mostly reduced with the greatest declines in AIM (−21%) and ENVISAGE (−18%). An exception is EPPA with a 13% increase in cropland. With climate change, the opposite is projected with highest expansion rates from MAGNET (+43%) and AIM (27%). In MAGNET cropland expansion exceeds 200 million ha in 2050, mostly in Canada.

In the past 50 years, Latin America (OAM) was the region with the greatest expansion of cropland, increasing from around 100 to 160 million ha between 1960 and 2005 (HYDE). ENVISAGE, IMPACT, and GLOBIOM continue this trend, to around 220 million ha in 2050. FARM, GTEM, and to a lesser extent GCAM and AIM observe a slowing down of expansion, whereas MAgPIE projects an accelerating trend to 280 million

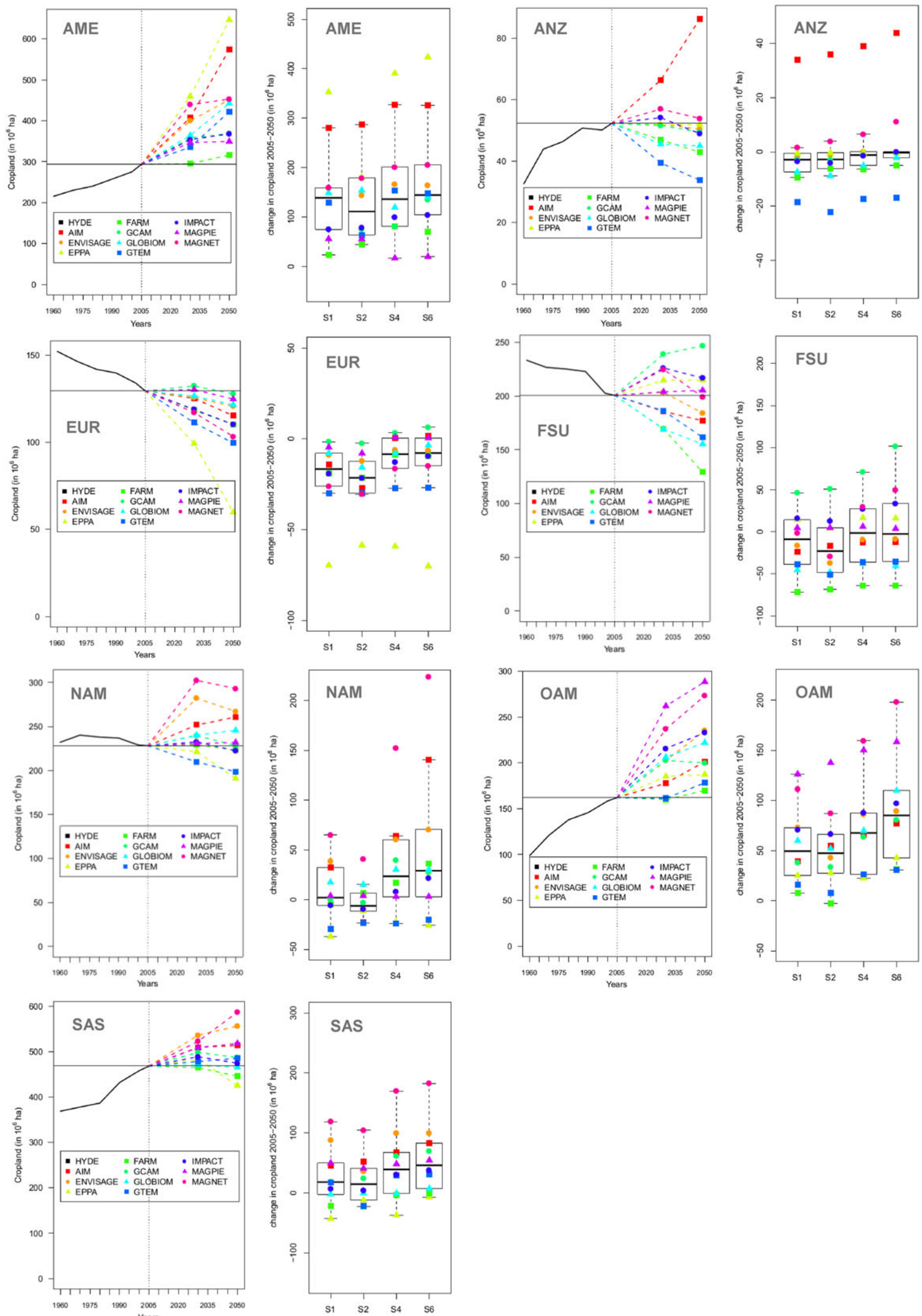

Fig. 3. Development of cropland in the each of the seven regions in S1 (cropland from the models is normalized to HYDE data from 2005) (left graph) and change in cropland between 2005 and 2050 in S1, S2, S4, and S6 (mean and standard deviation). The boxplots display the median (black line), the upper and lower quartile (box), the minimum and maximum of the distribution (whiskers), and the outlier (dots; Fig. S7 in color).

Table 5
Impacts of climate change on cropland expansion (mean of all models); Figs. 1 and 3 show the standard deviations and the outliers to the respective means

	Cropland expansion by 2050		Difference due to climate change	
Region	in S1 (10^6 ha)	in S4/S6 (10^6 ha)	absolute (10^6 ha)	as share of total cropland
AME	145.6	168.5	22.9	7.7%
ANZ	−0.4	3.1	3.5	6.7%
EUR	−20.1	−13.3	6.8	5.3%
FSU	−11.6	1.8	13.4	6.7%
NAM	8.1	41.8	33.7	14.8%
OAM	56.7	83.7	27.0	16.6%
SAS	27.6	51.0	23.4	5.0%
World	192.7	317.2	124.5	8.1%

ha. Climate change increases cropland area with rates ranging from 5% to 25%. SSP3 has a low, but largely negative impact with highest reduction in ENVISAGE (−13%).

The projections in South Asia (SAS) are similar to OAM in relative terms by having overall increasing rates of cropland use, except for FARM and EPPA. However, the rates are much lower with the maximum of 40% (AIM). The impact of the fragmentation scenario is mixed across the models, whereas climate change results in positive but low cropland development.

Table 5 summarizes the regional and global results for the reference scenario (S1) and the climate change scenarios (S4/S6) in physical units (ha), as well as the absolute difference and the percentage difference compared to 2005. By far the largest cropland expansion is projected in Africa (+121 million ha). OAM and SAS also see significant increases in land converted to agricultural use, driven by socioeconomic changes. The differences due to climate change are largest in North America (+34 million ha), which is mainly triggered by the high expansion in MAGNET, followed by OAM (+27 million ha). These two regions account for around 15% of the initial cropland area in 2005. Globally, almost 200 million ha are converted in the S1 scenario (with no climate change) and 320 million ha under climate change (mean).

4. Discussion of differences in model results

One possibility is that model structure explains the differences in land-use changes across the models. Figure 4 plots model types (CGE, PE, or spatial PE) on the horizontal axis, land-use modeling approach on the vertical positive axis, and land data source on the vertical negative axis.

From Fig. 4 groups of models can be identified, which have at least a similar approach to modeling land-use change. FARM, GTEM, MAGNET, and ENVISAGE use the CET approach to allocate land to the different uses. MAGNET and ENVISAGE use a land supply curve for modeling cropland expansion. While AIM is a CGE model and GCAM is a PE model, they both use a nested logit approach and rely on data from GTAP and FAO. They differ in how they nest crops within the AEZ structure. GCAM assumes that each crop is classified into 18 AEZs in a region and every production is described as a fixed-coefficient production function, while AIM assumes that each crop sector in a region is defined by three aggregated AEZ lands nested by a logit function.

MAgPIE and GLOBIOM are both spatially explicit land-use models, which base their expansion on the land rent approach, but use different data sources. EPPA has a similar land rent approach but embeds this in a general equilibrium framework with GTAP and the TEM model as the main data sources.

In addition, we can differentiate two groups according to their trade assumptions. One group is the trade-restrictive models, which use the Armington assumption (all CGE models; Hertel et al., 2007) and MAgPIE as it uses the self-sufficiency approach with restrictive liberalization assumptions. On the other hand, the other PE models (GCAM, GLOBIOM, and IMPACT) are more trade responsive due to their integrated market representation. More about the differences in trade and the impact on the results is discussed in Ahammad et al. (2014) and Nelson et al. (2013).

From the point of results, ENVISAGE and MAGNET are the closest group due to their similar implementation. MAGNET is usually a bit higher caused by the different available land pools. In addition, the elasticity of substitution between land and other factors is five times higher in ENVISAGE and equal to 0.5. This induces more substitution effects when the land price gets higher and subsequently the land expansion is less. In many cases the group of FARM and GTEM estimate future land use more conservative compared to other models. This can be partly explained by relatively low elasticities of transformation for allocating land. Furthermore, FARM is the only model that indicates a decrease in global cropland, and FARM is with AIM the only CGE model that includes forestry within a CET structure. In FARM, simulations of future land use are sensitive to two types of parameters: Relative rates of land-augmenting technical change, and income elasticities of demand for forest products. Exogenous rates of yield improvement for managed forests are much lower than rates of yield improvement for crops.

In contrast, the other CGE models are usually at the upper end, especially MAGNET and AIM and to a lower extent EPPA and ENVISAGE. The increasing trends in AIM and MAGNET are caused by the assumption that still a lot of additional land can be made available for agriculture. In MAGNET, these potentials are based on the IMAGE model, which indicates that still a lot of land can be taken into production in Africa, South America, and North America (especially Canada). In other words, these countries are on the flat part of the supply curve where more land can be taken into production without much additional costs. Furthermore, their production trees imply that land has a low degree of substitutability with other factors such as capital and labor. In AIM, there are especially limited substitution possibilities of land with other factors, as compared with the other models in this study (see, also Robinson et al., 2014).

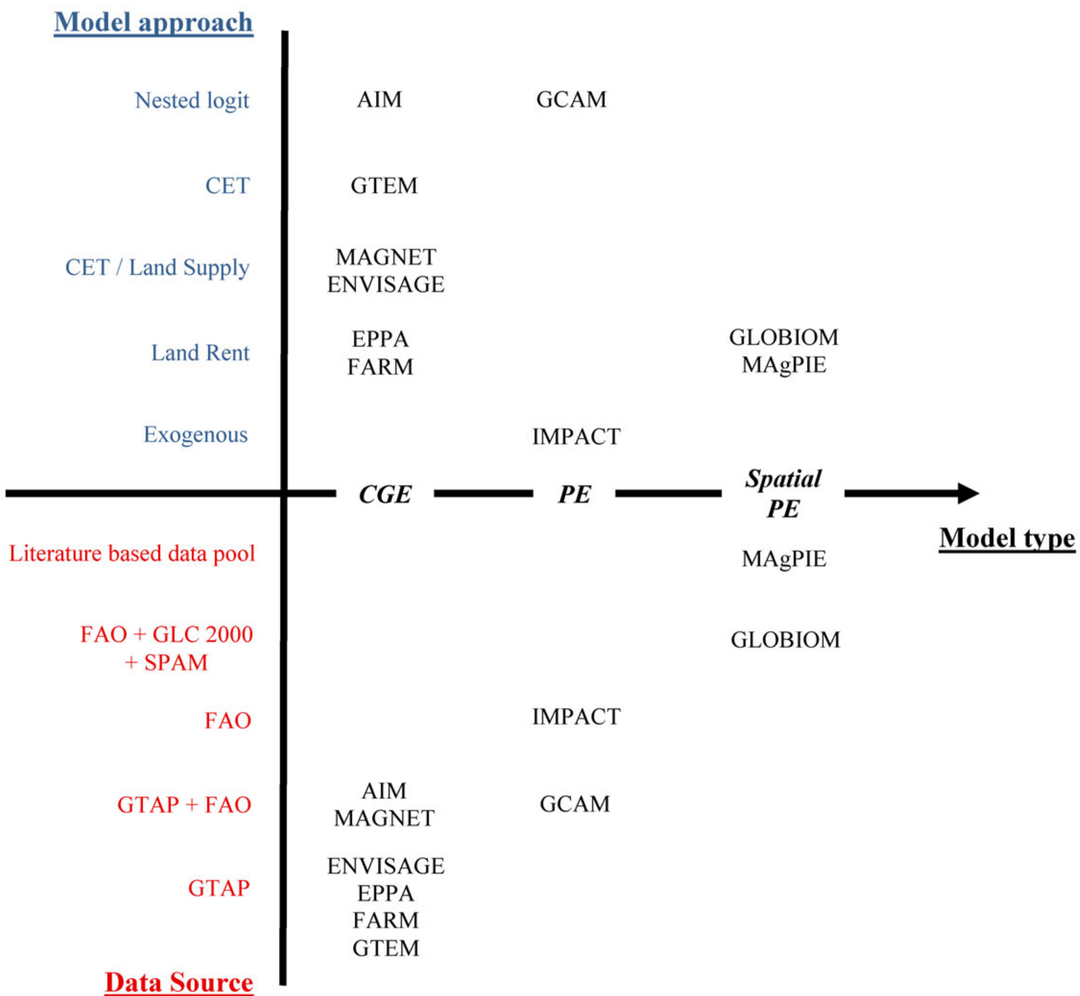

Fig. 4. Structuring of models according to their used data and methods.

Except for OAM, MAgPIE project only modest expansion of cropland area in the different regions. One reason is available land for conversion. In the version of MAgPIE used here, only natural vegetation and intact and frontier forest can be converted to cropland. Especially in sub-Sahara Africa this makes a huge difference as compared to other models, since MAgPIE already uses the entire land potential in the S1 scenario (see also Table S1). In addition, MAgPIE considers land conversion costs (as explained in Section 2). The same holds for GLOBIOM, which mostly increases cropland in AME and OAM. For FSU, GLOBIOM sees considerable decreases due to low profitability of agriculture.

Another source of uncertainty is the assumed bioenergy demand. Except ENVISAGE, FARM, and GTEM, all models assume first generation bioenergy demand in the future. Whereas, GLOBIOM, MAgPIE, and GCAM have harmonized their demand for future first generation bioenergy according to current policy mandates (constant after 2030), MAGNET, for instance, has relatively high first generation biofuel targets in countries like the United States and Brazil. This puts additional pressure on cropland in contrast to models with lower bioenergy demand. Land devoted to second generation bioenergy is not reported here, but still reduces the potential cropland pool for expansion.

The fragmentation scenario (S2, SSP3) differs from the middle-of-the-road scenario (S1, SSP2) by a much higher population growth and a much lower GDP growth. The differences between the scenarios are especially large in developing countries. Significant decreasing global cropland is obtained for AIM, ENVISAGE, EPPA, GTEM, and MAGNET (all CGE models). Hence, it seems that in the CGE models (except FARM) lower cropland demand due to lower GDP effects dominate the increase in demand for cropland due to a higher population. In S2, GDP is 32% lower than in S1 but population only 11% higher by 2050. Since most of the crops are consumed via processed products with relatively high income per capita demand elasticities, the demand in S2 is lower than in S1 (see Valin et al., 2014 for the differences in demand between SSP2 and SSP3 and the income elasticities). For FARM, the results are opposite and there are largely positive effects of SSP3 indicating that population effects dominate GDP effects due primarily to low income elasticities of demand for crops. The PE models are hardly affected by the different SSP assumptions.

Climate change induces a relatively large increase in area in AIM, GCAM, and MAGNET. The mechanism is similar to the baseline: Large potential land availability and in case of MAGNET and AIM low endogenous yield effects. Other models indicate no or very little cropland change and assume that (almost) all negative effects in yield can be compensated by endogenous yield effects in their model. This is because land expansion is largely exogenous (IMPACT), adaptation through switches across production systems and also reallocation across the SimUs (GLOBIOM) or substitution possibilities (ENVISAGE, GTEM) are easy. Moreover, except for MAgPIE, the demand side adjusts due to the climate change pressure (see Valin et al., 2014) and international trade is rather flexible (especially for IMPACT and GLOBIOM with homogenous goods assumption, to a lesser extent for the CGE models with Armington assumptions). In MAgPIE, cropland even decreases due to climate change as it adjusts for climate change effect by investing in TC (TC effects all crop groups to the same extent). A second reason is the different implementation of climate change induced yield shocks. In contrast to the other models, climate change impacts are not considered on FPU level, but on grid cell level (see Nelson et al., 2014 for more details). This allows MAgPIE to consider the large heterogeneity of climate change within FPUs and leads to more specialization and lower effects of climate change.

Turning now to the analysis of the regional-specific results, we obtain the largest cropland expansion in Africa and the Middle East (AME). EPPA and AIM increase cropland by around 100–120% due to the combination of a 2.5-fold population increase, economic growth, and only 50% yield increase of other agriculture products, which dominate in AME. Another reason for EPPA is the low land conversion and institutional costs in Africa, resulting in a large land supply response. ENVISAGE, GLOBIOM, MAGNET, and GTEM get an increase in cropland use around 50%. The PE models MAgPIE and IMPACT observe a relatively moderate increase of about 15%. Key to this result is the land availability, or how easy it is to get new land into production. As explained, the potential cropland in MAgPIE in Africa is limited (see also Table S1). In the fragmentation scenario (S2) we see for most models an increase in cropland and that differs from the global situation discussed earlier. Population effects dominate GDP impacts in AME. EPPA and GTEM, however, show the opposite with cropland decreases a lot in S2 relatively to S1. While cropland productivities are identical in S1 and S2, GTEM enables differential land productivity shocks across scenarios for livestock. Since a general negative productivity shock implied under S2 relative to S1 is distributed across inputs and sectors, including land used in the livestock sector, and since the demand for livestock products is relatively price insensitive (a feature of GTAP-based CDE parameters), livestock sector uses more land per unit of output under S2 relative to S1. Consequently, land moves out of crops into pastoral activities displaying a relative decline in the cropping land. In the case of EPPA, GDP shocks are applied through labor productivity changes, nulling the effect of the population shock. The decrease in productivity to reach the prescribed GDP in EPPA is the largest in AME and the lowest in EUR, changing agriculture comparative advantage in favor of EUR.

GLOBIOM and especially GTEM assume a strong reduction in cropland in ANZ which is in contrast to the historical trend. In GTEM, this has two reasons: First, total agricultural land drops by 27% significantly over the projection period (in GTEM aggregate land supply for agriculture is exogenous at a regional level and based on a 20-year historical trend as described in Section 2); second, export-driven growth in livestock sector raises land rental in livestock sector relative to crops sector such that land moves out of crops into pasture.[7] In addition, one has to consider the distribution of agricultural land in ANZ. Ninety percent of agricultural land is used by the livestock sector, while only 10% is used by cropping sectors in total. Because of this relation, a small increase in the pastoral activity would mean a big drop in land used by the cropping sectors in a relative sense. AIM, on the other hand, assumes that a lot of potential cropland is available in ANZ. GTEM expects also a decrease in cropland in the fragmentation scenario (S2) mainly due to the lower GDP growth rate and related demand. Climate change impacts are slightly positive for this region.

In Europe, models agree on the downward trend for Europe in S1. EPPA even projects a bisection of European cropland since in S1 EUR is losing competitiveness in crop production to regions with low costs of cropland conversion. In contrast, in S2 EPPA shows that EUR is gaining comparative advantage due to the lowest shock in labor productivity compared to other regions, leading to almost 20% more cropland use than in S1. Climate change impacts increase cropland use in all models in Europe. The impacts are highest for AIM and MAGNET as land is more abundant than in other models and the substitution elasticity is lower.

In the region FSU, most CGE models plus GLOBIOM[8] see a decrease in area until 2050. Among the other models, especially GCAM allows for considerable cropland expansion. This expansion in GCAM occurs in part due to low base-year (2005) land profit rates for the dominant agricultural crops, which become substantially more profitable in the future due to the assumed baseline improvements in yields. This expansion

[7] In GTEM, cropping productivity is governed by the crop model results whereas livestock productivity is governed by the economy-wide productivity growth implied by the exogenous GDP growth paths. Because GDP differs between S1 and S2, livestock productivity is also different.

[8] Likely due to the nonlinear trade cost in GLOBIOM, which tend to maintain some inertia in the trade patterns. Hence, a fast crop yield growth, decreasing population and medium strong GDP growth may lead to further land abandonment.

also occurs because of a large amount of land that is potentially available for agricultural conversion—approximately 1,700 million ha, with about 200 in relatively productive AEZs. A bottleneck for this region is the future labor supply that will determine if this land will be exploited or not.

In North America, the key difference between the models is the potential land that can be taken into production. IMAGE-based models, like MAGNET and AIM, show large potential, especially in Canada, whereas other models see very limited potential. Therefore, land increase is highest in MAGNET and AIM. The increase in ENVISAGE is much less as these models assume much higher substitution elasticities between land and other production factors. Almost all models show decreasing land in the Fragmentation scenario (S2) as the lower demand effect to a lower GDP in NAM dominates the slightly lower population effects in NAM. Climate change impacts are very high in MAGNET and AIM as the lower yields lead directly to land expansion as possibilities are there and incentives for higher yields therefore are low.

The results for South Asia (including China) show in average a moderate increase in cropland. Similarly to NAM, MAGNET shows the highest potential of cropland in SAS and EPPA is very restricted in terms of land expansion.

The assumptions on land availability in Brazil and other countries containing a lot of natural vegetation determine the results in OAM. Another source of uncertainty is that those countries have recently seen a considerable slowdown in land clearing (Soares-Filho et al., 2010), indicating a beginning forest transition, as observed in countries like Thailand or Vietnam (Meyfroidt et al., 2010; Meyfroidt and Lambin, 2011). The Fragmentation scenario lowers cropland use in OAM quite substantially in almost all models as the "exporter of the world" suffers more than the average from lower economic growth rates. In FARM, cropland expansion is slightly negative as forestry is more competitive and counterbalances the demand from agriculture.

5. Conclusions

The future of human influence on land is critical from environmental and climate perspectives. The expansion of cropped area threatens biodiversity, carbon stocks, and ecosystem services. Projections of future land use have seen widely varying results. We analyze methodological differences among different agro-economic models on the basis of the results of a comprehensive agro-economic model intercomparison exercise. We harmonized key input data and assumptions across 10 different models.

Global cropland without the impact of climate change increases on average across all models by almost 200 million ha between 2005 and 2050 (mean). The standard deviations are high with −40 and +110 million ha. Pasture land area expands in most models that model pasture explicitly. Climate change further increases the pressure on land resources by increasing cropland expansion to more than 300 million ha in average. Most of the cropland expansion takes place in Africa, followed by OAM due to their large potential of suitable cropland. The sensitivity to climate change in North America is surprising and related to the huge land potential there seen by some of the models. Together with OAM most of the cropland is expanded due to climate change in those two regions. In contrast, in sub-Saharan Africa climate change-induced cropland expansion is moderate.

With respect to methods used, all of the models approach land-use change from an economic perspective. However, since the models come from different backgrounds, their individual focus is very different. Whereas the CGE models were initially built to analyze macro-economic and trade policy issues and have only recently entered the climate change and land-use change research fields, most of the PE models approaches have a long history of application to agricultural sectors responses, although they do not always cover all production factor markets. A particular strength of spatial PEs lies in their fine resolution. It allows the models to consider the spatial heterogeneity of biophysical factors, like the soil quality or the impacts of climate change, which are critical when analyzing land-use change. The same holds for the different land types, which are much better represented in the spatial PE models than in the stand-alone CGE models. In addition to the economic behavior, social, political, and cultural factors have to be considered as well. Here, land-use modeling is still at the beginning of this trajectory. Modeling future TC is decisive due to its direct link with land expansion. Endogenous approaches are emerging but still in its infancy. Data and empirical studies are the main challenges. A further big field of future research should be devoted to the interaction of cropland and pasture. Too little is known about the costs of converting one land type into the other and about the biophysical and socioeconomic availability of pasture for cropland conversion. Another challenge is the interaction between cropland and managed forest area, which seems to gain competitiveness as energy prices continue to rise. Here the different time scales of agriculture and forestry is a major challenge for modelers (see e.g., Sohngen et al., 2009). A critical need for modeling economic land-use change is the availability of data. Although the data basis on global land use has improved considerably (see Section 2), especially data on potential cropland and their suitability on a global level and data about the ease of converting this land into cropland are lacking. With the latter, we refer to land conversion costs and substitution elasticities. A lot of qualitative assumptions are taken in those fields, leading to biased results and a low replicability. Especially Africa and the northern countries, like Canada and Russia (due to climate change) leave us with high uncertainty concerning potential cropland. In OAM, data availability is much better but high uncertainty exists concerning forest protection.

During this first comprehensive agro-economic model intercomparison, it became clear that more emphasis has to be put on the underlying supply elasticities. Unfortunately, on the supply side, too many models are relying on complex nested structure for production function. Others are managing land-use change through explicit conversion costs, without elasticity-driven functions. Therefore, estimating these elasticities requires specific controlled experiment to be performed by all models, which was not undertaken under this first round of comparison activities. Such technical investigations are however on the work plan of the next round of comparison, which will start at the end of this year. Finally, the need for validating agro-economic models is apparent. First attempts have been presented at the recent GTAP conference (e.g., Baldos and Hertel, 2013; Bonsch et al., 2013) trying to approach the question: How well are the approaches suited to describe past and current developments? Hind casting (model starts in the past) or back casting (model forecasts into history) would be options to validate the model outcome with observed data. It is only through such systematic research that it will be possible to eliminate the least promising approaches and focus on those that are worthy of further attention.

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