Forecasting technological change in agriculture - An endogenous implementation in a global land use model

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Abstract

Technological change in agriculture plays a decisive role for meeting future demands for agricultural goods. However, up to now, agricultural sector models and models on land use change have used technological change as an exogenous input due to various information and data deficiencies. This paper provides a first attempt towards an endogenous implementation based on a measure of agricultural land use intensity. We relate this measure to empirical data on investments in technological change. Our estimated yield elasticity with respect to research investments is 0.29 and production costs per area increase linearly with an increasing yield level. Implemented in the global land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") this approach provides estimates of future yield growth. Highest future yield increases are required in Sub-Saharan Africa, the Middle East and South Asia. Our validation with FAO data for the period 1995-2005 indicates that the model behavior is in line with observations. By comparing two scenarios on forest conservation we show that protecting sensitive forest areas in the future is possible but requires substantial investments into technological change.

Key words: technological change, land use, agricultural productivity, land use intensity, research and development

1. Introduction

More than 200 years ago Thomas Malthus published his rather pessimistic population essay, in which he stated that population growth would be restricted by a slow growth rate in food production [1]. Now the world is inhabited by almost seven billion people, which marks an increase by about 600% since Malthus' times. One of the main shortcomings of his essay was the underestimation of technological change (TC) in agriculture [2].

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However, during Malthus' times technological change was negligible and higher food production was almost exclusively due to an increase in production factors [3]. Important innovations in agriculture from the 19th century onwards changed this pathway [4]. Since then land-saving technological change has been the main driver for growth in agricultural output [5, 6]. Figure 1 shows the strong correlation between agricultural output and population during the last 200 years. Agricultural output has increased considerably, paving the way for strong population growth. Most of such increases in agricultural output have been the result of technological change induced by investments in Research & Development (R&D). One example is the so called "Green Revolution" in Asia and Latin America, initiated by international agricultural research institutes [7][3].

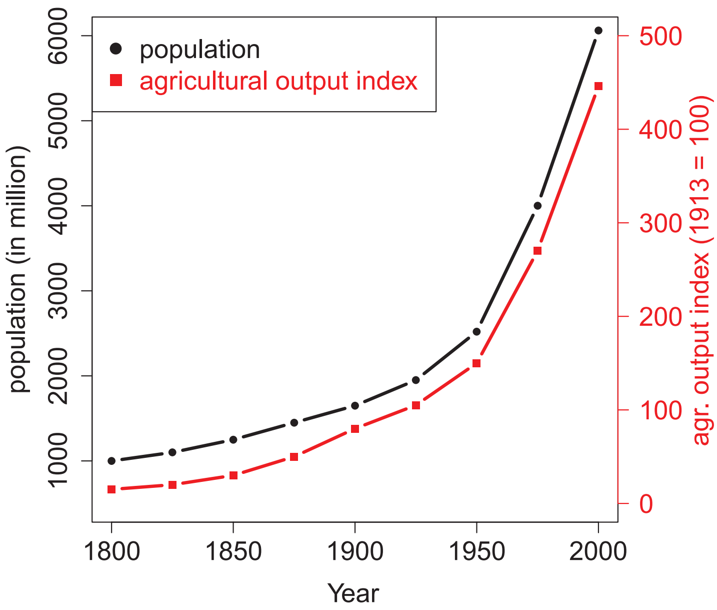

Figure 1: Historic development of agricultural production and population [own illustration based on Federico [3] and United Nations [8]]

The importance of TC for the agricultural sector is widely acknowledged in the scientific literature. For instance, some recent studies document the need of agricultural innovation and progress for satisfying global food demand and keeping food prices at tolerable levels [9, 10]. Thirtle et al. [11] point out that growth in the agricultural sector has a much higher impact on poverty reduction in Africa and Asia than growth in other sectors. Sub-Saharan Africa particularly profits from R&D investments mostly in terms of increases in agricultural productivity and poverty alleviation [12].

Notwithstanding, in agricultural sector models or models of land use change, TC is implemented as an exogenous driver [13–17]. In these models, projections primarily depend on a fixed technology path rather than on internal model dynamics. This may lead to serious biases in

[3]During the 1960s and 70s the International Maize and Wheat Improvement Center (CIMMYT) and the International Rice Research Institute (IRRI) developed high-yielding wheat and rice seeds.

model results due to an underestimation of the adaptability in the agricultural sector, especially in the longer run.

The main reason for using an exogenous TC path in most models is that although the relationship between R&D investments in agriculture and technological change is well documented [9, 11, 12, 18, 19], the exact influence of R&D on technological change is still unknown. Several reasons exist for this knowledge gap. First, available time series of R&D investments are still relatively short (less than 30 years) and often incomplete [20]. Second, as Evenson [21] showed, spillover effects are of major importance in agricultural research and hamper the correct attribution of R&D investments to their impact. Third, success in R&D is hard to predict. High investment may fade away without producing any output, whereas in other instances low investment may create marvelous results. Finally, no clear boundary exists between R&D investments in different sectors. In many cases inventions in one sector are based on inventions in other sectors. In a sectoral analysis of a specific R&D sector, e.g. agricultural R&D, these cross-connections cannot be considered.

Due to improved data on agricultural R&D investment [22] and a measure for agricultural land use intensity, we are able to present a new attempt of implementing endogenous technological change in a land use model, which uses a deterministic investment-improvement ratio and ignores possible spillovers from other sectors. Within a sectoral model and with the current data availability to analyse the relationship of R&D investments and agricultural productivity this is the only option to endogenise technological change. With the new approach presented here, the model can freely decide on the optimal rate of technological change, which is of central importance for long-term projections over several decades and dynamics under increasingly limited production resources. For this purpose, we relate investments in technological change and corresponding yield growth to agricultural land use intensities. As a second step, we estimate empirically how the level of agricultural production costs per area evolves with the yield level. The methods are implemented in the global land use optimisation model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") [23–25] and the resulting technological change rates are validated with independent data. Finally, in order to illustrate the importance of the dynamic behaviour of TC, we compare two extreme scenarios on forest conservation which reflect the trade-off between agricultural land expansion and technological change.

2. Methodological framework

The endogenous implementation of agricultural TC is based on production costs and the effectiveness of R&D investments on yield changes (investment-yield ratio, IY) (see Table 1 for definitions). The IY ratio, describing TC investments required per unit of yield growth, evolves with the agricultural land use intensity. Accordingly, production costs (i.e. for use of inputs) are based on yield levels. For the purpose of measuring agricultural land use intensity we use the τ-factor developed by Dietrich et al. [26]. The τ factor is an output-related measure of land use intensity and captures the full spectrum of yield increasing technology and management options. It is the ratio of actual yields and reference yields under a spatially and temporally fixed land use intensity.

2.1. Investment-Yield Ratio

Based on the τ factor it is possible to link investment costs for generating technological change directly to the level of land use intensity. We differentiate between two types of investment costs which influence the rate of technological change: first, public and private investments

concept	description
agricultural land use intensity	degree of yield amplification caused by human activities [26]
τ-factor	measure proportional to agricultural land use intensity [26]
technological change (TC)	more efficient usage of the input factors land, labour or capital [27]
TC investments	composite of annual investments in R&D and infrastructure (e.g. transport and telecommunication) [US$/year]
investment-yield ratio (IY ratio)	TC investments required per human-induced unit yield growth and area [US$/ha]

Table 1: Concepts and terms used in this paper

in agricultural R&D, and second, investments in infrastructure (e.g. transport and telecommunication). Data for public and private R&D investments is taken from IFPRI for the year 1981 [22] and data for infrastructure investments is from the GTAP database, version 7 [28] (discounted from 2004 to 1995)[4]. Unfortunately, the GTAP database does not distinguish between one-time investments in infrastructure and maintenance costs. To get an estimate for annual investments in infrastructure the total GTAP infrastructure costs are corrected with a factor of 0.65, which is the average fraction of one-time investments on total infrastructure costs based on OECD [29]. The remaining 35% of the total infrastructure costs are maintenance costs and are treated as additional production costs.

Both investment costs, R&D investments and infrastructure investments, are divided by the average yield growth rate observed in the years 1990-1999 taken from FAO [30] to achieve investment costs per unit of yield growth. The reason for taking the R&D investment data of the year 1981 is the typical time lag between investment in R&D and its impact. The literature offers quite a wide range of various delays and lag-structures proposed for agriculture, ranging from a few years to several decades [19, 31–33]. Chavas [34] summarizes results from empirical studies suggesting a time lag of 8-15 years for private investments and 15-25 years for public investments. Based on that, the chosen delay of 15 years matches the average delay used in literature. Furthermore, according to Alston et al. [18, 35], it agrees with the time which is needed to reach the maximum value of gross annual benefits.

The absolute amount of investment still depends on the size of a region: the bigger the region, the higher the variation in physical conditions. As a consequence, more research is needed to produce the same average growth rate compared to a smaller region with less variation in biophysical crop conditions. Consequently, we normalised investment relative to the agricultural area of a region. Specific R&D investment per unit of yield growth are computed as the ratio of R&D expenditures per area and the yield growth 15 years later. The same concept is applied for infrastructure investment, except that no time delay is assumed. Both components add up to the investment-yield ratio IY describing the TC investment per area required per unit of yield growth.

The relationship between IY ratio and τ is described by the elasticity ϵ_{τ}^{IY}, i.e. the propor-

[4] Infrastructure investments are composed of investments in transport, water and energy distribution, telecommunication and financial services, all related specifically to the agricultural sector according to GTAP 7.

tional relationship between an increase in τ and an increase in the IY ratio.

$$\frac{dIY(\tau)}{IY(\tau)} = \epsilon_\tau^{IY} \cdot \frac{d\tau}{\tau} \tag{1}$$

The elasticity ϵ_τ^{IY} is estimated via a regression analysis. Since agricultural R&D data is generally aggregated over all agricultural sectors and spillover effects are expected [21, 36], we used an aggregated version of τ covering all crops for the regression.

The results of the regression analysis is shown in equation 2. Figure 2 illustrates the relationship in a graph for the 10 world regions of the MAgPIE model.

$$IY(\tau_i) = (1.9 \pm 0.4) \cdot 10^3 \cdot \tau_i^{2.4 \pm 0.9} \tag{2}$$

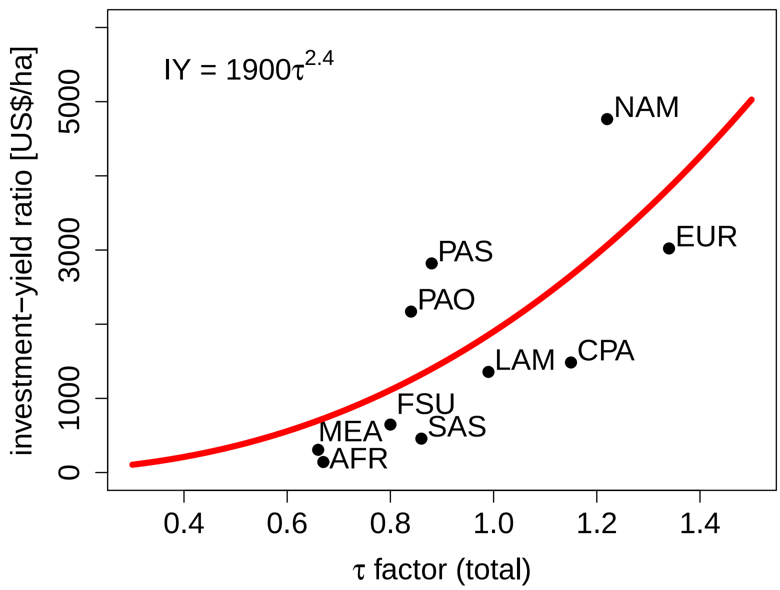

Figure 2: investment-yield ratio in relation to τ-factor

P-values of the t-tests for prefactor a and exponent/elasticity ϵ are $p_a = 0.002$ (**) and $p_\epsilon = 0.04$ (*). The elasticity between IY ratio and the τ-factor ϵ_τ^{IY} has a value of 2.4 with a standard error of 0.9. As previously explained, changes in τ are proportional to changes in yield, and therefore we can transform this elasticity into an elasticity of yield with respect to accumulated TC investments (I), which is a more common representation (Equation 3). The result is close to the value of $\epsilon_I^{yld} = 0.296$, as reported by [37].

$$\epsilon_I^{yld} = \frac{1}{\epsilon_\tau^{IY} + 1} = 0.29 \pm 0.08 \tag{3}$$

2.2. Correlation with Production Costs

With improving agricultural technology and rising crop yields, production costs per hectare for fertilizer, machinery, and other input factors also rise. Since we endogenise the relationship between TC investment and land use intensity (Eq. 1), we also have to describe the relationship between yield levels and production costs. Data for production costs is taken from the GTAP 7 Data Base [28] and yield data is taken from FAOSTAT [30]. The data for small producing countries is expected to be insufficiently accurate [38]. Therefore, only the top producing countries for each crop are taken into account, representing at least 90% of total crop production and at minimum 1/3 of all available countries (31 countries) in the analysis (an exception is oil palm, which is only produced in 20 countries worldwide).

A standard linear regression analysis of this data shows that the residuals are not normally distributed and would give biased results. Therefore, we have applied a correlation analysis between (a) yield and costs per area and (b) yield and costs per ton using the Pearson correlation coefficient [39] as well as the Kendall rank correlation coefficient [40]. We use two different correlation coefficients, in order to reveal potential measure-related biases in the analysis. Whereas the Pearson correlation coefficient measures the magnitude of the linear dependence between two variables, the Kendall rank correlation coefficient measures just any correlation based on a rank test [41]. Since residuals in our data set are non-normally distributed, the significance of the Pearson test may be biased, if samples sizes are too small [42].

With regard to the relationship between production costs and yield level, Table 2 shows the Pearson correlation coefficients and the Kendall rank correlation coefficients. All correlations are positive and in most cases at least significant at the 95% level. In the Kendall rank correlation test all crops except tropical cereals, oil palm and sugar cane show significant correlations at the 99.9% significance level. In the Pearson correlation tests the results are less significant, but still 10 out of 16 crops show significant correlations at the 95% level.

crop types		**Pearson**			**Kendall**		
		correlation		p-value	correlation		p-value
cereals	temperate	0.81	***	0.000	0.63	***	0.000
	tropical	0.49	*	0.019	0.23		0.140
	maize	0.70	***	0.000	0.61	***	0.000
	rice	0.42	*	0.019	0.57	***	0.000
oilcrops	groundnut	0.17		0.410	0.47	***	0.001
	oil palm	0.07		0.803	0.23		0.228
	rapeseed	0.56	**	0.002	0.55	***	0.000
	soybean	0.08		0.689	0.47	***	0.000
	sunflower	0.68	***	0.000	0.45	***	0.000
sugar	beet	0.65	**	0.002	0.53	***	0.001
	cane	0.37		0.107	0.14		0.422
others	cassava	0.35		0.084	0.47	***	0.001
	potato	0.37	*	0.046	0.58	***	0.000
	pulses	0.75	***	0.000	0.52	***	0.000
	cotton	0.26		0.171	0.49	***	0.000
	others	0.62	***	0.000	0.43	***	0.001

Table 2: Correlation between yield and production costs per area(* p$\geq$95%, ** p$\geq$99%, *** p$\geq$99.9%)

Table 3 shows the same information for the relationship between yields and production costs per ton. However, almost none of the tested crop types shows a significant correlation. Comparing the results in both tables suggests the existence of a positive correlation between yields and area-related production costs, but no correlation between yields and output-related production costs. A linear relation with a positive gradient between yields and area-related production costs is the simplest solution which replicates this pattern. Since area-related production costs can be also calculated as a product of yield and output-related production costs the linearity in area-related costs leads to constant output-related costs. Based on this result production costs per ton have been implemented as a constant input for the model. We derived these costs as mean of measured costs per ton.

crop types		**Pearson**			**Kendall**		
		correlation		p-value	correlation		p-value
cereals	temperate	-0.06		0.771	0.15		0.250
	tropical	0.02		0.941	-0.07		0.676
	maize	0.27		0.151	0.25		0.058
	rice	0.28		0.126	0.29	*	0.022
oilcrops	groundnut	-0.10		0.628	0.23		0.118
	oil palm	-0.03		0.912	0.15		0.450
	rapeseed	0.29		0.136	0.26		0.055
	soybean	-0.06		0.753	0.25		0.066
	sunflower	0.12		0.531	0.22		0.103
sugar	beet	0.42		0.068	0.30		0.074
	cane	-0.22		0.352	-0.13		0.461
others	cassava	0.32		0.118	0.25		0.088
	potato	0.22		0.246	0.33	**	0.010
	pulses	0.43	*	0.040	0.38	**	0.010
	cotton	0.00		1.000	0.28	*	0.029
	others	0.42	*	0.025	0.24		0.072

Table 3: Correlation between yield and production costs per ton(* p$\geq$95%, ** p$\geq$99%, *** p$\geq$99.9%)

Table 4 shows the calculated costs per ton together with the number of countries included in this calculation and the share of total production covered by these countries. These costs per ton are used in MAgPIE for the calculation of production costs (see Appendix Appendix C).

2.3. Model Implementation

The global land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") has been developed to generate future land use and agricultural production patterns, addressing a wide range of scenarios on population and income growth throughout the 21st century. It is a recursive dynamic model working on a regular spatial grid with a cell size of about $0.5° \times 0.5°$ (approximately $50 \times 50 km^2$ at the equator). The model works on ten-year time steps. On the biophysical side, it uses spatially explicit data on potential crop yields, land and water availability taken from the dynamic global vegetation model LPJmL [43]. Economic data is used at the aggregate level of 10 economic world regions [5]. For future demand trajectories

[5]AFR = Sub-Sahara Africa, CPA = Centrally Planned Asia (incl. China), EUR = Europe (incl. Turkey), FSU = Former Soviet Union, LAM = Latin America, MEA = Middle East and North Africa, NAM = North America, PAO =

crop types		costs [US$/t]	countries	prod. share
cereals	temperate	130	31	0.95
	tropical	70	31	0.97
	maize	90	31	0.96
	rice	110	31	0.99
oilcrops	groundnut	180	31	1.00
	oil palm	30	20	1.00
	rapeseed	210	31	0.99
	soybean	150	31	1.00
	sunflower	130	31	0.99
sugar	beet	220	31	0.98
	cane	50	31	0.99
others	cassava	350	31	0.99
	potato	1230	31	0.91
	pulses	160	31	0.94
	cotton	620	31	0.99
	others	1130	31	0.92

Table 4: Crop-specific, average costs per ton, number of countries used for averaging and the total production share of these countries

the model derives specific land use patterns and costs of agricultural production for each grid cell. These patterns are initially based for the year 1995 on external data for population [44] and gross domestic product (GDP) [45] (see Appendix A). Future projections are internally derived based on future scenarios defined in the ADAM project [6] and eplained in van Vuuren et al. [46]. The food energy demand for the year 1995 is taken from FAOSTAT [47]. The share of traded goods is kept constant over time and is based on self-sufficiency ratios for the year 1995 [47]. More information on model structure and features can be found in detail in Lotze-Campen et al. [23, 24], Popp et al. [25, 48]. A mathematical description of the model is presented in Appendix C.

Figure 3 shows a schematic overview of the endogenous implementation of technological change in MAgPIE. Investments in TC lead to increases in land use intensity which let yields increase as well. At the same time the higher land use intensity forces an increase in production costs per area as well as a rise in the IY ratio which can also be interpreted as an efficiency drop for further TC investments: In order to achieve one unit of yield increase in a subsequent time step, a larger amount of TC investments has to be mobilized than in the previous period. In Appendix B we explain some further implementation issues dealing with the recursive dynamic structure of MAgPIE.

2.4. Validation and Scenarios

For the validation we compare long-term trends of simulated τ development from 1995 to 2060 with observed data from 1960 to 2005, with a special focus on the overlap in 1995-2005.

Pacific OECD (Australia, Japan and New Zealand), PAS = Pacific Asia, SAS = South Asia (incl. India)

[6]Adaptation and Mitigation Project, URL: http://www.adamproject.eu/

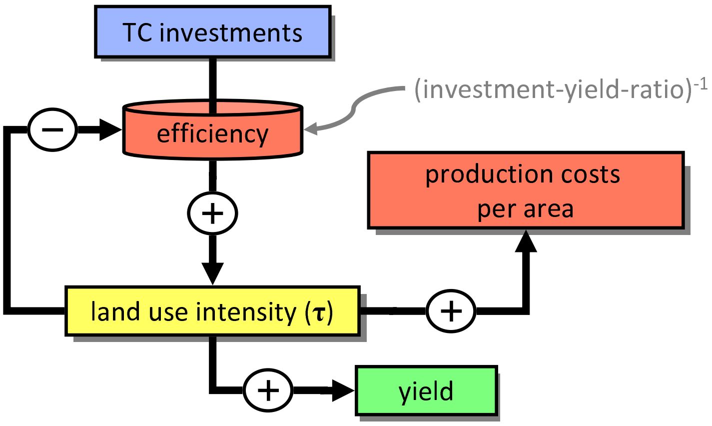

Figure 3: Implementation of technological change in MAgPIE (schematic)

We use historical data from FAO on yield growth, which was neither part of the model parameterization nor calibration. Based on this data the changes in τ are calculated backwards starting from 2005.

In order to show the interplay between rates of deforestation and endogenous technological change in agriculture we have compared two scenarios: one scenario which is assuming full conservation of all intact and frontier forests (IFF) and a second scenario without any IFF conservation. IFF is defined as undisturbed natural forest (i.e. the Amazonian rainforest) which includes intact forest landscapes and frontier forests [49]. IFF conservation in MAgPIE is modeled by excluding the IFF areas from the land area available for agricultural land expansion. Expansion involves additional costs for intraregional transport and physical conversion. Intraregional transport costs reflect the distance to the next market and account for the accessibility and quality of the infrastructure. The costs are based on GTAP transport costs [28] and a 30 arc-second resolution data set on travel time [50]. The second cost type, land conversion costs, involves the preparation of the land and basic infrastructure and is based on country-level marginal access costs [51].

We have chosen these two extreme scenarios to represent the full spectrum of possible policy decisions. On the one hand, forest protection is a clearly stated objective of many governments and international organisations [52] but on the other hand, deforestation of IFF is happening all over the world [53] and efficient protection mechanism are still lacking [54]. The scenarios help to make the full trade-off between agricultural land expansion and technological change transparent. Besides the differences in handling of the IFF areas, both scenarios apply the same conditions as explained in section 2.3.

3. Simulation Results

Figure 4 shows the projected τ development (2005-2060) for maize compared to past observations of the FAO (1960-2005) in the forest conservation scenario. Maize is chosen as an example since this is one of the most important crops and is grown in all parts of the world. Regions like Sub-Saharan Africa (AFR) and North America (NAM) show very strong increases in τ. However, the strongest increase is projected for the Middle East and North Africa region

(MEA). This enormous increase is in line with FAO data for this region for the period since the 1980s. Overall three groups can be distinguished: Regions with increasing growth rates (MEA, AFR), constant rates (NAM, LAM, SAS and PAS) and decreasing rates (CPA, EUR, FSU, PAO). PAO is a special case with small growth rates in the past but vanishing growth rates in the projections until 2040.

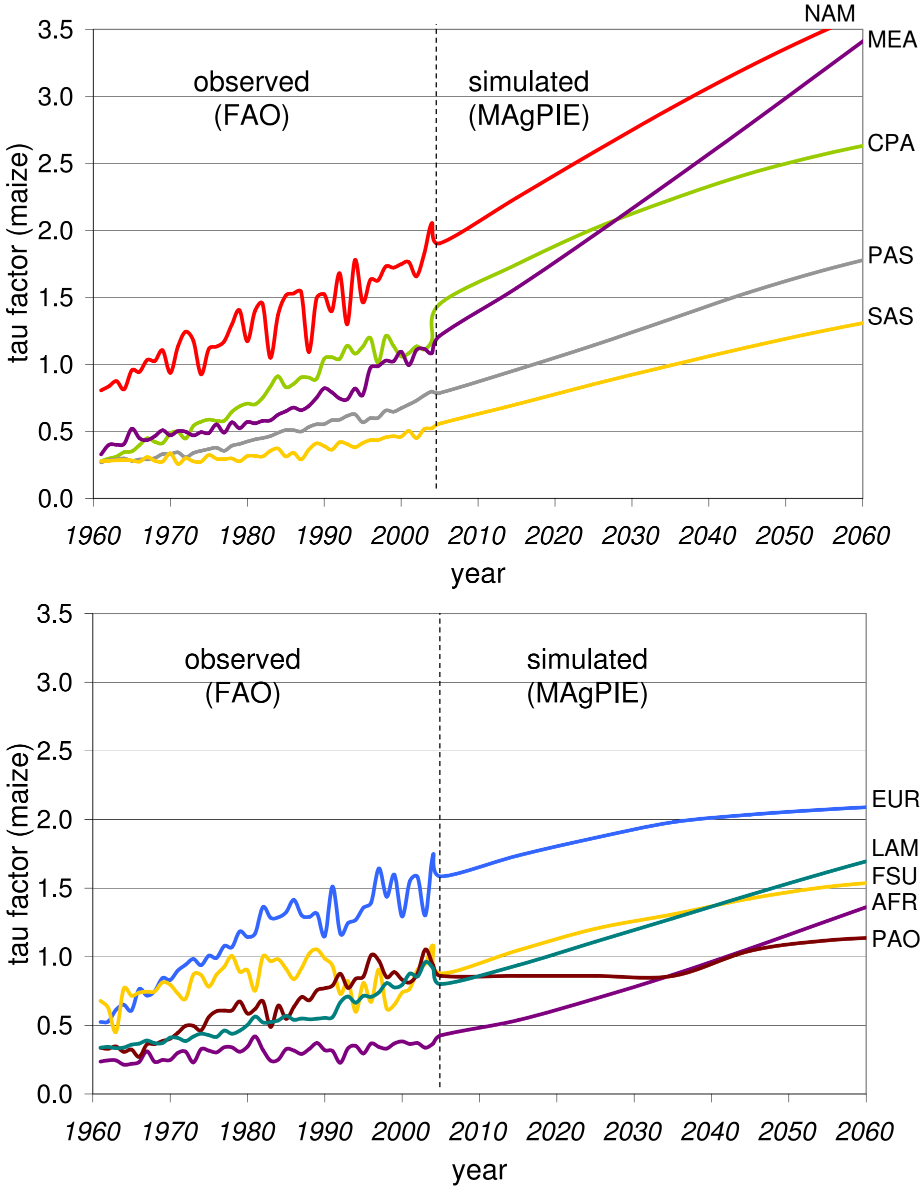

Figure 4: Observed and simulated τ-factor for maize in the ten world regions under a forest protection scenario

Figure 5 shows the model results of both scenarios (full forest conservation and no forest conservation) compared with FAO observations in greater detail for the aggregate of all crops. It is important to note that the FAO data used for validation was not taken as model input, neither as direct source, nor for calibration purposes. For a direct comparison between observations and model results, we focus on the overlap from 1995 to 2005. Moreover, the model results can be validated against the general trend in the observed data.

For some regions the scenario projections deliver quite similar or even identical results while the projections for other regions strongly depend on the chosen scenario. Especially, the three regions with huge rainforest areas (LAM, AFR, and PAS) show large differences in projections. Looking at these three regions also the agreement between observation and validation is quite diverse: In AFR historic growth rates are significantly lower compared to the rates of both projections. However, at the 10 year overlap (1995-2005) the differences are smaller, especially in the scenario without forest conservation. In contrast, LAM shows the exact opposite behavior. In the scenario without forest conservation, growth rates are underestimated, while in the forest conservation scenario projections are in good agreement with historic trends, although the model still seems to underestimate the observed growth rates in the overlapping period. In PAS, historic trends fit quite well to the forest conservation projection, whereas in the overlapping period observational data shows some stagnation. The projection without forest conservation illustrates the same effect, even though in a more extreme manner (20 years stagnation instead of only 5 years).

In the remaining regions the differences between both scenarios are small. For EUR, MEA, and NAM the general trend as well as the overlap show a good agreement between observation and simulation. In CPA the trend fits well, but in the observed data from 1995 on appears a stagnation (similar to the situation in PAS) which is not reproduced by the simulations. The results for FSU are hard to judge, because the historic data is strongly affected by fluctuations due to the political transformation after 1990. PAO shows weak growth rates in the historic trend, but none in the simulations until 2040 and none in the observed data between 1995-2005. For SAS it seems that both projections slightly overestimate the real trend, even though the differences are only marginal. Overall, we can state that none of the regions shows huge discrepancies between observation and simulation, but for some regions the forest-conservation scenario shows a better agreement (LAM, PAS) while other regions agree more with the no-forest-conservation scenario (AFR, CPA, SAS).

Differences in TC rates between scenarios also directly affect land use patterns. Figure 6 and 7 show the share of cropland in total land area in 2065 for the forest conservation scenario (Figure 6) and the scenario without forest conservation (Figure 7). The largest differences are obtained in the regions LAM, AFR and PAS, which are also most sensitive in the τ-factor comparison. In these three regions Brazil, the Democratic Republic of the Congo and Indonesia are most strongly affected from deforestation. Smaller changes are simulated in Canada, Russia, Mexico and Australia. Due to the absence of relevant IFF areas in the rest of the world, no other significant changes do occur.

4. Discussion

Technological change is the crucial driver for increasing agricultural yields. However, in land use models technological change is usually implemented in an exogenous way leading to static pathways without any dynamic interaction (i.e. [16, 17]). Reasons for this are manifold as described in section 1. The endogenous implementation of TC as described here now allows for better modeling of long-term land-use dynamics, even though some aspects, such as spillovers

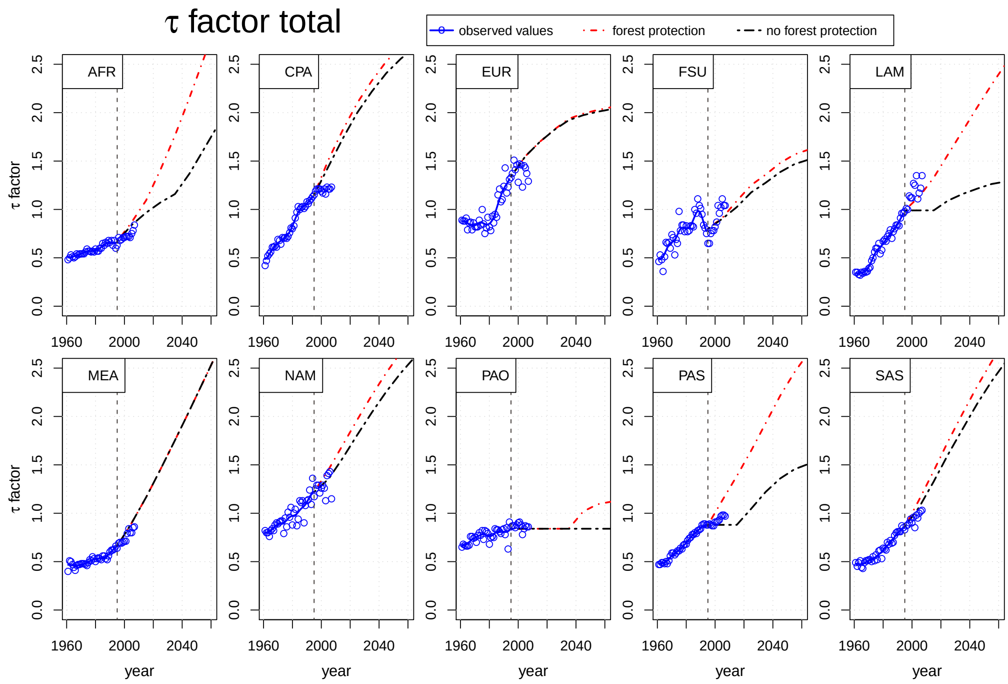

Figure 5: Comparison of MAgPIE model projections 1995-2060 in a forest protection scenario (red dotted line) and a scenario without forest protection (black dotted line) with FAO observations 1960-2005 (blue dots) and its running mean (blue line)

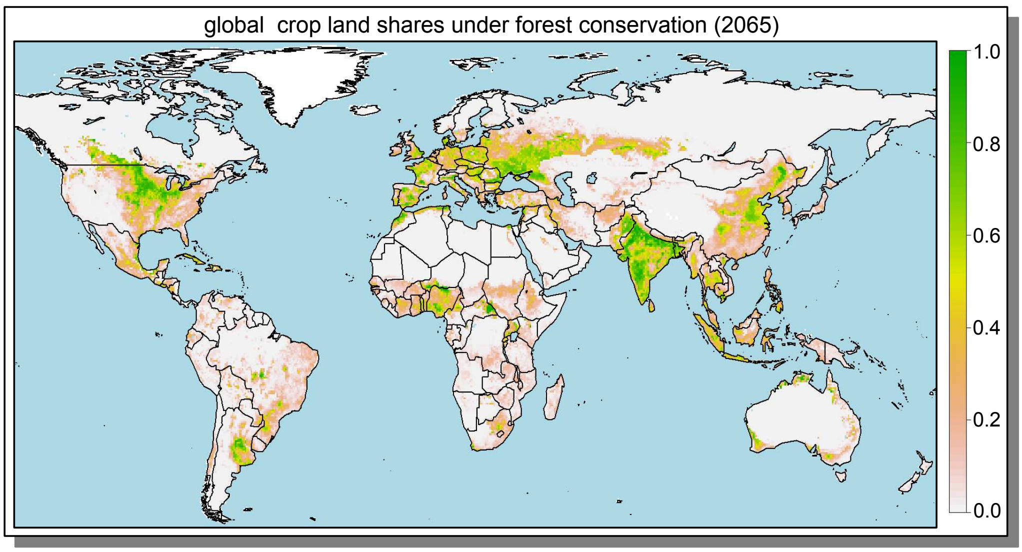

Figure 6: Global total cropland shares in a intact and frontier forest protection scenario in 2065

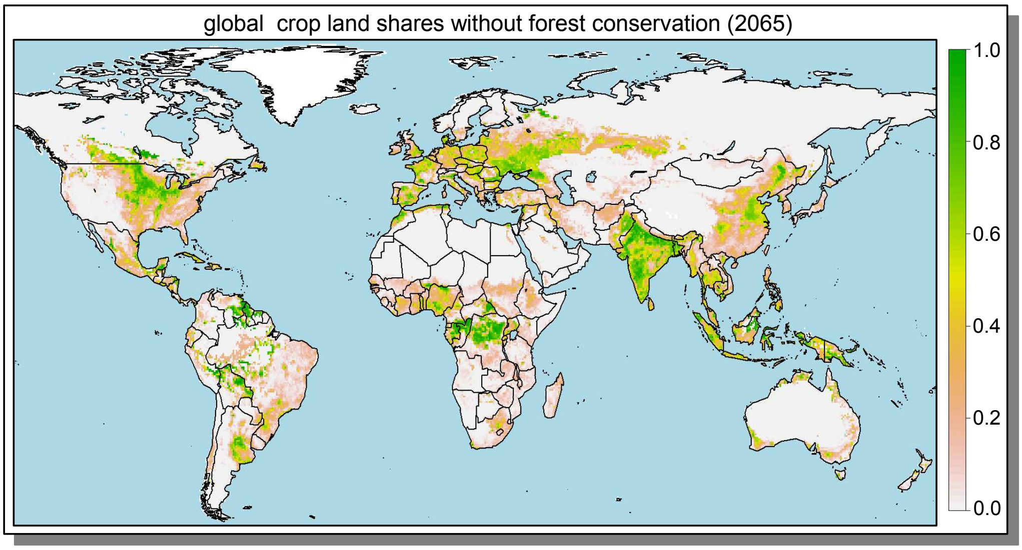

Figure 7: Global total cropland shares in absence of any intact and frontier forest protection in 2065

from R&D in other sectors, had to be taken as non-existent for lack of suitable data. The problems of high uncertainty and unpredictable rates of return associated with investments and the problem of spillovers are partially compensated for by using a high aggregation level of only ten world regions. On the other hand, this means that our approximation is only valid at coarse scales and becomes invalid when applied to finer scales. In addition, we address the problem of missing time series data by using the land use intensity indicator as proxy and assuming the same development path for all world regions. Our approach estimates the level and evolution of the investment-yield ratio relative to the τ factor, an output-related measure for agricultural land use intensity. The main advantage in this context over other measures, like the yield gap analysis [55], is that any yield increase due to improved technology will be reflected by an increase in τ, but may be at least partially undetected by the yield gap, as the potential yield rises as well and the gap remains constant. A more detailed comparison to other concepts which analyse agricultural potentials is provided in Dietrich et al. [26]. In addition to that, the τ approach conceptually does not contain any upper limit. What might be rather worrying from the perspective of current technologies and knowledge is an essential feature of the presented implementation necessary for long-term projections: While it is reasonable to assume upper yield limits in short- to medium-term analyses with relatively stable price structures and technologies, such an assumption is less appropriate for longer time scales or strong increases in market prices. Yield gap assessments are typically based on the current perception of the agricultural sector and evaluate potentials based on technologies which seem to be realistic assuming current market pressures. However, for long-term projections, investments in new technologies that are capable of achieving yields far beyond current levels should not be categorically ruled out - as they would if we define yield plateaus based on current knowledge and technologies. Example of such technologies include the transfer of C4 photosynthesis into C3 plants (e.g. [56]) although some assess the potential of such technologies to be small [57]. This could also be combined with fully artificial growing conditions that are not even limited by incoming radiation [58]. Producing crops on more than one level (or layer) will - from a technological perspective - easily allow to double or triple yield potentials per unit of land. Moreover, there are far more realistic technologies such as greenhouses which have the ability to push yields above the level reported by yield potential assessments. They are optimizing parameters such as temperature, solar radiation, water supply or CO_2 concentration which are often assumed non-manageable in analyses of potential yields (following the yield potential definition from [59]). Therefore, the presented approach does only limit the economic feasibility of TC, it does not introduce a general upper limit.

The regression analysis reveals that a higher level of agricultural land use intensity coincides with a higher IY ratio. Furthermore, the estimated yield elasticity with respect to accumulated TC investments $\epsilon_I^{yld} = 0.29$ is in line with an expert assessment [37]. Correlation results suggest that the yield level is correlated with production costs per area whereas marginal production costs are independent. That leads to an implementation in which every additional production unit faces the same amount of additional costs. Consequently, farmers in this setting will adopt the new technology since they expect higher yields at constant costs per ton.

Due to limited data availability the results of this analysis have to be treated with caution. In the absence of time series data on R&D investments the study relies on a single time slice. Therefore, the impact of time varying disturbances such as changing oil prices could neither be incorporated nor are they detectable in the given framework. Furthermore, the limited quality of data constrains the validity of the applied statistical evaluation. Better data availability in the future can help to check and improve the robustness of the presented results and the shape of the production cost-yield relationship. For the available data, this is best described by a linear form, even though a non-linear form would also be possible from a theoretical point of view.

Our τ projections for maize provide rich insights with regard to future yield trends. The strong increase in Africa indicates what kind of yield growth rates are required to meet the soaring demand under a forest conservation scenario. North America, as the leading region for maize production, continues with high yield growth rates. The Middle East and North Africa region (MEA) require even higher growth rates. This region faces unfavorable cropping conditions and at the same time a higher demand increase. Under these conditions, huge investments in technological change are required. In contrast, Europe continues along its trend over the past two decades when maize yields have not improved much. The Asian regions, starting from a lower yield level and facing a higher demand pressure in the future, have higher growth rates compared to Europe. Lastly, Latin America follows its strong yield growth path since the early 1990s, with high investments in the agricultural sector.

Judging the validation results it should be considered that the simulated data is not an interpolation of observed data. Both data sets are independent of each other. Notwithstanding, the validation indicates that our model results are in line with historical data. The long-term trend is reproduced well for most regions, while the observed data in the overlapping period 1995-2005 often shows some unexpected changes in dynamics, such as stagnation in some cases. A hint for an interpretation of these changes in dynamics can be found in the simulation results of the scenario without forest conservation: The projections for LAM as well as for PAS show also a temporary stagnation in growth rates similar to the observed stagnations in CPA and PAS. In the model, additional production is achieved exclusively by land expansion into IFF. However, in both regions the model switches again to yield increases due to technological change.

AFR is represented best by the scenario without forest conservation, LAM by the forest conservation scenario, and PAS by a mixture of both. This is in line with the political situation in these regions. While LAM is able to trigger investments in R&D on a level which is sufficient to remove the land expansion pressure based on agricultural demands (there are still other reasons for deforestation), AFR fails to do so. PAS seems to have a mixed situation with partial success. The results illustrate that, especially in AFR, R&D investments have to be increased tremendously to meet the demand without cutting down the rainforest in Central Africa. A possible reason for relatively weak validation results in a few regions is that demand and trade are rather inflexible in the current version of the MAgPIE model. In regions, like LAM or CPA, this might have strong impacts on future productivity levels.

5. Conclusion

During the lifetime of Thomas Malthus and before, growth in agricultural output was almost exclusively a result of growth in the use of input factors. This changed by the end of the 19th century and since then agricultural output has been mainly driven by increases in productivity. However, agricultural sector and land use models do not cover technological change as an endogenous driver. In order to fill this gap, we have presented a model approach for an endogenous implementation of technological change.

Our statistical analysis indicates that the investment-yield ratio increases in a disproportionate way to land use intensity (measured by the τ-factor) and that production costs are linearly correlated with yield levels. Our simulation model results show that regions with high demand projections, like Sub-Saharan Africa, or with low potentials for land expansion, like Middle East and South Asia, have to make huge investments in future technological change. While the Middle East region and South Asia show this trend already in the observed data, Sub-Saharan Africa shows this trend only since 1995. Hence, to meet the projected challenges in economic development and growing agricultural demand, it seems indispensable for countries in Sub-Saharan Africa to increase investments in R&D and infrastructure in order to meet the demand. The scenario on forest conservation exemplifies that investments in agricultural R&D have to be increased considerable in order to be able to protect sensitive forest areas under otherwise unchanged conditions.

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Appendix A. Population and GDP

year	1995	2005	2015	2025	2035	2045	2055	2065
AFR	553	743	926	1,125	1,313	1,481	1,629	1,753
CPA	1,281	1,480	1,582	1,651	1,673	1,677	1,659	1,632
EUR	554	589	586	575	559	532	505	480
FSU	276	293	295	295	285	275	262	246
LAM	452	550	623	687	739	780	810	830
MEA	278	357	423	486	541	590	633	671
NAM	292	332	355	375	391	400	404	403
PAO	134	145	148	147	146	144	140	132
PAS	383	462	517	565	614	652	674	684
SAS	1,270	1,572	1,797	1,998	2,149	2,265	2,347	2,398

Table A.5: Population in million from 1995 to 2065 aggregated to ten world regions [44]

year	1995	2005	2015	2025	2035	2045	2055	2065
AFR	1,513	1,627	1,826	2,080	2,448	3,221	4,242	5,430
CPA	3,299	5,855	8,908	12,311	16,270	20,512	24,720	28,579
EUR	16,128	20,123	25,189	30,654	36,115	41,080	45,851	50,672
FSU	3,521	4,081	6,094	8,496	11,143	15,264	20,235	25,698
LAM	6,527	7,840	9,769	11,853	14,131	17,144	20,809	24,989
MEA	4,940	5,855	7,352	9,215	11,408	14,142	17,346	21,002
NAM	26,765	33,920	39,349	44,489	49,842	55,597	61,383	67,106
PAO	21,469	24,240	28,672	34,841	41,224	45,297	49,037	52,935
PAS	3,649	4,614	6,692	9,324	12,371	16,211	20,322	2,569
SAS	1,461	2,139	3,181	4,406	5,805	7,769	9,827	11,923

Table A.6: GDP per capita (US$ per number of people in purchasing power parities (PPP)) [45]

Appendix B. Specific implementation characteristics of MAgPIE

For the implementation of technological change in MAgPIE some characteristics of the model and the agricultural sector have to be considered: Typically, for endogenous technology implementations in economic models an intertemporal optimisation approach is used due to the need of some kind of planning foresight [60]. In contrast, MAgPIE is a recursive dynamic optimisation model which solves each time step separately. To be able to reproduce planning foresight in MAgPIE we use the annuity approach to transfer lump-sum TC investment to periodic payments including interest [61]. Investment decisions are taken by the model under the assumption of a 20-year lifetime of TC yield gains.

Another issue is the implementation of a 15-year lag between R&D investment and yield impact. The model decides, based on the expectations for 15 years later, how much should be invested. However, since there is no other cross-connection between these time steps, it is possible to shift the investments to the time step when its impact takes place. This means: if the model needs yield growth in the year 2025 due to higher demand expectations, these 2025 model investments must have been made in 2010. However, the costs for R&D in 2010 in the model will be compounded and paid in 2025. This implementation allows for endogenising technological change in a land use model without using intertemporal optimisation.

A non-intertemporal implementation has the advantage of reproducing the observed effect of continuous underinvestment in agricultural R&D [62, 63]. This market failure is caused by the limited foresight of decision makers concerning investments in R&D [64]. An intertemporal optimisation model, however, would anticipate all the future benefits of R&D investments, which would lead to an optimal R&D investment path in R&D and an overestimation of yield increases, compared with observed trends.

Appendix C. MAgPIE mathematical description (TC Branch Rev 2987)

MAgPIE (Model of Agricultural Production and its Impact on the Environment) is a nonlinear recursive dynamic optimization model that links regional economic information with grid-based biophysical constraints simulated by the dynamic vegetation model LPJmL. A simulation run with the simulation period T can be described as a set

$$X = \{x_t \mid t \in T\} \subseteq \Omega \tag{C.1}$$

of solutions of a time depending minimization problem, i.e. for every timestep $t \in T$ the following constraint is fulfilled

$$\forall y \in \Omega : g_t(x_t) \leq g_t(y), \tag{C.2}$$

where the goal function for $t \in T$

$$g_t(x_t) = g(t, x_t, x_{(t-1)}, ..., x_1, P_t) \tag{C.3}$$

depends on the solutions of the previous time steps $x_{(t-1)}, ..., x_1$ and a set of time depending parameters P_t. We may interprete a MAgPIE simulation run $X = \{x_t \mid t \in T\} \subseteq \Omega$ as an element of the vector space $\Omega_T = \Omega \times T$.

Appendix C.1. Sets

The dimension of the domain Ω, on which for each timestep the minimization problem is defined, and of Ω_T depends on the following sets:

- $T = \{\text{time steps } t\}$: Simulation time steps, where t denotes the current time step, $t-1$ the previous time step and so on. The first simulated time step is $t = 1$.
- $I = \{\text{world regions } i\}$: Economic world regions in MAgPIE.
- $J = \{\text{spatial cells } j\}$: Highest disaggregation level in MAgPIE.
- $K = \{\text{simulated products } k\}$: Union of vegetal products V and livestock products L ($K = V \cup L$).

- $L = \{$simulated livestock products $l\}$: Products simulated within the livestock sector of MAgPIE.
- $V = \{$vegetal products $v\}$: Products simulated within the crop sector of MAgPIE.
- $W = \{$water supply types $w\}$: Currently two types are implemented: rainfed 'rf' and irrigation 'ir'
- $C = \{$crop rotation groups $c\}$: Groups of crops, which produce similar effects in terms of crop rotation.

To highlight the substance of our model equations with regard to the agricultural and economic contents, we split our variable x_t into

$$x_t = \left(x_t^{area} \in \Omega^{area}, x_t^{prod} \in \Omega^{prod}, x_t^{tc} \in \Omega^{tc} \right) \in \Omega, \tag{C.4}$$

where the respective domains can be identified as the following vector spaces

$$\Omega^{area} = \mathbb{R}^{|J|} \times \mathbb{R}^{|V|} \times \mathbb{R}^{|W|} \tag{C.5}$$

$$\Omega^{prod} = \mathbb{R}^{|J|} \times \mathbb{R}^{|L|} \tag{C.6}$$

$$\Omega^{tc} = \mathbb{R}^{|I|} \tag{C.7}$$

As a result, we may specify the dimension of the solution space for each timestep as $dim\Omega = |J| \cdot |V| \cdot |W| + |J| \cdot |L| + |I|$ and the dimension of $\Omega_T = \Omega \times T$ as $dim\Omega_T = |T| \cdot dim\Omega = |T| \cdot (|J| \cdot |V| \cdot |W| + |J| \cdot |L| + |I|)$.

In the following, variables and parameters are provided with subscripts to indicate the dimension of the respective subdomains. Subscripts written in quotes are single elements of a set. The order of subscripts in the variable, parameter and function definitions does not change. The names of variables and parameters are written as superscript.

Appendix C.2. Variables

Since MAgPIE is a recursive dynamic optimization model, all variables refer to a certain time step $t \in T$. In each optimization step, only the variables belonging to the current time step are free variables. For all previous time steps, values were fixed in earlier optimization steps. As we have seen above, we currently distinguish three variables $x_t^{area} \in \Omega^{area}$, $x_t^{prod} \in \Omega^{prod}$ and $x_t^{tc} \in \Omega^{tc}$ that can be described as follows:

- $x_{t,j,v,w}^{area}$: The total area of each vegetal production activity v for each water supply type w, each cell j and each time step t [ha]
- $x_{t,j,l}^{prod}$: The total production of each livestock product l, for each cell j at each time step t [ton dry matter]
- $x_{t,i}^{tc}$: The amount of yield growth triggered by investments in R&D [-]

Appendix C.3. Parameters

Besides variables, the model is fed with a set of parameters P_t. These parameters are computed exogenously and are in contrast to variables of previous time steps fully independent of any simulation output. Although most parameters are time independent, there exist also some parameters which are time dependent.

- $p^{yield}_{t,j,v,w}$: Yield potentials for each time step, each cell, each crop and each water supply type taking only natural variations into account and excluding changes due to technological change [ton/ha]
- $p^{dem}_{t,i,k}$: Regional food and material demand in each time step for each product [10^6 ton]
- $p^{fshr}_{i,l,k}$: Feed share describing the share of each product k of total feed production for livestock product l and corresponding transformation from GJ feed in ton dry matter [ton/GJ]
- $p^{feed}_{i,l}$: Feed requirements for each livestock product l in each region i [GJ/ton]
- $p^{byprod}_{i,k,l}$: Feed energy delivered by the byproducts of k that are avaiable as feedstock for the livestock product l [GJ/ton]
- $p^{frv}_{i,v}$: Area related factor requirements for each crop and each region. The parameter is the product of observed yields in 1995 [65] and the production costs shown in table 4 [US$/ha]
- $p^{frl}_{i,l}$: Production related factor requirements for livestock products for each livestock type and each region [US$/ton]
- p^{lcc}_{i}: Area related land conversion costs for each region [US$/ha]
- p^{tcc}: Technological change costs factor containing an interest correction, an expected lifetime factor and a general cost factor [US$/ha]
- $p^{\tau 1}_{i,v}$: τ-Factor representing the agricultural land use intensity in the first simulation time step for each crop in each region [-]
- p^{cxp}: Correlation Exponent between τ-Factor and technological change costs [-]
- $p^{seed}_{i,v}$: Share of production that is used as seed for the next period calculated for each crop in each region [-]
- $p^{xs}_{t,i,k}$: Regional excess supply for each product and each time step describing the amount produced for export [10^6 ton]
- $p^{sf}_{i,k}$: Regional self sufficiencies for each product [-]
- p^{tb}: Trade balance reduction factor. This factor is always less or equal 1 and is used to relax the trade balance constraints depending on the particular trade scenario.
- p^{land}_{j}: Total amount of land available for crop production in each cell [10^6 ha]
- $p^{ir.land}_{j}$: Total amount of land equipped for irrigation in each cell [10^6 ha]
- $p^{watreq}_{j,k}$: Cellular water requirements for each product [$m^3/ton/a$]

- p_j^{water}: Amount of water available for production in each cell $[m^3/a]$
- p_c^{rmax}: Maximum share of crop groups in relation to total agricultural area [-]
- p_c^{rmin}: Minimum share of crop groups in relation to total agricultural area [-]

[all ton units in dry matter]

Appendix C.4. Sub-functions

To lighten the general model structure, some model components which appear more than once in the model description and depend on the variables of the current time step t are arranged as functions:

$$f_{t,i}^{growth}(x_t) = \prod_{\tau=1}^{t} (1 + x_{\tau,i}^{tc}) \tag{C.8}$$

$$f_{t,i,k}^{prod}(x_t) = \sum_{j_i} \begin{cases} x_{t,j,k}^{prod} & : k \in L \\ \sum_w x_{t,j,k,w}^{area} p_{t,j,k,w}^{yield} f_{t,i}^{growth}(x_t) & : k \in V \end{cases} \tag{C.9}$$

$$f_{t,i,k}^{dem}(x_t) = p_{t,i,k}^{dem} + \sum_l p_{i,l,k}^{fshr} \left(p_{i,l}^{feed} f_{t,i,l}^{prod}(x_t) - \sum_\kappa p_{i,\kappa,l}^{byprod} f_{t,i,\kappa}^{prod}(x_t) \right). \tag{C.10}$$

- $f_{t,i}^{growth}$: Growth function describing the aggregated yield amplification due to technological change compared to the level in the starting year for each year t and region i.
- $f_{t,i,k}^{prod}$: Function representing the total regional production of a product k in region i at timestep t. In the case of vegetal products, it is derived by multiplying the current yield level with the total area used to produce this product. In the case of livestock products, it is represented by the related production variable.
- $f_{t,i,k}^{dem}$: Function defining the demand for product k in region i at timestep t. It consists of an exogenous demand for food and materials $p_{t,i,k}^{dem}$ and an endogenous demand for feed, which is calculated as the feed demand generated by the livestock production minus the feed supply gained through byproducts.

Appendix C.5. Goal function

$$g_t(x_t) = g(t, x_t, x_{(t-1)}, ..., x_1, P_t) \tag{C.11}$$

The goal function describes the value that is minimized in our recursive dynamic optimization model structure in each timestep. It is time dependent, i.e it differs for each time step, depending on the solutions of the previous time steps. We define the goal function as follows (with $\Theta(x)$ as Heaviside step function):

$$
\begin{aligned}
g_t(x_t) = &\sum_{i,v} \left(p_{i,v}^{frv} f_{t,i}^{growth}(x_t) \sum_{j_i,w} x_{t,j,v,w}^{area} \right) \\
&+ \sum_{i,l} \left(p_{i,l}^{frl} f_{t,i,l}^{prod}(x_t) \right) \\
&+ \sum_{i} \left(p_i^{lcc} \sum_{j_i,v,w} \left(x_{t,j,v,w}^{area} - x_{t-1,j,v,w}^{area} \right) \Theta \left(x_{t,j,v,w}^{area} - x_{t-1,j,v,w}^{area} \right) \right) \\
&+ p^{tcc} \sum_{i} \left(x_{t,i}^{tc} \left(\frac{1}{|V|} \sum_{v} p_{i,v}^{\tau 1} f_{t,i}^{growth}(x_t) \right)^{p^{cxp}} \sum_{j_i,v,w} x_{t-1,j,v,w}^{area} \right).
\end{aligned}
\tag{C.12}
$$

The function describes the total costs of agricultural production. The total costs can be splitted in four terms: 1. The area depending factor costs of vegetal production, which increase with the yield gain due to technological development. 2. The factor costs of livestock production depending on the production output. 3. The land conversion costs which arise, when non-agricultural land is cleared and prepared for agricultural production. 4. The costs, which arise by investing in technological development to increase yields by new inventions and improvements in management strategies. The technological change costs are proportional to the total cropland area of a region and increase disproportionate with the yield growth bought in the current timestep and the agricultural land-use intensity.

Appendix C.6. Constraints

Constraints are used to describe the boundary conditions, under which the goal function is minimized.

Appendix C.6.1. Global demand constraints (for each activity k)

$$
\sum_i \frac{f_{t,i,k}^{prod}(x_t)}{1 + p_{i,k}^{seed}} \geq \sum_i f_{t,i,k}^{dem}(x_t) \tag{C.13}
$$

These constraints describe the global demand for agricultural commodities: The total production of a commodity k adjusted by the seed share required for the next production iteration has to meet the demand for this product.

Appendix C.6.2. Tradebalance (for each region i and product k)

$$
\frac{f_{t,i,k}^{prod}(x_t)}{1 + p_{i,k}^{seed}} \geq p^{tb} \begin{cases} f_{t,i,k}^{dem}(x_t) + p_{t,i,k}^{xs} & : p_{i,k}^{sf} \geq 1 \\ f_{t,i,k}^{dem}(x_t) p_{i,k}^{sf} & : p_{i,k}^{sf} < 1 \end{cases} \tag{C.14}
$$

The trade balance constraints are similar to the global demand constraints, except that it acts on a regional level. In the case of an exporting region (self sufficiency for the product k is greater than 1), the production has to meet the domestic demand supplemented by the demand caused due to export. In the case of importing regions (self sufficiency less than 1), the domestic demand is multiplied with the self sufficiency to describe the amount which has to be produced by the region itself. In both cases the demand is multiplied with a so called ”trade balance reduction factor”. This factor is always less or equal 1 and is used to relax the trade balance constraints depending on the particular trade scenario, that is run.

Appendix C.6.3. Land constraint (for each cell j)

$$\sum_{v,w} x^{area}_{t,j,v,w} \leq p^{land}_{j} \tag{C.15}$$

$$\sum_{v} x^{area}_{t,j,v,'ir'} \leq p^{ir.land}_{j} \tag{C.16}$$

The land constraints guarantee, that no more land is used for production than available. The first set of land constraints ensures the land availability for agricultural production in general. The second one secures, that irrigated crop production is restricted to areas that are equipped for irrigation.

Appendix C.6.4. Water constraints (for each cell j)

$$\sum_{v} x^{area}_{t,j,v,'ir'} p^{yield}_{t,j,v,'ir'} f^{growth}_{t,i(j)}(x_t) p^{watreq}_{j,v} + \sum_{l} x^{prod}_{t,j,l} p^{watreq}_{j,l} \leq p^{water}_{j} \tag{C.17}$$

In MAgPIE, the production of animal commodities as well as vegetal goods produced with irrigation requires water. The required amount of water is proportional to the production volumne. The whole cellular water demand must be less or equal to the water available for production in this cell.

Appendix C.6.5. Rotational constraints (for each crop rotation group c, cell j and irrigation type w)

$$\sum_{v_c} x^{area}_{t,j,v,w} \leq p^{rmax}_{c} \sum_{v} x^{area}_{t,j,v,w} \tag{C.18}$$

$$\sum_{v_c} x^{area}_{t,j,v,w} \geq p^{rmin}_{c} \sum_{v} x^{area}_{t,j,v,w} \tag{C.19}$$

The rotational constraints are used to describe crop rotations, but also other aspects such as cultural preferences or efforts of autonome food production systems. This is achieved by defining for each vegetal product a maximum and minimum share relative to total area under production in a cell. While crop rotation structures are exclusively described with the maximum share constraints, cultural preferences and autonomy efforts are basically described with the minimum constraints.

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