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Beyond land-use intensity: Assessing future global crop productivity growth under different socioeconomic pathways

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Highlights

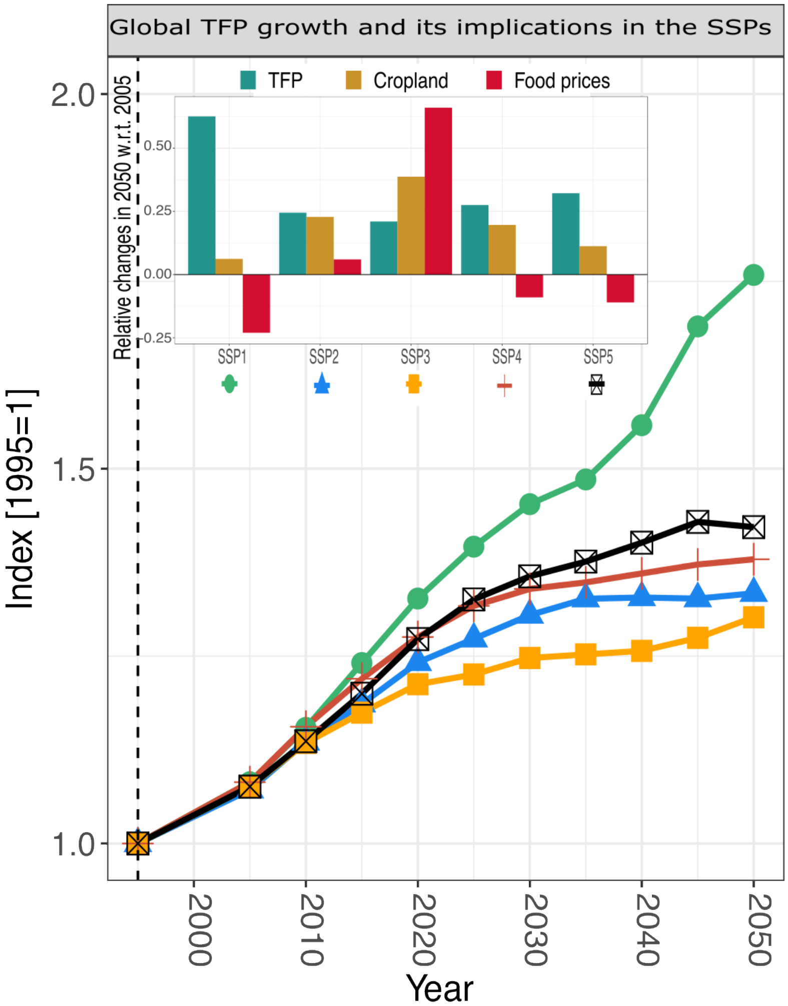
- The study combines agricultural modeling with TFP estimates to project productivity changes.
- The study explores the productivity implications of Shared Socioeconomic Pathways.
- The ratio of cropland expansion to productivity growth impacts changes in food prices.
- Investing in productivity improvement is an effective means of ensuring food availability.
- Different measures highlight different parts of the productivity changes in the scenarios.

Abstract

Productivity growth is essential to meet the increasing global agricultural demand in the future, driven by the growing world population and income. This study develops a hybrid approach to assess future global crop productivity in a holistic way using different productivity measures and improves the understanding of productivity implications of socioeconomic factors by contrasting different shared socioeconomic pathway assumptions. The results show that the global productivity is likely to continue to grow, whereas the productivity growth varies pronouncedly among different future socioeconomic conditions. The fast growth of total factor and partial factor productivity can be reached when slow population growth and high economic growth entail moderate food demand and low investment risks. In contrast, high population growth and low economic growth could lead to relatively high land-use intensity due to the extreme pressure on agricultural production, however, associated with low total factor productivity growth. The model results indicate that the ratio of the total factor productivity growth to cropland expansion has significant impacts on food prices, with increasing prices when cropland increases faster than productivity, and vice versa. Investing in productivity improvement appears to be an effective means of ensuring food availability and sparing cropland, contributing to the achievement of sustainable development goals.

Keywords: endogenous technological change; productivity growth; land-use intensification; cropland expansion; socioeconomic pathways

Graphical abstract



1 Introduction

Agricultural development is essential in the broader development context, exerting impacts not only on poverty reduction and food security but also on ecosystems (Barrett et al., 2010; Sayer and Cassman, 2013; Wang et al., 2016). Increasing output in the agricultural sector in the past mainly depended on land expansion (Hansen and Prescott, 2002). It is estimated that the global cropland area and grassland area increased by approximately 1,500 million hectares and 2,600 million hectares, respectively, in the past three centuries (Lambin et al., 2003). Although the pace of land expansion has been lower in the past decades and a significant decoupling between food production increases and cropland expansion has occurred since 1960 (Lambin et al., 2003), land expansion is still taking place, some of which is on plots with high ecological value. Overall, 83% of all newly converted agricultural land from the 1980s to 2000s was formerly tropical forest (Gibbs et al., 2010), and deforestation contributed to 12–20% of the global anthropogenic carbon emissions in the last two decades (van der Werf et al., 2009). The exact amount of land needed for agricultural production varies, depending on the state of the applied agricultural technology and land quality (Lotze-Campen et al., 2010; Wang et al., 2016). For instance, technological progress associated with the green revolution successfully increased crop yields without a corresponding expansion of cropland to meet the increasing food needs of Asia's growing population (Sayer and Cassman, 2013).

To meet future agricultural demand, technological progress in the agricultural sector has become more critical than ever (Wiebe et al., 2003; Tester and Langridge, 2010). The essential role of technologies in promoting agricultural productivity and inclusive economic growth is widely recognized (Barrett et al., 2010), and the intrinsic properties of technological change (TC) are extensively studied (Arrow, 1962; Romer, 1986; Lucas, 1988; Romer, 1990). In contrast to the assumption about exogenous TC in the early neoclassical growth theory (Solow, 1957), TC is found to be an endogenous process (Arrow, 1962; Lucas, 1988; Romer, 1990). In the agricultural sector, TC can occur through the adoption of new crop varieties, management improvements, and the expansion of irrigation infrastructures (Griliches, 1957; Lin, 1991; Schneider et al., 2011; Baker et al., 2012). Advancing agricultural technology is generally triggered by investment in R&D (Griliches, 1963) and can be associated with population pressure (Boserup, 1975), while the underlying driving forces for advancing agricultural technology are changes in relative resource endowments and factor prices (Ruttan, 2002). The importance of the endogeneity of TC is recognized by modelers, but studies often assume that it is exogenous due to limited data. To study the impacts of productivity changes on land use changes and food security, existing economic models often treat productivity changes as parameters, either as a shifter of crop yields in partial equilibrium models (Robinson et al., 2014) or as a factor that alters productivity level in a production function in general equilibrium models (Hertel et al., 2016), while few exceptional analyses assume endogenous TC (van der Mensbrugghe, 2005; Dietrich et al., 2014; Akgul et al., 2016).

Different methods have been employed to improve productivity measures (Alston, 2018). The methodological differences reflect the conceptual differences between partial factor productivity (PFP) and total factor productivity (TFP). Productivity measured as PFP (Wiebe et al., 2003; Rozelle and Swinnen, 2004; Verburg et al., 2008; Havlík et al., 2013) is informative for understanding the underlying factors behind productivity changes but can be misleading since not all production inputs are taken into account. For instance, high crop yields may be driven by high fertilizer use or high labor input. Hence, despite increased land productivity, overall productivity might remain constant or even deteriorate. In contrast to PFP measures, TFP provides a holistic measure of the productivity growth attributed to all input factors (Ludena et al., 2007; Fuglie, 2008). The social accounting approach (Fuglie, 2008; Solow, 1957) or econometric techniques (Ludena et al., 2007) can be used to estimate TFP changes. A reduced form, with a lack of economic behavioral assumptions, is often used in empirical studies to simplify the estimation (Del Gatto et al., 2011)[1], although it provides, to some extent, comparable estimates as the structural approach (Gong and Sickles, 2020). However, there is seldom a prediction of TFP due to the uncertainty in the future, although it is equally important to have (Hertel et al., 2016). Exceptionally, Ludena et al. (2007) provide forecasts of TFP based on the assumptions of trends in technological changes and extrapolations of efficiency changes using estimates from logistic regressions. The prediction relies on information from limited time series data without considering possible structural changes in the future (e.g., changes in the food demand, demography and biofuel demand), which could potentially underestimate or overestimate productivity changes.

To fill the existing gaps and to improve the understanding of productivity changes under future socioeconomic conditions, this study combines agricultural modeling with TFP estimation techniques in a two-step approach. This approach not only facilitates the projection of endogenous PFP changes induced by TC and land expansion, as reported by the applied model but also extends it with TFP estimates derived in an ex-post analysis. In the first step, it employs a quantitative economic modeling approach to simulate the endogenous land-use intensity growth in the crop sector under different future socioeconomic scenarios. In the second step, the study applies a nonparametric estimation method to estimate TFP changes with the Malmquist productivity index (MPI) based on simulated crop production to further complement the analysis. To overcome the dimensionality issue related to estimating the global TFP, this study uses a theoretically sound approach by constructing a weighted average index based on the distance functions estimated from the regional data. This study also contributes to the strand of literature that uses structural equation models and CGE models to understand the interactions between all these underlying factors and their mutual interactions (De Loecker, 2007; Akgul et al., 2016; Balistreri et al., 2018) by providing detailed information on the agricultural and land-use sectors.

The remainder of the article is organized as follows. Section 2 introduces the model structure and the methods for measuring productivity changes. Section 3 briefly describes the scenarios based on the Shared Socioeconomic Pathways (SSPs) and the representation of the major features in the modeling framework. The results about projections of land productivity and TFP growth at

[1] One exceptional study is De Loecker (2007) who uses the Olley–Pakes method, a structural model, to estimate the impact of trade on productivity changes.

the global and regional levels in the SSPs are presented, and their interactions with cropland expansion and impacts on food prices are discussed in Section 4. Section 5 draws the conclusions.

2 Methods

2.1 Simulation method

MAgPIE (Model of Agricultural Production and its Impact on the Environment) is a partial equilibrium, agro-economic model for the optimization of land use and production patterns under given agricultural demand and subject to spatially explicit biophysical constraints (Lotze-Campen et al., 2008; Popp et al., 2014). The model covers 10 world regions[2] (Supplementary information **Error! Reference source not found.**), the classification of which is based on the geo-economic conditions of each country. The food demand for crop and livestock products enters the model as exogenous projections based on the population and income growth and dietary preferences (Bodirsky et al., 2015). The demand for crop products is divided into four sub-categories, including the food demand, material and seed demand, feed demand and bioenergy demand. Increasing agricultural yields through technological investments and cropland expansion is the primary means of providing a sufficient supply of agricultural goods (Dietrich et al., 2014). International trade is implemented based on self-sufficiency ratios and regional comparative advantages to reallocate production among regions (Schmitz et al., 2012). A trajectory of trade barrier reductions is assumed over time, indicating increasing trade openness. The major associated costs are technological investments, land conversion costs, costs of production input factors, and transportation costs. Socioeconomic constraints such as trade liberalization in terms of fast trade barrier reductions are prescribed at the regional level, while biophysical constraints such as crop yield potentials and water availability derived from the global crop, hydrology and vegetation model LPJmL (Bondeau et al., 2007; Müller and Robertson, 2014) and land availability are prescribed at the 0.5 degree grid level (Krause et al., 2013). The presented simulation covers the period from 1995 to 2050 at intervals of five years with 500 simulation units based on a k-means clustering algorithm aggregating 59,199 spatial grid cells (Dietrich et al., 2012) to facilitate nonlinear optimization. The detailed documentation of the model is archived online (Dietrich et al., 2019)[3].

2.2 Computing productivity indices beyond the land-use intensity

MAgPIE is in line with the induced innovation theory (Ruttan, 2002). The representation of the endogenous TC entails an explicit specification of the maximizing behavior by producers subject to technology constraints and input costs, which is a key feature distinguishing MAgPIE from other partial equilibrium models, such as GCAM, IMPACT, and GLOBIOM (Valin et al., 2013; Robinson et al., 2014). The endogenous implementation of TC in MAgPIE provides a projection of the land-use intensity (see the details in S2). It is an output-oriented measure of land

[2] AFR is Sub-Saharan Africa; CPA includes China and other centrally planned countries in East and Southeast Asia; EUR is Europe; FSU contains regions in the former Soviet Union; LAM is Latin America; MEA is the Middle East and North Africa region; NAM refers to the U.S.A and Canada; PAO is the Pacific OECD countries, excluding South Korea, i.e., Japan, Australia, and New Zealand; PAS is mainly island countries in Southeast Asia; and SAS includes India, Pakistan and other countries in South Asia.

[3] The online documentation is archived from https://redmine.pik-potsdam.de/projects/magpie/wiki.

productivity, representing the increase of yields due to a potential suite of changes in management and technological advances without considering biophysical characteristics (Dietrich et al., 2014).

In addition to the land-use intensity measure, average yields are computed to represent another form of land productivity. As shown in equation (1), they can be decomposed as a product of the cumulative land-use intensity in region i at time t, $f_{i,t}^{growth}(\cdot)$, and a weighted mean of the observed yields in the initial period for spatial unit j for crop k and irrigation type w, $p_{j,k,w}^{refyield}$, with weights $\omega_{j,t,k,w}$. To reduce the complexity, climate impacts on yields are excluded in the study, and therefore the initial biophysical yield potential remains constant over time. The initial yields represent the land quality, which is determined by the water availability and other biophysical conditions. Increasing land-use intensity will raise the average yields, as stated in *proposition S.1*. Because the initial yields vary among different spatial units and between different irrigation types of cropland, cropland expansion can lead to either an increase or decrease of the average yields (*proposition S.2*). This indicates that the yield increase is driven by improved land-use intensity and is affected by cropland expansion involving heterogeneous land quality that depends on the attributes of the cropland, such as the available water for irrigation.

$$x_{i,t}^{yield} = \frac{\sum_k x_{i,t,k}^{production}}{\sum_k x_{i,t,k}^{area}}$$

$$= f_{i,t}^{growth}(\cdot) \sum_k \sum_{j_i} \sum_w \omega_{j,t,k,w} p_{j,k,w}^{refyield} \tag{1}$$

where $\omega_{j,t,k,w} = \frac{x_{j,t,k,w}^{area}}{\sum_k \sum_{j_i} \sum_w x_{j,t,k,w}^{area}}$

While the land-use intensity and yield index measure the PFP by focusing on a specific input (in this case land), the TFP indicates the changes in the productivity by accounting for all the inputs. In this study, the TFP change is estimated as an (output-oriented) MPI, which is based on the estimate of the Shephard output distance function using data envelopment analysis (DEA) to construct a piecewise linear production frontier for each year in the sample (Färe et al., 1994; Nin et al., 2003; Coelli and Rao, 2005). It treats the aggregated amount of crop commodities as outputs, y, and the cropland area, production factors and amount of water used as inputs, x_n. The distance function[4] is $D_o(x,y) = (sup\{\theta: (x, \theta y) \in S\})^{-1}$, where S denotes the production technology transforming inputs $x \in R_+^N$ into possible outputs $y \in R_+^M$: $S = \{(x,y)\ such\ that\ x\ can\ produce\ y\}$, and θ is the infimum coefficient for dividing y to project the observed output vector radially on the frontier production vector, given x (Nin et al., 2003). The MPI is estimated as the geometric mean of two Malmquist matrixes by solving the following linear-programming problems to obtain estimations of four types of distance functions[5] (Färe et al., 1994).

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[4] It is identical to $D_o(x,y) = inf\{\theta: (x, y/\theta) \in S\}$.

[5] $D_t(x_{t,}y_t)$ is a column vector of the distance function for all the regions, e.g., $D_t(x_{t,}y_t) = \left(D_{1,t}(x_{1,t,}y_{1,t}), \ldots, D_{I,t}(x_{I,t,}y_{I,t})\right)$. The notation in the distance functions and MPI is in line with Färe et al., 1994, but it slightly differs from that in the other indices. x refers to the input and y is the output. The specification should be clear in the context.

$$
\begin{aligned}
&(D_{\psi}(x_{ii,\phi}, y_{ii,\phi}))^{-1} = max\theta_{ii} \\
&\quad s.t. \\
&\quad \theta_{ii} y_{ii,\phi,n} \leq \textstyle\sum_{i=1}^{I} z_{i,\psi}\, y_{i,\phi,n} \\
&\quad \textstyle\sum_{i=1}^{I} z_{i,\psi}\, x_{i,\phi,m} \leq x_{ii,\phi,m} \\
&\quad z_{i,\phi} \geq 0 \\
&\quad \psi, \phi = s, t
\end{aligned}
\tag{2}
$$

where $i, ii \in \{1, \ldots, I\}; I = 10; t \in \{1, \ldots, T\}; T = 11$; $x_{i,\phi,m}$ refers to m inputs and $y_{i,\phi,n}$ is n outputs in time step ϕ. In the presented analysis, $M = 3$ includes the production factor requirement costs (a package of capital, labor and fertilizer costs in MAgPIE), cropland area and amount of water used for irrigation. $N = 1$ refers to the aggregated crop production, and $z_{i,\psi}$ is the weights applied to both the inputs and outputs in time step ψ. We assume constant returns to scale so that no additional constraints on the weights are required.

The MPI is then calculated using the following general form:

$$
M(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{D_{t+1}(x_{t+1,}y_{t+1})}{D_t(x_{t,}y_t)} \left[\frac{D_t(x_{t+1,}y_{t+1})}{D_{t+1}(x_{t+1,}y_{t+1})} \frac{D_t(x_{t,}y_t)}{D_{t+1}(x_{t,}y_t)} \right]^{\frac{1}{2}} \tag{3}
$$

The TFP change can be decomposed into the shift of technology (i.e., technical change, the part inside the square brackets, which is estimated as the geometric mean of the technological shifts evaluated at t and $t+1$), and the catch-up to the frontier (the part outside the square brackets) (Färe et al., 1994). The latter refers to the gaps between the observed production and the maximum potential production for the two time steps, representing that regions converge toward the long-term production frontier. The long-term production frontier is SSP-specific, but it is assumed to be common for all the regions in a single SSP. To overcome the dimensionality problem (Coelli and Rao, 2005), various crops are aggregated into one single output for the estimation of the MPI. Different from constructing land quality indicators based on shares of irrigated land to correct the biases in the analysis of the TFP (Craig et al., 1997; Wiebe et al., 2003; Fuglie, 2008), we estimate the MPI by considering the amount of water directly as an input, which represents the land quality adjusted by the weights for irrigated and rain-fed cropland.

Estimating the global MPI directly for each SSP is infeasible because the linear programming problems for the estimation cannot be solved. To overcome this problem, studies incorporate global data directly with regional data (Ludena et al., 2007), but this violates a key assumption of DEA that the production units under assessment are comparable to each other (Dyson et al., 2001). A more theoretically sound way to compute the global MPI is by constructing a weighted average index based on the distance functions estimated from the regional data with appropriate weighting (Färe and Zelenyuk, 2003; Coelli and Rao, 2005). The aggregation scheme in this study is adopted according to the method derived by Färe and Zelenyuk (2003) and Zelenyuk (2006) based on production duality (see the details in S4). Similar to the regional MPI, the global MPI can also be decomposed into the shift of the production frontier and the catch-up to the frontier. To sum up, this study applies a modeling approach in combination with nonparametric estimation (Tab.1) to study the channels of improving productivity and its interaction with cropland expansion and impacts on food prices.

Tab.1. Main features of the different productivity measures used in the study.

Productivity index	Type of productivity measure	Included input factors	Estimation method
Land-use intensity	PFP	Investment in R&D, production factor costs	Endogenously determined by solving the optimization problem
Average yields	PFP	Investment in R&D, production factor costs, cropland area	Postcalculation based on the model output
MPI	TFP	Production factor costs, cropland area, used water amount	Postcalculation based on the model output

3 Scenarios

3.1 Shared socioeconomic pathways

In the future, as the global population continues to grow, intertwined with higher purchasing power, especially in developing and emerging countries, increasing demand for crops and livestock products can be anticipated (Bodirsky et al., 2015; Ruttan, 2002). Since the demand strongly depends on uncertain trends such as population and economic growth, it is unclear how the demand for agricultural goods will evolve, and it is uncertain how land dynamics, especially productivity patterns, will respond to the future demand. The recently developed SSP framework, depicting the plausible future changes in demographics, the economy, technology, and the environment (O'Neill et al., 2017; Popp et al., 2017; Riahi et al., 2017), has been applied in combination with the modeling approach to explore the coherent formulation of strategies for achieving the sustainable development goals (SDGs) (van Vuuren et al., 2015; Obersteiner et al., 2016). The SSP framework will be used in this study to construct five different scenarios with respect to the socioeconomic conditions for the analysis.

3.2 Assumptions of relevant factors in SSPs

Different assumptions of SSPs regarding the stylized indicators are shortly introduced as follows.

- SSP1 (Sustainability): A sustainably developed world with low population growth and high per-capita income, along with reduced global inequalities. These developments go hand in hand with high education and fast technological progress, also in the agricultural sector. The lifestyles are sustainable and the environmental legislation is progressive.
- SSP2 (Middle of the road): A middle of the road scenario means business as usual, keeping the currently observed trends. SSP2 is considered to be the benchmark in this study.
- SSP3 (Regional rivalry): A world with regional conflicts and limited cooperation between regions, e.g., trade conflicts, leads to reduced global trade flows, slow technological

change and development, a fast growing population, low investments in human capital, and unfavorable and weak institutions.

- SSP4 (Inequality): A separate and unequal world in which there is rapid technological development and economic growth in developed regions while some of the least-developed regions become disconnected from progress in the remaining world and face high population growth, poor governance and low economic growth.
- SSP5 (Conventional development): A world in which rapid and globalized economic growth is based on rapid technological progress, free trade, and conventional carbon-intensive development. Living standards are high throughout the world and go along with high energy consumption, and dietary patterns are characterized by high per-capita demand, in particular for animal-based products. Institutional stability allows for a favorable investment environment.

The qualitative storylines of the SSPs, the quantitative population (Kc and Lutz, 2017) and income scenarios (Dellink et al., 2017) are used to parameterize the MAgPIE model, e.g., with respect to the trends in trade liberalization, environmental restrictions and costs of technological change (**Error! Reference source not found.**). The population and income scenarios of the SSPs are translated into demand for crop and livestock products, while different trajectories of economic development influence dietary preferences such as the share of meat consumption and the amount of calories consumed or wasted per person. The projections of the crop demand under different SSPs are shown in Fig.SI-2. The SSP indicator "environment" is implemented in the model through the protection levels of ecosystems, such as forests. "Technology" in MAgPIE is parameterized as the soil nitrogen uptake efficiency and livestock efficiency (the amount of feed needed to produce a certain amount of livestock products), but crop productivity changes are determined endogenously in the optimization. Implementing trade liberalization based on different self-sufficiency rates in the model represents the dimension of "globalization" of the SSP storylines. By following the narratives about institutional quality, we include risk-accounting factors to represent political stability and governance performance in SSPs, which affects investment risks and uncertainties through different discount rates. High investment risks reduce capital investments in agricultural production and encourage cropland expansion (Deacon, 1994, 1999; Bohn and Deacon, 2000). We, therefore, use the annual interest rates as discount rates, based on a literature range of 4–12% (IPCC, 2007), as a proxy for the risk-accounting factors associated with governance performance (Wang et al., 2016).

4 Results and discussion

4.1 Land productivity growth under SSPs

The land productivity is measured as PFP using both the land-use intensity and yield index, where the land-use intensity refers to homogenous land quality and the yield index encompasses heterogeneous land quality. By 2050, the global land-use intensity is expected to increase by 94.8% and 77.3% under SSP5 and SSP1, respectively (Fig.1). SSP3 also shows a relatively strong increase in land-use intensity of 74.2%, while SSP2 and SSP4 experience relatively low land-use intensity growth, at the rates of 60.8% and 45.9%, respectively.

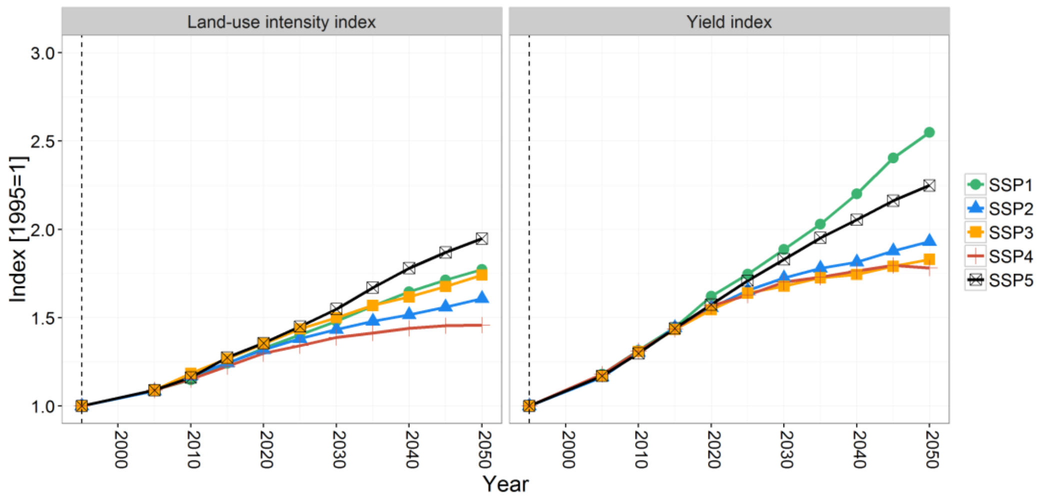

Fig.1. Global land-use intensity (left panel) and yield index (right panel) for each SSP by 2050.

The land-use intensity in the model is mainly affected by two factors, namely, the risks associated with investment and the pressure from the increasing crop demand. Investment risks and uncertainties associated with investments, which determine the attractiveness of agricultural technologies, are influenced by the institutional environment (Deacon, 1994, 1999; Bohn and Deacon, 2000; Deininger et al., 2014; Wang et al., 2016). In particular, Wang et al. (2016) find that land-use intensity increases when the governance performance is strong. Following the same logic, SSP5 and SSP1 are characterized by fast economic growth and a stable institutional environment, resulting in fast technological progress and high land-use intensity. This leads to a deceleration of cropland expansion in these two scenarios since the increasing demand is mainly satisfied by intensified production and yield improvements resulting from technological investments. In contrast, there is more cropland expansion in SSP2, SSP3, and SSP4 than in SSP1 and SSP5 (**Error! Reference source not found.**).

Pressure from the demand side, which is transmitted to the production side (**Error! Reference source not found.**), is another key factor driving the land-use intensity. As shown in Fig.1, the global land-use intensity growth rate in SSP3 is 13.4 percentage points higher than that in SSP2 in 2050 and close to that in SSP1, despite the lower investment risks in SSP1 and SSP2. This is due to the high population growth increasing the demand for crop products and the limited opportunities for international trade in SSP3 (**Error! Reference source not found.**). Thus, technological progress as an endogenous response mechanism is the last resort for increasing the land-use intensity. This is specifically true for the developing regions, such as AFR, MEA, and SAS, which have very high population growth in SSP3 and, therefore, even higher land-use intensity increases than those in the developed regions (**Error! Reference source not found.**). In this scenario, it is arguable whether the projected increase in the per-capita demand can actually be realized since high prices would lead to reduced demand, including a higher degree of undernourishment.

The yield index, i.e., the average yield change, also indicates the continuous growth of the global land productivity over time for all SSPs (Fig.1). By 2050, SSP1 has the highest average yields, which are more than twice as high as those in 1995, followed by SSP5 (124.9%) and SSP2 (93.1%). SSP3 and SSP4 have the lowest growth rates of average yields at 83.0% and 78.1%, respectively. Since the yield index is a weighted measure, the model results indicate that the average yield is driven by cropland expansion into areas with different agricultural suitability and land-use intensity growth. For instance, in SSP1 that features low investment risks and population pressure with globalized international trade, modest cropland expansion and high land-use intensity lead to high average yields, and vice versa for SSP3. Cropland expansion affects average yields through the initial yields of newly converted cropland, which is mainly dependent on irrigation conditions. From 1995 to 2050, the shares of irrigated area in SSP1, SSP2 and SSP5 increase by 18%, 13%, and 10%, respectively, indicating that crop production is mainly concentrated in the irrigated area (Tab.2). In particular, the share of the irrigated area continues to rise at a steady pace in SSP1 from 2015 to 2050. By contrast, the shares of irrigated area in SSP3 and SSP4 reach the highest levels in 2025 and 2015, respectively, and then decrease hereafter. This is due to the large expansion of rain-fed cropland area, in particular in SAS for SSP3 and in NAM for SSP4 (**Error! Reference source not found.**). The relatively low initial yield of rain-fed cropland can decrease the average yield level.

Tab.2. Changes in the share of irrigated area w.r.t. the total cropland area.

Year	SSP1	SSP2	SSP3	SSP4	SSP5
1995	1.00	1.00	1.00	1.00	1.00
2005	1.03	1.01	1.01	1.03	1.01
2010	1.08	1.05	1.04	1.06	1.05
2015	1.03	1.09	1.07	1.04	0.97
2020	1.04	1.10	1.10	1.04	0.96
2025	1.04	1.10	1.13	1.01	0.96
2030	1.06	1.10	1.08	1.01	0.99
2035	1.11	1.09	1.05	0.97	1.01
2040	1.15	1.09	1.03	0.98	1.01
2045	1.17	1.11	1.03	0.99	1.03
2050	1.18	1.13	1.01	1.00	1.10

The lower yields in newly converted rainfed cropland in SSP3 result in lower average yields compared to SSP2, which offset the effects of the higher land-use intensity in SSP3. Due to a similar reason, SSP1 has higher average yields than SSP5, despite the lower land-use intensity. The findings are consistent with *Proposition S.2* derived in the method section, stating that expanding cropland into areas with lower than average yields leads to a decreasing yield index. They also explain why the order of future land productivity in the SSPs indicated by the land-use intensity index is different from the order indicated by the yield index. The combined effects of land-use intensity growth and the initial yields of newly converted cropland jointly determine the changes in the average yields at the regional level. Taking the regional yield index in SSP3 as an example, AFR has a larger increase in land-use intensity and average yields (**Error! Reference source not found.** and **Error! Reference source not found.**) than LAM because AFR has to rely on increasing technological investments for fulfilling the demand driven by very high population growth while regions such as LAM and FSU with less increase in the agricultural demand can still expand their cropland area. Hence, if there is a high enough land-use intensity growth, it is possible to overcome the adverse effects of cropland expansion on average yields, resulting in an overall high average yield growth.

4.2 TFP growth under SSPs by 2050

The productivity growth measured by the land-use intensity and yield index shows how different parts of the land productivity will develop under different socioeconomic conditions. The global cumulative MPI derived in the study captures the full scope of the output growth relative to the growth of all the inputs including the cropland area, production factor costs and amount of water used for irrigation. The projection of TFP growth is first compared to the available historical and projection data in the literature (Ludena et al., 2007). In contrast to the prediction based on the estimates of historical data, which is likely to be the extrapolation of the historical productivity growth, the results in the presented study indicate that the projection has large spans when taking into account the changes in socioeconomic conditions (Fig.2). In combination with the other two productivity measures, the results show that the annual growth rates of the regional productivity vary across different SSPs (**Error! Reference source not found.**), suggesting the important influences of the socioeconomic factors on productivity changes.

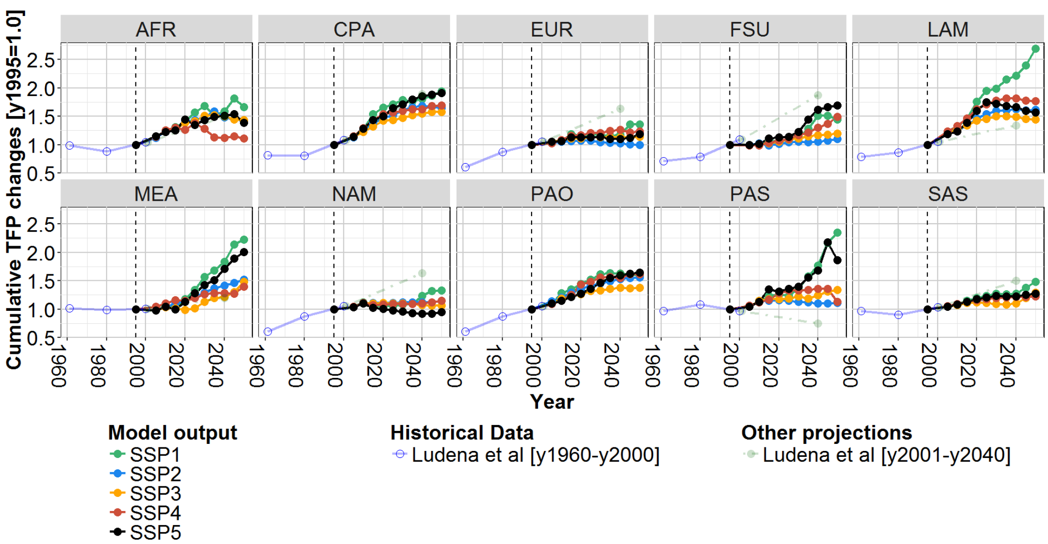

Fig.2. Regional cumulative TFP growth. The validation data is derived based on the annual average rate of TFP changes from the periods of 1960-1980, 1981-2000, and 2000-2040 based on the study of Ludena et al. (2007).

By 2050, there is the highest growth of the global TFP in SSP1 (75.9%), followed by SSP5 (42.2%), SSP4 (37.9%) and SSP2 (33.4%) (Fig.3). SSP3 lies at the bottom, indicating the lowest growth in TFP, with an increase of 30.2% by 2050. Instead of relying on a limited time series of historical data to estimate TFP changes, the approach in the present study is likely to capture the structural change due to changes in socioeconomic conditions.

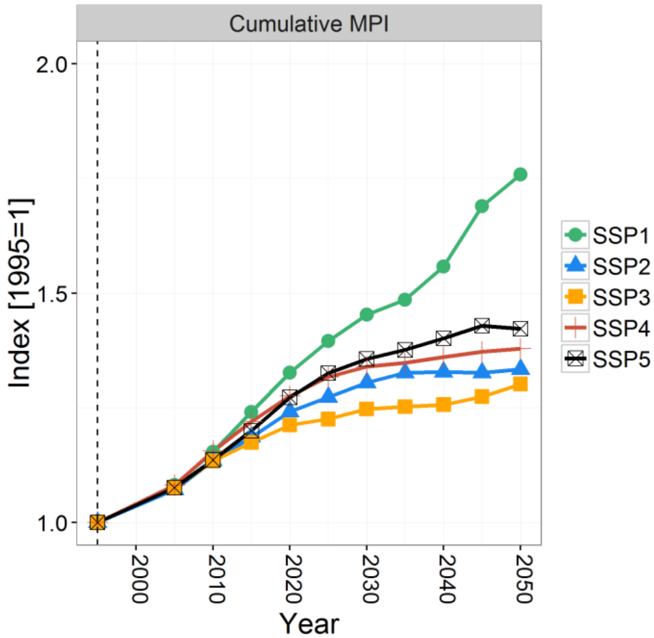

Fig.3. Global cumulative TFP growth for each SSP by 2050.

The TFP growth has profound implications for food prices. The model results suggest that changes in food prices are negatively associated with TFP growth but positively associated with cropland expansion (Fig.4). Specifically, the ratio between the TFP growth and cropland expansion has significant impacts on food prices, with prices decreasing when productivity grows faster than cropland expands and vice versa. SSP1 and SSP5 are projected to have pronounced TFP growth of 62.6% and 32.2%, respectively, from 2005 to 2050. The substantial TFP growth in SSP1 and SSP5 is associated with decreased food prices (23.0% in SSP1 and 11.0% in SSP5) and minor increases in cropland area (6.2% in SSP1 and 11.2% in SSP5). In SSP2 and SSP4, there is also TFP growth, but it is associated with increased food prices and slightly higher cropland expansion compared to SSP1 and SSP5. Conversely, in SSP3, food prices increase substantially, while the TFP grows by 21.0% and cropland expands by 38.7% from 2005 to 2050. The results of an ordinary least squares estimation (**Error! Reference source not found.**) confirm that increasing the ratio between the TFP growth and cropland expansion has a negative and statistically significant effect on food prices, suggesting that increasing the ratio by one unit will decrease the global food prices by 17.83%. Investing in productivity improvements appears to be an effective way to ensure the availability of food, which is essential for reducing poverty and hunger, and to spare cropland, which improves the sustainable use of terrestrial ecosystems as part of the SDGs(Foley et al., 2011; Tilman et al., 2011; Havlik et al., 2013).

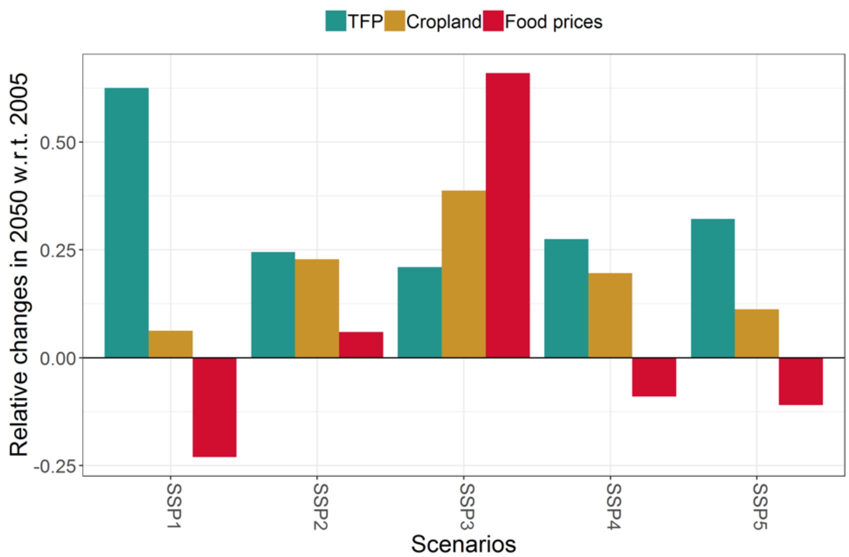

Fig.4. Growth rates of the TFP, food prices and cropland in 2050 w.r.t 2005 for the SSPs.

The global TFP growth is mainly driven by technological progress (i.e., shifts of the production frontier) rather than the convergence of regions to the maximum production potential (i.e., catch-up), as shown in Tab.3. In particular, there is a large shift of the production frontier in SSP1 at the global level, with an annual average increase of 1.4% from 1995 to 2050. Since the global MPI is derived as a weighted average of the regional MPIs, it is worth looking at the components of the TFP at the regional level. Taking SSP2 and SSP4 as examples, the higher global TFP growth in SSP4 than in SSP2 reflects that the large production regions, such as CPA, LAM, and NAM, have higher regional TFP growth in SSP4. The order of the SSPs indicated by the MPI generally corresponds to the SSP narratives, in particular for SSP3. It is noticeable that the regional TFP, especially in developing regions, is also mainly driven by shifts of the production frontier (i.e., 32 of 40 regional catch-up scores are less than unity), consistent with the historical trend (Nin et al., 2003). Several regions in SSP5, such as AFR, FSU, LAM, MEA, PAS, and SAS, converge to the long-term production frontier. This suggests that SSP5 is the pathway with the fastest convergence of productivity for developing regions. Among all regions, LAM is the only region showing convergence (with an average annual rate of 0.1%) across all SSPs, while CPA has a unity score for convergence in all SSPs.

Tab.3. Average rates of the shift of technology, catch-up, and TFP change from 1995 to 2050 across the SSPs.

		AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS	Global
	Shift of technology	1.013	1.012	1.011	1.009	1.017	1.018	1.013	1.017	1.017	1.013	1.014
SSP1	Catch-up	0.996	1.000	0.994	0.998	1.001	0.997	0.993	0.992	0.998	0.995	0.997
	TFP change	1.009	1.012	1.006	1.007	1.018	1.015	1.005	1.008	1.016	1.007	1.010
	Shift of technology	1.006	1.009	1.004	1.005	1.008	1.010	1.005	1.009	1.007	1.005	1.006
SSP2	Catch-up	1.000	1.000	0.996	0.997	1.000	0.997	0.997	0.999	0.995	0.999	0.999
	TFP change	1.006	1.009	1.000	1.002	1.009	1.008	1.003	1.008	1.002	1.004	1.005
	Shift of technology	1.007	1.008	1.003	1.005	1.006	1.008	1.004	1.007	1.008	1.004	1.006
SSP3	Catch-up	1.000	1.000	0.999	0.998	1.000	1.000	0.997	0.999	0.997	1.001	0.999
	TFP change	1.007	1.008	1.002	1.003	1.007	1.007	1.001	1.006	1.005	1.005	1.005
	Shift of technology	1.005	1.010	1.005	1.007	1.009	1.009	1.004	1.008	1.008	1.006	1.007
SSP4	Catch-up	0.997	1.000	0.999	1.000	1.001	0.997	0.998	1.001	0.994	0.998	0.999
	TFP change	1.002	1.010	1.004	1.007	1.010	1.006	1.002	1.009	1.002	1.004	1.006
	Shift of technology	1.006	1.012	1.005	1.010	1.008	1.011	1.003	1.010	1.010	1.003	1.007
SSP5	Catch-up	1.000	1.000	0.998	1.000	1.000	1.002	0.996	0.999	1.002	1.002	1.000
	TFP change	1.006	1.012	1.003	1.010	1.008	1.013	0.999	1.009	1.011	1.004	1.006

Note: Values larger than unity indicate an increase in the shift of technology or catch-up. For comparison reasons, the values are given with three digits after the decimal.

Although the average results (Tab.3) show an increase in the shift of the production frontier for all regions in all SSPs, they do not identify which regions push forward the long-term production frontier. Recall that the MPI measures capture the performance of the productivity relative to the best practice in the sample, where the best practice represents the “world frontier” (Färe et al., 1994). By looking at the component distance functions in the index of the shift of the production frontier (see the details in Färe et al. (1994)), the study finds that regions such as EUR, NAM, CPA, and LAM often determine the global frontier in the first time steps, and CPA and LAM often determine the global frontier in the later time steps (**Error! Reference source not found.**). Rather than using techniques such as second-stage regressions (Chen et al., 2008; Headey et al., 2010) to pinpoint the underlying driving factors behind the MPI, the study can provide insights into the possible factors affecting the shift of the production frontier with a priori information from simulating land dynamics in the MAgPIE model and the insights gained from analyzing PFP measures. Taking CPA and LAM as examples, the average rate of the shift of the production frontier for the SSPs is 0.8-1.2% and 0.6-1.7%, respectively, indicating robust growth. One source of the shift of the production frontier is due to changes in management and increases in technological investments, which are partly affected by the overall institutional environment. For instance, the empirical analysis of the TFP in the literature shows the positive impacts of institutional change in China on the adoption of new rice varieties during the rural reform period (Lin, 1991) and the overall agricultural productivity (Gong, 2018). The positive effect of irrigation technologies on production is another cause of the shift of the frontier. The result is consistent with other studies that indicate that irrigation mainly affects the shift of the production frontier (Fan, 1991; Jin et al., 2002; Chen et al., 2008).

5 Conclusions

Measuring productivity entails different ways that consider different types of production inputs. By synthesizing the findings of productivity growth indicated by the PFP and TFP measures, the study shows that there is likely to be a continuous growth of the global crop productivity for a broad span of different future socioeconomic conditions, but the ranking of the SSPs regarding growth rates varies across productivity measures. In particular, SSP5 has the highest land-use intensity by 2050 while SSP1 has the highest average yields and TFP. In a world with fast economic growth, strong governance performance and relatively slow population growth (SSP1 and SSP5), the food demand in 2050 can be met without aggressive cropland expansion. Productivity growth occurs through the adoption of high-yield technologies and improved irrigation. In contrast, low economic growth, weak governance performance, and very high food demand driven by fast population growth (SSP3) will require high land-use intensity together with vast cropland expansion into rain-fed areas to fulfill the demands but this will result in low TFP growth. Whether it is feasible to feed an increasing population under these circumstances can be doubted based on the results. A reason for concern is the low TFP growth in SSP3, especially in developing regions. Under the conditions of high population and low income growth, food insecurity in SSP3 is likely to become worse in developing regions. In all SSPs except SSP5, the TFP growth is driven not only by shifts of the production frontier, based on investments in yield-augmenting technologies and management improvements affecting land-use intensity, but also by the investment in irrigation technologies, which is not part of the land-use intensity measure. This confirms the necessity of increasing investment in R&D and infrastructure to meet the increasing food demand and to avoid large-scale cropland expansion, especially in the face of fast population growth. SSP5 is featured as a pathway with fast convergence toward the long-term production frontier across developing regions. The ratio between the TFP growth and cropland expansion has significant impacts on food prices, with decreasing prices when productivity grows faster than cropland expands and vice versa. Investing in productivity improvement appears to be an effective means for ensuring food availability and sparing cropland, which can contribute to the achievement of SDGs.

Author contributions

XW, JPD, and HLC developed the research idea. XW and JPD developed and implemented the research method. XW conducted the analysis and wrote the manuscript. XW and BB contributed to the method of improving the estimation of global productivity changes, and XW implemented the method. JPD, HLC, BLB, AB, MS, AP, and XW developed the MAgPIE model. JPD, AB, HLC, BLB, AP, MS, and BB provided comments.

Author statement

The authors declare that there is no conflict of interest. The usual disclaimer applies.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore. 2020.120208.

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