Future Employment in Global Agriculture: Trends and Drivers in the Shared Socioeconomic Pathways

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Abstract

In 2021, 27% of global employment was in agriculture, forestry, hunting, or fishery. The income from agricultural employment is of crucial importance for rural livelihoods. Despite expanding production to provide food for a growing world population, agricultural employment has drastically decreased for many decades. The role of agricultural employment, e.g. in the context of rural development and poverty reduction, has been widely discussed in qualitative literature. However, global quantitative projections are absent in modelling scenarios of the land-use system. The future development of agricultural employment will be strongly influenced by changes on both the producer and consumer side of agricultural production. The Shared Socioeconomic Pathways (SSPs) explore a range of future socioeconomic developments with varying implications for agricultural employment. Here we use a global agro-economic model to analyze how agricultural employment evolves across the SSPs and what drives these changes over time. Despite increases in the demand for agricultural products by 39-58% between 2020 and 2050, our results show a strong decline in the share of employment in agriculture in all SSPs from 16.7% of the working age population in 2020 to 4.1-12.3% in 2050, with increasing labor productivity being the strongest driver. The continuing shift from labor to capital as production factor further reduces the need for agricultural labor, especially in current low-income regions. If other sectors cannot absorb labor at the same pace, upcoming reductions in agricultural employment can lead to higher unemployment, loss of livelihoods, and increased poverty. Our study shows that to provide the future population with decent jobs and livelihoods, investments in establishing new job opportunities and training programs to facilitate the transition of primarily rural populations out of agriculture will be needed, and provides an estimate of the magnitude of this transformation.

1 Introduction

Agricultural activities are linked to most of the Sustainable Development Goals (SDGs) of the United Nations [1], as they are key to both environmental and social challenges: On the one hand, agriculture, landuse, and landuse change are responsible for about 25% of global greenhouse gas emissions [2], and drive air and water pollution, destruction of natural habitats, and loss of biodiversity [3]. On the other hand, the majority of poor people in developing countries live in rural areas, and income from agriculture is crucial to most rural livelihoods [4, 5].

In 2021, 27% of the global labor force was employed in agriculture (i.e., crop and livestock production), forestry, hunting or fishery [6]. The number of people employed in agriculture has been continuously decreasing over the past decades, as increases in productivity have outpaced the increases in demand for agricultural products [7, 8]. Especially in middle-income countries, this has led to a strong outflow of labor from agricultural production to other sectors [9], with agricultural employment dropping from 609 mio. people in 2000 to 422 mio. people in 2019 (own calculations based on [10]). At the same time, in low-income regions (i.e., Sub-Saharan Africa and India) absolute numbers are still on the rise, increasing from 355 mio. people in 2000 to 389 mio. people in 2019 (own calculations based on [10]).

Increasing labor and land productivity in agriculture is often seen as a primary objective in developing countries to improve rural livelihoods and reduce poverty [5, 11]. Such productivity improvements are a central aspect of structural change – shifting the economic focus from agriculture and other primary production towards the secondary (manufacturing) and tertiary (services) sector – which is generally associated with positive economic development [12–14]. While increased productivity can raise agricultural wages and decrease food prices [5], it will also lead to reduced labor demand in agriculture [15], potentially leading to a trade-off between the quality of agricultural livelihoods and the number of people directly profiting. In addition, the majority of agricultural workers are informally employed and thus particularly vulnerable, making a positive structural transformation even more challenging [11].

While the role of agricultural employment in the regional and international context has been widely discussed in qualitative literature (see, e.g., [5, 11, 16, 17]), quantitative studies mostly focus on local and short-term aspects. These explore, e.g., the effects of a national minimum wage in agriculture on work time arrangements based on an econometric approach [18] or reasons for farmers to move in or out of agriculture using short-term agent-based modelling [19], but without taking a spatially broader and long-term perspective. Leimbach et al. use an econometric approach to estimate global and regional sectoral labor shares until 2050 for the Shared-Socioeconomic Pathways but do not estimate absolute employment numbers [20]. Computable General Equilibrium models (CGEs) such as GTAP (*Global Trade Analysis Project*, [21]) or MAGNET (*Modular Applied GeNeral Equilibrium Tool*, [22]) mostly include a representation of the labor market and are used for both local and global studies, e.g. on the effect of labor mobility on water protection policies in the U.S.A. [23] or the effect of labor supply assumptions on global food security projections [24]. Still, global modelling projections of agricultural employment numbers are only available from very few studies. A recent publication by Nico and Christiaensen quantifies the future of employment in agri-food systems for a business-as-usual scenario with and without climate change impacts, using an econometric relationship between cereal yield growth and the agricultural employment share, with yield projections provided by the IMPACT model [25, 26]. M'Barek et al. quantify the achievement of the SDGs in alternative bioeconomy scenarios until 2050 using the CGE MAGNET, including the number of agricultural jobs for SDG 8 *Decent work and economic growth* [27].

While CGE models are able to cover the full economy, they have the disadvantage of reduced detail in specific sectors and calibrating elasticities to represent the current structure of the economy, thus not being well suited to simulate the long-term structural change in an economy such as a reduction in size of the agricultural sector [28]. Partial equilibrium models (PEs) or Integrated Assessment Models (IAMs) that focus on the food and land-use system specifically can explicitly incorporate biophysical constraints and detailed representations of the interrelations within the agricultural sector, allowing a deeper understanding of developments under given scenarios, including larger deviations from the status quo. This has led to a call for global PEs or IAMs to integrate agricultural employment into modelling analysis of future development of the food and land-use sector [15, 23, 24].

However, international or global long-term projections of agricultural employment are absent in scenarios implemented by models of the food- and land-use system, despite the central role of agricultural employment in tackling global challenges. As policies affecting agriculture are likely to substantially impact rural development and poverty through their effect on agricultural employment [11], scenarios analyzing the future development of the food and land-use system need to incorporate the respective effects on agricultural employment. For a sustainable development pathway to be feasible, the drivers as well as impacts of changing labor demand in agriculture need to be better understood and quantified.

To fill this gap, we here use the agro-economic model MAgPIE (*Model of Agricultural Production and its Impact on the environment*, [29]) to quantify possible futures of agricultural employment until 2100 based on the Shared-Socioeconomic Pathways (SSPs). The SSPs describe five alternative socio-economic development scenarios, following different narratives in terms of challenges for adaptation and mitigation of climate change [30], and have been widely adopted [31].

We first discuss trends in the projection of agricultural employment and related indicators over time for the five SSPs. We then identify main drivers of the changes in agricultural employment and quantify their respective contribution through a Kaya-like decomposition analysis. We analyze all results globally and in the context of high- and low-income world regions and the respective SSP storylines.

2 Method

2.1 MAgPIE

This study uses the Model of Agricultural Production and its Impact on the environment (MAgPIE) [29, 32] to analyze the development of agricultural employment under alternative scenarios. MAgPIE is a spatially explicit partial-equilibrium modeling framework of the global land system. It projects land use and production patterns in five-year time steps until 2100 under given socio-economic and biophysical constraints by minimizing overall costs while fulfilling the demand for agricultural products.

Agricultural demand includes the demand for food, feed, and material use and can be fulfilled by regional production or through trade. Agricultural production uses land, seeds, water (rainfed or irrigated), nitrogen, capital, and labor as inputs. These inputs are linked to respective costs. In addition, land expansion or investments into R&D to increase production further add to the production costs. A more detailed description of dynamics within MAgPIE can be found in SI Sec. 1.1. For this study, MAgPIE was extended to include projections of agricultural employment under alternative developments of the food and land-use system.

2.2 Integration of agricultural employment in MAgPIE

Agricultural employment in MAgPIE refers to the number of people employed in crop and livestock production. The central equation, evaluated on regional level and for each time step, is the following:

$$empl = \frac{c_{lab}}{c_{hour} \cdot h_{year}}, \tag{1}$$

where *empl* is agricultural employment (mio. people), c_{lab} are annual total labor costs in crop and livestock production (mio. USD), c_{hour} are hourly labor costs in agriculture (USD/h), and h_{year} are the average hours worked per person in a year (h/year). Note that – all other things kept equal – an increase in hourly labor costs will lead to reduced agricultural employment, as Eq. 1 is based on the assumption that hourly labor costs develop proportionally to labor productivity. A complete historical dataset on employment in crop and livestock production was derived by combining two datasets provided by the Statistical Database of the International Labour Organization (ILOSTAT, [10]), see SI Sec. 1.2 for details.

Total MAgPIE-internal labor costs are derived on regional level as the product of projected production quantity, factor requirements (i.e., the sum of capital and labor required per production unit in mio. USD/t DM), and the labor costs share in input factor costs. Historic factor requirements for each crop and livestock category are calculated by scaling the overall Value of Production per production unit, as provided by the Food and Agriculture Organization of the United Nations Statistical Database (FAOSTAT, [33]), with factor cost shares. These shares for crop and livestock production, respectively, are derived from a dataset of the United States Department of Agriculture (USDA), reporting historic cost shares out of total agricultural production costs on the country level [34]. For crop categories, future factor requirements are kept constant at 2010 values. For livestock categories, historic factor requirements are used to define a linear relationship between factor requirements and livestock productivity (based on FAOSTAT data, [33]), which is then used to project factor requirements into the future based on respective livestock productivity scenarios. Feed demand is covered explicitly within MAgPIE and thus not part of livestock factor requirements.

The labor and capital cost shares in input factor requirements are assumed to change over time according to regional economic development, with the capital share following a log-linear relationship with GDP per capita PPP (see Eq. 2). Historic labor and capital cost shares are again based on the above-mentioned USDA dataset.

$$s_{cap} = 0.3586 \cdot log_{10}(GDP_{pc\ PPP}) + calib_{reg} \tag{2}$$

In addition to MAgPIE-internal labor costs in crop and livestock production, annual labor costs in Eq. 1 also include subsidized labor costs in agriculture [35] and labor costs for livestock categories not covered in MAgPIE (i.e., wool, beeswax, honey, silk-worms) based on FAO and USDA data [33, 34]. The absolute value of these additional labor costs is kept constant for future years.

Historical values for average hours worked by an agricultural worker in a year and hourly labor costs are again based on a dataset from ILOSTAT [10]. Future values of average hours worked are kept constant at the most recent reported value. For hourly labor costs, a log-log relationship with GDP per capita MER was derived and calibrated on the country level (see Eq. 3 and SI Sec. 1.3 and SI Sec. 1.4 for details on the regression and calibration).

$$c_{hour} = exp(1.1226 \cdot ln(GDP_{pc\ PPP}) - 9.124 + calib_{iso}) \tag{3}$$

Aggregation of the calibrated hourly labor costs to the regional level uses the total number of hours worked in agriculture in 2010 as aggregation weight.

2.3 Kaya-type identity to decompose drivers of agricultural employment

We decompose the projected number of people employed in agriculture to six underlying drivers using the following Kaya-type identity [36–38]:

$$empl = pop \cdot \frac{dem}{pop} \cdot \frac{prod}{dem} \cdot \frac{c_{fac}}{prod} \cdot \frac{c_{lab}}{c_{fac}} \cdot \frac{empl}{c_{lab}},$$

where *empl* is the number of people employed in agriculture (mio. people), *pop* is the population size (mio. people), *dem* is the total demand for crop and livestock products (mio. tonnes of dry matter), *prod* is the total production of crop and livestock products (mio. tonnes of dry matter), c_{fac} are the total input factor costs (i.e., the sum of labor and capital costs) in crop and livestock production (mio. USD MER05), and c_{lab} are the total labor costs in crop and livestock production (mio. USD MER05).

Each factor of the identity describes a driver of overall agricultural employment (see Tab. 1 for an explanation of respective dynamics within MAgPIE). Based on the Kaya-identity, the extended Laspeyres model [39] can be used to express changes in agricultural employment as the weighted sum of changes in each driver (see SI Sec. 1.5 for details). The additive decomposition of changes in employment allows to analyze and compare the respective strength of drivers over time, across regions, and between scenarios.

Driver	**Dynamics of driver**
Population size pop	A change in population will affect the overall demand for agricultural products and, hence, the demand for agricultural labor.
Per capita demand dem/pop	Demand for agricultural products is related to different uses: food consumption, feed, processing (to oils, sugar, and alcohol), bioenergy, material use, seeds, as well supply chain losses. Reducing hunger and underweight, changing dietary preferences following economic development, and increased demand for non-food agricultural products or reductions in food waste will change the per capita demand in terms of raw-product equivalents, thus influencing overall agricultural demand independent of population growth.
Self-sufficiency ratio $prod/dem$	While demand and production are assumed to be in balance within MAgPIE on a global level, regionally, the ratio between demand and production can change due to inter-regional trade, with a self-sufficiency ratio larger than one describing a region with net-exports. Changes in self-sufficiency lead to a relocation of agricultural employment from regions with decreasing self-sufficiency ratios to regions with increasing self-sufficiency ratios.
Average factor requirements $c_{fac}/prod$	While factor requirements for each specific crop category are assumed constant over time within MAgPIE, the composition of production – e.g., a shift from staple crops to labor and capital-intensive vegetables – can affect average factor requirements. For animal-based commodities, factor requirements additionally increase over time relative to livestock productivity. Assuming that other variables stay constant, increasing factor requirements will lead to higher demand for agricultural labor.
Labor cost share c_{lab}/c_{fac}	The labor cost share out of input factor costs decreases with economic development, leading to reduced demand for agricultural labor.
Labor intensity $empl/c_{lab}$	The ratio between the number of people employed and total labor costs is the inverse of the annual labor costs per agricultural worker. As labor costs are assumed to develop proportional to labor productivity, the demand for labor decreases together with labor intensity (i.e., with increasing labor productivity).

Table 1: Definition and description of dynamics for main drivers of changes in agricultural employment.

3 Results

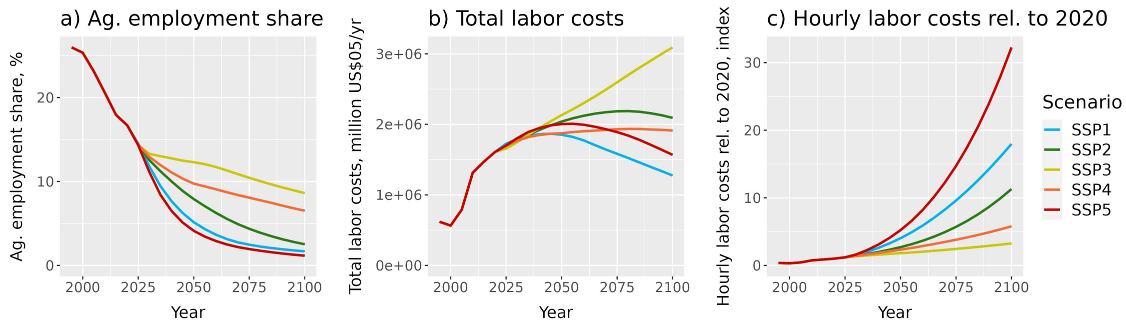

Figure 1: Global development of labor in agriculture. Development until 2100 under the five SSPs for a) Share of working age population (aged 15 to 65) employed in agriculture, b) Total labor costs in crop and livestock production, and c) Hourly labor costs in agriculture relative to 2020.

3.1 Projected trends in agricultural employment across the SSPs

The share of employment in agriculture (i.e., crop and livestock production) is projected to continuously decrease across SSPs, from 16.7% of the global working age population (aged 15 to 65) in 2020 to between 4.1% (SSP5) and 12.3% (SSP3) in 2050 (1.2-8.6% in 2100) (see Fig. 1 a). In absolute terms, this corresponds to 236-771 mio. people (39-710 mio. people) engaged in agriculture in 2050 (2100) across SSPs (see Tab. 2 a), i.e. 90-626 mio. jobs (150-822 mio. jobs) are projected to be lost within agricultural production between 2020 and 2050 (2100).

Projections of total labor costs in agriculture at first increase across all SSPs but then diverge to -20.4% (SSP1) to +96.7% (SSP3) in 2100 compared to 2020 (see Fig. 1 b and Tab. 2 b). The development of total labor costs is driven by the respective agricultural demand, factor requirements, and the labor cost share in agricultural production (see Sec. 2.2 for a more detailed explanation of dynamics within MAgPIE). Hourly labor costs are projected to continuously increase in all SSPs (see Fig. 1 c), but the rate of increase is closely linked to economic growth, leading to a factor between 1.8 (SSP3) and 5.2 (SSP5) for hourly labor costs in 2050 relative to 2020 (3.3-32.3% in 2100 relative to 2020) (see Tab. 2 c). The increase in hourly labor costs is assumed to reflect the increase in labor productivity with economic

a) Ag. employment (mio. people)

	2050	2100
SSP1	295.27	55.64
SSP2	474.59	134.09
SSP3	771.25	710.90
SSP4	576.83	365.50
SSP5	235.73	38.91

b) Total labor costs rel. to 2020 (%)

	2050	2100
SSP1	16.50	-20.42
SSP2	28.45	32.46
SSP3	34.27	96.74
SSP4	17.70	20.78
SSP5	26.41	-1.05

c) Hourly labor costs rel. to 2020 (factor)

	2050	2100
SSP1	4.03	17.97
SSP2	2.70	11.30
SSP3	1.81	3.25
SSP4	2.33	5.79
SSP5	5.22	32.25

Table 2: Global development of labor in agriculture. The tables show values for 2050 and 2100 for all SSPs for a) Employment in crop and livestock production in mio. people, b) Global annual total labor costs in crop and livestock production as percentage change relative to 2020, and c) Global average hourly labor in agriculture as factor relative to 2020.

development (see Sec. 2.2 for details).

3.2 Global drivers of agricultural employment dynamics

Fig. 2 decomposes the global change of agricultural employment over time by its five main drivers. The sixth driver, agricultural self-sufficiency, is only relevant on the regional level (see Sec. 3.4). A definition of the six drivers and an explanation of the corresponding dynamics can be found in Tab. 1.

The dominating driver across all SSPs is the decrease in labor intensity, i.e., the number of people employed over total labor costs. As labor productivity is assumed to develop proportional to hourly labor costs, decreasing labor intensity coincides with increasing labor productivity, i.e., less labor is needed for agricultural production, leading to reduced agricultural employment over time (see Tab. 1). In SSP2, the impact of this driver decreases at a steady rate over time, as the decrease in labor intensity is projected to be fastest in the upcoming decades and slow down later in the century (see Fig. 2). Between 2020 and 2050, changes in labor intensity alone would lead to a reduction of agricultural employment by 555 mio. people in SSP2 (see SI Fig. 4). The development of the labor cost share in agricultural input factor costs (i.e., labor and capital costs) is also projected to have a consistent negative impact on the future number of agricultural employment in SSP2, falling from 32.6% in 2020 to 25.3% (15.8%) in 2050 (2100) (see SI Fig. 5). The labor cost share reflects the changes in mechanization level as regions develop economically, leading to a substitution of labor by capital as input to agricultural production, which slows down over time.

Per capita demand for agricultural products, as well as the average factor requirements, are consistently positive drivers of future agricultural employment in SSP2. At the current time, the increase in per capita demand mainly comes from a strong increase in demand for animal-based products (and thereby feed) as well as processed goods, driven by economic development and corresponding dietary shifts. After 2060, increased use of agricultural products as biomass for bioenergy production is projected to be the main reason behind increasing agricultural demand per capita in SSP2 (see SI Fig. 6). The average factor requirements depend on the composition of agricultural demand, with a shift towards higher value products – in SSP2, more specifically, a shift towards higher demand for animal-based products, especially in low-income countries (see SI Fig. 7) – leading to higher average factor requirements. Population growth in SSP2 initially leads to higher agricultural employment due to higher overall demand for agricultural products but turns into a slightly negative driver after the projected peak in global population around 2070 (see SI Fig. 5).

Underlying drivers in SSP1 and SSP5 show similar patterns to those in SSP2. Again, the dominant driver is labor intensity. Especially in the coming decade, labor intensity falls faster than in SSP2, matching the faster decrease in agricultural employment in the first half of the century, which slows down in the second (see Fig. 1). However, negative drivers are stronger in SSP5 than in SSP1, with labor intensity and labor cost share dropping faster (see SI Fig. 5). This points to the very different underlying socio-economic assumptions in SSP1 and SSP5: both storylines include low population growth (see SI Fig. 5) and rapid

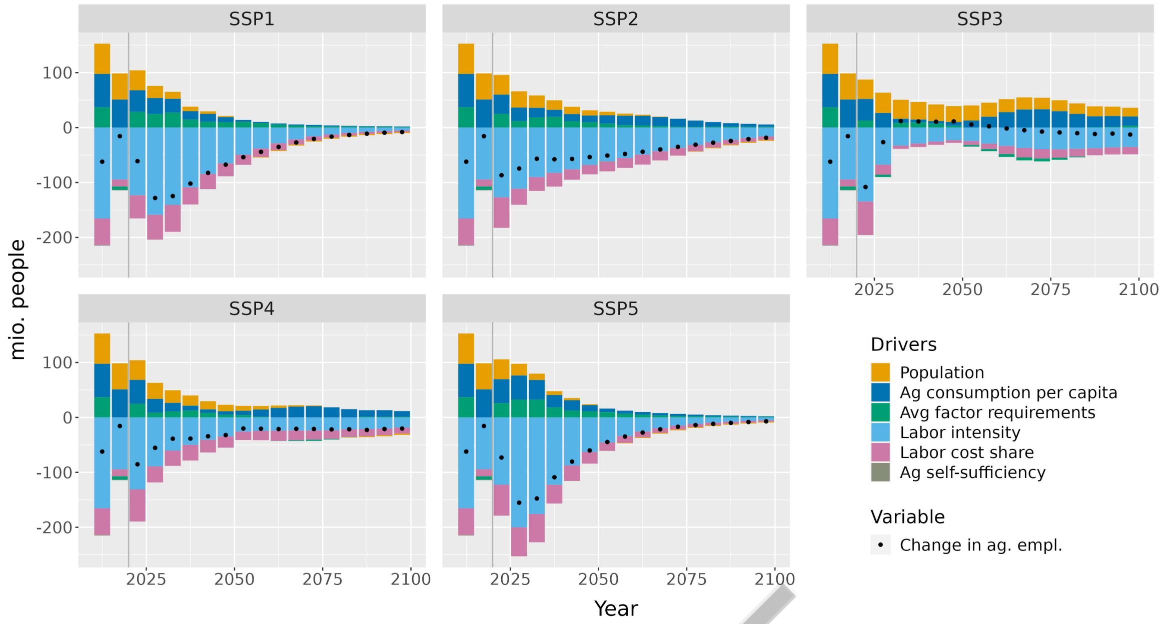

Figure 2: Global decomposition of changes in agricultural employment to respective drivers for the five SSP scenarios. The black dots indicate the absolute change in agricultural employment over the course of each five-year time step. Bars show the additive decomposition of the development in agricultural employment by driver.

technology development and transfer. However, SSP5 is a resource-intensive scenario with highly managed agriculture, meat-rich diets, and high demand for agricultural products (see SI Fig. 6). SSP1 is a more sustainable pathway with rapid diffusion of best practices and diets low in meat [30]. The higher overall demand for agricultural products is balanced by a faster decrease in labor intensity in SSP5, linked to faster economic growth and rapid development of developing countries, which overall leads to slightly less employment in agriculture than in SSP1 (see Tab. 2).

In comparison, drivers of agricultural employment show a different pattern in SSP3 and SSP4. Decreasing labor intensity is still the strongest negative driver in SSP4 in the first part of the century, but with impact on employment numbers decreasing quickly. In contrast, population growth is the strongest driver in SSP3 in the next decades, with labor intensity gaining strength as driver in the second half of the century. In SSP3, this relates to the slow economic growth in general, while in SSP4, economic growth is only low in currently less developed regions and at a medium pace in other regions [30]. In the second half of the century, also the shift in average factor requirements reduces agricultural employment in SSP3, after first rising from an average of 831 USD/kg DM in 2020 to 872 USD/kg DM in 2050 and then decreasing back to 846 USD/kg DM by 2100, as demand for livestock products as well as fruits and vegetables is slightly decreasing while the share of staples crops remains high (see SI Fig. 7). The change in per capita demand in SSP3 and SSP4 increases in force as a driver of agricultural employment in the second half of the century, increasing by 36.8% and 36.6% between 2050 and 2100 in SSP3 and SSP4, respectively (see SI Fig. 5). SSP3 has the fastest population growth and is the only scenario where the global population is not

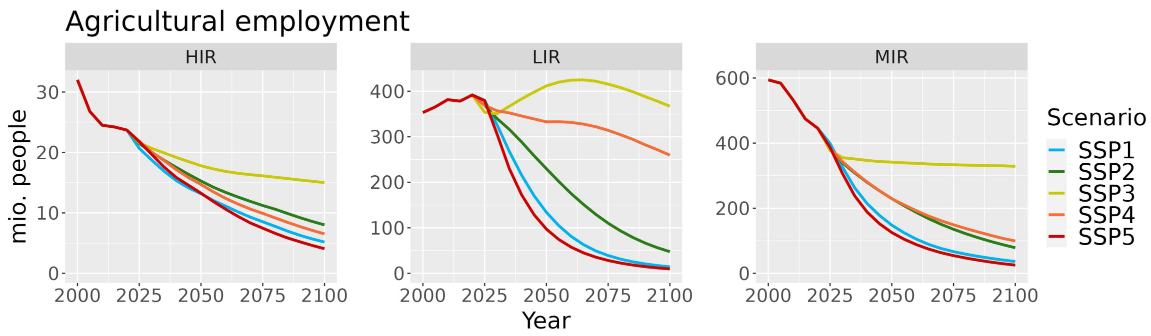

Figure 3: Agricultural employment by economic region for all SSPs. Each panel shows the development of agricultural employment over time for all SSPs for high-income, low-income, and middle-income regions, respectively.

expected to peak within this century (see SI Fig. 5). The strong population growth, together with a slow decrease in labor intensity, are the key reasons that SSP3 is the only pathway for which agricultural employment is projected to increase in the coming decades, reaching 779 mio. people in 2060 before decreasing again (see Fig. 1).

3.3 Trends in agricultural employment by economic region

Structural change is projected to continue across all economic development levels and for all scenarios (see Fig. 3). Of the 861 mio. people employed in agriculture in 2020, 24 mio. people were employed in high-income regions (3% of working age population), while 392 mio. people were employed in low-income regions (25% of working age population), and the remaining 446 mio. people in middle-income regions (16% of working age population). In a continuation of past trends (SSP2), the decrease in agricultural employment both in absolute and relative terms is fastest in middle-income regions, which lose almost half of the jobs in agriculture (49%) between 2020 and 2050, corresponding to 216 mio. people. While low-income regions also lose a substantial number of jobs in agriculture in absolute terms (162 mio. between 2020 and 2050), they have a lower relative decrease (41%). High-income regions lose 36% of agricultural jobs between 2020 and 2050, which, however, corresponds to only 8 mio. people in absolute terms, as agricultural employment is already at a low level. In SSP3, the only scenario with temporarily increasing numbers of agricultural employment, this behavior is fully due to increases in employment numbers in low-income regions, which exceed the reduction of employment in middle- and high-income regions.

3.4 Drivers of agricultural employment in SSP2 by economic region

As on global level, the dominating driver of agricultural employment in SSP2 is the development of labor intensity for all world regions (see Fig. 4). Another negative driver across economic regions is the labor cost share in input factor costs, which shows the strongest impact on agricultural employment in low-income regions, where the labor share currently is still very high (48.0% of total labor and capital costs in 2020, decreasing to 27.1% in 2050 and 13.9% in 2100, see SI Fig. 5). In contrast, per capita demand is a consistently positive driver in all regions for SSP2. The strongest impact can again be observed in low-income

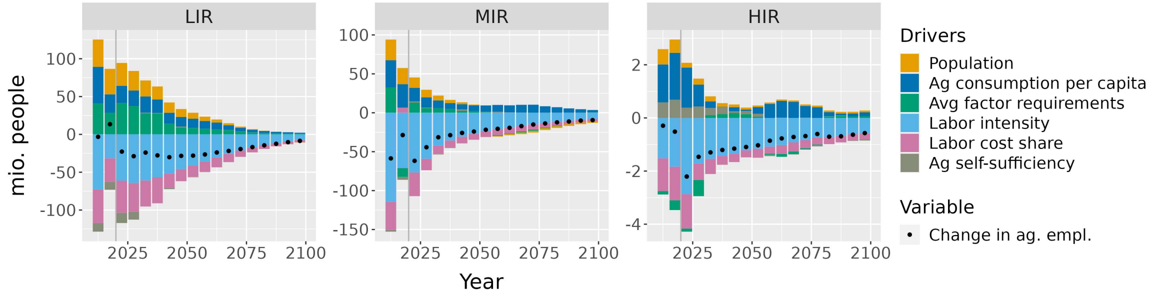

Figure 4: Regional decomposition of changes in agricultural employment to respective drivers in SSP2 in low-, middle- and high-income countries. The black dots indicate the absolute change in agricultural employment throughout each five-year time step. Bars show the additive decomposition of the development in agricultural employment by driver.

regions, where in particular the per capita demand for animal-based food products, and thus feed, is strongly increasing over time (see SI Fig. 6). Nonetheless, per capita demand for agricultural products in low-income regions is not projected to catch up with agricultural demand per capita in middle- and high-income regions, increasing from 0.42 t DM per capita in 2020 to 0.89 t DM per capita in 2100 in low-income regions compared to 1.52 t DM per capita (1.98 t DM per capita) in middle-income (high-income) regions. Increased production of animal-based products also leads to strongly increasing average factor requirements in low-income regions in the next decades (increasing by 61.2% between 2020 and 2050), while average factor requirements are only a weak driver in middle- and high-income regions (see SI Fig. 5).

While demand and production are balanced at global level, trade between regions can lead to different regional self-sufficiency ratios and, thereby, a spatial relocation of agricultural employment. In SSP2, high-income regions – which are already net-exporter in 2020 with a self-sufficiency ratio of 1.12 – further increase their self-sufficiency ratio, balanced by a decreasing self-sufficiency ratio in low-income regions, where agricultural production does not keep up with growing demand (see SI Fig. 5). Also the effect of population growth varies between economic regions. In middle-income regions, the population is expected to peak around mid-century in SSP2, while in low-income regions, the population peak is only expected to occur by the end of the century. In the coming decades, the fast population growth in low-income regions is a strong driver that slows the reduction in agricultural employment, as population growth alone would add 119 mio. jobs in agriculture between 2020 and 2050 (see SI Fig. 8). In high-income countries, the population is projected to continuously increase until the end of the century, though very slowly, thereby having only a small positive impact on agricultural employment.

For regional dynamics of drivers in the other SSPs, see SI Fig. 9.

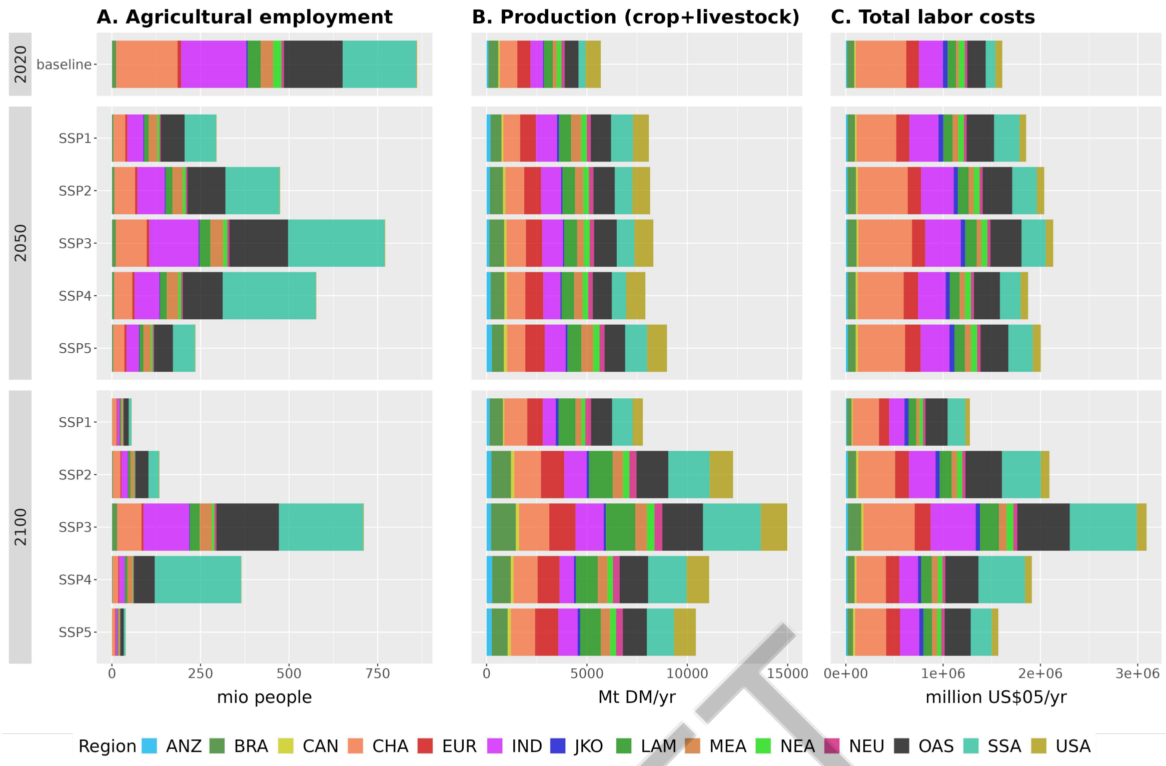

Figure 5: Regional projections for agricultural employment, production, and total labor costs for 2020, 2050, and 2100 for all SSP scenarios. a) shows the development of agricultural employment, b) shows the development of agricultural production (crop and livestock), and c) shows the development of total labor costs in agricultural production. The world is subdivided into 14 regions: Australia & New Zealand (ANZ), Brazil (BRA), Canada (CAN), China (CHA), European Union (EUR), India (IND), Japan & South Korea (JKO), Latin America (excl. Brazil) (LAM), Middle East & North Africa (MEA), Northern Eurasia (NEA), Europe (Non-EU) (NEU), Other Asia (OAS), Sub-Saharan Africa (SSA), United States of America (USA).

3.5 Regional distributions of agricultural production and related employment

Regional shares in agricultural production vary strongly from shares in agricultural employment due to the large differences in labor productivity and labor cost share (see Fig. 5). For example, the USA produced 13% of primary agricultural products in 2020 (9.8-12.1% across SSPs in 2050, 6.5-10.5% in 2100), despite having only a minimal share in global agricultural employment with 0.3% in 2020 (0.2-0.6% across SSPs in 2050, 0.2-1.5% in 2100). While agricultural employment already varies substantially between SSPs by 2050, agricultural production and total labor costs, as well as their regional distribution, are still comparable between SSPs in 2050, but scenarios diverge by 2100.

For low-income regions such as Sub-Saharan Africa (SSA) and India (IND), differences in labor productivity development are substantial across the different SSPs. While overall production in SSA in 2050 is still roughly the same for all SSPs (710-1097 mio. t. DM), employment needed for agricultural production shows a strong divergence (62-272 mio. people). Total labor costs in SSA, however, are similar across the SSPs in 2050 (212-262 bil. US$05), as productivity correlates with hourly labor costs. While, e.g., SSP3 (low labor productivity) would provide jobs in agriculture to a much larger share of the population in SSA in 2050

(272 mio. people, 20.3% of working age population), people employed in agriculture in SSP5 (high labor productivity) in SSA (62 mio. people, 5.5% of working age population) would be substantially better paid (2.28 USDMER05/h compared to 0.52 USDMER05/h in SSP3).

4 Discussion

Agricultural employment has been decreasing globally in the last decades [10] as economies have increasingly shifted from a focus on the primary sector to the secondary (manufacturing) and tertiary (services) sectors [20]. Especially in countries with higher economic development, the share of the working-age population engaged in agriculture is already low (3.0% in 2020), with middle-income countries following that development. However, the speed of this process has been increasing, with developing countries now taking less time to move from 50% to 10% of the workforce employed in agriculture [7].

The implications of a fast reduction in labor demand in agriculture are ambiguous. With agriculture typically being a sector with low productivity and low wages, a shift to other sectors can be part of a positive economic development, as was the case in China's "Green Revolution" leading to fast economic growth over the past few decades [40, 41]. However, especially in rural areas of developing countries, large parts of the population are currently still depending on income from agriculture [4, 5]. If the reduction of agricultural labor demand takes place at a speed that does not allow other sectors to keep up, higher unemployment and the loss of rural livelihoods can be the consequence [42]. This can already be seen in Sub-Saharan Africa, where low access to urban markets and bad infrastructure impedes the growth of the rural non-agricultural sector, leading to rapid agricultural exits while economic growth is slow [13, 43].

In line with the literature, our analysis shows that the decreasing trend in agricultural employment is likely to continue and will potentially pick up in speed. For all Shared Socioeconomic Pathways, we project that the share of the working-age population that is employed in agriculture will continuously decrease until the end of the century. Only SSP3, the "Regional Rivalry" pathway, shows a slight increase in absolute numbers of agricultural employment in the coming decades due to fast population growth and relatively slow development in labor productivity. Though not reporting absolute numbers of agricultural employment, the projected agricultural employment shares (out of total employment) in the five SSPs based on an econometric approach by Leimbach et al. show similar patterns to our results, with agricultural employment shares decreasing fastest in SSP5 and SSP1, and slowest in SSP3 [20].

With regard to the modelling caveats, our implementation of agricultural employment within MAgPIE is based on a calibrated top-down approach, relying on total labor costs, which in turn are calculated based on production quantities and labor costs per output unit in the respective regions. These labor requirements change over time, based on a labor share out of factor requirements. While factor requirements for livestock production follow a regression with SSP-specific livestock productivity projections, factor requirements for crop production are assumed constant in the future, as historical patterns show no clear trend. A more detailed representation of factor requirements for crop production might lead to higher labor costs and thus weaken the projected decrease in agricultural employment.

Employment numbers in MAgPIE are calibrated to historical data by the International Labor Organisation (ILO), which is based on labour force surveys or household surveys and modelling approaches to expand the raw data to a complete dataset. While conceptionally this dataset should include all forms of agricultural employment – e.g., part-time and full-time employment, formal and informal labor, work from family members and labor work, seasonal and long-term employment, migrant and local workers – in reality, surveys might not be able to capture the full picture, which could mean an underestimation of historic agricultural employment [44]. As especially marginal groups – e.g., informal workers or migrant seasonal workers – are likely to be underrepresented in these surveys, also resulting data on average working times could be biased. Historical data on hourly labor costs in agriculture is very sparse, with the respective ILO dataset only covering 30 countries, thus making the derivation of a complete dataset as well as future projections difficult.

MAgPIE considers employment in the agricultural sector in isolation, implicitly assuming a perfect connection between the labor markets of separate sectors. The omission of barriers and catalysts of cross-sectoral labor movements can lead to an under- or overestimation of future agricultural employment numbers. Especially in regions with currently high employment in agriculture where other sectors cannot absorb large quantities of freed labor in the coming decades, large parts of the rural population might stay locked in subsistence farming and precarious agricultural employment for want of better options. At the same time, employment opportunities in other sectors can lead to labor shortages in agriculture, as is already the case in many developed countries [45]. But even with existing demand for labor in other sectors, movement out of agriculture might be impeded by a required change in location or by qualifications not being transferable. This could lead to a decoupling of the agricultural wage rate and labor productivity from the rest of the economy. However, historic hourly labor costs in agriculture show a strong log-log relationship with GDP per capita, suggesting that this relation holds true over different economic development stages.

In general, we identified decreasing labor intensity (agricultural workers per labor costs) as the strongest driver of decreasing agricultural employment across all scenarios. Labor intensity is inversely proportional to average annual labor costs per agricultural worker, which are assumed to develop proportional to labor productivity. The development of hourly labor costs – and thus labor productivity – within MAgPIE follows the above-mentioned log-log relationship with GDP per capita. As our projections of hourly labor costs in agriculture use a regression based on historical data, we assume that the general development in labor productivity keeps following historical patterns. Country-level calibration is necessary to match historical values of hourly labor costs and impute values for countries not covered by the historical dataset. However, by keeping calibration factors constant over time, we assume that regional differences in the relation between GDP per capita and agricultural hourly labor costs and thus labor productivity are not resolved over time. Considering the

SSP storylines, especially in SSP1 and SSP5, which assume effective global collaboration on development goals, regional differences might be reduced over time, leading to a faster growth in labor productivity in currently less developed countries. Such distinctions are not included in this study, and could lead to an even faster decrease in agricultural employment in SSP1 and SSP5 than we project. Other factors potentially affecting the development of labor productivity, such as the impact of climate change, are not included in this study. Impacts of heat stress on labor productivity are expected to be dominant in Sub-Saharan Africa and Southeast Asia [46], where agricultural employment is currently the highest, thus slowing down the projected decrease in agricultural employment.

5 Conclusion

Agriculture and agricultural employment are central to rural development and both social and environmental goals. By including employment in a spatially explicit model of the land use system, we make a joint analysis of changes in the land use sector following socio-economic drivers – leading, e.g., to dietary change, productivity changes, and relocation of agricultural production – and their consequences on agricultural employment possible. In this study, we provide a first quantification of future agricultural employment on regional and global levels for the five Shared Socioeconomic Pathways using the agro-economic model MAgPIE. We discuss projected trends in agricultural employment and related indicators until 2100 in the global and regional contexts and disaggregate the future change in agricultural employment by six main drivers related to changes on both the producer and consumer sides of agricultural production.

We project a decreasing share of agricultural employment out of the total working age population for all SSPs, with only SSP3 showing a slight increase in absolute employment numbers in the coming decades. We identified increasing labor productivity as the main driver for decreasing agricultural employment across all scenarios, reinforced by a continuing substitution of labor by capital as input into agricultural production. Drivers slowing down the loss of agricultural employment are the growing global population as well as increased demand per capita for agricultural products. Despite limitations of the modelling approach, our projections can show the extent of structural change that would be necessary under the respective scenarios to allow people to move from low-productivity, low-return agricultural work to other sectors. The decomposition of changes in agricultural employment by main drivers allows the dynamics of the development of agricultural employment to be better understood, which is crucial in envisioning an inclusive strategy for structural change, meeting social, economic, and environmental targets.

While structural change leads to a reduction of employment in the agricultural sector, a sustainable development of agricultural practices could also create new jobs in environmental protection, resource management, agritourism or organic agriculture [17, 47]. Even without taking current trends such as increasing productivity into account, around 600 mio. additional jobs would be needed between 2013 and 2030 – globally and across all sectors – to keep the employment rate constant despite population growth [16]. However, new green jobs in the agricultural sector are mostly connected to new challenges, as they may be located in different regions and require new skills sets or higher skill levels, making increased investments in educational and training programs to re-skill and up-skill workers as well as social protection programs and labor policies to support the transition period necessary [17, 48]. Therefore, a transformation away from current practices could – if not handled carefully – also lead to increasing inequality and poverty [48].

To support such a transformation, agricultural employment needs to play a more central role in different modelling approaches. In particular, additional studies explicitly integrating agricultural employment into development scenarios of the food and land use system are necessary. Analyzing agricultural employment trends and the underlying drivers of change in such modelling exercises can disclose potential trade-offs, e.g., between an increase in labor productivity and employment effects, but also co-benefits such as additional jobs created by sustainability measures. Thereby it can facilitate structural change and the development of an inclusive transformation pathway for the food and land use system, which is needed to meet Sustainable Development Goals such as *No poverty* (SDG 1) and *Decent work and economic growth* (SDG 8).

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Supplementary Material
Future Employment in Global Agriculture: Trends and Drivers in the Shared Socioeconomic Pathways

April 12, 2024

1 Supplementary methods

1.1 MAgPIE

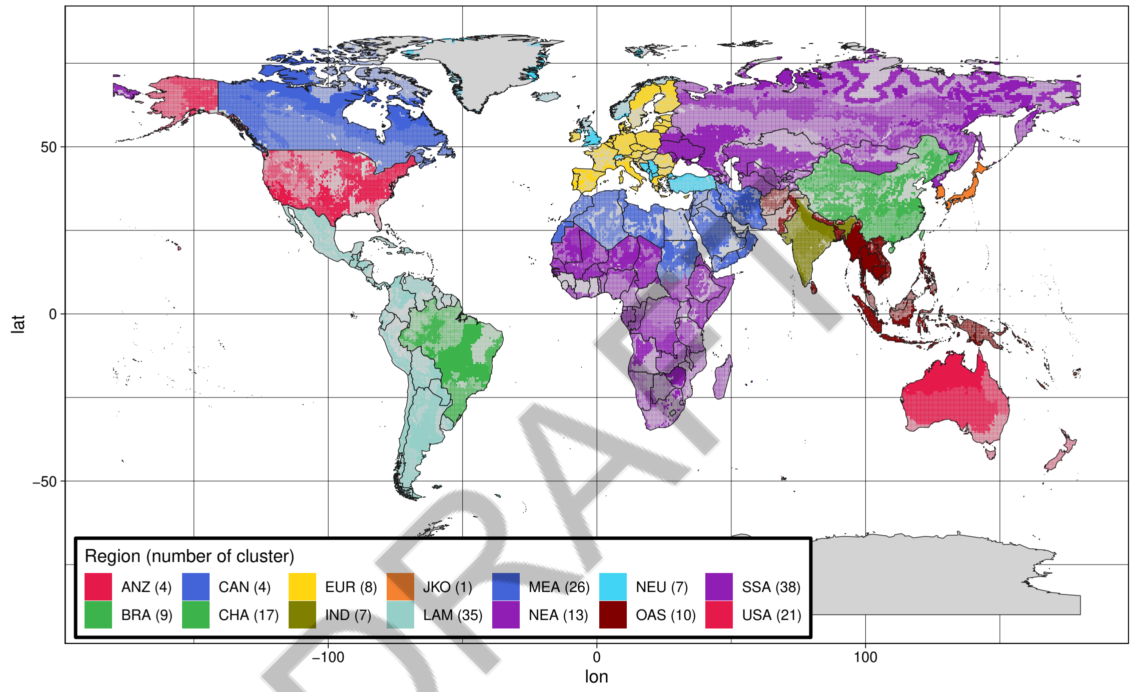
MAgPIE (Model of Agricultural Production and its Impact on the Environment) is a spatially explicit partial-equilibrium modeling framework of the global land system [1, 2]. It projects land use and production patterns as well as related output indicators – e.g., emissions from land-use and land-use change – in five-year time steps until 2100 under given socio-economic and biophysical constraints by minimizing overall costs while fulfilling the demand for agricultural products.

Agricultural demand includes the demand for food, feed, and material use. Food demand - including food waste - is projected by a food demand model linked to MAgPIE [3] based on external population and GDP projections, and takes into account the distribution of BMI, age groups, and gender, as well as different dietary compositions. Demand is differentiated between 19 crop groups, eight processed plant-based food items, five livestock commodities, and three types of crop residues. Feed demand for livestock production is estimated based on region- and product-specific feed baskets [4, 5]. Material demand includes the demand for first and second-generation bioenergy as well as other usage of agricultural products (e.g., industrial starch or cosmetics).

Inputs into agricultural production are land, water, nitrogen, capital, and labor. Agricultural land is disaggregated into croplands, pastures, forestry plantations, natural forests, urban areas, and other land. Cropland can either be rainfed or irrigated, with respective crop yields given by the global dynamic vegetation, hydrology, and crop model Lund Potsdam Jena Model managed Land (LPJmL) [6, 7]. Agricultural production can be increased through cropland expansion, competing with other land uses such as nature preservation or afforestation. Alternatives are investments into agricultural research and development to intensify agricultural production and obtain higher yields [8], irrigation, or a change of spatial production patterns. Costs of agricultural production include factor costs (i.e., labor and capital costs), fertilizer costs, costs for feed and seeds, and land rents. In addition, costs for land expansion and investments into yield-improving technologies and management practices are included.

Demand can be fulfilled by regional production or through the trade of agricultural commodities. Trade within MAgPIE includes intra-regional transportation and international trade between major world regions [9]. International trade partially follows historical trade patterns, while an additional "free trade pool" is traded according to relative competitiveness. Trade costs include export and import tariffs as well as trade margins (transport and administrative costs), based on the GTAP 7 database [10].

MAgPIE combines different levels of spatial resolution, with some results, such as crop production or nitrogen budgets, being reported on grid-cell level (59199 0.5°x0.5° grid cells), while others are reported on the country (e.g., food demand) or world-region level (e.g., international trade and technological progress). For computational reasons, the optimization is not carried out on the grid level. Instead, grid cells are aggregated using a clustering algorithm. Agricultural employment is currently reported on the world-region level but can be disaggregated to country values using post-processing routines of the MAgPIE model. For this study, MAgPIE was run with 14 world regions, which are shown in SI Fig. 1. In order to analyze results by economic development, world regions were categorized into low-income regions, middle-income regions, and high-income regions, see SI Tab. 1.



SI Figure 1: MAgPIE world regions used for this study. For explanation of the regional abbreviations see SI Tab. 1.

1.2 Derivation of a complete historical dataset on agricultural employment

To derive a complete historical dataset on employment in crop and livestock production, we use two datasets provided by the International Labour Organization (ILO). The first is an ILO-modelled dataset reporting employment in agriculture, forestry, and fishery as a single aggregated sector ('Employment by sex and economic activity – ILO modelled estimates, Nov. 2020 (thousands)') [11]. This dataset covers 188 out of the 249 countries included in MAgPIE. To estimate employment in agriculture, forestry, and fishery for missing countries (mostly small island states), the following relationship between the share s of the population that is employed in this sector and the GDP per capita was used, keeping s constant after $\frac{1}{2}\min s_{observed}$ is reached to avoid increasing employment share for high GDP per capita (see Eq. SI 1 and SI Fig. 2):

$$\sqrt{s} \sim log_{10}(\text{GDP per capita PPP}) \tag{SI 1}$$

Region	Regional abbreviation	Economic development categorization
Australia & New Zealand	ANZ	High-income region
Brazil	BRA	Middle-income region
Canada	CAN	High-income region
China	CHA	Middle-income region
European Union	EUR	High-income region
India	IND	Low-income region
Japan & South Korea	JKO	High-income region
Latin America (excl. Brazil)	LAM	Middle-income region
Middle East & North Africa	MEA	Middle-income region
Northern Eurasia	NEA	Middle-income region
Europe (Non-EU)	NEU	High-income region
Other Asia	OAS	Middle-income region
Sub-Saharan Africa	SSA	Low-income region
United States of America	USA	High-income region

SI Table 1: World regions used in this MAgPIE study and their regional abbreviations as well as their classification by economic development status.

To disaggregate the resulting employment dataset into agriculture, forestry, and fishery, we use a second dataset by ILO ('Employment by sex and economic activity - ISIC level 2 (thousands) — Annual') [11]. This dataset on employment is incomplete but reports employment in agriculture, forestry, and fishery as separate sectors (85% of values missing when considering the available years from 1993 to 2002 and all 249 countries covered in MAgPIE). Resulting shares out of overall agricultural employment were linearly interpolated and kept constant for extrapolation while assigning world average shares to missing countries. The completed dataset of sectoral employment shares was then applied to the aggregated values of the modelled dataset to get a complete disaggregated dataset.

1.3 Hourly labor cost regression

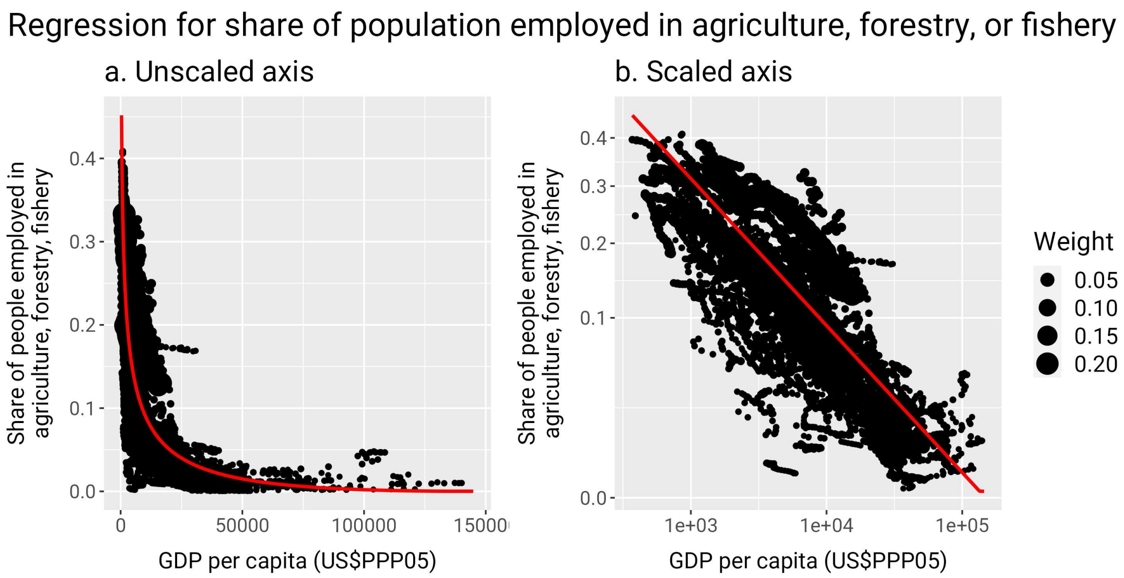
Historical data on hourly labor costs in agriculture are taken from ILO ('Mean nominal hourly labour cost per employee by economic activity') [11]. However, this dataset only provides data for 33 countries, with 30 countries remaining after removing outliers with unreasonably low or high hourly labor costs. Hourly labor costs for India and China were added from regional sources [12, 13, 14].

To both complete the historical dataset and project hourly labor costs into the future for different socio-economic scenarios, a regression analysis was carried out, yielding a log-log linear relationship between hourly labor costs and GDP pc US$MER05 (see SI Fig. 3).

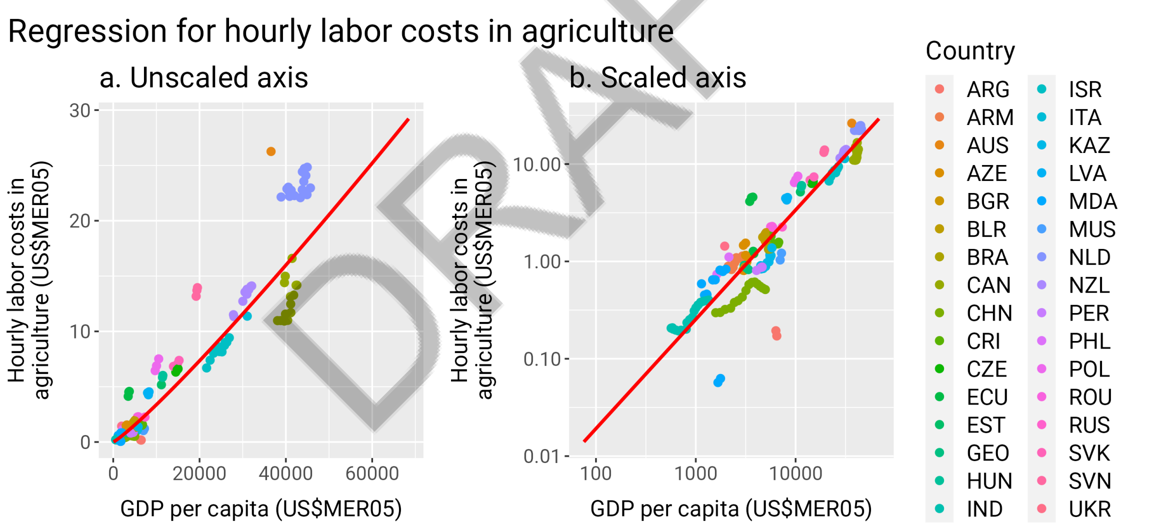
1.4 Calibration

We calibrate agricultural employment between the historical dataset (see SI Sec. 1.2) and MAgPIE results on country level, using 2010 as calibration year. Within MAgPIE, agricultural employment is calculated top-down, based on total labor costs in agricultural production (see also Main Sec. 2.2):

$$empl = \frac{c_{lab}}{c_{hour} \cdot h_{year}}, \tag{SI 2}$$



SI Figure 2: Regression for share of population employed in agriculture, forestry, or fishery. Linear regression between $\sqrt{s}$, where s is the share of population employed in agriculure, forestry, or fishery, and the log_{10}(GDP per capita US$PPP05): $\sqrt{s} = -0.2581731 \cdot log_{10}(GDP_{pc}) + 1.335372$, with s kept constant after $\frac{1}{2} \min s_{observed} = 0.013\%$ to avoid increasing employment shares for high GDP per capita. Population share out of global population was used as regression weight. Adjusted R-squared: 0.71, p-value: $< 2.2e-16$. **a)** shows the regression for unscaled variables, **b)** shows the linear form of the regression for scaled variables.



SI Figure 3: Regression for hourly labor costs in agriculture. Log-log linear regression between hourly labor costs c_{hour} and GDP per capita US$MER05: $ln(c_{hour}) = 1.122614 \cdot ln(GDP_{pc}) - 9.124118$. Adjusted R-squared: 0.87, p-value: $< 2.2e-16$. **a)** shows the regression for unscaled variables, **b)** shows the linear form of the regression for scaled variables.

where $empl$ is agricultural employment calculated in MAgPIE (mio. people), c_{lab} are annual total labor costs in crop and livestock production (mio. USD), c_{hour} are hourly labor costs in agriculture (USD/h), and h_{year} are the average hours worked per person in a year (h/year).

We can ensure consistency by correcting the hourly labor costs as follows:

$$\tilde{c}_{hour} = \frac{c_{lab}}{empl_{hist} \cdot h_{year}}, \qquad \text{(SI 3)}$$

where $empl_{hist}$ is agricultural employment as reported in the historical dataset.

We then use the resulting value of hourly labor costs in 2010 $\tilde{c}_{hour}^{2010}$ to calibrate the hourly labor cost regression on the country level by adjusting the intercept of the log-log linear relationship:

$$c_{hour} = exp\big(1.1226 \cdot ln(GDP_{pc}) - 9.124 + calib\big), \tag{SI 4}$$

where the country-specific calibration factor is defined as:

$$calib = ln(\tilde{c}_{hour}^{2010}) - [1.1226 \cdot ln(GDP_{pc}^{2010}) - 9.124]. \tag{SI 5}$$

Note that while this calibration incorporates regional differences in hourly labor costs into our approach and allows to complete the sparse dataset on hourly labor costs with more detail than e.g., using global averages for countries without historic data, it is not solely a calibration of hourly labor costs. Instead, the calibration is targeted at matching MAgPIE results to historic agricultural employment and thereby also corrects for potential additional inconsistencies between data sources used in the modelling.

Remaining discrepancies between historic agricultural employment and MAgPIE results can be explained by total labor costs within MAgPIE not exactly matching the historic total labor costs used in the calibration approach.

1.5 Kaya-like identity and decomposition

To decompose the change in agricultural employment by main drivers, we set up the following kaya-like identity:

$$empl = pop \cdot \frac{dem}{pop} \cdot \frac{prod}{dem} \cdot \frac{c_{fac}}{prod} \cdot \frac{c_{lab}}{c_{fac}} \cdot \frac{empl}{c_{lab}}.$$

Given any indicator E written as the product of driving indicators X_i, i.e. $E = \prod_{i=1}^{n} X_i$, the change in E can be written as weighted sum of changes in X_i, using the extended Laspeyres model [15]. It is:

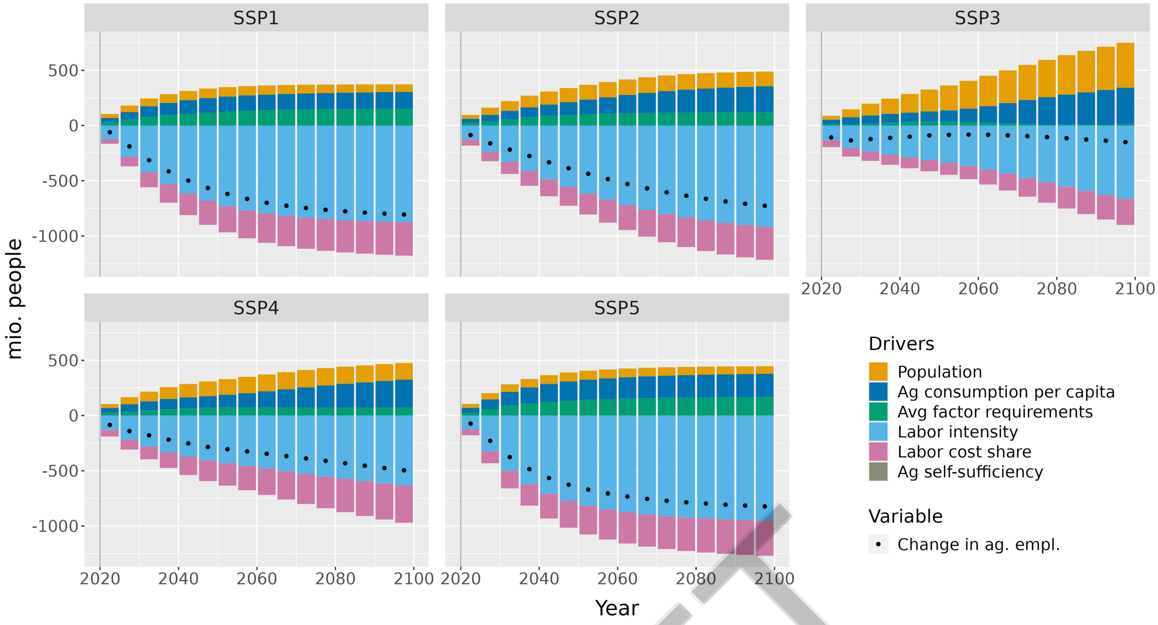
$$\Delta E = \prod_{i=1}^{n} X_i^t - \prod_{i=1}^{n} X_i^{t-1} = \sum_{k=1}^{n} \left(\sum_{i_1 \neq \ldots \neq i_k} \frac{E^{t-1}}{X_{i_1}^{t-1} \cdots X_{i_k}^{t-1}} \Delta X_{i_1} \cdots \Delta X_{i_k} \right) = \sum_{i=1}^{n} \tilde{X}_i$$

with

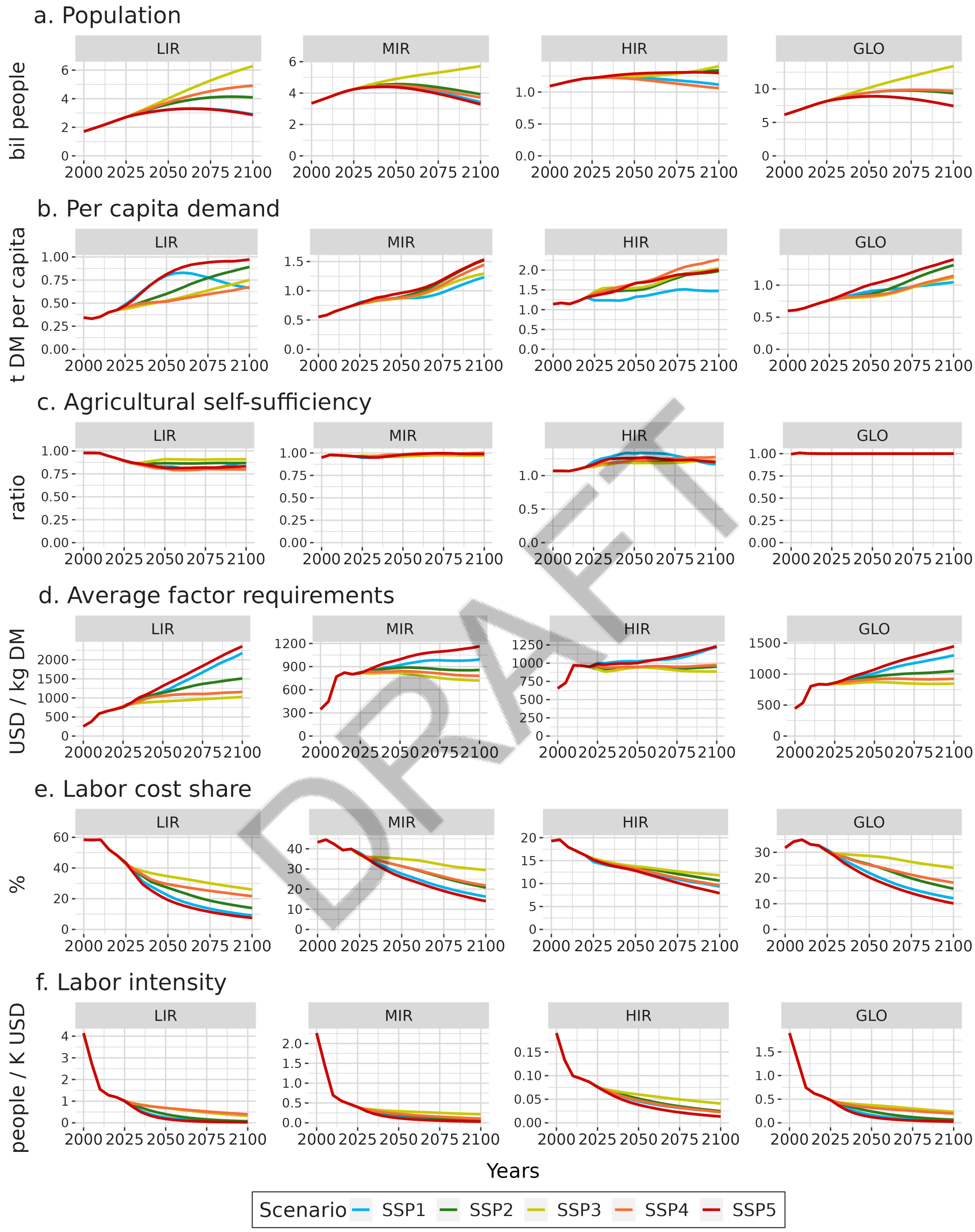
$$\tilde{X}_i := \Delta X_i \cdot \left[\frac{E^{t-1}}{X_i^{t-1}} \cdot \left(1 + \sum_{k=1}^{n-1} \left(\frac{1}{k+1} \sum_{i_1 \neq \ldots \neq i_k \neq i} \frac{\Delta X_{i_1} \cdots \Delta X_{i_k}}{X_{i_1}^{t-1} \cdots X_{i_k}^{t-1}} \right) \right) \right].$$

This allows to calculate an additive decomposition of changes in agricultural employment and attribute respective changes to the drivers defined in the kaya-like identity.

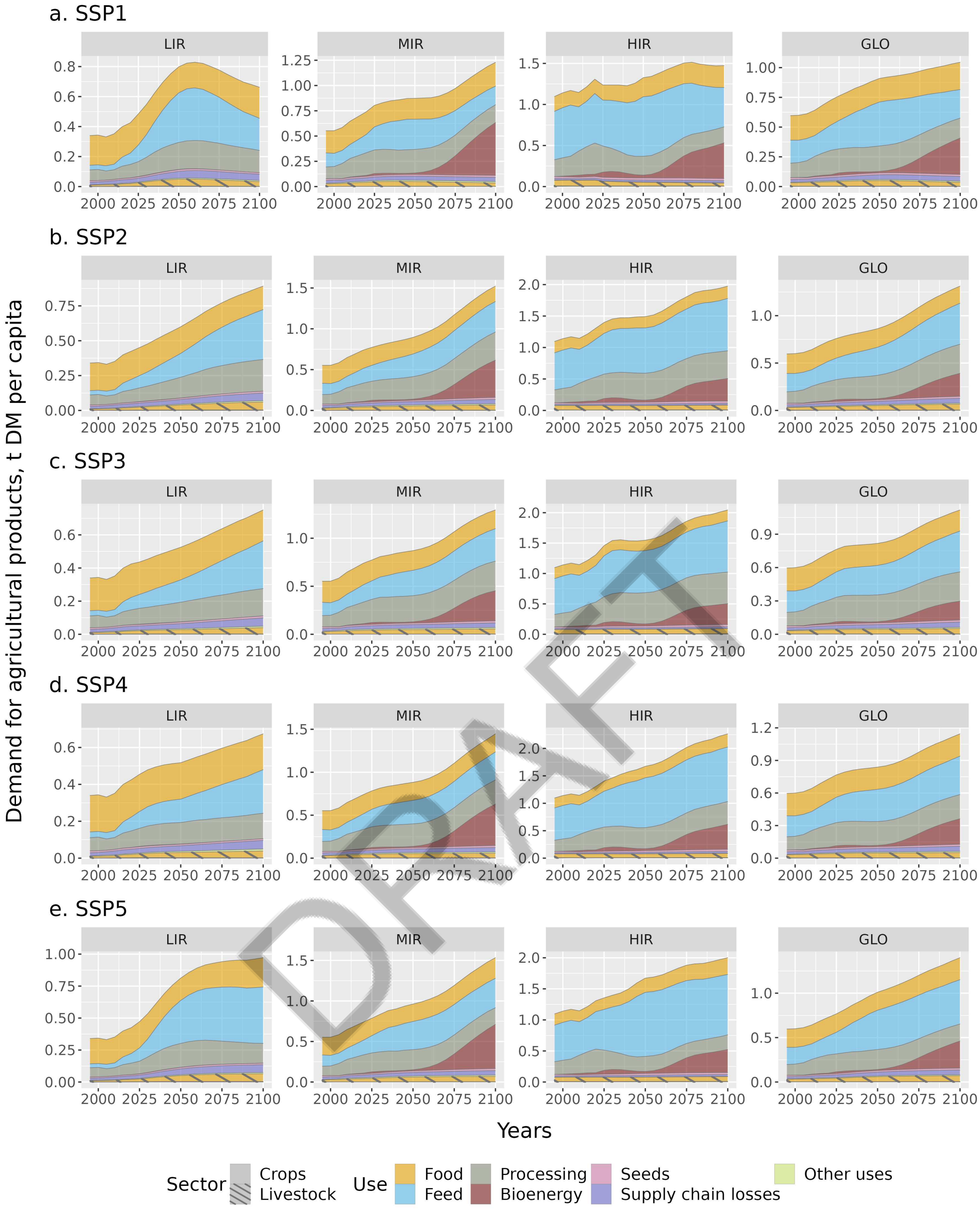
2 Supplementary results



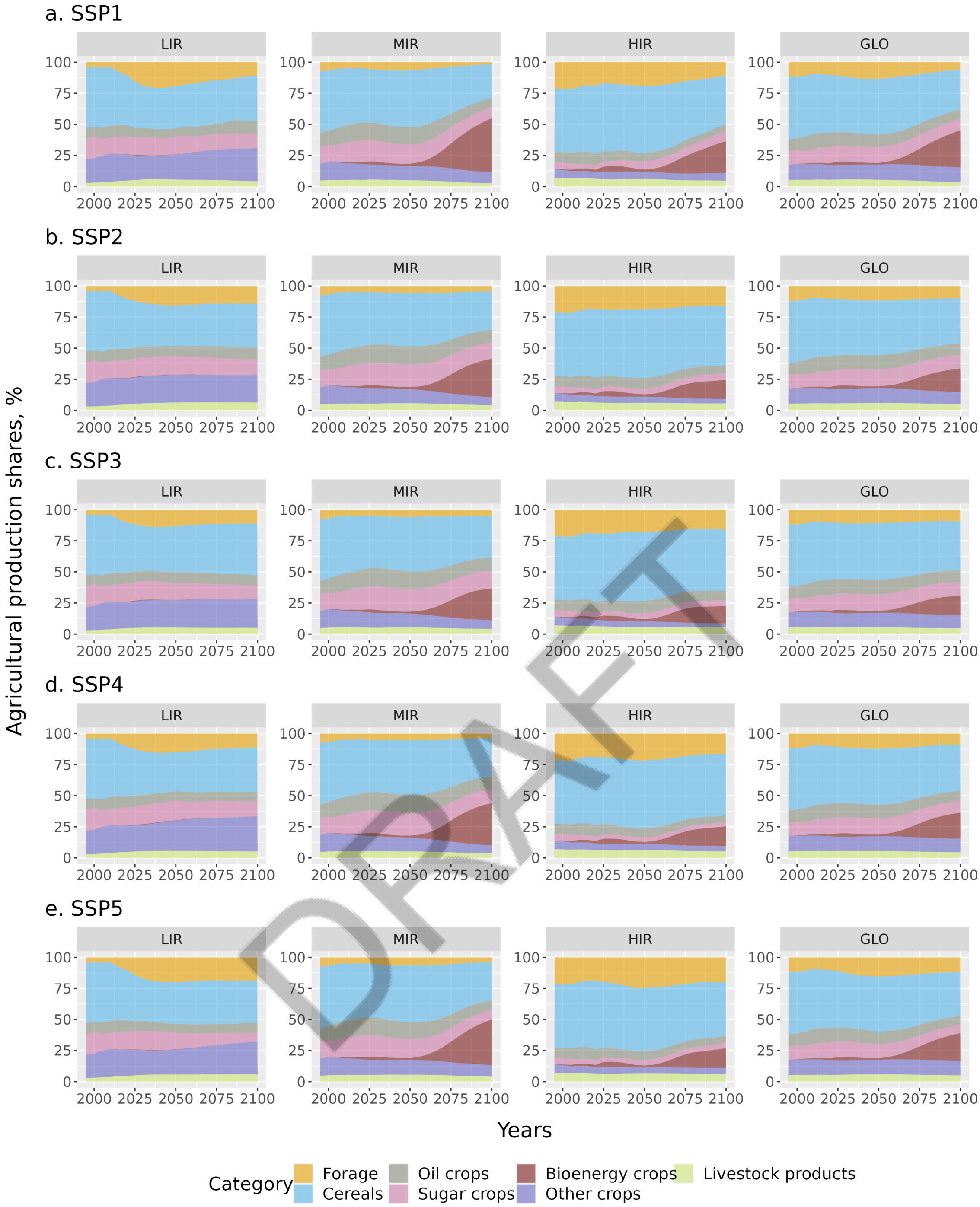
SI Figure 4: Cumulative change in global agricultural employment relative to 2020 and decomposition to main drivers for the five SSP scenarios. The black dots indicate the absolute change in agricultural employment relative to 2020 after each five-year time-step. Bars show the additive decomposition of the development in agricultural employment by driver.



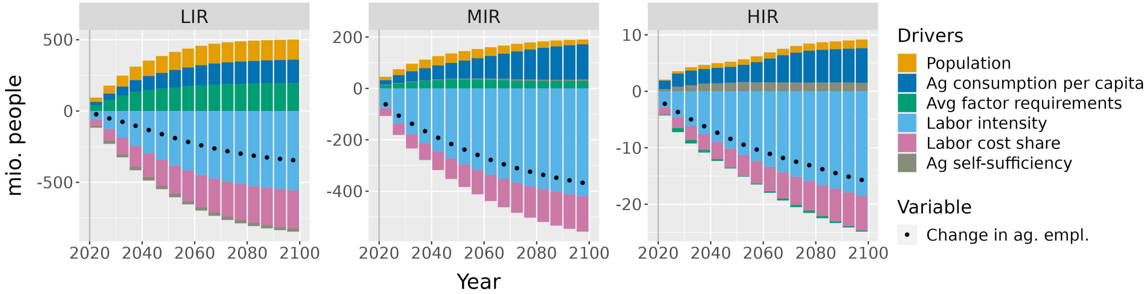
SI Figure 5: Drivers of agricultural employment for all SSPs. The panels show the six drivers of agricultural employment over time for low-income regions (LIR), middle-income regions (MIR) and high-income regions (HIR), as well as globally (GLO).



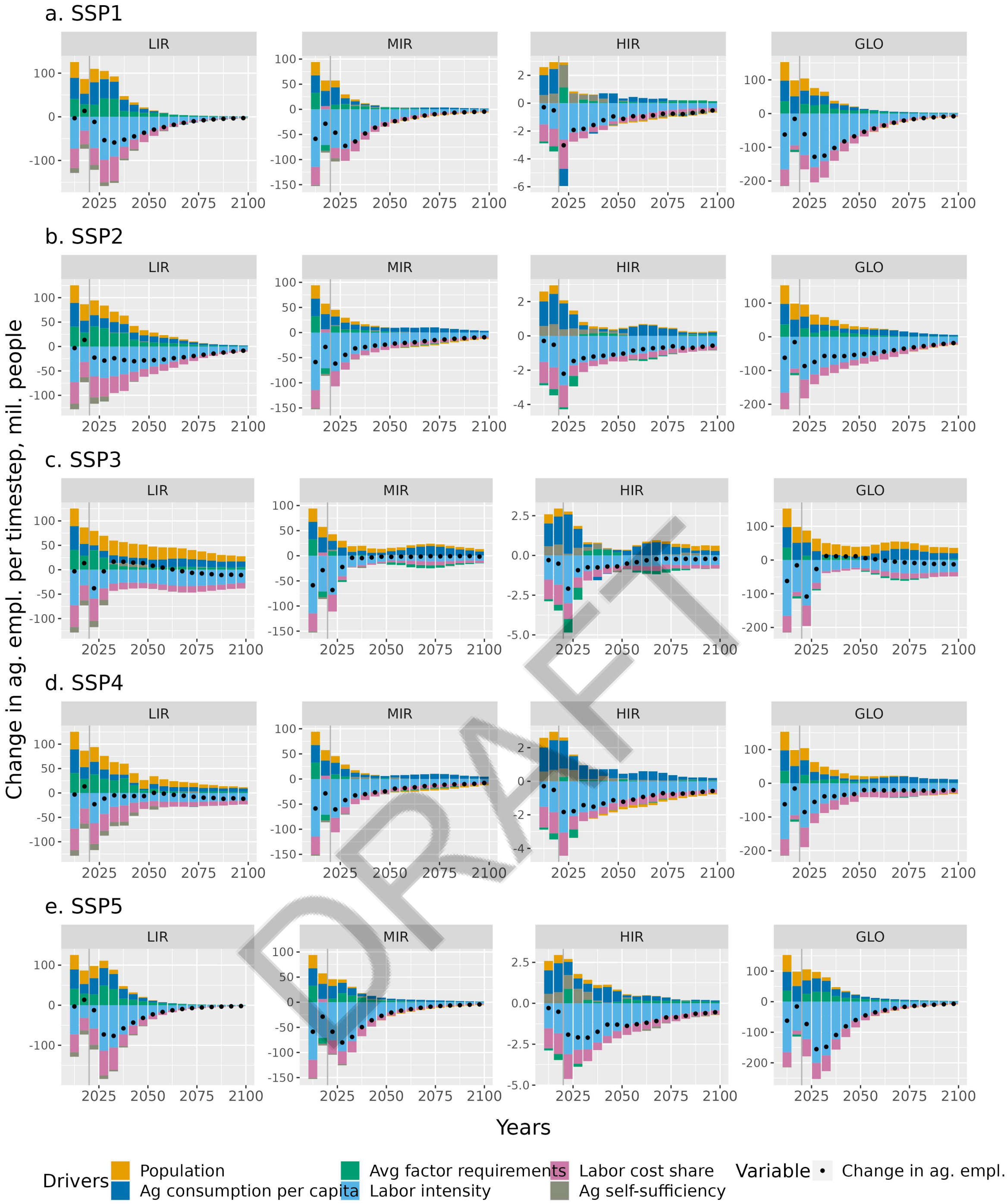
SI Figure 6: Average per capita demand over time. Each panel shows per capita demand for the respective SSP. The average per capita demand is shown for low-income regions (LIR), middle-income regions (MIR) and high-income regions (HIR), as well as globally (GLO). Demand is split by sector (crop products and livestock products) and by use (food, feed, processing, bioenergy, seeds, supply chain losses, other uses).



SI Figure 7: Composition of agricultural production in terms of tonne DM over time. Each panel shows production shares of forage, cereals, oil crops, sugar crops, bioenergy crops, other crops (fruits, vegetables, nuts), and livestock products out of overall agricultural production for the respective SSP. Share are shown for low-income regions (LIR), middle-income regions (MIR) and high-income regions (HIR), as well as globally (GLO).

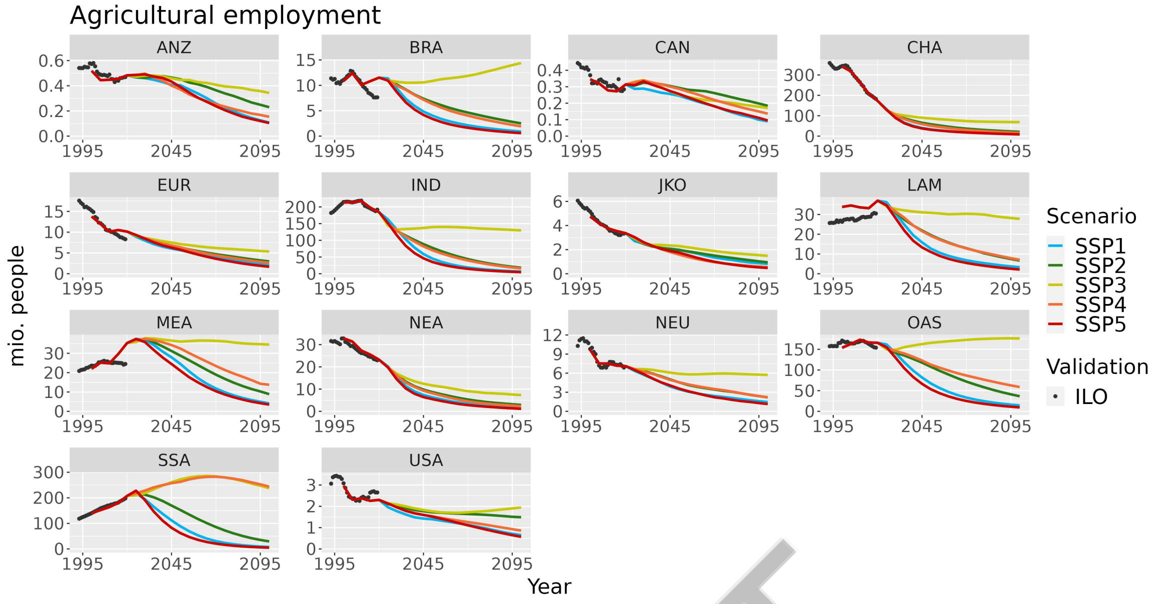


SI Figure 8: Cumulative change in global agricultural employment relative to 2020 and decomposition to main drivers for SSP2 by economic region. The black dots indicate the absolute change in agricultural employment relative to 2020 after each five-year time-step. Bars show the additive decomposition of the development in agricultural employment by driver.

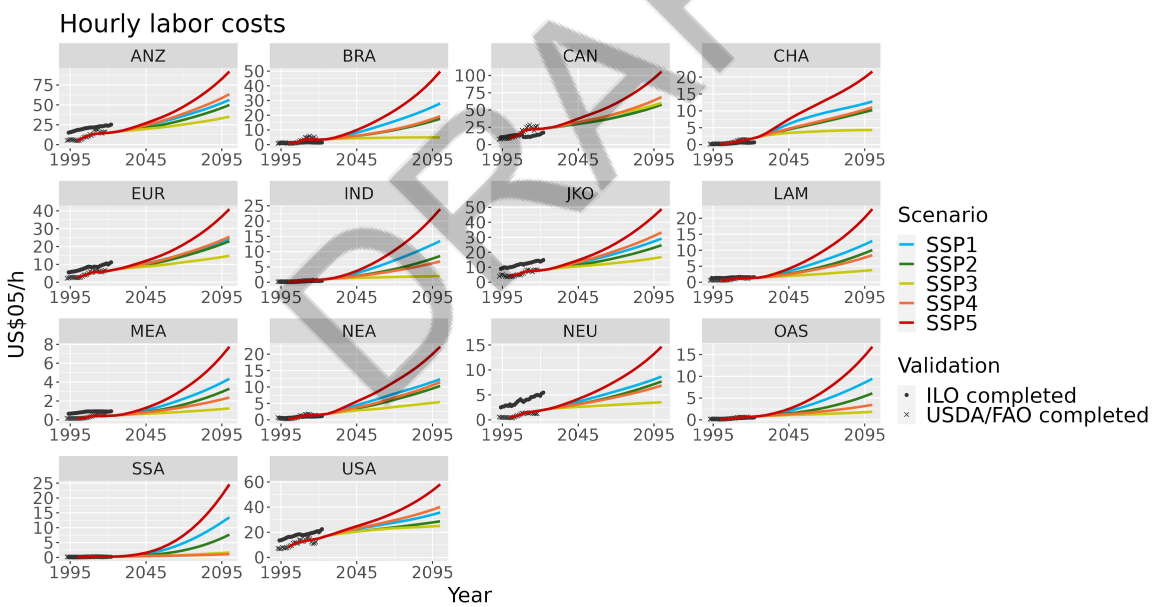


SI Figure 9: Regional attribution of changes in agricultural employment to respective drivers for all SSPs. Each panel shows the change in agricultural employment for the respective SSP for low-income regions (LIR), middle-income regions (MIR) and high-income regions (HIR), as well as globally (GLO). The black dot shows the absolute change in agricultural employment over the course of each five-year time-step. Bars show the additive decomposition of the development in agricultural employment by driver.

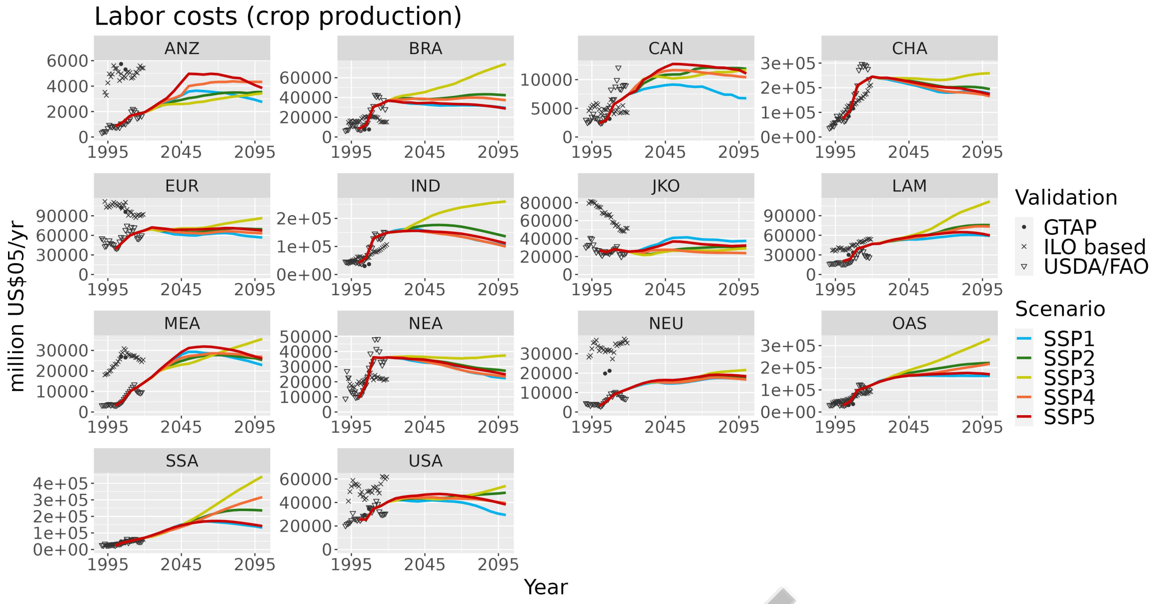
3 Validation of key indicators



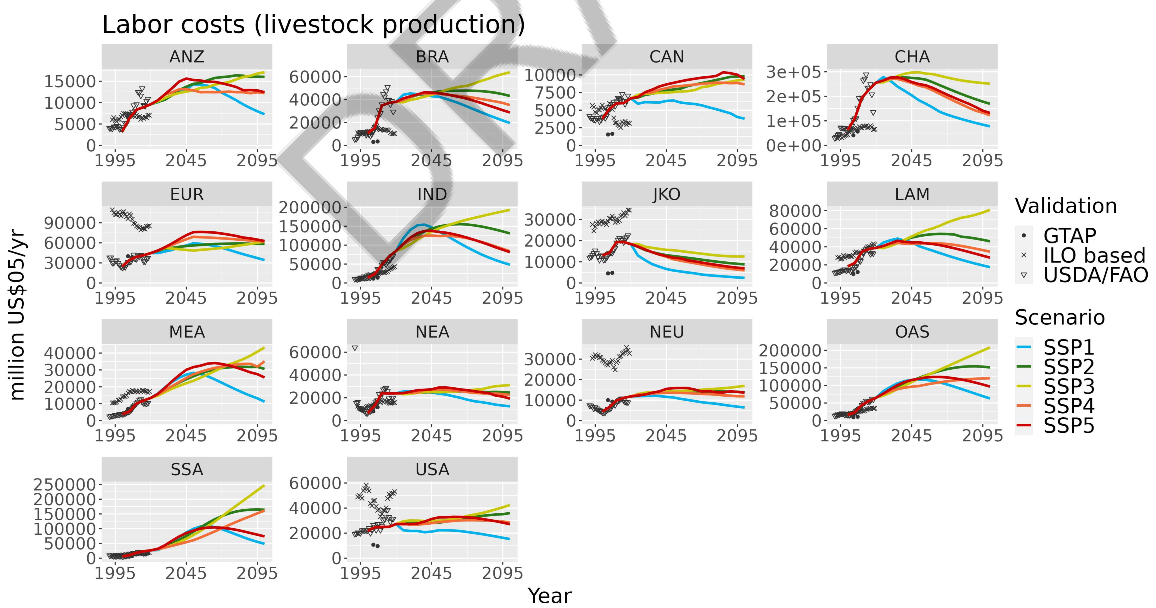
SI Figure 10: Validation of agricultural employment on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic agricultural employment based on ILO data (see Eq. SI 2, [11])



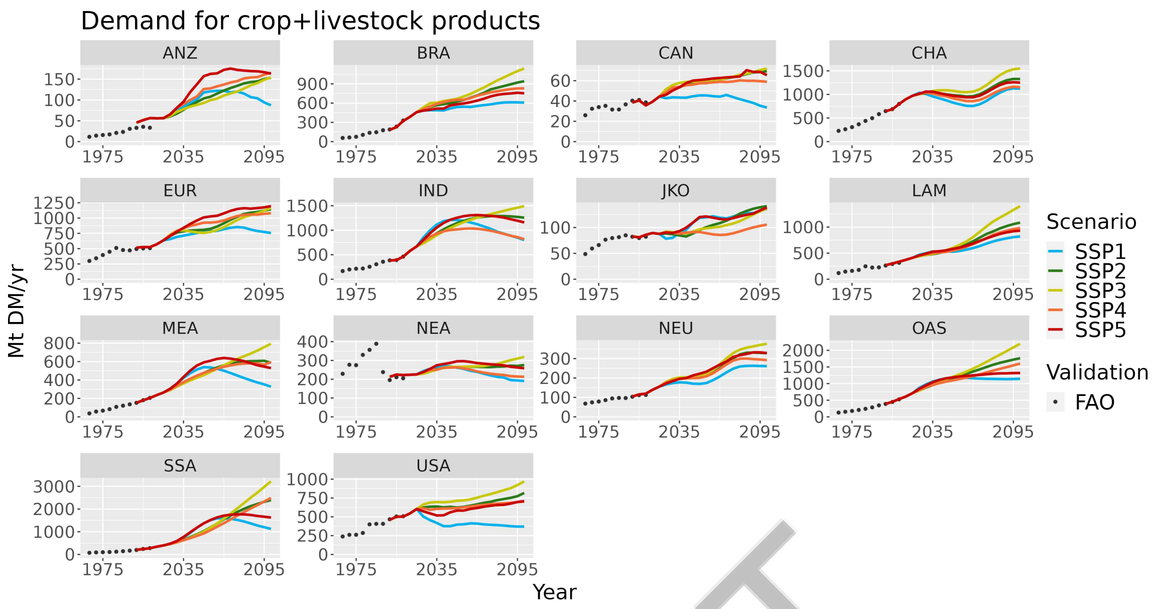
SI Figure 11: Validation of hourly labor costs on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic hourly labor costs based on different sources: **USDA/FAO completed** uses hourly labor costs as calculated from Eq. SI 3 and completed using the calibrated regression described in SI Sec. 1.4. **ILO completed** is solely based on the ILO hourly labor costs [11], completed using the regression, however only calibrated for countries included in the ILO dataset. For missing countries, the uncalibrated regression is used. As for some world regions none of the respective countries are included in the ILO dataset on hourly labor costs, the two validation datasets can differ quite strongly.



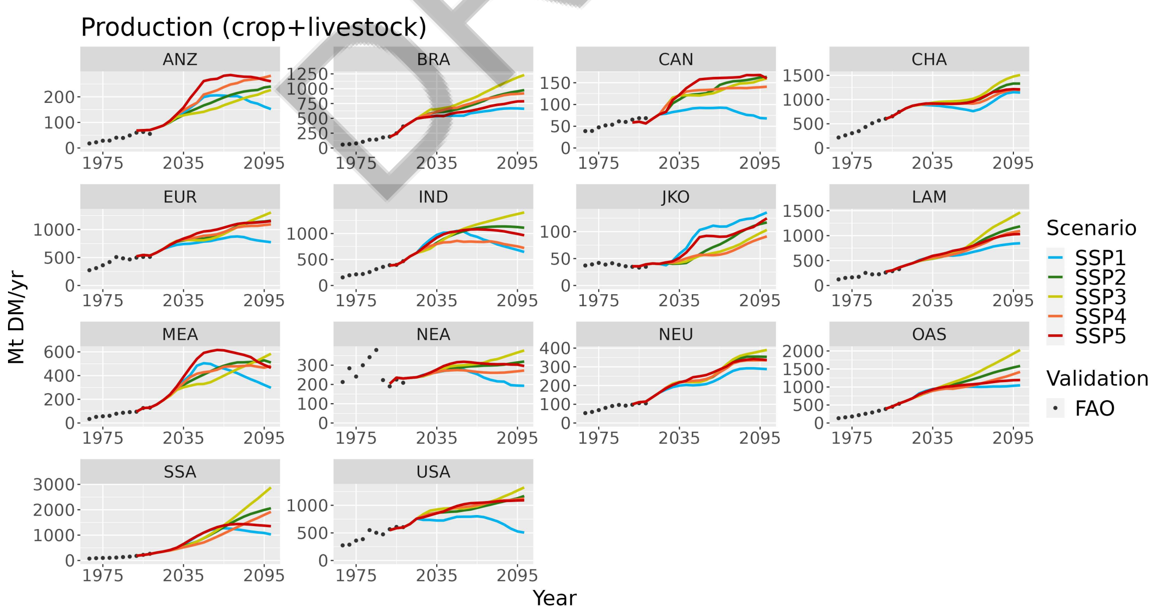
SI Figure 12: Validation of total labor costs in crop production on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic total labor costs in crop production based on different sources: **GTAP** uses the GTAP 8 database [16], **ILO based** is calculated as the product of ILO historic agricultural employment in crop production, hourly labor costs (using ILO completed hourly labor cost data, see SI Fig. 11) and average annual hours worked [11], **USDA/FAO** is calculated by applying the USDA labor cost share out of total production costs to FAO Value of Production of crop production. Due to the sparse data availability in the ILO hourly labor cost dataset, ILO based validation data can differ quite strongly from other results (see also SI Fig. 11)



SI Figure 13: Validation of total labor costs in livestock production on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic total labor costs in livestock production based on different sources: **GTAP** uses the GTAP 8 database [16], **ILO based** is calculated as the product of ILO historic agricultural employment in livestock production, hourly labor costs (using ILO completed hourly labor cost data, see SI Fig. 11) and average annual hours worked [11], **USDA/FAO** is calculated by applying the USDA labor cost share out of total production costs to FAO Value of Production of livestock production. Due to the sparse data availability in the ILO hourly labor cost dataset, ILO based validation data can differ quite strongly from other results (see also SI Fig. 11)



SI Figure 14: Validation of agricultural demand for crop and livestock products on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic agricultural demand for crop and livestock products based on FAO data [17]



SI Figure 15: Validation of agricultural production of crop and livestock products on world region level. Colored lines show MAgPIE results for the five SSPs. Grey points show historic agricultural production of crop and livestock products based on FAO data [17]

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