https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

AIM-ALPHA v1.0: A partial equilibrium model of global agriculture and land use at basin-level resolution

Ryo Totake[1], Hiroki Yoshida[1], Tomoko Hasegawa[2,1], Shinichiro Fujimori[1]

[1] Department of Environmental Engineering, Kyoto University, C1-3 361, Kyotodaigaku Katsura, Nishikyoku, Kyoto, 615-8540, Japan

[2] Research Organization of Science and Technology, Ritsumeikan University, 1-1-1, Nojihigashi, Kusatsu, Shiga, 525-8577, Japan.

Correspondence to: Ryo Totake (totake.ryo.85s@st.kyoto-u.ac.jp)

Abstract. This paper introduces AIM-ALPHA v1.0, a global partial equilibrium model that explicitly represents agricultural markets and land-use dynamics with high spatial resolution at the national and subnational river-basin levels. The model covers 166 countries on the demand side and 400 production units on the production side, balancing supply, demand, prices, trade, and land allocation across 23 agricultural commodities from 2015 to 2100. AIM-ALPHA is a comprehensive framework that analyses global socioeconomic and environmental challenges such as food security, climate change, biodiversity loss, and their mitigation. This paper describes the model structure, evaluates performance against historical data, and demonstrates application via a case study on the impacts of climate-change mitigation on global food security. Validation shows that AIM-ALPHA reproduces the historical statistics around 2015 and remains within ±10% of observed values up to 2020, confirming numerical consistency. The baseline projections are broadly consistent with those of other integrated assessment and agricultural economic models. We also present a scenario analysis using a 1.5°C climate-change mitigation pathway, which incorporates global carbon pricing, bioenergy expansion, and afforestation. The results show that agricultural production declines while food prices rise, reducing calorie intake, particularly in developing regions. The country-level resolution of the model reveals considerable heterogeneity within aggregated regions, with several developing countries in Africa and Asia facing particularly large reductions in food availability. Such distributional effects are largely obscured in more regionally aggregated models. These findings highlight the trade-offs between climate-change mitigation and food security and the importance of national-level assessments that capture socioeconomic and spatial heterogeneity. AIM-ALPHA serves as a comprehensive platform when exploring linkages between human and environmental systems and analysing sustainable land-use transitions and policy design at national and regional levels.

1 Introduction

Future projections of agricultural output and land use are becoming increasingly important. Rising food demand driven by population growth, increasing meat consumption associated with higher incomes, and the expanding field of bioenergy have intensified pressures on land resources (Godfray et al., 2010; Tilman et al., 2011). Agriculture and land-use policies play

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

central roles when addressing multiple global challenges such as climate change, food security, and biodiversity loss. Climate change, which affects temperature and precipitation patterns, can reduce crop yields and thereby worsen food security (Wheeler and von Braun, 2013; Hasegawa et al., 2018). The agriculture, forestry, and other land use (AFOLU) sector accounts for 13-21% of anthropogenic greenhouse gas (GHG) emissions. Mitigation is essential to reduce climate change (Nabuurs et al., 2022). However, afforestation, the expansion of bioenergy crops, and the reduction of non-CO_2 emissions, have been shown in previous studies to increase food prices and heighten hunger risks (Fujimori et al., 2022). In addition, land-use changes associated with mitigation actions and socioeconomic factors may further impact natural ecosystems and biodiversity (Ohashi et al., 2019; Leclère et al., 2020; Pereira et al., 2024). An understanding of the complex interactions between human activities and the natural environment is essential when designing sustainable pathways for the future.

Model-based approaches exploring long-term future trends usefully analyse the complex links between the economy, the environment, and society. In particular, agriculture and land-use models, and integrated assessment models (IAMs), have been widely used to evaluate GHG emissions, climate-change mitigation, and food security under different future scenarios. Representative examples include IMAGE (Stehfest et al., 2014), AIM (Fujimori et al., 2017), GCAM (Calvin et al., 2019), MAgPIE (Dietrich et al., 2019), and GLOBIOM (IBF-IIASA, 2023). These models integrate economic behaviour with biophysical processes, enabling quantitative assessment of land-use changes and the implications thereof in terms of global sustainability. The various models differ substantially in terms of the structural assumptions made, spatial resolution, and treatment of socioeconomic processes (Stehfest et al., 2019). Such differences often lead to different projections, emphasising the importance of multi-model comparisons when seeking to understand uncertainty and enhance policy robustness (Nelson et al., 2014; Hasegawa et al., 2018; Popp et al., 2017). Complementary models that employ distinct spatial or sectoral details contribute to a more comprehensive understanding of global land-use dynamics.

Agricultural and land-use issues are inherently spatial, being shaped by geographic factors such as climate, soil, water availability, and country-specific socioeconomic conditions. Therefore, capture of spatial and regional heterogeneity is essential for realistic analysis of the interactions among agriculture, land use, and climate policies (Roe et al., 2021; Harper et al., 2018). Although many global agriculture and land-use models consider biophysical processes (such as crop yields and land-use change) at relatively detailed spatial scales, food demand and trade are often modelled at aggregated regional levels. The capacity to examine country-specific or subnational issues, including dietary diversity, income disparities, and trade dependencies, therefore remains limited. Although several national-level multimarket models, such as IMPACT (Robinson et al., 2015) capture agricultural markets at the country scale; to the best of our knowledge, no model yet simultaneously considers market mechanisms at the national level and also explicitly examines land-use competition and the associated environmental impacts.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

The Asia-Pacific Integrated Model (AIM) framework has been widely used to explore various issues in the agriculture and land-use sectors, including climate-change mitigation (Fujimori et al., 2022; Hasegawa et al., 2024, 2025), food security (Hasegawa et al., 2018, 2021), and environmental impacts (Hirata et al., 2024; Ohashi et al., 2019). Within the general AIM framework, AIM-Hub (Fujimori et al., 2017), a computable general equilibrium (CGE) model, plays a central role in the development of globally consistent socioeconomic and emission pathways. AIM-Hub has been coupled with other models such as AIM-PLUM (Hasegawa et al., 2017), a land-use downscaling model that enables grid-level spatial projections, and AFOLUB (Hasegawa et al., 2025), which considers country-level GHG emissions and mitigation potentials. However, although AIM-Hub is a global CGE model, it operates at an aggregated regional scale and considers rather few agricultural production systems and commodity markets. It is difficult to capture detailed regional heterogeneity, country-specific food system challenges, and the bottom-up food production technology assumptions that are crucial when engaging in agricultural and land-use analysis.

To address these limitations, this paper introduces AIM-ALPHA, a new partial equilibrium model of the agriculture and land-use sectors that offers high spatial resolution at national and subnational river-basin levels. The model covers the entire world and enables consistent projections of food consumption, agricultural production, and land-use changes under various socioeconomic and climate scenarios. By explicitly linking country-level food demand and trade structures to detailed land-use representation, AIM-ALPHA enables integrated assessment of policy and behavioural impacts, ranging from the effects of land-based mitigation measures on national food security to the impacts of shifts in dietary patterns or trade conditions on environmental outcomes.

AIM-ALPHA is designed to complement the existing AIM model suite by providing detailed bottom-up representation of agricultural markets and land-use competition, which, again, is lacking in the current AIM modelling framework. AIM-ALPHA will enhance the representation of country-specific agricultural-system dynamics and can be integrated with downscaling and environmental-impact models (Hasegawa et al., 2017; Ohashi et al., 2019; Hasegawa et al., 2025). Such links will ensure that spatial analyses include national-level socioeconomic characteristics, enabling more geographically and socially plausible assessments of sustainable land-use transitions. The model will advance global sustainability research and inform national and sectoral policy design within the comprehensive AIM framework.

The remainder of this paper is organised as follows. Section 2 describes the model framework and structure. Section 3 outlines the scenarios used for analysis. Section 4 presents the simulation results. Section 5 discusses the main findings and the conclusions. This paper overviews the model; the details are available at https://github.com/KUAtmos/AIMALPHAdoc (last access: 25 November 2025).

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

2 Model description

2.1 Overview of the model

The Asia-Pacific Integrated Model - Agricultural Land-use Partial equilibrium model for Harmonized Analysis (AIM-ALPHA) is a recursive, dynamic, partial equilibrium model of agricultural markets and land use (Fig. 1) that endogenously balances supply, demand, prices, land-use changes, and trade flows for each country and agricultural commodity at annual time steps from 2015 to 2100. AIM-ALPHA represents 166 countries on the demand side and 400 production units on the supply side. Food production is classified into 13 primary crops, 6 livestock products, and 4 types of processed goods.

The model is formulated as a mixed complementarity problem (MCP) with a set of simultaneous equations but no explicit objective function. There are approximately 200,000 variables. The core framework, including base-year calibration, future projections, and the processing of simulation outputs, is implemented in a general algebraic modelling system (GAMS) using PATH as the large-scale MCP solver. Model outputs are stored as GDX files for post-processing and analysis. R is used to handle and organise input data and to visualise the results.

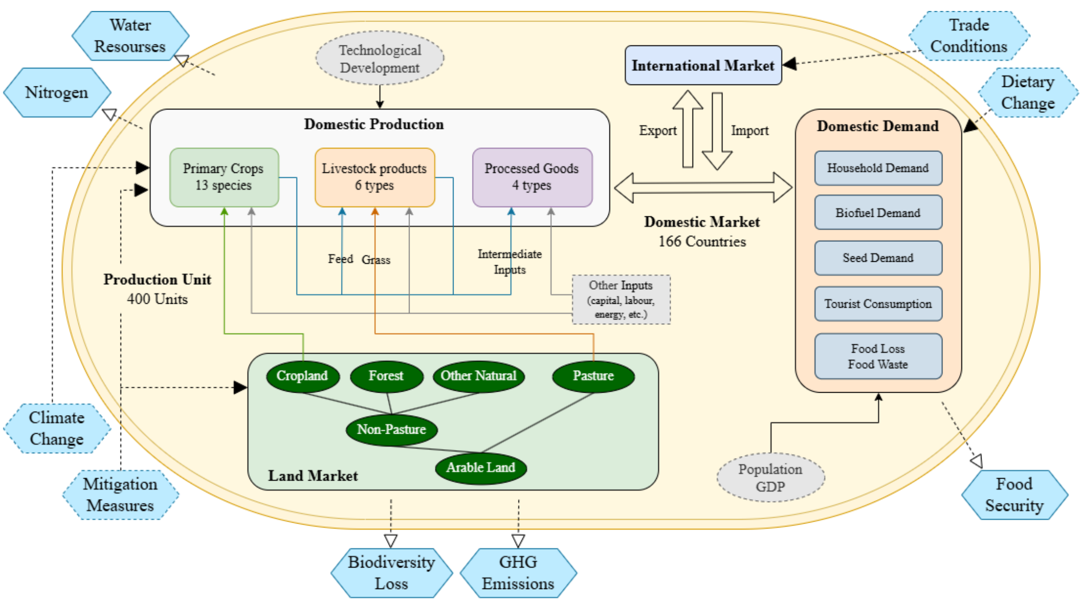


Figure 1. Overview of AIM-ALPHA.

2.2 Spatial resolution and land-use representation

In terms of spatial resolution, the model covers 166 countries on the demand side and 400 production units on the supply side, defined by overlaying national boundaries (World Bank, 2025) with the 230 major river basin divisions of the FAO (FAO

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Land and Water Division, 2011) (Fig. 2). Each production unit represents a unique combination of a country and a river basin, allowing spatially explicit representation of agricultural production and land use.

Agricultural markets are represented at both the national and global levels. Commodities are traded across 166 domestic markets as well as internationally. On the supply side, the model determines production quantities, land allocations, yields, and production systems (such as irrigated or rainfed cultivation of crops, and grazing-based or mixed farming of livestock) at the production-unit level for primary crops and livestock products. In contrast, processed goods are assumed to not require land inputs and are therefore modelled at the national level.

Land use is endogenously determined for cropland, pasture, forest, and other natural land, whereas urban areas and ice and water bodies are fixed at their base-year levels. In each production unit, cropland and pasture serve as the land inputs required for primary crop and livestock production, respectively. This allows competition among different land uses to be explicitly represented. The details of the endogenous land-use transitions are given in Sect. 2.7.

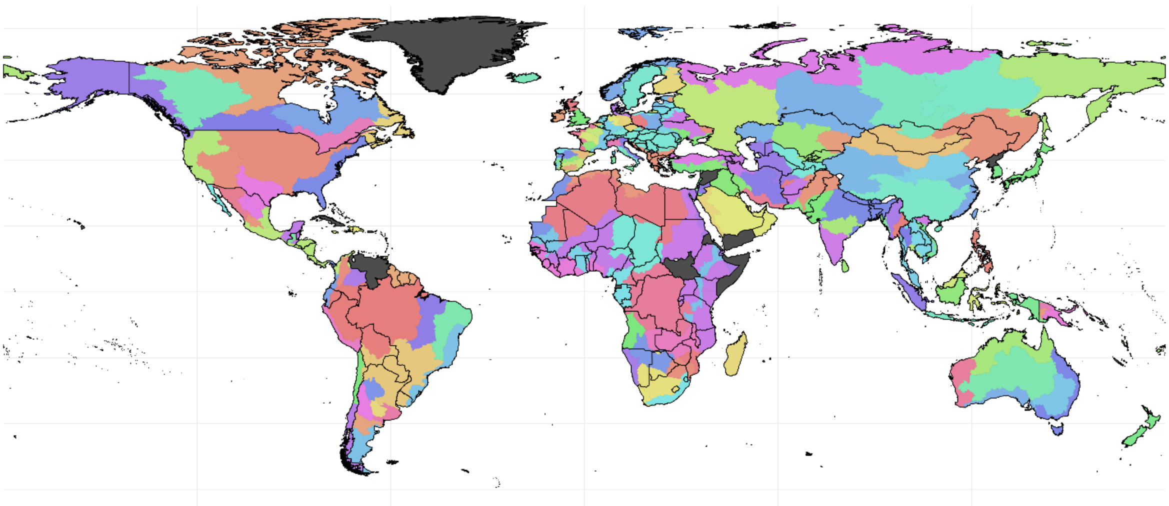


Figure 2. 166 countries and 400 production units of AIM-ALPHA. Regions that are not covered are shown in grey. This figure is a derivative work based on the FAO Major Hydrological Basins dataset (FAO Land and Water Division, 2011; licensed under CC BY-NC-SA 3.0 IGO) and the World Bank Official Boundaries dataset (World Bank, 2025; licensed under CC BY 4.0).

2.3 Commodities

AIM-ALPHA explicitly considers production of 13 primary crops (wheat, rice, corn, other grains, starchy roots, sugar crops, legumes, nuts, oilseeds, vegetables, fruit, stimulants, and spices), 6 livestock products (beef, sheep and goat meat, poultry meat, other meat, eggs, and raw milk), and 4 processed products (sweeteners, vegetable oils, alcoholic beverages, and dairy products).

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

These commodity categories broadly correspond to those of the FAOSTAT food balance sheets (FAO, 2025) and cover most major food items. For commodities not explicitly represented (such as fish, aquatic products, offal, animal fats, honey, etc.), base-year consumptions are exogenously extracted from FAOSTAT and scaled with population growth to maintain consistency in terms of national calorie estimates.

Processed goods are assumed to be produced using specific raw materials. Sweeteners are taken to be derived primarily from sugar crops; vegetable oils from oilseeds; dairy products from raw milk; and alcoholic beverages from wheat, rice, corn, other grains, and fruit. Livestock production is assumed to require concentrates of wheat, rice, corn, other grains, starchy roots, sugar crops, legumes, oilseeds, and/or vegetables. In addition, the model incorporates biofuel demand, with corn, sugar crops, and vegetable oil serving as feedstocks for biofuel production.

2.4 The partial equilibrium mechanism

This section explains how equilibrium is determined under the MCP formulation of AIM-ALPHA. An MCP expresses an economic equilibrium as a system of market-clearing identities combined with inequality constraints that are linked to non-negative activity variables (the complementarity conditions). The fundamental structure of a complementarity condition is:

$$f(x) \geq 0 \ \perp \ x \geq 0 \ \Leftrightarrow \ f(x) \geq 0\,,\ x \geq 0,\ f(x) \cdot x = 0 \qquad (1)$$

meaning that either the inequality constraint binds $[f(x) = 0]$ or the corresponding activity becomes zero ($x = 0$). In AIM-ALPHA, complementarity conditions are used widely across agricultural and land-use systems to control whether economic activities are active or inactive. For example, agricultural land-use transitions are constrained by biophysical limitations such as slope and soil suitability, and trade flows operate only when the price bounds justify import or export. The complementarity relationships allow the model to endogenously determine the activities that occur under a given economic environment. Explicit case distinctions are not required.

An equilibrium in each country and commodity is achieved when the following principles simultaneously hold:

(1) Market clearing: Supply equals demand in the domestic market after accounting for trade flows.
(2) Feasible price conditions: Domestic prices are within technological or trade-related bounds.
(3) Non-negative activities: Activities such as trade volumes or production are always non-negative, occurring only when economically justified.

Figure 3 focuses on how these principles operate in terms of international trade. For each country and commodity, the domestic price is restricted by an import price (linked to the international price plus tariffs, margins, and exchange rates) that sets an upper bound and an export price (analogously linked) that sets a lower bound. Depending on the relative position of the domestic equilibrium price, three equilibrium regimes can arise, as shown in Figure 3:

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

(1) No trade: the domestic equilibrium price lies between the import and export price bounds, and both the import and export volumes are zero (Country A in Fig. 3).
(2) Import regime: the domestic price equals the import price; domestic demand exceeds domestic supply, and the gap is met by positive imports (Country B).
(3) Export regime: the domestic price equals the export price; domestic supply exceeds domestic demand, and the surplus is shipped as positive exports (Country C).

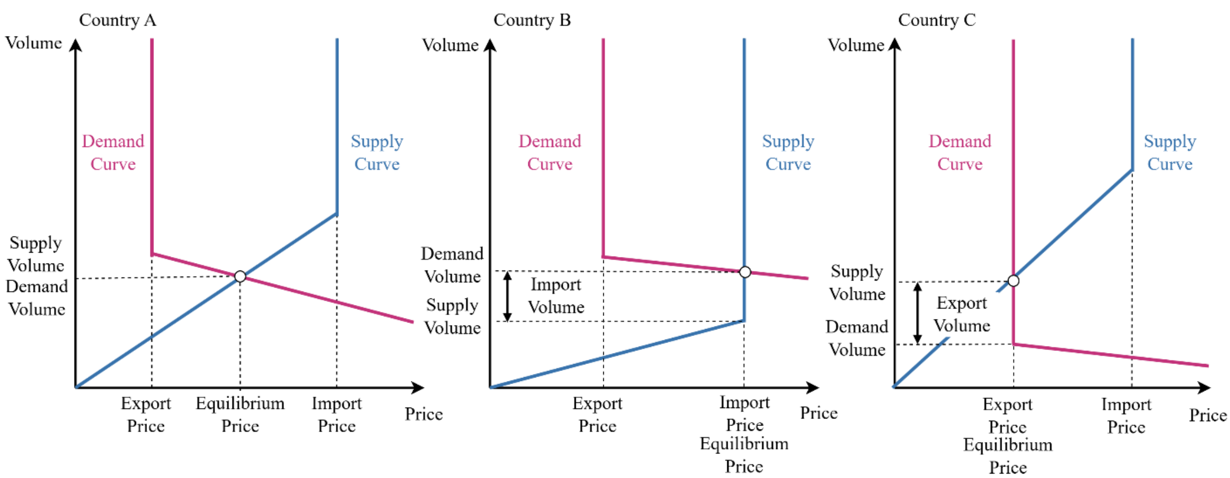


Figure 3. The trade mechanism in the model.

These relationships are implemented by setting complementary conditions akin to the standard formulations of multimarket models (Robinson et al., 2015):

$$PM_{c,cty} \geq PB_{c,cty} \perp QM_{c,cty} \geq 0 \quad (2)$$

$$PB_{c,cty} \geq PE_{c,cty} \perp QE_{c,cty} \geq 0 \quad (3)$$

where $PM_{c,cty}$, $PB_{c,cty}$, and $PE_{c,cty}$ are the import, domestic, and export prices respectively, and $QM_{c,cty}$ and $QE_{c,cty}$ are the import and export quantities for commodity c by country cty. Domestic market clearing is modelled by equating domestic supply ($QSUP_{c,cty}$), demand ($QDEM_{c,cty}$), and trade flows, as shown in Eq. (4):

$$QSUP_{c,cty} - QDEM_{c,cty} + QM_{c,cty} - QE_{c,cty} = 0 \quad (4)$$

The international market clears by balancing global exports and imports via changes in the international price, as shown in Eq. (5):

$$\sum_{cty} QE_{c,cty} - \sum_{cty} QM_{c,cty} = 0 \quad (5)$$

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

2.5 Agricultural demand

Food demand is determined by several factors, including prices, population, and the GDP. The total domestic demand for each commodity includes household consumption, feed use, intermediate inputs in terms of food processing, biofuel production, seed use, consumption by travellers, food loss and waste, and other minor uses. All volumes of these components are calibrated to the base-year data of FAOSTAT.

Among the above, household consumption changes over time in response to population growth. The model considers both the income and price elasticity of demand. In contrast, non-household demand components are assumed to vary principally with changes in prices. This view allows the model to capture both structural shifts in consumption patterns driven by economic growth and short-term responses to price fluctuations. Price elasticities are based on USDA estimates (Muhammad et al., 2013) and then further adjusted by the per capita GDP; they thus vary by economic growth. The income elasticities are detailed in the documentation (https://github.com/KUAtmos/AIMALPHAdoc, last access: 25 November 2025).

2.6 Agricultural production

A Leontief-type production function explores how each commodity is produced via the combination of specific input factors such as cropland, pasture, feed, and raw materials. Other inputs, such as labour, capital, and energy, are aggregated and treated as a single, composite production factor. Producer prices and production volumes for each country are calibrated to the base-year data of FAOSTAT, and the prices of individual input factors are those of the Global Trade Analysis Project (GTAP) database (Aguiar et al., 2019).

2.6.1 Primary crop production

The model distinguishes between different production technologies and explicitly considers biophysical and technological heterogeneity in terms of crop yield determination. For primary crops, both irrigated and rainfed production technologies are thoroughly analysed. In the base year, the national-level production quantities and harvested areas of FAOSTAT are spatially disaggregated to the river-basin level using information in the Global Agro-Ecological Zones (GAEZ) database (FAO and IIASA, 2025). Irrigated and rainfed systems are distinguished. The cropping intensities (the ratios of harvested to physical areas) are adopted from those of IFPRI (2024) to ensure consistency in terms of regional cultivation patterns. In summary, the model derives crop yields for each production unit and each production technology in the base year. For future projections, the exogenous yield improvement rates driven by technological progress are those of Robinson et al. (2015). The yield change rates associated with climate change are those of the GAEZ database, which considers both the direct impacts of temperature and precipitation changes and the CO_2 fertilization effect in terms of crop productivity.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

2.6.2 Livestock production

For livestock production, differences across climatic zones and between grazing-based and mixed farming production systems are explicitly considered. The share of each production system is assumed to change with the per capita GDP, as estimated via regression analysis. Differences among production systems trigger variations in feed requirements and composition, particularly the proportions of forage and concentrate feed. Both the feed requirement coefficients and the feed composition are assumed to change with the per capita GDP, reflecting improvements in production efficiency associated with economic development. For the base year, the FAOSTAT national-level livestock production information is disaggregated into production units, climatic zones, and production systems using the datasets of Herrero et al. (2018) and Robinson et al. (2018). The extent of forage (pasture grasses) is assumed to depend on the available pasture area; forage supply varies. In contrast, concentrate feed relies on primary crops such as grains, which therefore serve as key inputs to livestock feed.

2.6.3 Processed-goods production

Processed-food products are produced using intermediate input goods. To simplify the model, the types of raw materials used for processing are limited to the predefined set of Sect. 2.3. Processed-food production is influenced by the domestic prices of the raw materials. For the base year, the quantities of processed goods produced, the inputs of raw materials, and the input shares are calibrated to the FAOSTAT data.

2.6.4 Energy crops

The regional productions of energy crops are exogenously sourced, based on the annual production quantities of the aggregated regions of the AIM-Hub model (Fujimori et al., 2017). These quantities are then allocated across production units by their relative prices and yields. These determine the production volume and the corresponding land use of each unit. Such allocation allows the model to capture the competition for land between energy and food-crop production.

2.7 Land use

The land use within each production unit is determined using a multi-nested logit structure that allocates land among alternative uses but maintains the total land balance. Allocation decisions are driven by land rents, reflecting the relative profitability of competing land uses. The logit formulation enables smooth land allocation among competing uses while ensuring that the total land area remains consistent (Fujimori et al., 2014). Figure 4 illustrates the nested structure of land-use allocation.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

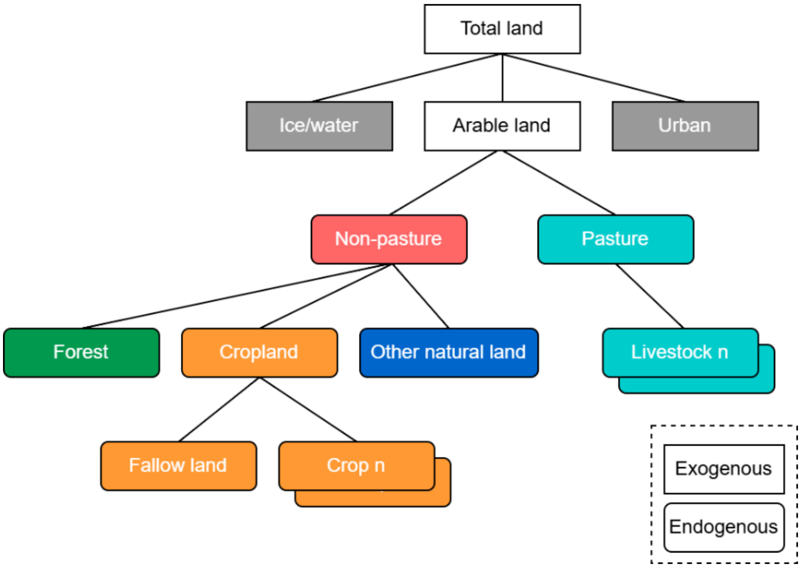


Figure 4. Land allocation.

255 The model endogenously considers four major land-use categories: cropland, pasture, forest, and other natural land. For each production unit, the total land area is first adjusted by subtracting ice and water bodies and urban areas, which are treated as exogenous and fixed at their base-year levels. This yields the total arable land, which is then divided into pasture and non-pasture. Pasture is further allocated among the individual livestock-production activities, and non-pasture is subdivided into cropland, forest, and other natural land. Cropland is further distributed between fallow land and the harvest areas of the individual primary crops. Among these, land areas associated with no direct human use, such as forests, other natural land, and fallow land, are assigned exogenous land prices fixed at their base-year levels. Biophysical constraints, including slope and soil suitability, impose limits on the total area available for agricultural use. Land-use areas for each category are calibrated to the base-year information of the Land-Use Harmonization (LUH2) dataset (Hurtt et al., 2020) at the production-unit level.

2.8 International trade

Trade volumes are expressed as net exports (exports minus imports), and domestic market equilibrium is achieved when production, domestic demand, and net trade are balanced via price adjustments. At the global level, international prices are endogenously determined. Total exports and imports are balanced (see Sect. 2.4). Export and import prices are linked to the international market price using fixed parameters such as tariffs, trade margins, and exchange rates. Trade in food commodities is viewed as a complementarity problem, as described in Sect. 2.4. For example, when the import price exceeds the domestic price, imports fall to zero; conversely, imports commence once the import price declines to the level of the domestic price.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Similarly, when the border price exceeds the export price, exports fall to zero, but exports begin when the export price rises to the border price.

Global trade losses are explicitly considered. In the base year, the discrepancy between the FAOSTAT-reported global exports and imports is treated as a residual loss and held constant throughout the projection period. This residual term represents the physical losses along supply chains and trade flows associated with countries not explicitly represented in the model. In the base year, the trade volumes and prices are calibrated using FAOSTAT data and the tariff rates, trade margins, and exchange rates are those of the GTAP database.

2.9 GHG reduction measures and emissions

A uniform global carbon price, estimated by the AIM-Hub model that considers the extent of climate-change mitigation, is exogenously introduced to the model. When the carbon price is applied, the implementation levels and costs of various emission-reduction technologies are determined by the marginal abatement cost (MAC) curves (Harmsen et al., 2019). Both the carbon costs associated with residual emissions and the abatement costs are added to the producer prices of each commodity, thereby increasing domestic market prices. In terms of afforestation, introduction of a carbon price imparts an economic value to the carbon stock of forests. This value is incorporated into the land rent of forested areas, leading to an expansion of forest land. The carbon value used is a discounted value, assuming a forest lifetime of 60 years and an interest rate of 5%. The extent of carbon sequestration via afforestation varies with the age of the forest. For energy crops, as described in Sect. 2.6.4, the regional production levels estimated by the AIM-Hub model are exogenously supplied, and allocated across production units by the relative prices and yields.

GHG emissions are estimated based on the production level of each food commodity, and land-use emissions are estimated from the area of each land-use type. All emission coefficients are calibrated to the FAOSTAT base-year data .

2.10 Socioeconomic assumptions

Future population levels and GDPs are exogenously derived from the Shared Socioeconomic Pathways (SSP) v3.0 database (KC et al., 2024; Crespo Cuaresma, 2017). The SSP framework considers alternative global development trajectories, ranging from SSP1 to SSP5, each featuring distinct levels of economic growth, demographic change, and technological development (Riahi et al., 2017). SSP1 models a sustainable world with low population growth and strong economic development; SSP2 is a middle-of-the-road pathway along which existing social and economic trends continue in a moderate manner; SSP3 assumes slow economic growth but high population growth, leading to regional disparities and challenges in terms of development; SSP4 depicts a world with large inequalities between and within countries; SSP5 imagines rapid economic growth based on

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

fossil-fuel use and extensive globalisation. The differences in population and GDP among the SSP scenarios influence various aspects of the models, including food demand, technological progress in terms of production, and other socioeconomic drivers of agricultural and land-use systems.

3 The scenarios

This section describes the scenarios used for the following analyses. First, for each SSP, a business-as-usual (BaU) scenario is simulated. This does not consider climate-change mitigation measures or impacts. Table 1 summarises the key socioeconomic assumptions specific to each SSP, and Fig. 5 illustrates the projected changes in population and GDP per capita under each pathway.

In addition, for SSP2, a mitigation scenario corresponding to the 1.5°C target is analysed. This incorporates three major climate-change mitigation measures:
(1) introduction of a carbon price on GHG emissions,
(2) expansion of bioenergy crop production, and
(3) enhancement of afforestation.
As described in Sect. 2.9, the model uses a uniform global carbon price estimated by AIM-Hub. In this scenario, the global carbon budget for the rest of the century is 500 Gt CO_2, which corresponds to the 1.5°C target (Fujimori et al., 2025). Figure 6 shows the global carbon price trajectory assumed in the mitigation scenario. Bioenergy production is exogenously introduced based on the production amounts for 17 aggregated regions (also provided by AIM-Hub). These are subsequently allocated to production units by employing the land prices. The afforestation response to the carbon price is an increase in forest land rents, reflecting the value of forest carbon stocks.

By comparing the mitigation and BaU scenarios, we evaluate the impacts of climate-change mitigation on food security and land use.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Table 1. Assumptions of each SSP scenario.

	SSP1	SSP2	SSP3	SSP4	SSP5	Remarks
Food demand	Varies with population and GDP per capita, with consideration of income elasticity					Income elasticity is estimated using the food demand model. See the model formulation document for the parameters.
Price elasticity	Varies with the GDP per capita					Regression analysis is based on that of Muhammad et al. (2013)
Crop yield	20% higher annual growth rate in developing countries relative to the baseline assumptions	10% reduction in annual growth from baseline	70% reduction in annual growth from baseline	Same as SSP2	Same as SSP1	The assumptions are consistent with those of AIM-CGE in Popp et al. (2017). The baseline yield growth follows that of Robinson et al. (2015)
Livestock productivity	The production system shares, feed demands, and concentrate feed ratios vary with the GDP per capita					Regression analysis is based on Herrero et al. (2018)
International trade	The tariff and producer support rates are fixed at the base-year levels					
Land protection	Only physical restrictions on agricultural land use (e.g., slope and soil suitability) are considered					

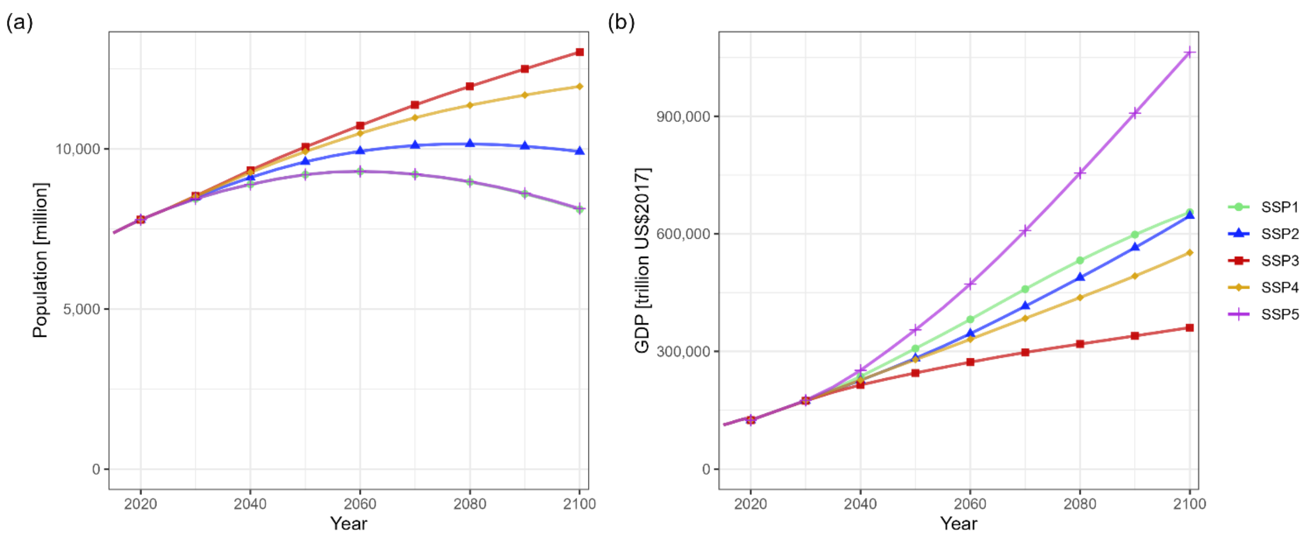


Figure 5. Global population and GDP projections under SSP1-5 (KC et al., 2024; Crespo Cuaresma, 2017).

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

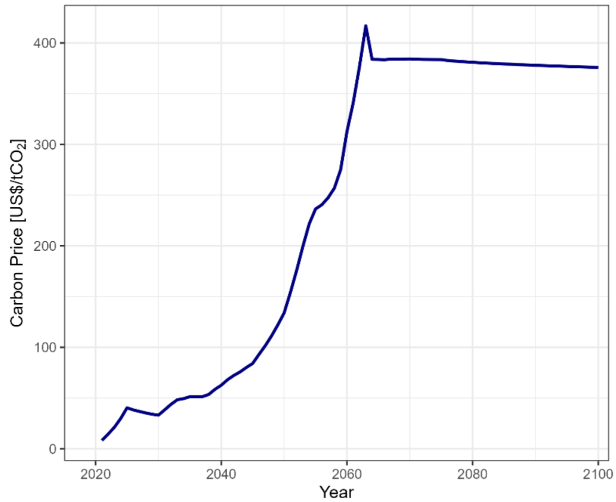


Figure 6. Carbon price under the SSP2-mitigation scenario of AIM-Hub (Fujimori et al., 2025).

4 Model outputs

This section presents the results of simulations. First, those of the BaU scenario, which does not include any climate-change mitigation measure, are shown (the baseline data). The results include comparisons among the five SSPs and historical observations. Next, the results of the mitigation scenario corresponding to the 1.5°C target are presented. Here, the socioeconomic conditions are those of SSP2, and the outcomes are compared to those of the BaU baseline to assess the effects of climate-change mitigation on major agricultural and land-use indicators.

4.1 Baseline

4.1.1 Baseline and alternative socioeconomic pathways

Figure 7 presents the simulations of agricultural consumption, production, land use, and CH_4 and N_2O emissions under the SSP2–BaU scenario of the AIM-ALPHA model. The figure includes comparisons with historical data (FAO, 2025; European Commission et al., 2024; Hurtt et al., 2020), and projections from other IAMs that are in the SSP database (Popp et al., 2017; Riahi et al., 2017). Production and consumption of both primary crops and livestock products increase steadily through 2100, reflecting the combined effects of population growth and rising incomes. The base-year values align with the FAOSTAT data and remain within ± 10% of the latest available observations, which extend to 2022. Compared to other IAMs, AIM-ALPHA exhibits similar trajectories but slightly more consumption after 2060. In terms of the land-use projections, cropland expands

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

continuously (to +223 million ha in 2100) and pastureland increases to mid-century and then declines (+361 million ha in 2100). This trend reflects the model structure. The ratio of roughage to concentrate feed depends primarily on the per capita GDP, associated with greater pasture demand in the early decades. Forest area decreases moderately (–230 million ha in 2100). The land-use data are consistent with those of LUH2 in the base year. The slightly smaller cropland area relative to those of other IAMs is likely attributable to the assumption that future yields will improve because of technological progress. In terms of the GHG emissions, those of both CH_4 and N_2O continue to rise throughout the projection period, as in other IAMs.

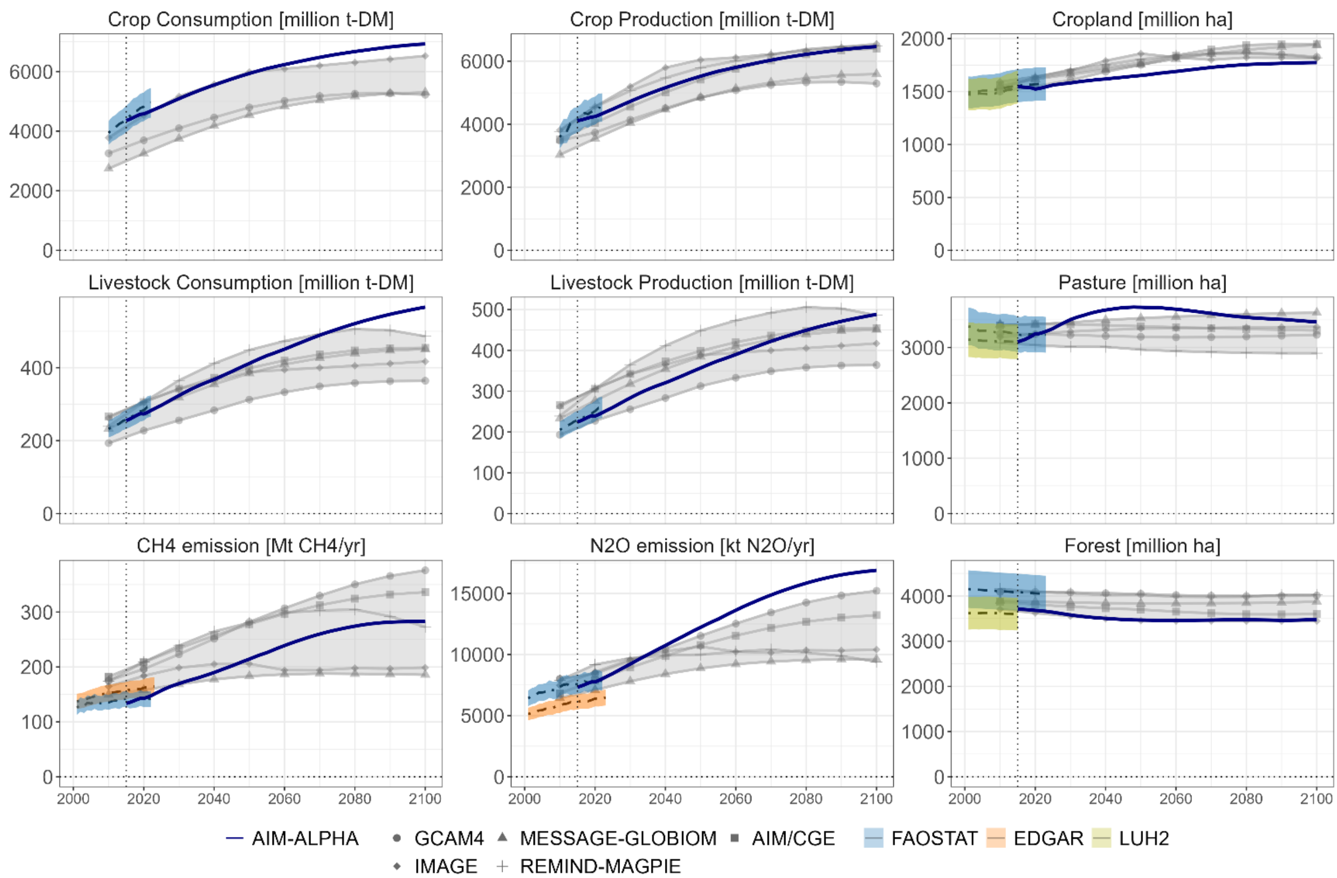
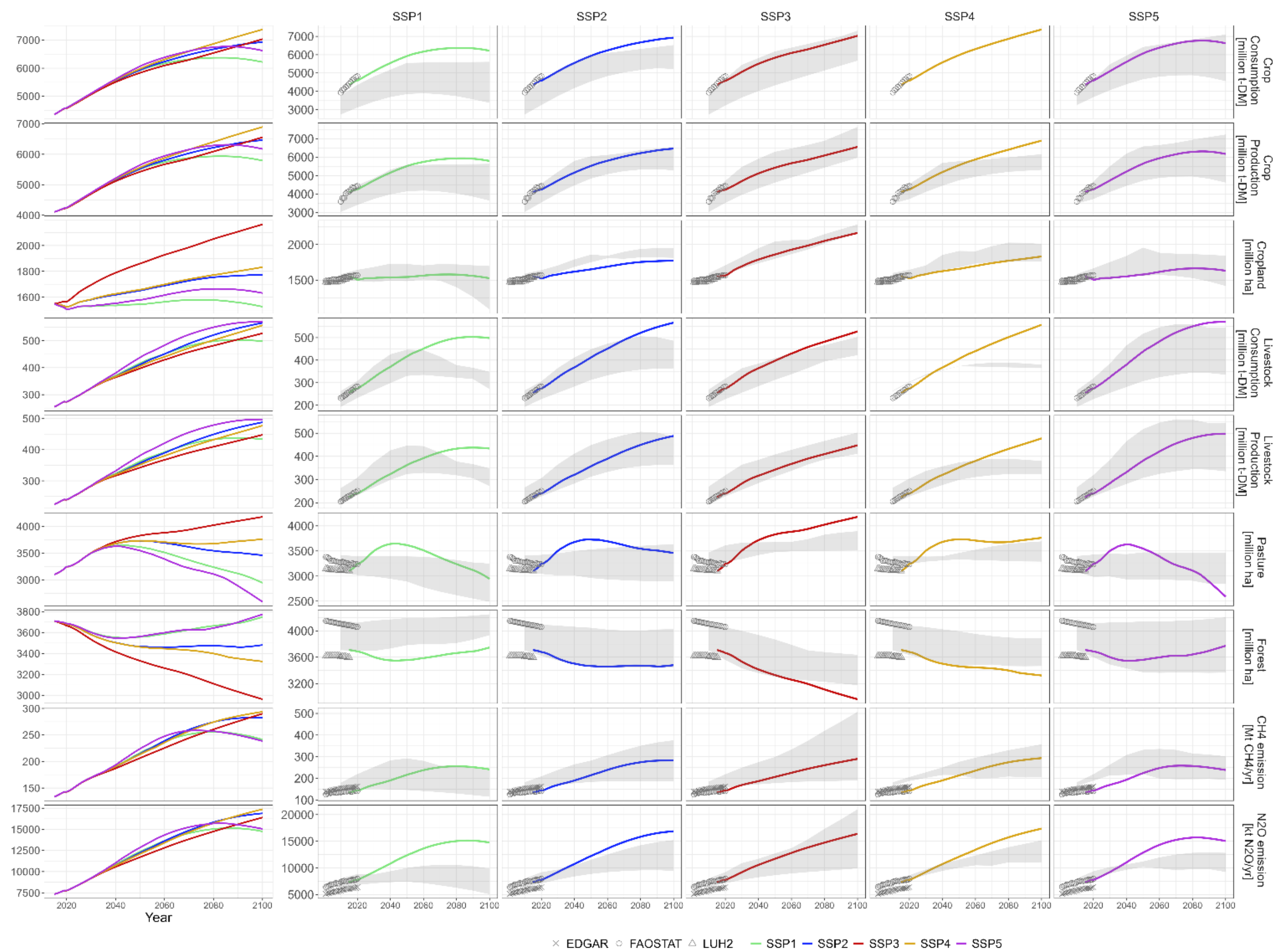


Figure 7. Global results for the major indicators under the SSP2–BaU scenario, compared to historical data and the projections of other IAMs. The shaded bands for FAOSTAT (FAO, 2025), EDGAR (European Commission et al., 2024), and LUH2 (Hurtt et al., 2020) show the ± 10% ranges of historical values. The gray area is that between the maximum and minimum projections of the SSP2–baseline scenario of other IAMs (Popp et al., 2017; Riahi et al., 2017).

Figure 8 illustrates the projected results for the major indicators of the five SSPs. Of these, the most pronounced differences across the SSP scenarios are those of land use. For cropland, the projected area varies substantially depending on the assumed

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

future yield improvement. Cropland expands most under SSP3 (+191 million ha in 2100), in which technological progress is relatively limited, and is smallest under SSP1 (+49 million ha in 2100), which assumes rapid advances in agricultural productivity. For pasture, divergence among the SSPs becomes evident after about 2040, principally because of differences in the per capita GDP trajectories. Such variations affect the composition of livestock-production systems and the share of concentrate feed. Changes in agricultural land trigger marked variations in forest area, with a substantial decline projected under SSP3 because of agricultural land expansion. Compared to other IAMs, AIM-ALPHA projects higher livestock consumption under SSP1, primarily because of the assumptions adopted (Table 1). In this scenario, no explicit attempt is made to consider potential dietary shifts toward reduced meat consumption. Livestock demand is primarily determined by income elasticity, which differs across the SSPs. Therefore, livestock production remains relatively high in SSP1, leading to larger N_2O emissions from manure compared to those of other models.



https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Figure 8. Global results for the major indicators under alternative socioeconomic pathways, compared to historical data and projections from other IAMs. The gray shaded area indicates the range between the maximum and minimum projections of each SSP‐baseline scenario across the other IAMs (Popp et al., 2017; Riahi et al., 2017).

4.1.2 Comparison with historical data

Figure 9 compares the regional near-term projections of each SSP with historical data. For most regions, the results are well aligned with observations made in 2015, indicating successful base-year calibration. In addition, the near-term projections remain within approximately ± 10% of the most recently available statistics for a wide range of indicators. Certain discrepancies are observed in the Middle East and Africa, particularly in terms of livestock production and forest area in the base year. These are primarily attributable to data inconsistencies and missing observations. Adjustments were required during calibration. The pasture area in Latin America, the Middle East, and Africa increases after the base year. This reflects a livestock-system assumption. Low-income regions are highly reliant on grass-based feed, increasing the pasture demand as meat consumption grows.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

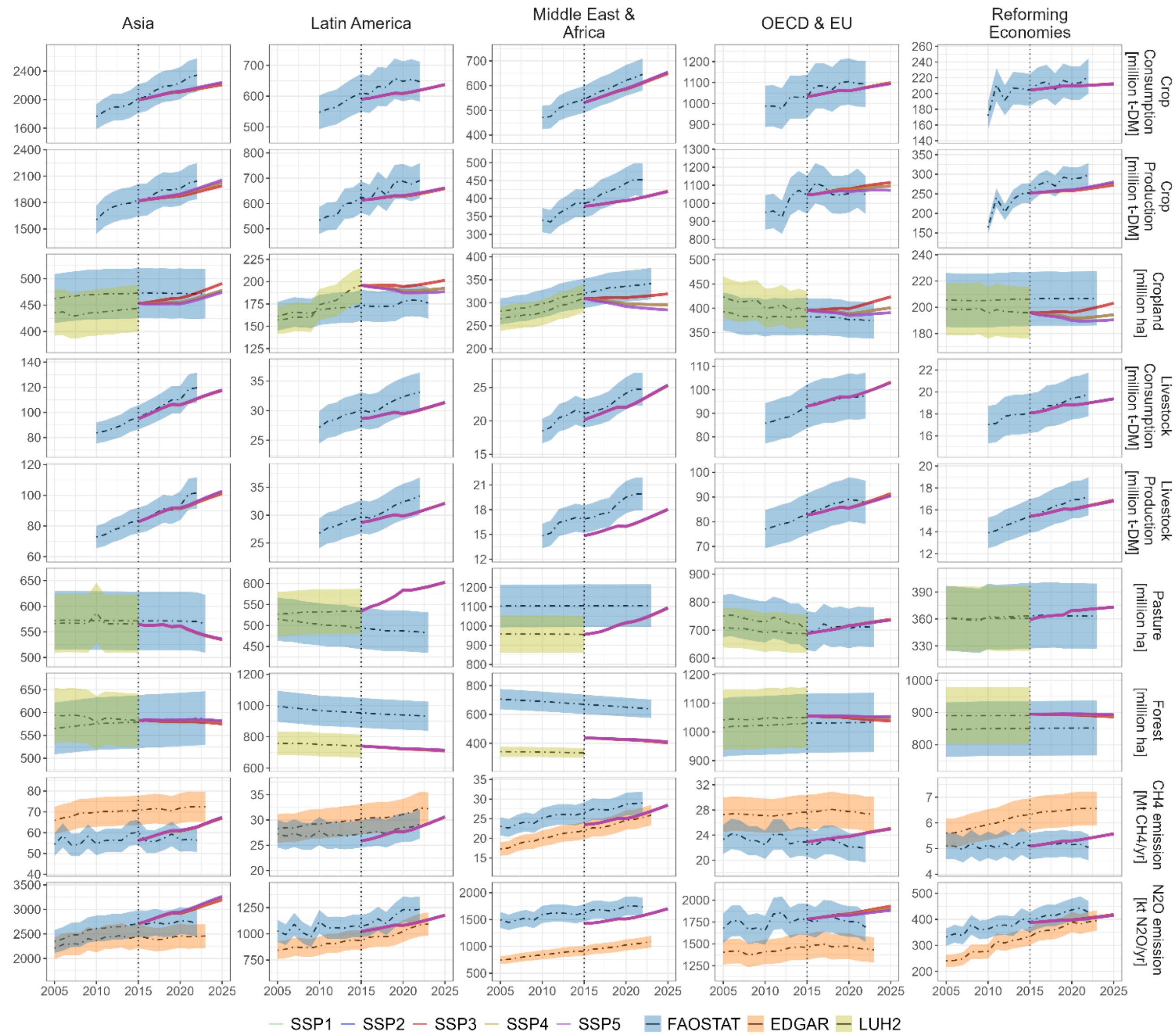


Figure 9. Regional comparison of near-term projections and historical values. The shaded bands for FAOSTAT (FAO, 2025), EDGAR (European Commission et al., 2024), and LUH2 (Hurtt et al., 2020) show the ± 10% ranges of historical values.

Figure 10 compares the model results with the FAOSTAT data for each country and commodity in 2015 and 2020. In the base year (2015), the model reproduces household consumption and the supply quantities well. However, some discrepancies are apparent in terms of the harvested area and crop yield. These are attributable to adjustments made during model calibration to ensure equilibrium conditions in the base year. By 2020, the deviations between the simulated and observed values become

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

larger for several indicators, with the greatest differences being those of import volumes. This is likely because the model views trade flows as complementarity relationships, rendering trade volumes particularly sensitive to small changes in the relative prices and boundary conditions.

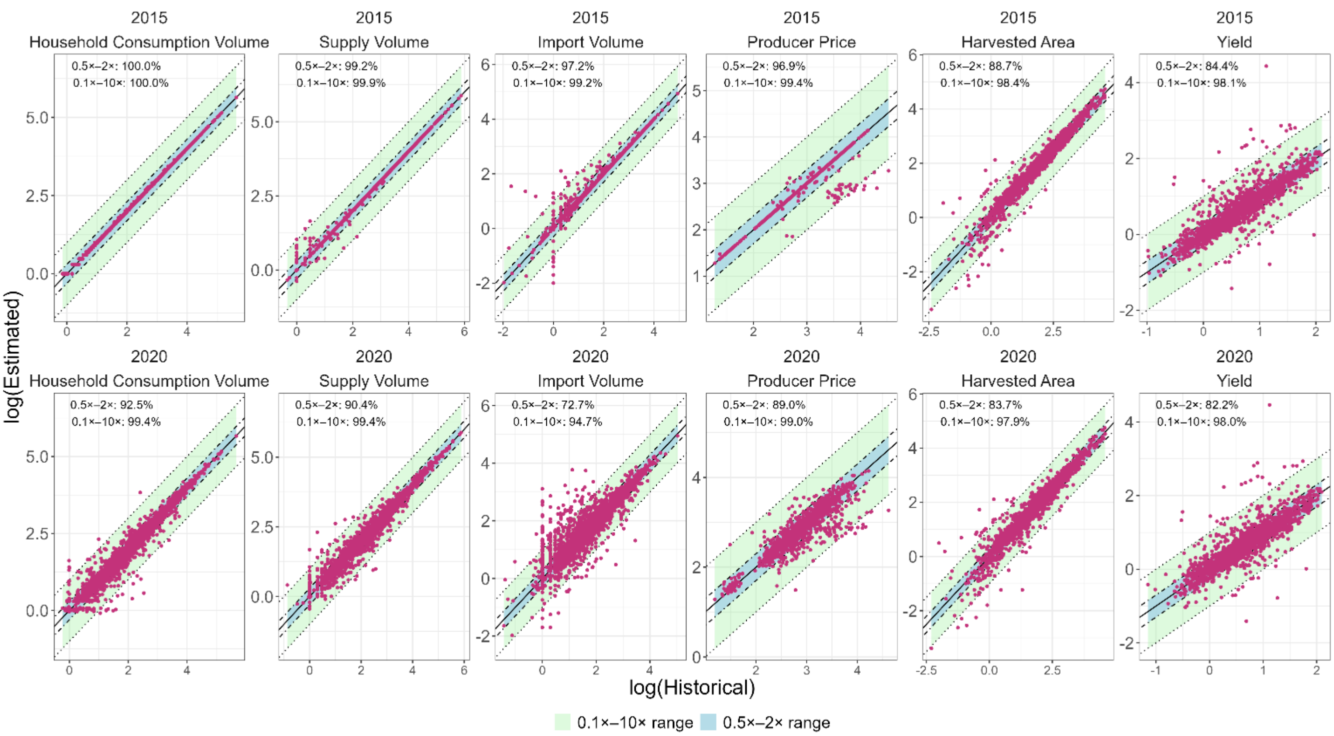


Figure 10. Comparisons between the estimated and historical values by country and commodity. Each point represents a country–commodity pair. The estimated data are those of SSP2-BaU. Historical data were obtained from FAOSTAT (FAO, 2025). The shaded areas indicate the tolerance ranges of the historical values within factors of 2 (0.5×–2×) and 10 (0.1×–10×). The percentages are the proportions of data points within each range.

4.2 Climate-change mitigation scenario

This section presents the effects of climate-change mitigation under SSP2. Figure 11 compares the global outcomes of key indicators under the BaU and mitigation scenarios. Both agricultural consumption and production decrease relative to BaU. Cropland area expands (+512 million ha greater than BaU in 2100) as bioenergy crop production increases. This competes with food crops for arable land. However, pasture declines markedly (–1,822 million ha less than BaU in 2100), attributable to introduction of a carbon price for residual non-CO_2 emissions and the associated abatement costs. This reduces livestock

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

production/consumption. The cost is also influenced by the growing competition for land between pasture, bioenergy crops, and afforestation, the latter being stimulated by the carbon price via an effect on the economic value of forest carbon stocks. Although the pasture area decreases substantially, the reduction in total livestock consumption is relatively moderate. This is explained by two main factors. First, allocation of livestock production shifts toward regions with higher productivity, enabling overall production to be maintained despite the decline in total pasture area. Second, the livestock consumption indicator includes both ruminant and non-ruminant products, but only ruminant production requires pasture resources. Consumption of non-ruminant products, such as poultry and pork, remains relatively stable, moderating the overall decline in livestock consumption. Forest area increases substantially under the mitigation scenario (+753 million ha greater than BaU in 2100), reflecting the enhanced afforestation incentive. The various land-use adjustments collectively (and significantly) reduce non-CO_2 emissions compared to those of the BaU baseline. The general direction of all changes described above is broadly consistent with those of other IAMs, supporting the notion that the model responses to mitigation policies are reliable.

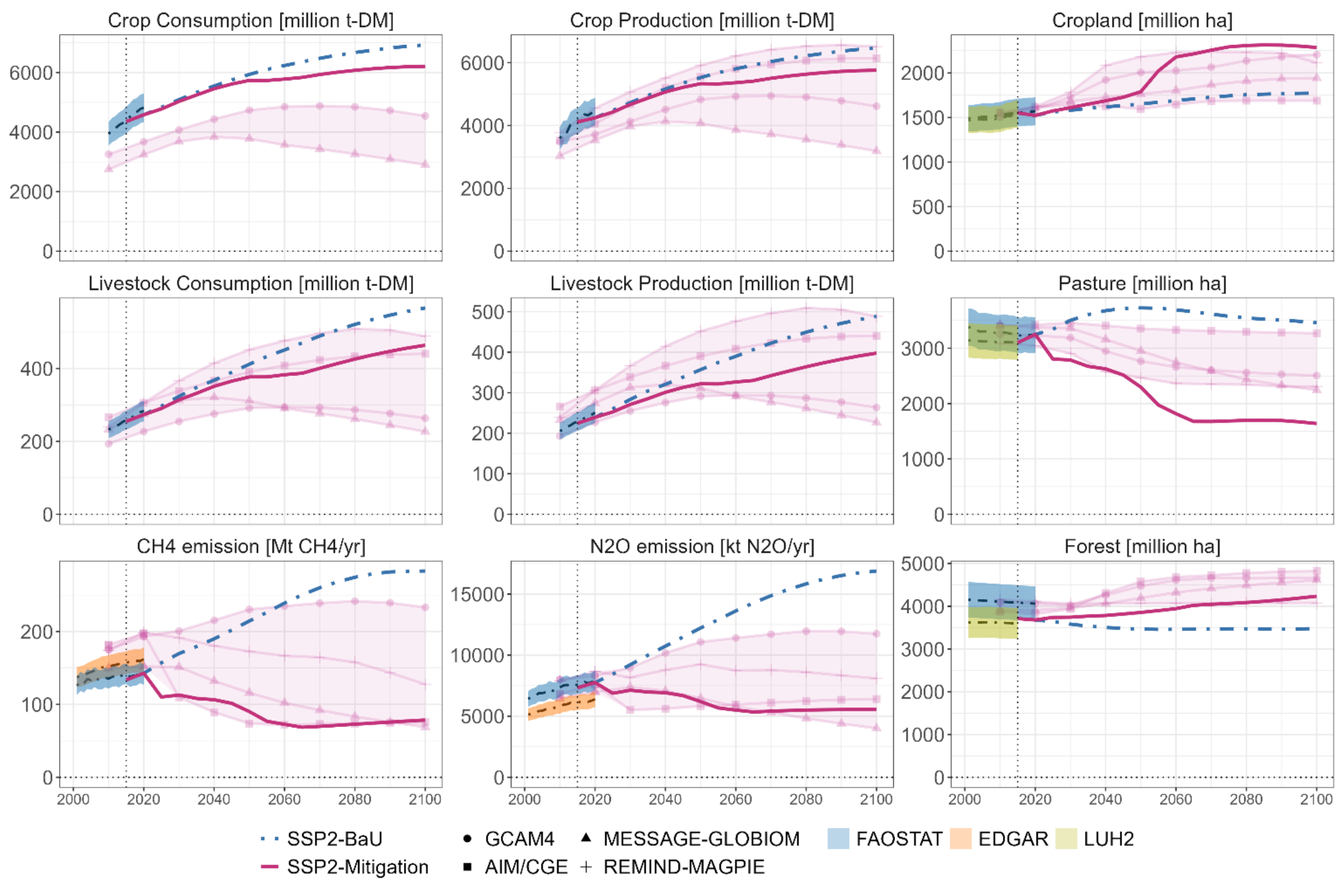
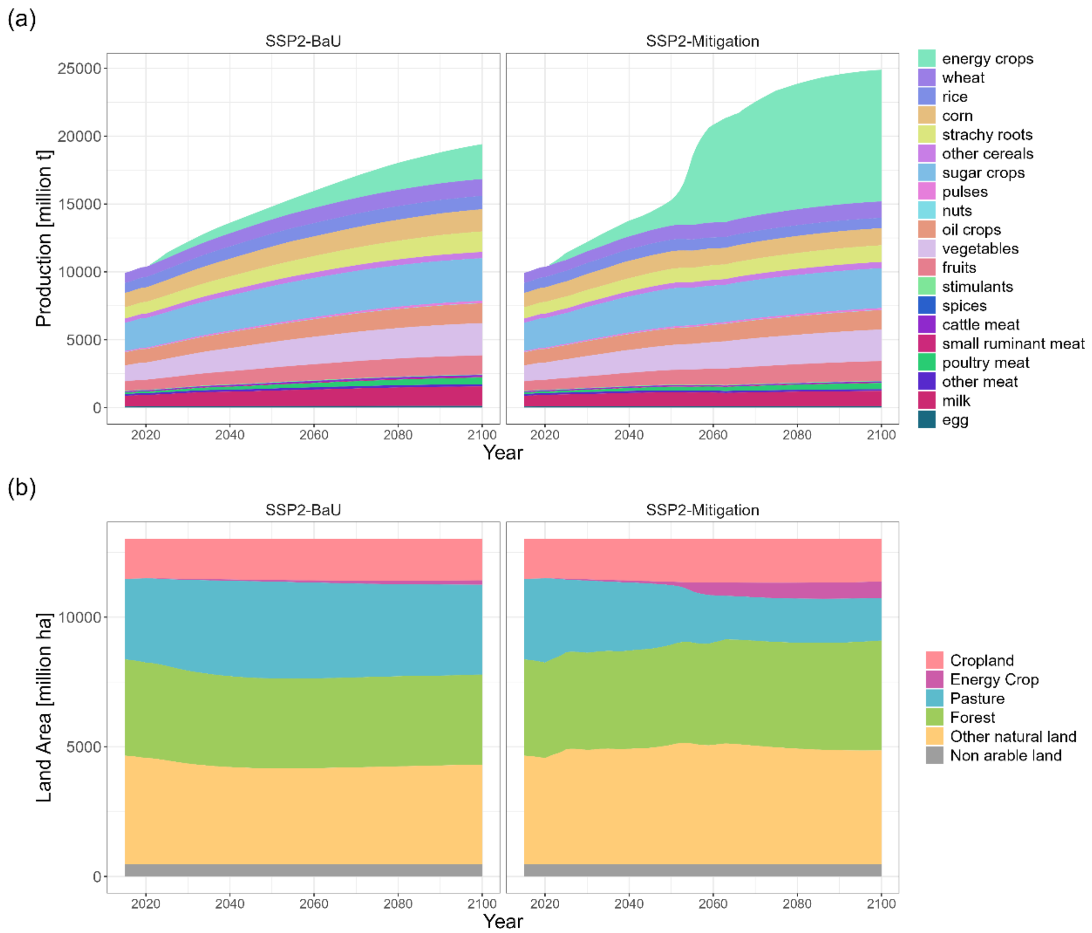


Figure 11. The global results of the SSP2–BaU and SSP2–mitigation scenarios compared to historical data and projections from other IAMs. The shaded bands for FAOSTAT (FAO, 2025), EDGAR (European Commission et al., 2024), and LUH2 (Hurtt et al., 2020) represent the

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

± 10% ranges of historical values. The pink area is the range between the maximum and minimum projections of the SSP2–19 scenario across other IAMs (Riahi et al., 2017; Rogelj et al., 2018).

Figure 12 shows the global changes in commodity-specific production and land-use areas under the BaU and mitigation scenarios. As described in Sect. 2.6.4, bioenergy crop production values are exogenously sourced from the AIM-Hub model. Under the mitigation scenario, such production increases substantially after 2050 (+ 9,704 million tonnes in 2100) but food commodity production values decline relative to those of BaU. As shown in Fig. 12b, energy crop cultivation and forest area both expand under the mitigation scenario, reflecting the strong incentive offered by the carbon price in terms of bioenergy production and afforestation. In contrast, pasture contracts significantly because land use shifts toward bioenergy crops and afforestation.



https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Figure 12. Global changes in commodity-specific production levels (a) and land-use areas (b) under the SSP2-BaU and SSP2-mitigation scenarios. Production levels are shown in fresh matter weight.

Figure 13 shows the shares of bioenergy crops and forest area relative to the total land area at the production-unit level. Implementation of mitigation substantially expands bioenergy crop cultivation, particularly in South America (Brazil and Argentina), South Asia, Southeast Asia, and Australia. In contrast, most forest area increases occur in Russia, Central Africa, the United States, and New Zealand, implying that afforestation would be actively promoted in these regions.

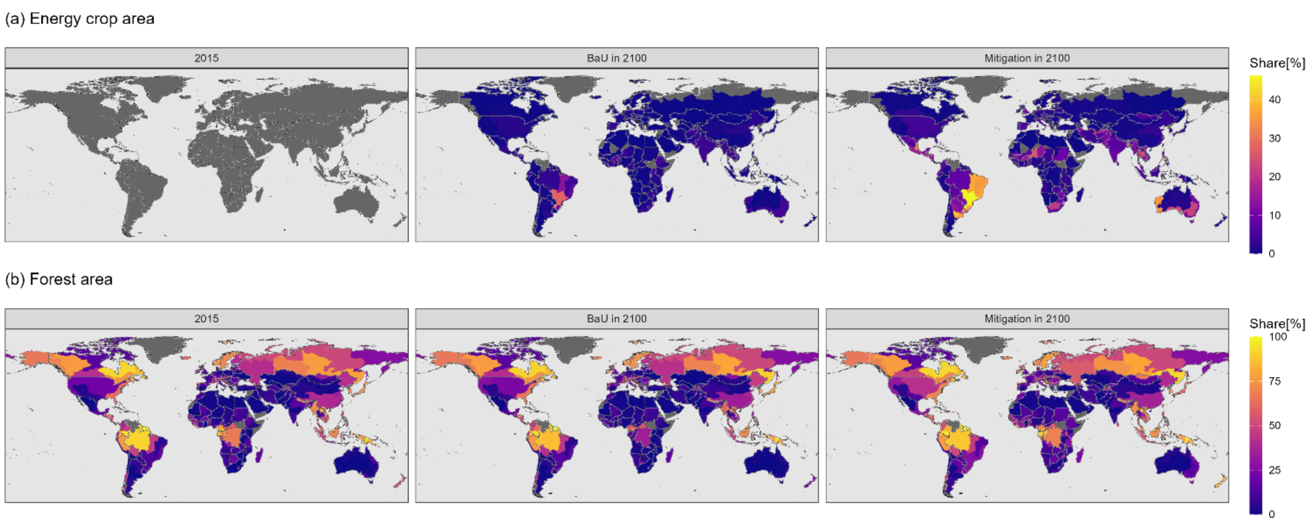


Figure 13. Spatial distributions of the proportions of bioenergy crops (a) and forest areas (b) relative to the total land area at the production-unit level.

Figure 14 shows the impacts of mitigation on food security. In 2100, the consumer prices of major cereals increase by approximately 38% globally compared with the BaU scenario (Fig. 14a). As a consequence, the average per capita calorie intake declines by about 7% worldwide (Fig. 14b). At the regional level, the largest reductions in calorie intake are observed in Asia, where the increase in food prices is particularly pronounced. In the Middle East and Africa, the effects are more heterogeneous, with substantial decreases in several countries such as Zimbabwe, Chad, and Jordan, indicating heightened vulnerability to food price shocks under the mitigation scenario (Fig. 14c). These results imply that climate-change mitigation, although effective in terms of reducing emissions, may exacerbate the food security risks in certain regions, highlighting the need for complementary policies to address such distributional impacts. The national-level representation of food demand in the AIM-ALPHA model enables identification of distributional impacts that are often obscured in models with more aggregated regional structures. This highlights the need to incorporate detailed country-level heterogeneity into future assessments of global mitigation policies and food security outcomes.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

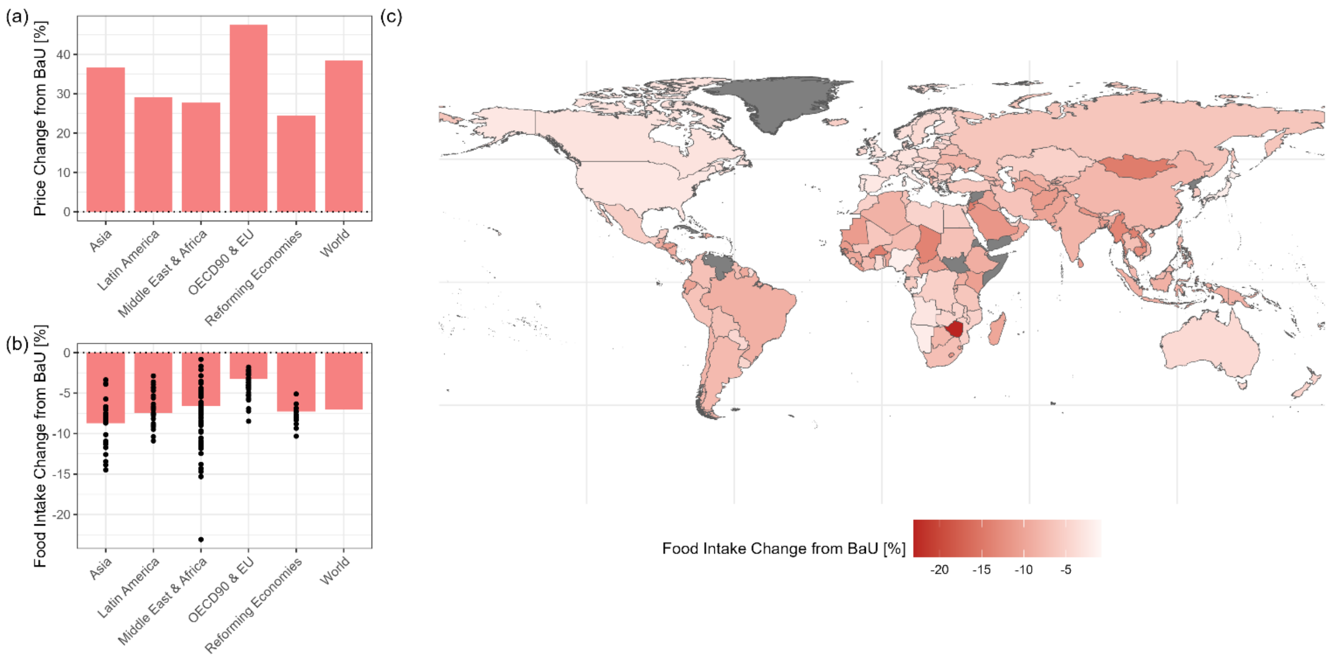


Figure 14. Impacts of mitigation measures on food security indicators in 2100. (a) Changes in the consumer prices of major cereals in 2100 under the mitigation scenario relative to the BaU scenario by region. (b) Changes in average daily per capita calorie intake in 2100 under the mitigation scenario relative to BaU by region (black dots represent individual countries within each region). (c) Spatial distribution of percentage changes in daily per capita calorie intake at the national level in 2100.

5 Discussion and conclusion

This study developed the AIM-ALPHA model, a partial equilibrium framework that represents both agricultural demand and production at high spatial resolution. This enables comprehensive assessment of the complex interactions between human activities and the global environment, allowing consistent analysis of issues such as food security, climate change, and land-use dynamics. By linking detailed socioeconomic processes to environmental outcomes, AIM-ALPHA seeks to bridge the gap between the economic and biophysical representations of global land-use models.

Model validation against historical data indicates that most indicators are in good agreement with historical observations around the base year, confirming the validity of the underlying data, calibration, and the numerical solution. In addition, global projections under the baseline scenario fall within the range of other IAMs, demonstrating consistency in terms of both the quantitative figures and qualitative trends. The comparisons confirm that AIM-ALPHA delivers plausible projections of agricultural and land-use dynamics at the global scale.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Model applicability was further demonstrated in a case study examining the impacts of climate-change mitigation on the agricultural and land-use sectors. Mitigation policies such as carbon pricing, afforestation, and bioenergy expansion significantly influence land-use patterns and food prices. Notably, the impacts on food security vary considerably across countries, even within the same aggregated region, emphasising the need for a high spatial resolution that captures such heterogeneity. It is important to conduct country-level assessments when evaluating the socioeconomic consequences of global mitigation.

A key strength of AIM-ALPHA is its ability to link socioeconomic processes and environmental outcomes at a nationally disaggregated scale, allowing detailed representation of agricultural production, consumption, trade, and land-use dynamics. Such fine spatial resolution captures regional heterogeneity and identifies country-specific vulnerabilities to global challenges such as climate change and food security. By filling this spatial-resolution gap within the AIM modelling framework, AIM-ALPHA facilitates evaluation of national policy options and supports coherent, multi-scale sustainability assessments.

However, several limitations remain. First, forestry activities are not yet explicitly represented, and, therefore, competition for land between timber and food producers is not considered. This may affect the land-use dynamics (Mishra et al., 2021). Second, the model currently assumes that livestock productivity parameters (such as feed requirements and the ratio of concentrate to roughage feed) are affected by only economic growth. In reality, the shares may also respond dynamically to relative prices and technological innovation. Third, because international trade is formulated using complementarity conditions, trade volumes may respond sharply to small changes in prices, rendering model outcomes volatile. Fourth, water resources, fertilizer inputs, and other resource constraints are not yet explicitly represented. The potential biophysical limitations of—and the input-price feedbacks on—agricultural production are not captured. Fifth, the current land-use classification could be further refined. Distinguishing between primary and secondary forests, and managed pasture and rangeland, would better represent the land-use dynamics. This would be particularly important when analysing the ecological consequences of land-use changes, including potential impacts on ecosystems and biodiversity (Barlow et al., 2007; Alkemade et al., 2013).

Future work will focus on the identified limitations, and coupling of AIM-ALPHA to other frameworks such as downscaling (Hasegawa et al., 2017) and biodiversity (Ohashi et al., 2019) models. This will enable more detailed and comprehensive assessments of many environmental and socioeconomic indicators, including biodiversity loss, land-use impacts, and wider forms of sustainability. By improving both model behavioural realism and integration with environmental systems, AIM-ALPHA will serve as a reliable platform when exploring pathways toward sustainable, global land-use and food systems.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Appendix A: Model implementation and computational requirements

The AIM-ALPHA model code is available on Zenodo (https://zenodo.org/records/17720501, Totake, 2025a). A separate document includes a detailed description of the model equations, and usage instructions (https://github.com/KUAtmos/AIMALPHAdoc, last access: 25 November 2025).

The overall model workflow has five major stages.

1. Preprocessing: Raw datasets in CSV, Excel, and gridded formats are converted to GDX files.
2. Data import and calibration: The processed data are imported into GAMS, where parameter estimation via regression and base-year calibration are performed.
3. Projection: The model computes equilibrium solutions for each simulation year.
4. Postprocessing: Simulation outputs are aggregated and converted into standardized formats such as those of the Agricultural Model Intercomparison and Improvement Project and the Integrated Assessment Modeling Consortium templates.
5. Visualisation: Optional R scripts allow users to visualise results and conduct further analysis.

AIM-ALPHA requires GAMS (version 38 or higher) and the PATH solver for large-scale MCP computation. All core routines for data processing, calibration, and equilibrium solving are implemented in GAMS. If users wish to perform data preprocessing or visualise results, R (version 4.3.2 or higher) is also required. The necessary R libraries are listed in the model formulation document and the GitHub repository. The entire workflow is controlled by shell scripts, and the model can be executed on Linux or on Windows with Cygwin.

Running of a single scenario requires approximately 4 GB of temporary storage (including log files) and 700 MB for the output data. The model uses about 10 GB of RAM per scenario and runs on a single thread, although multiple scenarios can be executed in parallel using separate threads. A full simulation covering 2015–2100 typically takes 2.5–4 h, depending on scenario complexity and the computational environment.

Code and data availability

The current version of AIM-ALPHA described in this paper is available on Zenodo (https://zenodo.org/records/17720501, Totake, 2025a) under the Apache License 2.0. The model formulation document and user guide are also available on GitHub (https://github.com/KUAtmos/AIMALPHAdoc, last access: 25 November 2025) and archived on Zenodo (https://doi.org/10.5281/zenodo.17725095, Totake, 2025b). The simulation outputs and scripts used to plot the results are archived on Zenodo (https://doi.org/10.5281/zenodo.17695636, Totake, 2025c).

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Author contributions

HY wrote the original model. HY and RT developed the model. SF and TH built the initial modelling framework and supervised model development and the overall research. The simulations were conducted by RT and analysed by all authors. RT created the figures with support from HY. RT prepared the manuscript and all authors contributed to the writing and discussion.

Competing interests

The authors declare that they have no conflict of interest.

Financial support

This research is financially supported by Environment Research and Technology Development Fund (JPMEERF20241001 and JPMEERF20252002) of the Environmental Restoration and Conservation Agency provided by the Ministry of Environment of Japan, the Sumitomo Electric Industries Group CSR Foundation, and JSPS KAKENHI of the Japan Society for the Promotion of Science (25K03335).

References

Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., and van der Mensbrugghe, D.: The GTAP Data Base: Version 10, J. Glob. Econ. Anal., 4, 1–27, https://doi.org/10.21642/JGEA.040101AF, 2019.

Alkemade, R., Reid, R. S., van den Berg, M., de Leeuw, J., and Jeuken, M.: Assessing the impacts of livestock production on biodiversity in rangeland ecosystems, Proc. Natl. Acad. Sci., 110, 20900–20905, https://doi.org/10.1073/pnas.1011013108, 2013.

Barlow, J., Gardner, T. A., Araujo, I. S., Ávila-Pires, T. C., Bonaldo, A. B., Costa, J. E., Esposito, M. C., Ferreira, L. V., Hawes, J., Hernandez, M. I. M., Hoogmoed, M. S., Leite, R. N., Lo-Man-Hung, N. F., Malcolm, J. R., Martins, M. B., Mestre, L. A. M., Miranda-Santos, R., Nunes-Gutjahr, A. L., Overal, W. L., Parry, L., Peters, S. L., Ribeiro-Junior, M. A., da Silva, M. N. F., da Silva Motta, C., and Peres, C. A.: Quantifying the biodiversity value of tropical primary, secondary, and plantation forests, Proc. Natl. Acad. Sci., 104, 18555–18560, https://doi.org/10.1073/pnas.0703333104, 2007.

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R. Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S. J., Snyder, A., Waldhoff, S., and Wise, M.: GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems, Geosci. Model Dev., 12, 677–698, https://doi.org/10.5194/gmd-12-677-2019, 2019.

Crespo Cuaresma, J.: Income projections for climate change research: A framework based on human capital dynamics, Glob. Environ. Change, 42, 226–236, https://doi.org/10.1016/j.gloenvcha.2015.02.012, 2017.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Dietrich, J. P., Bodirsky, B. L., Humpenöder, F., Weindl, I., Stevanović, M., Karstens, K., Kreidenweis, U., Wang, X., Mishra, A., Klein, D., Ambrósio, G., Araujo, E., Yalew, A. W., Baumstark, L., Wirth, S., Giannousakis, A., Beier, F., Chen, D. M.-C., Lotze-Campen, H., and Popp, A.: MAgPIE 4 – a modular open-source framework for modeling global land systems, Geosci. Model Dev., 12, 1299–1317, https://doi.org/10.5194/gmd-12-1299-2019, 2019.

European Commission, Joint Research Centre (JRC) and International Energy Agency (IEA): EDGAR (Emissions Database for Global Atmospheric Research) Community GHG Database: IEA-EDGAR CO_2, EDGAR CH_4, EDGAR N_2O, and EDGAR F-GASES, version 2024, 2024.

FAO: FAOSTAT, https://www.fao.org/faostat/en/#home, last access: 22 October 2025.

FAO and IIASA: Global Agro-Ecological Zones version 4 (GAEZ v4), http://www.fao.org/gaez/, last access: 25 November 2025.

FAO Land and Water Division: Major Hydrological Basins of the World, https://data.apps.fao.org/catalog/iso/7707086d-af3c-41cc-8aa5-323d8609b2d1 (last access: 25 November 2025), 2011.

Fujimori, S., Hasegawa, T., Masui, T., and Takahashi, K.: Land use representation in a global CGE model for long-term simulation: CET vs. logit functions, Food Secur., 6, 685–699, https://doi.org/10.1007/s12571-014-0375-z, 2014.

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., Hijioka, Y., and Kainuma, M.: SSP3: AIM implementation of Shared Socioeconomic Pathways, Glob. Environ. Change, 42, 268–283, https://doi.org/10.1016/j.gloenvcha.2016.06.009, 2017.

Fujimori, S., Wu, W., Doelman, J., Frank, S., Hristov, J., Kyle, P., Sands, R., van Zeist, W.-J., Havlik, P., Domínguez, I. P., Sahoo, A., Stehfest, E., Tabeau, A., Valin, H., van Meijl, H., Hasegawa, T., and Takahashi, K.: Land-based climate change mitigation measures can affect agricultural markets and food security, Nat. Food, 3, 110–121, https://doi.org/10.1038/s43016-022-00464-4, 2022.

Fujimori, S., Han, R., Zhao, S., Asayama, S., Hasegawa, T., Nishiura, O., Shiraki, H., and Takahashi, K.: Financial transfer to resolve the equity trade-off between developed and developing countries for national net-zero commitments, Res. Sq. Prepr., https://doi.org/10.21203/rs.3.rs-5972293/v1, 2025.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., and Toulmin, C.: Food Security: The Challenge of Feeding 9 Billion People, Science, 327, 812–818, https://doi.org/10.1126/science.1185383, 2010.

Harmsen, J. H. M., van Vuuren, D. P., Nayak, D. R., Hof, A. F., Höglund-Isaksson, L., Lucas, P. L., Nielsen, J. B., Smith, P., and Stehfest, E.: Long-term marginal abatement cost curves of non-CO2 greenhouse gases, Environ. Sci. Policy, 99, 136–149, https://doi.org/10.1016/j.envsci.2019.05.013, 2019.

Harper, A. B., Powell, T., Cox, P. M., House, J., Huntingford, C., Lenton, T. M., Sitch, S., Burke, E., Chadburn, S. E., Collins, W. J., Comyn-Platt, E., Daioglou, V., Doelman, J. C., Hayman, G., Robertson, E., van Vuuren, D., Wiltshire, A., Webber, C. P., Bastos, A., Boysen, L., Ciais, P., Devaraju, N., Jain, A. K., Krause, A., Poulter, B., and Shu, S.: Land-use emissions play a critical role in land-based mitigation for Paris climate targets, Nat. Commun., 9, 2938, https://doi.org/10.1038/s41467-018-05340-z, 2018.

Hasegawa, T., Fujimori, S., Ito, A., Takahashi, K., and Masui, T.: Global land-use allocation model linked to an integrated assessment model, Sci. Total Environ., 580, 787–796, https://doi.org/10.1016/j.scitotenv.2016.12.025, 2017.

Hasegawa, T., Fujimori, S., Havlík, P., Valin, H., Bodirsky, B. L., Doelman, J. C., Fellmann, T., Kyle, P., Koopman, J. F. L., Lotze-Campen, H., Mason-D'Croz, D., Ochi, Y., Pérez Domínguez, I., Stehfest, E., Sulser, T. B., Tabeau, A., Takahashi, K., Takakura, J., van Meijl, H., van Zeist, W.-J., Wiebe, K., and Witzke, P.: Risk of increased food insecurity under stringent global climate change mitigation policy, Nat. Clim. Change, 8, 699–703, https://doi.org/10.1038/s41558-018-0230-x, 2018.

Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., and Masui, T.: Extreme climate events increase risk of global food insecurity and adaptation needs, Nat. Food, 2, 587–595, https://doi.org/10.1038/s43016-021-00335-4, 2021.

Hasegawa, T., Fujimori, S., Ito, A., and Takahashi, K.: Careful selection of forest types in afforestation can increase carbon sequestration by 25% without compromising sustainability, Commun. Earth Environ., 5, 1–10, https://doi.org/10.1038/s43247-024-01336-4, 2024.

Hasegawa, T., Fujimori, S., Tsuchiya, K., Ito, A., and Takahashi, K.: National Land-based Climate Mitigation Scenarios Dataset, Sci. Data, 12, 1077, https://doi.org/10.1038/s41597-025-05427-5, 2025.

Herrero, M., Havlik, P., Valin, H., Notenbaert, A., Rufino, M., Thornton, P. K., Blümmel, M., Weiss, F., Grace, D., and Obersteiner, M.: Livestock production systems, , https://doi.org/10.4225/08/5aa068b33fe06, 2018.

Hirata, A., Ohashi, H., Hasegawa, T., Fujimori, S., Takahashi, K., Tsuchiya, K., and Matsui, T.: The choice of land-based climate change mitigation measures influences future global biodiversity loss, Commun. Earth Environ., 5, 1–10, https://doi.org/10.1038/s43247-024-01433-4, 2024.

Hurtt, G. C., Chini, L., Sahajpal, R., Frolking, S., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fisk, J., Fujimori, S., Klein Goldewijk, K., Hasegawa, T., Havlik, P., Heinimann, A., Humpenöder, F., Jungclaus, J., Kaplan, J. O., Kennedy, J., Krisztin, T., Lawrence, D., Lawrence, P., Ma, L., Mertz, O., Pongratz, J., Popp, A., Poulter, B., Riahi, K., Shevliakova, E., Stehfest, E., Thornton, P., Tubiello, F. N., van Vuuren, D. P., and Zhang, X.: Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6, Geosci. Model Dev., 13, 5425–5464, https://doi.org/10.5194/gmd-13-5425-2020, 2020.

IBF-IIASA: Global Biosphere Management Model (GLOBIOM) Documentation 2023 - Version 1.0, Integrated Biospheres Futures, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, 2023.

Global Spatially-Disaggregated Crop Production Statistics Data for 2020, Version 2.0: https://doi.org/10.7910/DVN/SWPENT.

KC, S., Moradhvaj, Potancokova, M., Adhikari, S., Yildiz, D., Mamolo, M., Sobotka, T., Zeman, K., Abel, G., Lutz, W., and Goujon, A.: Wittgenstein Center (WIC) Population and Human Capital Projections - 2023, https://doi.org/10.5281/zenodo.10618931, 2024.

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., Mace, G. M., Ohashi, H., Popp, A., Purvis, A., Schipper, A. M., Tabeau, A., Valin, H., van Meijl, H., van Zeist, W.-J., Visconti, P., Alkemade, R., Almond, R., Bunting, G., Burgess, N. D., Cornell, S. E., Di Fulvio, F., Ferrier, S., Fritz, S., Fujimori, S., Grooten, M., Harwood, T., Havlík, P., Herrero, M., Hoskins, A. J., Jung, M., Kram, T., Lotze-Campen, H., Matsui, T., Meyer, C., Nel, D., Newbold, T., Schmidt-Traub, G., Stehfest, E., Strassburg, B. B. N., van Vuuren, D. P., Ware, C., Watson, J. E. M., Wu, W., and Young, L.: Bending the curve of terrestrial biodiversity needs an integrated strategy, Nature, 585, 551–556, https://doi.org/10.1038/s41586-020-2705-y, 2020.

Mishra, A., Humpenöder, F., Dietrich, J. P., Bodirsky, B. L., Sohngen, B., P. O. Reyer, C., Lotze-Campen, H., and Popp, A.: Estimating global land system impacts of timber plantations using MAgPIE 4.3.5, Geosci. Model Dev., 14, 6467–6494, https://doi.org/10.5194/gmd-14-6467-2021, 2021.

https://doi.org/10.5194/egusphere-2025-5911
Preprint. Discussion started: 9 January 2026

Muhammad, A., Seale, Jr., James L., Meade, B., and Regmi, A.: International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data, U.S. Department of Agriculture, Economic Research Service, 2013.

Nabuurs, G.-J., Mrabet, R., Abu Hatab, A., Bustamante, M., Clark, H., Havlík, P., House, J., Mbow, C., Ninan, K. N., Popp, A., Roe, S., Sohngen, B., and Towprayoon, S.: Agriculture, Forestry and Other Land Uses (AFOLU). In IPCC, 2022, in: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Shukla, P. R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., and Malley, J., Cambridge University Press, Cambridge, UK and New York, NY, USA, https://doi.org/10.1017/9781009157926.009, 2022.

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., Robinson, S., Schmid, E., Schmitz, C., Tabeau, A., and Willenbockel, D.: Climate change effects on agriculture: Economic responses to biophysical shocks, Proc. Natl. Acad. Sci., 111, 3274–3279, https://doi.org/10.1073/pnas.1222465110, 2014.

Ohashi, H., Hasegawa, T., Hirata, A., Fujimori, S., Takahashi, K., Tsuyama, I., Nakao, K., Kominami, Y., Tanaka, N., Hijioka, Y., and Matsui, T.: Biodiversity can benefit from climate stabilization despite adverse side effects of land-based mitigation, Nat. Commun., 10, 5240, https://doi.org/10.1038/s41467-019-13241-y, 2019.

Pereira, H. M., Martins, I. S., Rosa, I. M. D., Kim, H., Leadley, P., Popp, A., van Vuuren, D. P., Hurtt, G., Quoss, L., Arneth, A., Baisero, D., Bakkenes, M., Chaplin-Kramer, R., Chini, L., Di Marco, M., Ferrier, S., Fujimori, S., Guerra, C. A., Harfoot, M., Harwood, T. D., Hasegawa, T., Haverd, V., Havlík, P., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Hirata, A., Hoskins, A. J., Humpenöder, F., Janse, J. H., Jetz, W., Johnson, J. A., Krause, A., Leclère, D., Matsui, T., Meijer, J. R., Merow, C., Obersteiner, M., Ohashi, H., De Palma, A., Poulter, B., Purvis, A., Quesada, B., Rondinini, C., Schipper, A. M., Settele, J., Sharp, R., Stehfest, E., Strassburg, B. B. N., Takahashi, K., Talluto, M. V., Thuiller, W., Titeux, N., Visconti, P., Ware, C., Wolf, F., and Alkemade, R.: Global trends and scenarios for terrestrial biodiversity and ecosystem services from 1900 to 2050, Science, 384, 458–465, https://doi.org/10.1126/science.adn3441, 2024.

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., Kriegler, E., Lotze-Campen, H., Fricko, O., Riahi, K., and Vuuren, D. P. van: Land-use futures in the shared socio-economic pathways, Glob. Environ. Change, 42, 331–345, https://doi.org/10.1016/j.gloenvcha.2016.10.002, 2017.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., and Tavoni, M.: The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview, Glob. Environ. Change, 42, 153–168, https://doi.org/10.1016/j.gloenvcha.2016.05.009, 2017.

Robinson, S., Mason-D'Croz, D., Sulser, T., Islam, S., Robertson, R., Zhu, T., Gueneau, A., Pitois, G., and Rosegrant, M. W.: The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model Description for Version 3, https://doi.org/10.2139/ssrn.2741234, 26 November 2015.

Robinson, T. P., Thornton, P., Franceschini, G., Kruska, R., Chiozza, F., Notenbaert, A., Cecchi, G., Herrero, M., Epprecht, M., Fritz, S., You, L., Conchedda, G., and See, L.: Global distribution of ruminant livestock production systems V5 (5 minutes of arc) (1.1), https://doi.org/10.7910/DVN/WPDSZE, 2018.

Roe, S., Streck, C., Beach, R., Busch, J., Chapman, M., Daioglou, V., Deppermann, A., Doelman, J., Emmet-Booth, J., Engelmann, J., Fricko, O., Frischmann, C., Funk, J., Grassi, G., Griscom, B., Havlik, P., Hanssen, S., Humpenöder, F., Landholm, D., Lomax, G., Lehmann, J., Mesnildrey, L., Nabuurs, G.-J., Popp, A., Rivard, C., Sanderman, J., Sohngen, B., Smith, P., Stehfest, E., Woolf, D., and Lawrence, D.: Land-based measures to mitigate climate change: Potential and feasibility by country, Glob. Change Biol., 27, 6025–6058, https://doi.org/10.1111/gcb.15873, 2021.

Rogelj, J., Popp, A., Calvin, K. V., Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Strefler, J., Hasegawa, T., Marangoni, G., Krey, V., Kriegler, E., Riahi, K., van Vuuren, D. P., Doelman, J., Drouet, L., Edmonds, J., Fricko, O., Harmsen, M., Havlík, P., Humpenöder, F., Stehfest, E., and Tavoni, M.: Scenarios towards limiting global mean temperature increase below 1.5 °C, Nat. Clim. Change, 8, 325–332, https://doi.org/10.1038/s41558-018-0091-3, 2018.

Stehfest, E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Biemans, H., Bouwman, A., den Elzen, M., Janse, J., Lucas, P., van Minnen, J., Müller, C., and Prins, A.: Integrated Assessment of Global Environmental Change with IMAGE 3.0: Model description and policy applications, The Hague: PBL Netherlands Environmental Assessment Agency, 2014.

Stehfest, E., van Zeist, W.-J., Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fujimori, S., Humpenöder, F., Lotze-Campen, H., van Meijl, H., and Wiebe, K.: Key determinants of global land-use projections, Nat. Commun., 10, 2166, https://doi.org/10.1038/s41467-019-09945-w, 2019.

Tilman, D., Balzer, C., Hill, J., and Befort, B. L.: Global food demand and the sustainable intensification of agriculture, Proc. Natl. Acad. Sci., 108, 20260–20264, https://doi.org/10.1073/pnas.1116437108, 2011.

Totake, R.: Model source code for "AIM-ALPHA v1.0: A partial equilibrium model of global agriculture and land use at basin-level resolution," , https://doi.org/10.5281/zenodo.17720501, 2025a.

Totake, R.: KUAtmos/AIMALPHAdoc: v1.0.0 https://doi.org/10.5281/zenodo.17725095, 2025b.

Totake, R.: Data and Visualization Code for "AIM-ALPHA v1.0: A partial equilibrium model of global agriculture and land use at basin-level resolution," https://doi.org/10.5281/zenodo.17695636, 2025c.

Wheeler, T. and von Braun, J.: Climate Change Impacts on Global Food Security, Science, 341, 508–513, https://doi.org/10.1126/science.1239402, 2013.

World Bank: World Bank Official Boundaries, https://datacatalog.worldbank.org/search/dataset/0038272/World-Bank-Official-Boundaries, last access: 25 November 2025.