Contents:

Supplementary Methods

1. Overall research framework

The conceptual framework and detailed modelling approaches are shown in ED Fig.1 and ED Fig.2. Conceptually, carbon neutrality requires a substantial amount of negative emissions to enhance hard-to-abate residual emissions in the broader socioeconomic system, and these negative emissions could be provided by bioenergy with carbon capture and storage technology (BECCS). However, energy plantation expansion-related land-use change triggers a series of unintended sequential sustainability consequences related to food security (per capita calorie intake, food price, and self-sufficiency rate), cropland and pasture expansion, greenhouse gas (GHG) emissions from agriculture, forestry and other land use (AFOLU), irrigation water use and fertilizer use such as nitrogen. Methodologically, the Global Biosphere Management Model (GLOBIOM)-China model plays a central role in simulating the quantitative telecouplings of the interconnected system, with exogenous inputs from the MESSAGE model (e.g., woody bioenergy from the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) model) or projects (e.g., biofuel from the Agricultural Model Intercomparison and Improvement Project (AgMIP)). At the same time, the virtual sustainability impacts embedded in the food trade are also estimated based on bilateral trade quantities projected by GLOBIOM and the related intensity parameters. In this study, we did not explicitly consider the impacts of climate change on food production such as crop yield. Instead, the sensitivity analysis assumes alternative futures for crop yield, dietary shift, etc., which can encompass climate change impacts.

2. Validation and verification of the GLOBIOM-China model

2.1 General features of the GLOBIOM basic model

GLOBIOM [1] [2] is a global, bottom-up, recursive, and dynamic partial equilibrium economic model of agriculture (including livestock), forestry, and bioenergy. It provides a detailed representation of the main land-use sectors at a 2° × 2° grid cell resolution. Products are expressed in physical units rather than as monetary variables in contrast to those in general equilibrium models, allowing for a more accurate assessment of biophysical and socioeconomic impacts. Bilateral trade flows are calculated endogenously in the spatial equilibrium model following the Enke–Samuelson–Takayama–Judge spatial equilibrium approach assuming homogeneous goods[3]. Trade occurs across 37 economic regions according to each region's marginal production prices and transportation costs, making this model particularly suitable for assessing bilateral trade [4].

GLOBIOM represents the competition between six land-cover types: croplands, grasslands, short rotation plantations, managed forests, unmanaged forests and other natural vegetation lands. The model can switch from one land-cover type to another depending on the relative profitability of the primary product, by-product, and final-product production activities. Spatially explicit land conversions over the simulation period are endogenously determined within the available land resources and considering conversion costs. Land conversion possibilities are further restricted through biophysical land suitability, production potentials, and a matrix of potential land-cover changes. Energy plantations (short-rotation plantations) are permitted to expand into the following land-cover types: croplands, grasslands, and other natural vegetation areas. In principle, direct conversion of forests to short-rotation plantations is not allowed in the model due to sustainability concerns, but this case could occur indirectly when energy plantations are established on agricultural land (croplands and grasslands), with agriculture expanding into forests. The allocation of acreage by crop (food crops and energy crops for bioenergy) and management system is determined by potential yields, production costs, and expansion constraints (e.g., land and water). GLOBIOM covers major GHG emissions from AFOLU, including CO_2 emissions from above- and belowground biomass changes related to land-use changes, N_2O from the application of synthetic fertilizer and manure to soils, N_2O from manure on pastures, CH_4 from rice cultivation, N_2O and CH_4 from manure management and CH_4 from enteric fermentation.

Data on agricultural regional market variables, including demand and production, are harmonized with FAOSTAT[5] for the base year. The spatially explicit land-use allocation is initialized for 2000 with GLC2000[6], which attributes specific land cover to each 1x1 km resolution pixel using remote-sensing techniques. Grassland is where ruminant grazing occurs, which explains why model grassland areas differ from grassland statistics. The remaining grasslands are included as other natural lands because they provide more ecological function than agricultural use. The spatially explicit productivity of crops, grasslands, forests and short-rotation plantations is estimated together with related environmental parameters (GHG budgets, nutrient and water balance) at the level of the simulation units. For crops, the 18 crops represent more than 70% of the total globally harvested area and 85% of the vegetal calorie supply. The demand for agricultural commodities within each region is endogenously calculated based on population, gross domestic product (GDP) and equilibrium prices. The crop supply was calculated using the biophysical Environmental Policy Integrated Climate (EPIC) model[7, 8]. Each crop can be produced using four approaches: subsistence, low-input rainfed, high-input rainfed and high-input irrigated. The spatially explicit crop fertilizer use is from the EPIC model rescaled by FAOSTAT country values. The water demand of each crop is obtained from the EPIC model, and rescaled to the country's total irrigation water withdrawals in FAO AQUASTAT[9] to adjust for water use efficiency. The irrigation area is from the Spatial Production Allocation Model (SPAM)[10]. For forest parameters, GLOBIOM relies on the outputs of a dynamic forest management model, the Global Forest Model (G4M) [11]. Grassland productivity is determined by combining results from the EPIC model and the CENTURY biogeochemistry model[2, 12]. Livestock production systems are parameterized with the global database developed by Herrero et al. [13]. Parameters of livestock production are calculated based on a digestion and metabolism model (RUMINANT) [13]. Energy plantation yields are estimated based on net primary productivity (NPP) maps[14] and the GLOBIOM model's calculations, as described in Havlík et al. (2011)[1]. A detailed overview of the model data sources for the environmental indicators is described in a previous study[15].

2.2 Localization of the GLOBIOM-China

The GLOBIOM basic model was modified and calibrated [15] to improve the local representation of China's AFOLU sector and its bilateral food trade. Most notably, relevant Chinese agriculture policies, such as 'zero chemical fertilizer growth by

2020'[16], the trade policy of maintaining self-sufficiency in terms of the main staple foods at 95% [17], and the transition of monogastric production structure policy, were represented in the GLOBIOM-China to better capture the historical and long-term trends in Chinese agriculture development. The detailed modifications and the related policies are summarized in Suppl. Table 1 and described below.

Adjusted afforestation and deforestation areas. Forest area is an important driver of land-use change that can indirectly compete with land use for bioenergy production via agricultural land. The forest area over 2000-2020 was calibrated based on statistical data[18]. The afforestation target by 2060 for China was assumed to follow the data from G4M under the Reference scenario, leading to the cumulative afforestation areas from 2020 to 2030, 2040, 2050, and 2060 being 10.3 Mha, 14.7 Mha, 17.0 Mha, and 18.5 Mha, respectively, which are slightly lower than those under the carbon neutrality scenario[19]. Moreover, since this study focused on the insufficiently investigated aspect of the negative emission potential generated by large-scale bioenergy deployment, we kept the afforestation target constant across scenarios to prevent irrelevant land competition caused by afforestation. On the other hand, deforestation has been prohibited in China, Europe, and the U.S. since 2020, based on the observed policy regulations or declared legislation targets. As a result, China's future forest areas by 2030, 2040, 2050, and 2060 would be 236.5 Mha, 240.9 Mha, 243.3 Mha, and 244.7 Mha, respectively.

Adjusted food demand. Total food demand is represented by daily per capita calorie demand multiplied by the total population in the model, which is driven by population, GDP and food price. We updated the population for China to capture the recent population trend and the new projections for the future based on Chen et al. [20]. The income elasticity of food demand was adjusted (e.g., lowered) to be more inelastic to China's fast economic growth[21], thus making food demand follow the past trend. The validation of the model is shown in Suppl. Fig. 24 and Suppl. Fig. 25. In the DietHealth scenario and its sensitivity analysis (DietHealth-H and DietHealth-L), per capita animal-based consumption after 2020 was adjusted based on the Chinese Dietary Guidelines (2022). Specifically, we assumed a shift towards less animal-based diets, closing the gap between current consumption quantities and the recommended values while maintaining total calorie consumption consistent with that in the Reference scenario by increasing calories from crops. Thus, the share of animal-based food in terms of total calorie consumption in the DietHealth scenario, DietHealth-H and DietHealth-L assumptions decline to 18%, 20% and 16%, respectively, by 2060 (Suppl. Fig. 32).

Adjusted pork and poultry production and consumption structure. Diets in China are characterized by a high proportion of pork. Through the government's active promotion during the past decades, the production structure has experienced a large transition from smallholder to industrial systems [22]. Correspondingly, the GLOBIOM-China was improved to capture the production system transition of pig and poultry during 2000-2020. After 2020, we assumed that all monogastric products were produced by industrial systems. The consumption of pork in China has exceeded the value recommended by the Dietary Guidelines for Chinese Residents (2022). We adjusted China's per capita pork consumption in the GLOBIOM-China after 2020 by narrowing the discrepancies between per capita pork consumption and the recommended metabolic requirement.

Refined bilateral trade considering FAO trade flow and China's self-sufficiency redlines. The bilateral trade flows in the GLOBIOM are endogenously determined, driven by commodity prices and trade costs. Trade costs include transport costs, tariffs, and trade expansion costs. In particular, trade expansion costs represent persistence in trade patterns, which decelerates the short-term expansion of trade flows. At the same time, the GLOBIOM can also represent nonexistent new bilateral trade flows that were not observed in the base year. Mathematically, trade costs for trade flow observed in the base year can be represented by an exponential function (Equation 1), while for new trade flows, a quadratic cost function is used (Equation 2).

$$\mathrm{Tcost_t} = \frac{\varepsilon}{1+\varepsilon} \times \frac{\mathrm{Tariff + Transport\ \ cost}}{\mathrm{Shipment}_{t-1}^{1/\varepsilon}} \times \mathrm{Shipment}_t^{\frac{1}{\varepsilon}+1} \quad (1)$$

$$\mathrm{Tcost_t} = (\mathrm{Tariff + Transport\ \ cost}) \times \mathrm{Shipment_t} + 0.5 \times \mathrm{slop} \times \mathrm{Shipment}_t^2 \quad (2)$$

Tariffs and transport costs remain constant. Trade costs in time tare calculated with elasticity ε and slope. We adjusted elasticity and slope in Equations (1) and (2) to make the bilateral trade flows between China and its trade partners match the Food and Agriculture Organization trade matrix statistics[23]. The validation of trade flows can be found in Suppl. Figs. 27-28.

Moreover, a new constraint equation (Equation 3) was added to the model to maintain the self-sufficient rate redlines (95%) for wheat, rice and corn in Reference and Bioenergy scenarios based on China's food security policy[17].

$$\mathrm{Import} \leq 0.05 * \mathrm{Demand} \tag{3}$$

Enhanced fertilizer use efficiency to stabilize fertilizer use. The policy of "zero fertilizer use growth after 2020" issued by the Chinese government aimed to increase fertilizer use efficiency and decrease environmental impacts[16]. We increased the fertilizer use efficiency gradually by 60% by 2060 based on the related literature[24, 25].

Calibrated crop yield and harvest area. We calibrated the crop yield growth by manipulating the exogenous yield shifters in the model to match the trend from FAOSTAT[23]. The harvest area of cotton, oilseeds, and sugar crops was stabilized in the model according to China's policy of "adjustment of the planting structure"[26]. The validation is shown in Suppl. Figs. 22-23. After 2020, the yield growth for three main staple crops (wheat, rice and corn) was adjusted based on their attainable yield in China, which has been achieved in 153 site-year field experiments that cover the main agroecological areas in China[25]. Specifically, in the YieldUp scenario, we assume that the average rice, wheat and corn yields increase from their current levels to ~75% of the attainable yield by 2060, which increase to ~70% and ~80% of the attainable yield by 2060 for the YieldUp-L and YieldUp-H assumptions, respectively (Suppl. Fig. 31).

Adjusted grass yield and harvest efficiency. We aggregated grass yield[2] in the GLOBIOM from each pixel to the provincial level and adjusted the yield and harvest efficiency based on China's provincial grass statistics. The calibrated grassland values better matched the national statistics and affected domestic production and imports of livestock products due to bioenergy expansion.

Suppl. Table 1. Modifications for GLOBIOM-China.

Modification description	Data source
Calibrated bilateral trade	FAO trade matrix[23]
Maintained the self-sufficiency rate redlines (95%) for wheat, rice and corn in Reference and Bioenergy scenarios	Outline of Medium- and Long-Term Plan for National Food Security[27]
Calibrated crop yields and maintained crop area	National Bureau of Statistics of China[18], adjustment of the planting structure[26], and Chen et al. (2014)[25]
Updated grass yield and harvest efficiency	Chinese pasture statistics[28]
Calibrated daily per capita calorie demand	FAOSTAT 2020[23] and Chinese Dietary Guidelines (2022)[29]
Rescaled agricultural irrigation water	FAO AQUASTAT database[5, 9]
Increased fertilizer use efficiency	Zero growth of fertilizer use[16]
Adjusted production structure of monogastric animals by increasing breeding scale	Accelerating the standardized scale of livestock and poultry breeding[30]

2.3 Validation of the GLOBIOM-China

The model was carefully calibrated over the 2000–2020 period, especially for bilateral trade. Data from FAOSTAT, Chinese national statistics and Organisation for Economic Co-operation and Development-Food and Agriculture Organization (OECD–FAO) Agricultural Outlook projections[31] were used to validate the model performance (Suppl. Figs.22-28), taking crop yield and area[32], per capita calorie consumption[29], food demand, production and trade[5] as representative examples.

As shown in Suppl. Table 2, in 2020, the crop production estimated by the GLOBIOM-China is 4.7% lower than the FAOSTAT data and the livestock production estimated by the GLOBIOM-China is 20.8% higher than the FAOSTAT data, resulting in a 1.2% deviation for China's total agricultural production. Remarkably, there is a large deviation (38.7%) for pork, which could have been caused by swine fever in 2019 and 2020. Corn production estimated by the GLOBIOM-China is 12% lower than the FAOSTAT data, mainly caused by different statistical methodologies. Deviations in production for rice, wheat, ruminant meat, mutton, dairy products, poultry, and eggs are within 10%.

Suppl. Table 2. Comparison of food production (in Mt) from the GLOBIOM-China and data from FAOSTAT in 2020.

Categories	GLOBIOM-China	FAOSTAT	Difference
Agriculture	1081.8	1095.4	-1.2%
Crops	901.8	946.4	-4.7%
Livestock	180.0	149.0	20.8%
Rice	200.5	213.6	-6.1%
Wheat	127.3	134.3	-5.2%
Corn	229.2	260.9	-12.1%
Ruminant meat	12.4	12.4	-0.0%
Dairy products	41.6	39.2	6.2%
Poultry	20.7	20.2	2.8%
Pork	58.4	42.1	38.7%
Eggs	33.8	35.1	-3.9%

Agriculture includes 18 crop products (crops) and 7 livestock products in the GLOBIOM-China. The difference represents the difference between the results from the GLOBIOM-China and data from FAOSTAT.

Food consumption in 2020 estimated by the GLOBIOM-China compares well to the FAOSTAT data (Suppl. Table 3). There was only a 0.1% deviation for total agricultural product consumption and 1.5% for crop product consumption. Livestock product consumption estimated by the GLOBIOM-China was 9.6% higher than the FAOSTAT data, mainly due to the overestimation of pork consumption (19.5% higher) and dairy consumption (22.9%). The deviations for corn and wheat consumption were 11.9% and 12.6%, respectively. For other products, the deviations were within 10%.

Suppl. Table 3. Comparison of the food consumption (in Mt) from the GLOBIOM-China and data from FAOSTAT in 2020.

Categories	GLOBIOM-China	FAOSTAT	Difference
Agriculture	1276.1	1276.9	-0.1%
Crops	1093.5	1110.2	-1.5%
Livestock	182.6	166.7	9.6%
Rice	201.4	215.1	-6.4%
Wheat	131.1	150.1	-12.6%
Corn	238.4	270.6	-11.9%
Ruminant meat	14.2	15.5	-8.2%
Dairy products	50.4	41.0	22.9%
Poultry meat	21.7	22.7	-4.6%
Pig meat	62.5	52.3	19.5%
Eggs	33.9	35.2	-3.8%

Agriculture includes 18 crop products (crops) and 7 livestock products in the GLOBIOM-China. The difference represents the discrepancy between the GLOBIOM-China results and FAOSTAT data.

To determine the factors that caused large deviations for pork, dairy products, corn and wheat, we compared the results over 2010-2020 from the GLOBIOM-China with data from different sources and provided explanations for the gaps.

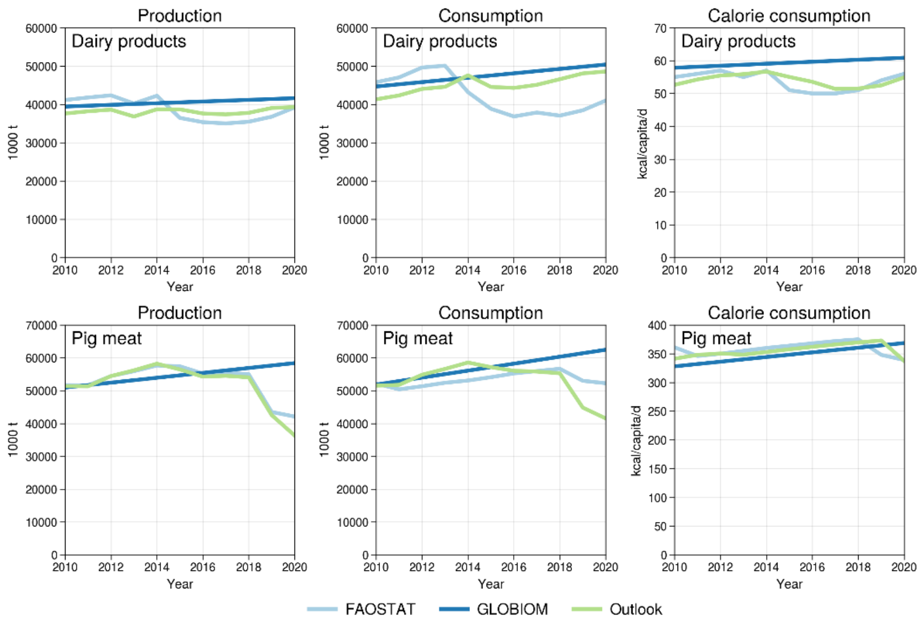
For dairy products, the seeming overestimations of the GLOBIOM-China compared to those of the FAOSTAT data were mainly caused by the update of the FAOSTAT methodology after 2013, which sharply reduced dairy production and consumption (Suppl. Fig. 1). The GLOBIOM trend agrees with those from other mainstream data sources. For instance, the OECD outlook shows a slight increasing trend over 2010-2020 with a mild fluctuation, and the historical trend of per capita milk consumption from the National Bureau of Statistics of China (NBSC) also shows a similar trend (Suppl. Fig. 2).

For pork, African swine fever occurred in 2018 and substantially decreased China's pork production and consumption (Suppl. Fig. 1), leading to obviously lower production in 2019 (43.5 Mt) and 2020 (42.1) compared with 2017 (55.5 Mt) and 2018 (55.0). As a result of the “Three-year action plan for accelerating the recovery and development of pig production” in 2019, pork production recovered to 53.9 Mt in 2021.

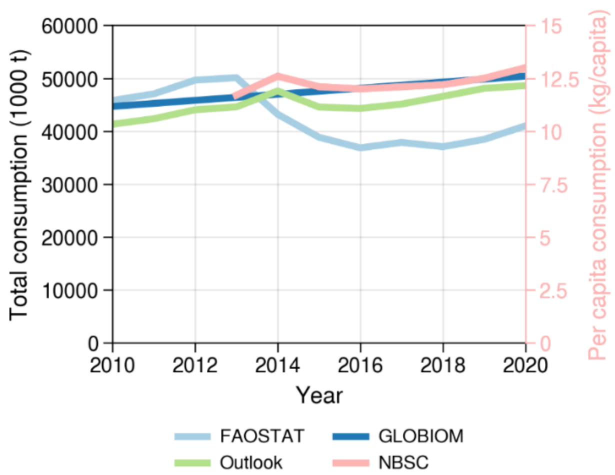
For corn, a change in the Chinese statistical method in 2017 resulted in a sudden increase in corn production of 20% in 2016 (Suppl. Fig. 3 and Suppl. Fig. 4). Although such a jump is easily captured by FAO statistics, it is difficult for it to be captured by the process-based models such as the GLOBIOM.

For wheat, we found a sharp increase in wheat demand and net imports after 2019, as they were 104% and 18% higher in 2020 than in 2019 (Suppl. Fig. 5), respectively. This case could have been caused by food security concerns due to international market disturbances to ensure adequate food reserves. The projections of the OECD outlook show that the short-term peak will be gradually smoothed over time, and the results of the GLOBIOM-China match well with the long-term projections.

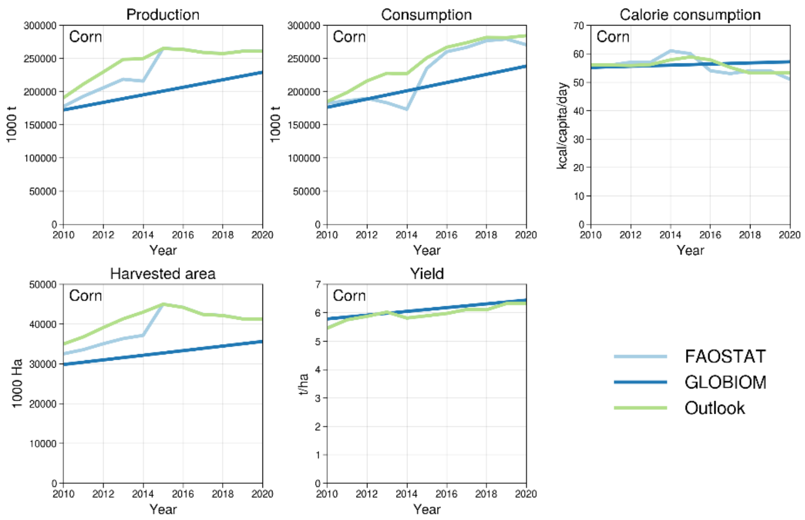
In summary, the large deviations between the results of the GLOBIOM-China and the FAOSTAT data for pork, dairy products, corn, and wheat were caused by methodological shifts or temporary policy interventions, which could eventually return to normal and fall within the range of model projection again. The deviations for other major foods were less than 10%. Therefore, GLOBIOM-China was well calibrated and could provide long-term projections for this study.



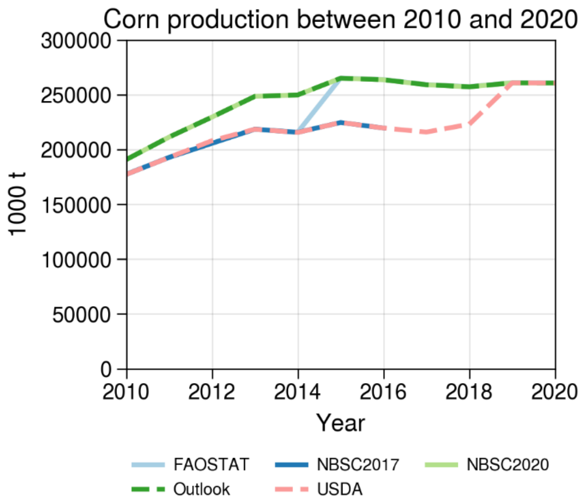
Suppl. Fig.1: Production and consumption of dairy products and pork over 2010-2020 from the GLOBIOM-China, FAOSTAT and OECD-FAO Agricultural Outlook.



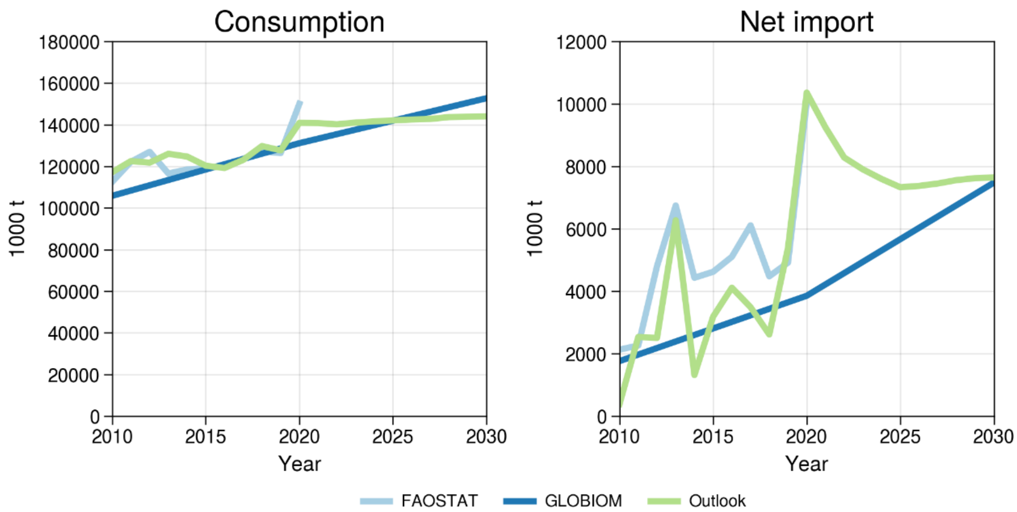
Suppl. Fig.2: Consumption of dairy products in China over 2010-2020 from the GLOBIOM-China, FAOSTAT, and OECD-FAO Agricultural Outlook; per capita milk consumption is from the National Bureau of Statistics of China (NBSC).



Suppl. Fig. 3: Production, consumption, harvested area and yield of corn over 2010-2020 from the GLOBIOM-China, FAOSTAT and OECD-FAO Agricultural Outlook.



Suppl. Fig. 4: Corn production over 2010-2020 from FAOSTAT, OECD-FAO Outlook, two versions of National Bureau of Statistics of China (NBSC) 2017 and 2020 version and U.S. Department of Agriculture (USDA) (China: Grain and Feed Annual report).



Suppl. Fig. 5: Wheat consumption and net imports between 2010 and 2030 from the GLOBIOM-China under the Reference scenario, FAOSTAT, and OECD-FAO Outlook.

3. **Bioenergy supply and demand estimation**

The GLOBIOM simulates both food-based liquid biofuels and woody lignocellulosic bioenergy. Liquid biofuels are pivotal for decarbonizing the transportation sector, while woody lignocellulosic bioenergy is key for decarbonizing other sectors (such as the power and heat sector) and, more importantly, providing negative emissions potential. The demand for liquid biofuels in the GLOBIOM-MESSAGE framework was based on the Agricultural Model Intercomparison and Improvement Project (AgMIP) projections[33] (Suppl. Table 4). The demand for woody lignocellulosic bioenergy was projected to increase to 15.6 EJ in 2060 (Suppl. Fig. 33 and Suppl. Fig. 34) based on the GLOBIOM-MESSAGE, which is equivalent to approximately 1292.9 Mt CO_2 of negative emissions in 2060 (Equation (4)).

Energy plantations and forestry residues are two feedstock sources of woody lignocellulosic bioenergy in the GLOBIOM. Energy plantations are short-rotation plantations (SRPs) covering short-rotation (i.e., 2 to 5 years) coppice and longer-rotation (~10 years) forestry for the production of energy wood such as poplar, willow, and eucalyptus. Forestry residues are the by-products (e.g., branches, stumps, bark, sawdust and saw chips) produced during the final product production processes and can be used for energy purposes. Agricultural residues are also potential bioenergy feedstock noted by recent studies[34-36], but they are not explicitly represented in the GLOBIOM for China. However, sustainably available crop residues were estimated to reduce 54.27 Mt CO_{2eq} per year in China, which is far from meeting the projected negative emissions (349-3847 Mt CO_{2eq}) using BECCS for China's carbon neutrality target[37]. Therefore, this study assumed that the additional bioenergy demand for China's carbon neutrality target will be obtained from bioenergy crops (energy plantations).

Land suitability criteria determine the land suitable for energy plantations based on aridity, temperature, elevation, population, and land-cover data. The yields of energy plantations are based on net primary productivity (NPP) maps [14] and the GLOBIOM model's calculations as described in Havlík et al. (2011)[1]. Energy plantations can expand to land-cover types of cropland, grassland, and other natural vegetation lands. Energy plantation area expansion is determined based on the land-use change constraints and the relative profitability of alternative land-use options. Land-use change constraints define which land areas can be changed to plantations and how much of these areas can be changed within each period and region (so-called inertia conditions). Land-use inertia conditions limit the maximum feasible plantation expansion to 5% of available areas for each period. For example, plantation area expansion to cropland and grassland depends on the economic trade-off between food and wood production. Hence, the competition between alternative uses of land is modeled explicitly. When carrying out simulations over several periods, changes made in one period are consistently transferred into the next, introducing recursive dynamics into the model. More details are provided in Havlík et al. (2011)[1], Lauri et al (2014)[38] and Li et al. (2020)[39]. Considering China has a water shortage and a higher transpiration rate of energy plantations, we assume no irrigation for energy crops.

GLOBIOM has a detailed simulation for the forest sector and its supply chains[40] based on the Global Forest Model (G4M)[11, 41], which is a spatially explicit process-based model. The model defines five primary forest products (sawn wood, plywood, fiberboard, chemical pulp, mechanical pulp, other industrial roundwood, fuelwood, and energy wood) and five by-products (sawdust, woodchips, bark, black liquor, and recycled wood). Detailed information on the forest sector is provided by Lauri et al. [40] [38]. Biomass for bioenergy can be sourced from forest industry by-products. However, considering the environmental and sustainability concerns, their availability and the share that can be used for bioenergy are limited. We assume forestry residues that are available for bioenergy remain constant under different scenarios.

Suppl. Table 4. Future trends in China's ethanol demand (10^6 G.J.).

	2010	2020	2030	2040	2050	2060
Ethanol	7.25	15.65	24.04	24.04	24.04	24.04

4. Calculation of the negative emission potential from biomass

To determine the negative emission potential that can be obtained via BECCS, we assumed that bioenergy is used to produce electricity in biomass-fired power plants equipped with carbon capture and storage (CCS). The amount of negative emission potential Q_{CO_2} is calculated as:

$$Q_{CO_2} = Q_{Bio} \cdot CC \cdot EC \cdot 3.67 \quad (4)$$

where Q_{Bio} is the biomass consumption quantity; CC is the carbon content in biomass, for which we use 47.1%[35]; EC is the efficiency of CO_2 capture of CCS, for which we use 90%[42, 43]; 3.67 is the conversion factor of C to CO_2[35]; and the heat content of biomass is 19 GJ/t biomass[44]. The calculated negative emissions are shown in Suppl. Fig. 34.

5. Calculation of food consumption for plausible dietary shifts

We calculated food consumption in the DietHealth scenario as follows:

(1) We estimated the gap in animal-based food consumption between the current consumption quantity and the recommended values in the Chinese Dietary Guidelines released in 2022. The gap (Δ) was estimated based on the difference between the current animal-based food consumption quantity and the recommended values (upper bound) (Suppl. Table 5). The GLOBIOM calculates the current animal-based food consumption quantity. The Chinese Dietary Guidelines only recommend a meat consumption value,

and the specific type of meat consumption values for bovine meat, mutton and goat meat, pork, and poultry was further determined based on the recommended value of the planetary health diet.

(2) We adjusted China's future food consumption. The gap between the animal-based food consumption quantity and the recommended value was shown to gradually narrow by approximately 20% by 2060. Meanwhile, we gradually increased the crop-based food consumption to ensure total calorie consumption was consistent with the Reference scenario.

Suppl. Table 5. Animal-based food consumption in 2020 for China from GLOBIOM and the recommended consumption values of Chinese Dietary Guideline 2022 and planetary health diet.

	GLOBIOM 2020	Planetary health diet [45]		Chinese Dietary Guideline 2022[29]
Item	kcal/capita/day	g/capita/day	kcal/capita/day	g/capita/day
Bovine Meat	28	7*	15*	40-75**
Mutton & Goat Meat	17			
Pigmeat	317	7	15	
Poultry Meat	59	29	62	
Eggs	71	13	19	40-50
Milk	61	250	153	300

* The data is for the beef and lamb, ** The data is for meat

6. Calculation of elasticity

The elasticity ε for sensitivity analysis is calculated as:

$$\varepsilon = \frac{\frac{O_S - O_B}{O_B}}{\frac{I_S - I_B}{I_B}} \tag{5}$$

where O_S is the model output (selected sustainability indicators) under the sensitivity scenario, O_B is the model output under the corresponding baseline scenario, I_S is the input under sensitivity scenario, and I_B is input under the corresponding baseline scenario. The mapping of sensitivity scenarios, baseline scenarios, and inputs and the proxy variables of inputs for calculating elasticities is shown in Suppl. Table 11.

Supplementary Discussion

1. Robustness of results

As the future developments driving our scenario results are by definition uncertain, we conducted a systematic sensitivity analysis with different assumptions on socioeconomic and bioenergy supply, covering alternative assumptions on key parameters related to the food supply and consumption, bioenergy supply trajectory, population, gross domestic product (GDP) and trade conditions (Suppl. Tables 8-10, Suppl. Figs.30-33) to assess the robustness of the above-presented results. Our results show that domestic food prices are sensitive to population and dietary shifts, SSR for three main staple crops are sensitive to trade and crop yield, and the virtually imported environmental impacts are more sensitive to trade and dietary shifts.

(1) Population and GDP

Shared Socioeconomic Pathway (SSP)1 assumes low population and high GDP growth, whereas SSP3 has a high population and low GDP growth [46]. Changes in population and GDP affect food demand. A higher population implies more food demand, resulting in a lower daily per capita calorie intake due to food price increases. For instance, switching population growth in the Bioenergy scenario to a higher value in SSP3 increases food prices by 7.3% and decreases daily per capita calorie intake by 2.9% in 2060 (ED Fig.4). Meanwhile, a higher GDP (in SSP1) increases animal-based food consumption, especially for ruminant meat, resulting in higher impacts on agricultural land and GHG emissions. For instance, enhancing GDP in the Bioenergy scenario to a higher level in SSP1 increases virtual agricultural land and GHG emission imports in 2060 by 8.7% and 13.1%, respectively. Changes in the assumptions for population growth result in similar sustainability impacts (-13.7%~29.2%) compared with changes in assumptions for the combination of population and GDP (-

17.8%~23.2%).

(2) Trade

Assumptions related to trade are the key determinant of the changes in virtually imported environmental impacts (ED Fig.4) mainly because there is heterogeneous food production efficiency in different regions and food trade patterns. Higher trade barriers (in SSP3) decrease food imports, particularly for ruminant products, thus decreasing virtually imported environmental impacts. However, this assumption (FreeTrade-3) challenges domestic food security by increasing domestic food prices by 6.6% and decreasing daily per capita calorie intake by 3.1% compared with those values in the FreeTrade scenario. We found that both higher (FreeTrade-3) and lower (FreeTrade-1) trade barriers result in negative virtual cumulative GHG emissions imports due to lower bovine meat imports, as bovine meat is a GHG-intensive product. Under the lower trade barrier assumption (SSP1), lower bovine meat imports are driven by higher rice and pork imports, as China’s diet is characterized by a high proportion of rice and pork.

(3) Bioenergy supply and its composition

Assumptions on bioenergy supply level have the most significant influence on sustainability indicators (ED Fig.4). Changing the bioenergy supply level can ease or intensify the competition between food and energy plantations, impacting sustainability mainly by altering food production, consumption and trade. Compared with the Bioenergy scenario, increasing bioenergy supply by 30% (Bioenergy-H) leads to an additional 22.3 Mha in bioenergy plantation area and a 10.0% (21.5 Mha) decrease in agricultural land, resulting in a 29.0% increase in food prices and a 4.9% (131.7 kcal) decrease in daily per capita calorie intake in 2060. Accordingly, lower domestic food production decreases domestic overall agricultural land, water, fertilizer use and GHG emissions by 10.0% (21.5 Mha), 4.7% (17.1 km^3), 4.3% (1.0 Mt), and 32.0% (111.3 Mt CO_{2eq}), respectively. Moreover, in comparison to the Bioenergy scenario, the Bioenergy-H scenario results in an increase in virtual agricultural land and GHG emission imports of 3.1% (4.3 Mha) and 14.0% (30.3 Mt CO_{2eq}), respectively, which are mainly driven by increased livestock product imports. In contrast, lowering the bioenergy supply by 25% (Bioenergy-L) would significantly ease sustainability pressures. Changing bioenergy composition by substituting approximately 15% of bioenergy plantations with forest residues results in a 0.2% increase in managed forest area and a 5.4% increase in forest management emissions in 2060 compared with the Bioenergy scenario.

(4) Dietary shift

Based on the difference between the projected animal-based food consumption under the Reference scenario and the recommendations of the Chinese Dietary Guidelines in 2022, we set up two more scenarios with DietHealth-L as a lower ambition and DietHealth-H as a higher ambition dietary shift, using animal-based food consumption levels under the Reference scenario as starting points. The corresponding animal-based food consumption is 10% higher in [L] and 10% lower [H] than that under the DietHealth scenario. Specifically, we mainly reduce the consumption of pork (since Chinese people consume more pork than recommended) in the DietHealth-L scenario and further reduce bovine meat consumption in the DietHealth-H scenario. Moreover, by increasing calories from crops, we maintain the total calorie consumption of the two dietary shift assumptions consistent with that in the Reference scenario.

The results show that assumptions on dietary shifts are vital determinants of the changes in sustainability impacts. Both animal-based food consumption levels and their sources (i.e., pork versus bovine meat) are vital (ED Fig.4). For example, reducing animal-based food consumption by 10% (DietHealth-H) decreases domestic agricultural land, irrigation water, nitrogen fertilizer, and GHG emissions in 2060 by 16.4% (32.5 Mha), 1.0% (3.4 km^3), 0.5% (0.1 Mt), and 28.0% (78.6 Mt CO_{2eq}), respectively, compared with DietHealth scenario. In contrast, higher animal-based food consumption (DietHealth-L) results in a 2.1% (4.2 Mha) reduction in agricultural land, a 2.5% (8.6 km^3) increase in irrigation water, a 4.1% (0.9 Mt) increase in nitrogen fertilizer, and a 1.2% (3.4 Mt CO_{2eq}) reduction in GHG emissions. A closer look at the lower animal-based food consumption (DietHealth-H) assumption shows that the significant declines in agricultural land and GHG emissions are mainly driven by reduced ruminant meat consumption, as ruminant meat is a land- and GHG-intensive product. However, the higher animal-based food consumption (DietHealth-L) assumption also results in negative changes in domestic agricultural land and GHG emissions compared with the DietHealth scenario. This result is mainly due to the lower ruminant meat consumption caused by its higher prices compared with those in the DietHealth scenario. A higher pork consumption (DietHealth-L) assumption results in a higher pork supply, which can further increase input prices and thus increase ruminant meat prices. Changes in dietary shift assumptions cause comparable absolute changes in environmental impacts in China and its trade partners. If animal-based food consumption is assumed to be 10% lower than that under the DietHealth scenario, then the virtual agricultural land, water, nitrogen fertilizer, and GHG emission imports will decrease by 26.6% (25.2 Mha), 25.3% (9.4 km^3), 27.7% (0.8 Mt), and 26.3% (31.8 Mt CO_{2eq}), respectively, which are similar to the domestic changes.

(5) Combination of trade and compensatory measures

The sustainability impacts differ considerably under various combinations of assumptions on socioeconomic development compared with those under the FoodSystem scenario (Fig. 5, ED Fig.4, and Suppl. Tables 12-14). For instance, under more optimistic assumptions (FoodSystem-1-H-H)), the combination of lower trade barriers (trade in SSP1), higher crop yield growth (YieldUp-H), and the lower animal-based food consumption assumption (DietHealth-H) improves global sustainability, which is partly due to the increased input efficiency through trade, but more importantly, due to the increased domestic food supply by implementing complementary domestic measures. We also find that under the ambitious bioenergy demand assumption, the combination of lower trade barriers, lower crop yield growth, and the higher animal-based food consumption assumption cannot eliminate the negative impacts of bioenergy deployment in China on virtual water and fertilizer imports, while shifting the trade in the combination to SSP3 would challenge domestic food prices. Nevertheless, different assumptions would not change the main conclusions.

(6) Other uncertainties

The sustainability impacts of changes in GDP (-10.3%~10.7%) and bioenergy supply in the rest of the world (-8.1%~10.8%) are less sensitive.

The sustainability performance under the FoodSystem scenario and its alternative assumptions are superior to that under the Reference scenario (Fig. 5). The SSR for wheat under the FoodSystem scenario (92%) is slightly lower than 95%. However, under most of the variants of the FoodSystem scenario, the SSR for wheat is higher than 95%, except for a few highly pessimistic assumptions. The SSR for rice (95%~100%) and corn (97%~99%) under all alternative assumptions on the FoodSystem scenario can maintain the SSR redlines (95%). Shifting multifactor from the FoodSystem scenario results in more difference in domestic GHG emissions (-58% and 41%) and virtual water import (-27% and 52%), while results in less difference in domestic irrigation water (-3%~7%) and SSR for rice (-4%~1%) and corn (-1%~1.5%) (Suppl. Tables 12-14). Therefore, despite a wide range of results for alternative assumptions of the FoodSystem scenario, our conclusions remain solid, especially for SSR.

2. Challenges in dietary shifts

In reality, a dietary shift is challenging and impacted by many socially inertial factors. For example, healthy diet recommendations are difficult to translate into specific food choices[47] due to a lack of nutrition literacy[48] and instructions actionable for China's regionally heterogeneous food culture and taste preferences [49]. Meanwhile, China is in the middle of the global diet spectrum regarding daily animal-based food consumption per capita, which is expected to increase rapidly, driven by income growth[50], further challenging the achievement of dietary recommendations [51].

3. Additional aspects that could be further considered

Despite the integrated and holistic approach, there are some additional aspects that could be further considered. For example, implementing compensatory measures, especially dietary shifts, contributes to decreasing GHG emissions from the food system, one of the major sources of global GHG emissions, and thus decreases the required level of BECCS in China for carbon neutrality by 2060; however, these are not explicitly considered in this study and could be further explored. For the sensitivity analysis, further identifying the key thresholds of sensitive parameters (e.g., the level of animal-based food consumption per capita, food loss and waste, crop yield, etc.) using global sensitivity analysis methods would be more helpful to make more solid policy recommendations. The impacts of bioenergy deployment induced by collective global ambitious climate actions on biodiversity loss due to diminished natural land use also deserve further assessment.

Supplementary Tables

Suppl. Table 6. Comparison of the projected animal source food consumption in China by 2060 under different scenarios in this study and from other literature. Unit: kg/capita/ year

	Dairy milk	Poultry eggs	Pig meat	Poultry meat	Beef and buffalo meat	Sheep and goat meat
Reference	56.5	29.9	53.6	19.1	9.9	5.2
FreeTrade	52.2	28.6	51.2	18.1	9.5	4.4
Bioenergy	51.3	28.3	50.1	18.1	9.5	4.3
FoodSystem	58.3	29.2	36.8	17.3	6.9	3.9
DietHealth	54.5	25.7	34.3	15.3	6.6	3.5
FoodLossDown	52.6	30.9	52.7	19.1	9.9	4.7
YieldUp	54.7	30.2	53.4	19.3	9.5	4.5
Bai et al., 2018[22]	82	33	53	25	8.6	4.9
Alexandratos and Bruinsma, 2012[52]	56	-	51	29	7.7	5
FAO BAU scenario, 2018[53]	38	-	50	17	6.5	3.6

Suppl. Table 7. Quantitative drivers of the alternative scenarios for China.

	Unit		Reference	FreeTrade	Bioenergy	FoodSystem	DietHealth	FoodLossDown	YieldUp
		2020				2060			
Total calorie availability	kcal/cap/day	3080	3518	3336	3220	3603	3527	3394	3393
Crop calorie availability	kcal/cap/day	1941	2176	2064	1977	2385	2374	2085	2079
Livestock calorie availability	kcal/cap/day	636	824	781	768	654	600	810	816
Corn yield	kg/ha	6436	7676	7978	8105	12270	8400	8445	11048
Wheat yield	kg/ha	5187	6573	6666	6249	6890	6550	6802	6903
Rice yield	kg/ha	6913	7439	7541	7520	8280	7700	7904	7841
Soybean yield	kg/ha	2009	2164	2164	2164	2210	2160	2176	2193
Crop production quantity	Mt	901.8	1016.3	866.6	867.9	863.1	800.2	886.0	956.3
Livestock production quantity	Mt	166.9	207.6	189.6	180.2	184.4	164.2	199.8	203.2
Crop consumption quantity	Mt	1093.5	1272.0	1180.4	1107.6	1113.4	1084.7	1161.0	1250.3
Livestock consumption quantity	Mt	182.6	228.7	215.5	212.2	200.4	183.6	223.2	225.4
Crop import quantity	Mt	194.0	191.9	260.7	241.3	261.8	293.1	315.5	277.9
Livestock import quantity	Mt	15.9	20.9	21.2	32.2	16.5	19.8	20.3	23.5

Suppl. Table 8. Assumptions for sensitivity analysis using the one-at-a-time method

Scenario name	Uncertain input variable and its assumption														
	GDP		Population		Trade		Bioenergy supply			Yield		Dietary shift		ROW
	SSP1	SSP3	SSP1	SSP3	SSP1	SSP3	High	Low	Composition	High	Low	High	Low	High
	(1)	(3)	(1)	(3)	(1)	(3)	(H)	(L)	(C)	(H)	(L)	(H)	(L)	(ROW)
Reference	√	√	√	√										
Bioenergy	√	√	√	√			√	√	√					√
FreeTrade	√	√	√	√	√	√								√
YieldUp	√	√	√	√						√	√			√
DietHealth	√	√	√	√								√	√	√
FoodLossDown	√	√	√	√										√
FoodSystem	√	√	√	√	√	√	√	√	√	√	√	√	√	√

Note: 52 additional sensitivity scenarios are generated based on the one-at-a-time method.

Suppl. Table 9. Assumptions for sensitivity analysis using the two-at-a-time method

Scenario name	Uncertain input variable and its assumption (combination)			
	GDP		Population	
	SSP1	SSP3	SSP1	SSP3
	(1)	(3)	(1)	(3)
Reference	√		√	
		√		√
Bioenergy	√		√	
		√		√
FreeTrade	√		√	
		√		√
YieldUp	√		√	
		√		√
DietHealth	√		√	
		√		√
FoodLossDown	√		√	
		√		√
FoodSystem	√		√	
		√		√

Note: 14 additional sensitivity scenarios are generated based on the two-at-a-time method.

Suppl. Table 10. Assumptions for sensitivity analysis using the two-at-a-time method

Scenario name	Uncertain input variable and its assumption (combination)								
	Trade		Bioenergy supply			Yield		Dietary shift	
	SSP1	SSP3	High	Low	Composition	High	Low	High	Low
	(1)	(3)	(H)	(L)	(C)	(H)	(L)	(H)	(L)
FoodSystem	√					√		√	
		√				√		√	
	√						√		√
		√					√		√
	√		√			√		√	
		√	√			√		√	
	√		√				√		√
		√	√				√		√
	√			√		√		√	
		√		√		√		√	
	√			√			√		√
		√		√			√		√

Note: 12 additional sensitivity scenarios are generated based on the two-at-a-time method.

Suppl. Table 11. Mapping of sensitivity scenarios, baseline scenarios, and inputs and the proxy variables for calculating elasticities.

Sensitivity scenario	Sensitive scenario symbol in ED Fig.4	Baseline scenario	Uncertain input	Proxy variable of inputs
Reference_GDPSSP1	Reference-1	Reference	GDP	-
Reference_GDPSSP3	Reference-3	Reference		
Bioenergy_GDPSSP1	Bioenergy-1	Bioenergy		
Bioenergy_GDPSSP3	Bioenergy-3	Bioenergy		
FreeTrade_GDPSSP1	FreeTrade-1	FreeTrade		
FreeTrade_GDPSSP3	FreeTrade-3	FreeTrade		
YieldUp_GDPSSP1	YieldUp-1	YieldUp		
YieldUp_GDPSSP3	YieldUp-3	YieldUp		
FoodLossDown_GDPSSP1	FoodLossDown-1	FoodLossDown		
FoodLossDown_GDPSSP3	FoodLossDown-3	FoodLossDown		
DietHealth_GDPSSP1	DietHealth-1	DietHealth		
DietHealth_GDPSSP3	DietHealth-3	DietHealth		
FoodSystem_GDPSSP1	FoodSystem-1	FoodSystem		
FoodSystem_GDPSSP3	FoodSystem-3	FoodSystem		
Reference_POPSSP1	Reference-1	Reference	Population	-
Reference_POPSSP3	Reference-3	Reference		
Bioenergy_POPSSP1	Bioenergy-1	Bioenergy		
Bioenergy_POPSSP3	Bioenergy-3	Bioenergy		
FreeTrade_POPSSP1	FreeTrade-1	FreeTrade		
FreeTrade_POPSSP3	FreeTrade-3	FreeTrade		
YieldUp_POPSSP1	YieldUp-1	YieldUp		
YieldUp_POPSSP3	YieldUp-3	YieldUp		

FoodLossDown_POPSSP1	FoodLossDown-1	FoodLossDown		
FoodLossDown_POPSSP3	FoodLossDown-3	FoodLossDown		
DietHealth_POPSSP1	DietHealth-1	DietHealth		
DietHealth_POPSSP3	DietHealth-3	DietHealth		
FoodSystem_POPSSP1	FoodSystem-1	FoodSystem		
FoodSystem_POPSSP3	FoodSystem-3	FoodSystem		
Bioenergy_ROW	Bioenergy-ROW	Bioenergy	ROW	Bioenergy supply level in the remainder of the world
FreeTrade_ROW	FreeTrade-ROW	FreeTrade		
YieldUp_ROW	YieldUp-ROW	YieldUp		
FoodLossDown_ROW	FoodLossDown - ROW	FoodLossDown		
DietHealth_ROW	DietHealth-ROW	DietHealth		
FoodSystem_ROW	FoodSystem-ROW	FoodSystem		
Bioenergy_Low	Bioenergy-L	Bioenergy	Quan (Bioenergy supply level)	Total bioenergy supply in China
Bioenergy_High	Bioenergy-H	Bioenergy		
FoodSystem_BioH	FoodSystem-H	FoodSystem		
FoodSystem_BioL	FoodSystem-L	FoodSystem		
Bioenergy_Comp1	Bioenergy-C	Bioenergy	Comp (Bioenergy composition)	The share of energy plantations in the total bioenergy supply in China
FoodSystem_Comp	FoodSystem-C	FoodSystem		
FreeTrade_SSP1	FreeTrade-1	FreeTrade	Trade	China's net imports of agricultural products
FreeTrade_SSP3	FreeTrade-3	FreeTrade		
FoodSystem_TrdSSP3	FoodSystem-3	FoodSystem		
FoodSystem_TrdSSP1	FoodSystem-1	FoodSystem		

YieldUp_High	YieldUp-H	YieldUp	Yield	Crop yield in China
YieldUp_Low	YieldUp-L	YieldUp		
FoodSystem_YieldUpL	FoodSystem-L	FoodSystem		
FoodSystem_YieldUpH	FoodSystem-H	FoodSystem		
DietHealth_High	DietHealth-H	DietHealth	Diet	Caloric food consumption of animal-based food, per capita
DietHealth_Low	DietHealth-L	DietHealth		
FoodSystem_DietHealthL	FoodSystem-L	FoodSystem		
FoodSystem_DietHealthH	FoodSystem-H	FoodSystem		

Suppl. Table 12. Change in outputs from the FoodSystem scenario in 2060 (the first and second column of every indicator are absolute and relative change, respectively)

Sensitivity scenario	Calorie intake		Price		Water		Agriculature land	
	kcal/cap/d	%	$/ton	%	km^3	%	Mha	%
FoodSystem_GDPSSP1	38.1	1.2	-11.1	-3.3	5.3	1.6	1.4	0.7
FoodSystem_GDPSSP3	26.9	0.8	-2.4	-0.7	7.7	2.3	0.5	0.2
FoodSystem_POPSSP1	84	2.6	-19.5	-5.8	-5.9	-1.8	-3.1	-1.6
FoodSystem_POPSSP3	-43	-1.3	12.1	3.6	11.3	3.4	4.5	2.3
FoodSystem_ROW	31.4	1	-5	-1.5	5.6	1.7	1.4	0.7
FoodSystem_YieldUpL	-6.2	-0.2	4.8	1.4	6.4	1.9	-0.1	-0.1
FoodSystem_YieldUpH	71.9	2.2	-15.9	-4.8	0.8	0.2	1.4	0.7
FoodSystem_DietHealthL	-6	-0.2	-2.9	-0.9	9.7	2.9	1.7	0.9
FoodSystem_DietHealthH	39.3	1.2	-41.4	-12.4	-7.7	-2.3	-31.7	-16.1
FoodSystem_BioL	134.8	4.1	-28	-8.4	11.7	3.5	11.7	5.9
FoodSystem_BioH	-102.7	-3.1	31.9	9.6	-10.8	-3.3	-14.9	-7.6
FoodSystem_Comp	140.9	4.3	-26.6	-8	10.4	3.1	8.7	4.4
FoodSystem_TrdSSP3	42.2	1.3	-10.4	-3.1	8.5	2.6	4.6	2.3

FoodSystem_TrdSSP1	45	1.4	-8.9	-2.7	7.9	2.4	3	1.5
FoodSystem_POP&GDPSSP1	89.4	2.7	-25	-7.5	-2	-0.6	-1.2	-0.6
FoodSystem_POP&GDPSSP3	-30.5	-0.9	9.7	2.9	15.5	4.7	5.7	2.9
FoodSystem_TrdSSP1_YieldUpH_DietHealthH	33.4	1	-45.8	-13.7	-5.7	-1.7	-30.9	-15.7
FoodSystem_TrdSSP1_YieldUpL_DietHealthL	22	0.7	-14.1	-4.2	6.1	1.8	4.2	2.1
FoodSystem_TrdSSP3_YieldUpH_DietHealthH	-91	-2.8	-12.4	-3.7	8.5	2.6	-31.8	-16.2
FoodSystem_TrdSSP3_YieldUpL_DietHealthL	-88.4	-2.7	25.6	7.7	23	6.9	8.7	4.4
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioH	-58	-1.8	-19.7	-5.9	-1.4	-0.4	-38.4	-19.5
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioL	132.4	4	-64.1	-19.2	7.6	2.3	-22.2	-11.3
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioH	-146.5	-4.4	37.2	11.1	-4.2	-1.3	-19.8	-10
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioL	81.5	2.5	-25	-7.5	12.3	3.7	14.5	7.4
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioH	-138.9	-4.2	0.3	0.1	-9.8	-2.9	-45.9	-23.3
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioL	144.9	4.4	-66.2	-19.8	8	2.4	-23.5	-11.9
FoodSystem_TrdSSP3_YieldUpL_DietHealthL_BioH	-253.4	-7.7	81	24.3	-8.1	-2.4	-12.2	-6.2

Suppl. Table 13. Change in outputs from the FoodSystem scenario in 2060 (the first and second column of every indicator are absolute and relative change, respectively)

Sensitivity scenario	Nitrogen fertilizer		GHGs		SSR for wheat		SSR for rice		SSR for corn	
	Mt	%	$MtCO_2eq/yr$	%		%		%		%
FoodSystem_GDPSSP1	0.4	1.7	8.6	3.1	1.3	1.4	1	1.1	0	0
FoodSystem_GDPSSP3	0.2	0.7	-4.6	-1.6	-0.4	-0.4	0	0	0.1	0.1
FoodSystem_POPSSP1	-0.5	-2.1	-16	-5.7	1.4	1.5	-0.6	-0.6	0	0
FoodSystem_POPSSP3	0.7	3.1	24.9	8.8	-2.5	-2.8	-1	-1	0.2	0.2
FoodSystem_ROW	0.2	1	7.3	2.6	2.8	3.1	-0.2	-0.2	0.1	0.1
FoodSystem_YieldUpL	0.3	1.6	-3.5	-1.2	-2.5	-2.8	-1.4	-1.4	-0.3	-0.3
FoodSystem_YieldUpH	0.1	0.3	4.6	1.6	3.7	4	-0.3	-0.3	0.3	0.3
FoodSystem_DietHealthL	0.6	2.8	18.9	6.7	-1.4	-1.5	-0.2	-0.3	0.3	0.3
FoodSystem_DietHealthH	0.1	0.3	-70.6	-25.1	5.8	6.3	0.6	0.6	-0.3	-0.3
FoodSystem_BioL	0.8	3.8	38.3	13.6	7.2	7.9	0.7	0.7	0.2	0.2
FoodSystem_BioH	-0.4	-1.9	-78.8	-27.9	-12.4	-13.5	-1.8	-1.8	-0.3	-0.3
FoodSystem_Comp	1	4.6	56	19.9	5.8	6.3	0.5	0.5	0.2	0.2

FoodSystem_TrdSSP3	0.5	2.4	19.3	6.9	4.9	5.3	0.5	0.5	0.8	0.8
FoodSystem_TrdSSP1	0.1	0.3	15.8	5.6	-5.5	-6	-2.5	-2.6	1.3	1.3
FoodSystem_POP&GDPSSP1	0	-0.1	-4.5	-1.6	4	4.3	-0.1	-0.1	-0.1	-0.1
FoodSystem_POP&GDPSSP3	0.9	4.1	25.2	8.9	-1.7	-1.9	-1	-1	0.2	0.2
FoodSystem_TrdSSP1_YieldUpH_DietHealthH	0	0.2	-67.6	-24	8.3	9.1	0.7	0.7	1.1	1.2
FoodSystem_TrdSSP1_YieldUpL_DietHealthL	0.2	1	30.8	10.9	0.1	0.1	-3.6	-3.6	1.4	1.4
FoodSystem_TrdSSP3_YieldUpH_DietHealthH	0.8	3.7	-80.9	-28.7	4.2	4.6	0	0	0.3	0.3
FoodSystem_TrdSSP3_YieldUpL_DietHealthL	2.1	9.9	46.9	16.7	2.6	2.8	-0.9	-0.9	0.8	0.8
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioH	0.7	3.5	-135.6	-48.1	0	0	-0.6	-0.6	-0.6	-0.6
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioL	0.3	1.5	1.7	0.6	10.2	11.1	1.4	1.4	1.2	1.3
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioH	0.4	2	-62	-22	-14.2	-15.6	-3.5	-3.6	-0.8	-0.8
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioL	0.7	3.5	35.3	12.5	8	8.8	1	1	1.5	1.5
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioH	0.4	1.8	-164.2	-58.2	2.3	2.5	-0.3	-0.3	0.1	0.1
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioL	0.2	1	-12	-4.2	10.3	11.2	1.3	1.3	0.8	0.8
FoodSystem_TrdSSP3_YieldUpL_DietHealthL_BioH	0.3	1.5	-68.1	-24.2	-3.3	-3.7	-1.3	-1.3	0.1	0.1

Suppl. Table 14. Change in outputs from the FoodSystem scenario in 2060 (the first and second column of every indicator are absolute and relative change, respectively)

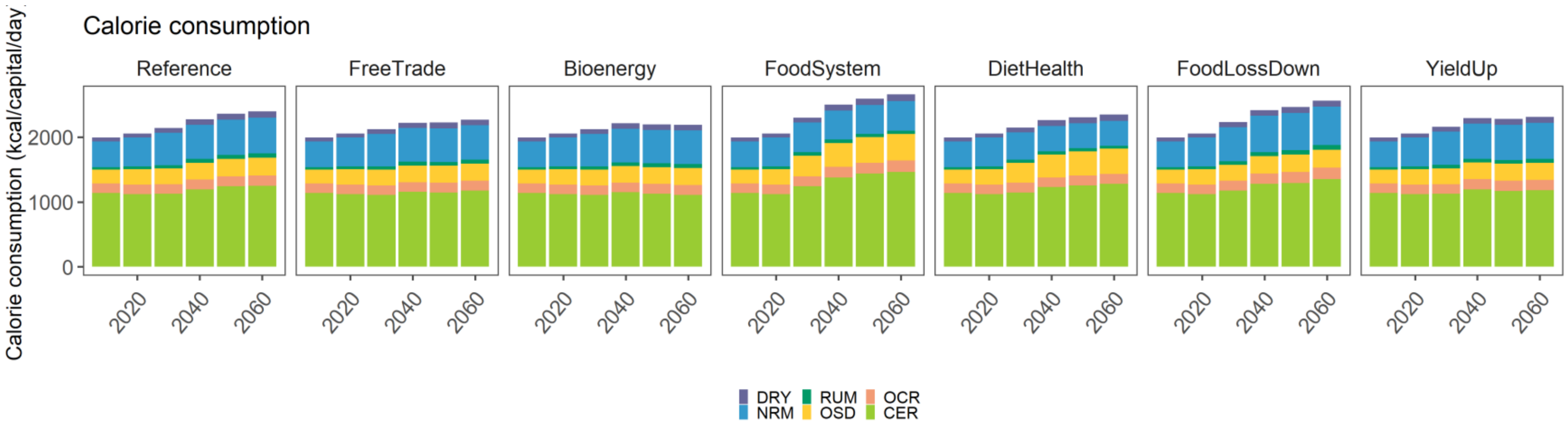
Sensitivity scenario	Virtual GHGs		Virtual nitrogen		Virtual water		Virtual agri-land	
	$MtCO_2eq$	%	Mt	%	km^3	%	Mha	%
FoodSystem_GDPSSP1	-3.9	-0.1	-0.1	-6.5	-2.5	-10.3	-3.3	-4.2
FoodSystem_GDPSSP3	-38.5	-0.9	0	0.8	1	4.1	0	0
FoodSystem_POPSSP1	-228.8	-5.4	-0.2	-8.6	1.9	8.1	-9.7	-12.2
FoodSystem_POPSSP3	189.3	4.5	0.4	16.9	5.5	22.9	10	12.5
FoodSystem_ROW	-167.4	-4	-0.1	-6	2.6	10.8	-6.4	-8.1
FoodSystem_YieldUpL	73.4	1.7	0.1	4.8	4.3	18	2.1	2.7
FoodSystem_YieldUpH	-2.8	-0.1	-0.1	-3.7	2.9	12	-0.8	-0.9
FoodSystem_DietHealthL	73.5	1.7	0.3	14.6	4	16.7	4.9	6.2
FoodSystem_DietHealthH	-1037.7	-24.5	-0.6	-26.5	-4.4	-18.3	-21.4	-26.9
FoodSystem_BioL	-115.6	-2.7	-0.2	-10.6	-0.3	-1.4	-5.9	-7.5
FoodSystem_BioH	119.6	2.8	0.4	19.1	5.9	24.6	8	10
FoodSystem_Comp	-49.9	-1.2	-0.2	-8.2	-0.2	-1	-3.3	-4.2
FoodSystem_TrdSSP3	-478.3	-11.3	-0.3	-12.3	-1.4	-5.9	-1.6	-2.1

FoodSystem_TrdSSP1	-359.5	-8.5	0.1	3.1	7	29.1	16	20.2
FoodSystem_POP&GDPSSP1	-169.6	-4	-0.3	-16	-0.3	-1.3	-14.1	-17.8
FoodSystem_POP&GDPSSP3	142.6	3.4	0.4	16.9	5.6	23.2	9.4	11.9
FoodSystem_TrdSSP1_YieldUpH_DietHealthH	-1092.2	-25.8	-0.8	-35.6	-5.6	-23.2	-10.3	-12.9
FoodSystem_TrdSSP1_YieldUpL_DietHealthL	-369.2	-8.7	0.1	5.2	11.9	49.7	16.2	20.4
FoodSystem_TrdSSP3_YieldUpH_DietHealthH	-1097.9	-25.9	-0.5	-24.4	-3.5	-14.7	-13.2	-16.7
FoodSystem_TrdSSP3_YieldUpL_DietHealthL	-219.1	-5.2	0.2	9.2	5.4	22.3	10.2	12.8
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioH	-649.7	-15.3	-0.3	-15.4	0.3	1.3	-20.7	-26.1
FoodSystem_TrdSSP1_YieldUpH_DietHealthH_BioL	-1136.5	-26.8	-0.8	-34.8	-6.4	-26.5	-10.1	-12.7
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioH	400	9.4	0.8	38.1	12.4	51.6	6.3	7.9
FoodSystem_TrdSSP1_YieldUpL_DietHealthL_BioL	-523.7	-12.4	-0.2	-10.3	0.2	0.6	11.1	14
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioH	-1166.1	-27.5	-0.6	-25.8	-3.6	-15	-14.5	-18.3
FoodSystem_TrdSSP3_YieldUpH_DietHealthH_BioL	-1301.5	-30.7	-0.7	-31.5	-5.5	-22.9	-19.1	-24.1
FoodSystem_TrdSSP3_YieldUpL_DietHealthL_BioH	-284.5	-6.7	0.2	11.4	4.8	19.8	6.7	8.4

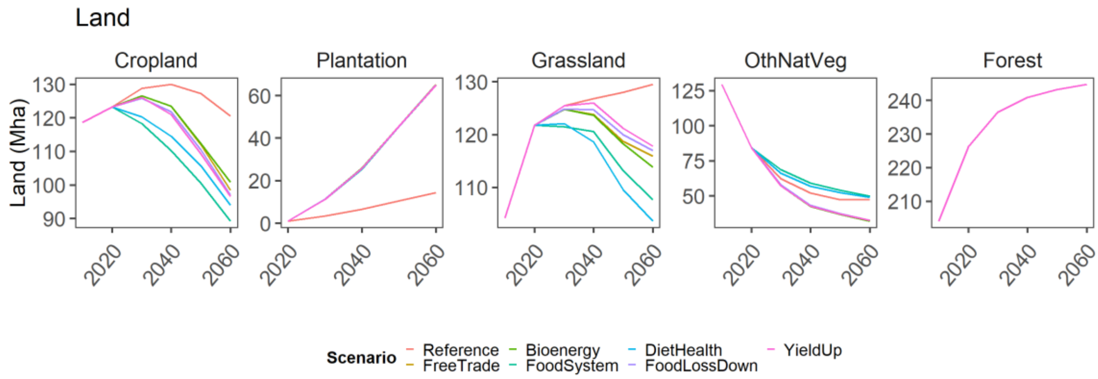
Note, FoodSystem_X assumed that shift the uncertain input variables from the values under the FoodSystem scenario to their alternative projections. For example, FoodSystem_TrdSSP1_YieldUpH_DietHealthH assumed that the trade, yield growth and dietary shifts are shifted from these in the FoodSystem scenario to lower trade barriers (1), high yield growth (H) and the high dietary shift (H) assumptions simultaneously.

Supplementary Figures

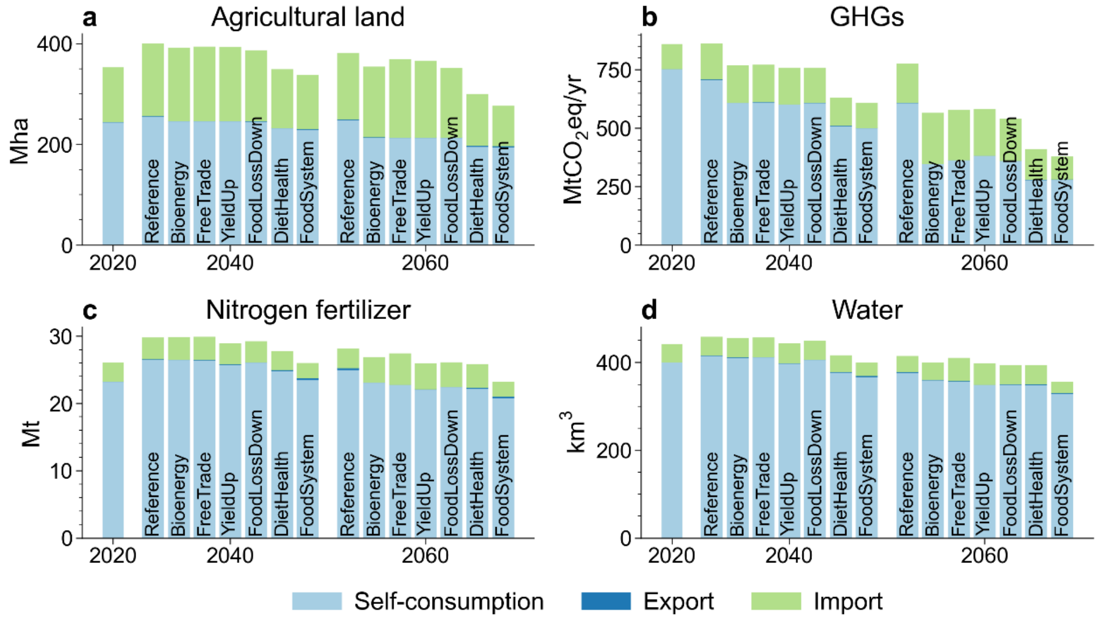
Suppl. Fig. 6: Projections of production (top), consumption (middle) and net import (bottom) of agricultural products for 7 scenarios in China. The agricultural products can be further decomposed into dairy products (DRY), ruminant meat (RUM), pig and poultry products (NRM), cereals (CER), oil crops (OSD), and other crops (OCR).



Suppl. Fig. 7: Projections of food calorie consumption (intake) of agricultural products for 7 scenarios in China. The agricultural products can be further decomposed into dairy products (DRY), ruminant meat (RUM), pig and poultry products (NRM), cereals (CER), oil crops (OSD), and other crops (OCR).



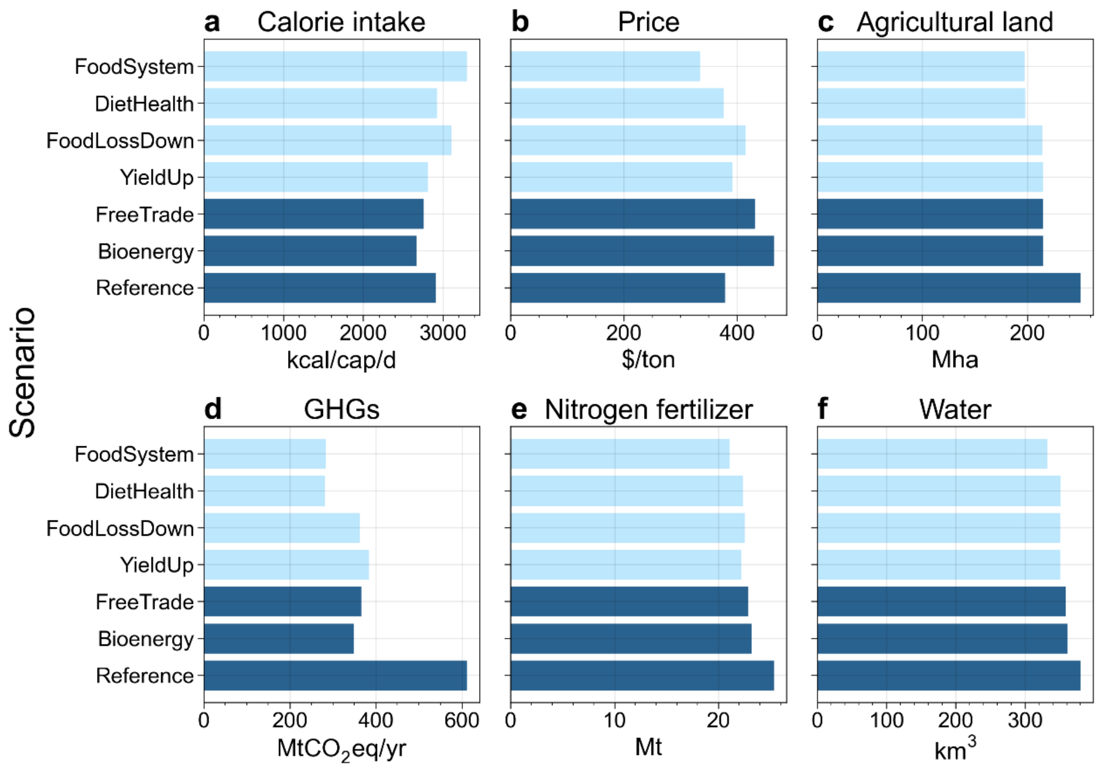
Suppl. Fig. 8: Projections for land use change in China under different scenarios. The GLOBIOM model assumes the area of other lands (131 Mha) and other agricultural lands (26 Mha) remain unchanged during the research period, which is not shown in the figure. OthNatVeg means other natural lands; Other agricultural land means agricultural land whose products are not explicitly modeled in GLOBIOM, for example, land for growing vegetables; Other land means the not directly relevant land including wetland, water bodies, snow, and ice, etc.



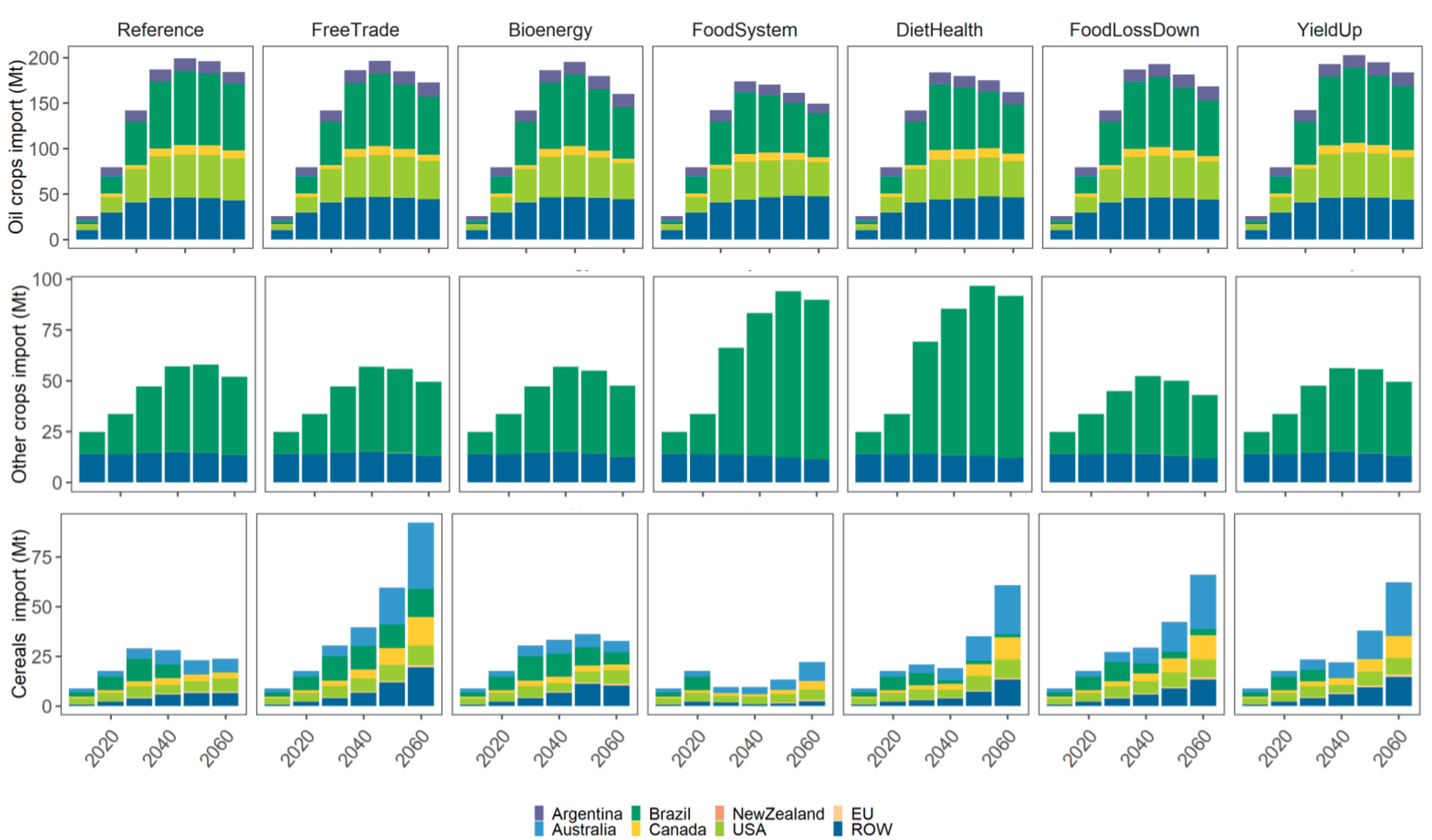
Suppl. Fig. 9: Projections of environmental impacts distributions, including domestic self-consumption impacts and impacts due to export and import.

Suppl. Fig. 10: Projections of China's domestic environmental impacts of agricultural product production under 7 scenarios. Irrigation water use of crop production (top) and agricultural land area of grazing and crop production (bottom). The agricultural products can be further decomposed into dairy products (DRY), ruminant meat (RUM), cereals (CER), oil crops (OSD), and other crops (OCR).

Suppl. Fig. 11: Projections of China's domestic environmental impacts of agricultural product production under 7 scenarios. Nitrogen use of crop production (top) and GHG emissions (bottom). The agricultural products can be further decomposed into dairy products (DRY), ruminant meat (RUM), pig and poultry products (NRM), cereals (CER), oil crops (OSD), and other crops (OCR). GHG emissions from land use change are presented as LUC. Plantation represents bioenergy crops.

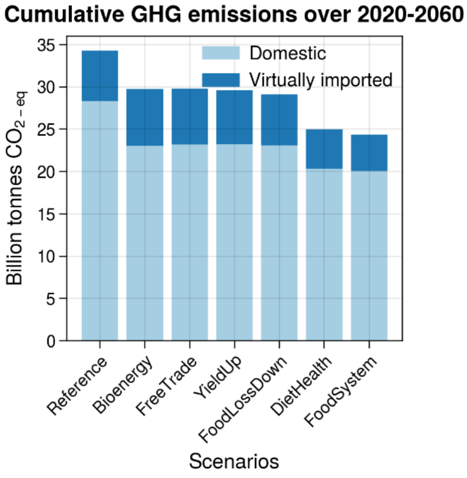


Suppl. Fig. 12: Projections of indicators related to food security and environmental impacts for China in 2060. a, Calorie intake. b, Agricultural commodity price. c, Agricultural land. d, GHG emissions. e, Nitrogen fertilizer. f, Irrigation water.

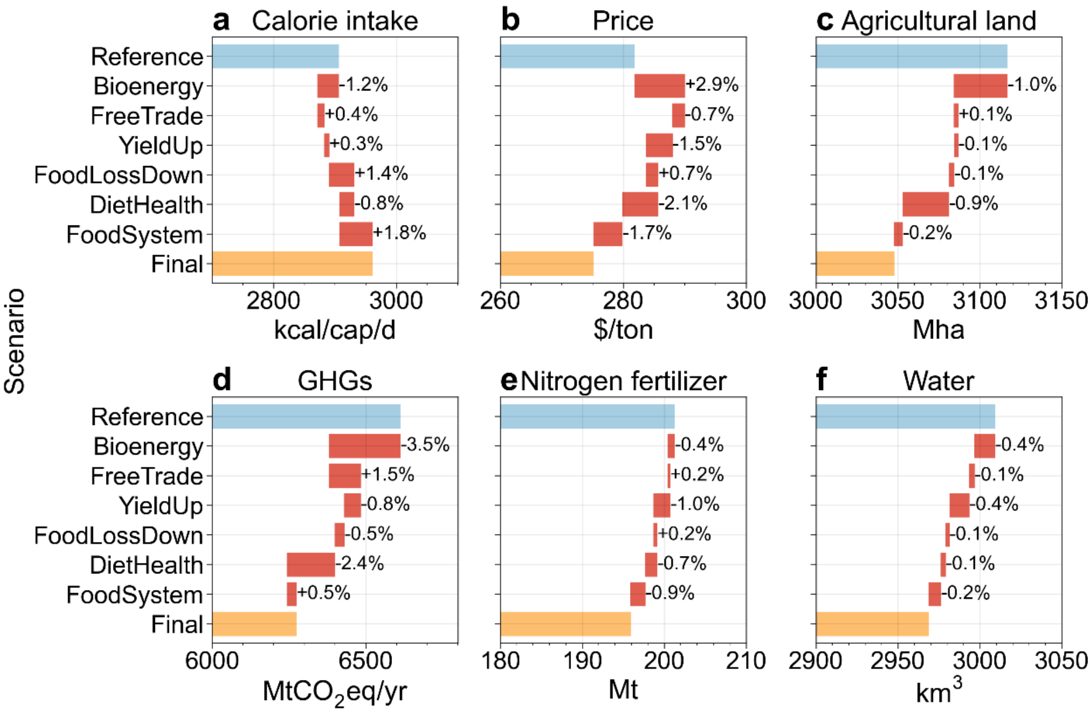


Suppl. Fig. 13: Projections of China's food import from its major trading partners under 7 scenarios. Oil crops (top), other crops (middle), and cereals (bottom). ROW are regions except for China and its seven trading partners.

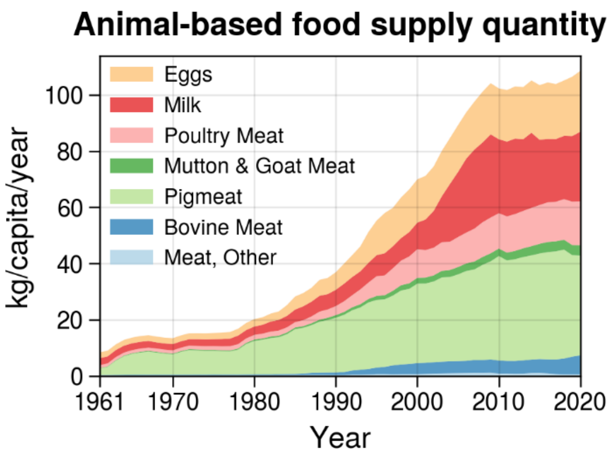
Suppl. Fig. 14: Projections of China's food import from its major trading partners under 7 scenarios. Ruminant meat (top), dairy products (middle) and pig and poultry products (bottom). ROW are regions except for China and its seven trading partners.



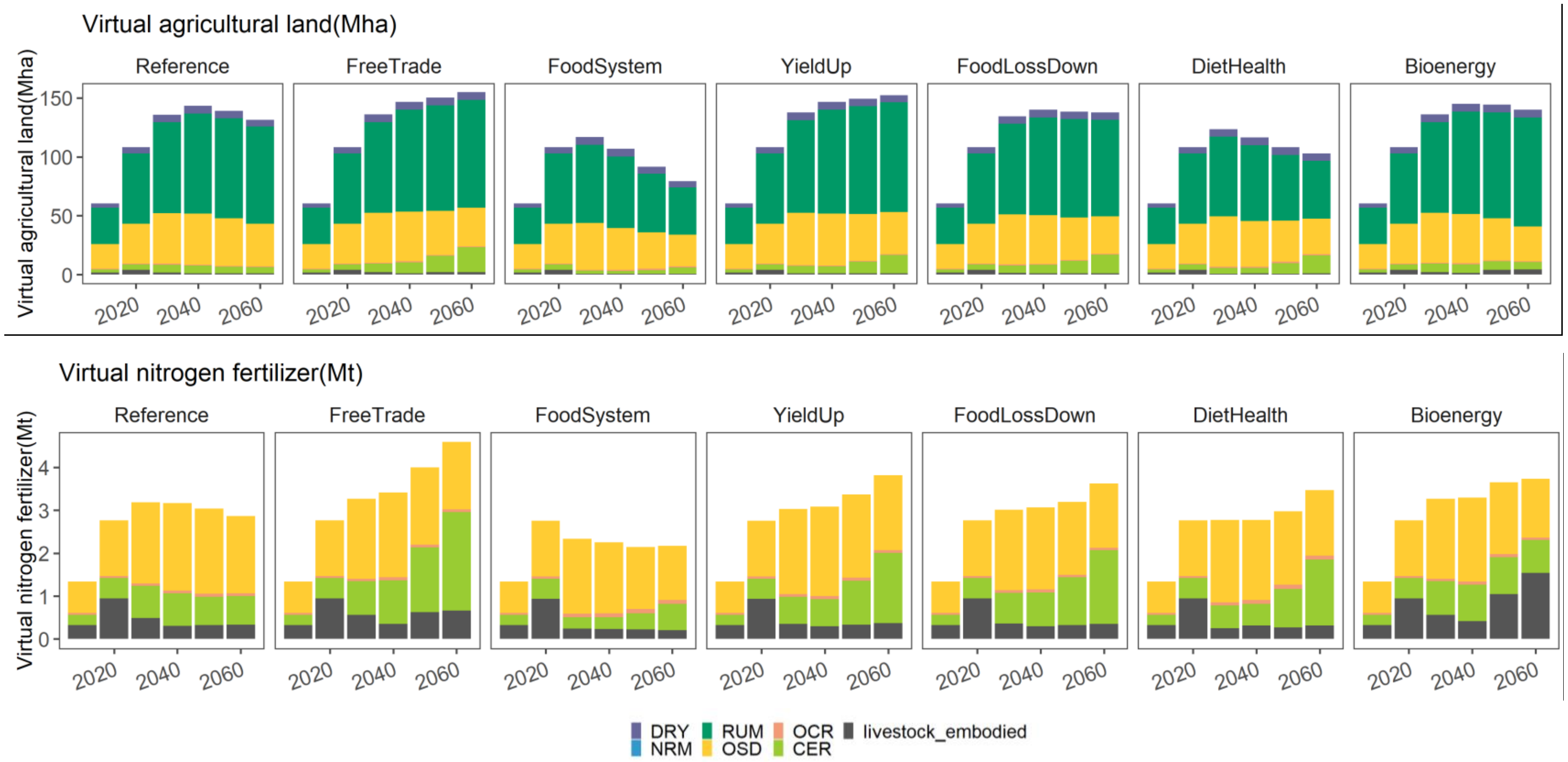
Suppl. Fig. 15: Projections of cumulative China domestic GHG emissions and the cumulative virtually imported GHGs emissions from the AFOLU (agriculture, forestry and other land use) sector over 2020-2060.

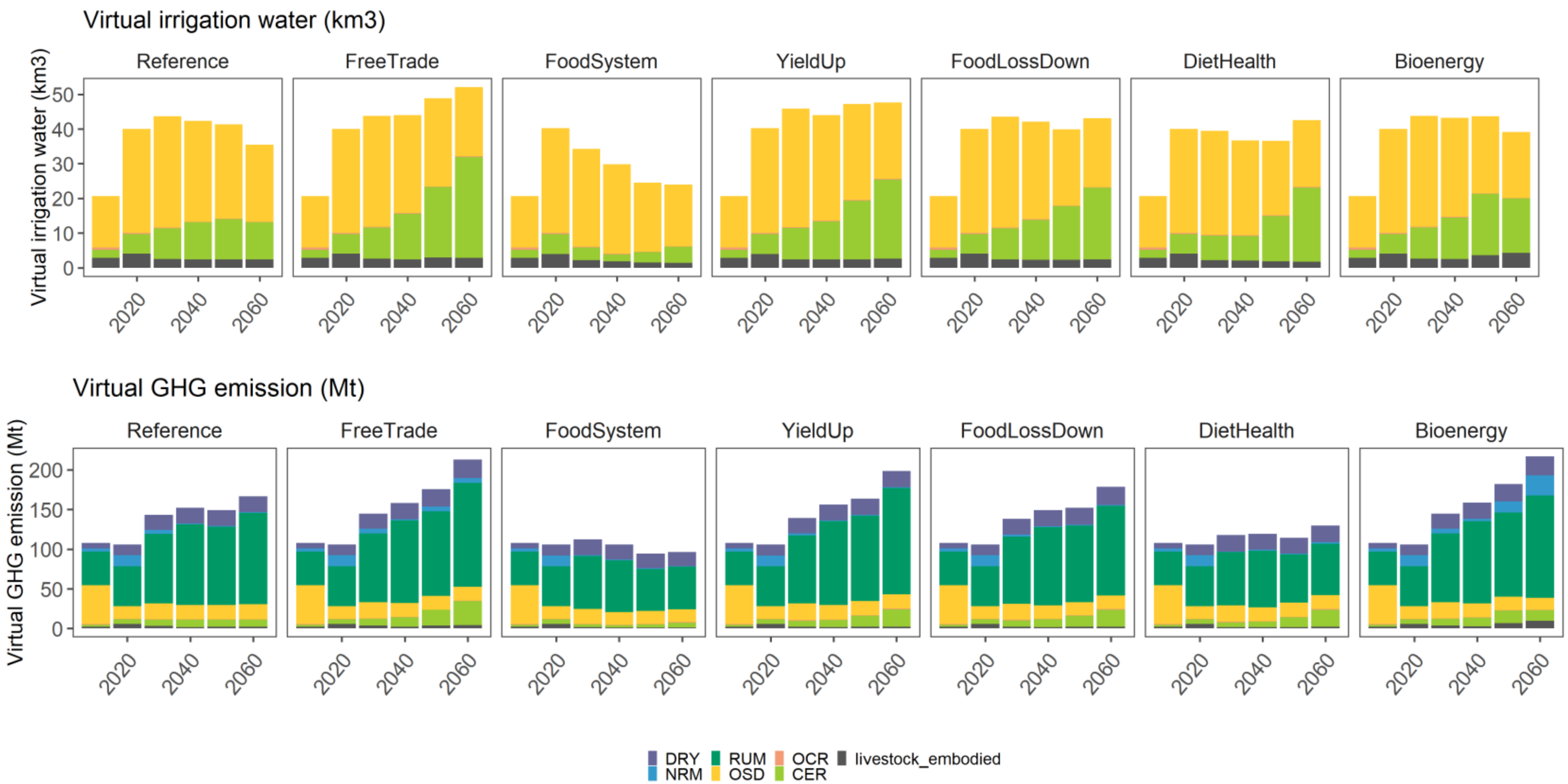


Suppl. Fig. 16: Global food security and environmental impacts. a, Calorie intake. b, Agricultural commodity price. c, Agricultural land. d. GHG emissions. e, Nitrogen fertilizer. f, Irrigation water. The lengths of the red suspended bars indicate the absolute marginal change in each scenario compared with the scenario to its above; the number beside each red bar is obtained by dividing the abovementioned absolute change by the corresponding values in the Reference scenario. The sum of all the numbers beside the red bars gives the change in the FoodSystem scenario relative to the Reference scenario in 2060, and the length of the final bar is the value for the FoodSystemc scenario. Please note that YieldUp, DietHealth, and FoodLossDown are individual scenarios; the three compensatory measures implemented in the YieldUp, DietHealth and FoodLossDown scenarios are simultaneously implemented in the FoodSystem scenario.

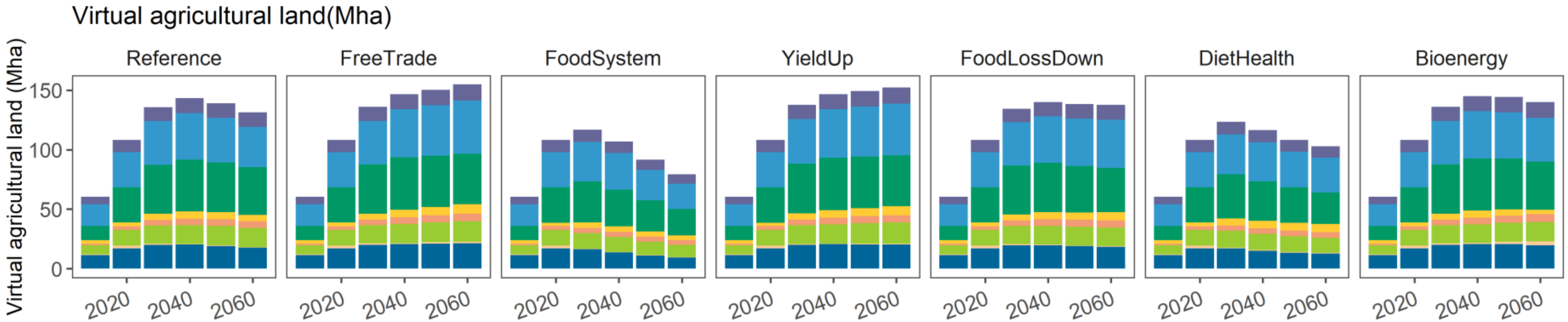


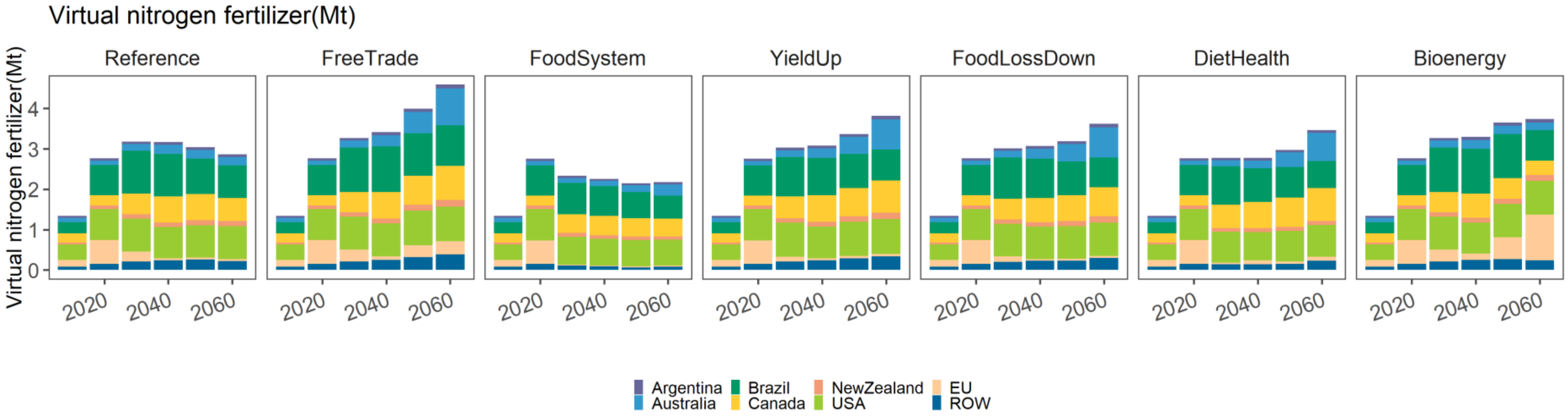
Suppl. Fig. 17: Animal-based food supply in China from 1961–2019. The data is taken from the Food and Agriculture Organization (FAO) (https://www.fao.org/faostat/en/#data).


Virtual agricultural land(Mha)
Reference
FreeTrade
FoodSystem
YieldUp
FoodLossDown
DietHealth
Bioenergy
Virtual agricultural land(Mha)
150
100
50
0
2020
2040
2060
Virtual nitrogen fertilizer(Mt)
Reference
FreeTrade
FoodSystem
YieldUp
FoodLossDown
DietHealth
Bioenergy
Virtual nitrogen fertilizer(Mt)
4
3
2
1
0
2020
2040
2060
DRY
NRM
RUM
OSD
OCR
CER
livestock_embodied

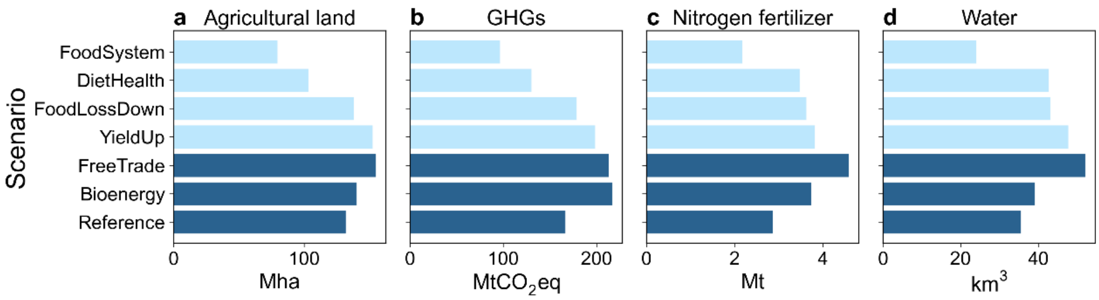


Suppl. Fig. 18: Virtually imported environmental impacts due to the agricultural products import of China under different scenarios. Agricultural land area (crop harvested area and pasture), nitrogen use, irrigation water use and GHG emissions. The agricultural products can be further decomposed into dairy products (DRY), ruminant meat (RUM), pig and poultry products (NRM), cereals (CER), oil crops (OSD), and other crops (OCR). Environmental impacts from feed crop production for livestock products are also included and presented as livestock_embodied.

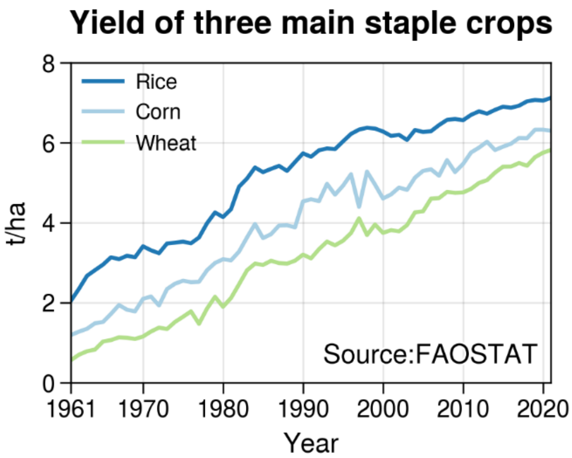

Virtual agricultural land(Mha)
Reference
FreeTrade
FoodSystem
YieldUp
FoodLossDown
DietHealth
Bioenergy
Virtual agricultural land (Mha)
0
50
100
150
2020
2040
2060


Virtual nitrogen fertilizer(Mt)
Reference
FreeTrade
FoodSystem
YieldUp
FoodLossDown
DietHealth
Bioenergy
Virtual nitrogen fertilizer(Mt)
0
1
2
3
4
2020
2040
2060
Argentina
Australia
Brazil
Canada
NewZealand
USA
EU
ROW

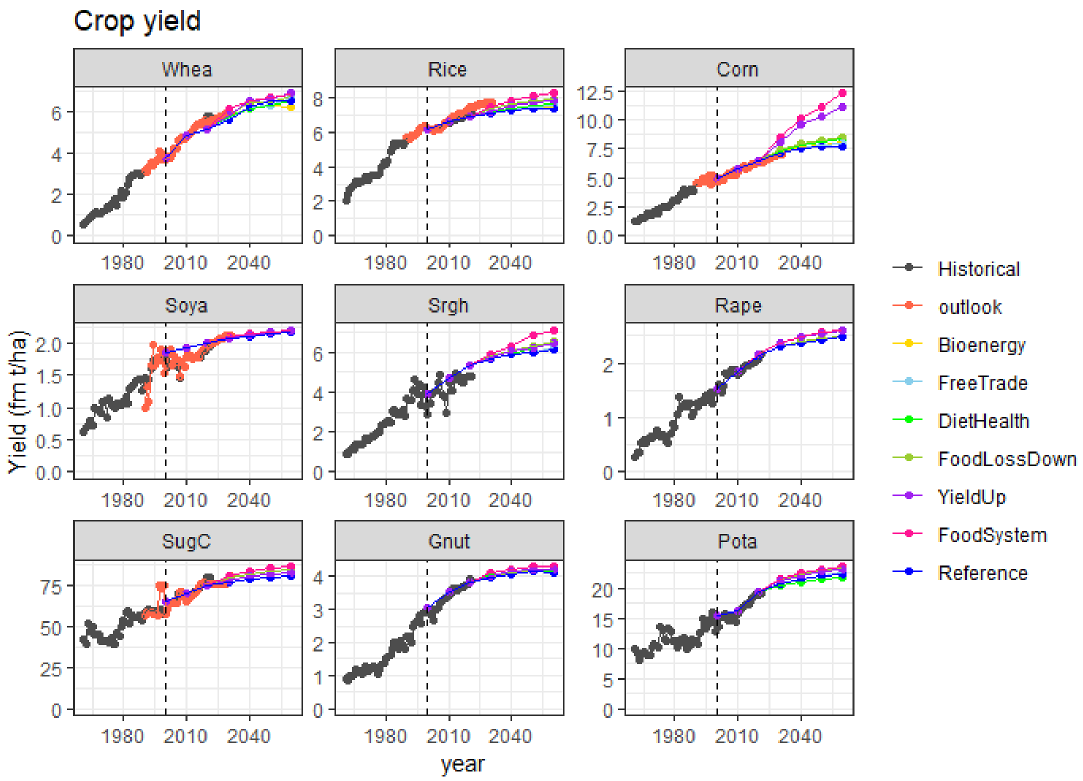
Suppl. Fig. 19: Virtually imported environmental impacts due to the agricultural products import of China under different scenarios. Agricultural land area (crop harvested area and pasture), nitrogen use, irrigation water use and GHG emissions. ROW are regions except for China and its seven trading partners.



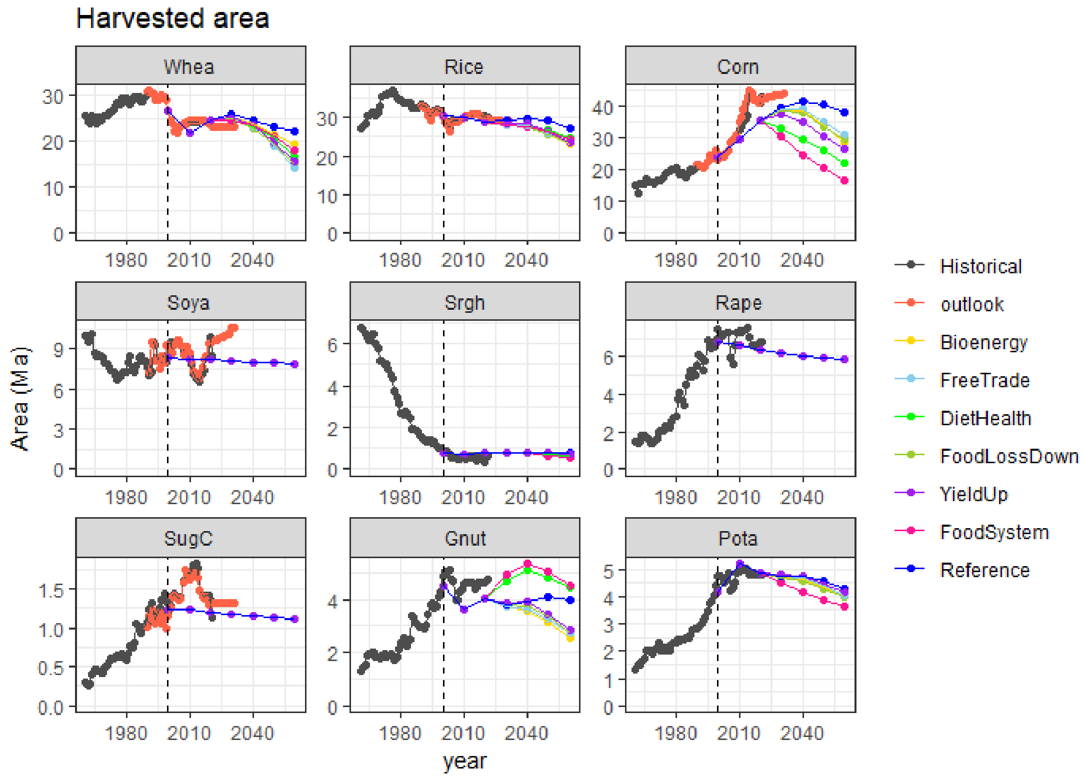
Suppl. Fig. 20: Projections of virtually imported environmental impacts of China from China's trade partners in 2060. a, Agricultural land. b, GHG emissions. c, Nitrogen fertilizer. d, Irrigation water.



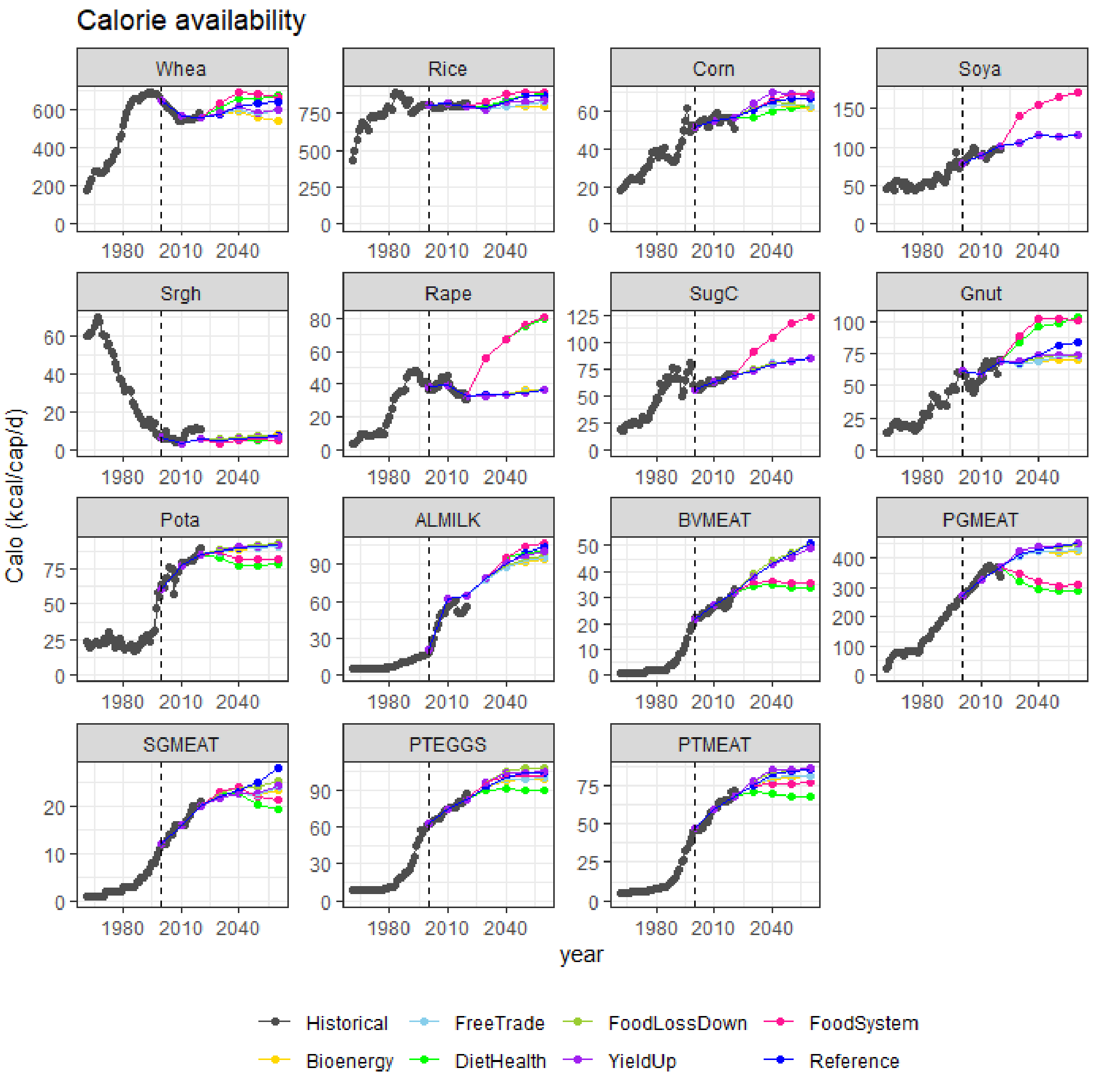
Suppl. Fig. 21: Yield of wheat, rice and corn for the past 60 years in China. The data is taken from the FAOSTAT (https://www.fao.org/faostat/en/#data).



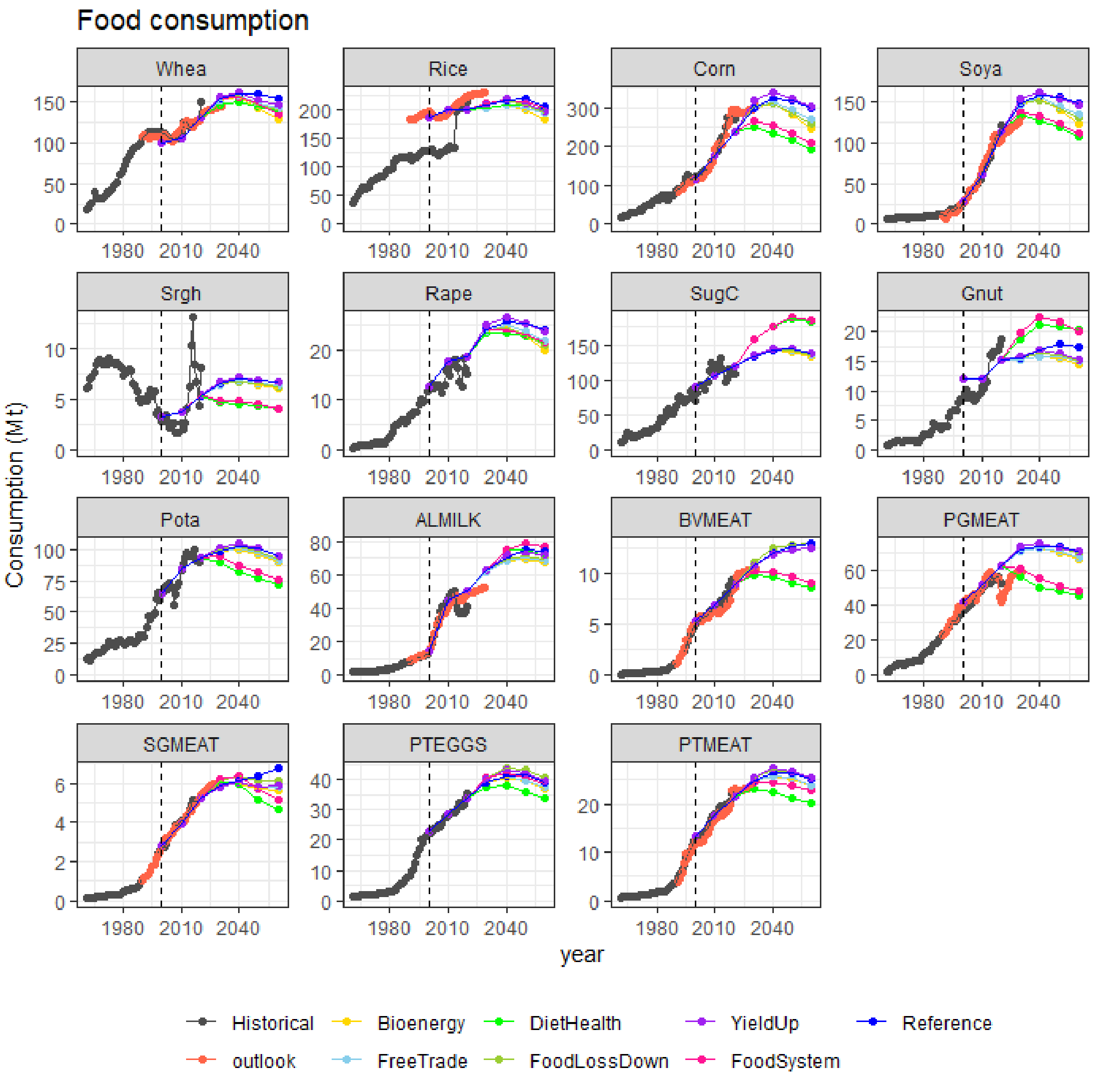
Suppl. Fig. 22: Yields of major crops in China. Historical data for 1961-2021 is from FAOSTAT, and outlook data for 1990-2031 is from OECD Outlook. The values for seven scenarios are from GLOBIOM-China. The major crops are wheat (Whea), rice, corn, soybean (Soya), sorghum (Srgh), rapeseed (Rape), sugarcane (SugC), groundnut (Gnut), and potato (Pota).



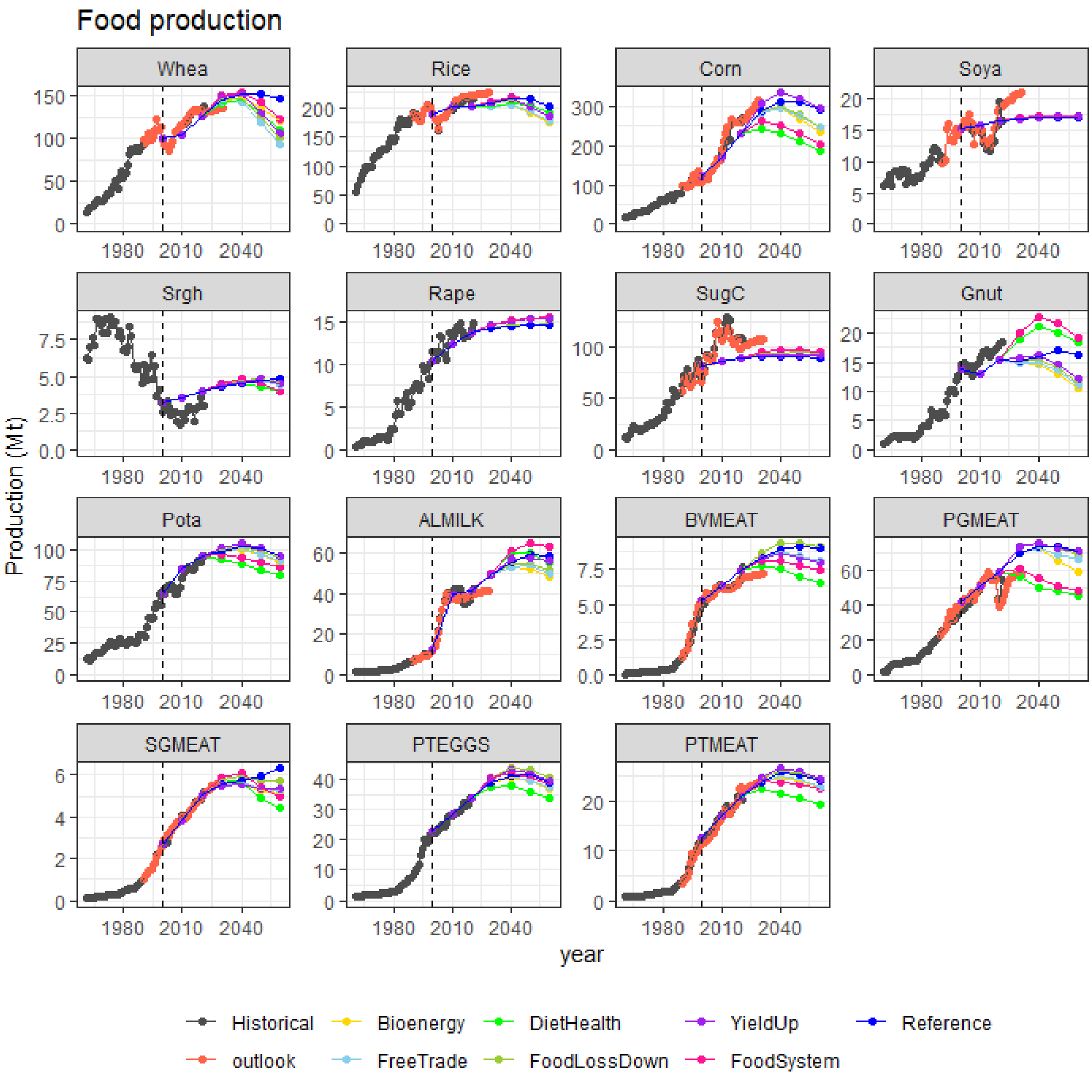
Suppl. Fig. 23: Harvested area for major crops in China. Historical data for 1961-2021 is from FAOSTAT, and outlook data for 1990-2031 is from OECD Outlook. The values for seven scenarios are from GLOBIOM-China. The major crops are wheat (Whea), rice, corn, soybean (Soya), sorghum (Srgh), rapeseed (Rape), sugarcane (SugC), groundnut (Gnut), and potato (Pota).



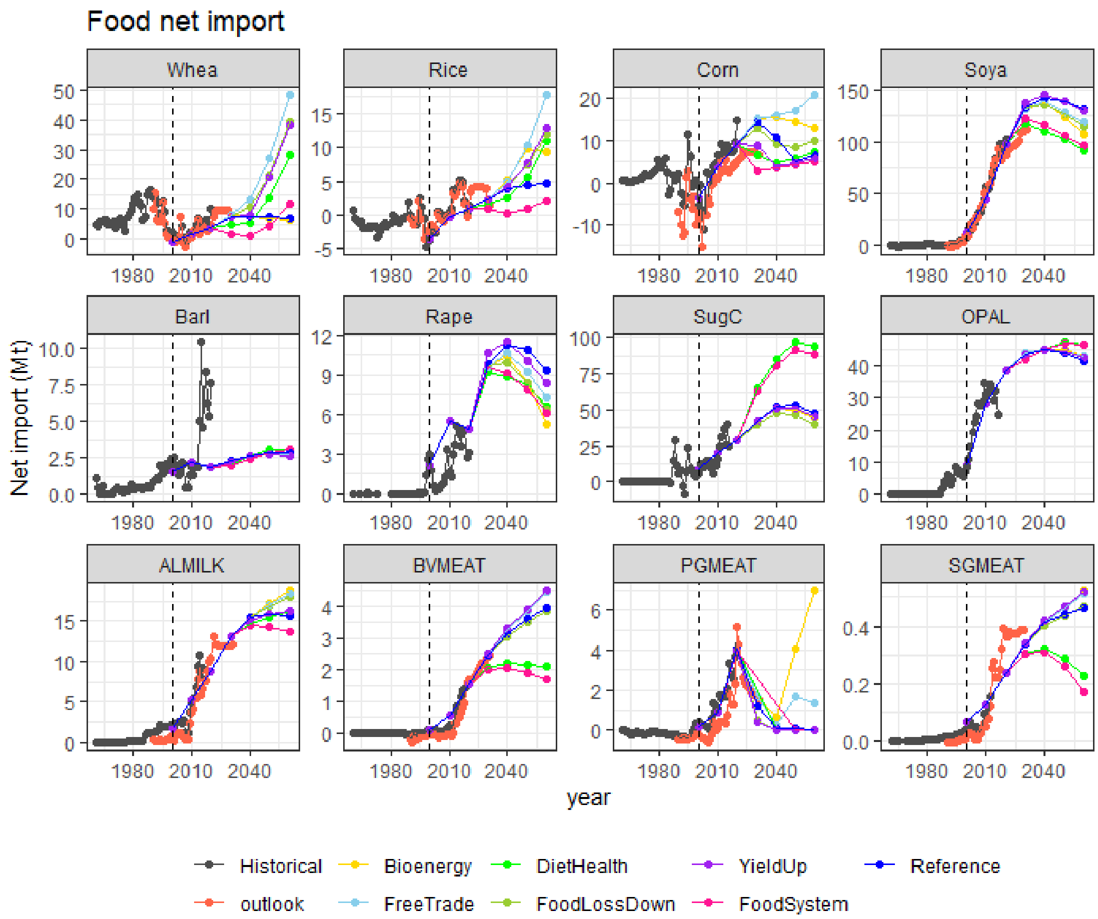
Suppl. Fig. 24: Calorie availability in China. Historical data for 1961-2020 is from FAOSTAT. The values for seven scenarios are from GLOBIOM-China. Calories from wheat (Whea), rice, corn, soybean (Soya), sorghum (Srgh), rapeseed (Rape), sugarcane (SugC), groundnut (Gnut), potato (Pota), dairy products (ALMILK), bovine meat (BVMEAT), pig meat (PGMEAT), sheep and goat meat (SGMEAT), poultry eggs (PTEGGS), and poultry meat (PTMEAT) are presented.



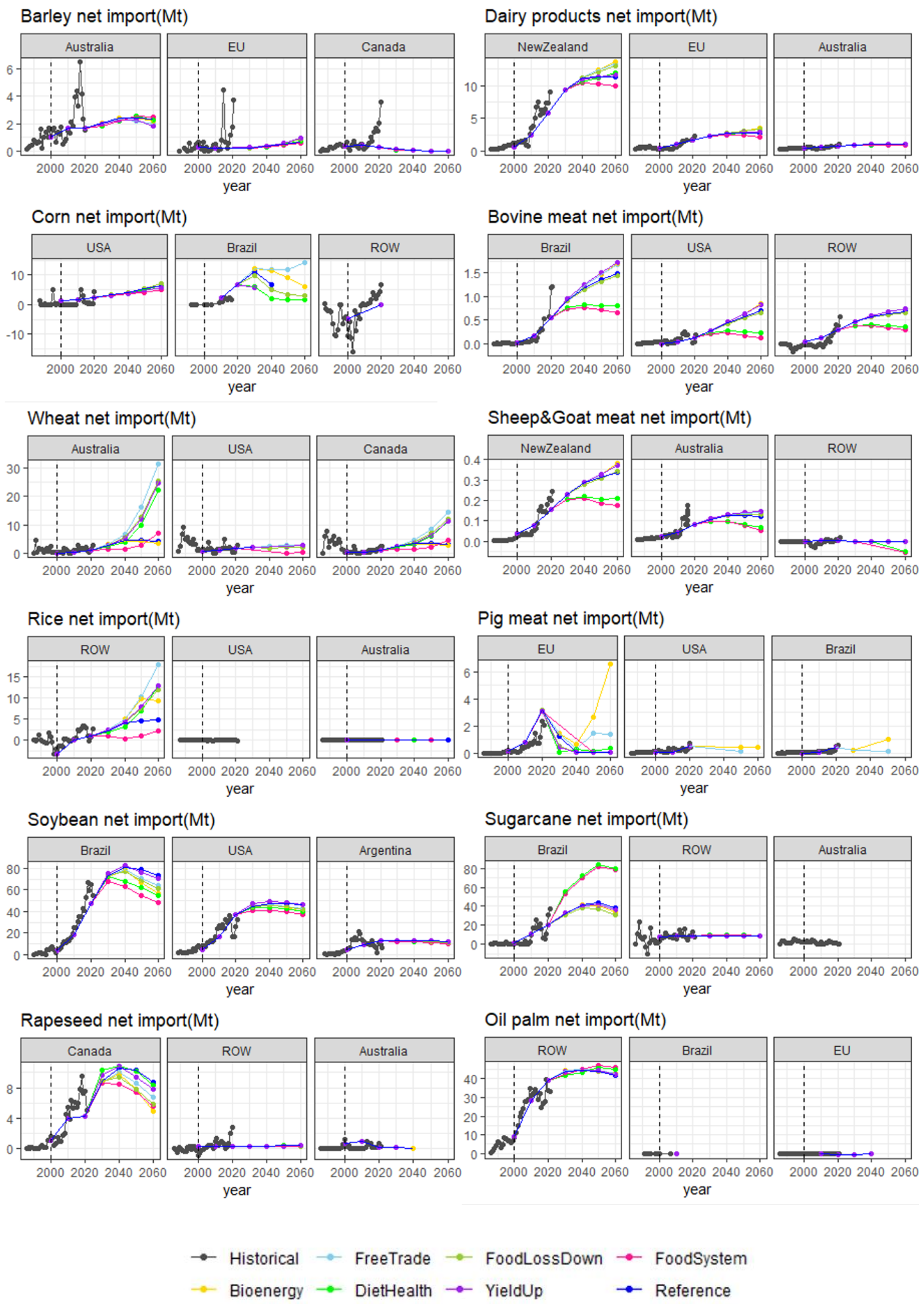
Suppl. Fig. 25: Food consumption for major products in China. Historical data for 1961-2020 is from FAOSTAT, and outlook data for 1990-2031 is from OECD Outlook. The values for seven scenarios are from GLOBIOM-China. Major products are wheat (Whea), rice, corn, soybean (Soya), sorghum (Srgh), rapeseed (Rape), sugarcane (SugC), groundnut (Gnut), potato (Pota), dairy products (ALMILK), bovine meat (BVMEAT), pig meat (PGMEAT), sheep and goat meat (SGMEAT), poultry eggs (PTEGGS), and poultry meat (PTMEAT).



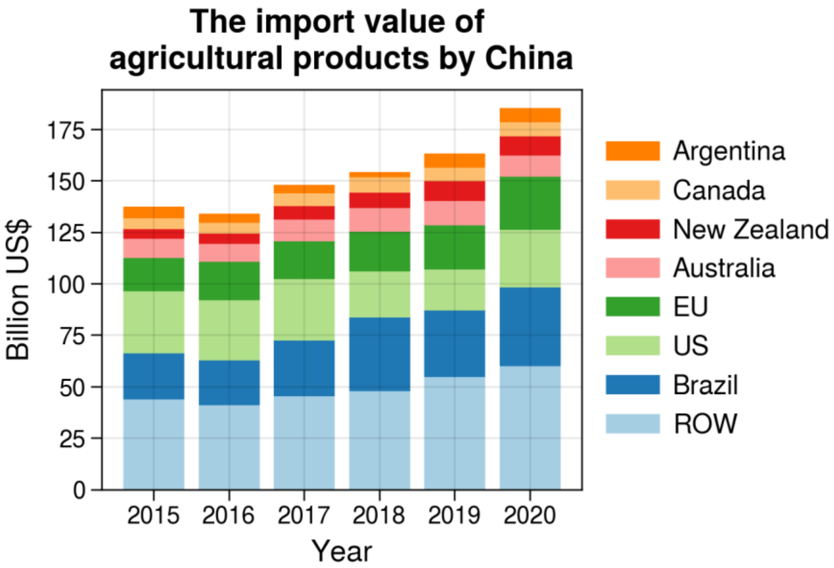
Suppl. Fig. 26: Food production for major products in China. Historical data for 1961-2021 is from FAOSTAT, and outlook data for 1990-2031 is from OECD Outlook. The values for seven scenarios are from GLOBIOM-China. Major products are wheat (Whea), rice, corn, soybean (Soya), sorghum (Srgh), rapeseed (Rape), sugarcane (SugC), groundnut (Gnut), potato (Pota), dairy products (ALMILK), bovine meat (BVMEAT), pig meat (PGMEAT), sheep and goat meat (SGMEAT), poultry eggs (PTEGGS), and poultry meat (PTMEAT).



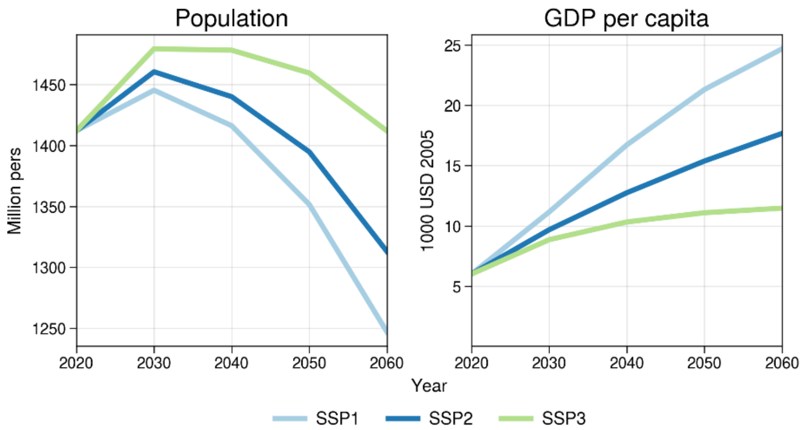
Suppl. Fig. 27: Food net import for major products in China. Historical data for 1961-2020 are from FAOSTAT, and outlook data for 1990-2031 is from OECD Outlook. The values for seven scenarios are from GLOBIOM-China. Major products are wheat (Whea), rice, corn, soybean (Soya), barley (Barl), rapeseed (Rape), sugarcane (SugC), oil palm (OPAL), dairy products (ALMILK), bovine meat (BVMEAT), pig meat (PGMEAT), sheep and goat meat (SGMEAT).



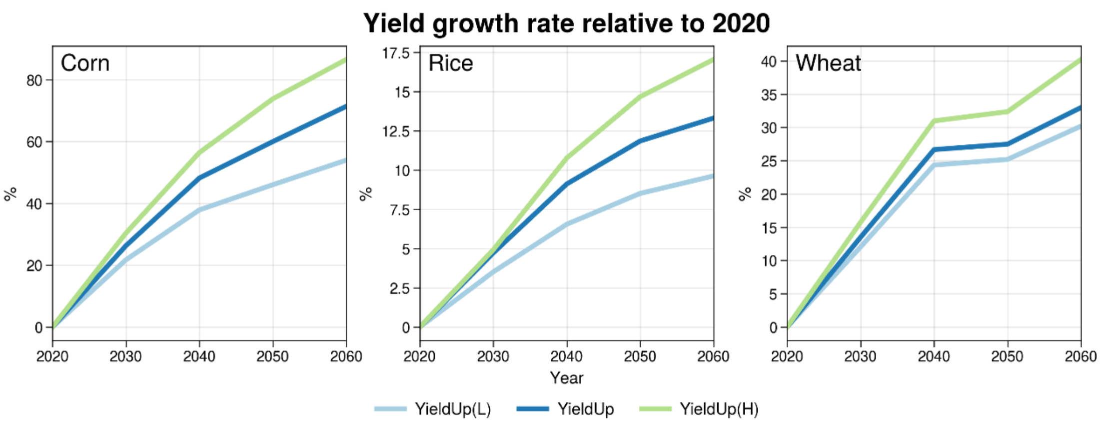
Suppl. Fig. 28: Trade flows for major agricultural products between China and its major trade partners. The top three exporting regions are listed for each agricultural product. Historical data for the period 1990-2021 is from the FAOSTAT trade matrix (http://www.fao.org/faostat/en/#data/TM). The values by GLOBIOM-China are the projections under seven scenarios. ROW are regions except for China and its seven trading partners.



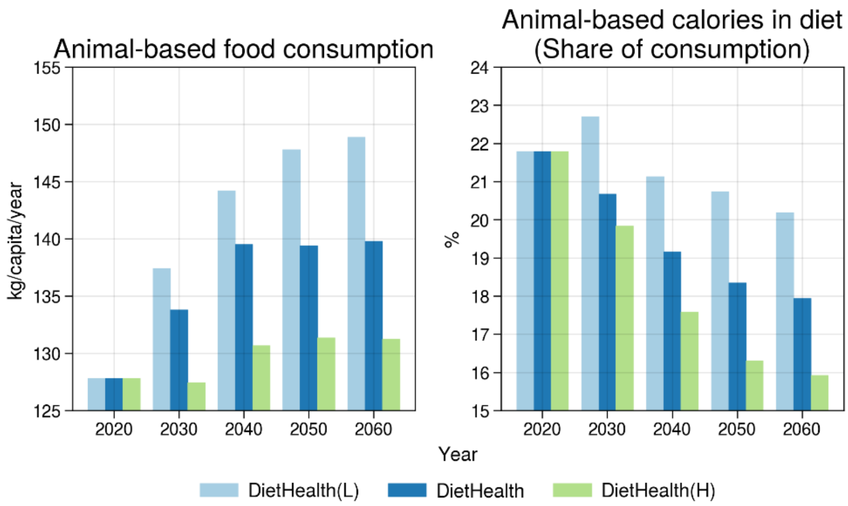
Suppl. Fig. 29: The import value of agricultural products by China from its major trading partners from 2015 to 2020. ROW are regions except for China and its seven main trading partners. Data is derived from FAOSTAT (https://www.fao.org/faostat/en/#data)



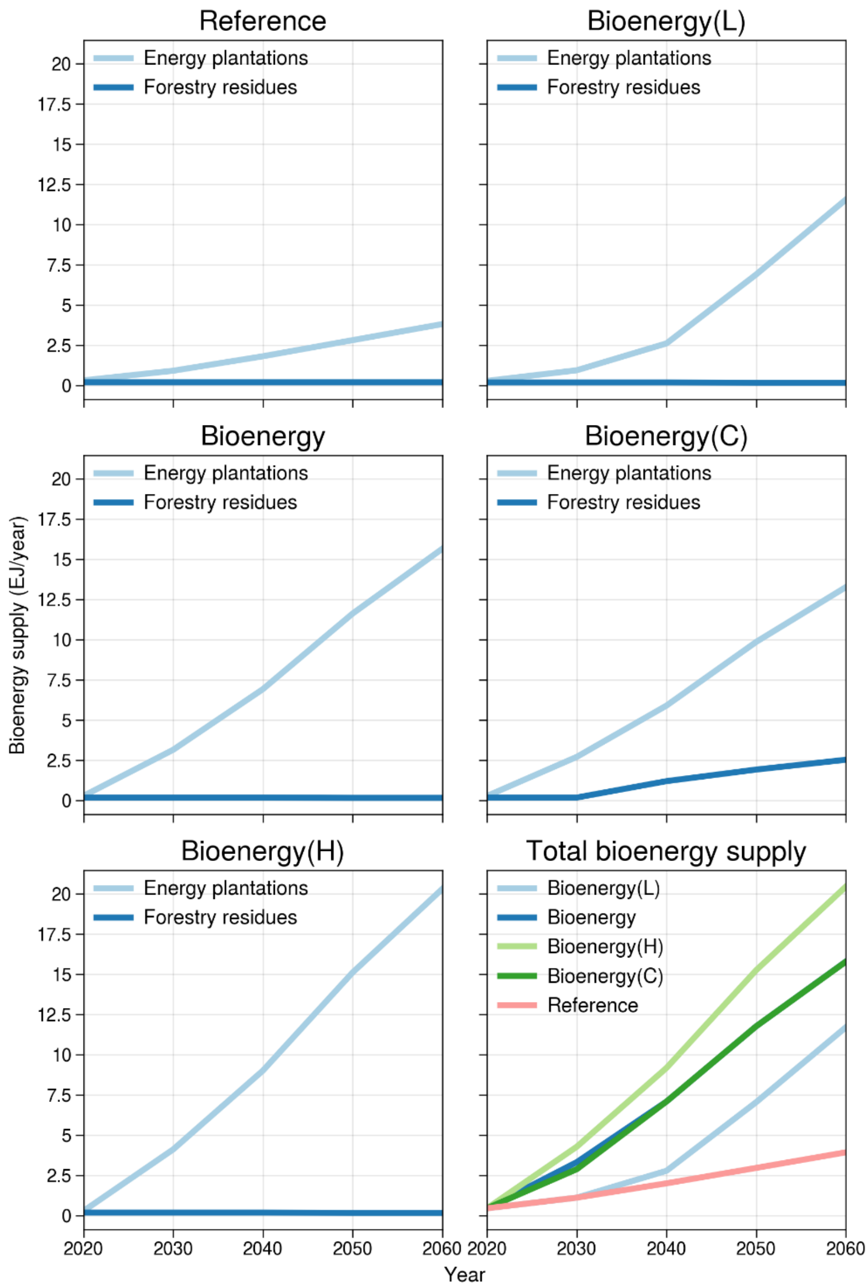
Suppl. Fig. 30: Population and GDP per capita for SSP1-SSP3 in China.



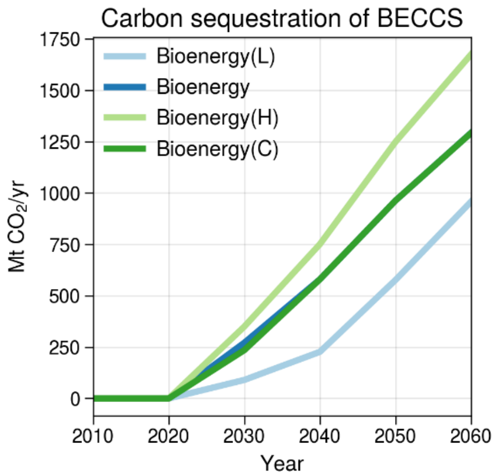
Suppl. Fig. 31: Crop yield growth rate relative to 2020 in China.



Suppl. Fig. 32: Animal-based food consumption and its calories in the diet.



Suppl. Fig. 33: Bioenergy supply in Reference and Bioenergy scenarios and sensitivity analysis assumptions. The bioenergy demand under the six policy scenarios (Bioenergy, FreeTrade, YieldUp, DietHealth, FoodLossDown, and FoodSystem) are the same. The data is taken from the GLOBIOM-MESSAGE framework [54, 55].



Suppl. Fig. 34: Projections of the carbon sequestration of BECCS.

Supplementary References

1. Havlik, P., et al., Global land-use implications of first and second generation biofuel targets. Energy Policy, 2011. **39**(10): p. 5690-5702.
2. Havlik, P., et al., Climate change mitigation through livestock system transitions. Proceedings of the National Academy of Sciences of the United States of America, 2014. **111**(10): p. 3709-3714.
3. T. Takayama, H.H., N.D. Uri, Spatial and temporal price and allocation modeling: Some extensions. Socio-Economic Planning Sciences, 1984. **18**(4): p. 227-234.
4. Janssens, C., et al., Global hunger and climate change adaptation through international trade. Nature Climate Change, 2020. **10**(9): p. 829-835.
5. Food and Agriculture Organization of the United Nations, FAOSTAT: Food and Agriculture Data (FAO, 2023). Available from: http://www.fao.org/faostat/en/.
6. Bartholome, E. and A.S. Belward, GLC2000: a new approach to global land cover mapping from Earth observation data. International Journal of Remote Sensing, 2005. **26**(9): p. 1959-1977.
7. Williams, J.R., et al., The epic crop growth-model. Transactions of the Asae, 1989. **32**(2): p. 497-511.
8. Balkovic, J., et al., Global wheat production potentials and management flexibility under the representative concentration pathways. Global and Planetary Change, 2014. **122**: p. 107-121.
9. Food and Agriculture Organization of the United Nations (FAO). AQUASTAT.; Available from: https://www.fao.org/aquastat/statistics/query/index.html;jsessionid=3809C97E5A093982059F3B272F7C68A0.
10. Liu, J., et al., Water conservancy projects in China: Achievements, challenges and way forward. Global Environmental Change-Human and Policy Dimensions, 2013. **23**(3): p. 633-643.
11. Kindermann, G.E., et al., A global forest growing stock, biomass and carbon map based on FAO statistics. Silva Fennica, 2008. **42**(3): p. 387-396.
12. Parton, W., et al., Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. Global Biogeochemical Cycles, 1993. **7**(4): p. 785-809.

13. Herrero, M., et al., Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proceedings of the National Academy of Sciences of the United States of America, 2013. **110**(52): p. 20888-20893.
14. Cramer, W., et al., Comparing global models of terrestrial net primary productivity (NPP): overview and key results. Global Change Biology, 1999. **5**: p. 1-15.
15. Zhao, H., et al., China's future food demand and its implications for trade and environment. Nature Sustainability, 2021. **4**(12): p. 1042-1051.
16. Ministry of Agriculture and Rural Affairs of the People's Republic of China.2015.Implementing Plan to Promote the Action to Achieve Zero Growth of Chemical Fertilizer Use by 2020.; Available from: http://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923401.htm.
17. Central People's Government of the People's Republic of China. Outline of National Mid-Long-Term Plan for Food Security (2008–2020). Available from: http://www.gov.cn/jrzg/2008-11/13/content_1148414.htm.
18. National Bureau of Statistics. China Statistical Yearbook 2022. (China Statistical Press, 2022).
19. Fujimori, S., et al., A framework for national scenarios with varying emission reductions. Nature Climate Change, 2021. **11**(6): p. 472-480.
20. Chen, Y.D., et al., Provincial and gridded population projection for China under shared socioeconomic pathways from 2010 to 2100. Scientific Data, 2020. **7**(1).
21. Chen, D., et al., A meta-analysis of food demand elasticities for China. Applied Economic Perspectives and Policy, 2016. **38**(1): p. 50-72.
22. Bai, Z.H., et al., China's livestock transition: Driving forces, impacts, and consequences. Science Advances, 2018. **4**(7).
23. Food and Agriculture Organization of the United Nations. FAOSTAT: Food and agriculture data. 2022; Available from: https://www.fao.org/faostat/en/#home.
24. Cui, Z., et al., Pursuing sustainable productivity with millions of smallholder farmers. Nature, 2018. **555**(7696): p. 363-366.
25. Chen, X.P., et al., Producing more grain with lower environmental costs. Nature, 2014. **514**(7523): p. 486-489.
26. Ministry of Agriculture and Rural Affairs of the People's Republic of China. National adjustment of the planting structure plan (2016-2020). 2016; Available from: http://www.moa.gov.cn/govpublic/ZZYGLS/201604/t20160428_5110638.htm.
27. The Central People's Government of the People's Republic of China. Outline of Medium- and Long-Term Plan for National Food Security (2008-2020). 2008; Available from: http://www.gov.cn/jrzg/2008-11/13/content_1148414.htm.
28. National animal husbandry station. Chinese pasture statistics 2015. (China Agriculture Press, 2019).
29. Chinese Nutrition Society. Chinese Dietary Guidelines 2022. http://dg.cnsoc.org/newslist_0402_1.htm.
30. Ministry of Agriculture and Rural Affairs of the People's Republic of China. Policy from MOA 2010 “Accelerating the Standardization of Livestock and Poultry Intensification”.http://www.moa.gov.cn/nybgb/2010/dsiq/201805/t20180530_6148351.htm.
31. OECD/FAO (2022), OECD-FAO Agricultural Outlook 2022-2031, OECD Publishing, Paris, https://doi.org/10.1787/f1b0b29c-en.
32. Ministry of Agriculture and Rural Affairs of the People's Republic of China. The National

Adjustment Plan of Crop Farming Structure (2016-2020). Available from: http://www.moa.gov.cn/govpublic/ZZYGLS/201604/t20160428_5110638.htm.

33. Lotze-Campen, H., et al., Impacts of increased bioenergy demand on global food markets: an AgMIP economic model intercomparison. Agricultural Economics, 2014. **45**(1): p. 103-116.

34. Xing, J., Song, J., Liu, C. et al. Integrated crop–livestock–bioenergy system brings co-benefits and trade-offs in mitigating the environmental impacts of Chinese agriculture. Nat Food 3, 1052–1064 (2022). .

35. Xing, X.F., et al., Spatially explicit analysis identifies significant potential for bioenergy with carbon capture and storage in China. Nature Communications, 2021. **12**(1).

36. Yang, Q., Zhou, H., Bartocci, P. et al. Prospective contributions of biomass pyrolysis to China's 2050 carbon reduction and renewable energy goals. Nat Commun 12, 1698 (2021). .

37. Duan, H.B., et al., Assessing China's efforts to pursue the 1.5 degrees C warming limit. Science, 2021. **372**(6540): p. 378-385.

38. Lauri, P., et al., Woody biomass energy potential in 2050. Energy Policy, 2014. **66**: p. 19-31.

39. Li, W., et al., Mapping the yields of lignocellulosic bioenergy crops from observations at the global scale. Earth System Science Data, 2020. **12**(1): p. 789-804.

40. Lauri, P., et al., Impact of the 2 degrees C target on global woody biomass use. Forest Policy and Economics, 2017. **83**: p. 121-130.

41. Kindermann, G., et al., Global cost estimates of reducing carbon emissions through avoided deforestation. Proceedings of the National Academy of Sciences of the United States of America, 2008. **105**(30): p. 10302-10307.

42. Anderson, K. and G. Peters, The trouble with negative emissions. Science, 2016. **354**(6309): p. 182-183.

43. Lu, X., et al., Gasification of coal and biomass as a net carbon-negative power source for environment-friendly electricity generation in China. Proceedings of the National Academy of Sciences of the United States of America, 2019. **116**(17): p. 8206-8213.

44. Kumar, A., J.B. Cameron, and P.C. Flynn, Biomass power cost and optimum plant size in western Canada. Biomass & Bioenergy, 2003. **24**(6): p. 445-464.

45. Semba, R.D., et al., Adoption of the 'planetary health diet' has different impacts on countries' greenhouse gas emissions. Nature Food, 2020. **1**(8): p. 481-484.

46. Popp, A., et al., Land-use futures in the shared socio-economic pathways. Global Environmental Change, 2017. **42**: p. 331-345.

47. Jessica, B., et al., Translating MyPlate into Food Selections that Meet Dietary Guidelines Recommendations. Journal of Human Sciences and Extension, 2016. **4**(3).

48. Wall, C.L., et al., Dietary intake in midlife and associations with standard of living, education and nutrition literacy. New Zealand Medical Journal, 2014. **127**(1397): p. 30-40.

49. Kennedy E, Davis CA. Dietary guidelines 2000--the opportunity and challenges for reaching the consumer. J Am Diet Assoc. 2000 Dec;100(12):1462-5.

50. Bai Z, Lee MRF, Ma L, et al., Global environmental costs of China's thirst for milk. Glob Chang Biol. 2018 May;24(5):2198-2211.

51. Marion Nestle, et al., Behavioral and Social Influences on Food Choice, Nutrition Reviews, Volume 56, Issue 5, May 1998, Pages 50–64.

52. Alexandratos, N. and Bruinsma, J. (2012) 'WORLD AGRICULTURE TOWARDS 2030 / 2050 The 2012 Revision. Global Perspective Studies Team, FAO Agricultural Development

Economics Division. ESA Working Paper No. 12-03’, (12).

53. FAO. 2018. The future of food and agriculture – Alternative pathways to 2050. Rome. 224 pp. Licence: CC BY-NC-SA 3.0 IGO.

54. Frank, S., et al., Reducing greenhouse gas emissions in agriculture without compromising food security? Environmental Research Letters, 2017. **12**(10).

55. Fricko, O., et al., The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change-Human and Policy Dimensions, 2017. **42**: p. 251-267.