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The social welfare value of the global food system

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ABSTRACT

The global food system provides nourishment to most of the world's eight billion people, generates trillions of dollars of goods and services, and employs more than one billion people. On the other hand, it generates substantial dietary health costs and environmental harms. Policymakers are asking about the overall contribution of the global food system to social welfare and how much larger it might be on a sustainable path. This paper describes our efforts to answer these questions. We couple multiple domain-specific models into a large-scale integrated assessment modelling framework capable of quantifying the outcomes of different food-system scenarios for incomes, health and the environment up to 2050, at a highly disaggregated level. We take these multi-dimensional outcomes and value them using a system of nested utility functions, building on recent work in environmental economics. We find that, relative to current trends, the bundle of measures in a Food System Transformation scenario would provide a large boost to global social welfare equivalent to increasing global GDP by about 7 %. Changes in income, environment and health all contribute positively. Measures to change diets are particularly beneficial, although a caveat is that our welfare estimates exclude possible consumer disutility from dietary changes. The results are robust to changes in key utility/damage parameters.

1. Introduction

The global food system provides nourishment to most of the world's population, generates trillions of dollars of goods and services,[1] and employs more than one billion people (Davis et al., 2023). On the other hand, the same system leaves c. 3/4 of a billion people undernourished (Ritchie et al., 2023), generates substantial health costs through over-nutrition and unhealthy diets, and causes a range of environmental harms, including local air and water pollution, greenhouse gas (GHG) emissions, and biodiversity loss (Willett et al., 2019). Few of these negative impacts are captured in economic aggregates such as agricultural output/value added. In food policy, they are often referred to as "hidden costs" (FOLU, 2019).[2]

What then is the overall contribution of the global food system to social welfare and how might it evolve in the future along different development paths? How much greater could the contribution be – how large would the net economic benefits be – if the global food system shifted to a sustainable path? These questions are increasingly being asked by policymakers who in recent years have adopted a food-systems perspective and want to transform food systems in pursuit of the United Nations' 2030 Agenda for Sustainable Development and the Sustainable Development Goals.[3] Policy reports by the EAT-Lancet Commission (Willett et al., 2019) and the Food and Land Use Coalition (FOLU, 2019) have started to explore the capacity of the food system to meet health

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[1] Gross value added from agriculture, forestry and fishing was US$4.3 trillion in 2023 (World Bank, 2024). This is a narrow measure of food systems in that it only focuses on the primary sector, although it includes forestry and agricultural activity outside the food sector. The World Economic Forum estimated in 2020 that the global food, land and ocean use system generated around $10 trillion annually (World Economic Forum, 2020). This is a broad measure but still appears to include activities outside the food sector.

[2] Most hidden costs are negative externalities, but some are internalities, particularly those related to overnutrition.

[3] See in particular the High Level Panel of Experts on Food Security and Nutrition, (HLPE, 2017), and the 2021 United Nations Food System Summit (UNFSS, 2021).

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and inclusion goals without compromising environmental constraints, but so far there has been no attempt to provide estimates of the total economic value of the global food system in different future scenarios, which are comprehensive, integrated, and model-based.

This paper describes our efforts to provide such estimates. The task is somewhat like valuing the net economic benefits of global climate mitigation and estimating optimal global GHG emissions (Nordhaus, 1992; Stern, 2007), but arguably it is harder. Compared to climate, a food-system transformation is more multi-dimensional, including not only climate and real incomes, but also dietary health, local nitrogen pollution, biodiversity, etc. And compared to climate, some of the key environmental impacts of the food system are more local in nature and require spatially explicit modelling.

We tackle this formidable problem in two steps. The first step is to construct a set of linked models that simulate the joint evolution of land use, food supply/demand, dietary health, energy, climate, incomes, and biodiversity worldwide on different scenarios that we defined together with policy stakeholders. The resulting modelling framework is notable for being much broader in scope than most simulation models used to study global environmental change, and for being highly multi-disciplinary. Examples of previous work that has coupled global models across a subset of these domains include Johnson et al. (2023) and Popp et al. (2017). The modelling framework and scenario design are described in detail in an accompanying paper (Bodirsky et al., 2024). The second step, which is the focus of this article, is to estimate the overall economic value of the model outcomes. A wide range of model outputs are used to calculate social welfare using a system of nested utility functions, which is able to capture the value of changes in income, environment and health in a structured, theory-driven way incorporating recent developments in environmental economics (Hoel and Sterner, 2007; Sterner and Persson, 2008; Baumgärtner et al., 2015, 2017; Drupp, 2018; Drupp and Haensel, 2021). An unprecedented level of spatial disaggregation is achieved relative to comparable models – outcomes are simulated and valued for representative individuals across the whole income distribution in each country and some environmental outcomes are modelled at a spatial resolution of 0.5° latitude x 0.5° longitude. Among other things, this allows us to value, albeit incompletely, the social cost of inequalities caused by the global food system, both between and within countries.

Based on this combination of integrated assessment modelling and applied welfare analysis, we find that shifting the trajectory of the global food system from current trends to a sustainable path would provide a large increase in social welfare, equivalent to around 7 % of global GDP. Environmental improvements contribute most to this welfare gain, closely followed by increases in income and reductions in income inequality, with dietary health gains also contributing. Among the food system measures evaluated, shifting to healthy diets stands out as providing particularly large net benefits, as not only would doing so improve health outcomes, but it would also relieve pressure on the production system. However, an important caveat is that our welfare estimates do not include possible consumer disutility from dietary changes. The headline number is strikingly robust to variations in the key parameters of the social welfare, utility and damage functions.

The remainder of this paper is structured as follows. Section 2 describes the integrated assessment modelling framework. Section 3 describes the scenarios for future development of the global food system. Section 4 describes the approach to welfare valuation. Section 5 presents the results and Section 6 provides a discussion.

2. An integrated assessment model of the global food system and its primary impacts

The global food system can be defined as the totality of agri-food systems worldwide. FAO has defined agri-food systems as "the entire range of actors and their interlinked value-adding activities involved in the production, aggregation, processing, distribution, consumption and disposal of food products that originate from agriculture, forestry or fisheries and parts of the broader economic, societal and natural environments in which they are embedded" (FAO, 2018, p1). The global food system is thus highly complex and spans multiple domains, including land use, agricultural markets, health, energy, climate, biodiversity, water, and wider socio-economic conditions.

In turn, valuing the global food system requires quantifying outcomes in all these domains, a modelling challenge of tremendous scope. Our approach is to assemble a set of domain-specific quantitative models (mostly open-source) and link them together to make a coherent integrated assessment modelling framework, called the Potsdam Integrated Assessment Modelling framework (PIAM). The central component of the framework for this assessment is the land and food-system model MAgPIE (Model of Agricultural Production and its Impact on the Environment; Dietrich et al., 2019). MAgPIE simulates the allocation of land globally at the 0.5° x 0.5° grid-cell level[4] between many different agricultural, forestry and other uses, based on demand for food, materials and bioenergy. Land is allocated to minimise production costs subject to biophysical, technological and socio-economic constraints. Agricultural production can be increased at the intensive margin through, e.g., innovation and irrigation, and at the extensive margin through land conversion. International trade and domestic supply-utilization accounts make sure that global production meets demand. International trade is simulated based on cost-competitiveness, taking into account endogenous marginal production costs as well as trade costs from the GTAP database (Center for Global Trade Analysis, 2008), and constrained to have limited divergence from historical trade patterns. Agricultural land use and land-use change have multiple environmental impacts in the model, including GHG emissions, nitrogen pollution, water withdrawal and biodiversity reduction.

MAgPIE receives its food demand projections from a food demand model (Bodirsky et al., 2020). Based on exogenous socio-economic scenarios that determine demographics and incomes per capita, the model estimates consumption of different food types, food waste and the distribution of body weight/height at the country level, differentiating between ages and gender. These output variables are then fed into a model of dietary health (Springmann et al., 2020), which estimates the effects of diets on mortality. The model uses a comparative risk assessment method, similar to the Global Burden of Disease studies (GBD 2017 Causes of Death Collaborators, 2018). The method converts outputs from the food demand model relating to dietary composition and body weight into risk factors (e.g., high consumption of red meat; low consumption of vegetables; underweight), which affect mortality from different non-communicable diseases such as coronary heart disease and cancer. The mortality responses are parameterised using meta-analyses of cohort studies from the epidemiology and public-health literatures.

To generate an estimate of global temperature over time, Agriculture, Forestry, and Other Land Use (AFOLU) emissions from MAgPIE are combined with emissions from the energy sector, industry and waste from the macro-economic model REMIND (Baumstark et al., 2021). The REMIND model also provides bioenergy demand projections to MAgPIE to ensure correspondence between land and energy-sector mitigation. These combined emissions are then fed into the reduced-complexity climate model MAGICC (Meinshausen et al., 2020). MAGICC is run in a probabilistic setup following the IPCC's latest WG1 report (Cross-Chapter Box 7.1 in Forster et al., 2021). For emissions not included in REMIND-MAgPIE (e.g., Montreal Protocol species), we followed the infilling methodology of the latest WG3 report (Kikstra et al., 2022).

We then harmonise temperatures from MAGICC with high-resolution weather data from the Earth System Model MRI-ESM2 (Yukimoto et al., 2019), which is required to run the LPJmL vegetation, hydrology and crop model (Schaphoff et al., 2018). LPJmL simulates soil and vegetation dynamics in natural and managed ecosystems, explicitly accounting

[4] Approximately 55 × 55 km at the equator.

for water, carbon and nitrogen fluxes within and between ecosystems. It estimates the yields of various crop types (in both rainfed and irrigated systems), corresponding requirements for irrigation water, and carbon stocks in natural vegetation, and it does so at the same spatial resolution as MAgPIE. LPJmL requires weather data from an ESM (in our case, MRI-ESM2) as a driver that represents the changing climate over time. We harmonise these different models by identifying the Representative Concentration Pathway (RCP) that demonstrates the smallest temperature deviation from our MAGICC results.[5] This bootstrapping process ensures consistency between the warming that emerges from the emissions generated by REMIND-MAgPIE and the corresponding LPJmL datasets required by MAgPIE. For our baseline scenario, we find that SSP2–6.0 best matches projected emissions, while for our transformation scenario SSP1–1.9 is the best match. More information on the scenarios is provided in the following section.

The exogenous socio-economic scenarios, as well as estimated food expenditures from MAgPIE, feed into a poverty model (Soergel et al., 2021), which estimates country-level income distributions and poverty rates. Baseline average incomes and income inequality are set by the socio-economic scenarios. Changes in spending on agricultural products affect real incomes, as does any redistribution of revenues from environmental taxes implemented.[6]

Fig. 1 depicts the linkages between the individual models in PIAM. For computational reasons, the different models are soft-linked, meaning they are not run together but rather run individually, exchanging input/output boundary conditions with each other.

3. Food system scenarios

The PIAM models are run under different scenarios up to 2050. An obvious benchmark is a baseline scenario, which projects the system forward under ‘business as usual’/current trends. Our preferred baseline is the Shared Socio-Economic Pathway SSP2 scenario (Riahi et al., 2017), although for robustness/sensitivity analysis we also run the model under the four other SSPs as alternative baselines. Our task is then to characterise an alternative future for the global food system designed to meet a variety of economic, environmental, health and social policy goals – a sustainable path. In climate research, the policy and research communities have over time established a common set of scenarios to project alternative futures (Riahi et al., 2022). This is not the case in global food policy, however, so we rely on a set of bespoke policy scenarios presented in a parallel paper (Bodirsky et al., 2024).

The building blocks of these policy scenarios are a diverse set of 23 Food System Measures (FSMs) across four policy areas: (i) changing diets; (ii) improving rural livelihoods; (iii) conserving ecosystems; and (iv) improving agricultural management. These are listed on the vertical axis of Table 2 and described in more detail in the Appendix. Examples include the adoption of healthy diets as defined by the EAT-Lancet Commission (Willett et al., 2019), trade liberalisation, enlargement of protected areas, and a carbon price on soil carbon.[7] These FSMs were identified based on a review of previous literature and with reference to consensus policy goals for the global food system.[8] FSMs are analysed individually, in packages corresponding to each of the four policy areas mentioned above, and altogether. When simulated altogether, the 23 FSMs define a Food System Transformation (FST) path. The FST is not a unique representation of a sustainable path for the global food system nor is it an optimal path: it is not the outcome of optimising the PIAM models, which is computationally infeasible. Rather, it should be interpreted as a feasible future path for the global food system, which implements a range of measures identified in policy discussions.

4. Welfare valuation

When asked to evaluate the consequences of different policies or courses of action, welfare economists try to estimate the change in welfare as given, explicitly or implicitly, by a social welfare function (SWF). In this context, it is combinations of FSMs that are evaluated, including the overall FST scenario. In many economic applications, there is just one outcome that determines utility and that is an individual’s aggregate consumption of goods and services. However, there can also be multiple determinants of utility. Given the multi-dimensional nature of food-system transformations, a practical and theoretically attractive approach is to directly specify a system of nested utility functions, which explicitly models how each food system outcome – each output variable from PIAM – affects overall welfare. This approach applies foundational work in environmental economics on the substitutability of environmental/non-market goods and services, and how their relative value changes along development paths as they become more or less scarce (Hoel and Sterner, 2007; Sterner and Persson, 2008; Baumgärtner et al., 2015, 2017; Drupp, 2018; Drupp and Haensel, 2021).

4.1. Social welfare and utility functions

The SWF is average utilitarian:

$$W = \sum_{t=0}^{T} \overline{U}_t (1+\delta)^{-t} \tag{1}$$

where W is a real-valued measure of social welfare, $\overline{U}$ is average utility at time t and δ is the utility discount rate. The initial year $t = 0$ is 2020 and the final year for which we have data on all dimensions from PIAM, $t = T$, is 2050.

The use of average utilitarianism is open to debate. In cases where population does not vary across scenarios, classical/total utilitarianism may be preferred (i.e., substituting average utility in Eq. (1) with total utility over the population). However, population sometimes varies between scenarios we consider (i.e., between different SSP socio-economic scenarios), which means that welfare analysis using classical/total utilitarianism may in principle lead to a scenario being preferred just because it has a higher population. The aim is to avoid this outcome given our focus on food-system interventions that would have at most indirect effects on total population.

Individual utility depends on measures of (i) income, (ii) environmental quality and (iii) health. Average utility is calculated over a set of individuals i using the following function:

[5] Importantly, this process is robust to varying the RCP used in the initial MAgPIE run, because the second-order feedback of climate impacts on emissions is relatively small.

[6] Because country-level income data do not allow agricultural incomes to be distinguished from other sources of income, the model cannot account for the effects of changes in agricultural wages on national income distributions.

[7] We considered measures targeting food processing, marketing or waste as out of scope for this study.

[8] (1) consumption of healthy diets by all; (2) strong livelihoods throughout the food system; (3) protection of intact land and restoration of degraded land; (4) environmentally sustainable production throughout the food system; (5) resilient food systems that maintain food and nutrition security in the short and long run. Since the models comprising PIAM simulate long-term dynamics without short-run shocks, the formal modelling presented in this paper could only address goals (1)–(4).

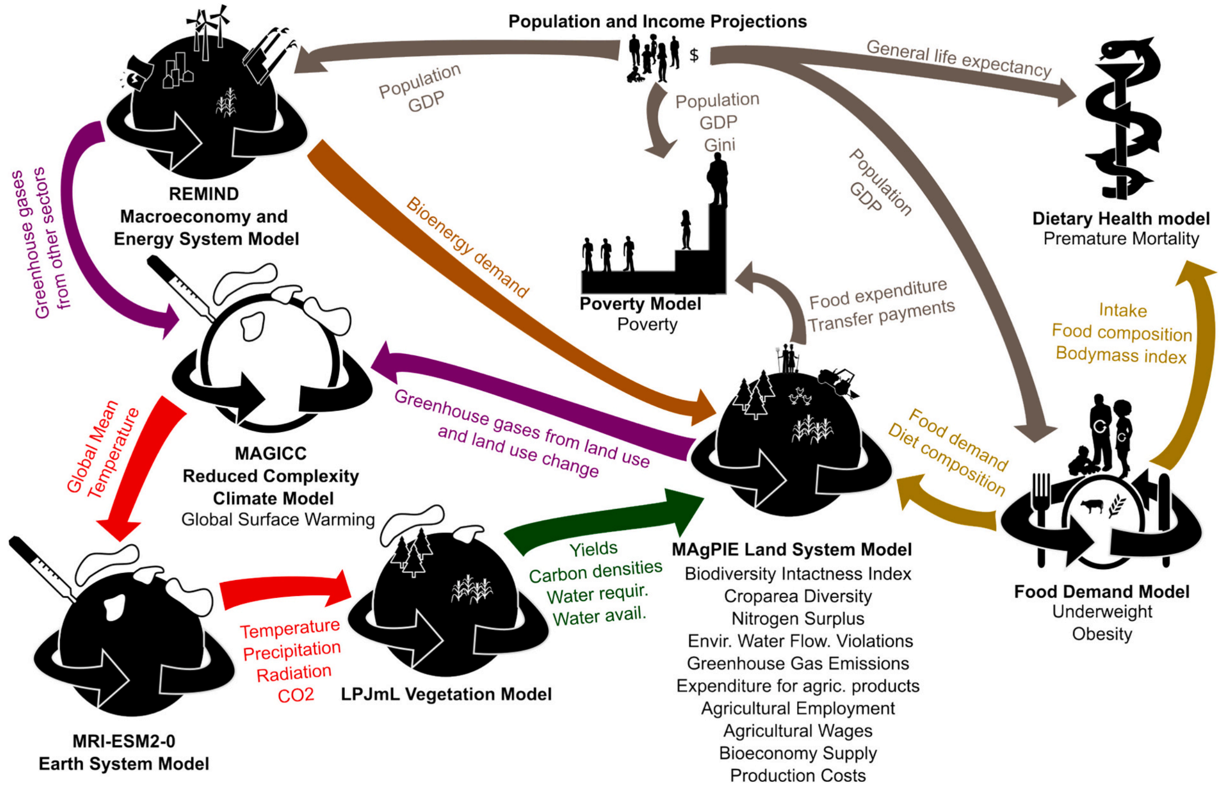

Fig. 1. Flow diagram of the Potsdam Integrated Assessment Modelling framework (PIAM) and further models integrated for this study. Arrows indicate inputs and outputs exchanged between models; black font indicates model names as well as core outputs from each model.

$$U_{i,t} = \frac{1}{1-\eta}\left[a_C C_{i,t}^{\rho_C} + (1-a_C)\left[a_E E_{i,t}^{\rho_E} + (1-a_E) H_{i,t}^{\rho_E}\right]^{\frac{\rho_C}{\rho_E}}\right]^{\frac{1-\eta}{\rho_C}} \tag{2}$$

where C stands for consumption/income,[9] E for environmental quality and H for health. The structure of the utility function assumes E and H are combined in a nest to form non-material consumption and this is in turn combined with material consumption to generate overall utility. This structure is supported by evidence on the substitutability of C and E being similar to that between C and H (Drupp and Haensel, 2021). The parameter $\rho_C \in (-\infty, 1]$ governs the substitutability of material and non-material consumption, while $\rho_E \in (-\infty, 1]$ governs the substitutability of environment and health. Further, $\rho_d = 1 - 1/\sigma_d$, $d \in \{C, E\}$, where σ_d is the elasticity of substitution between the two elements of utility in question. Thus, the function assumes a constant elasticity of substitution (CES). The parameter $a_C \in [0,1]$ is the share of material consumption in utility relative to non-material consumption, similarly $a_E \in [0,1]$ is the share of environment in non-material consumption relative to health.

The parameter $\eta > 0$ is the elasticity of marginal utility. This is assumed to be positive, so there is diminishing marginal utility with respect to the $C/E/H$ composite. This in turn has the effect of introducing aversion to inequality in consumption, environmental quality and health, both over time and between individuals at time t.

4.2. Environmental quality and health

Health is a function of dietary health specifically and is measured in terms of years of life lost per capita (YLL). These are converted into the health index H (a good) using the following health 'damage function':

$$H_{i,t} = 1/\left(1 + \gamma_H \mathrm{YLL}_{i,t}{}^2\right) \tag{3}$$

where γ_H is the health damage coefficient. Only our diet-related scenarios contain variation in deaths avoided (FSMs in our Diets bundle and the overall FST scenario).

Environmental quality E is a function of (i) global climate services, (ii) local ecosystem services, and (iii) local nitrogen balance. The determinants of E reflect what is available from the integrated assessment modelling system. The three elements of environmental quality are combined using a CES function,

$$E_{i,t} = \left(a_G G_{i,t}^{\rho_G} + a_B B_{i,t}^{\rho_G} + a_N N_{i,t}^{\rho_G}\right)^{1/\rho_G} \tag{4}$$

where G stands for global climate services, B for local ecosystem functioning and N for the absence of local nitrogen pollution (local nitrogen balance), $\rho_G \in (-\infty, 1]$ governs the substitutability of each of these, and the share parameters $a_G + a_B + a_N = 1$ and are individually non-negative.

Each measure of environmental quality represents a transformation of the raw outputs from the integrated assessment modelling system.

4.2.1. Global climate services

Global mean surface temperature T is used to calculate a flow of global climate services using the following function,

$$G_t = 1 - \gamma_G T_t^2 \tag{5}$$

Thus, global climate service flows are a quadratic decreasing function of temperature, with the steepness of the slope governed by the coefficient γ_G. PIAM includes climate impacts on crop yields and natural carbon stocks by coupling MAgPIE, MAGICC, MRI-ESM2 and LPJmL. Emissions from MAgPIE (and REMIND) drive global and local climatic changes through MAGICC and MRI-ESM2, and these feed back into

[9] These concepts will be treated as interchangeable, even though in reality (dis)saving drives a wedge between consumption and income. The integrated assessment modelling system provides income as an output, not consumption.

managed and natural systems at a granular level through LPJmL and MAgPIE (see Fig. 1).[10] Therefore, some of the effects of climate change on the food system are already embodied in estimates of other determinants of utility. However, since these effects only represent a fraction of the overall welfare impact of climate change, we include additional impacts in a simple, reduced-form manner that tracks a global public good rather than local effects.

4.2.2. Local ecosystem services

The value of the Biodiversity Intactness Index (BII) is used to calculate local ecosystem services using the following relationship,

$$B_{i,t} = \left(1 - \left(1 - \mathrm{BII}_{i,t}\right)\right)^{\gamma_B} = \mathrm{BII}_{i,t}{}^{\gamma_B} \tag{6}$$

Thus, local ecosystem services are an increasing function of BII. The BII is the estimated percentage of the original number of species that remain and their abundance in any given area. Isbell et al. (2015) argue that theoretical and empirical results from ecology support a coefficient $0 < \gamma_B < 1$, so local ecosystem service flows are a decreasing function of BII. That means the loss of ecosystem functioning tends to be small for initial losses in biodiversity but increases more steeply as further biodiversity is lost.

4.2.3. Local nitrogen balance

Local nutrient surpluses cause a wide range of environmental effects via the nitrogen cascade, including local air and water pollution. Agriculture is a major source of reactive nitrogen in the environment. Nitrogen balance N is inversely proportional to the local nutrient surplus as estimated by PIAM:

$$N_{i,t} = 1 \Big/ \left(1 + \gamma_N \mathrm{nsurplus}_{i,t}^2\right) \tag{7}$$

where γ_N is the slope coefficient and nsurplus is the local nutrient surplus in units of kg N/ha/yr.

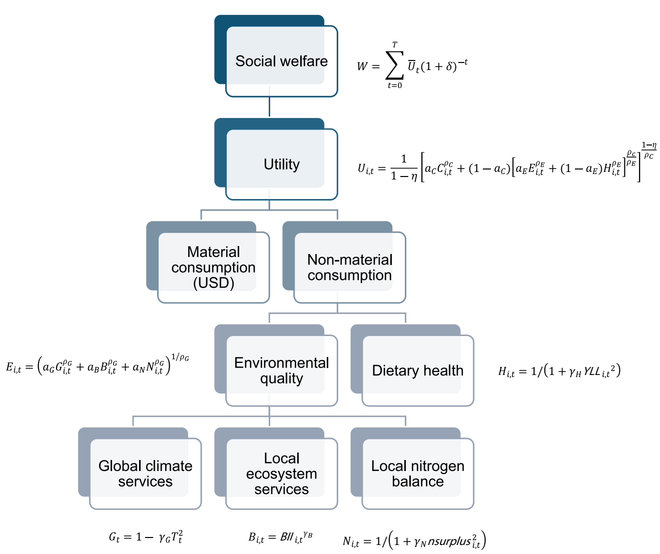

Fig. 2. Flow diagram depicting the system of nested social welfare, utility and damage functions.

[10] The coupled models include the climate impacts of changing patterns of temperature, precipitation, radiation and CO_2 on crop yields and on natural carbon stocks, as well as adaptation (Molina Bacca et al., 2023), but exclude impacts from other extreme events such as floods and storms, and climate impacts on livestock, labour productivity, and supply chains.

Fig. 2 summarises the system of social welfare and utility functions used in this study.

4.3. Spatial resolution

Spatial resolution is an important feature of the modelling, i.e., what defines individual utility U_i that gets aggregated by the SWF. Different variables are available at different resolutions from PIAM. Global mean temperature is the same for all individuals worldwide by definition. Data on BII and nutrient surplus are available on an 0.5° latitude x 0.5° longitude grid from MAgPIE. Income and health data from the poverty and health models respectively are available at the country level only. However, further disaggregation of income is possible, because for each country estimates of GDP per capita and the Gini coefficient are provided by the poverty model. Assuming income is lognormally distributed over the population of each country, GDP per capita and the Gini coefficient can be used to estimate the mean and standard deviation of the income distribution using the following pair of formulae,

$$\mu_t = ln(\mathrm{GDPpcap}_t) - \sigma_t^2/2 \tag{8}$$

$$\sigma_t = 2\mathrm{erf}^{-1}(\mathrm{GINI}_t) \tag{9}$$

In turn, the mean and standard deviation of the income distribution can be used to estimate individual incomes at different percentiles of the distribution.

Putting these data sets together, we approximate a distribution of individuals i within each 0.5° x 0.5° grid cell. Thus, in principle every individual worldwide can experience a unique combination of income, environmental quality and health, with climate services determined at the global level, income and health at the national level and ecosystem services and nitrogen balance determined locally. This relatively high level of disaggregation enables inequality/inclusion concerns to be incorporated to a much fuller extent than is usual in integrated economy-environment modelling, albeit the disaggregation is not complete.

4.4. Calibration

The above model of social welfare contains a set of parameters to be calibrated. Some of these parameters have been estimated by previous literature and those estimates can be imputed directly. For example, there is an extensive literature on the utility discount rate δ and the elasticity of marginal utility of consumption η. While these parameters remain the subject of vigorous debate, it is relatively straightforward to obtain a measure of central tendency from the range of estimates in the literature (e.g., from Drupp et al., 2018), plus the range itself can be used in sensitivity analysis. Estimates are also available for ρ_C, the substitutability of material and non-material consumption (Drupp and Haensel, 2021), and some of the damage function parameters.

For the remaining parameters – including the share parameters, some of the substitution parameters and some of the damage function parameters – there is a lack of previous estimates based on empirical evidence. This is a problem facing all research that seeks to directly specify utility functions depending on non-market goods, including the papers cited above. Given this challenge, calibration of these remaining parameters relies to a large extent on expert judgement, including judgements made by other scholars about corresponding parameters in previous studies.

However, it is still possible to partially constrain these unknown parameter values using empirical evidence. The model can be used to compute implicit shadow prices of the environmental and health variables, then these can be checked against corresponding empirical estimates and the unknown parameters tuned until they match. There are more unknown parameters than shadow prices, so this approach cannot uniquely identify all the unknown parameters. But equally, many combinations of unknown parameter values cannot be reconciled with the set of empirical shadow prices. Further details of the calibration are provided in the Appendix.

Table 1 lists the parameters of the model, their values and the sources used for calibration.

5. Results

To illustrate the health, environmental and economic effects of the scenarios, Table 2 reports a range of outcomes of modelling the FSMs in PIAM, focusing on the year 2050. The FSMs are implemented individually, in packages/bundles, and collectively as the FST. They are compared with both 2020 base-year values and 2050 outcomes on the baseline SSP2 scenario. In general, individual FSMs interact with each other in complex ways as a function of the structural relationships in PIAM, thus the effects of bundles of FSMs are not equal to the sum of the effects of individual FSMs. Note that for expositional purposes Table 2 illustrates a wider range of outcomes than just the PIAM inputs to the welfare analysis.

Comparing 2020 outcomes with the 2050 SSP2 outcomes shows that baseline undernutrition decreases at the global level, but obesity increases. These changes are primarily driven by baseline economic growth – global GDP per capita grows at about 2 % per year on SSP2, which alleviates undernutrition but facilitates increasing numbers of people adopting unhealthy diets high in calories but low in nutrients. On net, baseline dietary change increases mortality. Extensification and intensification of agriculture are key causes of increasing environmental degradation. Land conversion is the primary reason why biodiversity intactness falls in hotspots and intact forest landscapes. Agglomeration of cropland and reduced landscape heterogeneity results in biodiversity falling on cropland too. Agricultural intensification causes nitrogen pollution to increase. Annual GHG emissions from land use and land-use change fall, as emissions from agriculture, forestry and other land use are compensated by negative emissions from re/afforestation, but the net reduction is small. Combined with other GHG emissions, this trend causes global temperatures to keep rising. Economic growth, especially in low-income regions, causes poverty to fall a long way, as measured by the number of people living on less than US$3.20/day. In the background, rising labour productivity in agriculture causes wages to rise and employment to fall. Expenditure on agricultural products and agricultural production costs rise in response to growing food demand, but agriculture's share of global GDP continues to fall.

Table 1
List of parameters, values and notes on calibration.

Parameter	Description	Central value	Sensitivity analysis (low – high)	Source
δ	Utility discount rate/pure rate of time preference	0.5 %	0.1 – 2.5 %	Drupp et al. (2018) expert survey
η	Elasticity of marginal utility of consumption	1.01	0.5 – 2.4	Drupp et al. (2018) expert survey
$\boldsymbol{a_C}$	Share of material consumption in utility	0.19	0.09 – 0.48	Calibration (target share of 0.7)
ρ_C	Substitutability of material and non-material consumption	0.23	−1 – 1	Drupp and Haensel (2021) meta-analysis
$\boldsymbol{a_E}$	Share of environment in non-material consumption	0.7	0.5 – 0.9	Calibration (target share of 0.5)
ρ_E	Substitutability of environment and health	0.01	−1 – 1	Assumption (approximates Cobb-Douglas)
$\boldsymbol{a_G}$	Share of global climate services in environmental quality	0.5	n/a	Calibration
$\boldsymbol{a_B}$	Share of local ecosystem services in environmental quality	0.25	n/a	Calibration
$\boldsymbol{a_N}$	Share of local nitrogen balance in environmental quality	0.25	n/a	Calibration
ρ_G	Substitutability of climate services, local ecosystem services and local nitrogen balance	0.01	−1 – 1	Assumption (approximates Cobb-Douglas)
γ_H	Health damage coefficient	328	164 – 492	Calibration
γ_G	Temperature damage coefficient	0.016	0.008 – 0.024	(Drupp and Haensel, 2021)
γ_B	Biodiversity damage coefficient	0.3	0.1 – 0.5	(Isbell et al., 2015)
γ_N	Nitrogen damage coefficient	3E-4	1.5E-4 – 4.5E-4	Calibration

Relative to the baseline, the bundle of dietary measures most obviously improves health outcomes, but it also relieves pressure on the production system by reducing demand for certain food products like ruminant meat that are both costly to produce and environmentally intensive. That means most dietary measures also provide positive environmental and economic outcomes, as does the overall bundle. The strongest environmental and economic benefits are delivered by the dietary FSMs that involve shifting to less resource-intensive diets, either by reducing waste or by substituting animal- with plant-based foods (LowMonogastrics, LowRuminants, HalfOverweight). It is important to point out we assume dietary change does not reduce utility from food consumption. We discuss this issue further in the following section.

The livelihoods, biosphere and agriculture bundles mostly improve environmental outcomes, they are modelled as having no effect on dietary health, but unlike dietary measures these bundles present trade-offs by negatively affecting some environmental and economic outcomes. Within the livelihoods bundle, the trade liberalisation FSM actually provides benefits across the environmental and economic indicators and is thus an exception to the rule that such measures come with trade-offs. Liberalising trade benefits the environment because inputs of land and fertilizer are used more efficiently. Biosphere FSMs deliver significant increases in biodiversity and reductions in GHG emissions. However, they mostly increase nitrogen pollution because conservation creates a need for agricultural intensification. As a bundle, agriculture FSMs improve the environment on all dimensions, but with significant diversity between individual FSMs. For example, increasing nitrogen uptake efficiency (NitrogenEfficiency) has the primary purpose of reducing nitrogen pollution, but as a side effect it requires agricultural extensification. Conversely, establishing permanent habitats within the agricultural landscape (LandscapeHabitats) increases biodiversity but creates a need for agricultural intensification as a side effect, which increases nitrogen pollution. The biosphere and agriculture FSMs increase agricultural production costs in almost all cases, which drives up food expenditure and tends to marginally increase poverty, albeit the effect is small relative to the baseline reduction in poverty.

Combining the diets, livelihoods, biosphere and agriculture bundles, the overall FST scenario provides positive outcomes on all the dimensions included in Table 2. The diets bundle appears particularly important, because it allows for positive economic outcomes overall, something the livelihoods, biosphere and agriculture bundles individually do not. Our next task is to determine how valuable these outcomes are in social-welfare terms.

Fig. 3 presents the results of the welfare analysis. The top bar is the headline: it shows that the bundle of FSMs contained in the FST scenario would increase social welfare globally, relative to a baseline SSP2 scenario, by the equivalent of US$9.6 trillion per year (in 2020 Purchasing

Table 2
Key impacts of FSMs on health, environment and economy. Green shading indicates an improvement on the SSP2 baseline in 2050; red indicates a deterioration. Darker shades indicate a bigger improvement/deterioration. The FSMs are elaborated in more detail in the Appendix. Dollar amounts are in 2005 prices as per the SSP scenarios.

		Health	Environment				Economy		
		Premature mortality (millions of years of life lost)	Biodiversity Intactness Index on cropland	Biodiversity Intactness Index in hotspots and intact landscapes	Nitrogen surplus (Mt N/yr)	AFOLU GHG emissions (GtCO2eq/yr)	Expenditure on agricultural products (USD/person/yr)	Poverty (millions of people below USD3.20/day)	Agricultural production costs (billion USD/yr)
	2020	281	70.71	91.43	239	11.9	428	2104	3285
	Base_SSP2 2050	364	69.83	90.77	297	10.4	515	852	4636
Diets	**Diets bundle**	163	70.46	91.17	221	2.3	293	792	3100
	LowProcessed	318	69.82	90.74	297	10.6	478	843	4289
	HighLegumes	340	69.75	90.59	294	11.1	527	854	4696
	LowMonogastrics	356	70.14	90.9	272	9	427	830	4027
	LowRuminants	355	70.36	91.2	257	3.7	411	812	4039
	HighVegFruitNuts	331	69.77	90.7	301	10.7	546	862	4887
	HalfOverweight	327	69.92	90.82	291	10	498	847	4500
	NoUnderweight	224	69.84	90.75	300	10.7	523	854	4698
	LowFoodWaste	364	70.03	90.9	280	8.8	464	837	4265
Livelihoods	**Livelihoods bundle**		70.15	90.94	295	8.8	647	856	4555
	LibTrade		70.05	90.88	295	8.8	495	835	4517
	MinWage		69.95	90.84	297	10.4	665	862	4621
	CapitalSubst		69.8	90.79	297	10.6	521	851	4711
Biosphere	**Biosphere bundle**		70.54	91.92	300	6.1	558	884	4679
	REDD+		70.37	91.32	299	6.4	554	882	4691
	LandConservation		70.05	91.43	297	10.1	521	853	4648
	PeatlandRewetting		69.68	90.82	299	8.4	521	851	4665
	WaterConservation		69.86	90.77	297	10.4	518	851	4629
	BiodivOffset		70.42	91.36	299	8.4	523	859	4639
Agriculture	**Agriculture bundle**		71.15	91.3	214	2.5	643	896	5612
	NitrogenEfficiency		69.79	90.65	214	9.6	548	859	4870
	CropRotations		69.64	90.6	296	11.1	514	852	4647
	LandscapeHabitats		71.04	90.82	298	10.3	518	852	4647
	RiceMitigation		69.93	90.86	297	9.9	518	851	4674
	LivestockManagement		69.45	90.73	298	7.6	579	872	5226
	ManureManagement		69.89	90.79	292	10.1	527	854	4750
	SoilCarbon		69.97	91.38	300	6.3	537	867	4661
	FST_SSP2 2050	163	71.82	92.45	168	-5	490	830	3539

Power Parity prices) or 7.2 % of global GDP in 2020. The Appendix gives further details on the monetisation step, which is not trivial in this setting.

The next bar approximates a decomposition of the overall welfare increase into the contributions from changes to income, environmental quality and health.[11] Although nominal incomes are modelled as being unaffected by the FST (i.e., both baseline and FST nominal incomes follow the SSP2 scenario), real incomes increase for most people because production costs fall. This fall in production costs also slightly reduces income inequality across countries, which is socially valuable given concave utility. The welfare value of these income changes is equivalent to boosting global GDP by US$3.5 trillion per year, or 2.6 % in 2020. The FST also improves environmental quality on all dimensions, which is worth the equivalent of US$3.7trn per year, or 2.7 % of global GDP in 2020. Health improvements due to the FST are worth the equivalent of US$2.3trn per year, or 1.7 % of global GDP in 2020.

In the next set of bars, the impact of specific FSM bundles can be seen – diets, livelihoods, biosphere and agriculture. These all increase the social value of the global food system but by differing amounts. The largest increase in social welfare comes from dietary measures, followed by agriculture, livelihoods and biosphere. This is consistent with the outcomes reported in Table 2.

Fig. 3 also contains a sensitivity analysis, which tests the sensitivity/robustness of the results to variations in the key parameters of the social welfare, utility and damage functions. The results are robust to many

[11] This is done by calculating the change in welfare from changes in health, environment and income individually. Given utility is a non-linear function of each, there is a slight discrepancy between the sum of the individual changes and the total change in welfare from health, environment and income together, thus the decomposition is approximate.

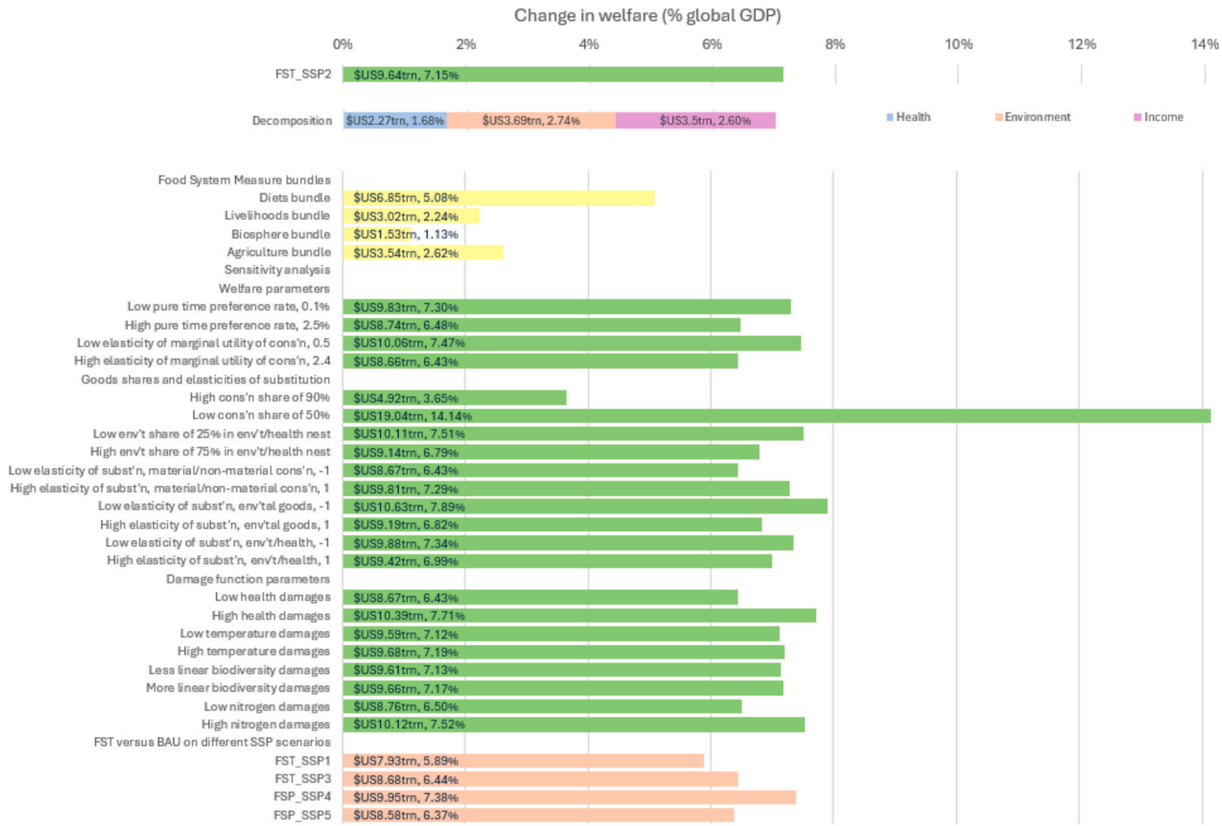

Fig. 3. Welfare changes resulting from comparing different food system scenarios, including one-factor-at-a-time sensitivity analysis. Welfare changes are reported for each item first in 2020 $US trillions (PPP), then as a percentage of 2020 GDP.

parametric variations, including the pure rate of time preference, the elasticity of marginal utility of consumption, the environment's share in non-material consumption, the various elasticities of substitution, and the damage function parameters.

The only sensitive dependence is to the share of material consumption in utility. The social value of the FST is higher, the lower is this material consumption share, because more weight is put on improvements in environmental quality and health, and FST delivers larger relative improvements in these outcomes than in incomes. However, it is important to note that low-end/high-end values for the share of material consumption are hard to reconcile with empirical data on the shadow prices of health, carbon emissions and nitrogen pollution, via the calibration procedure explained in the appendix. Thus, although the results depend sensitively on this parameter, its value is significantly constrained by data.

The bottom bars compare the FST with business as usual using different SSP scenarios as the reference. The FST scenario increases social welfare regardless of the SSP, but the increase is highest for SSP4, which has the highest baseline income inequality, and lowest for SSP1, which has the most favourable baseline income trends.

6. Discussion

This paper has presented our attempt to quantify the net economic benefits of a global food-system transformation. Our results suggest large benefits of shifting from business as usual/current trends to a sustainable path. Thus, our results provide an evidence base to support efforts to prioritise food-system transformations across overlapping international policy fields including agriculture, climate and development. Our FST scenario simulations make the case for a food system transformation in broad terms. Our simulations of FSMs and bundles of FSMs are intended to provide more detail on the likely consequences of specific measures and how they might work together. A strong finding in this regard is the benefits that could be realised by shifting food consumption towards healthy diets.

The concept of an FSM is quite deliberate. We do not consider the political economy of achieving them, nor do we usually specify which policy instruments are used to deliver them. That is because the choice of policy instruments will usually be broad, including taxes, subsidies, regulations, public provision, and moral persuasion. The preferred instrument(s) will vary at least to some extent by economic, institutional and political context. Nonetheless, our analysis can help to benchmark the necessary ambition of real-world policies because each FSM is modelled quantitatively in terms of its implementation and/or effects (Gaupp et al., 2021).

An important caveat to our findings on healthy diets is that our welfare estimates do not account for consumer (dis-)utility from changing diets. The environmental, health and income benefits of dietary changes are a 'free lunch' (forgive the pun), which is equivalent to the assumption that consumers change their dietary preferences so that they meet the recommended intake quantities of various food groups and of overall calories. If consumers would instead need to be incentivised to change their diets, large changes in prices might well be required, leading to large consumer disutility. This is the implication of research into the relationship between food expenditures/intakes and prices, which generally shows that the price elasticity of demand for different food groups is low. For example, using global data Muhammad et al. (2017) estimated own-price elasticities of food intake mostly in the range 0 to −1 across food categories (mostly towards −1). Building on similar data, Springmann et al. (2018) estimated that the price of processed meat would need to increase by 25 % to reduce demand by 16 %. Latka et al. (2021) estimated tax rates of up to several thousand percent would be required to reduce demand for sugar, and red and processed meat by 50 %. However, these studies warn of the limitations of extrapolating price elasticity estimates derived from small price/quantity changes under conditions of fixed consumer preferences and institutional constraints on choice, information, etc., which is the approach they took.

Instead, it is plausible that dietary preferences are not exogenous and fixed but rather endogenous, which would allow for at least some dietary change without disutility. The case of preferences for chili peppers nicely illustrates that, in addition to genetic, personality and gender determinants of food preferences, culture and exposure are important (Siebert et al., 2022). There is good evidence that a wide set of food preferences can be formed in early childhood (Issanchou and Nicklaus, 2014), and that non-price behavioural interventions affect food choices, even if the effects are small (Nugent et al., 2023). Food-preference changes have also been observed empirically when looking at consumption shifts over longer time-spans (Moschini, 1991). Given that preferences are likely endogenous, the consumer disutility from dietary change should be lower than that estimated using conventional price elasticities, probably much lower. A strand of literature with the potential to capture a wider set of factors has investigated the link between diet and subjective well-being (e.g., is vegetarianism linked to more or less subjective well-being?). This literature has yielded no clear results either in theory or empirically, especially after controlling for confounding socio-demographic factors (Pfeiler and Egloff, 2020). At the very least, there is no evidence that healthy diets are associated with less subjective well-being. Our estimates of the social welfare benefits of healthy diets should be interpreted as an upper bound due to the omission of consumer disutility from changing diets, but we are confident in the sign of the effect.

It remains an open research question which policy instruments can achieve a major shift in diets. In terms of our dietary FSMs, the most plausible interpretation of the large changes simulated is that they are achieved by a portfolio of synergistic policies (Fesenfeld et al., 2020), crucially including policies that improve the availability of healthy alternatives and that seek to shift preferences (e.g., healthy and sustainable public food procurement, marketing restrictions, education in self-regulation and nutrition, nutrition counselling in the healthcare system, nudging in food delivery apps, etc.) and improve food access (e.g. subsidised school meals, food support programs, etc.).

Our finding of large benefits survives under a wide range of alternative assumptions about how income, environment and health contribute to social welfare, and about baseline socio-economic development, although we have not attempted to fully quantify the uncertainties around our estimates, which would be a massive task given the complexity of the PIAM integrated assessment framework. Notably, we use only one vegetation model (LPJmL) and one ESM (MRI-ESM2) to generate future projections of crop yields, carbon densities, and water availabilities. This choice is pragmatic but reduces the breadth of future outcomes possible as the climate warms and represents a key assumption within our framework. Previous studies have attempted to quantify this uncertainty. Jaegermeyr et al. (2021), for example, explore the entire breadth of productivity outcomes by conducting an intercomparison of climate models and crop models, including MRI-ESM2 and LPJmL. While productivity remains stable in the optimistic case, in the worst-case scenarios it falls significantly. Maize yields, for instance, may decrease by 24 % on average by the end of the century. The authors highlight the large diversity in responses among ensemble members. Li et al. (2025) reach similar conclusions using a mixed-effects meta-analysis of more than 8000 experimental yield observations: under SSP5–8.5 they project a 22 % mean decline in maize yields and show that model-choice uncertainty alone explains over half of the variance in soybean outcomes. Computable General Equilibrium modelling using GTAP-DynW projects a 6–14 % global calorie loss, with roughly one billion additional severe food-insecure people by 2050 under similar SSP-RCP combinations (Kompas et al., 2024). Finally, Molina Bacca et al. (2023) use MAgPIE together with an ensemble of different crop models from CMIP6 to show that while they project a modest 4 % median global yield loss for the four main staples under SSP5-RCP8.5, the associated land-use responses remain deeply uncertain, ranging from a 5 % contraction to a 24 % expansion of rainfed cropland and driving adaptation costs anywhere between a reduction of USD17 billion and an increase of USD209 billion per year by 2100, underlining that substantial model-driven uncertainty in land-use adaptation persists despite apparently smaller average yield impacts. These results together illustrate that our single-model pipeline should be interpreted as a mid-range scenario.

The robustness of the results is nonetheless important and perhaps surprising. What it shows is that a food-system transformation presents no major trade-offs across generations, countries or constituents of utility. While individual FSMs and bundles of FSMs do create trade-offs, implementing all measures as part of an FST scenario improves all the economic, environmental and health outcomes we consider, and it does so monotonically. In terms of methodology, our approach illustrates the potential of coupling IAMs developed in different domains to analyse linked, multi-dimensional problems, and it also illustrates a policy application of recent work in environmental economics conceptualising how non-material goods, particularly environmental goods, affect utility and welfare.

CRediT authorship contribution statement

Simon Dietz: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benjamin Bodirsky:** Writing – review & editing, Methodology, Conceptualization. **Michael Crawford:** Investigation, Formal analysis, Data curation. **Ravi Kanbur:** Writing – review & editing, Methodology, Conceptualization. **Debbora Leip:** Methodology, Investigation, Formal analysis, Data curation. **Steven Lord:** Writing – review & editing, Methodology, Conceptualization. **Hermann Lotze-Campen:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Alexander Popp:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix for online publication

A.1. Description of food system measures

Table A1 provides further description of the Food System Measures (FSMs) used in this study.

Table A1
Description of Food System Measures (FSMs) used in this study.

FSM name	Description
LowProcessed	The intake of sugars is capped at the recommended intake of the planetary health diet (Willett et al., 2019), while the intake of plant-based oils and fats converges towards the planetary health diet. Alcohol consumption is limited to a maximum of 1.4 % of calorie intake (Lassen et al., 2020). In the health model, we assume that grains are consumed as wholegrains. The consumption of staple foods (cereals, roots, tubers) is adjusted to keep total food calorie intake constant.
HighLegumes	The intake of legumes is increased to the recommended level in the planetary health diet (Willett et al., 2019) in countries where these levels are not already met. The consumption of staple foods (cereals, roots, tubers) is reduced to keep total food calorie intake constant.
LowMonogastrics	The intake of poultry meat, monogastric meat and eggs is capped at the recommended intake of the planetary health diet (Willett et al., 2019). The consumption of staple foods (cereals, roots, tubers) is adjusted to keep total food calorie intake constant.
LowRuminants	The intake of ruminant meat and milk products is capped at the recommended intake of the planetary health diet (Willett et al., 2019). The consumption of staple foods (cereals, roots, tubers) is adjusted to keep total food calorie intake constant.
HighVegFruitNutsSeeds	The intake of vegetables, fruits, nuts and seeds is increased to levels recommended by the planetary health diet (Willett et al., 2019). The consumption of staple foods (cereals, roots, tubers) is adjusted to keep total food calorie intake constant.
HalfOverweight	Calorie intake is reduced to achieve a reduction of overweight and obesity by 50 % relative to the baseline scenario. Calorie reduction is BMI-class-, country-, age-group- and sex-specific. Intake of half of the people overweight or obese (BMI > 25 for adults, BMI +/-1STD for children) is reduced to intake recommended for a healthy BMI (20–25, BMI < +1STD). Relative dietary composition is not affected. Intake of people in other BMI-classes is not affected.
NoUnderweight	Calorie intake is increased in line with a complete eradication of underweight by 2050 for all age cohorts and sex classes in all countries. Calorie increase is BMI-class-, country-, age-group- and sex-specific. Caloric intake of adults with BMI < 20 and children with BMII < -1STD is increased to the intake recommended for a healthy BMI (20–25, BMI < +1STD). Relative dietary composition is not affected. Intake of people in other BMI-classes is not affected.
LibTrade	Trade is less oriented along historical trade patterns and more along relative competitiveness. MAgPIE uses two trade pools (Schmitz et al., 2013): the "historic trade pool" is based on historical trade patterns, with importing countries importing a constant share of their domestic demand, and exporting countries providing a constant share of global trade. This reflects historical trade distortions and dependencies. The "liberal trade pool" is based on relative cost-competitiveness, in terms of production and trade margins and tariffs. In the LibTrade scenario, the share of the liberal trade pool is increased from 20 % to 30 % for crops, and from 10 to 20 % for livestock and secondary products.
MinWage	A global minimum wage increases wages in lower-income countries. The minimum wage scenario increases wages to at least 3 USD05MER per hour by 2050. In the model, it raises production costs, causes substitution of labour by capital, and increases nominal incomes.
CapitalSubst	In countries with high capital intensity, capital is substituted by labour. We set a global target for the labour/capital share of 80:20. If countries exceed the capital share, we reduce the difference to this target by 50 % by 2050. Substituting capital by labour increases agricultural employment but results in additional production costs.
REDD+	Deforestation is disincentivised and regeneration of original vegetation is incentivised through a carbon price on C in above-ground vegetation on non-agricultural land (Humpenöder et al., 2014). Regeneration uses growth curves and carbon stocks of natural vegetation based on LPJmL. The growth curves are parameterised based on Braakhekke et al. (2019).
LandConservation	Global land area under protection is doubled from ~15 % currently to ~30 % by 2030. We assume that the enlargement of protected areas includes both a reactive and proactive component (Brooks et al., 2006; Kreidenweis et al., 2018). The reactive component focuses on biodiversity hotspots (BH), the proactive component considers large areas (>500 km2) of unprotected intact forest landscapes (IFL), mainly in the Amazon and Congo basins and in the boreal zone.
PeatlandRewetting	Drainage of intact peatlands is penalised and rewetting of drained peatlands is incentivised through the AFOLU GHG price. GHG emissions from drained und rewetted peatlands are estimated based on IPCC wetland GHG emissions factors (Humpenöder et al., 2020). Drainage of peatlands is linked to the expansion of managed lands (cropland, pasture, forestry). Likewise, rewetting of peatlands is linked to the reduction of managed lands.
WaterConservation	Minimum environmental water flow requirements (following the method of Smakhtin et al., 2004) have to be maintained and cannot be withdrawn (for irrigation or non-agricultural usage).
BiodivOffset	The Biodiversity Intactness Index (BII) in each biome of each world region cannot decrease after 2020. BII reduction at one place can be compensated by increasing BII values in other places under the condition that they belong to the same biome in the same world region.
NitrogenEfficiency	Nitrogen uptake efficiency is increased through technical measures such as improved land manure application, spreader maintenance, improved agronomic practices, sub-optimal fertilizer applications, nitrification inhibitors, and fertilizer free zones. We use maximum mitigation rates and the associated costs from Harmsen et al. (2023), increasing labour and capital demand based on general regional cost shares in agricultural production. Mitigation rates are translated to changes in soil nitrogen uptake efficiency to improve consistency with our nitrogen budgets.
CropRotations	Crop rotations are incentivised with payments. Exceeding typical rotation lengths is priced to account for the external costs of less diverse agriculture.
LandscapeHabitats	Permanent habitats are established within agricultural landscapes. Cropland expansion per cluster is constrained to 80 % of the available potential cropland. The area of available potential cropland at grid-cell level is derived from Zabel et al. (2014). This aims to conserve at least 20 % permanent semi-natural habitats at the landscape level (e.g. for pollination, pest control, soil protection). Semi-natural habitats include forest, non-forest and grassland habitats that can maintain and restore native species diversity.
RiceMitigation	Technical measures such as direct seeding, improved residue management, alternated flooding and drainage, and changed fertilisation. We use the marginal mitigation cost curve by Harmsen et al. (2023) to reduce baseline emissions.
LivestockManagement	Livestock systems are intensified in particular in ruminant systems in low-income countries, resulting in a more efficient conversion of feed into products and associated shifts in feed baskets from roughage to concentrate feed (Weindl et al., 2017a; Weindl et al., 2017b). In addition, emissions from enteric fermentation are mitigated via a set of technical measures from Harmsen et al. (2023) and associated costs.
ManureManagement	Improved animal waste management reduces losses and emissions during collection and storage of manure using a set of measures at additional costs. 50 % of manure excreted in confinement is managed in anaerobic digesters, while the remainder is still managed according to the current mix. Anaerobic digesters are assumed to have a 90 % recycling rate of manure, accounting for some remaining losses in stables and waste collection.
SoilCarbon	Soil carbon degradation is disincentivised and soil carbon sequestration is incentivised through a carbon price on C in soil carbon (including litter layer). Disincentivised measures include transition of natural land or pasture to cropland; incentivised measures include irrigation or perennial crops.

A.2. Further details on calibration

Five parameters are calibrated by matching the implicit shadow prices of environmental and health variables estimated by the model with values in the literature: the share of global climate services in environmental quality α_G; the share of local ecosystem services in environmental quality α_B; the share of local nitrogen balance in environmental quality α_N; the health damage coefficient γ_H; and the nitrogen damage coefficient γ_N.

Shadow prices of the environmental and health variables are given by the marginal rate of substitution of consumption for the variable in question.

For (i) dietary health, this is $\partial U_{i,t}/\partial YLL_{i,t}$ / $\partial U_{i,t}/\partial C_{i,t}$. This marginal rate of substitution is the monetary value of a life year and can be compared with data/literature on the same quantity. To do this, the individual/spatial unit i and time period t for which the comparison is made need to be specified. We use global average values in 2020. The same procedure can be followed for (ii) GHG emissions and (iii) local nitrogen surplus, two quantities for which there are also empirical literatures estimating shadow prices.[12] The procedure also yields a shadow price of the Biodiversity Intactness Index, but this is less useful for calibration as empirical counterparts do not exist. Thus, a set of three implicit shadow prices is obtained, which the calibration procedure seeks to match with empirical counterparts by varying the unknown parameters.

The shadow prices we calibrate on are as follows. For the marginal rate of substitution of consumption for a life year, we use US$41,000/YLL. This is based on combining two lines of evidence: (i) lost output from a YLL as a proxy for lost consumption, using global average GDP per person employed (World Bank, 2024) and (ii) estimates of the value of a statistical life from the literature on willingness to pay to reduce mortality risk (Viscusi and Masterman, 2017). For the marginal rate of substitution of consumption for emissions, we use US$0.10/t$CO_2$. This is $\partial Ut/\partial Pt$ / $\partial U_{i,t}/\partial C_{i,t}$. Note the numerator entering this shadow price expression is the marginal disutility in 2020 of emissions in the same year. Thus, this quantity is not the same as the so-called 'social cost of carbon', which is the discounted stream of marginal disutilities from an emission in 2020 over all future years. Rather, it is instantaneous damages from an emission. According to the leading study of the social cost of carbon by Rennert et al. (2022), which is almost unique in providing data on marginal damages per year from an emission in 2020, a comparable damage quantity is c. US$0.10/t$CO_2$ (after adjusting to avoid double-counting of agricultural impacts of climate change). Their corresponding estimate of the social cost of carbon is $185/t$CO_2$, which we consider to be representative of recent literature using advanced damage-estimation methods. For the shadow price of nitrogen surplus, $\partial U_{i,t}/\partial nsurplus_{i,t}$ / $\partial U_{i,t}/\partial C_{i,t}$, we use US$15/kg N/ha based on (Van Grinsven et al., 2013).

Constraints on possible values of the parameters are given in the main text. We then search for parameter vectors that minimise the distance between the model estimates and the target values, using a coarse rather than continuous grid of values. The distance-minimising vector is not uniquely defined given we calibrate five unknown parameters using only three empirical moments, so we exercise judgement on the most plausible vector. For the preferred parameter vector of $\alpha_G = 0.5$, $\alpha_B = 0.25$, $\alpha_N = 0.25$, $\gamma_H = 328$ and $\gamma_N = 3E-4$, the model estimates the value of a life year is US$42,000, the marginal rate of substitution of consumption for emissions is US$0.37/t$CO_2$ and the marginal rate of substitution of consumption for nitrogen balance is US$15/kg/ha.

A separate calibration procedure is used to set the share of material consumption in utility α_C and the share of environment in non-material consumption α_E. The calibration does not involve matching empirical evidence, because we are not aware of any relevant evidence. But calibration is still required because the elements of individual utility are measured on different scales, i.e., they have different units. Consumption is measured in dollars, while the environmental and health variables, through their respective damage-function transformations (3) and (5)–(7), end up being measured on an index from zero to one.[13] Therefore, the share parameters must be estimated with care. Setting $\alpha_C = 0.7$ does not imply that material consumption has a 70 % share of utility given that consumption is measured on a different scale to the health/environment composite. Rather, α_C and α_E are calibrated by explicitly targeting particular shares of each element in overall utility using data on average consumption, health and environmental outcomes in 2020. We target a share of material consumption in utility of 70 %, which gives $\alpha_C = 0.19$, and a share of environment in non-material consumption of 50 %, which gives $\alpha_E = 0.7$.

A.3. Calculating the change in welfare

Welfare lacks an intuitive measure, and, in any case, utility is only unique up to a positive, affine transformation, so it is standard to express changes in welfare using a money metric. A simple way to do this is to convert the difference in W between any pair of scenarios into an equivalent amount of money using the marginal utility of (material) consumption in 2020. However, this method faces complications. First, the marginal utility of consumption depends on the levels of consumption, environmental quality and health. For this simple conversion of the overall difference in W into money units, a single combination of consumption, environmental quality, and health must be chosen, for example it could be the 2020 average. But this will only approximate the weighted average marginal utility of consumption calculated at the values actually enjoyed by each individual and it could be a poor approximation. Second, this method relies on a marginal (first-order) approximation of what could be a large, non-marginal difference in welfare between scenarios.

An alternative method is to calculate equivalent variations in consumption for each individual, and then discount and average these variations across all individuals. Take two food system scenarios, business as usual (BASE) and the FST. For each i and t, one can calculate the level of consumption that, when combined with BAU environmental and health outcomes, delivers the same utility as the FST consumption, environmental and health outcomes:

$$\widehat{C}_{i,t}^{BASE} = \left[\frac{1}{\alpha_C}\left((1-\eta)U_{i,t}^{FST}\right)^{\frac{\rho_C}{1-\eta}} - \frac{1-\alpha_C}{\alpha_C}\left(X_{i,t}^{BASE}\right)^{\rho_C}\right]^{\frac{1}{\rho_C}} \tag{A.1}$$

where X denotes non-material consumption for convenience.

The difference between this level of consumption and BASE consumption is the equivalent variation:

$$EV_{i,t} = \widehat{C}_{i,t}^{BASE} - C_{i,t}^{BASE} \tag{A.2}$$

Each i's stream of EV over time is then discounted back to 2020 using individual-specific consumption discount factors priced on the BASE trajectories, before the average is taken over all individuals. This can be summed across all individuals to give an aggregate amount.

Once a monetary equivalent of the difference in W is obtained, there remains one last question – how to express it in an intelligible way. Recall the difference in W is measured as the discounted sum of utility flows over thirty years (2020–2050). Therefore, taking the monetary equivalent of this difference and expressing it relative to annual income today (2020, say) would yield an extremely large proportion that is liable to be misinterpreted.

[12] For GHG emissions, global mean surface temperature is converted into CO_2 emissions using the Transient Climate Response to cumulative carbon Emissions relationship, $T_t = \zeta P_t$ (Collins et al., 2013), where P is cumulative CO_2 emissions. The parameter ζ is set to 0.00044 (Knutti et al., 2017).

[13] G can be exactly zero whereas zero is an asymptote for B and N.

Arguably a more intuitive measure of the relative monetary value of the welfare gain is obtained by converting it into an annuity that pays out over the analysis period, i.e., 2020–2050. That is, this measure tells us what constant flow of income from 2020 to 2050 would be equivalent to the monetary value of W, and we can express that as a share of current income.

Data availability

Data will be made available on request.

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