Notes on a global dataset of national marginal costs of environmental externalities and dietary risk internalities associated to food system activities under the Shared Socioeconomic Pathways: FOODCoST SSPs Dataset

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Summary of dataset

This note describes an open dataset of per unit environmental external costs from greenhouse gas (GHG) emissions, blue water withdrawal, nitrogen losses, and land-use transitions to and from cropland and pasture, and labour productivity costs of non-communicable diseases per unit of exposure to dietary risk such as low per capita fruit and vegetable consumption. The format of the dataset and accompanying files are described alongside clarification on the use and scope of the cost estimates. A brief overview of the calculation approach and validation are given, referring further to the documentation of the SPIQ-FS model on which the calculations are based. A list and summary of studies and evaluations which used previous versions of the dataset is provided.

The publishing of the open dataset satisfies Deliverable 1.3 under Work Package 1 of the 2022-2026 EU Horizon Europe project FOODCoST for an "EU-global database on externality costs including an open-source dataset of national external cost values".

Metadata

Title of the dataset

"FOODCoST global dataset of national per unit costs of environmental externalities and dietary risk internalities associated to food system activities under the SSPs"

Shorter version

"FOODCoST global dataset of per unit costs under the SSPs"

Shortest version

"FOODCoST SSPs Dataset"

Citation

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Availability

A folder containing 5 comma-separated values (CSV) files and 1 text file with UTF-8 encoding. Commas (UTF-8 0x2C) are used as separators in the .csv and periods (UTF-8 0x2E) for decimal points. The _S variant of the folder contains the non-parametric samples. The _S variant of the folder is a larger download (1 GB) than the parametric version without samples (3 MB).

Download link: https://ora.ox.ac.uk/objects/uuid:7c116abc-92fe-4725-ad38-aaa5ff68bef5

Dataset

SPIQ_Marginal Cost_FOODCOST_Data_E.csv (or SPIQ_Marginal Cost_FOODCOST_Data_E_S.csv)

SPIQ_Marginal Cost_FOODCOST_Data_H.csv (or SPIQ_Marginal Cost_FOODCOST_Data_H_S.csv)

Accompanying Files

B: SPIQ_Marginal Cost_FOODCOST_Cost.csv

C: SPIQ_Marginal Cost_FOODCOST_Ctry.csv

D: SPIQ_Marginal Cost_FOODCOST_Proj.csv

E: License.txt

License

The License .txt file contains the following text.

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Description

Use

For estimates of economic risks arising from environmental externalities and dietary risk internalities of food system activities. Estimates can be used in cost-benefit assessment of the economic potential of transforming EU and global food systems.

Impact quantities

Co-products of food system activities that result in externalities or internalities that could lower future gross product (Table 1). Examples include metric tons of carbon dioxide emissions that results in future agricultural and labour productivity losses from heat stress due to the radiative forcing of the emitted carbon dioxide, and exposure to current unhealthy patterns of dietary consumption in the population that lowers future labour productivity. 12 impact quantities associated to environmental externalities and 15 impact quantities associated to dietary risk internalities are covered. For convenience, the first 3 columns of Table 1 concerning impact quantities are tabled in the accompanying file B.

Cost

To future gross product in purchasing power terms per additional unit of impact quantity. Measured in present purchasing power in 2020 (2020 PPP).

Spatial coverage

Estimates of per unit cost for the impact quantities listed in Table 1 are provided for 153 countries. The list of countries and administrative data are provided in accompanying file C. For convenience countries are identified in the dataset by: name according to the country names used in the World Integrated Trade Solution (WITS) and

World Development Indicators (WDI) databases of the World Bank; unique ISO 3166-1 alpha-3 code, and; United Nations (UN) numerical classification system of sovereign countries and territories number.

The first 3 columns of the dataset .csv files provide the country identifiers.

CountryName	Country names used by the World Bank https://wits.worldbank.org/wits/wits/witshelp/content/codes/country_codes.htm
CountryCode	ISO 3166-1 alpha-3 country code https://www.iso.org/iso-3166-country-codes.html
M49	UN numerical classification system of sovereign countries and territories https://unstats.un.org/unsd/methodology/m49/

Temporal coverage

Covers production of Table 1 impact quantities over the period 2020 to 2050 in 5-year timesteps under 5 Shared Socioeconomic Pathways. More information about the SSPs and future projections is discussed in the *Approach*.

Columns 4-5 of the datasets indicate the year of production of the impact quantity (an emission, withdrawal, loss, land clearance, or consumption) and the future scenario assumed.

Year	2020, 2025, 2030, 2035, 2040, 2045, 2050	
Scen	1	SSP1-RCP2.6. **SSP1: Sustainability (Taking the Green Road):** Focuses on inclusive development and sustainable practices. High cooperation and reduced inequality lead to better environmental outcomes. **RCP2.6**: Ambitious mitigation with strict climate action. Below 2 degrees of warming by 2100 above pre-industrial baseline.
	2	SSP2-RCP4.5. **SSP2: Middle of the Road:** Represents a moderate path with balanced socioeconomic progress and challenges continuing current trends. Inequalities persist but are not extreme, and policy developments are incremental. **RCP4.5**: Moderate efforts to stabilize emissions. Policies support gradual shifts. Between 2-3 degrees of warming by 2100 above pre-industrial baseline.
	3	SSP3-RCP6.0. **SSP3: Regional Rivalry (A Rocky Road):** Depicts a fragmented world with regional tensions, slow economic growth, and limited climate action, leading to high vulnerability to climate change. **RCP6.0**: Limited action and slower transitions. Market-driven technological developments. Above 3 degrees of warming by 2100 above pre-industrial baseline.
	4	SSP4-RCP7.0. **SSP4: Inequality (A Road Divided):** Highlights a world of stark inequalities. Affluent regions thrive while poorer areas struggle, exacerbating social and environmental problems. **RCP7.0:** Baseline. Above 3.5 degrees of warming by 2100 above pre-industrial baseline.
	5	SSP5-RCP8.5. **SSP5: Fossil-Fueled Development (Taking the Highway):** Prioritizes economic growth with heavy reliance on fossil fuels, leading to high greenhouse gas emissions and environmental degradation. **RCP8.5**: Minimal policy, continued high emissions. Above 5 degrees of warming by 2100 above pre-industrial baseline.

For example, a metric ton of carbon dioxide emitted in 2035 (Year) under SSP2 (Scen) in Zambia (Country) is costed for its future impact after 2035 due to additional radiative forcing in the SSP2-4.5 scenario. The SSP2 GDP and population projections are used to discount the future purchasing power losses to 2020 PPP. Another example is a kilogram of nitrogen in the form of ammonia is volatilized to air from synthetic fertilizer applied to cropland in Belgium in 2050 under SSP3-6.0. Cost estimates use SSP3-6.0 projections for precursors to particulate matter formed from volatilized ammonia, including NOx emissions, SOx emissions, population density and average temperature, GDP, and demographics to estimate the additional disease outcomes from the air pollution and the value of lost labour. SSP3 GDP and population projections are used to discount the future purchasing power losses to 2020 PPP.

Each SSP and RCP combination portrays distinct trajectories of societal development, cooperation, climate policy and environmental impact. To assist users to match the 5 SSP-based future projections to a user customized future scenario, the accompanying file D lists some of the projections used in the cost modelling including GDP (in fixed 2020 international dollars), population density, percentage of the population over 65 years of age, urbanisation, industrial pollution, and human development index, for the 153 countries in the 5-year timesteps of 2020 to 2050 for the 5 SSPs.

Quantity and units

Columns 6-8 of the datasets correspond to the impact quantity from Table 1 and the unit of the marginal cost. 'Unit 2' refers to 2020 PPP. 'Unit' is the measurement unit of the impact quantity. The unit of the cost per unit is Unit2 per Unit.

Quantity	Impact quantities. Listed in Column 2 of Table 1
Unit2	Economic unit. 2020 PPP.
Unit	Impact quantity units. Listed in Column 3 of Table 1

The units for GHG emissions are in metric tons of the respective gases, not in CO2-equivalents. For N losses the units are the mass of nitrogen in the reactive nitrogen species. For exposure to dietary risks the unit are either g/capita^2/day or % energy intake /capita^2/day. This unit can be interpreted as the annual per capita cost of increasing consumption across the population of the exposure variable by 1 g/capita/day or by 1% of energy intake/capita/day. The annual cost to the economy of that country can be obtained by multiplying by the population of that country. Populations are provided in the accompanying file D. For some exposure variables like calcium 1g/capita/day is a large shift in intake. The cost is obtained by a partial derivative formula, not an average, so costs for intake such as calcium or fatty acids can by scaled down lower to mg (one thousandths of a gram).

Value and uncertainty

Cost per additional unit is modelled as a random variable. The datasets provide the random variable in parametric and non-parametric forms. Column 9 provides the mean value of the cost per unit.

Mean	Mean value of 1000 samples of the cost per unit generated by the SPIQ-FS cost models

Parametric form

Columns 10-11 contain two parameters for the per unit cost treated as a log-normally distributed random variable. The evidence and practicality for treating the per unit cost as log-normally distributed is discussed in the *Approach*. Samples of the per unit cost can be generated from sampling a normal distribution of mean Mu and standard deviation Sigma. Exponentiating (base e) the resulting samples gives samples of the per unit cost.

Mu	Mean value of log(X) where X is cost per unit and log is the natural logarithm
Sigma	Standard deviation of log (X) where X is cost per unit and log is the natural logarithm

The mean of the samples reconstructed from the parametric form will deviate from the mean in Column 9, mainly because of the chance of outliers from a log-normal distribution and, to a lesser extent, due to adjustments in the cost models between parametric forms and final values. By design, the mean in Column 9 matches the mean of the non-parametric empirical distribution represented by samples in Column 12.

Non-parametric form

Column 12 provides 1000 samples from a joint empirical distribution of the cost per unit random variables. At present in the SPIQ-FS model correlations are embedded most strongly between impact quantities – for example, where future climate change causes above-average impacts and costs, it may be correlated with more significant impact and losses from land-use change or water scarcity (Quantity). Correlations are weaker over countries where aspects such international trade disperses price impacts of lost agricultural production (Country), and even weaker across years within scenarios (Year, Scen).

Samples	Each column represents a joint sample of the per unit cost across impact quantities, countries, years and scenarios.

The parametric form can only reconstruct the marginals of the underlying joint empirical distribution represented by the samples and not the correlation structure.

Other central measures can be calculated from marginal Samples. Generally, the cost per unit marginals are skewed, so the mean can be significantly higher than the median and mode.

Calculation

Per unit costs from the FOODCoST SSPs dataset are multiplied by annual additional units of an impact quantity to estimate the total loss of future gross product in present purchasing power.

Totals are intended to be used in comparisons.

Aggregation

Aggregation of totals across quantities includes the assumption of substitutability across natural, human and produced capital, and risks potential double-counting. One reason to limit the number of impact quantities is the risk of double-counting. The first 25 impact quantities in Table 1 are designed to be additive, bar the caveats on substitution and potential double counting. Cost of diets low in fibre and low in milk have significant overlaps with diets low in fruits, vegetables, whole grain, legumes and calcium. Fibre and milk are included for separate consideration.

When aggregating across countries, years, or quantities additional care must be taken with the parametric form. The sum of two normally distributed random variables is normally distributed, but the sum of two log-normally distributed random variables is not log-normally distributed and its distribution is not well approximated by a log normal distribution, as a general case. The Mean and the Samples are additive, but the parameters Mu and Sigma are not. Other central measures are not additive if significantly different than the mean.

Limitations

Limitations of the cost estimates and omissions from the list of impact quantities are discussed under *Use and Scope*, and *Approach*, in the accompanying text.

Tables

Table 1. Input quantities with corresponding marginal costs per unit and indicative activities

Cost category	Impact quantity	Unit	Type	Marginal cost	Examples of activities
GHG emissions	CH_4 emission	metric ton (t)	Environmental externality	Social cost of CH_4: residual damages to global future GDP PPP (in NPV in 2020) from contribution to climate change at the optimal amount of abatement, attributed to the country of emission	Enteric fermentation in livestock, methanogens in flooded rice fields, organic waste in landfill
GHG emissions	CO_2 emission	metric ton (t)	Environmental externality	Social cost of CO_2: residual damages to global future GDP PPP (in NPV in 2020) from contribution to climate change at the optimal amount of abatement, attributed to the country of emission	Fertiliser production, cold-chain storage, shipping commodities, consumer food preparation, loss of soil carbon
GHG emissions	N_2O emission	metric ton (t)	Environmental externality	Social cost of N_2O: residual damages to global future GDP PPP (in NPV in 2020) from contribution to climate change at the optimal amount of abatement, attributed to the country of emission	Volatilization from manure, applied fertiliser, and soils. Secondary emission from N losses to the environment
Water use	Blue water withdrawal	cubic metre (m3)	Environmental externality	Future costs to agricultural productivity and labour productivity (in NPV in 2020) from non-renewable water consumption and the reduction of water resources for economic use, attributed to the country of withdrawal.	Irrigation
Land-use change	Forest habitat loss	hectares of habitat lost (ha)	Environmental externality	Value of effective hectares of present and future lost ecosystem services (in NPV in 2020) in the country of land-use transition due to the destruction or degradation of forest ecosystem	Deforestation to clear land for palm oil plantations or livestock grazing
Land-use change	Forest habitat return	hectares of habitat returning (ha)	Environmental externality	Value of effective hectares of present and future returned ecosystem services (in NPV in 2020) in the country of land-use transition due to recovery or re-establishment of ecosystem	Abandoned agricultural land reforestation. Afforestation on agricultural land
Land-use change	Other natural habitat loss	hectares of habitat lost (ha)	Environmental externality	Value of effective hectares of present and future lost ecosystem services (in NPV) in the country of land-use transition due to the destruction or degradation of other natural land ecosystem	Conversion of wetlands to cropland or natural grassland to high density livestock pasture
Land-use change	Other natural habitat return	hectares of habitat returning (ha)	Environmental externality	Value of effective hectares of present and future returned ecosystem services (in NPV in 2020) in the country of land-use transition due to recovery or re-establishment of ecosystem	Marginal agricultural land abandoned and returning to natural state
Nitrogen losses	NH_3 loss to air	mass of NH3 that contains 1 kg of nitrogen (N-kg)	Environmental externality	Productivity losses (in NPV in 2020) in the country of emission due to the burden of disease from particulate matter formation, agricultural and ecosystem service losses from nutrient	Ammonia volatilization from manure left on pasture and application of fertilizer

Cost category	Impact quantity	Unit	Type	Marginal cost	Examples of activities
				imbalance and the acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to deposition runoff	
Nitrogen losses	NO_x loss to air	mass of NO_2 that contains 1 kg of nitrogen (N-kg)	Environmental externality	Productivity losses (in NPV in 2020) in the country of emission due to the burden of disease from particulate matter formation, agricultural and ecosystem service losses from nutrient imbalance and the acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to deposition runoff. Agricultural losses from release of surface level ozone.	Release of nitrogen oxides from burning of fossil fuels in farm machinery and transport. Burning of crop residues. Manure and fertilisers
Nitrogen losses	NO_3- loss in runoff from agricultural land	mass of NO_3- that contains 1 kg of nitrogen (N-kg)	Environmental externality	Ecosystem services losses (in NPV in 2020) from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to nitrate load in surface water	Manure left on pasture and surplus fertilizer
Nitrogen losses	NO_3- loss in soil leaching on agricultural land	mass of NO_3- that contains 1 kg of nitrogen (N-kg)	Environmental externality	Ecosystem services losses (in NPV in 2020) from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to nitrate load in surface water (from subsurface flows emerging into surface water) and productivity losses in the country of emission due to the burden of disease from human nitrate intake in drinking water from groundwater.	Manure left on pasture and surplus fertilizer
Dietary patterns (high in processed foods and additives)	Diet high in processed meat	g/capita^2/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from overexposure, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes.	Overconsumption in the national population.
Dietary patterns (high in processed foods and additives)	Diet high in sugar-sweetened beverages	g/capita^2/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from overexposure, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Overconsumption in the national population.
Dietary patterns (high in processed foods and additives)	Diet high in sodium	g/capita^2/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from overexposure, predominantly, stomach cancer. Does not include effects on systolic blood pressure.	Overconsumption in the national population.
Dietary patterns (high in processed foods and additives)	Diet high in trans fatty acids	% of energy intake /capita^2/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from overexposure, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Overconsumption in the national population.

Cost category	Impact quantity	Unit	Type	Marginal cost	Examples of activities
Dietary patterns (consumption of animal whole foods)	Diet high in red meat	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from overexposure, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Overconsumption in the national population.
Dietary patterns (low in essential nutrients)	Diet low in calcium	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in plant whole foods)	Diet low in fruits	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in plant whole foods)	Diet low in vegetables	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in plant whole foods)	Diet low in whole grains	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in plant whole foods)	Diet low in legumes	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in plant whole foods)	Diet low in nuts and seeds	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in beneficial fatty acids)	Diet low in polyunsaturated fatty acids	% of energy intake /capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in beneficial fatty acids)	Diet low in seafood omega-3 fatty acids	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (consumption of animal whole foods)	Diet low in milk	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.
Dietary patterns (low in essential nutrients)	Diet low in fibre	g/capita²/day	Dietary risk internality	Productivity losses (in NPV in 2020) in the country of consumption due to the burden of disease from, predominantly, cardiovascular disease, neoplasms, and type-2 diabetes	Underconsumption in the national population.

Notes: CO_2 = carbon dioxide; CH_4 = methane; DALYs = disability-adjusted life years; N = nitrogen; N_2O = nitrous oxide; NH_3 = ammonia; NO_x = nitrogen oxides; NO_3- = nitrate; NPV = net present value; PPP = purchasing power parity. Marginal costs of diet low in essential nutrients (calcium and fibre) are not compatible with diet low in food-group based estimates.

1. Use and Scope

The purpose of the SPIQ-FS FOODCoST SSP dataset is to facilitate estimates of

- economic risks arising from food system activities and
- the economic potential of transforming EU and global food systems

by providing a pre-generated set of costs per unit for co-products of food production and food consumption such as greenhouse gas emissions and blue water withdrawal. Such co-products are referred to as impact quantities. The impact quantities and units within the scope of the dataset are listed in Table 1. Section 3 describes studies of economic risk and potential using previous versions of the dataset.

Methodologically, the objective of the dataset is to provide estimates based on cost-modelling that

- are consistent in estimating the loss of value from natural and human capital impacts, the future period of impacts and discounting, and the econometric metric.
    - There are common modules for discount rates, ecosystems services and labour productivity losses that are used across the cost models for future impacts on natural capital and human capital.
    - Impacts of GHG emission, water withdrawal, land-clearing and N losses etc. occur over different time frames from a present activity. The time frames and impact level are estimated as part of the modelling, as well as changes in vulnerability of economies over time. Future costs are discounted to present (in 2020) purchasing power loss to be comparable.
    - The economic measure is gross purchasing power.
- captures uncertainty about the pathway of exposure, vulnerability, and costs (impact pathway) and the future.
    - Errors in models, in the form of residuals or statistical methods like Bayesian regression, are transmitted along the impact pathway.
    - Probability distributions capture the shape of the uncertainty to assess risk.
    - Macro-economic parameters can adjust cost estimates under future conditions such as the Shared Socioeconomic Pathways (SSPs).

The dataset is generated by a set of linked cost models called the Shadow Prices of Impact Quantities – Food System (SPIQ-FS) model developed by the Environmental Change Institute at the University of Oxford. Without modelling, it is difficult to obtain the same consistency in economic scope, discounting, and natural and human capital costs by collecting literature cost estimates across the impact areas (GHG emission, water withdrawal, habitat loss, N losses, dietary risks). Consistency and uncertainty representation are the emphasis of SPIQ-FS. Many model components in SPIQ-FS such as the transmission of nitrogen loadings in waterways from nitrogen losses are derived from existing process-based models or simpler regressions. Section 2 describes the basis for the economic and statistical cost modelling. For the full specification of formulas and statistical methods the user needs to consult the SPIQ-FS documentation.

The dataset estimates the 2020 present value of future loss of purchasing power from per unit emission, abstraction, habitat loss, consumption, etc. for 27 impact quantities in the period 2020 to 2050 (5-year timesteps) under the widely used Shared Socioeconomic Pathways (5 SSPs) for 153 countries. It covers what are regarded as the largest global environmental external costs of food system production and dietary risk factors. The countries included cover over 95% of global food production and consumption.

Omission of additional environmental external costs and social cost factors from distributional failures such as low agricultural wages are discussed in Section 1.8. However, we clarify two omissions that may appear notable.

Agricultural sources of externally caused biodiversity losses in the present and future are predominantly covered within future climate change (the impact pathway for costing of GHG emissions), trophic disruption from excess reactive nitrogen loading to the environment (within the impact pathway for N losses), loss of environmental flows from future water scarcity, and loss of established ecosystems under land-use changes such as deforestation (within the impact pathway of land-use changes). Adding off-site biodiversity impacts from agricultural activities as a distinct quantity would overlap with the impact pathways of the existing impact quantities and lead to double-counting costs of co-products. Potential for improving coverage of biodiversity loss is discussed in Section 1.8.

In the dataset, the labour productivity loss from change in exposures to most dietary risks to population health are measured from 1 gram (per capita per day) deviation in population exposure. The estimation is based on publicly available risk factors and data from the Global Burden of Disease study (GBD). GBD diet exposure variables are scaled to average energy intake. Excess energy intake and the consequences of obesity are not explicitly costed by the dataset. The complication in including exposure to excess consumption of sugar and saturated fat as risk factors for high body mass index, and subsequent disease burden and productivity costs of obesity, is discussed in Section 1.8.

In practical terms the dataset is simple to use. Per unit costs from the FOODCoST SSPs dataset are multiplied by units of an impact quantity to estimate the total loss of future gross product in present purchasing power. The user provides the amounts of the impact quantities. Section 1.6 derives the multiplication formula for approximating total loss over annual timeframes.

The real use of the dataset lies in interpreting the totals and understanding what has been calculated.

1.1 Cost to who, of what, and when

1.1.1 Cost of what

Co-products

Co-products of food system activities included in the dataset are

- greenhouse gas emissions (GHG) including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) in metric tonnes of the respective gases [1, 2]
- blue water withdrawals from activities such as irrigation in cubic meters [3-5]
- effective hectares of lost and returning habitat from land-use change [6-8]
- reactive nitrogen losses to the environment of ammonia (NH_3), nitrogen oxides (NO_x), and nitrate (NO_3^-) from livestock production and processing and application of fertilizers in N-kg [9-12]
- the burden of disease due to exposure to dietary risks [13, 14].

The co-products, also called impact quantities in this document, are associated with future economic costs and market failures [15-22]. The first four co-products are termed environmental externalities. Not because the impact on a future economy comes from damages only to natural capital, but because the impact pathway (described below) originates from biophysical interactions in the environment and spreads through the environmental pathways including air and water. The four environmental co-products cover much of the environmental damage and planetary risk from food system activities indicated by frameworks such as the planetary boundaries [23-25].

Section 1.8 discusses the omission of other significant co-products such as pesticide residues.

The environmental co-products are costed as additional quantities produced within an annual timeframe. Section 1.6 provides more detail. The additional quantities are added to stocks in the environment that are the predominant drivers of exposure and harm to natural and human capital. Stocks are a combination of cumulative additions and subtractions. For example, subtractions include breakdown and therefore removal of most of the radiative forcing create by the additional CH_4 by the hydroxyl radical, the denitrification of reactive nitrogen, and the recharge of blue water sources. For reactive nitrogen (N) losses, the unit is the mass of nitrogen in the losses in the reactive species, known as N-kg. GHG emissions should not be converted to CO_2-equivalents.

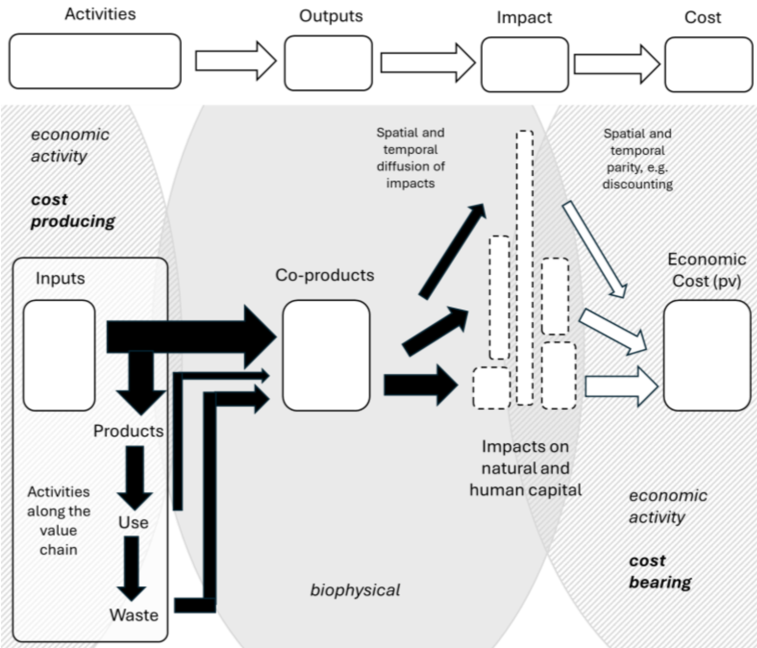
The unit for the cost of population exposure to dietary risks is g/cap^2/day or % energy/cap^2/day. This should be interpreted as the annual per capita cost of an increase in exposure (dietary intake in the population) measured in g/cap/day or % energy/cap/day. The exposure is not additional in the sense of 1g/cap/day is added to population diets for just for one year, like the environmental co-products. The cost is calculated as the additional annual cost under the assumption that the constant population exposure that led to annual incident rates is increased (or reduced) by 1g/cap/day. More simply, the annual cost per capita from everyone in the population changing their diets by the additional amount. The costs of dietary risks are calculated as partial derivatives, so 1g/cap/day increase in diets low in fruits, for examples, means that underexposure to fruit intake is reduced by 1g/cap/day across the population but all other exposure variables remain at current intake levels.

Impact pathways

Within the "what" of the costs is also the "how". How a co-product like a greenhouse gas emission turns into future economic damages is called an impact pathway [26, 27]. At the level of economic actors, the impact pathway is also the connection between the cost-producer and the cost-bearers at the end. Cost bearing, cost producing, and benefit receiving for co-products is discussed in [28]. The cost producer is the economic actor, or actors, associated to the food system activities that generate the co-products. Cost-producing, cost bearing and benefit receiving can cross national borders and time. The example of international and intergenerational cost-bearing from the production of GHG emissions is an example of spatiotemporal separation between cost producer and cost bearer [29-34]. The flow of returns to financial investors in fossil fuel energy [35], GHG intensive livestock production [36, 37], and construction [38], where the financial industry itself has low GHG emissions, are examples of the separation between cost production and benefit receiver.

Cost models are developed around the impact pathway, primarily the exposure and vulnerability of present and future human and natural capital to the co-products and its biophysical consequences, and then the exposure and vulnerability of a national economy to change in human and natural capital [39, 40](Figure 1). This is analogous to the approach described in FOODCoST Deliverable 1.1, with different terminology in Deliverable 1.1 based on life cycle analysis concepts of inventory, midpoints, and endpoints [41]. For public health, dose-response models follow the same principle with human physiology within the biophysical pathways. Inclusions and notable omissions of effects in the pathway describe the scope of costing for the individual co-products. The impact pathway details for the FOODCoST SSPs dataset and subsequent calculations are described in the SPIQ-FS model documentation [42-47]. Updates and a general description of the pathways are provided in Section 2.

Figure 1: Conceptualization of impact pathways linking cost production to cost bearing



Notes: Impact pathways for co-products in the FOODCoST SSPs dataset have the same abstract configuration. They originate in food production or consumption, through biophysical pathways, different for each co-product, natural and human capital become exposed to impacts. The exposure is dispersed through time and space by the complex processes in each. Those impacts re-emerge into economies of the future through dependency of the economy on human and natural capital. To obtain a measure of the aggregate cost produced by the co-products the future costs have to be commensurable across time and space. The FOODCoST SSPs dataset used purchasing power parity to compare economic impacts across nations, and social discount rates to compare economic impacts across time.

Source: Author's elaboration

The impact pathway should also conceptually map from cost-producer to benefit receiver, but this requires a dedicated dataset of financial flows. In food value chains agricultural production is often the polluter but not the majority benefit receiver of the pollution.

1.1.2 Cost to who

Impacts on natural and human capital from co-products can result in multiple cost-bearers in future economies and multiple forms of cost-bearing. Some economic impacts from natural capital changes can already be captured in current economic models or observations, such as water inputs or temperature sensitivity of crop production.

Others, such as broader economic effects from loss of ecosystem services are less captured in current economic models and more uncertain. Individuals bear costs such as loss of farm income, reduced income from air pollution from PM2.5 exposure, paying for pumps and additional electricity to draw water from a lowering water table, treatment costs for cardiovascular disease accelerated by poor diets, etc.

The FOODCoST SSPs dataset estimates, up to limitations and caveats in the modelling, the national loss of gross purchasing power not individual loss. Therefore, the cost is the total loss of future gross product in purchasing power terms measured in present purchasing power in 2020 (2020 PPP).

The per unit costs to the impact quantities in Table 1 are reported in the dataset in 2020 PPP, which is the present value of losses in 2020 international dollars [48, 49]. Conversion of national currencies to international dollars is known as purchasing power parity. Exchange of a loss of purchasing power is not an exchange of currency. Even though purchasing power is standardised to the equivalent goods in the US purchased by US dollars, purchasing power parity should not be confused with converting to US dollars by currency exchange. The IMF and the World Bank publish conversion factors between purchasing power of national currencies and their exchange rates. 2020 PPP should also not be confused with measuring the cost of an emission in, say, 2050 by fixed 2020 international dollars. The economies of 2050 under all SSPs experience growth in real purchasing power. The term present purchasing power refers to present value. 2020 PPP indicates that the cost of a co-product generated by an activity in 2050 in fixed 2020 international dollars is discounted to present value in 2020 using a social discount rate based on the growth in real purchasing power. As with the standard notion of present value, the cost (that is, purchasing loss) in the future is made comparable to a purchasing loss borne in 2020. 2020 PPP is an economic measure which allows comparison of costs in economies separated in space and time – and allows the losses dispersed into the future to be integrated to the per unit cost.

Productivity losses to gross purchasing power are still welfare estimates in the basic sense of goods and services purchased, or the capacity to do so through savings, provides welfare. However, they are very different estimates to willingness to pay. See Chapter 6 in [50] for a summary of valuation methods. Damage costing assumes the impacts from co-products will become severe enough to demonstrably impact the economic activity. This is very different from how much purchasing power a current generation is willing to trade for what they conceive are the impacts of current pollution. Similarly, using total purchasing power loss from future labour productivity impacts across the population and its public health is very different to Value of a Statistical Life (VSL) [51-53], which is based on an individual assessment of current willingness to pay to avoid risk of death. Social welfare functions and utility estimates form a complementary analysis to 'expenditure' for governments to consider. Both 'hidden cost' (impacts are observed and realised in the economy of the future) and a 'social welfare' (impacts effect utility of based on current generation of individual willingness to trade purchasing power for non-market health and environmental goods) have been conducted in studies mentioned in Section 3 below.

1.1.3 Cost when

The cost-bearing of co-products generated in a current year is dispersed by biophysical processes into the future. For GHG emissions, a metric ton of CO2 emitted now can add to radiative forcing in the atmosphere for over a century. The increased temperature and change in climate and weather patterns can affect labour and agricultural production, reducing output from what it would have been without radiative forcing. This is the modelling basis for the estimation of warming potential and the so-called social costs of GHG [54-58]. For blue water withdrawal, the accumulated deficit between abstraction for economic use and natural recharge results in future water scarcity [3-5]. Future economic uses face reduced availability of water for economic output due to the non-renewable component of current abstraction. Some agricultural regions in northwest India and

Pakistan already face limitation in water for agricultural use, where other regions of the world currently have economic use below available flows, but the current surplus is diminishing at an observable rate.

Across the impact pathways of the co-products the costs are not occurring, or not concentrating, at the same time in the future. The per unit costs have different sensitivity to parity components such as the discount rate. This is mentioned again in Section 2. Here we note some contrasts between the impact pathways and hence co-products to illustrate when of costs in the calculations behind the dataset.

Greenhouse gas emissions and reactive nitrogen losses

Average residence time in the atmosphere carbon dioxide is over a century. During that long residence it adds to an excess of radiative forcing in the atmosphere. The attributable economic impacts of this forcing are spread over this long-time frame of exposure, and the assumptions discount rate to calculate the present value of the impacts create large uncertainty about the damage costs per metric ton of CO2 emitted.

In contrast, for reactive nitrogen the exposure times are short, and the cumulative effect is one of flux not stock. For example, nitrate losses from cropland and pasture add to reactive nitrogen loading in ecosystems in downstream waterways. If, in the next few years, repeated nitrate loading was eliminated, the ecosystem would most likely recover the loss of ecosystem services from ecosystem degradation due to acidification and trophic impacts, including eutrophication. The cumulative damage to the ecosystem is from repeated loading. The longest lasting stock and the greatest time delay for nitrate is due to its accumulation in the vadose zone [159]. Discounting the ecosystem service losses over a few-year attribution of impacts to exposure is not a major uncertainty to nitrate costs, what is highly uncertain is the vulnerability of economies to ecosystem services (ecosystem service values), and the lack of scientific knowledge of productivity functions between nitrate loading and ecosystem output.

Land use change and blue water withdrawal

The contrast between land-use change versus water withdrawal is delay of exposure due to renewal rates. Both the forest or other natural land hectare and the blue water body act as natural resources and natural capital assets. Economies receive a stream of goods and services from the assets. When an establish habitat is removed by land clearing, most of the value flow of the original goods and services is gone. Future economies are exposed to the lost stream of services from the act of clearing and the present value is calculated by discounting the lost stream. Natural renewal rates, if renewal is allowed at all with the new land-use, act slowly and do not contribute much to diminishing the lost stream of services. Land-use change costing becomes highly uncertain to discounting, the structure of future economies and their vulnerability to the lost stream of services, and the uncertainty in ecosystem services. The per unit land-use change costings have the highest uncertainty in the FOODCoST SSPS dataset.

In contrast, for water, the economy will not be exposed until the non-renewable component of current water abstraction contributes to water deprivation from economic use. Recharge of the water bodies through precipitation acts to delay or mitigate the services that may be lost through reduction of the water body relative to economic use. Exposure is delayed until future water scarcity. At the point of scarcity, then the resource is diminished and there is a future stream of losses from a reduced asset. But that asset stream is displaced into the future, so it is more heavily discounted than the immediate exposure to loss of ecosystem services from habitat destruction. Variation among nations in future water scarcity is a more significant source of uncertainty for water costing than the discount rate.

1.2 Irreducible uncertainty in future liability of food system activities

The FOODCoST SSPs dataset views the present purchasing power loss of the future economic impacts due to GHG emissions, water withdrawal, habitat loss, N losses and dietary risks as inherently uncertain. It takes the position that it is more efficient to accept the uncertainty and potentially price it in, in practice and in theory, rather than to treat the eventual costs of complex externalities that impact natural and human capital like market transactions. In market transactions, centralisation from frequent transactions "discovers" prices and reduces uncertainty about market costs.

Damage costs depend upon future factors which are unknowable in the present. As an example, the radiative forcing produced during the rest of this century by CO2 emitted today depends upon the overall stock of CO2 in the atmosphere over time. What the emissions trajectory will be can be assumed in scenarios or hazarded as a probability amongst all other future emissions trajectory, but it is not certain.

One way to describe this using an analogous idea in physics is the present value of future damages are like a “Schrodinger’s cost”. They are not revealed until the future unfolds. Presently, depending on a future like the Shared Socioeconomic Pathway (SSP) 1, or SSP3, today’s CO2 emission could cost up to twice as much in present purchasing power terms. The current accounting item which represents the future liabilities of current activities is in a state of multiple values.

All future returns or losses are uncertain, for financial liabilities as well as those produced by complex environmental and human physiological pathways. Conceptually, it is the degree of uncertainty in externalities and dietary risks which may be different rather than the presentation and principle, and that the uncertainty is not easily reduced by available knowledge.

The FOODCoST SSPs dataset per unit costs are damage costs. Damage to future gross purchasing power. They should be distinguished from pricing. Pricing includes pricing in the risk of what the uncertain damages may be. Instruments offering payments to avoid costs or imposing fiscal penalties for producing costs are pricing. Prices imposed or agreed to can reduce an uncertain cost to a number, but there is no guarantee that the prices set or discovered will be the eventual costs. Damages remain uncertain even if prices are determined. Informing prices that can include risk premiums is one of the reasons for representing per unit costs as random variables in the SPIQ-FS model and the FOODCoST SSPs dataset.

1.2.1 Random variables and generating samples

Per unit costs are treated as random variables due to the irreducible uncertainty in the future liability of co-products. Random variables can be thought of as an uncertain number [59]. The distribution of a random variable represents the chances that a random variable will be a certain number. The minimum to maximum values of the distribution represents the range of possible values that the random variable can take. The shape of the distribution expresses the different chances of the values that the random variable can take within its range.

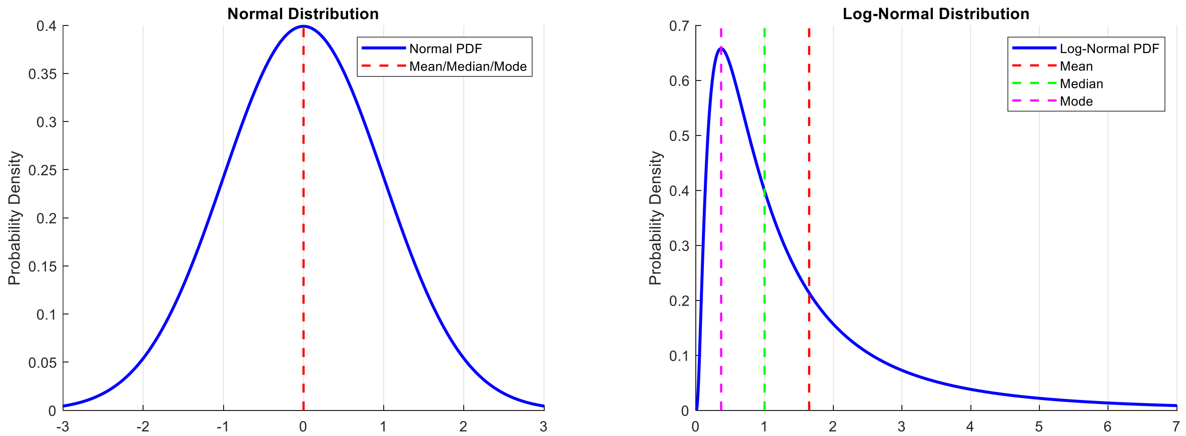
A random variable is “sampled” by taking random draws according to its distribution. The samples represent possible values that the random variable may take.

Parametric form

The parametric form of the distributions of the costs per unit given in the dataset provide a log-normal approximation of the distribution of the per unit costs [60]. Log-normal distributions are expressed by two parameters Mu and Sigma, which define a normal distribution with mean Mu and standard deviation Sigma. Exponentiating the normal distribution defines the log-normal distribution (Figure 2). Mu and Sigma are not the mean nor the standard deviation respectively of the log-normal distribution.

A log-normal random variable can be sampled by exponentiating samples of the corresponding normal random variable.

Figure 2. A random variable X is log-normally distributed if $X = e^{\mathrm{Mu}+\mathrm{Sigma}\cdot Z}$ for a real number Mu, a positive number Sigma>0, and Z is a random variable that has normal distribution N(0,1) with mean Mu=0 and standard deviation Sigma=1 (left panel). Right panel shows the distribution of the random variable $X = e^{Z}$. Log-normal distributions are right skewed and the mean, median and mode are not the same. Distributions of random variables are also called probability density functions (PDF).



The documentation on the cost models of SPIQ-FS indicates why many of the costs estimated fit a log-normal shape reasonably well. A broad conceptual reason for this may be that in long environmental impact pathways the sequential randomness of processes (products) dominates over the randomness in parallel additive components (sums). Like sums of random variables tends towards a normal shape, products of random variables tend toward a log-normal shape. Not all the per unit costs fit log-normal shapes. The other reason to use the log-normal parametric form is pragmatism and the principle that it is better to include an approximate uncertainty to per unit costs than not to include uncertainty at all, given the irreducible nature of uncertainty in costing mentioned above. Under this principle the simplest form that most users may have knowledge of is normal distributions.

- Most spreadsheet programs, including Microsoft Excel, have cell functions that sample normal distributions. This makes it easy in a spreadsheet to generate samples for the parametric form of the per unit costs and more likely users of the dataset will incorporate uncertainty.
- Joint log-normal distributions (per unit costs that are correlated) can be generated explicitly and easily by a user. There is a unique mapping between a multivariant normal distribution with parameters MU and SIGMA (SIGMA embodies a correlation structure) and a joint log-normal distribution. A user can generate joint samples in a program like Excel and exponentiate them to explore correlations in the per unit costs.

Trade-offs to the ease of calculation of log-normal samples include outliers. A rare value sampled in the right tail of a normal distribution can be an extremely large sample of the log-normal distribution. Such rare samples can bias the mean of the samples of the log-normal distribution towards a higher estimate, and they may represent implausible cost values. The pragmatism of using log-normal distributions should be balanced by users assessing plausibility of outliers.

Non-parametric form

For users to explore uncertainty in the cost estimates, a version of the dataset can be downloaded that contains 1000 samples of the per unit costs. These samples are generated and carried through the cost models directly from components such as the empirical distributions of residuals in historical fits. The samples are ordered in the dataset file so that they represent 1000 joint samples of the per unit costs with embedded correlations. Section 2.4 refers to the method of joint sampling.

1.3 Externalities and internalities

What is the origin of the terminology for the per unit costs in the FOODCoST SSPs dataset?

Section 1.1 describes the cost to whom, to what and when in terms of an impact pathway. Cost producers of, and benefit-receivers from, the co-products of food system activities such as GHG emissions, N losses, food consumption, etc. receive a benefit. The cost-bearers at the end of the impact pathway bear the costs of the co-products. Without any compensation paid by benefit receivers to cost-bearers, or additional costs of production to reduce the co-products, benefit receivers are not paying the full costs of production from which they receive benefits from. The part of the cost borne by cost bearing of co-products is called an external cost. The aspect of production that generates external costs is called an externality. Attempts to pay compensation or to increase costs of production to reduce co-products that generate external costs are called internalization.

The definition of externalities and internalization for the FOODCoST project can be found in Deliverable 1.1 of the project. There are many discussions of externalities in economic texts [61, 62]. A boundary is implied in an externality, it is external with respect to a set of economic actors involved in production that generates co-products.

Externalities are one type of market failure that could lead to lower total purchasing power for a future economy due to cost-bearing from current activities. Other market failures in the context of agrifood systems and costs to the future that are not accounted for in present economic metrics are discussed in Chapter 1 of [63]. From imperfect information or other failure, an actor or a group of beneficiaries can produce costs upon their future self that they have not fully considered. This is not called an externality but is commonly called an internality.

The purchasing power losses produced by GHG emissions, water scarcity from non-renewable water abstraction, N losses to the environment, and habitat loss due to agricultural clearing, are considered external costs in the FOODCoST SSPs dataset. The environmental externalities also have their own internality components. The use of fossil fuels by agricultural producers is potentially changing temperature and precipitation as inputs to their own future agricultural production. Non-renewable components of water abstraction for irrigation are shrinking the future capacity for economic output in the same catchment as the irrigated farm. Externalities borne by economic sectors, or the natural and human capital, on which the food sector depends become internalities. The Natural Capital Protocol discusses internalities (called by the Protocol dependencies) of businesses for natural capital with food sector examples [39].

However, the size of the external cost of the environmental externalities tends to exceed internalities. There is a large global disparity between who receives the benefits of the production, processing, and retail in the global food sector, and who pays the costs. Climate change and biodiversity loss [32, 34, 64], health burdens [65, 66], and scarcity of resources [67, 68], are among the impacts disproportionately effecting marginalised and poorer groups. The same groups have less power to affect market correction due to corruption and proportionately lower representation, ownership, and share of profits [69, 70]. Nitrogen loads are borne downstream or downwind, often far from the origin of the pollution. GHG emissions are dispersed globally and the locations where most GHGs are utilised in intensive production are not the same as locations that will bear most of the impacts of climate change. For each of the environmental externalities considered in the FoodCOST dataset there is significant dispersion through complex biophysical processes. The dispersion occurs across time, and the main costs only accumulate at the societal level. For example, the cost of the carbon emissions or the nitrogen leached from one farm to produce a bushel of corn is not observed until combined with other farms and other food sector activities. The dispersion through the environmental pathways not only creates physical and temporal distance between cost producers and cost bearers, but also jurisdictional distance. Air pollution crosses national boundaries, water pollution (from nitrogen loading and lost ecosystem services like water filtration or erosion prevention from land clearing) and water scarcity cross borders in major river systems. Jurisdictions add additional boundaries that prevent costs being reflected from cost-bearers back onto the cost producers.

Exposure to dietary risks through food consumption results in cumulative health effects to the consumer in years after consumption. Dietary risks can have external cost components. In a public health care system, treatment costs for disease burden are spread across taxpayers disproportionately to disease burden. In a private system insurance performs the same dispersion of cost. Whether this is imperfect information or institutional failure, disease burden from dietary risks is a failure of a different nature than environmental externalities. Payers of insurance premiums and taxpayers are receiving some private compensation of the cost-bearing for their private risk reduction. The main consideration for the FOODCoST SSPs dataset for the costs of dietary risks is consistency with the externalities which cost present value of gross purchasing power loss. For dietary risks, it is the loss of labour to the household from health effects, at a societal level the lost labour productivity in purchasing power terms, which is the main loss that aggregates to lost gross purchasing power. Payments for treatment costs are transactions within the economy and would generally cancel out in gross purchasing power.

For the sake of classification, and first order consideration of policy or behavioural changes because of the main type of failure, the term environmental externalities are used for co-products that have an environmental pathway to natural and human capital impacts. The term dietary risk internality is used where the major impact on gross purchasing power is on future labour consequences to the individual or their household from their own exposure to dietary risks through consumption.

1.4 Does the calculation of external costs and productivity loss from unhealthy diets mean the food system is broken or not providing value?

The activities and outcomes of the global food system contribute 30% of annual anthropogenic CO_2-equivalent emissions [71], including over 50% of CH_4 and N_2O emissions [72], use 70% of blue water withdrawals [73], and are responsible for over 50% of nitrogen and phosphorous losses [74] and habitat loss [75, 76]. Dietary risks exceed tobacco and alcohol combined in terms of preventable disease burden [13]. Using per unit costs like the FOODCoST SSPs dataset and global datasets of emissions, land-use change, etc., the global losses to purchasing power produced by annual external costs and dietary risk internalities are comparable to the global gross value added from agricultural production, food manufacturing, and retail. This rough equivalence has been observed in several studies, from studies of the food business sector to national accounting. See Section 3.2.1 for estimates from the FAO State of Food and Agriculture 2023 and 2024.

As the dominant global primary industry utilising natural capital, providing a highly perishable good which is a daily necessity for the provision of the human capital stock of a population of billions, agriculture and food processing and retail should be expected to produce large environmental and health liabilities. The State of Food and Agriculture 2023 starts by acknowledging the enormous benefits for labour and economic development of low-cost provision of food. However, the large external and internal costs raise concern on narratives about the value of agrifood systems, and, understandably, raises the question of who would pay the costs to reduce and avoid future liabilities from the co-products of agrifood system activities.

The FOODCoST SSP dataset provides per unit costs of future liabilities for the purpose of understanding how to increase the value provided by food systems to purchasing power of present and future persons, not what is the value of food systems per se. The dataset does not indicate responsibility for external costs. If co-products can be avoided, then estimates of the economic benefits of avoided co-products (reduction of damage costs in the terminology of the next Section) compared to the costs of avoiding them (abatement costs in the next Section) increase the overall value provided by food systems.

The use of per unit costs for environmental externalities and dietary risks does not suppose that the damages are avoidable at an abatement cost below the level of damages. That is for studies, and repeated studies, to examine. The dataset is information to enable those studies. It could be that food system transformation is uneconomic, and that the other sectors of the economy must bear the future costs of the agricultural sector for the provision of nutrition to labour. Or that human preferences cannot change, and that the welfare of enjoyment from consumption and current diets are already optimally balanced against future health. Given the evidence of food system impacts this is unlikely, but it is a question for investigation. It is for economic studies to rule against the economic optimality of current food systems and their current trends.

Every commentator on food systems would agree that, at some point, utilisation and degradation of all natural and human resources leads to economic collapse. The two extremes of ecosystem collapse wiping out all purchasing power and a fairy tale of lush green farms producing wholesome food without cumulative environmental costs or dietary risks are where the marginal costs of co-products dominate the marginal value of production or the marginal value of production dominates the marginal costs of the co-products, respectively. The real question at hand for economics then, and the real debate, is the position of marginal costs and their rate of change between these extremes, the irreversibility of damage, and the balance with risks between economic development and ecological and human capacity. At what point do the costs of production need to be balanced with the costs of co-products? That can only be examined by costing the co-products, which is what the FOODCoST SSPs dataset does, and challenging the estimates and refining them over time.

After the State of Food and Agriculture 2023 and 2024, multiple countries are testing the validity of damage costs for food system activities at national scale. The FOODCoST SSPs dataset is provided in the spirit of an intermediate product with many limitations mentioned below, notwithstanding the looming limitation of irresolvable uncertainty, and is provided as a step toward developing economic models that acknowledge the cost of co-products. The approach of the SPIQ-FS model is to acknowledge the very broad uncertainty in estimates, a component of which is irreducible, and to encode uncertainty in the approach to these estimates which further models can refine. It contributes to the economic and scientific development of modelling tools that can inform the goal of countries in the EU and globally to balance priorities and seek to increase the welfare of their citizens.

As a final general point on the interpretation of damage costs calculated in studies, there is concern who should pay to reduce the external costs or dietary risks. The high proportion of benefits to manufacturers and retailers, their investors, and society through the provision of nutrition to labour, means that beneficiaries of the pollution are spread across the whole economy at their own aggregate future expense. Targeting farmers with the cost of externalities because they are the main polluters may be inefficient generally and likely to prove politically untenable. The principle of polluter pays is more correctly described as the beneficiaries of the pollution pay. Farmers are not the main beneficiaries of the pollution and generally have neither the market power nor the capital reserves to pass pollution costs, or the abatement costs to avoid them, along the value chain in proportion to benefit receiving in the chain. All labour and production in the economy benefits through nutrition, providing a basis for broad taxation or general revenue to address the economic risks and economic potential from food systems. For reasons explored in Deliverable 1.3, and in Work Packages 2 and 3 of the FOODCoST project, internalization of damages does not always lead to efficient or effective reduction in external costs without removing barriers and careful design.

1.5 How does the dataset contribute to economic studies?

The dataset is designed for macro-economic studies of economic risk from current food system activities, or the economic potential in national, regional, or global food system transformation. The primary purpose is macro-economic counterfactual studies. Section 3.2 studies give examples of use in both counterfactual and risk studies.

Most of the studies conducted using prior versions of the FOODCoST SSP dataset are global macro-economic studies, including counterfactual trade studies of removal of global agricultural border measures, regional packages of food transformation policies within the Food System Economic Commission compared to current trends, global dietary change compared to current diets, and national studies of sustainable food system pathways in the UK. Most of the studies were counterfactual and paired the SPIQ-FS model with a computable general equilibrium or partial equilibrium agro-economic model. The per unit costs can be used for business financial reporting and for large product portfolios, but we note below the caveats to these use cases given the scope of the FOODCoST SSPs dataset.

1.5.1 Economic potential of food system transformation – counterfactual studies

Counterfactual studies compare two or more scenarios for difference in economic outcomes [77]. The scenario may be a what if about a single year – what if agricultural subsidies in the form of direct farmer support and border measures were removed globally, how would the modelled equilibrium economy of 2020 compare to current subsidy settings?

The FOODCoST SSPs dataset contains costs from 2020 to 2050 so it can be used for counterfactual studies under future scenarios [78]. There is usually a baseline scenario based upon projecting current trends, the factual, and then alternative scenarios starting in 2020 and diverge from the baseline over 3 decades. An economic model tracks the differences in the production of impact quantity, and other macro-economic variables, between the two scenarios. For compatibility with SSPs the long-term scenarios need to be matched, which is discussed further in Section 2.3. Matching is a limitation of a pre-generated dataset. To fully customise per unit costs to scenarios requires using the SPIQ-FS model. By pairing the FOODCoST SSPs dataset per unit costs with the impact quantity trajectories, the difference in the present value of the future liabilities generated by the food system activities under the scenarios can be compared. See the study in Section 3.2.2.

Counterfactuals studies may or may not be full cost benefit studies, so care is needed with interpretation. The comparison of impact quantities and the purpose of the FOODCoST dataset is to show the change in the future liability. This is information about the counterfactual trajectory, a benefit component if alternative futures for regional or global food systems reduce impact quantities. If some externalities reduce but others or dietary risks increase, then Section 1.7.1 discusses trade-off and substitution.

For a full cost benefit then the abatement costs need to be considered alongside the change in impact quantities, see Chapter 6 in [40] or Deliverable 1.1 of the FOODCoST project. The FOODCoST SSPs dataset is a dataset of damage costs [79]. It does not contain abatement costs. Abatement costs should be considered the costs to avoid the damage costs [80, 81], that is the full costs incurred in the transition for the baseline to an alternative scenario. Those costs broadly have two components, and the second is often ignored or assumed to be zero

- The costs to purchasing power to reduce the impact quantities in the alternative, which may be abatement costs and technologies for GHG emission, mitigation measures from farm N losses, water saving technology or crops, education or public procurement policies to lower exposure to dietary risks, payments for ecosystem services to reduce land clearing for agriculture, etc.
- The costs to production and consumption outside of reducing impact quantities, which may involve changes in labour or changes in sectorial output.

Comparison of abatement cost to damage cost in the FOODCoST SSPs dataset needs to be change in gross purchasing power to be comparable. Note that the market cost of a technology is not directly the contribution to gross purchasing power. Normally, market costs of abatement measures or potential policies will be inserted into the agro-economic model to calculate the two components required in output terms. See the study in Section 3.2.2.

With damage cost compared to abatement cost, then the social surplus of the alternative scenario compared to the baseline scenario can be calculated. Keeping cost estimates aligned between damage cost (costs of inaction) or abatement cost (costs of actions) can be a challenge when there is a paucity of economic data available. The uncertainties between damage costing and abatement costing are of a very different nature [82, 83], but this does not imply that abatement costing is more certain [84]. One of the main uncertainties in abatement costs is whether the spending achieves the behaviour or outcome as expected [85, 86].

Because of the complexity of abatement costing, most counterfactual studies are reporting the benefit component from the change of impact quantities – the difference in damages, which is valuable information, but only a component of a full cost benefit analysis of the economic potential of food system transformation.

1.5.2 Economic risk of food system activities – attribution studies

An attribution study considers only the damage costs in the baseline, without a specified counterfactual or a consideration of abatement costs.

The State of Food and Agriculture 2023 outlined in Section 3.2.1 is an attribution study. It estimates the future damages from current global agrifood activities from annual production of impact quantities and per unit costs. The Food System Economic Commission study outlined in Section 3.2.2 is a cost-benefit study, with some caveats. As discussed in Section 1.4, an attribution study of damages is not indicating the damages that can be avoided by transition to alternative food systems. The global estimate for the annual future liability of current agrifood systems was around 15 trillion 2020 PPP dollars in the State of Food and Agriculture 2023 and 2024. Over three decades, the ambitious FST scenario in the Food System Economic Commission study avoids only 33% of the damages generated by the baseline scenario. In annualised terms, around 5 trillion 2020 PPP dollars.

The purpose of an attribution study is awareness, priorities and target setting. Before the State of Food and Agriculture 2023 there were few global estimates built from national data and consistent across the impacts of GHG emissions, N losses, water withdrawal and habitat loss. The scale of the economic risk from the externalities and the dietary risks of the current food system are largely unmeasured. As future liabilities they do not appear on national accounts. With information about damages then a process can start on remediations, treatments, what policy can or cannot shift, and an understanding of the costs incurred in reduction to the impacts, [63]. Standard risk governance and policy cycles are built on cycles of assessment, formulation and choices of treatment, implementation, and then monitoring and evaluation [87]. An attribution study like the State of Food and Agriculture 2023 adds to assessment stages, and cost-benefit analysis examines treatment options.

The State of Food and Agriculture 2023 national estimates raise awareness about risks to growth and development from the future liabilities of co-products of food production and consumption. One aspect to note about the marginal costs of production and of co-products like those in agrifood systems is diminishing returns [88]. As GHG emission increase, and nature diminishes, then the additional units of pollution or additional land clearing become increasingly costly. Conversely, as agriculture expands into marginal land or millions of smallholder farmers lack capital to invest in efficient production, the value of each additional unit of production related to the co-products can decrease. Eventually, this acceleration in the marginal costs of co-products, and the deceleration in the marginal value of production linked to the co-products, would lead eventually to one overtaking the other. Costs of agrifood system impacts are likely to grow faster than the general economy given lack of action, leading to decreasing capacity and thereby risk to service future liabilities.

Risk assessment can lead to other kinds of economic analysis besides cost-benefit studies. The damages (costs of inaction) can influence political targets for the damage-causing quantities such as GHG emissions and N losses. With targets, a national economic study could focus on cost-effective abatement of those quantities to the targets (costs minimization). The focus of the abatement is meeting the political target, not in the amount of social surplus that comes from transforming the food system. Political targets for the reduction of impact quantities and economically optimal targets that maximise social surplus are not necessarily the same.

1.5.3 True cost accounting in business accounts and international value chains

The 'true cost' of food has been introduced by researchers, civil society, and business groups, concerning the recognition and rectification of costs that are not reflected in corporate accounting and market transactions [89-91], including externalised environmental costs [92, 93], issues around fair wages and justice [94], and inequitable exchanges of natural and social capital [19, 95-98]. Full cost accounting, or more recently true cost accounting, has a significant history in ecological, environmental and welfare economics. The FOODCoST project Deliverables 1.1 and 1.5 provide discussion and guidance on true cost accounting incorporating externalities of food system activities. Many of the case studies in Work Package 5 of the FOODCoST project relate to true cost accounting. See also Chapter 7 in [40], and the Natural Capital Protocol Food and Beverage guide [39].

In response to pressure from civil society and investors, the corporate sector has developed multi-capital accounting to report on a company's impact on natural, social, and human capital [99, 100]. Accounting firms (e.g. KPMG [101], Deloitte, EY, PwC) and food companies, produce – or sell services to produce – reports for multi-capital accounts and estimates of their contribution to environmental externalities as part of their annual financial statements or sustainability report. Valuation of impacts is used in some accounts to demonstrate an overall financial position [40, 100, 101]. The accounting has appeared under names such as Integrated Profit and Loss (IP&L). Most examples of the reporting involve an inventory of annual impact quantities, such as GHG emission, water withdrawals, often including supply chains, and the use of per unit costs to turn the inventory into a financial amount.

For large multinational firms, whose operations span multiple countries, multiple product lines, and produce GHG emissions, N losses, water abstraction, in their supply chains from many locations and producers within countries, the FOODCoST SSPs dataset can be used in an integrated profit and loss statement with appropriate consideration of substitution between capitals [102]. Similarly, large multinational flows in value chains, such as cocoa production and trade from Ghana or coffee production and trade from Vietnam, are amenable to a true cost study using per unit costs from the FOODCoST SSPs dataset [103].

The per unit costs can be used for small firms for benchmarking against large firms or overall supply chains. Beyond this, the FOODCoST SSPs dataset per unit costs should not be used for local or site-specific studies.

Users should understand the scope of the FOODCoST dataset. The costs are not the cost-bearing to the individuals that produced the good, the coffee, etc., nor the costs to the consumer of health treatment, they are the costs to gross purchasing power of the economy in which the individuals produce or consume. Firms and government regulation should consider the difference between accounting for the forward liability for society – which is what the FOODCoST per unit costs estimate, and what that forward liability may represent for the firm.

1.6 Marginality of per unit costs

In economics, a marginal cost is understood by most users as the cost of one more unit of production additional to the current level of production.

Mathematically, this description of a marginal cost is accurate when a cost of production is a function of only a single quantity of production. The marginal cost is the partial derivative of the cost of production at the current quantity of production.

For complex costs, the cost of production can have multiple dependences and be imagined as a function of many variables. For climate change, the costs to future gross product of "producing" a GHG like carbon dioxide (CO2) depends on future trajectories of all greenhouse warming gases, and earth system parameters affecting radiative forcing and sinks. This includes atmospheric concentrations of other aerosols and exchanges between land systems, and hence land-use, and oceans. The variation of the cost can be significant for many of the underlying earth system variables and the socio-political emission trajectories. The marginal cost becomes a set of partial derivatives of this cost function of many variables at a given setting of those variables.

The SPIQ-FS macro-economic use cases described in Section 5.3 are based upon average annual cost production. Some of those quantities in a year can vary, particularly for nitrogen and some ecosystem services. Damages to agricultural production are also seasonal if not considered an annual average. For macro-economic purposes the averaging smoothens out intra-annual variances. What becomes of interest is the change in the average annual costs and per unit costs of GHG emissions, N losses, etc. with additional annual amounts of the impact quantities.

These per unit costs might not be very sensitive to the annual addition and therefore accord less with the basic economic idea of the additional cost from "one additional unit of production". For GHGs, the per units costs are most sensitive to the total stock of GHGs resident in the atmosphere over the time in which the emission contributes to radiative forcing. The stocks of CO2, for example are very large compared to the annual amounts added, and it takes several years to decades before annual additions make a substantial shift in the per unit cost by itself. Economic growth affecting the economic vulnerability to climate damages and discount rates are more sensitive variables than annual emissions. The social cost of methane (CH4) is much less sensitive to the stock of CH4 in the atmosphere than the accumulated stock of CO2. Even for reactive nitrogen losses, which annually have a large flux into the environment but also denitrification processes on short timescales, most of the change in damages occurs from accumulated nitrogen loading and changes through repeated exposure of ecosystems.

For dietary risks, there is a clearer connection between the per unit cost and its own impact quantity. Partly because the unit is defined by annual disease burden from a sustained shift in intake across the entire population. However, the exposure and vulnerability levels change over development and societal trajectories into the future.

Using existing models or by its own calculations, the SPIQ-FS model accounts for marginality in the per unit costs and current levels of stocks or exposure. As an example, if most of the population is already consuming enough calcium, then the calculated benefits in additional mg/capita/day of calcium consumption are much smaller than in a population that is not. If the population already has large exposure to sugar-sweetened beverages (SSBs), then the calculated costs of one unit of additional consumption are larger than a population which is consuming few SSBs. Dividing the current disease burden of overexposure dietary risks by the current population average intake would give an erroneous idea of the value of additions to current intake. As another example, the social cost of CO2 in 2050 under SSP1-2.4 is half the cost per unit then SSP3-7.0 in 2050. This is a combination of the reduced stock of GHG by 2050 under SSP1 versus SSP3, and poor socio-economic development under the SSP3 pathway.

Marginal costs of complex cost dependent on multiple variables can be treated as a set of partial derivatives to the cost surface, or, alternatively, as the partial derivative along a 1-dimensional curve on the cost surface. The 1-dimensional curve represents a trajectory over time, a scenario, of the variables on which the cost depends. The cost along the curve can be rebuilt from integrating against the partial derivative in the direction of the curve. When the average costs are assumed to have only small variance in annual periods, but do change over longer time frames, then the integral reduces to the simpler and more familiar multiplication formula for calculating total costs - multiply the annual amount of the impact quantity against the per unit cost. See Box 1, which is reproduced from the discussion in Annex 1 of [28].

SPIQ-FS considers the marginality of per unit costs in this sense as the partial derivative along a 1-dimensional trajectory of variables over time (a scenario).

Formula for calculation of annual costs

Damage costs from the production of the impact quantities over one year $\Delta Cost$ are calculated from marginal damage costs,

$$\Delta Cost = Cost(q(t_0)) - Cost\big(q(t_1)\big) = \int_{t_0}^{t_1} \nabla Cost(q(t), s) \cdot q'(t)\, dt$$

where

$$\nabla Cost(q, s) = \left(\dots, \frac{\partial Cost}{\partial q_i}(q, s), \dots\right) \qquad i = 1, \dots, 25$$

are the partial derivates of damage with respect to the impact quantities, and q is a trajectory $q: [t_0, t_1] \to \mathbb{R}^{25}$ of quantity from the beginning of the year t_0 to the end of the year t_1, and s is additional parameters for the calculation of cost in that year besides quantity. The parameters s may include future projections of GDP per capita, rates of renewal of nature capital, vulnerability of populations to disease, and so, and they may change for calculation of annual cost in a different year. For simplicity s over the one year is assumed constant. The trajectory q does not specify just the quantity produced in the calculation year, $q(t_0)$ can specify, as for CO2 emissions, the level of emission in previous years up to t_0 and future emission after t_1 to indicate stocks of pollutants in the environment or pre-existing burden of disease.

Impacts from the food system arise from multiple quantity changes and, *a priori*, the gradient of cost $\nabla Cost(\cdot, s) : \mathbb{R}^{25} \to \mathbb{R}^{25}$ with the marginal damage cost in NPV at some time t_0 for impact quantities at the level $q(t)$ at time t is a function on all impact quantities. As a concrete example, interactions between the nitrogen cycles, and carbon and methane cycles, and their effects on vegetation, terrestrial chemistry, and atmospheric chemistry, means that the cost from an additional unit of a GHG emission has dependence on the levels of nitrogen emissions. Additional complications for calculating the impacts of the food system are that nitrogen emissions at $t' > t$ affect the damages of CO2 and N2O emissions at time t. For simplicity, we are not incorporating temporal lag into this formula.

If the marginal damage costs in NPV at some time t_0 are approximated by the damage from additional production from some reference level of production $q^* \in q([t_0, t_1])$ (that is, they are approximately constant over the annual portion of the trajectory $q([t_0, t_1])$), then the calculation simplifies to

$$\Delta Cost = \nabla Cost(q^*, s) \cdot \big(q(t_1) - q(t_0)\big) = \sum_{i=1}^{25} \frac{\partial Cost}{\partial q_i}(q^*, s) \times \Delta q_i$$

where Δq_i is the additional production of the impact quantity i over the annual period. The validity of the simpler formulas relies on the fact that the number $\frac{\partial Cost}{\partial q_i}(q^*)$ approximates the partial derivative of the cost function in NPV at some time t_0 for an additional unit of the quantity q_i along the annual trajectory of changes $q([t_0, t_1])$. Error in the approximation transmits to error in the estimation of total costs.

The SSP context changes the estimation of average annual marginal damage cost for emissions over the period 2020-2050 as well as the calculation of annual quantities of emission and disease burden. The example was given above of the change in the marginal social cost of CO2 under SSP1-2.4 compared to SSP3-7.0, the global GHG emissions trajectory is lower, creating less radiative forcing into the future and less climate changes damages.

Analogous considerations, such as historical observation of increasing value of ecosystem services to primary industries as low to middle income countries develop and transit to upper-middle income economies, create adjustments in external costs of lost ecosystems services from land-use change and NO3- runoff to surface water and leaching to groundwater. Increasing population density and background industrial emissions of NOx and SOx precursors to air pollution changes the exposure levels of PM2.5 produced by NH3 and NO2 emissions to air for countries over the period 2020-2050. This illustrates the basic mechanics of the calculation of the difference in total costs from environmental externalities and dietary internalities between the scenarios – a combination of changes in food system impact quantities and changes in marginal costs due to development in the food system, environment conditions, and the wider economy.

1.7 Aggregation and accounting

Aggregation in the context of the FOODCoST SSPs dataset means adding up the external costs across countries or income groups, or across the individual impact quantities, or both. Because it is an extensive topic, brief remarks about assumptions in the FOODCoST SSPs dataset and use of the dataset are made here.

1.7.1 Substitution

Purchasing power parity (PPP) is a representation of the utility provided by basic goods. It was designed by the IMF and World Bank for comparing the gross domestic product (GDP) of countries. Low and lower-middle income countries have higher GDP in purchasing power terms than in exchange rate terms (https://www.worldbank.org/en/programs/icp). China is the world's largest economy and India is third in PPP terms. The losses created by externalities like nitrogen pollution for low-income countries are higher in purchasing power than they would be in exchange terms. However, high income countries still have significantly greater purchasing power even with price adjustment for basic goods.

Where this can distort a study using costs of externalities and dietary internalities is assigning priorities and trading off costs and benefits. Should human capital benefits in a higher income country of imported healthier food come at the expense of natural capital costs incurred from external costs of production in a lower income country? Even in purchasing power, naively adding the benefits and subtracting the costs across the two countries would generally exhibit an overall net benefit in favour of the high-income country.

Generally, this is a question of substitution and compensation which is studied in environmental and ecological economics [104-106].

In the FOODCoST dataset, a consideration of equity weighting beyond purchasing power is not applied [102]. The focus of the costing is on the impact in the economy where the co-product is produced. Caveats are made about transboundary effects and compensation to make this view consistent. Labour productivity loss in purchasing power parity terms is not a value of human life. It is a representation limited to the impact of the labour provided by capital in the economy where the labour is performed. In studies, relative economic impacts, that is, comparing a country's purchasing power loss from externalities with its own gross purchasing power, or a similar country's, should be examined alongside aggregation. The study in Section 3.2.1 provides an example of relative economic impacts on nations by income group, but the same principle applies to the financial accounts or supply chains of multinational companies.

1.7.2 Production and consumption accounting

At a global level, the global economy is cost producer, cost bearer and benefit receiver - a closed system. National agrifood systems are open systems for exchange of externalities. There are three main exchanges depicted in Figure 4.

- Exchange by transboundary biophysical effects
- Exchange by traded goods
- Exchange by migration

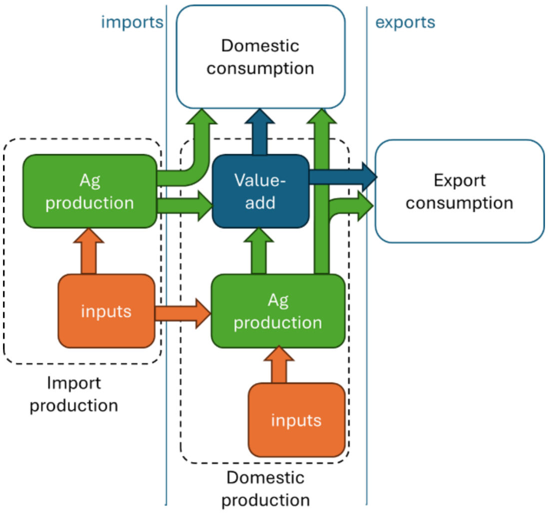
Transboundary pollution occurs when pollution that is emitted in one country is transported by air or waterways and has a biophysical impact on the natural and human capital of another country. One example is air pollution in Europe, where nitrogen and sulphur dioxides emitted from factories and cars, and ammonia from agriculture, form ammonium particulate matter and are dispersed over other neighbouring countries. The Gothenburg Protocol, adopted in 1999 under the UNECE Convention on Long-range Transboundary Air Pollution, aims to reduce air pollution and its harmful effects on human health and the environment [107]. Air can disperse pollution widely, and water can disperse pollution from upstream countries to downstream countries in large water basins. The emission of well-mixing greenhouse gases is transboundary pollution.

The cost estimation for the FOODCoST SSPs dataset does not include transboundary pollution cost adjustment as mentioned in the limitations below. Cost-bearing of climate change is assumed to be transferred to the country of emission by future damage and loss payments to cost-bearers [108]. Blue water consumption creates future water scarcity in the same country. Air pollution and deposition of volatilized N species occurs in national boundaries. Ecosystem services losses from habitat loss occur in the same country as the habitat loss. The damage costs incurred by a country because of what it contributes to global GHG emissions is the payment into a global loss and damage fund. This is different than the future damages inflicted by the total stock of GHG emissions (contributed to all by all countries) on that country.

Exchange by migration is depicted in Figure 4, which is where the productivity loss from past exposure of human capital is borne in the destination country of migration and the benefits which the exposure is co-product to accrue in the origin country. Exchange by migration is not discussed further.

The FOODCoST dataset can be used for cross-border exchanges through traded goods. For example, benefits are received to the economies of the EU from imported Brazilian beef [109]. Brazil is the cost-producer of the external costs from beef production. The future Brazilian economy is the cost-bearer of the excess nitrogen associated to beef exported for the benefits of consumption to labour in EU economies. The global economy is the cost-bearer of methane emissions and, if the beef is associated to deforestation, reduced carbon sequestration from Brazil's production. In production accounting, the external costs of the imported beef production are accounted to the nation of Brazil. In consumption accounting, the external costs are accounted to the importer in the EU. This is the same principle as production and consumption accounting for GHG emissions [110]. Production and consumption scopes are depicted in Figure 3.

Figure 3: Production and consumption scopes for accounting



Notes: Production accounting for a nation considers the externalities from domestic production that goes toward domestic and export consumption. Consumption accounting for a nation considers the externalities from import and domestic production that go toward domestic consumption. Shown in the figure are the most relevant components of production and consumption. Variants that factor in compensation and proportionality to benefits received are discussed in the text.

Source: Author's elaboration

To perform production and consumption accounting using the FOODCoST SSPs dataset, the quantities that are exported into one country and imported to another need to be tracked, and the appropriate national per unit costs from the dataset applied. The two accounting scopes are conceptualised for trade in global and bilateral national food systems. However, they can also be applied in terms of the use case of financial accounts of a multinational food company, where revenue received for final goods are treated as end products. The cradle-to-grave approach for product lines in life-cycle analysis (LCA) is also a form of consumption accounting.

1.7.3 Cost bearing formulations

This section outlines the conceptual formulation for a national study if the scope of the study is broadened from national cost bearing to the total cost-bearing for national benefit receiving. Practically, and politically, countries would only act on the largest cross-border flows of costs and benefits that risk distorting the global and national agrifood system. More studies are required in this area to understand the magnitude of cross-border externalization of costs, and which flows and impact pathways are relevant. The formulations are extracted from [111], which provides more information.

Table 2: List of symbols used in Figure 4 for simplified consideration of bilateral cost-bearing.

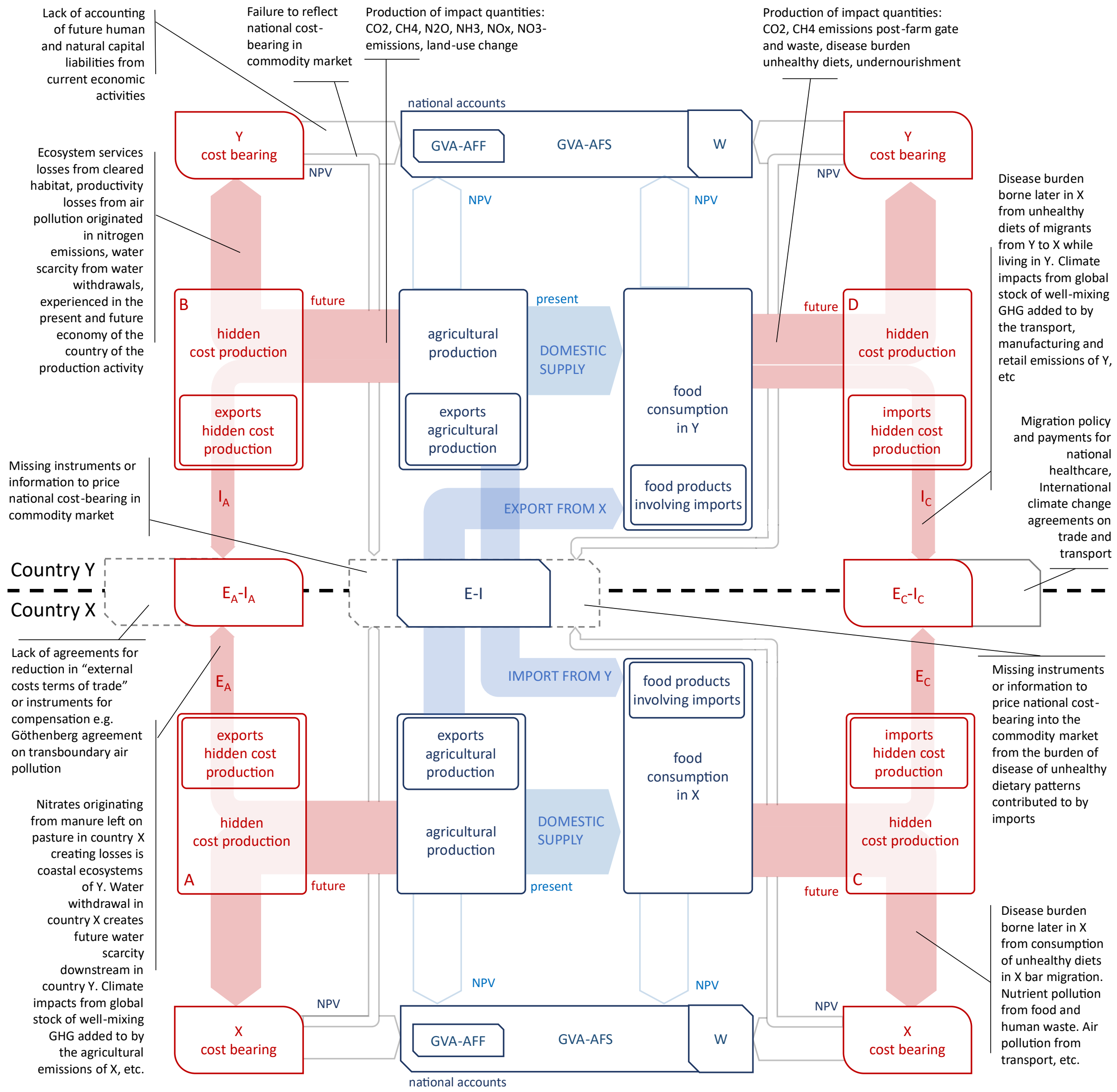
Symbol	Description
A	Hidden costs produced in country X from agricultural production in country X, $A = A_d + A_e$
B	Hidden costs produced in country Y from agricultural production in country Y, $B = B_d + B_e$
A_d	Hidden costs produced in country X from agricultural production for domestic use in country X
A_e	Hidden costs produced in country X from agricultural exports of country X to country Y
B_d	Hidden costs produced in country Y from agricultural production for domestic use in country Y
B_e	Hidden costs produced in country Y from agricultural exports of country Y to country X
I_A	Cost bearing of country X from agricultural cost production in country Y
E_A	Cost bearing of country Y from agricultural cost production in country X
I	Value of imports to country X from production in country Y
E	Value of exports from production in country X
I_C	Cost bearing of country X for cost production of consumption in country Y
E_C	Cost bearing of country Y for cost production of consumption in country X
C	Cost production of country X from consumption in country X, $C = C_d + C_i$
D	Cost production of country Y from consumption in country Y, $D = D_d + D_i$
C_d	Hidden costs produced in country X from consumption in country X associated to domestic production in country X
C_i	Hidden costs produced in country X from consumption in country X associated to imports from country Y
D_d	Hidden costs produced in country Y from consumption in country Y associated to domestic production in country Y
D_i	Hidden costs produced in country Y from consumption in country Y associated to imports from country X
$GVA\text{-}AFF_A$	Benefit of gross value add of agricultural production in country X
$GVA\text{-}AFS_{A,C}$	Benefit of gross value add of agrifood system activities in country X
W_C	Contribution to total productivity in other sectors from food consumption through labour productivity and potential "consumer surplus" welfare components such as enjoyment.

Notes: Gross value add from agrifood system activities includes value-add from activities such as agricultural production, trading of agricultural commodities and food products, food manufacturer and retail.

Source: Author's elaboration

Figure 4 shows a bilateral view of exchanges between countries in terms of cost-production, cost-bearing and benefit-receiving for trade of agricultural productions and dietary benefits and risks. It is shown to formulate cost-bearing scopes and approaches. Hidden costs in Figure 4 refers to external costs, dietary risk internalities or both. The formulations are shown to understand the scope of the FOODCoST SSPs dataset with respect to transboundary external costs.

Figure 4: Cross-border flows of externality and internality cost-bearing from agricultural production and food consumption.



Notes: More complex layers of processing of agricultural commodities into food products are not shown for brevity. Missing accounting, agreements and instruments means that the externalities remain unaccounted for and hidden. Blue shows physical flows of goods or services or visible costs and benefits that are accounted such as agricultural production volumes, terms of trade and gross value add. Red shows impacts or loss of services associated to production or consumption that are unaccounted. Grey shows missing accounting, market, or mechanisms needed to correctly account, compensate, or price for hidden cost-bearing.

Source: Reproduced from Figure 2 in [111].

Cost bearing without compensation

National cost bearing

National hidden cost bearing from agrifood activity is equal to:

$$A - (E_A - I_A) + C - (E_C - I_C)$$

made up of the components: $A - E_A$ of what the nation bears within national borders from their own cost production from agricultural production, and I_A of what the nation bears from hidden costs produced by agricultural production outside national borders; and $C - E_C$ of what the nation bears within national borders from their own cost production from food consumption, and I_C of what the nation bears from hidden costs produced by agricultural production outside national borders.

Total cost bearing for national benefits received

A nation receives benefits from national agrifood activity, included value-add from agrifood system activities such as agricultural production, trading, food manufacturing and retail and ultimate consumption of imports. In addition to standard national accounts, attributable benefits from the consumption of food and provision of sustenance and nutrition to labour may include the provision of nutrition as an input to total factor productivity outside of the agrifood system industries and consumer surplus welfare components such as enjoyment (demanding on the chosen representation of economic costs and benefits). Net national benefit is equal to:

$$GVA\text{-}AFF_A + \left(GVA\text{-}AFS_{A,C} - GVA\text{-}AFF_A\right) + W_C.$$

National cost bearing formulated in the first paragraph does not represent the total cost-bearing for national benefits received from the agrifood system. The total cost bearing for national benefits received is:

$$A - (E_A - I_A) + C - (E_C - I_C) + B - B_d + D - D_d$$

$B - B_d = B_e$ is a cross-term for produced costs in country Y from agricultural exports to country X and enabling benefits in country X. Similarly, $D - D_d = D_i$ is a cross-term for the disease burden in country Y created by the imports from country X. The terms B_e and D_i are cost-bearing in country Y associated to benefits received in country X. If they are non-zero, then the total cost-bearing associated to benefits received in country X are greater than the cost-bearing of country X.

Like Scope 3 GHG accounting, total cost bearing using cross-term amounts is not additive unless all country cross-terms are zero. The total cost bearing for country X benefits and the total cost bearing for country Y benefits will add up to more than the sum of each country's cost bearing. The respective cross-terms are counted twice. Therefore, total cost bearing for benefits is not suitable for global accounting and is a scope to use in national or regional hidden exercises.

Cost bearing with compensation

National cost bearing with compensation

Unless country X and country Y participate in a common market or agreement on emissions, pollution, water-use in a shared catchment, etc. the "terms of trade" in external costs of agricultural product $E_A - I_A$ may not be included in price setting for goods and services traded between country X and country Y. The trade in externalities need not follow the trade in goods. Even in the two-country closed system country X and country Y may have no agricultural commodity trade but still exchange asymmetric external costs. Compensation through a correction mechanism would mean that country X compensates the amount E_A for the costs their production imposes on country Y and gets compensated I_A. With compensation payments borne and received by respective countries, the national cost bearing for country X with compensation is:

$$A - (E_A - I_A) + (E_A - I_A) + C - (E_C - I_C) + (E_C - I_C) = A + C,$$

which equates to country X cost production.

When cross border effects diminish, for example when the exercise considers regions that do not share catchments, are geographically separated by sparsely populated areas, and have low rates of net migration, then the sum of cost bearing of countries in the region and the sum of cost production in the region tend toward each other. Greenhouse gases, because of their assumed complete mixing in the atmosphere globally, become the deficit between cost production and cost bearing, which is why compensation is always assumed through payment into a global loss and damage fund at the rate of the social cost of the respective greenhouse gases.

Cost bearing with compensation and no cross-border effects except for GHG is the base assumption for the FOODCoST SSPs dataset. This assumption equates cost-bearing and cost production for countries.

With this scope on cost-bearing, production and consumption accounting can allocate this cost-bearing to either the country of production or consumption. Retaining just the scope of national cost-bearing is production accounting.

Total cost bearing with benefit-proportioned compensation

For the cost bearing A_e by country X, country X has benefited from exports, but country Y has been able to create benefits from the imported agricultural goods. After compensating from the terms of trade of hidden costs of production, $E_A - I_A$, then the cost bearing A of country X with some compensation according to benefits received introduces the terms

$$A_d + \alpha \cdot A_e + (1-\beta) \cdot B_e + C_d + (1-\beta) \cdot C_i + \alpha \cdot D_i.$$

The co-efficient α is the portion of the total benefits in both countries generated by country X in producing and then exporting agricultural goods. Total hidden costs for the exports after compensation are then apportioned in the same ratio. Similarly, for β. Unlike total cost bearing, cost bearing with benefit-proportioned compensation for cost bearing is additive since cost bearing is apportioned by benefit weights that equal 1 when country X and country Y are added together.

Note that $E_A - I_A$, which is linked to cost-bearing for GHG emissions, N losses, cross border services from ecosystems, and water withdrawal in shared water catchments, can be considered as benefit proportioned in the above total. Without exchange of goods and services, the countries receive no benefits for the cost-bearing of transboundary pollution (pure national externality) and therefore the proportion rests entirely on the cost producers as the only benefit receivers.

Cost bearing with benefit-proportioned compensation for cost bearing would be suitable for global accounting. Consumption accounting is a special case where $\alpha = 0$ and $\beta = 0$.

1.8 Limitations in scope and omissions

1.8.1 Limitations in use

The intended use of the FOODCoST SSP dataset involves aggregation across countries and quantities, for example, in global studies of dietary change, macro-economic studies of shifting trade policy on agricultural commodities, or for multinational company or value chain estimates of impact with large product bases. The marginal cost estimates should not be used for local or site-specific studies, or small volume product value chains even if they cross national borders.

The dataset estimates aggregated economic loss to a present or future economy as gross purchasing power but without transfers between individual economic actors or sectors (e.g., payments from households to the health sector for health care costs). Therefore, the costs may underestimate cost-bearing of individuals or subgroups in the economy and are not intended for that use.

Given irreducible uncertainty about the future liabilities from present actions, it not recommended to use the mean values from the dataset without reporting the uncertainty available in parametric or non-parametric forms. As discussed in the next section, the Monte Carlo samples contained in the dataset form a joint sample. Economic risk or economic potential is generally underestimated without using joint sampling.

The marginal damage costs in the dataset **do not include the value (benefits) provided to society from the production associated to the impact quantities.** There is no comparison in the dataset estimates with a counterfactual to estimate the balance of value between avoided damages from co-products and the costs to abate them. That is part of a study design, as discussed in Section 3, which utilises the dataset.

Reducing GHG emissions, N losses, dietary risks, etc. will not 'save the costs' to the global economy of amounts in the dataset. Damage costs should be paired with abatement costs and counterfactuals to determine the economic potential in food system transformation.

Limitations in purchasing power parity, including cross-country comparison of external costs and dietary risk internalities, are discussed in Section 2.

The FOODCoST dataset is pre-generated. It cannot reflect major policy changes that influence impact pathways outside the effect of the macro-economic projections assumed. Also discussed in Section 2 is the assumption of stationarity, that functional relationships identified in historical data persist into the future. Many of the costs are estimated as partial derivatives calculated at current and projected levels of the determinants of the costs, such as stocks of GHG. The functional relationships developed are non-linear, but the per unit costs represent a linear approximation. For example, the costs from a large dietary shift - where intake shifted in the population is considerable, or concentrated in subpopulations, will only be approximated by the partial derivative based on current intakes.

1.8.2 Limitations in scope

The impact quantities of the FOODCoST SSPs dataset are not exhaustive of the environmental externalities created by agricultural production nor the productivity losses associated to food consumption.

SPIQ-FS excludes several significant cost categories due to data limitations, modelling constraints, and resource availability. Harmonizing the environmental externalities that SPIQ-FS does include requires consistent global spatial estimates of future natural or human capital harms, that do not significantly overlap and double count. Not all the cost types called “externalities” in other studies or Deliverable 1.1 in FOODCoST had datasets that were available, suitable, or consistent with the externalities and the future purchasing power scope of SPIQ-FS. Omitted categories —phosphorous pollution [112, 113], soil erosion [114], pesticide impacts [115], antimicrobial resistance (AMR) [116], and nutritional deficiencies [117], have been included in prior studies and could represent substantial costs to society. [18, 118-120]. For a comparison of the impacts of food systems considered in recent global studies see Table 1 in the FAO State of Food and Agriculture 2023 [63].

Two background reports for the FAO State of Food and Agriculture 2024, [111, 121], included an examination of omitted categories in the SPIQ-FS model. We indicate briefly what components of other categories of food system impacts are likely, or not likely, to have data consistent with the scope of SPIQ-FS and do not overlap with the existing FOODCoST SSP estimations.

Phosphorous Pollution

Phosphorous runoff from fertilizers and manure affects riverine and coastal ecosystems, often in conjunction with nitrogen pollution [22, 122]. When nitrogen costs are included, current phosphorous impacts are likely to be captured due to existing contributing effects to observed eutrophication and acidification. What is not captured is the effect of large changes to phosphorous pollution if nitrogen levels were to remain fixed [123-125]. Future datasets could model partial derivatives for both nutrients to assess cost-benefit outcomes of food system reforms.

Soil Erosion

Agricultural expansion is a major driver of soil erosion, especially in developing regions. Soil erosion leads to on-site internality productivity losses and off-site externalities such as dust pollution and sedimentation [126-128]. While nutrient losses from erosion are already included under nitrogen and GHG categories, and are likely the majority external cost factor globally, the effects of dust and sedimentation can be significant for some countries [129].

Pesticides

Impacts include acute and chronic health effects on agricultural workers and ecosystem degradation, especially pollinator loss [115, 130-133]. While some national estimates exist, global data on productivity losses from pesticide exposure are scarce [134-139]. Pollination services, partially dependent on wild pollinators affected by pesticides, contribute significantly to ecosystem output. 9.5% of global agricultural production was attributable to pollination services, [140]. However, quantifying potential losses globally is difficult due to data gaps and ecological complexity [93, 141].

Antimicrobial Resistance (AMR)

AMR is a growing public health threat [116], with around 0.25 million premature deaths attributed to agricultural sources in 2019 [142, 143]. This compares to around 11 million from dietary risks. Agricultural use of antibiotics (AMU) contributes to resistance, though the exact share is uncertain [144]. Economic models estimate that global AMR-related costs could reach $500 billion annually by 2050. Attributing the cost to AMU is the key large uncertainty and is likely to remain so in future estimates.

Nutritional Deficiencies

Prior versions of the FOODCoST dataset provided costs per person undernourished according to the FAO definition of undernourishment [145], which equates to protein-energy malnutrition. See the studies in Section 3. The studies show that significant population costs for undernourishment, and poverty, as another indicator of social distributional failures, are highly concentrated in certain countries. Undernourishment is based on loss of productivity, using WHO’s estimates of DALYs due to protein–energy malnutrition [146]. Other lost productivity or later-life socio-economic consequences of chronic and hidden hunger required a separate study to enable consistency with the future purchasing power loss approach. Table 1 and Figure 1 in [111] compare the global burdens under the IMHE nutritional deficiency risks. Globally, protein-energy malnutrition and dietary iron deficiency are the largest burdens and costs. Nutrient deficiency and other disease outcomes from childhood malnutrition [117] are available and could be incorporated. For adults, it is unclear without more sophisticated public health modelling how to resolve the potential double count between nutrient deficiencies in hidden hunger, like calcium and iron deficiency, and the overlap between risk from diets low in fruits, vegetables, legumes, nuts and seeds, and diets high in red meat. Iron deficiency is probably the most important separate nutritional deficiency for future efforts to capture.

Based on the feedback from [111, 121] complementary components of soil erosion, pesticides, and dietary iron deficiency that do not double count with existing costs categories would be recommended as initial additional categories to be included in future global and national hidden cost exercises. Their inclusion could improve the coverage of environmental externalities and dietary risks in the FOODCoST SSP dataset, resources and data permitting.

Inclusion of soil erosion and pesticides would further strengthen the coverage of biodiversity losses in the FOODCoST SSP dataset impact quantities. Agricultural sources of externally caused biodiversity losses in the present and future are part of the future climate change (the impact pathway for costing of GHG emissions), trophic disruption from excess reactive nitrogen loading to the environment (within the impact pathway for N losses), loss of environmental flows from future water scarcity, and loss of established ecosystems under land-use changes such as deforestation (within the impact pathway of land-use changes). Adding pesticides and soil erosion would cover the main drivers of off-site biodiversity loss from food system activities. Adding off-site biodiversity impacts from agricultural activities as a distinct quantity would overlap with the impact pathways of the existing impact quantities and lead to significant double-counting of costs of co-products.

Double counting and attribution are significant challenges for the other omitted categories of impact.

Excessively high-caloric diets and the consumption of foods that impair metabolic functioning have contributed to the human burden of disease through high BMI [147]. Attribution of the burden of disease from high BMI to agrifood systems is debated in literature due to cofactors such as physical activity [148-152]. The interaction between BMI and the 15 dietary risk categories is intended to control for confounders, such as body weight or physical activity, in the studies that provide relative risk estimates. The mediation between high BMI and dietary risks is minimal in the GBD studies, which typically exclude diets high in sugar-sweetened beverages when calculating the joint burden of dietary risks and high BMI. Like the combination of dietary risks and nutrient deficiencies, the interaction between body weight and dietary risks is unclear and raises problems with respect to double counting potential beneficial or harmful effects. More sophisticated simulation of cohorts in the economy that could resolve the joint effects is not available at present as a global model or a reduced complexity version of such a model.

Data and models relating to distributional failures such as poverty and hunger or other social harms are not developed to the same level as environmental and dietary risk modelling. As discussed in the next Section, the purpose of the SPIQ-FS model that generates the FOODCoST SSP dataset is to be a statistical model that improves on meta-sampling of cost numbers from literature. Social determinants of health and labour participation are a possible way to bridge productivity costs to social harms. Generally, most estimates are abatement costs of poverty, that is, the income gap that must be filled to lift individuals above a defined poverty or living wage line - rather than the damages to future productivity from human capital impaired by social harms. The latter is the scope of the FOODCoST dataset, to ensure consistency with the other costs. In many countries, nutritional deficiencies and diets are strongly correlated with income. Double counting is a significant challenge in this case. Models need to be sufficiently articulated to consider taking partial derivatives, enabling the isolation of the portion of costs attributable to income from those arising from other social harms.

As discussed in Section 1.7.3, the FOODCoST SSP dataset estimates can be used for consumption or production accounting of countries, but transborder effects in cost models are simplified or negated by assumptions about compensation. For example, productivity losses for the future disease burden from the present consumption of unhealthy diets ignores future migration and travel. Consumption in country creates productivity loss in country. Cost-bearing of climate change is assumed to be transferred to the country of emission by future damage and loss payments to cost-bearers [108]. The compensation assumed to equate per unit national cost production and national cost bearing represents only one possible compensation policy.

Blue water consumption creates future water scarcity in the same country. Air pollution and deposition of volatilized N species occurs in national boundaries. Ecosystem services losses from habitat loss occur in the same country as the habitat loss. These limitations are discussed further in the current SPIQ-FS version 0 documentation [40, 42-46]. The structure of the SPIQ-FS model allows transboundary impact pathways with the expectation that later studies would improve modelling of N and water scarcity external costs to understand transfers from cost producing to cost bearing countries and integrate an open-source climate damages model [153]. Without the complication of consistent global modelling, national exercises could consider cross-border exchanges between cost-producer and cost-bearer, with the focus nation generating costs for other countries and bearing the costs imposed by other countries.

2 Approach

The FOODCoST dataset represents the first open dataset pre-generated by SPIQ-FS for activities over the 2020 to 2050 timeframe and calibrated to the forward projections of the widely used SSPs. The SPIQ-FS model has been documented elsewhere, as referenced below. This section provides an overview of the cost modelling.

2.1 General approach

SPIQ-FS is a statistical model with three main parts.

It uses historical data to estimate present costs. The historical modelling is based upon other data, models, and impact pathways. An impact pathway represents how the co-products of food system activities lead from cost-producers to cost-bearers. The pathway begins in a production or consumption activity, but it can be a long and complex chain of biophysical interactions, leading eventually to impact on ecosystems or humans in the present or future. Broadly, through environmental pathways or human physiology, human and natural capital is exposed to potential harm. Harm to the natural capital base or the human capital base leads to productivity losses represented in loss of purchasing power. Error in model fitting is represented by random variables and perpetuated through individual components of the impact pathway, or derived overall, depending on the cost model.

Quantities such as GHG emission and N losses change over time, but the biophysical processes resulting in exposure and the vulnerability of natural and human capital to that exposure also change. For example, the concentration of nitrogen oxides (NOx) and sulphur oxides (SOx) in the atmosphere are precursors to the formation of PM2.5 ammonium compounds. Clean air policies and economic development affect the level of precursors and therefore the amount of air pollution created by an ammonia (NH3) emission. This reduction of particulate matter can be countered by an increase in exposure due to increasing population and population density near agricultural areas through urbanisation. As another example, the relationship between the FAO prevalence of undernourishment indicator and WHO estimates of rates of death or disability from protein-energy malnutrition is heavily moderated by the human development index (HDI). Undernourishment may be present and is itself vulnerable to an increase in water scarcity or drop in crop productivity, but development and social safety nets moderates the degree to which exposure to undernourishment translates into disease burdens from acute and chronic hunger. In SPIQ-FS, macro-economic or other dependencies such as these are included as variables in the impact pathway or overall. Residuals to model errors are examined for heteroscedasticity amongst the macro-economic conditions that change in the future, so that the historical costs as a random variable can have a projection into the future. The shape of the costs can change in addition to change in the central measures like the expected value. Joint error is also considered within and across co-products. NH3 and NOx agricultural emissions in a country share common biophysical pathways, they reinforce particulate formation, they are subject to the same dispersion in wind patterns, and the particulate matter they form is deposited on the same populations. Therefore, in complex atmospheric models, the impacts of NH3 and NOx losses originating from a similar location show a strong correlation.

With the present cost estimate and its error, and macro-economic handles for how exposure, vulnerability and costs change, the final part of the modelling calculates future cost estimates under future projections using the handles. For example, the SSPs vary significantly in terms of GDP projections, population projections, urbanisation rates, demographics, etc. This affects development and income, which in turn changes, for example, the relative value of ecosystem services to economies that are shifting from agriculture to manufacturing and service-based economies.

For further information on the cost models where historical data is used to estimate present costs and residuals, refer to Annex A SPIQ-FS documentation [42-45, 47]. An overview of the SPIQ-FS cost models is available in Annex C SPIQ-FS documentation [46], which also discusses the macro-economic handles and future projection. Documentation on SPIQ-FS is available at https://foodsivi.org/what-we-do/projects/spiq-food-system-v0/. The rationale for an intermediate model between meta-sampling of literature and process-based extended computable general equilibrium (CGE) modelling is developed in [40].

2.1.1 Representation of uncertainty

The choices of historical data, models, future scenarios, assumptions about the environmental or human exposure created by the same unit of co-product (tonne GHG emissions, kg N loss, etc.), the vulnerability of exposed ecosystems and human populations, scarcity and interaction corrections, purchasing power loss as a welfare measure, the discount rate, and the choice of parity, all result in different estimates of per unit cost. Sources of uncertainty in cost modelling and those partly captured by SPIQ-FS are summarised in Table 3.

SPIQ-FS accounts for uncertainty in per unit cost. Overall cost estimates compound error in the unit cost and the error in the units of co-products produced by food system activities. For further discussion see Chapter 6 in [40].

Table 3: Sources of uncertainty in the per unit cost modelling.

Component	Source	Coverage SPIQ-FS
Measurement error	Historical data such as atmospheric emission inventories, prevalence of undernourishment, causes of death, studies in the value of ecosystem services, GDP, prices of foods and basic goods, labour participation, etc.	No stochasticity for measurement error.
Modelling error	Non-linear and linear regressions, benefit transfer of air pollution, estimates of non-renewable water use and nitrogen loading, vulnerability of populations, etc. Transfer of disease burden to years of productive life lost.	Bayesian regressions and residuals used to compound some exposure and vulnerability components.
Future error	GHG stocks in atmosphere, demographic trends, economic growth and technologies, geopolitics and trade, etc.	SSP scenarios provide different economic, emission and demographic futures. Some future losses, such as subsequent decadal land-use after initial clearing and water scarcity treated as stochastic process. No stochasticity in growth and technology.
Comparison error	Social discounting parameters, change in future prices of goods for purchasing power parity, choice of goods in comparison baskets, etc.	Growth in SSP scenarios provide different discount rates. No stochasticity in discounting parameters or purchasing power.

Unclear sensitivity

There is insufficient research on the uncertainty in costing the future liability of current food system activities to determine whether SPIQ-FS captures the major uncertainties in costing. For climate change, the 2007 Stern report highlighted discount rates as a major uncertainty [30, 31, 154-156]. It is not clear this should be concluded across all food system costs. Economic consequences of obesity and dietary risks can be intergenerational [157, 158], and they are major sources of impact from food systems, but how large is the intergenerational effect into the future? Is it significant enough to increase the sensitivity of the final cost estimates to discount rate? Nitrogen losses expose ecosystems and human populations in the shorter term – the accumulating effects arise from a constant flux of reactive nitrogen to the environment rather than from a stock, except in the case of accumulating nitrate in the vadose zone [159]. Major uncertainties in the nitrogen cost model are how ecosystem productivity changes under nitrogen forcing. Some magnitudes of variation for the components in Table 3 are discussed in Chapter 6 in [40], see p. 112.

Use of random variables

Choosing economic policies for food system transformation constitutes decision-making under uncertainty because of the large uncertainty in future liabilities and the magnitude of cost estimates from studies for the co-products of food system activities (Section 3). The uncertainty embedded in different cost models is inherently a representation of human lack of knowledge (Table 3). Many authors distinguish between stochastic or aleatory uncertainty (random processes), epistemological uncertainty (lack of knowledge) and ambiguity [160, 161]. Conceptually, the latter two are considered reducible, while true random processes are observable only through the distribution of measurements. In practice, the incomplete nature of knowledge and reductionism can cause observations to appear as a random process.

Decision-making under uncertainty uses probability distributions to represent observables but also has theories that do not [162-165]. Beyond epistemological honesty, that is, admitting that cost estimates are highly uncertain, the aim of treating per unit cost as uncertain in SPIQ-FS is to enable

- Robust choices amongst policies or other decision options
- Risk-pricing in policies or instruments based on reducing externalities or dietary risk internalities (see Section 2.4.3).

Using random variables is pragmatic to represent uncertainty despite other conceivable risk pricing mechanisms for environmental impacts [166-169]. Stochastic dominance and other risk orders offer evidence of robustness, and statistics of random variables are the most common risk pricing tool used in finance and insurance.

Random variables in SPIQ-FS are considered jointly distributed rather than independent, meaning that correlations between the per unit cost items should be considered. Without wanting to complicate the use of the dataset, this is an important consideration. Perverse outcomes and underestimation of risk can result from aggregating random variables that are treated as independent but are not. Chapter 6 in [40] makes further observations, but one extreme example is arbitrary precision. A mistaken assumption of independence can become a large error term in itself in calculations. Should every unit (e.g., every tonne of GHG emitted) be treated as an independent random variable? This is the argument in [170]. When adding up the cost of millions of tonnes of emitted GHG, the central value becomes almost certain by the central limit theorem of statistics and there would be no risk in the costs of climate change. Another example is the principle of benefit transfer. Benefit transfer across and within nations should increase the uncertainty in per unit cost estimation [171, 172]. However, if GHG emission and N losses, etc. examined at finer resolution in localities are treated as independent, whether across nations or in subnational regions, the aggregated cost would again appear more precise through summing independent random variables. What should be increasing uncertainty of benefit transfer to finer scales can be lost by an arbitrary assumption of independence.

2.2 Cost items

Per unit GDP PPP damage costs for the 153 countries in the FOODCoST SSPs dataset are calculated using the SPIQ-FS version 0.2 marginal damage cost model [42-47]. Formulae and impact pathways are detailed in the SPIQ-FS documentation. Calculation summaries for the FOODCoST dataset are provided below along with adjustments beyond the documentation. Section 1.6 discussed calculating total hidden cost to future GDP PPP in 2020 for annual additions of impact quantities and the partial derivatives of the total cost function. To approximate the total cost, FOODCoST SSPs dataset cost per unit of impact quantity can be multiplied against the impact quantities. The studies in Section 3 show examples of using the dataset. Section 3 also notes some of the evolution of the cost models.

Future damages are discounted back to present purchasing power in the 2020 economy for comparison. A Ramsey social discount rate is assumed, with a time preference of 0 and a constant expected marginal utility of consumption of 1.5 [173, 174]. The literature on social discount rates is extensive [175, 176], but it is recommended to use a conservative value for intergenerational wealth transfer [29, 177, 178]. National GDP PPP growth rates or global growth rates of GDP PPP are used in the discount rate depending on whether cost models project and aggregate damages at a national level (e.g., nitrogen cost models or productivity losses from illness or informal care) or a global level (e.g., GHGs).

2.2.1 Costing GHG emissions

GHG emissions increase radiative forcing, changing climate variables such as temperature and precipitation [179]. The increase in extreme events in the short-term, and changes in ecosystems and water cycles in the medium term, directly affect human capital through heat stress, increase in diseases, and lost agricultural production. The prominent GHGs are well mixing gases, meaning that the emission in one country can create costs globally.

SPIQ-FS resamples the Interagency Working Group on the Social Cost of Greenhouse Gases (IWG-SCGHG) simulations of the social cost of GHGs in 2020 to 2050 [180, 181]. Social costs of GHGs are one of the costing methods discussed in the FOODCoST Deliverable 1.1. The IWG-SCGHG simulations are provided for three discount rates (2.5 percent, 3 percent and 5 percent) at 10 year time steps (2020,2030,2040,2050) and five socio-economic scenarios used by integrated climate modelling groups to inform IPCC reports [180]. The years 2025, 2035, and 2045, were linearly interpolated. By using national GDP growth projections for SSP scenarios to 2100 [182], global rates are matched to a IWG-SCGHG simulation discount rate. Given the discount rate, the IWG-SCGHG scenarios were matched to SSP scenarios. As examples, for SSP1 the most optimistic IWG-SCGHG scenario called “5-th scenario” with 550ppm CO2 concentration was used, which is still higher than the peak CO2ppm ~460ppm expected under SSP1-1.9. For SSP2 we matched GDP and population projections to scenarios of IWG-SCGHG CO2ppm concentrations and sampled uniformly from social costs GHG estimates for the IWG-SCGHG “IMAGE” and “MinCAM” base scenario simulations.

Simulations from the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) model were excluded due to implausible temperature curves for GDP PPP damages [180]. Overall, the changes produced higher social costs of GHG estimates for the 2024 report than its previous edition. Social costs represent marginal damage costs under a future pathway of optimal economic abatement [54]. Using the social cost reflects increasing internalisation of the costs of GHGs in emissions markets or state taxation.

IWG-SCGHG simulations provide social costs for emission of a metric ton of CO2, CH4 and N2O. CO2-equivalents are not used, and the gases are costed separately [183]. Converting to CO2 equivalents and multiplying by the social cost of CO2 would underestimate the total damages, since CH4, in particular, has shorter term effects and future damages due to CH4 are less discounted [183-185].

Economic costs from GHG emissions are borne globally through global atmospheric changes, and then climatic changes. To attribute the cost of an emission to the country responsible for it, it is assumed that economic actors within that country are required to pay an amount per emission equal to the social cost of the respective GHG, for example, to a global loss and damage fund.

2.2.2 Costing water use

Current water withdrawals for irrigation can exceed the recharge rates for blue water surface bodies and groundwater [4, 186]. The non-renewable portion of the withdrawal gradually reduces the annual water resources available for economic use in the future [187]. Models generally consider the impact of future water scarcity on agricultural production, in turn influencing wages and productivity losses through malnutrition [3, 5, 188].

The impact pathway SPIQ-FS uses is based on the LCIA calculation in [189] -which is one of the water scarcity methods discussed in FOODCoST Deliverable 1.1. However, the temporal component of future water scarcity created by a present withdrawal and renewal rates are not considered in [189]. Water deprivation factors for withdrawal of 1 cubic metre were updated for the FOODCoST SSP dataset using the global hydrological model H08 estimates for non-renewable water abstraction [190]. H08 estimates of water scarcity were used to adjust future water scarcity under the 5 SSPs [191]. Exactly what contribution a present withdrawal makes to water scarcity at a given future time is uncertain and not given by process based hydrological models. The SPIQ-FS costing model uses a Poisson process [192] to allocate deprivation effects to future years, which are then aggregated by discounting to 2020 PPP. The adjustments from the H08 model and future resource losses result in higher water withdrawal per unit costs than reported in earlier versions [44].

Following other models, lost income and the productivity effects of malnutrition were the costed human capital impacts. Marginal damages for water withdrawal may still underestimate external costs due to lack of data on damages from loss of environmental flows [193].

For malnutrition, FAOSTAT provide data changes in the number of undernourished – i.e. the number of people in a country with food intake below minimum energy requirements [145]. SPIQ-FS cost modelling calculates the number of DALYs from energy-protein malnutrition from the number of undernourished using World Health Organization (WHO) data [194-196]. The productivity losses of energy-protein malnutrition are costed using national labour productivity data from the World Bank [197]. Labour productivity is used in place of GDP per capita to account for the caring burden of young and old-age dependents in households. The same productivity loss estimates are used to cost DALYs lost for neoplasms, cardiovascular disease and metabolic diseases from diets low or high in risk factors (below), and the DALYs attributable to air pollution from reactive N losses to the environment (also below). Uncertainty in the cost of the burden of protein–energy malnutrition is obtained directly from modelling residuals in a truncated quadratic regression between the Human Development Index (HDI), prevalence of undernourishment and DALYs per capita obtained from historical WHO data [44]. As HDI increases in SSP pathways, the quadratic Bayesian regression incorporates decreasing vulnerability to exposure to undernourishment.

For income loss, the present value of a unit of blue water (irrigation) to crop production was determined from a mechanistic biophysical model in [198]. The valuation examined 16 major crops at the global scale on a 10-km grid using a productivity function approach. It used 2019 farm gate market prices of the current crops produced on the land cell. FAOSTAT producer prices converts local currencies into internationals dollars (PPP). Production is assumed to not be limited by other inputs, including nitrogen (N) and phosphorous (P). Effects on other economic activity from reduced agricultural production is not included. Assuming the same demand, then prices would increase. The change in prices due to simultaneous scarcity occurring in other basins may imply that the economic return from the remaining production of crops outweighs the loss of production at previous prices [187] – this kind of correction needs to be accounted for in more sophisticated estimates, with caveats on the ability of crop producers in various countries to engage with international trade. Present dependence is partially captured in the correlation structure of joint uncertainty in historical FAO producer prices [199].

2.2.3 Costing land-use changes

Agricultural land expansion such as deforestation and mangrove clearing changes the basic functioning of ecosystems (habitat loss, disruption of biophysical inputs, disruption of biological cycles and food chains, etc.). This results in a loss of services provided by ecosystems to the human economy. In several countries, abandoned agricultural land provides a potential hidden benefit. However, compared to abrupt loss of an established ecosystem, biodiversity and ecosystem services can take decades to recover on abandoned cropland and pasture [200, 201]. Most land-clearing for agriculture has effectively been permanent with near- to long-term effects depending on economic adaptation [202].

Costs of land-use changes in terms of lost ecosystem services from one hectare (ha) lost, or one ha of services effectively lost due to degraded habitat, are derived from the ESVD [93], which uses the Economics of Ecosystems and Biodiversity (TEEB) classification and the Common International Classification of Ecosystem Services (CICES, version 5.1) [203, 204]. Distribution-families dependant on HDI were derived for the total value of ecosystem services from 8 biomes associated to land-use change and nitrogen loading. The dependence on HDI enabled the value of ecosystem services to economies to change under the SSPs as countries changed income classes and development tiers. Costing land-use change by loss of biodiversity or loss of ecosystems services is one of the costing methods discussed in FOODCoST Deliverable 1.1.

Valuations derived from the ESVD are given in hectares per year. The duration into the future over which ecosystem services are lost or provided after a ha of land-use change is an additional assumption [205-207]. No recovery of nature-provided services was assumed for 50 to 80 years after a transition from established natural habitat. The gain from agricultural services in transition to agricultural land use is assumed to be included in GDP growth. National-level discount rates to 2100 under the SSPs were used to discount up to 80 years of lost ecosystem services for deforested land to obtain cumulative values for a hectare of land use change. This is a simplification. Transition in land use can occur from forestry or agricultural use, abandonment, and then return to forestry or agricultural use. However, no detailed transition forecasts were available for the SSPs for SPIQ-FS use. For abandoned agricultural land resulting in habitat return, evidence suggests an average of 14 years of returned ecosystem services [208]. A random period between 7–28 years with mean 14 years – distributed to maximise entropy [209] – of returning ecosystem services was used to obtain the cumulative value for a hectare of habitat return.

Forest loss and return indicators do not distinguish between tropical and temperate forest habitat, while marginal costs per hectare of land-use change from the ESVD does. To reconcile cost and quantity categories, a marginal cost per hectare of forest habitat change was chosen randomly from tropical and temperate marginal cost samples in proportion to historical national tropical and temperate forest areas from the Worldwide Fund for Nature (WWF) ecoregions dataset [210]. For countries crossing tropical and temperate latitudes, this is an approximation in the absence of a historical dataset of tropical and temperate forest transitions to agricultural use. Unlike the TEEB classification used for ecosystem service valuations, the WWF ecoregions dataset does not distinguish between grassland, woodland and shrubland. The ecosystem service samples for these habitats are combined in SPIQ-FS to create a national-level cost quantity for other natural land.

The provision of services from abandoned land can be of a lower value than intact ecosystems [208, 211], with previously forested areas progressing through regenerative stages of grassland, shrubland and then reforestation [201, 212]. Given the nature of progressive stages of regeneration of both ecosystem and ecosystem services, we assume services provided by abandoned agricultural land return at a linear rate to an equivalent hectare of forest or unmanaged grassland after a random period between 15–30 years, with a mean of 20 years [201, 211, 213]. The combination of the gradual return of ecosystem services and the time observed for recovering land to be utilised again for agricultural production produces the asymmetry observed in the dataset between the costs of a ha of established habitat lost from conversion to agricultural use, versus the benefits of returning habitat on abandoned agricultural land.

GHG emissions from land-use change should be accounted for under the GHG emissions impact quantity. The ESVD database includes carbon sequestration as an ecosystem services valuation. To the degree possible, carbon sequestration services were excluded from the valuation of service per hectare estimated from the ESVD to avoid double counting.

An update to the ESVD database was introduced in May 2023 [214], which contained around 60 percent more studies and 80 percent more valuations relevant to the costing of land-use change and nitrogen impacts on terrestrial and coastal biomes. The FOODCoST dataset used the updated ESVD, whereas the SPIQ-FS documentation used the 2020 version [45], with the main difference being a decrease in the valuation of tropical forests, coastal systems and coral reefs for middle-income countries, and an increase in the value of temperate forests and unmanaged grasslands.

2.2.4 Costing reactive nitrogen losses

Nitrogen pollution includes ammonia and nitrogen oxides that volatilise to air, as well as leaching and run-off of reactive nitrogen from manure and fertiliser application. Ammonia and nitrogen oxides create productivity loss from air pollution in the near- and mid-term and also contribute to crop losses in the near-term through terrestrial acidification and ozone production [215]. Redeposited volatilised nitrogen, leaching, and run-off to waterways create ecosystem service losses downwind and downstream [216]. Nitrogen load accumulate in terrestrial ecosystems fed by the water sources and then reach coastal ecosystems [217]. Acidification and eutrophication are primary drivers of ecosystem impacts [218, 219]. The effects of nitrogen pollution on waterways and ecosystems occur relatively quickly [220] and are mostly near-term. However, sustained nutrient loading can cause permanent alteration of ecosystems and nitrogen impacts can be delayed by storage in long-term reservoirs such as groundwater reservoirs [221]. Nitrogen damages can cross national boundaries from the site of emissions, either through air plumes of particulate matter, deposition, or in shared water catchments.

The SPIQ-FS version 0 nitrogen emissions costing model estimates marginal damages from the volatilization of NH_3 and NOx to air, and runoff of soluble NO_3- into surface waters and soil leaching. Economic losses occur through labour productivity losses from air pollution, crop losses and loss of ecosystem services [43]. Spatial datasets on ecosystem distribution, population density, average temperature, deposition, and riverine transport are used to transfer marginal damages derived from the European Nitrogen Assessment [222, 223]. The most developed modelling of the air and surface water pathways has been done for the US [224], the European Nitrogen Assessment [223], and to an increasing degree in China [225, 226]. The most comprehensive study on marginal costs was conducted in the European Nitrogen Assessment [227].

The SPIQ-FS nitrogen emissions costing model version 0 estimates damages in 2020 PPP for a kilogram of nitrogen lost to the environment by volatilization of NH3 (ammonia) and NOx (nitrous oxides) to air [228], and run-off of reactive nitrogen into surface waters, predominantly soluble NO3- (nitrate) [216]. Marginal costs for leaching of nitrate into subsoils and deep-water sources [124, 159] are included in the cost model, but these costs, in both marginal cost and total cost from quantity terms are generally less than the run-off to surface waters [229]. Costing acidification, eutrophication, and air pollution separately as midpoints in LCIA are discussed in FOODCoST Deliverable 1.1. The SPIQ-FS model does not rely on LCIA inventory to midpoint calculations to transform N losses into midpoint impacts.

Due to the heterogeneity of manure treatment methods, the application of fertilizers, and climatic and soil conditions, it is difficult to base marginal costing on the quantities of application of synthetic fertilizer or head of livestock per acre [230]. The user of a SPIQ-FS dataset is required to calculate four types of N losses (NH3 to air, NOx to air, NO3- runoff, NO3- leaching) but does not have to use an LCIA weighting approach to derive acidification, eutrophication or air pollution separately. The nitrogen costing model does not include marginal N2O damage costs from N losses [231], as they are included in the GHG costing model.

The damage costs from volatilization concentrate on human health effects, but also contribute to crop losses through terrestrial acidification and ozone production [215]. The human health modelling is most advanced, with high- and low-resolution chemical transport models available to model the exposure of human populations to sources of emissions [232-234]. The modelling calculates attributable DALYs by intersecting population densities with the contribution of ammonium particles to PM2.5 pollution. The SPIQ-FS model uses value transfer of a detailed county-level resolution of attributable DALYS from United States NH3 and NOx air pollution [235]. The United States has over 3000 counties. Transfer parameters for marginal cost included population density, temperature, NOx emissions, SOx emissions, and NH3 emissions [235, 236]. SOx and NOx emissions appear for several reasons, because most NH3 human health damage factors through the formation of ammonium compounds which require NOx and SOx to be present in the atmosphere [215], and NOx is also a proxy for economic activity due to its production by transport and energy sectors. DALYs are costed as productivity losses using the same module as for malnutrition from water scarcity and exposure to dietary risks. NH3 and NOx human damage costs are strongly correlated, and this correlation was estimated from the sample set of 3000 counties and is applied in the SPIQ-FS uncertainty modelling.

Ozone costs from NOx emissions are transferred using FAO farm-gate cereal prices [216, 226, 237]. The transfer of the marginal costs of reactive nitrogen in surface waters is based upon the proportional transport of nitrogen to inland and coastal waterways, using a global spatial dataset [124]. The relative value of ecosystem services in inland or coastal areas is used to value transfer, based on a constant proportion between effective hectares of lost ecosystem services and emissions to surface waters [43]. Value of ecosystem services are provided by the module used for the land-use cost model. The marginal costs of deposition on land are transferred using the same method based on proportion of deposition retained on land and relative value of ecosystem services from terrestrial ecosystems (tropical forests, temperate forests, woodland & shrubland, and grass & range-land) [238-240].

The effects of nitrogen pollution on waterways and ecosystem occur relatively quickly [220], so discounting is not used in the costing model for ecosystem effects. Time displacement between exposure to particulate matter and respiratory disease burden is assumed to be 10 years [229]. There is a considerable time lag between the onset of leaching and the nitrogen in deep water causing effects as nitrate in drinking water [220, 241]. Discounting is applied to this time lag. For future N losses, parameters for the air pollution benefit transfer such as NOx background concentrations, SOx concentrations, temperature and population densities are adjusted and recalculated for SSP projections using SSP datasets (Section 2.3). Aspects of the nitrogen loading in waterways are adjusted under the SSPs using projections from [242]. Exposure of the economy to ecosystem service losses is adjusted under SSPs through income and development as mentioned.

Interactions between the global nitrogen, carbon, and methane cycles [216, 243, 244] are not fully represented by the separation of costing models. While excess nitrogen is responsible for biodiversity loss [245, 246] it increases sequestration through growth of biomass [243], so the effect on ecosystem services can be mixed. This interaction is not modelled directly, but factors into the correlation between nitrogen and CO2 marginal costs within SPIQ-FS.

2.2.5 Costing dietary risk

Unhealthy diets have been associated with preventable morbidity and mortality in national populations from neoplasms (cancers), cardiovascular disease, and type II diabetes [13, 147]. Labour productivity losses from illness or informal care occur in the near-term from intake, exacerbating existing co-morbidities, and in the longer-term from the onset of morbidities from dietary patterns.

Diets low in fruit, vegetables, nuts, wholegrains, calcium and protective fats, have been identified as underexposure variables and diets high in sodium, sugar-sweetened beverages, saturated fats and processed meat as overexposure in disease burden studies [13]. Collectively the exposure variables and associated disease burden are called dietary risk factors. The FOODCoST dataset provides the productivity cost for a change in national consumption of 1 g/capita/day for consumption of fruits, vegetables, etc. Diets high in trans-fats and low in polyunsaturated fats are measured in percentage of energy intake, so they estimate the productivity cost for a change in national consumption of 1% of energy intake /capita/day (see Table 1). Increasing intake of fruits, vegetables, etc. are reducing underexposure, so the per unit cost is negative (a benefit).

SPIQ-FS models the change in the joint burden of disease for dietary risks, quantified by DALYs, using an emulator of the Global Burden of Disease 2017 study (GBD 2017). An explicit formula for the partial derivative of the joint burden of disease function with respect to an exposure variable is available, and this is calculated using the current intake distribution for each country in 30 age and sex subgroups in the population and relative risk and theoretical minimum exposure levels of the GBD 2017 study. For more information see [46] and [47]. Costing labour productivity losses from unhealthy diets and the PAF method of disease burden calculation that the GBD is based on are discussed in FOODCoST Deliverable 1.1

Under the SSPs, the partial derivative is taken with respect to projected intake level and disease rates. Dietary intake trajectories are projected from 2020 to 2050 using proportional adjustment of present intake obtained from [247]. An adjustment to preference for plant whole foods and processed foods was also made based upon SSP narratives, [248]. Total rates of neoplasms, cardiovascular disease and type II diabetes are estimated under the SSPs using demographic adjustments to GBD disease burden projections to 2050 [249]. Changes in vulnerability of populations to dietary risks, which may reduce through technology or other factors, are not projected forward under the SSPs – the same relative risk factors are used in all SSPs.

Uncertainty in the partial derivatives is estimated using Monte Carlo simulation. Ranges for relative risk factors, for theoretical minimum exposure levels, for disease rates, and for mean and standard deviations of intake are available for all countries, age and sex subgroups in the population. The ranges for these parameters were sampled using maximal entropy distributions [209], and the model run one thousand times for each jointly sampled set of parameters. This approach follows the uncertainty modelling in the Global Burden of Disease study where no joint correlations in the parameters are accounted for.

The burden of preventable morbidity and mortality on human capital is measured in DALYs for each country. To estimate productive years of life lost, the disease burden experienced by those under 70 years was considered representative of working-age individuals and thus provided a lower estimate of productive years of life lost due to the disease burden across all age groups. Roughly two thirds of the disease burden occur in working age, but it varied by country. The productivity years lost due to disease or disability are multiplied by the national labour productivity value used in other cost modules to obtain a measure of productivity lost per DALY from dietary risks.

In Table 1 the 13 dietary risk factors that exclude diets low in milk and diets low in fibre are modelled for their joint disease burden. The per unit costs across those 13 impact quantities can be added. To avoid double counting, the 2 dietary risk factors of diets low in milk and low in fibre should be considered distinct. The categories of diets low in milk and fibre are excluded because they are mediated in the GBD formulation of joint dietary risks with diets low in calcium and low in fruits, vegetables and wholegrains. Some nutrients and additives, like sodium, have a complicated relationship with processed meats and fruits and vegetable consumption, mediated by their effects on high systolic blood pressure. More limitations in the dietary risks modelling are discussed in Section 2.5 below.

The SPIQ-FS model uses a GBD 2017 emulator despite updates in 2019 and 2021 to the GBD dietary risk model. Between the GBD 2019 [250] and 2021 studies [251], the DALY estimates changed for most of the 15 categories, as the model updated its burden of proof, risk-outcome pairs and relative risk functions [252]. Trans fat estimates, for example, for the same year were reduced by up to 90 percent in many countries, while disease burden from diets low in fruit increased. An error in the GBD 2017 trans-fat calculations were corrected in the SPIQ-FS emulator. Disease burden from unprocessed red meat consumption experienced a sharp increase between the 2017 and 2019 rounds of the GBD study [253], while, for example for Brazil, there was a reduction by nearly 50 percent between 2019 and 2021 [254]. In the GBD 2021 study, both diets low in milk and diets high in red meat intake have U-shaped relative risk curves [254], meaning that both overconsumption of milk and underconsumption of red meat are associated with dietary risks, with this reflected in the modelling. Due to categorical quirks in the labelling of dietary risks in the GBD 2021, this sometimes results in a negative disease burden. For example, if the protective effect of consuming red meat outweighs its potential adverse health impacts, a diet high in red meat could be associated with a negative national disease burden in the GBD 2021 study. Overall, the relative risk factors for dietary risks are not stabilised, so the GBD 2017 model was preferred on these grounds and the fact that the representation of relative risk is more accessible in the GBD 2017 version.

2.3 Future projections

Annex C of the SPIQ-FS documentation describes projected marginal costs based on historical estimates for future agrifood system activities [46]. The approach in previous sections indicate where GDP PPP, population, demographics indicators such as old age dependency, urbanisation, temperature, background pollutants such as nitrogen and sulphur oxides, and development indicators such as HDI, are used in adjustments to exposure, vulnerability, and productivity loss under the shared socioeconomic pathways (SSPs).

The SSPs were chosen as they represent widely known and used future scenarios in climate and environmental modelling [255]. They form the basis for IPCC integrated modelling assessment of future emissions and impacts of climate change [256, 257]. For the narratives of the SSPs see [258]. A large body of literature exists for consistent quantitative projections of socio-economic variables and emissions under the SSPs with a repository hosted by IIASA as part of the Integrated Assessment Modelling Consortium (IAMC) https://iiasa.ac.at/models-tools-data/ssp . Given the long-term nature of radiative forcing from a present GHG emission, the future effects of water scarcity, and future stream of ecosystem services loss from land-use change, the long-term nature of the projections are an advantage [259]. Most projections are available now up to 2150, providing one hundred years of projections after a GHG emission, N loss, etc. occurs in 2050. Limitations of the SSPs are described further below.

A second advantage is that SSP narratives represent very different futures, mixing global inequality (SSP4), continuation of present trends (SSP2), a green economic revolution (SSP1), and an intensification of fossil-fuel driven growth (SSP5). This provides users a rich, but not exhaustive, set of future conditions to explore differences in cost estimates, risk and economic potential of food system transformation. For this purpose, the dataset download includes a file of information on the quantitative projections used by SPIQ-FS to generate the FOODCoST SSPs dataset. Users with custom growth or population scenarios in a global or national study can attempt to map or match their scenario to the features of the SSPs using the file.

Future conditions affect the cost of current GHG emissions, water-use, and land-use change, especially. As an example, from the dataset, the social cost of a tonne of CO2 emitted 2020 is around 80 2020 PPP dollars under SSP1-2.6 (scen=1) and around 100 2020 PPP dollars under SSP3-7.0 (scen=3) and SSP5-8.5 (scen=5). By 2050, the social costs of a tonne of CO2 emitted in 2050 under SSP1-2.6 is around half the social cost of CO2 emitted in 2050 under SSP3-7.0. The differences in 2050 are a combination of emission trajectory and economic growth in the respective scenarios, since the costs are expressed in present purchasing power in 2020. The very high growth assumed under SSP5, means that the Ramsey discount rate equates the present purchasing power value of CO2 emitted in 2050 *per tonne* under SSP1-2.6 and SSP5-8.5 despite the higher climate impacts in SSP5-8.5. Comparing per unit costs in the dataset is limited and cautioned against. Net CO2 emissions by 2050 under SSP5-8.5 are around five times more than SSP1-2.6 [257]. Total costs provide a better picture for comparison, see the Studies in Section 3.2.

Data on socio-economic GDP growth, income, population and demographic projections under the SSPs were obtained from [182], [260], and [261]. Urbanisation projections under the SSPs were obtained from [262]. Data on GDP PPP, population, old age dependence, and urbanisation in 2020 were downloaded for all countries from the World Bank Development indicators (NY.GDP.MKTP.PP.CD, SP.POP.TOTL, SP.POP.DPND.OL, and SP.URB.TOTL.IN.ZS respectively). The 2020 World Bank values were projected forward using the country specific rates of change in the SSP datasets.

Data on average national surface level temperatures under the SSPs from CMIP6 projections [263] were downloaded from https://climate.copernicus.eu/. Specifically, projections from the Community Earth System

Model Version 2 were used for the SSP and RCP pairs SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5 [264], and the GISS E2 Model for SSP4-6.0 [265, 266].

CMIP6 projections based on SSP and RCP combinations [267] require projections of atmospheric pollutants to run the atmospheric chemistry models [268]. Downscaled projections to national scale of NH3, NOx and SO2 pollutants under SSP trajectories were obtained from [269]. National inventories of those pollutants for 2020 were obtained from EDGARv8.0 [270, 271] and projected forward using the country specific rates of change of the pollutants from [269].

Projections under the SSPs from 2020 for the human development index (HDI) and the proportion of labourers per capita were extrapolated from the other socio-economic data (GDP, population, demographics, urbanisation) based on 2020 for HDI and labour/capita values and regression models of historical rates of change. HDI, historically, is tightly bound to GDP and demographics, a non-linear regression model with an adjusted R-square of 0.912 was used to project forward rates of change from current HDI obtained from the UNDP https://hdr.undp.org/data-center/human-development-index#/indicies/HDI. Labourer per capita is a compound of working age and labour force participation. While working age is provided by SSP projections under demographic projections, labour force participation has larger errors for regression using the available macro-indicators of GDP, population and urbanisation. A non-linear regression model with an adjusted R-square of 0.365 was used to project forward rates of change from current World Bank Development statistics (SL.TLF.CACT.ZS). Version of both the HDI and labourer per capita regressions are described in [272].

2.4 Calculations

Calculations for the per unit cost of environmental externalities were performed in MATLAB R2023a [273]. Calculations for the per unit disease burden of dietary risk internalities were performed in Python 3.11.7 (with libraries Pandas, Numpy, Scipy and Sympy) and imported into MATLAB R2023a for costing.

2.4.1 Calculation process

The code has a build stage, a cost modelling stage, and then a joint calculation stage.

The build stage imports information about countries including administrative information, economic statistics, population, pollution rates, area of subnational ecoregions, etc. Data on scenario projections - for the FOODCOST dataset, this refers to data on SSPs as indicated in Section 2.2 and Section 2.3 - are imported, cleaned and processed and then used to create projections of growth and other country level data in a build table. Information that is used across costing models and final calculations is then inserted into a build file. The build file also specifies global variables and settings used in cost models such as the mapping between the SSPs and the IWG-SCGHG simulation scenarios. The comma-separated-value file "SPIQ_Marginal Cost_FOODCOST_Proj.csv" accompanying the dataset is an extract from the build table.

The cost-modelling stage first builds common modules used across the individual cost models of GHG emissions, water-use, N losses, land-use change, etc. The common modules include growth rates, ecosystem service valuations (costs of natural capital impacts) and labour productivity as GDP per labourer (costs of human capital impacts). Some information built in one cost model but used in a subsequent one is stored in the build file.

Individual cost models are then run. The code follows a general structure - importing specific additional data, particularly on historical relationships for the impact pathway, constructing an impact pathway and costing based on historical data, then finally, projecting the cost under the scenarios.

In the individual models the costs are, except for the water module, in 2020 international dollars. The calculation module performs discounting to present purchasing power, joint sampling across cost models beyond the correlations included within cost models, and checking available information across countries and years from the individual cost models to form a consistent and complete list.

For full studies with both per unit costs and impact quantities that are multiplied together, there is a quantity stage that imports and processes impact quantity information from another economic model. The calculation module checks countries, units, and available information across quantities and per unit costs built, and also has graphing and documenting code.

The dataset has per unit costs for 153 countries (see Annex 3 for a list of the countries) for the years 2020–2050 in 5-year times steps and 5 SSP scenarios (see p. 7). With 27 per unit cost items for 153 countries the dataset consists of 144,585 individual random variables as per unit costs.

The parameter fits are conducted in the individual cost models, resulting in the parametric form for the random variables described by Mu and Sigma in the dataset. The mean, mode and median of the log-normal distribution can be calculated directly from the parameters [60]

Mean	$e^{\mathrm{Mu}+\frac{\mathrm{Sigma}^2}{2}}$
Median	e^{Mu}
Mode	$e^{\mathrm{Mu}-\mathrm{Sigma}^2}$

and quantiles from the cumulative distribution function of the standard normal distribution. Users should note that the mean of the per unit cost random variable depends on both Mu and Sigma.

The non-parametric form of the per unit costs as random variables consists of 1000 samples from the individual cost models generated through Monte-Carlo sampling [274]. MATLAB R2023a uses a pseudo-random number generator, [275]. How a joint sample is generated from the individual samples is described next.

2.4.2 Correlations and joint sampling method

The samples within any 1 of the 27 cost items are already sort ordered for potential spatial and temporal correlations determined by the individual cost model in SPIQ-FS. For example, empirically, marginal costs of NH_3 and NO_x emissions in the same location are highly correlated [43] as both affect the same surrounding population by similar air pollution mechanisms, and the presence of either chemical reinforces the production of particulate matter. Annex B in the SPIQ-FS documentation describes joint sampling across the categories by a block correlation sort order method [276]. There are 5 blocks for the SSPs dataset, consisting of the GHG emission costs per unit, the water-use cost per unit, the N loss cost per unit, the land-use cost per unit, and the dietary risk exposure costs per unit. The block correlation sort order method preserves order in individual blocks while sort-ordering samples to match correlation between blocks. In this way a joint distribution with the specified correlations and fixed marginals is approximated.

This joint sampling has three settings to conduct sensitivity analysis – full block correlation, an expert assessed correlation block matrix, and no correlation. 1000 joint samples were generated. Full correlation represents that each time a social cost of a GHG emission, say, is above its expected value then costs of N loss, water-use, land-use change, and dietary risk are also above their expected values. The middle, expert-derived, set of correlations represents a best estimate of the additional economic risk from joint effects [277].

For tractable computation, the joint distributions for each year and scenario are not sampled as a single joint distribution of 143,640 random variables, potentially ignoring the effects of correlation over time between cost blocks and between SSP scenarios.

Joint samples are used to explore risk in aggregated costs. Figure 5 in Section 3.2 below shows the shape of the distribution of global total cost of agrifood system GHG emissions, N losses, etc. obtained from aggregating (adding up) 5698 uncertain cost items. The skewed shape in the distribution reflects the influence of the joint sampling and correlation between cost items. It would be erroneous to assume the 4104 cost items associated to one scenario in one year in the FOODCoST SSPs dataset were independent –this assumption would generally lead to a normal distribution (bell shape) with lower variance due to aggregating so many items due to the Central Limit Theorem of Statistics. The independence assumption would be an underestimate of economic risk.

2.4.3 Estimates of economic risk

Co-products from food system activities involves not only society eventually absorbing the purchasing power damages or paying to abate them but taking on risk because of the uncertainty in what those damages or payments will turn out to be. The risk in an external cost is being transferred from cost-producers such as businesses to cost-bearers which may be individuals spread across society in the present and in the future. A business gets a certain outcome in terms of value-added from the production of the co-product and society gains uncertainty in the damages or payments associated to that production in return.

The countering risk is that society will lose purchasing power enabled by production if it reduces GHG emissions, N losses, agricultural land expansion and water abstraction. This risk is captured by the uncertainty in abatement outcomes. However, current studies consider the damage costs of inaction outweighed by the abatement costs of action [278, 279]. The risk is skewed toward inaction and bearing unnecessary damages.

As society underwrites most of the risk in future damages, instruments such as Pigovian taxes that reduce impact quantities should consider a risk premium. The FOODCoST SSPs dataset and the SPIQ-FS model estimating per unit damages as random variables enable the consideration of risk bearing.

To summarise the implications of risk pricing without technical details:

- One way to incorporate the uncertainty in damage cost estimates into a single value is with a risk premium derived from the distribution of damages costs - how insurance currently prices risk.
- The risk premium is how much society should "charge" to take on the uncertainty in damages associated to the co-products produced by a product, practice, or company for private benefits.
- Businesses in the same sector have the same playing field if marginal damage or abatement costs and their uncertainty are standardised. This incentivises the sector to invest in the societal process for better information about impacts and cost estimation to reduce the uncertainty and so reduce the risk premium.
- Businesses in the same sector can compete on impact quantity reduction and on disclosure (more information about impact quantities reduces the uncertainty in impact quantities, which through the pricing mechanism, reduces the premium).
- It makes the valuation, known to have large error bars, more credible as issues in methods such as benefit transfer are acknowledged in the distribution and become part of the pricing.
- The uncertainty is highly likely to be right-skewed, meaning a greater chance of higher costs. The risk premium will then be a positive amount added on to the expected cost.
- Pricing in a risk premium has the effect of making sustainable food products and practices more valuable as abatement measures.
- Care must be taken while considering the aggregated premium and correlations. If risk premiums are applied to per unit costs individually, risk premiums do not add.
- Assumptions valid for market exchange value about centralising prices are unlikely to hold. Impact must be valued differently from expected and central limit theorem assumptions in normal financial markets. Uncertainty in damage costs is likely to exhibit a long tail from coincident and correlated impact. The revealed damages are high consequence and not frequently observed.
- Summing uncertain benefits and costs, even if they have the same expected benefit or expected cost, does not cancel the uncertainty out.

2.5 Limitations in approach and calculations

The following limitation are noted in the calculation of the FOODCoST SSPs dataset, some of which would introduce additional error to the estimates.

Welfare measure

Using gross present purchasing power loss means that costs can be aggregated at global, regional and income level and compared with macroeconomic indicators such as the gross value added of agriculture in PPP terms. It can also facilitate comparison to current and potential national expenditure required to mitigate GHG and nitrogen emissions, habitat loss from land-use change, malnutrition, and dietary risks. Even though PPP represents the welfare provided by the consumption of a basic goods basket – and is preferrable to a GDP comparison based on exchange rates – it is a limited economic measure of social welfare [92, 280-284]. It does not weight differently between cost bearing at different income levels, which partial derivatives of a more general social welfare function could show. It also underestimates cost bearing by individuals. For example, treatment costs to individuals from the disease burden of unhealthy diets are additional to the labour productivity loss [285].

Calculating present purchasing loss requires social discounting of future purchasing power losses to present. To do this no changes to the relative prices of basic goods are assumed into the future from the 2021 iteration of the World Bank and IMF International Comparison Program https://www.worldbank.org/en/programs/icp

[286]. Social discounting has a large literature discussing limitations, including whether future technological progress enabling a greater expected marginal utility of consumption, and thereby a future society being relatively richer and potentially less vulnerable to economic loss, should apply to the discounting of environmental harms [29, 105, 287, 288].

Costing GHG emissions

GHG social cost modelling relies on the 2020 update to the US EPA IGWG-SCGHG simulations, which originated from modelling in 2011 and a 2016 update [180, 181, 183]. Newer estimates from EPA modelling, not finalised by the IGWG, place the SC-CO2 up to 60% higher but SC-CH4 lower [289]. The IGWG chose not to use GDP PPP damage functions in estimates of economic damages within IAM models, so they potentially undercount the payment transfer to cost bearers in the social cost calculation that could be higher in PPP terms. The IGWG-SCGHG simulations are based on old integrated assessment modelling scenarios and have not been updated to the SSP-RCP combinations, requiring mapping and interpolation between scenarios.

Costing water use

Water cost modelling in SPIQ-FS is limited by a lack of data on magnitude and time in the future of the deprivation of water for use in the production of economic value due to a water withdrawal in the present. The calculations are not catchment-based and not process based beyond the use of outputs of hydrological models [191]. Error in the prediction of hydrological models is not captured in the estimates [290]. The costs associated with reduced environmental flows cannot be calculated due to lack of data on the water productivity for natural ecosystems [193, 291]. The inability to reflect damages from natural capital impacts in water use – unlike for GHG, and nitrogen emissions, and land – led to the omission of blue water use as an impact category in *The State of Food and Agriculture 2024* exercise. The effects of diminished water quality such as salinity are not included.

Loss of agricultural production occurs inside national boundaries, there is no transboundary accounting for the different cost of production if withdrawal in one country reduces the resources of a catchment that spans several countries. The limitations of the productivity of water to agricultural output dataset used are noted in [198]. Undernourishment is based on loss of productivity from WHO estimates of DALYs due to protein-energy malnutrition [146]. Other lost productivity or later-life socio-economic consequences of undernourishment are not included. Nutrient deficiency and other disease outcomes from childhood malnutrition [117] were not used.

Costing land-use changes

Valuation in the ESVD database [93] does not use a consistent damages methodology [292], requires benefit transfer from lack of sufficient country data [293], and may overestimate GDP PPP damages. Estimates from the ESVD between the 2020 and 2023 versions can also show large differences and means are sensitive to new additions.

Land-use change represents a natural capital loss with a future liability of the loss of future services from that asset. SPIQ-FS uses a basic stochastic process from literature estimates to estimate how long services are lost for. Adaptation and structural change in the economy or return to natural management are considerations for the period of the liability, alongside the reduction in the value of the services through discounting. Similar considerations are required for the future processes governing if abandoned agricultural land returns to agricultural or other economic land-use. While land-use coverage projections are available for SSPs, no suitable data product could be found on land-use transitions between the land-cover classes at national or subnational resolution [294]. Large differences are also observed between integrated assessment models. Historic land-use transition data is available from the Historic Land Dynamics Assessment (HILDA+) land-use transitions 1km dataset [6]. The HILDA+ land-use transition dataset shows large agricultural land-use transitions for France, the United States, and Australia that are potential misclassifications. Forest clearing without clear agricultural re-use is also an uncertainty for land-use transition in Baltic states. Therefore HILDA+ was not used.

Costing nitrogen losses

Nitrogen cost modelling involves benefit transfer from the European Nitrogen assessment accounting for national variation in ecosystem distributions, temperature, population density, background non-agricultural NH3, NOx, and SOx emissions [227]. The transfer for NH3 and NOx uses additional data from the EASIUR model of over 3000 US counties [235]. Errors in transfer are the basis for uncertainty modelling. The errors may not capture fully the uncertainty introduced by benefit transfer, uncertainty on distribution of nitrogen species along the nitrogen cascade [215, 216], and lack of knowledge on the value of ecosystem services [171, 295, 296].

Variation in the value of ecosystem services is large and introduces additional uncertainty in calculations of deposition and run-off, which compounds with lack of knowledge on the damage to ecosystem productivity from nitrogen loading [216].

Air pollution, deposition and nitrogen loading is assumed to occur inside national boundaries, there is no transboundary accounting for the different costs if reactive nitrogen transport spans several countries. Integrated Model to Assess the Global Environment–Global Nutrient Model (IMAGE-GNM) spatial data sets were used to apportion the regional fate of nitrogen surplus to soil between direct nitrate NO3- run-off to surface waters and nitrate leaching to soil which undergoes denitrification before joining surface waters or concentrating in deeper aquafers and has the limitations noted in [242].

Costing dietary risks

For productivity losses from dietary risks, there are several limitations in the GBD study. Overlap between categories, such as sodium and processed meats or wholegrains and fibre, are imputed by simple mediation factors; moreover, relative risk factors and risk-outcome pairs change between studies [253, 297]. The GBD uses historical consumption and outcomes in age groups from control studies as an indicator of the burden of disease. To reflect the outcomes from consumption now, it assumes that the future dietary patterns and the preventative factors and technology remain similar in historical patterns. The GBD extrapolates dietary intake and its distribution in populations for national and sub-national population using statistical methods, and there can be significant differences in intake estimates between the GBD and other global sources such as the Global Dietary Database (GDD) [298].

Changes in disease rates are projected forward using GBD estimates. Therefore, the overall vulnerability of the population per capita to disease outcomes is considered. Vulnerability of populations to dietary risks specifically, which may reduce through technology or other factors, are not projected forward under the SSPs – the same relative risk factors are used in all SSPs.

The mapping between productive years lost due to years of life lost to disease or disability is simple. It is based on labour participation. Country-specific data on informal care and productivity burdens of various diseases would improve estimates. Cost of illness, such as treatment costs, are not included, since the marginal costs measure loss in gross product [299], while direct costs represent economic exchanges between sectors and actors within the economy, which are excluded [300]. Outside of productivity losses, few estimates capture the inefficiency in GDP terms of direct costs incurred by the health sector from individuals or governments. Following the study [301], which used the same underlying structure for determining DALYs from dietary intake as the GBD, labour productivity for the poorest countries in the lower World Bank income group are replaced by average labour productivity of the income group.

The burden of preventable morbidity and mortality for the 15 individual dietary risks are not mutually exclusive and not additive. The joint burden of disease for dietary risks quantified by DALYs is less than the sum of the DALYs estimated for the 15 individual categories of dietary risks. The 13 summable categories in Table 1 partially address the double count by excluding the 2 categories of diets low in milk and fibre, which are mediated in the GBD formulation of joint dietary risks by diets low in calcium and diets low in fruits, vegetables and wholegrains. But some of the nutrients and additives included in the 13 categories such as sodium also have a complicated relationship in some countries with the category of processed meats and with fruits and vegetables through the mediation of high systolic blood pressure. For adults, it is unclear how to resolve the potential double count between nutrient deficiencies in hidden hunger, like calcium and iron deficiency, and the overlap between risk from diets low in fruits, vegetables, legumes, nuts and seeds, and diets high in red meat.

Historical conditions

Official data from FAOSTAT and the World Bank are sometimes imputed from the last reported value for countries in prior years. Estimating global quantities based on national reporting is not precise. For most datasets and countries, data was available for the years up to 2021. Averaging across 2019-2021 enabled representative impact quantities for the agrifood system in 2020.

The interpolation of data and extrapolation for this study used similar simple methods. GDP PPP figures missing from World Bank Data such as Eritrea were estimated from other sources. Guinea, Libya, Mozambique, Somalia, South Sudan, the Syrian Arab Republic, Uganda and Zimbabwe do not report prevalence of undernutrition. Regional prevalence of undernutrition was used as a proxy.

Statistical model

SPIQ-FS is a statistical model using geospatial data, collected and reported data, and calculations from process models, to develop prediction relationships for estimation of cost or spatiotemporal benefit transfer. It is not a process model that simulates explicitly the fate of an additional GHG emission, kg of N in the form of ammonia, etc. Impact pathways are represented in more detail for some cost models than others. The relationships are based upon prediction and not inference of causation [302], and the representation of the variation of exposure and vulnerability under future conditions is limited and not exhaustive. Despite the macro-economic handles to adjust future costs SPIQ-FS is limited by an assumption of stationarity, that historical predictive factors retain predictive power into the future [303].

The purpose of developing SPIQ-FS was to

- capture some of the irreducible uncertainty inherent in externalities that create large future liabilities,
- acknowledge that costs of current activities occur over different timeframes, and
- to use consistent and common modules of ecosystem services, labour productivity, and social discount rates, across the cost models.

In this way, it is an improvement over meta-sampling costs across GHG, water-use, N losses, and land-use conversion from individual literature studies that have different scopes, use different discount rates if at all, and conceptually different valuations of nature's services and labour.

2.6 Source code availability

The GBD 2017 emulator used for dietary risk internalities is written in Python 3.11.7. The code will be restructured, cleaned, and annotated and available free-of-charge later in 2025 on Github. The calculation code and environmental externality cost models are written for MATLAB R2023a. The code is available on request. When there is the opportunity for the code to be restructured, cleaned, and annotated it will be available free-of-charge on Github.

3 Studies and validation

3.1 Validation

Validation of the historical based relationships is discussed in the SPIQ-FS Annex A documentation [42-47]. It includes references to the individual original research articles that describe validation of the data and models used. For example, on a global data set of the value of water as a production input to agriculture [198], or the reduced complexity EAUSIER model on which transfer of air pollution impacts from NH3 and NOx pollution is based [232, 235]. As a general statement, models and data collections such as IMAGE-GNM [124] and the global hydrological model H08 [190, 191] have reasonable fit statistics during validation exercises. Discussion of the datasets used in the costing models and their validation highlights the national scope of the per unit costs [304-306], and the decrease in their representation of the volume of impacts quantities and pathway of impacts at subnational scales, e.g. [306]. The global models used mean that per unit costs in the FOODCoST SSP dataset are not suitable for local or site-specific studies.

For some cost models the original research datasets provided data to fit linear or non-linear predictive regressions as described in Section 2. The models account for future macroeconomic and development variables such as GDP PPP, population, and the human development index, which is further detailed in SPIQ-FS Annex C documentation [46] and in the SPIQ-FS Annex A documentation. The predictive power through adjusted-R-squared is reported in the documentation and residuals were examined and used as the basis for incorporated error in the fits through parametric fitting or other methods such as Bayesian regression. Bayesian regression assigns probabilities amongst a family of possible functional relationships. The residuals were examined for heteroscedasticity in shape across relevant variables including the exogenous variables used for future projections. In this way, not only historical fit was used to projected mean values into the future, but also the historical error could change shape into the future.

Validating modelled future damage costs suffers from the same limitation as willingness to pay methods. There is fundamental uncertainty about the future. Unfortunately, there is a lack of accounting information about externalities in the past. Historical validation of costing built up from the models of the impact pathway would require cost modelling to reconstruct the past, like the situation for attribution modelling for extreme climate events [307].

In the absence of quantitative benchmarks for validating cost models, expert consensus and review processes, refinement through studies and their critique [118], and comparison across studies, contribute to qualitative validation and verification.

The rationale for using random variables in the SPIQ-FS modelling of per unit costs is two-fold. In addition to speculation about the future, the model is structured to allow (some of) the epistemological uncertainty to be captured. Keeping broad uncertainty in the design of the tools and use allows data advancement over the subsequent decade to refine uncertainty bands, rather than jump around between single estimates generated by studies for an irreducible cost. In the area of full cost or true cost accounting there is also a considerable amount of ontological uncertainty making comparison across studies for benchmarking through systematic analysis difficult. Practitioners can struggle to define clearly the scope of costs, mixing costs to individuals such as treatment or VSL with aggregate estimates such as the social cost of carbon. Studies also mix damage costs and abatements costs or fail to place the costs in future or present economies with or without applying consistent discounting of future costs.

Table 4 lists seven studies of food system environmental externalities and dietary risk internalities that paired an agricultural economic model with a dataset of per unit costs generated by the SPIQ-FS model.

The State of Food and Agriculture (SOFA) 2023 and *2024* reports convened an Advisory Group of experts for both reports, who reviewed and commented on the report including its hidden cost estimates and assumptions. Outputs of the SPIQ-FS per unit costs were compared across other global studies of environmental externalities and dietary risks [63, Chapter 1]. Experts and divisions within the FAO covering agriculture, externalities, nutrition, forestry, and economics provided feedback internally to calculations in the SOFA.

As an example regarding land-use change, the 2023 FAO report acknowledged potential misclassification by the HIstoric Land Dynamics Assessment+ (HILDA+) dataset [6]. The disparity with national datasets of land-use change was confirmed by national teams during stakeholder consultations conducted by the Food, Agriculture, Biodiversity, Land-Use and Energy (FABLE) consortium in six countries. as part of a background paper commissioned for the 2024 report. *The State of Food and Agriculture (SOFA) 2024* commissioned the UN SDNS and country teams within the FABLE consortium to examine and report feedback on their respective national estimates in the SOFA 2023 report [121].

The Food System Economics Commission consisted of 21 expert commissioners in climate change, health, nutrition, agriculture, and natural resources from 19 institutions. The commissioners, and other researchers that contributed to the body of commissioned work including the International Food Policy Research Institute and the Potsdam Institute for Climate Impact Research, scrutinized and commented on the modelling and the cost estimates. The SPIQ-FS estimates were compared to other estimates for GHG emissions, N losses, and land-use change from independent modelling teams.

The FOODCoST project summarised methods and approaches for costing externalities and dietary risk internalities in Deliverable 1.1 in Work Package 1. The SPIQ-FS cost models follow many of the listed approaches, such as PAF calculations for dietary risk, and Deliverable 1.1 provides a record of limitations and alternatives in addition to those limitations listed in this document.

The SPIQ-FS model's primary purpose is a statistical intermediate product that can be used to bring attention to unaccounted costs from food system activities, that may be associated to avoidable economic risks to development, and sponsor more sophisticated follow-up studies and estimates. Refinement through the studies has focussed on validation and verification for that purpose.

3.2 Studies

The SPIQ-FS model has been used in studies since 2022 in collaboration with a range of institutions and paired with computable general equilibrium models, partial equilibrium land-use modules, spreadsheet calculators, and desktop exercises. Table 4 summarises the studies and their contributions to the development of the product provided by FOODCoST project support. Links to background papers for the studies are provided further below.

Table 4. List of studies using versions of the dataset

Partner and paired model	Description	Innovation	Development for per unit costs
IFPRI, FSEC, MIRAGODEP computable general equilibrium model (2022)	Counterfactual global comparison of GHG emissions, blue water-use, nitrogen use in agriculture, and land-use change between unmanaged and agricultural land, between 2020 economy equilibrium with current agricultural subsidies (direct support and border measures) and without (removing all protection and support).	Trade off of expansion of agricultural land in high productivity countries with low support (Australia, Brazil, Argentina), and the reduced GHG emissions and N losses from reduced distortion of global agricultural production. CGE represents income group and infer HDI changes in the counterfactual. Identical demand. No dietary change. Production accounting for over 150 countries	MIRAGRODEP has a detailed household representation for assessment of poverty and undernourishment. Poverty alleviation and protein-energy malnutrition productivity costs were developed based on World Bank and WHO data, while reducing chance of double counting. Version 0 historical-based cost models developed and documented under Annex A and Annex B documentation.
PIK, FSEC, MAgPIE partial equilibrium model (2023). Global study.	Scenario comparison 2020-2050 of globally implemented policy packages and associated behavioural dietary change. Compares business-as-usual "current trends", "dietary change" (demand change only), and	Comparison over time, driven by exogenous customised futures. MAgPIE PE model determines land-use activities based on policies and demand constraint, and reports GHG emissions,	Added future costs projection and coupling to macro-economic indicators. Introduced unidirectional coupling from dynamic impact quantity changes to marginal cost calculation, especially relevant for NH3

	"food system transformation" dietary change and full package of producer incentives such as carbon payments, manure management, landscape-based conservation minimum mandates, minimum environmental flows for water abstraction.	N losses, land-use conversion, etc. over the three pathways. Production accounting. Comparison between NPV per unit future liability to purchasing power and social welfare function approaches. One of the first studies to consistently cost labour productivity losses between dietary shifts and environmental pathways with air pollution.	pathways. Documented in Annex C documentation and study background papers.
FAO, SOFA 2023, desktop exercise (2023)	Attributional desktop risk study for 2016-2023 for 153 countries, with forecasting of the effect of COVID-19. Covering GHG emissions, nitrogen losses, blue water-use, land-use change, poverty of agrifood workers, protein-energy undernourishment and dietary patterns including diets low in nutrients for whole foods.	Income groups and major countries examined. Indices of economic risk reported for countries. Comparison table between other global studies and identification of different types of failures behind food system hidden costs beyond externalities. Production accounting.	Rewrote aggregation and graphics code. Restructured to improve calculation. Documented the marginal nature of per unit costs in study background papers.
PIK, FOLU, FSEC, MAgPIE partial equilibrium model (2023). Regional studies.	Regional studies based on regional MAgPIE variants in combination with local FOLU teams for Brazil, India, China, and EU. Dietary	Production accounting. Working with country teams on the policy implications for results. Uncertainty in costs becomes high at country level, additional examination and reporting of random variables of cost and levels of uncertainty	Rewrote sampling of joint per unit costs to allow correlation over time within scenarios.
FAO, SOFA 2024, desktop exercise (2024)	Attributional desktop risk study for 2020 for 154 countries, with data collected by the UN covering effects of COVID-19. Similar impact quantity coverage as SOFA 2023, with dietary patterns represented by individual GBD exposures.	Production accounting. Updated data from FAOSTAT, the World Bank (for poverty indicators), and the 2021 GBD study. By standardising to UN data aim was to improve accessibility to UN member states and improve the fitness of UN statistics for conducting hidden cost calculations.	Updates to Nitrogen cost model and Ecosystem Services Common Module. Introduced options for costing labour productivity losses based on assumptions about working age and informal care. Dietary patterns based on GBD dietary exposures introduces as impact quantities. Background papers contributed for SOFA 2024 indicated how to consider consumption accounting of external costs of nations.
UN SDSN, FABLE consortium countries,	Scenario comparison 2020-2050 of implemented policy packages and associated	Review of SOFA 2023 results and model programming by country	First applied a Global Burden of Disease dietary risks emulator written in

FABLE spreadsheet calculator (2024)	behavioural dietary change for six FABLE countries.	teams. Connection of food supply to dietary intake using machine learning algorithm. Feedback and iteration on results and their uncertainty with country teams. Paired with the FABLE calculator and used country-derived macro-economic projections instead of global scenarios. Dietary change main lever for avoided externalities in most countries. Production accounting.	Python to a study to calculate production losses direct from exposure variables.
Swiss Federation FOAG-BLK, Agroscope, SWISSfoodSys Model (2024)	Scenario comparison 2020-2050 between a business as usual and Swiss "Vision2050" national scenario using Agroscope's recursive dynamic model SWISSfoodSys	First national study to attribute externality costs of imports toward the benefits of Swiss consumption and nourishment of labour. Examined change in import share of costs between scenarios up to 2050. Consumption accounting.	Added consumption accounting to calculation code.
Upcoming studies (2025+)	FAO Common County Analysis (CCA) FOLU India national FABLE study Consumption accounting studies for Germany and Brazil.	The FAO CCA process is invited UN consultation by member states for policy analysis of national agrifood systems and micro- and macro-economic analysis.	FOODCoST SSP pregenerated dataset to be used in combination with SOFA2024 desktop numbers at Level 1. FOODCoST SSP pregenerated dataset will be utilised in spreadsheet appraisal at Level 2.

Notes: UN = United Nations; FSEC = Food system economic commission; FAO = United Nations Food and Agriculture Organization; IFPRI = International Food Policy Research Institute; PIK = Potsdam Climate Research Institute; SOFA = The State of Food and Agriculture flagship report; UN SDNS = United Nations Sustainable Development Solutions Network; FABLE = The Food, Agriculture, Biodiversity, Land-Use and Energy (FABLE) Consortium; FOLU = Food and Land-Use Coalition; FOAG-BLK = Swiss national food and agricultural department; GBD = Global Burden of Disease study based in IMHE University of Washington; GHG = greenhouse gases; NPV = net present value; NH_3 = ammonia; FAOSTAT = database of national statistics of the FAO. Production or consumption accounting refers to national scope. Annual additions of GHG, N losses, land-use change are attributed to a country based upon the generation of co-products within national borders in production accounting. In consumption accounting the additions to impact quantities and costs generated are attributed based upon end products consumed in national borders.

3.2.1 FAO The State of Food and Agriculture 2023 and 2024

The State of Food and Agriculture (SOFA) 2023 and *2024* reports prepared by the Food and Agriculture Organization of the United Nations (FAO) contained economic risk studies.

Impact quantities

Both reports involved compiling annual emissions, annual N losses, etc. attributed to food system activities for 154 countries. *The State of Food and Agriculture 2024* incorporated United Nations (UN) data for the COVID-19 impacted years 2020 and 2021, which was released after the publication of *The State of Food and Agriculture 2023*. Impact quantity categories beyond Table 1 were considered in the reports, but we indicate the data compiled relevant to Table 1.

FAO Tier 1 country-level emissions for CO_2, CH_4 and N_2O (both direct and indirect) in metric tons for each greenhouse gas for the years 2019–2021 were downloaded from FAOSTAT [308-311]. FAO national blue water use for agriculture was retrieved from AQUASTAT, [312].

The SOFA 2023 edition relied on the Emissions Database for Global Atmospheric Research (EDGAR) version 5 for estimating nitrogen emissions by sector [313]. This was replaced by FAOSTAT's nitrogen emissions indicators [314, 315] and complemented by EDGAR (version 8) to understand missing FAOSTAT information on the proportion of nitrogen emission to air by species of pollutant [270, 271]. Similarly, the Integrated Model to Assess the Global Environment–Global Nutrient Model (IMAGE-GNM) was also updated to 2020 and used to understand the fate of nitrogen emissions to soil [242].

Net forest and natural habitat loss and return in SOFA 2024 were inferred from FAOSTAT's land cover data [316]. However, FAOSTAT only reports net land cover, and overlooks loss and gains [6, 317, 318] relevant to net change in ecosystem services. There is uncertainty across estimates for agricultural land-use transitions. FAO's FRA uses remote sensing and country inventories [319]. High-resolution remote sensing indicates that FAOSTAT underestimates cropland expansion [76]. However, algorithm errors in remote sensing of cropland and pasture changes also show up from inventories [320]. SOFA 2023 used HILDA+ based on remote sensing which estimates transitions in land cover changes [6]. However, HILDA+ potential misclassification of agricultural land transition was discussed in [28] and also highlighted by a review process in SOFA 2024 [121]. Remote sensing for determining permanent or semi-permanent change from agricultural land-use remains challenging. The per unit cost calculations were updated in SOFA 2024 due to a new version of the Ecosystem Service Valuation Database (ESVD) [93] released in December 2023 [214].

The Global Burden of Disease (GBD) 2021 study by the Institute of Health Metrics and Evaluation (IHME), published in April 2024 [251] was used for exposure to 13 categories of dietary risks for SOFA 2024, while GBD 2019 was used for SOFA 2023 [321].

Together the SOFA 2023 and 2024 represent an inventory of global national impact quantities for 154 countries following Table 1. The SOFA 2024 update does not necessarily increase accuracy over previous assessments. By relying on updated data from the UN and reference studies such as the Global Burden of Disease, the intention of the update was to shift the onus from choices of models or datasets in individual exercises, to a process of improving the fitness of UN statistics for hidden cost calculations and making assessment more accessible to member states of the UN. For more information and availability of data see the background reports [28] and [111].

Results

The compiled impact quantities were multiplied by per unit costs generated from SPIQ-FS for the exercise. The resulting hidden costs [119] in the SOFA 2023 and 2024 were interpreted as national cost-bearing, which meant losses to the future national economy in 2020 PPP from food production and consumption activities within national borders. The caveats in this interpretation are discussed in [28] and [111].

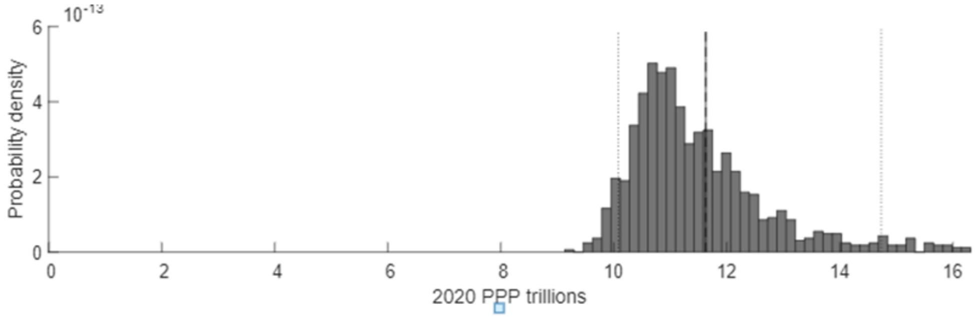
Three noteworthy results emerged from the SOFA 2023 and 2024 exercises

- the overall size and split globally between environmental externalities from agricultural production and diet related internalities
- the relative economic risk across World Bank income groups by comparing annually generated externalities and internalities from agrifood systems as a fraction of annual gross purchasing power

- the absolute size and split between the major food producing and consuming nations

Global hidden costs generated in 2020 (meaning future purchasing power losses in present value from the agrifood system activities that generated the impact quantities as co-products) according to the 2024 edition remain in the range 10–15 trillion 2020 PPP dollar (Figure 5). For context, the future liability would be about 9-10% of global GDP PPP generated in 2020. Diet internalities from dietary patterns account for 50-80 percent of hidden costs followed by environmental external costs. The split on internalities and externalities is expected given the central position of labour in economic metrics and endemic impacts of current diets on public health.

Figure 5. Distribution of future purchasing power losses in present value from agrifood system activities that generated impact quantities as co-products in 2020.

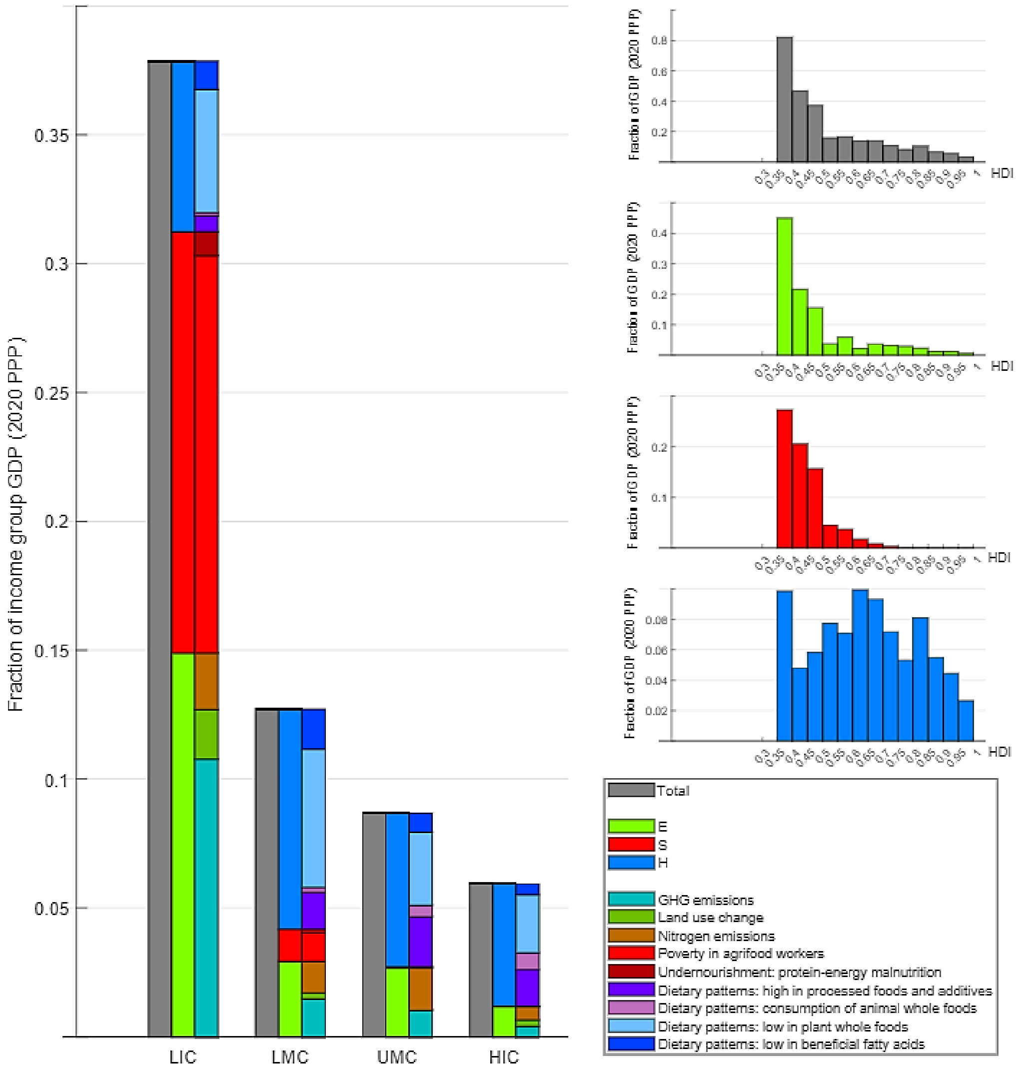


Notes: PPP = purchasing power parity. Solid line shows mean global hidden costs at around 11.6 trillion 2020 PPP dollars. The distribution is right skewed to higher damages with a mode around 11 trillion 2020 PPP dollars. Grey small-dashed lines show 5th and 95th percentiles. Hidden costs are likely are in the range of 10–15 trillion 2020 PPP dollars. Proportionally, the uncertainty at country level is higher than at global level due to aggregation. This uncertainty is sensitivity tested in the degree of correlation between GHGs, nitrogen, land-use change, water use, undernourishment and dietary patterns cost items.

Source: Reproduced from Figure A6 in [111]

Low-income countries were observed to bear the highest relative costs of agrifood system hidden costs generated in 2020, equivalent to over 30 percent of the group's gross domestic product (GDP) PPP in 2020, with cost bearing decreasing in proportional terms with increasing income (Figure 6).

Figure 6: Mean hidden costs of agrifood systems generated in 2020 as a share of GDP in 2020, by income group



Notes: E = environmental externality costs; GDP = gross domestic product; GHG = greenhouse gas; H = health internality costs; HDI = Human Development Index; HIC = high-income country; LIC = low-income country; LMC = lower-middle-income country; PPP = purchasing power parity; UMC = upper-middle-income country; S = social hidden costs (gap to international moderator poverty line and productivity loss from protein-energy malnutrition). Both hidden costs and GDP are measured in 2020 PPP dollars. Left panel shows an increase in economic burden of cost-bearing for low-income countries. Estimate of burden on low-income countries is over 36 percent in *The State of Food and Agriculture 2024* compared to 26 percent in 2023 due to a higher estimate of the social costs of GHGs. Social costs of GHG emission are paid as compensation at a global average and become increasing unaffordable to lower income countries. Intensive systems in higher income countries displace future costs of related GHGs to lower-income countries by global climate impacts. Trade displaces nitrogen emissions and land-use changes to the country of production. Income addresses poverty and chronic hunger, but low consumption of whole plant foods is a global burden with different reasons for its persistence across groups and development levels. At higher income levels, the economic burden of overconsumption of sugar, salt, processed foods and red meats increases.

Source: Figure reproduced from [111].

In SOFA 2023 a set of economic risk indicators were generated for each country in the study. The largest food producing and food consuming blocs were compared, including the EU.

The countries with the highest net hidden costs generated by agrifood systems are the world's largest food producers and consumers: the United States and the BRIC countries (Brazil, Russian Federation, India and China). Hidden costs for USA, China, India, and Russia are predominantly (> 75%) from dietary risks; Brazil is the exception with larger environmental externalities. Except for Brazil, diet internality costs prevail in all countries. As a bloc, the European Union has comparable hidden costs to the United States of America (Table 5A in Annex

1), including in terms of the split between environmental externalities and dietary risk internalities, the total estimate of hidden costs generated in 2020 (mean value 1.3-1.4 trillion 2020 PPP), and the fraction of hidden costs to GDP PPP. Relative costs for nitrogen losses are higher in Brazil, China, and the EU, with some of Brazil's cost-bearing originating from exports to China and the United States of America. Since China and India's agriculture contribution to GDP is higher, the ratio of hidden costs to value production is much lower than in the United States of America and the EU. For a detailed breakdown, major costs and components for countries are shown in Figure 11A in Annex 1.

Discussion on risk studies

The high future costs associated to agricultural production and current diets estimated, since they affect directly the natural and human capital base of the economy, would hinder future growth and development. The costs, currently unaccounted, therefore become a concern for productivity commissions, long-term economic planning, and international development.

Risks studies such as the State of Food and Agriculture indicate the economic impact of activities or pollutants, their distribution globally amongst key dimensions, such as income, and identify areas for potential action and potential benefits of reducing hidden costs. Until the abatement costs to avoid externalities and internalities are factored into the equation in a counterfactual study of economic potential the hidden costs calculated in a risk study are not any indication of the costs avoidable by transitioning to more sustainable agrifood systems (except a theoretical maximum with zero abatement costs). Counterfactual and scenario studies that identify the potential of the net social surplus in avoiding hidden costs was the purpose of the next set of studies.

3.2.2 Food System Economic Commission global and regional food system transformation pathways

The Economics of the Food System Transformation global reports prepared by the Food System Economic Commission (FSEC) considered benefits of transforming food system from 2020 to 2050 [278]. The Food System Economics Commission consisted of 21 expert commissioners in climate change, health, nutrition, agriculture, and natural resources from 19 institutions. A scenario study was conducted in collaboration with the Potsdam Institute for Climate Impact Research (PIK) using a recursive dynamic partial equilibrium model [322]. For more information and availability of data on the cost exercise see the background report [272].

Impact quantities

The annual GHG emissions, annual N losses, and effective hectares (ha) of lost habitat from land-use change under food system transformation pathways for 153 countries over the period 2020-2050 were modelled in MAgPIE [188]. MAgPIE was coupled with a dietary demand model to estimate exposure to dietary risks [247]. Marco Springmann from the University of Oxford calculated the disease burden from exposure and the resulting years of life lost from disease burden and informal care were costed.

Pathways were defined by successful adoption or not of 15 Food System Measures (packages of policies and behavioural change) over the period 2020 to 2050. See Table 1 in [272]. Costs for mitigation of nitrogen, incentives for carbon sequestration, trade liberalisation and minimum agricultural wages, and impacts of control policies on biodiversity intactness and minimum environmental flows, are modelled in MAgPIE, which is based on cost-minimisation of land-use activities constrained by meeting demand and other exogenous parameters. Food waste and dietary changes are mainly considered as normative preference shifts supported by education, increasing availability and affordability of substitutes, and nutrition support [323]. Abatement costs arising from transfers to counter distributional effects of increased food prices and other costs not modelled directly in MAgPIE, were added separately [324].

For brevity we describe the results comparing the baseline business-as-usual pathway (labelled CT) and a normative pathway where all policy and behavioural measures are realised (labelled FST). CT and FST are based on the demographic and socio-economic scenario of SSP2 [258]. The implementation of the full set of packages in FST dictates their divergence over the period 2020 to 2050. We indicate the results for the MAgPIE EUR region, inclusive of the EU. Global results are available from [272]. Results comparing a dietary change only to the baseline are reported in [279].

While production and other parameters are calibrated to historical values from FAOSTAT by MAgPIE, MAgPIE estimates of GHG emissions, land-use change, and N losses are calculated separately from FAOSTAT sources.

The focus of the FSEC study was on net avoided hidden costs under transformation pathways, but the study does contain an estimate of the 2020 impact quantities and hidden costs that can be compared to the SOFA 2023 and 2024 global exercises. The mean costs from the study are in the same range of 10–15 trillion 2020 PPP dollars from the FSEC study with broad agreement in the breakdown into environmental externalities and its subcategories and dietary risks. There are some scope mismatches between the studies – MAgPIE does not calculate on-farm energy emissions or post farm-gate emissions which is usually handled by REMIND in the REMIND-MAgPIE integrated model [325].

Results

Change in the impact quantities under the FST and CT pathways were estimated by the PIK led modelling for 153 countries at five-year intervals from 2020 to 2050. They were multiplied by per unit costs generated by SPIQ-FS for each pathway accounting for GDP PPP adjustments and changes to total industrial pollution under FST [46]. The resulting hidden costs [119] were interpreted as national cost-bearing. The caveats and limitations in the modelling are discussed in [272] and MAgPIE documentation.

The output of interest for the cost exercise is the avoided costs between CT and FST over 2020-2050 minus abatement cost adjustments to gross product with the limitations noted in [272]. The net avoided costs represent future economic benefits of increased gross purchasing power under FST if they are positive. Another FSEC study conducted by the London School of Economics performed a complementary social welfare analysis of the benefits of FST based on a similar framework [326].

Noteworthy results emerged from the FSEC exercises

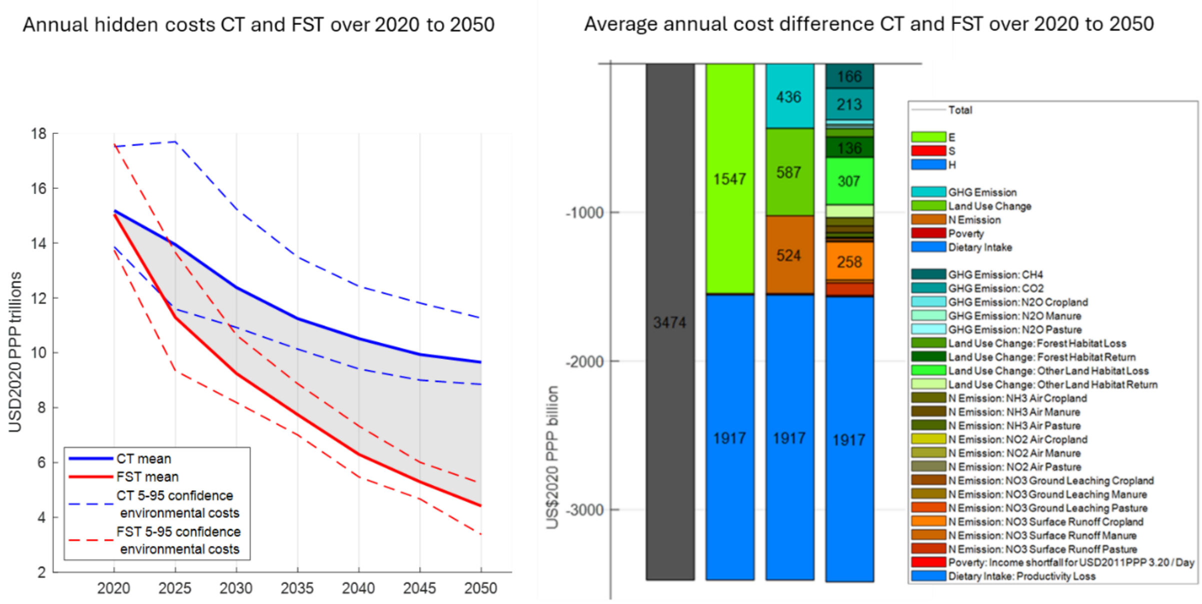
- the size and split globally of net avoided environmental externalities and diet related internalities under FST
- the major components of FST benefits varied across regions, from lowering dietary risks in EUR, to a combination of lowering nitrogen losses and avoiding dietary risks in China, and a transition in Brazil from environmental losses to environmental services. Sub-Saharan Africa (SSA) avoids a triple burden under CT of environmental externalities from inefficient and increasing GHG emissions and nitrogen use and productivity losses from obesity and unhealthy diets that eclipse the costs of poverty and hunger in SSA by 2050.

The left panel of Figure 7 shows the trajectory of avoided annual hidden costs for CT and FST in 2020 PPP. The area between the two trajectories shows a mean reduction of ~104 trillion 2020 PPP in hidden costs under FST from 2020 to 2050 at an average of ~3.5 trillion 2020 PPP per annum, or 2.2% of global GDP PPP in 2020. Approximately 30% of the future liability generated under CT over 2020 to 2050 is avoided under FST.

Under FST, land policy and carbon payment incentives are realised by 2030 while graduated dietary change provides an increasing and larger reduction in productivity losses toward 2050. Averaged over the period, the right panel of Figure 7 shows that mean benefits from avoided costs of environmental externalities and dietary risk internalities are roughly equal. Additionally, within environmental externalities, the mean benefits of GHG emission reduction, reduction in N losses reduction, and avoided loss from conversion to agricultural land or return of habitat from abandoned agricultural land are ~500 billion 2020 PPP per annum, with roughly equal contributions, subject to the uncertainty in the estimates. Over time, the contribution of land-use change stabilises toward 2050, while the value of nitrogen use efficiency measures under FST gets larger toward 2050.

The FSEC global results suggest that a significant share of hidden costs of agrifood systems under CT are avoidable under the optimistic FST pathway.

Figure 7. Annual avoided hidden costs under the FSEC FST global pathway over 2020 to 2050.



Notes: PPP = purchasing power parity. CT= current trends baseline scenario. FST = FSEC food system transformation scenario. E = environmental externalities. S = poverty below the moderate poverty line (2011). H = dietary risk internalities. Trajectory of global annual hidden costs for CT (blue) and FST (red) in 2020 PPP in left panel. Shaded area between the trajectories indicates the avoided future liability under FST over the period 2020-2050. Trajectories of the 5-th and 95-th percentiles of the respective distributions of annual hidden cost are shown, accounting for uncertainty in environmental externalities. Right panel shows the breakdown of avoided costs globally by their average over 2020-2050. Total in grey in column 1. At the level of individual impact quantities in column 4. Progressively more aggregated quantities in column 3 and then column 2.

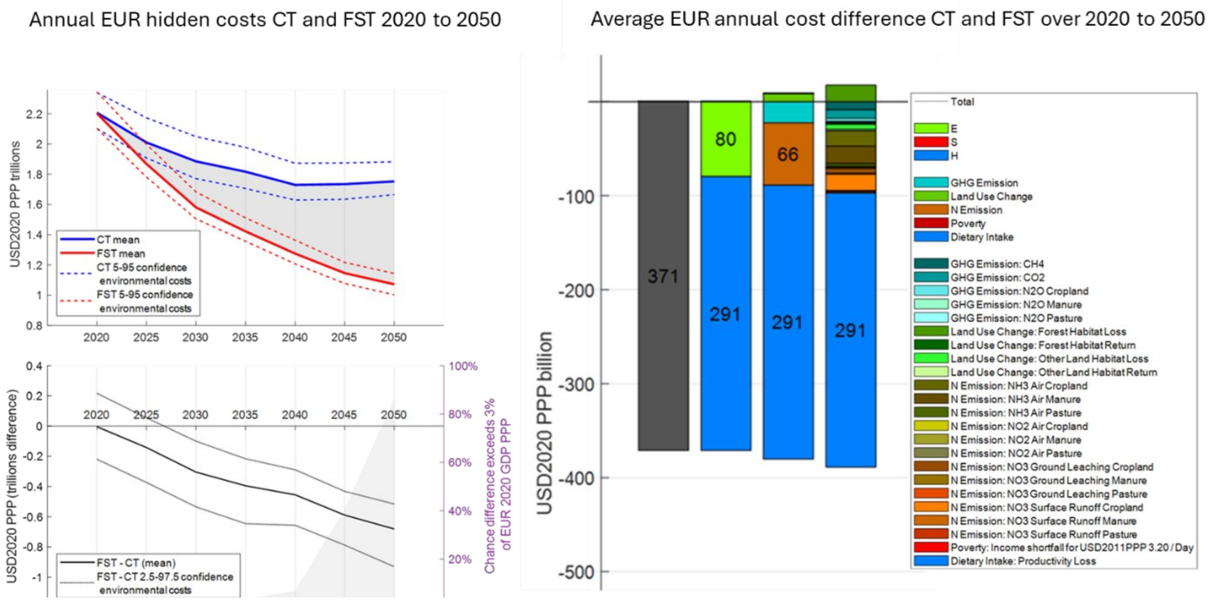
Source: Reproduced from Figure 1S and 4S in [272]

Regional results for the EU

MAgPIE has regional variants for Brazil, China, India and the EU. FSEC commissioned regional studies and policy briefs to examine how the benefits and cost of FST varied across regions. We describe the results of the cost study for the MAgPIE EUR region which included the UK, Switzerland, Norway and 24 EU member states [327]. Malta, Cyprus, and Luxembourg were excluded due to data limitations.

For EUR, the FST pathway would reduce future liabilities generated over 2020 to 2050 by food systems by 20% (Figure 8). On average, this was approximately 370 billion 2020 PPP per annum. Due to normative assumptions of FST on dietary change and the high value of labour in the EUR, reduction in dietary risk internalities contribute the most benefits to EUR under FST. The transition to healthy diets is introduced linearly over the period, resulting in labour productivity improvements of 291 billion 2020 PPP, on average. Avoided damages from reactive nitrogen (N) loss (66 billion 2020 PPP), GHG emissions (22 billion 2020 PPP), make the largest contributions to average annual avoided hidden costs from agricultural production. Ammonia emissions and associated air pollution are the main components of the benefits from reducing N losses.

Figure 8. Annual EUR avoided hidden costs under the FSEC FST global pathway over 2020 to 2050.



Notes: PPP = purchasing power parity. CT= current trends baseline scenario. FST = FSEC food system transformation scenario. E = environmental externalities. S = poverty below the moderate poverty line (2011). H = dietary risk internalities. Trajectory of global annual hidden costs for CT (blue) and FST (red) in 2020 PPP in left panel. Shaded area between the trajectories indicates the avoided future liability under FST over the period 2020-2050. Trajectories of the 5-th and 95-th percentiles of the respective distributions of annual hidden cost are shown, accounting for uncertainty in environmental externalities. Right panel shows the breakdown of avoided costs globally by their average over 2020-2050. Total in grey in column 1. At the level of individual impact quantities in column 4. Progressively more aggregated quantities in column 3 and then column 2.

Source: Reproduced from Figure 1S and 3S in [327]

Change in the random variable of environmental costs in EUR under the FSEC FST scenario over 2020 to 2050 is illustrated in Figure 12A. Risk of higher environmental externalities decreases by half under FST compared to CT. The change in shape of the distribution of residual environmental external costs arises from the sum of uncertain benefits (CO2 sequestration and ecosystem services from return of forest habitat) and uncertain costs (ammonia emissions from cropland and manure and nitrate run-off from croplands).

Discussion on cost-benefit scenario studies with PE models

The left panel of Figure 7 is useful to highlight the difference between an economic risk study that identifies large potential future liability and an economic cost-benefit study that estimates the net social profit, or economic potential, in reducing it. Or more simply, the difference between cost components and counterfactual cost-benefit. In graphical terms the equivalent of the annual economic risk in the SOFA exercises for the years over 2020 to 2050 is the area under the blue line in Figure 7. The shaded area between the red and blue lines is approximately 30% of the area under the blue line and represents the social profit in avoiding the future liabilities in CT once constraints and costs of the transition to the FST pathway are factored in.

Detailed land-use PE models like MAgPIE incorporate the cost of conforming to policies in food transformation pathways in land-use optimisation and the allocation of agricultural labour and capital. However, costs in the wider economy, either as secondary output effects of abatement, or damage costs resulting from biophysical effects in the impact pathways of co-products such as labour effect from air pollution, cannot be treated endogenously [328].

3.2.3 Global counterfactual study of removing agricultural support and border measures

For many countries, agricultural subsidies distort agricultural production toward inefficient land-use and overproduction of commodities [329, 330]. A counterfactual study conducted with the International Food Policy Research Institute (IFPRI) examined the change in global GHG emissions, N losses and land-use impact from removal of agricultural subsidies. Recent quantitative studies had considered changes in GHG emissions under removal of subsidies [331, 332], but not the redistribution of nitrogen use and land-use. The UN studies [333-

335] utilised the MIRAGRODEP computable general equilibrium model (CGE) [336] to examine GHG emissions and a global agricultural subsidy database from the International Food Policy Research Institute (IFPRI) [337]. MIRAGRODEP was extended to account for additional environmental pressures including water use and land-use change, enabling a quantitative study in which per unit costs of environmental externalities were used to examine economic trade-off of land-expansion with reduced GHG emissions and N losses in the counterfactual with global subsidy removal [338].

Impact quantities

MIRAGRODEP provides estimates of changes in impact quantities for 152 countries between a modelled 2020 economy with current global agricultural subsidies in place and a counterfactual 2020 economy with all support removed. Agricultural subsidies include direct public support to the farming sector or border policies on agricultural products or inputs.

MIRAGRODEP outputs net changes in national CH4, CO2 and direct and indirect N20 emissions in kilo-tonnes for each gas by source categories that reflect FAOSTAT GHG items (see Table 2 in [338]). MIRAGRODEP provides cumulative net changes in blue and green water use per production item in the model. Production items use FAO item codes. Blue water use for crops were aggregated to obtain national change in blue water use for crops. The model also outputs national net changes in agricultural land-use for crops and livestock, including estimates of transition of Forest and Other Land Habitat into cropland and pasture, and transition of cropland and pasture into Forest and Other Land Habitat.

MIRAGRODEP outputs cumulative national changes in N-weight of synthetic fertiliser application, energy use in agriculture as a percentage, head of beef cattle and buffalo, head of dairy cows, and head of sheep and goats. IFPRI modelling provided changes in head count of dairy cattle for milk, and beef cattle, market swine, and sheep and goats for meat using FAO item codes. IPCC Tier 1 default regional calculations were used to convert synthetic fertiliser application and head count changes into N-weight kg emissions of combined NH3 and NOx to air and combined Nr run-off and leaching. National historical proportions of agricultural sector emissions for NH3 and NOx to air using Edgar 5.0 were used to apportion NH3 emissions to air and NOx emissions to air [9, 313]. Similarly, IMAGE-GNM was used to apportion Nr surface run-off and ground water leaching [124, 339].

MIRAGRODEP modelling provides change in the percentage of energy use in agriculture at a national level. Data on 2019 fossil fuel energy use in agriculture from the FAO, EIA and EDGAR provided an estimate of the change in NOx emissions from change in energy use.

Food demand profile, which was equated to dietary composition, was kept constant for the counterfactual. No dietary risk internalities were calculated in the study. Undernourishment and poverty in households are calculated by MIRAGRODEP and were costed in the study as distributional failures.

Results

Trade-offs around agricultural land expansion and lower greenhouse gas emissions (GHG) and nitrogen pollution should be expected when distortions are removed. Agricultural land area and supported productivity on that land has expanded in regions such as North America and Europe. Changing support would lead to some production shifting to regions where agricultural land expansion has been economically constrained. Many of those regions in the Global South are more biophysically efficient regarding inputs, resulting in reduced emissions and nitrogen use. However, habitat returned from spared agricultural land could be less than the habitat lost from expansion due to marked agricultural productivity gradients between North America and Europe and other regions. Benefits to the poor from the production shift may also be mixed. Regions with the lowest present support, with economic capacity for agricultural expansion, and the least productivity gradient to North America and Europe, such as Australia, Argentina and Brazil were considered likely to absorb the production shift and the shift in agricultural incomes.

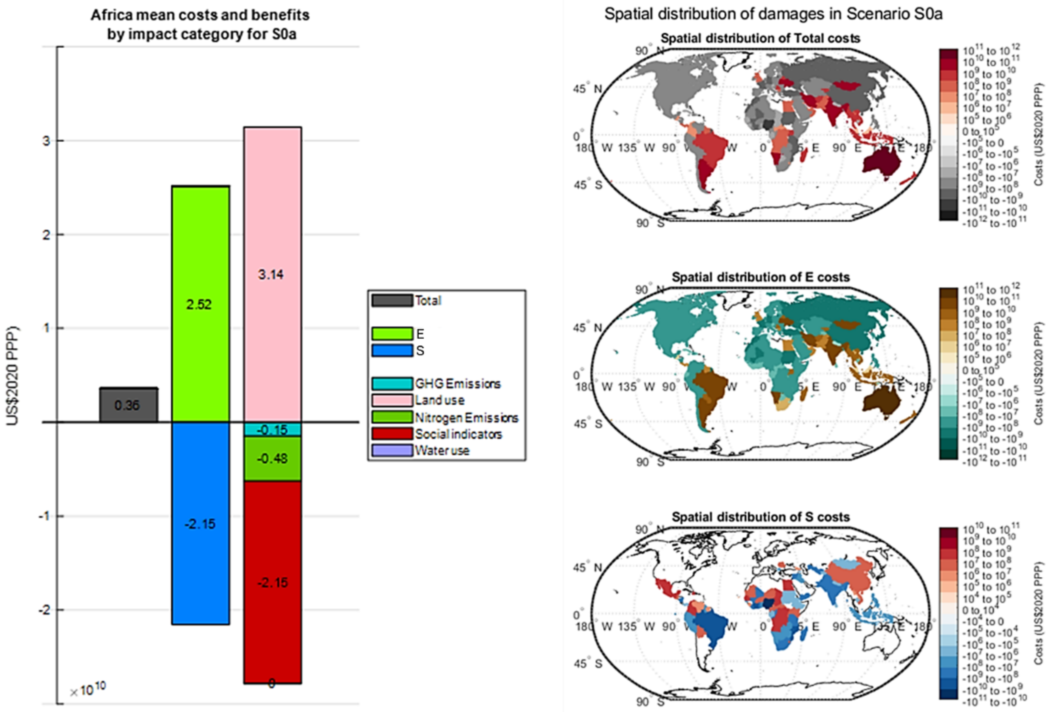
The study confirmed that global removal of agricultural subsidies in the IFPRI database results in a net global reduction of GHG emissions and nitrogen pollution, but also a net loss of 11 million hectares of forest and other habitat from agricultural land expansion and mixed benefits for lower income households. Comparing reduced GHG against habitat loss in biophysical terms is difficult. Per unit costs of the externalities enabled an economic assessment of the trade-off.

Whilst some of the reorganisation of land-use allows production in locations that are more efficient, lowering GHG costs and N losses in the order of 20-40 billion 2020 PPP combined, the hidden cost of agricultural land expansion was estimated in the order of 200-400 billion 2020 PPP and not compensated by the returning ecosystem services on abandoned land.

In the counterfactual, the agricultural land expansion is an upfront capital cost – it is incurred once. The benefits of GHG costs and N losses are operational costs, each year into the future of the counterfactual world, all else being equal, it emits less GHG and loses less N from agricultural production. Therefore, assuming weak substitution, another economic view of the trade-off is the time it takes for the future liabilities of the land-use change in the counterfactual world to be compensated by the reduction in liabilities from GHG and N efficiencies. Roughly, according to the study, it would take 10-20 years for the efficiencies of the redistribution of agricultural production induced by removing subsidies to “pay off” the upfront cost of the expanded area of land under agricultural use.

This “pay off” is in global total purchasing power and does not imply distributional fairness. Those impacted by lost ecosystem services due to the land expansion are not necessarily those who gain benefits from the reduced GHG and N losses. At a regional level, the complex mix of subsidy instruments across countries and their diverse productional potential means that countries across Africa and Latin and South America experience varied poverty alleviation (Figure 9). For Africa overall, income improvement to the extreme poor is the same order as the liability for agricultural land expansion. Efficiencies in reduced GHG emissions and N losses, estimated at ~6 billion 2020 PPP annually, provide a net positive outcome under subsidy removal (Figure 9 left panel). However, some countries receive the income benefits and in other countries extreme poverty is expected to increase (Figure 9 right panel).

Figure 9. Africa net hidden costs incurred (positive) or avoided (negative) under the removal of all forms of support.



Notes: PPP = purchasing power parity. SOa = global removal counterfactual. E= environmental externalities. S = distributional failures including protein-energy malnutrition and extreme poverty at 1.90 2011 PPP dollars/day. Africa is expected to avoid ~21 billion 2020 PPP damages from reduction in poverty and undernourishment and an annually recurring ~6 billion 2020 PPP benefit from reduction in GHG emissions and N losses. The first bar in left panel shows net mean damages, the second panel environmental (E) and human (S) sources of damages are show, the third bar breaks E down into GHG emissions, N emissions, water use and land-use. The right panel shows the country level distribution of damages for total, and the breakdown by E and S cost types.

Source: Reproduced from Figure 21 and 26 in [338]

Discussion

Government support of agricultural production through direct subsidies or through border measures represents nearly US$600 billion in annual funds that could be repurposed toward transforming food systems [332]. While global removal is an unlikely policy option, the results of the study point to similar trade-offs under repurposing scenarios if land-leakage and productivity gradients are not addressed. The study influenced subsequent work on repurposing scenarios by IFPRI and the FAO.

3.2.4 UN Sustainable Development Solutions national pathways using the FABLE calculator

The UN Sustainable Development Solutions Network (UN SDSN) directs and coordinates the Food, Agriculture, Biodiversity, Land-Use, and Energy (FABLE) Consortium. The FABLE consortium examines sustainable future pathways for food systems using agricultural economic models and the input of country teams from 24 nations through a process called Scenathon. The country teams specify their exogenous future scenarios, including GDP growth, population, and dietary pathways using national statistics and forecasts as part of the process.

Global PE and CGE modelling are generally top-down custom exercises that require expertise and time to complete. In contrast with CGE or PE modelling, country teams utilise a spreadsheet model of agricultural production called the FABLE calculator. The calculator allows countries to see results of potential policies in a feedback cycle within the Scenathon. Using the exogenous and the country-led description of sustainability pathways for their national food systems, per unit costs were calculated for six countries in the FABLE Consortium (Australia, Brazil, Colombia, Ethiopia, India, and the United Kingdom). The study with UN SDSN and FABLE compared environmental externalities and dietary risk internalities for the "global sustainability" (optimistic pathway) and "national commitments" (meet current policy statements) pathways for the six countries over the period 2020 to 2050 to a business-as-usual baseline [121].

Impact quantities

The FABLE calculator estimates annual GHG emissions over 5-year time steps using the exogenous information provided by country teams, and effective hectares (ha) of lost habitat from land-use change under [340]. As of the date of the study the FABLE calculator does not calculate N losses by species of reactive nitrogen. For the study, the fertiliser application and manure left on pasture outputs were converted to N losses of NH_3, NO_x to air and NO_3^- from runoff and leaching.

Dietary risk exposure was estimated from model information and additional modelling. Countries specified dietary pathways from present. Generally, business-as-usual projected historical patterns, while national commitments might follow national dietary guidelines. The global sustainability pathway for most countries involved diets with additional environmental impact, usually involving replacing red meat by protein sources such as legumes. Where the specification of country diets had a clear dietary risk exposure category, such as fruit intake per capita per day, red meat consumption, etc. the proportional change of this intake over the pathway was applied to the 2020 exposure levels in the GBD model for that country. Other dietary risk exposure variables had no clear specification, such as processed meat intake, or sweet and sugary beverage intake. Change in these variables were modelled from parameters elicited from country teams concerning processed food intake under the pathway.

Overall, 13 of the 15 dietary risk exposure variables (excluding fibre and calcium intake as nutrients) had trajectories over 2020 to 2050 that captured the dietary transitions of the national pathways. Using the trajectories of exposure to dietary risks, and population adjusted projections of overall incidence of non-communicable diseases to 2050 [341], a Python emulator of the GBD model was used to calculate the years of life lost to disability and mortality in working age groups [47]. Those years were then costed at the projected annual labour productivity rate in 2020 PPP under the different pathways. This same procedure is approximated by the FOODCoST SSP per unit costs for dietary risk internalities.

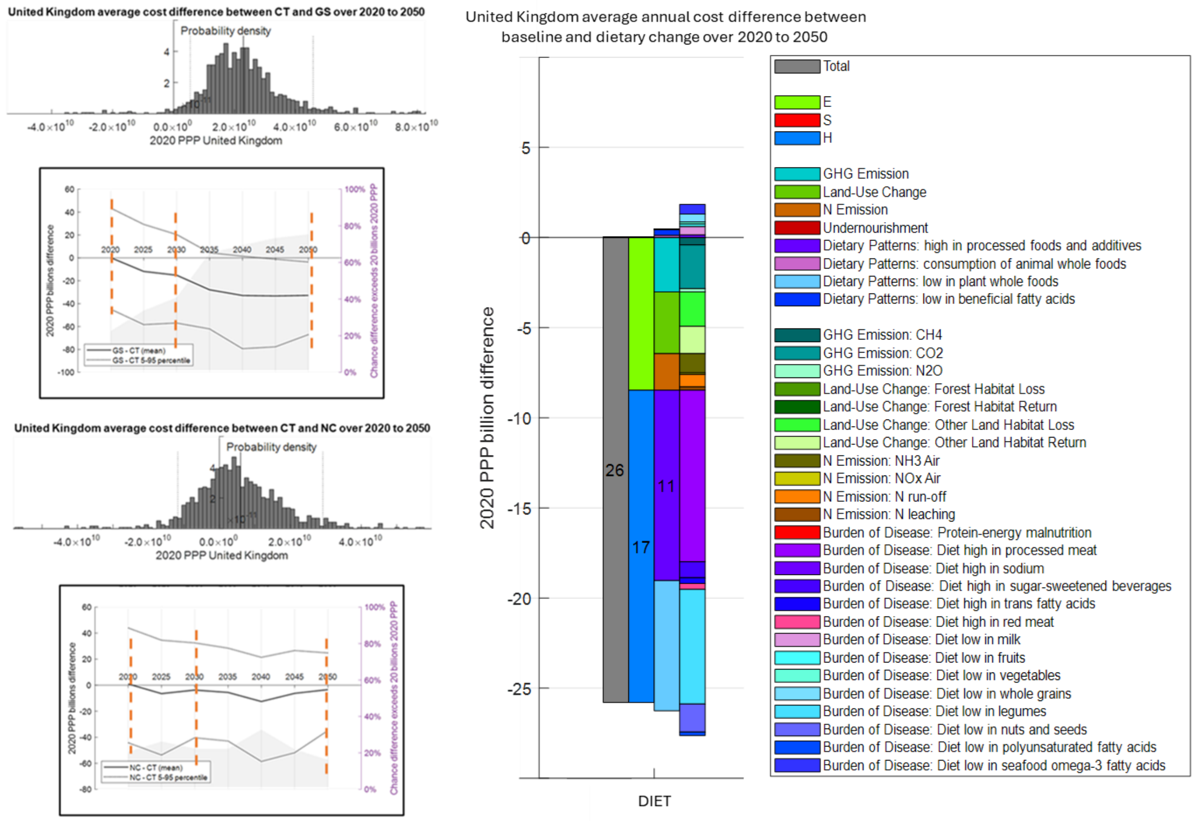
Results

National teams reviewed the results on costs of environmental externalities and dietary risk internalities and utilised results in their own national reports in addition to contributing national studies to *The State of Food and Agriculture 2024* [121].

As in the FSEC study in Section 3.2.2, national pathways toward sustainable food systems can be compared to a baseline business-as-usual pathway. A benefit component can be estimated by costs of environmental externalities and dietary risk internalities avoided by the pathway compared to the baseline over 2020 to 2050. Across all countries except for Ethiopia, the avoided future liability under the “global sustainability” pathway over 2020 to 2050 was more than 4 times greater than the “national commitments” pathway. With the uncertainty modelled in the costs, the benefit in the “national commitments” pathway was not always clear and there was a risk that national commitments provided no additional benefits beyond the baseline. In the global sustainability pathway, additional benefits above the “national commitments” pathway driven by the change in diets (DIET lever), and the level of benefits combined with reduction of risk in high costs from land-use and N losses led to more certainty in the benefits provided by the “global sustainability” pathway.

This is illustrated in the United Kingdom (UK) study. The difference of avoided costs under “national commitments” (NS) for the UK (average value ~6 billion 2020 PPP) is highly uncertain, with a 37% chance in cost simulations of avoided costs being negative (Figure 10 lower left panel). In contrast, the chance of avoided costs under “global sustainability” (GS) being zero or negative is decreasing to 2050 (Figure 10 upper left panel). There was a 2.3% chance of avoided costs being negative, with a mean of average annual avoided costs under GS of 23 billion 2020 PPP, a median around 18 billion 2020 PPP, and a 5% chance of average avoided costs of over 46 billion 2020 PPP. Much of the additional environmental and health benefits of GS arise from a considerable reduction in current trends of red and processed meat intake to higher intake of legumes and pulses in the UK pathway (Figure 10 right panel).

Figure 10. Reduction in environmental externalities and dietary risk internalities under the UK “global sustainability” pathway.



Notes: PPP = purchasing power parity. CT = baseline current trends pathway. NC = national commitments pathway. GS = global sustainability pathway. DIET = dietary change only pathway. E= environmental externalities. S = distributional failure. H = dietary risk internalities.

Source: Author’s elaboration.

3.2.5 Swiss Hidden Cost Assessment of Vision2050

Switzerland imports approximately 50% of its food supply from other countries. Whether consumed in Switzerland for the benefit of nourishment to labour, or exported as value-added goods, the imports increase the output of the Swiss economy. The environmental externalities from agricultural production are borne by the future economy of the source country of the import, or globally in the case GHG emissions. Switzerland imports net amounts of fruits, vegetables, and finished products, for domestic consumption from neighbours in the EU, mainly from Germany, France and Italy. Switzerland also imports, cocoa, coffee and similar commodities from Ghana, Brazil, Colombia, Guatemala, Ecuador and Vietnam. The re-export of these commodities in value-added products are around 30% of Switzerland's total agrifood exports in value [342].

In the previous studies of this section, externalities were accounted to nations by production within domestic borders. In the formulations of Section 1.7, the previous studies have been national cost-bearing with compensation. The air pollution in Germany from fertiliser application or the ecosystem loss from agricultural land expansion in Ghana from products imported into Switzerland are accounted in the production accounts of Germany and Ghana, respectively, as the countries of production. With consumption accounting, the externality is attributed to either the consumer, which may be Switzerland, or attributed in proportion to the revenue received by all production and value-adding countries in addition to the end consumer countries.

A study with the Swiss Federation FOAG-BLK and the Swiss research bodies Agroscope and FiBL examined environmental externalities and dietary risk internalities of the Swiss food system. The study considered externalities produced in countries exporting to Switzerland, with a scenario comparison 2020-2050 of the change in external costs and dietary risk internalities between a business as usual and Swiss "Vision2050" national scenario based on targets in the Federal Council's Sustainable Development Strategy 2030.

Impact quantities

Impact quantities for the two pathways from 2020 to 2050 were calculated using Agroscope's recursive dynamic model SWISSfoodSys. GHG emissions are estimated in the model for domestic farm-gate emissions, land-use change, and other emissions relating to inputs, transport, manufacturing, retail and consumption. Emissions for imports are provided as a total excluding GHG emissions from land-use change and GHG emissions from land-use change. The model calculates change in area of land dedicated to agricultural use and blue water consumption for imports and domestic production.

GHG emissions, N losses, land-use changes, and blue water consumption associated to imports are not differentiated by country of origin in SWISSfoodSys. Estimate external costs for imports assumed compensation amounts – costs were calculated as incurred by Switzerland by paying compensation for purchasing power losses in the importing countries as if the external costs had been incurred in Switzerland.

Results

Results of the study are incorporated in a Swiss report to the Federal Council which is still under embargo. With a broad view, actions on food loss, focussing on domestic and organic production, and dietary change with improvements in whole plant food intake and diets lower in animal foods, reduce the cost of environmental externalities and dietary internalities by approximately the same amount under Vision 2050. The externalities associated to imports reduce significantly by 2050 in the Vision2050 scenarios.

3.2.6 Future studies and use of the dataset

As of publishing of the FOODCoST SSP dataset, the SPIQ-FS cost model is scheduled to be used in a Food and Land Use Coalition (FOLU) India national FABLE study and consumption accounting studies for Germany and Brazil. The FOODCoST SSP dataset will be used as a product for FAO Common County Analysis (CCA).

The FAO CCA process is invited UN consultation by member states for policy analysis of national agrifood systems and micro- and macro- economic analysis. The process has levels of engagement involving preparation of products and engagement between stakeholders on risks and priority actions. Level 1 country briefs will include economic risk information on agrifood system hidden costs. Level 2 involves spreadsheet appraisal of potential policy, which includes cost-benefit analysis a component of which is benefits from avoided hidden costs. Level 3 if engagement progresses involves more comprehensive-economic modelling exercises on behalf of the member state. The FOODCoST SSP dataset to be used in combination with SOFA 2024 desktop numbers at Level 1 briefing in the CCA. The FOODCoST SSP dataset will also be utilised in spreadsheet appraisal at Level 2.

Internally to the FOODCosT project, the dataset contributed to MAGNET modelling in Work Package 2 and dietary risk estimates in Case Study 9.

There are more structural opportunities to embed environmental externalities and dietary risk internalities into CGE models of the global food system. Particularly those that have an existing representation of environmental pressures (impact quantities) and households with their labour structure and food demand such as MAGNET and MIRAGRODEP. Labour and its contribution to output is directly modelled in CGEs and natural capital provides goods and services to the production base of sectors represented in CGEs. There are challenges for CGE modelling, however, with timescale of impacts from the co-product of food system activities up to a century into the future and the resolution of biophysical impacts along impact pathways, which presently favours partial equilibrium models.

The SPIQ-FS cost model, and therefore the FOODCoST SSP dataset, are intermediate and partial products as mentioned in Section 1.7 and Section 2.1. Ultimately, the products are designed to:

1. highlight the possible magnitude of future liabilities and to account for the risk of environmental and unhealthy diets where there is currently little or no accounting,
2. bridge a gap given the longer development time of more sophisticated models, and,
3. build the argument for research support for those sophisticated models to guide public and private instruments to realise the economic benefits in food system transformation.

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Annex 1. Additional tables

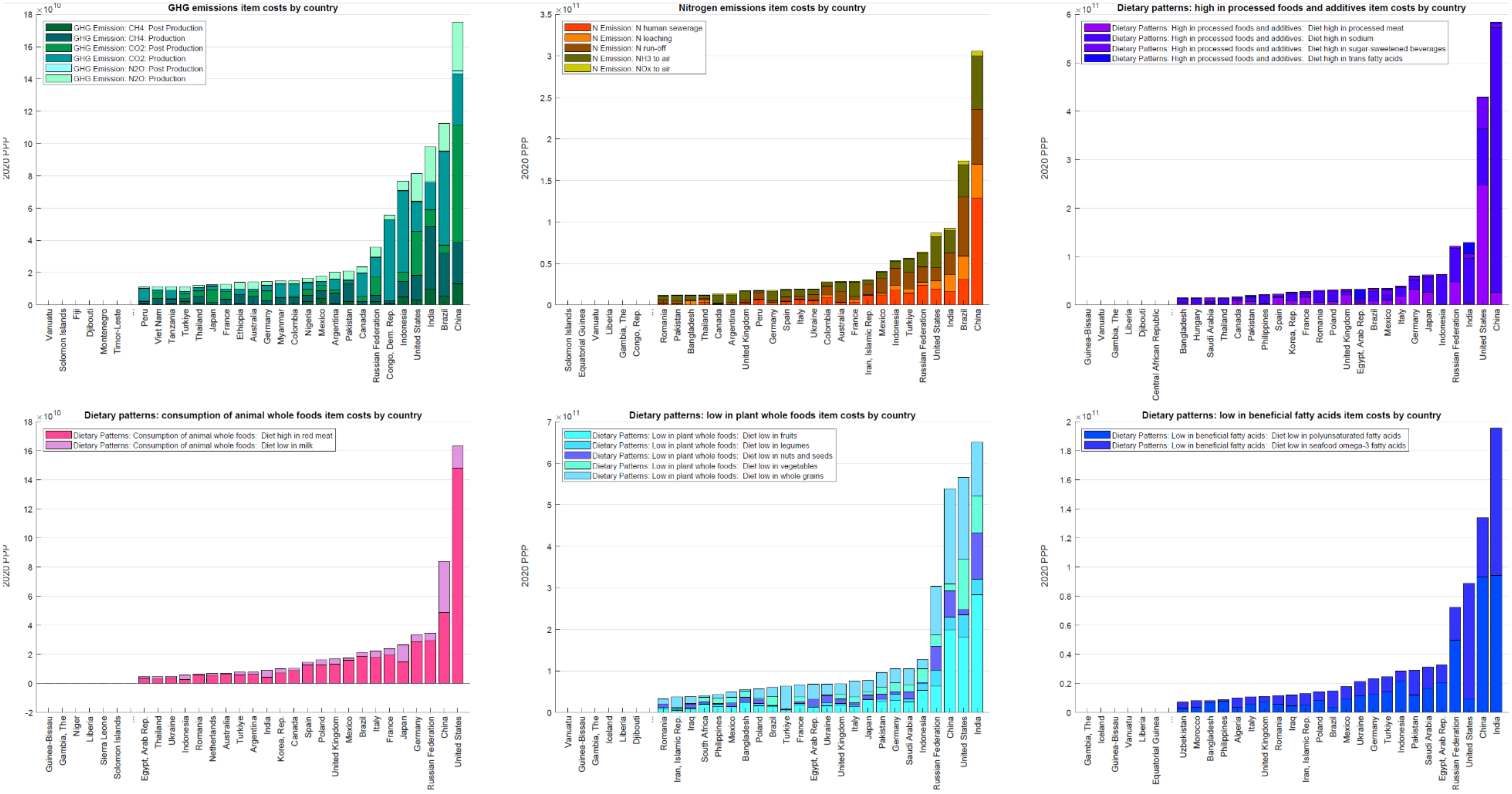
Table 5A. Agrifood systems hidden costs in the 2024 of *The State of Food and Agriculture* by World Bank income group and major food producing and consuming countries

	Share of hidden costs to GDP PPP (percentage)	**Hidden costs generated in 2020 per capita** (2020 PPP dollars)	**Total hidden costs** (billion 2020 PPP dollars)	**Environmental externality costs** (billion 2020 PPP dollars)	**Poverty and protein-malnutrition costs** (billion 2020 PPP dollars)	**Diet internality costs** (billion 2020 PPP dollars)
World	8.8		11 628	2 951	564	8 112
Low-income	37.9	770	496	195	214	87
Lower-middle-income	12.7	967	3 299	758	327	2 213
Upper-middle-income	8.7	1 633	4 064	1 254	23	2 787
High-income	5.9	3 176	3 769	744	-	3 025
United States of America	6.6	4 362	1 442	194	-	1 248
China	7.3	1 291	1 820	478	-	1 342
European Union	6.4	3 029	1 303	243	-	1 060
India	13.8	959	1 338	190	164	984
Brazil	12.9	2 002	424	294	-	130
Russian Federation	13.9	4 391	632	100	-	532

Notes: GDP = gross domestic product. PPP = purchasing power parity. All hidden costs reported are the net mean value in 2020 PPP of the distributions calculated during the SOFA 2024 exercise. Environmental externalities include GHG emissions, nitrogen emissions and land-use change; diet internality costs refer to productivity losses from dietary patterns; and social hidden costs to distributional failures resulting in protein–energy malnutrition from undernourishment and agrifood worker poverty below the international moderate poverty line.

Annex 2. Additional figures

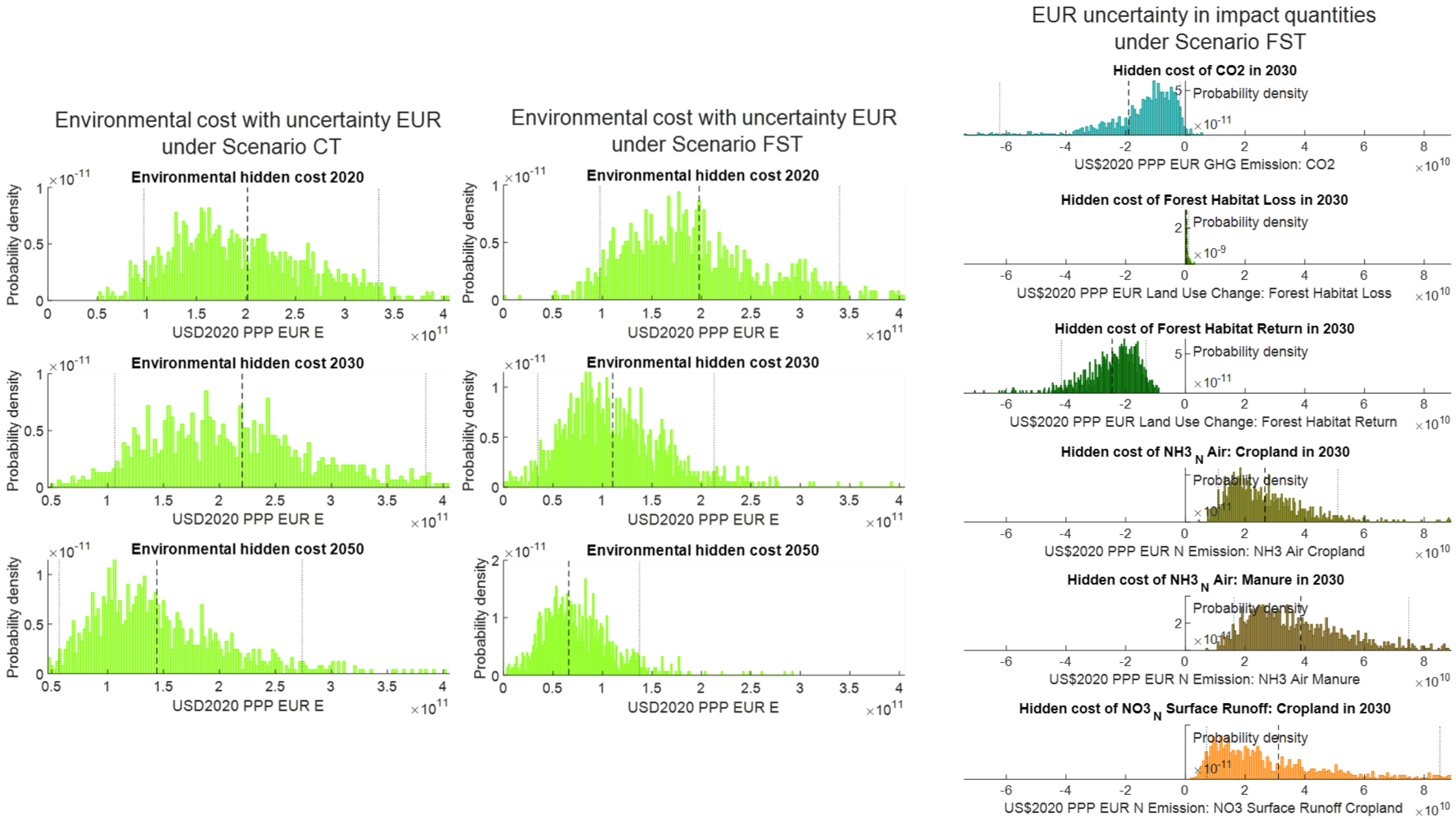
Figure 11A. External environmental costs and productivity losses from dietary risk internalities by country



Notes: CO_2 = carbon dioxide; CH_4 = methane; GHG = greenhouse gas; H = health hidden costs; N = nitrogen; N_2O = nitrous oxide; NH_3 = ammonia; NO_3 = 0nitrate; NO_x = nitrogen oxides. Each graph includes the 24 countries with the highest net hidden costs by category (right) and the 6 countries with the lowest net hidden costs (left). Regarding GHG emissions, Brazil, the Democratic Republic of Congo and Indonesia have significant CO_2 emissions from deforestation during production. In countries like Canada, China, Japan and the United States of America, the main sources of CO_2 are transport, cold chain logistics, manufacturing, retail and domestic energy use. CH_4 and N_2O emissions dominate in Ethiopia, India and Pakistan due to large livestock herds. Nitrogen emissions, particularly NO_3- emissions from agricultural runoff and leaching into surface waters, are prevalent across major middle-income producers. In contrast, ammonia (NH_3) emissions predominant in industrial agrifood systems, such as in western Europe and the United States of America, where NO_x emissions and nitrogen runoff into surface waters are more strictly regulated. For dietary patterns, cultural patterns matter: in Germany and the United States of America, for example, salt is primarily used in processed meats, while in Eastern- and South-eastern Asia, such as in China and Indonesia, it is more commonly used as a direct additive to dishes. The choice *in The State of Food and Agriculture 2024* to use food groups, means that results on low milk intake are not necessarily representative of calcium low intake. Affordability and cultural use of nuts, seeds and legumes shows in the variation in whole plant food categories across countries. Diets low in wholegrains, fruits and vegetables are common across countries as the major productivity costs from unhealthy diets based on GBD 2021 results.

Source: Reproduced from Figure A6 in [111].

Figure 12A: Change in economic risk of environmental externalities in EUR under the FSEC FST scenario over 2020 to 2050.



Notes: The FSEC study used non-parametric empirical distributions of residual external costs from MAgPIE model output and samples per unit costs generated by the SPIQ-FS model. Left panel shows the distribution of environmental external costs generated in 2020, 2030 and 2050 under the baseline scenario CT. Under FST the distribution transitions to higher mass on lower costs by 2050, with a two-fold reduction in the 95-th percentile (middle panel). Uncertainty in the residual external costs under FST by 2030 resides in benefits items (CO2 sequestration and ecosystem services from return of forest habitat) and cost items (ammonia emissions from cropland and manure and nitrate run-off from croplands), see right panel, with a similar pattern in 2050.

Source: Reproduced from Figure 6S in [327].

Annex 3. Countries included in the dataset

Table 6A: 153 countries included in the exercises by food system typology, development and income group

Country	Region	FAO Agrifood System Typology	UNDP Human Develop. Index (HDI)	World Bank Income group
Afghanistan	Asia	Protracted crisis	0.483	LIC
Albania	Europe	Formalizing	0.794	UMC
Algeria	Africa	Diversifying	0.736	LMC
Angola	Africa	Expanding	0.59	LMC
Azerbaijan	Asia	Expanding	0.73	UMC
Argentina	Americas	Formalizing	0.84	UMC
Australia	Oceania	Industrial	0.947	HIC
Austria	Europe	Industrial	0.913	HIC
Bangladesh	Asia	Traditional	0.655	LMC
Armenia	Asia	Diversifying	0.757	UMC
Belgium	Europe	Industrial	0.928	HIC
Bhutan	Asia	Traditional	0.668	LMC
Bolivia	Americas	Expanding	0.694	LMC
Botswana	Africa	Expanding	0.713	UMC
Brazil	Americas	Formalizing	0.758	UMC
Bulgaria	Europe	Formalizing	0.802	UMC
Myanmar	Asia	Traditional	0.6	LMC
Burundi	Africa	Protracted crisis	0.426	LIC
Belarus	Europe	Formalizing	0.807	UMC
Cambodia	Asia	Traditional	0.596	LMC
Cameroon	Africa	Traditional	0.578	LMC
Canada	Americas	Industrial	0.931	HIC
Central African Republic	Africa	Protracted crisis	0.407	LIC
Sri Lanka	Asia	Expanding	0.78	LMC
Chad	Africa	Protracted crisis	0.397	LIC
Chile	Americas	Formalizing	0.852	HIC
China	Asia	Diversifying	0.764	UMC
Colombia	Americas	Formalizing	0.756	UMC
Congo, Rep.	Africa	Expanding	0.574	LMC
Congo, Dem. Rep.	Africa	Protracted crisis	0.479	LIC
Costa Rica	Americas	Formalizing	0.816	UMC
Croatia	Europe	Formalizing	0.855	HIC
Cuba	Americas	Diversifying	0.781	UMC
Cyprus	Asia	Formalizing	0.894	HIC
Czechia	Europe	Industrial	0.892	HIC
Benin	Africa	Traditional	0.524	LMC
Denmark	Europe	Industrial	0.947	HIC
Dominican Republic	Americas	Formalizing	0.764	UMC

Country	Region	FAO Agrifood System Typology	UNDP Human Develop. Index (HDI)	World Bank Income group
Ecuador	Americas	Diversifying	0.731	UMC
El Salvador	Americas	Expanding	0.672	LMC
Equatorial Guinea	Africa	Diversifying	0.599	UMC
Ethiopia	Africa	Protracted crisis	0.498	LIC
Eritrea	Africa	Protracted crisis	0.494	LIC
Estonia	Europe	Industrial	0.892	HIC
Finland	Europe	Industrial	0.938	HIC
France	Europe	Industrial	0.898	HIC
Djibouti	Africa	Expanding	0.51	LMC
Gabon	Africa	Diversifying	0.71	UMC
Georgia	Asia	Expanding	0.802	UMC
Gambia, The	Africa	Expanding	0.501	LIC
Germany	Europe	Industrial	0.944	HIC
Ghana	Africa	Traditional	0.632	LMC
Greece	Europe	Industrial	0.886	HIC
Guatemala	Americas	Expanding	0.635	UMC
Guinea	Africa	Traditional	0.466	LIC
Guyana	Americas	Diversifying	0.721	UMC
Haiti	Americas	Protracted crisis	0.54	LMC
Honduras	Americas	Expanding	0.621	LMC
Hungary	Europe	Formalizing	0.849	HIC
Iceland	Europe	Industrial	0.957	HIC
India	Asia	Traditional	0.642	LMC
Indonesia	Asia	Expanding	0.709	LMC
Iran, Islamic Rep.	Asia	Diversifying	0.777	LMC
Iraq	Asia	Expanding	0.679	UMC
Ireland	Europe	Formalizing	0.943	HIC
Israel	Asia	Industrial	0.917	HIC
Italy	Europe	Industrial	0.889	HIC
Cote d'Ivoire	Africa	Traditional	0.551	LMC
Jamaica	Americas	Diversifying	0.713	UMC
Japan	Asia	Industrial	0.923	HIC
Kazakhstan	Asia	Diversifying	0.814	UMC
Jordan	Asia	Formalizing	0.723	UMC
Kenya	Africa	Traditional	0.578	LMC
Korea, Rep.	Asia	Industrial	0.922	HIC
Kuwait	Asia	Formalizing	0.822	HIC
Kyrgyz Republic	Asia	Expanding	0.689	LMC
Lao PDR	Asia	Traditional	0.608	LMC
Lebanon	Asia	Diversifying	0.726	LMC

Country	Region	FAO Agrifood System Typology	UNDP Human Develop. Index (HDI)	World Bank Income group
Latvia	Europe	Formalizing	0.871	HIC
Liberia	Africa	Protracted crisis	0.48	LIC
Libya	Africa	Expanding	0.703	UMC
Lithuania	Europe	Formalizing	0.879	HIC
Luxembourg	Europe	Industrial	0.924	HIC
Madagascar	Africa	Traditional	0.501	LIC
Malawi	Africa	Traditional	0.516	LIC
Malaysia	Asia	Formalizing	0.806	UMC
Mali	Africa	Protracted crisis	0.427	LIC
Mauritania	Africa	Protracted crisis	0.556	LMC
Mexico	Americas	Diversifying	0.756	UMC
Mongolia	Asia	Formalizing	0.745	LMC
Moldova	Europe	Diversifying	0.766	UMC
Montenegro	Europe	Formalizing	0.826	UMC
Morocco	Africa	Expanding	0.679	LMC
Mozambique	Africa	Traditional	0.453	LIC
Oman	Asia	Formalizing	0.827	HIC
Namibia	Africa	Expanding	0.633	UMC
Nepal	Asia	Traditional	0.604	LMC
Netherlands	Europe	Industrial	0.939	HIC
New Zealand	Oceania	Industrial	0.936	HIC
Nicaragua	Americas	Expanding	0.654	LMC
Niger	Africa	Protracted crisis	0.401	LIC
Nigeria	Africa	Traditional	0.535	LMC
Norway	Europe	Industrial	0.959	HIC
Pakistan	Asia	Traditional	0.543	LMC
Panama	Americas	Diversifying	0.801	HIC
Paraguay	Americas	Expanding	0.73	UMC
Peru	Americas	Expanding	0.762	UMC
Philippines	Asia	Expanding	0.71	LMC
Poland	Europe	Diversifying	0.876	HIC
Portugal	Europe	Formalizing	0.863	HIC
Guinea-Bissau	Africa	Traditional	0.483	LIC
Timor-Leste	Asia	Traditional	0.614	LMC
Qatar	Asia	Formalizing	0.854	HIC
Romania	Europe	Diversifying	0.824	HIC
Russian Federation	Europe	Formalizing	0.83	UMC
Rwanda	Africa	Traditional	0.532	LIC
Saudi Arabia	Asia	Formalizing	0.87	HIC
Senegal	Africa	Traditional	0.513	LMC

Country	Region	FAO Agrifood System Typology	UNDP Human Develop. Index (HDI)	World Bank Income group
Serbia	Europe	Diversifying	0.804	UMC
Sierra Leone	Africa	Protracted crisis	0.475	LIC
Slovak Republic	Europe	Formalizing	0.857	HIC
Viet Nam	Asia	Expanding	0.71	LMC
Slovenia	Europe	Formalizing	0.913	HIC
South Africa	Africa	Diversifying	0.727	UMC
Zimbabwe	Africa	Protracted crisis	0.6	LMC
Spain	Europe	Industrial	0.899	HIC
South Sudan	Africa	Protracted crisis	0.386	LIC
Sudan	Africa	Protracted crisis	0.51	LIC
Suriname	Americas	Diversifying	0.743	UMC
Eswatini	Africa	Expanding	0.61	LMC
Sweden	Europe	Industrial	0.942	HIC
Switzerland	Europe	Industrial	0.956	HIC
Syrian Arab Republic	Asia	Protracted crisis	0.577	LIC
Tajikistan	Asia	Traditional	0.664	LMC
Thailand	Asia	Expanding	0.802	UMC
Togo	Africa	Traditional	0.535	LIC
United Arab Emirates	Asia	Formalizing	0.912	HIC
Tunisia	Africa	Diversifying	0.737	LMC
Turkiye	Asia	Formalizing	0.833	UMC
Turkmenistan	Asia	Diversifying	0.741	UMC
Uganda	Africa	Traditional	0.524	LIC
Ukraine	Europe	Diversifying	0.775	LMC
North Macedonia	Europe	Formalizing	0.774	UMC
Egypt, Arab Rep.	Africa	Expanding	0.734	LMC
United Kingdom	Europe	Industrial	0.924	HIC
Tanzania	Africa	Traditional	0.548	LMC
United States	Americas	Industrial	0.92	HIC
Burkina Faso	Africa	Traditional	0.449	LIC
Uruguay	Americas	Industrial	0.821	HIC
Uzbekistan	Asia	Expanding	0.721	LMC
Venezuela, RB	Americas	Formalizing	0.695	LMC
Yemen, Rep.	Asia	Protracted crisis	0.46	LIC
Zambia	Africa	Traditional	0.57	LIC

Note: For a description of the agrifood systems typology methodology, see *The State of Food and Agriculture 2024.* Income group refers to the World Bank income group classification of 2020 by GNI using the Atlas method.

Source: Author’s own elaboration.

Annex 4. Acronyms and Terms

AFF	agricultural, forestry and fishing
AMR	antimicrobial resistance
AMU	agricultural use of antibiotics
BMI	body mass index
CH_4	methane
CO_2	carbon dioxide
CICES	Common International Classification of Ecosystem Services
DALY	disability-adjusted life years
EDGAR	Emissions Database for Global Atmospheric Research
EPA	Environmental Protection Agency
ESVD	Ecosystem Services Valuation Database
FAO	Food and Agricultural Organization of the United Nations
FAOSTAT	FAO statistical database
FSEC	Food system economic commission
GBD	Global Burden of Disease study
GDP	gross domestic product
GHG	greenhouse gas
HDI	Human Development Index
HIC	high-income country
Hidden Cost	future liabilities from environmental externalities and dietary risk internalities are often termed hidden costs because they are not considered in present economic assessment or accounted for in national accounts
HILDA	HIstoric Land Dynamics Assessment
IFPRI	International Food Policy Research Institute
ILO	International Labour Organization
IPCC	Intergovernmental Panel on Climate Change
IWG-SCGHG	Interagency Working Group on the Social Cost of Greenhouse Gases
LCA	Life-Cycle Analysis
NH_3	Ammonia
NO_x	Nitrogen oxides
NO_2	Nitrogen dioxide
NO_3^-	Nitrate
N_2O	Nitrous oxide
NPV	Net Present Value
PAF	Population Attributable Fraction
PM	Particulate Matter
POU	prevalence of undernourishment

PIK	Potsdam Institute for Climate Impact Research
PPP	purchasing power parity
RCP	Representative Concentration Pathway
SDSN	Sustainable Development Solutions Network
SO_x	Sulphur oxides
SOFA	State of Food and Agriculture
TEEB	The Economics of Ecosystems and Biodiversity
VSL	Value of a Statistical Life
WHO	World Health Organization
WWF	Worldwide Fund for Nature