WORKING PAPER

Comparative Hidden Costs of the Food System Economic Commission Current Trends and Food System Transformation Pathways to 2050

Steven Lord

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Background Report for the
Food System Economic Commission

Comparative hidden costs of the Food System Economic Commission current trends and food system transformation pathways to 2050

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Abstract

Based on hidden costs from greenhouse gas (GHG) emissions, nitrogen (N) pollution, lost and returned habitat from land-use change, poverty, and productivity losses from obesity, undernourishment, and noncommunicable diseases from dietary intake, the Food System Economic Commission (FSEC) food system transformation pathway started in 2020 would provide a reduction in hidden costs worth, on average, 3.5 trillion of GDP PPP in present value 2020 USD PPP (Purchasing Power Parity) per year from 2020 to 2050 compared to a current trends food system pathway. The FSEC food system transformation (FST) pathway and the current trends (CT) pathway assume a similar economic development outside the food system based on the IPCC Shared Socioeconomic Pathway 2 (SSP2). If economic development follows SSP1 for the food system transformation pathway and economic development for the current trends pathway follows SSP2, then the comparative hidden cost reduction is worth an average of 5.1 trillion of GDP PPP in 2020 USD PPP per year from 2020 to 2050.

Regional and country results highlight health, environmental and social transition under the food system transformation pathway. Under the FST China avoids a western style trajectory of burden of disease from dietary intake, reducing potential productivity losses from obesity and noncommunicable disease attributed to dietary intake by 30% over 2020 to 2050, worth an estimated 300 billion 2020 USD PPP to GDP PPP per year. China also reduces the expected external costs and risks of nitrogen pollution by 30% under FST over 2020 to 2050, worth 100 billion 2020 USD PPP to GDP PPP per year. Under FST Brazil transits from nearly 300 billion 2020 USD PPP per annum in GHG emissions, N pollution and habitat loss damages to an expected 200 billion of avoided damages through carbon sequestration and returning ecosystem services in 2050. Potentially translating into a 200 billion GDP PPP benefit per annum in nature-based payments to the GDP PPP of Brazil. Globally, the FST is expected to become environmental cost neutral by 2050. The savings from sequestered carbon and recovering ecosystem services from forest and other habitat are expected to equate to the residual damage costs of methane emissions and nitrogen pollution from food production, but there is uncertainty in this conclusion. The 5-th to 95-th percentiles for FST net environmental costs in 2050 range from 1 trillion in global 2020 USD PPP benefits to 0.5 trillion in global 2020 USD PPP costs. Under CT projections, Sub-Sahara Africa (SSA) faces a triple economic burden of 540 billion 2020 USD PPP by 2050. Environmental hidden costs in SSA, including growing nitrogen use, account for 240 billion 2020 USD PPP, and productivity losses from obesity, undernourishment, and noncommunicable disease due to dietary intake account for 190 billion 2020 USD PPP. Both nitrogen external costs and productivity losses associated to diets eclipse the residual cost of poverty in SSA estimated at 110 billon 2020 USD PPP in 2050. This triple economic burden for SSA is avoided under FST by halving costs of dietary intake and eliminating environmental costs (5-th to 95-th percentiles for FST environmental costs in SSA in 2050 are -71 billion 2020 USD PPP to 24 billion 2020 USD PPP).

This study shows the potential to reduce hidden costs under the FSEC food system transformation pathway. For a complete picture of the economic potential of the FSEC food system transformation pathway, the reductions should be compared with the costs of realising the pathway in subsequent studies.

Summary

External economic damages from GHG emissions, nitrogen emissions, lost habitat from land-use change, and costs to governments, business and consumers of poverty and productivity losses from the preventable burden of disease due to dietary intake, are not visible in most markets. A primary reason for a lack of accounting of these costs is that they are generated by present food system activities that contribute value add to the present year's national accounts, but the costs are borne beyond national borders or distributed into the future. There is no reckoning or adjustment for the losses outside national borders or to the future in current accounts. Collectively, the costs are called hidden food system costs by the Food System Economic Commission (FSEC) [1]. Regional and national changes in hidden costs under the FSEC food system transformation pathway (FST) (Table 1 and Table 2) compared to a current trends pathway (CT) were modelled in collaboration with the Potsdam Institute for Climate Research (PIK) for 153 countries. Changes in hidden costs between FST and CT are estimated out to 2050.

From the MAgPIE partial equilibrium model (PE) land-use model at PIK, changes could be calculated at a regional and national level for greenhouse gas (GHG) emissions, reactive nitrogen (N) emissions, land-use changes, and poverty headcount at the $3.20/day (2011 PPP) for the FST and CT scenarios. Years of life lost (YLL) from the preventable burden of disease from dietary intake in national populations was calculated at the Environmental Change Institute (ECI) at Oxford University based on MAgPIE food composition and body mass index. The difference in total damages to GDP PPP in 2020 USD PPP (Purchasing Power Parity) incurred or avoided under the scenarios were estimated from the emissions, land-use, headcount, and YLL quantity changes using the SPIQ-FS model of external marginal costs developed for FSEC at the ECI at Oxford University. Marginal and total hidden costs are calculated in 2020 international dollars, denoted by 2020 USD PPP.

The food system CT and FST pathways require context of wider economic conditions for MAgPIE modelling and marginal cost calculations. CT occurs in the context of the Shared Socio-economic Pathway (SSP) SSP2, and FST was examined occurring in SSP2 and SSP1 (Table 2). Comparison of the difference in hidden costs between the CT and FST pathways, which largely translates to avoided hidden costs due to a global food system transformation, is not a cost-benefit analysis. Subsequent work should compare the net costs of the transition from the CT trajectory to the FSEC FST pathway over 2020 to 2050 with the reduction in hidden costs.

Hidden costs of CT and FST

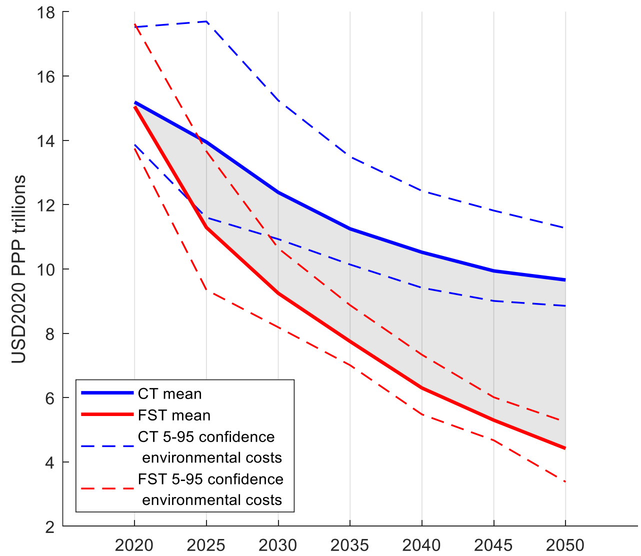
For comparative hidden costs and due to the partial equilibrium modelling being in 5-year time steps the FSEC FST and the CT pathway diverge starting in 2020. The FSEC FST assumes the full implementation of the food system measures by 2050 under SSP2 (Table 1). Comparison of CT with FSEC FST under SSP1 is discussed in the main text. Annual total hidden costs are linearly interpolated between the five-year time steps.

Trajectory of hidden costs and hidden cost reduction

Figure 1S top panel shows the trajectory of global total annual hidden costs for CT and FST in 2020 USD PPP. The area between the two trajectories shows a total reduction of ~104 trillion 2020 USD PPP in hidden costs under FST from 2020 to 2050, at an average of ~3.5 trillion 2020 USD PPP per annum. 3.5 trillion 2020 USD PPP equates to 2.2% of global GDP PPP in 2020. Discounting causes the total hidden costs trajectories to decrease into the future in 2020 USD PPP terms. A sign that hidden costs from the food system are relatively accelerating under CT is the levelling out of the CT hidden cost trajectory (blue) toward 2050 in Figure 1S top panel. GDP growth does not slow under SSP2 until after 2050, so damages are not levelling due to discounting.

The global hidden cost reduction under FST is not uniform over the period 2020 to 2050 (Figure 1S bottom panel). FST assumes rapid and global implementation of environmental regulation in the early period. That, combined with discounting, indicates that the largest acceleration in hidden cost reduction is in the early period. Despite the effect of discounting the global hidden cost reduction exceeds 5 trillion 2020 USD PPP per annum in 2050 and estimated to still be increasing.

A breakdown of global hidden cost reduction in Figure 4S and discussed below shows an approximately equal contribution to reduction from "environmental" hidden costs associated to production (reduction in greenhouse gas (GHG) and reactive nitrogen (N) emissions, reduction in lost habitat from land use changes and increase in returned habitat from abandoned agricultural land) and "health" hidden costs associated to undernourishment or over-consumption (reduction in years of life lost (YLL)).



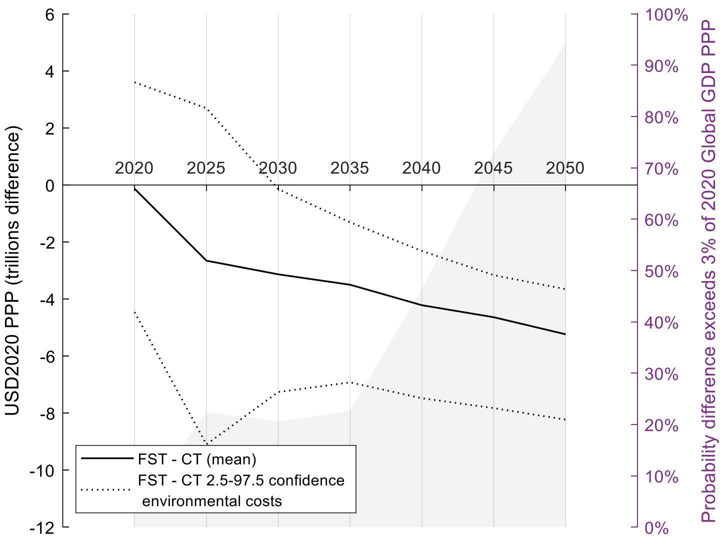


Figure 1S: Trajectory of global total annual hidden costs and cost reduction for CT and FST in 2020 USD PPP. Top panel shows the global total expected hidden costs under CT (blue) and FST (red). The shaded area between the trajectories indicates the value of the total reduction under FST over the period 2020-2050 in 2020

USD PPP. Trajectories of the 5-th and 95-th percentiles of the respective distributions of global hidden cost are shown, accounting for uncertainty in the "environmental" costs (greenhouse gas (GHG) and reactive nitrogen (N) emissions, lost habitat from land use changes and returned habitat from abandoned agricultural land). Even with high uncertainty in environmental costs the bottom panel shows that hidden cost reduction under FST is very likely (>97.5%) by 2030 with an increasing probability that the reduction exceeds 3% of global 2020 GDP PPP.

Uncertainty in hidden costs, hidden cost reduction, and changes in economic risk

To illustrate the economic risk of hidden costs we show the distribution of annual hidden costs for the CT and FST pathways, both under SSP2, in annual snapshots in 2020, 2030 and 2050 (Figure 2S). FST in 2050, by reducing the land-use and nitrogen run-off costs with large uncertainty (Annex R), translates a right skew in the hidden cost distribution of CT in 2020 and 2050 toward higher hidden costs (top and middle panels Figure 2S) to a left skew distribution toward lower hidden costs (bottom panel Figure 2S). The FST scenario changes the economic risk posed by the environmental hidden costs as well as reducing the expected annual costs.

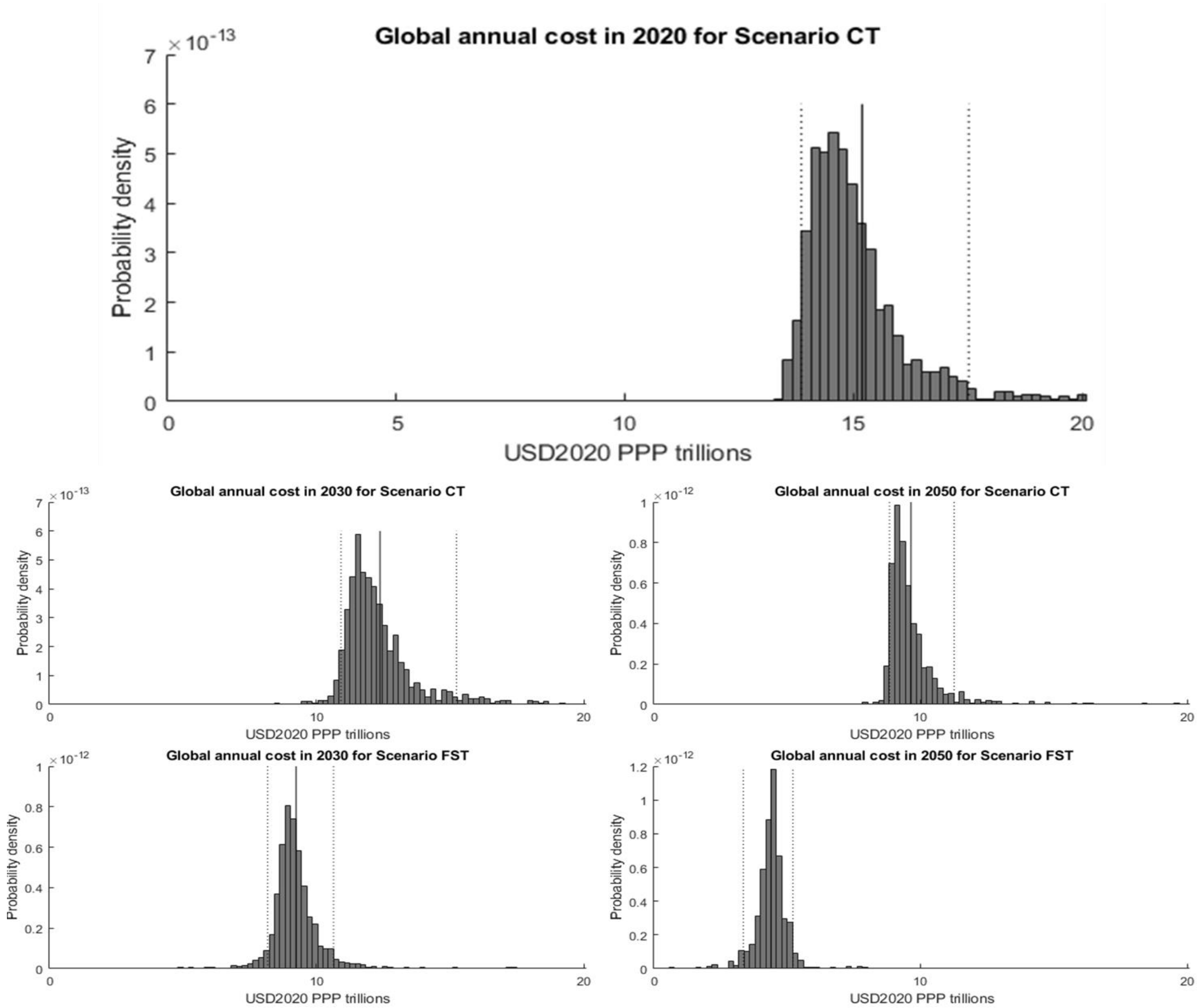


Figure 2S: Distribution of global total annual hidden costs for CT and FST in 2020 USD PPP in 2020, 2030 and 2050. Hidden costs are modelled with uncertainty in this study. Figure 1S top panel shows the trajectory of the mean and the 5-th and 95-th percentile statistics of the distributions of global annual hidden cost under FST and CT. The top, middle and bottom panels shows cross-sections of the full distribution of global annual hidden costs in the years 2020, 2030 and 2050. The percentiles, and the shape of the distribution of hidden costs show uncertainty in environmental hidden costs. Under FST the skew in the CT distributions toward higher hidden *costs is translated to a skew to lower hidden costs by 2050 due to avoided costs of land-use change and uncertain value in returning ecosystem services of recovering forest and other habitat.*

Economic risk of uncertain but potentially large environmental hidden costs in CT (5% chance of exceeding 2.4 trillion 2020 USD PPP in extra annual global hidden costs above the expected cost of 15.1 trillion 2020 USD in top panel Figure 2S) is translated into the opportunity for uncertain but potentially large hidden cost reduction in FST (5% chance of exceeding 1.3 trillion 2020 USD PPP in lower than expected environmental global hidden costs (Figure 2S bottom panel) and additional reduction of hidden costs on average in FST (Figure 3S bottom panel)).

Accounting for uncertainty in environmental costs, average annual hidden cost reduction under FST over 2020 to 2050 is estimated to have less than a 5% chance of being less than 2 trillion 2020 USD PPP and a 5% chance of exceeding 5.7 trillion 2020 USD PPP (Figure 3S bottom panel).

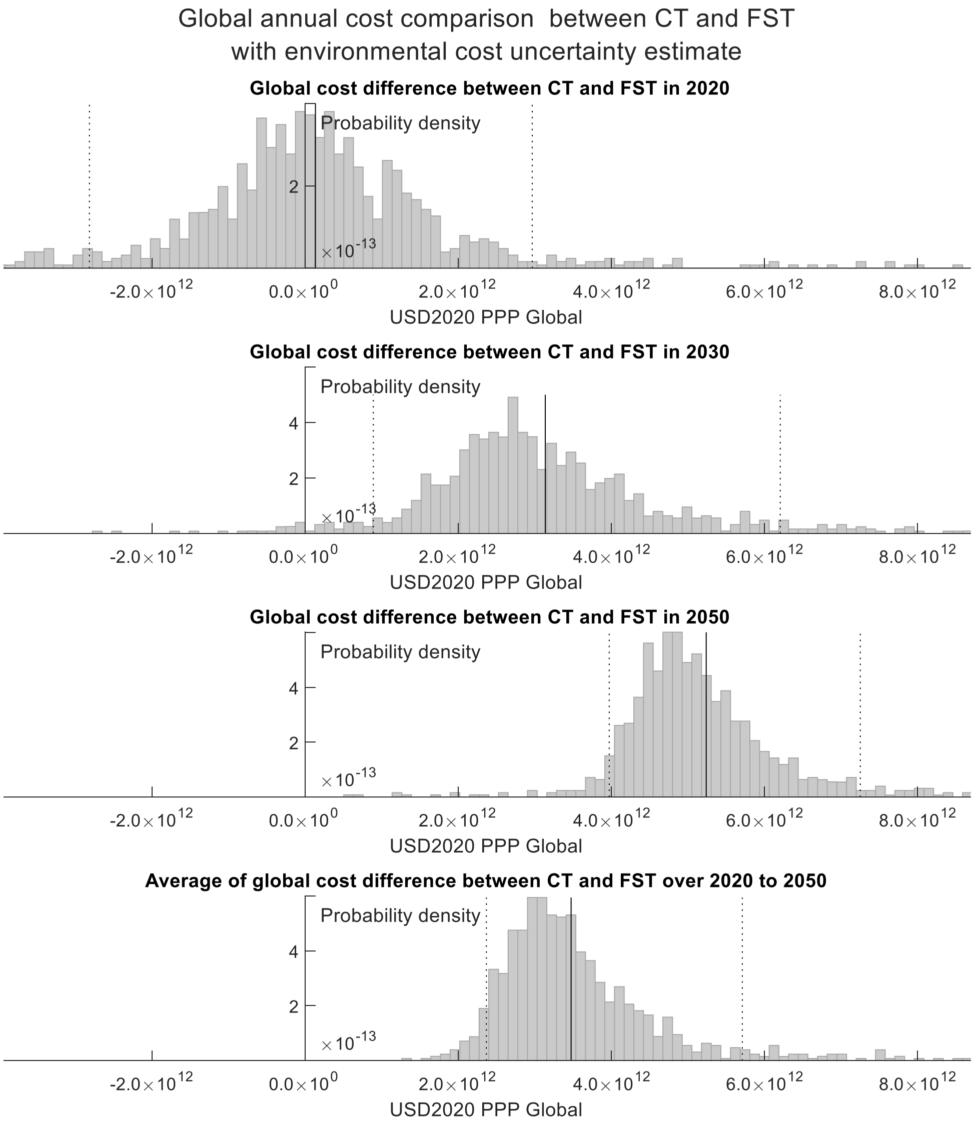


Figure 3S: Distribution of global total annual hidden cost reduction under FST in 2020 USD PPP in 2020, 2030 and 2050. Hidden cost reduction can be examined with uncertainty in environment costs in this study. Figure 1S bottom panel shows the trajectory of the mean and the 5-th and 95-th percentile statistics of the distributions of global annual hidden cost reduction under FST. The top, second to top, and second to bottom panels shows cross-section of the full distribution of global annual hidden costs reduction in the years 2020, 2030 and 2050. The bottom panel shows the distribution of the total cost reduction divided by the 30 years *study period. The conclusion that FST reduces hidden costs by 2030, that average annual hidden cost reduction under FST is greater than 2 trillion USD 2020 PPP, and that annual hidden cost reduction by 2050 exceeds 4 trillion USD 2020 PPP, are robust to the modelled uncertainty in the marginal costs of GHG, N emissions, and ecosystem services.*

Uncertainty is due to the difficulty in estimating marginal costs of GHG emissions, ecosystem services loss, and N pollution. Uncertainty in YLL costs were not available and income shortfall from the $3.20/day (PPP 2011) World Bank poverty line showed limited uncertainty in variation in GDP PPP pass through rates due to the addition of many, summed independent, random variables (central limit principles). The estimates are not full risks in hidden cost and hidden cost reduction since the marginal damages from burden of disease and poverty are estimated with limited uncertainty and quantity estimates were not modelled with uncertainty.

The most uncertain cost category is the value of returned ecosystem services from abandoned cropland and pasture (Annex R). A correlation sensitivity test showed that the economic risk of external costs is not substantially changed if the values of returned ecosystem services are higher than expected when the costs of GHG, nitrogen emissions, habitat loss and water withdrawal are lower than expect.

Breakdown of hidden cost reduction

Mean global hidden cost reduction broken down by “environmental” (E) hidden costs associated to production (reduction in greenhouse gas (GHG) and reactive nitrogen (N) emissions, reduction in lost habitat from land use changes and increase in returned habitat from abandoned agricultural land), “health” (H) hidden costs associated to undernourishment or over-consumption (reduction in years of life lost (YLL)), and “social” (S) hidden costs (poverty reduction) is shown in Figure 4S (overpage).

GHG hidden costs are measured at the level of social costs of CO_2 emission from land-use changes, CH_4 emission primarily from rice production, waste, and enteric fermentation, and N_2O emission primarily from soil, non-organic fertiliser application and livestock manure left on pasture or used in organic fertiliser. N hidden costs are measured by NH_3 volatilization to air from fertiliser application and livestock manure, NO_2 volatilization to air from fertiliser, manure, and crop residues, soluble NO_3^- runoff to surface waters from pasture and cropland, and soluble NO_3^- leaching into groundwater sources. Habitat loss is distinguished by forest and other land biome habitat loss, and forest and other land biome habitat return primarily from abandoned cropland and pasture. Cumulative value of ecosystem services from a hectare (ha) of avoided loss of established habitat and regenerating habitat is asymmetric, hence the distinction in loss and return categories for land-use change.

Assumed rapid realisation of environmental measures provides a sustained annual hidden cost reduction over the period, while graduated dietary change provides an increasing and larger reduction in productivity losses toward 2050 (Figure 4S). Over the period 2020 to 2050, up to the uncertainty in environmental costs, the environmental and health costs contribute equally to average annual hidden cost reduction. In environmental costs, the contribution of GHG emission reduction, N pollution reduction, and avoided loss or return of habitat from land-use change provide hidden cost reduction of ~500 billion 2020 USD per annum and equal contributions on average up to the uncertainty in the average hidden cost reduction. 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 (Figure 4S). This conclusion is robust to uncertainty in environmental costs (Annex R).

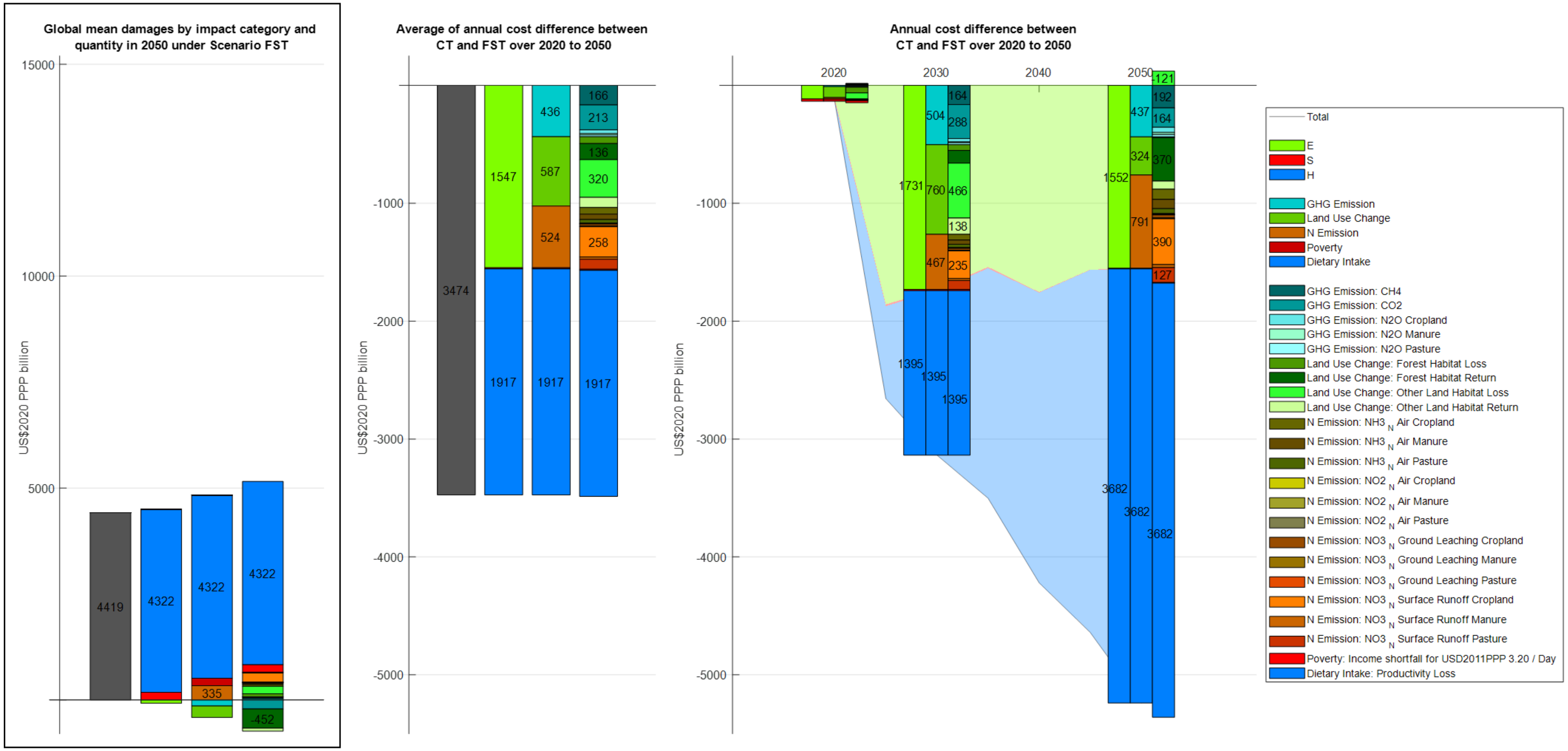


Figure 4S: Breakdown of global annual hidden cost reduction under FST in 2020 USD PPP in 2020, 2030 and 2050. Large average hidden cost reductions under FST over 2020-2050 come from burden of disease from food consumption, CH4 and CO2 emission reductions, forest habitat return, avoided loss of other land habitat, and NO3- run-off from cropland (middle panel). Up to uncertainty in environmental costs, GHG emission reduction, avoided loss and return of habitat, and reduction in N pollution, provide equal contribution to hidden cost reduction over the period 2020-2050 (middle panel). Reduction in N pollution contributes more later in the period (right panel). Environmental hidden cost reduction and productivity losses from burden of disease from food consumption have an approximately equal contribution to hidden cost reduction over the period 2020-2050 (middle panel). Environmental hidden cost reduction stabilises while the avoided productivity losses from burden of disease increase over the period (right panel). Residual hidden costs by 2050 under the FST trajectory (Figure 1S top panel) are predominately productivity losses from food consumption since mean net global environmental costs cancel (left panel). There is little difference between CT and FST in income shortfall from the $3.20/day (2011 PPP) poverty line. Poverty reduction is driven by economic growth of all sectors in SSP2, not in the implementation of FST measures.

In 2030, dietary change, CH4 emission reduction, and avoided loss of other land habitat from a reduction in agricultural land expansion are the largest reductions in hidden cost under FST. Reversal of land expansion slows to 2050, and dietary change, reduction in NO3- surface run-off from cropland, and reforestation are the largest reductions in hidden cost under FST in 2050. NO3- surface run-off from cropland and returning forest and other land habitat have the highest uncertainty as modelled, equating to the highest risk in environmental costs under CT and potential opportunity under FST by 2050, respectively (Annex R).

Expected hidden costs under FST in 2050 (left panel Figure 4S) are predominately residual burden of disease from dietary intake. Globally, the FST is expected to become environmental cost neutral by 2050 (Figure 4S), with caveats on substitution of returns and losses of natural capital. Expected savings of 215 billion 2020 USD PPP from sequestered carbon and 452 billion 2020 USD PPP in other ecosystem services on returning forest habitat in Latin and South America potentially offset agricultural land expansion in China (Figure 5S) and residual global nitrogen pollution costs. There is uncertainty in this conclusion. The 5-th to 95-th percentiles for FST net global environmental costs in 2050 range from 1 trillion 2020 USD PPP benefits to 0.5 trillion 2020 USD PPP in costs (Annex R).

Regional hidden costs

FSEC regional analysis covers 14 regions and countries. Hidden cost trajectories, reductions, and uncertainty are available for all 14 regions, and 153 countries (excluding CH4 and CO2 hidden costs at a country level), in the data files available https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8. In this report we focus on developing regions and major producers.

Developing regions and major producers

Productivity losses from diets dominate hidden costs and hidden cost reduction in EU 27 countries (EUR) and USA. Slower GDP growth and ageing population under SSP2 lock in high productivity losses in 2020 USD PPP in EUR and USA despite having smaller populations than China (CHA), India (IND) and Sub-Sahara Africa (SSA). CHA and IND avoid repeating a western trajectory under FST with proportionally larger reductions in productivity losses from diets.

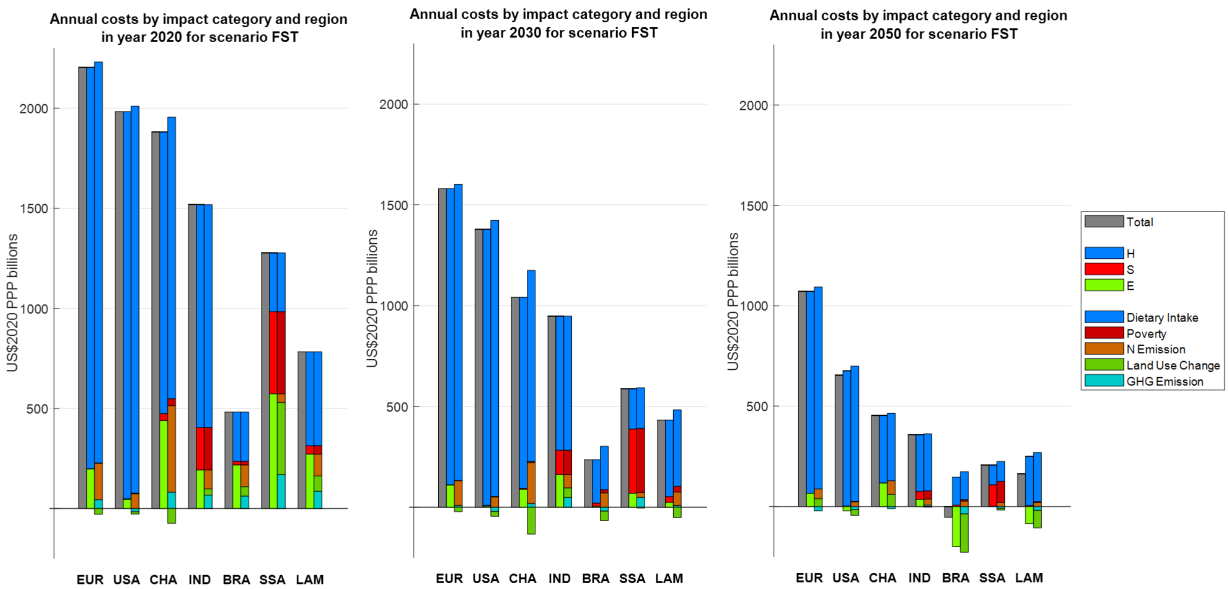


Figure 5S: Breakdown of annual hidden costs under FST in 2020 USD PPP in 2020, 2030 and 2050 for 7 FSEC regions. Regional trajectories show transitions in productivity loss from diets and N pollution in China (CHA), *land-use change in Brazil (BRA) and Sub Sahara Africa (SSA), and residual poverty in India (IND) and SSA under SSP2.*

Most regions show large reductions in productivity losses from diets and all categories of environmental hidden under FST. FST transitions from environmental costs in 2020 to benefits in 2050 in Brazil (BRA) and the rest of South and Latin America (LAM) from returning habitat and reduction in GHG emissions. BRA and LAM are largely responsible for FST reaching environmental "net-zero" costs by 2050. Poverty reduction in IND and SSA is predominately driven by economic growth of all sectors in SSP2, not in the implementation of FST measures.

Environmental, health, and social transition under FST

Regional and country results highlight health, environmental and social transition under the food system transformation pathway, illustrated by hidden costs reduction in 3 regions.

Under FST, China avoids a western style trajectory of burden of disease from dietary diets, reducing potential productivity losses from obesity and noncommunicable disease attributed to diets by ~30% over 2020 to 2050 compared to CT (Figure 6S). In average annual terms, the avoided productivity loss is worth an estimated ~300 billion 2020 USD PPP to GDP PPP per year. China has the world's largest economy in GDP PPP terms, but the productivity boost is worth 1% of China's 2020 GDP PPP. China, currently the world's largest agricultural nitrogen polluter, reduces the expected external costs and risks of nitrogen pollution by ~30% under FST over 2020 to 2050, worth ~100 billion 2020 USD PPP to GDP PPP per year (Figure 6S).

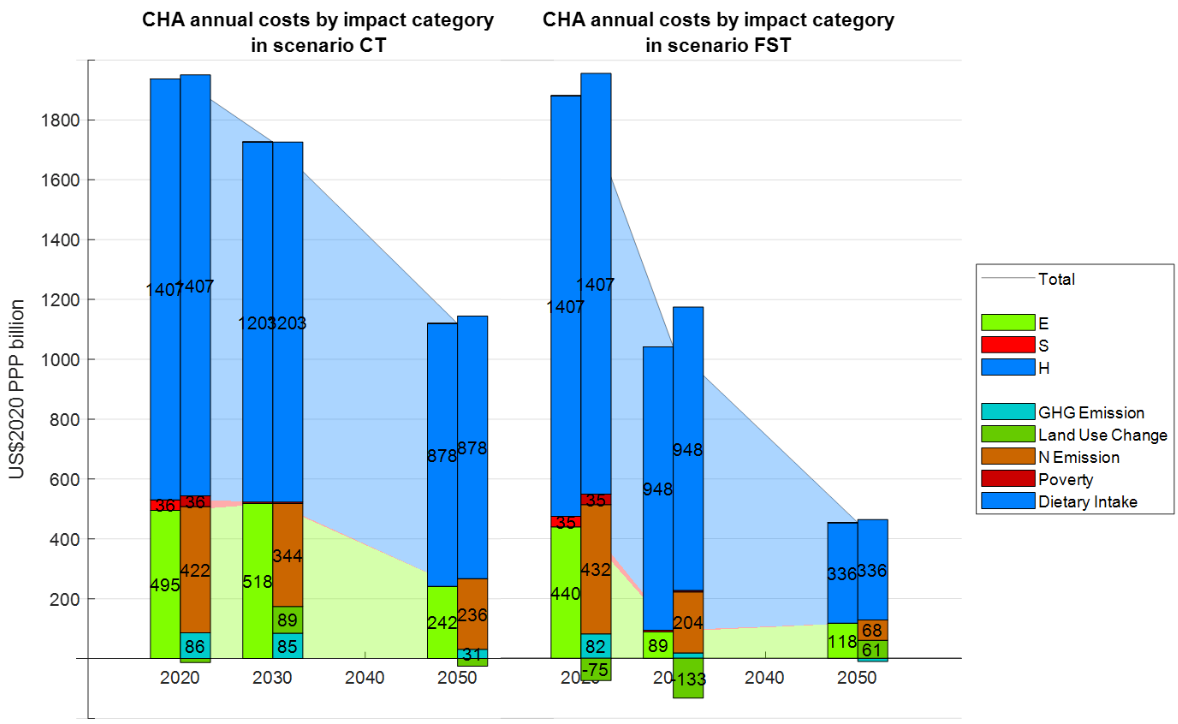


Figure 6S: Transition in diets and annual hidden cost reduction under FST in 2020, 2030 and 2050 and for China (CHA).

Under FST, Brazil (BRA) transits from nearly 250 billion 2020 USD PPP per annum in GHG emissions, N pollution and habitat loss damages to an expected 200 billion of avoided damages through carbon sequestration and returning ecosystem services in 2050 (Figure 7S). Potentially translating into a 200 billion GDP PPP benefit per annum in nature-based payments to the GDP PPP of Brazil. Benefits of 190 billion 2020 USD PPP are estimated for ecosystem services from returning forest habitat and 37 billion 2020 USD PPP in CO2 sequestration, offset by 17 billion 2020 USD PPP hidden costs of residual agricultural other land expansion. For context, 190 billion is approximately 6% of GDP PPP of Brazil in 2020 and equal to the Gross Value Add (GVA) of the Agriculture, Forestry and Fishery (AFF) sector. Damages from nitrogen pollution is reduced by 66% by 2050 in Brazil under FST compared to CT.

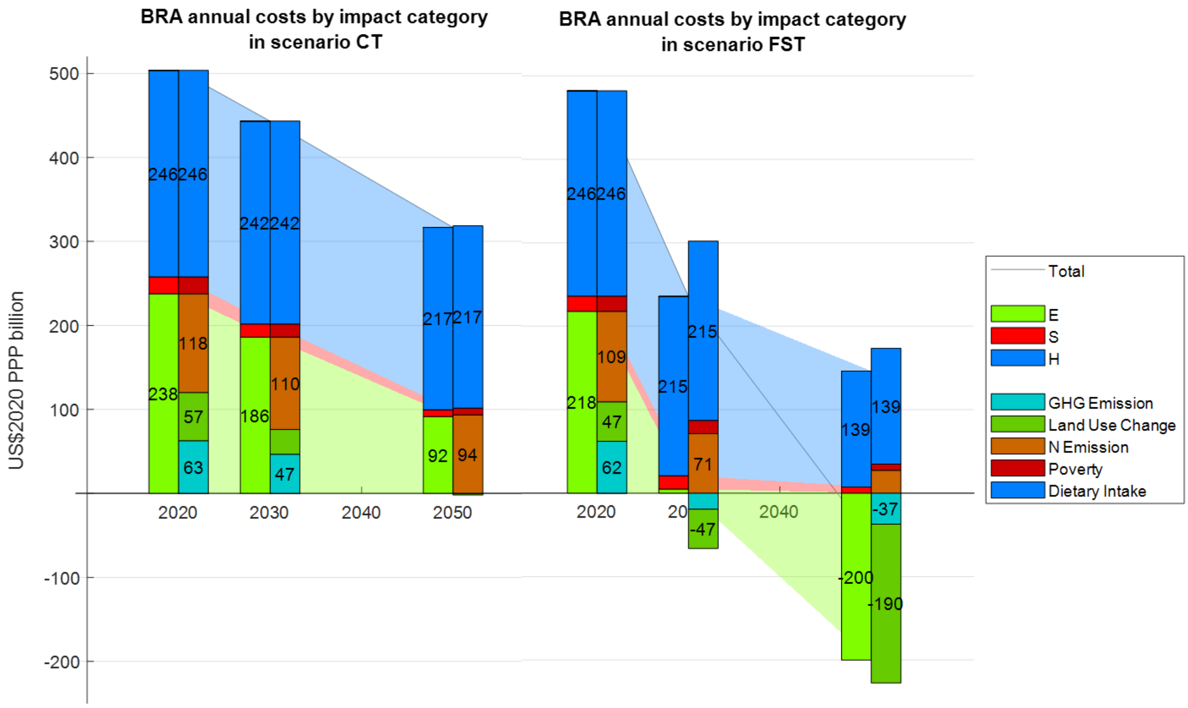


Figure 7S: Environmental transition and annual hidden cost reduction under FST in 2020, 2030 and 2050 for Brazil (BRA).

Uncertainty is large for the environmental benefits of FST in 2050 for BRA due to the uncertainty in the value of ecosystem services (Figure 8S). 190 billion 2020 USD PPP in benefits is the mean value. There is opportunity in a 5% chance that benefits may exceed 750 billion 2020 USD PPP in 2050, and conversely risk in a 5% chance that Brazil may have environment costs exceeding 32 billion 2020 USD PPP in 2050.

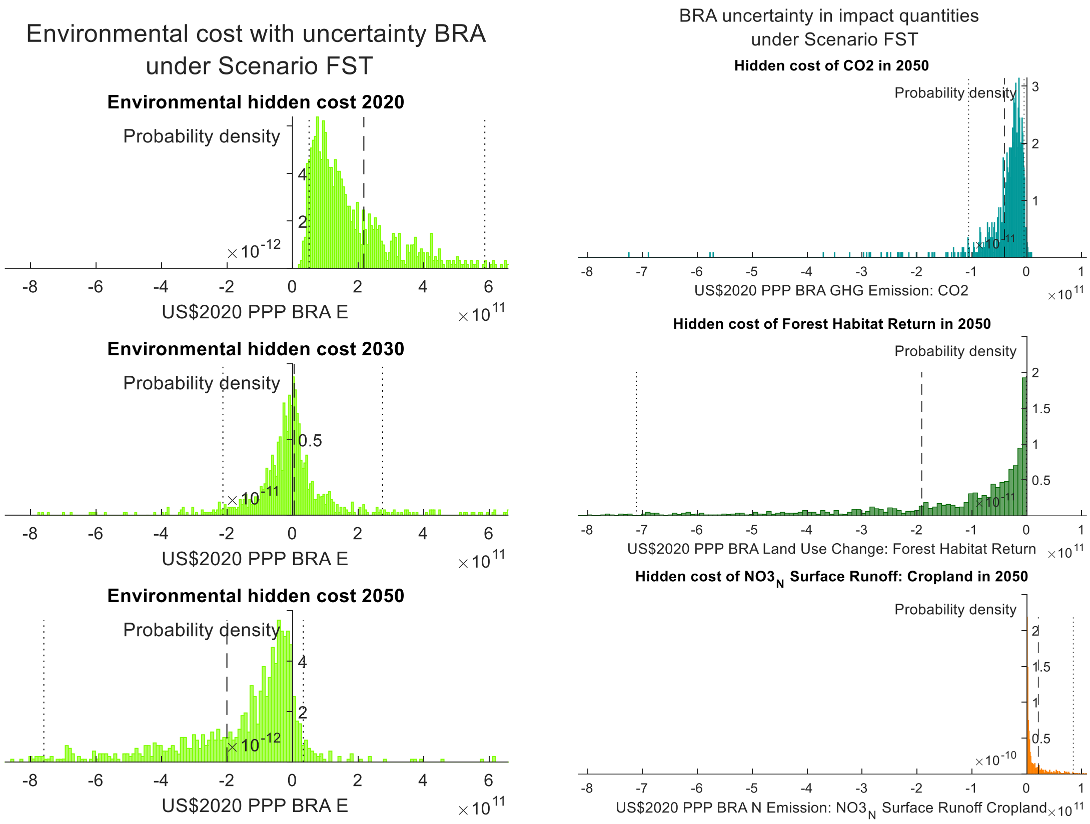


Figure 8S: Distribution of environmental annual hidden cost reduction under FST in 2020, 2030 and 2050 for Brazil (BRA). Left panel shows the distribution of environmental hidden costs, which transitions from a right skew and a long-tail of risk of higher hidden costs to a left-skew toward opportunity for higher benefits in 2050. Right panel shows the major components of the uncertainty in terms of GHG emissions, land-use change, and N pollution. Return of forest habitat and CO2 sequestration are the main sources of uncertainty in the transition from risk of costs to benefits.

Overall, as far as the modelled uncertainty can indicate, with a left-skew toward increasing benefits and with 89% of the support of the distribution of environmental hidden costs on benefits (Figure 8S left panel), hidden cost results indicate an opportunity for environmental benefits under FST. The main components of the uncertainty in environmental benefits are CO2 sequestration, return of forest habitat and NO3- run-off from cropland (Figure 8S right panel).

Under CT projections, Sub-Sahara Africa (SSA) faces a triple economic burden of 540 billion 2020 USD PPP by 2050 (Third set of bars from left in Figure 9S). Environmental hidden costs in SSA, including growing nitrogen use, account for 240 billion 2020 USD PPP, and productivity losses from obesity, undernourishment, and noncommunicable disease due to dietary intake account for 190 billion 2020 USD PPP, both eclipsing the residual cost of poverty in SSA in 2050 estimated at 110 billon 2020 USD PPP. This triple economic burden for SSA is avoided under FST by halving costs of dietary intake and eliminating environmental costs (Rightmost bars in Figure 9S) (5-th to 95-th percentiles for FST environmental costs in SSA in 2050 are -71 billion 2020 USD PPP to 24 billion 2020 USD PPP).

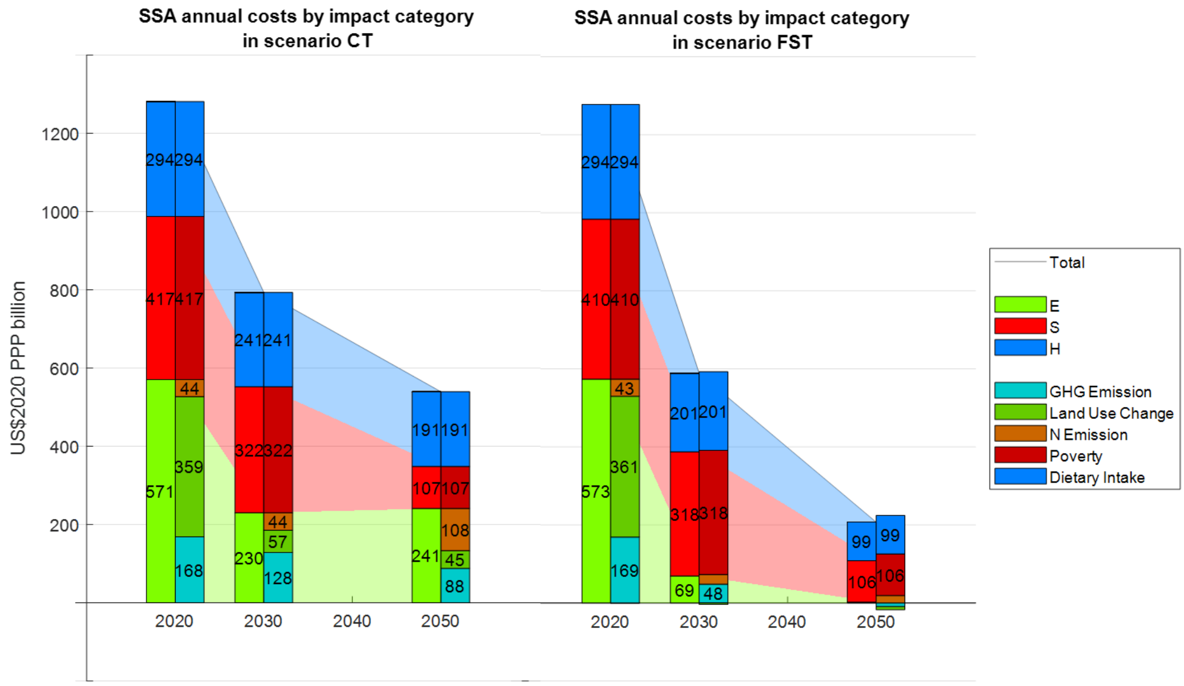


Figure 9S: Triple economic burden of poverty, productivity losses from diets, and environmental damages avoided by 2050 under FST for Sub-Sahara Africa (SSA

Conclusion

FST under SSP2 shows average annual hidden cost reduction in the order of 2-3% of 2020 global GDP PPP over the period 2020-2050 compared to CT. Up to the modelled uncertainty in environmental costs and the implementation of FST as modelled, exceeding reduction equivalent to 3% of 2020 global GDP PPP by 2050 is very likely and may reach as high as 4% (around a 5% chance). Hidden cost reduction from FST against CT is still increasing in 2050 in 2020 USD PPP terms, with productivity gains from dietary change the largest and increasingly larger proportion of hidden cost reduction by 2050. Global nitrogen pollution is the largest residual damage from food production under CT in 2050. ~1.1 trillion USD PPP in estimated nitrogen pollution damages in CT in 2050 are reduced by over 66% to ~350 billion under FST in 2020, while meeting dietary intake that reduces undernourishment, obesity, and noncommunicable disease from diets.

FSEC regions face different hidden cost reductions under FST, with transitions in environmental, health and social costs. China and India avoid a western trajectory of burden of disease from diets, with substantial combined productivity gains in the order of 500 billion 2020 USD PPP GDP per annum. Brazil and other Latin and South American countries transition from greater than 250 billion of cost-bearing of habitat loss to 200 billion USD of potential benefits from carbon sequestration and habitat return. Under FST Sub-Sahara Africa avoids a 540 billion 2020 USD PPP GDP triple economic burden of hidden costs from poor diets, environmental damage, and residual poverty in 2050, halving costs of dietary intake and becoming, without considering substitution issues, cost neutral in environmental hidden costs.

Contents

Tables and Figures

Description

A new model of the marginal external damage costs of food systems developed at the University of Oxford Environmental Change Institute for the Food System Economic Commission (FSEC) was paired with output from the MAgPIE global agricultural and land-use model at the Potsdam Institute for Climate Research (PIK) and associated models to examine the change in "hidden costs" under the FSEC food system transformation pathway (FST) compared to a current trends (CT) food system pathway [1].

Annual production of quantities associated to "hidden costs" from external costs and market failures of the food system [2-9] include: greenhouse gas emissions (GHG) [10, 11], nitrogen emissions (N emissions) [12-15], effective hectares (ha) of lost habitat from land-use change [16-18], burden of disease from low body-mass index (BMI) [19-22], high BMI [23-26], and noncommunicable disease due to dietary intake [27, 28], and number of people in poverty below the $3.20/day (2011 PPP) poverty line [29-31]. Change in these 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. Pairing the annual quantities with national marginal damage costs for the 153 countries, also calculated at five-year intervals from 2020 to 2050 as described in the Methodology, allows hidden costs of the CT food system pathway and the FSEC food system transformation pathway (FST) to be compared over the period 2020 to 2050 at the global and regional level.

The CT food system pathway is set in the demographic and socio-economic trajectory of the IPCC Shared Socio-economic Pathway (SSP) 2, [32], from 2020 up to 2150 for the consideration of the future economic costs of long-term gases residing in the atmosphere and effects of lost habitat. The FST food system pathway is set in the context of SSP2 and a second FDSP scenario with the same food system changes is set in the context of SSP1 [32, 33], to examine what additional effects in the wider economy and society may have on comparative hidden costs. The calculated marginal damage costs respond to the economic and demographic conditions of the SSPs as well as food system changes [34, 35], and the difference in the total hidden costs described in the Results are a combination of changes in annual quantity and changes in the annual average marginal costs.

Methodology

Annual costs and trends in those costs are calculated by multiplying emissions and the other quantities associated to externalities and market failures attributable to food production and consumption (called impact quantities), against an estimate of their average annual marginal damage cost in the years 2020-2050. Quantities (Table 3) and their marginal damages costs are estimated at a national level (Annex S) for 153 countries (Annex U), multiplied together (Annex F), and then aggregated to obtain regional and global totals (Annex T). Data files showing the country quantities, the marginal costs, and totals are available at https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8.

Damage costs for all countries and all years are measured in 2020 USD PPP (Purchasing Power Parity), also known as 2020 International Dollars, [36, 37], and represent GDP PPP loss. Purchasing power parity represents the equivalent amount of a basic goods basket in 2020 USD that 1 USD, once exchanged to local currency, purchases in that country. The goods represent welfare provided by their consumption. Damage costs measured in 2020 USD PPP represent the reduction in welfare due to reduced purchasing power and avoided damage costs represents the benefit in an avoided reduction in welfare.

A FSEC study conducted by the London School of Economics performs a high-level analysis of social welfare beyond the consumption of basic bundles of goods and services for the CT and FST pathways (FSEC Background Report, The social value of the global food system, Simon Dietz).

Modelling food system pathways

PIK modelling of the CT and FST food system pathways from 2020 to 2050 are described in a separate report. The FST pathway is defined by 15 Food System Measures (FSMs), which adjusts food demand, level of food waste, agricultural productivity, incentives such as trade liberalization and carbon tax payments, land-use regulations, etc. from a current trends baseline over the 2020-2050 timeframe The FSMs alter exogenous projections used for the modelling and adjust parameters inside the calculation models.

Food system measures

The food system measures assumed to be realised under the FDSP pathway by 2050 are summarised as bundles in Table 1 from the PIK modelling report.

Table 1: Food System Measures (FSM) assumed to be realised by 2050 in the FST pathway

FSM bundle	**Short description**	**Implementation**
Dietary Change	Recommended intake of sugar, vegetable oils and fats, alcohol, wholegrains, legumes, poultry meat, monogastric meat, ruminant meat, eggs, vegetables, fruits, nuts, and seeds. Appropriate caloric intake.	The scenario converges towards national daily per capita intake values in age and sex groups in 2050 of the EAT Lancet diet with all grain consumption switched to wholegrain, [6]. Consumption of staple foods (cereals, roots, tubers) is adjusted to increase food calorie intake of adults with a BMI<20 and of children with < -1 standard deviation (SD) from the reference BMI, aged 0-14 years, until 50% in each age and sex group in 2050 reach a BMI of 20--25 and a BMI between -1 SD and +1 SD from reference BMI, respectively, and decrease intake of adults with a BMI>25 and of children with > +1 standard deviation (SD) from the reference BMI, aged 0-14 years, until 50% in each age and sex group in 2050 reach a BMI of 20--25 and a BMI between -1 SD and +1 SD from reference BMI, respectively.
Food waste	Household food waste reduction	Projected household food waste, which is calculated based on GDP regressions [38], is gradually reduced to a level of 20% waste on a caloric basis in 2050. Caloric baseline is adjusted to the dietary change requirements for assumed increase or decrease of BMI.
Labour and Markets	Trade liberalization, minimum wages, and livelihoods.	Distortions and historically bilateral trade dependencies transition to trade based on relative cost-competitiveness. The share of a free trade pool in simulations is increased from 20% to 30% for crops, and from 10 to 20% for livestock and secondary products. Baseline hourly labour payments below an exchange-rate equivalent minimum wage of 5 USD2005 per hour in 2050 are linearly interpolated to meet the minimum wage in 2050. The potential substitution from labour to capital from higher labour costs is checked by a constraint on share of labour and capital in crop production. Regions with an existing share of labour higher than the threshold can decrease to the constraint.
Environmental	Regulatory targets	Avoided deforestation and regeneration of original vegetation is

Protection	for environmental protection of land, biodiversity, water, and forests	incentivised by payments for carbon sequestration based on the REDD+ scenario. By 2030 the land area under protection (currently about 15%) is doubled so that protected areas including biodiversity hotspots make up 30% of the global land surface. Biodiversity intactness is preserved under any land-use change and cropland expansion is constrained to 80% of potential cropland in local landscapes. Minimum environmental flows are required in water catchments globally.
Agricultural practices	Incentives for crop rotation, nitrogen use efficiency, rice production, livestock management, soil carbon storage.	Mitigation costs are paid for reducing CH4 emissions for rice production and to radically improve nitrogen use efficiency. Failure to rotate crops is taxed. Mitigation costs are paid for improved livestock practices, improving livestock productivity included concentrated feedstuffs, implementing methane mitigation for enteric fermentation and methane and nitrous oxide mitigation for waste management. Carbon price incentives realise practices that increase, or avoid emission, of soil carbon.

Calculation models

The food system pathways are assumed to be realised, and the PIK MAgPIE model [39], under the exogenous assumptions and FSM settings, calculates the spatial configuration at a 0.5deg resolution of variables such as land-use, trade of agricultural commodities, agricultural employment, that meets endogenous constraints and the imposed exogenous constraints. MAgPIE calculates the environmental pressures associated to the spatial configuration such as GHG emissions, habitat loss from land-use change, N surpluses, blue water use, and social pressures such as poverty headcount at World Bank poverty lines [40]. MAgPIE has a regression model that simulates physical activity levels in age and gender groups, further refines dietary intake composition from food demand and food waste projections, and estimates low and high BMI for age and gender groups [38]. Disease burden in terms of years of life lost (YLL) from low or high BMI, and intake of dietary risk factors such as low consumption of fruits, vegetables, nuts, and legumes, is calculated using a comparative risk assessment method (Supplemental Information in [41]) similar to the Global Burden of Disease study [23, 27].

MAgPIE is a partial equilibrium (PE) model land-use model [39] – it depends upon future projections of GDP PPP and demographics, external specification of food demand and demands from other sectors of materials such as timber and fibre and materials for bioenergy [42]. It requires specification of GHG emissions of other sectors, and external climate models to indicate changes in temperature and precipitation that MAgPIE uses to simulate climate effects on crop production through the Lund Potsdam Jena vegetation, hydrology, and crop model (LPJmL) [43, 44].

Future economic and demographic projections

Table 2 describes economic and demographic projections for the FSEC future scenarios in the modelling led by the Potsdam Institute for Climate Research (PIK).

Table 2: Scenarios of food system pathways in the context of socio-economic and environmental future described by the shared socio-economic pathways (SSPs).

Scenarios
1: CT-SSP2 (or **CT** in shortened form): the food system follows a current trends continuation of food production in line with historical productivity improvements and management practices,

dietary composition, and food waste. Other socio-economic and GHG emission factors outside the agri-food system follow the same trajectory as the IPCC SSP2 scenario.
2: FST-SSP2 (or **FST** in shortened form): food system measures defined in Table 1 are implemented, but GDP PPP growth, population growth, demographic changes, urbanisation, and other socio-economic indicators outside the agri-food system follow the same trajectory as the CT-SSP2 scenario. The broad narrative is that food production and consumption undergoes radical transformation according to the realisation of the FST measures, but the broader political economy, and other economic sectors, continue on SSP2 trajectories. The climate trajectory under FST-SSP2 is not the same as CT under IPCC SSP2 . The large change in land use sponsored by the FST measures creates additional carbon sinks, and large reductions in CH_4 and N_2O emissions, altering the radiative forcing trajectory from SSP2 with a current trends food system.
3: FST-SSP1: food system measures defined in Table 1 are implemented, and GDP PPP growth, population growth, demographic changes, urbanisation, and other socio-economic indicators outside the agri-food system follow the same trajectory as the IPCC SSP1 scenario. The broad narrative is that food production and consumption undergoes radical transformation realised by the FST measures in the context of the rapid but sustainable cooperative development of the global economy on a SSP1 trajectory. Interaction between the land-use sector and SSP1 "greener" economies (termed external measures in the PIK modelling report) include 30% replacement of plastics by bioplastics, increased timber demand for urban dwellings, less water demand from other sectors, and additional displacement of fossil fuel energy production by bioenergy.

Under the scenarios in Table 2, changes in the quantities described in Table 3 were derived from the output of the MAgPIE PE model. A general feature of SSP1-1.9 economic and demographic trajectories is rapid development and lower population growth alongside decarbonisation of all sectors (Figure 10 and Figure 11). MAgPIE calculates changes in land-use consistent with dietary demand, and the changes in CO_2 annual emissions from changes in land-use, and changes in CH_4, N_2O, NH_3, NO_2 and NO_3^- annual emissions from farm activities (ruminant herds, synthetic fertilizer application, manure, etc.) and land-use. Differences in Land-Use and Land-Use Change (LULUC) emissions between scenarios are driven by changes in food consumption and agricultural production and infrastructure improvements, incentives, regulations, technology, etc. enabled by the FSMs and the development and demographics trajectory in SSP1. For example, smaller population growth under SSP1 makes a direct difference to agricultural land-use for food production at the same per capita dietary composition. Climate change effects on crop production also factor into the differences in food production between SSP1 and SSP2. In this way, the dietary intake and the environmental impact quantity changes are associated to food system changes in the context of the SSP future. In this analysis, the hidden costs of the 2 scenarios FST and FST-SSP1 are compared to the hidden costs in the CT scenario to examine the reduction in GDP PPP damages from implementing the food system measures with and without the context of the rapid and "greener" development in SSP1.

Effect of the future economic and demographic projections on marginal damages

The SSP context of the scenarios in Table 2 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. For example, under SSP1 the global GHG emissions trajectory is lower, creating less radiative forcing into the future and less climate changes damages. At the same time the rapid development of many countries under SSP1 means that countries are relatively richer (Figure 11). The combination of effects means that the social costs of CO_2, CH_4 and N_2O can be up to half under an SSP1 future than they are under SSP2. Food system emissions also halve under FST-

SSP1 versus CT. Combined quantity and marginal cost changes means that external costs for GHG emissions in 2050 for FST-SSP1 measured in 2020 USD PPP can be half of the costs in FST in 2050, and a quarter of the costs of CT in 2050. This illustrates the basic mechanics of the calculation of the difference in total hidden costs 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.

Adjustments for the marginal cost of CO2 and NO2 emissions occur, mostly, due to the time the emission contributes to radiative forcing in the future. 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, and increasing population density and background industrial emissions of NOx and SOx precursors to air pollution, create adjustments in external costs of lost ecosystems services from land-use change and reactive N emissions (NH3 and NO2 emissions to air, NO3- runoff to surface water and leaching to groundwater) for countries over the period 2020-2050. We were unable to incorporate distinct discount rates considering the supporting nature of natural capital-called environmental discount rates [45-47]. The assumption on substitutability of goods and services provided by ecosystems and produced capital is therefore "weak" [48-50] – ecosystem service losses under rapid growth for many naturally endowed low income countries (LIC) and lower-middle income (LMIC) countries in SSP1 is discounted at general GDP PPP growth rates when comparing costs in 2020 USD PPP (2020 International dollars).

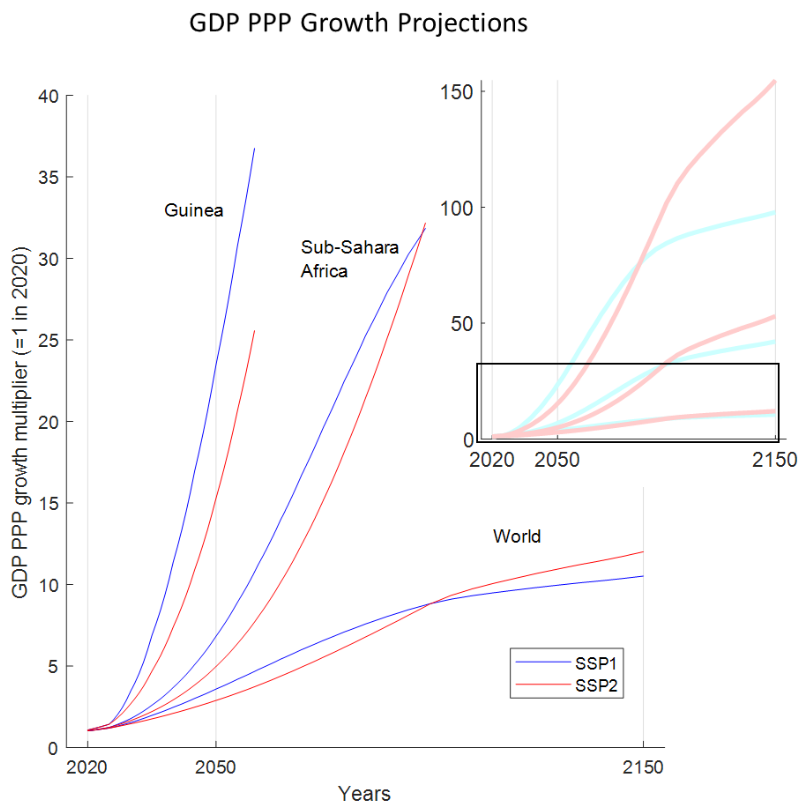


Figure 10: GDP PPP growth projections for SSP1 and SSP2 in the PIK led modelling. SSP1 assumes rapid growth until 2080-2100. Under SSP1 the economy of most Sub-Saharan African (SSA) countries are 50-60% larger by 2050 than SSP2. Guinea is used as an example of a low income and development country that undergoes rapid growth. The rapid growth rates imply rapid economic development which has increasing and decreasing effects in the calculation of marginal costs of production and consumption in future years. A richer society in SSP1

decreases the PV in 2020 USD PPP of damages, however the more rapid development from the present structure of many SSA economies increases, for example, among other variables, ecosystem services values through increasing utilisation of natural capital.

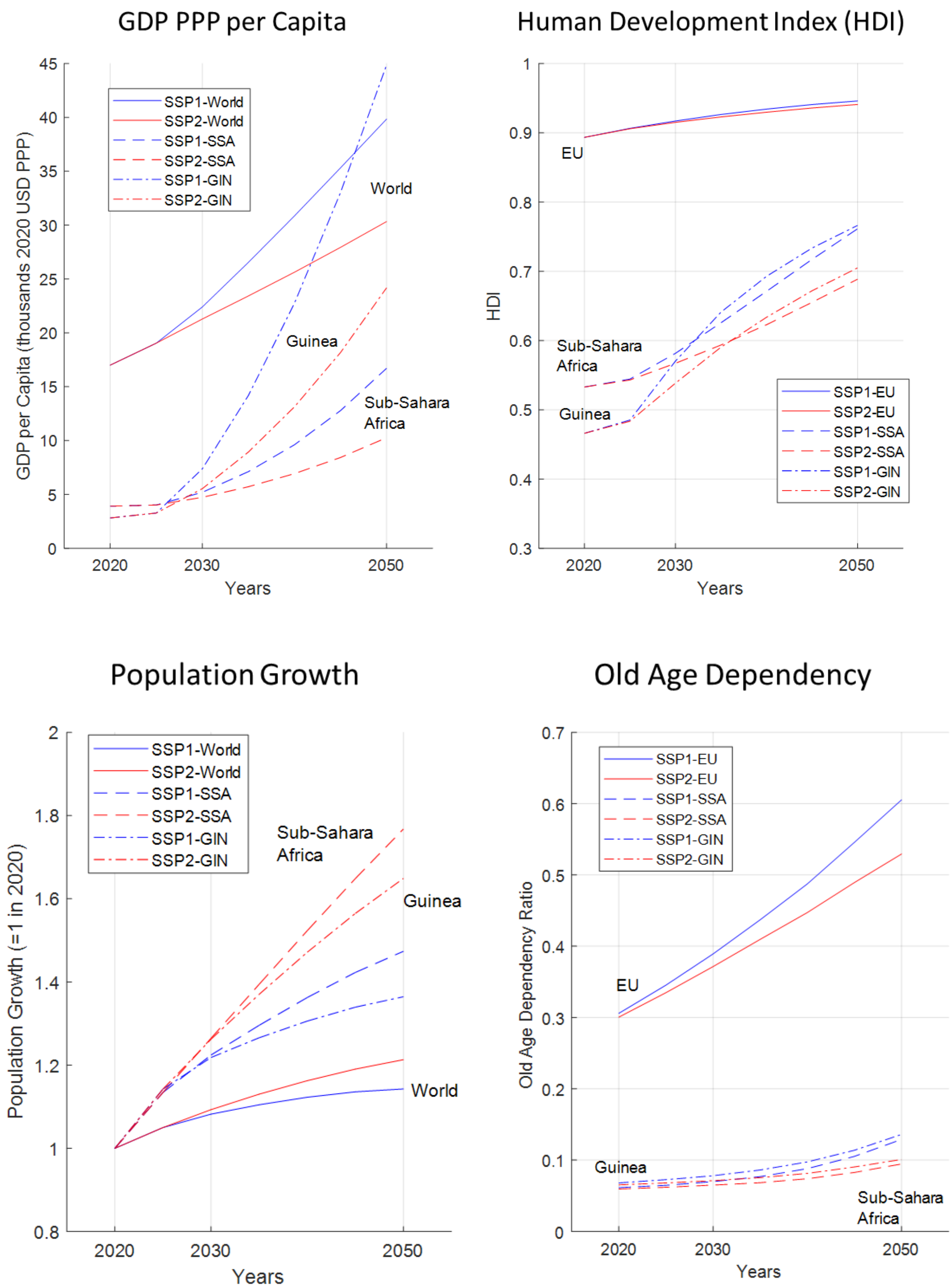


Figure 11: Development and demographic projections for SSP1 and SSP2 in the PIK led modelling. SSP1 has lower population growth rates which, combined with rapid GDP PPP growth, implies 50-100% growth in GDP PPP per capita for most countries by 2050. Guinea is used as an example of a low income and development country that undergoes rapid GDP per capita growth. Development projections, indicated by the Human

Development Index HDI (see Annex P), for SSP1 show rapid development for low- and middle-income countries. Old Age Dependency Ratio, the ratio of population aged over 65 years to the working population aged 15-64 years, increases more rapidly under SSP1 then SSP2. This has increasing effects for the calculation of productivity losses due to ill-health and informal care – under SSP1 the GDP PPP per labourer in 2050 is higher than SSP2, and mixed effects for the average marginal damages of air pollution from N emissions due to changes in urbanisation and population density, amongst other variables.

Note that the different futures affect the damage costs of GHG emissions that are already emitted. The external cost of 2020 food system GHG emissions are different between CT-SSP2 and FST-SSP1, even though the scenarios had identical metric tons of annual GHG emissions in 2020. Temporal components in the costs of land-use change and N emissions also affect the costs of land-use change and N emissions occurring in the present, though to a lesser degree.

While the dietary intake and the environmental impact quantity changes estimated by the modelling are associated to food system measures, the changes in poverty are driven by the broader economy in the SSP future. In all three scenarios, results from the PIK modelling show that employment in agriculture reduces by 2050, though the average income of those employed in agriculture improves.

Impact quantities

Modelling led by PIK provided estimates of annual production of impact quantities described in Table 3 under CT and FST for 5-year timesteps from 2020-2050 for 153 countries.

GHG quantities. The land-use emissions tracked by MAgPIE include CO2 from land-use change, CH4 from rice production, animal waste management, and enteric fermentation, and N2O from animal waste management and agricultural soils (specifically from organic and inorganic fertilizers, the decay of crop residues, soil organic matter loss, and pasture management). Outputs are provided in Mt for each gas, not in CO2-equivalents. N2O emissions are also categorised by source of agricultural activity, indicated by application of inorganic fertiliser on cropland, livestock activity on pasture included manure left in place, and livestock manure treated and used as organic fertiliser (Table 3). CH4 and CO2 emissions are provided in for FSEC regions (below), while N2O emissions are aggregated to national level from 0.5deg grid resolution.

Land use change quantities. MAgPIE outputs Mha of cropland, pasture, built-up-land, forestry, (natural) forest, and other land resulting from spatially-explicitly competition for the most profitable use. Loss and return of hectares (ha) of forest habitat, and loss and return of other land habitat as a single category representing biomes such as unmanaged grassland and savannah, is derived from differences in output over timesteps for forest, built up-land, and other land. For this study outputs were aggregated to a national overall loss or return, which is a limitation for costing since the costs of lost habitat and the benefits of returned habitat are asymmetric. Disambiguation of forest and other land habitat for costing is described in the costing notes below.

Nitrogen (N) quantities. Reactive N emissions are derived from N surpluses in MAgPIE. N inputs tracked by MAgPIE include N in manure and crop residues, atmospheric deposition, and N from free-living nitrogen-fixing bacteria, inorganic fertilizers, as well as reactive nitrogen (Nr) released from soil organic matter after land conversion [51]. Nitrogen surpluses for crops are estimated as the difference between nitrogen inputs in the form of organic and inorganic fertilizers, and the withdrawals in form of harvested biomass. Global nitrogen surpluses are estimated as the sum of the nitrogen surpluses in croplands, pastures, animal waste management and natural vegetation, and reported in N-Mt for volatilization on NH3 and NO2, and surplus soluble NO3-. N emissions are aggregated to national level from 0.5deg grid resolution. Historical proportions from IMAGE-GNM models [52, 53] were used in this study to proportion the fate of agricultural NO3- surpluses between leaching to deep groundwater and run-off to surface waters.

Food consumption burden of disease quantity. Years of life lost (YLL) is a measure of premature mortality accounting for both frequency of deaths and the age at which it occurs. Standard life tables are used to represent lost years compared to life expectancy. One YLL represents the loss of one year of life.

Poverty quantity. MAgPIE estimates poverty headcount in number of people below the $3.20/day (2011 PPP) World Bank poverty line.

Marginal cost calculations

Marginal damage costs for the 153 countries are calculated using the SPIQ-FS version 0 marginal damage cost model developed for the Food System Economic Commission [54-58]. Damages from GHG emissions, land-use change, N emissions, experience of poverty, and food consumption in a year *t* within {2020,2025,2030,2035,2040,2045,2050} manifest in the economy of year *t* and future economies in years $t' > t$ under a scenario s from Table 2. Damage to future economies is estimated using the same quantification of GDP PPP growth, population, and demographics in scenario s used for the PIK led modelling of impact quantities production in the year t' under scenario *s*. The SPIQ-FS model uses additional projections of macro socio-economic parameters in years $t' \geq t$ such as urbanisation and human development to estimate costs in year *t'*. The additional projections are described in Annex P. An overview of the SPIQ-FS cost models and the parameters used for temporal projection of costs is available in [59]. Documentation on SPIQ-FS is available at https://foodsivi.org/what-we-do/projects/spiq-food-system-v0/.

SPIQ-FS version 0 makes estimates in USD PPP 2020 (2020 international dollars [36, 37]) of marginal damages to GDP PPP per unit of impact quantity. Costs in international dollars of future years under different scenarios cannot be directly compared. Future damages must be discounted back to the "net present value" in the 2020 economy shared by each scenario for comparison. A Ramsey social discount rate (SDR) is assumed with time preference of 0 and constant marginal expected marginal utility of consumption of 1.5 [60, 61]. The literature on SDR is extensive [62, 63], but it is recommended to use a conservative value for intergenerational wealth transfer given current wealth generation from food system activities may be endogenous to the risk of the ability to enjoy deferred resource use [64-66]. The potential volatility of future welfare accrual and the nature of consumption as a proxy for welfare in a future with environmental and health damages, means that lower settings for the elasticity of marginal utility are recommended [67-69]. National GDP PPP growth rates, WB income group average GDP PPP growth rates, or global GDP PPP growth rates, are used in the discount rate depending on the whether the cost models project and aggregate damages at national level (for example the nitrogen cost models), income group (for example productivity losses from illness or informal care in low income countries), or global level (greenhouse gases).

Annex F discusses the assumption of using an estimate of an average annual marginal damage cost of an impact quantity in year t to calculate the total hidden cost produced in year t in USD PPP 2020. Annex S lists the marginal damages costs generated by the SPIQ-FS model.

Costing GHG emissions

SPIQ-FS resamples IWG-SCGHG simulations of the social cost of emission of a metric ton of CO_2, CH_4 or N_2O in 2020 to 2050, [70, 71]. IWG-SCGHG simulations are provided for three discount rates (2.5%, 3% and 5%), at 10 year time steps (2020,2030,2040,2050) and five socio-economic scenarios used by integrated climate modelling groups to inform IPCC reports, [70]. Year of emission and PIK scenarios from Table 2 were paired with IWG-SCGHG year of emission, discount rate, and socio-economic scenario using weights. Samples are drawn from IWG-SCGHG distributions in proportion to the weights. For FST-SSP1 we used the most optimistic IWG-SCGHG scenario called "5-th scenario" with 550ppm CO2 concentration, which is still higher than the peak CO2ppm ~460ppm expected under SSP1-1.9. We matched FSEC GDP and population projections of CT-SSP2 to GDP and population scenarios of IWG-SCGHG CO2ppm concentrations and sampled uniformly from social costs GHG estimates for the IWG-SCGHG "IMAGE" and "MinCAM" Base scenario simulations. SSP1 and SSP2 global GDP projections were used to match discount rates. Social costs represent marginal damage costs under a future pathway of optimal economic abatement [72].

IWG-SCGHG simulations provides social costs for emission of a metric ton of CO2, CH4 and N2O. CO2-equivalents are not used, and the gases are costed separately. Converting to CO2e and multiplying by the social cost of CO2 would underestimate the total damages, since CH4, in particularly, has shorter term effects and future damages due to CH4 are less discounted [73-75].

Costs of a GHG emission in a country are borne globally through global atmospheric and then climatic changes [76]. To attribute the cost of an emission as a cost to the country that made the emission, it is assumed that economic actors in that country are required to pay an amount per emission equal to the social cost of the respective GHG, and that the amount paid is dispersed perfectly to the cost-bearers in PPP terms from the emission inside or outside the country.

Costing water withdrawals

MAgPIE endogenously tracks the effect of water consumption on crop yields, influencing wages and malnutrition [39]. Impacts of water consumption through income loss are therefore reflected in poverty estimates and malnutrition through low BMI estimates. It would double count impacts to cost blue water consumption using SPIQ-FS which is based on income loss and malnutrition effects [77]. Therefore, blue water withdrawals were not costed and not included as an impact quantity. Damages for water withdrawal factoring through poverty and low BMI in CT-SSP2 are likely underestimates. Due to lack of data, damages from loss of environmental flows [78] could not be added to cost estimates for CT-SSP2. Minimum environmental flows are assumed in FSM measures (Table 1) so the additional damages in CT-SSP2 would be mitigated in FST-SSP1 and FST-SSP2.

Costing habitat loss and return

Costs of land use changes in terms of lost, retained, or returned ecosystem services are derived from the Ecosystem Service Valuation Database (ESVD) [79, 81]. Valuations from ESVD are given in ha/yr. How many years into the future ecosystem services are lost or provided after land use change in the current year is an additional assumption [82-84]. No habitat return after a transition from established habitat were assumed for 50-80 years after transition. This is a simplification. Transition in land use can occur from forestry or agricultural use, abandonment, and then return to forestry or agriculture use. Land abandoned in the past is more likely to be reused, and evidence suggests an average of 14 years of returned ecosystem services for abandoned land [85]. The value of the services in future years can also change due to changes in the supply and demand for ecosystem services, resulting in so-called environmental discount rates [46]. Environmental discount rates were not used. National level discount rates over a random period uniformly distributed between 50-80 years after transition were used to discount lost ecosystem services to obtain cumulative values for a ha of for habitat loss. For "abandoned" land resulting in habitat return, a random period between 7-28 years with mean 14 years (distributed to maximise entropy [86]) of returning ecosystem services were used to obtain cumulative value for a ha of habitat return.

MAgPIE provided data for four categories of relevant land-use transition.

Forest habitat loss provided by the model refers to deforestation. This is treated as a loss of forest ecosystem services. The gain from agricultural services in transition to agricultural land use is assumed to be included in GDP growth. GDP PPP growth and the income-equivalent welfare it provides should be compared separately to welfare losses from damage costs. MAgPIE forest areas do not distinguish between tropical and temperate forest habitat. Marginal costs for ha of land use change from the SPIQ dataset and the Ecosystem Services Valuation Database distinguish between tropical and temperature forests. ESVD uses the TEEB Classification and CICES (v5.1) classification systems of ecosystems and services [87, 88]. To reconcile cost and quantity categories, a marginal cost for ha of forest habitat loss was sampled randomly from tropical and temperate marginal cost samples in proportion to national tropical and temperature forest historical areas. 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.

MAgPIE other non-urban area was used as a proxy for other land habitat loss, which is a broad category including shrubland, grassland, and unmanaged rangeland terrestrial land classifications in the Ecosystem Services Valuation Database. The Ecosystem Services Valuation Database has few valuations in these categories even when national estimates are aggregated into Human Development Index brackets. Global spatial datasets of land area and land transitions for habitats, such as the WWF ecoregions dataset (https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world) and the HILDA+ transitions dataset [16], do not distinguish between grassland and shrubland. For this study, the ecosystem service samples for these habitats are combined in SPIQ-FS, to create a national level cost quantity for “unmanaged grasslands” to match the MAgPIE other non-urban land category. The costing is conservative, as it excludes loss of high-value inland wetlands and coastal wetlands such as mangroves for crops like rice and palm oil [89].

Area gains in MAgPIE forest and other non-urban categories were treated as returning habitat. The provision of services from returning habitat can be of lower value than intact ecosystems [85, 90], with previously forested areas progressing through regenerative stages of grassland, shrubland and then reforestation [91, 92]. Historically, land may transition back within decadal time spans [85]. Given the nature of progressive stages of regeneration of both ecosystem and ecosystem services, we assume services provided by abandoned cropland and pasture return at a linear rate to an equivalent ha of forest or unmanaged grassland after a random period between 15-30 years with a mean of 20 years [90, 92, 93].

GHG emissions from land-use change are counted under GHG emissions. The ESVD database includes carbon sequestration as an ecosystem service valuation. To the degree possible, carbon sequestration services were excluded from the valuation of service per ha estimated from the ESVD to avoid double counting.

Costing nitrogen emissions

The SPIQ-FS version 0 nitrogen emissions costing model estimates marginal damages in N-kg from volatilization of NH_3 (ammonia) and NO_x (nitrous oxides) to air, and run-off of reactive nitrogen into surface waters and soil leaching, predominately soluble NO_3^- (nitrate). Economic losses occur through labour productivity losses from air pollution, crop losses, and loss of ecosystem services [55]. Spatial datasets on ecosystem distribution, population density, average temperate, deposition, and riverine transport, are used to transfer marginal damages derived from the European Nitrogen Assessment [94, 95].

Costing preventable burden of disease from dietary intake

Version 0 of the SPIQ-FS model costs a YLL in a country by productivity loss [96]. Productivity losses for a year of life lost are costed by projecting historical ILO labour productivity data (https://ilostat.ilo.org/data/), [59]. Labour productivity is used in place of GDP per capita to account for informal care of dependents. The same productivity loss estimates are used to cost YLLs lost for neoplasms, cardiovascular disease, and metabolic diseases attributable to diets low or high in risk factors and high body mass index.

Since the marginal costs need to be consistent in the economic measure of damages in GDP PPP terms across costing models, the cost from burden of disease focus uses only "indirect costs" [97]. Direct costs such as treatment costs amount to economic exchanges between sectors and actors within the economy, [20], and are not included since, outside of productivity losses, there are few estimates of the inefficiency in GDP terms of the direct costs flowing to the health sector from individuals or government. Income equivalent welfare treats the population homogeneously, so it does not include potential welfare losses from direct costs being borne disproportionately by lower income households.

SPIQ-FS uses common modules for consistency. The same productivity loss estimate is used for costing air pollution effects on humans from nitrogen pollution in the nitrogen cost model [98]. The productivity loss module has productivity losses available at a national level or average at World Bank (WB) income group level. At a national level the difference between low income countries and high income countries can be up to 2 orders of magnitude in PPP terms. Following the study [99], which used the same model for determining YLLs from dietary intake in this study, productivity loss per YLL is assigned to low-income countries or low middle income countries based on WB average income group if the productivity loss from a YLL is below the WB income group average. This averages productivity losses for the poorest countries in the lower WB income group. A country's WB income group is determined at five year time steps based on GNI projections under SSP1 and SSP2 (Annex P).

Costing poverty

MAgPIE output provides headcounts of moderate poverty defined at the World Bank international line of income below $3.20/day (2011 PPP) [29]. The damage cost of poverty is calculated as the transfer payment required to eliminate poverty below the $3.20/day poverty line, which equates to the national income shortfall from the $3.20/day poverty line.

Costing national income shortfall in 2020USD GDP PPP requires projecting the average income shortfall per person in poverty below the $3.20/day (2011 PPP) poverty line (the average cost) and multiplying by the poverty headcount below $3.20/day (2011 PPP) (the quantity).

Historical data on the $3.20/day (2011 PPP) per day headcount and poverty gap over 2005-2020 was downloaded from the World Bank [https://data.worldbank.org/indicator/SI.POV.GAPS]. Poverty gaps were converted into income shortfall per annum using historical population and adjusted by inflation in PPP terms to 2020 PPP.

Projections of income shortfall should account for both the changing income of the moderate poor and the background shift of individuals in and out of moderate poverty which is determined by MAgPIE output. Historical average income shortfall per annum was projected to 2050 using an equidistributed pass through rate of GDP growth https://blogs.worldbank.org/opendata/projecting-global-extreme-poverty-2030-how-close-are-we-world-banks-3-goal . The pass through rate for each year was treated as a random variable uniformly distributed between [0.7,1] with mean 0.85. Path dependence was accounted for in pass through rates over years jointly sampled with autocorrelation 0.8.

Poverty is treated differently to other impact quantities, using an average instead of a marginal cost. GHG emissions, N emissions, and habitat loss or return are treated as additional quantities. They are new emissions added to the existing stock of emissions in the atmosphere, etc. For natural capital, the impact models account for natural renewals and stocks such as fluxes of CH_4 between atmosphere and land. The total impact of the emission in the given year is costed in present value for its lasting effect on stocks and the value flows from changes in those stocks. Similarly, YLLs represent the additional burden of disease produced by consumption or caloric inadequacy in that year. The equivalent impact quantity for poverty is the addition or avoided addition of new individuals in moderate poverty each year. A similar stock and renewal process applies to costing the quantity of additional individuals in poverty, in that economic development reduces the number of people in poverty in the future. The time that the individual put into moderate poverty in the given year spends in poverty needs to be modelled and the present value of the total transfer of the income shortfall over the years they spent below the poverty line is the marginal cost of an additional person in moderate poverty.

Without an economic model attributing new individuals, or avoided individuals in moderate poverty, distinct from the stock of existing poverty headcount and accounting for their fate over future years, rural poverty was costed annually in the following fashion. All individuals in poverty in a given year were treated as additions, so they were considered to be out of poverty at the end of the year and the new headcount in poverty in the next year were put into poverty at the beginning of the year. Treating all individuals as additions in this manner, meant they spent one year in poverty. The marginal damage cost used was the average income shortfall in that year as obtained from World Bank data, GDP PPP projections and headcount constraints from the MAgPIE output.

Uncertainty in costs and estimates of economic risk

Marginal costs in SPIQ-FS are provided with uncertainty estimates in non-parametric form and in the form of parameterised probability distributions [54-57]. This provides uncertainty estimates in the annual total "hidden" cost of the impact quantities for each scenario in Table 2. Cost of YLL was costed directly using projected ILO data and was not modelled with uncertainty. Technically it is treated as a random variable distributed on a single value. Poverty estimates were also not very sensitive to the uncertainty in pass through rate. The uncertainty observed in the results is predominately coming from the uncertainty in the marginal cost of GHG emissions, N emission, and habitat loss or return from land-use change. SPIQ models some damage costs jointly within a cost model based on historical data. The impact of the integrated nature of changes in environmental conditions on economic costs when totalled across categories (GHG emissions, N emissions, land-use change) is reflected in SPIQ-FS by correlation in damage costs across categories.

Total estimates of the economic damages resulting from changes in environmental pollutants and land-use change are derived from jointly sampling marginal costs. Three sets of correlations are used to explore the joint effects of GHG emissions, N emissions, and land-use change in marginal costing on total economic costs: no correlation, an expert derived set of correlations, and perfect correlation.

These three representations in risk from joint effects can be used to contrast ignoring joint effects with the case where higher than expected GHG damage costs will always coincide with higher than expected N damage costs, etc. The middle, expert-derived, set of correlations represents a best estimate of the additional economic risk from joint effects [100].

The full distribution of change in total economic costs may reflect risk in moving from CT, as well as risk in staying with CT. Figure 2S showed the changing risk profile coming from uncertainty in marginal costs of GHG emissions, N emissions and land-use change. Toward 2050 the CT-SSP2 scenario distribution shows risk in the order of 1 trillion USD 2020 in higher damages, which contrasts to the shape of the distribution of total costs under FST or FST-SSP1 where carbon sequestration and returning ecosystem services on large tracts of spared land shows opportunity in the order of 1 trillion USD 2020 in lower damages and additional benefits from the FST pathway.

Limitations

In cost modelling

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 [70, 71, 75]. Newer estimates from EPA modelling not finalised by the IGWG place the SC-CO2 up to 60% higher but SC-CH4 lower [101]. 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. MAgPIE output does not include change in non-land use GHG emissions. Emissions from inputs such as fertilizer production, post-farm gate emissions from food manufacturing and retail, and emissions from food waste and food waste management, [10], are not accounted for in the potential “hidden cost” difference between CT and FST pathways.

Damages from reduced environmental flows from blue water consumption are not included [78].

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 [102]. The transfer for NH3 and NOx uses additional data from the EASIUR model of over 3000 US counties [103]. Errors in transfer are the basis for uncertainty modelling. The large uncertainty in the results below for nitrogen and land-use change reflect the uncertainty introduced by benefit transfer, uncertainty on distribution of nitrogen species along the nitrogen cascade [104, 105], and lack of knowledge on the value of ecosystem services [106-108]. 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 [105]. Valuation in the ESVD database [81] does not use a consistent damages methodology [109], requires benefit transfer from lack of sufficient country data [110], and may overestimate GDP PPP damages.

By the World Bank definition of moderate poverty [111], it is eliminated by transfer of the income shortfall to the moderate poor. Moderate poverty does not incorporate all economic consequences of income inequality [112]. Income transfer is an underestimate of GDP PPP damages of moderate poverty under the assumption that income transfer is cost effective in abating the GDP PPP damages of moderate poverty, i.e. for every 1 2020 USD PPP spent on income transfer the return on investment in terms of additional generation of GDP PPP will be greater than 1 2020USD.

MAgPIE, from lack of historical World Bank poverty data, does not provide moderate poverty headcounts for 15 out of the 153 countries: Afghanistan, Bhutan, Cambodia, Cuba, Djibouti, Equatorial Guinea, Eritrea, Guyana, Haiti, Lebanon, Libya, Solomon Islands, Somalia, Suriname, and Turkmenistan. So that environmental damages could be included in the study, these countries were included in global and regional aggregations albeit with a setting of zero income shortfall for all years and all scenarios. Income shortfall may be underestimated for missing moderate poverty headcounts for the 15 countries. YLL estimates were not available for 6 out of the 153 countries: Burundi, Bhutan, Equatorial Guinea, Eritrea, Somalia, West Bank and Gaza. So that environmental damages could be included in the study, these countries were included in global and regional aggregations albeit with a setting of zero YLLs for all years and all scenarios. Bhutan, Equatorial Guinea, Eritrea, and Somila, lack both poverty headcount and burden of disease estimates, and should only be examined in the context of 'environmental' hidden costs: GHG emissions, N emissions, and habitat loss and return.

In not being a social welfare or cost benefit analysis

The economic measure of hidden costs is loss of welfare from reduced consumption in purchasing power terms [37, 113]. This measure is suitable for use in national accounts and policy analysis considered GDP PPP return on investments. It can be incorporated in social welfare functions but is a limited measure of social welfare itself [114]. As an example, comparative welfare from the pure consumer surplus in the pleasure of food consumption in CT and the pure consumer surplus of additional health from diets in FST are not measured by incurred or avoided GDP PPP damages. Lost intangible value is reflected indirectly in consequences for present or future economies in the measure of value to humans discovered through the exchange of goods and services on visible markets [115, 116]. Risk in the delay, or lack, of transmission of present intangible value into visible markets is not accounted for.

Comparison of the difference in hidden costs between the CT and FST pathways is not a cost-benefit analysis of the transition from the CT pathway to the FST pathway. They indicate one component of GDP PPP benefit (reduction of damages costs from GHG emissions, N emissions, habitat loss and return from land-use change, poverty reduction, and productivity losses from illness and informal care) in the transition. A subsequent analysis is required to compare the cost-effectiveness of implementing abatement measures to achieve the FST scenario with the damage cost reduction.

Abatement costing has direct and indirect components. Direct components relate to the cost to implement the measures, such as the capital and operation cost of improved livestock management [117-119]. Some abatement costs are assumed to be paid and their payment is incorporated in land-use optimisation and allocation of agricultural labour and capital within the MAgPIE PE model. However, GDP PPP growth pathways are exogenous in a PE study. Indirect components are the GDP PPP effects on AFF and other sectors of the economy of the CT to FST transition when the partial equilibrium assumption is dropped and GDP PPP growth becomes endogenous [120].

Results

Results from the PIK-led modelling on the three future food system pathways (CT-SSP2, FST-SSP2, FST-SSP1 - Table 2), provided 23 items of produced quantity relating to externalities or market failures (impact quantities in Table 3) for 153 countries for each year and each scenario.

1 item relates to CO_2 emissions from land-use change, 1 item relates to emissions of CH_4, and 3 items relate to direct or indirect emission of N_2O. N_2O emissions are broken down by cropland (surplus from organic and inorganic fertilizers, the decay of crop residues, soil organic matter loss), pasture (pasture management included manure left in place) and manure (animal waste management).

4 items relate to land-use transition of forest habitat, and other land habitat, as described in the Methodology section.

12 items relate nitrogen emissions of volatilized NH3 and NOx and run off or leaching of Nr, broken down by the origin categories of cropland, pasture, and manure.

1 item indicates the headcount people in moderate poverty (annual income below the World Bank $3.20/day (20171PPP)) in that country in that year.

1 health item indicates the burden of disease per country from diets (food consumed in that year), in the form of a calculation of disability adjusted life years due to the combined effects of high body-mass-index and non-communicable disease from diets low in fruits, vegetables, wholegrains, nuts and seeds, milk, omega 3 and 6 fatty acids, and diets high in transfats, processed meats, and sodium.

To facilitate examination between environmental and production sources of costs (E) with social ones (S) and consumption costs (H), 21 items are classified by cost type E, 1 poverty item is classified by cost type S, and 1 food consumption item is classified by cost type E (Table 3).

Table 3: Input quantities disaggregated into cost items with attached marginal costs.

Cost Category	Item	Impact Quantity	Cost Type	Marginal Cost
GHG Emission	GHG Emissions (CH4): rice, manure, and enteric fermentation	CH4 metric ton	E	Social cost of CH4 – residual damages to global future GDP PPP in NPV at the optimal amount of abatement, attributed to the country of emission
GHG Emission	GHG Emissions (CO2): land Use change	CO2 metric ton	E	Social cost of CO2 – residual damages to global future GDP PPP in NPV at the optimal amount of abatement, attributed to the country of emission
GHG Emission	GHG Emissions (N2O): cropland	N2O metric ton	E	Social cost of N2O – residual damages to global future GDP PPP in NPV at the optimal amount of abatement, attributed to the country of emission
GHG Emission	GHG Emissions (N2O): pasture	N2O metric ton	E	Social cost of N2O – residual damages to global future GDP PPP in NPV at the optimal amount of abatement, attributed to the country of emission
GHG Emission	GHG Emissions (N2O): manure	N2O metric ton	E	Social cost of N2O – residual damages to global future GDP PPP in NPV at the optimal amount of abatement, attributed to the country of emission
Land Use Change	Forest Habitat Loss	ha	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to destruction or degradation of forest ecosystem
Land Use Change	Forest Habitat Return	ha	E	Value of equivalent hectares of present and future returned ecosystem services in NPV in the country of land-use transition due to recovery or re-establishment of ecosystem
Land Use Change	Other Land Habitat Loss	ha	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to destruction or degradation of forest ecosystem
Land Use	Other Land Habitat	ha	E	Value of equivalent hectares of present

Change	Return			and future returned ecosystem services in NPV in the country of land-use transition due to recovery or re-establishment of ecosystem
N Emission	NH3 emissions to air: cropland	NH3 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NH3 emissions to air: pasture	NH3 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NH3 emissions to air: manure	NH3 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NO2 emissions to air: cropland	NO2 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from ozone formation, nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NO2 emissions to air: pasture	NO2 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from ozone formation, nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance,

				acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NO2 emissions to air: manure	NO2 N-kg	E	Productivity losses in the country of emission due to burden of disease from particulate matter formation, agricultural and ecosystem services losses from ozone formation, nutrient imbalance and acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off
N Emission	NO3- leached to groundwater: cropland	NO3- N-kg	E	Productivity losses in the country of emission due to burden of disease from human nitrate intake
N Emission	NO3- leached to groundwater: pasture	NO3- N-kg	E	Productivity losses in the country of emission due to burden of disease from human nitrate intake
N Emission	NO3- leached to groundwater: manure	NO3- N-kg	E	Productivity losses in the country of emission due to burden of disease from human nitrate intake
N Emission	NO3- run-off to surfacewater: cropland	NO3- N-kg	E	Ecosystem services losses from nutrient imbalance, acidification, and eutrophication riverine, wetlands, and coastal systems due to run-off
N Emission	NO3- run-off to surfacewater: pasture	NO3- N-kg	E	Ecosystem services losses from nutrient imbalance, acidification, and eutrophication riverine, wetlands, and coastal systems due to run-off
N Emission	NO3- run-off to surfacewater: manure	NO3- N-kg	E	Ecosystem services losses from nutrient imbalance, acidification, and eutrophication riverine, wetlands, and coastal systems due to run-off
Poverty	Poverty headcount at $3.20 a day (2011 PPP)	ppl	S	Cost in PPP terms of the income shortfall below poverty line of individual in poverty below $3.20 a day (2011 PPP)
Dietary Intake	Burden of non-communicable diseases, and low and high body-mass-index (BMI) attributable to diets (food consumption or lack of)	YLL	H	Productivity losses in the country of consumption from death, illness, and informal care due to burden of disease

Annex T provides each quantity (23) in Table 3 with the matching marginal cost, for each country with data (153), for each year (7), and each scenario (3). The total is 73899 individual cost items in Annex T. The full Annex T without samples is available in the datafile at https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8. Annex U lists the 153 countries included in the analysis.

The matching marginal costs from SPIQ-FS are described in Annex S. Individual cost models in SPIQ-FS output samples of the uncertainty for 12 marginal cost items (CO2 emission, CH4 emission, N2O emission, Forest Habitat Loss, Forest Habitat Return, Other Habitat Loss, Other Habitat Return, NO2 emission to air, NH3 emission to air, NO3- run-off to surface water, NO3- leaching to groundwater, Person in moderate poverty) for 153 countries (Annex S). The full Annex S without samples is available in the datafile at https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8.

The samples within any 1 of the 12 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 NH3 and NOx emissions in the same location are highly correlated [55] as both effect 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. This joint sampling has three settings to conduct sensitivity analysis as described in the Methodology. 1000 joint samples were generated.

Multiplying a joint sample of the marginal cost items of Annex S matched against the quantities in Annex T provides 23 joint distributions for 3519 random variables of cost. For tractable computation, the 23 joint distributions for each year and scenario are not sampled as a single joint distribution of 73899 random variables, potentially ignoring the effects of correlation over time between cost categories and between FST scenarios.

Results below show the shape of the distribution of global total cost in a year obtained from aggregating (adding up) 3519 uncertain cost items. The skewed shape and “fat tails” in the distribution reflect the influence of the joint sampling and correlation between cost items. It would be erroneous to assume the 73899 cost items associated to one scenario in one year 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.

To analyse hidden costs in the CT and FST food system pathways, subsequent sections describe aggregation of the 3519 cost items per scenario and trends and differences across the years 2020, 2030 and 2050. The aggregations are global and by FSEC region to get a finer scale understanding of distributional changes in cost-bearing due to the FSMs and SSPs. Aggregations also occur by cost category (Table 3) at global and regional scale.

Distributions of the total global costs are provided, and the mean value and 5-th and 95-th percentile statistics. The distributions and statistics are used to derive conclusions on the potential damage cost reduction in GDP PPP terms of the FST pathway.

Global net damages, damage reduction, and economic risk from uncertainty in environmental costs

Global net hidden costs and hidden cost reduction

Table 4: Comparitive global annual hidden and hidden costs reduction between CT, FST-SSP1 and FST. Mean value (mean), 5-th percentile (P5) and 95-th percentile (P95) in billions USD 2020 PPP.

Geo	Name	Category	Scen	Year	Mean	P5	P95
Global	World	Total	CT	2020	15188	13865	17519
Global	World	Total	FST-SSP1	2020	13971	12865	16069

Global	World	Total	FST	2020	15053	13743	17622
Global	World	Total	CT	2030	12380	10927	15239
Global	World	Total	FST-SSP1	2030	7137	6246	8365
Global	World	Total	FST	2030	9244	8186	10643
Global	World	Total	CT	2050	9658	8853	11269
Global	World	Total	FST-SSP1	2050	2744	1839	3405
Global	World	Total	FST	2050	4419	3380	5242
Global	World	Difference	CT.FST-SSP1	2020	1087	-1314	3481
Global	World	Difference	CT.FST	2020	135	-2817	2967
Global	World	Difference	CT.FST-SSP1	2030	5074	3224	7563
Global	World	Difference	CT.FST	2030	3137	891	6205
Global	World	Difference	CT.FST-SSP1	2050	6895	5789	8500
Global	World	Difference	CT.FST	2050	5238	3972	7250
Global	World	Difference Average	CT.FST-SSP1		5217	4120	6799
Global	World	Difference Average	CT.FST		3474	2368	5710
Global	World	Difference Total	CT.FST-SSP1		156499	123592	203960
Global	World	Difference Total	CT.FST		104214	71027	171296

Supplemental figure Figure 33 in Annex R show that economic risk represented by the distributions of was not sensitive to correlations between the costs of GHG emissions, N emissions and land use change joint distributions. Annex A and Annex B documentation of SPIQ-FS discusses correlations between the marginal costs and the settings for the sensitivity test.

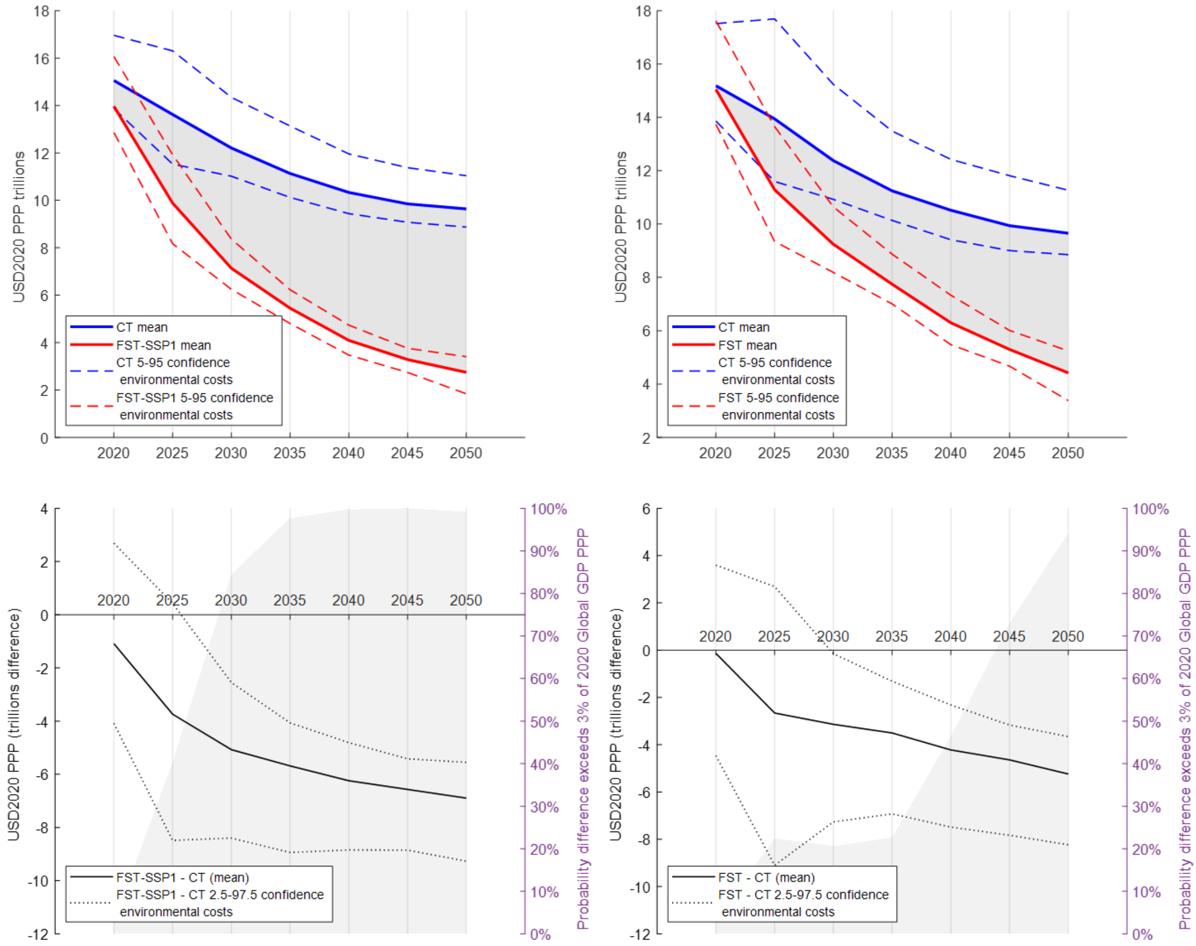


Figure 12: Trajectories of global annual hidden and hidden costs reduction between CT, FST-SSP1 and FST over 2020 to 2050. In the richer world of SSP1, additional quantity reduction, adjustments to marginal costs, and additional effects of expected marginal utility of consumption in the social discount rate increase the hidden cost reduction of FST over 2020 to 2050. Statistics in Table 4

Under FST-SSP1 the average hidden cost reduction is 5.2 trillion USD 2020 PPP versus 3.5 trillion USD 2020 PPP in FST. The reduction of environmental hidden costs is largely the same, with changes in marginal environmental costs under SSP1 matching changes in quantity. Hidden cost reduction is still increasing in 2050 under FST 1 (Figure 12) and mean reduction in 2050 exceeds 6.8 trillion USD 2020 PPP versus 5.2 trillion USD 2020 PPP under FST2. Productivity losses from diets display the largest difference in hidden cost reduction in FST-SSP1 (Figure 17).

Uncertainty in hidden costs, hidden cost reduction, and changes in economic risk

Table 4 shows the 5-th and 95-th percentile for hidden cost reduction. The shape of the uncertainty in hidden cost reduction in FST-SSP1 and FST are largely the same (Figure 13).

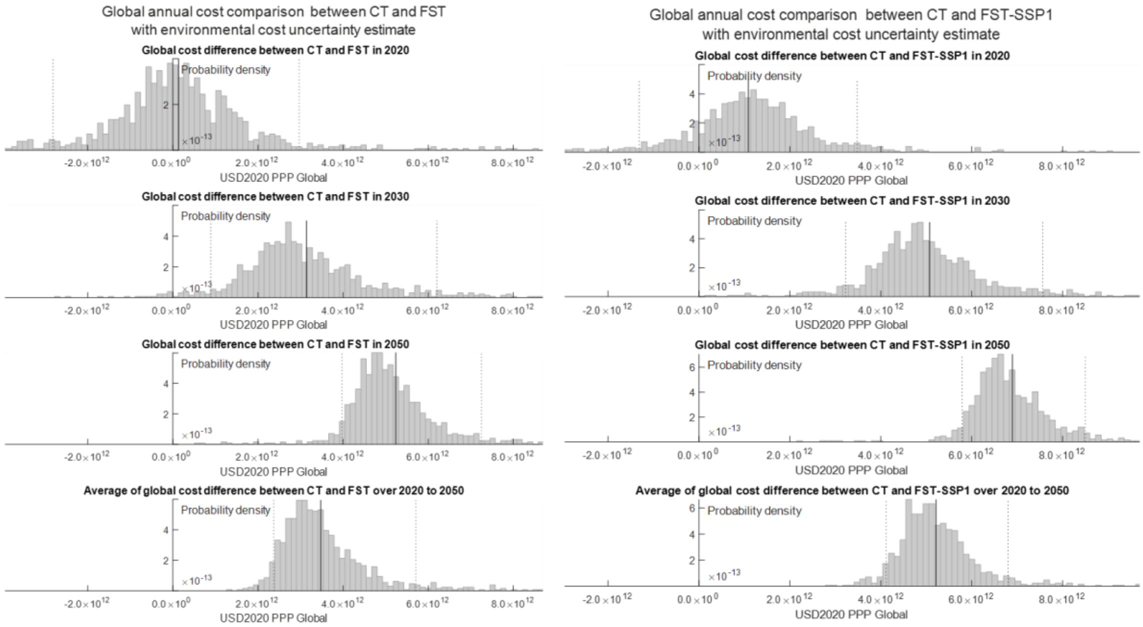


Figure 13: Distribution of global total annual hidden cost reduction under FST-SSP1 and FST in 2020 USD PPP in 2020, 2030 and 2050. The shape of the uncertainty in environmental hidden cost reduction in the years 2020, 2030 and 2050 is largely the same between FST-SSP1 and FST. Distributions are translated by additional reduction in productivity losses from diets in FST-SSP1.

Supplemental figure Figure 34 in Annex R shows that the shift from right skew toward higher environmental hidden costs under CT to left skew toward higher environmental benefits under FST was largely unchanged between FST-SSP1 and FST scenarios. FST shifted economic risk from CT food system GHG emissions, N emissions, and land-use change to opportunity for benefits. Returning habitat and carbon sequestration were the drivers of the shift.

Breakdown of hidden costs and hidden cost reduction

Table 5 summarise the hidden costs and hidden cost reduction broken down by “environmental” (E) hidden costs associated to production (reduction in greenhouse gas (GHG) and reactive nitrogen (N) emissions, reduction in lost habitat from land use changes and increase in returned habitat from abandoned agricultural land), “health” (H) hidden costs associated to undernourishment or over-consumption (reduction in years of life lost (YLL)), and “social” (S) hidden costs (poverty reduction).

GHG hidden costs are measured at the level of social costs of CO2 emission from land-use changes, CH4 emission primarily from rice production, waste, and enteric fermentation, and N2O emission primarily from soil, non-organic fertiliser application and livestock manure left on pasture or used in organic fertiliser. N hidden costs are measured by NH3 volatilization to air from fertiliser application and livestock manure, NO2 volatilization to air from fertiliser, manure, and crop residues, soluble NO3- runoff to surface waters from pasture and cropland, and soluble NO3- leaching into groundwater sources. Habitat loss is distinguished by forest and other land biome habitat loss, and forest and other land biome habitat return primarily from abandoned cropland and pasture. Cumulative value of ecosystem services from a hectare (ha) of avoided loss of established habitat and regenerating habitat is asymmetric, hence the distinction in loss and return categories for land-use change.

Figure 14 to Figure 16 shows global mean hidden costs for CT, FST and FST-SSP1 broken down into above hidden cost items.

Table 5: Comparitive global annual hidden and hidden costs reduction between CT, FST-SSP1 and FST in cost categoties. Aggregated "environmental" (E) hidden costs associated to production (reduction in greenhouse gas (GHG) and reactive nitrogen (N) emissions, reduction in lost habitat from land use changes and increase in returned habitat from abandoned agricultural land) and "health" (H) hidden costs associated to undernourishment or over-consumption (reduction in years of life lost (YLL)). Poverty reduction is (S). Mean value (mean), 5-th percentile (P5) and 95-th percentile (P95) in billions USD 2020 PPP.

Geography	Cat	Scen	Year	Mean	P5	P95
World	E	CT	2020	2901	1578	5231
World	S	CT	2020	921	921	921
World	H	CT	2020	11366	11366	11366
World	E	CT	2030	2411	958	5269
World	S	CT	2030	593	589	598
World	H	CT	2030	9376	9376	9376
World	E	CT	2050	1471	668	3084
World	S	CT	2050	182	178	186
World	H	CT	2050	8004	8004	8004
World	E	FST-SSP1	2020	2371	1265	4469
World	S	FST-SSP1	2020	903	903	903
World	H	FST-SSP1	2020	10697	10697	10697
World	E	FST-SSP1	2030	495	-395	1727
World	S	FST-SSP1	2030	481	477	485
World	H	FST-SSP1	2030	6161	6161	6161
World	E	FST-SSP1	2050	-159	-1065	500
World	S	FST-SSP1	2050	43	41	44
World	H	FST-SSP1	2050	2860	2860	2860
World	E	FST	2020	2784	1475	5353
World	S	FST	2020	903	903	903
World	H	FST	2020	11366	11366	11366
World	E	FST	2030	680	-378	2075
World	S	FST	2030	583	579	587
World	H	FST	2030	7981	7981	7981
World	E	FST	2050	-81	-1120	743
World	S	FST	2050	177	174	181
World	H	FST	2050	4322	4322	4322
World	E Difference Total	CT.FST-SSP1		47532	25360	94980
World	S Difference Total	CT.FST-SSP1		3711	3678	3746
World	H Difference Total	CT.FST-SSP1		105256	105256	105256
World	E Difference Average	CT.FST-SSP1		1584	845	3166
World	S Difference Average	CT.FST-SSP1		124	123	125
World	H Difference Average	CT.FST-SSP1		3509	3509	3509
World	E Difference Total	CT.FST		46415	19958	116467

World	S Difference Total	CT.FST		284	279	288
World	H Difference Total	CT.FST		57515	57515	57515
World	E Difference Average	CT.FST		1547	665	3882
World	S Difference Average	CT.FST		9	9	10
World	H Difference Average	CT.FST		1917	1917	1917

Supplemental figure Figure 36 in Annex R provides boxplots of the hidden costs for uncertainty in the components of GHG emissions, N emissions, and land-use. Lost and returned habitat, CH4 emissions, CO2 emissions and NO3- runoff from cropland are hidden costs with the greatest uncertainty under CT, FST-SSP1 and FST.

Figure 4S in the summary showed the break down of hidden cost reduction for CT versus FST. The break down of hidden cost reduction for CT versus FST-SSP1 is shown in Figure 17.

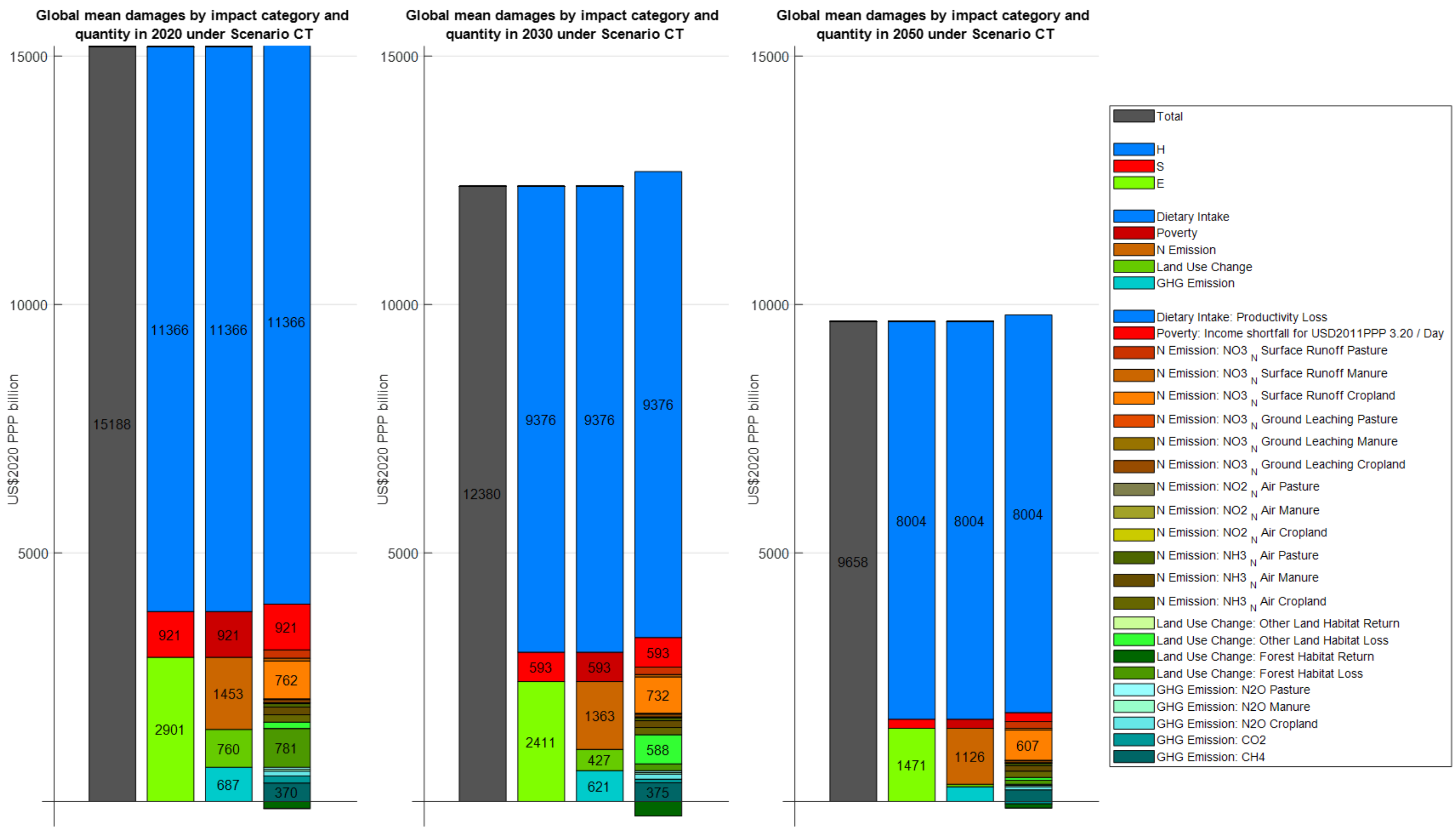


Figure 14: Breakdown of global annual hidden costs under CT in 2020 USD PPP in 2020, 2030 and 2050. Mean values shown in USD 2020 PPP billions..

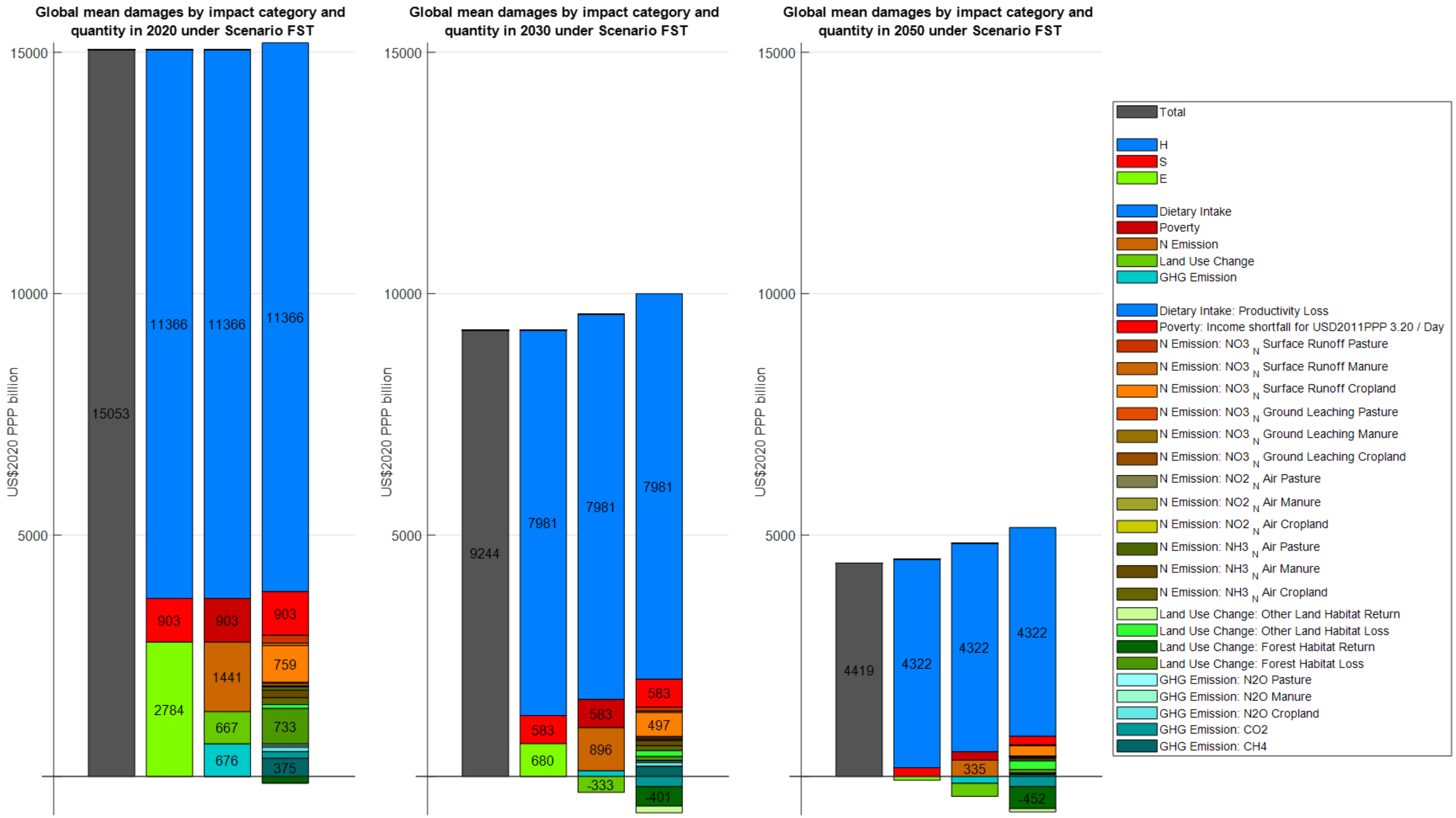


Figure 15: Breakdown of global annual hidden costs under FST in 2020 USD PPP in 2020, 2030 and 2050. Mean values shown in USD 2020 PPP billions.

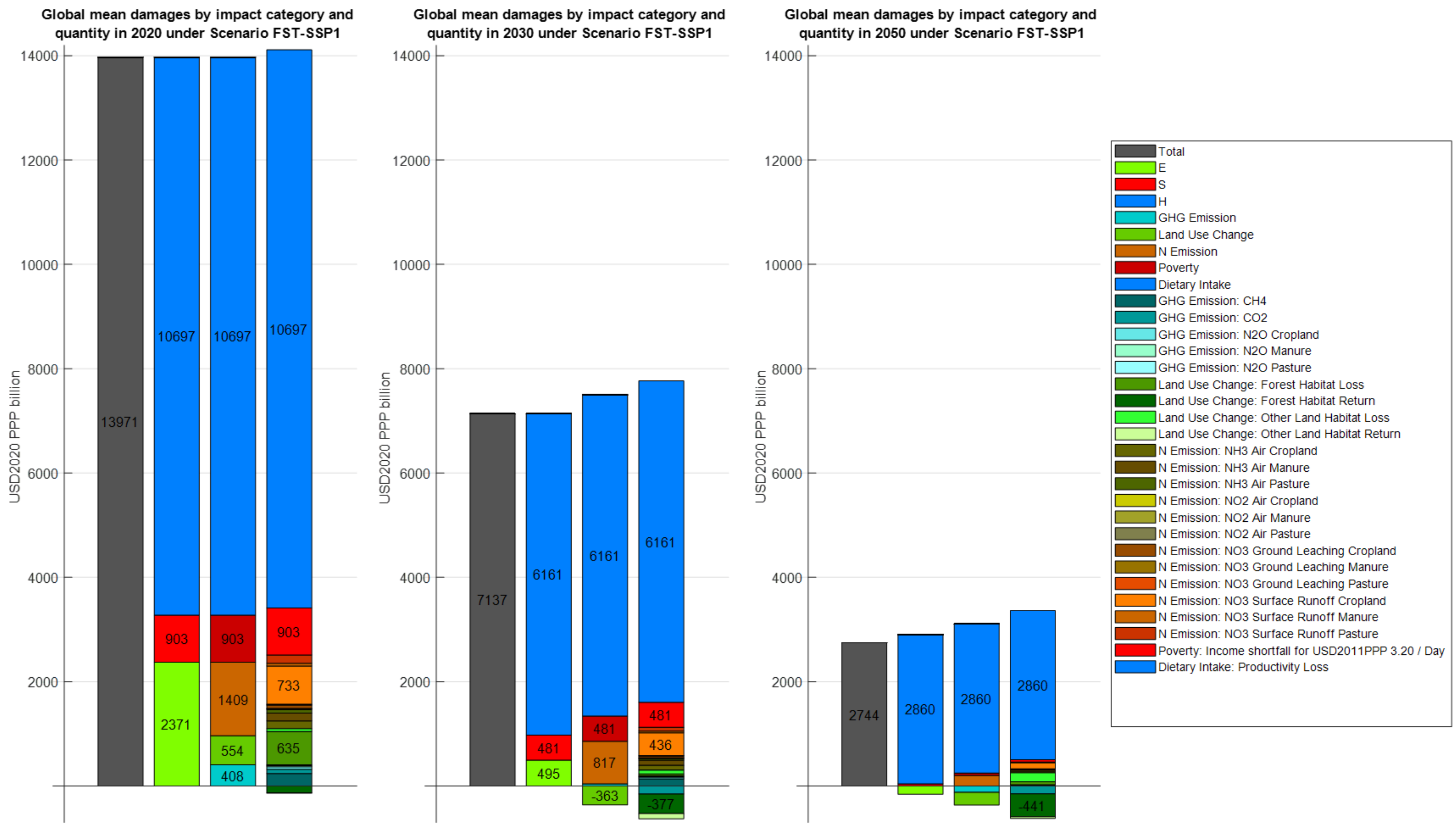


Figure 16 Breakdown of global annual hidden costs under FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050. Mean values shown in USD 2020 PPP billions.

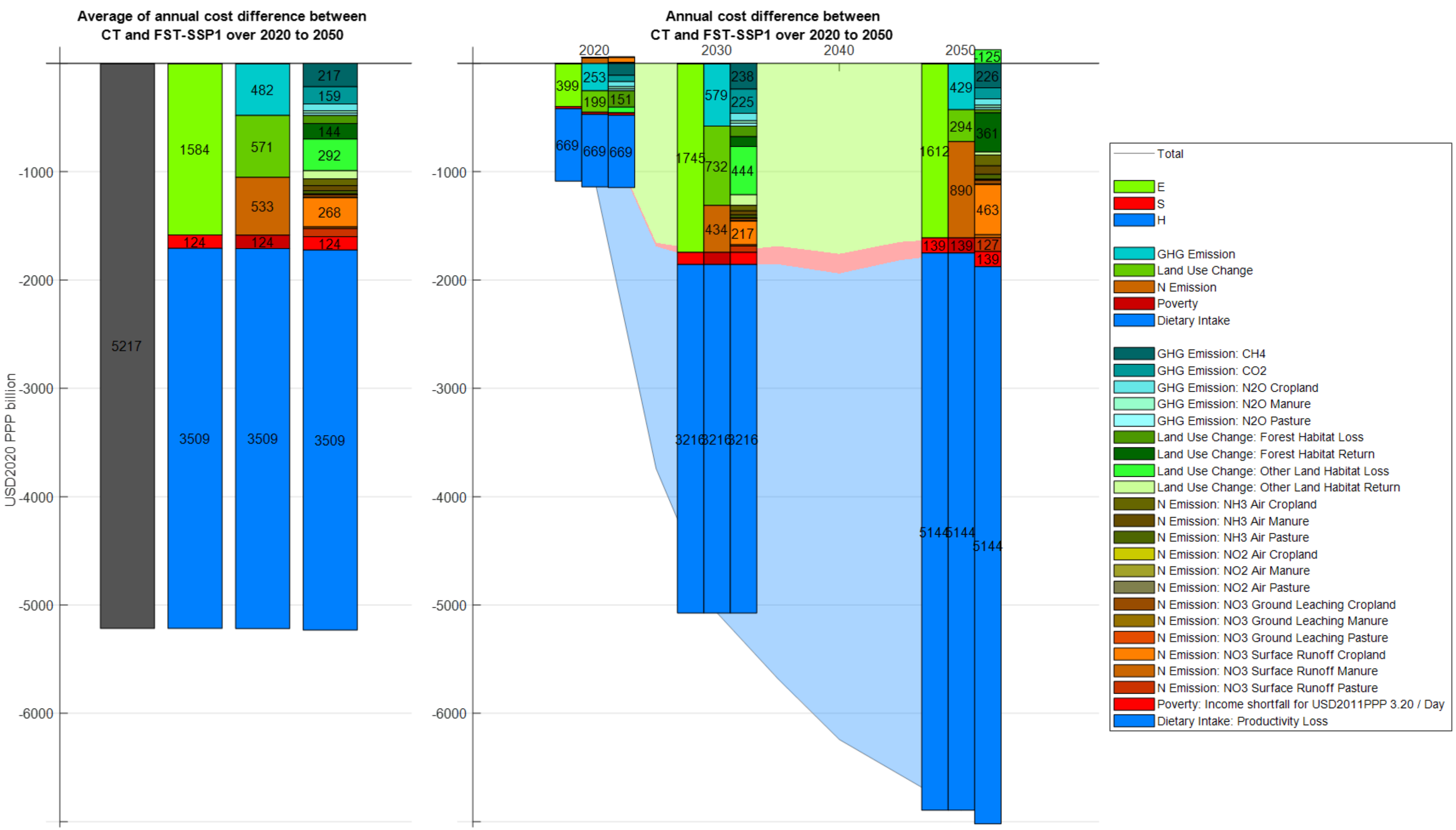


Figure 17: Breakdown of global annual hidden cost reduction under FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050. In comparison with FST (Figure 4S) the pathway FST-SSP1 has large additional hidden cost reductions from dietary change. The additional discounting to 2020 USD PPP under SSP1 from wealthier future economies explains most of the difference of environmental hidden cost reduction compared to FST. Poverty reduction is driven by greater economic growth of all sectors in SSP1 compared to SSP2, not in the implementation of FST measures.

Breakdown of hidden costs by FSEC region

14 FSEC regions based upon MAgPIE country groupings were examined for hidden costs and hidden costs reduction under FST-SSP1 and FST. Results for a cross-section of 7 major producers, the EU-27 countries (EUR), USA, China (CHA), India (IND), and Brazil (BRA) and developing regions of Sub-Sahara Africa (SSA) and Latin and South America excluding Brazil (LAM) are reported.

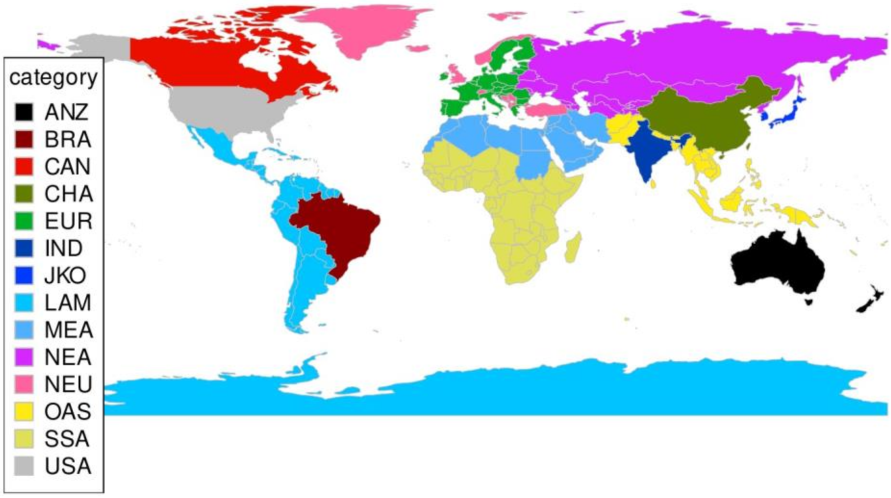


Figure 18: FSEC regions for the hidden cost analysis. (Source: MAgPIE documentation)

Figure 19 to Figure 21 shows global mean hidden costs for the 7 FSEC regions for CT, FST and FST-SSP1.

Trajectories of hidden costs for CHA, BRA and SSA, showing health, environmental and social transitions under FST for FSEC regions are examined in more detail in Figure 19 to Figure 21

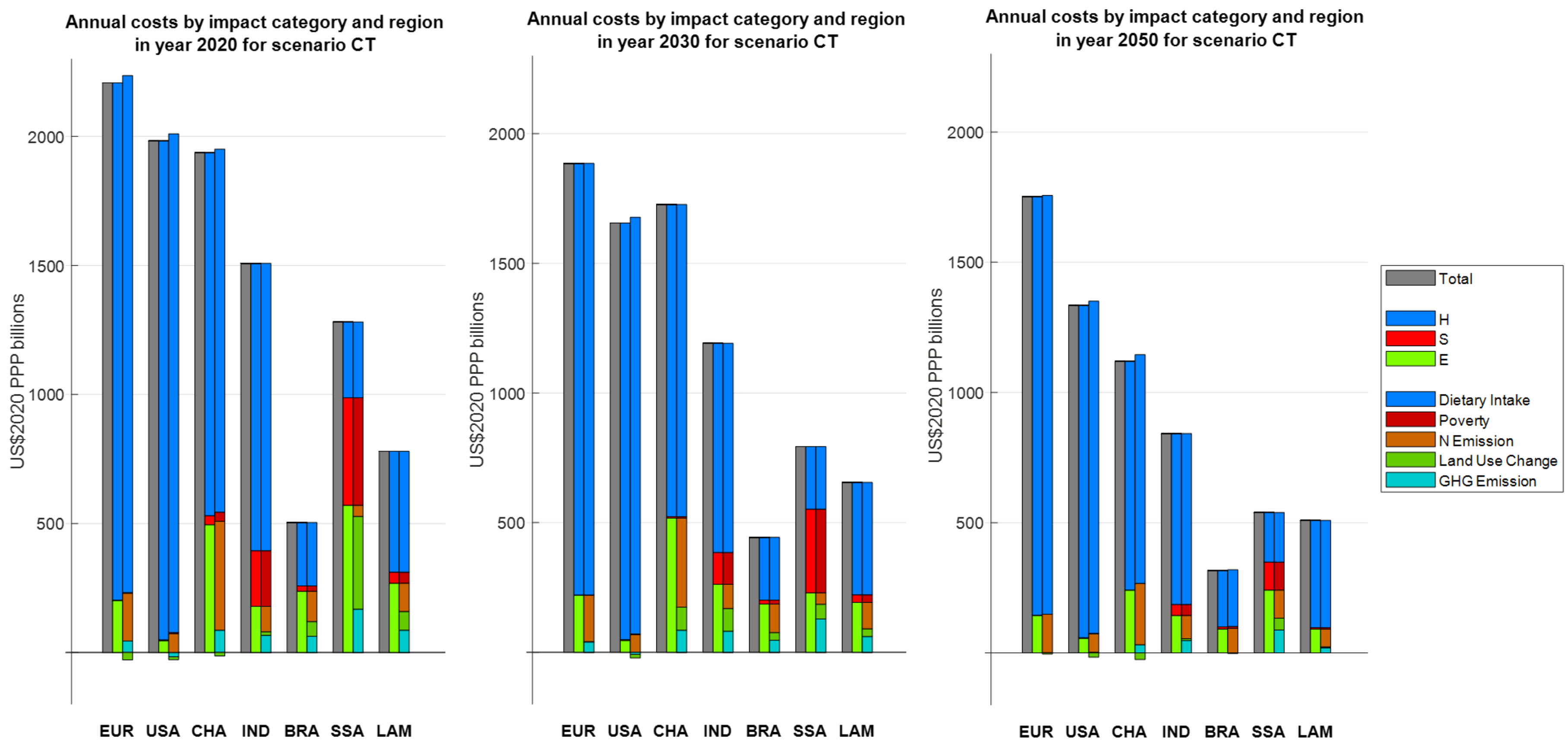


Figure 19: Breakdown of global annual hidden costs under CT in 2020 USD PPP in 2020, 2030 and 2050 by FSEC regions. Mean values shown in USD 2020 PPP billions..

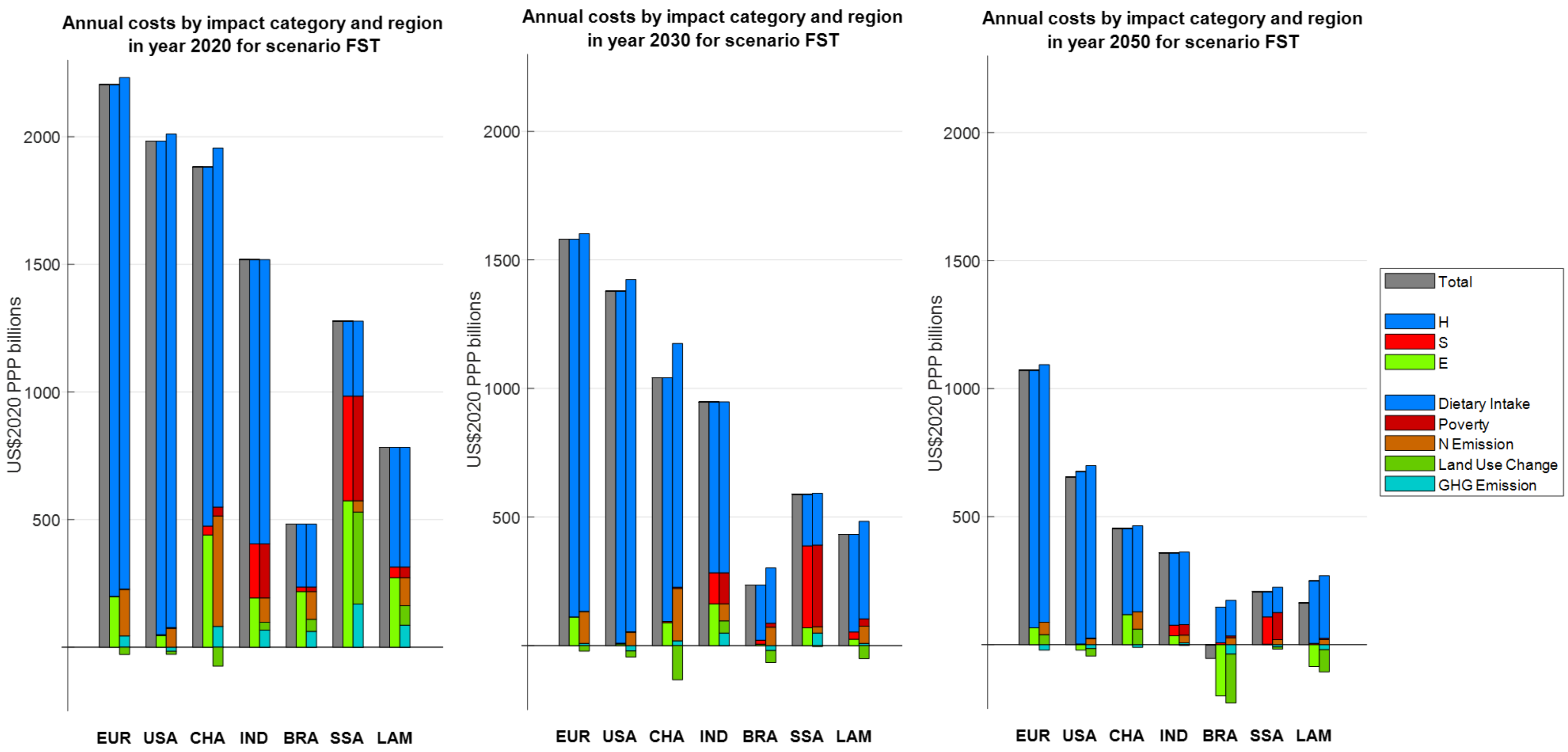


Figure 20: Breakdown of global annual hidden costs under FST in 2020 USD PPP in 2020, 2030 and 2050 by FSEC regions. Mean values shown in USD 2020 PPP billions. Diets and N hidden costs are reduced by over 30% and 60%, respectively, under FST compared to CT-SSP2 in 2050. Land-use costs in BRA and AM transit to benefits from returned habitat and carbon sequestration.

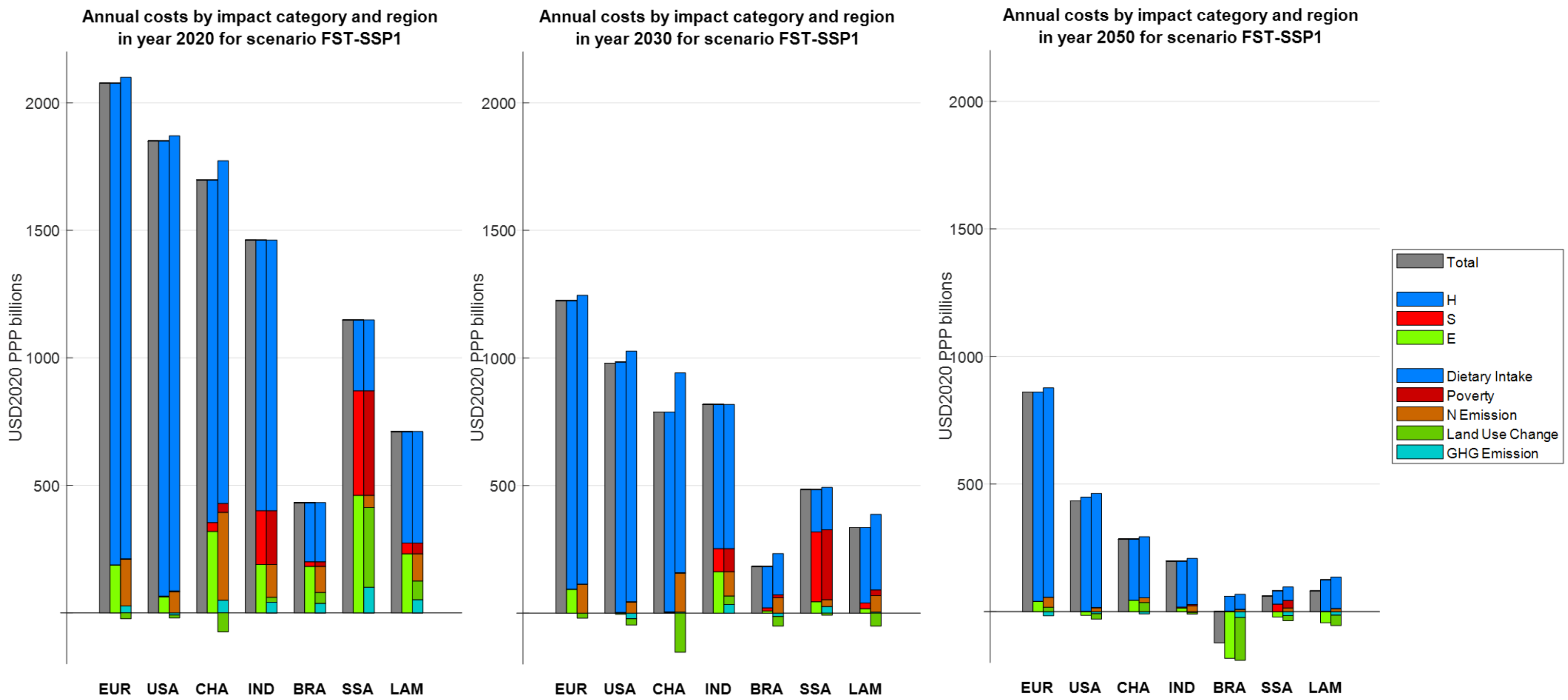


Figure 21 Breakdown of global annual hidden costs under FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050 by FSEC regions. Mean values shown in USD 2020 PPP billions. Poverty, and productivity losses from diets, are reduced even further under FST-SSP1 compared to FST.

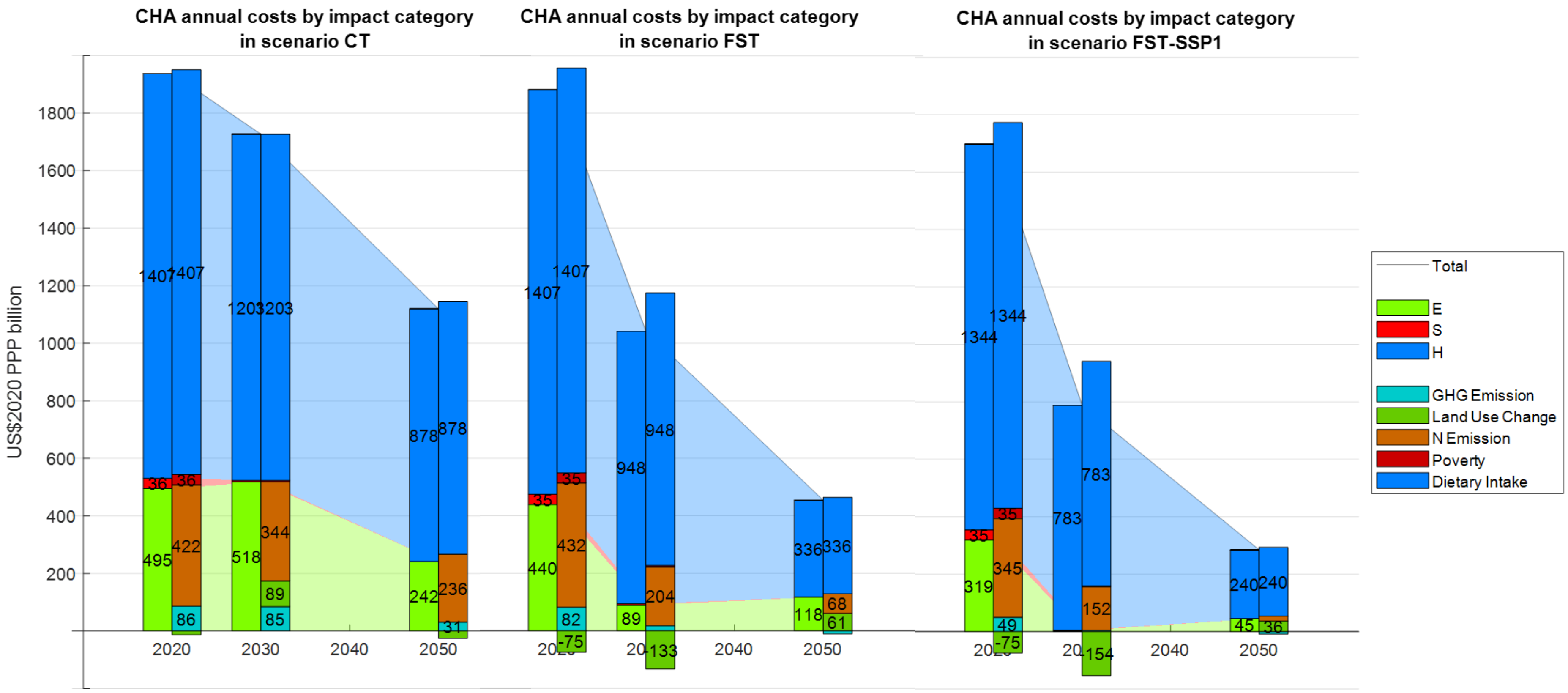


Figure 22: Breakdown and comparison of global annual hidden costs CHA under FST-SSP1 and FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050. In comparison with FST (Figure 6S) the pathway FST-SSP1 has large additional hidden cost reductions from dietary change in 2030 which are retained to 2050. Other changes are within the change in discount rate between SSP2 and SSP1. Environmental measures in China produce mid term reversal of agricultural land-expansion. This stabilises to a small amount of agricultural land expansion in 2050 to meet demand from population increases. Productivity losses from diets in CHA, currently on a trajectory of burgeoning burden of disease from increasing obesity and NCD associated to dietary intake, show a 55-66% reduction under FST.

Figure 23: Breakdown and comparison of global annual hidden costs BRA under FST-SSP1 and FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050. In comparison with FST (Figure 7S) the pathway FST-SSP1 has a 60% increase in hidden cost reductions from dietary change by 2050. The additional discounting to 2020 USD PPP under SSP1 from wealthier future economies explains most of the difference of environmental hidden cost reduction compared to FST except for additional N reductions. SSP1 has a smaller and richer global population in 2050 eating healthy diets, reducing overall global food demand for BRA as a major food exporter. FST shows approximately a 300 billion transition to BRA obtaining net benefits from habitat restoration.

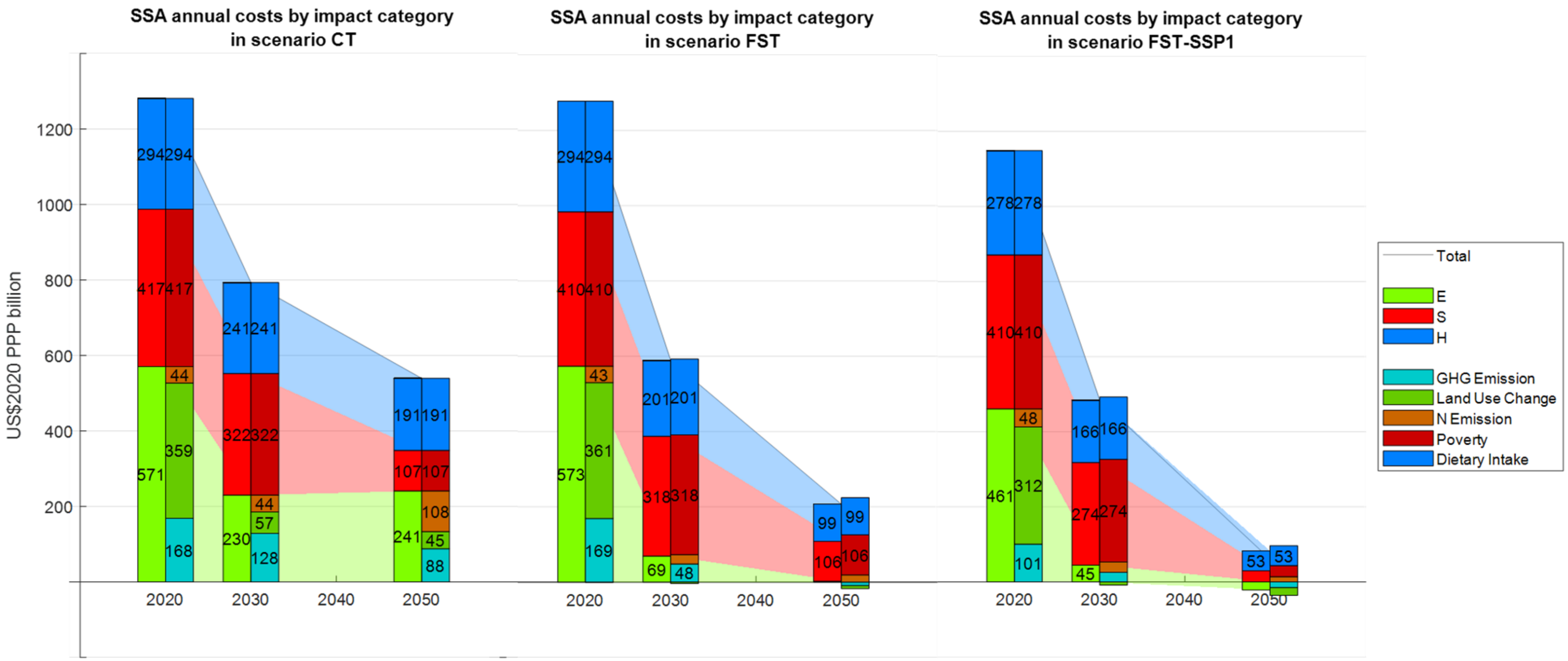


Figure 24: Breakdown and comparison of global annual hidden costs SSA under FST-SSP1 and FST-SSP1 in 2020 USD PPP in 2020, 2030 and 2050. In comparison with FST (Figure 9S) the pathway FST-SSP1 has large additional hidden cost reductions from dietary change. Poverty reduction in SSA under SSP1 is driven by greater economic growth of all sectors in SSP1 compared to SSP2. SSP1 has higher GDP PPP projections across all developing countries with smaller populations in 2050. The triple burden of poverty, malnutrition, and environmental damages predicted for SSA under CT is avoided under FST.

References

1. Gaupp, F., et al., *Food system transformation pathways for healthy, nature-positive and inclusive food systems.* Nature Food, 2021. **2**(12): p. 928-934.
2. Lord, S., *Valuing the impact of food*. 2020, Food System Impact Valuation Initiative: Oxford, UK.
3. Godfray, H.C.J., et al., *The future of the global food system.* Philosophical Transactions of the Royal Society of London B: Biological Sciences, 2010. **365**(1554): p. 2769-2777.
4. FABLE, *Pathways to Sustainable Land-Use and Food Systems. 2019 Report of the FABLE Consortium.* 2019, International Institute for Applied Systems Analysis (IIASA) and Sustainable Development Solutions Network (SDSN): Laxenburg and Paris.
5. FOLU, *Growing Better: Ten Critical Transitions to Transform Food and Land Use, The Global Consultation Report of the Food and Land Use Coalition.* 2019, Food and Land Use Coalition: New York.
6. Willett, W., et al., *Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems.* The Lancet, 2019. **393**(10170): p. 447-492.
7. Vandevijvere, S., et al., *Global trends in ultraprocessed food and drink product sales and their association with adult body mass index trajectories.* Obesity Reviews, 2019. **20**(S2): p. 10-19.
8. Springmann, M., et al., *Global and regional health effects of future food production under climate change: a modelling study.* The Lancet, 2016.
9. Penuelas, J., et al., *Anthropogenic global shifts in biospheric N and P concentrations and ratios and their impacts on biodiversity, ecosystem productivity, food security, and human health.* Global Change Biology, 2020. **26**(4): p. 1962-1985.
10. Crippa, M., et al., *Food systems are responsible for a third of global anthropogenic GHG emissions.* Nature Food, 2021. **2**(3): p. 198-209.
11. Saunois, M., et al., *The Global Methane Budget 2000–2017.* Earth Syst. Sci. Data, 2020. **12**(3): p. 1561-1623.
12. Crippa, M., et al., *Gridded emissions of air pollutants for the period 1970–2012 within EDGAR v4.3.2.* Earth Syst. Sci. Data, 2018. **10**(4): p. 1987-2013.
13. McDuffie, E.E., et al., *A global anthropogenic emission inventory of atmospheric pollutants from sector- and fuel-specific sources (1970–2017): an application of the Community Emissions Data System (CEDS).* Earth Syst. Sci. Data, 2020. **12**(4): p. 3413-3442.
14. Kanter, D.R., et al., *A framework for nitrogen futures in the shared socioeconomic pathways.* Global Environmental Change, 2020. **61**: p. 102029.
15. Uwizeye, A., et al., *Nitrogen emissions along global livestock supply chains.* Nature Food, 2020. **1**(7): p. 437-446.
16. Winkler, K., et al., *Global land use changes are four times greater than previously estimated.* Nature Communications, 2021. **12**(1): p. 2501.
17. Leclère, D., et al., *Bending the curve of terrestrial biodiversity needs an integrated strategy.* Nature, 2020. **585**(7826): p. 551-556.
18. Foley, J.A., et al., *Global Consequences of Land Use.* Science, 2005. **309**(5734): p. 570.
19. Global Panel, *The Cost of Malnutrition: Why Policy Action is Urgent* in *Technical Brief*. 2016, Global Panel on Agriculture and Food Systems for Nutrition: London.
20. Nugent, R., et al., *Economic effects of the double burden of malnutrition.* The Lancet, 2020. **395**(10218): p. 156-164.
21. Swaminathan, S., et al., *The burden of child and maternal malnutrition and trends in its indicators in the states of India: the Global Burden of Disease Study 1990–2017.* The Lancet Child & Adolescent Health, 2019. **3**(12): p. 855-870.
22. Perez-Escamilla, R., et al., *Nutrition disparities and the global burden of malnutrition.* BMJ, 2018. **361**: p. k2252.

23. Dai, H., et al., *The global burden of disease attributable to high body mass index in 195 countries and territories, 1990–2017: An analysis of the Global Burden of Disease Study.* PLOS Medicine, 2020. **17**(7): p. e1003198.
24. Swinburn, B.A., et al., *The Global Syndemic of Obesity, Undernutrition, and Climate Change: The Lancet Commission report.* The Lancet, 2019. **393**(10173): p. 791-846.
25. Okunogbe, A., et al., *Economic impacts of overweight and obesity: current and future estimates for eight countries.* BMJ Global Health, 2021. **6**(10): p. e006351.
26. Tremmel, M., et al., *Economic Burden of Obesity: A Systematic Literature Review.* International journal of environmental research and public health, 2017. **14**(4): p. 435.
27. Afshin, A., et al., *Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017.* The Lancet, 2019. **393**(10184): p. 1958-1972.
28. Clark, M.A., et al., *Multiple health and environmental impacts of foods.* Proceedings of the National Academy of Sciences, 2019: p. 201906908.
29. The World Bank, *Poverty and Shared Prosperity 2022: Correcting Course*. 2022, World Bank Group: Washington, DC.
30. Botreau, H. and M.J. Cohen, *Chapter Two - Gender inequality and food insecurity: A dozen years after the food price crisis, rural women still bear the brunt of poverty and hunger*, in *Advances in Food Security and Sustainability*, M.J. Cohen, Editor. 2020, Elsevier. p. 53-117.
31. Cervantes-Godoy, D. and J. Dewbre, *Economic Importance of Agriculture for Poverty Reduction*, in *OECD Food, Agriculture and Fisheries Papers*. 2010, OECD Publishing: Paris.
32. O'Neill, B.C., et al., *The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century.* Global Environmental Change, 2017. **42**: p. 169-180.
33. O'Neill, B.C., et al., *A new scenario framework for climate change research: the concept of shared socioeconomic pathways.* Climatic Change, 2014. **122**(3): p. 387-400.
34. Valin, H., et al., *The future of food demand: understanding differences in global economic models.* Agricultural Economics, 2014. **45**(1): p. 51-67.
35. Rogelj, J., et al., *Scenarios towards limiting global mean temperature increase below 1.5 °C.* Nature Climate Change, 2018. **8**(4): p. 325-332.
36. Barro, R.J., *Economic Growth in a Cross Section of Countries*.* The Quarterly Journal of Economics, 1991. **106**(2): p. 407-443.
37. Shapiro, A.C., *What does purchasing power parity mean?* Journal of International Money and Finance, 1983. **2**(3): p. 295-318.
38. Bodirsky, B.L., et al., *The ongoing nutrition transition thwarts long-term targets for food security, public health and environmental protection.* Scientific Reports, 2020. **10**(1): p. 19778.
39. Dietrich, J.P., et al., *MAgPIE 4–a modular open-source framework for modeling global land systems.* Geoscientific Model Development, 2019. **12**(4): p. 1299-1317.
40. Soergel, B., et al., *Combining ambitious climate policies with efforts to eradicate poverty.* Nature Communications, 2021. **12**(1): p. 2342.
41. Springmann, M., et al., *The healthiness and sustainability of national and global food based dietary guidelines: modelling study.* BMJ, 2020. **370**: p. m2322.
42. Klein, D., et al., *The value of bioenergy in low stabilization scenarios: an assessment using REMIND-MAgPIE.* Clim Change, 2014. **123**.
43. Bondeau, A., et al., *Modelling the role of agriculture for the 20th century global terrestrial carbon balance.* Global Change Biology, 2007. **13**(3): p. 679-706.
44. Schaphoff, S., et al., *LPJmL4 – a dynamic global vegetation model with managed land – Part 1: Model description.* Geosci. Model Dev., 2018. **11**(4): p. 1343-1375.
45. Markandya, A. and D.W. Pearce, *Development, the Environment, and the Social Rate of Discount.* The World Bank Research Observer, 1991. **6**(2): p. 137-152.

46. CTmgärtner, S., et al., *Ramsey Discounting of Ecosystem Services.* Environmental and Resource Economics, 2015. **61**(2): p. 273-296.
47. Hoel, M. and T. Sterner, *Discounting and relative prices.* Climatic Change, 2007. **84**(3): p. 265-280.
48. Figge, F., *Capital Substitutability and Weak Sustainability Revisited: The Conditions for Capital Substitution in the Presence of Risk.* Environmental Values, 2005. **14**(2): p. 185-201.
49. Dietz, S. and E. Neumayer, *Weak and strong sustainability in the SEEA: Concepts and measurement.* Ecological Economics, 2007. **61**(4): p. 617-626.
50. Davies, G.R., *Appraising Weak and Strong Sustainability: Searching for a Middle Ground.* Consilience, 2013(10): p. 111-124.
51. Bodirsky, B.L., et al., *Reactive nitrogen requirements to feed the world in 2050 and potential to mitigate nitrogen pollution.* Nature Communications, 2014. **5**(1): p. 3858.
52. Beusen, A.H.W., et al., *Coupling global models for hydrology and nutrient loading to simulate nitrogen and phosphorus retention in surface water – description of IMAGE–GNM and analysis of performance.* Geosci. Model Dev., 2015. **8**(12): p. 4045-4067.
53. Beusen, A.H.W., et al., *Global riverine N and P transport to ocean increased during the 20th century despite increased retention along the aquatic continuum.* Biogeosciences, 2016. **13**(8): p. 2441-2451.
54. Lord, S., *Estimations of marginal social costs for GHG emissions*, in *SPIQ-FS Dataset Version 0*. 2021, University of Oxford.
55. Lord, S., *Estimation of marginal damage costs from reactive nitrogen emissions to air, surface waters and groundwater*, in *SPIQ-FS Dataset Version 0*. 2021, University of Oxford.
56. Lord, S., *Estimation of marginal damage costs from water scarcity due to blue water withdrawal*, in *SPIQ-FS Dataset Version 0*. 2021, University of Oxford.
57. Lord, S., *Estimation of marginal damage costs for loss of ecosystem services from land-use change or ecosystem degradation*, in *SPIQ-FS Dataset Version 0*. 2021, University of Oxford.
58. Paulus, E. and S. Lord, *Estimation of marginal damage costs from consumption related health risks*, in *SPIQ-FS Dataset Version 0*. 2022, University of Oxford.
59. Lord, S., *Adjustments to SPIQ-FS marginal damage cost models to estimate damages in future scenarios*, in *SPIQ-FS Dataset Version 0*. 2022, University of Oxford.
60. Kolstad, C., et al., *Social, Economic and Ethical Concepts and Methods*, in *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, O. Edenhofer, et al., Editors. 2014, Cambridge University Press: New York, NY. p. 207-282.
61. Evans, D.J., *The Elasticity of Marginal Utility of Consumption: Estimates for 20 OECD Countries.* Fiscal Studies, 2005. **26**(2): p. 197-224.
62. Moore, M.A., et al., *"Just Give Me a Number!" Practical Values for the Social Discount Rate.* Journal of Policy Analysis and Management, 2004. **23**(4): p. 789-812.
63. Drupp, M.A., et al., *Discounting Disentangled.* American Economic Journal: Economic Policy, 2018. **10**(4): p. 109-34.
64. Lowe, J., *Intergenerational wealth transfers and social discounting: Supplementary Green Book guidance*. 2008, HM Treasury: London.
65. Roche, J., *Intergenerational equity and social discount rates: what have we learned over recent decades?* International Journal of Social Economics, 2016. **43**(12): p. 1539-1556.
66. Weitzman, M., *On Modeling and Interpreting the Economics of Catastrophic Climate Change.* The Review of Economics and Statistics, 2009. **91**(1): p. 1-19.
67. Gollier, C., *Pricing the planet's future : the economics of discounting in an uncertain world*. University Press Scholarship Online. 2017, Princeton: Princeton University Press.
68. Gollier, C., *Valuation of natural capital under uncertain substitutability.* Journal of Environmental Economics and Management, 2019. **94**: p. 54-66.

69. Gollier, C. and M.L. Weitzman, *How should the distant future be discounted when discount rates are uncertain?* Economics Letters, 2010. **107**(3): p. 350-353.
70. IWGSCGG, *Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis*. 2016, Interagency Working Group on Social Cost of Greenhouse Gases, United States Government: Washington DC.
71. IWGSCGG, *Technical Support Document: Technical Update of the Social Cost of Carbon, Methane and Nitrous Oxide Interim Estimates under Executive Order 13990*. 2021, Interagency Working Group on Social Cost of Greenhouse Gases, United States Government: Washington DC.
72. Nordhaus, W.D., *Revisiting the social cost of carbon.* Proceedings of the National Academy of Sciences of the United States of America, 2017. **114**(7): p. 1518.
73. Errickson, F.C., et al., *Equity is more important for the social cost of methane than climate uncertainty.* Nature, 2021. **592**(7855): p. 564-570.
74. Etminan, M., et al., *Radiative forcing of carbon dioxide, methane, and nitrous oxide: A significant revision of the methane radiative forcing.* Geophysical Research Letters, 2016. **43**(24): p. 12,614-12,623.
75. Marten, A.L. and S.C. Newbold, *Estimating the social cost of non-CO2 GHG emissions: Methane and nitrous oxide.* Energy Policy, 2012. **51**: p. 957-972.
76. Metcalf, G.E. and J.H. Stock, *Integrated Assessment Models and the Social Cost of Carbon: A Review and Assessment of U.S. Experience.* Review of Environmental Economics and Policy, 2017. **11**(1): p. 80-99.
77. Li, Y., Y. Dong, and J. Qian, *Higher-order analysis of probabilistic long-term loss under nonstationary hazards.* Reliability Engineering & System Safety, 2020. **203**: p. 107092.
78. Liu, X., et al., *Environmental flow requirements largely reshape global surface water scarcity assessment.* Environmental Research Letters, 2021. **16**(10): p. 104029.
79. Costanza, R., et al., *The value of the world's ecosystem services and natural capital.* Nature, 1997. **387**(6630): p. 253-260.
80. Winkler, K., et al., *HILDA+ Global Land Use Change between 1960 and 2019*. 2020, PANGAEA.
81. de Groot, R., et al., *Global estimates of the value of ecosystems and their services in monetary units.* Ecosystem Services, 2012. **1**(1): p. 50-61.
82. Veerkamp, C.J., et al., *Future projections of biodiversity and ecosystem services in Europe with two integrated assessment models.* Regional Environmental Change, 2020. **20**(3): p. 103.
83. Rosa, I.M.D., et al., *Challenges in producing policy-relevant global scenarios of biodiversity and ecosystem services.* Global Ecology and Conservation, 2020. **22**: p. e00886.
84. Carpenter, S.R., E.M. Bennett, and G.D. Peterson, *Scenarios for Ecosystem Services: An Overview.* Ecology and Society, 2006. **11**(1).
85. Crawford, C.L., et al., *Rural land abandonment is too ephemeral to provide major benefits for biodiversity and climate.* Science Advances. **8**(21): p. eabm8999.
86. Guiasu, S. and A. Shenitzer, *The principle of maximum entropy.* The Mathematical Intelligencer, 1985. **7**(1): p. 42-48.
87. Ring, I., et al., *Challenges in framing the economics of ecosystems and biodiversity: the TEEB initiative.* Current Opinion in Environmental Sustainability, 2010. **2**(1): p. 15-26.
88. Haines-Young, R. and M.B. Potschin-Young, *Revision of the Common International Classification for Ecosystem Services (CICES V5.1): A Policy Brief.* One Ecosystem, 2018. **3**: p. e27108.
89. Richards, D.R. and D.A. Friess, *Rates and drivers of mangrove deforestation in Southeast Asia, 2000–2012.* Proceedings of the National Academy of Sciences, 2016. **113**(2): p. 344-349.
90. Isbell, F., et al., *Deficits of biodiversity and productivity linger a century after agricultural abandonment.* Nature Ecology & Evolution, 2019. **3**(11): p. 1533-1538.

91. Anpilogova, D. and A. Pakina, *Assessing ecosystem services of abandoned agricultural lands: a case study in the forested zone of European Russia.* One Ecosystem, 2022. **7**: p. e77969.
92. Le Provost, G., et al., *Land-use history impacts functional diversity across multiple trophic groups.* Proceedings of the National Academy of Sciences, 2020. **117**(3): p. 1573-1579.
93. Rozendaal, D.M.A., et al., *Biodiversity recovery of Neotropical secondary forests.* Science Advances. **5**(3): p. eaau3114.
94. van Grinsven, H.J.M., et al., *Costs and Benefits of Nitrogen for Europe and Implications for Mitigation.* Environmental Science & Technology, 2013. **47**(8): p. 3571-3579.
95. Sutton, M.A., et al., *Too much of a good thing.* Nature, 2011. **472**(7342): p. 159-161.
96. Mitchell, R.J. and P. Bates, *Measuring health-related productivity loss.* Popul Health Manag, 2011. **14**(2): p. 93-8.
97. Rice, D.P., *Cost of illness studies: what is good about them?* Injury Prevention, 2000. **6**(3): p. 177.
98. Domingo, N.G.G., et al., *Air quality–related health damages of food.* Proceedings of the National Academy of Sciences, 2021. **118**(20): p. e2013637118.
99. Springmann, M., *Valuation of the health and climate-change benefits of healthy diets*, in *FAO Agricultural Development Economics Working Papers. No 20-03*. 2020, Food and Agriculture Organization of the United Nations: Rome.
100. Caldara, D., C. Scotti, and M. Zhong, *Macroeconomic and Financial Risks: A Tale of Mean and Volatility*, in *International Finance Discussion Papers*. 2021, Board of Governors of the Federal Reserve System (U.S.): Washington, DC.
101. Rennert, K., et al., *Comprehensive evidence implies a higher social cost of CO2.* Nature, 2022. **610**(7933): p. 687-692.
102. *The European Nitrogen Assessment: Sources, Effects and Policy Perspectives*. 2011, Cambridge: Cambridge University Press.
103. Heo, J., P.J. Adams, and H.O. Gao, *Reduced-form modeling of public health impacts of inorganic PM2.5 and precursor emissions.* Atmospheric Environment, 2016. **137**: p. 80-89.
104. Fowler, D., et al., *The global nitrogen cycle in the twenty-first century.* Philosophical Transactions of the Royal Society B: Biological Sciences, 2013. **368**(1621): p. 20130164.
105. Erisman, J.W., et al., *Consequences of human modification of the global nitrogen cycle.* Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 2013. **368**(1621): p. 20130116-20130116.
106. Hamel, P. and B.P. Bryant, *Uncertainty assessment in ecosystem services analyses: Seven challenges and practical responses.* Ecosystem Services, 2017. **24**: p. 1-15.
107. Johnson, K.A., et al., *Uncertainty in ecosystem services valuation and implications for assessing land use tradeoffs: An agricultural case study in the Minnesota River Basin.* Ecological Economics, 2012. **79**: p. 71-79.
108. Schmidt, S., A.M. Manceur, and R. Seppelt, *Uncertainty of Monetary Valued Ecosystem Services – Value Transfer Functions for Global Mapping.* PLOS ONE, 2016. **11**(3): p. e0148524.
109. National Research Council, *5: Economic methods of valuation*, in *Perspectives on Biodiversity: Valuing its role in an everchanging world*. 1999, The National Academies Press: Washington DC.
110. Plummer, M.L., *Assessing benefit transfer for the valuation of ecosystem services.* Frontiers in Ecology and the Environment, 2009. **7**(1): p. 38-45.
111. Ferreira, F.H.G., et al., *A Global Count of the Extreme Poor in 2012 : Data Issues, Methodology and Initial Results.*, in *Policy Research Working Paper; No. 7432*. 2015, World Bank: Washington.
112. Holzer, H.J., et al., *The economic costs of poverty in the United States : subsequent effects of children growing up poor. Institute for Research on Poverty Discussion Paper no. 1327-07*. 2007, Center for American Progress: Washington DC.

113. Silver, M., *IMF Applications of Purchasing Power Parity Estimates*. 2010, International Monetary Fund: Washington DC.
114. Adler, M., *Cost-Benefit Analysis and Social Welfare Functions*, in *Oxford Handbook of Ethics and Economics.*, M.D. White, Editor. 2019, Oxford University Press: Oxford UK.
115. Tinch, R., *Debating Nature's Value: The Role of Monetary Valuation*, in *Debating Nature's Value: The Concept of 'Natural Capital'*, V. Anderson, Editor. 2018, Springer International Publishing: Cham. p. 39-47.
116. Sandelin, B., H.-M. Trautwein, and R. Wundrak, *A short history of economic thought*. 3rd ed. 2014, London: Routledge.
117. Eory, V., et al., *Marginal abatement cost curves for agricultural climate policy: State-of-the art, lessons learnt and future potential.* Journal of Cleaner Production, 2018. **182**: p. 705-716.
118. Kesicki, F. and P. Ekins, *Marginal abatement cost curves: a call for caution.* Climate Policy, 2012. **12**(2): p. 219-236.
119. Moran, D., et al., *Marginal Abatement Cost Curves for UK Agricultural Greenhouse Gas Emissions.* Journal of Agricultural Economics, 2011. **62**(1): p. 93-118.
120. La Torre, D., D. Liuzzi, and S. Marsiglio, *Pollution diffusion and abatement activities across space and over time.* Mathematical Social Sciences, 2015. **78**: p. 48-63.
121. Nicolaisen, J. and P. Hoeller, *Economics and the Environment: A Survey of Issues and Policy Options*, in *OECD Economics Department Working Papers*. 1990, OECD Publishing: Paris.
122. TEEB, *TEEB for Agriculture & Food: Scientific and Economic Foundations*. 2018, UN Environment: Geneva.
123. Murphy, D.M. and A.R. Ravishankara, *Trends and patterns in the contributions to cumulative radiative forcing from different regions of the world.* Proceedings of the National Academy of Sciences, 2018. **115**(52): p. 13192-13197.
124. Ji, J.S., *Air pollution and cardiovascular disease onset: hours, days, or years?* The Lancet Public Health, 2022. **7**(11): p. e890-e891.
125. Cai, M., et al., *Short-term air pollution exposure associated with death from kidney diseases: a nationwide time-stratified case-crossover study in China from 2015 to 2019.* BMC Medicine, 2023. **21**(1): p. 32.
126. Li, G., et al., *Long-Term Exposure to Ambient PM(2.5) and Increased Risk of CKD Prevalence in China.* J Am Soc Nephrol, 2021. **32**(2): p. 448-458.
127. Lord, S., *Valuing the impact of food: Towards practical and comparable monetary valuation of food system impacts*. 2020: Oxford. p. 224.
128. Friedlingstein, P., et al., *Global Carbon Budget 2022.* Earth Syst. Sci. Data, 2022. **14**(11): p. 4811-4900.
129. Dietz, S., *The Treatment of Risk and Uncertainty in the US Social Cost of Carbon for Regulatory Impact Analysis.* Economics, 2012. **6**(18): p. 0_1-12A.
130. Abdullah, A., et al., *The number of years lived with obesity and the risk of all-cause and cause-specific mortality.* International Journal of Epidemiology, 2011. **40**(4): p. 985-996.
131. Heaney, R.P., *Long-latency deficiency disease: insights from calcium and vitamin D.* The American Journal of Clinical Nutrition, 2003. **78**(5): p. 912-919.
132. Guasch-Ferré, M. and W.C. Willett, *The Mediterranean diet and health: a comprehensive overview.* Journal of Internal Medicine, 2021. **290**(3): p. 549-566.
133. Addicott, E.T. and E.P. Fenichel, *Spatial aggregation and the value of natural capital.* Journal of Environmental Economics and Management, 2019. **95**: p. 118-132.
134. Bryan, B.A., et al., *Land-use change impacts on ecosystem services value: Incorporating the scarcity effects of supply and demand dynamics.* Ecosystem Services, 2018. **32**: p. 144-157.
135. Gómez-Baggethun, E., et al., *The history of ecosystem services in economic theory and practice: From early notions to markets and payment schemes.* Ecological Economics, 2010. **69**(6): p. 1209-1218.

136. Bouwman, A.F., L.J.M. Boumans, and N.H. Batjes, *Estimation of global NH3 volatilization loss from synthetic fertilizers and animal manure applied to arable lands and grasslands.* Global Biogeochemical Cycles, 2002. **16**(2): p. 8-1-8-14.
137. Paulot, F., et al., *Ammonia emissions in the United States, European Union, and China derived by high-resolution inversion of ammonium wet deposition data: Interpretation with a new agricultural emissions inventory (MASAGE_NH3).* Journal of Geophysical Research: Atmospheres, 2014. **119**(7): p. 4343-4364.
138. van der Zanden, E.H., et al., *Trade-offs of European agricultural abandonment.* Land Use Policy, 2017. **62**: p. 290-301.
139. Keenleyside, C., G. Tucker, and A. McConville, *Farmland Abandonment in the EU: an Assessment of Trends and Prospects.* Institute for European Environmental Policy, London, 2010.
140. Skjøth, C.A. and C. Geels, *The effect of climate and climate change on ammonia emissions in Europe.* Atmos. Chem. Phys., 2013. **13**(1): p. 117-128.
141. Jones, L., et al., *A review and application of the evidence for nitrogen impacts on ecosystem services.* Ecosystem Services, 2014. **7**: p. 76-88.
142. Compton, J.E., et al., *Ecosystem services altered by human changes in the nitrogen cycle: a new perspective for US decision making.* Ecology Letters, 2011. **14**(8): p. 804-815.
143. de Vries, W., *Impacts of nitrogen emissions on ecosystems and human health: A mini review.* Current Opinion in Environmental Science & Health, 2021. **21**: p. 100249.
144. Durand, P., et al., *Nitrogen processes in aquatic ecosystems*, in *The European Nitrogen Assessment: Sources, Effects and Policy Perspectives*, A. Bleeker, et al., Editors. 2011, Cambridge University Press: Cambridge. p. 126-146.
145. Krupa, S.V., *Effects of atmospheric ammonia (NH3) on terrestrial vegetation: a review.* Environmental Pollution, 2003. **124**(2): p. 179-221.
146. Rabalais, N.N., *Nitrogen in Aquatic Ecosystems.* Ambio, 2002. **31**(2): p. 102-112.
147. Ballard, T.C., E. Sinha, and A.M. Michalak, *Long-Term Changes in Precipitation and Temperature Have Already Impacted Nitrogen Loading.* Environmental Science & Technology, 2019. **53**(9): p. 5080-5090.
148. Meinshausen, M., et al., *The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500.* Geosci. Model Dev., 2020. **13**(8): p. 3571-3605.
149. Leimbach, M., et al., *Future growth patterns of world regions – A GDP scenario approach.* Global Environmental Change, 2017. **42**: p. 215-225.
150. Kc, S. and W. Lutz, *The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100.* Global Environmental Change, 2017. **42**: p. 181-192.
151. van Vuuren, D.P., et al., *The Shared Socio-economic Pathways: Trajectories for human development and global environmental change.* Global Environmental Change, 2017. **42**: p. 148-152.
152. Rao, S., et al., *Future air pollution in the Shared Socio-economic Pathways.* Global Environmental Change, 2017. **42**: p. 346-358.
153. Jiang, L. and B.C. O'Neill, *Global urbanization projections for the Shared Socioeconomic Pathways.* Global Environmental Change, 2017. **42**: p. 193-199.
154. Harrell, F.E., Jr., *Regression modeling strategies*. Springer Series in Statistics. 2016, Cham, Switzerland: Springer International Publishing.
155. Saleh, A.K.M.E., M. Arashi, and B.M.G. Kibria, *Theory of Ridge Regression Estimation with Applications*. 2019, New Jersey: John Wiley & Sons.
156. Smith, G., *Step away from stepwise.* Journal of Big Data, 2018. **5**(1): p. 32.
157. FAO, *Agriculture producer prices indices. 2015-2019.*, in *FAOSTAT Analytical Brief 26*. 2021, Food and Agricultural Organization of the United Nations: Rome.

158. Galloway, J.N., et al., *Transformation of the Nitrogen Cycle: Recent Trends, Questions, and Potential Solutions.* Science, 2008. **320**(5878): p. 889.
159. Van Damme, M., et al., *Industrial and agricultural ammonia point sources exposed.* Nature, 2018. **564**(7734): p. 99-103.
160. Olivier, J.G.J., et al., *Global air emission inventories for anthropogenic sources of NOx, NH3 and N2O in 1990.* Environmental Pollution, 1998. **102**(1, Supplement 1): p. 135-148.
161. Zhu, L., et al., *Sources and Impacts of Atmospheric NH3: Current Understanding and Frontiers for Modeling, Measurements, and Remote Sensing in North America.* Current Pollution Reports, 2015. **1**(2): p. 95-116.
162. Anderson, T.W., *On the Distribution of the Two-Sample Cramer-von Mises Criterion.* The Annals of Mathematical Statistics, 1962. **33**(3): p. 1148-1159.

Annex A – Documentation of SPIQ-FS v0 cost models

Annex A in the SPIQ-FS documentation details the SPIQ-FS version 0 cost models, providing Supplemental Information for the Methodology. Documentation can be found at https://foodsivi.org/what-we-do/projects/spiq-food-system-v0/documentation-0/

Annex B – Documentation of SPIQ-FS version 0 joint sampling

Annex B in the SPIQ-FS documentation details the SPIQ-FS version 0 procedure for joint sampling of joint distributions of marginal costs for GHG emissions, N emissions, and land-use change.

Annex C – Documentation of SPIQ-FS version 0 cost projection

Annex C in the SPIQ-FS documentation details basic temporal projection in the SPIQ-FS version 0 cost models for future times under future scenarios specifying a range of economic, demographic, and environmental variables.

Annex F – Approximation of marginals costs and calculation of total costs

SPIQ-FS calculates costs based on multiplying an estimate of average annual marginal cost against the annual production of an impact quantity per country. Conceptually, marginal costs are functions

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 $q: [t_0, t_1] \to \mathbb{R}^{23}$ 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 $\nabla Cost(\cdot, s) : \mathbb{R}^{23} \to \mathbb{R}^{23}$ 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 the formulas.

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

$$\Delta Cost = \nabla Cost(q^*, s) \cdot \big(q(t_1) - q(t_0)\big) = \sum_{i=1}^{23} \frac{\partial Cost}{\partial q_i}(q^*, s) \times \Delta q_i$$

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.

that depend on the current levels of impact quantities and, to calculate the total external costs over the span of a year, the marginal costs should be integrated against the change in quantities at the beginning of the year to the end of the year (see the Box - Formula for calculation of costs).

Marginal costs in SPIQ-FS version 0 are based on, in most cases, data up to 2020 and for additional units of production of the impact quantity based on the level of the quantity in 2020. SPIQ-FS was designed to be used for counterfactual studies of emissions and activities of the present food system at the national and global level. Factors have been incorporated in the SPIQ-FS model to allow marginal costs to be estimated for the emission or production of additional units of an impact quantity in later annual periods up to 2050, under the assumption of exogenous economic and food system trajectories. This study calculated costs over 2020 to 2050 at 5-year intervals using the levels of quantities and the exogenous scenarios from PIK led modelling described in the Methodology. Quantities and marginal costs were linearly interpolated over the 5 year intervals to calculate total and average hidden cost reduction over 2020 to 2050.

Three kinds of error in using

$$\nabla Cost(q^*, s)$$

are:

1. Uncertainly in $\nabla Cost(q^*, s)$. That is, given the level of quantities q^* at some time $t \in [t_0, t_1]$, what is the NPV cost to the GDP PPP of present and future economies from an additional unit of one of the quantities.
2. Error in $\nabla Cost(q^*, s)$ as an approximation of $\nabla Cost(q(t), s),\ t \in [t_0, t_1]$.
3. Error in linearly interpolating between $\nabla Cost(q^*, s)$ in year $[t_0, t_1]$ and $\nabla Cost(r^*, s)$ in $[t_0 + 5, t_1 + 5]$ as an approximation of $\nabla Cost(p^*, s)$ in a year between $[t_0, t_1]$ and $[t_0 + 5, t_1 + 5]$.

The one unit of additional quantity in 1. is produced somewhere in the country at time $t \in [t_0, t_1]$ therefore the combination of 1. and 2. relate to intra-annual spatial and temporal uncertainty in the national production of impact quantities. Conceptually, taking the mean value of the random variable $\nabla Cost(q^*, s)$ equates to the spatial and temporal average of the intra-annual marginal cost of the national production of an additional unit of the impact quantity. In practice, the calculation in SPIQ-FS version 0 is more pragmatic and limited. Some of the costing models consider national averaging of marginal costs for production of impact quantities such as nitrogen pollution and blue water withdrawal. Epistemological uncertainty in calculating 1. due to long-term economic and emission trajectories, e.g. for GHG marginal costs, or lack of knowledge, e.g. value of ecosystem services or ecosystem productivity losses from nitrogen input loading, is considered in cost models.

Here we discuss intra- and short term inter-annual variation given a calculation of 1. as caveats of the use of the approximation in Box - Formula for calculation of hidden costs.

Diffusion along impact pathways

There are two basic averaging processes to consider in attributing a marginal cost to an additional quantity produced in one year and in a country. Further considerations and limitations are discussed in the Annex A SPIQ-FS version 0 documentation.

The first averaging process involves cumulative exposure of natural or human capital as an intermediary to the damages to national GDP PPP of a present or future economy dependant on natural and human capital flows [121, 122]. This process can disperse and average impacts to GDP PPP even though rates of emission and exposure vary spatially and temporally over the year. An example is the effects of radiative forcing in the atmosphere due cumulative CO2 emissions [123]. Removal processes in combination with accrued emissions from other GHG, aerosols, and pollutants determine the accumulated CO2 in the atmosphere and its contribution to radiative forcing [74]. Due to global atmospheric mixing, it becomes impossible to attribute radiative forcing to spatially distinct emissions, and the rate of emissions during the year do not cause sufficient deviation in the accumulated CO2 levels to produce large differences in radiative forcing. Another example is the effects of nitrogen loading on human populations or ecosystems. Attribution of noncommunicable diseases to air pollution manifest through cumulative or ancillary exposure [124-126], in this cause humans are the intermediary capital. Large changes in biodiversity, vegetation, soil chemistry, etc. in ecosystems from nitrogen loading is also the effect of cumulative exposure, [105], even though nitrogen loading from agricultural sources such as cropland can be seasonal. Effects of temporally variable nitrogen loading are temporally dispersed to effects on ecosystem services as flows to the human economy by the complex diffusive biological and chemical processes in the ecosystem . Using a dispersion argument ignores impulse peak-over-threshold exposure events where pollutants reach biologically toxicity levels.

Unlike the atmosphere as an intermediary which diffuses the effect of GHG emissions globally, ecosystems are exposed to spatially specific N emissions (such as nitrate run-off in a catchment) and the loss of ecosystem services is experienced by, in most cases a spatially limited set of, economic actors using those services. Marginal change in national emissions is a potentially inaccurate proxy for marginal change of emissions within catchments if historical spatial distributions if N use deviates in the future, so improved marginal cost modelling would separate impact quantities like nitrogen into finer spatial categories [127]. However, spatial dependence of GDP PPP economic effects to additional or reduced N emissions within national borders are conceptually less than the spatial dependence of biological effects, due to the dispersing processes of markets and the economy itself. Mechanisms such as insurance distribute income failures from crop losses exacerbated by loss of ecosystem services from the directly exposed economic actors to a wider set of actors in the economy, again averaging out spatial and temporal variance in GDP PPP losses across marginal changes in catchments or subnational regions. Transboundary exposure of economic actors to marginal changes in quantities is a constraint in SPIQ-FS version 0 modelling.

The second averaging process concerns dispersion of economic effects to GDP PPP from exposed economic actors through exchanges, markets, price transmission, substitution in demand, and the lack of accounting of distributional effects in GDP PPP itself. As discussed in the last paragraph, this process can further disperse and average impacts to GDP PPP from spatial and temporal marginal change in emissions and exposure through dispersing the effects of changes in natural and human capital flows. This general principle of diffusion fails in the presence of market failures that do not efficiently distribute GDP PPP losses, and in joint market reactions such as contagion from losses in a small group of economic actors.

Conceptually, it seems likely that natural and human capital act more to diffuse the economic effects of exposure over temporally, while diffusion in the economy which can occur rapidly in some markets, can act more to diffuse spatial effects.

Cumulative exposure and interannual variability

Using an annual approximation for the marginal costs of CO2 emission in 2020 is reasonable since damages depend on the cumulative stock of CO2 existing in the atmosphere. The aggregated emissions of the food system between the first tonne of CO2 produced in 2015 and the last tonne produced in 2020 are a small portion (approximately 1%) of the overall stock added since 2000 [10, 128]. The full stock of anthropogenic post-Industrial Age emissions determines the increase in radiative forcing attributed to additional warming. Similar arguments apply for N2O because of its persistence in the atmosphere. IGWG-SCCGHG estimates social costs of GHG in 10 year intervals to account for changes in stocks in the atmosphere of GHG, pollutants and aerosols [71]. Vulnerability of human and natural systems to damage from heat stress and other climate may increase over a 5-year interval due to sustained and increasing exposure to historically high average and maximum temperatures, however this difference contributes marginally to the accumulation of damages over the lifetime of the radiative forcing. Uncertainty in estimating the social cost of CO2 and N2O due to variation in long term economic and emission trajectories (that is 1. In the last section) is likely to far exceed intra-annual and interannual variation in the background stock and atmospheric conditions influencing radiative forcing in a 1-year or 5-year period [76].

The cumulative stock of additional CH4 in the atmosphere is a different consideration than CO2. CH4 added in one year contributes to radiative forcing for 12 years on average. Agricultural is the largest anthropogenic emitter of CH4 https://www.iea.org/reports/methane-tracker-2021/methane-and-climate-change and 5 years of agricultural emissions from 2015 constitutes a significant portion of the added CH4 in the atmosphere in 2020. The cumulative stock of CH4 emission from the food system increased 1.1% between 2004-2016 [11]. A similar rate of increase over the period 2017-2035 would mean that the stock of CH4 is higher for the duration of a 2025 emission than a 2020 emission. However, the variability in cumulative CH4 and potential increase in an interannual period remains low at approximately 0.1% historically. Under FST versus the CH4 emissions from agriculture globally reduce from 228 Mt to 132 Mt in 2030, 247Mt to 84 Mt in 2040 and 262 Mt to 42 Mt in 2050. This is approximately a 7% reduction in the CH4 cumulative stock under SSP2 if FST is implement in 2030, and approximately a 20% reduction in CH4 cumulative stock by 2050, assuming CH4 emissions from other sectors under SSP2 do not change under FST. The average rate of change over one year in cumulative CH4 stock, which is the driver of radiative forcing and external costs, remains below 1%. Over the lifetime of a metric ton CH4 emission in the atmosphere its contribution in 20 year GWP is 86 times that of a metric ton of CO2 [74]. The social cost of CH4 will therefore be more sensitive to short-term variation in the vulnerability of economies to temperature [75]. To make a significant variation to the social cost, variation in vulnerability of economies would need to occur jointly across major economies. The errors in assuming a constant marginal cost over an annual period, and interpolating within 5 -year estimates, are expected to be larger for CH4 than for CO2 and N2O. However, given the low annual change rates in cumulative CH4 stock, and the lower sensitivity of economic damage to temperature changes in the period 2020-2050 assumed in GDP PPP damage estimates, is still likely that the modelled uncertainty in future economic conditions and emission trajectories in the IGWG-SCCGHG [76, 129] is larger than the intra-annual variability.

Changes in vulnerability to human disease factors and diets over the period 2020-2050 should be factored into the calculation of the impact quantity YLL. The calculation of YLLs uses a population model, so the YLLs calculated are already aggregated individuals at the population level. The population models are stratified into age groups, so it is possible in a different study to estimate productivity losses in terms of direct illness or effect on labourers in the same household according to the age of mortality. Models of finer resolution could indicate sector or income group variability of YLLs as the equivalent consideration of spatial variability in emissions of environmental pollutants. In terms of intra-annual variability of national food consumption, the YLLs are assumed to occur in the future and attributable to cumulative exposure to dietary intake, potentially over decades for obesity, cardiovascular disease and neo-plasms [130-132]. From YLLs to productivity losses, the main factors are changes in productivity, and changes in workforce participation due to illness in labourers or dependents. Due to the cumulative exposure to dietary intake and the nature of YLLs which project the years from premature mortality in the future to a standard life expectancy, intra-annual and short term inter-annual food consumption are largely influenced by a shared long-term trajectory of changes labour productivity, population, and labourers per capita. Only near-term disease outcomes attributable to dietary intake are relevant to intra-annual or near-term inter-annual variability in labour productivity conditions. This breaks down to what was the contribution of dietary intake in the present year to mortality in the next year. Assume an average of 20% contribution per year to the cumulative effect leading to mortality (up to 5 years exposure leads to mortality on average). For 2019 the Global burden Disease study the average number of YLLs per mortality for dietary risks is 20 years, [27], so 1 year covers 5% of the span of the reduced life expectancy. With these number, 2% of the YLLs from food consumption in one year do not overlap with the same labour productivity conditions as food consumption in the next year. Labour productivity growth from 2011 to 2018 since the global financial crisis (GFC) has been approximately constant, almost zero for advanced economies and about 3% for emerging and developing economies (EMDE) https://thedocs.worldbank.org/en/doc/996591593465312454-0050022020/original/GlobalProductivityChapter1.pdf. ILO statistics show a less than 10% variation in labour productivity among nations during the pandemic, https://ilostat.ilo.org/topics/labour-productivity/ , and World Bank statistics show a less than 20% variation in number of labourers among nations during the pandemic https://data.worldbank.org/indicator/SL.TLF.TOTL.IN . Per labourer contribution to GDP PPP varied by up to 32% during the pandemic. With these figures, assuming a COVID-19 pandemic shock to productivity in the average 2% of the future distributions of attributable years of life lost that do not overlap for inter-annual food consumption, marginal productivity losses per YLL varies by less than ~0.7%. This study does not consider variation in the attribution of YLL to dietary intake and incorporate that in productivity loss estimates. Using the variation from Monte Carlo simulation of YLLs in the 2019 GBD [27], that variation (uncertainty that would be incorporated in 1. in the last section) is substantially larger than the expected intra- and near inter-annual variation in productivity loss estimates (2. and 3. in the last section) given an estimate of 1.

Spatially and temporally, the value of ecosystem services are highly variable https://esajournals.onlinelibrary.wiley.com/doi/full/10.1890/080126 [133]. Documentation for SPIQ-FS dataset at https://foodsivi.org/wp-content/uploads/2022/11/SPIQ-v0-A-Marginal-Costs-3-Land-Use_DRAFT.pdf demonstrates the high uncertainty for calculating national and annual averages from large databases of studies of the values of ecosystem services. Changes to national and annual averages of per hectare loss or return of a forest, grassland, waterway, wetland, or coastal ecosystem, would depend on large scale changes in utilisation of natural capital by the economy outside of agricultural provisioning or the economic goods and services supported by natural capital [121, 134, 135]. Lost established habitat entails a long-term loss of services, the cumulative amount of which are calculated to attribute losses per ha. Global studies indicate that returned habitat from agriculture slowly returned and are available for, on average, 14 years [85]. Therefore the value of services on returned habitat could vary more between one effective ha returned within a year and one effective ha returned in the next year. One of the main indicators of changes in utilisation are changes in land-use itself. Land transitions to returned habitat involve less than 1% of current land used for agriculture and forestry HILDA+ [16], indicating that changes in utilisation occur over a longer time frame. Under FST overall change rates are higher but shifting from agricultural production to forestry, or from crop production to livestock production, still involves substantial changes in capital stock and transition in economic activity, requiring time . The value of economic goods and services supported by natural capital are likely to cause more intra-annual variability and variability between years than the transition in the produced capital base.

Over the period of the pandemic agricultural, growth in forestry and fishing value add was highly variable between 2016 and 2021, and highly variable between countries https://data.worldbank.org/indicator/NV.AGR.TOTL.KD.ZG. However, given the damage calculation from lost services extends over decades, only a small fraction of which time is not shared by intra or short-term intra-annual habitat loss or return, and the very large uncertainty from lack of knowledge of the historical value of national ecosystem services, it is expected that the several order of magnitude uncertainty in the calculation of the value of ecosystem services in a given year outweighs intra- and short term inter-annual variability. Sudden return of land to nature within a year after loss of established habitat is tempered by gradual regeneration of lost-ecosystem services and discounting. Sudden re-conversion within a year of abandoned agricultural land creates very large variation. These conversion processes would have to be intra-temporal though to not conceptually be incorporated in 1., meaning they have large differences in the probability of occurring in the one year as opposed to the next.

Productivity losses from 1 N-kg of spatially and temporally variable volatilized NH3 and NOx depend on atmospheric conditions, and distributions of populations and agricultural land, and vulnerability of the exposed populations [136, 137]. Agricultural land transitions involve less than 1% of current land used for agriculture and forestry, and the main increases in tropical forest and abandoned agricultural land occur further from dense populations sources [138, 139], indicating likely stability of sources to exposed populations. Modelling of marginal costs of NH3 and NOx marginal costs included uncertainty in population exposure which conceptually captures aspects such as variable atmospheric conditions in peak periods for fertiliser application on cropland [137]. The probability of such atmospheric conditions is not assumed to change substantially over a short-term inter-annual period (it should be incorporated in the calculation of 1. In the previous section) [140]. It is unclear if rural to urban transitions change exposure directly, most likely through urban expansion displacing agricultural land, but large-scale changes in urban and rural populations is not assumed over short periods. The consideration from cumulative exposure to YLL and from YLL to productivity losses is the same as discussed for dietary YLLs. It is expected that the spatial uncertainty calculation outweighs inter- annual fluctuation due to changes in exposed populations and their vulnerability [55, 141]. Marginal costs of deposition of NH3 and NOx, and surface water run-off, rely on temporally and spatially variable nitrogen loading in terrestrial ecosystems, mainly inland waterways and wetlands, transportation to coastal ecosystems, and the vulnerability to nitrogen loading of the ecosystem services provided [52, 53, 142]. Changes in ecosystem services from nitrogen loading on established vegetation are assumed to be cumulative over several years [143-145]. For transient biomass responsible for eutrophication and algal blooms, seasonal events show regular frequency with similar seasonal nitrogen loadings [146]. Changes in utilisation and value of ecosystem services was discussed above. Changes in concentrations of loading and vulnerability likely have a functional relationship to the absolute level of loading, which is relatively stable at annual levels over 2016-2021 in terms of fertiliser use and livestock manure (FAOSTAT) compared to the order of magnitude uncertainty in the value of the ecosystem services provided. Nitrate run-off decreases under FST at a global rate of 2%. Nitrogen loading can vary substantially annually from precipitation at the times of cropland application, but the probability of such atmospheric conditions and the probability of intra-annual events such as algal blooms is not assumed to change substantially over a short-term inter-annual period (it should be incorporated in the calculation of 1. In the previous section) [147].

In this study, an additional person in moderate poverty is costed by transfer of the average income shortfall, and all persons in moderate poverty in that country in that year are treated as additions. Poverty is not costed by a marginal rate of damages from the time that the additional person spends in poverty over future years. It is assumed that an individual in poverty receives the payment irrespective of where in the country and at what time during the year the individual enters moderate poverty.

Annex P – Spatial and temporal projections of economic and demographic factors

The Annex P output of SPIQ-FS contains supplemental information on the spatial and-temporal projection of economic and demographic factors. Annex C documentation of SPIQ-FS version 0 documents how the spatial and temporal projections are used to project marginal costs.

The SSP scenarios have quantitative projections of GDP PPP, GHG emissions, population, and population in age and sex groups [148-152]. MAgPIE and PIK historical data and projections of GDP PPP, populations and age and sex groups in five-year time intervals were available from 1960 to 2150 for the present study. Additional time series projections under SSPs from literature were used for urban rural ratio [153]. The cost models required additional projections of the Human Development Index (HDI), Gross National Income (GNI), Labourers per capita, the Average FAO Food Producer Price Index (FPPI), and total NH3, NOx and SOx emissions.

MAgPIE projections GDP PPP, GDP PPP per capita, and Age Dependency projections, and [153] for urban rural ratio were used as the basis for projecting HDI and other correlated socio-economic and demographic variables based on historical relationships. To identify historical relationships, data from 1991-2020 on GDP PPP, Population, Age Dependency, and Urban Rural Ratio data from the World Bank were matched to the historical values of the indicator as regressee. For each regressee, a stepwise linear model with interactions terms was used was to identify potential regressors amongst GDP, GDP per capita, Population Density, Population, Age Dependency, Age Dependency per capita, etc. [154]. The regressor are highly correlated so additional ridge regression and visual examination were used to identify a minimal set of regressors and non-linear models [155, 156]. Both absolute and first difference relationships were examined.

Projection based upon the following models were used for growth rate projection. That is, 2020 values for HDI, GNI (in 2020 USD), Labourers per capita, the Average FAO Food Producer Price Index (FPPI), and total NH3, NOx and SOx emissions, were increased according to the predicted growth rate in the model. The derivatives of the general models are the most important indicators of reasonable projections.

HDI projection

HDI time series from 1991 to 2020 was downloaded from UNDP https://hdr.undp.org/data-center/human-development-index#/indicies/HDI . Paired with GDP and population data regressors described above provided N=4771 data points. GDP per capita on its own explains approximately 0.814 (R^2=0.814) of the variance of HDI across countries across all years in a general exponential model. Age dependency (AgeDep) acted as an additional proxy for development improving explanation to R^2=0.9122 (Figure 25).

General model: x is national GDP PPP per capita in 2020 USD PPP, y is (Old) Age Dependency ratio
$$f(x,y) = 1 - exp(-a * x^b - c * (y * x)^d)$$
Coefficients (with 95% standard error confidence bounds):
a = 0.006273 (-0.006322, 0.01887)
b = 0.3828 (0.2238, 0.5419)
c = 0.1376 (0.09821, 0.1771)
d = 0.2905 (0.2653, 0.3156)
Goodness of fit:
N=4471

R-square: 0.9122

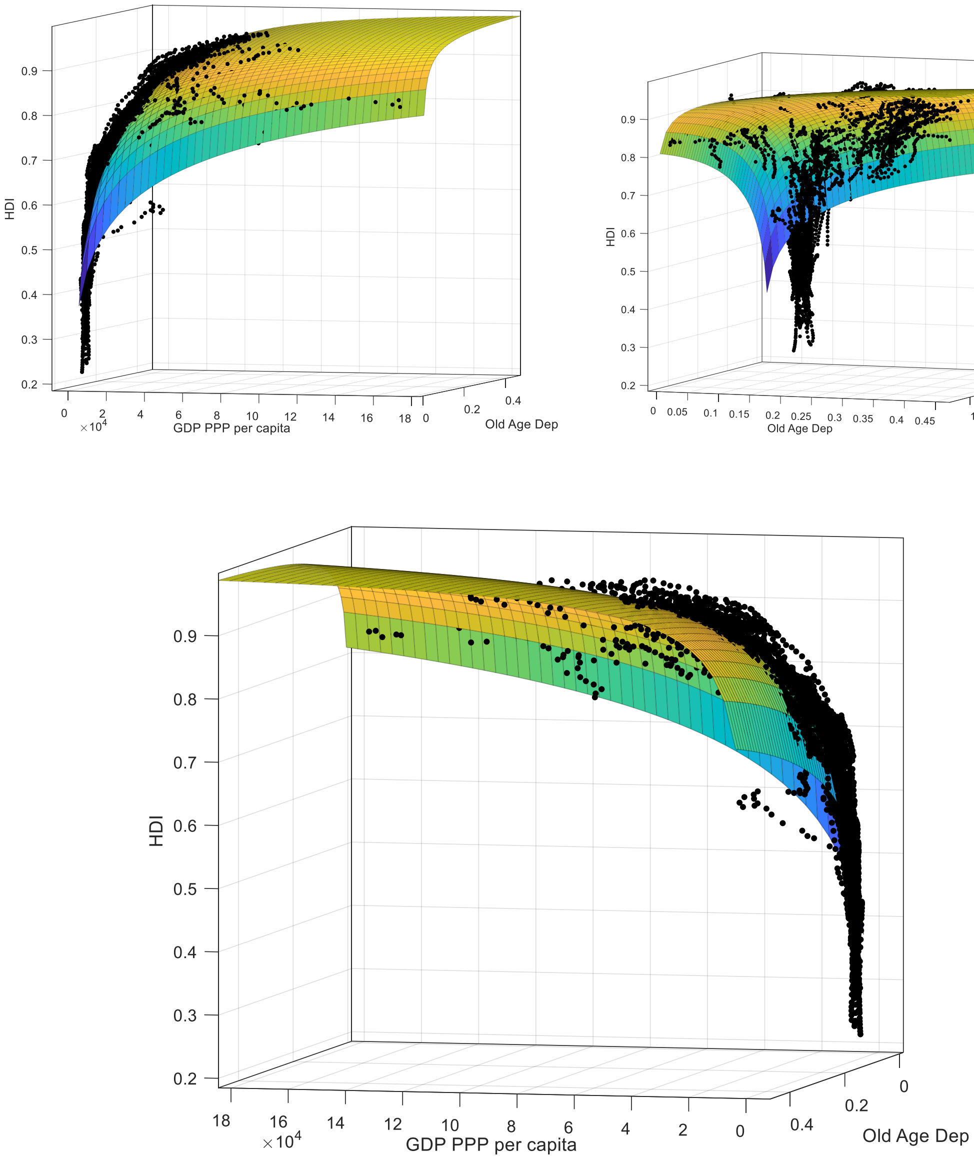


Figure 25: General model fit for N=4471 data points for HDI 1991-2020 based on GDP per capita and (Old) Age Dependency.

GNI Atlas growth

Time series of GNI 1991-2020 calculated using the Atlas method was downloaded from the World Bank https://data.worldbank.org/indicator/NY.GNP.PCAP.CD . Paired with GDP and population data regressors described above provided N=4935 data points. GDP per capita and an interaction term of GDP per Capita and AgeDep explains approximately 0.8817 of the variance of GNI across countries across all years.

General model: x is national GDP PPP per capita in 2020 USD PPP, y is (Old) Age Dependency ratio
$f(x,y) = a * x + b * x * y$ current USD
Coefficients (with 95% confidence bounds):

a =	0.327 (0.3169, 0.337)
b =	2.48 (2.42, 2.541)
Goodness of fit:	
R-square: 0.8817	
N = 4935	

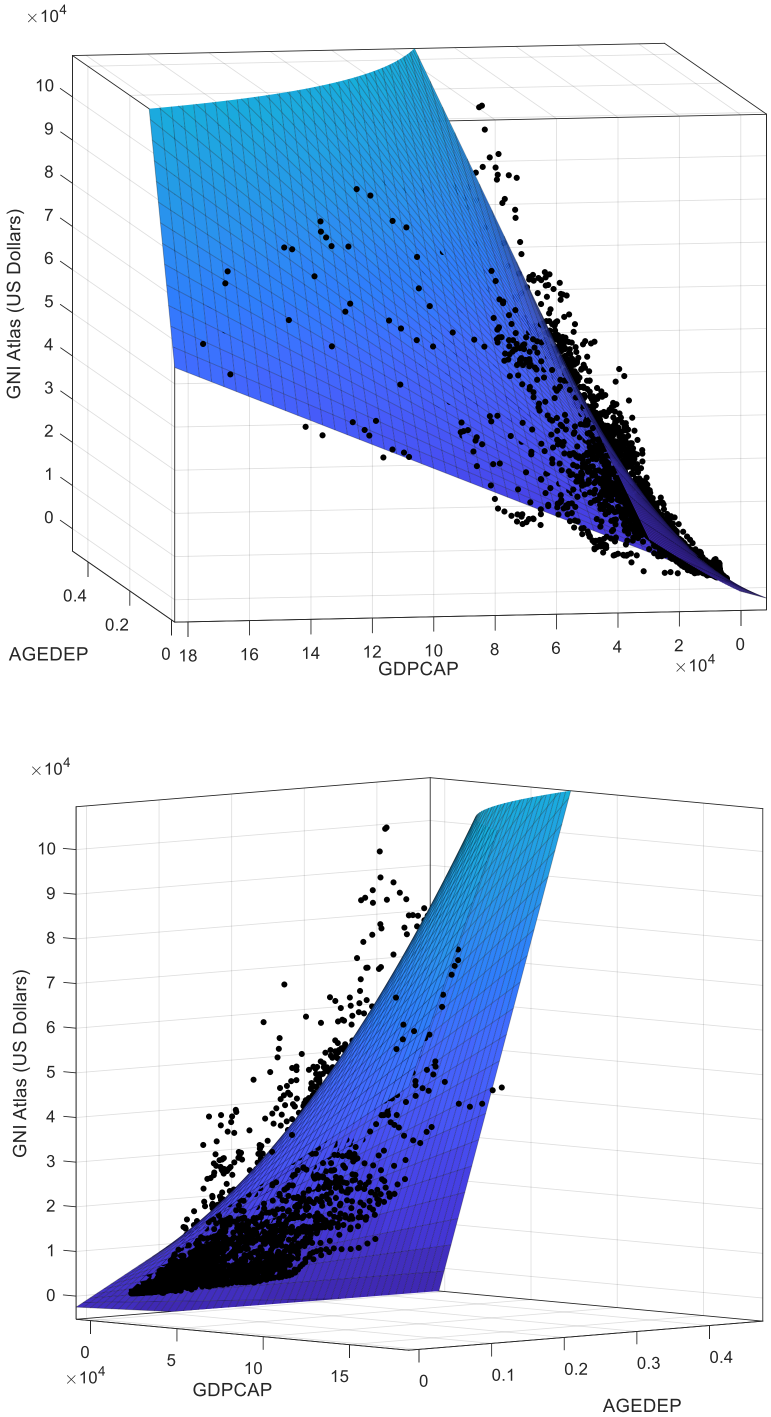


Figure 26: General model fit for N=4935 data points for GNI 1991-2020 based on GDP per capita and (Old) Age Dependency.

Average labour force growth or decline

Time series from World Bank on Labour force headcount and population was downloaded, and labourers per capita was examined from 1991 to 2020 https://data.worldbank.org/indicator/SL.TLF.TOTL.IN . There were small anomalies between labour force headcount data and population data for 2 data points (more labourers than population). Transient populations and labourers in countries with small populations were assumed to explain the anomaly. Paired with GDP and population data regressors described above provided N=4948 data points. AgeDep was the most significant regressor and explained approximately 0.35 of the variance of labourers per capita across countries across all years. GDP, urban ratios, population density, and other indicators did not significantly improve explanation of variance. However, adjusted for starting level of labours per capita in 1991, explanation improved as a growth rate model capturing decline in labourer per capita with increasing age dependency and then a plateau due to structural development of the economy and demographic development observed in temporal tracks of countries in the data (captured by a quartic relationship). As Old Age dependency increases toward 100% then Labourer force decreases to 0% as they are based on exclusive age brackets in the population. The general model captured these constraints, at 0 AgeDep (no old age dependants) labours per capita sharply rise based on observed data to very high levels of labourers per capita, and the general model has a smooth vanishing of Labourers per Capita as Age Dependency increases to 100% (Figure 27).

Projections of AgeDep under SSP2 and SSP1 from 2020 to 2050 for most countries in this study are between 0.1 and 0.4, which involves small growth rates in labourers per capita and then plateau in the general model and average of historical data. EUR and other developed regions with existing ageing populations exceed AgeDep of 0.4 at 2020 or during 2020 to 2050. At high levels of AgeDep (> 0.43) then Labourers per capita begin to decline in an increasingly ageing population, making productivity losses more costly to GDP PPP (Figure 11). Under SSP1, population rate growth is slower and ageing in the population is quicker. In this case the labourer headcount is decreasing more rapidly as GDP increases in SSP1 more quickly, leading to large values for labour productivity. There is evidence in the data of an inflection to decreasing labour per capita rates in an ageing population at AgeDep level below 0.425. However, shifting the inflection down would more sharply increase the value of labour productivity in developed countries. In this way, keeping the inflection in labourers per capita at an Age Dependency of 0.425, the YLL costing is conservative .

General model: x is (Old) Age Dependency ratio
$f(x) = (a * x^4 + b * x^3 + c * x^2 + d * x + 1) * exp(-e * x)$
Coefficients (with 95% confidence bounds):
a = 2954 (2564, 3343)
b = -1493 (-1609, -1377)
c = 351.7 (333.6, 369.8)
d = -21.17 (-21.73, -20.6)
e = 9.999 (9.328, 10.67)
Goodness of fit:
R-square: 0.3536
N=4948 data points

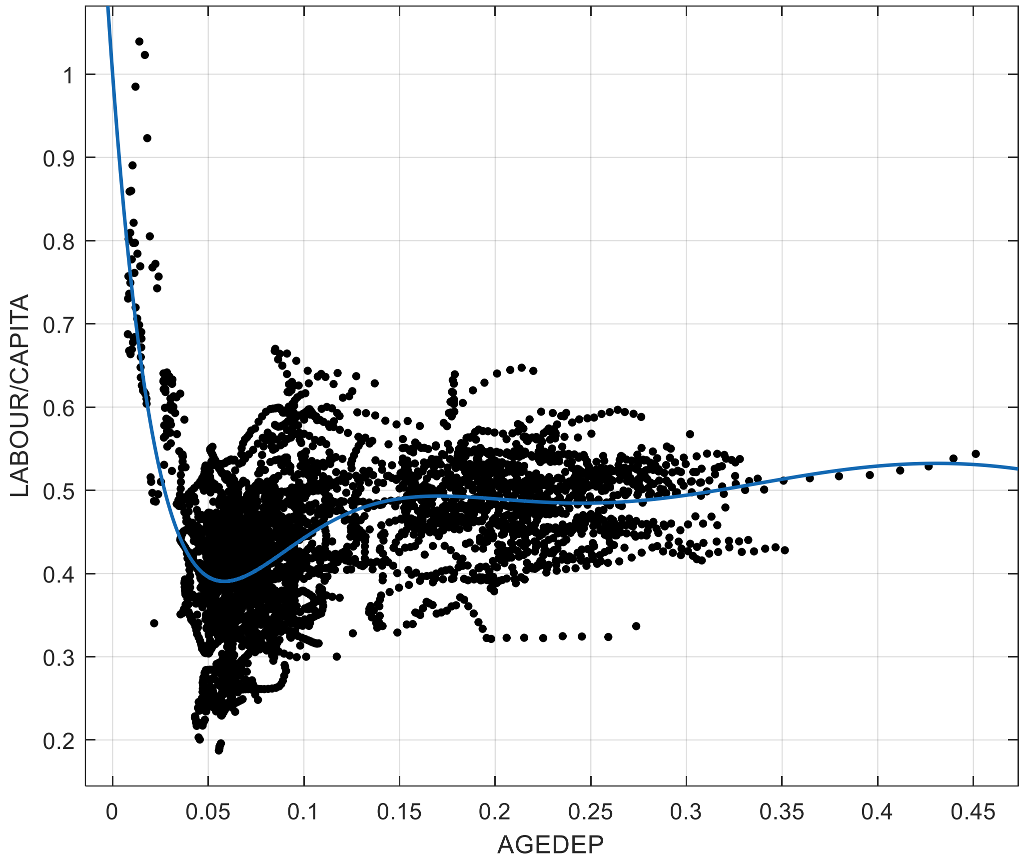


Figure 27: General model fit for N=4948 data points for Labourers per capita 1991-2020 based on GDP per capita and (Old) Age Dependency.

Average growth in food producer price index

Time series from the FAO food producer price index (FPPI) for cereals (total) was downloaded from FAO for 1991-2020 [157]. Paired with GDP and population data regressors described above provided N=3842 data points. Inter annual and inter country variation in annual farm-gate prices is large from market forces, environmental conditions, etc. The intention is to understand average change in the index under development and demographic trajectories. Growth in average FPPI (the derivative of FPPI) is used to adjust the average value of crops for cost models, for example in the damages of ozone from agricultural NOx emissions. GDP per capita was the most significant regressor and explained approximately 0.2 of the variance of FPPI across countries across all years under a power model (Figure 28). The power model captures rapid increase in producers prices for low income countries as GDP per capita increases, and then plateau at higher GDP per capita.

General model: x is GDP PPP per capita in 2020 USD PPP
$$f(x) = a * x^b$$
Coefficients (with 95% confidence bounds):
a = 12.43 (10.87, 13.98)
b = 0.1976 (0.1845, 0.2107)
Goodness of fit:

R-square: 0.1964	
N=3842 data points	

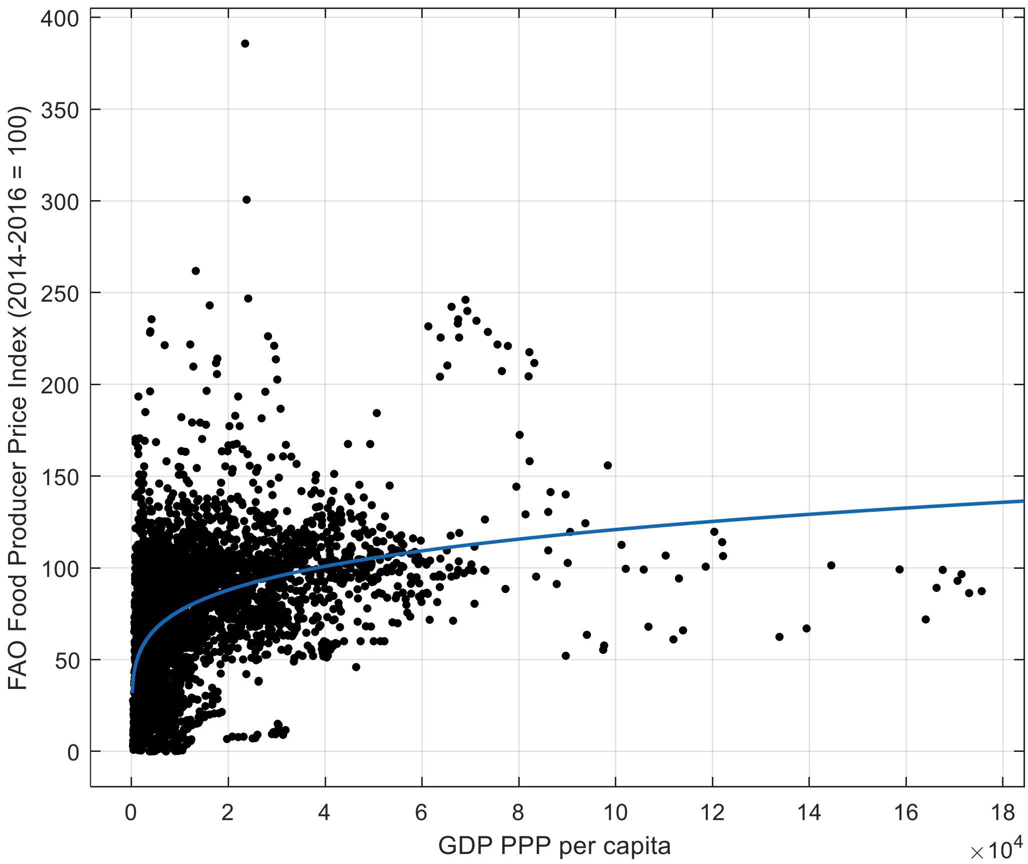


Figure 28: General model fit for N=3842 data points for FPPI 1991-2020 based on GDP per capita.

Projecting total national emissions of pollutants NOx and SOx

Total annual national emissions of pollutants NH3, NOx and SOx are used in the projection of air pollution damages from agricultural NH3 and NOx emissions. Background NOx and SOx act are precursors to particulate matter formed from NH4 (ammonium nitrate) compounds, and background NH3 levels can saturate ammonium nitrate formation from additional NH3 emissions [105, 158].

Time series of total annual emissions NH3, NOx, SOX for 160 countries over 1990-2015 was obtained from the EDGAR v5.0 dataset [12, 159], and tested for historical relationships with GDP PPP, Population, GDP per capita, AgeDepency, Urban Rural ratio and interaction terms. N=3701 data points were available.

NOx and SOx show an expected linear relationship to GDP PPP (R^2=0.76 for NOx and R^2=0.55 for SOx). NOx and SOx emissions are related primarily to industrial production and transport combustion. Annual variation in NOx and SOx can be high from atmospheric variation as well as variation in production and economic activity. There is still 25 40% of the variance in NOx and SOx emissions between years and countries not explained in GDP. More significantly, examination of the data points for SOx and GDP shows a significant effect of SOx mitigation policy in the EU and US (Figure 29). Downward tracks counter to rising GDP at high levels of development begin after 1990 (the first US Clean Act was introduced in 1990).

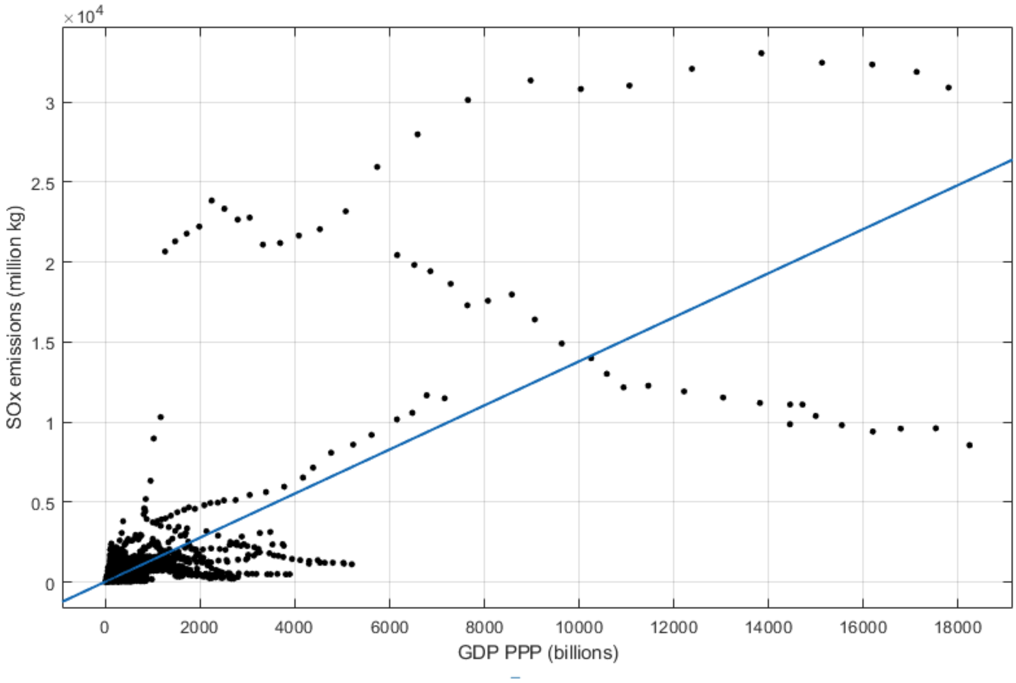


Figure 29: relationship between total SOx pollution (in millions of kg) and GDP PPP for 160 countries over 1990-2015. Both downward and upward tracks of SOx emission are observable with increasing GDP PPP. The introduction of the 1990 Clean Air Act in the US is responsible for the downward track of US GDP. The track of highest emissions is China, where SOx regulation is levelled emissions. The third upward track is India.

A quadratic model with AgeDep as an additional proxy for development proxy improves the explanation of variance and allows the observed ability of advanced economies and industrial and transport technology to decouple GDP and SOx emissions to be incorporated at high GDP PPP and AgeDep combinations (R^2=0.84).

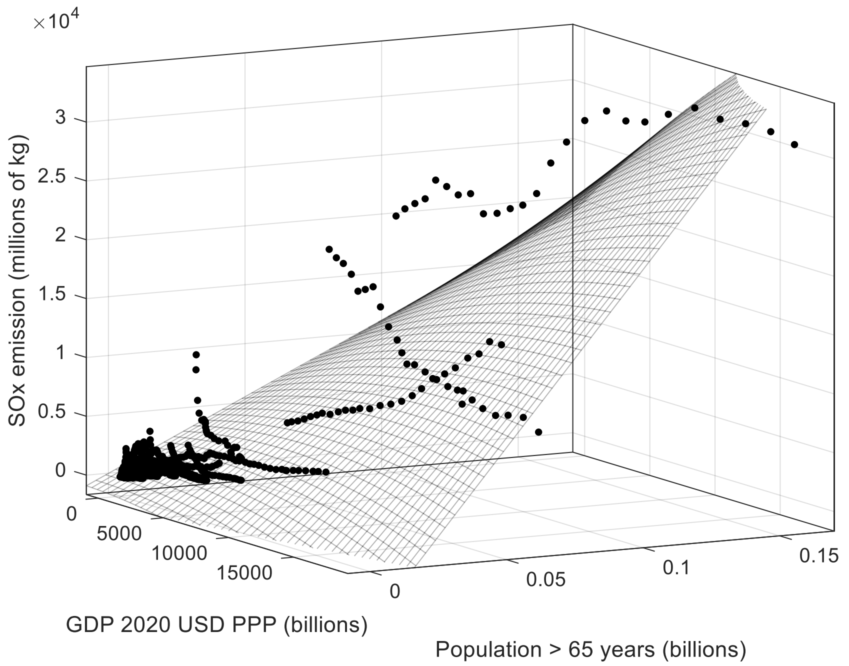


Figure 30: General model fit for N=3701 data points for total annual SOx emissions 1990-2015 based on GDP PPP, Population and (Old) Age Dependency.

A more detailed approach could identify other pollution impact factors such as population density and technology transfer that are likely for future national trajectories to affect the 'turnaround' level of GDP for mitigation of SOx and NOx emissions.

General model: x = GDP PPP in billions in 2020 USD PPP, y = AGEDEP * POP in billions
$f(x, y) = p01 * y + p20 * x^2 + p11 * x * y$ million kg SOx
Coefficients (with 95% confidence bounds):
p01 = 1.178e+05 (1.137e+05, 1.218e+05)
p20 = -1.705e-05 (-2.108e-05, -1.302e-05)
p11 = 8.59 (7.833, 9.346)
Goodness of fit:
N=3701
R-square: 0.8414

Similar but less pronounced features of decouple GDP PPP and NOx emissions at high GDP PPP and AgeDep combinations were observed for annual NOx emissions. A quadratic model with GDP PPP, Population and AgeDep as an additional proxy for development proxy improves the explanation of variance over using GDP PPP alone (R^2=0.89).

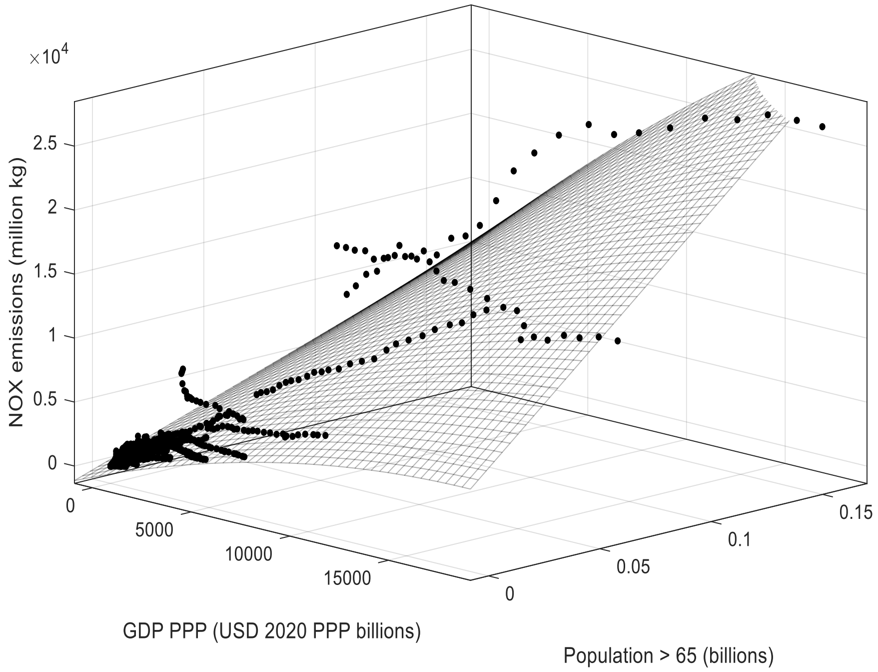


Figure 31: General model fit for N=3701 data points for total annual SOx emissions 1990-2015 based on GDP PPP, Population and (Old) Age Dependency.

General model: x = GDP PPP in billions in 2020 USD PPP, y = AGEDEP * POP in billions
$f(x, y) = p10 * x + p01 * y + p20 * x^2 + p11 * x * y$ million kg NOx
Coefficients (with 95% confidence bounds):
p10 = 0.7005 (0.6433, 0.7577)
p01 = 6.496e+04 (6.063e+04, 6.928e+04)
p20 = -1.733e-05 (-2.226e-05, -1.24e-05)

p11 = 4.894 (4.311, 5.477)
Goodness of fit:
R-square: 0.8939

Projecting total national NH3 emissions

MAgPIE outputs include estimated annual NH3 emission to air from agricultural sources. Agricultural NH3 emissions are known to be a high proportion of total NH3 emissions [12, 136, 160, 161]. Unlike NOx and SOx, we can use MAgPIE output for 2020-2050 directly to project total NH3 emissions. Data from EDGAR v50 shows that agricultural NH3 emissions, using categories 4B, 4D1, 4D2, 4D4 and 4F in the 1996 IPPC emissions classification, are responsible for ~80-90% of total NH3 emissions. An observed linear relationship (R^2 = 0.993) between agricultural and total NH3 emissions is very strong, especially at high NH3 emissions, which contribute most to error in damage cost estimation. This indicates that change in agricultural emissions can be used as a proxy for change in total emissions. We use a slightly quadratic relationship to better fit trajectory of mid and high levels of emission.

General model: x is annual NH3 agricultural emissions in million kg
$f(x) = p1 * x^2 + p2 * x$ total annual NH3 emissions in million kg
Coefficients (with 95% confidence bounds):
p1 = -1.8e-05 (-1.895e-05, -1.702e-05)
p2 = 1.212 (1.205, 1.218)
Goodness of fit:
R-square: 0.995
N=3251

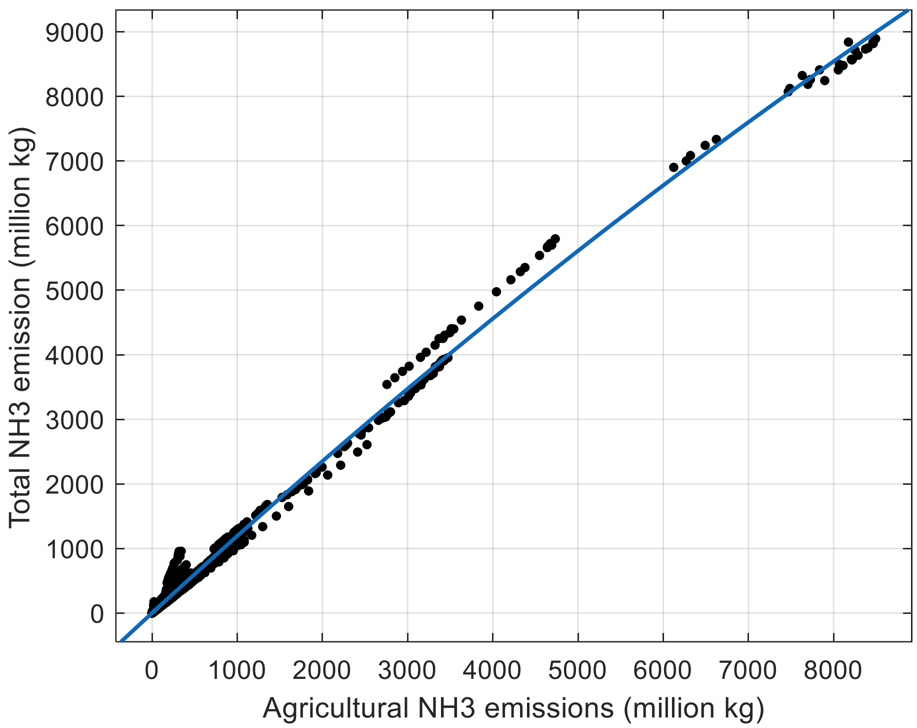


Figure 32: General model fit for N=3251 data points for total annual NH3 emissions 1990-2015 based on agricultural NH3 emissions.

Annex R – Supplemental Figures

The Annex R output of SPIQ-FS contains supplemental technical figures.

Figure 33: Results of sensitivity analysis of global annual costs to correlations between the joint distributions of marginal costs of GHG emissions, N emissions, and land-use change. The change in the shape and position of the distributions of total cost are insignificant ($p < 0.01$) for a two sample Cramér–von Mises test [162]. The 5-th and 95-th percentiles vary by less the 4% across all distributions, indicating that economic risk is not significantly underestimated or overestimated by using a joint distribution of marginal costs without correlations between marginal costs of GHG emissions, N emissions, and land-use change. Original samples generated by the cost models without were used in combination as a sample of the joint distribution without correlations.

Figure 34: Breakdown of global annual cost distributions in 2020, 2030 and 2050 under CT, FST-SSP1 and FST (grey). Distributions of GHG emission external costs (CO2 emission from land-use changes, CH4 emission primarily from rice production, waste, and enteric fermentation, and N2O emission primarily from soil, non-organic fertiliser application and livestock manure left on pasture or used in organic fertiliser) (cyan), reactive N emission external costs (NH3 volatilization to air from fertiliser application and livestock manure, NO2 volatilization to air from fertiliser, manure, and crop residues, soluble NO3- runoff to surface waters from pasture and cropland, and soluble NO3- leaching into groundwater sources) (brown), and external cost of forest and other land biome habitat loss, and forest and other land biome habitat return primarily from abandoned cropland and pasture (green). FST-SSP1 and FST-SSP2 show similar risk and opportunity profiles for environmental external cost reduction.

Figure 35: Uncertainty in environmental hidden cost distributions in 2020, 2030 and 2050 under CT, FST-SSP1 and FST and by FSEC region. Environmental (E) hidden costs aggregate hidden costs associated to production (reduction in greenhouse gas (GHG) and reactive nitrogen (N) emissions, reduction in lost habitat from land use changes and increase in returned habitat from abandoned agricultural land). Boxplots of median and interquartile ranges estimate the uncertainty of conclusions in environmental “net zero costs” for world and FSEC regions. FST-SSP1 shows greater likelihood and opportunity for net environmental benefits under FST globally and in regions.

Figure 36: Further breakdown of global annual hidden cost distributions in 2020, 2030 and 2050 under CT, FST-SSP1 and FST by impact quantity. Boxplots with median and interquartile ranges shown for CO2 emissions from land-use changes, CH4 emission primarily from rice production, waste, and enteric fermentation, and N2O emission primarily from soil, non-organic fertiliser application and livestock manure left on pasture or used in organic fertiliser, NH3 volatilization to air from fertiliser application and livestock manure, NO2 volatilization to air from fertiliser, manure, and crop residues, soluble NO3- runoff to surface waters from pasture and cropland, and soluble NO3- leaching into groundwater sources, and external cost of forest and other land biome habitat loss, and forest and other land biome habitat return primarily from abandoned cropland and pasture. Forest habitat loss, forest and other land habitat return, and NO3- runoff from cropland are impact quantities associated to the largest uncertainty in hidden costs, followed by hidden costs of CO2 and CH4 emission. FST-SSP1 shows greater opportunity for benefits from forest habitat return and carbon sequestration, and less risk from NO3- runoff hidden costs.

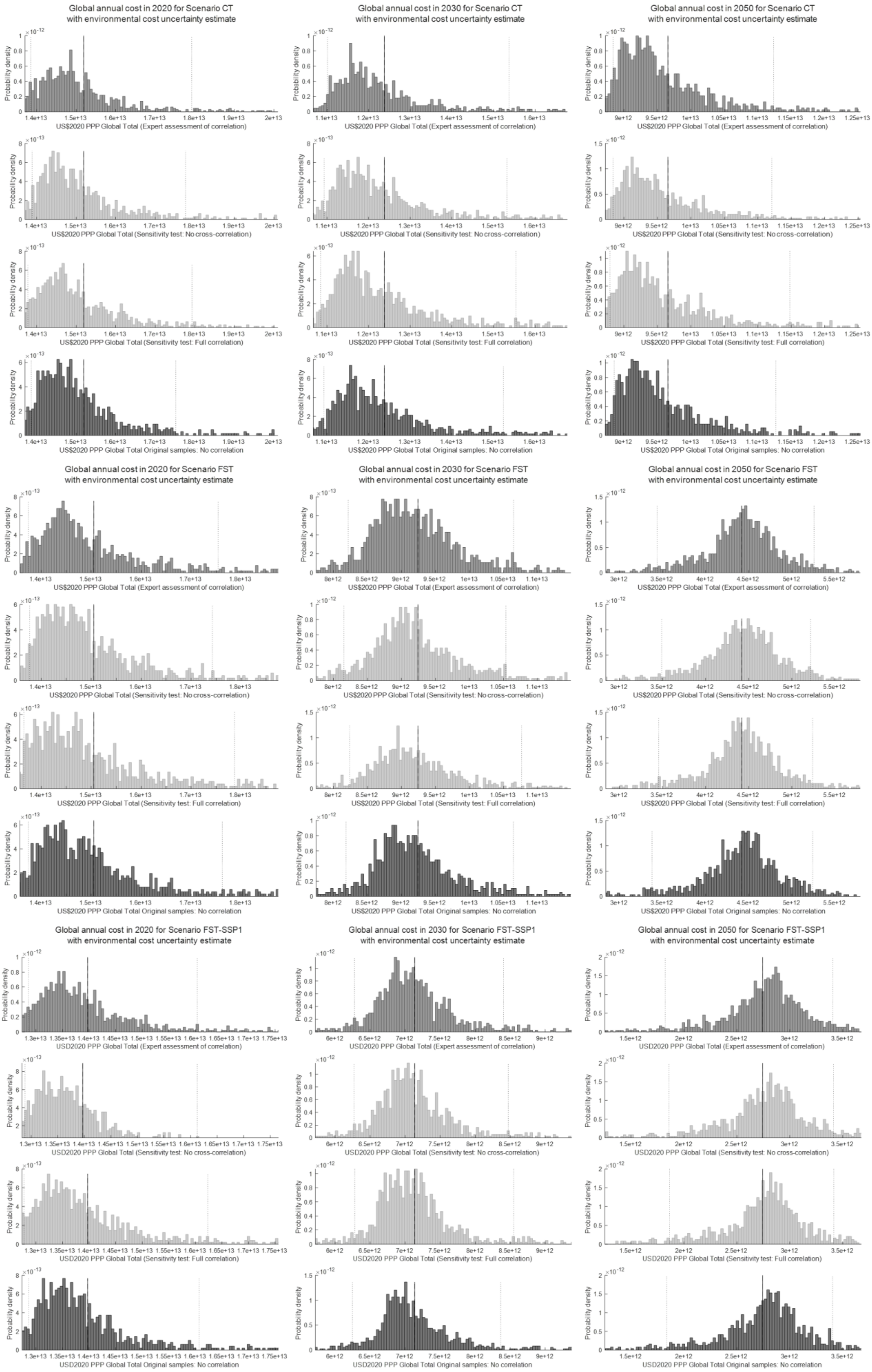


Figure 33: Distributions of global annual cost with correlation sensitivity analysis. Description in the main text of Annex R

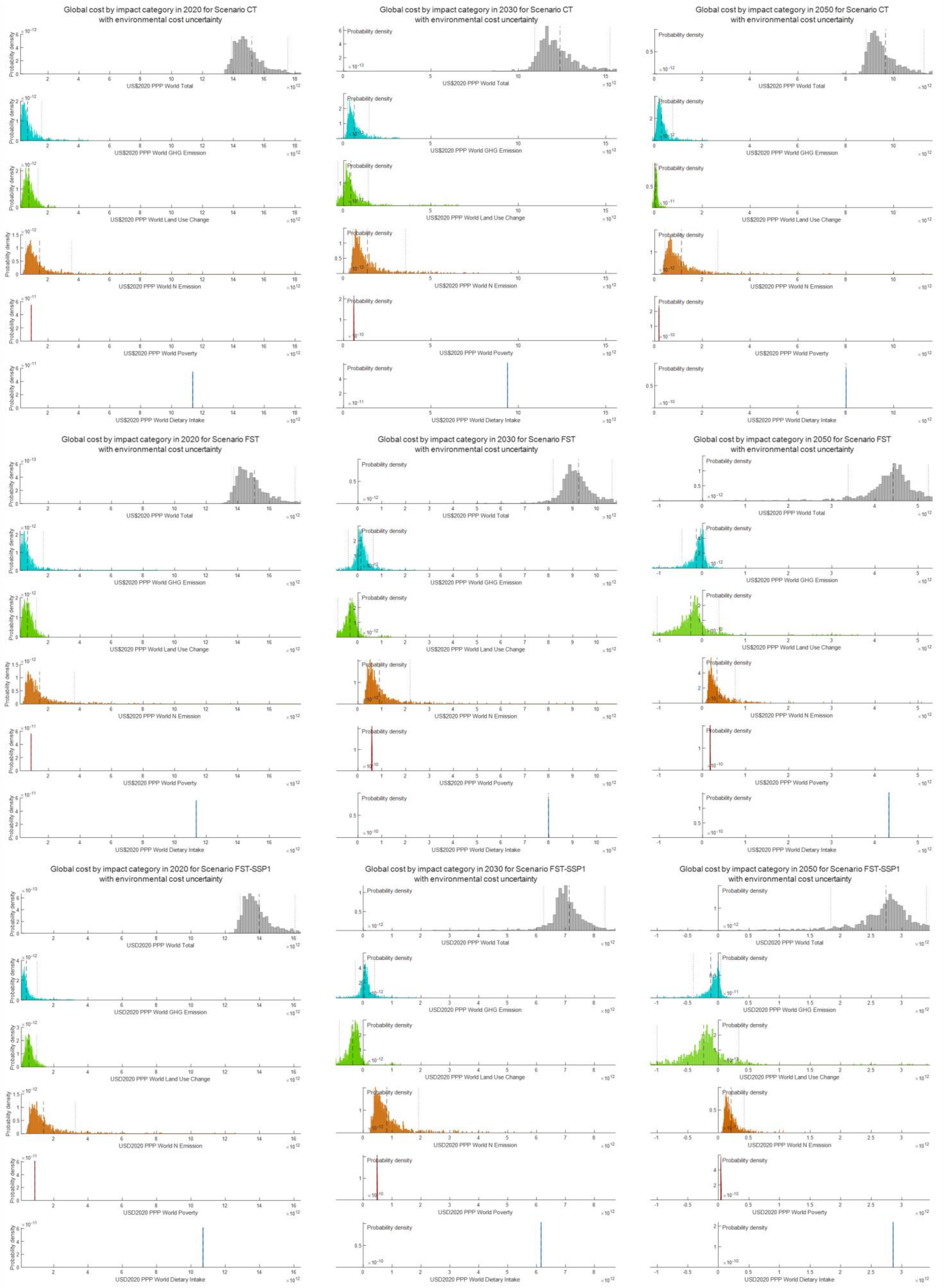


Figure 34: Global annual costs in 2020, 2030, and 2050 by category with uncertainty. Description in the main text of Annex R

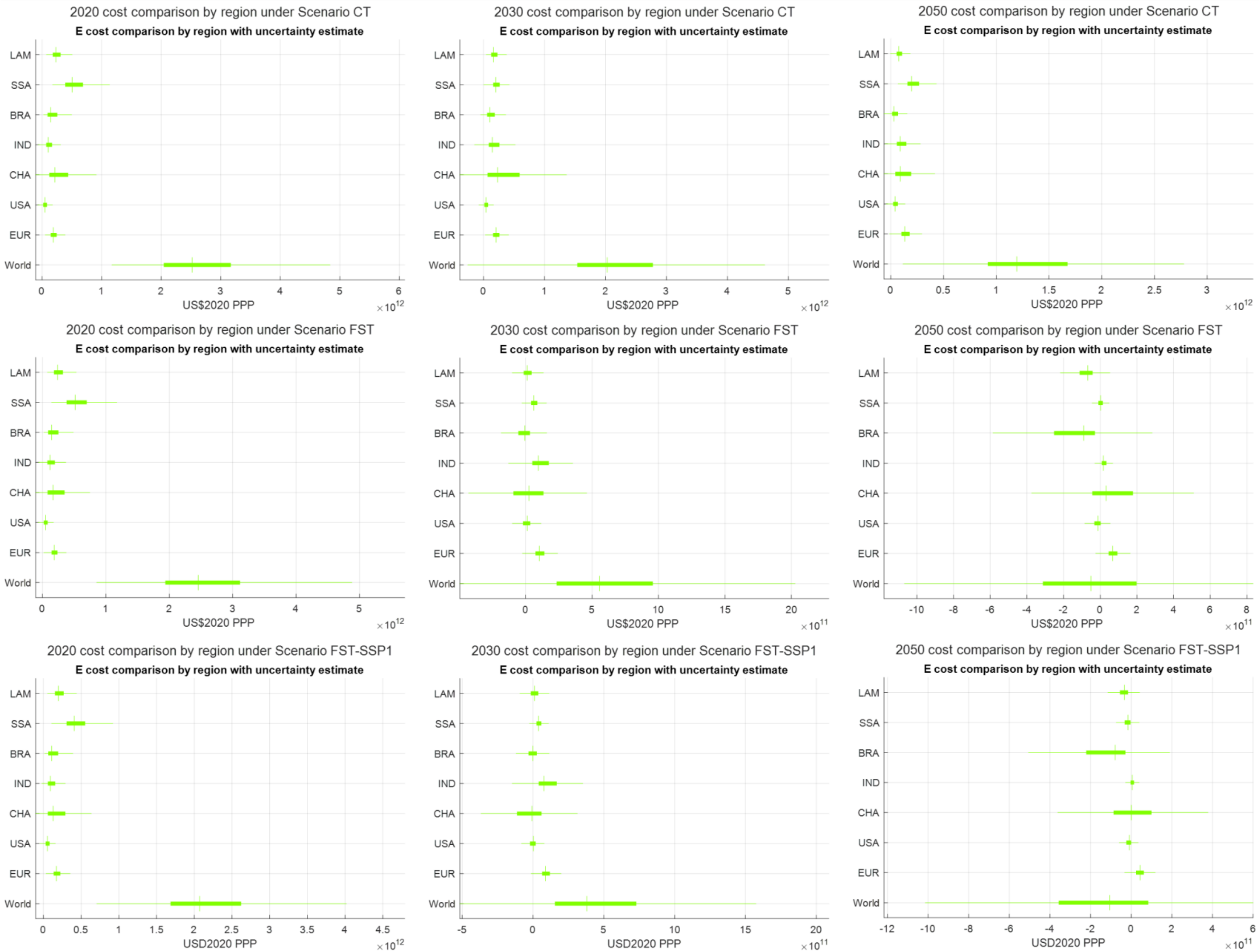


Figure 35: Environmental costs by FSEC Region with uncertainty. Description in the main text of Annex R

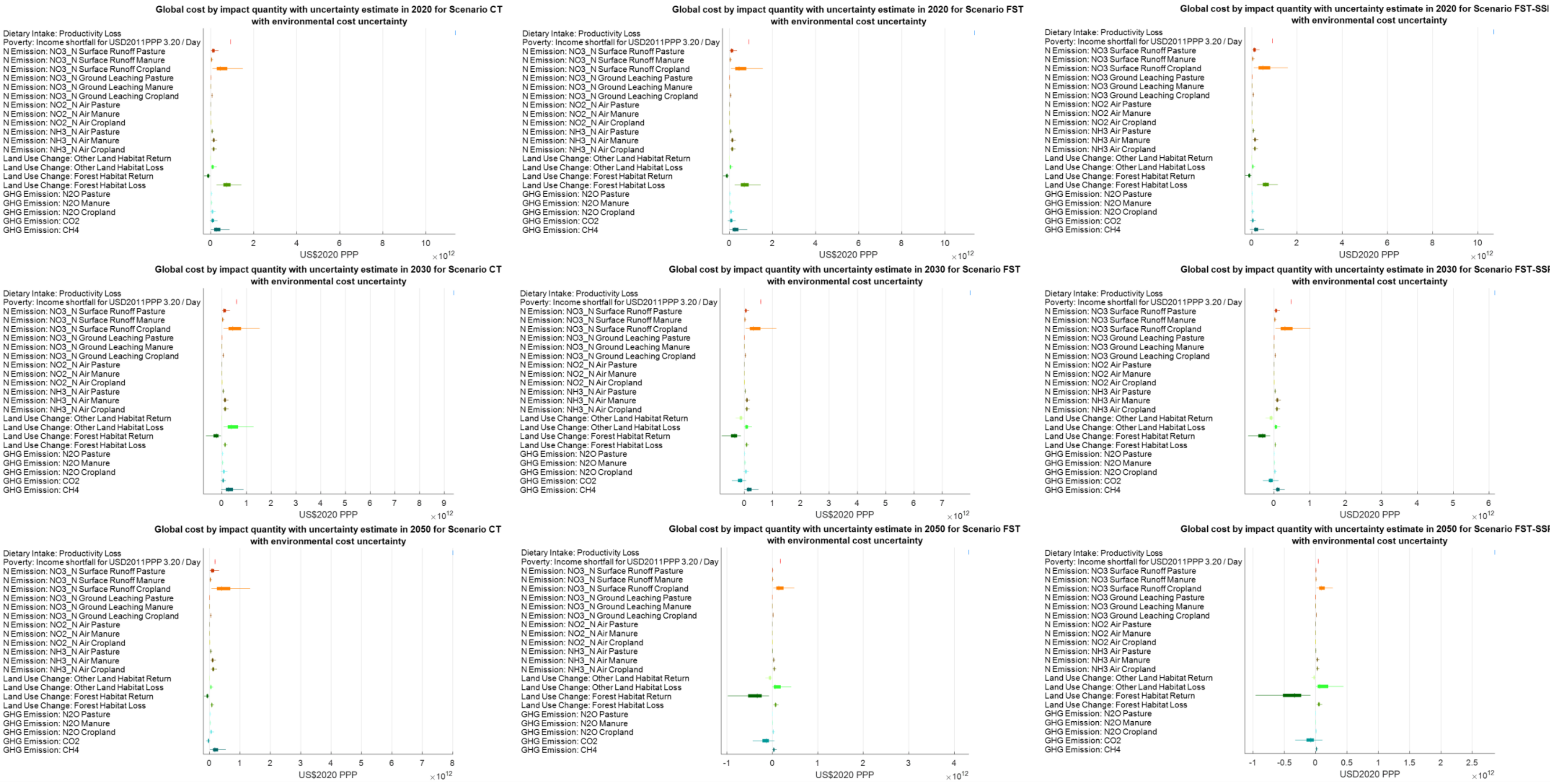


Figure 36: Global annual costs in 2020, 2030, and 2050 by cost item with uncertainty. Description in the main text of Annex R

Annex S

The Annex S output datafile of a SPIQ-FS calculation contains the marginal cost item for each country (in this case 153), for each scenario and year (in this case counterfactual 2020 for 3 policy scenarios). Since there are 12 unique marginal cost items (see Table 3), the Annex S file for this study contains 38556 individual rows. The Annex S file contains a 38556x1000 block of double precision data that specifies 1000 joint samples of the 38556 marginal cost items treated as random variables. To indicate the contents of the Annex S output we show two cross-sections of the file, the first two countries for the same cost item across years and scenarios (Table S1), and the second all 12 cost items for the same country, year, and scenario (Table S2).

The full Annex S file with and without samples can be accessed at the Oxford Research Archive https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8.

Table S1: A snapshot of marginal cost items generated by the SPIQ-FS model for 153 countries. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the UN numerical classification system of sovereign countries and territories (https://unstats.un.org/unsd/methodology/m49/)..

Country Name	Country Code	M49	Scen	Year	quantity	unit2	unit	mean
Canada	CAN	124	CT	2020	Burden of Disease	US$2020 PPP	YLL	98850
Canada	CAN	124	CT	2025	Burden of Disease	US$2020 PPP	YLL	87704
Canada	CAN	124	CT	2030	Burden of Disease	US$2020 PPP	YLL	78546
Canada	CAN	124	CT	2035	Burden of Disease	US$2020 PPP	YLL	72328
Canada	CAN	124	CT	2040	Burden of Disease	US$2020 PPP	YLL	67483
Canada	CAN	124	CT	2045	Burden of Disease	US$2020 PPP	YLL	63321
Canada	CAN	124	CT	2050	Burden of Disease	US$2020 PPP	YLL	59710
Canada	CAN	124	FST-SSP1	2020	Burden of Disease	US$2020 PPP	YLL	98850
Canada	CAN	124	FST-SSP1	2025	Burden of Disease	US$2020 PPP	YLL	87399
Canada	CAN	124	FST-SSP1	2030	Burden of Disease	US$2020 PPP	YLL	78982
Canada	CAN	124	FST-SSP1	2035	Burden of Disease	US$2020 PPP	YLL	73527
Canada	CAN	124	FST-SSP1	2040	Burden of Disease	US$2020 PPP	YLL	69417
Canada	CAN	124	FST-SSP1	2045	Burden of Disease	US$2020 PPP	YLL	66103
Canada	CAN	124	FST-SSP1	2050	Burden of Disease	US$2020 PPP	YLL	63868
Canada	CAN	124	FST	2020	Burden of Disease	US$2020 PPP	YLL	98850
Canada	CAN	124	FST	2025	Burden of Disease	US$2020 PPP	YLL	87704
Canada	CAN	124	FST	2030	Burden of Disease	US$2020 PPP	YLL	78546

Canada	CAN	124	FST	2035	Burden of Disease	US$2020 PPP	YLL	72328
Canada	CAN	124	FST	2040	Burden of Disease	US$2020 PPP	YLL	67483
Canada	CAN	124	FST	2045	Burden of Disease	US$2020 PPP	YLL	63321
Canada	CAN	124	FST	2050	Burden of Disease	US$2020 PPP	YLL	59710
Indonesia	IDN	360	CT	2020	Burden of Disease	US$2020 PPP	YLL	28120
Indonesia	IDN	360	CT	2025	Burden of Disease	US$2020 PPP	YLL	22458
Indonesia	IDN	360	CT	2030	Burden of Disease	US$2020 PPP	YLL	18824
Indonesia	IDN	360	CT	2035	Burden of Disease	US$2020 PPP	YLL	16848
Indonesia	IDN	360	CT	2040	Burden of Disease	US$2020 PPP	YLL	15630
Indonesia	IDN	360	CT	2045	Burden of Disease	US$2020 PPP	YLL	14607
Indonesia	IDN	360	CT	2050	Burden of Disease	US$2020 PPP	YLL	13495
Indonesia	IDN	360	FST-SSP1	2020	Burden of Disease	US$2020 PPP	YLL	28120
Indonesia	IDN	360	FST-SSP1	2025	Burden of Disease	US$2020 PPP	YLL	22407
Indonesia	IDN	360	FST-SSP1	2030	Burden of Disease	US$2020 PPP	YLL	18427
Indonesia	IDN	360	FST-SSP1	2035	Burden of Disease	US$2020 PPP	YLL	15921
Indonesia	IDN	360	FST-SSP1	2040	Burden of Disease	US$2020 PPP	YLL	14270
Indonesia	IDN	360	FST-SSP1	2045	Burden of Disease	US$2020 PPP	YLL	12693
Indonesia	IDN	360	FST-SSP1	2050	Burden of Disease	US$2020 PPP	YLL	11111
Indonesia	IDN	360	FST	2020	Burden of Disease	US$2020 PPP	YLL	28120
Indonesia	IDN	360	FST	2025	Burden of Disease	US$2020 PPP	YLL	22458
Indonesia	IDN	360	FST	2030	Burden of Disease	US$2020 PPP	YLL	18824
Indonesia	IDN	360	FST	2035	Burden of Disease	US$2020 PPP	YLL	16848
Indonesia	IDN	360	FST	2040	Burden of Disease	US$2020 PPP	YLL	15630
Indonesia	IDN	360	FST	2045	Burden of Disease	US$2020 PPP	YLL	14607
Indonesia	IDN	360	FST	2050	Burden of Disease	US$2020 PPP	YLL	13495

Table S2: A snapshot of marginal cost items generated by the SPIQ-FS model for 12 marginal cost item for 1 country in 2 scenarios. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the UN numerical classification system of sovereign countries and territories (https://unstats.un.org/unsd/methodology/m49/). FST and CT marginal costs are similar, being mostly shaped by wider environmental and socio-economic conditions under SSP2. Mean value is in USD 2020 PPP / unit. Variation between FST-SSP1 and CT marginal costs is explained in the Methodology, and occurs as a combination of different GDP PPP and population growth rates before and after 2050, different development trajectories, different background cumulative emissions of GHG and N pollutants, and different economic, environmental, and demographic conditions. Note that emission or land-use change that have occurred (e.g. 2020 emissions) can have different costs according to their cumulative effect on present and future economies under different scenarios.

Country Name	Country Code	M49	Scen	Year	quantity	unit2	unit	mean
Brazil	BRA	76	CT	2020	Burden of Disease	US$2020 PPP	YLL	35415.3
Brazil	BRA	76	CT	2020	CH4	US$2020 PPP	metric ton	1763.5
Brazil	BRA	76	CT	2020	CO2	US$2020 PPP	metric ton	72.7
Brazil	BRA	76	CT	2020	Forest Habitat Loss	US$2020 PPP	ha	39524.1
Brazil	BRA	76	CT	2020	Forest Habitat Return	US$2020 PPP	ha	4750.5
Brazil	BRA	76	CT	2020	Mean income shortfall (2020 PPP)	US$2020 PPP	pp	531.9
Brazil	BRA	76	CT	2020	N2O	US$2020 PPP	metric ton	26204.9
Brazil	BRA	76	CT	2020	NH3 emissions to air	US$2020 PPP	N-kg	9.9
Brazil	BRA	76	CT	2020	NO3- leaching to groundwater	US$2020 PPP	N-kg	1.7
Brazil	BRA	76	CT	2020	NOx emissions to air	US$2020 PPP	N-kg	13.6
Brazil	BRA	76	CT	2020	Nr run-off to surface water	US$2020 PPP	N-kg	61.0
Brazil	BRA	76	CT	2020	Other Habitat Loss	US$2020 PPP	ha	19583.8
Brazil	BRA	76	CT	2020	Other Habitat Return	US$2020 PPP	ha	2201.9
Brazil	BRA	76	FST-SSP1	2020	Burden of Disease	US$2020 PPP	YLL	35415.3
Brazil	BRA	76	FST-SSP1	2020	CH4	US$2020 PPP	metric ton	1208.8
Brazil	BRA	76	FST-SSP1	2020	CO2	US$2020 PPP	metric	43.2

							ton	
Brazil	BRA	76	FST-SSP1	2020	Forest Habitat Loss	US$2020 PPP	ha	31884.9
Brazil	BRA	76	FST-SSP1	2020	Forest Habitat Return	US$2020 PPP	ha	4639.7
Brazil	BRA	76	FST-SSP1	2020	Mean income shortfall (2020 PPP)	US$2020 PPP	pp	531.9
Brazil	BRA	76	FST-SSP1	2020	N2O	US$2020 PPP	metric ton	13446.7
Brazil	BRA	76	FST-SSP1	2020	NH3 emissions to air	US$2020 PPP	N-kg	10.5
Brazil	BRA	76	FST-SSP1	2020	NO3- leaching to groundwater	US$2020 PPP	N-kg	1.6
Brazil	BRA	76	FST-SSP1	2020	NOx emissions to air	US$2020 PPP	N-kg	14.3
Brazil	BRA	76	FST-SSP1	2020	Nr run-off to surfacewater	US$2020 PPP	N-kg	65.8
Brazil	BRA	76	FST-SSP1	2020	Other Habitat Loss	US$2020 PPP	ha	16166.1
Brazil	BRA	76	FST-SSP1	2020	Other Habitat Return	US$2020 PPP	ha	2407.8

Annex T

The Annex T output datafile of a SPIQ-FS calculation contains the quantities associated to each cost item (in this case up to 23 see Table 3) for each country (in this case 153), for each scenario and year (3 scenarios and 7 five-year time steps between 2020 and 2050). The Annex T file for this study contains up to 73899 individual rows. The marginal cost items and their joint sample in Annex S are matched to each quantity cost item, units are checked, and for most items each quantity cost item is multiplied by the 1000 marginal cost item samples to obtain 1000 total cost item samples. This method assumes validity in a first order approximate of change in total damages (Annex F). The Annex T file contains a 73899x1000 block of double precision data that specifies 1000 joint samples of the 73899 marginal cost items treated as random variables. To indicate the contents of the Annex T output we show two cross-sections of the file, the first by country and scenario for the same cost item (Table T1), and the second all 23 cost items for the same country and the same scenario (Table T2).

The full Annex T file with and without samples can be accessed at the Oxford Research Archive https://ora.ox.ac.uk/objects/uuid:490d37cb-fb59-4d1e-8ce1-cb62bc2917d8.

Table T1: A snapshot of total cost items calculated by the SPIQ-FS model for 153 countries. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the UN numerical classification system of sovereign countries and territories (https://unstats.un.org/unsd/methodology/m49/). Mean in units of USD 2020 PPP billions.

Country	ISO3	M49	Scen	Year	Cost Type	Cost Category	Element	Item	Quantity Unit	Quantity	Marginal Unit	Marginal Cost	Total Unit	Mean
Canada	CAN	124	CT	2020	E	GHG Emission	CH4		t CH4	952900	metric ton	1763.5	US$2020 PPP B	1.680
Canada	CAN	124	FST-SSP1	2020	E	GHG Emission	CH4		t CH4	951800	metric ton	1208.8	US$2020 PPP B	1.151
Canada	CAN	124	CT	2025	E	GHG Emission	CH4		t CH4	959800	metric ton	1859.1	US$2020 PPP B	1.784
Canada	CAN	124	FST-SSP1	2025	E	GHG Emission	CH4		t CH4	732800	metric ton	1329.0	US$2020 PPP B	0.974
Canada	CAN	124	CT	2030	E	GHG Emission	CH4		t CH4	982400	metric ton	1684.6	US$2020 PPP B	1.655
Canada	CAN	124	FST-SSP1	2030	E	GHG Emission	CH4		t CH4	618900	metric ton	1012.5	US$2020 PPP B	0.627
Canada	CAN	124	CT	2035	E	GHG Emission	CH4		t CH4	983500	metric ton	1437.5	US$2020 PPP B	1.414
Canada	CAN	124	FST-	2035	E	GHG	CH4		t CH4	524000	metric	859.6	US$2020	0.450

			SSP1			Emission					ton		PPP B	
Canada	CAN	124	CT	2040	E	GHG Emission	CH4		t CH4	993400	metric ton	1177.0	US$2020 PPP B	1.169
Canada	CAN	124	FST-SSP1	2040	E	GHG Emission	CH4		t CH4	414000	metric ton	662.4	US$2020 PPP B	0.274
Canada	CAN	124	CT	2045	E	GHG Emission	CH4		t CH4	994300	metric ton	1068.6	US$2020 PPP B	1.063
Canada	CAN	124	FST-SSP1	2045	E	GHG Emission	CH4		t CH4	335500	metric ton	532.6	US$2020 PPP B	0.179
Canada	CAN	124	CT	2050	E	GHG Emission	CH4		t CH4	994100	metric ton	925.4	US$2020 PPP B	0.920
Canada	CAN	124	FST-SSP1	2050	E	GHG Emission	CH4		t CH4	258100	metric ton	439.2	US$2020 PPP B	0.113
Rwanda	RWA	646	CT	2020	E	Land Use Change	Forest Habitat Loss		ha	2198	ha	17909.8	US$2020 PPP B	0.039
Rwanda	RWA	646	FST-SSP1	2020	E	Land Use Change	Forest Habitat Loss		ha	680	ha	15891.7	US$2020 PPP B	0.011
Rwanda	RWA	646	CT	2025	E	Land Use Change	Forest Habitat Return		ha	53421	ha	-2918.0	US$2020 PPP B	-0.156
Rwanda	RWA	646	FST-SSP1	2025	E	Land Use Change	Forest Habitat Return		ha	58839	ha	-2465.2	US$2020 PPP B	-0.145
Rwanda	RWA	646	CT	2030	E	Land Use Change	Forest Habitat Return		ha	28737	ha	-2582.6	US$2020 PPP B	-0.074
Rwanda	RWA	646	FST-SSP1	2030	E	Land Use Change	Forest Habitat Return		ha	69934	ha	-2160.2	US$2020 PPP B	-0.151
Rwanda	RWA	646	CT	2035	E	Land Use Change	Forest Habitat Return		ha	117046	ha	-2239.0	US$2020 PPP B	-0.262
Rwanda	RWA	646	FST-SSP1	2035	E	Land Use Change	Forest Habitat Return		ha	182371	ha	-1912.5	US$2020 PPP B	-0.349
Rwanda	RWA	646	CT	2040	E	Land Use	Forest		ha	2837	ha	12172.7	US$2020	0.035

						Change	Habitat Loss						PPP B	
Rwanda	RWA	646	FST-SSP1	2040	E	Land Use Change	Forest Habitat Return		ha	53171	ha	-1733.3	US$2020 PPP B	-0.092
Rwanda	RWA	646	CT	2045	E	Land Use Change	Forest Habitat Loss		ha	6566	ha	11139.0	US$2020 PPP B	0.073
Rwanda	RWA	646	FST-SSP1	2045	E	Land Use Change	Forest Habitat Return		ha	18414	ha	-1588.8	US$2020 PPP B	-0.029
Rwanda	RWA	646	CT	2050	E	Land Use Change	Forest Habitat Loss		ha	6266	ha	10333.8	US$2020 PPP B	0.065
Rwanda	RWA	646	FST-SSP1	2050	E	Land Use Change	Forest Habitat Return		ha	298533	ha	-1436.1	US$2020 PPP B	-0.429

Table T2: A snapshot of cost items calculated by the SPIQ-FS model for up to 23 cost items for 1 country in scenario CT and FST-SSP1. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the UN numerical classification system of sovereign countries and territories (https://unstats.un.org/unsd/methodology/m49/). Mean in units of USD 2020 PPP billions.

Country Name	Count Code	M49	Scen	Year	Cost Type	Cost Category	Cost	Item	Quantity	Quantity Unit	Marginal Unit	Marginal Cost	Total Unit	Mean
United States	USA	840	CT	2030	E	GHG Emission	CH4		9568700	t CH4	metric ton	1684.6	US$2020 PPP B	16.12
United States	USA	840	FST-SSP1	2030	E	GHG Emission	CH4		4690300	t CH4	metric ton	1012.5	US$2020 PPP B	4.75
United States	USA	840	CT	2030	E	GHG Emission	CO2		-635779200	t CO2	metric ton	60.2	US$2020 PPP B	-38.27
United States	USA	840	FST-SSP1	2030	E	GHG Emission	CO2		-718488400	t CO2	metric ton	42.4	US$2020 PPP B	-30.48
United States	USA	840	CT	2030	H	Dietary Intake	Dietary Intake Health Impacts		14104121	YLL	YLL	113921.9	US$2020 PPP B	1606.77
United States	USA	840	FST-SSP1	2030	H	Dietary Intake	Dietary Intake		8702174	YLL	YLL	112837.3	US$2020 PPP B	981.93

United States	USA	840	CT	2030	E	Land Use Change	Health Impacts Forest Habitat Return		1490472	ha	ha	-10146.3	US$2020 PPP B	-15.12
United States	USA	840	FST-SSP1	2030	E	Land Use Change	Forest Habitat Return		1916149	ha	ha	-10542.8	US$2020 PPP B	-20.20
United States	USA	840	CT	2030	E	GHG Emission	N2O	Cropland	380327	t N2O	metric ton	23070.9	US$2020 PPP B	8.77
United States	USA	840	FST-SSP1	2030	E	GHG Emission	N2O	Cropland	205118	t N2O	metric ton	11373.4	US$2020 PPP B	2.33
United States	USA	840	CT	2030	E	GHG Emission	N2O	Manure	199120	t N2O	metric ton	23070.9	US$2020 PPP B	4.59
United States	USA	840	FST-SSP1	2030	E	GHG Emission	N2O	Manure	118647	t N2O	metric ton	11373.4	US$2020 PPP B	1.35
United States	USA	840	CT	2030	E	GHG Emission	N2O	Pasture	65969	t N2O	metric ton	23070.9	US$2020 PPP B	1.52
United States	USA	840	FST-SSP1	2030	E	GHG Emission	N2O	Pasture	28862	t N2O	metric ton	11373.4	US$2020 PPP B	0.33
United States	USA	840	CT	2030	E	N Emission	NH3_N Air	Cropland	1558331703	kg NH3-N	N-kg	5.3	US$2020 PPP B	8.23
United States	USA	840	FST-SSP1	2030	E	N Emission	NH3_N Air	Cropland	800701917	kg NH3-N	N-kg	5.3	US$2020 PPP B	4.28
United States	USA	840	CT	2030	E	N Emission	NH3_N Air	Manure	1947357214	kg NH3-N	N-kg	5.3	US$2020 PPP B	10.28
United States	USA	840	FST-SSP1	2030	E	N Emission	NH3_N Air	Manure	1128059671	kg NH3-N	N-kg	5.3	US$2020 PPP B	6.03
United States	USA	840	CT	2030	E	N Emission	NH3_N Air	Pasture	360351465	kg NH3-N	N-kg	5.3	US$2020 PPP B	1.90
United States	USA	840	FST-SSP1	2030	E	N Emission	NH3_N Air	Pasture	157747988	kg NH3-N	N-kg	5.3	US$2020 PPP B	0.84
United States	USA	840	CT	2030	E	N Emission	NO2_N Air	Cropland	64930488	kg NO2-N	N-kg	19.4	US$2020 PPP B	1.26
United States	USA	840	FST-SSP1	2030	E	N Emission	NO2_N Air	Cropland	33362580	kg NO2-N	N-kg	19.9	US$2020 PPP B	0.66

United States	USA	840	CT	2030	E	N Emission	NO2_N Air	Manure	19673131	kg NO2-N	N-kg	19.4	US$2020 PPP B	0.38
United States	USA	840	FST-SSP1	2030	E	N Emission	NO2_N Air	Manure	11396268	kg NO2-N	N-kg	19.9	US$2020 PPP B	0.23
United States	USA	840	CT	2030	E	N Emission	NO2_N Air	Pasture	15014644	kg NO2-N	N-kg	19.4	US$2020 PPP B	0.29
United States	USA	840	FST-SSP1	2030	E	N Emission	NO2_N Air	Pasture	6572833	kg NO2-N	N-kg	19.9	US$2020 PPP B	0.13
United States	USA	840	CT	2030	E	N Emission	NO3_N Ground Leaching	Cropland	3275739095	kg NO3--N	N-kg	4.5	US$2020 PPP B	14.62
United States	USA	840	FST-SSP1	2030	E	N Emission	NO3_N Ground Leaching	Cropland	1772674975	kg NO3--N	N-kg	4.5	US$2020 PPP B	7.96
United States	USA	840	CT	2030	E	N Emission	NO3_N Ground Leaching	Manure	276939654	kg NO3--N	N-kg	4.5	US$2020 PPP B	1.24
United States	USA	840	FST-SSP1	2030	E	N Emission	NO3_N Ground Leaching	Manure	143839400	kg NO3--N	N-kg	4.5	US$2020 PPP B	0.65
United States	USA	840	CT	2030	E	N Emission	NO3_N Ground Leaching	Pasture	250551942	kg NO3--N	N-kg	4.5	US$2020 PPP B	1.12
United States	USA	840	FST-SSP1	2030	E	N Emission	NO3_N Ground Leaching	Pasture	109681987	kg NO3--N	N-kg	4.5	US$2020 PPP B	0.49
United States	USA	840	CT	2030	E	N Emission	NO3_N Surface Runoff	Cropland	1472335830	kg NO3--N	N-kg	21.6	US$2020 PPP B	31.80
United States	USA	840	FST-SSP1	2030	E	N Emission	NO3_N Surface Runoff	Cropland	796758474	kg NO3--N	N-kg	22.9	US$2020 PPP B	18.26
United States	USA	840	CT	2030	E	N Emission	NO3_N Surface Runoff	Manure	124475169	kg NO3--N	N-kg	21.6	US$2020 PPP B	2.69
United	USA	840	FST-	2030	E	N	NO3_N	Manure	64651029	kg NO3--N	N-kg	22.9	US$2020	1.48

States			SSP1			Emission	Surface Runoff						PPP B	
United States	USA	840	CT	2030	E	N Emission	NO3_N Surface Runoff	Pasture	112614769	kg NO3--N	N-kg	21.6	US$2020 PPP B	2.43
United States	USA	840	FST-SSP1	2030	E	N Emission	NO3_N Surface Runoff	Pasture	49298407	kg NO3--N	N-kg	22.9	US$2020 PPP B	1.13
United States	USA	840	CT	2030	S	Poverty	People Below USD2011PPP 3.20 / Day		2830581	ppl	pp	983.2	US$2020 PPP B	2.78
United States	USA	840	FST-SSP1	2030	S	Poverty	People Below USD2011PPP 3.20 / Day		2512809	ppl	pp	974.2	US$2020 PPP B	2.45
United States	USA	840	CT	2030	E	Land Use Change	Other Land Habitat Loss		27635	ha	ha	22081.3	US$2020 PPP B	0.61
United States	USA	840	FST-SSP1	2030	E	Land Use Change	Other Land Habitat Return		2113720	ha	ha	-2306.9	US$2020 PPP B	-4.88

Annex U – Countries included in the study

Table U1: 153 countries included in the analysis by subregion, region, Human Development Index (HDI), and World Bank Income Group in 2020. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the UN numerical classification system of sovereign countries and territories (https://unstats.un.org/unsd/methodology/m49/).

Country	ISO3	M49	SubRegion M49	Sub Region	Region M49	Region	Region FSEC	HDI	HDI Tier	WB Income Group
Afghanistan	AFG	4	34	Southern Asia	142	Asia	OAS	0.511	Low	Low income
Angola	AGO	24	202	Sub-Saharan Africa	2	Africa	SSA	0.581	Medium	Lower middle income
Albania	ALB	8	39	Southern Europe	150	Europe	NEU	0.795	High	Upper middle income
United Arab Emirates	ARE	784	145	Western Asia	142	Asia	MEA	0.89	Very high	High income
Argentina	ARG	32	419	Latin America and the Caribbean	19	Americas	LAM	0.845	Very high	Upper middle income
Armenia	ARM	51	145	Western Asia	142	Asia	NEA	0.776	High	Upper middle income
Australia	AUS	36	53	Australia and New Zealand	9	Oceania	ANZ	0.944	Very high	High income
Austria	AUT	40	155	Western Europe	150	Europe	EUR	0.922	Very high	High income
Azerbaijan	AZE	31	145	Western Asia	142	Asia	NEA	0.756	High	Upper middle income
Burundi	BDI	108	202	Sub-Saharan Africa	2	Africa	SSA	0.433	Low	Low income
Belgium	BEL	56	155	Western Europe	150	Europe	EUR	0.931	Very high	High income
Benin	BEN	204	202	Sub-Saharan Africa	2	Africa	SSA	0.545	Low	Lower middle income
Burkina Faso	BFA	854	202	Sub-Saharan Africa	2	Africa	SSA	0.452	Low	Low income
Bangladesh	BGD	50	34	Southern Asia	142	Asia	OAS	0.632	Medium	Lower middle income
Bulgaria	BGR	100	151	Eastern Europe	150	Europe	EUR	0.816	Very high	Upper middle income
Bosnia and Herzegovina	BIH	70	39	Southern Europe	150	Europe	NEU	0.78	High	Upper middle income
Belarus	BLR	112	151	Eastern Europe	150	Europe	NEA	0.823	Very high	Upper middle income
Bolivia	BOL	68	419	Latin	19	Americas	LAM	0.718	High	Lower

				America and the Caribbean						middle income
Brazil	BRA	76	419	Latin America and the Caribbean	19	Americas	BRA	0.765	High	Upper middle income
Bhutan	BTN	64	34	Southern Asia	142	Asia	OAS	0.654	Medium	Lower middle income
Botswana	BWA	72	202	Sub-Saharan Africa	2	Africa	SSA	0.735	High	Upper middle income
Central African Republic	CAF	140	202	Sub-Saharan Africa	2	Africa	SSA	0.397	Low	Low income
Canada	CAN	124	21	Northern America	19	Americas	CAN	0.929	Very high	High income
Switzerland	CHE	756	155	Western Europe	150	Europe	NEU	0.955	Very high	High income
Chile	CHL	152	419	Latin America and the Caribbean	19	Americas	LAM	0.851	Very high	High income
China	CHN	156	30	Eastern Asia	142	Asia	CHA	0.761	High	Upper middle income
Cote d'Ivoire	CIV	384	202	Sub-Saharan Africa	2	Africa	SSA	0.538	Low	Lower middle income
Cameroon	CMR	120	202	Sub-Saharan Africa	2	Africa	SSA	0.563	Medium	Lower middle income
Congo, Dem. Rep.	COD	180	202	Sub-Saharan Africa	2	Africa	SSA	0.48	Low	Low income
Congo, Rep.	COG	178	202	Sub-Saharan Africa	2	Africa	SSA	0.574	Medium	Lower middle income
Colombia	COL	170	419	Latin America and the Caribbean	19	Americas	LAM	0.767	High	Upper middle income
Costa Rica	CRI	188	419	Latin America and the Caribbean	19	Americas	LAM	0.81	Very high	Upper middle income
Cuba	CUB	192	419	Latin America and the Caribbean	19	Americas	LAM	0.783	High	Upper middle income
Czech Republic	CZE	203	151	Eastern Europe	150	Europe	EUR	0.9	Very high	High income
Germany	DEU	276	155	Western Europe	150	Europe	EUR	0.947	Very high	High income
Djibouti	DJI	262	202	Sub-Saharan Africa	2	Africa	SSA	0.524	Low	Lower middle income
Denmark	DNK	208	154	Northern Europe	150	Europe	EUR	0.94	Very high	High income
Dominican Republic	DOM	214	419	Latin America	19	Americas	LAM	0.756	High	Upper middle

				and the Caribbean						income
Algeria	DZA	12	15	Northern Africa	2	Africa	MEA	0.748	High	Lower middle income
Ecuador	ECU	218	419	Latin America and the Caribbean	19	Americas	LAM	0.759	High	Upper middle income
Egypt, Arab Rep.	EGY	818	15	Northern Africa	2	Africa	MEA	0.707	High	Lower middle income
Eritrea	ERI	232	202	Sub-Saharan Africa	2	Africa	SSA	0.459	Low	Low income
Spain	ESP	724	39	Southern Europe	150	Europe	EUR	0.904	Very high	High income
Estonia	EST	233	154	Northern Europe	150	Europe	EUR	0.892	Very high	High income
Ethiopia	ETH	231	202	Sub-Saharan Africa	2	Africa	SSA	0.485	Low	Low income
Finland	FIN	246	154	Northern Europe	150	Europe	EUR	0.938	Very high	High income
France	FRA	250	155	Western Europe	150	Europe	EUR	0.901	Very high	High income
Gabon	GAB	266	202	Sub-Saharan Africa	2	Africa	SSA	0.703	High	Upper middle income
United Kingdom	GBR	826	154	Northern Europe	150	Europe	NEU	0.932	Very high	High income
Georgia	GEO	268	145	Western Asia	142	Asia	NEA	0.812	Very high	Upper middle income
Ghana	GHA	288	202	Sub-Saharan Africa	2	Africa	SSA	0.611	Medium	Lower middle income
Guinea	GIN	324	202	Sub-Saharan Africa	2	Africa	SSA	0.477	Low	Low income
Gambia, The	GMB	270	202	Sub-Saharan Africa	2	Africa	SSA	0.496	Low	Low income
Guinea-Bissau	GNB	624	202	Sub-Saharan Africa	2	Africa	SSA	0.48	Low	Low income
Equatorial Guinea	GNQ	226	202	Sub-Saharan Africa	2	Africa	SSA	0.592	Medium	Upper middle income
Greece	GRC	300	39	Southern Europe	150	Europe	EUR	0.888	Very high	High income
Guatemala	GTM	320	419	Latin America and the Caribbean	19	Americas	LAM	0.663	Medium	Upper middle income
Guyana	GUY	328	419	Latin America and the Caribbean	19	Americas	LAM	0.682	Medium	Upper middle income
Honduras	HND	340	419	Latin America and the	19	Americas	LAM	0.634	Medium	Lower middle income

				Caribbean						
Croatia	HRV	191	39	Southern Europe	150	Europe	EUR	0.851	Very high	High income
Haiti	HTI	332	419	Latin America and the Caribbean	19	Americas	LAM	0.51	Low	Lower middle income
Hungary	HUN	348	151	Eastern Europe	150	Europe	EUR	0.854	Very high	High income
Indonesia	IDN	360	35	South-eastern Asia	142	Asia	OAS	0.718	High	Lower middle income
India	IND	356	34	Southern Asia	142	Asia	IND	0.645	Medium	Lower middle income
Ireland	IRL	372	154	Northern Europe	150	Europe	EUR	0.955	Very high	High income
Iran, Islamic Rep.	IRN	364	34	Southern Asia	142	Asia	MEA	0.783	High	Lower middle income
Iraq	IRQ	368	145	Western Asia	142	Asia	MEA	0.674	Medium	Upper middle income
Iceland	ISL	352	154	Northern Europe	150	Europe	NEU	0.949	Very high	High income
Israel	ISR	376	145	Western Asia	142	Asia	MEA	0.919	Very high	High income
Italy	ITA	380	39	Southern Europe	150	Europe	EUR	0.892	Very high	High income
Jamaica	JAM	388	419	Latin America and the Caribbean	19	Americas	LAM	0.734	High	Upper middle income
Jordan	JOR	400	145	Western Asia	142	Asia	MEA	0.729	High	Upper middle income
Japan	JPN	392	30	Eastern Asia	142	Asia	JKO	0.919	Very high	High income
Kazakhstan	KAZ	398	143	Central Asia	142	Asia	NEA	0.825	Very high	Upper middle income
Kenya	KEN	404	202	Sub-Saharan Africa	2	Africa	SSA	0.601	Medium	Lower middle income
Kyrgyz Republic	KGZ	417	143	Central Asia	142	Asia	NEA	0.697	Medium	Lower middle income
Cambodia	KHM	116	35	South-eastern Asia	142	Asia	OAS	0.594	Medium	Lower middle income
Korea, Rep.	KOR	410	30	Eastern Asia	142	Asia	JKO	0.916	Very high	High income
Kuwait	KWT	414	145	Western Asia	142	Asia	MEA	0.806	Very high	High income
Lao PDR	LAO	418	35	South-eastern Asia	142	Asia	OAS	0.613	Medium	Lower middle income
Lebanon	LBN	422	145	Western Asia	142	Asia	MEA	0.744	High	Upper middle income
Liberia	LBR	430	202	Sub-Saharan	2	Africa	SSA	0.48	Low	Low income

				Africa						
Libya	LBY	434	15	Northern Africa	2	Africa	MEA	0.724	High	Upper middle income
Sri Lanka	LKA	144	34	Southern Asia	142	Asia	OAS	0.782	High	Lower middle income
Lesotho	LSO	426	202	Sub-Saharan Africa	2	Africa	SSA	0.527	Low	Lower middle income
Lithuania	LTU	440	154	Northern Europe	150	Europe	EUR	0.882	Very high	High income
Latvia	LVA	428	154	Northern Europe	150	Europe	EUR	0.866	Very high	High income
Morocco	MAR	504	15	Northern Africa	2	Africa	MEA	0.686	Medium	Lower middle income
Moldova	MDA	498	151	Eastern Europe	150	Europe	NEA	0.75	High	Upper middle income
Madagascar	MDG	450	202	Sub-Saharan Africa	2	Africa	SSA	0.528	Low	Low income
Mexico	MEX	484	419	Latin America and the Caribbean	19	Americas	LAM	0.779	High	Upper middle income
North Macedonia	MKD	807	39	Southern Europe	150	Europe	NEU	0.774	High	Upper middle income
Mali	MLI	466	202	Sub-Saharan Africa	2	Africa	SSA	0.434	Low	Low income
Myanmar	MMR	104	35	South-eastern Asia	142	Asia	OAS	0.583	Medium	Lower middle income
Mongolia	MNG	496	30	Eastern Asia	142	Asia	NEA	0.737	High	Lower middle income
Mozambique	MOZ	508	202	Sub-Saharan Africa	2	Africa	SSA	0.456	Low	Low income
Mauritania	MRT	478	202	Sub-Saharan Africa	2	Africa	SSA	0.546	Low	Lower middle income
Malawi	MWI	454	202	Sub-Saharan Africa	2	Africa	SSA	0.483	Low	Low income
Malaysia	MYS	458	35	South-eastern Asia	142	Asia	OAS	0.81	Very high	Upper middle income
Namibia	NAM	516	202	Sub-Saharan Africa	2	Africa	SSA	0.646	Medium	Upper middle income
Niger	NER	562	202	Sub-Saharan Africa	2	Africa	SSA	0.394	Low	Low income
Nigeria	NGA	566	202	Sub-Saharan Africa	2	Africa	SSA	0.539	Low	Lower middle income
Nicaragua	NIC	558	419	Latin America	19	Americas	LAM	0.66	Medium	Lower middle

				and the Caribbean						income
Netherlands	NLD	528	155	Western Europe	150	Europe	EUR	0.944	Very high	High income
Norway	NOR	578	154	Northern Europe	150	Europe	NEU	0.957	Very high	High income
Nepal	NPL	524	34	Southern Asia	142	Asia	OAS	0.602	Medium	Lower middle income
New Zealand	NZL	554	53	Australia and New Zealand	9	Oceania	ANZ	0.931	Very high	High income
Oman	OMN	512	145	Western Asia	142	Asia	MEA	0.813	Very high	High income
Pakistan	PAK	586	34	Southern Asia	142	Asia	OAS	0.557	Medium	Lower middle income
Panama	PAN	591	419	Latin America and the Caribbean	19	Americas	LAM	0.815	Very high	Upper middle income
Peru	PER	604	419	Latin America and the Caribbean	19	Americas	LAM	0.777	High	Upper middle income
Philippines	PHL	608	35	South-eastern Asia	142	Asia	OAS	0.718	High	Lower middle income
Papua New Guinea	PNG	598	54	Melanesia	9	Oceania	OAS	0.555	Medium	Lower middle income
Poland	POL	616	151	Eastern Europe	150	Europe	EUR	0.88	Very high	High income
Portugal	PRT	620	39	Southern Europe	150	Europe	EUR	0.864	Very high	High income
Paraguay	PRY	600	419	Latin America and the Caribbean	19	Americas	LAM	0.728	High	Upper middle income
West Bank and Gaza	PSE	275	145	Western Asia	142	Asia	MEA	0.708	High	Lower middle income
Romania	ROU	642	151	Eastern Europe	150	Europe	EUR	0.828	Very high	Upper middle income
Russian Federation	RUS	643	151	Eastern Europe	150	Europe	NEA	0.824	Very high	Upper middle income
Rwanda	RWA	646	202	Sub-Saharan Africa	2	Africa	SSA	0.543	Low	Low income
Saudi Arabia	SAU	682	145	Western Asia	142	Asia	MEA	0.854	Very high	High income
Sudan	SDN	729	15	Northern Africa	2	Africa	MEA	0.51	Low	Low income
Senegal	SEN	686	202	Sub-Saharan Africa	2	Africa	SSA	0.512	Low	Lower middle income
Solomon Islands	SLB	90	54	Melanesia	9	Oceania	OAS	0.567	Medium	Lower middle income
Sierra Leone	SLE	694	202	Sub-	2	Africa	SSA	0.452	Low	Low

				Saharan Africa						income
El Salvador	SLV	222	419	Latin America and the Caribbean	19	Americas	LAM	0.673	Medium	Lower middle income
Somalia	SOM	706	202	Sub-Saharan Africa	2	Africa	SSA	0.285	Low	Low income
Serbia	SRB	688	39	Southern Europe	150	Europe	NEU	0.806	Very high	Upper middle income
Slovak Republic	SVK	703	151	Eastern Europe	150	Europe	EUR	0.86	Very high	High income
Slovenia	SVN	705	39	Southern Europe	150	Europe	EUR	0.917	Very high	High income
Sweden	SWE	752	154	Northern Europe	150	Europe	EUR	0.945	Very high	High income
Eswatini	SWZ	748	202	Sub-Saharan Africa	2	Africa	SSA	0.611	Medium	Lower middle income
Syrian Arab Republic	SYR	760	145	Western Asia	142	Asia	MEA	0.567	Medium	Low income
Chad	TCD	148	202	Sub-Saharan Africa	2	Africa	SSA	0.398	Low	Low income
Togo	TGO	768	202	Sub-Saharan Africa	2	Africa	SSA	0.515	Low	Low income
Thailand	THA	764	35	South-eastern Asia	142	Asia	OAS	0.777	High	Upper middle income
Tajikistan	TJK	762	143	Central Asia	142	Asia	NEA	0.668	Medium	Lower middle income
Turkmenistan	TKM	795	143	Central Asia	142	Asia	NEA	0.715	High	Upper middle income
Timor-Leste	TLS	626	35	South-eastern Asia	142	Asia	OAS	0.606	Medium	Lower middle income
Tunisia	TUN	788	15	Northern Africa	2	Africa	MEA	0.74	High	Lower middle income
Turkey	TUR	792	145	Western Asia	142	Asia	NEU	0.82	Very high	Upper middle income
Tanzania	TZA	834	202	Sub-Saharan Africa	2	Africa	SSA	0.529	Low	Lower middle income
Uganda	UGA	800	202	Sub-Saharan Africa	2	Africa	SSA	0.544	Low	Low income
Ukraine	UKR	804	151	Eastern Europe	150	Europe	NEA	0.779	High	Lower middle income
Uruguay	URY	858	419	Latin America and the Caribbean	19	Americas	LAM	0.817	Very high	High income
United States	USA	840	21	Northern America	19	Americas	USA	0.926	Very high	High income

Uzbekistan	UZB	860	143	Central Asia	142	Asia	NEA	0.72	High	Lower middle income
Venezuela, RB	VEN	862	419	Latin America and the Caribbean	19	Americas	LAM	0.711	High	Lower middle income
Vietnam	VNM	704	35	South-eastern Asia	142	Asia	OAS	0.704	High	Lower middle income
Yemen, Rep.	YEM	887	145	Western Asia	142	Asia	MEA	0.47	Low	Low income
South Africa	ZAF	710	202	Sub-Saharan Africa	2	Africa	SSA	0.709	High	Upper middle income
Zambia	ZMB	894	202	Sub-Saharan Africa	2	Africa	SSA	0.584	Medium	Lower middle income
Zimbabwe	ZWE	716	202	Sub-Saharan Africa	2	Africa	SSA	0.571	Medium	Lower middle income