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Hidden costs of agrifood systems and recent trends from 2016 to 2023

Background paper for *The State of Food and Agriculture 2023*

FAO AGRICULTURAL DEVELOPMENT ECONOMICS TECHNICAL STUDY

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Hidden costs of agrifood systems and recent trends from 2016 to 2023

Background paper for *The State of Food and Agriculture 2023*

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Contents

Figures

Tables

Box

Preface

In this study, we examine the annual hidden costs produced by agrifood systems from 2016 to 2023 for 154 countries. Hidden costs include: i) environmental hidden costs from greenhouse gas (GHG) emissions, nitrogen emissions, land-use transitions to and from cropland and pastureland, and blue water withdrawals; ii) social hidden costs from distributional failures, resulting in undernourishment in national populations and poverty among agrifood workers; and iii) health hidden costs from productivity losses due to obesity and non-communicable diseases (NCDs) resulting from food consumption (dietary patterns). The expected damage to global gross domestic product (GDP) at purchasing power parity (PPP) in 2023 from the hidden costs of agrifood systems is around 13 trillion 2020 PPP dollars and trending upwards. Modelled uncertainty suggests a 90 percent chance that the damage to global GDP PPP in 2023 from the considered hidden costs is between 11.3 trillion and 16.6 trillion 2020 PPP dollars.

Productivity losses from dietary patterns are the largest component of global and regional costs and are estimated to have increased by 14 percent from 2016 to 2023. In southern Asia, the productivity losses from dietary patterns increased 20 percent over the same period. In sub-Saharan Africa, productivity losses from obesity and NCDs from food consumption will eclipse the costs of undernourishment and moderate poverty among agrifood workers by 2030 if the trends of 2016–2023 continue. Overall, low-income countries bear the highest proportional costs of agrifood systems hidden costs, with annual costs equivalent to 27 percent of the group's GDP PPP in 2020. Nitrogen pollution from agrifood systems, mainly in the form of ammonia (NH_3) emissions to air and reactive nitrogen (Nr) runoff from cropland, generates similar external costs to the global emissions of pre-farm-gate, at-farm-gate and post-farm-gate GHGs by agrifood systems.

An estimated hidden cost of 13 trillion 2020 PPP dollars is roughly on a par with 10 percent of global GDP in purchasing power terms in 2023 and around 35 billion 2020 PPP dollars per day. Damages of 35 billion 2020 PPP dollars per day are equivalent to a June 2022 Pakistan flood every day or a September 2022 Hurricane Ian every four days. Left unchecked, the hidden costs generated by agrifood systems activities will depress future growth and development. Agrifood systems are not decoupling value production from the increasing economic risk of their impacts. Nitrogen pollution, methane emissions and dietary patterns are distinct challenges from carbon dioxide (CO_2) emissions. For policymakers, policies to reduce the increasing economic risk posed by agrifood systems activities and potentially boost global growth through the cost-effective reduction of damages are characteristically different to the decarbonization pathway demanded of other sectors.

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Abbreviations

AEIR	agricultural externalities impact ratio
AFF	agricultural, forestry and fishing
AFOLU	agricultural, forestry and other, land use and land-use change
ALEB	agrifood production and LULUC economic benefits
ALEC	agrifood production and LULUC external costs
ALENC	agrifood production and LULUC external natural capital cost
ALEOC	agrifood production and LULUC external other capital cost
AQUASTAT	FAO Global Information System on Water and Agriculture
BMI	body mass index
CEDS	Community Emissions Data System
CICES	Common International Classification of Ecosystem Services
DALY	disability-adjusted life year
DPIR	dietary patterns impact ratio
DPPCAP	dietary pattern productivity losses per capita
EDGAR	Emissions Database for Global Atmospheric Research
EPA	Environmental Protection Agency
ESVD	Ecosystem Services Valuation Database
FAO	Food and Agricultural Organization of the United Nations
FAOSTAT	FAO statistical database
GBD	Global Burden of Disease study
GDP	gross domestic product
GDPCAP	GDP PPP per capita
GHG	greenhouse gas
GNI	gross national income
GVA	gross value added
HDI	Human Development Index
HIC	high-income country
HILDA	HIstoric Land Dynamics Assessment
IEA	International Energy Agency
IFAD	International Fund for Agricultural Development
IFPRI	International Food Policy Research Institute
IIASA	International Institute for Applied Systems Analysis
ILO	International Labour Organization

IPCC	Intergovernmental Panel on Climate Change
IWG-SCGHG	Interagency Working Group on the Social Cost of Greenhouse Gases
LIC	low-income country
LMC	low- to middle-income country
LULUC	land use and land-use change
NCDs	non-communicable diseases
NOU	number of undernourished
NPV	net present value
Nr	reactive nitrogen
POU	prevalence of undernourishment
PPP	purchasing power parity
PV	present value
SDINC	total income of individuals below the international moderate poverty line
SDIR	social distribution impact ratio
SDPOUC	social distribution prevalence of undernourishment cost
SDPOVA	income shortfall of agrifood workers to the international moderate poverty line
SDR	social discount rate
SDSN	Sustainable Development Solutions Network
TEEB	The Economics of Ecosystems and Biodiversity
UMC	upper-middle-income country
UNICEF	United Nations Children's Fund
WFP	World Food Programme
WHO	World Health Organization
WWF	Worldwide Fund for Nature

Executive summary

In this paper, we examine the annual hidden costs produced by agrifood systems from 2016 to 2023 for 154 countries. Hidden costs include: i) environmental hidden costs from GHG emissions, nitrogen emissions, land-use transitions to and from cropland and pastureland, and blue water withdrawals; ii) social hidden costs from distributional failures resulting in undernourishment in national populations and poverty among agrifood workers; and iii) health hidden costs associated with productivity losses due to obesity and NCDs resulting from food consumption (dietary patterns). Costs and their uncertainty are examined at the global, regional and country level and in World Bank income groups. They are the present value of GDP PPP damages measured in 2020 PPP dollars, also known as 2020 international dollars.[a]

The damages calculated are not, in themselves, an indication of the amounts avoidable by transitioning from one agrifood system to another. They indicate the relative economic impact of activities or pollutants and identify areas for further study and potential action to reduce damages by public and private actors. Subsequent work should compare the costs of transformation with the value of reducing damages.

Global hidden costs and trends

The net global costs of global agrifood systems activities in 2023 are probably in the range of 11–15 trillion 2020 PPP dollars. The expected value is about 13.1 trillion 2020 PPP dollars. The distribution provides an idea of the spread of possible net global damages due to the high degree of uncertainty in the external costs of GHGs, nitrogen emissions, water withdrawal and so on. The value of 13.1 trillion 2020 PPP dollars is equivalent to around 10 percent of global GDP in purchasing power terms in 2023. Per day, these costs are equivalent to 35 billion 2020 PPP dollars, or to a June 2022 Pakistan flood every day or a September 2022 Hurricane Ian every four days.

Annual hidden costs show approximately a 9 percent increase from 2016 to 2023.

Hidden costs are not currently being measured by accounting systems like other economic indicators and the damages are estimated based on historical data, future projections and partial knowledge of the impact of pollutants on human and natural capital. Observation of the damages is not an experiment that can be repeated often. Central measures of risk, such as most likely costs and expected costs, support decision-making on frequently occurring and observed economic activities, such as market transactions. For low-observation and high-uncertainty features such as hidden costs, central measures need to be supported by additional risk measures, such as the 5th and 95th percentiles. For low-frequency observations, in a one-off game that is the unfolding future, in using such a risk measure, the decision-maker asks if they are willing to accept a 5 percent chance of loss above the corresponding percentiles of the damage cost distribution.

Using the modelled uncertainty, annual hidden costs in 2023 have a 5 percent chance of being 16.5 trillion 2020 PPP dollars or higher and a 95 percent chance of being 11.3 trillion 2020 PPP dollars or higher.

[a] The hidden costs presented in this paper for the year 2020 slightly differ from those presented in *The State of Food and Agriculture 2023* report due to misclassification in natural pastureland transitions for Australia in the former. Consequently, natural pastureland to cropland transitions were set to zero in the latter report. Slight differences are thus visible only in the global estimates, as well as those for Oceania and Australia, and the maps and figures associated with these.

Broadly categorizing the activities of agrifood systems as hidden cost-producing from environmental changes (GHG emissions, nitrogen emissions, water use, land-use change), the burden of disease from dietary patterns, and social distributional failures (undernourishment and moderate poverty), annual environmental external costs and productivity losses from diets are the largest hidden costs, in the range of 2–3 trillion to 8–10 trillion 2020 PPP dollars, respectively. The modelled risk is higher for environmental costs, primarily from a "fat tail" of nitrogen emission costs due to lack of knowledge about the damage to ecosystem productivity from nitrogen loading and compounding uncertainty along the nitrogen cascade. Environmental external costs averaged about 3 trillion 2020 PPP dollars over the 2016–2023 period, with a 95th percentile of around 6 trillion 2020 PPP dollars. Expected costs of the disease burden from diets averaged 9.3 trillion 2020 PPP dollars from 2016 to 2023.

The external costs of GHG and nitrogen emissions and food consumption are products of 5 billion hectares of agricultural land use and the biological and cultural needs of 8 billion people. Poverty and undernourishment are now more concentrated in scope, so the proportion of hidden costs in global agrifood systems – mostly the external costs of global agricultural production and productivity losses from dietary patterns in global consumption – is not surprising. Most of the costs of social distributional failures are concentrated in sub-Saharan Africa, and the breakdown of these costs and trends is discussed below.

Worryingly, losses from dietary patterns trended upwards at a rate of 2 percent or so per year in 2016–2023, while costs from nitrogen and GHG emissions trended upwards at the rate of about 1 percent per year. Expected productivity losses from dietary patterns increased 14 percent over the period, in an upward trend from 8.6 trillion to 9.8 trillion 2020 PPP dollars. In 2023, the hidden cost of nitrogen emissions has an expected value of about 1.5 trillion 2020 PPP dollars, while that of GHG emissions is around 0.9 trillion 2020 PPP dollars.

Damages from land-use changes attributable to agriculture (most likely between 0.25 trillion and 0.5 trillion 2020 PPP dollars in lost ecosystem services, excluding carbon sequestration) are trending downwards due to a decline in forest conversion (deforestation) and a rise in abandoned agricultural land. From 2021 to 2023, the costs of land-use changes were predicted to flatline due to higher commodity price in the post-pandemic inflationary period.

Trends in expected costs show that external costs from environmental sources became greater for low- to middle-income countries (LMCs) than for high-income countries (HICs) over the 2016–2023 period. Environmental external costs for upper-middle-income countries (UMCs), which include China and Brazil, are almost twice those of LMCs and HICs. Environmental external costs from national agrifood systems are increasing for LMCs (including India) and UMCs and are probably decreasing or stabilizing for HICs. Productivity losses from dietary patterns are the largest category of hidden costs for all income groups except low-income countries (LICs) and increasing across all income groups. Productivity losses from dietary patterns account for 62 percent of expected hidden costs in LMCs and 75 percent in UMCs and HICs.

LICs have a distinct proportion of hidden costs compared with other income groups. Total expected costs generated by LICs in 2023 are 381 billion 2020 PPP dollars, with 36 percent of expected costs (136 billion 2020 PPP dollars) from environmental pollutants and land-use change, 14 percent from productivity lost due to dietary patterns (56 billion 2020 PPP dollars) and 50 percent from moderate poverty among agrifood workers and undernourishment (190 billion 2020 PPP dollars). The two largest costs for LICs are GHG emissions (105 billion 2020 PPP dollars) and poverty among agrifood workers (179 billion 2020 PPP dollars). Unlike the other income groups, which can be seen more clearly in the country-level hidden costs below, only a small proportion of costs (15 billion 2020 PPP dollars) in LICs are associated with nitrogen pollution.

The costs of moderate poverty among agrifood workers and undernourishment surged for all income groups during the COVID-19 pandemic in 2020, and World Bank and Food and Agriculture Organization of the United Nations (FAO) projections expect them to resume a downward trend. World Bank analysis shows that government intervention prevented an expected large increase in poverty in some countries. In terms of total income shortfall from the 3.65 PPP 2017 dollar poverty line, LMCs' shortfall had been decreasing at the fastest rate prior to the COVID-19 pandemic and was most shocked by it in 2020. LICs remain unchanged on poverty alleviation, in part due to the concentration of the extreme poor in fewer countries with entrenched poverty. LMCs have double the total income shortfall of LICs, but nearly three times the population. Per capita, LICs bear the highest burden in terms of moderate poverty and undernourishment, with a recent non-decreasing trend.

Comparing the hidden costs of agrifood systems per capita with GDP PPP per capita in 2020 reveals that LICs bore the highest burden. The hidden costs of agrifood systems in LICs were equivalent to 27 percent of GDP PPP per capita. In HICs, the hidden costs of agrifood systems were equivalent to 8 percent of GDP per capita, predominantly from productivity lost as a result of dietary patterns.

Regional hidden costs and trends

FAO chose eight regions to complement the breakdown of agrifood systems hidden costs by World Bank income group. Productivity losses resulting from dietary patterns and the costs of nitrogen and GHG emissions remain the largest environmental costs at regional level, except in sub-Saharan Africa. Eastern and Southeastern Asia, the most populous region, with 2.25 billion people in 2020, has the largest total productivity losses from dietary patterns in 2023, at 3 017 billion 2020 PPP dollars. Productivity losses in eastern and Southeastern Asia from dietary patterns in 2020 equate to 1 268 2020 PPP dollars per capita. Productivity losses from dietary patterns increased 20 percent from 2016 to 2023 in Southern Asia.

Southern Asia, Eastern and Southeastern Asia, and Latin America and the Caribbean regions have the largest environmental external costs in both absolute and relative terms (estimated at 406 billion, 780 billion and 493 billion 2020 PPP dollars, respectively, in 2023). The largest external cost components are GHG and nitrogen emissions (nitrogen emission costs are estimated at 208 billion, 539 billion and 312 billion 2020 PPP dollars, respectively, in 2023). Hidden costs from nitrogen emissions in the three regions constitute 69 percent of the global cost of agrifood systems nitrogen emissions.

Agrifood worker poverty and undernourishment in the general population remain higher economic costs to sub-Saharan Africa (285 billion 2020 PPP dollars in 2023) than productivity losses from dietary patterns (242 billion 2020 PPP dollars in 2023). Agrifood worker poverty and undernourishment remained static from 2016 to 2023 due to the COVID-19 pandemic, while productivity losses from dietary patterns are estimated to have increased 14.5 percent over the period. Assuming productivity losses from dietary patterns continue to increase at the same rate, by 2030 or earlier, productivity losses from dietary patterns in sub-Saharan Africa will be a greater cost to GDP PPP than agrifood worker poverty and undernourishment. Costs of GHG emissions remained the largest category of external environmental costs for sub-Saharan Africa (estimated at 148 billion 2020 PPP dollars in 2023). Farm-gate CH_4 emissions, CO_2 emissions from land-use changes (deforestation) and nitrous oxide (N_2O) from fertilizer production are the largest contributors to the external costs of GHGs across sub-Saharan Africa.

The countries with the highest net hidden costs generated by agrifood systems are the world's largest food producers and consumers. The United States of America (around

1.64 trillion 2020 PPP dollars), the BRIC[b] countries – in order of expected costs, China (2.67 trillion 2020 PPP dollars), India (1.17 trillion 2020 PPP dollars), Brazil (0.53 trillion 2020 PPP dollars) and the Russian Federation (0.52 trillion 2020 PPP dollars) – are the top generators of costs in 2023 and were mostly unchanged in that order in 2016–2023. For China, India, the Russian Federation and the United States of America, most hidden costs stem (more than 75 percent) from dietary patterns. Brazil is the exception, with 45 percent of hidden costs being external costs from environmental sources. As a bloc, the European Union Member States would appear in third position, with total agrifood systems hidden costs of 1.82 trillion 2020 PPP dollars in 2023, of which 284 billion 2020 PPP dollars are from environmental sources and 1.54 trillion 2020 PPP dollars (84 percent of total costs) are productivity losses from dietary patterns.

Nitrogen emissions are the largest class of environmental external cost for all of the countries with the highest agrifood systems hidden costs. China (estimated 375 billion 2020 PPP dollars in 2023), Brazil (estimated 161 billion 2020 PPP dollars in 2023), India (estimated 144 billion 2020 PPP dollars in 2023) and the European Union (estimated 130 billion 2020 PPP dollars in 2023) have the largest external cost production – and likely cost bearing – from nitrogen emissions from agrifood systems. In the United States of America, the expected costs of nitrogen emissions (60 billion 2020 PPP dollars) and GHG emissions from agrifood systems (56 billion 2020 PPP dollars) are comparable. These figures are expected values and skewed towards higher damages for nitrogen emissions due to the larger degree of uncertainty involved.

In terms of risk, the tail of hidden costs is "fatter" for China than the United States of America due to large quantities of reactive nitrogen in surface waters from the runoff from agricultural land and human sewerage, and the uncertainty inherent in external costs. Using the 95th percentile of hidden costs as a risk indicator, China's economic risk from agrifood systems activities is up to two times higher than expected values (a 95th percentile of 4 trillion 2020 PPP dollars net hidden costs and a 95th percentile of 1.6 trillion 2020 PPP dollars for nitrogen emissions estimated for 2023). The economic risk in China from external nitrogen pollution is 10 times larger than in the United States of America (a 95th percentile of 2.3 trillion 2020 PPP dollars in net hidden costs and a 95th percentile of 147 billion 2020 PPP dollars for nitrogen emissions estimated for 2023, respectively). Expected value as a measure of central tendency can be sensitive to outliers. Using the median as a central measure, China has larger hidden costs (median 2023 hidden costs of 2 518 billion 2020 PPP dollars) than the United States of America (median 2023 external costs of 1 602 billion 2020 PPP dollars). Median external costs of agrifood systems nitrogen emissions in 2023 were almost three times higher in China (112 billion 2020 PPP dollars) than the United States of America (40 billion 2020 PPP dollars).

Farm-gate CH_4 emissions (Brazil, China, India, Pakistan and the United States of America), CO_2 emissions from deforestation (Brazil, Colombia, the Democratic Republic of the Congo and the United Republic of Tanzania) and CO_2 emissions from fertilizer production, manufacturing, retail and consumption (pre-and post-farm gate) in China, Germany, India, Iran, Japan, the Russian Federation and the United States of America are the predominant forms of emission contributing to external costs.

N_2O farm-gate emissions add to the significant costs of other forms of nitrogen pollution in Brazil, China, India and the United States of America. The external costs of N_2O and methane (CH_4) outweigh the costs of CO_2 emissions in many of the largest producers (Argentina, Brazil, China, India, Mexico, Pakistan and the United States of America). Deforestation for agricultural land expansion, in the form of conversion of forest habitat to cropland and

[b] BRIC = Brazil, Russian Federation, India and China.

pasture, is the predominant contributor to external costs from land-use change. Ammonia agrifood emissions (NH_3) and nitrate (NO_3) emissions to surface waters from agricultural runoff produce the main nitrogen costs in all of the countries with high external costs of agrifood nitrogen emissions. NH_3 emissions dominate in areas such as western Europe that already have regulations on nitrogen oxides (NOx) emissions and nitrates in surface waters.

Economic indicators

The largest agricultural producers and food consumers are expected to have the highest external costs. Additional comparison of regions and countries can involve economic ratios. If the gross value added (GVA) of agrifood systems activities for countries is available in PPP terms, the external costs can be divided by the GVA to obtain a basic cost–benefit measure. The United States of America publishes headline figures for agriculture, food manufacturing and food retail value added. Using the figures for 2021, US food and agricultural sector value added was 1.2 trillion 2020 PPP dollars and expected US food-sector hidden costs were 1.6 trillion 2020 PPP dollars, yielding a ratio of 1.33. Every 1 2020 PPP dollar in value added generated by the US food and agricultural sector produced 1.33 2020 PPP dollars in expected external costs.

Few other countries publish comparable value-added figures for agrifood systems. As a proxy, we use three measures for agrifood systems based on the nature of market failure and cost production source: i) agricultural production and land use to agricultural GVA; ii) productivity losses from dietary patterns to total productivity from labour; and iii) agrifood workers in moderate poverty and productivity losses from undernourishment in the moderately poor compared with the mean income of the moderately poor. The indicators interpret this as gross hidden cost – visible benefit ratios of agrifood systems. High values imply disproportionate cost-bearing from pollution, land-use change, dietary patterns and so on compared with the value of the agrifood goods and services enabled by the production of pollution, habitat loss, obesity and the like.

We link agricultural activities with the external costs of GHG emissions from the farm gate and land-use change, land-use transition to and from cropland and pasture, and blue water consumption. We divide the external costs of agricultural activities by agricultural, forestry and fishing (AFF) GVA in PPP terms, which is available for all countries in the study. We call this ratio the agricultural externalities impact ratio (AEIR). To minimize the influence of outliers, AEIR is calculated using expected external costs and AFF GVA averaged over 2016–2020.

The global AEIR is 0.31, indicating that 0.31 2020 PPP dollar of external cost is generated for every 1 2020 PPP dollar of agricultural value added. On average, a hectare of agricultural land globally produces 473 2020 PPP dollars of external costs and 1 532 2020 PPP dollars of GVA.

HICs generated approximately 11 percent of global AFF GVA PPP in 2020, but produced approximately 24 percent of external costs from agricultural production and land use and land-use change (LULUC). The AEIR for HICs is 0.76 (0.76 2020 PPP dollar in external costs for every 1 2020 PPP dollar of AFF GVA PPP) compared with an AEIR of 0.35 for UMCs, 0.17 for LMCs and 0.36 for LICs. The risk that developed countries are generating additional economic damage is higher: the 95th percentile of the AEIR for HICs is 1.22 compared with 0.87 for UMCs, 0.35 for LMCs and 0.74 for LICs. This contrast is apparent at country level, where the AEIR of China is 0.21 compared 1.14 for the United States of America. China has larger external costs of agricultural production, but China's AFF value added to GDP PPP is eight times larger than that of the United States of America. LMCs produce lower external costs for value added in agriculture according to the AEIR indicator. India has an AEIR of 0.13.

Regionally, Latin America and the Caribbean, Europe and North America have high AEIR indicators. There is little confidence in indicators for Oceania due to the uncertainty inherent in the net value of habitat loss and habitat return from land-use change. The Americas have the highest AEIR. Asia and Africa have the lowest AEIR. Southern Asia's AEIR of 0.14 is roughly half that of sub-Saharan Africa, at 0.28, not because the agricultural sector is less important in GDP PPP terms to sub-Saharan African economies, but because of their combination of low agricultural productivity and relatively high production of GHG emissions from farms and land-use change.

The largest producers and consumers of food do not have the highest AEIR indicators for 2020 among the 154 countries studied. The United States of America ranks 20th and Brazil ranks 17th on the AEIR indicator. A range of African and European countries rank highest: Botswana, the Central African Republic, the Democratic Republic of the Congo, Lesotho, South Sudan and Zambia all have an expected value of hidden costs greater than 2 2020 PPP dollars for every 1 2020 PPP dollar of agricultural value added. The European countries of Belgium, Denmark, Ireland and the United Kingdom of Great Britain and Northern Ireland have a higher AEIR indicator than the United States of America. Up to 2 2020 PPP dollars of external costs are generated for every 1 2020 PPP dollar of agricultural value added in Ireland and the United Kingdom of Great Britain and Northern Ireland. This indicates intensive use of agricultural inputs, particularly nitrogen emissions, for sectors that provide a low percentage of total GDP PPP.

The AEIR is an indicator of production. For consumption, dividing productivity losses from dietary patterns by national or regional GDP PPP forms an indicator we call the dietary patterns impact ratio (DPIR). The global DPIR is 0.072, indicating that global productivity losses from dietary patterns are equivalent to 7.2 percent of global GDP PPP in 2020. The DPIR indicator for LICs is about 0.04 compared with 0.09 for UMCs. The DPIR is in the range of 5–10 percent of regional GDP PPP across all regions, underscoring the global syndemic of obesity and NCDs from dietary intake. Sub-Saharan Africa had the lowest economic burden from dietary patterns in 2020, at 0.055. Southern Asia, however, is not largely different from Eastern and Southeastern Asia, with DPIR indicators of 0.072 and 0.075, respectively. Europe has the highest DPIR indicator, at 0.081.

Though China and the United States of America are among the world's largest food consumers, they both rank below 20th place among the 154 countries studied, with DPIR indicators of 0.09 and 0.064, respectively. India's DPIR is 0.072.

Eastern European countries rank highest on the DPIR indicator for 2020. Productivity losses in Belarus, Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, the Republic of Moldova, Poland, Serbia, Slovakia and Ukraine are equivalent to 15–30 percent of GDP PPP and more than twice the European Union and HIC average. Countries with a high DPIR risk damping economic growth with diets that are too high in calories, sugar, salt and transfats and insufficiently high in wholegrains, nuts and seeds, and fruit and vegetables.

As an indicator of distributional failure, we assume that a loss of productivity from undernourishment is experienced by the moderately poor. Therefore, both the income shortfall of agrifood systems workers in moderate poverty and productivity losses from undernourishment are considered impediments to moderate poverty alleviation through negative income effects. We divide their combined costs by the total national income of the moderate poor to form an indicator called the social distribution impact ratio (SDIR). The global SDIR is 0.31, indicating net costs of moderate poverty in agrifood workers and productivity losses from protein–energy malnutrition in the moderate poor, equivalent to 31 percent of the net global income of the moderately poor. Southern Asia and sub-Saharan Africa are the regions with the highest number of people in moderate poverty. At a regional level, the SDIR indicator largely follows income levels and the structure of economies.

Despite having similar net poverty costs, the SDIR indicator for southern Asia is half that of sub-Saharan Africa. The SDIR indicator for southern Asia is comparable to that of other regions, at 0.24, while sub-Saharan Africa has the highest SDIR, at 0.53, indicating a large intersection between agrifood systems and moderate poverty.

Discussion

Annual external costs from agrifood systems nitrogen emissions are estimated, up to the modelled uncertainty, to be of the same order as or to exceed agrifood systems GHG emissions at global and regional level and in the largest food-producing countries. Given the emphasis on agrifood GHG emissions in international forums, this finding may be surprising. Explanations include the fact that the large degree of uncertainty surrounding nitrogen emissions arises from a high degree of uncertainty in the estimates of the value of ecosystem services, the lack of spatially explicit data on the damage to ecosystem service productivity from nitrogen loading, and the compounding of uncertainty in the cost modelling along the nitrogen cascade.

Uncertainty modelling for GHG costs has been limited to a more prescriptive parameter substitution in economic integrated assessment modelling. Most nitrogen damage costs occur in the near future compared with GHGs, so discounting has a greater effect in reducing the present value of GHG costs. The losses to GDP of future emissions have also not been modelled in PPP terms, which reduces the GHG cost estimates. This study uses social costs of GHGs, which account for carbon markets and taxes that internalize damage costs into the future through GHG abatement. No similar instruments are on the horizon for nitrogen emissions. Despite the uncertainty in the modelling and the differences in cost estimation, it is more than likely that the magnitude of the present value of external costs of nitrogen emissions and GHG emissions is of the same order.

It should be emphasized that the estimates are for the damages of nitrogen emissions; the value of nitrogen fertilizer to the global economy and feeding the global population compared with the damages it produces while providing those benefits are subsequent considerations. The social costs of nitrogen emissions have not attracted the same scientific or policy attention as GHGs and are more difficult to calculate than the social costs of GHGs. The difference in damages and social costs can be marked. China is the world's largest agricultural nitrogen polluter and, in mean terms, the estimated costs of reactive nitrogen runoff are the largest component of external costs from production. However, on a value-added basis, when the external costs are compared with the value added of agricultural production in PPP terms, China produces a mean of 0.21 2020 PPP dollars in external costs for every 1 2020 PPP dollar of value added. Another significant agricultural nitrogen polluter, the United States of America, produces a mean of 1.15 2020 PPP dollars in external costs for every 1 2020 PPP dollar of value added.

In central sub-Saharan African countries, the production of external costs in the order of 2–5 2020 PPP dollars for every 1 2020 PPP dollar of value added indicates an urgent need for development and an investment focus on sustainable intensification. The agricultural sector should increase its contributions to GDP PPP while rapidly improving efficiency in terms of GHG emissions and land-use through technology, better infrastructure and access to high-quality fertilizer, as well as improvements in education and farm and land management practices. Countries with a high AEIR and a high percentage of AFF in overall GDP are at risk of damping economic growth and development by bearing the future economic burden of the external costs generated now by their agricultural activities.

Globally, this study and previous studies on the "true" costs of agrifood systems highlight the expected losses brought about by GHGs from agrifood activities; the air pollution and reduced ecosystem services arising from the change to the nitrogen cycle caused by the global application of synthetic fertilizers and increase in intensive livestock production; and the extensive productivity losses from dietary patterns in both the developing and developed world. Collectively, the costs are equivalent to around 10 percent of global GDP PPP and are increasing in line with GDP PPP growth – faster in developing regions.

On the surface, both nitrogen emissions and dietary patterns appear to offer joint negative abatement costs. Nitrogen use efficiency and the over-application of fertilizers implies that producers can save on nutrient input costs without sacrificing yield. Similarly, dietary change will result in better health for consumers and, in a developed world context, potential savings on food expenditure. A large body of literature exists on cost-effectiveness in public health interventions for obesity. Global growth and development could be boosted by a cost-effective reduction in damage. Despite the benefits of reducing the hidden costs of agrifood systems, production of the quantities associated with the largest costs continues to increase and hidden costs are trending upwards. Agrifood systems are not decoupling value production from the increasing economic risk of its impacts. For policymakers, policies to reduce the increasing economic risk posed by agrifood systems activities appear to remain challenging and characteristically different from the decarbonization pathway demanded of other sectors.

1 Introduction

A new model of the marginal external damage costs to national GDP PPP of agrifood systems developed at the University of Oxford Environmental Change Institute for the Food System Economic Commission has been paired with data from FAO and other sources on national agrifood systems' annual production of GHG emissions,[1, 2] nitrogen emissions,[3–6] land-use transitions to and from cropland and pastureland,[7–9] blue water withdrawals, the burden of disease from dietary patterns,[10–15] the prevalence of undernourishment (POU) (insufficient calories as defined by FAO)[16–19] and the number of agrifood systems workers in moderate poverty (below the 3.65 2017 PPP dollar per day international moderate poverty line defined by the World Bank).[20–22] This has enabled the estimation of "hidden costs" of agrifood systems at a national level for 154 countries by pairing quantities of emissions, land-use change and so on against their present value (in 2020 PPP dollars) per unit cost to GDP PPP in the year of emission, land-use change and so on and in future years.[23–31] Annual hidden costs are the net present value (NPV) cost of all such damaging activities of agrifood systems within the same year. Trends in annual hidden costs are estimated from 2016 to 2023 and examined at the global, regional and country level, as well as in World Bank income groups.

Previous studies have estimated annual hidden costs, or the "true costs", of agrifood systems at a global level using global average cost factors such as global GDP per capita and global average values for ecosystem services.[24, 27, 32, 33] This study uses the SPIQ-FS model of marginal external damage costs for hidden cost production at a national level based on GDP PPP losses.[34–38] Even though GDP PPP is an incomplete economic measure of social welfare,[39–44] measuring hidden costs in GDP PPP damages complements welfare studies by i) being comparable to national accounts such as the GVA of agriculture in PPP terms, and ii) being comparable to national expenditure aimed at reducing GHG emissions, nitrogen emissions, habitat loss through land-use change, malnutrition and poverty reduction. This study estimates costs at a national and regional level for 154 countries and considers real and projected costs from 2016 to 2023. The SPIQ-FS model uses random variables to represent large uncertainty in non-market unit cost calculations due to a lack of knowledge of the impact of agrifood systems activities on ecosystem services and other components of natural and human capital.[45] Previous studies have considered error bars on global hidden costs. This study estimates the economic risk of the hidden costs of agrifood systems by considering the probability distributions of national GDP PPP per unit of loss.

The annual hidden costs in this study do not reflect the GDP PPP loss that may be avoided by transitioning to more sustainable agrifood systems. Hidden costs for present agrifood systems equivalent to 10 percent of global GDP PPP in 2020 do not mean that counterfactual sustainable agrifood systems, COVID-19 pandemic notwithstanding, would have avoided the hidden costs and boosted global GDP PPP in 2020 by 10 percent. It is important to emphasize that the hidden costs of present agrifood systems may be avoidable, but that hidden cost damage estimates do not indicate the costs of transitioning to alternative agrifood systems. Subsequent studies are needed to compare the costs and benefits of alternative agrifood systems that reduce hidden costs.[27]

2 Concepts and methodology

KEY MESSAGES

- The model estimates, for a total of 154 countries over 2016–2023, the annual hidden costs of agrifood systems affecting environmental pathways (from GHG and nitrogen emissions, land and water use), health as a result of dietary patterns, and social pathways from undernourishment and moderate poverty.
- Hidden costs are measured in 2020 PPP dollars, or the equivalent amount of a basic goods basket that one dollar, once exchanged to local currency, would have purchased in a country in 2020. The consumption of these goods represents welfare and, consequently, hidden costs represent the loss in welfare brought about by reduced purchasing power, driven by losses in productivity.
- Hidden costs are calculated by multiplying emissions and other quantities associated with agrifood systems externalities and market failures (that is, impact quantities) over 2016–2023 against their marginal damage cost (that is, unit cost) to GDP PPP.
- Being at country level and presented as a monetary measure comparable to damage to GDP, the hidden costs can be aggregated at global, regional and income level and compared with macroeconomic indicators.

Annual costs and trends in these costs are calculated by multiplying emissions and other quantities associated with externalities and market failures attributable to agrifood systems in the years 2016–2023 (called impact quantities), against their per unit cost to GDP PPP (marginal damage cost) in the given and future years. Quantities (Table 1) and their marginal damage costs are estimated at a national level (Annex 2) for 154 countries (Annex 4), multiplied together (Annex 1) and then aggregated to obtain regional and global totals (Annex 3).

Data files showing the country quantities, the marginal costs and totals are available at Lord (2023).[46]

Damage costs to GDP PPP for all countries are measured in 2020 PPP dollars.[47, 48] Purchasing power parity represents the equivalent amount of a basic goods basket that one dollar, once exchanged to local currency, would have purchased in that country in 2020. Beyond a comparison of damage costs to the national accounts, PPP, as a limited welfare measure, represents welfare provided by the consumption of the basic goods basket. Damage costs measured in 2020 PPP dollars represent the reduction in welfare due to reduced purchasing power, while avoided damage costs represent the benefit from an avoided reduction in welfare.

TABLE 1 Impact quantities disaggregated into cost items with attached marginal costs

Cost category	Item	Impact quantity	Cost type	Marginal cost	Capital change
Climate	GHG emissions (CH_4): farm-gate emissions	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (CH_4): land-use change	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (CH_4): pre- and post-production	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (CH_4): farm-gate emissions	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (CH_4): land-use change	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (CH_4): pre- and post-production	CH_4 metric tonne	E	Social cost of CH_4 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (CO_2): farm-gate emissions	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (CO_2): land-use change	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (CO_2): pre- and post-production	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N

TABLE 1 (cont.) **Impact quantities disaggregated into cost items with attached marginal costs**

Cost category	Item	Impact quantity	Cost type	Marginal cost	Capital change
Climate	GHG emissions (CO_2): farm-gate emissions	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (CO_2): land-use change	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (CO_2): pre- and post-production	CO_2 metric tonne	E	Social cost of CO_2 – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (N_2O): farm-gate emissions	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (N_2O): land-use change	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (N_2O): pre- and post-production	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from agricultural losses in NPV at the optimal amount of abatement, attributed to the country of emission	N
Climate	GHG emissions (N_2O): farm-gate emissions	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (N_2O): land-use change	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O
Climate	GHG emissions (N_2O): pre- and post-production	N_2O metric tonne	E	Social cost of N_2O – residual damages to global future GDP PPP from mortality in NPV at the optimal amount of abatement, attributed to the country of emission	O

TABLE 1 (cont.) **Impact quantities disaggregated into cost items with attached marginal costs**

Cost category	Item	Impact quantity	Cost type	Marginal cost	Capital change
Water	Blue water withdrawal: agricultural use	Cubic metre	E	Agricultural losses and productivity losses in the country of withdrawal due to the burden of disease from protein–energy malnutrition, in the present and future in NPV, due to water deprived from economic use	N
Land	Land-use change: abandoned cropland to Forest	Effective hectares of lost of ecosystem services (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	N
Land	Land-use change: abandoned cropland to unmanaged grassland	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future returned ecosystem services in NPV in the country of land-use transition due to the recovery or re-establishment of ecosystem	N
Land	Land-use change: forest to cropland	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to the destruction or degradation of forest ecosystem	N
Land	Land-use change: forest to pasture	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to the destruction or degradation of forest ecosystem	N
Land	Land-use change: pasture to forest	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future returned ecosystem services in NPV in the country of land-use transition due to the recovery or re-establishment of ecosystem	N
Land	Land-use change: pasture to unmanaged grassland	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future returned ecosystem services in NPV in the country of land-use transition due to the recovery or re-establishment of other land ecosystem	N
Land	Land-use change: unmanaged grassland to cropland	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to the destruction or degradation of forest ecosystem	N

TABLE 1 (cont.) **Impact quantities disaggregated into cost items with attached marginal costs**

Cost category	Item	Impact quantity	Cost type	Marginal cost	Capital change
Land	Land-use change: unmanaged grassland to pasture	Effective hectares of lost of ecosystem services (ha)	E	Value of equivalent hectares of present and future lost ecosystem services in NPV in the country of land-use transition due to the destruction or degradation of other land ecosystem	N
Nitrogen	NH_3 emissions to air	NH_3 N-kg	E	Productivity losses in the country of emission due to the burden of disease from particulate matter formation	O
Nitrogen	NOx emissions to air	NH_3 N-kg	E	Agricultural and ecosystem service losses from nutrient imbalance and the acidification of terrestrial biomes due to deposition, ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to deposition runoff	N
Nitrogen	NOx emissions to air	NOx N-kg	E	Productivity losses in the country of emission due to the burden of disease from particulate matter formation	O
Nitrogen	NOx emissions to air	NOx N-kg	E	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, wetland and coastal systems due to deposition runoff	N
Nitrogen	NO_3- leached to groundwater	NO_3- N-kg	E	Productivity losses in the country of emission due to the burden of disease from human nitrate intake	O
Nitrogen	NO_3- loads due to runoff from agricultural land to surface water	Nr N-kg	E	Ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to runoff	N
Nitrogen	NO_3- loads due to effluent or human sewerage in surface water	Nr N-kg	E	Ecosystem services losses from nutrient imbalance, acidification and eutrophication of riverine, wetland and coastal systems due to runoff	N

▸▸

TABLE 1 (cont.) **Impact quantities disaggregated into cost items with attached marginal costs**

Cost category	Item	Impact quantity	Cost type	Marginal cost	Capital change
Poverty	Agrifood systems worker poverty headcount at 3.65 a day 2017 PPP dollars	Per person	S	Cost in PPP terms of the income shortfall below the moderate poverty line of agrifood workers	O
Undernourishment	Number of undernourished	Per person	S	Productivity losses in the country of consumption due to the burden of disease from protein–energy malnutrition	O
Dietary patterns	Burden of NCDs and high BMI attributable to dietary patterns (food consumption)	Burden of disease in DALYs	H	Productivity losses in the country of consumption due to the burden of disease from high BMI and NCDs	O

Notes: Cost type refers to external cost from environmental sources (E), productivity loss from dietary patterns (H) and cost of distributional failures (S). Capital change refers to costs arising from predominantly natural (N) or predominantly other (O) capital changes in the impact pathway. GHG – greenhouse gas; GDP – gross domestic product; PPP – purchasing power parity; NPV – net present value; NCDs – non-communicable diseases; BMI – body mass index; DALYs – disability-adjusted life years.

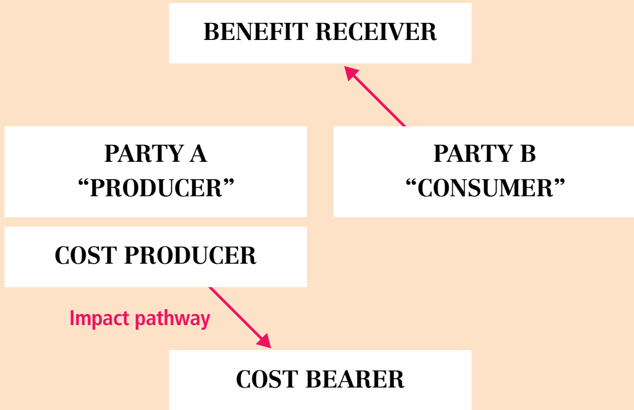
Source: Author's own elaboration.

2.1 Cost bearing and scope of hidden cost production by agrifood systems

External costs or costs from market failures (hidden costs in the terminology of Gaupp *et al.* [2021])[24] involve additional costs or benefits not captured in the private costs and benefits of market transactions.[40–45, 47–49] For externalities, the additional costs and benefits are borne or received by third parties. Cost production occurs from the activities of the parties to the transaction, which, in the case of distributional failures, may be multiple transactions in the value chain and value-chain actors. As an example of imperfect information,[50] consumers make decisions to account for the longer-term health of food consumption, and the cost bearer or benefit receiver is one of the parties when costs or benefits are revealed at a later time.

Figure 1 depicts the difference between cost producer, cost bearer and benefit receiver. Cost producing, cost bearing and benefit receiving can cross national borders and time. The example of international and intergenerational cost bearing from the production of GHGs is an example of spatiotemporal separation between cost producer and cost bearer.[51–56] The flow of returns to financial investors in fossil-fuel energy,[57] GHG-intensive livestock production[58, 59] and construction,[60] while the financial industry itself has low GHG emissions, are examples of the separation between cost production and benefit receiver. The transfer from cost production (such as polluting) to cost bearing is sometimes referred to in environmental assessments as an "impact pathway".[61]

FIGURE 1 Welfare economics recognizes additional costs and benefits in imperfect markets not factored into market costs and benefits



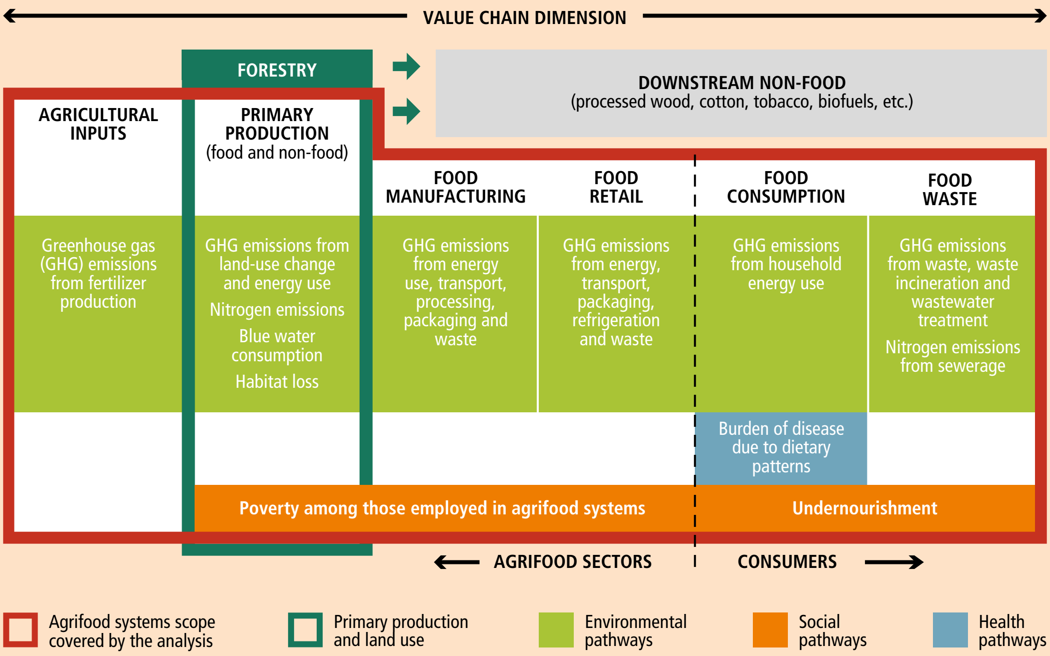
Notes: A cost bearer may be a third party or a party to the transaction at a later time. The benefit receiver here receives additional benefits due to the cost bearing of the cost bearer. Party A, party B or both may be cost producers or benefit producers due to their activities. The classical example is external costs of pollution in the production of goods, where damages caused by pollution are not included in the costs of production for A. The buyer B purchases at a lower price, enabling lower production costs and higher profit from the sale of B's own goods, which increases returns to investors, among benefit receivers. The cost bearer of pollution from A has paid for free benefits to the investor of B. The complex path from the production of pollution such as GHGs to the bearing of costs by economic actors in a future economy is one of the challenges in estimating agrifood systems external costs and the costs of market failures.

Source: Author's own elaboration.

Figure 2 and Table 1 characterise quantities associated with hidden cost production within the scope of agrifood systems. The quantities included are not exhaustive; other studies have included costs of antimicrobial resistance from the use of antibiotics in livestock production, productivity losses arising from lost pollination services due to pesticide use, and the attribution of distributional issues, such as living wages and micronutrient undernourishment in addition to chronic caloric undernourishment.[24, 27, 32, 33] For the first version of the SPIQ-FS costing model, there were no consistent spatial datasets available to derive annual average marginal costs to GDP PPP at a national level for additional units of antibiotic use or pesticide use.

Simplifying assumptions are needed to interpret the produced costs in this study in terms of national cost bearing. Transborder effects in cost models are simplified or ignored. For example, productivity losses arising from over-consumption or NCDs ignore future migration and travel. Consumption in country creates productivity loss in country. The cost bearing of climate change is assumed to be transferred to the country of emission by future damage and loss payments to cost bearers.[62, 63] Blue water consumption creates future water scarcity in the same country. Air pollution and the deposition of volatilized nitrogen species occurs in national boundaries. Ecosystem service losses from habitat loss occur in the same country as the habitat loss. These limitations are discussed in the current SPIQ-FS version 0 documentation. Later studies should improve the modelling of nitrogen and water scarcity external costs and help to understand transfers from cost-producing to cost-bearing countries.[64] To understand attribution and equity between cost bearers and the beneficiaries of cost bearing,[65] more data are required globally on the distribution of benefits across value chains for agrifood systems, potentially broadening the scope of financial flows to financers and investors. While there are new models of global multiregional physical flows for food systems,[66] the understanding of financial flows needed to attribute damage and loss in the presence of foreign ownership and international trade is still limited to certain value chains.[67]

FIGURE 2 Quantities associated with the production of hidden costs and market failures characterized by value chain activity and actors in agrifood systems



Notes: The definition of agrifood systems follows that of FAO (2021),[82] with the exception of the inclusion here of (non-food) input supply chains, such as fertilizer and pesticide. The scope of agrifood systems for this study is defined by the solid red border. Quantities from Table 1 are mapped to the scope. GHG emissions from energy use by the agricultural sector are excluded from the agricultural, forestry and other, land use and land-use change (AFOLU) scope by the Intergovernmental Panel on Climate Change (IPCC). Agrifood systems value chains exclude inputs, GHG emissions, nitrogen surplus, blue water use and consumption, and habitat loss associated with non-food agricultural commodities such as tobacco, cotton and biofuels. Value chain distribution refers to both physical and financial distributional failures: income shortfall from moderate poverty lines for agrifood workers despite order-of-magnitude higher retail revenues for food products, and caloric deficiency despite large surpluses in available global calories. Other studies have considered additional quantities, such as externalities from the use of antibiotics in livestock production, the use of pesticides, and further distributional effects, such as lower-than-living wages in manufacturing and retail, and the costs of healthy diets. Characterization of the production of external costs and market failures by sector of economic activity and economic actors does not imply attribution of damages. Attribution of damage costs should follow benefits proportionally. Large external costs associated with GHG emissions and nitrogen surplus from agricultural production, and habitat loss from agricultural land expansion, are due to the activity of farmers, but the benefits of food production are distributed throughout the value chain. As an example, cocoa farmers receive 6–8 percent of the retail sale value of cocoa products.[83] Private or public policies to reduce quantities at the point of production and thereby reduce damages may have their own distributional effects if the costs of mitigation do not transmit proportionally to benefits in the value chain. The agrifood systems scope limits proportional attribution in the value chains of non-food commodities (attribution to the production of health impacts of tobacco consumption and labour impacts in the fashion industry, and the attribution of agricultural production externalities to tobacco companies and fashion retailers). For counterfactual cost–benefit studies, the scope misses out post-farm-gate changes in external costs from shifts in non-food agricultural production and inputs, and land-use change interactions with forestry as a competing land user.

Source: Author's own elaboration.

The global economy is a cost producer, cost bearer and benefit receiver. For global estimates of the hidden costs of agrifood systems, the distinction between cost bearer, cost producer and attribution of costs proportional to benefits received does not arise. This study considers **national cost bearing** up to caveats of determination from national cost production, as indicated in the last paragraph (the simplification that cost production and cost bearing are the same), and then aggregates cost bearing at a regional and global scale. Responsibility for costs, in terms of attributing compensation for cost bearing among beneficiaries, is beyond the scope of this study.

A final conceptual dimension for this study is the capital changes involved in the impact pathway from cost production to cost bearing (Figure 1).[61]

Hidden costs face the ambiguity of being classified by either cost production, cost bearing or by the major components of the impact pathway leading to cost bearing, for example, productivity losses from obesity and NCDs due to dietary intake by consumers. Population studies are required to understand the burden of disease,[68, 69] so the cost bearing is productivity loss as an input to a national economic output in GDP PPP terms. The cost bearer is "society" through the national economy. Food consumption, as the cost producer, is a human activity. Vulnerability and changes in human capital in response to disease burden is the major component of the impact pathway between consumption and national productivity loss. Labour is the primary factor of cost bearing. Human food consumption–human capital–labour productivity is the primary axis from cost production to cost bearing. Referring to this hidden cost as the "health costs of food consumption" with the emphasis on cost production is inaccurate, as there are more costs than productivity losses from the burden of disease.[70] Referring to this hidden cost as "productivity losses from unhealthy diets" with the emphasis on cost bearing is also ambiguous, as diets require food products, and productivity losses occur from other health impacts in food production,[71] and they might also refer to productivity losses from undernourishment.[17] "Costs of obesity" with an emphasis on human disease as the major component of the impact pathway, too, is ambiguous. Other factors besides dietary intake influence the outcomes of obesity, and productivity losses are not the only costs.[72] Despite inaccuracies, productivity losses from obesity and NCDs from national food consumption are broadly classified as productivity losses of dietary patterns and it is implicit that change in human capital is the main intermediatory in the impact pathway.

Classifying the losses to future GDP PPP from present GHG emissions as a result of the changing climate or the losses to present and near-term GDP PPP from nitrogen emissions is more problematic. In the case of agricultural nitrogen emissions, the cost production is an environmental pollutant. The impact pathway of volatilized NH_3 involves air pollution,[73] for which the major component is exposed human capital, leading to national productivity losses.[74] The impact pathway of volatilized NH_3 also involves deposition on land and aquatic systems and runoff from inland aquatic systems to export to coastal ecosystems.[75, 76] Agricultural and natural ecosystems are among the major components of cost for the deposition pathway, creating income and ecosystem service losses.[77] Ecosystem services have complex connections, ultimately, through further natural and human capital changes to produced capital and factors of productivity at the scale of national GDP PPP.[78] Categorizing the external costs of NH_3 pollution as an environmental hidden cost refers only to cost production. Cost-bearing and the mechanisms leading to cost bearing involve multiple forms of capital and realizations of cost into a present and future national economy.

In this study, we use a primary classification by cost production in Table 1. Reducing the hidden costs of agrifood systems by mitigating quantities (cost production) is often the first best policy.[79] A secondary classification based on major capital components in impact pathways is employed for national indicators of cost bearing, introduced in Section 4.[80, 81] Though imperfect, it was considered helpful to policymaking on agrifood systems impacts associated with agricultural activities that classification be further separated by cost bearing arising from predominantly agricultural or natural capital impacts, or other, mainly human, capital impacts. Existing or new policy that influences the major components of the pathway to cost bearing may also be effective, as well as understanding the relative need or relative expenditure between natural or human capital interventions.

2.2 Impact quantities

Quantities associated with hidden cost production within the scope of agrifood systems are referred to as impact quantities in this study (Figure 2 and Table 1). Impact quantity data for 2016–2023 are reported by countries and modelled. Data were obtained from 2014 to 2020 for 154 countries. Missing data for 2014–2020 were interpolated using moving average or regional change rates. Data for 2021–2023 were extrapolated alongside GDP and other exogenous macroeconomic indicators using vector autoregression methods due to the COVID-19 pandemic. Data for moderate poverty and the POU used World Bank and FAO projections, respectively. Data series for land-use change and consumption disability-adjusted life years (DALYs) were only available for 2014–2019, so in this case, the years 2020–2023 were extrapolated.

GHG emissions. FAO Tier 1 CO_2, CH_4 and N_2O (direct and indirect) country-level emissions data 2014–2020 were downloaded from FAOSTAT.[84] FAO data estimate agrifood systems emissions under item codes 6669, 6516, 6517. Item 6516 attributes land-use change emissions to food production. Item 6517 attributes input emissions including energy use in synthetic fertilizer production, and post-farm-gate emissions including transport, retail and food waste disposal.[85–87] Data are converted to metric tonnes for each gas, not CO_2 equivalents.

Blue water use. Country-level blue water agricultural use data for 2014–2020 were downloaded from AQUASTAT.[88] AQUASTAT does not disaggregate crop production water use into food and non-food uses. Non-food crops utilize an estimated 5–8 percent of crop area (see Table 1 in Deepak *et al.* [2022]),[89] implying food production water use would be lower than the AQUASTAT amounts used. AQUASTAT does not estimate attributable agrifood systems water use for inputs and post-farm gate. Pre- and post-farm-gate water use would increase the attributable water use in agrifood systems.

Land-use conversion. Data on the conversion of forest and unmanaged grassland to cropland and pasture, and cropland and pasture to forest and unmanaged grassland over 2014–2019 were obtained from the global HIstoric Land Dynamics Assessment (HILDA+) land-use transitions 1km dataset.[7]

Nitrogen emissions. Impacts and the nitrogen cascade of nitrogen kilograms (N-kg) of volatilized ammonia (NH_3) and nitrogen oxides (NOx), and N-kg of leached or runoff reactive nitrogen are costed by the SPIQ-FS marginal cost dataset. NH_3 and NOx to air from agricultural production and energy use in 2015 are obtained from the Emissions Database for Global Atmospheric Research version 5.0 (EDGARv5.0).[90–94] Amounts of N-kg runoff to surface waters and leaching to deep waters of NO_3- are calculated from IMAGE-GNM spatial datasets.[95, 96] Data used based on agriculture sector reactive nitrogen emissions include non-food use (5–8 percent crop production by land area), but do not include emissions from livestock processing (less than 1 percent of agrifood system-attributable emissions by N-kg weight) or consumer waste (7–9 percent by N-kg weight). For consumer waste N emissions, a global spatial dataset of total nitrogen exported to inland and coastal waters in 2015 from treated and untreated human sewerage was used.[97] Total nitrogen estimates for sewerage were converted into national average NO_3- estimates using a spatial dataset estimating nitrate within total nitrogen in inland and coastal waters.[98]

Undernourishment. Data on the POU and number of undernourished (NOU) were obtained from FAOSTAT.[99] The number of undernourished provides the headcount of undernourished in each country in the years 2014–2020. Sufficient calories are available worldwide for zero hunger. The POU indicates a failure in distribution of available supply. Undernourishment is attributed as an impact or failure of agrifood systems.

Poverty. Data on poverty gaps and the headcount of moderate poverty at the 3.65/day 2017 PPP dollar income poverty line were obtained from the World Bank.[100] Country-level estimates of the share of agrifood systems workers in total employment were obtained from Davis *et al.* (2023).[101] The share of agrifood systems workers in total employment is used as a proxy for the share of agrifood systems workers in moderate poverty. The proxy is an underestimate for most countries with high levels of moderate poverty, as evidence suggests that agricultural workers make up the predominant share of agrifood systems workers and have a higher share of workers in poverty than other sectors.[102] Value added in in the US food manufacturing and food retail sectors alone was about 800 billion 2020 PPP dollars.[103] Globally, expenditure on food is estimated at 9 trillion 2020 dollars in nominal terms.[32] Poverty among agrifood systems workers was attributed as an impact or failure of agrifood systems due to the predominant share of poor workers worldwide in agricultural and agrifood systems activities, and an inability of workers to access or negotiate markets for a proportional share of value added in agrifood systems value chains.

Dietary patterns. Diets low in fruit, vegetables, nuts, wholegrains, calcium and protective fats and diets high in sodium, sugar-sweetened beverages, saturated fats and processed meat have been associated with preventable morbidity and mortality in national populations from neoplasms (cancers), cardiovascular disease and type II diabetes.[14] The burden of preventable morbidity and mortality on human capital is measured in DALYs. DALY estimates from dietary risks for each country for 2014–2019 were accessed from the Global Burden of Disease (GBD) study.[104] Similarly, diets in excess of recommended caloric intake based on age, sex and height and the eating of foods causing the impairment of metabolic functioning have contributed to the human burden of disease through high body mass index (BMI).[10] DALY estimates for high BMI for 2014–2019 for each country were accessed from the GBD study.[104] The GBD study uses mediation factors to avoid double attribution of DALYs to both high BMI and dietary factors such as diets low in wholegrains and diets high in sugar-sweetened beverages.[105, 106] Both factors share common intake factors, as well as metabolic pathways, leading to disease outcomes. Mediation factors were used to calculate DALYs due to dietary patterns as a combination of NCDs and high BMI. The corrections for double counting means that the DALYs represent one impact quantity per country per year, and the burden of disease from obesity and NCDs attributable to dietary patterns are not treated as two separate quantities.

Another complication is attributing the burden of disease to the activities of agrifood systems actors. For GHG emissions, nitrogen emissions, blue water withdrawal and land-use change, the production of impact quantities has a clearer attribution to the economic activity of agricultural producers, food manufacturers or food retailers. Broad, but arguable attributions are made to fully attribute undernourishment and poverty among agrifood systems workers to agrifood systems, broadening the scope to include distributors, commodity markets and government through policy. Producers generally do not choose undernourishment or poverty based on preferences believed to maximize their own welfare. The attribution of dietary patterns involves consumers and consumer surplus, and factors that affect disease outcomes for consumers, such as sedentary behaviour or socioeconomic status, combined with components of dietary patterns, such as excess fat or cereal intake.[107, 108] We do not fully attribute present DALYs from high body mass index to the economic activity of agrifood systems actors, using a baseline 75 percent attribution of DALYs from high BMI to agrifood systems. Attribution of the burden of disease of dietary patterns to consumers, producers, manufacturers and retailers is debated in literature.[50, 109–112] The attribution amount was varied uniformly in uncertainty estimates between 50 percent and 100 percent.

Interpolation and extrapolation

Official data from FAOSTAT, AQUASTAT and the World Bank are often imputed, sometimes from the last reported value for countries in prior years. Estimating global quantities based on national reporting is not precise. The interpolation of data and extrapolation for this study used similar simple methods. For most datasets, 2020 is the last reported year, and extrapolation to account for the COVID-19 pandemic is challenging.

The impact of the COVID-19 pandemic on the POU and NOU is estimated in FAO's *The State of Food Security and Nutrition in the World 2022*.[113] Missing years in the headcount of undernourished data were linearly interpolated up to the latest year reported in the FAO data. To extrapolate any missing data to 2021, subregional growth rates from Table 2 in *The State of Food Security and Nutrition in the World 2022* report were applied to the latest year reported. To extrapolate after 2021, regional projected growth rates in the headcount of undernourished to 2030 using the COVID-19 scenario in Figure 6 of *The State of Food Security and Nutrition in the World 2022* report were used. Guinea, Libya, Mozambique, Palestine, Somalia, South Sudan, the Syrian Arab Republic, Uganda and Zimbabwe do not report prevalence of undernutrition. Regional prevalence of undernutrition estimates for 2014–2020 from Table 1 in *The State of Food Security and Nutrition in the World 2022* report were used as proxies for those countries.

The impact of the COVID-19 pandemic on poverty and projections to 2030 were considered by the World Bank.[114] Data on the 3.65 2017 PPP dollar per day national poverty rate over 2005–2020 were downloaded from the World Bank.[100] Some countries had data up to 2021. For those countries without data on the poverty rate in 2020, regional changes in poverty rates were used to project the impact of COVID-19 (COVID [base] Table B.6).[115, 116] Following World Bank projections for 2021, where data were missing, the geometric mean of the rate of change in the poverty rate over 2018–2020 was used to project 2020 to 2021, while the geometric mean of the rate of change in the poverty rate over 2015–2019 was used to project poverty rates in 2022 and 2023. United Nations population data[117] and projections for 2016 to 2023 were multiplied against World Bank poverty rates100 to obtain national poverty headcounts of people below 3.65 2017 PPP dollars per day. Country-level estimates of the share of agrifood systems workers in total employment obtained from Davis *et al.* (2023) were treated as constant for projections.[101]

National quantities for GHG emissions, water use and land-use transitions were projected to 2023 using a simple one-lag first difference autoregression with exogenous real GDP per capita growth. World Bank real GDP national projections to 2023 in the June 2022 *Global Economic Prospects* report were used, which account for the impact of COVID-19.[118] This basic forecast assumes the response to demand changes during COVID-19 is reflected in real GDP dependence. We use the same simple method for consumption impacts, assuming that changes in population dietary intake and BMI were driven by exogenous economic shocks. Land-use transition projections used vector autoregression with simultaneous and one-lag terms due to the interaction between transitions.

EDGAR v6.1[92] provides data up to 2018 on NH_3 and NOx atmospheric emissions, but Integrated Model to Assess the Global Environment–Global Nutrient Model (IMAGE-GNM) global data are modelled based on geochemical and hydrological flows prior to 2015 and are not an empirical time series. Estimates of 2015 Nr emissions were carried forward to 2020 using proportional increases in organic and inorganic total nitrogen from FAO data (FAOSTAT element 5157 and item 3102, elements 723801, 723802, 723811, 723812 and central product classification (CPC) item F1755) due to insufficient time-series data for extrapolation of either emissions or imputed national emission factors. National historical proportions of agricultural sector emissions for NH_3 and NOx to air using EDGARv6.1 were used to apportion NH_3 emissions to air and NOx emissions to air.[3, 91] National historical proportions of agricultural sector Nr runoff and groundwater leaching from IMAGE-GNM were used to apportion Nr runoff and groundwater leaching.[95, 96] As with GHG emissions, water use and land use, nitrogen emissions were then projected to 2023 using a one-lag first difference autoregression with exogenous real GDP per capita growth. Nitrate emissions from human sewerage were carried forward from the 2015 estimate.

2.3 Marginal cost calculations

Basic interpolation and extrapolation of annual totals of impact quantities for the years 2016–2023 allows damage costs to be calculated using marginal damages (Annex 1). Marginal damage costs for the 154 countries are calculated using the SPIQ-FS version 0 marginal damage cost model developed for the Food System Economic Commission.[34–37, 119] An overview of the SPIQ-FS cost models is available in Lord (2022).[38] Current marginal damages are designed for counterfactual studies. Interpretation of cost estimates of current marginal damages applied to total annual production of quantities, rather than marginal changes in quantities in a counterfactual policy study or marginal changes along abatement pathways, should be limited to comparative discussion.[120]

SPIQ-FS version 0 makes estimates in 2020 PPP dollars of marginal damages to GDP PPP per unit of impact quantity.[47, 48] Damages from GHG emissions, land-use change, water withdrawals, poor livelihoods and consumption in the years 2016–2023 manifest in present and future economies. Future damages must be discounted back to the "NPV" in the 2020 economy for comparison. A Ramsey social discount rate (SDR) is assumed with a time preference of 0 and constant marginal expected utility of consumption of 1.5.[121, 122] The literature on SDR is extensive,[123, 124] but it is recommended to use a conservative value for intergenerational wealth transfer, as current wealth generation from food system activities may be endogenous to the risk of the ability to enjoy deferred resource use.[51, 125, 126] For this reason, the choice of time preference is zero. 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.[127–129] National GDP PPP growth rates, World Bank 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), by income group (for example, productivity losses from illness or informal care) or at global level (GHGs). Damage to future economies is estimated in present value, assuming business-as-usual future projections (IPCC shared socioeconomic pathway 2 [SSP2]).[130]

The SPIQ-FS model has macroeconomic parameters that can be varied, but impact quantities are calculated based on historical trajectories to 2020 and are generally not represented as parameters in the cost models endogenously. For very large changes in GDP PPP and other economic variables due to the produced impact quantities in the period 2016–2023 that produce a deviation from SSP2 or historical trends on which the SPIQ-FS calculations are based, changes in the external costs that are borne by the economies of the present or future would need to be accounted for in changing income, supply and demand of goods and services, prices and costs as part of the equilibrium calculations in an extended computable general equilibrium model. The marginal costs are not varied for the change in impact quantities over the years 2016–2023. Annex 1 discusses the assumption of fixed marginal damage costs for 2016–2023.

Costing GHG emissions

SPIQ-FS resamples Interagency Working Group on the Social Cost of Greenhouse Gases (IWG-SCGHG) simulations of the social cost of greenhouse gases in 2020.[131, 132] IWG-SCGHG simulations are provided for three discount rates (2.5 percent, 3 percent and 5 percent) and five socioeconomic scenarios used by integrated climate modelling groups to inform IPCC reports.[131] Using national GDP growth projections for SSP2 to 2100,[130] global rates matched a discount rate of 3 percent; this was used for the social cost of GHGs resampling. A Ramsey SDR is assumed with a time preference of 0 and constant elasticity of marginal utility of 1.5.[121, 122] Given the 3 percent discount rate, social costs under the five scenarios were sampled uniformly for additional uncertainty estimates of economic futures under SSP2. Social costs represent marginal damage costs under a future pathway of optimal economic abatement.[133] Using the social cost reflects the increasing internalization of the costs of GHG emissions in emissions markets or state taxation.

IWG-SCGHG simulations provide social costs for the emission of a metric tonne of CO_2, CH_4 and N_2O. CO_2 equivalents are not used and the gases are costed separately.[134] Converting to CO_2 equivalents and multiplying by the social cost of CO_2 would underestimate the total damages, as CH_4, in particular, has shorter-term effects and future damages due to CH_4 are less discounted.[134–136] Estimates in the reference were used to resample damages to agriculture and human mortality as proxies to damage from natural and human capital changes, respectively (Table 1).[137]

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

Costing water withdrawals

SSP2 discount rates were used for impacts of future water scarcity. With no comprehensive global spatial estimates of the temporal allocation of water resources derived from economic use under SSP2 from a spatially explicit water withdrawal in 2016–2023,[138] the costing model uses a Poisson process[139] to temporally allocate the national effects of water withdrawal after 2023.[37]

Marginal damages for water withdrawal in SPIQ-FS are underestimates due to a lack of data on accrued loss from water scarcity and damages from the loss of environmental flows.[140]

Costing land-use changes

Costs of land-use changes in terms of lost, retained or returned ecosystem services are derived from the Ecosystem Services Valuation Database (ESVD).[141, 142] Valuations derived from the ESVD are given in hectares/year. How many years into the future ecosystem services are lost or provided after land-use change in the current year is an additional assumption.[143–145] No changes in service were assumed for 50–80 years after a transition from established habitat. This is a simplification. Transition in land use can occur from forestry or agricultural use, abandonment and then return to forestry or agricultural use. For abandoned land, evidence suggests an average of 14 years of returned ecosystem services.[146] The value of the services in future years can also change due to shifts in the supply of and demand for ecosystem services, resulting in so-called environmental discount rates.[147] Environmental discount rates were not used. National-level discount rates to 2100 under SSP2 were used to discount up to 80 years of lost ecosystem services for deforested land to obtain cumulative values for a hectare of land-use change.[130] For abandoned land resulting in habitat return, a random period between 7 and 28 years with a mean of 14 years (distributed to maximize entropy)[148] of returning ecosystem services was used to obtain the cumulative value for a hectare of habitat return.

The HILDA+ dataset provides four categories of relevant land-use transition.

Forest habitat change provided by the model refers to deforestation or avoided deforestation. This is treated as a loss or retention, respectively, 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. HILDA+ forest transitions do not distinguish between tropical and temperate forest habitat, nor managed or unmanaged habitat. Marginal costs for a hectare of land-use change from the SPIQ dataset and the ESVD distinguish between tropical and temperature forests. The ESVD uses The Economics of Ecosystems and Biodiversity (TEEB) classification and the Common International Classification of Ecosystem Services (CICES) v5.1 classification systems of ecosystems and services.[149, 150] To reconcile cost and quantity categories, a marginal cost per hectare of forest habitat change was chosen randomly from tropical and temperate marginal cost samples in proportion to historical national tropical and temperature forest 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.

HILDA+ provides data on the transition of unmanaged grasslands, which is a broad category including shrubland, grassland and unmanaged rangeland classifications in the ESVD. The ESVD has few valuations in these categories, even when national estimates are aggregated into Human Development Index (HDI) brackets. Global spatial datasets of land area and land transitions for habitats, such as the Worldwide Fund for Nature (WWF) ecoregions dataset[151] and the HILDA+ transitions dataset,[7] 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 HILDA+ dataset. The costing is conservative, as it excludes conversion or avoided conversion of inland wetlands and coastal wetlands, such as mangroves, for crops such as rice and palm oil.[152]

HILDA+ transitions data include the transition of cropland and pasture to forest or “unmanaged grasslands”. The provision of services from abandoned land can be of lower value than intact ecosystems,[146, 153] with previously forested areas progressing through regenerative stages of grassland, shrubland and then reforestation.[154, 155] Historically, land may transition back within decadal timespans.[146] 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 hectare of forest or unmanaged grassland after 20 years.[153, 155, 156]

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

Costing nitrogen emissions

The SPIQ-FS version 0 nitrogen emissions costing model estimates marginal damages from the volatilization of NH_3 (ammonia) and NOx (nitrous oxides) to air and the runoff of reactive nitrogen into surface waters and soil leaching, predominantly soluble NO_3- (nitrate). Economic losses occur through labour productivity losses from air pollution, crop losses and the loss of ecosystem services.[36] 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.[157, 158]

Costing undernourishment and dietary risk

FAO data provide changes in the NOU, which is the number of people in a national population with food intake below minimum energy requirements, as defined by FAO.[159] SPIQ cost modelling includes a model from the NOU to DALYs from energy-protein malnutrition based on WHO data.[160–162] The productivity losses of energy-protein malnutrition are costed using historical International Labour Organization (ILO) labour productivity data.[163] Labour productivity is used in place of GDP per capita to account for the caring burden of young and old-age dependents in households. The same productivity loss estimates are used to cost DALYs lost for neoplasms, cardiovascular disease and metabolic diseases attributable to diets low or high in risk factors and high BMI.

Uncertainty in the cost of the burden of protein–energy malnutrition is obtained directly from modelling residuals in a truncated quadratic regression between the HDI, POU and DALYs per capita obtained from historical WHO data. Uncertainty in the cost of the burden of dietary patterns is compounded from three sources. The GBD study includes uncertainty modelling in estimates of DALYs. The uncertainty around the mean estimate of DALYs for each country over 2014–2019 can be reconstructed from data from the GBD study[104] of low, high and mean value using maximal entropy distributions. The DALYs from NCDs from 15 dietary risk categories, the DALY attributable to sugar-sweetened beverages and the DALYs from high BMI are treated as random variables and added or subtracted as random variables according to published mediation factors.[105] To account for uncertainty in mediation factors, the linear combination of random variables is randomly sampled between the maximum of each component (fully mediated) and their sum (published mediation). Lastly, to account for uncertainty in the attribution of cost to agrifood systems, the attribution is varied uniformly between 50–100 percent (mean 75 percent) for NCDs and 50–100 percent (mean 75 percent) for high BMI.

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.[71] The productivity loss module has productivity losses available at a national level or average at World Bank income group level. At a national level, the difference between LICs and HICs can be up to two orders of magnitude in PPP terms. Following the study,70 which used the same model for determining DALYs from dietary intake in this study, productivity loss per DALY is assigned based on World Bank average income group in 2020. This averages productivity losses for the poorest countries in the lower World Bank income group.

Since the marginal costs need to be consistent in the economic measure of damages in GDP PPP terms across costing models, the cost from the burden of disease uses only "indirect costs".[164] Direct costs such as treatment costs amount to economic exchanges between sectors and actors within the economy.[17] They are not included as, 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. GDP PPP treats the population homogeneously, so it does not include potential welfare losses from direct costs being borne disproportionately by lower-income households.

Costing poverty

Data on the 3.65 2017 PPP dollar per day national poverty gap over 2014–2020 were downloaded from the World Bank and adjusted by inflation in PPP terms to 2020 PPP.[100] Poverty gaps were converted into income shortfall per annum. Income shortfall per annum was projected to 2023 alongside World Bank GDP projections using an equidistributed pass-through rate (Table B.6 of Yonzan, Lakner and Gerszon Mahler [2020]).[114] The total attributable cost of poverty is defined as the amount society would pay for a cost-effective elimination of the economic damages of poverty. It is assumed that society would not make an additional dollar of payment per person if the average GDP PPP damage reduction per person were less than a dollar, and that such a payment is cost effective up to the international moderate poverty line. Under this assumption, the income shortfall per annum of agrifood workers, which is taken as the cost of poverty for this study, underestimates the GDP PPP productivity damages of moderate poverty among agrifood workers.

Agrifood worker poverty is treated differently to other impact quantities. GHG emissions, nitrogen emissions and blue water withdrawals are all additional quantities. They are new emissions attributed to agrifood systems activities and are added to the existing stock of emissions in the atmosphere and so on. For natural capital, the impact models account for natural renewals or stocks, such as the replacement of withdrawn water by precipitation or the fluxes of CH_4 between atmosphere and land. The total impact of the emission in a given year is costed in present value for its lasting effect on stocks and the value flows from changes in those stocks. Similarly, DALYs represent the additional burden of disease produced by consumption or caloric inadequacy in that year. The equivalent impact quantity for poverty is the production of new individuals in moderate poverty from agrifood systems activities in a given year. A similar 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 the individual put into 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.

Without an economic model attributing new individuals in poverty to agrifood systems activities and accounting for their fate over the years 2016–2023 and after, agrifood worker poverty was costed annually in the following way. All agrifood workers 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 total of agrifood workers in poverty in the next year was 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. Poverty was the only marginal cost used that varied each year over 2016–2023.

Estimates of economic risk

Marginal costs in SPIQ-FS are provided with uncertainty estimates in the form of parameterized probability distributions.[34–37] This gives uncertainty estimates in the annual total cost attributed to agrifood systems activities (for example, costs due to changes in GHGs, costs due to changes in water withdrawal and costs due to changes in undernourishment). Poverty was costed directly using World Bank data on the poverty gap and was not modelled with uncertainty. SPIQ models some damage costs jointly within categories based on historical data. The impact of the integrated nature of changes in environmental, health and social conditions on economic costs when totalled across categories is reflected in SPIQ-FS by correlations in damage costs across categories.

Total estimates of the economic damages resulting from the annual production of environmental pollutants, undernourishment and dietary patterns are derived from jointly sampling marginal costs. Three sets of correlation are used to explore the joint nature of environmental, health and social conditions on total economic costs: no correlation, an expert-derived set of correlations and perfect correlation.

These three representations of risk from joint effects can be used to contrast, ignoring the joint effects of environment and health, with a case in which higher-than-expected environmental damage costs will always coincide with higher-than-expected health damage costs. The middle, expert-derived set of correlations represents a best estimate of the additional economic risk of joint effects.[165] The full distribution of change in total economic costs may reflect risk in moving from the status quo, as well as the risk in sticking with it.

2.4 Limitations

GHG social cost modelling relies on the 2020 update to the US Environmental Protection Agency (EPA) IWG-SCGHG simulations, which originated from modelling in 2011 and a 2016 update.[131, 132, 134] Newer estimates from EPA modelling not finalized by the IGWG place the SCGHG up to 60 percent higher.[137] The IGWG chose not to use GDP PPP damage functions in estimating economic damages within integrated assessment models, so they potentially undercount the payment transfer to cost bearers in the social cost calculation.

Water cost modelling is limited by a lack of data on the future magnitude and time of the deprivation of water for use in the production of economic value due to water withdrawal in the present. Cost estimates are not catchment based, something that will be a future improvement. Damages from reduced environmental flows are not calculated due to a lack of data. National aggregation is used and transboundary effects are not included. Water cost estimation is conservative to account for limitations.

Limitations on GHG and blue-water use quantity estimates are detailed in FAOSTAT and AQUASTAT documentation.

Nitrogen cost modelling involves benefit transfer from the European Nitrogen Assessment, accounting for national variation in ecosystem distributions, temperature, population density, background non-agricultural NH_3, NOx and SOx emissions.[166] The transfer for NH_3 and NOx uses additional data from the EASIUR model of over 3 000 US counties.[167] 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,[73, 74] and lack of knowledge on the value of ecosystem services.[168–170] Variation in the value of ecosystem services is large and introduces additional uncertainty in calculations of deposition and runoff, compounded with a lack of knowledge as to the damage to ecosystem productivity from nitrogen loading.[74] Valuation in the ESVD database does not use a consistent valuation methodology,[142, 171] requires benefit transfer from a lack of sufficient country data,[172] and may overestimate GDP PPP damages. Nitrogen impact quantity data are modelled for 2015 and then imputed to 2023 from agricultural nitrogen use.

Undernourishment is based on loss of productivity from WHO estimates of DALYs due to protein–energy malnutrition.[173] Other lost productivity or later-life socioeconomic consequences of undernourishment are not included. Nutrient deficiency and other disease outcomes from childhood malnutrition were not used.[18] By the World Bank definition of moderate poverty,[174] it is eliminated by transfer of the income shortfall to the moderate poor. Moderate poverty does not incorporate all economic consequences of income inequality.[175, 176]

The HILDA+ land-use transition dataset shows large land-use transitions for the United States of America and Australia. For Australia, there is less confidence in the HILDA+ classification algorithm due to potential misclassification of use of natural outback pastoral land. Trends in environmental cost production for Oceania have low confidence, due to variability in land-use transitions. Forest clearing without clear agricultural reuse is also an uncertainty when it comes to land-use transition in the Baltic states due to potential misclassification by the HILDA+ dataset.

3 Results

KEY MESSAGES

- The global hidden costs of agrifood systems in 2023 are likely to range between 11 trillion and 15 trillion 2020 PPP dollars (the expected value is around 13.1 trillion), equivalent to about 10 percent of global GDP.
- Expected environmental costs averaged around 3 trillion 2020 PPP dollars over the 2016–2023 period. The expected costs of the burden of disease from diets averaged 9.3 trillion 2020 PPP dollars and the expected social hidden costs averaged 560 billion 2020 PPP dollars.
- Trends show an upward trend in net costs from 2016 to 2023, driven primarily by productivity losses resulting from dietary patterns. Expected values of hidden costs increased 8.6 percent over 2019 to 2023.
- HICs and UMCs bear approximately the same amount of hidden costs (between 4.5 trillion and 5 trillion 2020 PPP dollars). LMCs bear about half of this amount, despite being the largest population group. Unsurprisingly, LICs generate the lowest expected value of hidden cost, at 381 billion 2020 PPP dollars in 2023, or 558 2020 PPP dollars per capita.
- Health-related hidden costs are the largest across all world regions, with the exception of sub-Saharan Africa, where costs associated with moderate poverty and undernourishment are larger.

Data for 2016 to 2020 and trend extrapolation from 2021 to 2023 for quantities and marginal costs relating to external costs or market failures of global agrifood systems can be summarized in 37 cost items of combined activity, produced quantity and whether damages factor predominantly through natural or other capital changes (Table 1).

Eighteen categories relate to direct emissions of CO_2, CH_4 and direct or indirect emissions of NO2, per country per annum, and are broken down by FAOSTAT into elements that coincide with farm emissions, emissions from land-use change and emissions in inputs or post-farm gate.[177]

Eight categories relate to the land-use transition of forest habitat and other land habitat, per country per annum, as described in Section 2 (methodology).

Seven categories relate to nitrogen emissions of volatilized NH_3 and NOx and runoff to surface waters or leaching to groundwater of Nr, per country per annum, originating from the application of synthetic fertilizer, livestock manure and its management, or human sewerage, as described in Section 2.

One category of crop blue water use is an aggregate of the water use in agriculture, per country per annum, from AQUASTAT.

One health category indicates the burden of disease per country from diets (food consumed in that year) in the form of a calculation of DALYs due to the combined effects of high BMI and NCDs 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.

One category indicates NOU as defined by FAO (insufficient caloric intake) in that country in that year.

One category indicates the number of agrifood workers in poverty (income below the World Bank 3.65 2017 PPP dollars a day poverty line) in that country in that year.

The FAO POU and moderate poverty, as defined by the World Bank, make up two categories characterized as distributional failures.

To facilitate the comparison of trade-offs between hidden cost production from environmental sources (E) with dietary patterns (H) and social distributional failures (S), 34 categories are classified by cost type E, one category is classified by cost type H and two categories are classified by cost type S (Table 1).

Annex 3 provides each quantity (37) in Table 1, with the matching marginal cost for each country with data (154), for each year (8), for a total 45 584 individual cost items. Annex 4 lists the 154 countries included in the analysis.

The matching marginal costs from SPIQ-FS are described in Annex 2, as are individual cost models in SPIQ-FS output samples of the uncertainty for 20 marginal cost items for 154 countries (CO_2 emission agricultural losses, CO_2 emission mortality costs, CH_4 emission agricultural losses, CH_4 emission mortality cost, N_2O emission agricultural losses, N_2O emission mortality costs, blue water withdrawal, forest habitat loss, forest habitat return, other habitat loss, other habitat return, NOx emissions to air–air pollution, NOx emissions to air–deposition, NH_3 emissions to air–air pollution, NH_3 emissions to air–deposition, NO_3- runoff to surface water, NO_3- leaching to groundwater, persons undernourished, persons in moderate poverty, DALY health burden).

The samples within any one of the 20 marginal cost items for a country are already matched for correlations determined by the individual cost model in SPIQ-FS. For example, empirically, marginal costs of NH_3 and NOx emissions in the same location are highly correlated,[36] as both affect the same surrounding population by similar air pollution mechanisms, and the presence of either chemical reinforces the production of particulate matter. Annex B in the SPIQ-FS documentation describes joint sampling across the categories and countries by a block-correlation sort order method. This joint sampling has three settings for conducting sensitivity analysis, as described in Section 2 (methodology). One thousand joint samples were generated.

Multiplying a joint sample of the marginal cost items of Annex 2 matched against the quantities in Annex 3 provides 8 joint distributions for 5 698 random variables of cost (one set for each year and 8 × 5 698 = 45 584 cost items). For tractable computation, the 8 joint distributions for each year are not sampled as a single joint distribution of 45 584 random variables, potentially ignoring the effects of correlation over time.

Results below show the shape of the distribution of global total cost in a year obtained from aggregating (adding up) 5 698 uncertain cost items. The skewed shape and “fat tails” in the distribution reflect some of the influence of the joint sampling and correlation between cost items. It would be erroneous to assume the 5 698 cost items were independent; this assumption would generally lead to a normal distribution (bell shape) with lower variance as a result of aggregating so many items, due to the central limit theorem of statistics. The independence assumption would be an underestimate of economic risk.

Distributions of the hidden costs are provided, as well as the expected value and 5th and 95th percentile statistics. The distributions and statistics are used to derive conclusions on trends and the annual magnitude of the hidden costs generated by agrifood systems from the production of the listed impact quantities. We report on the estimated damage costs for the year 2023 and compare these with costs in 2020 and 2016 to indicate trends.

3.1 Global net damages, economic risk and changes in risk from interactions in cost bearing from GHG emissions, nitrogen emissions, water use, land-use change, undernourishment and dietary patterns

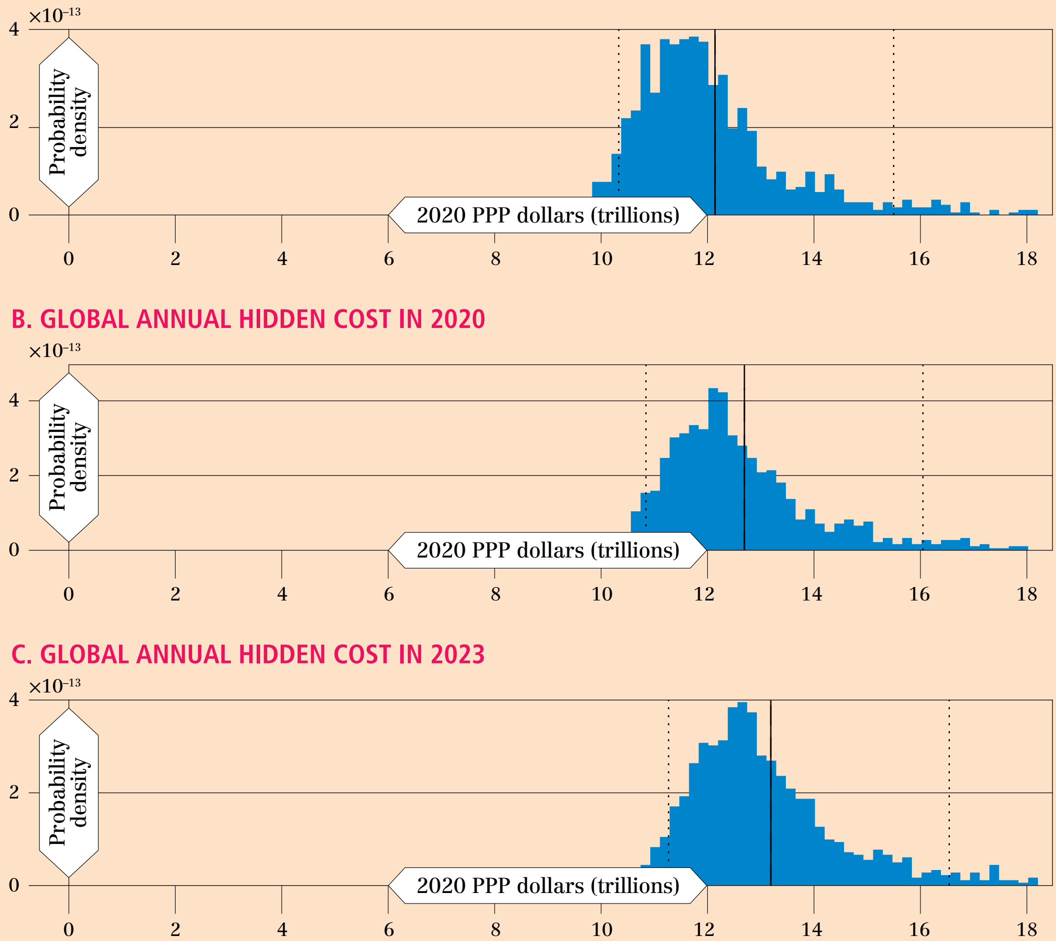
Figures 3 and 4 plot histograms of the samples for the sum of the 5 698 cost items for the years 2016, 2020 and 2023 in their joint order. That is, the histograms approximate the global net cost of the production of the impact quantities attributed to agrifood systems in 2020 PPP dollars for the years 2016, 2020 and 2023, and the uncertainty in the global net cost.

FIGURE 3 Trends in estimated costs of the production of the impact quantities over 2016–2023 of global agrifood systems in 2020 PPP dollars

A. GLOBAL ANNUAL HIDDEN COST IN 2016

B. GLOBAL ANNUAL HIDDEN COST IN 2020

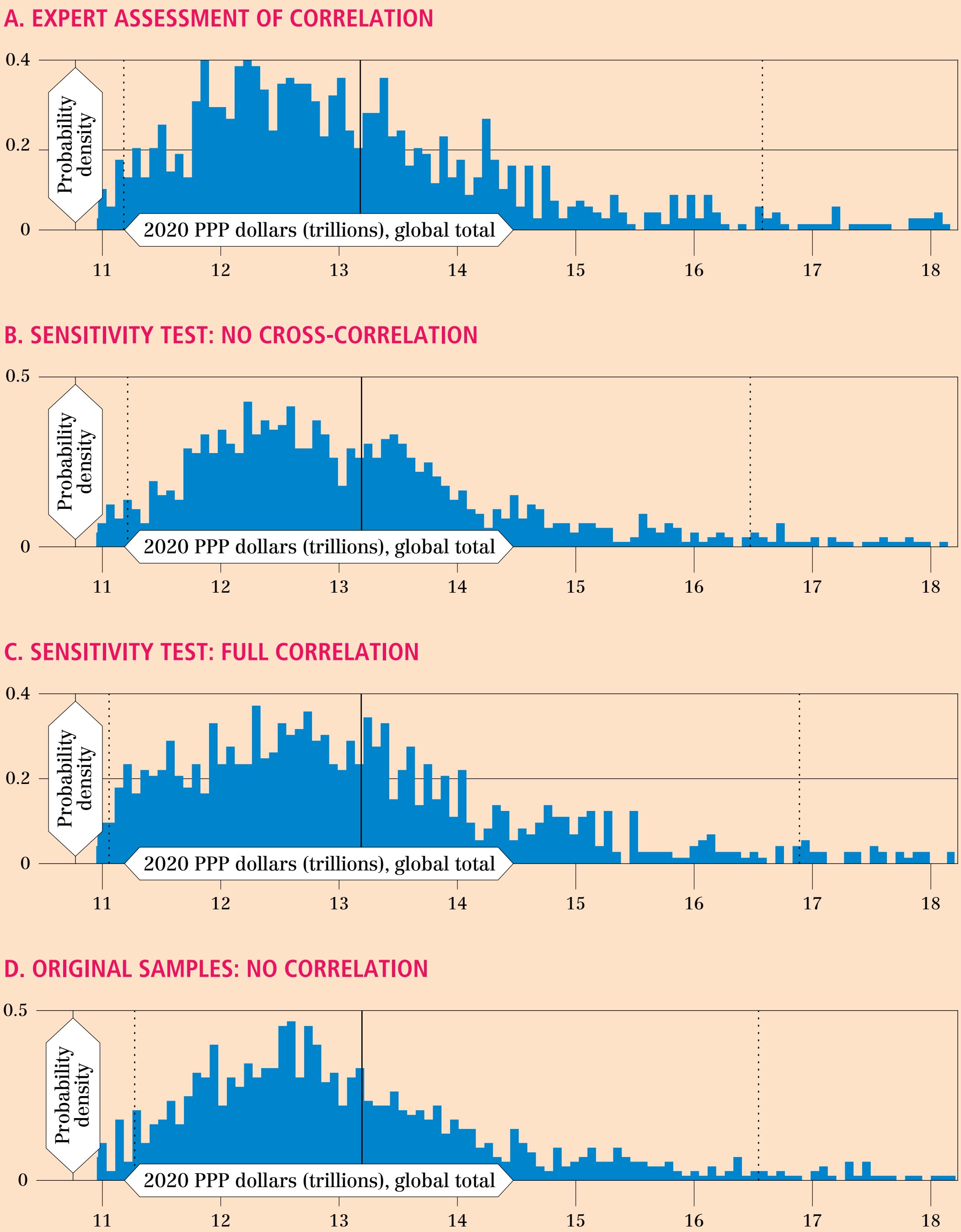
C. GLOBAL ANNUAL HIDDEN COST IN 2023



Notes: Mean refers to the expected value, and P5 and P95 refer to the 5th and 95th percentiles, respectively. Costs increased by 8.6 percent over 2019 to 2023. The change in the shape of the distribution, which is predominantly affected by trends in the individual impact quantities in this study, is not statistically significant.

Source: Author's own elaboration.

FIGURE 4 **Distribution of global hidden cost of the production of the impact quantities over 2023 attributable to global agrifood systems in 2020 PPP dollars**



Notes: Solid lines show the expected global total cost of around 13.1 trillion 2020 PPP dollars. The distributions are right-skewed towards higher damages. The grey small-dashed lines show the 5th and 95th percentiles. Likely costs are in the range of 11 trillion–15 trillion 2020 PPP dollars. The distributions show a sensitivity test in the degree of correlation between the GHG, nitrogen, land-use change, water use, undernourishment and dietary pattern cost items. The general shape, statistics and spread of possible total cost values are approximately the same. Correlations are described in Annex B of the SPIQ-FS documentation, and the block-correlation matrices for the sensitivity tests are repeated in Annex B of this report. The full correlation (third panel) indicates a marginally higher risk, as expected in this study.

Source: Author's own elaboration.

Estimated global damages produced in 2023

The net global costs of agrifood systems in 2023 are likely to be in the range of 11 trillion to 15 trillion 2020 PPP dollars (Figure 3 and Figure 4). The expected value is around 13.1 trillion 2020 PPP dollars. The distribution provides an idea of the spread of possible net global damages due to the high degree of uncertainty in the external costs of GHGs, nitrogen emissions, water withdrawal and so on. External costs are not currently being measured by accounting systems like other economic indicators, and the damages are estimated based on historical data and future projections. Observation of the damages is not an experiment that can be repeated often. Central measures of risk, such as most likely costs and average costs, support decision-making on frequently occurring and observed economic activities in visible market transactions. For low-observation and high-uncertainty features, such as external costs, central measures are supported by additional risk measures such as the 5th and 95th percentiles. For low-frequency observations, in a one-off game that is the unfolding future, the decision-maker has the additional consideration of whether they are willing to accept a 5 percent chance of loss above or below the corresponding percentiles of the net cost distribution.

Examining Figure 3 and Figure 4, due to the uncertainty in the cost of environmental, health and social impacts not visible to most economic markets, the net "hidden costs" produced by global agrifood systems have a 5 percent chance of being 16.5 trillion 2020 USD PPP or higher. Net "hidden costs" in the range of 11 trillion–15 trillion 2020 PPP dollars are the most likely outcome, with a 95 percent chance of being 11.3 trillion 2020 PPP dollars or higher. These estimates are robust to the uncertainty of costs coming from interactions between climate change, biodiversity loss and human health outcomes.

Trends from 2016

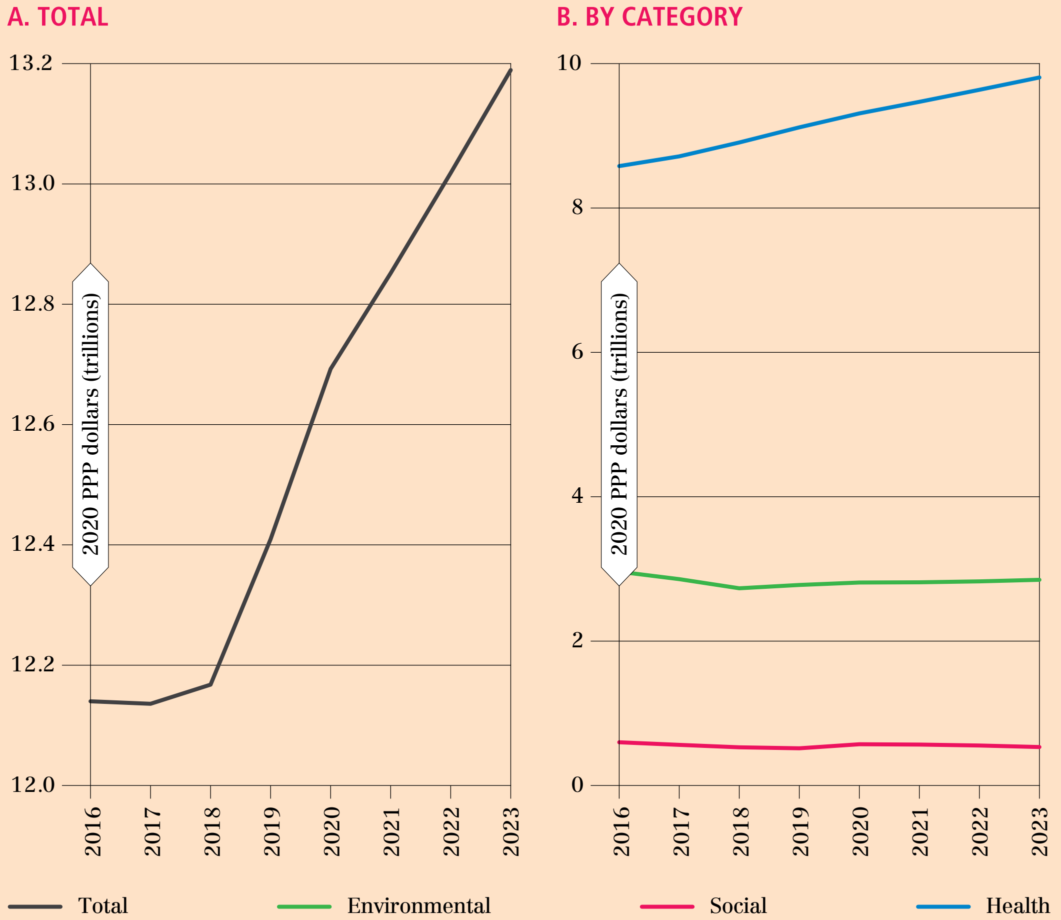
Figure 3 and Figure 4 show the global costs attributable to agrifood systems of producing the impact quantities in the years 2016, 2020 and 2030. The distributions are right-skewed to higher damages. It is not possible to use a statistical test to distinguish statistical significance in trends; the samples have been artificially generated and do not represent draws from a real population. The trends in the statistics of the distribution over 2016–2023 (Table 2) originate primarily from the change in the impact quantities; the marginal damage costs used are the same. Quantities from 2016 to 2020 are reported data from FAOSTAT and other sources. Quantities for 2021 to 2023 represent an extrapolation of the trend from 2014 to 2020, accounting for national GDP shocks experienced over 2020 and 2021 due to the COVID-19 pandemic. Acknowledging the large uncertainty, the left-hand panel in Figure 5 shows the trend in expected value of annual global costs from 2016 to 2023.

TABLE 2 **Statistics of the estimated global costs of producing the impact quantities in the years 2016–2023 attributable to agrifood systems in 2020 PPP dollars**

Geography	Name	Category	Year	Mean	P5	P95
Global	World	Total	2016	1.21E+13	1.03E+13	1.55E+13
Global	World	Total	2020	1.27E+13	1.08E+13	1.60E+13
Global	World	Total	2023	1.32E+13	1.13E+13	1.65E+13

Notes: Mean refers to the expected value, and P5 and P95 refer to the 5th and 95th percentiles, respectively.
Source: Author's own elaboration.

FIGURE 5 Trends in total hidden costs and hidden costs by category, 2016–2023



Notes: All values are expected values. Trends show a reduction and levelling out of costs from environmental sources at around 3 trillion 2020 PPP dollars. Expected costs from dietary patterns increased 14 percent over the 2016–2023 period, in an upward trend from 8.6 trillion to 9.8 trillion 2020 PPP dollars. The expected costs of undernourishment in the general population and moderate poverty in agrifood workers averaged around 500–600 billion 2020 PPP dollars over the period. A sharp upswing in social hidden costs due to the COVID-19 pandemic is muted by the scale in the right-hand panel, but observable in the breakdown by World Bank income group in Figure 11.

Source: Author's own elaboration.

- Trends show an upward trend in net costs from 2016 to 2023, driven primarily by productivity losses of dietary patterns. Expected value of net costs increased by 8.6 percent over 2019 to 2023 (Figure 5).
- Estimates are robust to the potential uncertainty in costs coming from interactions between climate change, biodiversity loss and human health outcomes.
- Trends in impact quantities are likely to be statistically significant given error bars in the reported data, but framing statistical significance of the trend in costs is challenging due to the uncertainty inherent in marginal costs (Figure 4) and the nature of the computational experiment. The most likely, expected and 95th percentile of costs have remained broadly in the region of 10 trillion–15 trillion 2020 PPP dollars for most likely costs, 12 trillion–13 trillion 2020 PPP dollars in expected costs, and in the range of 15.5 trillion–16.5 trillion 2020 PPP dollars for the 95th percentile of costs over the 2016–2023 period (Figure 3).

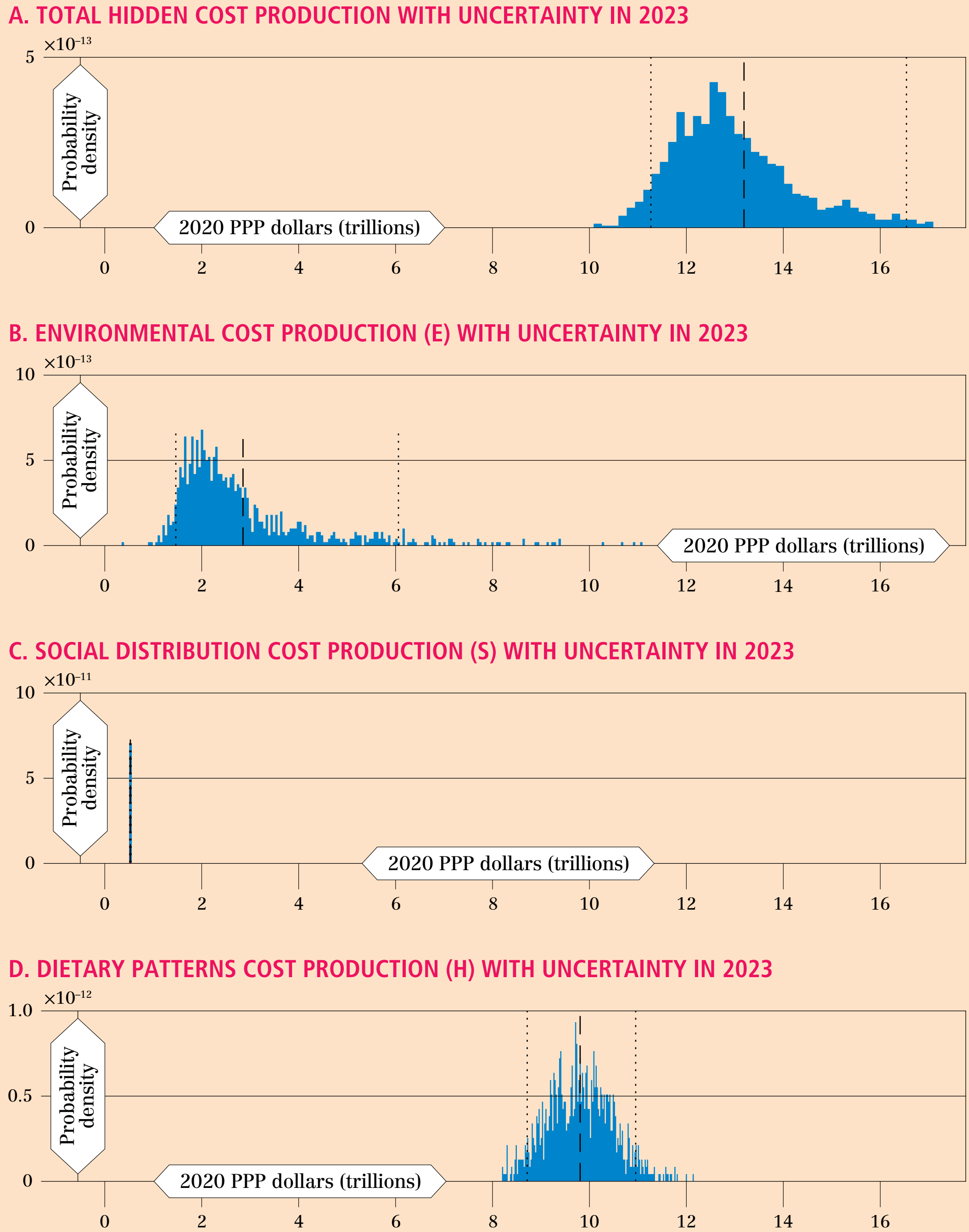
- The amount of 12 trillion–13 trillion 2020 PPP dollars is approximately 10 percent of global GDP in purchasing power terms in the 2016–2021 period.[178] The global value added of agriculture, forestry and fishing is approximately 4.2 percent in the same period,[178] and estimates put the additional value added of food manufacturing and food retail at 5 percent of global GDP PPP.[27] Per day, damages sum up to 35 billion 2020 PPP dollars, equivalent to a June 2022 Pakistan flood every day or a September 2022 Hurricane Ian every four days.[179, 180] Considering the ratio of hidden costs to value added is one measure of intensity of hidden costs, which, with the value of the ratio estimated for 2020 at about 1.09, would indicate that hidden costs of agrifood systems to global GDP PPP are greater than the current value added of agrifood systems.
- Establishing a similar indicator for agrifood systems at a regional or country level is difficult. There are no general estimates for the value added of agrifood systems in national accounts, as it crosses the traditional sectors of agriculture, commodities, manufacturing and retail, and no agreed scope on whether inputs, including inputs such as marketing and financial services, should count under agrifood systems activities. Most of the cost production labelled "environmental" (CH_4 emissions,[2] N_2O emissions,[181] nitrogen emissions,[6] land-use change,[7] blue water withdrawals)[182] is predominantly due to agricultural activities, though agricultural producers are not the only beneficiaries. Section 4 provides alternative indicators for which data from national accounts or the World Bank are available for most countries and regions.

3.2 Global net damages broken down by environmental sources, distributional failures, and dietary patterns

Subsequent sections show the breakdown of net global costs by categorization of impact quantity by cost production (column 1, Table 1). The methodology (Section 2) noted the ambiguity in classifying hidden costs depending either on source of cost production (for example, GHGs or nitrogen emissions), cost bearing (for example, agricultural losses or labour productivity losses), or the mechanisms that link cost production and cost bearing (for example, cardiovascular disease or habitat loss). Shown in Figure 6 are net costs and risk broken down into environmental (E) sources of external cost production in column 4 in Table 1 (GHG emissions, nitrogen emissions, water use and land-use change), societal distributional failures (S) (undernourishment in the general population as defined by the FAO and moderate poverty in agrifood workers as defined by the World Bank) and dietary patterns resulting in obesity and NCD burdens (H). The purpose is a high-level comparison between damages that originate from environmental emissions or resource use versus distributional changes in social distributions and human health changes from food consumption. As noted earlier, human health impacts are also costed within distributional failures and environmental sources of external cost, so the breakdown should not be characterized as environmental, health and social impacts, but a breakdown by cost production sources that coincides with different types of market failure (externalities, inefficient distribution and imperfect information or rationalization).

- External costs from environmental sources (E) are most likely in the range of 2 trillion–3 trillion 2020 PPP dollars per annum. Costs of dietary patterns (H) are increasing and most likely in the range of 8 trillion–10.5 trillion 2020 PPP dollars over 2016–2023 (Figure 6).
- The modelled uncertainty in environmental costs sources is higher than using a resampling of the uncertainty in BMI and dietary risks from the GBD study (Figure 6). Later sections indicate how the very high uncertainty in the impact of Nr runoff contributes to the right skew of the E distribution.

FIGURE 6 Global net costs broken down environmental cost production (E), dietary patterns (H) and social distribution (S) components



Notes: Classification of cost items by cost production is found in column 4 in Table 1. Grey dashed lines show the expected value. The grey small-dashed lines show the 5th and 95th percentiles.

Source: Author's own elaboration.

- The higher uncertainty and skew shape of the distribution indicate a higher risk in external costs from environmental sources of external cost and a higher expected value. Ninety-fifth percentiles for the environmental cost distributions (Table 3) show that external costs from environmental sources account for most of the risk in global net costs in this analysis.

- Due to the longer tail of environmental costs, the expected environmental costs averaged around 3 trillion 2020 PPP dollars over the 2016–2023 period. The expected cost of disease burden from diets averaged 9.3 trillion 2020 PPP dollars over the same period.
- Environmental external costs (E) and productivity losses from dietary patterns (H) are generated by global food production and consumption. Costs of distributional failures (S) are associated with disadvantaged subpopulations and, averaging 560 billion 2020 PPP dollars over the 2016–2023 period, are approximately 20 times less than those associated with the full market. Later results show the concentration of distributional failures in sub-Saharan Africa and southern Asia.

TABLE 3 Global hidden costs of agrifood systems by category, 2016–2023 (2020 PPP dollars)

Geography	Name	Category	Year	Mean	P5	P95
Global	World	E	2016	2.96E+12	1.61E+12	6.07E+12
Global	World	S	2016	5.98E+11	5.89E+11	6.10E+11
Global	World	H	2016	8.58E+12	7.63E+12	9.59E+12
Global	World	E	2020	2.81E+12	1.47E+12	5.91E+12
Global	World	S	2020	5.71E+11	5.59E+11	5.85E+11
Global	World	H	2020	9.31E+12	8.28E+12	1.04E+13
Global	World	E	2023	2.85E+12	1.46E+12	6.05E+12
Global	World	S	2023	5.32E+11	5.21E+11	5.46E+11
Global	World	H	2023	9.81E+12	8.72E+12	1.10E+13

Notes: E = environmental; S = social; H = health. Mean refers to the expected value and P5 and P95 refer to the 5th and 95th percentiles, respectively.

Source: Author's own elaboration.

Trends from 2016

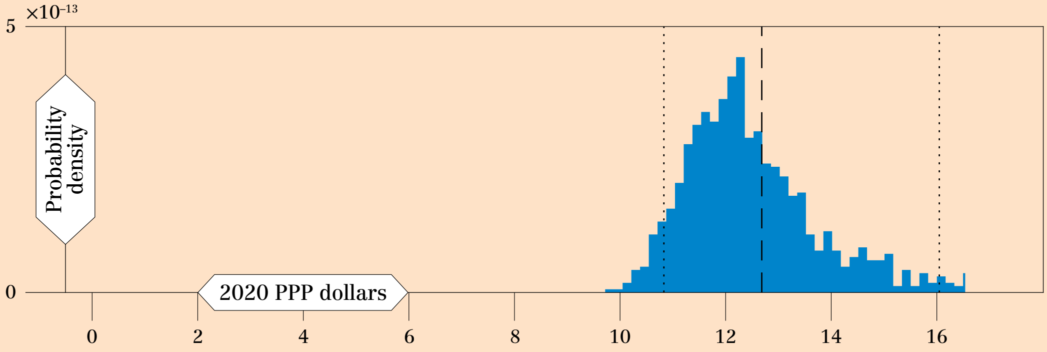
Figure 5 and Figure 6 show the expected value and distribution of costs, respectively, for the environmental cost production (E), dietary patterns (H) and social distribution (S) components of the estimated global costs in the years 2016–2023. Trends in expected value show a reduction and levelling out of costs from environmental sources at about 3 trillion 2020 PPP dollars. The next section indicates how environmental costs increased for GHG and nitrogen emissions, but decreased for land-use change. Costs from dietary intake increased 14 percent over the 2016–2023 period, in an upward trend from 8.6 trillion to 9.8 trillion 2020 PPP dollars. The expected cost of social indicators increased during the COVID-19 pandemic in 2020 and 2021, but resumed a long-term downward trend after 2021, following FAO and World Bank projections.

3.3 Global net damages by cost item category

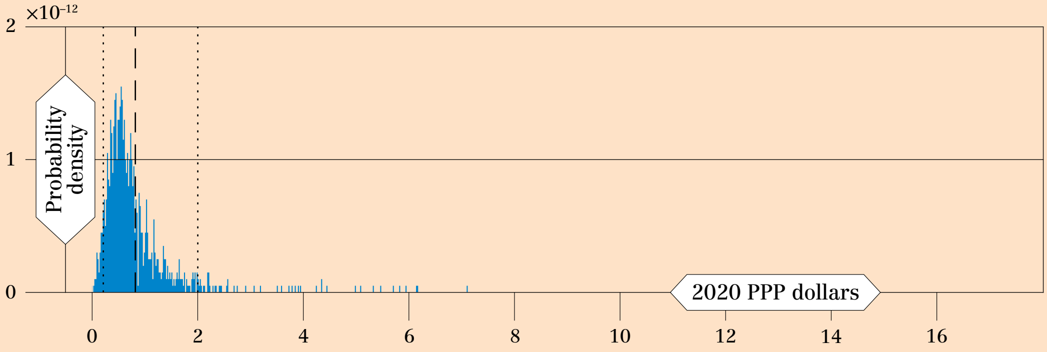
Figure 7 shows the contribution to the net global costs of net global damages from GHG emissions, nitrogen emissions, dietary patterns, water use, land-use change and social indicators (undernourishment and poverty) and trends. Subsequent sections show the contribution from each GHG gas (CH_4, CO_2, N_2O), type of land-use transition and form of reactive nitrogen (Nr) emission (NH_3 methane to air, NOx to air, Nr to surface waters from cropland and human sewerage, and NO_3- to groundwater).

FIGURE 7 Global net damages attributed to global agrifood systems in 2023 in cost categories

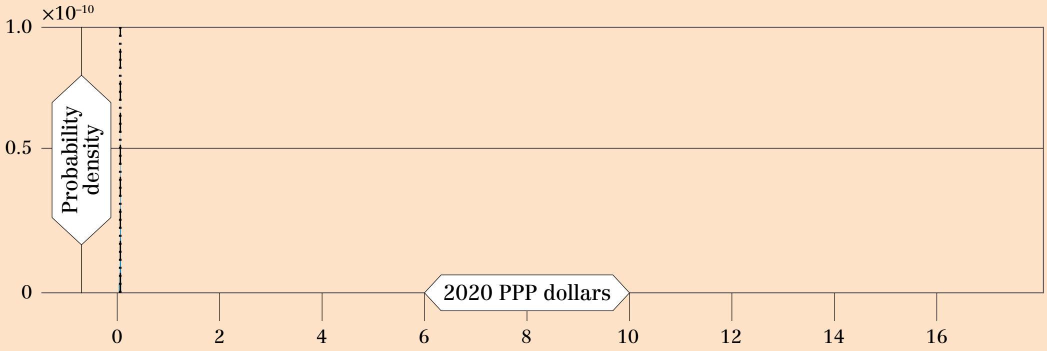
A. TOTAL



B. GREENHOUSE GAS EMISSIONS



C. WATER USE



D. LAND USE

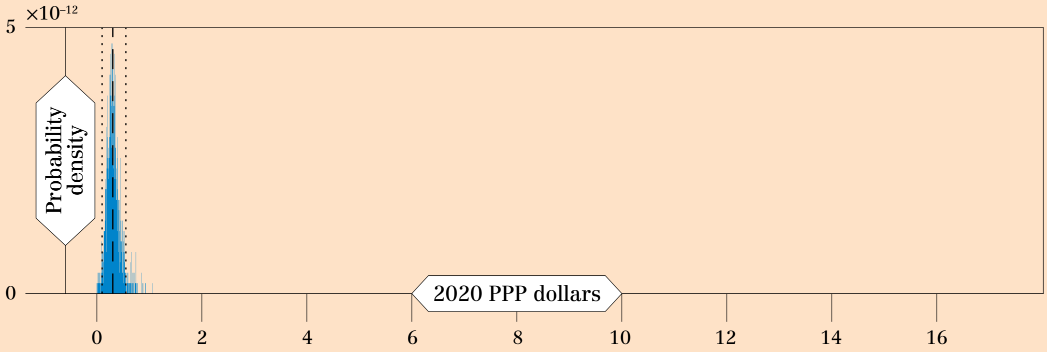
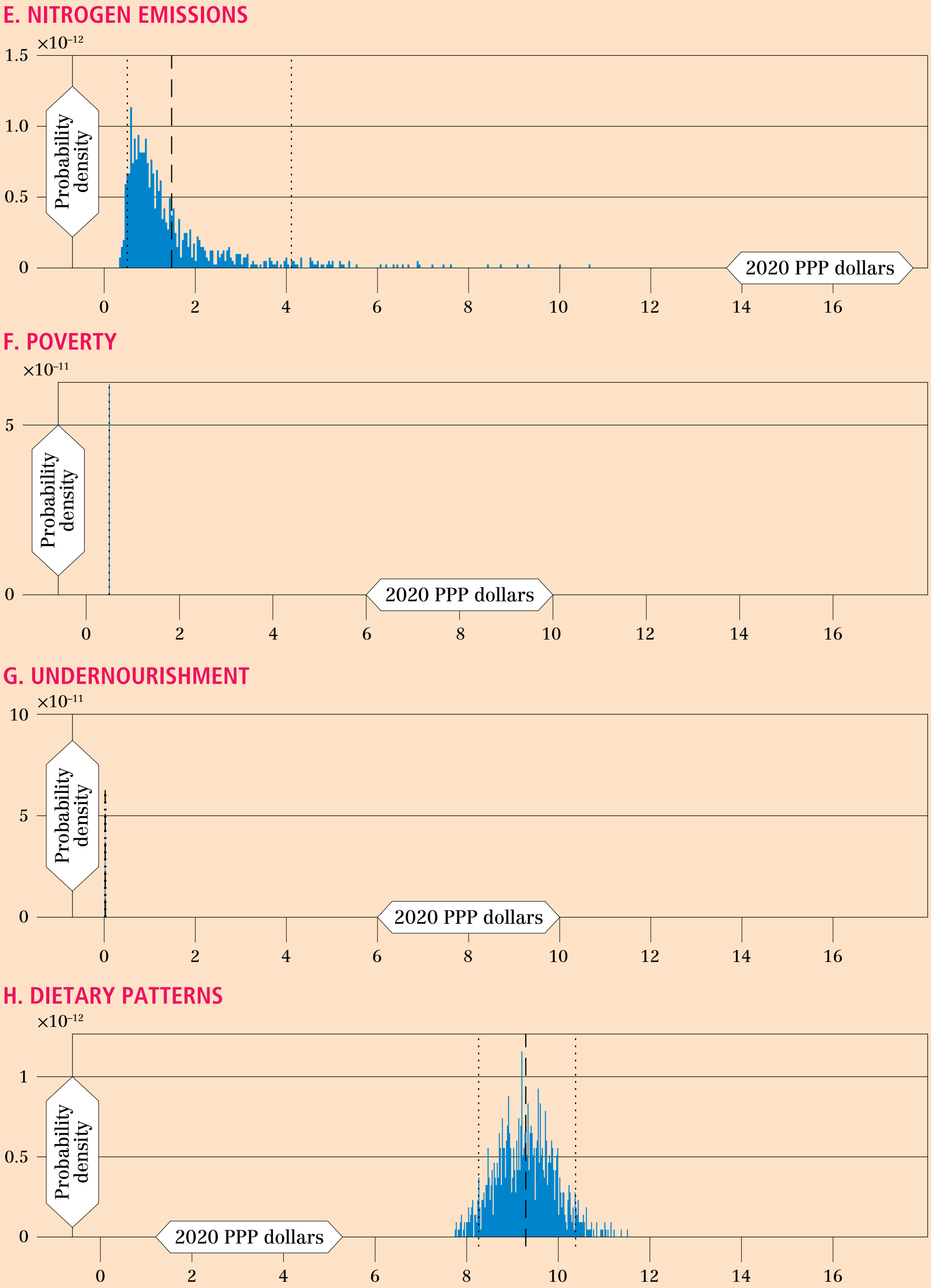


FIGURE 7 (cont.) **Global net damages attributed to global agrifood systems in 2023 in cost categories**



Notes: Shown are the uncertainty distributions of global net damages in 2020 PPP dollars by cost category (column 1 in Table 1). Costs of nitrogen emissions have high uncertainty, and environmental costs are composed of nitrogen emissions, GHG emissions and land-use change emissions, ranked in that order by expected costs. Costs of GHG emissions and nitrogen emissions have increased since 2016 and the costs of land-use change have decreased. This figure is further available for the years 2016 and 2020, with the latter included in FAO (2023).[193]

Source: Author's own elaboration.

Comparison of damages produced in 2023

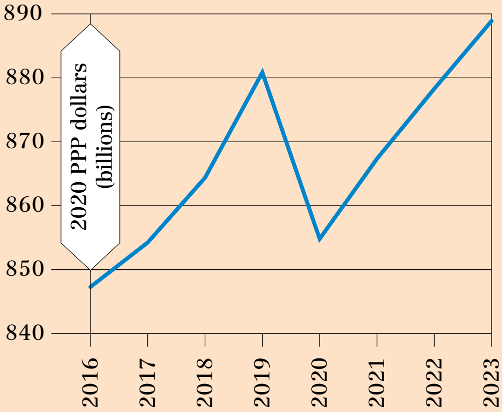
- External costs from environmental sources in 2023 are largest from nitrogen emissions (most likely 0.5–2 trillion 2020 PPP dollars), GHG emissions (most likely 0.25–1 trillion 2020 PPP dollars) and lost ecosystem services from land-use change (most likely 0.25–1.2 trillion 2020 PPP dollars).
- Due to the large uncertainty inherent in the cost of nitrogen emissions, the expected value is 1.5 times higher and the 95th percentile as a measure of economic risk of the cost of nitrogen emissions is twice as high as the respective measures of GHG emissions. The expected value of nitrogen emissions in 2023 is 1.54 trillion 2020 PPP dollars and the expected value of GHG emissions in 2023 is 0.88 trillion 2020 PPP dollars.
- There are several explanations for this, which together with the uncertainty, indicate that GHG emissions and nitrogen emissions generate external costs of the same order. The large uncertainty inherent in nitrogen emissions arises from high uncertainty in the estimates of the value of ecosystem services,[34] the lack of spatially explicit data on the damage to ecosystem service productivity from nitrogen loading,[77, 166] and the compounding of uncertainty in the cost modelling along the nitrogen cascade.[74] Uncertainty modelled for GHGs is limited to a more prescriptive parameter substitution in economic integrated assessment models.[183–185] The integrated models do not account for PPP in aggregated global attributable GDP damages.[183–185] Most nitrogen damage costs occur within the near future, unlike those of GHGs.[186] Discounting has a greater effect on reducing the present value of GHG costs in comparison.[51, 187] FAO estimates of GHG emissions are generally also slightly lower than other studies that attribute GHG emissions to agrifood systems.[1]
- With these considerations, it is still a robust conclusion that the economic effects of nitrogen pollution by global agrifood systems are of the same magnitude as the economic effects of GHG emissions attributed to global agrifood systems.

Trends since 2016

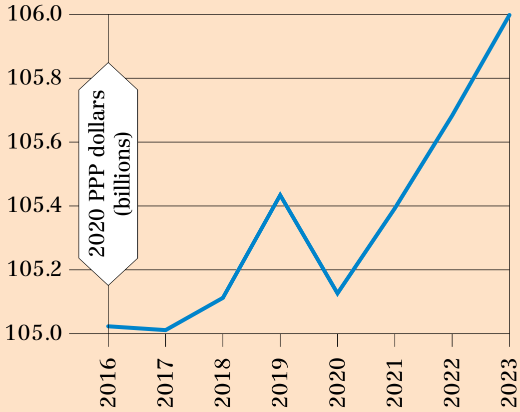
- Costs from dietary patterns trend upwards at a rate of 2 percent per year over 2016–2023 (Figure 5), while costs from nitrogen emissions and GHG emissions trend upwards at a rate of 1 percent per year (Figure 8). On the surface, both nitrogen emissions and dietary patterns appear to offer joint negative abatement costs. Nitrogen use efficiency and the over-application of fertilizers imply that producers can save on nutrient input costs without sacrificing yield.[188–190] Similarly, dietary change will result in better health for consumers and, in a developed world context, potential savings on food expenditure.[23, 191] A large body of literature exists on cost-effectiveness in public health interventions for obesity.[192]
- Damages from land-use changes attributable to agriculture trend downwards, with a 14 percent decrease in costs between 2016 and 2020. This is due to a decrease in forest-to-pasture conversion (deforestation)9 and increases in abandoned agricultural land, according to satellite observations and the detection algorithms of HILDA+.[7] From 2021 to 2023, land-use changes were predicted to stabilize due to commodity price increases during the post-pandemic inflation period.
- The shape of the probability distribution for the cost of land-use changes has a trend over 2016–2023. As abandoned agricultural land increases in terms of returned services, the land-use category of costs, as a sum of the positive random variables of the losses of established ecosystems and the negative random variables of the value from returning ecosystem systems, changes shape from being positively skewed to the sum of a positively and negatively skewed random variable (large mass on a wide central support and smaller, but fat tails to higher and lower costs).

FIGURE 8 Trends in expected hidden costs by category, 2016–2023

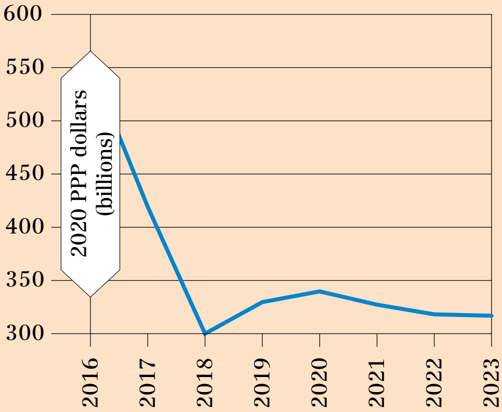
A. GLOBAL TREND IN HIDDEN COSTS FROM GREENHOUSE GAS EMISSIONS



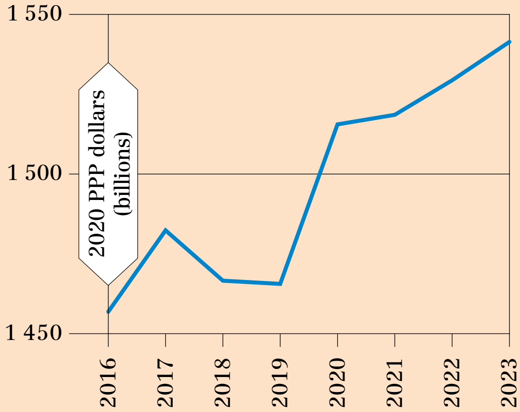
B. GLOBAL TREND IN HIDDEN COSTS FROM WATER USE



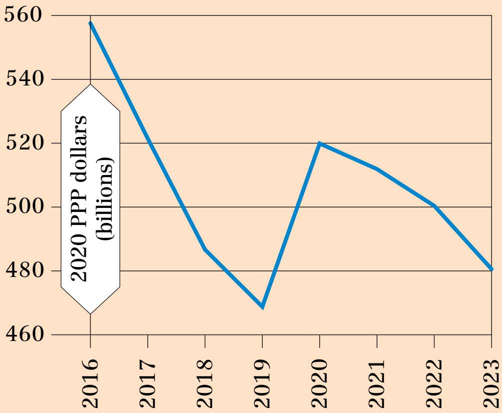
C. GLOBAL TREND IN HIDDEN COSTS FROM LAND-USE CHANGE



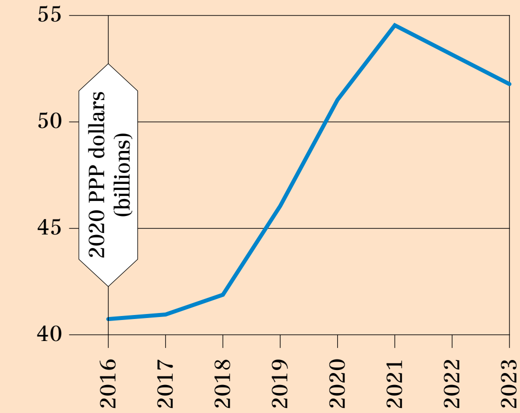
D. GLOBAL TREND IN HIDDEN COSTS FROM NITROGEN EMISSIONS



E. GLOBAL TREND IN HIDDEN COSTS FROM POVERTY IN AGRIFOOD WORKERS



F. GLOBAL TREND IN HIDDEN COSTS FROM UNDERNOURISHMENT



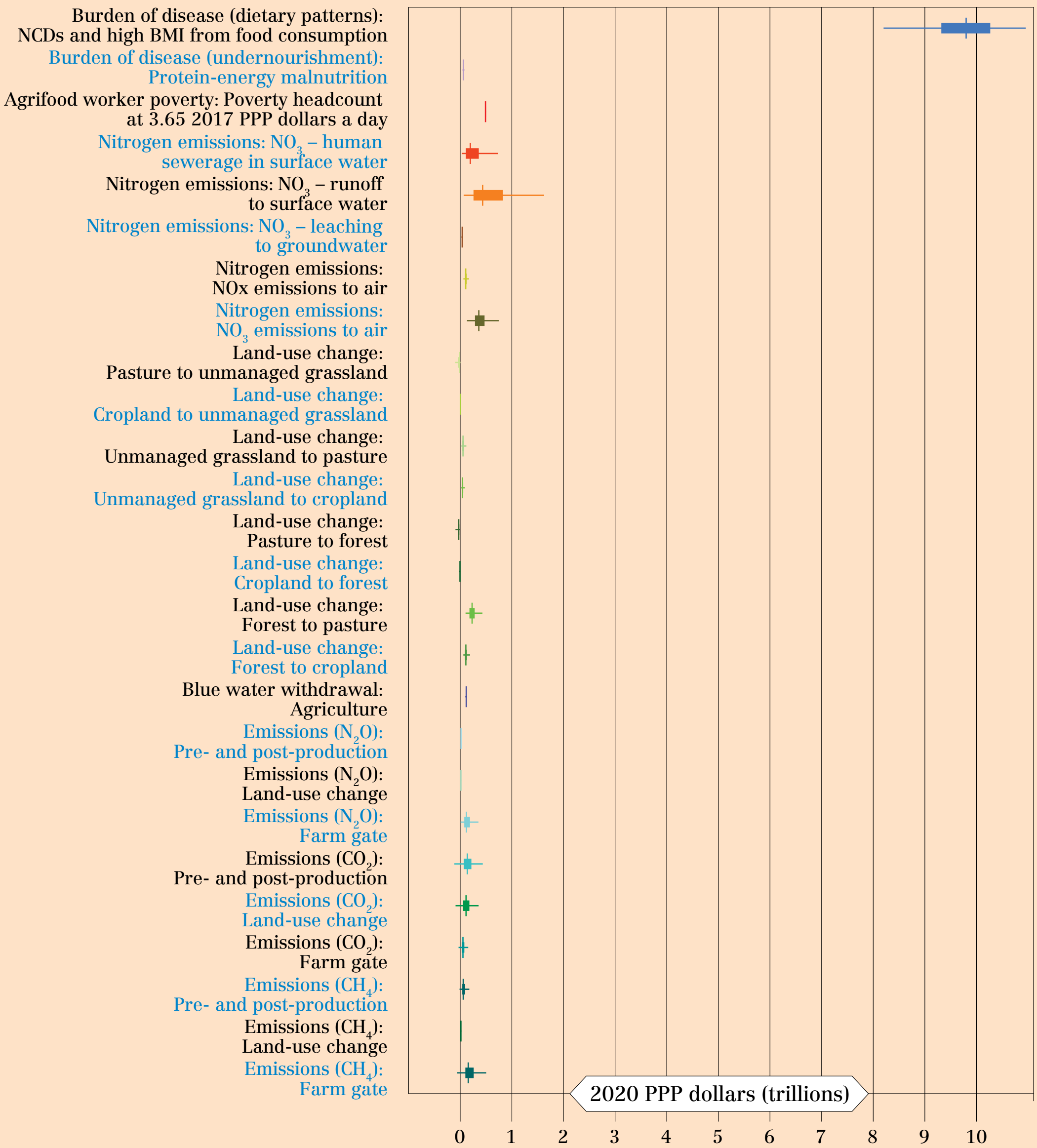
Notes: Costs from land-use change decreased, potentially due to classification uncertainty in the Hilda+ dataset. Surges in moderate poverty among agrifood workers and undernourishment follows World Bank and FAO projections of the effect of the COVID-19 pandemic.

Source: Author's own elaboration.

3.4 Global net damages by impact quantity

Figure 9 shows the contribution of costs of each GHG gas (CH_4, CO_2 and N_2O) and form of Nr emission (NH_3 methane to air, NOx to air, Nr to surface waters and human sewerage and NO_3- to groundwater), the land habitat type under both loss and return, and the contribution of undernourishment and moderate poverty in agrifood workers individually. Costs associated with these quantities are aggregated across all countries to understand the net contribution to global hidden costs attributable to the annual operations of agrifood systems in 2016–2023.

FIGURE 9 Net global costs of global agrifood systems estimated for 2023 broken down by impact quantities with individual cost items



Notes: The figures are boxplot representations of the distribution of global net costs for each quantity, showing the median as the vertical line, the interquartile range as the wider line and the min-to-max range as the thin line. Costs from Nr in surface waters and NH_3 emissions to air have the greatest relative uncertainty.

Source: Author's own elaboration.

Comparison of damages produced in 2023

- Costs from Nr in surface waters from agricultural land runoff, Nr in surface waters from human sewerage and NH_3 emissions to air are the major contributors to the cost of nitrogen emissions (expected values 645 billion 2020 PPP dollars, 325 trillion 2020 PPP dollars and 366 trillion 2020 PPP dollars, respectively).
- Costs from Nr surface runoff from agricultural land have the greatest uncertainty. The long tail towards higher damages of Nr runoff emissions means that there is considerable uncertainty and risk inherent in what the costs may be.
- Considering the mode of the Nr runoff from agricultural land and NH_3 to air cost distribution, broadly, NH_3 to air and Nr runoff are equal contributors to the cost of nitrogen emissions. Nr runoff from agricultural land and NH_3 emission costs, individually, are comparable to the combined cost of farm emissions of CO_2, CH_4 and N_2O using the social costs of the respective GHGs estimated by the US EPA intergovernmental panel modelling exercise.

Trends since 2016

- Avoided costs from abandoned cropland and pasture have increased since 2016. Costs of the conversion of forest and other land habitats to pasture declined between 2016 and 2020.

3.5 Global net damages by cost item category and impact quantity, displaying only the expected value

Table 4 and Figure 10 summarize the breakdown of net global damages incurred or avoided under each policy scenario. The summary displays only the average value of the distributions in Figure 4 to Figure 9.

TABLE 4 Summary statistics for the breakdown of external costs of global agrifood systems in 2023, by expected value, 5th percentile (P5) and 95th percentile (P95) in 2020 PPP dollars

Geography	Category	Year	Mean	P5	P95
Global	Emissions (CH_4): Farm gate	2023	2.15E+11	3.10E+10	5.77E+11
Global	Emissions (CH_4): Land-use change	2023	5.22E+09	7.52E+08	1.40E+10
Global	Emissions (CH_4): Pre- and post- production	2023	7.27E+10	1.05E+10	1.95E+11
Global	Emissions (CO_2): Farm gate	2023	6.70E+10	2.06E+09	2.04E+11
Global	Emissions (CO_2): Land-use change	2023	1.59E+11	4.90E+09	4.86E+11
Global	Emissions (CO_2): Pre- and post- production	2023	1.97E+11	6.05E+09	5.99E+11
Global	Emissions (N_2O): Farm gate	2023	1.57E+11	2.57E+10	4.02E+11
Global	Emissions (N_2O): Land-use change	2023	5.50E+09	8.99E+08	1.41E+10

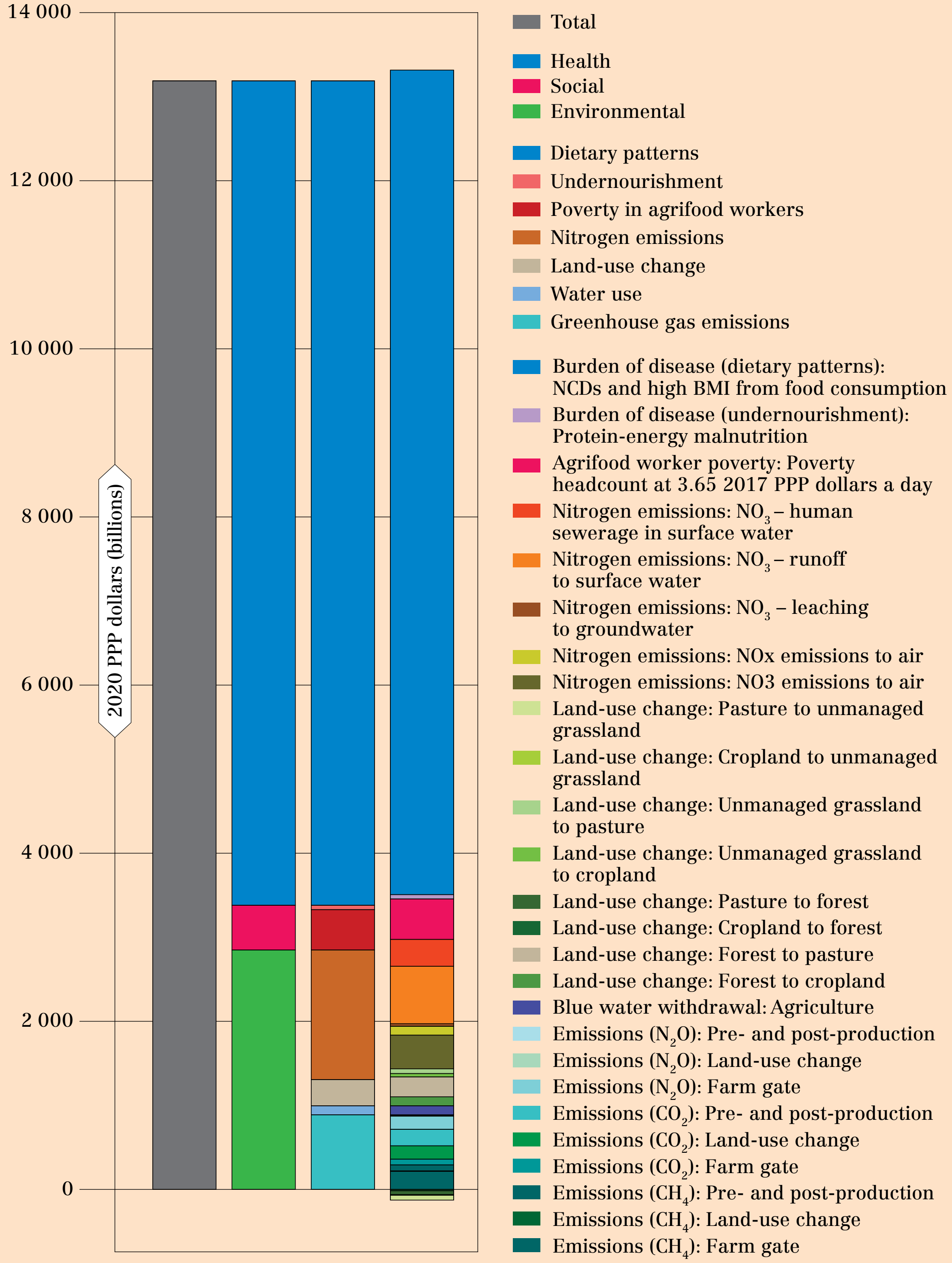
▸▸

TABLE 4 (cont.) **Summary statistics for the breakdown of external costs of global agrifood systems in 2023, by expected value, 5th percentile (P5) and 95th percentile (P95) in 2020 PPP dollars**

Geography	Category	Year	Mean	P5	P95
Global	Emissions (N_2O): Pre- and post- production	2023	1.01E+10	1.64E+09	2.57E+10
Global	Blue water withdrawal: Agriculture	2023	1.06E+11	8.95E+10	1.16E+11
Global	Land-use change: Forest to cropland	2023	1.06E+11	6.66E+10	1.72E+11
Global	Land-use change: Forest to pasture	2023	2.38E+11	1.32E+11	4.11E+11
Global	Land-use change: Cropland to forest	2023	–1.54E+10	–2.80E+10	–8.56E+09
Global	Land-use change: Pasture to forest	2023	–4.61E+10	–1.00E+11	–1.72E+10
Global	Land-use change: Unmanaged grassland to cropland	2023	4.03E+10	1.83E+10	7.73E+10
Global	Land-use change: Unmanaged grassland to pasture	2023	5.46E+10	2.31E+10	1.15E+11
Global	Land-use change: Cropland to unmanaged grassland	2023	–7.55E+09	–1.62E+10	–3.21E+09
Global	Land-use change: Pasture to unmanaged grassland	2023	–5.72E+10	–1.93E+11	–8.09E+09
Global	Nitrogen emissions: NH_3 emissions to air	2023	4.02E+11	1.98E+11	7.76E+11
Global	Nitrogen emissions: NOx emissions to air	2023	1.05E+11	6.87E+10	1.62E+11
Global	Nitrogen emissions: NO_3- leaching to groundwater	2023	2.97E+10	2.00E+10	3.98E+10
Global	Nitrogen emissions: NO_3- runoff to surface water	2023	6.83E+11	1.32E+11	2.19E+12
Global	Nitrogen emissions: NO_3- human sewerage in surface water	2023	3.21E+11	5.50E+10	1.16E+12
Global	Agrifood worker poverty: Poverty headcount at 3.65 2017 PPP dollars a day	2023	4.81E+11	4.81E+11	4.81E+11
Global	Burden of disease (undernourishment): Protein–energy malnutrition	2023	5.18E+10	4.01E+10	6.57E+10
Global	Burden of disease (dietary patterns): NCDs and high BMI from food consumption	2023	9.81E+12	8.72E+12	1.10E+13

Note: Mean values are expected values.
Source: Author's own elaboration.

FIGURE 10 Summary of breakdown of external costs of global agrifood systems by 26 cost items in 2023 using expected value



Notes: Observing trends since 2016, the cost breakdown shows that, globally, nitrogen and GHG costs are increasing. The predominant and increasing nitrogen costs are NH_3 to air and Nr in surface waters. Land-use costs are decreasing, apart from small increases in avoided costs from returned agricultural land, due to a reduction in the expansion of pasture and a smaller net contribution from abandoned agricultural land. Dietary patterns are increasing but not broken down into contributions from NCDs and high BMI, as the burden of disease is calculated using a joint mediation factor. Moderate poverty for agrifood workers is decreasing, but World Bank estimates and Figure 8 indicate that the COVID-19 pandemic set poverty reduction back seven to eight years.

Source: Author's own elaboration.

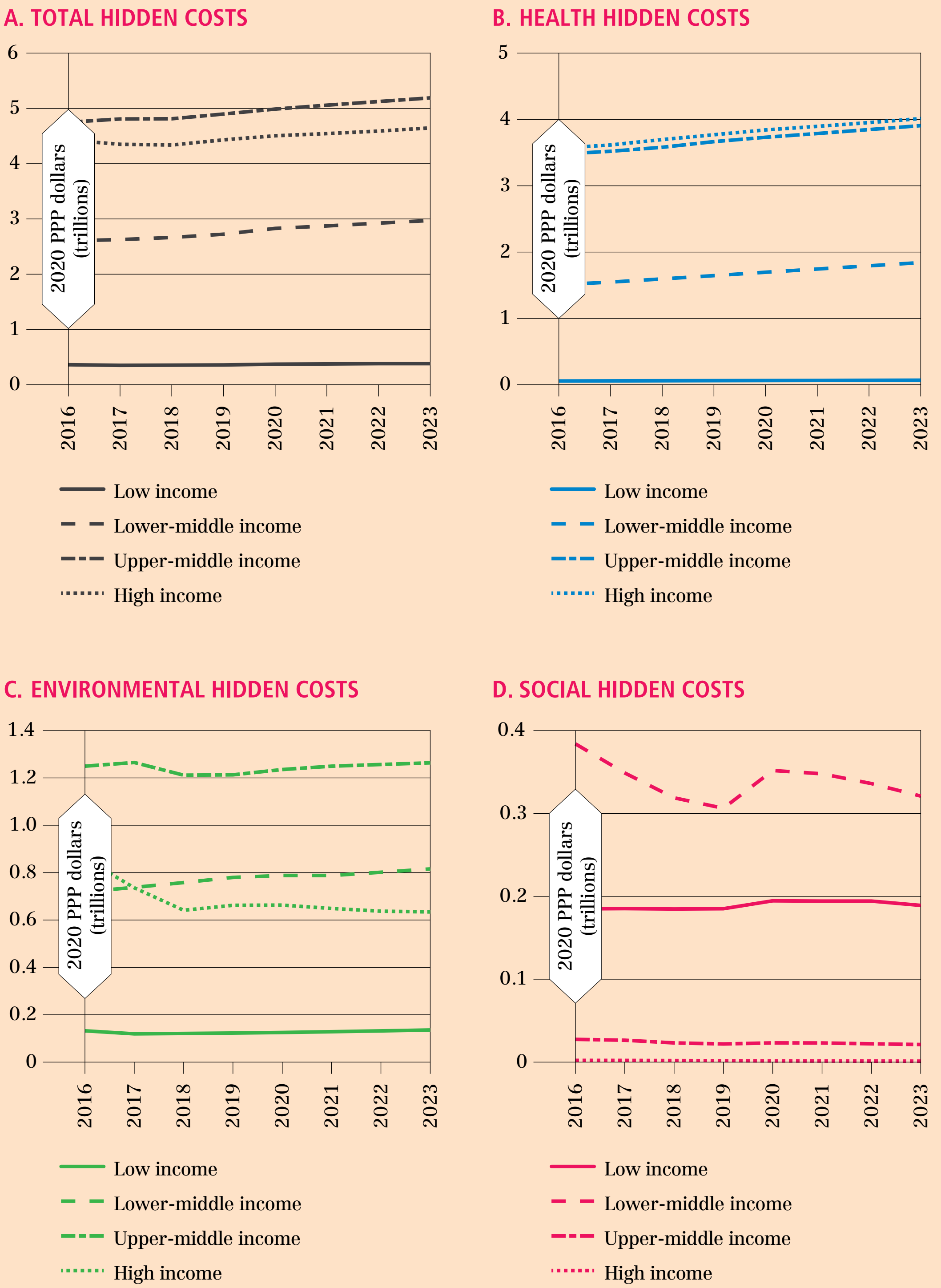
3.6 Damages by World Bank income group

Annex 3 contains 2020 data on the region, subregion and the HDI of the 154 countries in the study. With the caveats discussed in the methodology (Section 2), cost bearing of the hidden costs attributable to agrifood systems can be analysed at regional, HDI and national level.

The World Bank classifies countries in 2020 as LIC, LMC, UMC and HIC by their gross national income (GNI) per capita, determined by the Atlas method in 2020 dollar exchange rates. LICs had GNI per capita below 1 045 2020 PPP dollars, LMCs had GNI per capita of 1 045–4 095 2020 PPP dollars, UMCs had GNI per capita of 4 096–12 695 2020 PPP dollars and HICs had GNI per capita of more than 12 695 2020 PPP dollars.[194] Annex 4 lists the 154 countries in the study and their income group in 2020. Approximately 646 million people lived in LICs in 2020, predominantly in sub-Saharan Africa. About 3.35 billion people lived in LMCs, including India, and 2.48 billion people live in UMCs, including China and Brazil, in 2020. In 2020, the population of HICs was estimated at 1.2 billion people.

- Trends in expected costs show that UMC and HIC countries bear approximately the same hidden costs of agrifood systems, between 4.5 trillion and 5 trillion 2020 PPP dollars (Figure 11). The estimated hidden cost production per capita in 2023 for HICs is 3 872 2020 PPP dollars, while for UMCs, it is 2 093 2020 PPP dollars.
- For LMCs, the expected hidden costs of agrifood systems are 2.5–3 trillion 2020 PPP dollars, half that of UMCs and LMCs, despite having the greatest population of the income group blocs. The LMC estimated hidden cost production per capita in 2023 is 887 2020 PPP dollars. LICs generate the lowest expected value of hidden costs for 2023, at 381 billion 2020 PPP dollars, or 558 2020 PPP dollars per capita.
- Table 5 compares the hidden cost production per capita with GDP PPP per capita in 2020. The present and future economies of LICs face a higher relative economic burden from the hidden costs of agrifood systems. However, LICs also derive a greater share of GDP PPP from agrifood systems, so the ratio in Table 5 is not indicative of the economic benefits provided by agrifood systems compared with external costs, productivity losses and so on. Further indicators below perform a comparison of hidden costs with agriculture GVA.
- Productivity losses from dietary patterns are increasing across all income groups, at similar rates of about 2 percent per year (Figure 11). External costs from environmental sources are highest for UMCs, the income group that includes China and Brazil, at more than 1.2 trillion 2020 PPP dollars. External costs from environmental sources for LMCs, at around 700–900 billion 2020 PPP dollars over 2016–2023, are trending upwards and are probably larger than external costs from environmental sources for HICs, which are likely to trend downwards.
- The costs of moderate poverty among agrifood workers and undernourishment in the general population surged for all income groups in 2020 during the COVID-19 pandemic, and World Bank and FAO projections expect them to resume a downward trend. World Bank analysis shows that some countries avoided expected large poverty increases through government intervention.[116] In terms of total income shortfall to the 3.65 2017 PPP dollar poverty line, the LMC shortfall was falling at the fastest rate before the COVID-19 pandemic and was most shocked by it in 2020. LICs are unchanged in terms of poverty alleviation, in part due to the concentration of extreme poor in fewer countries with entrenched poverty.[116] LMCs have double the total income shortfall of LICs, but nearly three times the population. On a per capita basis, in terms of income shortfall due to moderate poverty and undernourishment, LICs bear the highest burden of distributional failure, with a non-decreasing trend.

FIGURE 11 Trends in the environmental (E), dietary pattern (H) and distributional failure (S) cost production components of the estimated global costs in 2016–2023 by World Bank income group



Notes: All values are expected values. Trends show increasing productivity losses from dietary patterns across all income groups. External costs from environmental sources are greater in LMCs than HICs and trending upwards. For distributional failures, decreases in costs for LMCs were halted by the COVID-19 pandemic, but then resumed. Costs of undernourishment and moderate poverty among agrifood workers in LICs are non-decreasing.

Source: Author's own elaboration.

TABLE 5 Expected value of hidden cost production and bearing by World Bank income group per capita

Income group	Year	Population (million)	Hidden costs PPP per capita	GDP PPP per capita	Ratio
Low-income countries	2020	646	575 (465, 781)	2 053	0.27 (0.22, 0.37)
Low- to middle-income countries	2020	3 335	848 (685, 1 161)	7 154	0.12 (0.10, 0.16)
Upper-middle-income countries	2020	2 475	2 015 (1 482, 2 846)	18 019	0.11 (0.08, 0.16)
High-income countries	2020	1 190	3 785 (3 217, 4 451)	50 000	0.08 (0.06, 0.09)

Notes: A comparison of the hidden costs produced by agrifood systems in 2020 in GDP PPP with GDP PPP per capita in 2020 shows that present and future economies of LICs face a higher relative economic burden from the hidden costs of agrifood systems. Mean values are expected values in 2020 PPP dollars, with 5th and 95th percentiles in brackets.

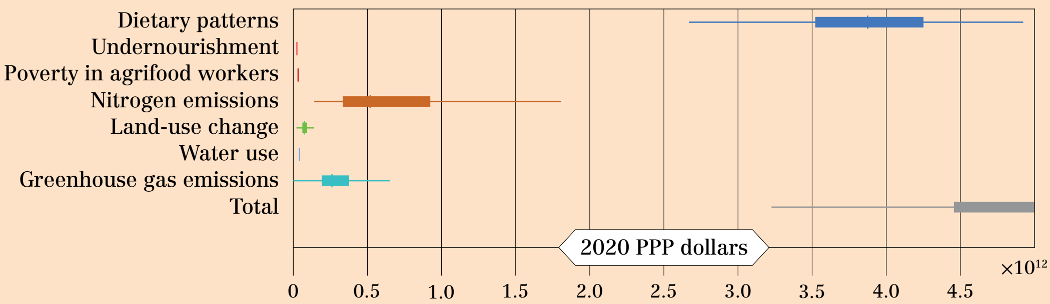
Source: Author's own elaboration.

Figure 12 and Figure 13 show the shares of and uncertainty inherent in GHG, nitrogen, land-use change and blue water withdrawal external costs, moderate poverty among agrifood workers, undernourishment distributional failures and productivity losses from dietary patterns in the total hidden costs of agrifood systems for World Bank income groups.

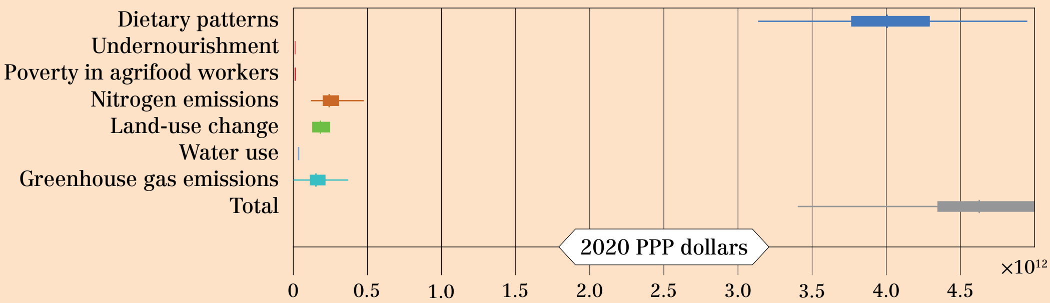
FIGURE 12

FIGURE 12 (cont.) Net global damages in 2023 broken down by cost category and World Bank income group

C. UPPER-MIDDLE-INCOME COUNTRIES ANNUAL COST BY COST PRODUCTION CATEGORY WITH UNCERTAINTY ESTIMATE



D. HIGH-INCOME COUNTRIES ANNUAL COST BY COST PRODUCTION CATEGORY WITH UNCERTAINTY ESTIMATE



Notes: The figures are boxplot representations of the components of the distribution of global net costs according to scenario, development bloc and cost category. Boxplots show the median as a vertical line, the interquartile range as a wider line and the 5th to 95th percentile range as a thin line.

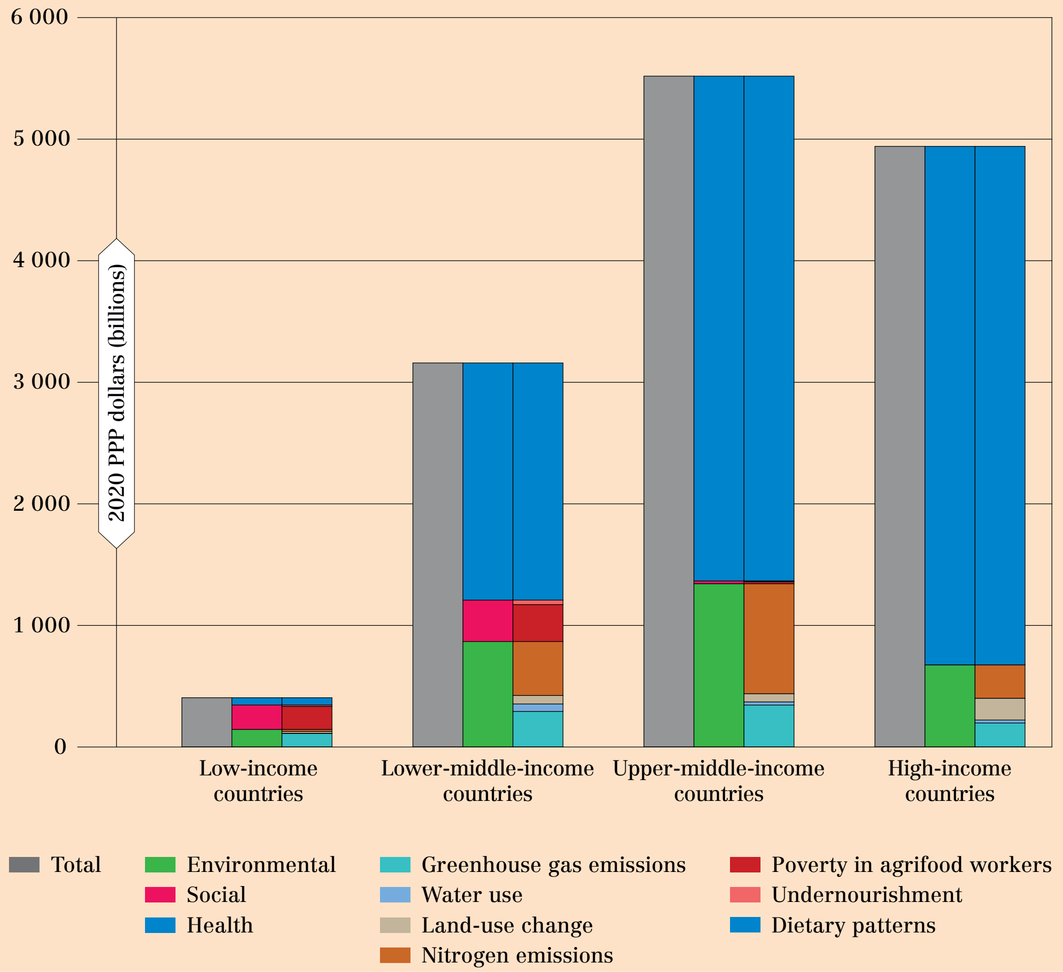
Source: Author's own elaboration.

- Total expected costs generated by LICs in 2023 are 381 billion 2020 PPP dollars, with 36 percent of expected costs (136 billion 2020 PPP dollars) from environmental sources, 14 percent from productivity losses resulting from dietary patterns (56 billion 2020 PPP dollars) and 50 percent from poverty and undernourishment (190 billion 2020 PPP dollars) (Figure 13). The two largest costs for LICs are GHG emissions (105 billion 2020 PPP dollars) and poverty among agrifood workers (179 billion 2020 PPP dollars). Unlike UMCs, only a small proportion of costs (15 billion 2020 PPP dollars) are associated with nitrogen pollution.
- Total expected costs generated by LMCs in 2023 are 2 970 billion 2020 PPP dollars, with 27 percent of expected costs (816 billion 2020 PPP dollars) from environmental sources, 62 percent from productivity loss from dietary patterns (1 830 billion 2020 PPP dollars) and 11 percent from poverty and undernourishment (321 billion 2020 PPP dollars) (Figure 13). LMCs' largest external environmental costs are GHG emissions (274 billion 2020 PPP dollars) and nitrogen pollution (418 billion 2020 PPP dollars). Both are comparable to or larger than the income shortfall among agrifood workers (286 billion 2020 PPP dollars). In LMCs, productivity losses from dietary patterns (1830 billion 2020 PPP dollars) already eclipse productivity losses due to poverty and undernourishment.
- Total expected costs generated by UMCs in 2023 are 5 190 billion 2020 PPP dollars, with 24.5 percent of expected costs (1 260 billion 2020 PPP dollars) from environmental sources, 75 percent from productivity losses due to dietary patterns (3 910 billion 2020

PPP dollars) and 0.5 percent from poverty and undernourishment (21 billion 2020 PPP dollars) (Figure 13). UMCs' largest external environmental costs are GHG emissions (324 billion 2020 PPP dollars) and nitrogen pollution (851 billion 2020 PPP dollars).

- Total expected costs generated by HICs in 2023 are 4 650 billion 2020 PPP dollars, with 14 percent of expected costs (634 billion 2020 PPP dollars) from environmental sources, 75 percent from productivity loss from dietary patterns (4 010 billion 2020 PPP dollars) and less than 0.1 percent from poverty and undernourishment (1 billion 2020 PPP dollars) (Figure 13). UMCs face approximately equal external environmental costs from GHG emissions (185 billion 2020 PPP dollars), nitrogen pollution (257 billion 2020 PPP dollars) and land-use change (169 billion 2020 PPP dollars).
- Environmental costs for LMCs and UMCs are generally higher than for HICs and have greater uncertainty. Additional economic risk for LMCs and UMCs comes from external environmental costs due to a long tail of damages from Nr runoff and GHG emissions (Figure 12). Nr runoff in China forms a substantial proportion of the expected damages and economic risk in UMCs.

FIGURE 13 Summary of breakdown of expected hidden costs of agrifood systems by World Bank income group in 2023



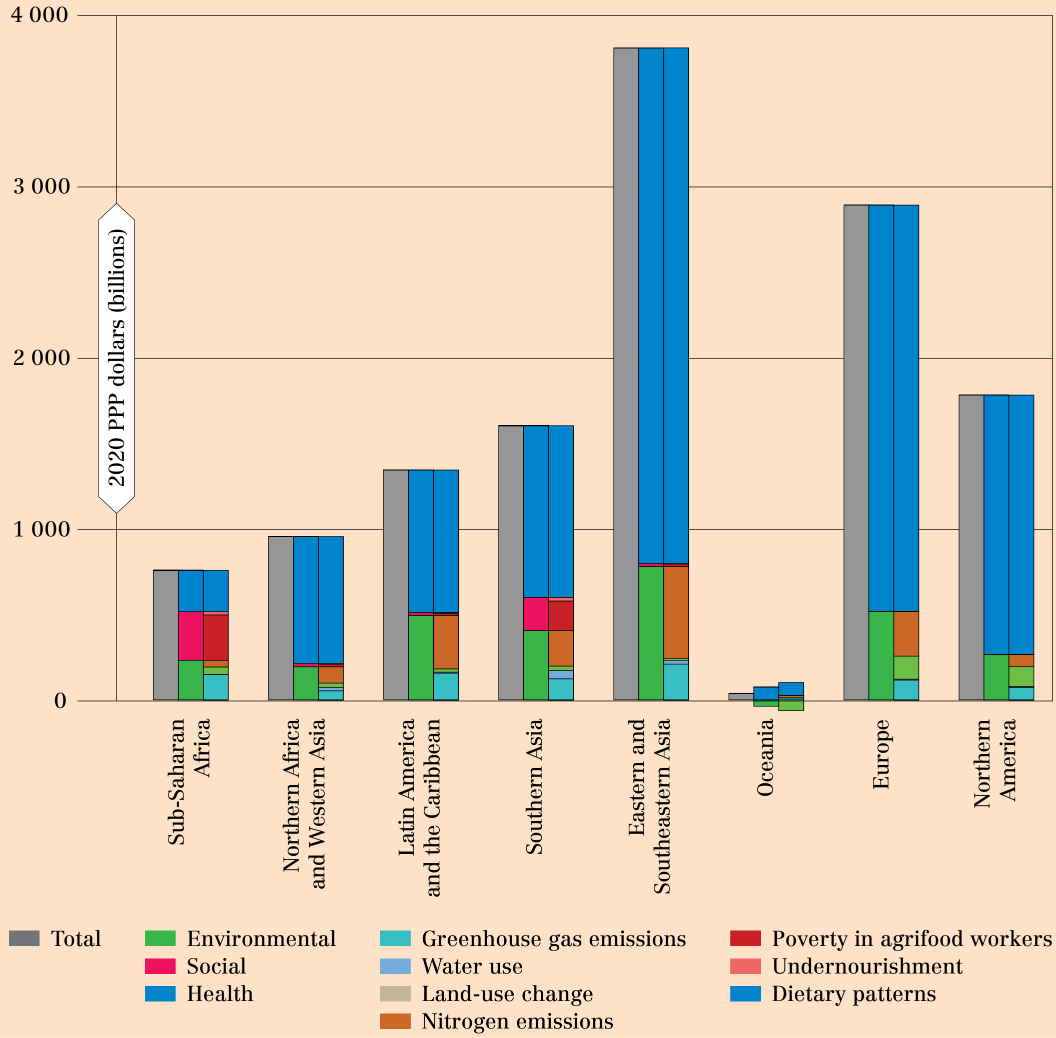
Notes: Overall expected damages incurred are greater for UMCs. UMCs have the highest proportion of nitrogen and GHG costs. GHGs form the greatest share of environmental external costs in LICs.
Source: Author's own elaboration.

The next section shows that within income groups, the cost bearing of external costs from environmental sources, productivity losses from dietary patterns and hidden costs of distributional failures are asymmetric. Even within regional breakdowns, the country-level analysis shows that the cost bearing by countries, such as China and India, is not representative of all UMC- or LMC-bloc countries, respectively.

3.7 Damages by region, by Human Development Index and by country

FAO chose eight regions to complement the breakdown of the hidden costs of agrifood systems by World Bank income group. Annex 4 lists the 154 countries in the study and their region. We omit figures showing the distributions of hidden costs aggregated by region. The risk profile follows broadly the order of the expected value in Figure 14. A higher expected value corresponds mostly to the large uncertainty and higher risk of incurred damages. Exceptions to this are noted below.

FIGURE 14 Summary of breakdown of expected hidden costs of agrifood systems in 2023 at the regional level



Note: Overall expected damages are lowest for Oceania and sub-Saharan Africa and highest for Eastern and Southeastern Asia and Europe.

Source: Author's own elaboration.

Distribution of damages by region

- Examining the distributions and considering uncertainty, productivity losses from dietary patterns are the largest category of hidden costs across all regions except sub-Saharan Africa. In sub-Saharan Africa, environmental externalities (estimated 231 billion 2020 PPP dollars in 2023) are of the same order of productivity loss as dietary patterns (estimated 242 billion 2020 PPP dollars in 2023). Since 2016, productivity losses from dietary patterns have grown to be on par with the costs of agrifood worker poverty and undernourishment in sub-Saharan Africa. Agrifood worker poverty and undernourishment in the general population remain higher economic costs in sub-Saharan Africa in 2023 (285 billion 2020 PPP dollars). Southern Asia is the other region with significant agrifood worker poverty and undernourishment (194 billion 2020 PPP dollars in 2023), but productivity losses from dietary patterns are larger (1 004 billion 2020 PPP dollars in 2023). Productivity losses from dietary patterns increased 20 percent from 2016 to 2023 in southern Asia.
- Eastern and Southeastern Asia, the most populous region, with 2.25 billion people in 2020, has the largest total productivity losses from dietary patterns, at 3 017 billion 2020 PPP dollars in 2023. Productivity losses in Eastern and Southeastern Asia from dietary patterns equated to 1 268 2020 PPP dollars per capita in 2020.
- Europe and North America have expected productivity losses from dietary patterns in the order of 2 376 billion 2020 PPP dollars and 1 517 billion 2020 PPP dollars in 2023, respectively, at 3 167 PPP dollars per capita and 3 905 PPP dollars per capita in 2020, respectively.
- Southern Asia, Eastern and Southeastern Asia, and Latin America and the Caribbean have the largest environmental external costs in either absolute or relative terms (estimated at 406, 780 and 493 billion 2020 PPP dollars, respectively, in 2023). The largest external cost components are GHG and nitrogen emissions (nitrogen emission costs are estimated at 208, 539 and 312 billion 2020 PPP dollars, respectively, in 2023). Expected values of external costs from nitrogen emissions in the three regions constitutes 69 percent of the global cost of agrifood systems nitrogen emissions.
- Land-use changes in Oceania (Australia and New Zealand), as estimated by the HILDA+ dataset, contributed most to the reduction in land-use change costs over the 2016–2023 period.

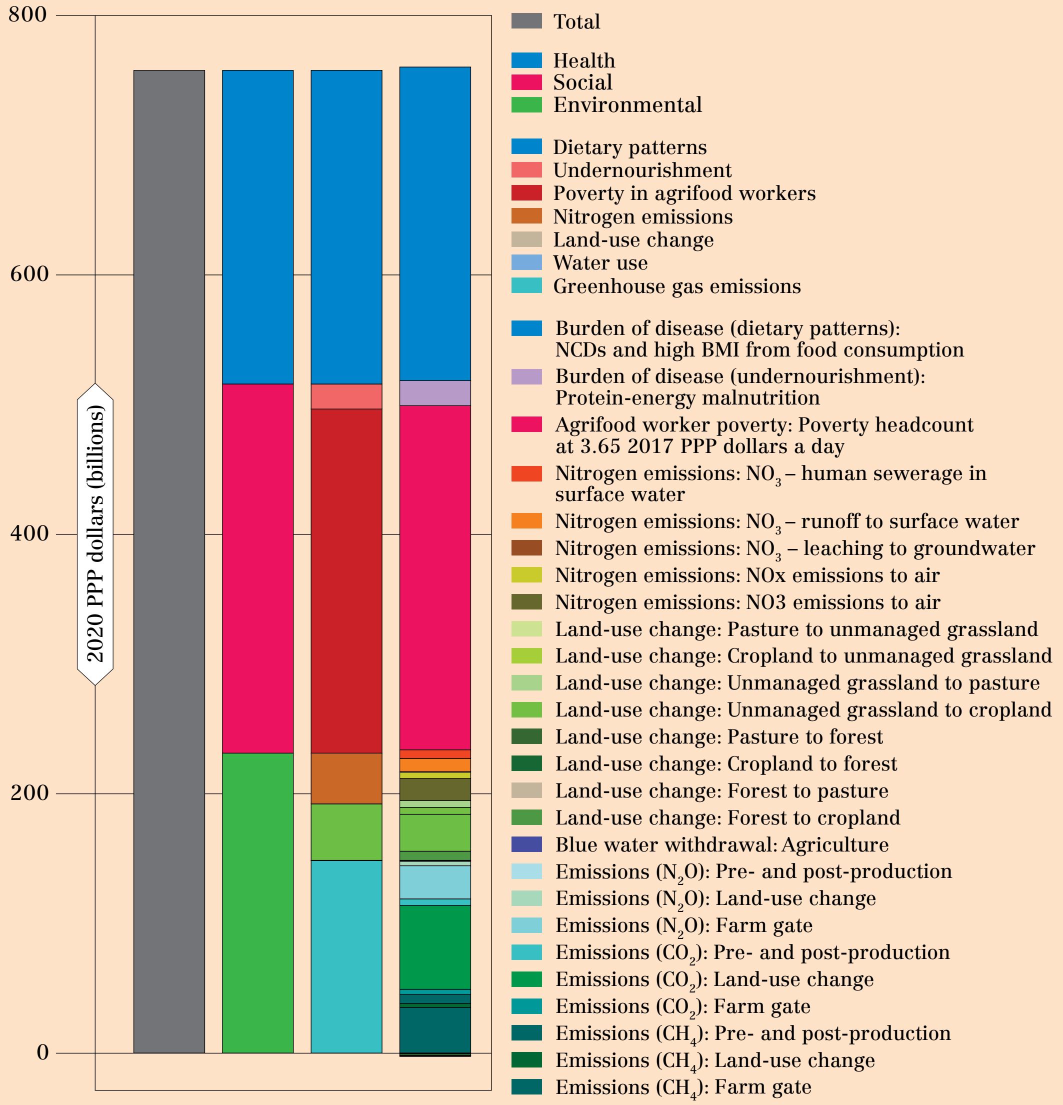
Figure 15 examines the expected costs in 2023 for sub-Saharan Africa.

Distribution of damages in sub-Saharan Africa

- Agrifood worker poverty and undernourishment in the general population remain higher economic costs to sub-Saharan Africa (285 billion 2020 PPP dollars in 2023) than productivity losses from dietary patterns (242 billion 2020 PPP dollars in 2023). Agrifood worker poverty and undernourishment remained static over the period due to the COVID-19 pandemic, while productivity losses from dietary patterns are estimated to increase by 14.5 percent over the 2016–2023 period.
- Assuming a continuation of the same rate of increase in productivity losses from dietary patterns, by 2030, or earlier if agrifood worker poverty and undernourishment resume reduction rates similar to those before 2016, productivity losses from dietary patterns in sub-Saharan Africa will be a greater cost to society than agrifood worker poverty and undernourishment in the general population.
- The costs of GHG emissions remained the largest category of external environmental costs for sub-Saharan Africa (estimated at 148 billion 2020 PPP dollars in 2023). Farm-gate CH_4 emissions, CO_2 emissions from land-use changes (deforestation) and

N_2O from fertilizer production are the largest contributors to the external costs of GHGs across sub-Saharan Africa (Figure 15).

FIGURE 15 Summary of breakdown of expected hidden costs of agrifood systems for sub-Saharan Africa in 2023



Notes: Agrifood worker poverty and undernourishment remain higher economic costs to society than productivity losses from dietary patterns. Compared with 2016, poverty and undernourishment remained static over the period due to the COVID-19 pandemic, while productivity losses from dietary patterns increased 14.5 percent. The costs of GHG emissions increased as the largest contributor to external costs from environmental sources, from 132 billion 2020 PPP dollars to 148 billion 2020 PPP dollars. The costs of GHG emissions remained the largest category of external costs.

Source: Author's own elaboration.

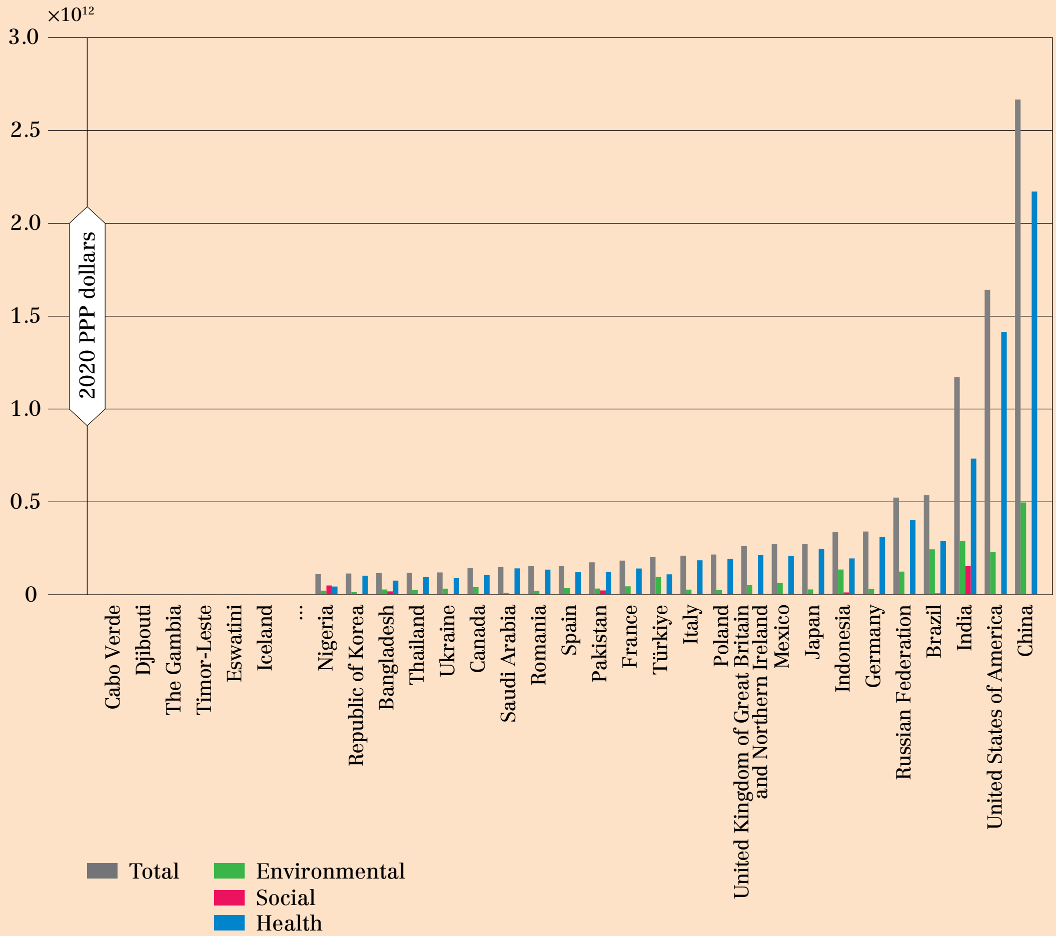
Distribution of damages by HDI

The distribution of expected costs over the HDI show no major trends over 2016 to 2023. The shape of the distribution – why brackets of HDI 0.75 to 0.8 (which include countries such as China and Brazil) have high nitrogen emissions or GHG emissions – is better explained by the country-level disaggregation below.

Distribution of damages by country

The countries with the highest net hidden costs generated by agrifood systems are the world's largest food producers and consumers (Figure 16). The United States of America (around 1.64 trillion 2020 PPP dollars) and the BRIC countries – in order of expected costs, China (2.67 trillion 2020 PPP dollars), India (1.17 trillion 2020 PPP dollars), Brazil (0.53 trillion 2020 PPP dollars) and the Russian Federation (0.52 trillion 2020 PPP dollars) – are the top generators of costs in 2023 and are mostly unchanged in that order over the 2016–2023 period (Table 6). Hidden costs for China, India, the Russian Federation and the United States of America are predominantly (more than 75 percent) from dietary patterns. Brazil is the exception, with 45 percent of hidden costs being external costs from environmental sources. As a bloc, the European Union Member States would appear in third position, with total hidden costs of agrifood systems of 1.82 trillion 2020 PPP dollars in 2023, of which 284 billion 2020 PPP dollars are from environmental sources and 1.54 trillion 2020 PPP dollars (84 percent of total costs) are productivity losses from dietary patterns.

FIGURE 16 Countries ranked by annual hidden costs produced by national agrifood systems for 2023



Notes: Shown are net costs and a breakdown into environmental (E) cost production per column 4, Table 1 (GHG emissions, nitrogen emissions, water use and land-use change), productivity losses from dietary patterns (H) and distributional failures (S) (undernourishment, as defined by FAO, and agrifood worker moderate poverty, as defined by the World Bank). Listed on the x-axis are six countries with the lowest net hidden costs and 24 countries with the highest net hidden costs.

Source: Author's own elaboration.

TABLE 6 Countries with the highest expected hidden costs of agrifood systems in 2023

	United States of America	China	European Union	India	Brazil	Russian Federation
Total (T)	1.64E+12	2.67E+12	1.82E+12	1.17E+12	5.33E+11	5.21E+11
Environmental (E)	2.27E+11	4.95E+11	2.84E+11	2.87E+11	2.42E+11	1.22E+11
Social (S)	9.90E+07	1.21E+09	3.31E+08	1.51E+11	4.53E+09	0.00E+00
Health (H)	1.41E+12	2.17E+12	1.54E+12	7.31E+11	2.87E+11	3.99E+11
E/T x100	14	19	16	25	45	23
S/T x100	0	0	0	13	1	0
H/T x100	86	81	84	63	54	77
Climate	5.61E+10	1.07E+11	6.29E+10	8.12E+10	7.62E+10	3.00E+10
Water	6.02E+09	8.43E+09	5.02E+09	3.63E+10	3.35E+07	1.16E+07
Land	1.05E+11	4.49E+09	8.68E+10	2.55E+10	5.36E+09	1.15E+10
Nitrogen	6.03E+10	3.75E+11	1.30E+11	1.44E+11	1.61E+11	8.04E+10
Poverty	9.90E+07	1.21E+09	3.10E+08	1.36E+11	3.48E+09	0.00E+00
Undernourishment	0.00E+00	0.00E+00	2.09E+07	1.48E+10	1.05E+09	0.00E+00
Dietary patterns	1.41E+12	2.17E+12	1.54E+12	7.31E+11	2.87E+11	3.99E+11

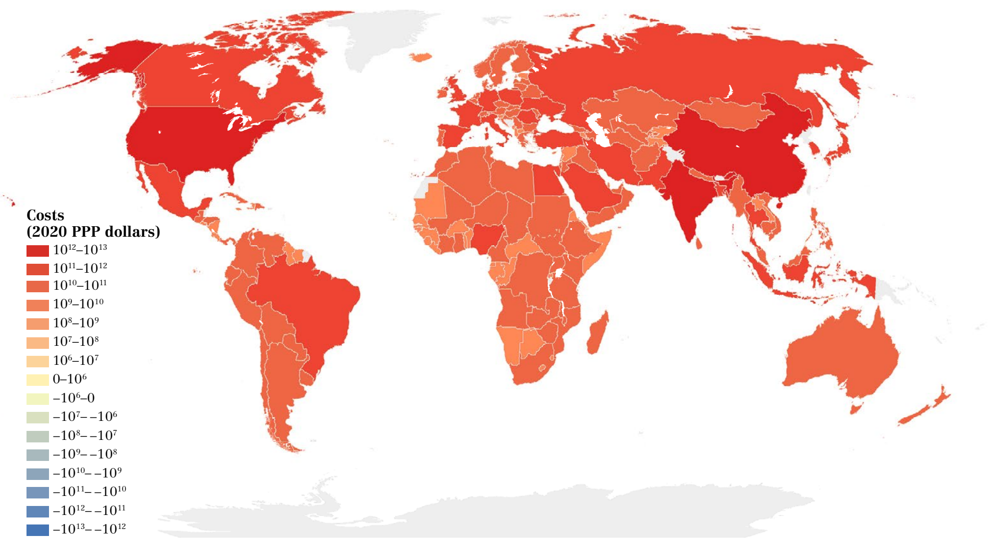
Source: Author's own elaboration.

Nitrogen emissions are the largest class of environmental cost for all countries with the highest costs (Table 6). China (estimated 375 billion 2020 PPP dollars in 2023), Brazil (estimated 161 billion 2020 PPP dollars in 2023), India (estimated 144 billion 2020 PPP dollars in 2023) and the European Union (estimated 130 billion 2020 PPP dollars in 2023) have the largest external cost production, and likely cost bearing, from nitrogen emissions from agrifood systems. In the United States of America, the expected cost of nitrogen emissions (60 billion 2020 PPP dollars) and GHG emissions from agrifood systems (56 billion 2020 PPP dollars) are comparable. These figures are expected values, which are skewed towards higher damages for nitrogen emission due to the larger uncertainty involved.

Order-of-magnitude costs for all countries in terms of expected net hidden costs, environmental sources of external costs, productivity losses from dietary patterns, and costs of poverty among agrifood workers and undernourishment in the general population are displayed as spatial maps in Figure 17. No significant spatial trends in terms of order-of-magnitude changes over 2016–2023 are discernible. India (136 billion 2020 PPP dollars estimated in 2023) and central sub-Saharan Africa have the largest costs of poverty and undernourishment. After India and sub-Saharan Africa, Indonesia, Brazil and Mexico (in order of magnitude) show residual expected costs of agrifood worker poverty and undernourishment. After the United States of America and the BRIC countries, Indonesia, Japan, Mexico and western Europe face the highest productivity losses from dietary patterns.

FIGURE 17 Spatial distribution of the expected hidden costs of global agrifood systems in 2023

A. SPATIAL DISTRIBUTION OF TOTAL COSTS



B. SPATIAL DISTRIBUTION OF SOCIAL COSTS

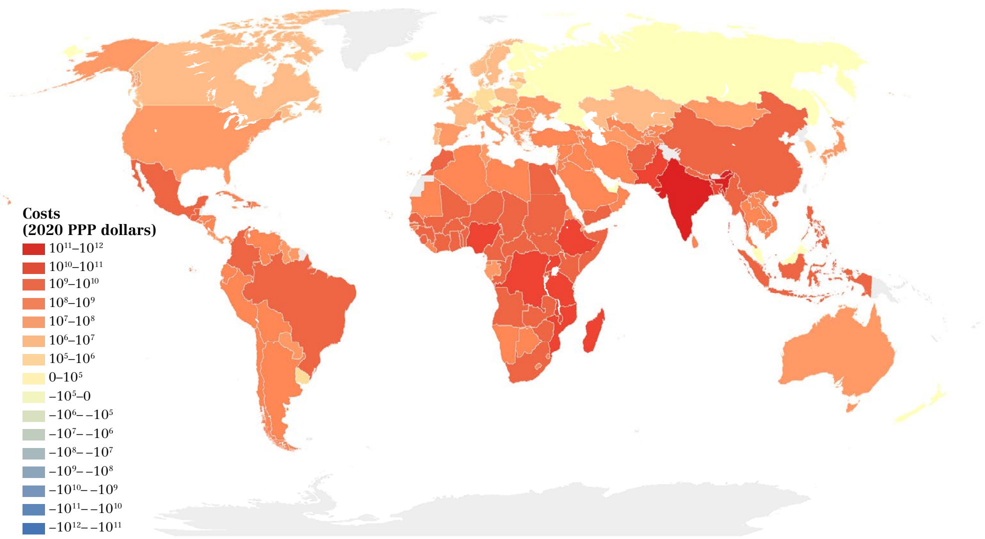
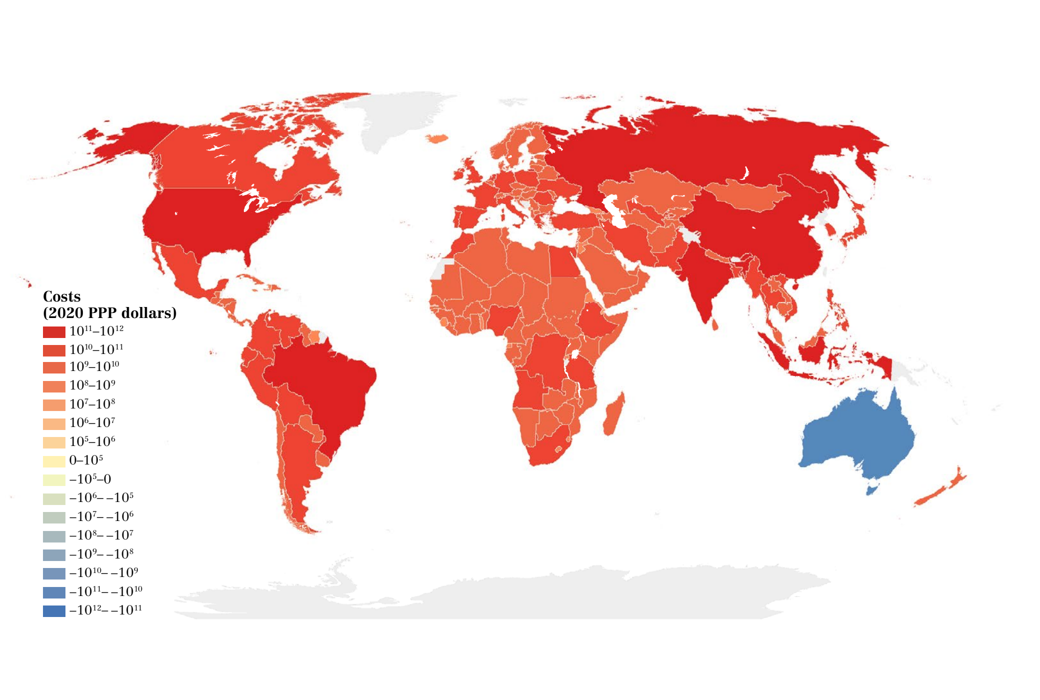
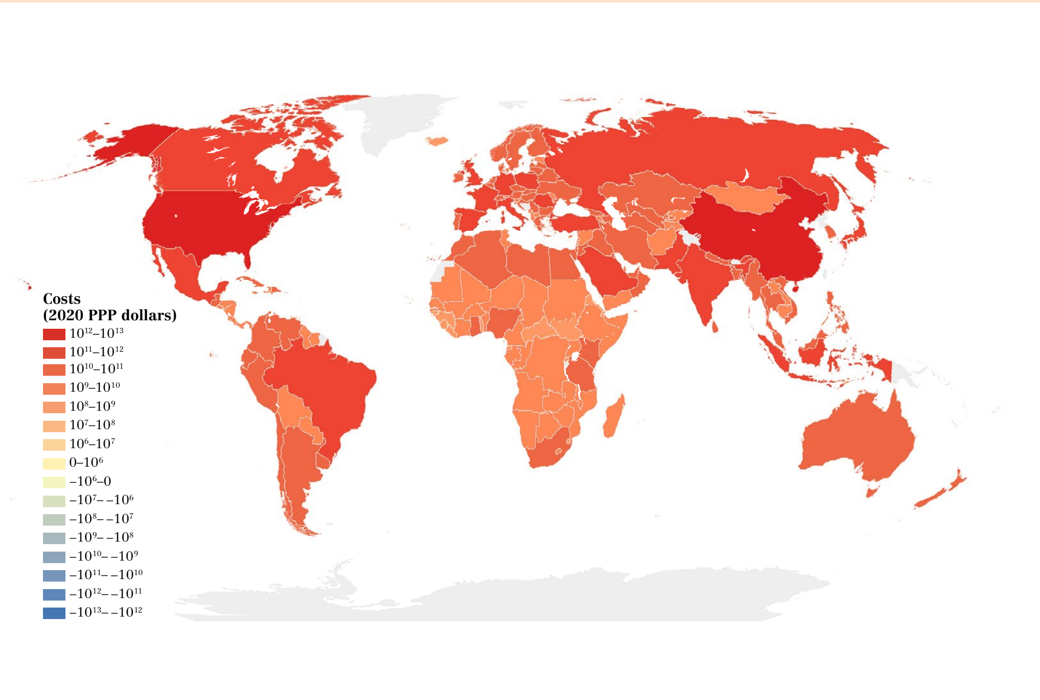


FIGURE 17 (cont.) Spatial distribution of the expected hidden costs of global agrifood systems in 2023

C. SPATIAL DISTRIBUTION OF ENVIRONMENTAL COSTS



D. SPATIAL DISTRIBUTION OF HEALTH COSTS



Notes: Final boundary between the Sudan and South Sudan has not yet been determined. Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties.

Source: United Nations Geospatial. 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

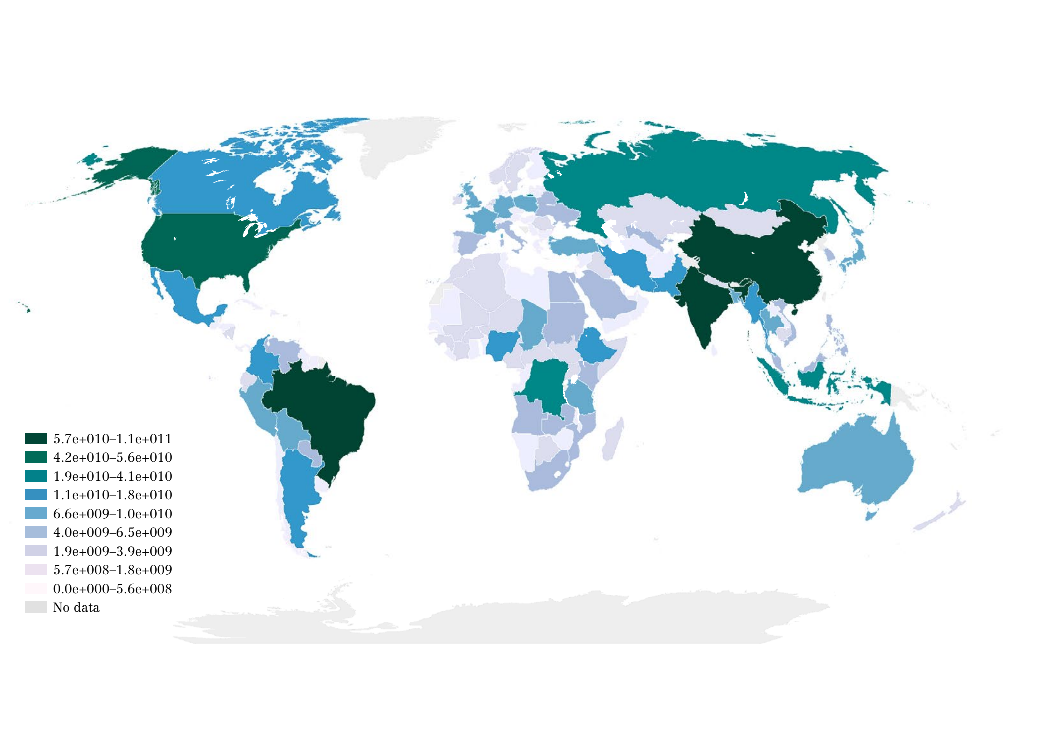
In terms of risk, the tail of total costs is much "fatter" for China than the United States of America due to large quantities of reactive nitrogen in surface water, resulting from runoff from agricultural land and human sewerage, and the uncertainty inherent in external costs. Using the 95th percentile of hidden costs as a risk indicator, China's economic risk from agrifood systems activities is up to two times higher than expected values (a 95th percentile of 4 trillion 2020 PPP dollars in net hidden costs and a 95th percentile of 1.6 trillion 2020 PPP dollars in nitrogen emissions estimated for 2023). The economic risk in China from external nitrogen pollution is 10 times larger than for the United States of America a (95th percentile of 2.3 trillion 2020 PPP dollars in net hidden costs and a 95th percentile of 147 billion 2020 PPP dollars in nitrogen emissions estimated for 2023). Expected value as a measure of central tendency can be sensitive to outliers. Nitrogen emissions and land-use change measured using the HILDA+ dataset, combined with the large uncertainty inherent in the value of ecosystem services, introduces a large skew in the distribution of hidden costs. Using the median as a central measure, China has larger hidden costs (median 2023 hidden costs of 2 518 billion 2020 PPP dollars) than the United States of America (median 2023 external costs of 1 602 billion 2020 PPP dollars). Median external costs of agrifood systems nitrogen emissions in 2023 were almost three times higher in China (112 billion 2020 PPP dollars) than the United States of America (40 billion 2020 PPP dollars).

Figure 18 displays as spatial maps the external environmental costs from GHG emissions, nitrogen emissions and land-use change, and Figure 19 their expected value for a selected number of countries in 2023. Figure 20 breaks down the external environmental costs of countries with the largest external costs in 2023.

- Farm-gate CH_4 emissions (by order of magnitude, China, Brazil, India, United States of America and Pakistan), CO_2 emissions from deforestation (Brazil, Democratic Republic of the Congo, Colombia and United Republic of Tanzania) and CO_2 emissions from fertilizer production, manufacturing, retail and consumption (pre-and post-farm gate) (China, Germany, India, Iran, Japan, Russian Federation and United States of America) are the pre-dominant forms of emission contributing to external costs (left panel, Figure 20).
- N_2O farm-gate emissions add to the significant costs of other forms of nitrogen pollution in Brazil, China, India and the United States of America. N_2O and CH_4 external costs outweigh the costs of CO_2 emissions in many of the larg-est producers (Argentina, Brazil, China, India, Mexico, Pakistan and United States of America).
- Deforestation for agricultural land expansion, in the form of conversion of forest habitat to cropland and pasture, is the predominant contributor to external costs from land-use change (middle panel, Figure 20). For the United States of America and Australia, the Hilda+ algorithm detects frequent transitions in land use, potentially conflat-ing management practices with habitat change. The external costs, or avoided external costs, of land-use change are likely overestimated in 2016, with the assumptions in the methodology (Section 2) of average periods of habitat loss.
- Ammonia agrifood emissions (NH_3) and NO_3- emissions to surface waters from agricultural runoff produce are the predominant costs across all countries with high external costs of agrifood nitrogen emissions (right panel, Figure 20). NH_3 emissions predominate in jurisdictions, such as western Europe, with existing regulations on NOx emissions and Nr in surface waters.

FIGURE 18 Spatial distribution of the expected external costs of global agrifood systems in 2023 for environmental impact quantities

A. SPATIAL DISTRIBUTION OF CLIMATE COSTS



B. SPATIAL DISTRIBUTION OF WATER COSTS

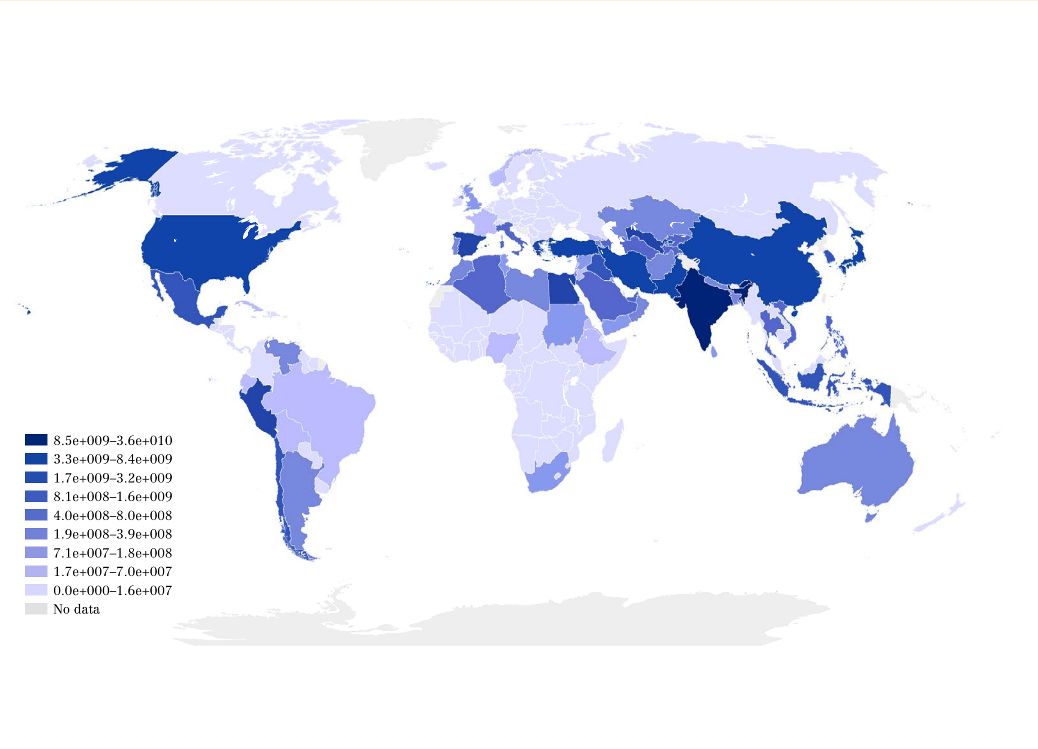
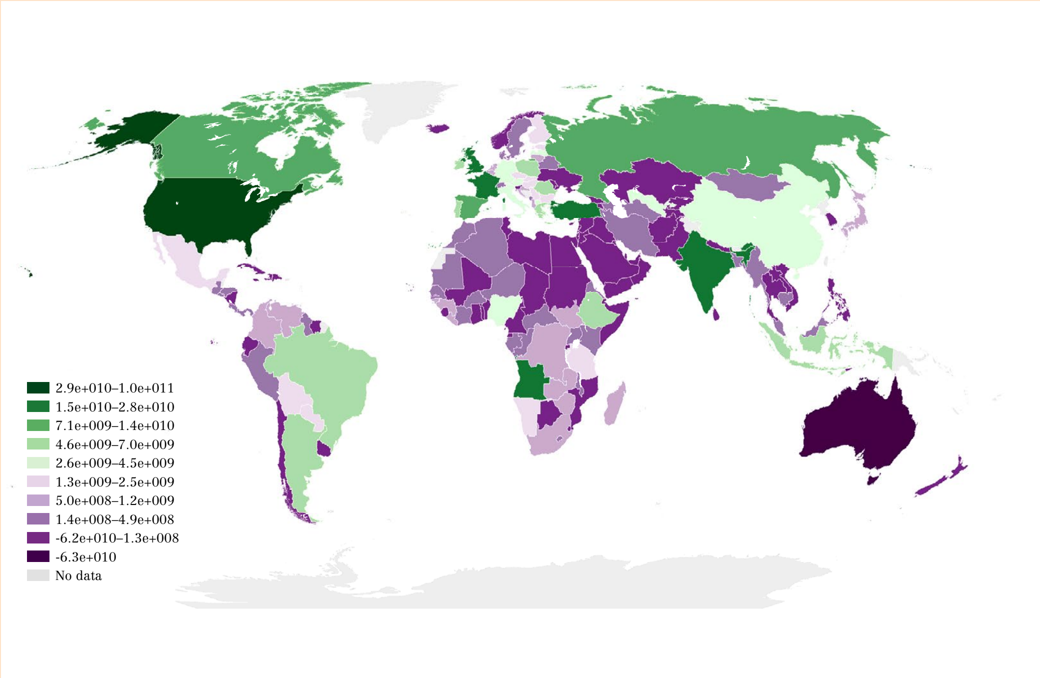
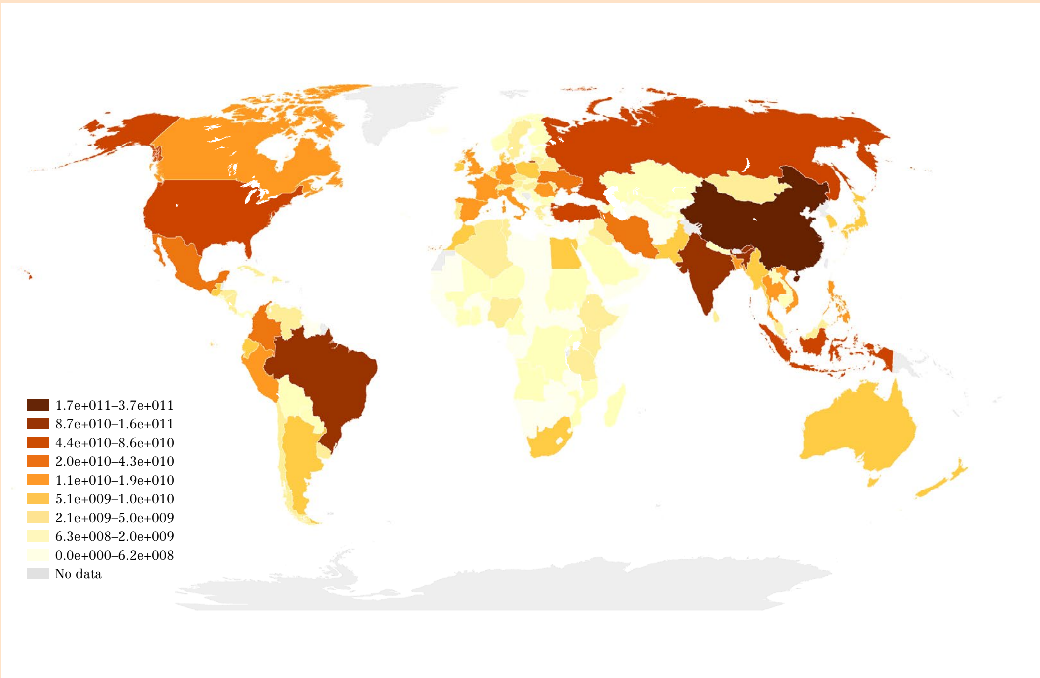


FIGURE 18 (cont.) **Spatial distribution of the expected external costs of global agrifood systems in 2023 for environmental impact quantities**

C. SPATIAL DISTRIBUTION OF LAND COSTS



D. SPATIAL DISTRIBUTION OF NITROGEN COSTS

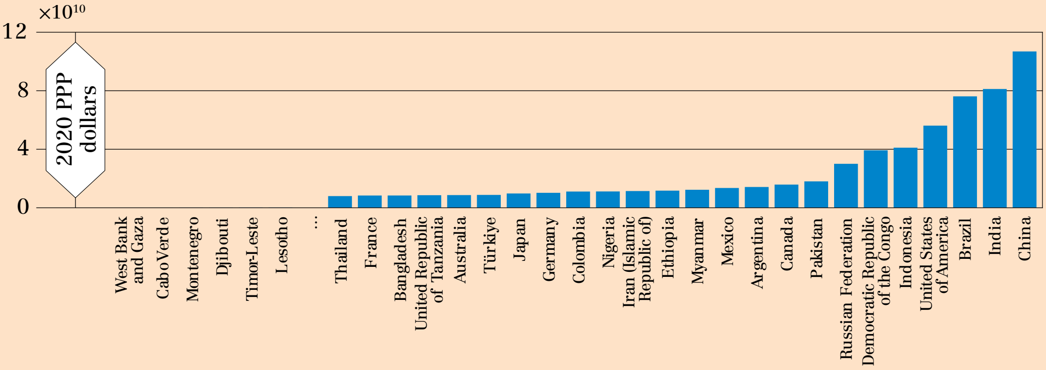


Notes: Final boundary between the Sudan and South Sudan has not yet been determined. Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Shown are environmental costs for each country by cost item category (column 1 in Table 1, GHG emissions, N emissions, water use, land-use change).

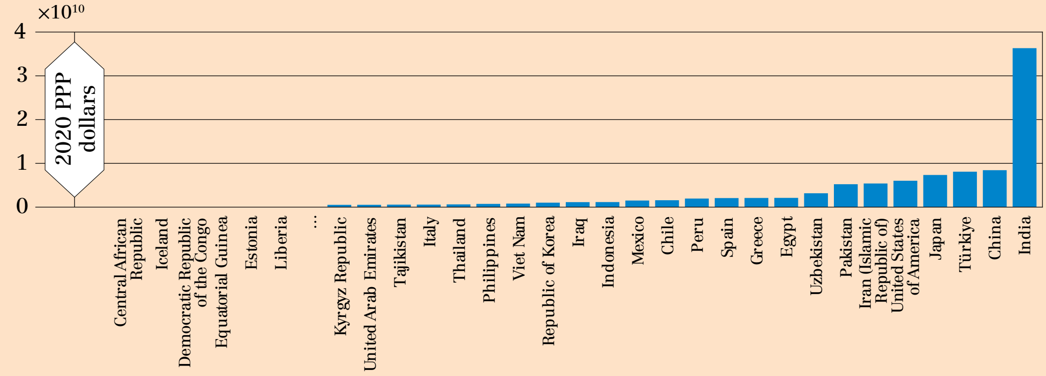
Source: United Nations Geospatial. 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

FIGURE 19 Expected hidden costs by country and cost item category in 2023

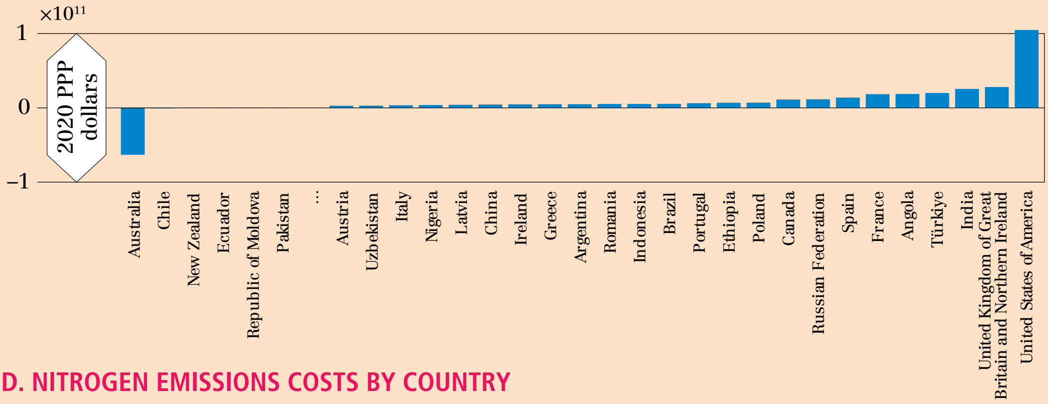
A. GREENHOUSE GAS EMISSIONS COSTS BY COUNTRY



B. WATER USE COSTS BY COUNTRY



C. LAND-USE CHANGE COSTS BY COUNTRY



D. NITROGEN EMISSIONS COSTS BY COUNTRY

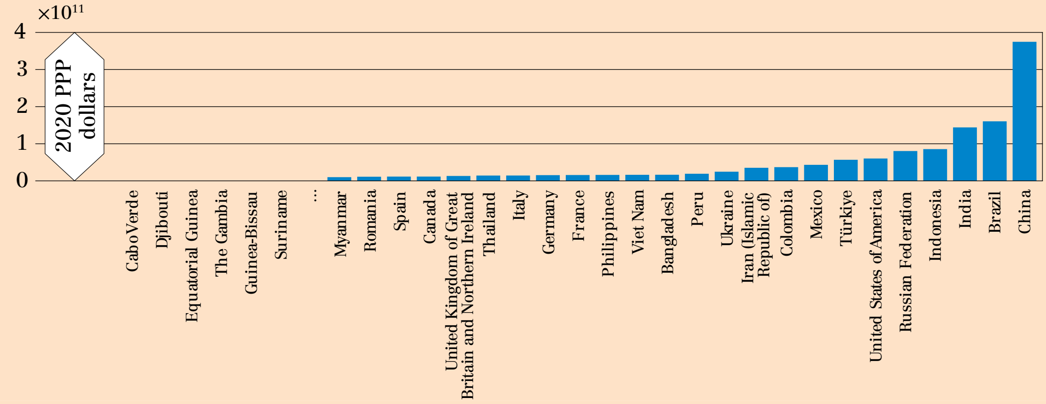
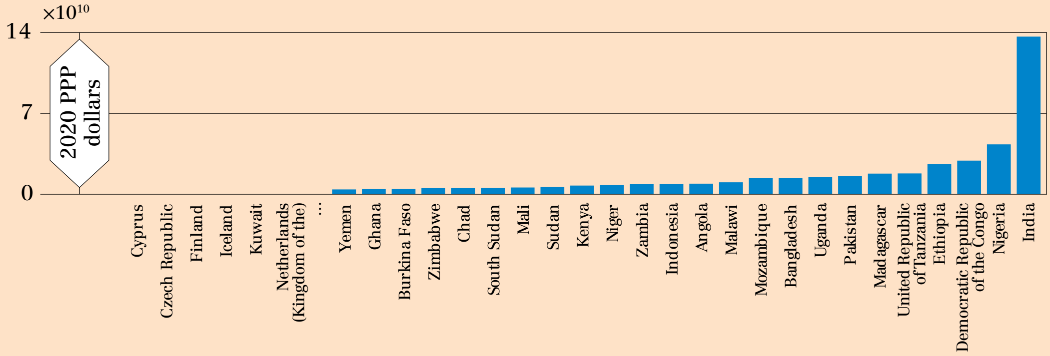
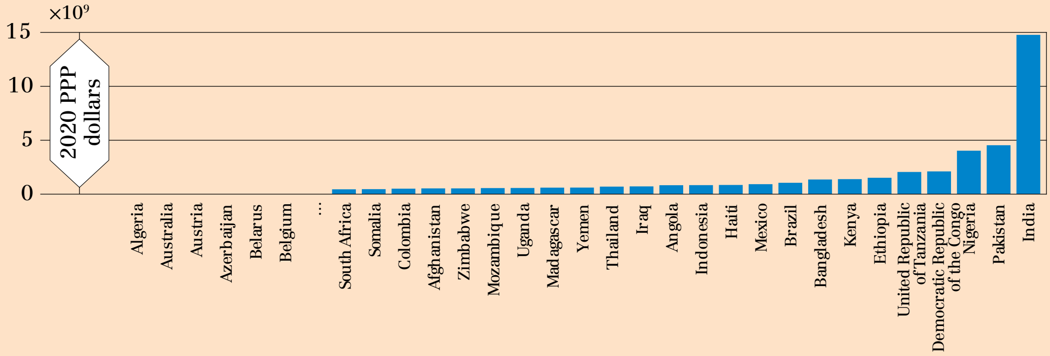


FIGURE 19 (cont.) Expected hidden costs by country and cost item category in 2023

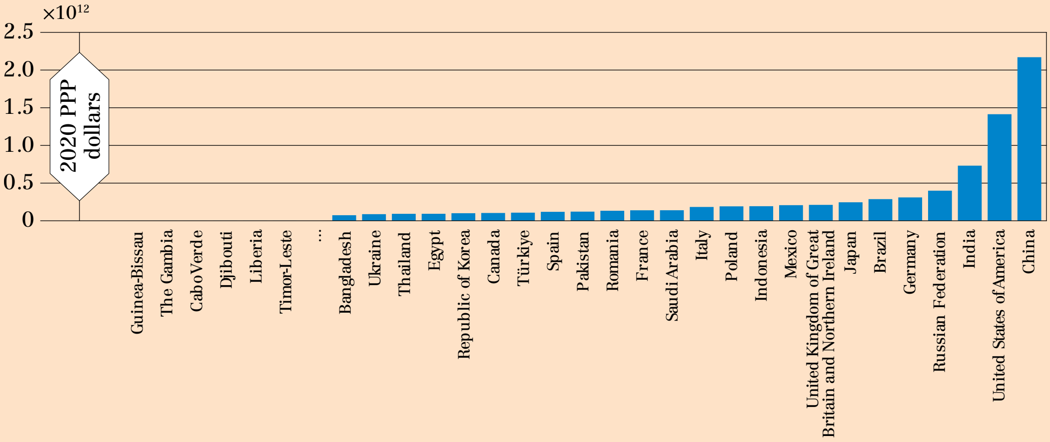
E. POVERTY IN AGRIFOOD WORKERS COSTS BY COUNTRY



F. UNDERNOURISHMENT COSTS BY COUNTRY



G. DIETARY PATTERNS COSTS BY COUNTRY

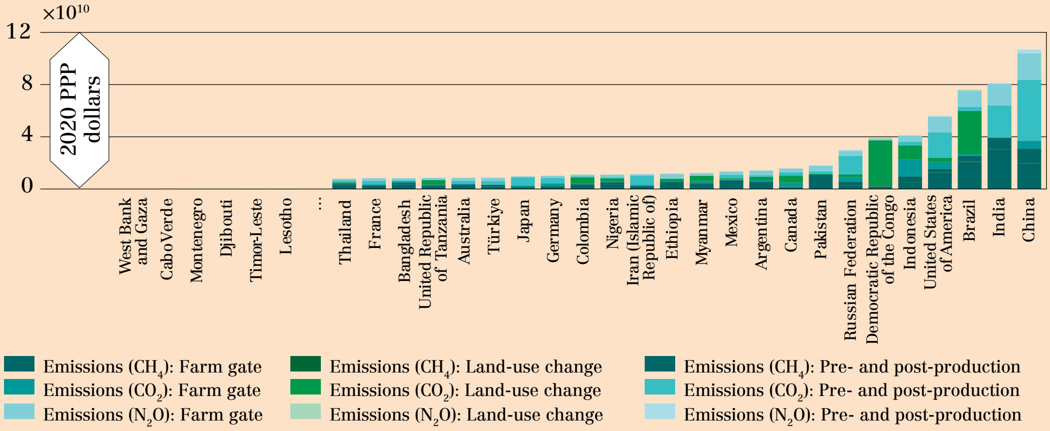


Notes: Shown are net costs for each country by cost item category (column 1, Table 1, external costs from GHG emissions, nitrogen emissions, water use, land-use change, productivity losses from dietary patterns, and costs of moderate poverty among agrifood workers and undernourishment in the general population). Listed on the right of the x-axes are 24 countries with the highest net cost. Listed on the left of the x-axes are six countries with the highest net avoided damages.

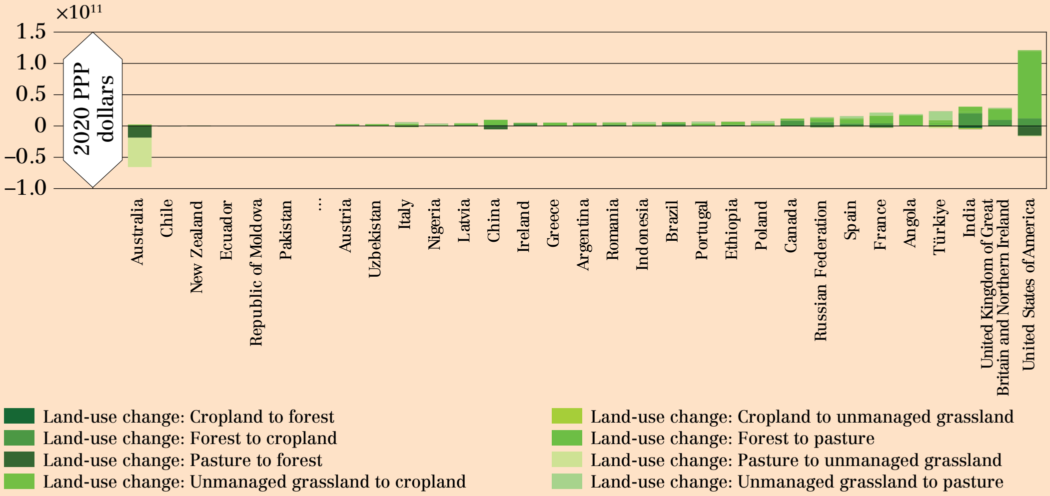
Source: Author's own elaboration.

FIGURE 20 Expected hidden costs by country and cost item category in 2023

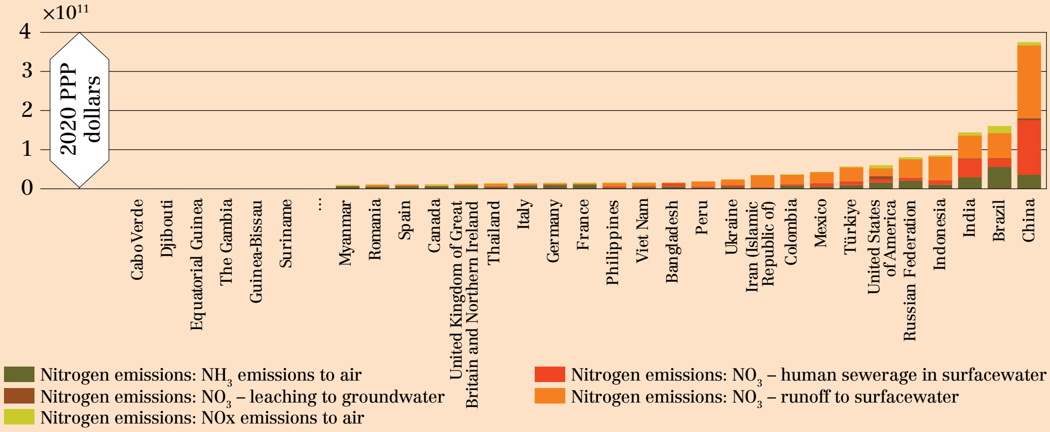
A. GREENHOUSE GAS EMISSIONS ITEM COSTS BY COUNTRY



B. LAND-USE CHANGE ITEM COSTS BY COUNTRY



C. NITROGEN EMISSIONS ITEM COSTS BY COUNTRY



Notes: Shown are net costs for each country by cost item (column 4, Table 1: GHG cost items broken down into individual gases and farm gate, land-use change, or pre- and post-farm-gate emissions; land-use change by habitat loss or return from cropland or pasture; and nitrogen by NH_3 or NOx emission to air or Nr in surface waters from agricultural runoff or human sewerage). Listed on the right-hand side of the x-axes are the 24 countries with the highest net cost in the cost item category. Listed to the left of the x-axes are the six countries with the lowest net cost in the cost item category.

Source: Author's own elaboration.

4 Comparative indicators of hidden costs of agrifood systems

KEY MESSAGES

- Combining net hidden costs with other relevant metrics – such as GDP and agricultural value added – three indicators have been developed that help identify entry points for the prioritization of interventions and investments.
- The AEIR indicator is the ratio between external costs from agricultural production and land-use change and the gross agricultural value added. The global AEIR is 0.31, indicating that 0.31 2020 PPP dollar of hidden costs are generated for every 1 2020 PPP dollar of agricultural value added.
- The DPIR indicator divides productivity losses from dietary patterns in GDP PPP terms by GDP PPP. Globally, the DPIR is, on average, 0.072, indicating that productivity losses from dietary patterns globally are equivalent to 7.2 percent of global GDP PPP in 2020.
- The SDIR indicator divides both the income shortfall of agrifood workers in moderate poverty and the productivity losses from undernourishment by the average income of the moderately poor. Globally, this value is 0.31, indicating that the net costs of moderate poverty among agrifood workers and malnutrition are equivalent to 31 percent of the net global income of the moderately poor.

The largest agricultural producers and food consumers would be expected to have the highest total cost production and cost bearing. Additional comparisons of regions and countries can be conducted using economic ratios. If the GVA of agrifood systems activities for countries were available in PPP terms, the external costs associated with agricultural production and land-use change could be divided by the GVA to obtain a basic cost–benefit measure. The United States of America publishes headline figures for agriculture, food manufacturing and food retail value added.[103] In 2021, US food and agricultural sector value added was 1.2 trillion 2020 PPP dollars, while expected US food-sector external costs produced and (based on assumptions in the methodology [Section 2]) borne were 1.6 trillion 2020 PPP dollars, giving a ratio of 1.33. For every 1 2020 PPP dollar in value added generated by the US food and agricultural sector, it produced 1.33 2020 PPP dollars in expected external costs.

Outside the United States of America, few other countries publish comparable value-added figures for agrifood systems. As a proxy, we use three measures for agrifood systems based on the nature of market failure and cost production source: i) agricultural production and land-use to agricultural GVA; ii) productivity losses from dietary patterns to total productivity from labour; and iii) agrifood workers in moderate poverty and productivity losses from undernourishment among the moderately poor compared with the mean income of the moderately poor. The indicators interpret this as gross hidden cost – visible benefit ratios of agrifood systems.

High indicator values imply disproportionate cost-bearing from pollution, land-use change, dietary patterns and so on compared with the value of the agrifood goods and services enabled by the production of pollution, habitat loss, obesity and so on. A zero, or negative, value for each indicator represents that net cost-bearing is eliminated or, for a negative value, that there are net benefits in the production of pollution alongside the visible economic benefits of the goods and services enabled by the pollution. There are simulations within the estimates of the social costs of CO_2, for example, where the benefits of climate change to agriculture in the future outweigh costs. The social benefits of GHG emissions are rarely observed in integrated models, being less than 2 percent of simulations, and are accounted for in the uncertainty distribution of the GHG emissions used in the study. Ecosystem services from the contraction of agricultural land and habitat return is the clearest "hidden" benefit term.

4.1 Agrifood production and land-use externalities

External costs from on-farm GHG emissions, nitrogen emissions from agriculture, agricultural water withdrawal land-use change (inclusive of land-use change GHG emissions) and ecosystem service losses are counted in the scope of hidden costs of agricultural production and LULUC (Figure 2). The present value of national cost-bearing measured in GDP PPP from agricultural production and LULUC externalities divided by the GVA of agriculture, forestry and fishing (GVA AFF) is the AEIR (equation 1). The external costs of agricultural production and LULUC are estimated by items 1–2, 4–5, 7–8, 10–11, 13–14, 16–17 and 19–33 in Table 1. GVA AFF is used, as data are available from national accounts for all 154 countries.[178] The use of GVA AFF is potentially conservative; ideally agricultural GVA would be available. Where available, agricultural GVA is greater than 85 percent and usually greater than 90 percent of GVA AFF.[195]

We form AEIR from three per-hectare land intensity components, which are separately informative. "Agrifood production and LULUC external natural capital cost" (ALENC) is a measure of the present value of external cost-bearing from agrifood production and LULUC cost production per hectare (ha) of agricultural land (FAOSTAT). Items 1–2, 7–8, 13–14, 19–27, 29, 31 and 33 are used in ALENC, as the cost-bearing is characterized as primarily occurring though natural capital changes, such as NO_3- in surface water from the runoff of nitrogen surpluses from cropland-lowering biodiversity in downstream and coastal ecosystems. "Agrifood production and LULUC external other capital cost" (ALEOC) measures the present value of external cost-bearing from agrifood production and LULUC cost production per ha of agricultural land occurring predominantly though other capital changes, mainly human capital changes. Items 4–5, 10–11, 16–17, 28, 30 and 32 are used in ALEOC. Examples would be volatilized NH_3 from manure on pasture results in ammonium compounds and particulate matter that causes economic impacts through human disease from air pollution. The "agrifood production and LULUC external costs" (ALEC) land intensity indicator is a measure of the external costs per hectare of agrifood production and LULUC:

$$ALEC = ALENC + ALEOC = \frac{PV\ external\ costs\ from\ agrifood\ production\ and\ LULUC}{Agricultural\ land\ area}$$

ALEC is measured in 2020 PPP dollars per hectare in this study and is the numerator of the AEIR indicator. The denominator, agrifood production and LULUC economic benefits (ALEB), is the GVA AFF per hectare of agricultural land

$$ALEB = \frac{GVA\ AFF}{Agricultural\ land\ area}$$

ALEB is measured in 2020 PPP dollars per hectare. The AEIR is defined by the formula

$$AEIR = \frac{ALEC}{ALEB} = \frac{PV\ external\ costs\ from\ agrifood\ production\ and\ LULUC}{GVA\ AFF}$$

The indicator can be formed at a global, regional or national level. Global ratios are calculated, for example, by dividing the global external costs by the global agricultural land area.

Table A5 lists the ALENC, ALEOC and ALEB land intensity components and the AEIR indicator for 154 countries. The external costs are averaged over 2016–2020. Data on agricultural land are obtained from FAOSTAT and averaged over 2016–2020. Data on GVA AFF are obtained from the World Bank as a percentage of GDP and then multiplied by GDP PPP. GVA AFF is averaged over 2016–2020.

4.2 Dietary pattern productivity costs

Productivity losses from obesity and NCDs associated with dietary intake are hidden costs of food consumption (Figure 2). Future costs of the burden of disease from dietary patterns in the present are potential market failures of imperfect information or rationalization. The present value of national productivity losses in GDP PPP from dietary patterns divided by GDP PPP forms the DPIR (equation 2). Productivity losses from obesity and NCDs are estimated by item 37 in Table 1. GDP PPP as total productivity from human capital input is used as the benefit measure of food consumption.

We form the DPIR indicator from two per capita measures. As agricultural land was a production unit for the external costs of agrifood production and LULUC, people are the production unit for productivity losses from dietary patterns. “Dietary pattern productivity losses per capita” (DPPCAP) indicate the average productivity loss per person in 2020 PPP dollars associated with obesity and NCDs from dietary intake. DPPCAP is used as the numerator. GDP PPP per capita (GDPCAP) is the denominator in the DPIR.

$$DPIR = \frac{DPPCAP}{GDPCAP} = \frac{PV\ productivity\ losses\ from\ obesity\ and\ NCDs\ dietary\ intake}{GDP\ PPP}$$

The DPIR indicates productivity losses as a proportion of GDP PPP. Population data are obtained from the United Nations World Population Prospects[117] and averaged over 2016–2020 for DPPCAP and GDPCAP. GDP PPP is obtained from World Bank data and averaged over 2016–2020.

Societal costs of distributional failure

Agrifood systems contribute to poverty by failing to distribute large retail revenues to workers. Food manufacturing and agriculture historically involve largely low-skilled labour and are among the lowest-paid sectors.[196–198] The global concentration of market power in trade and distribution, manufacturers and retailers in agrifood systems potentially lowers the ability of workers to negotiate larger shares of revenue in agrifood systems value chains.[199, 200]

The cost of removing agrifood systems worker poverty in this study is estimated using a transfer payment to cover the income shortfall of workers from the moderate international poverty line (3.65 2017 PPP dollars a day).

The second distributional failure considered is the material distribution of sufficient calories.[201] Global available calories per capita are around 2 900 kcal/day, about 50 percent higher than the minimum per capita calories required to prevent undernourishment.[202]

The productivity losses from protein–energy malnutrition are experienced as income reduction across sectors, not just the households of agrifood systems workers.[203]

For an indicator of distributional failure, we assume that the loss of productivity from undernourishment is experienced by the moderately poor.[203–205] Therefore, both the income shortfall of agrifood systems workers in moderate poverty and the productivity losses from undernourishment are considered impediments to moderate poverty alleviation through negative income effects. The sum of the two effects will be the numerator. As a denominator of the benefits of agrifood systems to moderate poverty, we take the average income of the moderately poor. The contributions to alleviating moderate poverty embodied in average income are twofold: employment of agrifood systems workers and nourishment for present and future labour inputs (prevention of undernourishment). The ratio of distributional costs and income benefits provides the SDIR.

"Social distribution moderate poverty agrifood workers" (SDPOVA) denotes the annual total income shortfall from the moderate poverty line of agrifood systems workers. "Social distribution prevalence of undernourishment cost" (SDPOUC) denotes the annual total productivity losses from undernourishment (assumed for simplicity to be experienced by the moderately poor). "Social distribution moderate poor income" (SDINC) denotes the annual total income of the moderately poor. Then

$$SDIR = \frac{SDPOVA + SDPOUC}{SDINC}$$

Note that the SDIR is an indicator of the contribution of agrifood systems to moderate poverty, that is, the overall distributional failure of revenues and calories. It is not an indicator of distributional failure solely for agrifood systems workers. The SDIR can decline due to a decrease in SDPOUC and/or an increase in SDINC, while SDPOVA remains constant. Decreasing productivity losses from improved nourishment (the distribution of calories) in moderately poor households not involved in agrifood sector employment would reduce productivity losses and increase the total income of the moderately poor.

The SDIR is calculated for this study by items 35 and 36 in Table 1, averaged over 2016–2020. The income of the moderately poor is obtained from World Bank data on the moderately poor poverty gap and averaged over 2016 to 2020.

A brief description of the three indicators and their components is presented in Table 7.

TABLE 7 Indicators and intensity components associated with the external costs, productivity losses and distributional failures of agrifood systems

Name	Description
ALENC	PV PPP of external costs from agrifood production and LULUC per hectare of agricultural land, where costs are experienced predominantly as the result of natural capital changes.
ALEOC	PV PPP of external costs from agrifood production and LULUC per hectare of agricultural land, where costs are experienced predominantly as the result of human, social, or produced capital changes.
ALEB	GVA PPP of AFF per hectare of agricultural land.
AEIR	Ratio of the PV of external costs from agrifood production and LULUC to the GVA PPP of AFF.

TABLE 7 (cont.) **Indicators and intensity components associated with the external costs, productivity losses and distributional failures of agrifood systems**

Name	Description
DPPCAP	PV PPP of productivity losses from obesity and NCDs due to dietary intake per capita.
GDPCAP	GDP PPP per capita.
DPIR	Ratio of the PV PPP of productivity losses from obesity and NCDs due to dietary intake to GDP PPP.
SDPOVA	PPP of the total income shortfall of agrifood systems workers that are moderately poor.
SDPOUC	PV PPP of productivity losses from protein–energy malnutrition in the moderately poor.
SDINC	PPP of total income of the moderately poor.
SDIR	Ratio of income shortfall and productivity losses of the moderately poor due to revenue and caloric distributional failure of agrifood systems to the income of the moderately poor.

Source: Author's own elaboration.

Annex 5 lists the AEIR, SDIR and DPIR for the 154 countries studied. A confidence interval is reported using the 5th and 95th percentiles of the samples of external costs and productivity losses from dietary patterns averaged over 2016–2020.

4.4 Results on agrifood systems market failure indicators at the global and regional level

The global AEIR in Table 8 is 0.31, indicating that 0.31 2020 PPP dollar of external cost is generated for every 1 2020 PPP dollar of agricultural value added. On average, a hectare of agricultural land globally produces 360 2020 PPP dollars in external costs and 1 532 2020 PPP dollars in GVA. The DPIR is 0.072, indicating that productivity losses from dietary patterns globally are equivalent to 7.2 percent of global GDP PPP in 2020. Productivity losses amounted to 1 179 2020 PPP dollars per person. The global SDIR is 0.31, indicating net costs of moderate poverty among agrifood workers and productivity losses from protein–energy malnutrition in the moderately poor are equivalent to 31 percent of the net global income of the moderately poor.

The population, AFF GVA in PPP terms and net income of the moderately poor used in the global indicators are the aggregates of the 154 studies studied, not total global population or global AFF GVA PPP or such. Similarly, regional indicators are calculated from the countries in the study in the given region or income group.

Per Table 8, HICs generated approximately 11 percent of global AFF GVA PPP in 2020, but produced around 24 percent of external costs from agricultural production and LULUC (Figure 13). The AEIR for HICs is 0.76 (0.76 2020 PPP dollar in external costs for every 1 2020 PPP dollar of AFF GVA PPP) compared with an AEIR of 0.35 for UMCs, 0.17 for LMCs and 0.36 for LICs. The risk that developed countries are generating additional economic damage is higher: the 95th percentile of the AEIR for HIC is 1.22, compared with 0.87 for UMCs, 0.35 for LMCs and 0.74 for LICs. This contrast is apparent at country level, where the

AEIR of China (Table 11) is 0.21 compared with an AEIR for the United States of America of 1.14. China has larger external costs, as seen in prior sections, but its AFF GDP PPP is eight times larger than that of the United States of America.[178] LMCs generate lower external costs for value added in agriculture, according to the AEIR indicator (the AEIR indicator of other income groups treated as random variables stochastically dominate the AEIR indicator of LMCs). Per Table 11, India has an AEIR of 0.13.

TABLE 8 Agricultural externalities impact ratio (AEIR) for 2020 at global and regional level

	Identifier	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR (dimensionless)
Global	World	360 (191, 762)	113 (61, 199)	1 532	0.31 (0.18, 0.60)
Income	Low-income countries	125 (54, 252)	71 (28, 151)	549	0.36 (0.15, 0.74)
Income	Low- to middle-income countries	432 (205, 946)	117 (59, 216)	3 263	0.17 (0.09, 0.35)
Income	Upper-middle-income countries	419 (146, 1 101)	83 (45, 147)	1 441	0.35 (0.14, 0.87)
Income	High-income countries	327 (177, 559)	173 (90, 311)	655	0.76 (0.47, 1.22)
Regional	Sub-Saharan Africa	141 (67, 276)	66 (28, 134)	741	0.28 (0.14, 0.55)
Regional	Northern Africa and Western Asia	138 (61, 308)	33 (17, 58)	892	0.19 (0.10, 0.39)
Regional	Latin America and the Caribbean	475 (162, 1 210)	125 (61, 233)	758	0.79 (0.33, 1.83)
Regional	Southern Asia	685 (293, 1 596)	154 (77, 287)	6 187	0.14 (0.06, 0.30)
Regional	Eastern and Southeastern Asia	584 (149, 1 989)	135 (73, 233)	3 257	0.22 (0.08, 0.65)
Regional	Oceania	49 (–168, 258)	28 (15, 52)	112	0.69 (–1.2, 2.5)
Regional	Europe	577 (337, 1 030)	327 (157, 608)	1 329	0.68 (0.42, 1.14)
Regional	Northern America	425 (165, 887)	104 (57, 175)	470	1.13 (0.53, 2.17)

Notes: ALENC – agrifood production and land use and land-use change (LULUC) external natural capital cost; ALEOC – agrifood production and LULUC external other capital cost; ALEB – agrifood production and LULUC economic benefits. 5th and 95th percentiles shown in brackets.

Source: Author's own elaboration.

There is large uncertainty, but expected values indicate that LMCs and HICs have similar external costs from agricultural production and LULUC per hectare, and LMCs may generate nearly 4.5 times more AFF GVA PPP per hectare for the same external cost. These figures are in purchasing power, not exchange rate terms. Regionally, Latin America and the Caribbean, Europe and North America have high AEIR indicators. There is little confidence in indicators for Oceania due to the uncertainty in the net value of habitat loss and habitat return from land-use change. The Americas have the highest AEIR. Asia and Africa have the lowest AEIR. Southern Asia's AEIR of 0.14 is roughly half that of sub-Saharan Africa, at 0.28, not because the agricultural sector is less important in GDP PPP terms to sub-Saharan economies, but due to a combination in sub-Saharan Africa of low productivity in the agricultural sector and the relatively high production of GHG emissions from farms and land-use change.

Approximately 85 percent of the global population in LICs and middle-income countries (MICs) consumed around 84.5 percent of global available calories in 2020 (FAOSTAT Food Balance Sheets).[206] Per person, productivity losses from dietary patterns are less for LICs, LMCs and UMCs (Table 9). In terms of per capita economic burden, though, productivity losses from dietary patterns as a proportion of GDP PPP in 2020 are similar in MICs and HICs and in the range of 5–10 percent taking into account confidence intervals.

Among the largest consumer and producer countries, the DPPCAP of China is 1 390 2020 PPP dollars, compared with 3 890 2020 PPP dollars in the United States of America (Table 11). China's per capita economic burden from dietary patterns is larger, though; it has a DPIR of 9 percent of GDP PPP compared with a DPIR of 6.4 percent of GDP PPP for the United States of America.

Regionally, the DPIR is similar across all regions, reflecting the global syndemic of obesity and NCDs from dietary intake.[11, 207] The country-level analysis in the next section indicates a pocket of higher DPIR values in eastern Europe. Sub-Saharan Africa had the lowest economic burden from dietary patterns in 2020. AEIR indicators for Oceania, primarily influenced by activity in Australia and New Zealand, are uncertain due to the non-inclusion of small island states.

TABLE 9 Dietary patterns impact ratio (DPIR) for 2020 at global and regional level

	Identifier	DPPCAP (2020 PPP dollars/ capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR (dimensionless)
Global	World	1 179 (1 049, 1 317)	16 345	0.072 (0.064, 0.081)
Income	Low-income countries	77 (68, 86)	2 008	0.038 (0.034, 0.043)
Income	Low- to middle-income countries	484 (410, 568)	6 921	0.070 (0.059, 0.082)
Income	Upper-middle-income countries	1 451 (1 157, 1 805)	16 765	0.087 (0.069, 0.108)
Income	High-income countries	3 123 (2 673, 3 603)	49 201	0.063 (0.054, 0.073)

TABLE 9 (cont.) Dietary patterns impact ratio (DPIR) for 2020 at global and regional level

	Identifier	DPPCAP (2020 PPP dollars/ capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR (dimensionless)
Regional	Sub-Saharan Africa	212 (180, 247)	3 859	0.055 (0.047, 0.064)
Regional	Northern Africa and Western Asia	1 090 (961, 1 235)	16 340	0.067 (0.059, 0.076)
Regional	Latin America and the Caribbe-an	1 160 (970,1 375)	15 316	0.076 (0.063, 0.090)
Regional	Southern Asia	448 (330, 585)	6 253	0.072 (0.053, 0.094)
Regional	Eastern and Southeastern Asia	1 212 (890, 1 569)	16 172	0.075 (0.055, 0.097)
Regional	Oceania	2 213 (1 497, 3 080)	49 124	0.045 (0.030, 0.063)
Regional	Europe	3 108 (2 779, 3 474)	38 605	0.081 (0.072, 0.090)
Regional	Northern America	3 742 (2 433, 5 285)	59 749	0.063 (0.041, 0.088)

Notes: DPPCAP – dietary pattern productivity losses per capita; GDPCAP – GDP PPP per capita. 5th and 95th percentiles shown in brackets.

Source: Author's own elaboration.

The SDIR indicates the concentration of income shortfall from moderate poverty among agrifood workers and productivity losses from protein–energy malnutrition in sub-Saharan Africa and southern Asia, as well as more broadly in the Global South (Table 10). The SDIR indicator is not a measure of absolute costs or costs per capita. The SDIR indicates the net costs of moderate poverty among agrifood workers and productivity losses from protein–energy malnutrition in the moderately poor, compared with the net global income of the moderately poor. Roughly, it is a measure of the contribution of distributional failure in agrifood systems to moderate poverty by expressing the costs against the income of the moderately poor.

The costs of distributional failures in agrifood systems were equivalent to 57 percent of the income of the moderately poor in LICs in 2000. The SDIR indicator decreased as GNI increased, except for the HIC group. Confidence in the SDIR indicator for HICs is low. The effect could be due to the high level of manufacturing employment associated with food in HICs and low-paid workers in food retail, but could also be caused by the low level of moderate poverty in HICs and the rounding of the poverty gap in World Bank poverty data. Microlevel data for HICs would be more informative for the SDIR indicator.

At a regional level, the SDIR indicator largely follows income levels and structure of economies. Despite having similar net poverty costs, the SDIR indicator for southern Asia is half that of sub-Saharan Africa. In India, the largest econo-my in southern Asia, AFF accounted for 18 percent of GDP in 2020. India's economy is structurally different to most countries in sub-Saharan Africa.[208]

TABLE 10 Social distribution impact ratio (SDIR) for 2020 at global and regional level

	Identifier	SDPOVA (billion 2020 PPP dollars)	SDPOUC (billion 2020 PPP dollars)	SDINC (billion 2020 PPP dollars)	SDIR (dimensionless)
Global	World	510.90	44.13	1763.00	0.31
Income	Low-income countries	178.90	8.01	325.50	0.57
Income	Low- to middle-income countries	311.50	30.45	1271.00	0.27
Income	Upper-middle-income countries	19.25	5.16	161.10	0.15
Income	High-income countries	1.28	0.52	5.88	0.31
Regional	Sub-Saharan Africa	266.40	15.49	530.50	0.53
Regional	Northern Africa and Western Asia	13.42	2.83	78.32	0.21
Regional	Latin America and the Caribbean	11.93	4.26	61.29	0.26
Regional	Southern Asia	190.30	18.95	884.40	0.24
Regional	Eastern and Southeastern Asia	27.52	2.44	203.10	0.15
Regional	Oceania	0.02	0.00	0.06	0.37
Regional	Europe	0.81	0.15	4.07	0.24
Regional	Northern America	0.46	0.00	1.36	0.34

Notes: SDPOVA – income shortfall of agrifood workers to the international moderate poverty line; SDPOUC – social distribution prevalence of undernourishment cost; SDINC – total income of individuals below the international moderate poverty line. The SDIR describes the net costs of moderate poverty in agrifood workers (SDPOVA) and productivity losses from protein–energy malnutrition in the moderately poor (SDPOUC) as a proportion of net income of the moderately poor (SDINC).

Source: Author's own elaboration.

4.5 Results on agrifood systems market failure indicators at country level

Table 11 shows the AEIR, DPIR and SDIR indicators for countries that are the largest agricultural producers and food consumers. The comparison is also shown graphically in Figure 21.

TABLE 11 Agrifood systems hidden cost indicators for the major producers and consumers in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR (dimensionless)
United States of America	431 (138, 959)	95 (52, 161)	457	1.15 (0.48, 2.33)
China	565 (80, 2 287)	86 (46, 158)	3 064	0.21 (0.05, 0.77)
European Union	846 (553, 1 294)	710 (327, 1 350)	2 105	0.74 (0.48, 1.15)
India	884 (341, 1 953)	166 (79, 317)	8 162	0.13 (0.06, 0.27)
Brazil	666 (133, 2 000)	155 (69, 302)	629	1.30 (0.36, 3.69)
Russian Federation	342 (59, 1 186)	39 (20, 70)	692	0.55 (0.13, 1.78)

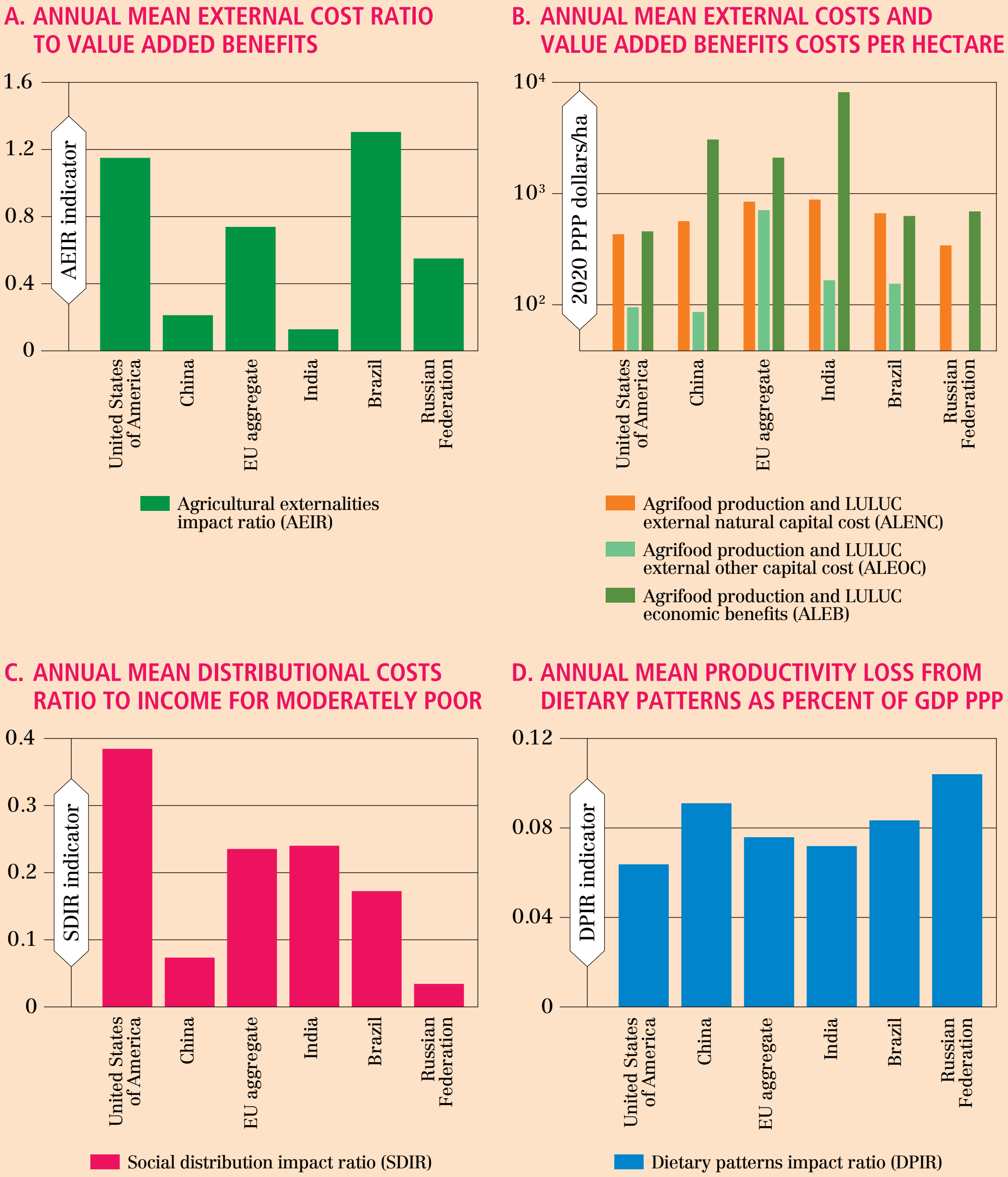
Country	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/capita)	DPIR (dimensionless)
United States of America	3 890 (2 452, 5 651)	61 038	0.064 (0.040, 0.093)
China	1 390 (899, 1 953)	15 272	0.091 (0.059, 0.128)
European Union	3 341 (2 943, 3 779)	44 050	0.076 (0.067, 0.086)
India	458 (296, 642)	6 370	0.072 (0.047, 0.101)
Brazil	1 231 (788, 1 743)	14 760	0.083 (0.053, 0.118)
Russian Federation	2 909 (1 853, 4 106)	27 961	0.104 (0.066, 0.147)

Country	SDPOVA (billion 2020 PPP dollars)	SDPOUC (billion 2020 PPP dollars)	SDINC (billion 2020 PPP dollars)	SDIR (dimensionless)
United States of America	0.46	0	1.20	0.38
China	6.07	0	82.63	0.07
European Union	0.60	0.02	2.65	0.24
India	151.70	13.09	686.30	0.24
Brazil	2.67	0.32	17.26	0.17
Russian Federation	0.02	0	0.40	0.03

Notes: ALENC – agrifood production and land use and land-use change (LULUC) external natural capital cost; ALEOC – agrifood production and LULUC external other capital cost; ALEB – agrifood production and LULUC economic benefits; AEIR – agricultural externalities impact ratio; DPPCAP – dietary pattern productivity losses per capita; GDPCAP – GDP PPP per capita; DPIR – dietary patterns impact ratio; SDPOVA – income shortfall of agrifood workers to the international moderate poverty line; SDPOUC – social distribution prevalence of undernourishment cost; SDINC – total income of individuals below the international moderate poverty line; SDIR – social distribution impact ratio. 5th and 95th percentiles shown in brackets.

Source: Author's own elaboration.

FIGURE 21 National indicators of hidden costs of agrifood systems in 2020 for the largest producers and consumers



Notes: AEIR – agricultural externalities impact ratio; SDIR – social distribution impact ratio; DPIR – dietary patterns impact ratio. The top left panel shows the ratio of external costs associated with agricultural production and land use and land-use change (LULUC) to national AFF GVA PPP (AEIR). The bottom left panel shows the ratio of total income shortfall of agrifood workers below the World Bank moderate poverty line (3.65 2017 PPP dollars per day) and productivity losses from undernourishment in the general population to the total income of the general population below the World Bank moderate poverty line (SDIR). The bottom right panel shows the ratio of productivity losses from dietary patterns per capita to GDP per capita in PPP terms (DPIR). The top right panel shows the external costs and GVA benefits of agricultural production (ALEB) and LULUC per hectare of agricultural land. ALENC describes the external costs that factor through natural capital changes and ALEOC through other capital, for example, human capital changes. The top right panel has a log10 y-axis that indicates that, except for the European Union, agricultural and LULUC external costs that factor through natural capital changes, such as losses of ecosystem services, are over twice the cost of external costs through human capital changes, for example, air pollution due to nitrogen agrifood emissions.

Source: Author's own elaboration.

Brazil has the highest AEIR indicator, but also a large range in the confidence interval. Large uncertainties come from the external costs of nitrogen emissions (Nr runoff from cropland and NH_3 emissions from fertilizers and livestock manure), GHG emissions (mainly farm-gate CH_4 emissions and CO_2 from deforestation) and land-use change (forest habitat loss).

Across all countries, ALENC was frequently more than twice the value of ALEOC, and rarely exceeded by ALEOC. The ratio between ALENC and ALEOC observed in Table 8 in global and regional averages is a general characteristic of country cost-bearing. External costs per hectare from agricultural production and LULUC that factor through natural capital changes exceed external cost factoring predominantly through human capital changes. ALENC rarely exceeds ALEB, but for several countries in 2020, the external costs through natural capital changes per hectare exceeded the value added per hectare. ALEOC can also exceed ALEB, with population density a factor in countries where this is the case. Disease burden from air pollution (mainly NH_3 emissions) is sensitive to population density. In regional estimates, the European Union, with its combination of high population density and high levels of NH_3 from fertilizer use and livestock manure, has the highest ALEOC indicator.

The high burden of dietary patterns in India (DPIR of 0.072) is indicative of the global disease burden from dietary patterns.

The largest agricultural producers and food consumers did not have the highest AEIR or DPIR indicators for 2020 among the 154 countries studied. The United States of America ranks 20th and Brazil ranks 17th for the AEIR indicator (Table 12). On the DPIR indicator, the United States of America ranks 12th (Table 13).

TABLE 12 Highest agricultural externalities impact ratio (AEIR) for 2020 at country level

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR (dimensionless)
Botswana	64 (10, 169)	43 (10, 110)	29	3.70 (0.76, 9.43)
South Sudan	88 (29, 222)	57 (25, 127)	40	3.59 (1.40, 8.49)
Ireland	1 416 (417, 3 186)	1 337 (557, 2 710)	872	3.16 (1.44, 5.75)
Estonia	2 153 (524, 4 968)	670 (297, 1 354)	1 043	2.71 (0.97, 5.59)
Latvia	2 457 (458, 5 586)	496 (205, 1 039)	1 121	2.63 (0.77, 5.54)
Central African Republic	394 (121, 977)	293 (131, 664)	266	2.58 (0.97, 6.18)
Zambia	160 (43, 389)	89 (37, 194)	100	2.50 (0.87, 5.60)
Lesotho	240 (30, 845)	37 (17, 72)	111	2.50 (0.50, 8.03)
Democratic Republic of the Congo	624 (63, 1 754)	468 (84, 1 219)	535	2.04 (0.29, 5.52)
United Kingdom of Great Britain and Northern Ireland	1 428 (414,3 179)	739 (290, 1 584)	1 067	2.03 (0.87,3.89)
Denmark	617 (227, 1 307)	2 011 (825, 4 106)	1 481	1.78 (0.86, 3.28)
Belgium	971 (338, 2 060)	3 667 (1 249, 8 023)	2 909	1.59 (0.65, 3.21)

TABLE 12 (cont.) Highest agricultural externalities impact ratio (AEIR) for 2020 at country level

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR (dimensionless)
Namibia	58 (18, 132)	15 (6, 29)	49	1.49 (0.56, 3.13)
Venezuela (Bolivarian Republic of)	359 (75, 936)	110 (47, 223)	350	1.34 (0.39, 3.50)
Lithuania	757 (204, 1 659)	689 (296, 1 409)	1 098	1.32 (0.57, 2.62)
Brazil	666 (133, 2 000)	155 (69, 302)	629	1.30 (0.36, 3.69)
Angola	377 (49, 1 283)	42 (19, 89)	345	1.22 (0.24, 3.89)
Mongolia	34 (11, 88)	14 (6, 28)	40	1.20 (0.47, 2.85)
United States of America	431 (138, 959)	95 (52, 161)	457	1.15 (0.48, 2.33)
Slovakia	1 083 (223, 2 806)	913 (322, 2 047)	1 762	1.13 (0.42, 2.28)

Notes: ALENC – agrifood production and land use and land-use change (LULUC) external natural capital cost; ALEOC – agrifood production and LULUC external other capital cost; ALEB – agrifood production and LULUC economic benefits. 5th and 95th percentiles shown in brackets. Countries are listed in descending order of the AEIR indicator.

Source: Author's own elaboration.

TABLE 13 Highest dietary patterns impact ratio (DPIR) for 2020 at country level

Country	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/capita)	DPIR (dimensionless)
Moldova	3 188 (2 056, 4 528)	10 569	0.302 (0.195, 0.428)
Lesotho	643 (391, 950)	2 583	0.249 (0.151, 0.368)
Romania	6 739 (4 306, 9 623)	28 735	0.235 (0.150, 0.335)
Latvia	6 692 (4 261, 9 512)	29 802	0.225 (0.143, 0.319)
Georgia	3 147 (1 989, 4 495)	14 107	0.223 (0.141, 0.319)
Hungary	6 944 (4 355, 9 780)	31 184	0.223 (0.140, 0.314)
Serbia	3 540 (2 270, 5 131)	16 554	0.214 (0.137, 0.310)
Bulgaria	4 536 (2 883, 6 742)	22 437	0.202 (0.129, 0.300)
Croatia	5 460 (3 451, 7 688)	27697	0.197 (0.125, 0.278)
North Macedonia	3 052 (1 891, 4 455)	16 137	0.189 (0.117, 0.276)
Slovakia	5 483 (3 499, 7 871)	30 852	0.178 (0.113, 0.255)
Armenia	2 340 (1 489, 3 324)	13 193	0.177 (0.113, 0.252)
Lithuania	6 131 (3 926, 8 696)	34 933	0.176 (0.112, 0.249)

TABLE 13 Highest dietary patterns impact ratio (DPIR) for 2020 at country level

Country	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/capita)	DPIR (dimensionless)
Belarus	3 228 (1 998, 4 637)	18 682	0.173 (0.107, 0.248)
Azerbaijan	2 307 (1 479, 3 307)	14 217	0.162 (0.104, 0.233)
Tajikistan	550 (352, 784)	3 489	0.158 (0.101, 0.225)
Haiti	502 (301, 740)	3 187	0.157 (0.094, 0.232)
Jamaica	1 566 (976, 2 261)	10 061	0.156 (0.097, 0.225)
Guyana	2 138 (1 301, 3 106)	13 870	0.154 (0.094, 0.224)
Ukraine	1 777 (1 175, 2 477)	11 797	0.151 (0.100, 0.210)

Notes: DPPCAP – dietary pattern productivity losses per capita; GDPCAP – GDP PPP per capita. 5th and 95th percentiles shown in brackets. Countries are listed in descending order of the DPIR indicator.
Source: Author's own elaboration.

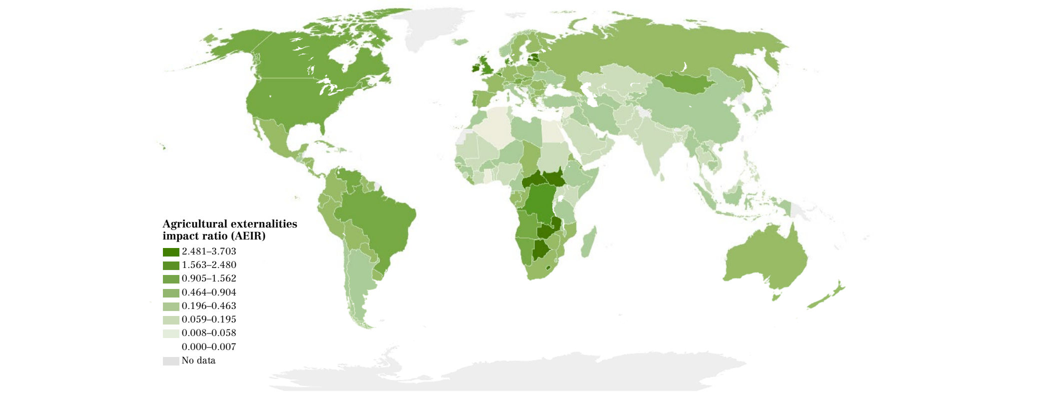
A range of African and European countries rank highest on the AEIR indicator for 2020 (Table 12). A spatial concentration for sub-Saharan Africa is observable for the AEIR in the top panel of Figure 22. For sub-Saharan African countries, such as the Central African Republic, South Sudan and Zambia, the high AEIR indicator comes from the external costs of GHG emissions combined with low value added from agricultural production. Agricultural sectors in sub-Saharan Africa need to increase their contributions to GDP PPP while improving efficiency in terms of GHGs emitted, through technology, improved infrastructure and improvements in education and farm and land management.[209] The high external cost production in the Democratic Republic of the Congo is due to CO_2 emissions from loss of forest habitat. Countries with a high AEIR and a high percentage of AFF in overall GDP are at risk of damping their economic growth and development by bearing the future economic burden of the external costs generated now by their agricultural activities.

The European countries of Belgium, Denmark, Ireland and the United Kingdom of Great Britain and Northern Ireland rank higher in the AEIR indicator than the United States of America. Expected values indicate that more than 1.5 2020 PPP dollars of external costs are generated for every 1 2020 PPP dollar of agricultural value added in Belgium, Denmark, Ireland and the United Kingdom of Great Britain and Northern Ireland. Examination of cost items for the four countries show intensive use of agricultural inputs, particularly NH_3 emissions, for sectors that provide a low percentage of total GDP PPP. The Baltic countries, such as Latvia, appear high on the AEIR list due to forestry activities, classified as cropland transitions by the HILDA+ dataset, which potentially have high transition rates combined with an asymmetry in costs between lost ecosystem services in established habitat and returning ecosystem services in regenerating habitat or managed forest.

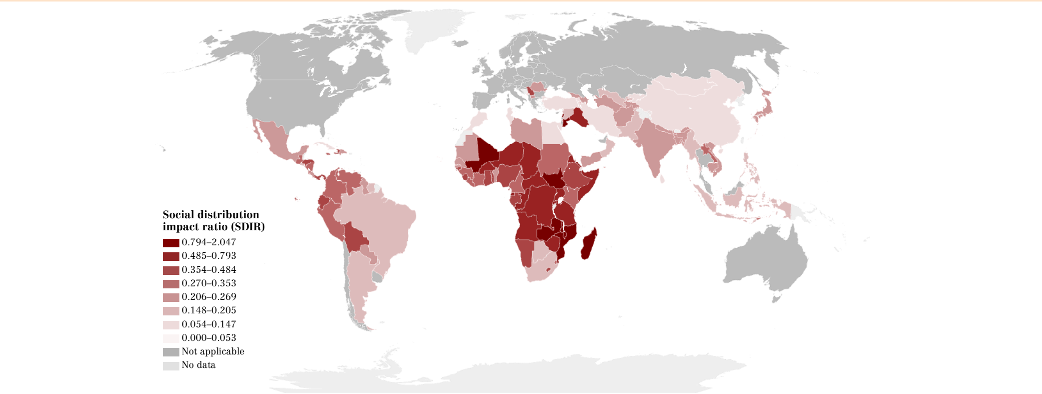
Eastern European countries rank highest on the DPIR indicator for 2020 (Table 13), and the bottom panel of Figure 22 shows the concentration of countries high in the DPIR indicator in eastern Europe. Countries with a high DPIR risk damping economic growth with diets that are too high in calories, sugar, salt and transfats and not high enough in wholegrains, nuts and seeds, fruit and vegetables. Productivity losses per capita for Belarus, Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Moldova, Poland, Serbia, Slovakia and Ukraine are equivalent to 15–30 percent of GDP PPP and approximately twice the European Union and HIC average.

FIGURE 22 Spatial distribution of indicators of hidden costs in the global agrifood systems in 2020

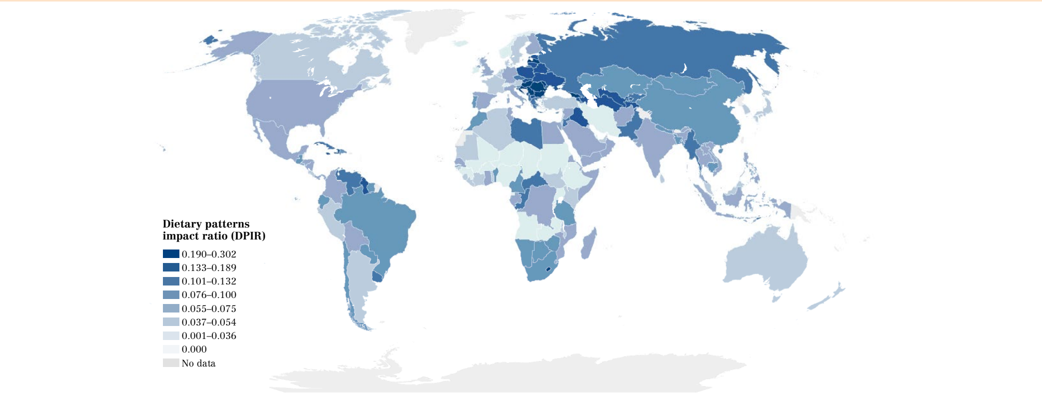
A. AGRICULTURAL EXTERNALITIES IMPACT RATIO (AEIR)



B. SOCIAL DISTRIBUTION IMPACT RATIO (SDIR)



C. DIETARY PATTERNS IMPACT RATIO (DPIR)



Notes: Final boundary between the Sudan and South Sudan has not yet been determined. Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The top map shows countries with the highest ratio of external costs associated with agricultural production and LULUC to national AFF GVA PPP (AEIR). The middle map shows the ratio of total income shortfall of agrifood workers below the World Bank moderate poverty line (3.65 2017 PPP dollars per day) and productivity losses from undernourishment in the general population to the total income of the general population below the World Bank moderate poverty line (SDIR). The bottom map shows the ratio of productivity losses from dietary patterns per capita to GDP per capita in PPP terms (DPIR).

Source: United Nations Geospatial. 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

A high POU in Jordan, Malaysia, Thailand, Iraq, Chile, and Moldova contributed to a high SDIR indicator in 2020 (Table 14). Sub-Saharan African countries with high incidence of extreme poverty are the other countries with high SDIR indicators. Figure 22 middle panel shows the concentration of countries high in the SDIR indicator in sub-Saharan Africa.

TABLE 14 Highest agricultural externalities impact ratio (AEIR) for 2020 at country level

Country	SDPOVA (billion 2020 PPP dollars)	SDPOUC (billion 2020 PPP dollars)	SDINC (billion 2020 PPP dollars)	SDIR (dimensionless)
Jordan	0.002071	0.1244	0.06176	2.05
Madagascar	17.12	0.5108	12.7	1.39
Malaysia	0.001132	0.0831	0.07537	1.12
Zambia	8.064	0.1717	7.539	1.09
Mali	5.859	0.06014	5.65	1.05
Moldova	0.002277	0.01848	0.02002	1.04
South Sudan	4.825	0.1841	5.038	0.99
Thailand	0.0526	0.6271	0.6861	0.99
Mozambique	14.63	0.4573	16.1	0.94
Malawi	9.069	0.1596	9.991	0.92
Central African Republic	1.451	0.1578	2.314	0.69
Niger	9.177	0.2123	14.16	0.66
Zimbabwe	4.218	0.4459	7.089	0.66
Tanzania (United Republic of)	19.74	1.91	33.33	0.65
Democratic Republic of the Congo	32.35	1.641	53.41	0.64
Uganda	14.99	0.46	24	0.64
Angola	7.072	0.564	12.16	0.63
Chad	4.828	0.3273	8.599	0.60
Equatorial Guinea	0.3305	0.03174	0.6419	0.56
Chile	0.02837	0.09102	0.2179	0.55

Notes: SDPOVA – income shortfall of agrifood workers to the international moderate poverty line; SDPOUC – social distribution prevalence of undernourishment cost; SDINC – total income of individuals below the international moderate poverty line. Highest 20 countries listed in descending order of the SDIR indicator.

Source: Author's own elaboration.

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Annexes

Annex 1. Approximation of marginal costs and calculation of total costs

BOX A1 Formula for the calculation of annual costs

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

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

where

$$\Delta Cost\ (q,s) = \left(\ldots, \frac{\partial Cost}{\partial q_i}\ (q,s), \ldots \right)\ i = 1, \ldots, 25$$

are the partial derivates of damage with respect to the impact quantities and q is a trajectory $q{:}[t_0,t_1] \rightarrow R^{37}$ 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 on, and they may change for the 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 CO_2 emissions, the level of emissions in previous years up to t_0 and future emissions after t_1 to indicate stocks of pollutants in the environment or the pre-existing burden of disease.

Impacts from the food system arise from multiple quantity changes and, *a priori*, the gradient of cost $\nabla Cost(\cdot,s) : R^{37} \rightarrow R^{37}$ 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 of 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 depends 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 CO_2 and N_2O 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

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

BOX A1 (cont.) **Formula for the calculation of annual costs**

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.

SPIQ-FS calculates costs based on multiplying an estimate of the average annual marginal cost against the annual production of an impact quantity per country. Conceptually, marginal costs are functions 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 Box A1).

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.

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 using $\nabla Cost(q^*,s)$ in year $[t_0,t_1]$ as an approximation of $\nabla Cost(p^*,s)$ in a year between $[t_0–4, t_1–4]$ and $[t_0+4, t_1+4]$.

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 the 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, for example, for GHG marginal costs or lack of knowledge, such as 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 A1.

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 the 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.[81, 210] 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 to cumulative CO_2 emissions.[211] Removal processes, in combination with accrued emissions from other GHG, aerosols and pollutants, determine the accumulated CO_2 in the atmosphere and its contribution to radiative forcing.[136] 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 CO_2 levels to produce large differences in radiative forcing. Another example is the effects of nitrogen loading on human populations or ecosystems. Attribution of NCDs to air pollution manifest through cumulative or ancillary exposure;[212–214] in this case, humans are the intermediary capital. Large changes in biodiversity, vegetation, soil chemistry and so on in ecosystems from nitrogen loading are also the effect of cumulative exposure,[184] 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.[78, 144] Using a dispersion argument ignores impulse peak-over-threshold exposure events where pollutants reach biological toxicity levels.

Unlike the atmosphere as an intermediary, which diffuses the effect of GHG emissions globally, ecosystems are exposed to spatially specific nitrogen emissions (such as nitrate runoff 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 of historical spatial distributions if nitrogen use deviates in the future, so improved marginal cost modelling would separate impact quantities like nitrogen into finer spatial categories.[28] However, the spatial dependence of GDP PPP economic effects on additional or reduced nitrogen emissions within national borders is 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 the 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 the 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 by 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 time, 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 CO_2 emissions in 2020 is reasonable, as damages depend on the cumulative stock of CO_2 existing in the atmosphere. The aggregated emissions of the food system between the first tonne of CO_2 produced in 2015 and the last tonne produced in 2020 are a small portion (approximately 1 percent) of the overall stock added since 2000.[1, 215] The full stock of anthropogenic post-industrial age emissions determines the increase in radiative forcing attributed to additional warming. Similar arguments apply for N_2O because of its persistence in the atmosphere. IGWG-SCCGHG estimates the social costs of GHGs in 10-year intervals to account for changes in stocks in the atmosphere of GHGs, pollutants and aerosols.[132] Vulnerability of human and natural systems to damage from heat stress and other climate may increase over a five-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 CO_2 and N_2O 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 one-year or eight-year period.[183]

The cumulative stock of additional CH_4 in the atmosphere is a different consideration to CO_2. CH_4 added in one year contributes to radiative forcing for 12 years, on average. Agriculture is the largest anthropogenic emitter of CH_4,[216] and eight years of agricultural emissions from 2015 constitute a significant portion of the added CH_4 in the atmosphere in 2020. The cumulative stock of CH_4 emissions from food systems increased 1.1 percent between 2004 and 2016.[2] A similar rate of increase over the 2017–2035 period would mean that the stock of CH_4 was higher for the duration of a 2025 emission than a 2020 emission. However, the variability in cumulative CH_4 and potential increase in an interannual period remains low, at approximately 0.1 percent historically. The average rate of change over one year in cumulative CH_4 stock, which is the driver of radiative forcing and external costs, remains below 1 percent. Over the lifetime of a metric tonne of CH_4 emission in the atmosphere, its contribution in 20-year global warming potential is 86 times that of a metric tonne of CO_2.[136] The social cost of CH_4 will, therefore, be more sensitive to short-term variations in the vulnerability of economies to temperature.[134] To make a significant variation in the social cost, variation in the vulnerability of economies would need to occur jointly across major economies. The errors in assuming a constant marginal cost over an annual period or short-term inter-annual periods are expected to be larger for CH_4 than for CO_2 and N_2O. However, given the low annual change rates in cumulative CH_4 stock and the lower sensitivity of economic damage to temperature changes in the 2016–2023 period assumed in GDP PPP damage estimates, is still likely that the modelled uncertainty in future economic conditions and emission trajectories in the IGWG-SCCGHG estimates are larger than the intra-annual variability.[183, 217]

Changes in vulnerability to human disease factors and diets over the 2016–2023 period should be factored into the calculation of the impact quantity in DALYs. The calculation of DALYs uses a population model, so the DALYs 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 sectoral or income-group variability of DALYs as the equivalent consideration of spatial variability in emissions of environmental pollutants. In terms of intra-annual variability of national food consumption, the DALYs are assumed to occur in the future and be attributable to cumulative exposure to dietary intake, potentially over decades for obesity, cardiovascular disease and neoplasms.[218–220] From DALYs 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 DALYs, which project the years from premature mortality in the future to a standard life expectancy, intra-annual and short-term interannual food consumption are largely influenced by a shared long-term trajectory of changes in labour productivity, population and labourers per capita. Only near-term disease outcomes attributable to dietary intake are relevant to intra-annual or near-term interannual 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 20 percent contribution per year to the cumulative effect leading to mortality (up to five years' exposure leads to mortality on average). For 2019, per the GBD study, the average number of DALYs per mortality for dietary risks is 20 years,[14] so one year covers 5 percent of the span of the reduced life expectancy. With these numbers, 2 percent of the DALYs 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, has been approximately constant, almost zero for advanced economies and about 3 percent for emerging and developing economies.[221] ILO statistics show a less than 10 percent variation in labour productivity among nations during the pandemic,[222] and World Bank statistics show a less than 20 percent variation in the number of labourers among nations during the pandemic.[223] Per labourer contribution to GDP PPP varied by up to 32 percent during the pandemic. With these figures, assuming a COVID-19 pandemic shock to productivity in the average 2 percent of the future distributions of attributable years of life lost that do not overlap for inter-annual food consumption, marginal productivity losses per DALY vary by less than 0.7 percent. This study does not consider variation in the attribution of DALYs to dietary intake or incorporate that into productivity loss estimates. Using the variation from the Monte Carlo simulation of DALYs in the 2019 GBD,[14] 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 is highly variable.[224, 225] Documentation for the SPIQ-FS dataset[34] 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 utilization of natural capital by the economy outside of agricultural provisioning or the economic goods and services supported by natural capital.[210, 226, 227] Lost established habitat entails a long-term loss of services, the cumulative amount of which is calculated to attribute losses per hectare. Global studies indicate that returned habitat from agriculture slowly returned and is available for, on average, 14 years.[146] Therefore the value of services on returned habitat could vary more between one effective hectare returned within a year and one effective hectare returned the next year. One of the main indicators of changes in utilization are changes in land-use itself. Land transitions to returned habitat involve less than 1 percent of current land used for agriculture and forestry HILDA+,[7] indicating that changes in utilization occur over a longer time frame. The value of economic goods and services supported by natural capital is likely to cause more intra-annual and interannual variability than the transition in the produced capital base. Growth in agricultural forestry and fishing value added was highly variable between 2016 and 2021 and highly variable between countries.[228] However, seeing as the damage calculation from lost services extends over decades, only a small fraction of which is not shared by intra- or short-term interannual 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 orders of magnitude of uncertainty in the calculation of the value of ecosystem services in a given year will outweigh intra- and short-term interannual variability. The sudden return of land to nature within a year of loss of established habitat is tempered by the gradual regeneration of lost ecosystem services and discounting. Sudden reconversion within a year of abandoned agricultural land creates very large variation. These conversion processes would have to be intra-temporal, though, not to be conceptually incorporated into 1., meaning they would have to 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 NH_3 and NOx depend on atmospheric conditions, the distribution of populations and agricultural land, and the vulnerability of the exposed populations.[229, 230] Agricultural land transitions involve less than 1 percent 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,[231, 232] indicating the likely stability of sources to exposed populations. Modelling of marginal costs of NH_3 and NOx marginal costs included uncertainty in population exposure, which conceptually captures aspects such as variable atmospheric conditions in peak periods for fertilizer application on cropland.[230] The probability of such atmospheric conditions is not assumed to change substantially over a short-term interannual period (it should be incorporated in the calculation of 1. in the previous section).[233] It is unclear whether 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 DALYs and from DALYs to productivity losses is the same as discussed for dietary DALYs. The spatial uncertainty calculation is expected to outweigh interannual fluctuation due to changes in exposed populations and their vulnerability.[36, 234] Marginal costs of deposition of NH_3 and NOx, and surface-water runoff 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.[95, 96, 235] Changes in ecosystem services from nitrogen loading on established vegetation are assumed to be cumulative over several years.[236–238] For transient biomass responsible for eutrophication and algal blooms, seasonal events show regular frequency with similar seasonal nitrogen loadings.[239] Changes in utilization and the value of ecosystem services were discussed above. Changes in the concentrations of loading and vulnerability probably have a functional relationship with the absolute level of loading, which is relatively stable at annual levels over 2016–2021 in terms of fertilizer use and livestock manure (FAOSTAT), compared with the order of magnitude of uncertainty in the value of the ecosystem services provided. Nitrogen loading can vary substantially from year to year 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 bloom is not assumed to change substantially over a short-term interannual period (it should be incorporated into the calculation of 1. in the previous section).[240]

In this study, an additional person in moderate poverty is costed by transferring 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 they are in the country and at what time during the year the individual enters moderate poverty.

Blue water costs depend on future water scarcity up to 2100. By the same arguments as above, long-term water scarcity and the economic conditions in which it occurs in the future are expected to be relatively insensitive to the fluctuations in intra-annual and short-term interannual hydrological conditions.

The costing model for undernutrition incorporates uncertainty in the protein–energy malnutrition vulnerability of populations exposed to undernourishment across more than 150 countries and 15 years of data. The historical period covers conflict, economic shocks and natural disasters, which may influence poorer health and increase the likelihood of an increased burden of disease from the same POU. Protein–energy malnutrition does require the same degree of cumulative exposure as NCDs from dietary patterns, and the COVID-19 pandemic created a larger economic and social shock than the financial crises and other events in the training period. Therefore, uncertainty in the marginal costs of undernourishment may not fully capture interannual variation in the 2016–2023 period. The costs of protein–energy malnutrition are lower in this study than other agrifood cost items, so the additional variability in the costs of undernourishment are unlikely to change the conclusions of the study, except for the ranking of the SDIR indicator where SDPOUC is the main component of the indicator.

Annex 2. A snapshot of marginal costs generated by the model

The Annex 2 output datafile of a SPIQ-FS calculation contains the marginal cost item for each country (in this case, 154). There are 27 unique marginal cost items (Table 1), as poverty marginal costs are provided for all eight years, and the Annex 2 file for this study contains 4 158 individual rows. The full Annex 2 file contains a 4 158x1 000 block of double precision data that specifies 1 000 joint samples of the 4 158 marginal cost items treated as random variables. To indicate the contents of the Annex 2 output, we show a cross-section of the file with 20 cost items in 2020 for two countries (Table A1).

The full Annex 2 file with and without samples can be accessed at Lord (2023).[46]

TABLE A1 A snapshot of marginal cost items generated by the SPIQ-FS model of 154 countries for the Plurinational State of Bolivia

ISO3	M49	Scen	Year	Quantity	Unit2	Unit	Mean	mu	sigma
BOL	68	1	2020	Blue water	2020 PPP dollars	m^3	0.033	–3.462	0.431
BOL	68	1	2020	Burden of disease	2020 PPP dollars	DALY	16 656.326	9.684	0.275
BOL	68	1	2020	CH_4 agriculture	2020 PPP dollars	metric tonne	813.075	6.170	1.124
BOL	68	1	2020	CH_4 mortality	2020 PPP dollars	metric tonne	678.322	6.256	0.670
BOL	68	1	2020	CO_2 agriculture	2020 PPP dollars	metric tonne	28.199	2.711	1.223
BOL	68	1	2020	CO_2 mortality	2020 PPP dollars	metric tonne	23.157	2.798	0.792
BOL	68	1	2020	Forest habitat loss	2020 PPP dollars	ha	32 676.134	9.191	1.895
BOL	68	1	2020	Forest habitat return	2020 PPP dollars	ha	4 453.063	7.196	1.895
BOL	68	1	2020	Mean income shortfall (2020 PPP)	2020 PPP dollars	ppl	552.013	6.314	0.000
BOL	68	1	2020	N_2O agriculture	2020 PPP dollars	metric tonne	10 486.316	8.748	1.095
BOL	68	1	2020	N_2O mortality	2020 PPP dollars	metric tonne	8 792.841	8.833	0.650
BOL	68	1	2020	NH_3 emissions to air: air pollution	2020 PPP dollars	N-kg	1.271	–0.054	0.755
BOL	68	1	2020	NH_3 emissions to air: deposition	2020 PPP dollars	N-kg	4.435	0.942	1.078
BOL	68	1	2020	NO_3- leaching to groundwater	2020 PPP dollars	N-kg	0.458	–1.099	1.014
BOL	68	1	2020	NO_3- runoff to surface water	2020 PPP dollars	N-kg	5.371	0.237	1.796
BOL	68	1	2020	NOx emissions to air: air pollution	2020 PPP dollars	N-kg	1.474	0.288	0.445

TABLE A1 (cont.) A snapshot of marginal cost items generated by the SPIQ-FS model of 154 countries for the Plurinational State of Bolivia

ISO3	M49	Scen	Year	Quantity	Unit2	Unit	Mean	mu	sigma
BOL	68	1	2020	NOx emissions to air: deposition	2020 PPP dollars	N-kg	8.911	2.054	0.484
BOL	68	1	2020	Other habitat loss	2020 PPP dollars	ha	16 153.210	8.644	1.500
BOL	68	1	2020	Other habitat return	2020 PPP dollars	ha	2 177.240	6.650	1.500
BOL	68	1	2020	Undernourishment	2020 PPP dollars	ppl	46.911	3.780	0.376

Notes: DALY – disability-adjusted life years. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the United Nations numerical classification system of sovereign countries and territories.[241] The parameters mu and sigma describe a log-normally distributed marginal fitted to cost model samples.

Source: Author's own elaboration.

Annex 3. A snapshot of total costs generated by the model

The Annex 3 output datafile of a SPIQ-FS calculation contains the quantities associated with unique cost items paired with unique marginal cost items (in this case, 37, see Table 1) for each country (in this case 154), for each year (in this case 2016–2023). The Annex 3 file for this study contains 45 584 individual rows. The marginal cost items and their joint sample in Annex 2 are matched to each quantity cost item, units are checked and, for most items, each quantity cost item is multiplied by the 1 000 marginal cost item samples to obtain 1 000 total cost item samples. This method assumes validity in a first order approximation of change in total damages (Annex 1). The Annex 3 file contains a 45 584x1 000 block of double precision data that specifies 1 000 joint samples of the 45 584 marginal cost items treated as random variables. To indicate the contents of the Annex 3 output, we show all 37 cost items for the same country in a single year (Table A2).

The full Annex 3 file with and without samples can be accessed at Lord (2023).[46]

TABLE A2 A snapshot of cost items calculated by the SPIQ-FS model for up to 37 cost items for one country in one year (Afghanistan)

ISO3	M49	Year	Cost type	Cost category	Element	Item	Quantity unit	Quantity	Marginal name	Marginal unit	Marginal cost	Total unit	Mean
AFG	4	2016	S	Poverty	Agrifood worker poverty	Poverty head-count at 3.65 2017 PPP dollars a day	ppl	1.03E+07	Mean income shortfall (2020 PPP)	ppl	425.47	2020 PPP dollars	4.39E+09
AFG	4	2016	E	Water	Blue water withdrawal	Agriculture	m³	2.00E+10	Blue water	m³	0.02	2020 PPP dollars	3.86E+08
AFG	4	2016	H	Dietary patterns	Burden of disease (dietary patterns)	NCDs and high BMI from food consumption	DALY	1.13E+06	Burden of disease	DALY	4 714.72	2020 PPP dollars	5.32E+09
AFG	4	2016	S	Under-nourishment	Burden of disease (under-nourishment)	Protein–energy malnutrition	ppl	7.86E+06	Under-nourishment	ppl	47.03	2020 PPP dollars	3.69E+08
AFG	4	2016	E	Climate	Emissions (CH_4)	Farm gate	metric tonnes	4.25E+05	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	3.45E+08
AFG	4	2016	E	Climate	Emissions (CH_4)	Farm gate	metric tonnes	4.25E+05	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	2.88E+08
AFG	4	2016	E	Climate	Emissions (CH_4)	Land-use change	metric tonnes	0.00E+00	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CH_4)	Land-use change	metric tonnes	0.00E+00	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CH_4)	Pre- and post-production	metric tonnes	1.09E+05	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	8.83E+07
AFG	4	2016	E	Climate	Emissions (CH_4)	Pre- and post-production	metric tonnes	1.09E+05	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	7.36E+07

TABLE A2 (cont.) A snapshot of cost items calculated by the SPIQ-FS model for up to 37 cost items for one country in one year (Afghanistan)

ISO3	M49	Year	Cost type	Cost category	Element	Item	Quantity unit	Quantity	Marginal name	Marginal unit	Marginal cost	Total unit	Mean
AFG	4	2016	E	Climate	Emissions (CO_2)	Farm gate	metric tonnes	1.82E+05	CO_2 agriculture	metric tonne	28.20	2020 PPP dollars	5.12E+06
AFG	4	2016	E	Climate	Emissions (CO_2)	Farm gate	metric tonnes	1.82E+05	CO_2 mortality	metric tonne	23.16	2020 PPP dollars	4.21E+06
AFG	4	2016	E	Climate	Emissions (CO_2)	Land-use change	metric tonnes	0.00E+00	CO_2 agriculture	metric tonne	28.20	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CO_2)	Land-use change	metric tonnes	0.00E+00	CO_2 mortality	metric tonne	23.16	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CO_2)	Pre- and post-production	metric tonnes	7.63E+05	CO_2 agriculture	metric tonne	28.20	2020 PPP dollars	2.15E+07
AFG	4	2016	E	Climate	Emissions (CO_2)	Pre- and post-production	metric tonnes	7.63E+05	CO_2 mortality	metric tonne	23.16	2020 PPP dollars	1.77E+07
AFG	4	2016	E	Climate	Emissions (N_2O)	Farm gate	metric tonnes	1.58E+04	N_2O agriculture	metric tonne	10 486.32	2020 PPP dollars	1.65E+08
AFG	4	2016	E	Climate	Emissions (N_2O)	Farm gate	metric tonnes	1.58E+04	N_2O mortality	metric tonne	8 792.84	2020 PPP dollars	1.39E+08
AFG	4	2016	E	Climate	Emissions (N_2O)	Land-use change	metric tonnes	0.00E+00	N_2O agriculture	metric tonne	10 486.32	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (N_2O)	Land-use change	metric tonnes	0.00E+00	N_2O mortality	metric tonne	8 792.84	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (N_2O)	Pre- and post-production	metric tonnes	6.76E+02	N_2O agriculture	metric tonne	10 486.32	2020 PPP dollars	7.08E+06
AFG	4	2016	E	Climate	Emissions (N_2O)	Pre- and post-production	metric tonnes	6.76E+02	N_2O mortality	metric tonne	8 792.84	2020 PPP dollars	5.94E+06
AFG	4	2016	E	Land	Land-use change	Cropland to forest	ha	0.00E+00	Forest habitat return	ha	−8 118.95	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Land	Land-use change	Cropland to unmanaged grassland	ha	0.00E+00	Other habitat return	ha	−2 114.69	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Land	Land-use change	Forest to cropland	ha	1.05E+02	Forest habitat loss	ha	51 437.21	2020 PPP dollars	5.41E+06
AFG	4	2016	E	Land	Land-use change	Forest to pasture	ha	1.00E+02	Forest habitat loss	ha	51 437.21	2020 PPP dollars	5.16E+06
AFG	4	2016	E	Land	Land-use change	Pasture to forest	ha	4.05E+02	Forest habitat return	ha	−8 118.95	2020 PPP dollars	−3.29E+06

TABLE A2 (cont.) A snapshot of cost items calculated by the SPIQ-FS model for up to 37 cost items for one country in one year (Afghanistan)

ISO3	M49	Year	Cost type	Cost category	Element	Item	Quantity unit	Quantity	Marginal name	Marginal unit	Marginal cost	Total unit	Mean
AFG	4	2016	E	Land	Land-use change	Pasture to unmanaged grassland	ha	0.00E+00	Other habitat return	ha	–2 114.69	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Land	Land-use change	Unmanaged grassland to cropland	ha	0.00E+00	Other habitat loss	ha	13 864.74	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Land	Land-use change	Unmanaged grassland to pasture	ha	0.00E+00	Other habitat loss	ha	13 864.74	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NH_3 emissions to air	N-kg	7.54E+07	NH_3 emissions to air: air pollution	N-kg	1.00	2020 PPP dollars	7.56E+07
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NH_3 emissions to air	N-kg	7.54E+07	NH_3 emissions to air: deposition	N-kg	3.42	2020 PPP dollars	2.58E+08
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NO_3- human sewerage in surface water	N-kg	1.00E+07	NO_3- runoff to surface water	N-kg	1.24	2020 PPP dollars	1.25E+07
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NO_3- leaching to groundwater	N-kg	3.95E+07	NO_3- leach-ing to groundwater	N-kg	0.14	2020 PPP dollars	5.70E+06
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NO_3- runoff to surface water	N-kg	7.32E+07	NO_3- runoff to surface water	N-kg	1.24	2020 PPP dollars	9.11E+07
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NOx emissions to air	N-kg	1.05E+07	NOx emissions to air: air pollution	N-kg	1.28	2020 PPP dollars	1.34E+07
AFG	4	2016	E	Nitrogen	Nitrogen emissions	NOx emissions to air	N-kg	1.05E+07	NOx emissions to air: deposition	N-kg	7.31	2020 PPP dollars	7.65E+07
AFG	4	2016	S	Poverty	Agrifood worker poverty	Poverty head-count at $3.65 a day (2017 PPP)	ppl	1.03E+07	Mean in-come short-fall (2020 PPP)	ppl	425.47	2020 PPP dollars	4.39E+09
AFG	4	2016	E	Water	Blue water withdrawal	Agriculture	m3	2.00E+10	Blue water	m3	0.02	2020 PPP dollars	3.86E+08
AFG	4	2016	H	Dietary patterns	Burden of disease (die-tary patterns)	NCDs and high BMI from food consumption	DALYs	1.13E+06	Burden of disease	DALY	4 714.72	2020 PPP dollars	5.32E+09
AFG	4	2016	S	Under-nourish-ment	Burden of disease (under-nourishment)	Protein–energy malnutrition	ppl	7.86E+06	Under-nourishment	ppl	47.03	2020 PPP dollars	3.69E+08
AFG	4	2016	E	Climate	Emissions (CH_4)	Farm gate	metric tonnes	4.25E+05	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	3.45E+08
AFG	4	2016	E	Climate	Emissions (CH_4)	Farm gate	metric tonnes	4.25E+05	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	2.88E+08

TABLE A2 (cont.) A snapshot of cost items calculated by the SPIQ-FS model for up to 37 cost items for one country in one year (Afghanistan)

ISO3	M49	Year	Cost type	Cost category	Element	Item	Quantity unit	Quantity	Marginal name	Marginal unit	Marginal cost	Total unit	Mean
AFG	4	2016	E	Climate	Emissions (CH_4)	Land-use change	metric tonnes	0.00E+00	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CH_4)	Land-use change	metric tonnes	0.00E+00	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	0.00E+00
AFG	4	2016	E	Climate	Emissions (CH_4)	Pre- and post-production	metric tonnes	1.09E+05	CH_4 agriculture	metric tonne	813.08	2020 PPP dollars	8.83E+07
AFG	4	2016	E	Climate	Emissions (CH_4)	Pre- and post-production	metric tonnes	1.09E+05	CH_4 mortality	metric tonne	678.32	2020 PPP dollars	7.36E+07
AFG	4	2016	E	Climate	Emissions (CO_2)	Farm gate	metric tonnes	1.82E+05	CO_2 agriculture	metric tonne	28.20	2020 PPP dollars	5.12E+06
AFG	4	2016	E	Climate	Emissions (CO_2)	Farm gate	metric tonnes	1.82E+05	CO_2 mortality	metric tonne	23.16	2020 PPP dollars	4.21E+06
AFG	4	2016	E	Climate	Emissions (CO_2)	Land-use change	metric tonnes	0.00E+00	CO_2 agriculture	metric tonne	28.20	2020 PPP dollars	0.00E+00

Notes: DALY – disability-adjusted life years; NCDs – non-communicable diseases. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the United Nations numerical classification system of sovereign countries and territories.[241]

Source: Author's own elaboration.

Annex 4. Countries included in the analysis

TABLE A3 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Afghanistan	AFG	4	Southern Asia	0.511	Low	LIC
Albania	ALB	8	Europe	0.795	High	UMC
Algeria	DZA	12	Northern Africa and Western Asia	0.748	High	LMC
Angola	AGO	24	Sub-Saharan Africa	0.581	Medium	LMC
Azerbaijan	AZE	31	Northern Africa and Western Asia	0.756	High	UMC
Argentina	ARG	32	Latin America and the Caribbean	0.845	Very high	UMC
Australia	AUS	36	Oceania	0.944	Very high	HIC
Austria	AUT	40	Europe	0.922	Very high	HIC
Bangladesh	BGD	50	Southern Asia	0.632	Medium	LMC
Armenia	ARM	51	Northern Africa and Western Asia	0.776	High	UMC
Belgium	BEL	56	Europe	0.931	Very high	HIC
Bolivia (Plurinational State of)	BOL	68	Latin America and the Caribbean	0.718	High	LMC
Botswana	BWA	72	Sub-Saharan Africa	0.735	High	UMC
Brazil	BRA	76	Latin America and the Caribbean	0.765	High	UMC
Bulgaria	BGR	100	Europe	0.816	Very high	UMC
Myanmar	MMR	104	Eastern and Southeastern Asia	0.583	Medium	LMC
Belarus	BLR	112	Europe	0.823	Very high	UMC
Cambodia	KHM	116	Eastern and Southeastern Asia	0.594	Medium	LMC
Cameroon	CMR	120	Sub-Saharan Africa	0.563	Medium	LMC
Canada	CAN	124	Northern America	0.929	Very high	HIC
Cabo Verde	CPV	132	Sub-Saharan Africa	0.665	Medium	LMC
Central African Republic	CAF	140	Sub-Saharan Africa	0.397	Low	LIC
Sri Lanka	LKA	144	Southern Asia	0.782	High	LMC
Chad	TCD	148	Sub-Saharan Africa	0.398	Low	LIC
Chile	CHL	152	Latin America and the Caribbean	0.851	Very high	HIC
China	CHN	156	Eastern and Southeastern Asia	0.761	High	UMC
Colombia	COL	170	Latin America and the Caribbean	0.767	High	UMC
Congo	COG	178	Sub-Saharan Africa	0.574	Medium	LMC

TABLE A3 (cont.) 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Democratic Republic of the Congo	COD	180	Sub-Saharan Africa	0.48	Low	LIC
Costa Rica	CRI	188	Latin America and the Caribbean	0.81	Very high	UMC
Croatia	HRV	191	Europe	0.851	Very high	HIC
Cuba	CUB	192	Latin America and the Caribbean	0.783	High	UMC
Cyprus	CYP	196	Northern Africa and Western Asia	0.887	Very high	HIC
Czechia	CZE	203	Europe	0.9	Very high	HIC
Benin	BEN	204	Sub-Saharan Africa	0.545	Low	LMC
Denmark	DNK	208	Europe	0.94	Very high	HIC
Dominican Republic	DOM	214	Latin America and the Caribbean	0.756	High	UMC
Ecuador	ECU	218	Latin America and the Caribbean	0.759	High	UMC
El Salvador	SLV	222	Latin America and the Caribbean	0.673	Medium	LMC
Equatorial Guinea	GNQ	226	Sub-Saharan Africa	0.592	Medium	UMC
Ethiopia	ETH	231	Sub-Saharan Africa	0.485	Low	LIC
Eritrea	ERI	232	Sub-Saharan Africa	0.459	Low	LIC
Estonia	EST	233	Europe	0.892	Very high	HIC
Finland	FIN	246	Europe	0.938	Very high	HIC
France	FRA	250	Europe	0.901	Very high	HIC
Djibouti	DJI	262	Sub-Saharan Africa	0.524	Low	LMC
Gabon	GAB	266	Sub-Saharan Africa	0.703	High	UMC
Georgia	GEO	268	Northern Africa and Western Asia	0.812	Very high	UMC
Gambia (the)	GMB	270	Sub-Saharan Africa	0.496	Low	LIC
West Bank and Gaza	PSE	275	Northern Africa and Western Asia	0.708	High	LMC
Germany	DEU	276	Europe	0.947	Very high	HIC
Ghana	GHA	288	Sub-Saharan Africa	0.611	Medium	LMC
Greece	GRC	300	Europe	0.888	Very high	HIC
Guatemala	GTM	320	Latin America and the Caribbean	0.663	Medium	UMC
Guinea	GIN	324	Sub-Saharan Africa	0.477	Low	LIC
Guyana	GUY	328	Latin America and the Caribbean	0.682	Medium	UMC
Haiti	HTI	332	Latin America and the Caribbean	0.51	Low	LMC

TABLE A3 (cont.) 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Honduras	HND	340	Latin America and the Caribbean	0.634	Medium	LMC
Hungary	HUN	348	Europe	0.854	Very high	HIC
Iceland	ISL	352	Europe	0.949	Very high	HIC
India	IND	356	Southern Asia	0.645	Medium	LMC
Indonesia	IDN	360	Eastern and Southeastern Asia	0.718	High	LMC
Iran (Islamic Republic of)	IRN	364	Southern Asia	0.783	High	LMC
Iraq	IRQ	368	Northern Africa and Western Asia	0.674	Medium	UMC
Ireland	IRL	372	Europe	0.955	Very high	HIC
Israel	ISR	376	Northern Africa and Western Asia	0.919	Very high	HIC
Italy	ITA	380	Europe	0.892	Very high	HIC
Côte d'Ivoire	CIV	384	Sub-Saharan Africa	0.538	Low	LMC
Jamaica	JAM	388	Latin America and the Caribbean	0.734	High	UMC
Japan	JPN	392	Eastern and Southeastern Asia	0.919	Very high	HIC
Kazakhstan	KAZ	398	Northern Africa and Western Asia	0.825	Very high	UMC
Jordan	JOR	400	Northern Africa and Western Asia	0.729	High	UMC
Kenya	KEN	404	Sub-Saharan Africa	0.601	Medium	LMC
Republic of Korea	KOR	410	Eastern and Southeastern Asia	0.916	Very high	HIC
Kuwait	KWT	414	Northern Africa and Western Asia	0.806	Very high	HIC
Kyrgyz Republic	KGZ	417	Northern Africa and Western Asia	0.697	Medium	LMC
Lao People’s Democratic Re-public	LAO	418	Eastern and Southeastern Asia	0.613	Medium	LMC
Lebanon	LBN	422	Northern Africa and Western Asia	0.744	High	LMC
Lesotho	LSO	426	Sub-Saharan Africa	0.527	Low	LMC
Latvia	LVA	428	Europe	0.866	Very high	HIC
Liberia	LBR	430	Sub-Saharan Africa	0.48	Low	LIC
Libya	LBY	434	Northern Africa and Western Asia	0.724	High	UMC
Lithuania	LTU	440	Europe	0.882	Very high	HIC
Madagascar	MDG	450	Sub-Saharan Africa	0.528	Low	LIC
Malawi	MWI	454	Sub-Saharan Africa	0.483	Low	LIC

TABLE A3 (cont.) 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Malaysia	MYS	458	Eastern and Southeastern Asia	0.81	Very high	UMC
Mali	MLI	466	Sub-Saharan Africa	0.434	Low	LIC
Mauritania	MRT	478	Sub-Saharan Africa	0.546	Low	LMC
Mexico	MEX	484	Latin America and the Caribbean	0.779	High	UMC
Mongolia	MNG	496	Eastern and Southeastern Asia	0.737	High	LMC
Moldova	MDA	498	Europe	0.75	High	UMC
Montenegro	MNE	499	Europe	0.829	Very high	UMC
Morocco	MAR	504	Northern Africa and Western Asia	0.686	Medium	LMC
Mozambique	MOZ	508	Sub-Saharan Africa	0.456	Low	LIC
Oman	OMN	512	Northern Africa and Western Asia	0.813	Very high	HIC
Namibia	NAM	516	Sub-Saharan Africa	0.646	Medium	UMC
Nepal	NPL	524	Southern Asia	0.602	Medium	LMC
Netherlands (Kingdom of the)	NLD	528	Europe	0.944	Very high	HIC
New Zealand	NZL	554	Oceania	0.931	Very high	HIC
Nicaragua	NIC	558	Latin America and the Caribbean	0.66	Medium	LMC
Niger	NER	562	Sub-Saharan Africa	0.394	Low	LIC
Nigeria	NGA	566	Sub-Saharan Africa	0.539	Low	LMC
Norway	NOR	578	Europe	0.957	Very high	HIC
Pakistan	PAK	586	Southern Asia	0.557	Medium	LMC
Panama	PAN	591	Latin America and the Caribbean	0.815	Very high	HIC
Paraguay	PRY	600	Latin America and the Caribbean	0.728	High	UMC
Peru	PER	604	Latin America and the Caribbean	0.777	High	UMC
Philippines	PHL	608	Eastern and Southeastern Asia	0.718	High	LMC
Poland	POL	616	Europe	0.88	Very high	HIC
Portugal	PRT	620	Europe	0.864	Very high	HIC
Guinea-Bissau	GNB	624	Sub-Saharan Africa	0.48	Low	LIC
Timor-Leste	TLS	626	Eastern and Southeastern Asia	0.606	Medium	LMC
Qatar	QAT	634	Northern Africa and Western Asia	0.848	Very high	HIC
Romania	ROU	642	Europe	0.828	Very high	HIC

TABLE A3 (cont.) 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Russian Federation	RUS	643	Europe	0.824	Very high	UMC
Rwanda	RWA	646	Sub-Saharan Africa	0.543	Low	LIC
Saudi Arabia	SAU	682	Northern Africa and Western Asia	0.854	Very high	HIC
Senegal	SEN	686	Sub-Saharan Africa	0.512	Low	LMC
Serbia	SRB	688	Europe	0.806	Very high	UMC
Sierra Leone	SLE	694	Sub-Saharan Africa	0.452	Low	LIC
Slovakia	SVK	703	Europe	0.86	Very high	HIC
Viet Nam	VNM	704	Eastern and Southeastern Asia	0.704	High	LMC
Slovenia	SVN	705	Europe	0.917	Very high	HIC
Somalia	SOM	706	Sub-Saharan Africa	0.285	Low	LIC
South Africa	ZAF	710	Sub-Saharan Africa	0.709	High	UMC
Zimbabwe	ZWE	716	Sub-Saharan Africa	0.571	Medium	LMC
Spain	ESP	724	Europe	0.904	Very high	HIC
South Sudan	SSD	728	Sub-Saharan Africa	0.433	Low	LIC
Sudan	SDN	729	Northern Africa and Western Asia	0.51	Low	LIC
Suriname	SUR	740	Latin America and the Caribbean	0.738	High	UMC
Eswatini	SWZ	748	Sub-Saharan Africa	0.611	Medium	LMC
Sweden	SWE	752	Europe	0.945	Very high	HIC
Switzerland	CHE	756	Europe	0.955	Very high	HIC
Syrian Arab Republic	SYR	760	Northern Africa and Western Asia	0.567	Medium	LIC
Tajikistan	TJK	762	Northern Africa and Western Asia	0.668	Medium	LMC
Thailand	THA	764	Eastern and Southeastern Asia	0.777	High	UMC
Togo	TGO	768	Sub-Saharan Africa	0.515	Low	LIC
United Arab Emirates	ARE	784	Northern Africa and Western Asia	0.89	Very high	HIC
Tunisia	TUN	788	Northern Africa and Western Asia	0.74	High	LMC
Turkey	TUR	792	Northern Africa and Western Asia	0.82	Very high	UMC
Turkmenistan	TKM	795	Northern Africa and Western Asia	0.715	High	UMC
Uganda	UGA	800	Sub-Saharan Africa	0.544	Low	LIC
Ukraine	UKR	804	Europe	0.779	High	LMC
North Macedonia	MKD	807	Europe	0.774	High	UMC

TABLE A3 (cont.) 154 countries included in the analysis by region, development and income group

Country	ISO3	M49	Region	HDI	HDI tier	Income group
Egypt	EGY	818	Northern Africa and Western Asia	0.707	High	LMC
United KingdomUnited King-dom of Great Britain and Northern Ireland	GBR	826	Europe	0.932	Very high	HIC
Tanzania (United Republic of)	TZA	834	Sub-Saharan Africa	0.529	Low	LMC
United States of America	USA	840	Northern America	0.926	Very high	HIC
Burkina Faso	BFA	854	Sub-Saharan Africa	0.452	Low	LIC
Uruguay	URY	858	Latin America and the Caribbean	0.817	Very high	HIC
Uzbekistan	UZB	860	Northern Africa and Western Asia	0.72	High	LMC
Venezuela (Bolivarian Republic of)	VEN	862	Latin America and the Caribbean	0.711	High	LMC
Yemen	YEM	887	Northern Africa and Western Asia	0.47	Low	LIC
Zambia	ZMB	894	Sub-Saharan Africa	0.584	Medium	LIC

Notes: SOFA – *The State of Food and Agriculture* (FAO report); LIC – low-income countries; LMIC – low- to middle-income countries; UMIC – upper-middle-income countries; HIC – high-income countries. ISO3 indicates the country ISO 3166-1 alpha-3 code, and M49 indicates the United Nations numerical classification system of sovereign countries and territories.[241] Income group refers to the World Bank income group classification by GNI using the Atlas method in 2020.

Source: Author's own elaboration.

Annex 5. Indicator results

The AEIR, DPIR and SDIR in 2020 for all 154 countries in the study (Annex 4) are calculated from samples of hidden costs using expected values. Where available, intervals report the 5th and 95th percentiles.

TABLE A4 Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Afghanistan	34 (17, 65)	13 (6,28)	513	0.09 (0.05, 0.18)	157 (96, 224)	2 096	0.075 (0.046, 0.107)	0.23
Albania	767 (137, 2 155)	510 (181, 1 161)	6 090	0.21 (0.07, 0.45)	1 724 (1 044, 2 527)	13 091	0.132 (0.080, 0.193)	0.27
Algeria	69 (22, 208)	11 (5, 24)	1 491	0.05 (0.02, 0.15)	565 (363, 827)	11 804	0.048 (0.031, 0.070)	0.04
Angola	377 (49, 1 283)	42 (19, 89)	345	1.22 (0.24, 3.89)	189 (113, 280)	6 871	0.027 (0.016, 0.041)	0.63
Argentina	129 (47, 283)	70 (35, 127)	493	0.40 (0.18, 0.80)	1 184 (766, 1 703)	22 247	0.053 (0.034, 0.077)	0.15
Armenia	383 (247, 6 38)	219 (83, 492)	3 044	0.20 (0.12, 0.32)	2 340 (1 489, 3 324)	13 193	0.177 (0.113, 0.252)	0.14
Australia	34 (–183, 236)	17 (9, 33)	82	0.63 (-2.02, 3.17)	2 193 (1 395, 3 196)	50 241	0.044 (0.028, 0.064)	0.37
Austria	1254 (299, 2 924)	878 (311, 1 938)	2 065	1.03 (0.42, 2.09)	2 727 (1 709, 3 910)	55 538	0.049 (0.031, 0.070)	0.40
Azerbaijan	277 (144, 507)	232 (93, 518)	1 742	0.29 (0.16, 0.52)	2 307 (1 479, 3 307)	14 217	0.162 (0.104, 0.233)	0.23
Bangladesh	853 (241, 2 227)	594 (274, 1 100)	9 512	0.15 (0.06, 0.31)	381 (246, 552)	4 474	0.085 (0.055, 0.123)	0.25
Belarus	428 (119, 996)	358 (160, 676)	1 499	0.52 (0.21, 1.04)	3 228 (1 998, 4 637)	18 682	0.173 (0.107, 0.248)	
Belgium	971 (338, 2 060)	3 667 (1 249, 8 023)	2 909	1.59 (0.65, 3.21)	2 312 (1 474, 3 321)	51 747	0.045 (0.028, 0.064)	0.00
Benin	188 (56, 438)	156 (65, 301)	2 616	0.13 (0.05, 0.27)	250 (152, 365)	3 127	0.080 (0.049, 0.117)	0.26
Bolivia	169 (42, 442)	72 (27, 163)	307	0.78 (0.24, 1.90)	460 (275, 693)	8 255	0.056 (0.033, 0.084)	0.45
Botswana	64 (10, 169)	43 (10, 110)	29	3.70 (0.76, 9.43)	1 232 (755, 1 859)	15 031	0.082 (0.050, 0.124)	0.18
Brazil	666 (133, 2 000)	155 (69, 302)	629	1.30 (0.36, 3.69)	1 231 (788, 1 743)	14 760	0.083 (0.053, 0.118)	0.17
Bulgaria	521 (127, 1 220)	204 (87, 420)	1 155	0.63 (0.23, 1.26)	4 536 (2 883, 6 742)	22 437	0.202 (0.129, 0.300)	0.22
Burkina Faso	122 (48, 278)	77 (36, 165)	696	0.29 (0.13, 0.63)	71 (42, 107)	2 069	0.034 (0.021, 0.051)	0.53
Cabo Verde	63 (20, 157)	240 (86, 551)	2 752	0.11 (0.04, 0.24)	376 (239, 542)	6 449	0.058 (0.037, 0.084)	0.12

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Cambodia	469 (145, 1 062)	319 (143, 625)	2 705	0.29 (0.12, 0.60)	415 (271, 595)	4 238	0.098 (0.064, 0.140)	0.24
Cameroon	217 (57, 536)	149 (57, 316)	1 646	0.22 (0.08, 0.51)	341 (205, 498)	3 777	0.090 (0.054, 0.132)	0.30
Canada	383 (133, 829)	169 (86, 303)	559	0.99 (0.46, 1.90)	2 418 (1 514, 3 508)	48 197	0.050 (0.031, 0.073)	0.02
Central African Re-public	394 (121, 977)	293 (131, 664)	266	2.58 (0.97, 6.18)	97 (59, 144)	860	0.113 (0.069, 0.167)	0.69
Chad	74 (24, 179)	52 (23, 116)	229	0.55 (0.21, 1.30)	56 (35, 84)	1 610	0.035 (0.022, 0.052)	0.60
Chile	139 (62, 233)	136 (56, 278)	1 210	0.23 (0.13, 0.39)	2 367 (1 487, 3 381)	24 832	0.095 (0.060, 0.136)	0.55
China	565 (80, 2 287)	86 (46, 158)	3 064	0.21 (0.05, 0.77)	1 390 (899, 1 953)	15 272	0.091 (0.059, 0.128)	0.07
Colombia	642 (88, 2 534)	115 (53, 231)	999	0.76 (0.16, 2.63)	858 (531, 1 237)	14 836	0.058 (0.036, 0.083)	0.29
Democratic Republic of the Congo	624 (63, 1 754)	468 (84, 1 219)	535	2.04 (0.29, 5.52)	60 (36, 88)	1 050	0.057 (0.034, 0.084)	0.64
Congo	68 (14, 178)	32 (11, 72)	156	0.64 (0.18, 1.48)	394 (237, 582)	3 796	0.104 (0.062, 0.153)	0.55
Costa Rica	1 472 (153, 5 745)	374 (145, 818)	2 698	0.68 (0.14, 2.30)	904 (552, 1 334)	20 928	0.043 (0.026, 0.064)	0.25
Côte d'Ivoire	81 (20, 205)	47 (17, 102)	1 224	0.11 (0.03, 0.23)	257 (157, 391)	5 049	0.051 (0.031, 0.077)	0.35
Croatia	702 (139, 1 983)	1 047 (338, 2 475)	2 271	0.77 (0.30, 1.63)	5 460 (3451, 7 688)	27 697	0.197 (0.125, 0.278)	0.19
Cuba	223 (62, 538)	146 (64, 297)	773	0.48 (0.19, 0.99)	1 548 (955, 2 235)	12 097	0.128 (0.079, 0.185)	0.14
Cyprus	1 120 (621, 2 057)	3 200 (951, 7 262)	5 157	0.84 (0.36, 1.74)	2 354 (1 468, 3 405)	28 109	0.084 (0.052, 0.121)	
Czechia	714 (209, 1 506)	856 (319, 1 809)	2 402	0.65 (0.29, 1.20)	5 342 (3 417, 7 696)	40 493	0.132 (0.084,0.190)	
Denmark	617 (227, 1 307)	2 011 (825, 4 106)	1 481	1.78 (0.86, 3.28)	2 268 (1 453, 3 176)	56 965	0.040 (0.026, 0.056)	0.29
Djibouti	17 (5,42)	22 (10, 42)	41	0.96 (0.40, 1.98)	336 (203, 501)	4 810	0.070 (0.042, 0.104)	0.06
Dominican Republic	795 (139, 2 260)	574 (208, 1 309)	4 207	0.33 (0.11, 0.71)	1 343 (812, 1 975)	17 407	0.077 (0.047, 0.113)	0.21
Ecuador	1 188 (133, 3 880)	359 (162, 709)	3 325	0.47 (0.10, 1.27)	1 067 (675, 1 512)	11 487	0.093 (0.059, 0.132)	0.41
Egypt	1 065 (692, 1 888)	390 (184, 778)	34 186	0.04 (0.03, 0.07)	775 (487, 1 153)	11 161	0.069 (0.044, 0.103)	0.10
El Salvador	701 (102, 2 508)	215 (94, 443)	2 463	0.37 (0.10, 1.09)	514 (306, 758)	8 780	0.058 (0.035, 0.086)	0.20

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Equatorial Guinea	799 (66, 2 291)	511 (76, 1 369)	3 393	0.39 (0.05, 1.03)	478 (283, 712)	17 594	0.027 (0.016, 0.040)	0.56
Eritrea	62 (23, 133)	22 (10, 45)	155	0.55 (0.24, 1.07)	138 (83, 210)	1 993	0.069 (0.042, 0.106)	0.52
Estonia	2 153 (524, 4 968)	670 (297, 1 354)	1 043	2.71 (0.97, 5.59)	5 068 (3 188, 7510)	35 382	0.143 (0.090, 0.212)	0.20
Eswatini	81 (29, 181)	77 (33, 156)	693	0.23 (0.10, 0.45)	634 (395, 942)	8 564	0.074 (0.046, 0.110)	0.30
Ethiopia	332 (105, 735)	123 (56, 263)	2 109	0.22 (0.09, 0.45)	41 (25, 61)	2 128	0.019 (0.012, 0.029)	0.37
Finland	1 167 (363, 2 673)	671 (330, 1 228)	2 786	0.66 (0.32, 1.31)	3 313 (2 141, 4 795)	48 590	0.068 (0.044, 0.099)	
France	839 (218, 1 866)	543 (225, 1 135)	1 664	0.83 (0.34, 1.57)	2 024 (1 286, 2 935)	48 052	0.042 (0.027, 0.061)	0.20
Gabon	456 (50, 1 438)	83 (20, 200)	804	0.67 (0.10, 1.97)	842 (518, 1 221)	14 528	0.058 (0.036, 0.084)	0.39
Gambia	169 (64, 362)	106 (49, 206)	1 720	0.16 (0.07, 0.31)	76 (46, 110)	2 046	0.037 (0.023, 0.054)	0.30
Georgia	96 (33, 227)	132 (56, 276)	1 523	0.15 (0.07, 0.27)	3 147 (1 989, 4 495)	14 107	0.223 (0.141, 0.319)	0.25
Germany	589 (203, 1 303)	952 (404, 1 875)	2 020	0.76 (0.37, 1.39)	3 502 (2 195, 5 060)	53 862	0.065 (0.041, 0.094)	0.06
Ghana	74 (24, 176)	47 (22, 87)	2 424	0.05 (0.02, 0.10)	377 (232, 553)	5 231	0.072 (0.044, 0.106)	0.36
Greece	1 039 (515, 2 183)	354 (126, 791)	1 973	0.71 (0.38, 1.32)	3 476 (2 218, 5 001)	29 091	0.120 (0.076, 0.172)	0.26
Guatemala	1 022 (121, 4 182)	379 (161, 731)	3 516	0.40 (0.10, 1.31)	810 (484, 1 187)	8 370	0.097 (0.058, 0.142)	0.34
Guinea	1 53 (42, 412)	63 (27, 130)	489	0.44 (0.16, 1.04)	71 (43, 104)	2 492	0.029 (0.017, 0.042)	0.32
Guinea-Bissau	795 (194, 1 880)	142 (65, 285)	1 667	0.56 (0.18, 1.22)	88 (53, 131)	1 870	0.047 (0.028, 0.070)	0.36
Guyana	748 (164, 1 935)	324 (89, 794)	1 694	0.63 (0.17, 1.49)	2 138 (1 301, 3 106)	13 870	0.154 (0.094, 0.224)	0.26
Haiti	164 (49, 422)	199 (90, 382)	3 643	0.10 (0.04, 0.21)	502 (301, 740)	3 187	0.157 (0.094, 0.232)	0.47
Honduras	1 311 (160, 4 804)	149 (71, 278)	1 818	0.80 (0.15, 2.73)	409 (240,605)	5 471	0.075 (0.044, 0.111)	0.41
Hungary	629 (152, 1 443)	802 (293, 1 764)	2 090	0.69 (0.29, 1.29)	6 944 (4 355, 9 780)	31 184	0.223 (0.140, 0.314)	0.12
Iceland	81 (20, 241)	78 (35, 157)	444	0.36 (0.15, 0.79)	1 952 (1 203, 2 850)	55 630	0.035 (0.022, 0.051)	
India	884 (341, 1 953)	166 (79, 317)	8 162	0.13 (0.06, 0.27)	458 (296, 642)	6 370	0.072 (0.047, 0.101)	0.24
Indonesia	1 368 (220, 4 357)	347 (124, 766)	6 552	0.26 (0.06, 0.82)	636 (383, 909)	11 529	0.055 (0.033, 0.079)	0.20

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Iran (Islamic Republic of)	691 (170, 2 005)	45 (23, 85)	2 709	0.27 (0.07, 0.76)	466 (301, 665)	13 122	0.036 (0.023, 0.051)	0.14
Iraq	322 (130, 765)	104 (45, 206)	1 676	0.25 (0.12, 0.52)	1 336 (826, 1 916)	9 784	0.137 (0.084, 0.196)	0.54
Ireland	1 416 (417, 3 186)	1 337 (557, 2 710)	872	3.16 (1.44, 5.75)	2 024 (1 241, 2 952)	83 673	0.024 (0.015, 0.035)	0.20
Israel	705 (463, 1 182)	1 605 (530, 3 730)	7 736	0.30 (0.15, 0.57)	1 605 (999, 2 376)	41 259	0.039 (0.024, 0.058)	0.04
Italy	882 (255, 2 183)	805 (287, 1 919)	3 858	0.44 (0.19, 0.93)	2 834 (1 791, 4 099)	42 367	0.067 (0.042, 0.097)	0.32
Jamaica	696 (69, 2 437)	544 (212, 1 195)	4 526	0.27 (0.08, 0.77)	1 566 (976, 2 261)	10 061	0.156 (0.097, 0.225)	0.28
Japan	2 680 (1 940, 4 083)	1 526 (672, 3 151)	12 876	0.33 (0.22, 0.50)	1 876 (1 178, 2 714)	41 963	0.045 (0.028, 0.065)	0.22
Jordan	234 (62, 712)	134 (57, 261)	4 370	0.08 (0.03, 0.20)	994 (615, 1 414)	9 605	0.103 (0.064, 0.147)	2.05
Kazakhstan	12 (4, 26)	6 (3, 11)	102	0.17 (0.08, 0.35)	1 965 (1 236, 2 758)	25 475	0.077 (0.049, 0.108)	0.05
Kenya	104 (35, 232)	73 (35, 148)	1 702	0.10 (0.04, 0.21)	218 (137,318)	4 495	0.048 (0.031, 0.071)	0.32
Republic of Korea	1 735 (866,3 952)	3 209 (1 304, 6 912)	2 3430	0.21 (0.10, 0.42)	1 658 (1 017, 2 407)	42 306	0.039 (0.024, 0.057)	0.04
Kuwait	889 (614, 1 485)	3 352 (997, 7 806)	6 318	0.67 (0.28, 1.38)	2 308 (1 459, 3 289)	47 793	0.048 (0.031, 0.069)	0.00
Kyrgyzstan	88 (61, 133)	33 (15, 65)	384	0.31 (0.21, 0.48)	607 (399, 865)	5 178	0.117 (0.077, 0.167)	0.11
Lao People's Democratic Republic	544 (153, 1 408)	406 (181, 794)	4 054	0.23 (0.09, 0.49)	486 (306, 713)	7 631	0.064 (0.040, 0.093)	0.28
Latvia	2 457 (458, 5 586)	496 (205, 1 039)	1 121	2.63 (0.77, 5.54)	6 692 (4 261, 9 512)	29 802	0.225 (0.143, 0.319)	0.15
Lebanon	126 (80, 239)	293 (105, 646)	4 559	0.09 (0.05, 0.18)	632 (396, 916)	17 156	0.037 (0.023, 0.053)	1.95
Lesotho	240 (30, 845)	37 (17, 72)	111	2.50 (0.50, 8.03)	643 (391, 950)	2 583	0.249 (0.151, 0.368)	0.47
Liberia	519 (62, 1 663)	180 (28, 477)	1 395	0.50 (0.09, 1.42)	81 (51, 120)	1 493	0.054 (0.034, 0.080)	0.35
Libya	39 (23, 77)	10 (5, 18)	235	0.21 (0.12, 0.39)	1 482 (921, 2 122)	13 710	0.108 (0.067, 0.155)	0.23
Lithuania	757 (204, 1 659)	689 (296, 1 409)	1 098	1.32 (0.57, 2.62)	6 131 (3 926, 8 696)	34 933	0.176 (0.112, 0.249)	0.24
Madagascar	57 (17, 139)	23 (10, 48)	251	0.32 (0.12, 0.70)	92 (55, 138)	1 576	0.059 (0.035, 0.087)	1.39
Malawi	157 (45, 392)	91 (39, 186)	1 144	0.22 (0.08, 0.47)	58 (34, 86)	1 514	0.038 (0.023, 0.057)	0.92

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Malaysia	614 (108, 2 081)	311 (108, 655)	8 124	0.11 (0.03, 0.31)	1 137 (712, 1 647)	26 891	0.042 (0.026, 0.061)	1.12
Mali	44 (14, 105)	26 (11, 58)	398	0.18 (0.07, 0.42)	62 (38, 91)	2 212	0.028 (0.017, 0.041)	1.05
Mauritania	16 (6, 33)	9 (4, 18)	127	0.19 (0.08, 0.39)	268 (170, 390)	5 389	0.050 (0.031, 0.072)	0.24
Mexico	409 (77, 1 347)	65 (32, 127)	877	0.54 (0.14, 1.62)	1 419 (880, 2 052)	19 843	0.072 (0.044, 0.103)	0.21
Moldova	792 (29, 3 210)	255 (88, 560)	1 515	0.69 (0.13, 2.30)	3 188 (2 056, 4 528)	10 569	0.302 (0.195, 0.428)	1.04
Mongolia	34 (11, 88)	14 (6, 28)	40	1.20 (0.47, 2.85)	1 049 (639, 1 571)	11 999	0.087 (0.053, 0.131)	0.12
Montenegro	1 506 (277, 3 791)	647 (208, 1 488)	3 477	0.62 (0.21, 1.32)	2 778 (1 707, 4 007)	20 198	0.138 (0.085, 0.198)	0.08
Morocco	200 (32, 708)	28 (13, 55)	972	0.23 (0.05, 0.75)	732 (447, 1 098)	7 601	0.096 (0.059, 0.144)	0.13
Mozambique	114 (27, 325)	48 (16, 107)	232	0.70 (0.20, 1.70)	73 (43, 110)	1 324	0.055 (0.033, 0.083)	0.94
Myanmar	864 (287, 2 201)	530 (247, 1 008)	4 438	0.31 (0.13, 0.69)	583 (363, 855)	4 675	0.125 (0.078, 0.183)	0.19
Namibia	58 (18, 132)	15 (6, 29)	49	1.49 (0.56, 3.13)	897 (545, 1 290)	10 263	0.087 (0.053, 0.126)	0.38
Nepal	472 (189, 950)	362 (168, 697)	5 857	0.14 (0.07, 0.27)	343 (209, 499)	3 666	0.094 (0.057, 0.136)	0.25
Netherlands (Kingdom of the)	963 (369, 2 030)	4 557 (1 642, 9 889)	9 152	0.60 (0.25, 1.22)	2 135 (1 348, 3 069)	56 562	0.038 (0.024, 0.054)	0.09
New Zealand	551 (120, 1 613)	410 (195, 770)	1 148	0.84 (0.33, 1.93)	2 316 (1 479, 3 361)	43 382	0.053 (0.034, 0.077)	
Nicaragua	547 (105, 1 529)	199 (79, 416)	1 119	0.67 (0.18, 1.81)	420 (256, 617)	5 668	0.074 (0.045, 0.109)	0.30
Niger	42 (16, 89)	21 (9, 46)	2 18	0.29 (0.12, 0.62)	43 (27, 64)	1 218	0.036 (0.022, 0.053)	0.66
Nigeria	143 (46, 309)	68 (33, 133)	3 246	0.06 (0.03, 0.13)	180 (111, 265)	5 183	0.035 (0.021, 0.051)	0.43
North Macedonia	1 059 (204, 2 485)	180 (63, 401)	2 276	0.54 (0.16, 1.18)	3 052 (1 891, 4 455)	16 137	0.189 (0.117, 0.276)	0.22
Norway	1 124 (389, 2 689)	1 262 (606, 2 261)	6 659	0.36 (0.18, 0.66)	1 959 (1 228, 2 830)	64 455	0.030 (0.019, 0.044)	0.13
Oman	304 (229, 473)	121 (54, 258)	2 225	0.19 (0.13, 0.30)	2 097 (1 310, 3 008)	34 663	0.060 (0.038, 0.087)	0.19
Pakistan	388 (206, 709)	241 (110, 473)	5 904	0.11 (0.06, 0.19)	481 (307, 684)	4 547	0.106 (0.067, 0.150)	0.20
Panama	410 (84, 1 126)	284 (118, 634)	1 389	0.50 (0.18, 1.11)	1 999 (1 182, 3 003)	30 020	0.067 (0.039, 0.100)	0.48

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Paraguay	281 (73, 758)	144 (61, 287)	562	0.76 (0.26, 1.72)	1 073 (651, 1 561)	13 823	0.078 (0.047, 0.113)	0.24
Peru	838 (152, 2 646)	148 (54, 308)	1 153	0.86 (0.19, 2.60)	639 (383, 947)	12 483	0.051 (0.031, 0.076)	0.31
Philippines	926 (195, 2 782)	273 (124, 536)	7 009	0.17 (0.05, 0.47)	550 (348, 796)	8 303	0.066 (0.042, 0.096)	0.15
Poland	755 (192, 1 838)	711 (281, 1 497)	2 163	0.68 (0.28, 1.33)	4 697 (2 966, 6 861)	31 235	0.150 (0.095, 0.220)	0.16
Portugal	1 422 (287, 3 640)	530 (184, 1 235)	1 951	1.00 (0.35, 2.22)	2 938 (1 845, 4 211)	33 967	0.086 (0.054, 0.124)	0.14
Qatar	733 (200, 1 808)	2 255 (835, 5 028)	8 150	0.37 (0.15, 0.80)	1 457 (937, 2 079)	91 960	0.016 (0.010, 0.023)	
Romania	712 (162, 1 940)	356 (136, 758)	1 822	0.59 (0.22, 1.30)	6 739 (4 306, 9 623)	28 735	0.235 (0.150, 0.335)	0.22
Russian Federation	342 (59, 1 186)	39 (20, 70)	692	0.55 (0.13, 1.78)	2 909 (1 853, 4 106)	27 961	0.104 (0.066, 0.147)	0.03
Rwanda	154 (52, 367)	117 (57, 236)	3 623	0.07 (0.03, 0.15)	53 (30, 81)	2 073	0.026 (0.015, 0.039)	0.54
Saudi Arabia	11 (5, 28)	6 (3, 11)	223	0.08 (0.04, 0.16)	3 247 (2 001, 4 608)	45 797	0.071 (0.044, 0.101)	
Senegal	116 (47, 243)	77 (37, 154)	901	0.21 (0.10, 0.42)	252 (155, 361)	3 401	0.074 (0.046, 0.106)	0.24
Serbia	634 (171, 1 485)	320 (134, 651)	2 229	0.43 (0.17, 0.88)	3 540 (2 270, 5 131)	16 554	0.214 (0.137, 0.310)	0.45
Sierra Leone	92 (29, 213)	54 (23, 107)	1 932	0.08 (0.03, 0.16)	71 (42, 107)	1 642	0.043 (0.026, 0.065)	0.41
Slovakia	1 083 (223, 2 806)	913 (322, 2 047)	1 762	1.13 (0.42, 2.28)	5 483 (3 499, 7 871)	30 852	0.178 (0.113, 0.255)	0.79
Slovenia	426 (132, 953)	1 510 (545, 3 326)	2 618	0.74 (0.32, 1.52)	3 564 (2 207, 5 333)	37 509	0.095 (0.059, 0.142)	
Somalia	40 (14, 88)	25 (10, 52)	300	0.22 (0.08, 0.47)	83 (50, 124)	1 143	0.072 (0.043, 0.108)	0.53
South Africa	87 (14, 269)	21 (11, 39)	194	0.56 (0.15, 1.47)	1 263 (816, 1 764)	13 969	0.090 (0.058, 0.126)	0.18
South Sudan	88 (29, 222)	57 (25, 127)	40	3.59 (1.40, 8.49)	50 (29, 75)	1 273	0.039 (0.023, 0.059)	0.99
Spain	833 (248, 1 882)	324 (129, 716)	1 931	0.60 (0.25, 1.18)	2 375 (1 480, 3 428)	39 399	0.060 (0.038, 0.087)	0.28
Sri Lanka	381 (118, 1 099)	180 (79, 356)	7 574	0.07 (0.03, 0.17)	564 (353, 817)	12 990	0.043 (0.027, 0.063)	0.12
Sudan	69 (26, 155)	41 (19, 90)	575	0.19 (0.08, 0.42)	131 (80, 189)	4 445	0.029 (0.018, 0.042)	0.32
Suriname	4 094 (380, 12 146)	2 981 (589, 7 681)	11 798	0.60 (0.09, 1.64)	1 734 (1 061, 2 510)	17 340	0.100 (0.061, 0.145)	0.20

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/capita)	DPIR	SDIR
Sweden	681 (193, 1 604)	838 (397, 1 572)	2 496	0.61 (0.27, 1.13)	2 534 (1 644, 3 696)	53 110	0.048 (0.031, 0.070)	0.20
Switzerland	477 (164, 1 062)	1 742 (608, 3 854)	2 609	0.85 (0.35, 1.73)	2 110 (1 343, 3 080)	70 542	0.030 (0.019, 0.044)	
Syrian Arab Republic	39 (17, 73)	18 (8, 36)	1 381	0.04 (0.02, 0.08)	175 (110, 258)	2561	0.068 (0.043, 0.101)	0.17
Tajikistan	200 (130, 309)	107 (44,218)	1 373	0.22 (0.14, 0.37)	550 (352, 784)	3 489	0.158 (0.101, 0.225)	0.21
Tanzania (United Republic of)	180 (61, 393)	98 (44, 195)	1 018	0.27 (0.11, 0.56)	217 (129, 317)	2 495	0.087 (0.052, 0.127)	0.65
Thailand	568 (142, 1 655)	238 (113, 434)	4 594	0.18 (0.06, 0.42)	1 081 (651, 1 591)	17 586	0.061 (0.037, 0.090)	0.99
Timor-Leste	269 (72, 765)	313 (128, 650)	2 047	0.28 (0.12, 0.62)	367 (221, 540)	3 508	0.105 (0.063, 0.154)	0.34
Togo	68 (26, 158)	43 (21, 88)	873	0.13 (0.06, 0.27)	78 (48, 113)	2 065	0.038 (0.023, 0.055)	0.40
Tunisia	175 (27, 664)	35 (16, 66)	1 281	0.16 (0.04, 0.55)	624 (368, 921)	10 976	0.057 (0.034, 0.084)	0.08
Türkiye	1 493 (324, 4 318)	165 (76, 306)	3 674	0.45 (0.13, 1.23)	1 182 (715, 1 675)	27 136	0.044 (0.026, 0.062)	0.09
Turkmenistan	43 (29, 73)	18 (9, 36)	277	0.22 (0.14, 0.39)	1 969 (1 234, 2 763)	14 247	0.138 (0.087, 0.194)	0.23
Uganda	163 (56, 363)	93 (43, 191)	1 506	0.17 (0.07, 0.35)	46 (27, 67)	2 248	0.020 (0.012, 0.030)	0.64
Ukraine	372 (56, 1 293)	74 (35, 150)	1 274	0.35 (0.08, 1.08)	1 777 (1 175, 2 477)	11 797	0.151 (0.100, 0.210)	0.16
United Arab Emirates	1 843 (1 532, 2 390)	1 008 (375, 2 207)	13 264	0.21 (0.15, 0.33)	3 438 (2 247, 4 917)	71 162	0.048 (0.032, 0.069)	
United Kingdom of Great Britain and Northern Ireland	1 428 (414, 3 179)	739 (290, 1 584)	1 067	2.03 (0.87, 3.89)	2 910 (1 827, 4 161)	46 856	0.062 (0.039, 0.089)	0.22
United States of America	431 (138, 959)	95 (52, 161)	457	1.15 (0.48, 2.33)	3 890 (2 452, 5 651)	61 038	0.064 (0.040, 0.093)	0.38
Uruguay	80 (17, 197)	203 (92, 387)	357	0.79 (0.35, 1.55)	2 922 (1 856, 4 198)	23 341	0.125 (0.080, 0.180)	0.05
Uzbekistan	292 (165, 493)	72 (34, 137)	2 522	0.14 (0.09, 0.23)	1 011 (633, 1 432)	7 385	0.137 (0.086, 0.194)	0.18
Venezuela (Bolivarian Republic of)	359 (75, 936)	110 (47, 223)	350	1.34 (0.39, 3.50)	615 (378, 911)	5 388	0.114 (0.070, 0.169)	0.28
Viet Nam	1 049 (263, 3 461)	343 (164, 661)	7 643	0.18 (0.06, 0.50)	489 (307, 703)	7 766	0.063 (0.040, 0.090)	0.24
West Bank and Gaza	67 (15, 118)	309 (82, 756)	4 688	0.08 (0.03, 0.18)	408 (253, 572)	5 970	0.068 (0.042, 0.096)	0.18

TABLE A4 (cont.) Agricultural externalities impact ratio (AEIR), dietary patterns impact ratio (DPIR) and social distribution impact ratio (SDIR) indicators and components for 154 countries in 2020

Country	ALENC (2020 PPP dollars/ha)	ALEOC (2020 PPP dollars/ha)	ALEB (2020 PPP dollars/ha)	AEIR	DPPCAP (2020 PPP dollars/capita)	GDPCAP (2020 PPP dollars/ capita)	DPIR	SDIR
Yemen	30 (15, 58)	12 (6, 25)	524	0.08 (0.04, 0.16)	123 (76, 180)	2 131	0.058 (0.036, 0.084)	0.25
Zambia	160 (43, 389)	89 (37, 194)	100	2.50 (0.87, 5.60)	79 (47, 117)	3 421	0.023 (0.014, 0.034)	1.09
Zimbabwe	110 (42, 241)	46 (21, 91)	270	0.58 (0.26, 1.17)	338 (211, 504)	3 446	0.098 (0.061, 0.146)	0.66

Notes: ALENC – agrifood production and land use and land-use change (LULUC) external natural capital cost; ALEOC – agrifood production and LULUC external other capital cost; ALEB – agrifood production and LULUC economic benefits; AEIR – agricultural externalities impact ratio; DPPCAP – dietary pattern productivity losses per capita; GDPCAP – GDP PPP per capita; DPIR – dietary patterns impact ratio; SDIR – social distribution impact ratio.

Source: Author's own elaboration.

This background paper to *The State of Food and Agriculture 2023* examines the annual hidden costs of agrifood systems across 2016–2023 for 154 countries. Hidden costs include environmental hidden costs from greenhouse gas emissions, nitrogen emissions, land-use transitions, and blue water withdrawals; social hidden costs associated with undernourishment and poverty; and health hidden costs from unhealthy dietary patterns. The expected value of hidden costs is around 13 trillion 2020 purchasing power parity (PPP) dollars. This is equivalent to approximately 10 percent of global gross domestic product (GDP) PPP in 2023 and around 35 billion 2020 PPP dollars per day.

Environmental hidden costs averaged around 3 trillion 2020 PPP dollars over the 2016–2023 period; health-related costs averaged 9.3 trillion 2020 PPP dollars; and social hidden costs averaged 560 billion 2020 PPP dollars. Health hidden costs are the largest across all world regions, apart from sub-Saharan Africa, where costs from poverty and undernourishment prevail. Hidden costs also report an upward trend from 2016 to 2023, driven primarily by health hidden costs. Overall, hidden costs place a disproportionate burden on low-income countries.

Left unchecked, these hidden costs will depress future growth and development. However, these hidden costs do not reflect the GDP PPP loss that may be avoided by transitioning to more sustainable agrifood systems. In other words, while these may be avoidable, the quantified hidden costs do not indicate the costs of transitioning to alternative systems. Subsequent studies are needed to quantify these.

31

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