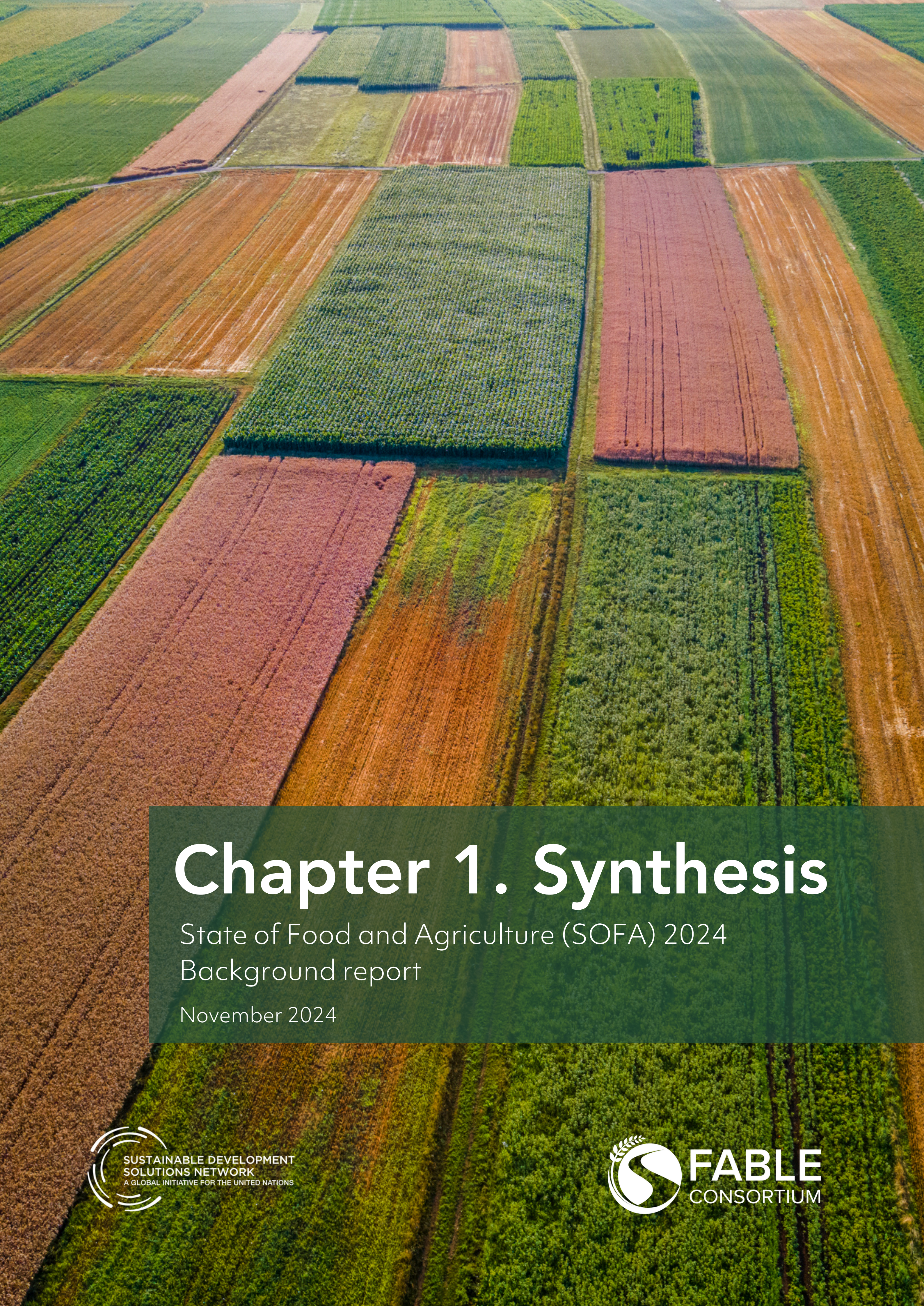

# Chapter 1. Synthesis

State of Food and Agriculture (SOFA) 2024
Background report

November 2024

SUSTAINABLE DEVELOPMENT SOLUTIONS NETWORK
A GLOBAL INITIATIVE FOR THE UNITED NATIONS

FABLE CONSORTIUM


**Authors**

Yiorgos Vittis (1), Aline Mosnier (2),* Alison Smith (3), Ricardo Arguello (4), John Chavarro Diaz (5), Wanderson Costa (6), Alexandre Köberle (7,8), Vartika Singh (7,9,10), Yonas Getaneh (11), Yirgalem Nigussie (12), Javier Navarro (13), Frank Sperling (13), Davide Cozza (2), Fernando Orduña-Cabrera (1), Steven Lord (3), Miguel Benitez Humanes (14).

(1) International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
(2) UN Sustainable Development Solutions Network (SDSN), Paris, France
(3) University of Oxford, Oxford, United Kingdom
(4) Independent consultant, Colombia
(5) Pontificia Universidad Javeriana (PUJ), Bogota, Colombia
(6) National Institute for Space Research (INPE), Sao Jose dos Campos, Brazil
(7) Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany
(8) Instituto Dom Luiz, Universidade de Lisboa, Portugal
(9) Indian Institute of Management Ahmedabad (IIMA), Ahmedabad, India
(10) International Food Policy Research Institute (IFPRI), New Delhi, India
(11) Alliance of Bioversity International and CIAT, Addis Ababa, Ethiopia
(12) Policy Studies Institute (PSI), Addis Ababa, Ethiopia
(13) Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia
(14) Food and Agriculture Organization (FAO), Italy

***corresponding author aline.mosnier@unsdsn.org**



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# Highlights

- This chapter summarizes the main findings about hidden costs in agrifood systems across six countries, Australia, Brazil, Colombia, Ethiopia, India, and the United Kingdom building on the results from SOFA 2023, the FABLE Consortium, and the Food System Economic Commission (FSEC) initiative.

- While the fact that unhealthy diets currently trigger the biggest hidden costs in most countries was a surprise for some stakeholders, there was a consensus that this is an important and growing issue that urgently needs to be addressed.

- Changing diets and increasing agricultural productivity have the largest impact on reducing the agrifood system's hidden costs in the future, but implementing an integrated strategy that can also target environmental protection has the largest benefits.

- Some hidden costs related to undernourishment are covered in the analysis, but they do not accurately reflect the size of the problem, particularly in low-income and lower-middle-income countries.

- Better local datasets should be used in hidden costs computation for GHG emissions and land cover change, and thresholds for poverty and undernourishment should be aligned with national statistics.

- There are challenges to communicating the complexity of the hidden costs method, but this topic is gaining momentum for policy planning, and several governments are already either utilizing or planning to develop similar metrics, so this analysis was a timely exercise.

# Contents

# Contents

## 1.1 Introduction

**True cost accounting (TCA) methods can support decisions to reduce existing hidden costs instead of perpetuating them and to transition towards just and sustainable agrifood systems**. The State of Food and Agriculture (SOFA) report 2023 showed that while agrifood systems generate significant benefits, they generate hidden costs around 12 trillion 2020 PPP (purchasing power parity) dollars, equivalent to 10% of global GDP. Three types of hidden costs are included in the analysis: external costs of agricultural production on natural resources, the costs of distributional failures within agrifood systems, and labor productivity losses due to current dietary patterns (SOFA 2023). These costs are generated by markets, and institutional and policy failures: **they are not included in private costs but are absorbed by society and the environment. They are usually ignored in decision-making, leading to unfair impacts**. The impacts of air and water pollution and losses of ecosystem services, for example, are borne by third parties that are not directly involved in the production or consumption of the goods. Similarly, poverty among agrifood workers results from unequal distribution of the value added generated by the agrifood systems. Unhealthy food leads to disabilities and premature mortality, but consumers may not be aware of these risks, or healthy food might be out of reach.

**For the SOFA 2023 report, annual hidden costs were computed for 154 countries over 2016 to 2023** using readily available and comparable data across many countries (Lord et al., 2023). They are expressed in 2020 PPP dollars to allow comparability across different capital flows, impacts and countries and allow aggregation to regional and global levels. Quantification of hidden costs requires combining impact modeling with monetary estimates. Monetary valuation of the hidden costs of agrifood systems focused on the economic component, e.g., measures of losses attributable to declines in labor or land productivity. Flows and impacts are numerous and many of them are difficult to quantify, while others are qualitative in nature (cf. Figure 2 in SOFA 2023). The impacts which have been included are volatilization and run-off of nitrogen applied on agricultural land and sewerage, GHG emissions along the entire value chain, conversion of natural ecosystems to agriculture, water withdrawals for irrigation, poverty of agrifood workers, the prevalence of undernourishment, and non-communicable diseases from food consumption choices converted into disability-adjusted life years (DALYs).

**The focus of the SOFA 2024 report is on targeted assessments of TCA (FAO 2024).** The initial assessments are incomplete and suffer from uncertainty but are a useful starting point for raising awareness and initiating a dialogue within countries. With input from in-country stakeholders and experts, country-specific information can be used to improve the initial preliminary quantification and analysis, leading to more in-depth assessments. Moreover, quantitative models can help to prioritize investments and policies by showing the magnitude of the change induced by each factor through scenario analysis. Comparing the outcomes from different scenarios highlights which actions might be the most desirable and urgent to implement. The research community can develop these models to foster collaboration between political, economic, and social actors through a common understanding of the underlying mechanisms of the system.

**The Food, Agriculture, Biodiversity, Land-Use, and Energy (FABLE) Consortium is a collaborative initiative** created in 2017 to support the development and transfer of quantitative models for integrated long-term analysis of food and land use systems by researchers and experts from local knowledge institutes. The tools developed by FABLE provide a framework for engaging stakeholders to anticipate and manage trade-offs between different land-use pressures, align shorter-term strategies with long-term ambitions, and avoid locking themselves into unsustainable land use systems. FABLE has built a decentralized framework to foster the availability of models for national food and land systems that can account for feedback between the national and global scales through so-called Scenathons (scenario marathons) (Mosnier et al., 2023). Research teams from 24 developed and developing countries spanning all continents are currently represented in the Consortium.

**This study focuses on six countries, Australia, Brazil, Colombia, Ethiopia, India, and the United Kingdom**, building on the TCA results from SOFA 2023, the SPIQ-FS true cost accounting model (Lord et al., 2023), and the network and tools of the FABLE Consortium. The objectives are: 1) to assess the plausibility of the SOFA 2023 results for these countries; 2) to highlight the opportunities and needs for a tailored assessment of TCA by country; and 3) to identify recommendations of potential entry points for reducing hidden costs through the simulation of different scenarios of agrifood system transformation. The first step of the analysis was to communicate the complex hidden costs concept and methodology to a wide range of stakeholders so that they can provide useful feedback. Then, we developed scenarios in an agrifood system model, the FABLE Calculator was used in five countries and MAgPIE was used in India, to highlight and prioritize entry points for reducing hidden costs and increase the overall sustainability of agrifood systems by 2030 and 2050. Finally, we soft-linked the FABLE Calculator and the MAgPIE models to the SPIQ-FS model to assess the most impactful scenarios for reducing hidden costs.

We first present the context of the country case studies and the stakeholder engagement process that occurred in each country. Then we present and compare the hidden costs computed in SOFA 2023 with available national data, and finally we compute the evolution of the hidden costs in alternative scenarios to identify the most promising entry points to reduce them.

## 1.2 Presentation of the case studies

### 1.2.1 Context of the country case studies

***Table 1-1**: Important characteristics of the six countries included in this analysis*

| | Australia | Brazil | Colombia | Ethiopia | India | UK |
|---|---|---|---|---|---|---|
| **Classifications** | | | | | | |
| **Marshall agrifood system** | Industrialized | Formalizing | Formalizing | Protracted crisis[a] | Traditional /rural | Industrialized |
| **Income group** | High income | Upper middle income | Upper middle income | Low income | Lower middle income | High income |
| **National priorities for agrifood systems** | | | | | | |
| **Land** | Livestock grazing on native vegetation > 50% of the land | Reduce illegal deforestation, restore degraded pasture, high intensity large-scale cropland. | Reduce illegal deforestation and illegal crops, increase productivity of pasture and silvopastoral systems. | High rates of deforestation and land degradation. | High rates of land degradation through the high application of nitrogen. | Almost half grassland, high population density, some peatland. |
| **Water** | Highly variable rainfall and temperature pose risks to rain-fed production; soil salinity problem related to irrigation. | Abundant water resources but high heterogeneity in availability; irrigation mostly for rice and sugarcane. | Water protection (increasing vulnerability due to climate variability). | Water scarcity, exacerbated by climate change. | Water scarcity, exacerbated by climate change. | Mainly rainfed, but climate variability becoming problematic. Groundwater resources declining, and poor water quality. |
| **Trade** | >70% of the food produced is exported. | Large exporter of beef, sugar, soybean, and corn. | Exports of coffee | Self-sufficiency in staples and higher exports is the objective. | Large exports of staple crops, imports of pulses, oils | Proportion of imports grew from 30% to 50% since 2020. |
| **AFOLU GHG** | 17% of total emissions, mainly from livestock. | 48% of total emissions from deforestation, 27% from agriculture. | 66% of total emissions. | Largest livestock herd in Africa; major source of GHG. | 6% of total emissions. | 12% of total emissions. |
| **Nitrogen and phosphorous** | | 80% of the nitrogen fertilizers are imported; phosphate is key for crop production. | Low average use of synthetic fertilizers with high concentration of use in a few crops. | Need to increase nitrogen use. | Extensive use of nitrogen and phosphorous, resulting in high nutrient deposition in soils. | High synthetic fertilizer use causes nitrogen pollution in water, but declining due to precision agriculture. |
| **Food and nutrition** | Meat consumption 24% higher than the Australian Dietary Guidelines. | 32% of the population faced moderate or severe food insecurity between 2020 and 2022. | 42% rural poverty rate and high prevalence of under-nourishment in rural areas | Under-nourishment persists, with 62% employed in agriculture, many trapped in poverty. | High prevalence of underweight, micronutrient-deficiency, and obesity. | High obesity rates (30% adults, 15% children). |

*Note: The agrifood systems typology presented in SOFA 2024 based on Marshall et al. (2021) captures the challenges countries face in delivering nutritious and healthy diets in an environmentally sustainable way using four variables: 1) the value added per worker in agricultural production; 2) the number of supermarkets per 100,000 people; 3) the share of calories from staples; and 4) urbanization. A sixth category was introduced to address the significant distortions caused by medium to long-term conflicts and fragilities in agrifood systems.*

*[a] The "protracted crisis" category includes countries listed by the FAO as being in protracted crisis as of September 2023 (FSIN and Global Network Against Food Crises, 2022). It encompasses countries that meet all of the following conditions: i) humanitarian assistance from official development assistance is greater than 10% of the country's GDP; ii) inclusion in the list of low-income food-deficit countries; and iii) assistance required for food in four consecutive years (2018–2021) or eight of the ten previous years (2012–2021). The list includes the following countries: Afghanistan, Burundi, Central African Republic, Chad, Democratic People's Republic of Korea, Democratic Republic of Congo, Eritrea, Ethiopia, Haiti, Liberia, Mali, Mauritania, Niger, Sierra Leone, Somalia, South Sudan, Sudan, Syrian Arab Republic, Yemen and Zimbabwe. In addition, Palestine is included in the category of countries/territories in protracted crisis in the typology. Note that this list does not include all countries in the world, and it is not necessarily endorsed by country governments.*

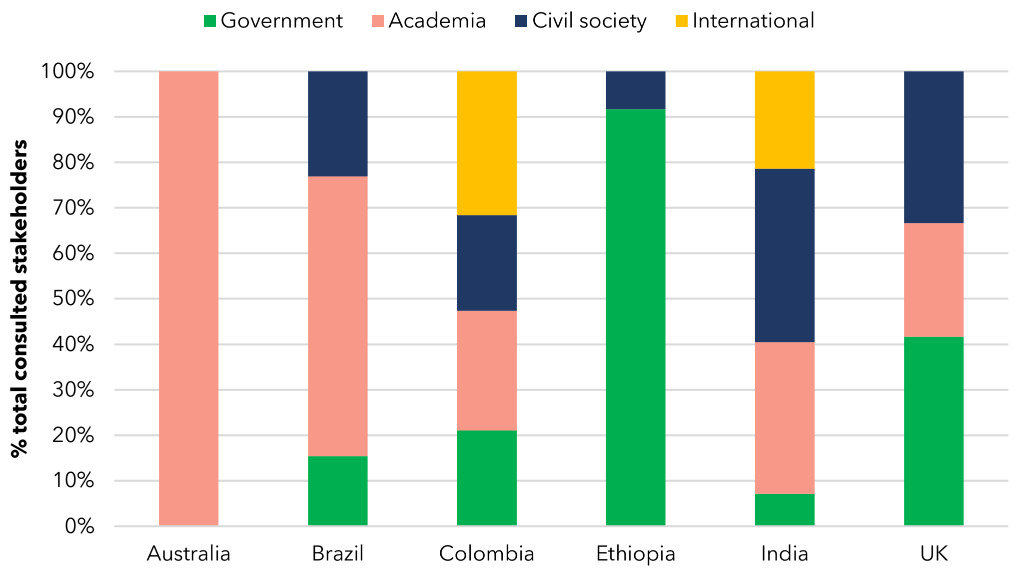
### 1.2.2 Stakeholder consultation

Feedback was collected from key stakeholders of the agricultural sector, including from academia, government, and civil society (Table 1-2). Some countries had already consulted on the underlying scenario assumptions prior to this study, for the 2023 Scenathon. With limited time and financial resources, the approach for stakeholder consultation on TCA was pragmatic: depending on the country, the consultations were in-person or online, with a large group, several small groups or bilaterally, and through online surveys. One significant constraint for stakeholder consultation was the overlap of the time of the study and the summer holiday in the Southern hemisphere. The response rate was 46% on average, with the lowest response rate among government institutes (28%) and the highest among international organizations (75%).

- In **Australia**, consultation focused on CSIRO staff who cover a broad range of expertise and are in regular contact with farming communities, government and industry representatives, and other stakeholders.
- In the case of **India**, more than 50 participants from all sectors –policy, academia, think tanks, and civil society– were represented. Most of the participants were from think tanks and the academia (51 and 25% respectively).
- In **Brazil**, the consultation was online, including a survey and a workshop. Of 51 stakeholders invited, 13 participants–primarily from academia–responded.
- **The UK** consultation included a range of highly relevant stakeholders and experts across business, research, civil society, and public administrations. Feedback was obtained directly in workshops, with an online survey for people to provide further feedback after the workshops.
- Stakeholder engagement in **Colombia** included consultation with 19 experts split between the private sector (representatives of growers' associations), government, and academia. The consultation process had support from the Centre of Studies on Production and Sectoral Trade of the Colombian Central Bank and the Colombia Office of the FAO, who were instrumental in calling participants to the meetings.
- Feedback on hidden costs in **Ethiopia's** agrifood system was collected through in-person meetings and phone interviews of experts, including policymakers, farmers and researchers. The total of 11 respondents participated in Ethiopia's stakeholder consultation.

Consequently, this consultation does not claim to be representative of all stakeholders in the country. Even if there was a good balance between representatives from government institutes, academia, civil society, and international organizations, most of the individuals who provided feedback are better characterized as experts rather than decision-makers. Some individuals were reluctant to participate in the consultation due to the complexity of the TCA methods and a feeling of insufficient knowledge on the topic.

***Figure 1-1:*** *Origin of the stakeholders consulted on average across all six case studies*




*Note: the frontier between these different groups is sometimes slim, e.g., in Australia, CSIRO is a government research entity so the staff who were consulted could be considered both government and academia.*

***Table 1-2:*** *Summary of the stakeholder consultation process for this analysis*

| | Who was consulted? | | How and when? | |
|---|---|---|---|---|
| **Australia** | CSIRO staff, broad range of expertise informed by industry and other stakeholders (cf. Chapter 2) | | Small workshop in December 2023 with selected CSIRO experts and Steven Lord and bilateral consultations in February | |
| **Brazil** | 51 stakeholders invited incl. recommendations from the FAO representative and from the Science Panel for the Amazon | 13 respondents (cf. Chapter 3) | Via online survey and 1 virtual workshop on 3 April 2024. | |
| **Colombia** | | 19 respondents (cf. Chapter 4) | 3 virtual and 1 in-person meetings | |
| **Ethiopia** | 15 persons invited | 11 respondents (cf. Chapter 5) | In-person workshop: 2 December 2024. | Follow-up online bilateral meetings with people who could not attend |
| **India** | 42 participants incl. 2 representatives from the FAO country office (cf. Chapter 6) | | 2 in-person workshops: 23 December 2023 and 23 January 2024 | |
| **UK** | 12 respondents (cf. Chapter 7) | | 3 online workshops with a follow-up survey and emails | |

## 1.3 Validation of the SOFA 2023 results for the current hidden costs of the agrifood systems

### 1.3.1 Overview of the SOFA 2023 method

Hidden costs in the SOFA 2023 report include those due to labor productivity loss, loss of ecosystem services, loss of environmental flows, the economic damages of poverty, higher mortality, and agricultural production losses. These costs are clustered into three categories: 1) **Health (H)**: productivity losses from the burden of disease due to dietary choices; 2) **Social (S)**: productivity losses from distributional failure (undernourishment), reflecting the amount society would pay for eliminating the economic damages of poverty; and 3) **Environment (E)** which includes the external costs of environmental damage caused by agriculture, i.e., labor productivity loss due to air pollution, loss of ecosystem services due to land conversion and water pollution by nitrogen, loss of environmental flows due to irrigation water withdrawal and losses of agricultural production due to climate and soil leaching. In addition, it should be noted that only 75% of the costs related to unhealthy diets were attributed to the agrifood system since other factors contribute, for instance, to obesity. The productivity losses considered are those associated with forgone labor and informal care.

The impact on well-being is measured as the overall economic losses of GDP in 2020 PPP dollars. The hidden costs are computed as the impact quantities multiplied by the marginal costs (Table 1-3). The global database for impact quantities uses different sources as shown in brackets while most of the marginal costs come from the SPIQ-FS database (Lord et al., 2023). This uses a discount rate of 3% that assumes a business-as-usual socioeconomic pathway (SSP2) for discounting the hidden costs that future generations will bear. Shadow prices are used for the marginal valuation of hidden costs (cf. marginal cost indicator column in Table 1-3) and are then compared with GDP. Shadow prices reflect the change in the value of an economic activity associated with one more unit of resource. The model used relies on shared assumptions about national growth rates, costs of burden of disease, future economic and demographic conditions, and ecosystem service values, allowing for better consistency and an ability to perform sensitivity analyses at different discount rates and diseases costs. Nitrogen costs have the highest uncertainty due to a gap in knowledge concerning the value of ecosystem services, the absence of spatially explicit data on the damage to ecosystem productivity from nitrogen loading, and the compounding uncertainty along the nitrogen cascade. Marginal costs of agricultural blue water use are underestimated due to a lack of cost data on the loss of environmental flows.

***Table 1-3:*** *Computation of the hidden costs by category as the impact quantities multiplied by marginal costs to GDP*

| | Total cost to GDP | Impact quantity indicator | Marginal cost indicator |
|---|---|---|---|
| **H** | **Costs of burden of disease due to dietary patterns** | Number of years lived with disability and years of life lost compared to expected life years (NCD) (DALYs) (Global Studies of Diseases, 2014–2019) | **Labor productivity** losses in the country of consumption due to burden of non-communicable diseases and high BMI in 2020 PPP dollars/DALY (ILO) |
| **S** | **Costs of undernourishment** | Number of people within a national population with food intake below minimum energy requirements (FAOSTAT, 2014–2020) transformed into DALYs using SPIQ-FS model | **Labor productivity** losses in the country of consumption due to burden of disease from protein-energy malnutrition in 2020 PPP dollars/undernourished person (SPIQ-FS, ILO, WHO) |

| | | | |
|---|---|---|---|
| **S** | **Cost of eliminating poverty among agrifood systems workers** | The share of agrifood systems workers in total employment is used as a proxy for the share of agrifood systems workers under the poverty line of $3.65 a day 2017 PPP (World Bank) | Conversion of poverty gaps into **income shortfall** per annum, i.e., financial transfers that would be needed to avoid moderate poverty |
| **E** | **Costs from agricultural production losses due to climate** | GHG emissions in $tCO_2e$ ($CO_2$, $CH_4$ and $N_2O$) from on-farm production, pre- and post-production, land use and land use change (Tier 1 - FAOSTAT 2014–2020) | **Agricultural production losses** (Interagency working group on the social cost of Greenhouse Gases IWG-SCGHG, 2020) |
| **E** | **Costs from higher mortality due to climate** | | From **higher human mortality** due to heat stress |
| **E** | **Net costs from loss of ecosystem services after conversion of natural ecosystems to agriculture** | Effective hectares of lost ecosystem services.<br>Area of temperate and tropical forest converted to cropland and pasture and forest regrowth on cropland and pasture.<br>Area of unmanaged grassland converted to cropland and pasture and unmanaged grassland recovery. (HIstoric Land Dynamics Assessment HILDA+, 2014–2019) | Marginal cost from **loss of provision of natural ecosystems** (Ecosystem Services Valuation Database ESVD and SPIQ-FS) |
| **E** | **Costs from loss of environmental flows due to irrigation withdrawal** | Blue water withdrawal for agricultural use in cubic meters (AQUASTAT 2014–2020) | **Agricultural production losses** |
| | | | **Labor productivity** losses in the country of withdrawal due to burden of disease from protein-energy malnutrition due to water deprived from economic use |
| **E** | **Costs from air pollution related to nitrogen application** | Volatilization of $NH_3$ (ammonia) and NOx (nitrous oxide) to air (European Commission's Emissions Database for Global Atmospheric research EDGAR v5.0, 2015) | **Labor productivity** losses due to air pollution |
| | | | **Agricultural production losses** |
| | | | **Ecosystem services losses**<br>- from ozone formation, nutrient imbalance, and acidification of terrestrial biomes due to deposition<br>- from nutrient imbalance, acidification, and eutrophication of riverine, wetlands, and coastal systems due to deposition run-off<br>(Ecosystem Services Valuation Database ESVD) |
| | | | **Labor productivity** losses in the country of emission due to burden of disease from particulate matter formation |
| **E** | **Costs from water pollution related to nitrogen application** | $NO_3^-$ leached to groundwater, $NO_3^-$ due to run-off from agricultural land to surface water and effluent or human sewerage in surface water.<br>(Calculated from Integrated Model to Assess the Global Environment – Global Nutrient model IMAGE-GNM spatial datasets) | **Labor productivity** losses in the country of emission due to burden of disease from human nitrate intake |
| | | | **Ecosystem services losses** from nutrient imbalance, acidification, and eutrophication of riverine, wetlands, and coastal systems due to run-off (Ecosystem Services Valuation Database ESVD) |
| **E** | **Costs from crop losses due to soil leaching** | Run-off of reactive nitrogen into surface waters and soil leaching, predominately soluble nitrate (European Nitrogen Assessment; IMAGE-GNM spatial datasets) | **Agricultural production losses** (crop) |

| | | | |
|---|---|---|---|
| E | **Costs from water pollution due to nitrogen run-off** | Run-off of reactive nitrogen into surface waters and soil leaching, predominately soluble $NO_{3^-}$ (nitrate) (IMAGE-GNM spatial datasets) | **Ecosystem services losses** |

*Note: H: Health, S: Social, E: Environment; source of the data indicated in brackets.*

### 1.3.2 Main sources of hidden costs in country case studies between 2016 and 2023

According to SOFA 2023 estimates, as the average income by country increases: a) the country's share of total global hidden costs tends to increase, b) the share of hidden costs in its national GDP tends to decrease, and c) the contribution of social hidden costs in national hidden costs decreases while the contribution of health hidden costs increases. Most of the total quantified hidden costs are generated in upper-middle-income countries (39%) and high-income countries (36%) with low-income countries only making up 3%. However, the share of total hidden costs in national GDP is highest in low-income countries (27%) and lowest in high-income countries (8%). Overall quantified hidden costs show an upward trend mostly driven by increasing health-related hidden costs from unhealthy diets. This is the only cost category that is on the rise across all income groups.

**Accounting for hidden costs would reduce global GDP PPP by 10% in 2020, and national GDP PPP by 16% in Brazil, 12% in Colombia, 16% in India, 6% in Australia and 8% in the UK.** In all countries but Ethiopia, the main hidden cost is the burden of disease due to dietary patterns (Figure 1-2) and this has been steadily increasing from 13% in 2016 to 33% in 2023. The estimated share of hidden costs related to the burden of disease due to undernourishment is low in all countries (less than 5%). These results show that countries face different challenges related to economic development (e.g., poverty), intensity and efficiency of production inputs (e.g., utilization of nitrogen and water for irrigation), and land use.

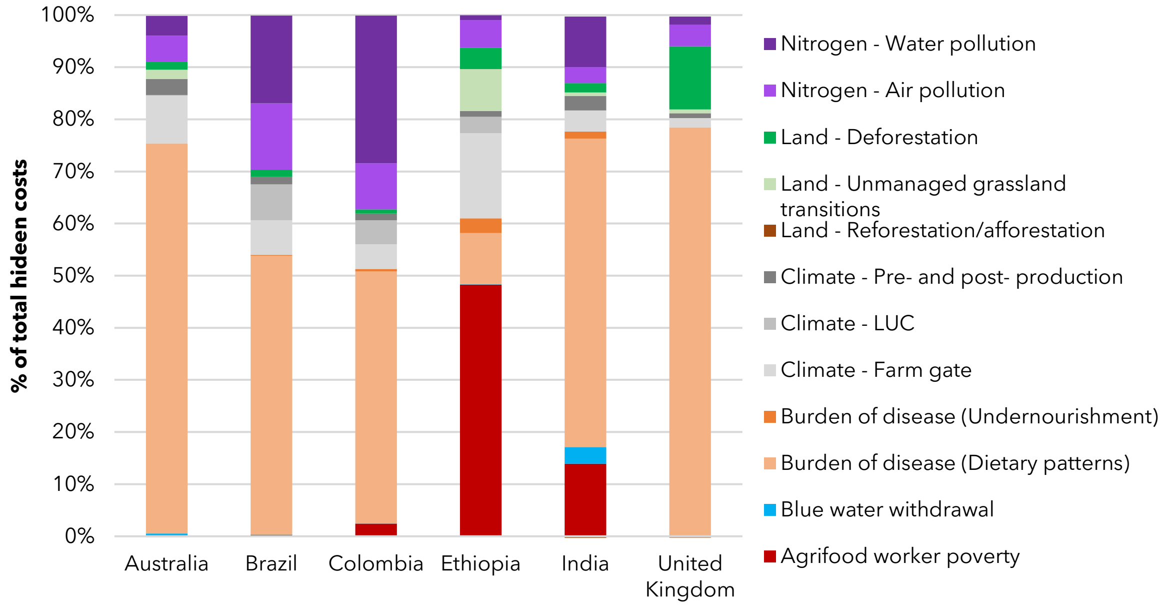
Brazil and Colombia share quite similar patterns, with half of the hidden costs coming from the burden of disease due to dietary choices, 30 to 37% coming from nitrogen (but with the highest share due to water pollution in Colombia), 11 to 15% coming from GHG emissions (split almost equally between land-use change and on-farm emissions), and a very small portion (1%) from the costs of deforestation (Figure 1-2). The costs from the burden of disease due to dietary choices and nitrogen have been steadily increasing from 2016 to 2023 (+14% and +23% respectively in Colombia).

Both in Australia and the UK, the cost of burden of disease due to dietary patterns represents more than the two thirds of the total (positive) costs, and land use change appears to be the second most important source of costs (positive in the UK and negative in Australia) (Figure 1-2). For land use change, the data appears to fluctuate considerably between 2016 and 2019, before the extrapolated period to 2023 where it stays constant, and there has been a gradual decline in the costs related to nitrogen (-11% for Australia and -14% for UK).

In Ethiopia, the pattern of hidden costs aligns with the observed cost structure in many low-income countries, where the social sector often bears the brunt of hidden costs associated with food production. Poverty among agrifood workers emerges as the most significant contributor (48%). This reflects the high concentration of rural populations living below the poverty line in Ethiopia. Climate and land-related costs from the environmental sector in Ethiopia follow closely representing 20% and 12% of the total average cost. GHG emissions primarily stem from livestock since Ethiopia has the largest livestock population in Africa with 65 million cattle and 90 million small ruminants in 2020 (Mekuriaw and Harris-Coble, 2021). All these costs have risen between 2016 and 2020.

In India, after the cost of the burden of disease from dietary patterns, the costs related to nitrogen flows (especially water pollution) and poverty among agrifood workers contribute the most to total hidden costs (~14% each). India reports hidden costs to the extent of 0.73 trillion PPP dollars 2020 due to health outcomes of agrifood systems in India. This is driven by the double burden of malnutrition and obesity that currently plagues India's population. Between 2016 and 2020, costs related to the burden of disease from dietary patterns and to nitrogen flows have risen (14% and 16% respectively) but costs related to poverty have reduced. India is the only country among the six country case studies where the hidden costs related to blue water withdrawal plays a role (3%).

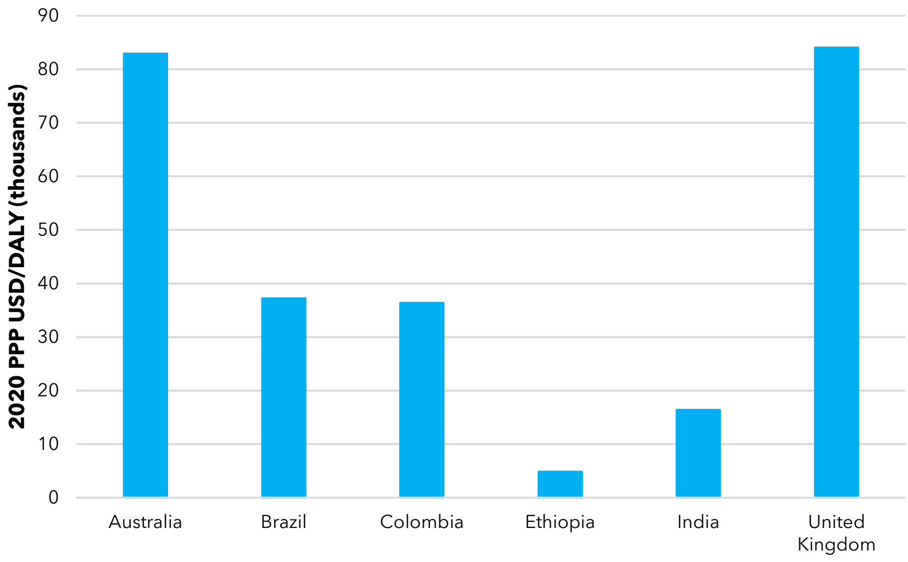
***Figure 1-2:*** *Comparison of agrifood system hidden costs for the six countries as % of total hidden costs in 2020*




*Source: Authors based on SOFA 2023*

The contribution of impact quantities and marginal costs to the total cost estimates varies between countries. Labor productivity loss is a major marginal cost indicator used to compute the hidden costs and can arise from health, social, or environmental impacts (Table 1-3), including: 1) burden of non-communicable diseases and high BMI due to dietary patterns; 2) burden of disease from protein-energy malnutrition; 3) burden of disease from protein-energy malnutrition due to water deprived from economic use; 4) air pollution; 5) burden of disease from particulate matter formation ($NH_3$ and NOx); and 6) burden of disease from human nitrate intake. Consequently, the assumption on labor productivity has a large impact on the resulting hidden costs and can partly explain the differences across countries (Figure 1-3). Other marginal costs include income shortfall, agricultural production losses, higher human mortality, and reduced provision of ecosystem services (Table 1-3).

**Figure 1-3:** *Comparison of the marginal cost of a DALY across countries*




In the high-income countries of the current report (Australia and United Kingdom), the hidden cost of dietary patterns in 2020 was driven by the high marginal cost of productivity losses (>80,000 2020 PPP dollars per DALY) while the estimated number of DALYs are moderate relative to the size of the population (0.7 and 2.3 million years respectively). In contrast, in Brazil and India the hidden costs of dietary patterns are driven by a high number of DALYs (7.3 and 40.7 million years) whereas the marginal costs are much smaller than the high-income countries (~37,000 and ~16,000 PPP dollars 2020 per DALY respectively). Colombia and Ethiopia have similar number of DALYs but total costs for Colombia are much larger because the marginal cost is seven times higher than in Ethiopia. In Ethiopia, the hidden cost estimate is dominated by poverty, driven mainly by the large number of people below the poverty line (54.4 million) rather than the marginal cost (453 PPP dollars 2020 per person). Poverty headcount is also large in India (358 million people), but the marginal cost is quite low (440 PPP dollars 2020 per person).

Regarding environmental costs, the UK features the highest marginal costs of land among the six countries with ~100 thousand PPP dollars 2020 per hectare compared to 27.8 and 13.6 marginal cost of forest and unmanaged grassland in Ethiopia. Environment costs in Brazil, Colombia and India relate predominantly to nitrogen flows ($NH_3$ emissions to air). The highest impact quantities are estimated for India (5.4 Mt of N) and this contributes the most to the cost estimate given the comparatively low marginal cost (1.4 and 3.6 PPP dollars 2020 per N kg for air pollution and deposition respectively). In contrast, the marginal costs seem to contribute the most to the estimates in Colombia and Brazil (13.2 and 11.9 PPP dollars 2020 per N kg), although Brazil also features a significant amount of $NH_3$ emissions to air (3.7 Mt of N).

### 1.3.3 Comparison with national datasets

Direct comparisons between the global datasets used in the hidden costs analysis and national statistics were in some cases not possible as they used inconsistent categories. To allow comparisons, we have combined subcategories among different datasets and highlight higher, lower, or similar levels of estimates (Table 1-4). The impact quantities indicators that have been used for land use change, poverty, undernourishment, nitrogen, water and GHG in SOFA 2023 tend to diverge from national datasets in almost all countries studied here, while other impact indicators such as dietary patterns tend to be mostly in line with national statistics.

***Table 1-4:*** *Comparison of SOFA 2023 hidden cost data with national statistics for the main cost components of the analysis (impact quantities)*

| | Land use | GHG | Nitrogen | Poverty | Dietary patterns | Under-nourishment | Water |
|---|---|---|---|---|---|---|---|
| **Australia** | Higher | Higher | | Lower | Similar levels | Lower | Higher |
| **Brazil** | Lower | | Similar levels | | Similar levels | | Lower |
| **Colombia** | Higher / Lower | Higher | Higher | | Similar levels | | Higher |
| **Ethiopia** | | Higher | | Higher | | Lower | |
| **India** | | Higher | | | Similar levels | | Similar levels |
| **UK** | Higher | Higher | Higher | | Similar levels | | Similar levels |

**SOFA 2023 data compared to national statistics**

Higher | Similar levels | Lower | No reported differences / or missing information

*Notes: This table does not show consistency of categories or units between the SOFA 2023 data and national statistics but simply highlights observed differences and similarities in the magnitude of impact quantities. Land use comparison refers to differences on distinctive land use changes by country with the dataset HILDA+ which has been used in SOFA 2023 (cf. paragraph on land use change). In cases where datasets were inconsistent or missing information, no comparison was made, and no differences are identified (white cells).*

### *Land use change*

The land use change patterns from 2016 to 2019 described by HILDA+ do not seem to match currently observed trends in many countries (Australia, Brazil, Colombia, and the UK). For the UK, many land use transitions assumed, including shifts between grassland, pasture, forest, and cropland, are not supported by UK-level datasets (UNFCCC, 2022a), potentially due to misclassifications of forest plantations that have been felled prior to restocking as land that has been deforested. Some land use transitions are not included, suggesting that certain important changes may be overlooked. For Brazil, while HILDA+ shows a decrease of forest conversion to agricultural land between 2017 and 2018, national data (Mapbiomas time series, Souza et al., 2020) show an increasing trend in natural vegetation loss during the same period. In Colombia, HILDA+ transitions of cropland and pasture to forests are considerably overestimated while conversions of forests to pasture are grossly underestimated (Second and Third Biennial Update Reports (BUR); UNFCCC, 2022). In Australia, the HILDA+ values of conversion of forest to cropland are three orders of magnitude different to the National Greenhouse Gas Inventory (NGGI) (Australian Government Department of Climate, Energy, the Environment and Water, 2021) and land clearing for grazing on native vegetation could be overestimated by two orders of magnitude.

### *Greenhouse gas emissions*

In the UK, Colombia, and Australia, GHG emissions from FAOSTAT are higher than emissions from national sources: the UK Greenhouse Gas Inventory (GHGI) (UNFCCC, 2022a), the Colombia Biennial Update Report (58% higher) (UNFCCC, 2022) and Australia's National GHG Inventory (7 to 65% higher) (as reported to the UNFCCC, DCCEEW, 2021). For Australia, this is mainly due to the use of more detailed Tier 2 and 3 methods in the national inventory compared to the basic Tier 1 approach in FAOSTAT. In Ethiopia, it is the opposite: the national-level assessment (FDRE, 2022) estimates higher $CO_2$ emissions than FAOSTAT (+54%) but total $CH_4$ and $N_2O$ emissions appear broadly comparable in both reports, though inconsistencies are observed for $N_2O$ manure management and land use-induced emissions. In India, discrepancies emerge due to $CO_2$ emissions from land use change, which are estimated to be zero, while data from the GHG platform indicate that there are negative emissions of approximately 180 million tonnes (UNFCCC, 2021). $CH_4$ emissions are also underestimated compared to official data.

***Nitrogen-related costs***

Estimated nitrogen-related costs compare reasonably well in the case of Brazil where costs are in line with past trends in nitrogen fertilizer use due to uptake of precision farming techniques. Specifically, nitrogen run-off in Brazil is associated with the increased application of fertilizer related to robust growth in agricultural production in the last decades, coupled with a lack of improvement in nitrogen use efficiency, which even shows signs of worsening according to a few studies (Pires et al., 2015; Santos et al., 2023). In the UK case study, the estimates of $NH_3$ emissions to air from agriculture appear to be larger than those in the National Atmospheric Emissions Inventory but smaller than those in the UK Environmental Accounts (the "Blue Book", Office for National Statistics, 2021). In the case of Colombia, the impact quantities are considerably larger than those corresponding to national historical data, although the latter also show an upward trend.

***Poverty***

Differences between the poverty estimates used in SOFA 2023 and official poverty estimates mainly come from the use of different poverty lines: in SOFA 2023, USD 3.65 per day corresponding to moderate poverty is used while a poverty line of USD 1.90 per day is used in Ethiopia (FDRE, 2012) and India (Panagariya and More, 2023). The method to compute poverty has limited applicability in Australia because it overlooks disparities in affordability across the country, particularly in remote areas, since the national metric does not account for heterogeneity in costs of essential products within the country (Davis et al., 2023; Box 1).

***Dietary patterns***

The cost of the burden of disease due to unhealthy diets is in line with the high and growing prevalence of obesity and levels of overweight currently observed in Brazil and the UK (Ferrari et al., 2022; National Statistics, 2015; Rocha et al., 2023). In India, the poor dietary patterns and corresponding burden of disease are supported by India's State of Health Report (ICMR et al., 2017a). Similarly, hidden costs due to unhealthy diets in Australia are in line with currently reported high prevalence of obesity and overweight levels (Lal et al., 2020; Australian Institute of Health and Welfare, 2019). Data on dietary patterns for Colombia used in the TCA method are sourced from the National Health Observatory from the Ministry of Health and Social Care and specifically the Global Burden of Disease, Injuries, and Risk Factors study (Forouzanfar et al., 2015) thereby no differences between national statistics and SOFA 2023 data are identified.

***Undernourishment***

Ethiopian official statistics define undernourishment as the income shortfall required to meet a predetermined minimum caloric intake (2,200 kilocalories per adult equivalent per day) ("food poverty"). Based on this definition, 24.8% of households, i.e., 22 million individuals, were considered undernourished in 2016, which is higher than the 14 million individuals used in SOFA 2023. This discrepancy persists even if we account for the higher caloric threshold for defining undernourishment in the national data. While it is not visible in the SOFA 2023 results because of the FAO definition of undernourishment, multiple sources and studies have highlighted the extent of food insecurity in Australia over the last few years (Foodbank, 2023).

***Water***

Quantities related to water compare reasonably for countries like India and the UK. Discrepancies are identified for Colombia, where national statistics (IDEAM, 2023) indicate that total water demand is much lower than SOFA 2023 data. In Brazil, where agriculture is mainly rainfed, the increase of water withdrawals for irrigation is questionable (only about 10% of the agricultural area is irrigated). In Australia, water use data used for the hidden costs estimation is 21–35% higher (during 2019 and 2020) than the national reported value (Water Use on Australian Farms (ABS, 2022).

### 1.3.4 Gaps in the SOFA 2023 analysis and suggestions for improvements

**Replacement of impact quantities data by national datasets:** As highlighted in the previous section, we recommend that for a tailored country analysis, the land-use change and GHG emissions data are systematically replaced by national datasets. Using different thresholds for poverty and calorie needs would make the comparison across countries more difficult but would increase the relevance of the hidden costs' computation to the national contexts. All countries highlighted that using sub-national statistics would also increase the relevance of the hidden costs' computation (Box 1).

**Suggestions for improvements** to compute hidden costs related to agrifood systems include extending the analysis to cover:

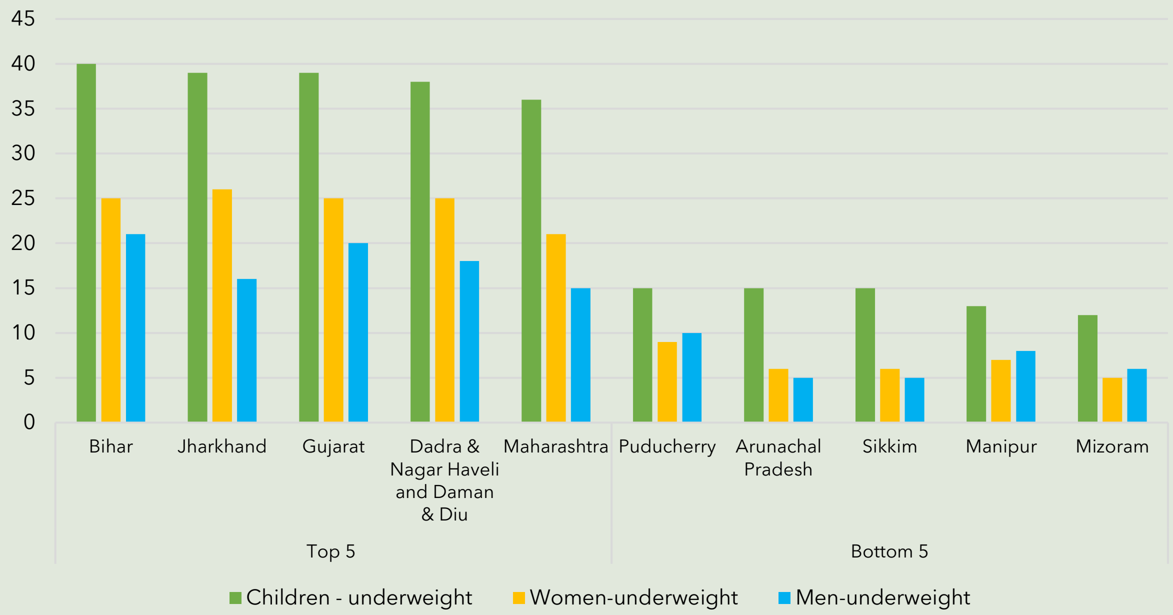
- Biodiversity losses and land degradation (e.g., soil erosion, desertification, salinization) and the potential benefits of certain practices or crops (e.g., enset) to ecosystem services, including pest and erosion control.
- GHG emissions and air pollution from household cooking.
- Other transitions to or from agricultural land (e.g., from cropland to pasture, or from unmanaged grassland to improved pasture or cropland).
- Alternative computation of the hidden costs related to food consumption taking place in the country instead of production. For example, the UK imports 50% of its food, and the impact of the imported food could be attributed to the choices of UK consumers.
- Water scarcity impacts on the loss of drinking water and the environmental cost for biodiversity, such as streams and wetlands drying out, or salinization of groundwater due to over-abstraction in coastal areas.
- Extending water use to processing (e.g., rice and sugar mills in India) and fertilizer production (e.g., in India CSE, 2019).
- Impacts of type 2 diabetes and hypertension on productivity loss (e.g., in Australia and India).
- Impacts of pesticides on human health and ecosystem services.
- Year-to-year fluctuations in undernourishment levels, particularly in response to climate anomalies like rainfall deviations and droughts. These events often trigger year-on crop failures and price fluctuations, potentially leading to significant increases in undernourishment. Accounting for this hidden cost would provide a more comprehensive understanding of the economic consequences and food insecurity because of climate variability.
- Lasting consequences of undernourishment during childhood on human capital and consequently on labor productivity.
- In specific country contexts (such as Australia) most malnutrition is due to micronutrient deficiencies, particularly calcium, magnesium and zinc (ABS, 2015) and thus, the method could better capture the respective hidden costs for health by further disaggregating undernourishment to a micronutrient intake basis.
- Improve the accuracy of health data as in specific contexts like Ethiopia where the traditional cereal-based diet and active rural lifestyles are likely to contribute to lower dietary-related costs compared to other countries. Relying solely on hospital records might underestimate the true burden of such illnesses, as many people may not seek medical care.

***Box 1:*** *The need to go to sub-national level for tailored country-level hidden costs assessments*

*The possibility of transforming the food and land systems towards greater sustainability is constrained by biophysical characteristics and the spatial organization of territory. National results based on national average values are likely to overestimate or undermine the magnitude of the impacts on hidden costs. Sometimes, a problem becomes even invisible at the national level as it can be offset by the other regions of the country. Thus, depending on data and resource availability, national level data should be complemented by spatial analyses, which will enable the heterogeneity of the main impacts and drivers of agrifood systems to be captured:*

- *For national GHG inventories, several countries use a Tier 3 approach that reflects the heterogeneity of carbon stocks in the country instead of a national average value in the Tier 1 approach which is used in the FAOSTAT database.*
- *In SPIQ-FS, marginal costs of ecosystem services are currently differentiated for temperate vs tropical forests, but a single value is used for unmanaged grassland which can encompass a wide range of ecosystems.*
- *When diverse agroecological zones in the country offer different opportunities and challenges to reduce hidden costs, e.g., highland area, very arid areas, different agricultural systems should be distinguished. This might be particularly topical for countries such as Ethiopia where small-scale farmers constitute 75% of the population.*
- *Dietary shifts should take account of affordability in remote areas, e.g., in remote Australian stores food baskets cost 39% more than in major supermarkets in capital cities (Davis et al., 2023), and population in those areas can be impacted more by higher commodity prices (National Indigenous Australians Agency, 2020).*
- *In India, while the hidden costs of undernourishment only represent a small share of the total hidden costs, the extent of the issue varies greatly from one state to another requiring different levels of prioritization by state (Figure 1-4).*

***Figure 1-4*** *– Share of undernourished children, women and men across top and bottom five states in India*




*Source: NFHS 5*

## 1.4 Evolution of hidden costs by 2030 and 2050

### 1.4.1 The agrifood system models and link with the TCA model

In this study, the FABLE Calculator (Mosnier et al., 2020) is used in Australia, Brazil, Colombia, Ethiopia, and the UK, building on the FABLE Scenathon 2023 results (FABLE, 2024). The MAgPIE partial equilibrium model (Dietrich et al., 2019) is used in India, building on the FSEC results (Bodirsky et al., 2023). Both the FABLE Calculator and MAgPIE focus on agriculture as the main driver of land use and land use change. They both rely on the assumption of equilibrium between demand and supply quantities in each region and country, for each commodity and each five-year time step (cf. 1.8.2 and Mosnier et al., 2023 for a detailed comparison of the two models). The FABLE Calculator is an Excel-based non-optimization model. It is a stepwise process where, except for the first step, all steps are dependent on variables that are estimated in the previous steps (cf. 1.8.1). MAgPIE is a global partial equilibrium model that optimizes food, material, and bioenergy demand through a cost-minimization approach accounting for biophysical, technological, and socioeconomic constraints. The MAgPIE model is integrated with two different health and poverty models that evaluate the impact of agricultural production and consumption decisions on health and poverty outcomes for all regions (Dietrich et al., 2023).

These tools have been adapted to fit the local contexts: e.g., through the replacement of the input data from global datasets with country datasets in Australia and the UK (Smith et al., 2022) (Navarro Garcia et al., 2022); the implementation of new features, e.g., representation of locally important crops such as teff, a cereal used as a staple food in Ethiopia (Molla and Woldeyes, 2020); the calibration of key parameters to align models' results with historical statistics over 2000–2015, e.g., Brazil for historical deforestation (Costa et al., 2020); and the improvement of the scenarios to better represent domestic policies or policy ambitions (cf. Annexes). These adaptations are documented in each country chapter. The FABLE Calculator is an open tool and can be downloaded here. The version which is used in this study is v44. The code of the MAgPIE model is available on GitHub. Version 4.7.3 has been used for this analysis (Dietrich et al., 2023).

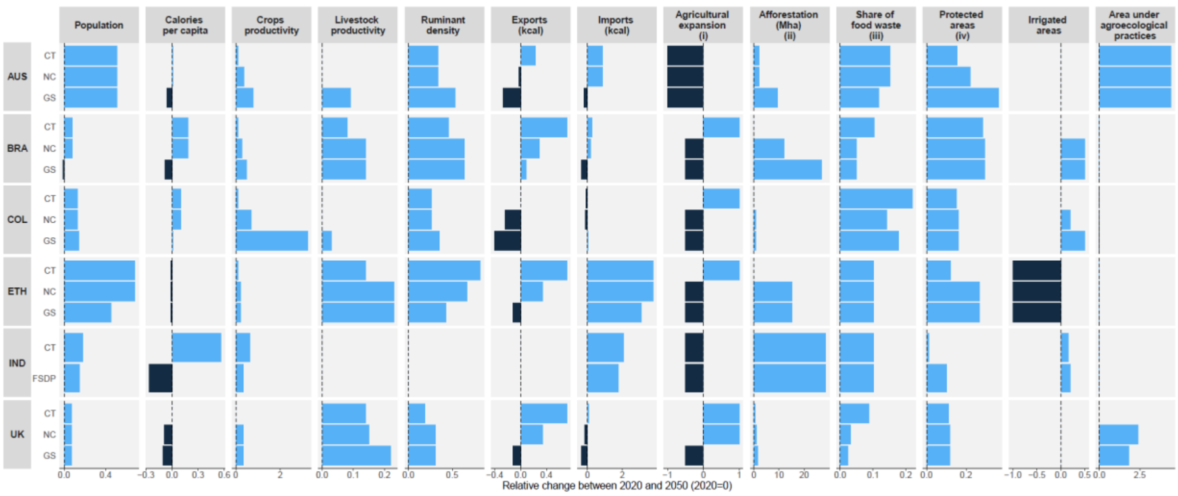
Hidden costs are projected into the future by using some of the outputs of FABLE Calculator or MAgPIE as inputs in the TCA model (cf. 1.8.3). This can be done for GHG emissions (excluding GHG from pre- and post-production), conversion of forest and unmanaged grassland to farmland, and blue water withdrawals for irrigation. For nitrogen, the FABLE Calculator only provides the quantities of nitrogen applied to soils (organic and inorganic) and nitrogen from manure left on pasture, while MAgPIE provides a more comprehensive set of outputs that are more compatible with the SPIQ-FS model. Both the FABLE Calculator and MAgPIE project the evolution of food consumption by food group (and at commodity level for the FABLE Calculator) but not the associated health impacts. An intermediate step was required to convert average food consumption by food groups into DALYs (disability-adjusted life years). This conversion was done for MAgPIE by Marco Springmann (Springmann et al., 2020) while the FABLE Calculator used the machine learning model built to estimate the health hidden costs linking food availability to food intake for the SOFA 2024 (see Box 7 in FAO 2024) and to DALYs using an emulator of the University of Washington 2017 global burden of disease (GBD) model.

### 1.4.2 Scenarios

The Australian, Brazilian, Colombian, Ethiopian, and UK case studies presented in this paper use the FABLE Scenathon 2023 framework with three pathways: 1) the *current trends* (CT) pathway represents a low ambition of feasible action towards environmental sustainability with a future strongly dependent on current policy; 2) the *national commitments* (NC) pathway reflects the actions that would be necessary to meet national commitments and targets; 3) the *global sustainability* (GS) pathway corresponds to efforts that would be compatible with the achievement of global sustainability targets. The Indian case study relies on the work which has been done in the framework of the FSEC commission. The business-as-usual (BAU) pathway aligns with the "middle-of-the-road scenario" of the shared socioeconomic pathways (SSP2) (Riahi et al., 2017; O Neill, 2017; Popp, 2017), where the plausible future state of the food system continues in line with current trends. The full sustainable development pathway (FSDP) represents a transformative pathway that integrates 23 individual food system measures (FSMs) [2]. The scope of the FSDP is very close to the global sustainability pathway.

Figure 1-5 shows the magnitude of the changes which have been assumed by each country for each scenario parameter and Table 1-5 lists all the assumptions which have been used to differentiate NC and GS from current trends in each country.

***Figure 1-5:*** *Overview of the underlying model assumptions in each pathway*




*Notes: 0.3 means a 30% increase in 2050 compared to 2020. Countries represented are AUS – Australia, BRA – Brazil, COL – Colombia, ETH – Ethiopia, IND – India, and the UK. Exports and imports reported here are calculated after the global trade equilibrium is computed in the FABLE-C. (i) Agricultural expansion: 1 corresponds to free expansion of agricultural land, -0.5 corresponds to no deforestation after 2030, and -1 corresponds to no expansion of agricultural land beyond the 2020 area; (ii) Afforestation is in absolute change (Mha); (iii) Food waste: results are expressed in % of consumption which is wasted; (iv) Protected areas: results are expressed in % of total land in 2050. For India: the relative change of exports and imports is computed using Mt dry matter; the unit for crop productivity is metric tonne dry matter per hectare; livestock productivity is endogenously computed in MAgPIE and ruminant density is not explicitly represented in MAgPIE; irrigated area is expressed in % of harvest area in 2050; no explicit agroecological module in the model.*

[2] The 28 transformation domains (comprising both within and outside food systems) are represented by five distinct packages or policy measure bundles: healthy diets and sustainable consumption patterns (Diets), nature-positive agricultural transition (Agriculture), biodiversity protection (Biodiversity), equitable livelihoods (Livelihood), and a broader socioeconomic development external to the food system (CrossSector).

***Table 1-5:*** *Number of scenario parameters activated in NC and GS compared to CT by country*

| Country | # | Scenario parameters tested separately |
|---|---|---|
| **Australia** | 11 | Diet, Food waste, Livestock productivity, Crop productivity (2 levels), Afforestation, Ruminant density on pasture, Protected areas expansion (2 levels), Post-harvest losses, Urban area expansion |
| **Brazil** | 14 | Population, Diet, Food waste, Livestock productivity, Crop productivity (2 levels), Constraints on the expansion of agricultural land, Afforestation (2 levels), Ruminant density on pasture, Protected areas expansion, Post-harvest losses, Biofuel demand, Irrigated area |
| **Colombia** | 21 | Population, Diet, Food waste (2 levels), Livestock productivity, Share of the consumption which is imported (2 levels), exports of main commodities, Crop productivity (2 levels), Livestock productivity (2), Constraints on the expansion of agricultural land, Afforestation, Ruminant density on pasture, Protected areas expansion, Post-harvest losses, Urbanization, Irrigated area (2 levels), Agroecological practices |
| **Ethiopia** | 11 | Population, Share of consumption, which is imported, Export of main commodities, Crop productivity, Livestock productivity, Constraints on the expansion of agricultural land, Afforestation, Protected areas expansion, Post-harvest losses, Urbanization, Irrigated area |
| **India** | 10 | Population, Diet (3 levels), Food waste, Livestock productivity and Feed efficiency, Yield increasing technologies, Manure management, Nitrogen efficiency, Water use efficiency and protection of environmental flows |
| **UK** | 21 | Diet (2 levels), Food waste (2 levels), Livestock productivity (2 levels), Crop productivity (2 levels), Constraints on the expansion of agricultural land, Afforestation (2 levels), Ruminant density on pasture, Protected areas expansion (2 levels), Post-harvest losses (2 levels), Biofuel demand, Urbanization (2 levels), Agroecological practices (2 levels) |

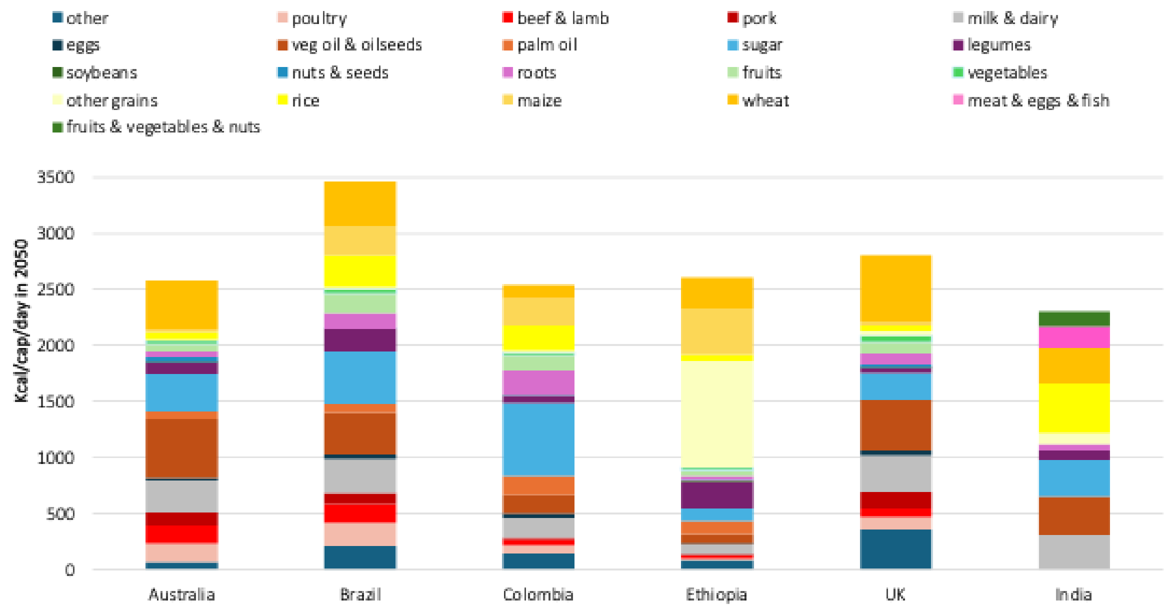
*Note: for India, afforestation and protected areas expansion, and trade liberalization scenarios have been included in the sustainable pathway but not included in the decomposition analysis as their impacts on the results were small.*

### *Assumptions under Current Trends*

Medium levels of **economic growth** and **population growth** are assumed in most countries in line with the global SSP2 scenario (India) or UN-DESA medium population scenario that corresponds to the median of several thousand distinct population trajectories. Australia integrates a country-specific target in line with the Australian Intergeneration report. This leads to strong population growth in Australia and Ethiopia (>50% increase between 2020 and 2050), a moderate increase in India (23%) and a low increase in Brazil, Colombia, and the UK (<13%).

**The average calorie intake per capita** is assumed to remain stable in Australia, Ethiopia and the UK and increases slightly in the other countries (Figure 1-5). In Brazil, the diet transition includes an overall increase of calorific consumption for both plant and animal calories (20% and 19% respectively compared to 2020). Australia assumes some small increases in consumption of legumes, vegetable oils, soybeans and pork, decreases of similar magnitude in consumption of fruits, vegetables, roots, and milk, and small reduction in beef and lamb consumption (-6%). In India, the composition of all food products uniformly increases by about 3%, except eggs and lamb that each increase by about 1%. Colombia assumes a reduction in animal-based calories consumption (-19%) while plant-based calories overall increase (+17%). Ethiopia assumes increases in animal calories consumption (+57%), mainly driven by poultry, eggs and milk consumption and a slight reduction in cereals and roots consumption, but in 2050, cereals still represent more than half of the calorie intake, with a large contribution of teff (Figure 1-6).

***Figure 1-6:*** *Composition of the average daily kilocalorie intake per capita per country by 2050*




*Note: the category "other" includes animal fat, alcoholic and non-alcoholic beverages, spices; oil – veg includes both oilseeds and vegetable oils except oil from palm which is in palm – oil; other grains include other cereals. MAgPIE has different product groups that could not always be matched with the group aggregation from the FABLE-C: meats, eggs and fish are grouped together as well as fruits, vegetables, and nuts, maize is included in other cereals, palm oil is included in veg. oil & oilseeds.*

**Crop productivity** follows a low- to medium-growth path (closing the yield gap by 30% to 50% by 2050) whereas **livestock productivity** reflects either current trends or business-as-usual improvements (same productivity growth as in the 2000–2010 period). In MAgPIE, crop yields growth is endogenous based on levels of claimed investments in R&D and infrastructure.

**Afforestation** is low or zero in most countries, but targets in India are in line with their Nationally Determined Contribution (NDC) to the Paris Agreement, to create an additional carbon sink of 2.5 to 3 billion tonnes of $CO_2$ equivalent through afforestation and reforestation by 2030. No change is assumed in **protected areas**. **Expansion of agricultural land** is prohibited only in Australia and India. As for **the evolution of trade**, exports for key commodities are assumed to increase by 50% between 2020 and 2050 in Colombia, Ethiopia, and India, and to double in Brazil, whereas Australia and the UK assume stable exported volumes. Shares of imports are assumed to be stable for most countries except Colombia and Ethiopia where they are assumed to increase.

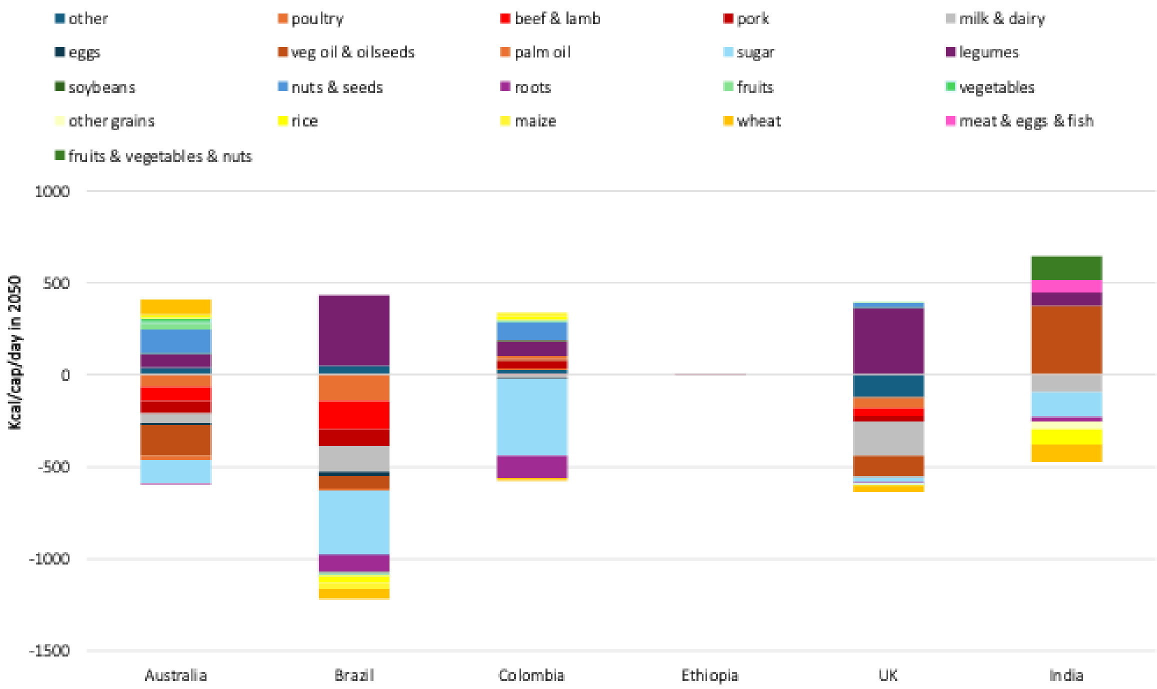
***How to increase sustainability in NC and GS pathways?***

To increase the sustainability of agricultural production, all countries featured in this study assume some changes in **crop and livestock productivity**, **stocking rate (ruminant density) on pasture**, and **post-harvest losses** (Table 1-5). Higher agricultural productivity is used to increase sustainability of the agrifood system of the country, although it is recognized that this could involve trade-offs with other environmental impacts such as nitrogen pollution from fertilizers.

**Dietary changes** are also seen as a key factor in increasing the sustainability of the agrifood systems in five countries. The UK derives the dietary change scenario from the UK Balanced Net Zero (BNZ) pathway of the Climate Change Committee (CCC) resulting in a 20% cut in meat and dairy calorie consumption by 2030 and a 35% cut by 2050 for meat, or a more ambitious target of a 50% cut in meat and dairy consumption by 2050. The other countries use a transition towards the average EAT-Lancet diet with the most dramatic changes being assumed for Brazil. Ethiopia is the only country that did not implement dietary change compared to current trends.

In most case studies, **deforestation is prevented beyond 2030** in the NC and GS pathways. **Afforestation** scenarios are used in most countries to increase carbon sequestration on land, assuming realization of official commitments to the Bonn challenge (Brazil, Colombia, Ethiopia, India) or other national targets (Australia, India, and the UK). Other scenario parameters such as changes in food waste, agroecological practices, and irrigation areas have been activated in some countries.

***Figure 1-7:*** *Assumed changes of per capita kilocalorie consumption by food group and country in 2050 in NC and GS compared to CT*




*Note: the category "other" includes animal fat, alcoholic and non-alcoholic beverages, spices; "oil – veg" includes both oilseeds and vegetable oils except oil from palm which is in "oil – palm"; "other grain" includes other cereals. MAgPIE has different product groups that could not always be matched with the group aggregation from the FABLE-C: meats, eggs and fish are grouped together as well as fruits, vegetables, and nuts, maize is included in other cereals, palm oil is included in veg. oil & oilseeds.*

## 1.4.3 Changes between 2020 and 2050 in Current Trends

***Australia***

The cropland area increases are accompanied by a reduction of grassland areas which potentially indicates that dietary changes reduce the demand for livestock production leading to the freeing up of pastureland. Marginal increases of forest area by 2050 are attributed to afforestation efforts targeted in Australia, (approximately 2 million hectares of new forest). Agricultural production $CO_2$ is estimated to increase marginally by about 4%. Methane emissions increase by 2%, which results primarily from livestock production related emissions. Nitrous oxide emissions increase slightly in Australia, by 5%.

***Brazil***

Cropland areas increase which is accompanied by a reduction of grassland areas indicating that cattle ranching intensification is sparing land for cropland expansion (mostly relevant in Brazil) and also that dietary changes reduce the demand for livestock production leading to freeing up pastureland. Forest area in the Current Trends pathway decreases in Brazil by 26%. $CO_2$ emissions from agricultural production in Brazil are estimated to increase by approximately 18%. Deforestation-related $CO_2$ emissions are estimated to increase by 24% between 2030 and 2050. Also, Brazil shows a substantial increase in other land use $CO_2$ emissions (OtherLUCCO2) that increase from -48 to 2 Mt $CO_2e$. Moderate increases in methane emissions are shown (8%) which mainly result from livestock production related emissions. Nitrous oxide emissions increase by 13%.

***Colombia***

Marginal increases of forest area are estimated by 2050 which are attributed to afforestation efforts of approximately 1 million hectares of new forest. Colombia is estimated to have a notable decrease of agricultural $CO_2$ emissions in the order of magnitude of 10%. Reductions are estimated for $CH_4$ emissions (-5%) which are driven by decreases in both livestock and crop related emissions. Nitrous oxide emissions remain stable in Colombia.

***Ethiopia***

Increases of agricultural land are estimated for Ethiopia (16%), primarily driven by increased cropland area (30%) and stable pastureland extent. As a result, agricultural $CO_2$ emissions increase by nearly half by 2050 (47%). Deforestation-related $CO_2$ emissions are estimated to decrease by 15%. An increase in methane emissions is estimated (47%) which is predominantly driven by increases in livestock production. Estimates show an increase of nitrous oxide emissions almost by half (increase by 47%) in 2050, compared to 2030 levels.

***India***

Cropland area increases are accompanied by a reduction of grassland areas which indicates that dietary changes reduce the demand for livestock production leading to freeing up pastureland. Forest area increases by 7%. Increases in agricultural production of $CO_2$ are estimated to be low (about 4%) while nitrous oxide emissions increase slightly through 2050, by 12%. Methane emissions remain at similar levels between 2030 and 2050.

***United Kingdom***

Both cropland and grassland increase until 2050, when no more unprotected land is available for conversion to farmland. Further urban expansion and tree planting therefore leads to a slight decrease in pasture in 2050, meaning that food production targets are not met. Forest area marginally increases by 2050 due to afforestation targets in the UK (approximately 1 million hectares of new forest). Agricultural production of $CO_2$ increases by about 21% while $CH_4$ and nitrous oxide emissions are estimated to increase by 10% and 12%, driven by increases in both livestock and crop production.

### 1.4.4 What are the most influential factors to reduce the hidden costs of agrifood systems?

As well as presenting the overall results from the combination of actions in each pathway, we also compute the individual impact of each action through a decomposition analysis (1.8.4), to help inform the prioritization of actions in each country. To do that, we fixed all the scenario parameters to the same value as in the CT pathway and then set individual parameters to the value used in the alternative pathways, recording the key output variables before moving on to the next parameter (Table 1-5). Results are shown in Figure 1-8.

***1. Managing demand***

The decomposition analysis highlights the important role of **changing diets** in reducing the impact quantities of several indicators that lead to hidden costs of the agrifood systems (Figure 1-8 a). Dietary change provides the largest reduction in DALYs, and in four out of the six countries a reduction of ruminant meat consumption provides the largest reduction in $CH_4$ emissions and pasture area compared to CT (Table 1-6).

For the UK and Brazil, changing diets is the most important factor for six of the eleven output indicators which are used for the hidden costs analysis, including nitrogen application and $CO_2$ and $N_2O$ emissions. The strong impact of dietary changes on environmental variables for these two countries is not surprising: Brazil uses the EAT-Lancet planetary diet, which partly builds on limiting climate change impacts, and the UK uses the Balanced Net Zero pathway of the UK Climate Change Committee which focuses on reducing consumption of animal produce to cut GHG emissions, leaving total calories, fat, and sugar consumption unchanged.

The dietary change assumed in Australia is the most effective for reducing DALYs compared to current trends by 2050 (-27% DALYs) as it reduced almost all the dietary risk categories. The most important changes are a higher consumption of nuts, fruits, vegetables, and legumes, and a lower consumption of processed meat, red meat, and sugar-sweetened beverages. In Brazil, Colombia, and the UK, the focus of dietary change is on reduced consumption of processed and red meat and sugar-sweetened beverages, with higher legumes and nuts consumption in Colombia and the UK. Moreover, all countries assumed reduced consumption of ultra-processed food compared to current trends. To further reduce the DALYs, a more significant increase of fruits, vegetables, and wholegrains consumption should be envisaged compared to the diets that have been tested here. In the UK, the Eatwell healthy diet recommended by the UK government could be used for a more holistic approach (Smith, Harrison et al., 2022).

In Ethiopia, lower **population** growth reduces demand in GS compared to CT. This projection aligns with the Ethiopian National Statistical Office's estimates, which forecast a reduced population growth rate due to increased contraceptive use (from 29% to 65% by 2050), delayed marriages, and higher school enrolment (CSA, 2013) and national policies aimed at reducing fertility rates, including the National Reproductive Health Strategy (FMoH, 2016), National Adolescents and Youth Health Strategy (FMoH, 2021), and the National Guideline on Family Planning (FMoH, 2011).

**Food waste** at the retail and household level is estimated at 26% and 27% respectively for cereals and fruits and vegetables in Europe. In the NC and GS pathways, the UK assumes a reduction of food waste share by 60% and 70% respectively which explains the significant impacts that this scenario has on the results. The reduction of demand due to lower food waste translates to lower cropland and pasture area by 2030 and is the main reason for reduced on-farm labor in 2030 and 2050 (revealing a potential trade-off with socio-economic goals). This is due to the high labor requirements per hectare to produce fruits and vegetables, which currently form a relatively large proportion of food waste.

### 2. *Increasing productivity*

Increasing **crop productivity** is the most important factor that reduces cropland area compared to CT (Figure 1-8 c). This also reduces the number of full-time equivalent workers in the agricultural sector, since labor intensity per hectare is assumed to be fixed over time in the FABLE Calculator. The reduction of cropland area avoids expansion onto natural land, with a significant positive impact on forest area in Brazil, Colombia, and Ethiopia, and on the area of other natural land particularly in Ethiopia. Increased crop productivity reduces GHG emissions due to lower $CO_2$ emissions from land use change, increased $CO_2$ sequestration on abandoned agricultural land, less $CH_4$ from rice cultivation (since a smaller area of flooded rice is needed), and a reduction in $N_2O$ emissions from application of synthetic nitrogen on cropland. In the FABLE Calculator, part of the increase of the crop productivity is achieved by higher nitrogen application but this is offset by the reduction of the cropland area since nitrogen application rates are computed per hectare of cropland.

**Higher productivity** per animal and higher ruminant stocking rate on pasture (ruminant density) have large impacts, particularly in countries with large livestock herds such as Australia, Brazil, and Ethiopia. These productivity gains reduce the required pasture area but not the cropland area (Figure 1-8 c) since it is assumed in the Calculator that livestock productivity gains will require higher feed ratios. As for crop productivity, the reduction of pasture expansion resulting from productivity gains in the livestock sector is beneficial for natural (mostly non-forest) land, mainly through the abandonment of pasture which is assumed to revert to other natural land with slightly higher carbon stocks. Reduction of GHG emissions is also achieved through lower $CH_4$ and $N_2O$ emissions per animal head. Ruminant density does not contribute significantly to the reduction of agrifood systems' hidden costs in Ethiopia in the decomposition analysis. This can be misleading as ruminant density is an important determinant of the future sustainability of livestock production, but in the Ethiopian model, it adjusts automatically to the demand to ensure that the total natural pasture area remains stable.

In the case of the UK, productivity gains lead to a slight increase in food consumption compared to CT. This is because targeted consumption could not be met under CT, as not enough unprotected natural land was available for the expansion of agricultural land. By increasing the possible production within the same land limits, productivity increase allows higher consumption, leading also to slightly higher GHG emissions. Another mechanism which is not represented in our model, but which could lead to similar patterns, is the rebound effect of increased demand following productivity increases due to lower prices. This has been widely documented in economic literature.

### 3. *Effective deforestation control*

Deforestation control has been assumed in Brazil, Colombia, and Ethiopia. The model does not say which incentives and policies need to be put in place to achieve this outcome, but our findings highlight the amount of avoided deforestation that could result from such actions: about 7 million hectares between 2045 and 2050 in Brazil, close to 5 million hectares in Ethiopia, and 0.5 million hectares in Colombia. There are potential trade-offs when this measure is implemented in isolation as it reduces the average level of food consumption in Brazil (Figure 1-8 a) and displaces agricultural expansion to non-forest natural land (Figure 1-8 c). This highlights the need of combining deforestation control with either changing diets and reduction of food loss and waste to reduce the demand, or with productivity gains to release the pressure on other land, as highlighted by the overall impact of the GS pathway.

### 4. *Afforestation*

Afforestation allows significant reduction of hidden costs related to GHG emissions through carbon sequestration (+ 10 million hectares in Australia, + 15 million hectares in Ethiopia, + 1.4 million hectares in the UK by 2050) (Figure 1-8 b). However, we can see that trade-offs can arise with other objectives. Afforestation reduces the area of non-forest natural land, either directly when this land is afforested, or indirectly when afforestation takes place on cropland or pasture but displaces cropland and pasture expansion onto other natural land (Australia, Brazil, Colombia, Ethiopia). This indirect effect can be observed in Brazil with additional deforestation resulting from afforestation when deforestation control is not implemented (Figure 1-8 c). Afforestation could also increase the delivery of ecosystem services, but this strongly depends on how afforestation is done, e.g., if it is through monoculture commercial plantations or assisted natural regeneration.

### 5. *Changing demand in the rest of the world*

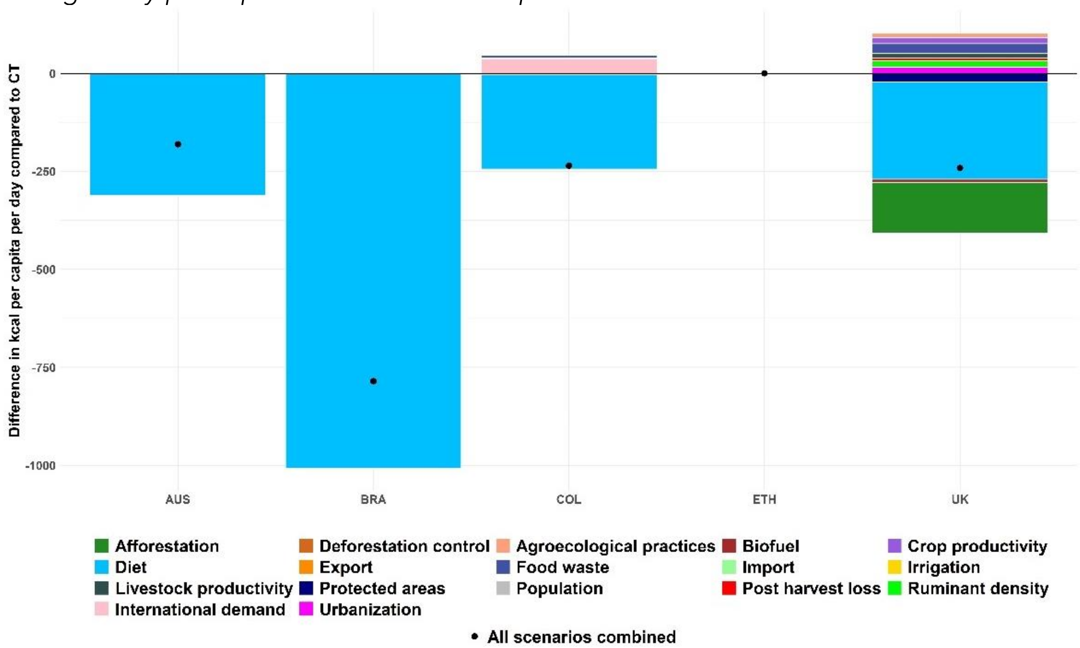
During the Scenathon, exports from each country are adjusted to meet the total aggregated imports from all countries and rest of the world regions for each product in each pathway. Changes in imports outside the country of interest affect hidden costs across the three pathways. Impacts are significant for major exporters like Australia and Brazil, where the impact of changes in international demand on cropland area is almost as important as domestic dietary change (Figure 1-8 c). In Australia, cropland reduction is driven by reduced exports of wheat (-17% in GS compared to CT in 2050), barley (-27%), and rapeseed (-38%) due to decreased global consumption of animal-based products and the resulting lower demand for cereals for animal feed, along with reduction of sugar exports (-25%). In Brazil, it is driven by the reduction of corn (-32%) and soybean exports (-11%) for animal feed, and sugar (-23%). These trade shifts significantly affect total nitrogen application in these two countries (Figure 1-8 d) because synthetic nitrogen application per hectare for corn and soybean in Brazil is above the average application rate for other crops. For Colombia, the evolution of international demand tends to increase hidden costs of agrifood systems in the GS pathway compared to CT because of higher Colombian exports of banana (+100% in 2050 in GS compared to CT) and coffee (+56%).

### 6. *Other impactful factors*

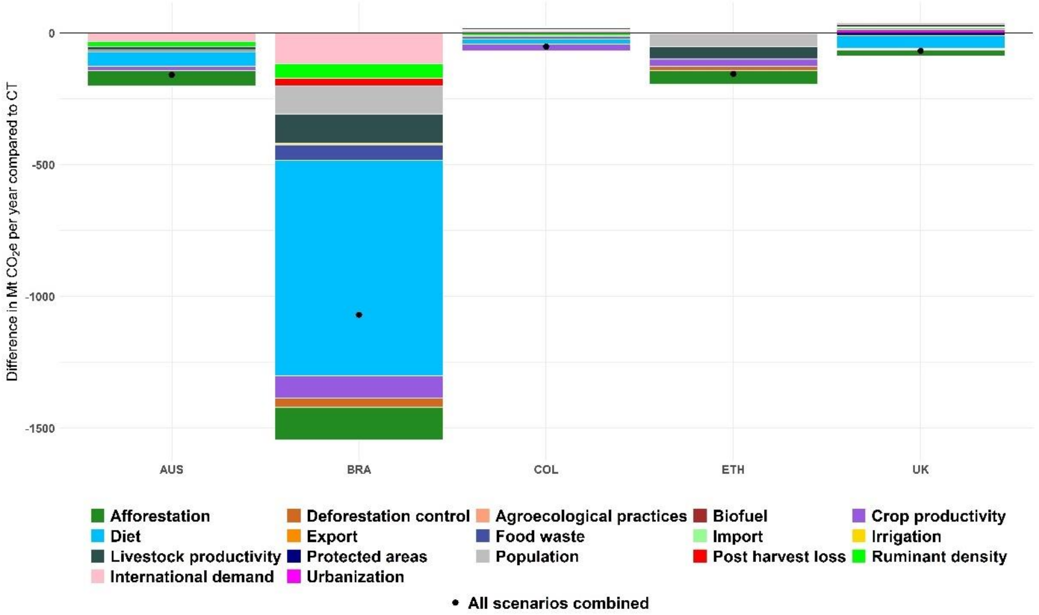
Agroecological practices play a major role in the UK for reducing nitrogen application and nitrogen emissions to air and water, with a target of 50% of cropland area under organic farming by 2050 in GS. This leads to a substitution of synthetic fertilizer with organic fertilizer and significantly reduces the amount of manure not applied to cropland (-84% in GS in 2050 compared to NC). Adoption of agroecological practices under GS also includes a large increase in cover crops and embedded natural land in agricultural land, but the resulting impacts on fertilizer use, $CO_2$ sequestration, and ecosystem services are not yet quantified in the FABLE Calculator. Through increases in nitrogen efficiency uptake rates in India, nitrogen surplus on land and manure is reduced by 61% by 2050.

***Figure 1-8***: *Impacts of each scenario parameter on the main hidden costs impact quantities when implemented alone, i.e., results of the decomposition analysis*

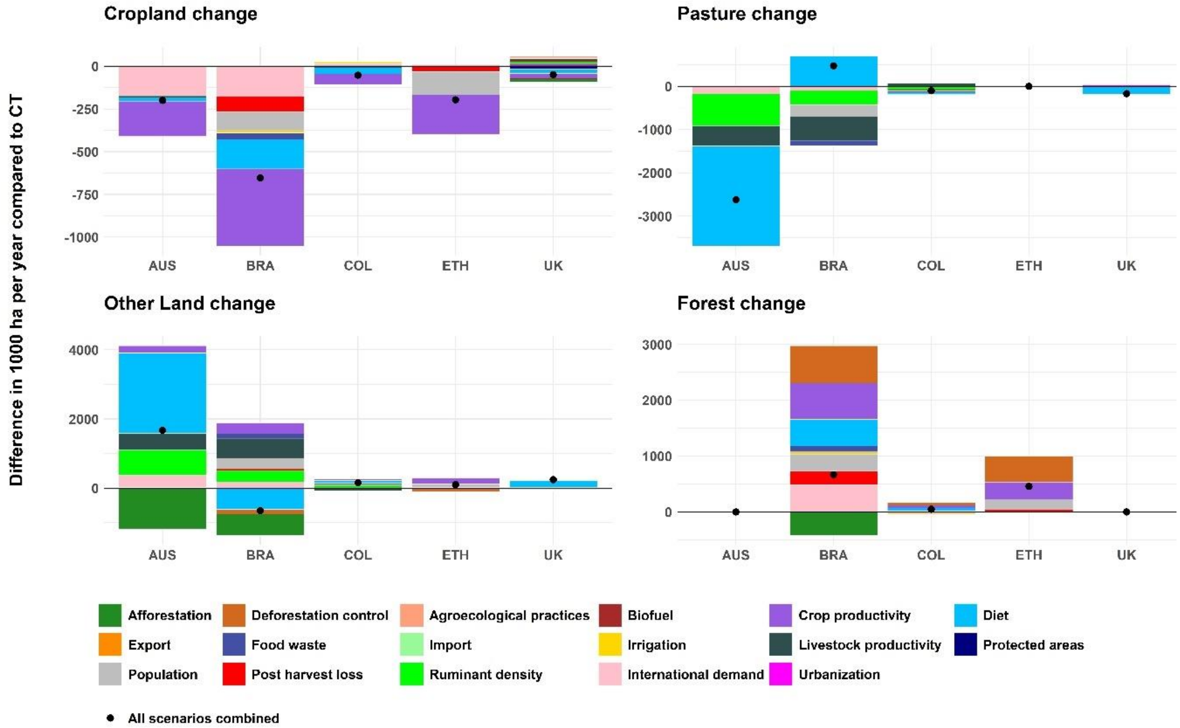
*a) Average daily per capita kilocalorie consumption*



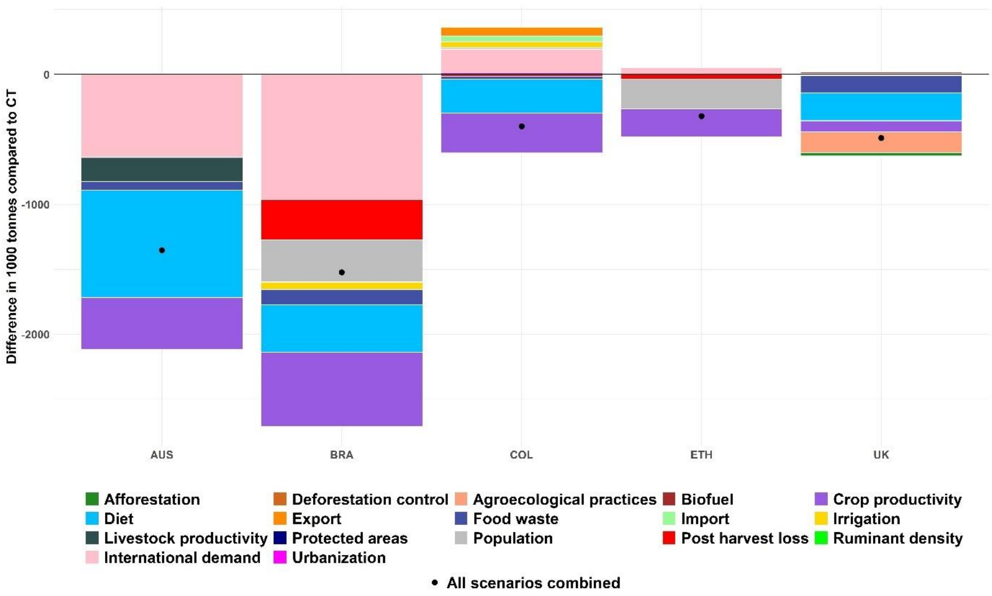
*b) AFOLU GHG emissions*




*c) Area by land cover type*



*d) Nitrogen application*




*Note: India is not represented in these figures because the scenarios are different than in the FABLE-C. See Chapter 6 for the decomposition analysis of the MAgPIE-India results.*

However, we can see some risks of trade-offs if these actions are taken in isolation: a) Dietary changes assumed in Brazil and the UK emphasize environmental benefits, but adjustments could be made to ensure larger health benefits and a better consideration of local preferences; b) Dietary changes could increase water demand (e.g., to grow more fruits and vegetables) and reduce on-farm employment (e.g., in the livestock sector), showing that this type of transition needs to be carefully managed at the local level; c) In some cases, productivity gain could increase demand further, which could offset some of the environmental benefits; d) Deforestation control could have negative effects on food consumption and displace agricultural expansion to non-forest natural land; e) Afforestation can lead to indirect deforestation or reduction of other natural land, while benefits from afforestation for ecosystem services strongly depends on how afforestation is done. To manage these trade-offs, an integrated strategy is required.

The Global Sustainability pathway leads to the best outcome compared to a path following current trends: between 2020 and 2050 our results show a reduction in accumulated hidden costs by 32% in Brazil, 24% in Colombia, 25% in Ethiopia, 57% in India, and 15% in the UK[3] (in 2020 PPP). In Australia, the reduction is 140%, i.e., the hidden deficit of current trends that would have accumulated over 2020–2050 is eliminated and benefits of the order of 40% of the CT hidden deficit are accumulated. Here, the agrifood system transitions from net hidden costs to net hidden benefits.

[3] This does not account for the hidden costs that are not computed based on the model's outputs, e.g., agri-food worker poverty.

***Table 1-6:*** *Most impactful scenarios affecting each of the model outputs used for the hidden cost computation by country in 2050*

| Sub-categories | Australia | Brazil | Colombia | Ethiopia | India | United Kingdom |
|---|---|---|---|---|---|---|
| **$CO_2$ emissions** | Afforestation | Dietary changes | Crop productivity | Constraints on agricultural expansion | Afforestation and expansion of protected areas | Dietary changes |
| **$CH_4$ emissions** | Dietary changes | Dietary changes | Food waste | Livestock productivity* | Dietary changes | Dietary changes |
| **$N_2O$ emissions** | Crop productivity | Dietary changes | Dietary changes | Livestock productivity* | Nitrogen efficiency | Dietary changes |
| **Total N** | Dietary changes | Dietary changes | Crop productivity | Livestock productivity* | Nitrogen efficiency | Dietary changes |
| **Cropland** | Crop productivity | Crop productivity | Crop productivity | Crop productivity* | Livestock management | Crop productivity |
| **Forest** | *No change* | Crop productivity | Constraints on agricultural expansion | Constraints on agricultural expansion | *No change* | *No change* |
| **Pasture** | Dietary changes | Dietary changes | Ruminant density | Ruminant density | Dietary changes | Dietary changes |
| **Other land** | Dietary changes | Dietary changes | Crop productivity | Afforestation | Livestock management | Dietary changes |
| **Water irrigation requirements** | Crop productivity | Irrigation | Trade | Crop productivity * | Dietary changes | Food waste |
| **Farm labour** | Crop productivity | Crop productivity | Crop productivity | Crop productivity * | Dietary changes | Food waste |
| **DALYs** | Dietary changes | Dietary changes | Dietary changes | *No change* | Dietary changes | Dietary changes |

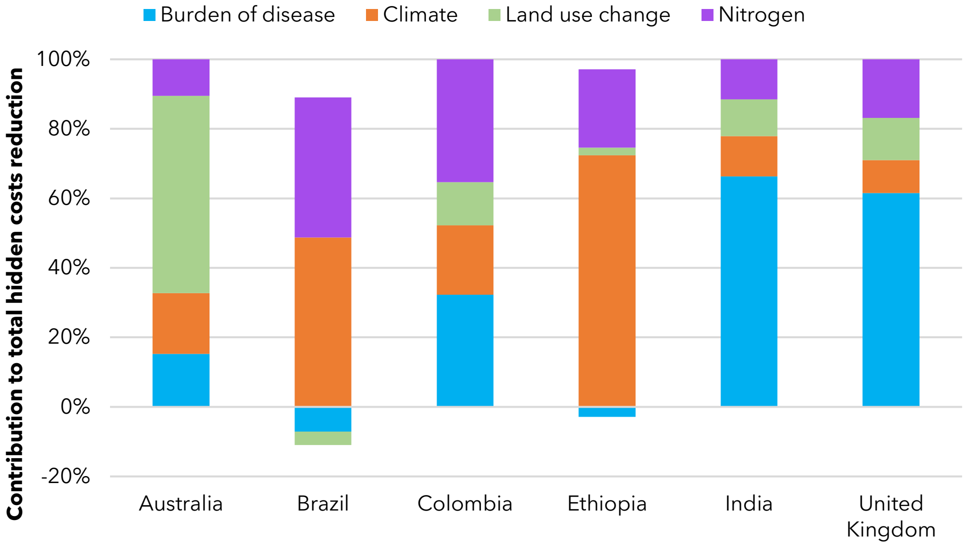
**Frequency**

| 1 | 2 | 3 | 7 | 16 | 31 |
|---|---|---|---|---|---|

*NOTES: $CO_2$ = carbon dioxide; $CH_4$ = methane; $N_2O$ = nitrous oxide; N = nitrogen; DALY = disability-adjusted life year; SSB = sugar-sweetened beverage. Dietary changes modelled include the following for each country: Australia – Higher intake of nuts and seeds, fruits, vegetables, legumes; lower intake of processed and red meat, and SSBs; Brazil – Lower intake of processed and red meat, and SSBs; Colombia – Lower intake of processed meat and SSBs; higher intake of legumes; India – Lower intake of sugars, salt, and processed foods; United Kingdom – Lower intake of processed meat; higher intake of legumes.*

**The Global Sustainability scenario in Ethiopia includes a lower population assumption in line with the Ethiopian National Statistical Office's projections. While the largest decrease in hidden costs in these subcategories is attributable to this assumption, we show the most impactful outcome related to agrifood systems transformation – namely, livestock and crop productivity improvements – in this table.*

***Figure 1-9:*** *Source of the computed reduction of hidden agrifood system costs in the sustainable pathway compared to current trends in 2050, by country*




In Figure 1-9, we can see that despite the dominant contribution of unhealthy diets to current hidden costs in all countries but Ethiopia, dietary change is only the first contributor for reducing hidden costs in India and the UK. Although the number of DALYs decreases in the GS pathway, the costs related to diets increase because each DALY is more expensive due to assumptions of higher GDP per capita, Human Development Index, and labor productivity in the SPIQ model (cf. Brazil and Ethiopia).

In Australia, most of the reduction in hidden costs comes from the afforestation program and natural regeneration of vegetation on abandoned agricultural land (land use change on Figure 1-9). In Brazil, demand-induced changes such as the assumed reductions in red meat intake in Brazil and globally contribute the bulk of the avoided costs savings from GHG emissions and nitrogen reduction. The increase of the hidden costs related to the global burden of disease in Brazil is due to lower intake of fruits and vegetables in GS that also resulted in a lower intake of wholegrains (correlation from the machine learning model, cf. 1.8.5). In Colombia, the reduction of hidden costs come mainly from the combination of dietary change and large productivity improvements that reduces overall nitrogen pollution from manure and feed production. In Ethiopia, the main source of the reduction of hidden costs is the reduction in GHG emissions achieved through the improvement in crop and livestock productivity, and reduced demand pressure.

The calculation of hidden costs involves significant uncertainty in the value of ecosystem services, the exposure and damage caused by nitrogen loading to ecosystem services and human health, and the long-term future economic conditions under climate change. Moreover, the disease burden from dietary risks from the GBD modeling also provides uncertainty. When these sources of uncertainty are included, this results in wide variance in the marginal costs of GHG emissions, reactive nitrogen pathways to air and soil, habitat loss, and productivity loss from food intake. In Australia, the scenarios used in the GS pathway magnify key uncertainties and shifts were not sufficient to provide robust conclusions given large uncertainty in hidden costs. To improve the sharpness and robustness of our results additional information in the ecosystem services of Australia's arid and semi-arid rangelands would be particularly needed.

## 1.5 Discussion and recommendations

***How do the estimates of hidden costs overlap with countries' priorities for agrifood systems?***

In all the case study countries of this report except Ethiopia, **unhealthy diets** trigger the biggest hidden costs (FAO, 2023). While some stakeholders in the five countries were surprised by the proportion of hidden costs related to unhealthy diets, there was a consensus that this is a significant and growing issue that urgently needs to be addressed.

Some hidden costs related to **undernourishment** are covered in the analysis but there was a feeling that they do not accurately reflect the size of the problem, particularly in low-income and lower-middle-income countries such as Ethiopia and India, but also in middle- and high-income countries where it might particularly affect some groups of the population and locations but not be visible at the aggregated national level. For future improvements of the hidden costs' methodology, it would be important to account for the lasting consequences of undernourishment during childhood on human capital and consequently on labor productivity, also to include the impacts of micronutrient deficiencies, and better consider the sub-national heterogeneity of undernourishment.

**Environmental costs** tend to be the second most important source of hidden costs, and thus, addressing them is the next most important priority. This coincides well with countries' commitments to halt deforestation, reduce GHG emissions (Paris Climate Agreement), and enhance biodiversity (Kunming-Montreal Global Biodiversity Framework). Environmental costs are likely underestimated as highlighted in SOFA 2023. Accounting for pesticide impacts on biodiversity would be a great improvement in the future. The hidden costs of GHG emissions and air pollution related to household traditional cooking could also be included in some countries where statistics are available, such as India, but this might be more difficult at the global level.

***How to ensure dietary shifts towards healthy food for all?***

In Australia, some recent trends towards more plant-based eating are encouraging and in India, there are current efforts such as the National Food Security and Nutrition Mission, to promote a higher consumption of legumes, fruits, vegetables, and nuts, but improvements are still limited. In the UK, stakeholders highlighted the need for more research on how to achieve dietary change. Potential actions include a carbon tax on food; a sugar tax; education about healthy food; warning labels on ultra-processed and high-sugar food and other properties related to high-risk health externalities (obesity, type 2 diabetes, etc.); emphasizing the benefits of a healthy diet; a reduction in the working week so people have more time to cook healthy food; free school meals; and a less unequal society. Education alone is not enough, as consumers live in an environment full of unhealthy food choices and marketing, so it needs to be backed by strong policy in other areas. For instance, the Welsh Government is working on a dietary-shift systems map which will identify key policy instruments.

Public procurement of healthy food with lower environmental impacts (e.g., in schools and hospitals) plays an important role. In Ethiopia, healthier diets require both incomes to be increased and the cost of healthy food to be reduced. The increase in income could be achieved by diversifying livelihood options, in which farmers can increase their income through non-agricultural employment (e.g., in industry and services), that will ultimately help them get out of poverty. The affordability of food could be increased by shifting the production focus from increasing food quantity to prioritizing nutritious food production. Several country profiles (including Ethiopia and Colombia) would potentially benefit from the establishment of better connections between producers and consumers, and the creation of cooperatives offering better infrastructure and market data, that can boost incomes and decrease costs due to more efficient marketing processes.

***Which policy instruments can be mobilized to reduce negative externalities of agricultural production?***

To mitigate negative environmental externalities resulting from agricultural production, governments might also utilize regulations imposing a carbon tax. For countries like Colombia, in which sustainable agricultural intensification is an ongoing effort, policies could enhance this process by facilitating technical assistance for producers to apply best practice and meet the demand while reducing GHG emissions, soil degradation, and water pollution. In the UK, agri-environment schemes including ELMS in England and similar schemes emerging in the other UK nations have a key role to play in reducing the hidden costs of agriculture, if uptake is significant. Extra support would be required for farmers who want to adopt certain agroecology practices to compensate for a possible reduction in production for the first few years. Pollution regulations are important and could improve nitrogen management around storage and application of manure and slurry. Schemes could potentially incentivize greater uptake of innovation through precision farming, which can limit the use of synthetic fertilizers and agro-chemicals and ultimately reduce negative agricultural impacts.

***How to protect and enhance ecosystem services?***

Actions for protecting and enhancing ecosystem services are key to several countries in the current report. Halting illegal deforestation in Brazil and Colombia is an ongoing effort. Deforestation-related restrictions could be also implemented in countries of consumption such as the EU regulation currently promoting the consumption of "deforestation-free" products. It should be noted that the link between reduction of ruminant meat consumption and pasture area might be more complex than modeled here. Some pasture expansion in the tropics is not directly related to meat production but more to land speculation, i.e., it is barely correlated with the demand for beef, milk or other cattle products. This type of deforestation can only be curbed by deforestation control measures and changes in the rules to claim land property rights. Additionally, the restoration of degraded areas, especially Brazilian pastures, has high potential to spare land that can be dedicated to other uses such as afforestation. National policies and programs towards those practices have the capacity to conserve water, sequester carbon and maintain and improve soil quality. As far as soil health and quality is concerned, many countries of the current report acknowledge its pivotal role (Brazil, UK and India) calling for further investments to enhance soil conservation, as this remains relatively underrepresented in policy and regulations. Finally, habitat protection is not just about creating more protected areas, but also about providing the resources needed to improve the condition of existing protected areas and manage them properly.

***Recommendations for modelling hidden costs***

- There remains a great need for comparison between the different iterations of the Global Burden of Disease assessment and other models such as Marco Springmann's since they use very different relative diet risk factors for different food groups, and more particularly meat. Transparency in this aspect is particularly needed in a context where a strong pushback against recommendations to change diets is observed across the world.
- Neither the FABLE Calculator nor the MAgPIE model can yet estimate the impacts of dietary changes on health. They need to be coupled with other models to translate consumption by food group to DALYs, and DALYs are then used as input to the SPIQ-FS model to compute the impact on labor productivity (cf. 1.8.5). It would be important to include an assessment of health impacts directly in the agrifood system models to help experts design and test dietary change scenarios better suited to health requirements and

cultural preferences. That would lead to better outcomes on total hidden costs.

- Improvements are needed to better include the factors that affect the evolution of undernourishment such as scenarios on the evolution of income distribution, the impact of extreme climate events, the evolution of stocks, and connectedness of rural areas to the rest of the country.
- Both the MAgPIE model and the FABLE Calculator have shortcomings to assess the evolution of agrifood workers' poverty. Productivity increases which are included in our models could improve farmers' income, but the final income effects will depend on the evolution of the quantity and prices of inputs used to reach higher productivity, and prices of the crops and livestock products which are sold by the different agents of the agrifood value chain. For instance, overproduction can cause prices to collapse and a degradation of farmers' income. Moreover, adoption of some practices might reduce employment needs in the agricultural sector but people might not have better employment alternatives. A Computable General Equilibrium model that covers the whole economy would be better suited to do this type of assessment. To assess the impacts of a more equal distribution of the value added generated within the whole chain of agrifood on workers' poverty, other models such as agent-based models would be more appropriate to represent the interactions between different agents.
- To facilitate the estimate of future hidden costs related to nitrogen in SPIQ-FS, the FABLE Calculator would need to be improved to compute the nitrogen balance in addition to nitrogen application.
- Different techniques are currently used to ensure models reproduce historical deforestation, often using an exogenous component that is calibrated as the difference between the historical deforestation and the computed commodity-driven deforestation. Improvements are needed in our agrifood system models to better represent the non-demand drivers of deforestation and consequently, provide more robust estimates of this deforestation and the impact of different policies on it.

## 1.6 Conclusion

Applying a national perspective to first review the hidden costs computed in SOFA 2023 and then model the impacts of context-specific scenarios on the evolution of the hidden costs by 2050 in Australia, Brazil, Colombia, Ethiopia, India, and the UK, was a very constructive process. First, both the authors of this study and stakeholders who have been consulted were able to gain a deeper awareness and understanding of the hidden costs generated by agrifood systems. There are challenges to communicate the complexity of the method, and the marginal costs are particularly hard to sense-check for non-experts on hidden costs. However, it was noticed that this topic is gaining momentum, including for policy planning, and several governments (e.g. the UK, Australia, India) are already either utilizing or planning to develop similar metrics so it was a timely exercise. Second, while it was not possible in the scope of this study to adapt the hidden costs model to specific countries, better local datasets have been identified that will improve the quality of hidden costs estimates in the six countries if a tailored assessment is envisaged. Third, important data gaps have been identified in countries, highlighting the need to invest in data collection, for instance for nitrogen application or the value of ecosystem services in different locations. Fourth, some improvements would be needed in the suite of models which have been used, particularly to increase the transparency and the number of iterations with stakeholders.

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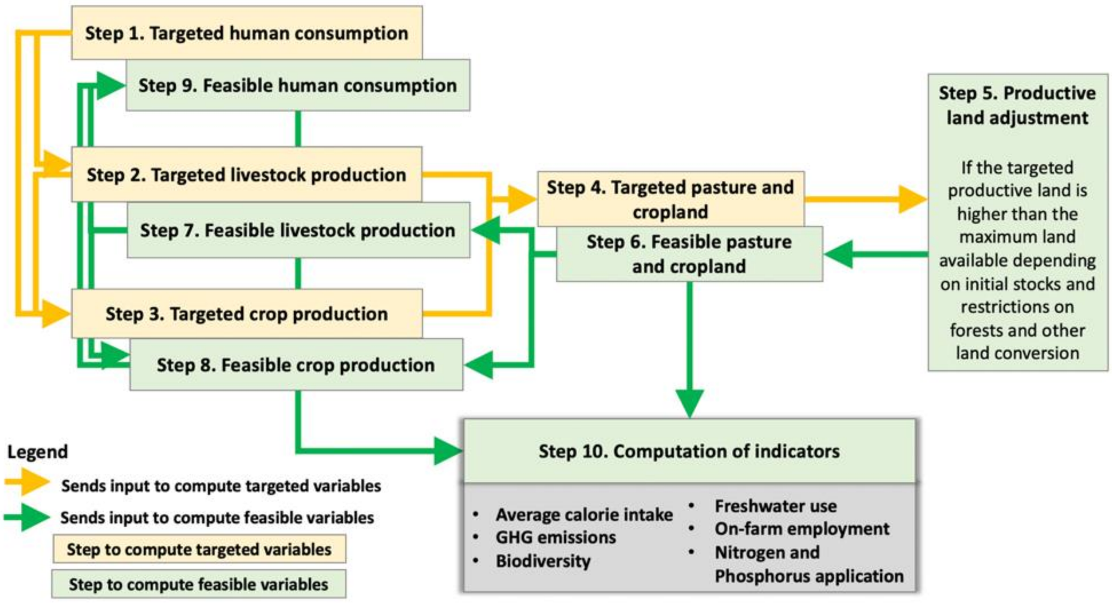
## 1.8 Annexes

### 1.8.1 FABLE Calculator

The FABLE Calculator represents the evolution of 88 agricultural raw and processed products, from both crop and livestock sectors, building on the FAOSTAT database. The integration of national and global scales in FABLE is done through Scenathons. National quantitative pathways are developed individually by country-level research teams while regional quantitative pathways are developed by the FABLE Secretariat for countries not currently represented in the Consortium. Export volumes from each exporting country and region are proportionally adjusted to match global imports for each product and time step and national and regional pathways are bound by trade volumes that align globally (Mosnier et al. 2013).

***Figure A1:*** *Computation steps in the FABLE Calculator*




The first step of computation includes the annual human demand for food consumption and non-food consumption. This step consists of three components: food, biofuels, and other non-food consumption. Food and non-food demand per product and capita for the historical years (2000–2020) is estimated using information on commodity balance derived from FAOSTAT (information on sources available in Table A1). The patterns of food consumption per capita depend on the selected scenario relevant to the evolution of the average kilocalorie consumption per food group and capita, per time step. By default, the other non-food demand per capita is fixed at the last historical year available (2020) level, a value that can be easily modified by the user. The final demand per capita, year, and product is estimated as the sum of a) non-food consumption per capita and b) food consumption per capita, adjusted by the share of consumption that is wasted at the retail and household level. Total demand is calculated by multiplying the average demand per capita by the total population and adding the demand for biofuels production. Targeted production is computed as human consumption that includes waste, increased by the post-harvest losses (accounted as a share). The demand for animal feed is added to human consumption of crop products. Imports depend on computed internal demand and the assumption about the share of this consumption that needs to be imported. Exports are exogenously driven.

The second step of the FABLE Calculator computes production from the livestock sector. This sector both supplies animal food products and consumes other agricultural products in the form of animal feed. For that reason, the livestock production calculations precede the crop sector calculations. This step calculates the evolution of the livestock herd which then determines the feed demand and the pasture area, which are used in the calculation steps that follow. The livestock herd comprises the livestock categories dairy cattle, other cattle, dairy sheep and goats, other sheep and goats, laying hens, chicken broilers, mixed poultry, and pigs. The number of animals is computed as the projected domestic production volume, multiplied by the contribution of each animal type and production system in the total production per animal product in 2000 as reported by Herrero et al. (2013). Animal numbers are reported in a tropical livestock unit (TLU) basis, which is computed by dividing the animal type and production system by the corresponding average productivity rate in the year 2000. Animal productivity until the year 2020 corresponds to calibrated productivity from FAOSTAT, and from 2020 onwards it depends on the selected animal productivity scenario.

Feeding requirements per TLU derived from Herrero et al. (2013) include corn, wheat, sorghum, rice, barley, other cereals, and soybean, for each animal type and production system. Feed requirements here are assumed to vary proportionally in connection with assumed changes in animal productivity. This assumption might lead to an overestimation of the increase in animal feed demand over time when productivity gains are high while improvements in breeding and animal health could also play a significant role in lowering the rate of increase in feed demand. The number of ruminants is then divided by the average ruminant density per hectare to estimate the targeted pasture area. Historical ruminant density is computed using FAOSTAT's ruminant numbers divided by the grassland area for 2000 to 2020 and kept constant at 2020 levels over the 2025–2050 period. An optional update package for implementing alternative scenarios on the evolution of ruminant density is available.

For estimating targeted crop production, the initial inputs are human consumption and feed demand which were computed in the previous steps. The volumes of imports are then estimated by multiplying the sum of human and feed demand by the share of the consumption that is imported, according to the selected import scenario. Exported quantity is taken from the selected export scenario.

Additional demand for crops comes from processing. This is related to the human and feed demand for processed commodities such as vegetable oils or refined sugar. Targeted production of processed commodities is computed similarly to the estimation of targeted crop production, with the addition of a computation step that is required to calculate the quantity of raw product (crop) that is needed to produce the targeted production of the final (processed) product. The processing coefficient is introduced, calculated as the reported production level of a processed product divided by the reported processed quantity of the raw product used as input in 2020 according to the FAO Commodity Balance (e.g., the production of sunflower oil divided by the sunflower quantity which is reported as processed). Targeted production is the sum of the targeted production of a crop which is used as the final product and the targeted production of a crop which is used for processing. Multiple products can stem from processing the same initial input. For example, after extracting oil from oilseeds, the remaining oilseed cakes can serve as animal feed. To accurately determine the harvested areas corresponding to specific production, it is vital to choose the primary input production that leads to a singular final processed product, preventing any double counting.

Harvested area is estimated as the total targeted production divided by the average annual yield on a tonne per hectare basis. Productivity levels (yield) are derived from FAOSTAT for the years 2000 to 2020, and for the period 2025–2050 yields vary depending on the productivity scenario that is selected. In some countries, multiple harvest rounds are possible during the same year, which results in estimates of lower cropland area than the total harvested area per year. The planted area is estimated by dividing the harvested area by the harvesting coefficient. The average harvesting coefficient is computed as the sum of the harvested area per crop divided by the total cropland area using historical FAO data. Where the total harvested area is lower than the cropland area, the harvesting coefficient is set to 1. This can be explained by missing crops in the FAO database but also because arable land includes "temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years)" (FAOSTAT, 2020), which are not yet explicitly considered in the FABLE Calculator. The difference is allocated to "other crops" and this area is set constant at 2000 levels for the whole period of the simulation.

The Calculator incorporates six distinct land cover categories: pasture, cropland, urban areas, forests, new forests, and other natural lands. The category "other natural land" in 2000 was derived by computing the difference between the total land area of a country or region and the combined area occupied by pasture for livestock, cropland, forests, and urban areas. As a result, this category can potentially include a range of diverse land types and varying levels of wilderness. Changes in pasture, cropland, urban, and new forest areas subsequently influence alterations in forest and other natural land as the overall land area remains constant. To determine the initial area for each land cover type at the beginning of a given period, historical data from 2000 is used as a baseline, while the computed feasible area from the previous period is used for following time steps. If the intended expansion exceeds the maximum allowable expansion due to scenario constraints or limited land availability, the maximum value is utilized to calculate the feasible productive land area. The adjustment factor for pasture and cropland is calculated by comparing the maximum feasible area for pasture and cropland with the targeted areas. Urban and afforested areas are excluded from this adjustment process.

Any disparity between the targeted and feasible areas for pasture or cropland is traced back to the cause-and-effect pathway to the consumption level. As a starting point, adjustments are made within the livestock sector. The targeted pasture area is first multiplied by the pasture adjustment ratio, determining the count of ruminant herds. The updated herd number is determined by re-estimating the feasible pasture area in relation to ruminant density. For feed, the demand for all crops and their processed products is initially multiplied by the cropland adjustment ratio. Subsequently, the adjusted feed demand, based on the feasible ruminant herd count, is computed according to feed requirements. The feasible feed demand is established as the minimum of the new feed demand derived from the adjusted herd and the adjusted feed demand from the cropland adjustment ratio. The feasible herd count is then calculated by dividing the feasible feed by the feed requirement. For both exports and final human consumption of livestock products, reductions are proportionally applied based on the ratio of the feasible herd to the targeted herd. In scenarios where "Fixed trade" is chosen, exports are not adjusted proportionally to compensate for production reduction caused by land constraints. Instead, the reduction is allocated exclusively between feed demand and final human consumption.

For crops, the targeted planted area for all crop products is adjusted by multiplying it with the cropland adjustment factor. This factor ensures a proportional reduction in the planted area, by crop, in line with the overall cropland reduction. The calculation of feasible production is based on multiplying the feasible planted area per crop by the average number of harvests per year and then by the productivity per hectare. Feasible feed, already determined in the previous step, remains unchanged, while imports are held constant. To maintain market equilibrium, feasible final human demand, feasible exports, and feasible processed demand are adjusted to compensate for the residual reduction in crop production.

***Table A1:*** *Main input data sources to the FABLE Calculator*

| | **FABLE Calculator** |
|---|---|
| **Demand** | FAOSTAT: Food, Feed, Process, Non-Food Demand, Post-harvest Losses, Imports, Export quantities |
| **Bioenergy** | OECD-FAO |
| **Crop production** | FAOSTAT: Production, Harvested area, yields |
| | (Mekonnen and Hoekstra, 2011): green, blue, and grey water footprint of crops; |
| **Livestock production** | FAOSTAT: milk, meat, and eggs production |
| | FAOSTAT: livestock herd number<br>(Herrero et al., 2013): feed requirements and output per production system and animal category |
| **Food** | FAOSTAT: Food Balance Sheets caloric, protein, and fat supply, dietary composition |
| | (Institute of Medicine, 2002): for minimum calorie requirements per day by age, sex and activity level<br>(Gustavsson et al., 2011): assumed waste per commodity group and region |
| **Land cover** | FAOSTAT: cropland, forest, pasture, other natural vegetation, and urban area |
| | ESA-CCI land cover map |
| **Prices, expenditures and costs** | FAOSTAT: producer prices |
| **Protected areas** | UNEP-WCMC and IUCN: Protected Areas |
| **Population** | SSP database |
| **GDP** | World Development Indicators: GDP between 2000 and 2010 |
| **GHG** | FAOSTAT: emissions factors for agriculture, average forest carbon stock<br>(Herrero et al., 2013): emission factors for livestock. |

## 1.8.2 Comparison between the FABLE Calculator and MAgPIE

***Table A2:*** *Main characteristics of the FABLE Calculator and MAgPIE*

<table>
<tr><th></th><th>FABLE Calculator</th><th>MAgPIE</th></tr>
<tr><td>FABLE Countries / Regions using this model in this study</td><td>Argentina, Australia, Brazil, Canada, China, Colombia, Ethiopia, Finland, Germany, Indonesia, Malaysia, Mexico, Norway, Russia, Rwanda, South Africa, Sweden, United Kingdom, United States, Rest of Asia and Pacific (ASP), Rest of Central and South America (CSA), Rest of European Union (ROEU), Rest of Europe non EU27 (NEU), Rest of North Africa, Middle East and Central Asia (NMC), Rest of Sub-Saharan Africa (SSA)</td><td>India<br><br>(MAgPIE is a global model solved for 12 regions in this exercise -but results are only used for India)</td></tr>
<tr><td>Model type</td><td>Agricultural and land use accounting model</td><td>Agricultural and land use sector equilibrium economic model</td></tr>
<tr><td>Objective function</td><td>No objective function (no optimization)</td><td>Minimization of global production costs (large-scale nonlinear optimization)<br><br>(Costs include agriculture production, land use change, yield-increasing technology, transport, trade, processing, irrigation expansion, and GHG emissions abatement costs in case of mitigation policy)</td></tr>
<tr><td>Software</td><td>Microsoft Excel</td><td>Written in R and GAMS; Solved in GAMS using the CONOPT solver</td></tr>
<tr><td rowspan="2">Main constraints</td><td colspan="2">National or regional market balance:<br>Food +Food waste+ Feed + Process + Bioenergy + Other Non-Food = Production –Losses - Imports + Exports<br>Cropland balance:<br>$\sum_{i=1}^{N}$ planted area $\text{crop}_i$ = cropland area<br>Land balance:<br>Cropland + pasture + primary forest + secondary forest + other land area + urban area = total land area (fixed)</td></tr>
<tr><td>Other land balances:<br>harvested area $\text{crop}_i$ / harvesting intensity= planted area $\text{crop}_i$<br>ruminant number x ruminant density per ha = pasture area</td><td>Global market balance:<br>Global supply ≥ Global demand<br>Other land balance:<br>pasture area x pasture yield = animal product x feed basket for pasture<br>Water balance:<br>Water availability = irrigated area x water requirements x irrigation efficiency + livestock production x water requirements</td></tr>
<tr><td rowspan="2">Model outputs</td><td colspan="2">Harvested area by crop, Area by land cover class, Land use change (incl. deforestation), GHG emissions, Food consumption, Blue water use, Net trade with the rest of the world per product, Land where natural processes predominate (LNPP)</td></tr>
<tr><td>Planted area by crop (1000ha), Number of livestock units (1000 TLUs)</td><td>Irrigated and rainfed crop specific area (1000ha), Crop Prices in USD of 2005 Market Exchange Rate, per ton of dry matter</td></tr>
<tr><td>Products</td><td>Crops: abaca, apple, banana, barley, beans, cassava, other cereals, other citrus, clove, cocoa, coconut, coffee, corn, cotton, date, other fruits, grape, grapefruit, groundnut, jute, lemon, millet, nuts, oats, oil palm fruit, other oilseeds, olive, onion, orange, peas, pepper, piment, pineapple, plantain, potato, other pulses, rapeseed, rice, rubber, rye, sesame, sisal, sorghum, soyabean, other spices, sugar beet, sugarcane, sunflower, sweet potato, tea, tobacco, tomato, other tubers, other vegetables, wheat, yams<br>Processed products: cotton lint, vegetable oils (11 types), oilseed cakes (7 types), sugar raw<br>Livestock products: chicken, eggs, milk, pork, mutton-goat, pork, beef, other meat<br>Bioenergy: first generation biofuels</td><td>Crops: Temperate cereals (wheat), maize, tropical cereals (sorghum, millet), rice, soy, rapeseed, groundnut, sunflower, pulses, potato, cassava, sugar cane, sugar beet fruits and vegetables, cotton<br>Processed products: oils, oilcakes, sugar, molasses, alcohol, ethanol, grain distillers, brans, single cell protein, fibers<br>Livestock products: ruminant meat, pork, chicken, eggs, milk, fish<br>Bioenergy: first generation bioenergy, second generation bioenergy (bioenergy grasses, bioenergy trees)<br>Feed roughage: fodder, grass</td></tr>
<tr><td rowspan="2">Scenario parameters</td><td colspan="2">population, diets, biofuel use, food waste at the consumer level, livestock and crop productivity, agricultural land expansion restrictions including protected areas, afforestation, climate change impacts on crops</td></tr>
<tr><td>share of domestic consumption that is imported, export quantity, share of the production lost during storage and transportation (i.e., post-harvest losses), ruminant density per hectare of pasture</td><td>GDP, nitrogen use efficiency, irrigation of bioenergy crops, protection of environmental flows, animal waste management systems, GHG price</td></tr>
</table>

*Source: Mosnier et al. (2023), Environmental Research Letters*

### 1.8.3 Outputs of the FABLE Calculator and MAgPIE used as input in SPIQ

***Table A3:*** *Comparison of agrifood models' outputs that can be used in TCA to compute the evolution of hidden costs in the future and across alternative scenarios and comparison with the original impact indicators used in SOFA 2023*

| Cost to GDP | How the output from the agrifood system models (the FABLE calculator (FC) and MAgPie) correspond to the impact quantity indicators used in SOFA 2023 |
|---|---|
| **Burden of disease due to dietary choices** | • SOFA 2023: number of DALYs<br>• FC: DALYs computed on the basis of average food availability by capita in g/day by MIRAGRODEP food groups using the machine learning model developed for SOFA 2024<br>• MAgPIE: for FSEC, Marco Springmann computed DALYs using dietary intake output to compare with eight diet and weight-related risk factors of five diseases. |
| **Undernourishment** | • SOFA 2023, FC and MAgPIE: Number of people with food intake below minimum energy requirements |
| **Eliminating poverty among agrifood systems workers** | • SOFA 2023: Number of workers in the agrifood system under poverty line of 3.65 PPP dollars 2017 a day<br>• FC: number of full-time equivalent on-farm workers – not compatible with TCA model<br>• MAgPIE: Translation of "Expenditure on Agricultural Products" from MAgPIE in average real incomes and inequality levels (Soergel 2021) |
| **Due to climate change (agricultural production losses and higher mortality)** | • SOFA 2023: GHG emissions ($CO_2$, $CH_4$ and $N_2O$) from on-farm production, pre- and post-production, land use and land use change (FAOSTAT)<br>• FC and MAgPIE: GHG emissions ($CO_2$, $CH_4$ and $N_2O$) from on-farm and land use change related GHG emissions – pre- and post-production not computed |
| **From loss of ecosystem services after conversion of natural ecosystems to agriculture** | • SOFA 2023: Temperate forest to cropland, temperate forest to pasture, tropical forest to cropland, tropical forest to pasture, cropland to forest regrowth, pasture to forest regrowth, unmanaged grassland to cropland and pasture, managed grassland to unmanaged grassland (HILDA)<br>• FC: land transitions endogenous (cf. Annex for all possible land transitions)<br>• MAgPIE: The different land uses represented are cropland, pasture, built-up land, forestry, forest, other land |
| **From loss of environmental flows due to irrigation withdrawal** | • SOFA 2023, FC, and MAgPIE: Blue water withdrawal for agricultural use in cubic meters |
| **Related to nitrogen application** | • SOFA 2023: Volatilization of $NH_3$ (ammonia) and NOx (nitrous oxide) to air and $NO_{3-}$ leached to groundwater, $NO_{3-}$ due to run-off from agricultural land to surface water and effluent or human sewerage in surface water (SPIQ-FS)<br>• FC: nitrogen application on cropland and nitrogen left in pasture – not compatible with TCA model<br>• MAgPIE: Nitrous oxide ($N_2O$) emissions from soils and manure management are calculated using IPCC (2006) emission factors, adjusting for nitrogen budgets. The rescaling of emission factors considers variations in regional soil nitrogen uptake efficiencies, ensuring proportional representation to total cropland nitrogen surplus and adjusting for changes in emissions with improved management practices and nitrogen uptake efficiencies. |
| **Costs from crop losses due to soil leaching** | • SOFA 2023: Run-off of reactive nitrogen into surface waters and soil leaching, predominately soluble nitrate (European Nitrogen Assessment)<br>• FC: nitrogen application in cropland and nitrogen left in pasture – not compatible with TCA model<br>• MAgPIE: Nitrogen surpluses from agricultural soils are estimated as the difference between nitrogen inputs in the form of organic and inorganic fertilizers, and the withdrawals in the form of harvested biomass. This budget approach provides the total quantity of reactive nitrogen leached, volatilized or denitrified. |
| **Costs from water pollution due to nitrogen run-off** | • SOFA 2023: Run-off of reactive nitrogen into surface waters and soil leaching, predominately soluble $NO_{3-}$ (nitrate)<br>• FC: nitrogen application in cropland and nitrogen left in pasture – not compatible with TCA model<br>• MAgPIE: Nitrogen application |

### 1.8.4 Explanation of the decomposition analysis

The decomposition analysis shows the **absolute change in the value of an output of the model for a specific year (2030 or 2050) after we change <u>only one scenario parameter</u>** from its value under current trends (CT) to its value under the national commitment (NC) pathway or the global sustainability (GS) pathway.

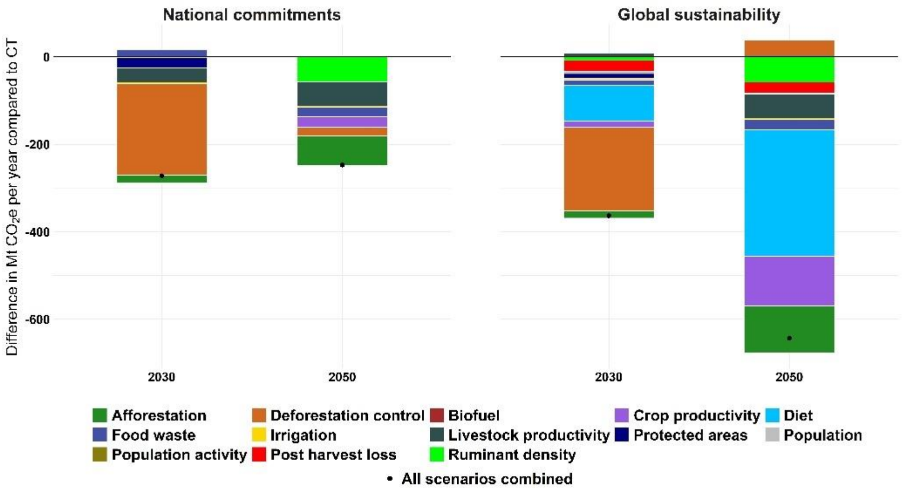
**No change** means that this specific parameter change assumption does not have an impact on this specific model output compared to current trends. In some cases, none of the scenarios change the output value compared to current trends. This can happen when there is a strong constraint that does not allow this output variable to change value across scenarios. For example, if deforestation is prohibited and afforestation does not vary across the three pathways (CT, NC and GS), it is expected that forest cover will be the same in all pathways, independent of the other parameters (cf. country annex for Australia). Alternatively, if none of the selected parameters are used in the computation of a certain model output then no change will result.

The **black dots** on the figures show the total impact of the national commitments (NC) pathway, or the global sustainability (GS) pathway compared to current trends, i.e., **when all the selected scenario changes are implemented simultaneously in the model**. The individual impact of each scenario change is represented as one item of stacked bars, e.g., the impact of the crop productivity change which is assumed in the NC pathway on $CO_2e$ emissions from agriculture. In most cases, the sum of the items in the stacked bar is not expected to be equal to the value shown by the black dot. This is because, when combined, some scenario changes reduce the impact of others. For instance, if we reduce the consumption of animal-based products in the diet scenario, this reduces the domestic production of livestock, and livestock productivity gains will apply to a smaller number of animals leading to lower benefits than when implemented alone. And if we increase agricultural productivity and prevent deforestation, benefits of dietary changes will be slightly reduced compared to when implemented alone.

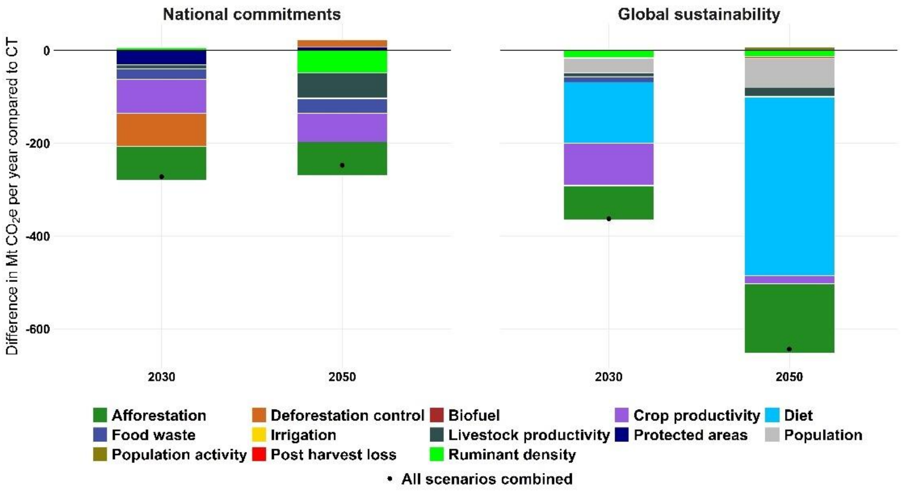
This is illustrated in the figures below for Brazil, which compares two different sequences for progressively changing the scenario parameters, in which sequence a is the reverse of sequence b (Figure A2). While the total impact – i.e., when all the scenarios are combined – is the same, the attribution of the different scenarios to the total varies depending on the sequence in which they are introduced. For instance, when deforestation control is introduced before dietary change (Figure A1 – a), it is attributed a big share of the total reduction of $CO_2$ emissions by 2030 compared to current trends, while when it is introduced after diet and crop productivity change (Figure A1 – b), this share is reduced because these other factors have already reduced much of the deforestation.

***Figure A2:*** *Comparison of the contribution of each scenario to $CO_2$ emissions when implemented cumulatively and depending on the sequence of implementation of the scenarios*

*a) Implementation of scenarios such as: 1- Irrigation 2-Biofuels 3-Post-harvest loss 4-Protected areas 5-Ruminant density 6-Afforestation 7-Deforestation control 8-Crop productivity 9-Livestock productivity 10-Food waste 11-Diet 12-Population*




*b) Implementation of scenarios as 1- Population 2- Diet 3- Food waste 4- Livestock productivity 5- Crop productivity 6- Deforestation control 7- Afforestation 8- Ruminant density 9-Protected areas 10- Post-harvest loss 11- Biofuels 12- Irrigation*




**On the level of calorie availability**: Scenario parameters can affect food consumption only if the desired consumption level cannot be achieved because of land scarcity. In this case, selecting scenario parameters that produce more food with the same amount of land (e.g. by increasing productivity or reducing waste) could increase the level of consumption to the desired level (e.g. see UK results). An alternative, which is not modelled in the FABLE Calculator, is that food imports could be increased to supply the deficit. Also, other scenario parameters could indirectly affect consumption through changes in prices, but the Calculator does not model this as it is not an economic/optimization model.

**Non linearities of the impacts**: Some impacts may be significant in 2030 but not in 2050, for different reasons. One reason is that population growth is often slower in 2030–2050 than in 2020–2030, i.e., there is a lower increase in food demand, thus reducing land use change and related emissions.

**Trade**: The trade adjustment in the FABLE Calculator is driven by the evolution of the international demand for goods. The exports of each country are proportionally adjusted to their computed market share so that total global exports match total global imports. Total imports depend on the assumptions of all other countries and rest of the world regions about the evolution of population, diet, animal feed composition, and the share of domestic consumption satisfied by imports.

### 1.8.5 Computation of the hidden costs related to dietary patterns

First, results from **the FABLE Calculator** on the average consumption per capita by product and by five-year time step are extracted from the Scenathon 2023 database (FABLE 2024) and aggregated by food group used in the machine learning model (Table A4).

Second, **the Machine Learning (ML) model** developed and run at the FAO to link food availability to food intake and DALYs is also used to convert the results of the FABLE Calculator into intakes for the seven processed food groups used to compute DALYs: processed meat, sodium, sugar-sweetened beverages (SSB), trans fatty acids, polyunsaturated fatty acids, seafood omega-3 fatty acids, and wholegrains. Intake is directly taken from the FABLE Calculator's results for the following food groups: red meat, fruits, legumes, milk, nuts and seeds, and vegetables.[4]

***Table A4:*** *Mapping between product groups used in the machine learning model to compute DALYs and the products for which consumption is computed in the FABLE Calculator*

| Food group used for DALYs computation | Products in the FABLE Calculator |
|---|---|
| **beef** | beef |
| **eggs** | eggs |
| **fish** | fish |
| **pork** | pork |
| **poultry** | chicken |
| **lamb** | mutton & goat |
| **rice** | rice |
| **maize** | corn |
| **milk** | milk |
| **wheat** | wheat |
| **soybean** | soybean |
| **other grains** | barley, millet, oats, rye, sorghum, other cereals |
| **fruits** | apple, banana, coconut, date, grape, grapefruit, lemon, orange, pineapple, plantain, other citrus, other fruits |
| **legumes** | beans, groundnut, peas, other pulses |
| **nuts and seeds** | nuts, sunflower |

[4] We know from the poor performance of linear regression amongst the ML models this direct proportionality from supply to intake is historically questionable, as supply to intake is not that linear or simple. However, using the 1-1- match for the categories we can use it for, though quite inaccurate, is more transparent and easier to understand.

| | |
|---|---|
| **oil palm** | palm oil, palm kernel oil |
| **other vegetable oil** | coconut oil, cotton oil, groundnut oil, olive oil, rapeseed oil, sesame oil, soybean oil, sunflower oil, other oil, cotton, rapeseed, sesame, olive, other oilseed |
| **roots** | cassava, potato, sweet potato, yams, other tuber |
| **sugar** | sugarbeet, sugarcane, sugar raw |
| **vegetables** | onion, tomato, other vegetables |
| **other** | clove, cocoa, coffee, pepper, piment, other spices, tea, tobacco |

The ML model is trained in historical data which shows that per capita intake of processed foods increases with higher HDI in most countries and to a lower extent with higher Gross National Income (GNI). It can reflect the historical fact that some high HDI countries have higher intake in fruits and vegetables and lower levels of processed foods (e.g., in Mediterranean diet countries), but it cannot observe or reflect planetary-health diets at high HDI for many countries as this is not seen in historical data. This cannot be changed because the ML was originally designed to estimate partial derivatives of cost versus intake for current dietary patterns, not hypothetical futures. Broad macroeconomic patterns combined with supply changes can lead to slight increases in processed meat and sugar-sweetened beverages under GS even though red meat and sugar intake goes down. This is reasonable if we assume the association between increased wealth and increased consumption of processed foods continues in line with historical trends, but it becomes less reasonable if GS assumes high HDI and dietary patterns that are breaking with historical trends. Therefore, for this study, we decided to make direct exogenous assumptions on the evolution of UPF (Table A5) entered into the ML.

***Table A5:*** *Assumptions on ultra-processed food consumption under the GS pathway*

| Country | UPF 2002 (kg/capita) | UPF 2016 (kg/capita) | Relative change between 2002 and 2016 | Assumed relative change between 2020 and 2050 | Implementation rate |
|---|---|---|---|---|---|
| **UK** | 156 | 141 | -10% | -50% | Linear |
| **Australia** | 109 | 109 | -1% | -67% | Linear |
| **Brazil** | 26 | 37 | 39% | -22% | Linear |
| **Colombia** | 15 | 21 | 37% | -20% | Linear |

*Source: for historical data: Euromonitor 2002 and 2016; for assumed relative change between 2020 and 2050: authors from each country. Note: for Ethiopia, we use the HDI-forced UPF projections, as the assumed dietary change is a continuation of historical trends.*

Third, **the global burden of disease (GBD) emulator** run at the Oxford University was used to estimate the DALYs from various diseases and 15 food groups and age brackets 15–70 and 70+. The emulator has been validated to reproduce the original 2017 GBD population attributable fractions (PAFs) per disease outcome and risk group and overall dietary risks (not 15 individual risks) in DALYs per disease outcome. The GBD relative risk factors vary across the years. For instance, red meat was not as high a risk factor in GBD 2017 as in 2019 and 2021. The risk factor for trans fats was also corrected due to a possible unit error in the GBD 2017. GBD 2021 and GBD 2019 use a different model to GBD 2017 and according to our validation of some of the data, the 2019 model is less reliable than in 2017. GBD 2021 could not be used for this study as it was just recently released. DALYs are not directly proportional to food intake because they are also impacted by life expectancy, variance in intake around mean intake, and demographic structure (intake and disease outcomes by age brackets).

Some effects cannot be calculated, due to the scope chosen for SOFA 2024 or the design of the GBD model. For example, in our emulator sodium affects the disease burden of stomach cancer but not the DALYs resulting from high systolic blood pressure, for which the full GBD model is needed. As systolic blood pressure DALYS are larger than the stomach cancer component (e.g., up to 17% of the overall dietary risk DALYS in China), 0–17% of the disease burden is missing (for most countries it is between 5–8%) because the effect on high systolic blood pressure of sodium is missing. However, this missing component is likely not playing a large role in our results as the relative change in disease burden between CT and GS due to change in sodium intake predicted by the ML model is small.

Sugar-sweetened beverages contribute directly to DALYS and indirectly through a higher Body Mass Index (BMI), which impact is larger according to the GBD. However, although the BMI impact is included in the hidden costs computation made with MAgPIE (FSEC 2024), it is not included for the FABLE Calculator outputs.

Finally, **the SPIQ model** (run by Steven Lord from Oxford University) computes the hidden costs of the DALYs based on labor productivity losses. The evolution of the marginal cost of labor productivity depends on the population trajectory (e.g., old age dependency), GDP per capita, and HDI. GBD modeling provides uncertainty estimates for the disease burden from dietary risks. Some epistemological uncertainty in benefit transfer methods is also included in the hidden costs model used, as indicated in the references cited in the SOFA 2023 and SOFA 2024 hidden cost methodology.