SPIQ-FS Dataset

Version 0

Estimations of marginal social costs for GHG emissions

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Summary

Marginal social costs in international dollars (US$2020 Purchasing Power Parity) per metric ton of carbon dioxide (CO2), methane (CH4) and nitrous oxide (N20) are evaluated for global CO2, CH4 and N2O emissions. The social costs estimate 2020 present value of present and future economic losses from 1 metric ton (1000 kg) of the respective Greenhouse Gas (GHG) emission in 2020.

The marginal social costs for the respective GHG emissions are provided as random variables of loss in parametric form in Table 3 on page 17. Two parameters, mu and sigma, are estimated for a lognormal distribution of probable US$2020 PPP present values given 1 metric ton of atmospheric emission. The samples from which the parametric forms are derived and the correlation matrix for covariance are available in the SPIQ-FS dataset.

It is not recommended to convert CH4 and N2O emissions into CO2-equivalent metric tons of emission and multiply them by the marginal social cost of CO2. The estimates of the US Intergovernmental Working Group on the Social Cost of Greenhouse Gases (IWG-SCGG) that are used cost CO2, CH4 and N2O separately. It is recommended to use the separate CO2, CH4 and N2O marginal social costs. **Statistical analysis indicates converting to CO2-equivalent quantities of emissions will underestimate the marginal social costs of CH4 and underestimate the marginal social costs of N2O by over 30%.**

Use for economic loss

The objective of the SPIQ-FS dataset is to enable estimates of economic risk due to food system activities and the economic potential of food system transformation. The intended use involves aggregation across countries and quantities, for example, in global studies of dietary change or for multinational company and value chain estimates of impact.

The social cost is an estimate of aggregated economic loss to a present or future economy (e.g. reduction in the Gross Domestic Product (GDP) or consumption as an income-equivalent welfare loss) and does not evaluate transfer amounts between individual economic actors or sectors (e.g. payments from households to the health sector for health costs).

The average present value of probable US$2020 PPP marginal economic loss given 1 metric ton of CO2, CH4 or N2O emission is reported in Table 3 on page 17. The average value should be used to calculate the average value of total economic losses across multiple countries and GHG emissions since it is additive.

To calculate risk in total economic losses from GHG emissions, the distribution of probable US$2020 PPP marginal economic loss given 1 metric ton of emission in Table 3 should be multiplied by the quantity of emissions. This may overestimate the uncertainty in total economic losses for a large quantity of emissions and may underestimate the uncertainty for a small quantity of emissions[1].

[1] Over- or under-estimation may result since it is unclear whether 1 metric ton of CO2 emission, say, by food system activities, represent independent lotteries of economic loss. When aggregating to a total economic loss for n metric tons emitted, the sum of n random variables each with lognormal distribution given by Table 3 as a representation of the uncertainty in total economic loss should not be used without a sufficient argument for independence within the impact pathways of each unit of emission. For example, the total economic impact of CO2 emissions, treating each emission as a random draw from the distribution of economic loss for 1 metric ton of CO2 emitted and summing the random variables, will result in a gross error if economic loss is not independent between each emission due to a common component in the impact pathway (e.g. a systematic

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To calculate risk in total economic losses across multiple GHGs, other impact quantities such as nitrogen emissions, and multiple countries, the correlation matrices in the SPIQ dataset should be used to reconstruct a joint distribution of probable US$2020 PPP present values for the impact quantities[2]. Samples from the joint distribution of marginal damages should be multiplied by their respective quantities for each country and then added. The resulting set is a sample of total economic losses. Economic risk or economic potential is generally underestimated without using joint sampling.

It is not recommended to use the average values in Table 3 separate from the uncertainty estimate.

Use for economic potential

Damage costs should be paired with abatement costs and counterfactuals to determine the economic risk from food system activities which produce GHG emissions and the economic potential in food system transformation which reduces GHG emissions.

Most estimates of the marginal social costs of GHG have a counterfactual world and abatement cost curve built in.

The marginal social costs in Table 3 therefore represent marginal damage costs for a 1 metric ton emission of the GHG when society has reduced emissions to an optimal level, as determined by the abatement costs curves and abatement assumptions built into the Integrated Assessment Models (IAMs) used by the IWG-SCGG.

For a particular study on food system abatement measures, it is unclear what role the measures may be assumed to have, or have not, played in the endogenous abatement in the IAM modelling. If it is not possible to conduct a dedicated modelling exercise to adjust the abatement costs in the IAMs to include the cost of changes in the food system, the simplest option is to treat the marginal social costs in Table 3 as an **underestimate** of the marginal damage cost of 1 metric ton emission in 2020, or assume that the food system action is additional to endogenous abatement in the IAM modelling.

Generally, the social costs in Table 3 represent the range of most damage cost estimates.

Methodology and caveats

Impact pathway

Emission of GHG change radiative forcing in the atmosphere, resulting in changes in climate from increased average energy in the atmosphere. Economic effects of change in global temperature are the main damage mechanism. CO2, CH4 and N2O emissions have other effects: N2O reduces stratospheric ozone alongside complex interactions with the global nitrogen cycle. Damage

underestimate in the physics of radiative forcing). Uncertainty estimates of economic loss for GHG emissions in integrated assessment models are a result of varying common factors for emissions. Uncertainty for marginal damage costs when quantities are unspecified is not resolved in SPIQ Version 0.

[2] Covariance in economic losses due to joint emission or production of impact quantities from food system activities, for example 1 kg of NH3 emission in country i and 1 metric ton of CO2 emitted in country j, is estimated in the document "SPIQ-FS Version 0: double counting and estimation of correlations between impact quantities". The parametric form given in Table 3 represents what is called the marginal distribution of a joint distribution across countries and quantities of marginal damages for the impact quantities associated to food system activities. Determination of the correlations considers spatial and temporal coincidence of impact. All SPIQ-FS Version 0 damages are for impact quantities produced in 2020. A later version may consider joint distribution across countries and quantities and years of emission/production.

mechanisms such as agricultural losses, forward projection of historical relationships between temperature and productivity, and sea level rise, are well-reported in a large body of literature on the economic modelling of climate change.

Calculation and uncertainty

The Intergovernmental Working Group on the Social Cost of Greenhouse Gases (IWG-SCGG) calculates the marginal social cost of CO2, CH4 and N2O using the three primary reduced complexity IAMS: Dynamic Integrated Climate-Economy model (DICE), Climate Framework for Uncertainty, Negotiation and Distribution (FUND) and Policy Analysis of the Greenhouse Effect model (PAGE). The 2016 update from IWG-SCGG harmonized input to the models and examined 5 projections of future emissions and socio-economic conditions as well as 3 choices of a discount rate. Monte Carlo simulations of variation in the components of the models, for example temperature sensitivity for a doubling of CO2 concentrations in the atmosphere, produce a distribution of potential values for the marginal social cost of CO2, CH4 and N2O, for each discount rate. Another IWG-SCGG update is due in January 2022.

Samples for the 3% discount rate are used for the SPIQ-FS dataset. The samples for all 5 projections and 3 models are used: the implicit assumption is that it is unknown which projected future will be realised and it is unknown which model correctly indicates damage for any gas in that future.

Theoretical arguments and projected consumption growth rates suggest that the 3% discount rate underestimates the present value of future climate change damage. National accounting guides suggest discount rate around 3%.

The major variation in the central tendency of the social costs for each gas is due to discrepancy between the 3 models and not the 5 future projections, providing three distinct subgroups in the samples that are lognormally distributed. A three-mixture Gaussian model fits the distribution of the logarithm of each marginal social cost almost exactly, indicating the influence of the models and their internal structure (products of independent random variables tend toward a lognormal distribution).

A lognormal distribution with a less exact fit (a Gaussian model for the logarithm of each marginal social cost) is used instead of the mixture model for convenience of the joint sampling of marginal damage costs with other quantities that produce impact in the food system, such as health costs of consumption.

The use of global values for the marginal social cost of CO2, and CH4 and N2O respectively, is not an indication that the costs of climate change are borne equally. Use of a global value represents an inability to attribute damage costs from climate change incurred within a country to GHG emissions by a food system actor, or GHG emissions within a geographic region.

Caveats in modelling the marginal social cost of GHG are well-reported in the large body of literature referenced below. They include sensitivity to the discount rate, the ethical consideration of generational transfer of costs and risks, and representation of the uncertainty in loss from extreme events and large-scale climate feedbacks.

Global perspective

For perspective, 2015 estimates of global CO2, CH4 and N2O emissions attributed to the food system (Figure 1) are paired with the IWG-SCGG marginal social costs (in Section 1.7 from page 24).

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Expected economic loss from food system GHG emissions in 2015 are US$2020 PPP 1 trillion, with a greater than 5% chance that losses are over US$2020 PPP 2.4 trillion (Figure 6). The expected value is approximately 10% of the global gross value add (the economic value) of food production, manufacturing, and retail.

Losses can be attributed to food system stage using the proportion of emissions estimated in Figure 1. Agriculture production and land-use change account for 75% of the total economic losses from annual food system CO_2, CH_4 and N_2O emissions (Figure 9). Over 50% of the total economic losses from annual food system emissions are due to CH_4 and N_2O emissions (Figure 6).

How much of this estimated economic loss can be recovered from transforming agricultural production and food systems is unclear without global modelling studies placing food system mitigation costs within the context of least cost abatement of GHG emissions.

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1 GHG

1.1 Quantities associated to impact

The food system is estimated to be associated to one third of all anthropogenic GHG emissions (Figure 1) [1, 2]. There were 18 Gt CO2-e emissions in 2015. Globally, 66% of the CO2-e emissions from the food system originate from the land-use sector associated with primary production, and 21% of CO2-e emissions are from the energy sector used mainly in processing, transport, distribution and retail (Figure 1) [1]. 9% of CO2-e emissions are due to CH4 from waste. The three categories of land-use, energy production, and waste cover 96% of emissions. The GHG gases CO2 (Carbon Dioxide 9.36 Gt emissions), CH4 (Methane 0.255 Gt emissions) and N2O (Nitrous Oxide 6.8 Mt emissions) cover 97% of emissions. The only other major category is F-gases at 2%, used in refrigerants which may increase in the future through changes in middle income country (MIC) consumption [1].

1.2 Mitigation and costs

GHG emission in processing, distribution, transport, and retail, is almost exclusively from the energy and transport sector. Except for uses of industrial waste or food waste post-consumption [3-5], economic changes and abatement measures for CO2 attributable to processing, distribution, transport, and retail in the food sector can be assumed to follow decarbonisation of the energy and transport sector [6]. Most of the energy requirement from the sector post farm-gate is low intensity which can be provided by renewables and storage technologies [7, 8].

Avoided land-use change (mainly deforestation) and restoration of terrestrial carbon sinks [9-11], reduction of CO2 in fertiliser production, reduction of N2O leakage from fertiliser applications and agricultural soils, and reduction of CH4 from enteric fermentation from livestock and rice cultivation, represent the main opportunities for mitigation in LULUC and agriculture [2, 12, 13]. Abatement targets vary, and projections of GHG budgets for the land-use sector, which is the origin of economic activity for the food sector, as well as fibre, forestry, and biofuel, often associate the land-use component to a net sink by 2050 [14, 15].

GHG emission mitigation and sequestration options in LULUC and agriculture differ from the energy sector. First, they involve reduction of mainly non-CO2 GHGs [16, 17]. Second, they involve more complicated economic and environmental trade-offs [18]. Agriculture competes with fibre, forestry, and bioenergy in the land-use sector [19-21]. Abatement and abatement costs assuming competition for land-use, and secondary effects on agricultural quantities and prices, have been estimated using global marginal abatement values [21, 22]. Labour changes and transmission to food prices (e.g. food security), which are not symmetric with other land uses (different land use may require a different number of labourers and result in different quantities and value of agricultural goods produced on the land area), would have additional welfare effects whose abatement has not been costed, especially in developing countries [23, 24]. New studies consider abatement constrained by social and environmental co-effects [25-27].

There are two main components of uncertainty in abatement costs: the risk of greater costs for the same abatement and the risk of less abatement at the proposed costs. Both components of uncertainty in abatement costs have been examined less than uncertainty in damage costs. The economic, social and environmental co-effects of abatement create barriers and divergence in policy response [28]. Agriculture is a heterogenous sector slowing realisation and effectiveness of technological improvements compared to energy and transport sectors [29]; non-CO2 emissions are greater and growing faster in developing contexts (73% of global food system CO2-e emissions) with challenges in uptake of technology, financing, and governance [30]; and uncertainty and time factors of natural processes present in LULUC abatement [27, 31]. Realisation of dietary substitution for equal calories and nutrients at given prices are uncertain; in contrast to the energy sector where, beyond price, consumption is largely agnostic to the source providing equal kW.

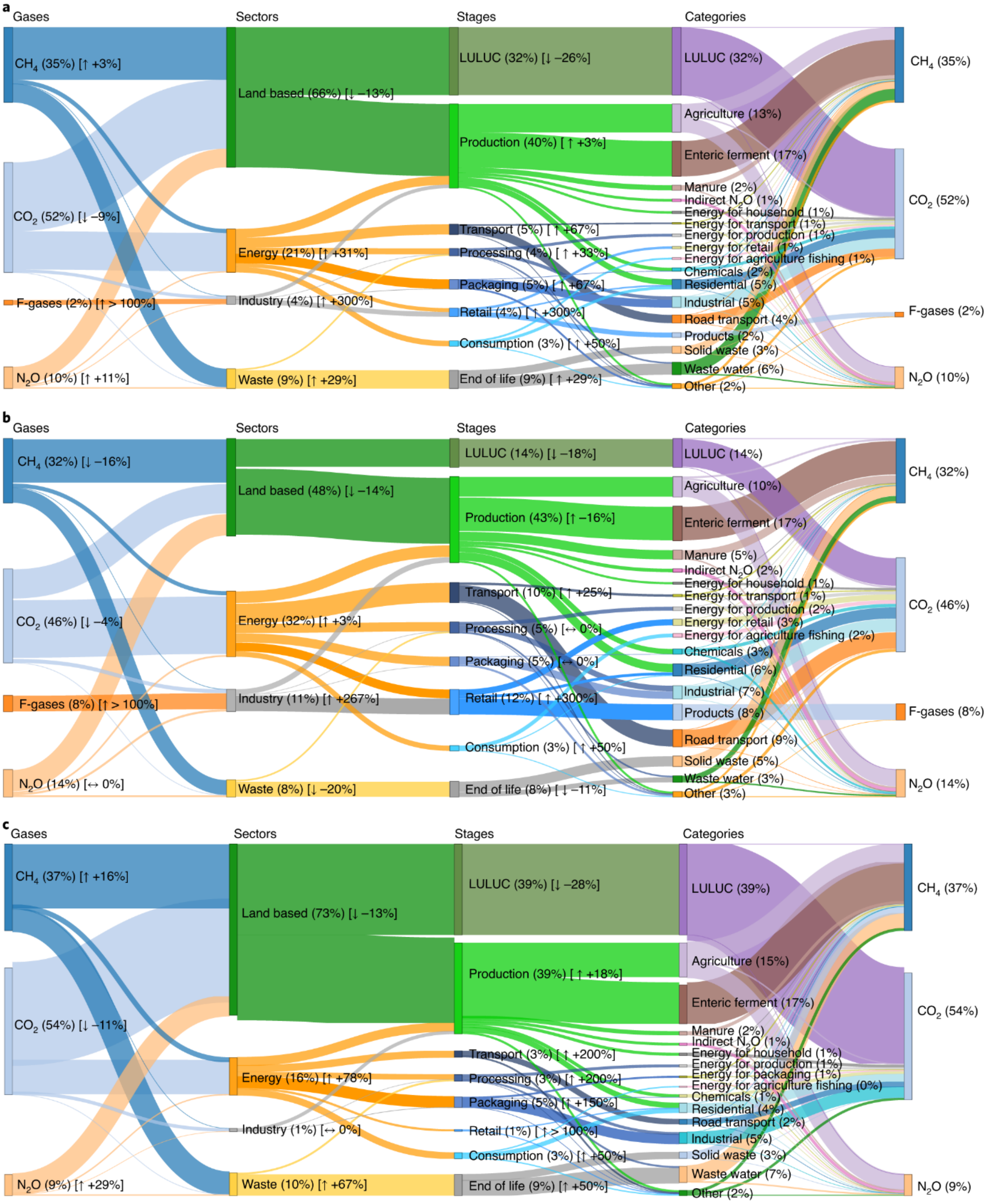

Figure 1: Source: [1] "a, Global. b, Industrialized. c, Developing countries (including China). Total GHG emissions of the food system were 18 Gt CO2e yr−1 in 2015. The qualitative information of the activities contributing to the food system provided by the Sankey diagram is complemented with the quantitative contribution of individual GHG and sector shares to the total GHG food-system emissions. Arrows and percentages indicate the change in gas, sector, stage and category contributions between 1990 and 2015. Numbers are rounded and therefore do not necessary sum up to 100%."

Abatement costs for food loss and waste (FLW) are also complicated [32, 33]. Large reduction in FLW in an industrial context entails either health effects from increased food consumption with possible welfare effects, or economic impacts for producers due to a potential large reduction in retail revenues and production volumes requiring study of the broader economic effects. FLW abatement resulting in decreased production acts as an emissions abatement measure in the components already identified (LULUC, agriculture, post-farm gate to fork). The other significant effect is reduction in the 9% of food system CO2-e emissions from waste. Household energy use reductions would be tiny compared to other emission sources. Fresh food is disproportionately wasted [34, 35], and it is unclear if large scale FLW abatement would alter consumption profiles of fresh foods with subsequent health effects [36]. Valorisation of residual waste mostly maintains food systems emissions and provides indirect emissions savings from reduction in other sectors (energy, materials, etc.). Emissions savings from other sectors, valorisation process emissions, and CH4 saved from waste, are seldom compared to the amount of reduction in the food system that valorisation is displacing. Savings and the displacement would be asymmetric in terms of substitution effects (different sectors) and the composition of GHGs involved. This complicates comparing waste valorisation costs and abatement costs of the displaced reduction.

Overall, abatement costing of food system GHG mitigation is likely to be highly heterogenous outside of post-farm gate CO2 emissions. Marginal abatement cost curves (MACCs) to mitigate CO2, CH4 and N2O from the food system have not been compiled for the major non-CO2 emitting agricultural economies. Using such curves to determine marginal abatement cost (MAC) is complicated by assumptions on the role of CH4 and N2O in Nationally Determined Contributions (NDCs) and global abatement targets, the position of demand-side measures (dietary substitution and FLW) in MACCs, and shaped by additional exogenous assumptions such as international trade in reductions (policies on mandatory or voluntary carbon markets). Global abatement values, which have been estimated for direct LULUC measures that also displace agricultural production, e.g. for deforestation and reforestation, may be under-costed for not considering secondary welfare changes and associated to large uncertainties [37, 38].

Without functioning Emission Trading System (ETS) markets with participation by the agricultural sector, it is difficult at present to complement modelling limitations in mitigation costs with econometric data [39].

1.3 Damage and costs

Except for consideration of industrial waste or food waste post-consumption, processing, distribution, transport, and retail mostly involve CO2 emissions which effect damages over the long term. CO2 emissions from the food sector enter the atmosphere and effect damages through the same mechanism as other CO2 emissions from global economic activity. The damage pathway is the same, and is recorded and explored in the literature on the Social Cost of Carbon (SC-CO2) and Integrated Assessment Models (IAMs) [40-43].

The contribution to radiative forcing of emissions and therefore damages from climate change occur over time. The SC-CO2 has large uncertainties which have been explored, including representation of the temperature damage function and the role of discounting [44-50]. Limitations of the modelling include inconsistencies between models [41, 51, 52]. Additional uncertainties relevant to changes to the food system include endogenous emission responses to damage. IAMs estimate agricultural losses from reduced yield and land change, which would likely cause new agricultural land-use conversion and hence an increase in emissions depending on assumptions on agricultural technology and productivity in Business As Usual (BAU) scenarios and competition with bioenergy.

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The central support of the distribution of SC-CO2 values developed by the IWG-SCGG (Figure 2) (mean 2020USD 51 at a discount rate of 3%) covers the range of the global marginal abatement cost of CO2 put forward by the High-Level Commission on Carbon Pricing (2020USD 40-80) [53]. Generally, the social costs from the IWG-SCGG assessment represent the range of most damage cost estimates [54]. SC-CO2 values from the IWG-SCGG were updated in 2010 and 2013 (inflated to US$2020 in [55]) and will be updated in January 2022. Updates in application of discount rates and scientific estimates of damages will likely increase the SC-CO2 [55].

The IWG-SCGG provides estimates for CO2, CH4 and N2O individually (Figure 2-Figure 4), which is valuable for economic estimates of impact from food system emissions. CO2, CH4 and N2O have different lifetimes and amounts of radiative forcing (Appendix 8.A [56]) resulting in different attributable Global Temperature Potential(GTP) from which economic damages occur at different times from emissions compared to CO2 [57]. The shorter lifetime of CH4 (12 years) results in less spread from discounting and uncertainty from future effects in the SC-CH4 distribution (Figure 3). At lower discount rates, mean SC-CO2 and mean SC-CH4 approach their GWP ratio, while the mean SC-CO2 and mean SC-N2O ratio is over 37% above GWP (Table 1). Using CO2-e and applying SC-CO2 would undervalue damage from N2O emissions and undervalue damage from CH4 emission for present generations. SC-CH4 will likely rise in future IWG-SCGG updates; recent estimations of radiative forcing for CH4 are 23% larger [58] than those in IPCC AR5 [56]. IWG-SCGG does not report correlations between the SC-CO2, SC-CH4 and SC-N2O distributions.

Table 1: Comparison of statistics of SC-GHG distributions in USD2020 versus GWP. Data from [55]

	$\frac{E(\text{SC-CH4})}{E(\text{SC-C02})}$ 5%	3%	2.5%	$\frac{P_{0.95}(\text{SC-CH4})}{P_{0.95}(\text{SC-C02})}$ 3%	GWP
2020	46.0	29.1	25.6	25.7	28
2030	48.4	31.6	28.0	27.8	
2050	52.3	36.1	32.4	31.4	
	$\frac{E(\text{SC-N2O})}{E(\text{SC-C02})}$ **5%**	**3%**	**2.5%**	$\frac{P_{0.95}(\text{SC-N2O})}{P_{0.95}(\text{SC-C02})}$ **3%**	**GWP**
2020	399.2	360.3	355.0	318.3	265
2030	402.8	368.8	365..4	323.1	
2050	416.3	389.7	388.5	339.2	

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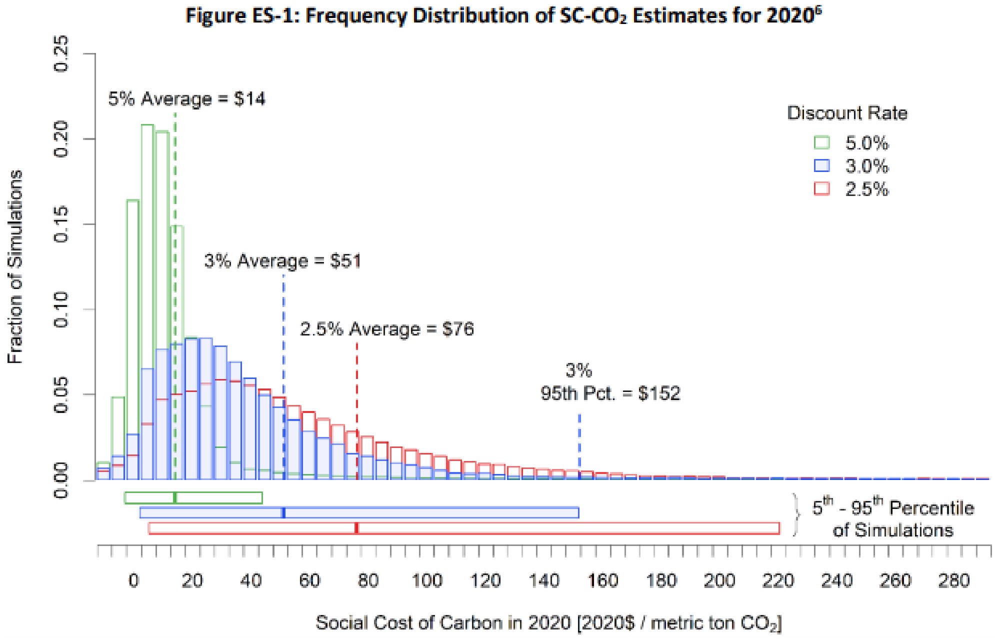

Figure 2: Monte-Carlo results from simulation of SC-C02 from [55]

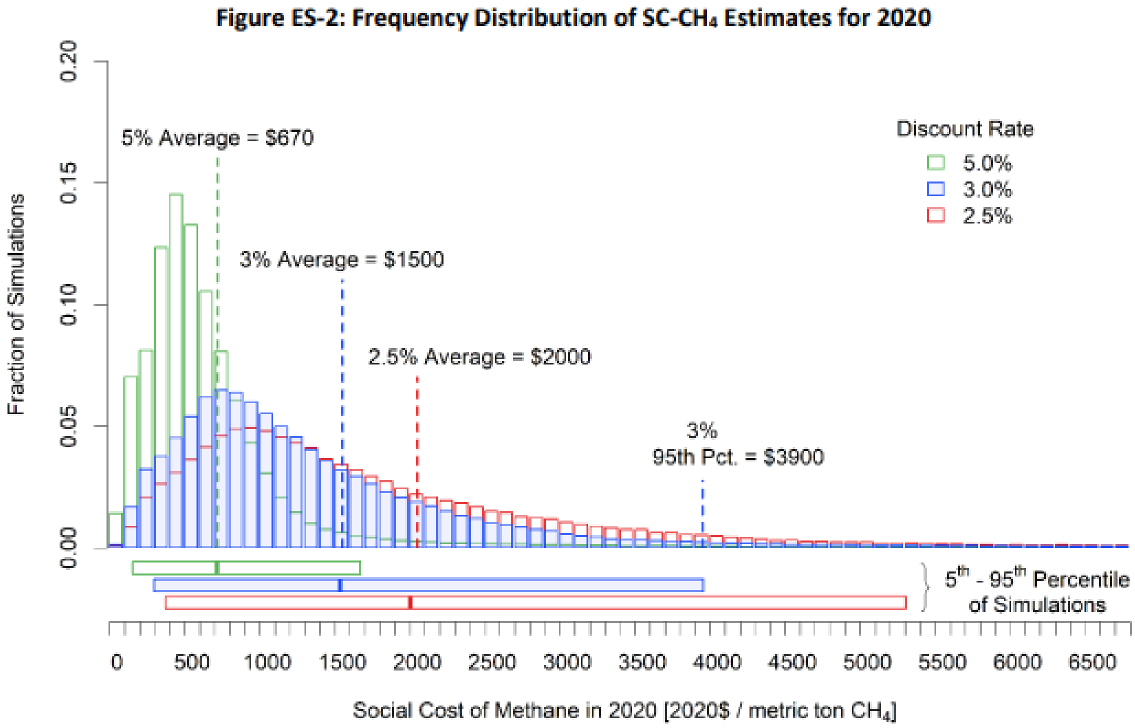

Figure 3: Monte-Carlo results from simulation of SC-CH4 from [55]

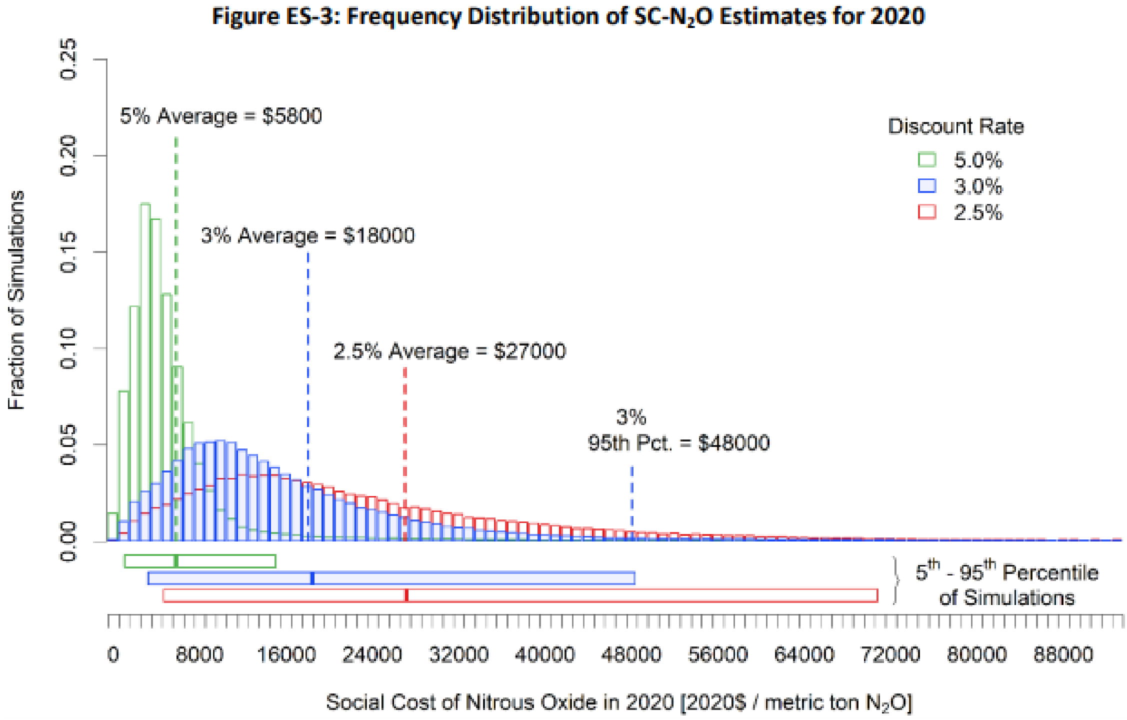

Figure 4: Monte-Carlo results from simulation of SC-N2O from [55]

IWG-SCGG estimates do not consider distributional effects [46, 59, 60] and are generally thought to underestimate risk of higher damages [61, 62]. Though CH4 emissions from agriculture have shorter lifespans, they have much higher Global Temperature Potential (GTP) over short timeframes than their GWP, complicating adaptation and increasing damages that are sensitive to rapid temperature increase including damages from extreme weather and potential social tipping points [63-65].

The distinction between marginal abatement costs and damage costs is reviewed in IPCC reports [66, Box 5, p. 58]. Optimising the value in removing damages against the cost for doing so, which the SC-GHG reflect, can result in a different level of total abatement than those set by a political process, such as the Paris Agreement [66, 67]. Marginal abatement costs for CO2, CH4 and N2O may be in different ratios than the ratio for SC-CO2, SC-CH4 and SC-N2O, reflecting different priorities for reduction in the three different gases in agriculture and land-use depending on whether the emphasis is on abatement at least cost or on the most value from abatement for the three different gases in agriculture and land-use.

1.4 Costing GHG impacts from large scale changes in food systems

Regular updates backed by dedicated scientific review [41], separate damage estimates for the 3 major GHG gases, representation of uncertainty, and global consistency for global analysis provide rationale to, at present, base costing of GHG impacts from large scale changes in food systems on the IWG-SCGG damage estimates.

Data on the IWG-SCGG estimates is currently available from https://www.whitehouse.gov/omb/information-regulatory-affairs/regulatory-matters/#scghgs. The data was the basis for parametric fitting for the final marginal costs displayed in Table 3.

1.4.1 The cost to whom?

All social cost of GHGs determine damage to consumption as a proxy for social welfare. Consumption is a component of the GDP, which is an aggregated total of benefits and costs to actors within an economy. SC-GHGs reflect the cost to society or an economy.

Consumption as a proxy for welfare is comparable across national economies through Purchase Price Parity (PPP). The unit of SC-CO2, SC-CH4, and SC-N2O, is 2020USD, understood for PPP comparisons as 2020 international dollars [68] (using PPP ratios from 2017 https://www.worldbank.org/en/programs/icp#5).

SC-GHGs do not describe costs transacted between sectors nor full costs for actors.

Impacts from GHG emissions are attributed uniformly to emitters because they enter a global atmospheric pool. There is a large asymmetry, though, in who receives benefits from the goods whose production emitted the GHG and who bears costs directly through damage or has costs shifted to them through abatement. Under climate change many Cote d'Ivoire cocoa growers face decreased precipitation and reduction in cocoa yield [69], increased hours working at higher temperatures [70]. In mitigation scenarios they face production restrictions through international deforestation policies with possible displacement to a country like Indonesia with greater capacity to pay mitigations costs [71, 72]. Consumers and retailers of chocolate in the northern US or northern Europe, who receive most of the benefits from the final good [73], bear less direct costs from climate change, currently have climate policies with few abatement costs shifted to them, and have greater capacity to bear costs. Some of the asymmetry is reversed for health impacts of chocolate consumption. The cocoa grower bears no marginal consumption impacts and has increasing benefits from increasing consumption of chocolate.

Costs from food system activities not accounted for in market prices are dispersed across sectors and geographies, and there is a similar dispersion of benefits through global value chains, global finance, and foreign investment. Maximising social welfare attempts to incorporate the trade-offs between end receivers of positive and negative impacts of emissions when aggregating costs and benefits of individuals into a cost to society. Turning a cost to society of food impacts into a cost per capita should be cautioned regarding its representativeness; few individuals in the food system would be bearing the average net cost and it makes the asymmetry in cost bearing at the individual level opaque.

For consistency when aggregating GHG costs with costs from other quantities associated to impacts (nitrogen, dietary intake, etc.), other expenses will be framed as reduction to costs to society. Full costs for actors should be adjusted to account for counterfactuals. In the case of cost to society, the counterfactual is the optimal social arrangement. This arrangement is unlikely to be a Pareto efficiency – i.e. that the societal alternative increases value for each individual or business [74].

1.4.2 Direct health costs of dietary intake compared to societal costs

Health costings of disease related to dietary intake, e.g. obesity and diabetes type II, for the food system have included treatment costs, which is a transaction from economic actors into the health sector (households, governments, business through insurance, depending on the health system of the economy). These costs translate into GDP through Gross Value Add (GVA), and the counterfactual is whether the saved treatment costs paid into another sector and the effect of better health on other sectors, e.g. though productivity increase, would result in greater GDP. To the individual the benefit of food has involved the cost paid to the food sector for provision and to the health sector for effects. The second cost is not fully covered in the transaction of the final consumed good. While the payment to the health sector increases the marginal cost of food for the individual, it is unclear the relation between the direct cost to individual and the aggregated effect of reducing this cost on social welfare. Consumption based modelling has been done by the Organisation for Economic Co-operation and Development (OECD) for obesity, estimating over 2020 -2050 an annual average 155 million Disability-Adjusted Life Years (DALYs) from obesity in the OECD at a cost of 3% of OECD GDP [75].

Framing costs of food system impact in a consumption based damage approach provides a basis for consistent application of a discount rate at, or below, the consumption rate of interest [53].

1.4.3 Corrections and correlates with other costs

There is a potential for double counting and errors from omitting correlations when aggregating marginal damage costs for quantities associated to food system impacts. Similar considerations are required for marginal abatement costs due to the mutual abatement potential of measures; a primary example of mutual abatement is dietary change from the Planetary Health diet [15].

As an example of double-counting; before application of SC-N2O on atmospheric N2O emissions from fertiliser application, nitrogen damage costs need to be checked that they exclude climate impacts of N2O emissions to the atmosphere.

IAM damage modelling includes effects of heat stress on human CVD and changes in terrestrial ecosystem services. Co-morbidity effects of heat stress and dietary intake (CVD is the predominate pathway for DALYs lost from dietary intake [76]) can simultaneously increase the years of life lost, but could produce double counting across cost estimates as premature death of the same vulnerable individuals may be counted twice. Without examination the magnitude of either the double-counting or positive correlation remains unknown. Additionally, variations in humidity and temperature effect the relationship between atmospheric ammonia emissions (from fertiliser application or untreated animal manure) and formation of PM2.5 with related health impacts [77-79].

IAM damage modelling includes costs of changes in terrestrial ecosystem services. Riverine nitrogen from agricultural run-off degrades ecosystem services, and many studies on food system costs include land-use conversion and costs explicitly. Double counting of costs with IAMs can occur, in that the same forest which in the IAM assumed to change to another ecosystem later in the century due to climate forcing could already be counted in the agricultural conversion or the more immediate effects of excess nutrients. Positive correlations are expected in the magnitude of degradation, climatic impact will reinforce with non-GHG agricultural sources of stress.

Since climate effects are global and have a potentially pervasive effect on other impact categories, corrections and correlations with climate change will be discussed in the documentation of the other impact categories.

Corrections and correlations are particularly important for aggregating the total costs of the food system. Many studies assume a first order linear approximation with constant marginal costs, and do not correct for the joint effects and joint uncertainty across the marginal costs [80]. More costs that are summed in this way (adding more impacts such as the cost of anti-biotic resistance, pollinator losses, etc.) under the assumption that they are biophysically and economically independent, introduce more error to the sum as an approximation of mean total costs if correlations are present. Protection from large errors is not guaranteed if marginal costs have individually been modelled by sophisticated Computable General Equilibrium (CGE) models and IAMs; the covariation between the models may be absent.

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Corrections and correlations apply for costs and quantities of CO2, CH4 and N2O emissions. Examination of IWG-SCGG raw data shows that the samples of SC-CO2 against SC-CH4 and SC-N2O within 5 scenarios and across 3 models (DICE, FUND, and PAGE) are correlated but not strongly (Table 2). For 2020 and a 3% discount rate there are 150000 runs each for SC-CO2, SC-CH4 and SC-N2O in the IWG-SCGG data. 10000 runs for each of the 15 combinations of a model and a scenario. Methods to jointly sample SC-CO2, SC-CH4 and SC-N2O are to: (a) randomly pick 3 choices between 1 and 150000, (b) to randomly assign 1 of the 5 scenarios and then 3 choices between 1 and 30000, or (c) to randomly pick 1 choice between 1 and 150000 and use the same run in the IWG-SCGG data for SC-CO2, SC-CH4 and SC-N2O. Using (b) is preferable over (a), since a sample of SC-CO2 is a damage estimate under the condition that probability 1 the world described by one of the scenarios is the future. The scenarios are assumed to be mutually exclusive versions of the future. For a joint sample of SC-CH4 and SC-N2O, the emission of one tonne of CH4 and N2O in replacement of the assumed emitted tonne of CO2 occurs in a world with the same future.

Using (b) is preferable over (c) as it does not assume that the model for the sample of SC-CO2 given probability 1 to be the correct damage estimate of SC-CO2 is also the correct model for SC-CH4 and SC-N2O. Correlations should be expected within scenarios since the mechanism for damages (temperature) is common to CO2, CH4, and N2O, so sampling between (b) and (c) would be most preferable (see the removal of correlations in option (b) in Table 2). Joint sampling should concentrate on uncertainty in the biophysical processes of radiative forcing and differences in carbon, methane and nitrogen cycles and sinks. However, the IWG-SCGG joint runs within scenarios are not disaggregated according to same settings for the temperature to economic damages component. Sampling within scenarios in the IWG-SCGG data (option (b)) therefore likely underestimates correlations between SC-CO2, SC-CH4 and SC-N2O. While 10000 runs in the IWG-SCGG data is valid to explore tail percentiles of the marginal distributions, using it naively gives artificial precision for bootstrapping statistics of the joint distribution of SC-CO2, SC-CH4, SC-N2O.

Beyond Table 1, there are other illustrative measures of the underestimate of costs using CO2-e (Table 2). The optimal coefficient λ that minimises the Wasserstein distance between the distributions SC-CH4 and λ*SC-CO2 is 33.8, not the GWP of 28. Similarly, the Wasserstein distance between the distributions SC-N2O and λ*SC-CO2 is minimised at λ=424 not the GWP of 265 (Table 2 column 3). These measures are larger than the comparisons in Table 1, and account for the difference in spread of the distributions as well as means.

Table 2: Comparison of joint statistics of SC-C2O versus SC-CH4 and SC-N2O distributions in USD2020 and 3% discount rate; using the runs as ordered in the IWG-SCGG data set and bootstrapped (within scenarios). W_1 denotes the Wasserstein distance for distributions on $(-\infty, \infty)$.

	$\mathbf{X}_\lambda = \text{SC-CH4} - \lambda * \text{SC-CO2}$			
	Prob($\mathbf{X}_\lambda$>0) $\lambda = 28$	**argmin λ |Prob($\mathbf{X}_\lambda > 0$) – Prob($\mathbf{X}_\lambda \leq 0$)|**	**argmin λ $W_1(X_\lambda, 0)$**	**GWP**
IWG-SCGG runs	63.4%	45	33.8	28
Bootstrapped	57.9% (53.9%-60.9%)	35		28
	$\mathbf{X}_\lambda = \text{SC-N2O} - \lambda * \text{SC-CO2}$			
	Prob($\mathbf{X}_\lambda$>0) $\lambda = 265$	**argmin λ |Prob($\mathbf{X}_\lambda > 0$) – Prob($\mathbf{X}_\lambda \leq 0$)|**	**argmin λ $W_1(X_\lambda, 0)$**	**GWP**
IWG-SCGG runs	73.7%	520	424	265
Bootstrapped	67.2% (63.3%-70.9%)	435		265

IWG-SCGG runs correlation matrix

SC-	CO2	CH4	N2O
CO2	1	0.14	0.1
CH4	0.14	1	0.67
N2O	0.1	0.67	1

Bootstrapped correlation matrix mean (95% confidence)

SC-	CO2	CH4	N2O
CO2	1	0 (-0.11,0.11)	0 (-0.11,0.11)
CH4	0 (-0.11,0.11)	1	0 (-0.11,0.12)
N2O	0 (-0.11,0.11)	0 (-0.11,0.12)	1

For the IWG-SCGG data with option (b) joint sampling with scenarios, the chance that a sample of 28*SC-CO2 gives an underestimate of SC-CH4 is 57.9% (53.9%-60.9% 95% confidence); this estimate and the confidence intervals come from bootstrapping the IWG-SCGG data. The chance that a sample of 265*SC-CO2 gives an underestimate of SC-N2O is 67.2% (63.3%-70.9% 95% confidence) (Table 2 column 1). The value λ=35 gives an approximately equal chance that a sample of λ*SC-CO2 underestimates or overestimates SC-CH4. The value λ=435 gives an approximately equal chance that a sample of λ*SC-CO2 underestimates or overestimates SC-N2O (Table 2 column 2).

There is clear bias to more conservative statistics from bootstrapping versus the IWG-SCGG sample (Table 2) (57.9% versus 63.4% for GWP*SC-CO2 an underestimate of SC-CH4, 67.2% versus 73.7% for GWP*SC-CO2 an underestimate of SC-N2O), with both chances of underestimation from the IWG-SCGG runs well above the 97.5th percentile of the bootstrap. The bias is from: (i) removal of correlation by not being able to bootstrap within runs set to the same parameters for the vulnerability of the economy to temperature; (ii) the bootstrap confidence intervals are not sufficiently wide enough as 10000 runs of the IAMs represent an artificial high number of samples from the "true" joint population of possible future damages. Subsampling without replacement instead of bootstrapping inside scenarios in the IWG-SCGG would reduce the bias in (ii), but it is unclear the correct size for subsampling.

1.4.4 Corrections to damage costs for changing emission trajectories

Damage costs depend on assumed emission trajectories. The marginal social costs are functions of total emissions. CH4 emissions from agriculture and waste has been estimated at 0.227 Gt CH4 yr^{-1} (61% of anthropogenic annual CH4 emissions) compared to fossil fuel production and use emissions of 0.108 Gt CH4 yr^{-1} (29% of anthropogenic annual CH4 emission) (Table 1 in [81]). A trajectory of decarbonisation of the energy and transport sectors, for example, has implications for pricing SC-CH4. Total CH4 emissions will fall affecting short-term large forcing. However, the temperature response of the remaining short-term forcing will still add to the background temperature response from the stock of CO2 already emitted. CO2 neutrality, or even CO2 sequestration, trajectories should affect SC-CO2 more than SC-CH4. CH4 damage costs relate to near-term temperature increase.

In contrast to the argument for maintaining agricultural CH4 emissions because of the short lifetime of CH4 in the atmosphere as a GHG, the short lifetime and the existing stock of CO2 in the atmosphere creates persistence in damage costs of CH4 under decarbonisation. From this view, the question of maintaining agricultural CH4 emissions in the face of reducing emissions in other sectors [64] rests on an economic argument not a political one, i.e. comparing the persistent SC-CH4 and marginal abatement costs for agricultural CH4 emissions with a reduced SC-CO2 meeting higher costs in the abatement curve for decarbonisation. The result may be similar to the role CH4 agricultural emissions play in meeting an abatement matching stabilised warming of 1.5 degrees [14]. The economic argument translates the technological and transition challenges for rapid and complete decarbonisation and carbon capture [82] into abatement costs for CO2 exceeding the decreasing SC-CO2. The political versus economic argument may end with similar implications and timelines for CH4 emissions reduction if the optimal abatement determined by the economics (all abatement measures with marginal cost below the relevant SC-GHG are realised) meets the abatement target determined politically in Paris. If the targets are not the same, the SC-GHG fail to represent an upper limit to marginal abatement costs to achieve the Paris Agreement past the optimal abatement.

1.4.5 Lognormal fitting

Gaussian joint sampling is one of the only efficient high dimensional methods to generate joint samples with a specified Pearson correlation matrix. Exponentiating gives lognormal joint samples given lognormal marginals and a correlation matrix. Lognormal marginals provide a reasonable Maximum Likelihood Estimate (MLE) fit to the IWG-SCGG estimates for CO2, CH4 and N2O.

Table 3: Parameters and fit statistics for the maximum likelihood estimate lognormal fit of the distributions of uncertain costs X=SC-CO2, SC-CH4, and SC-N2O for the year 2020 (in US$2020 PPP) and discount rate 3%. To fit lognormal distributions the negative values $X \leq 0$ and values of $X \geq x_\gamma$ above the $1-\gamma$ percentile x_γ were removed, where γ was chosen such that $E(X) = E\left(0 < X < x_\gamma\right)$.

$\boldsymbol{X}$	US$2020 PPP t^{-1} $\overline{\boldsymbol{X}}$	$\boldsymbol{Y} = \mathbf{exp}(\boldsymbol{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}))$ **MLE** $\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	Fit statistics $\boldsymbol{W_1}(\boldsymbol{X}, \boldsymbol{Y})$	$\boldsymbol{W_\infty}(\boldsymbol{X}, \boldsymbol{Y})$ K-S	$\boldsymbol{D_{KL}}(\boldsymbol{X}\Vert\boldsymbol{Y})$ Rel. entropy	**Prob (X<0)**	$\boldsymbol{\gamma}$
SC-CO2	51	3.41	1.03	4.4	0.0729	0.0568	0.038	0.0023
SC-CH4	1476	6.95	0.833	168.2	0.0354	0.0298	0.0011	0.0002
SC-N2O	18328	9.48	0.82	2121.6	0.0388	0.0370	0.001	0.0003

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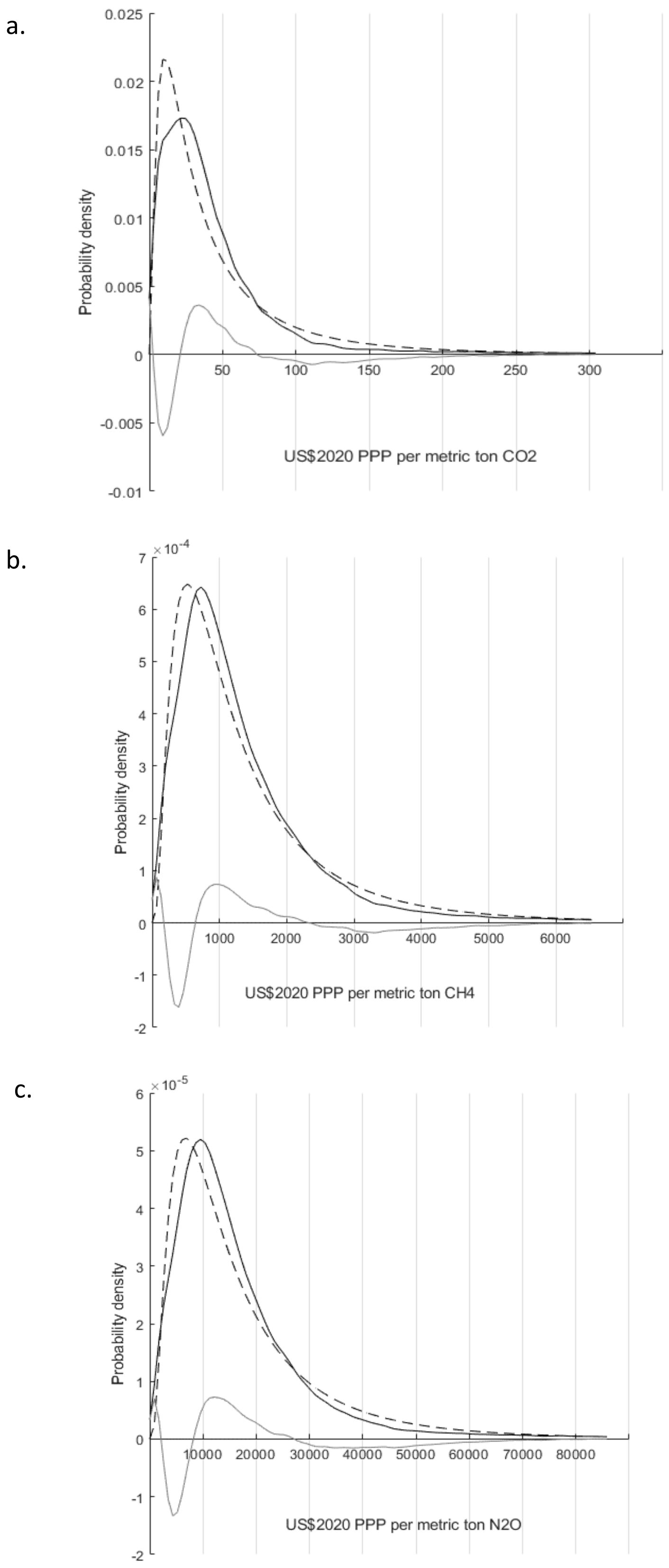

Figure 5: Maximum likelihood estimate lognormal fit of the distributions of uncertain costs X=SC-CO2 (panel a), X=SC-CH4 (panel b), and X=SC-N2O (panel c) for the year 2020 (in US$2020 PPP) and discount rate 3%.. Kernel density of X in solid black line, lognormal fit with parameters in Table 4 in dashed line, and the difference between the two probability density functions in dotted line. The lognormal fit is oversampling below the mode, and in mid-upper ranges from about 1.5E(X) to 5E(X). The fit is undersampling in the range from the mode to 1.5E(X) and beyond 5E(X).

Exponentiating a three-term Gaussian mixture model (a lognormal distribution is the exponentiation of a one-term Gaussian model) provides a better fit to each of SC-CO2, SC-CH4 and SC-N2O.

1.5 Consideration for use

1.5.1 Agricultural subsidy reform

Since subsidies are largely social welfare policies, economic arguments for subsidy reform should be framed as reduction in costs to society.

Global subsidy reform will involve potentially large changes in spatial distribution of agricultural production and volumes of commodities. Price effects change consumption and/or demand change for agricultural commodities, with a secondary correction to production distribution and volumes. Competition for land-use and spatial changes in production have effects on labour and inputs. General equilibrium modelling of changes to the economy, resulting in quantities associated to impacts, are appropriate for studies of subsidy reform. Economic losses framed as costs to society are appropriate for comparisons with general equilibrium modelling output.

Agricultural subsidy reform will likely change land-based emission sources and first stage transport (inputs to primary production, and primary production to manufacturing). Primary processing (e.g. slaughterhouses) may shift with spatial re-organisation of production, but unless there are large shifts in primary processing with large differences in the energy mix (shift from a high level of renewables in one country to a fossil-fuel dominant energy sector in another), post-farm gate emissions beyond first-stage transport are unlikely to be largely changed from spatial re-distribution of production. Similarly, unless demand substitutions from price effects create a considerable difference between processing, manufacturing, and cold-chain requirements then large changes in post-farm gate emissions are unlikely to be endogenous to subsidy reform. Such changes would more likely appear in exogenous scenarios set alongside subsidy reform.

The changes in agricultural production and land-use endogenous to subsidy reform provide rationale for costing GHG emissions CO2, biogenic CH4, and N2O separately.

Implicit in exogenous scenarios are emission trajectories. If setting exogenous scenarios, especially if they involve an abatement target consistent with 1.5°C warming [66], there should be consideration whether the marginal social costs SC-CO2, SC-CH4 and SC-N2O need adjustment over the timeline of the scenario [67].

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1.7 Appendix

1.7.1 Global economic losses from food system emissions by gas

Figure 6 provides an indication of total economic losses from global food system annual CH4, CO2 and N2O emissions. Total losses average US$2020 PPP 1 trillion.

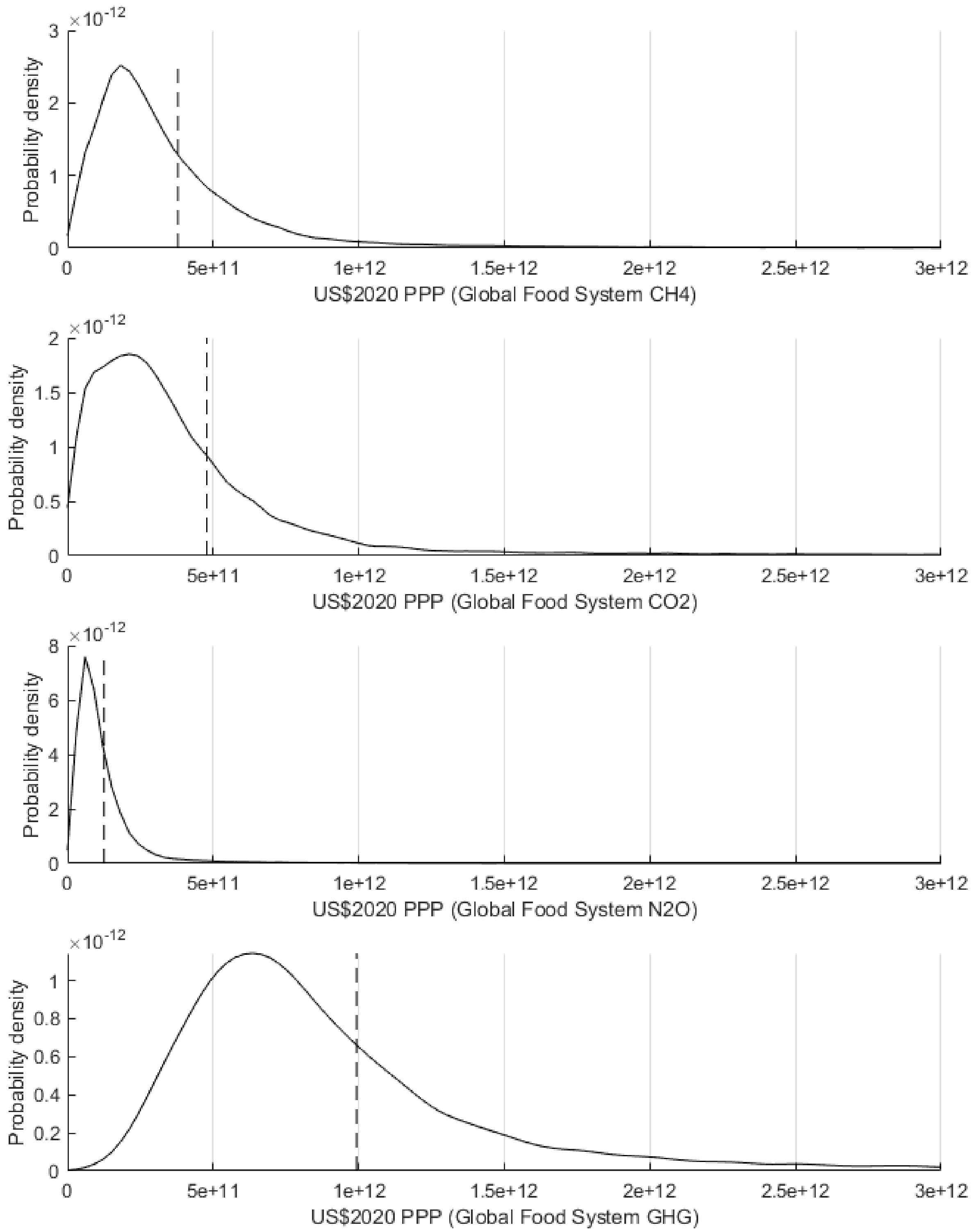

Figure 6: Economic losses from direct, energy, and industrial, GHG emissions in 2015 attributed to the food system. 2015 CH4, CO2 and N2O emissions from [1]. Losses determined by optimal abatement of GHG modelled by the DICE. FUND and PAGE models.

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At least according to the abatement modelling in DICE, FUND and PAGE, the amounts in Figure 6 are the amounts of present and future global GDP recoverable through spending on abatement of annual food system emissions. The addition cost of CH4 and N2O means that the economic losses are higher than CO2e. Food system CH4 and N2O emissions produce more total economic loss from climate change than CO2. The total losses (bottom panel in Figure 6) are formed from summing samples of the loss distributions of the individual gasses using the sampling method described in the main text (draws from the same future scenario). Due to the greater influence of the models on uncertainty than future scenario, the samples, essentially, are independently drawn. The shape of the distribution of total losses is not lognormal but is positively skewed. There is greater risk in higher losses. The 95-th percentile of the distribution of total economic loss is US$2020 PPP 2.4 trillion.

1.7.2 Economic losses by stage of food system

Economic losses from direct, energy, and industrial, GHG emissions in 2015 using samples of SC-CO2, SC-CH4 and SC-N2O from the IWG-SCGG dataset are attributed to stages of the food system in Figure 7. 2015 CH4, CO2 and N2O are attributed to stages according to data from [1].

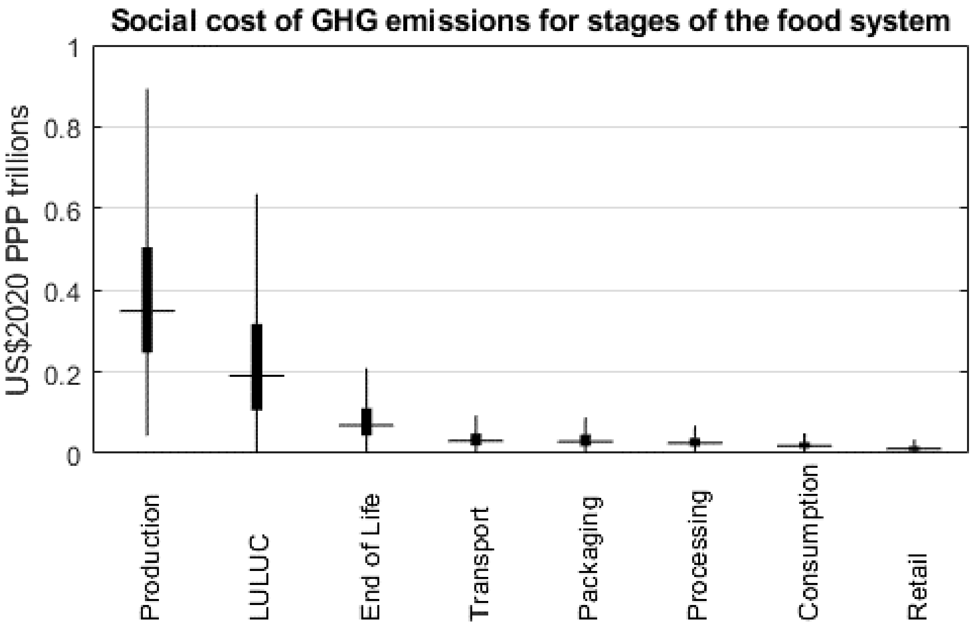

Figure 7: Economic losses from direct, energy, and industrial, GHG emissions in 2015 attributed to stages of the food system. 2015 CH4, CO2 and N2O attributed to stages according to data from [1]. Losses determined by optimal abatement of GHG modelled by the DICE. FUND and PAGE models. Median is black horizontal line, and thick vertical line represents interquartile range.

Direct emissions from agriculture and land-use dominate economic losses, with a median value of more than US$2020 500 billion and a mean value of more US$2020 700 billion. At least according to the abatement modelling in DICE, FUND and PAGE, these are the amounts of global GDP recoverable through spending on abatement. Interquartile range of the proportion attributed to post farm-gate and pre-waste stages is 11-19% of total economic loss (Figure 8).

Annex A

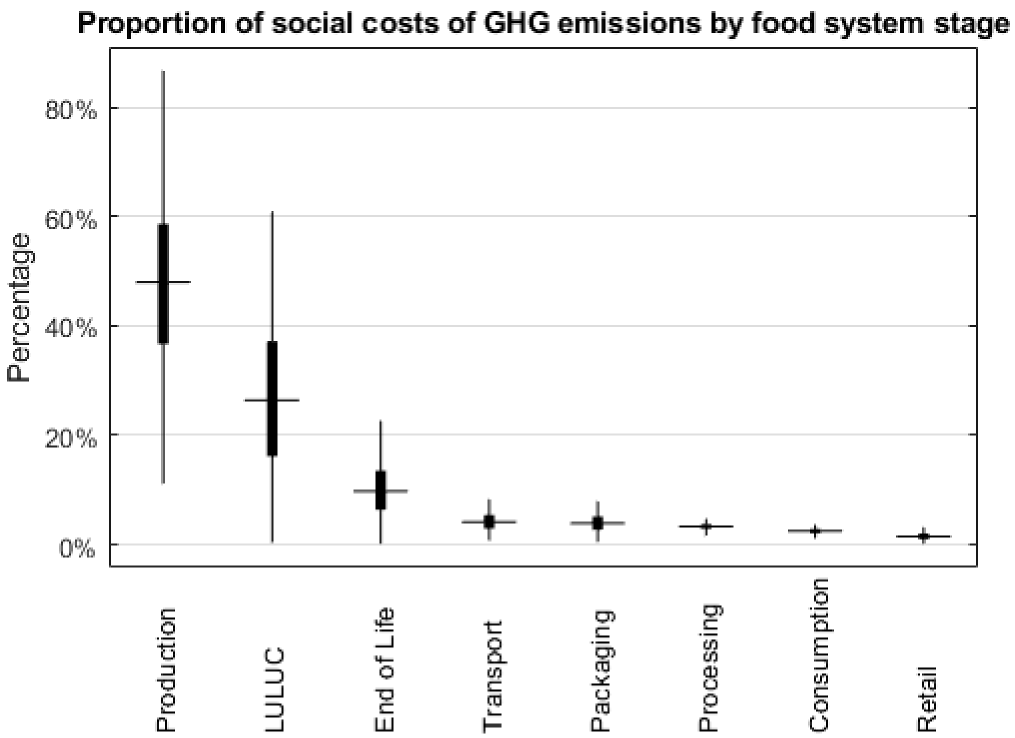

Figure 8: Percentage of the total economic losses from direct, energy, and industrial, CH4, CO2 and N2O emissions in 2015 by stage of the food system. 2015 CH4, CO2 and N2O attributed to stages according to data from [1]. Median is black horizontal line, and thick vertical line represents interquartile range.

The proportions of economic loss attributed to food system stages using mean values are shown in Figure 9.

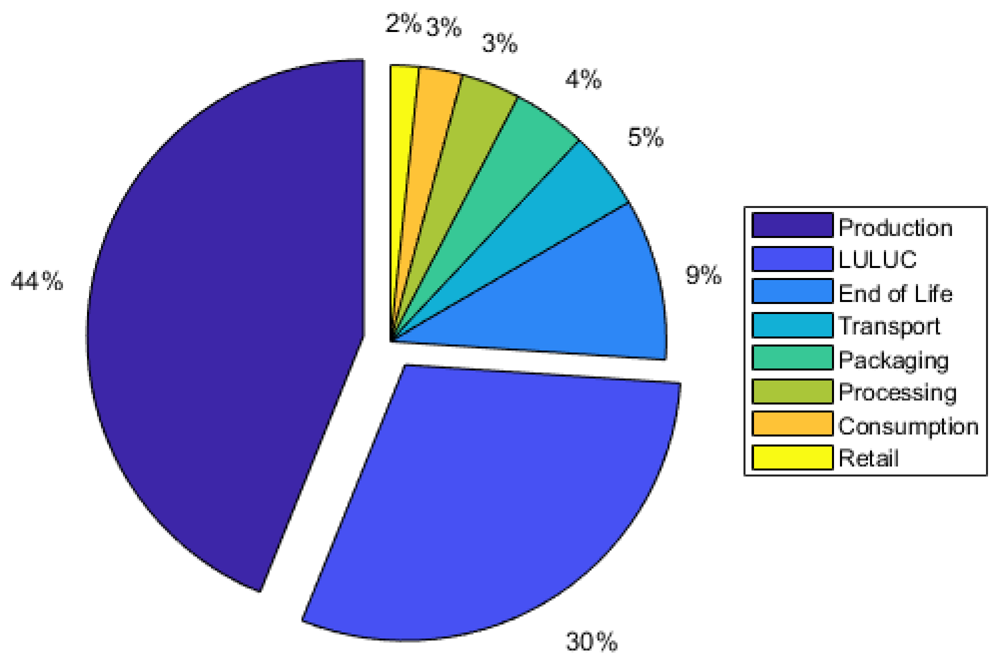

Figure 9: Percentage of mean total economic losses from direct, energy, and industrial, CH4, CO2 and N2O emissions in 2015 by stage of the food system. 2015 CH4, CO2 and N2O attributed to stages according to data from [1].