Quantifying a Range of Global Air Pollution Projections and Health Impacts under the Paris Agreement's Temperature Targets

by

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Abstract

Air pollution is a key sustainability challenge with similar emissions sources to anthropogenic climate change – making it critical to assess the effect of climate and air quality actions on pollutant emissions, the resulting health impacts, and broader sustainability metrics. This thesis responds to these needs by developing a new Tool for Air Pollution Scenarios (TAPS) and applying it to example policy effects on emissions, health impacts, and alternative metrics that are consistent with a stock-based sustainability framework of inclusive wealth. In Chapter 2, we develop and implement TAPS with three components: recent global anthropogenic emissions inventories, emitting activity scenarios from the MIT Economic Projection and Policy Analysis model, and emissions intensity trends based on recent scenario data from the Greenhouse Gas – Air Pollution Interactions and Synergies model. Initial results show the limits of existing policy and the importance of different policy levers for different pollutants – including climate action to reduce fossil fuel related air pollutants (such as sulfur and nitrogen oxides), and other air quality controls to reduce pollutants such as ammonia and organic carbon. Chapter 3 connects the tool's emissions results to health impacts, focusing on the difference between two pollution control scenarios under the common assumption that the Paris Agreement's climate targets are met. We find major differences in ambient fine particulate matter concentrations as well as impacts on premature mortality and morbidity – showing that climate action alone does not guarantee a clean-air future. We also find distributional differences between different measures of national impacts, especially when comparing standard or monetized health endpoints with our alternative that focuses on healthy life years. Finally, Chapter 4 concludes with future considerations for scenario development, analytical choices, and stakeholder considerations for integrating the health impacts of air pollution into sustainability decisions.

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And of course, my family. To Mom, Dad, Lucy, and all – I love you, very much, always.

Onward.

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1. Thesis introduction

Air pollution is an urgent issue for global health and sustainability. According to the latest State of Global Air report, ambient and household air pollution was the fourth leading cause of death in 2019 (Health Effects Institute, 2020) – with attribution to more global deaths in one year than COVID-19 has to this date (World Health Organization, 2022). Air pollution is associated with at least 20% of global deaths from stroke, diabetes, neonatal deaths and other causes (Health Effects Institute, 2020) – as well as dozens of cognitive, affective, behavioral, and economic impacts that have been documented in the literature (Lu, 2020). Such impacts may worsen spatial, racial, and socioeconomic disparities, as with the dual risks of chronic air pollution and COVID-19 in the United States and elsewhere (Chakraborty, 2021). Various pollutants can also exacerbate crop loss, acid rain, global temperature change, and more – as anthropogenic pollution adds considerably to natural sources (Hoesly et al., 2018). As a result, improving air quality is a key part of global sustainability efforts, such as the health-related Sustainable Development Goal (SDG) of the United Nations (UN).

Clean-air efforts often connect with actions to mitigate climate change, given the overlap between anthropogenic air pollution and greenhouse gas (GHG) emissions. Fossil fuels alone have been linked to more than one million (McDuffie et al., 2021) or even ten million deaths from fine particulate matter ($PM_{2.5}$) in a single year (Vohra et al., 2021), depending on the methods used. Ground-level ozone pollution is also related to the net impacts of climate change, showing increased concentrations in urban areas despite decreases in precursor emissions (Sicard, 2021). Reducing the emissions that drive climate change could lead to health benefits that are of greater magnitude than the costs of meeting the Paris Agreement's climate targets (Markandya et al., 2018). However, studies have found that climate action alone can only realize a fraction of the health benefits from optimal air pollution policy – especially when actions can occur at the level of a local source like a power plant (Reis et al., 2022; Tong et al., 2021). Thus, it is crucial to assess potential climate and air quality actions simultaneously (Selin, 2021; Vandyck et al., 2021) – and to involve stakeholders who might play a role in those actions. But given the diverse interests of potential stakeholders (Clark et al., 2016), more flexible and accessible tools are needed to capture the effects of wide-ranging scenarios on pollutant emissions and their health impacts.

Another challenge is to integrate those health impact estimates with broader sustainability metrics. Many sustainability goals reference the 1987 Brundtland Report, which defined sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (UN & WCED, 1987). However, most sustainability indices (such as the SDGs) focus on present-day conditions or near-term targets, evaluating future needs in a more indirect manner. The inclusive Wealth (IW) framework has emerged as a future-oriented alternative, earning praise as “one of the strongest contributions of science to sustainable development over the past two decades” (Clark and Harley, 2020). By shifting the focus from resource flows (such as GDP) to the need for non-declining “stocks" of produced, human, and natural capital, IW gives an increased focus on sustainable stocks for future generations (Polasky et al., 2015). But while health is seen as a central part of IW in theory (Arrow et al., 2012; Jumbri et al., 2018), applications have struggled to find consistency with the latest epidemiological literature, the stock-based framework, or each other.

This thesis responds to several needs by developing a new tool for flexible study of climate and air pollution policies, analyzing the pollutant emissions and health impacts from an example policy change, and presenting those impacts with an alternative choice of metrics that is compatible with the inclusive wealth framework. Chapter 2 describes the new capability as the Tool for Air Pollution Scenarios (TAPS), which scales standard anthropogenic air pollutant emissions inventories by the trends of polluting activities and their emission intensities. We also provide an evaluation of future emissions under several climate and pollution policy scenarios, as compared with other global estimates. Further description and documentation of the tool is available online (Atkinson et al., 2022a, 2022b). Chapter 3 uses the tool’s pollutant emissions outputs to calculate global health impacts from particulate matter pollution, focusing on the difference in pollution policy ambition even if the Paris Agreement’s climate targets are met. We quantify that difference using several metrics, including an inclusive wealth-based alternative that focuses on the cumulative effect on a population’s healthy life years. Finally, Chapter 4 concludes and offers some closing reflections on scenario development, analytical choices, and stakeholder considerations for integrating the health impacts of air pollution into sustainability decisions.

2. A Tool for Air Pollution Scenarios (TAPS v1.0) to enable global, long-term, and flexible study of climate and air quality policies

As of May 2022, the current form of this chapter is under review as a preprint at https://gmd.copernicus.org/preprints/gmd-2022-103/ (Atkinson et al., 2022b). It is available for distribution under the Creative Commons Attribution 4.0 License.

2.1 Introduction

Air pollution is an urgent global health threat, with similar sources to the greenhouse gas (GHG) emissions that drive anthropogenic climate change. Fine particulate matter ($PM_{2.5}$) from fossil fuels and other human sources may have caused millions of premature deaths in recent years (Lelieveld et al., 2019; McDuffie et al., 2021) – while ground-level ozone can exacerbate crop loss and worsen socioeconomic disparities (Saari et al., 2017). Projecting these impacts requires future scenarios for those air pollutants' precursor emissions – but more flexible and accessible tools are needed to elucidate the interdependent but distinct effects of economic, climate, and pollution policy on air quality and human health.

Many research efforts focus on the health "co-benefits" of reduced air pollutant emissions from mitigating GHG emissions (Gallagher and Holloway, 2020; Karlsson et al., 2020). Studies have found that the near-term health benefits from GHG reductions can be on par with or even greater than their near-term climate benefits (Markandya et al., 2018; Shindell et al., 2021). Health benefits vary strongly by region and sector (Vandyck et al., 2020), highlighting the importance of granular analyses and actions that prioritize reductions in high-emitting areas (Polonik et al., 2021). As such, climate action must be complemented by pollution-specific policies to maximize air quality benefits (Reis et al., 2022; Tong et al., 2021) – prompting calls for combined policy assessments to address both issues together (Selin, 2021; Vandyck et al., 2021).

For studies that do vary both climate and air quality policies, most use one of a few existing scenario sets. Current options include the shared socioeconomic pathways (SSPs), a set of global scenarios to 2100 that treat climate and air pollution separately but tie the latter to specific societal narratives (O'Neill et al., 2017; Riahi et al., 2017). Each SSP is associated with a specific pollution control ambition, with regional emissions intensity trends that depend on affluence levels (Rao et al., 2017). These trends were derived from two scenarios developed with the widely used Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) model: current legislation (CLE), which assumes compliance with existing source- and region-specific emission limits, and the maximum feasible reduction (MFR) case, which assumes gradually increasing application of the lowest-emitting, currently available technologies (Amann et al., 2011; Klimont et al., 2017). The resulting air pollutant emission trajectories are included in the sixth Coupled Model Intercomparison Project (CMIP6) and presented online (IIASA, 2018; Rogelj et al., 2018).

Other approaches have a different scope of economic assumptions, timescales, or pollutant species. While several studies vary climate and air quality scenarios across pollutants, they often project emissions intensities based on income rather than policy (Radu et al., 2016; Scovronick et al., 2019). Others have begun to internalize climate-health-economic linkages into optimal policy pathways (Reis et al., 2022), while still using SSP pollution assumptions as baselines. Studies in the Energy Modeling Forum (EMF)-30 use the GAINS scenarios more directly, focusing on black and organic carbon (Smith et al., 2020) or non-agricultural pollutants through 2050 (Vandyck et al., 2018). Since then, GAINS has been updated with more nuanced regions, sectors, and emissions trends (GAINS Developer Team, 2021) – such as recent SO_2 (Zheng et al., 2018) and black carbon (Kanaya et al., 2020) reductions in China, as well as revised data and SSP-consistent modeling for the waste management sector (Gomez Sanabria et al., 2021).

Some recent studies have used this updated GAINS model to explore more near-term results or policy extremes. Rafaj et al. (2021) use several integrated assessment models (IAMs) to assess health impacts around current climate policies, proposed policies, or likely attainment of the Paris Agreement's temperature targets (through 2050) – applying GAINS CLE and MFR to the 1.5°C case while maintaining CLE otherwise. Amann et al. (2020) develop a "Clean Air" scenario that includes additional climate, energy, agriculture, and food policies – finding that those additional policies (beyond GAINS' traditional air pollution controls) would lead to nearly double the benefits of reduced $PM_{2.5}$ exposure. I. Hamilton et al. (2021) use a related scenario of "health in all climate policies", including air pollution reductions, diet change, and active travel benchmarks in nine selected countries. Both these latter papers focus on aggregate effects (comparing base cases to scenarios of those policy levers combined together), and are limited geographically (I. Hamilton et al., 2021) or temporally to 2040.

We aim to present a more flexible model-based capacity for long-term global scenarios of air pollutant precursor emissions. The resulting Tool for Air Pollution Scenarios (TAPS) can efficiently assess a wide range of climate and air quality policy pathways – from broad to specific at the regional, sectoral, and fuel-based level. In addition, its emissions outputs can readily drive global atmospheric chemical transport models (CTMs) to assess health outcomes – avoiding dependence on previous CTM runs and base years. We demonstrate the tool with illustrative scenarios after coupling with the Economic Projection and Policy Analysis model (EPPA). EPPA is a global multi-region multi-sector recursive–dynamic computable global equilibrium (CGE) model that has been used to study a variety of climate and economic policy impacts (Y.-H. H. Chen et al., 2015, 2017; Paltsev et al., 2005). While prior efforts have sought to endogenize EPPA's air pollutant emissions trends based on the cost of pollution control options (Sarofim, 2007; Valpergue De Masin, 2003; Waugh, 2012), their use has been limited to select studies (Nam et al., 2013). In contrast, the TAPS framework can be exercised autonomously for flexible scenario development (**Figure 1**).

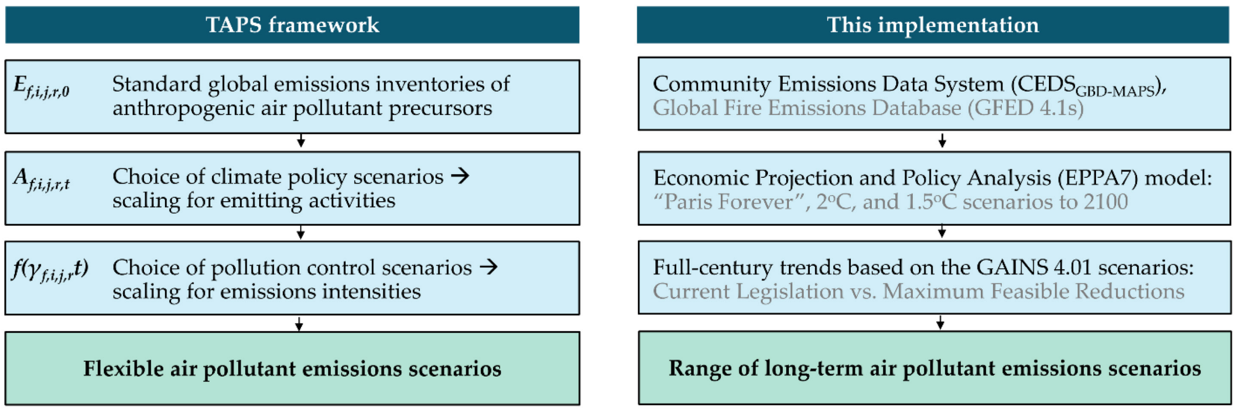

Figure 1. Summary of the Tool for Air Pollution Scenarios (TAPS) framework and implementation. Based on climate policy scenarios in EPPA7 and pollution control scenarios from the Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) model. Emissions trends are specific to each fuel f, sector i, pollutant species j, region r and time point t in the inventories and EPPA7 scenarios used.

First, we utilize emissions inventories that are well suited for atmospheric modeling work on health impacts – following the SSPs' sources but with updated estimates. Next, we scale those emissions by fuel-specific activities in EPPA, using climate policy scenarios from the global CGE model with full-century time horizons that are longer than most comparable works. Finally, we use updated emissions intensity scenarios from GAINS to assess policies specific to air pollution – while designing pathways that allow for future innovation beyond today's technology options. The following section will describe these steps in turn, before comparing results to SSP benchmarks and discussing next steps for tool refinement and health applications.

2.2 Methodology

Our estimates of air pollutant emissions involve three main inputs: a base-year emissions inventory (Sect. 2.2.1), a projected trend in energy use and other polluting activities (Sect. 2.2.2), and a projected trend in emissions intensity (Sect. 2.2.3). The following equation (based on **Figure 1**) summarizes these components:

$$E_{f,i,j,r,t} = E_{f,i,j,r,0} * A_{f,i,j,r,t} * f(\gamma_{f,i,j,r}t) \qquad (1)$$

In this way, the emissions $E_{f,i,j,r,t}$ of inventory fuel f, inventory sector i, pollutant species j, EPPA region r, and time t are calculated as the product of base-year emissions $E_{f,i,j,r,0}$, fuel-specific activity $A_{f,i,j,r,t}$, and the function $f(\gamma_{f,i,j,r}t)$ for scenario-specific emissions intensity over time. The below sections discuss each of these components in more detail, as well as the specific scenarios shown in this analysis (Sect. 2.2.4).

Public versions of the tool, outputs and underlying data are described in Atkinson (2022a). To facilitate coupling with global atmospheric CTMs for health impacts analysis, we also include the capability to produce gridded outputs for emissions scaling – following the inventory's spatial distribution as done for the SSPs (Feng et al., 2020). Inputs and Python code can be downloaded and modified to explore the effects of different climate or air quality policies at the region, sector or fuel-based level. While it is simplest to construct scenarios that maintain the structure of current data sources (adjusting from Sect. 2.2.4), future TAPS applications could theoretically be extended to other inventories or policy model outputs if the database integration steps were completed (adjusting from Sect. 2.2.1-2.2.3).

2.2.1 Base-year emissions inventory

This paper uses base-year emissions from the Community Emissions Data System's Global Burden of Disease Major Air Pollution Sources project ($CEDS_{GBD\text{-}MAPS}$), an updated version of the anthropogenic air pollutant emissions inventory used in the SSPs as well as atmospheric modeling of health impacts (GEOS-Chem, 2021). CEDS is a global inventory that includes sulfur dioxide (SO_2), nitrogen oxides (NO_x), ammonia (NH_3), black carbon (BC), organic carbon (OC), carbon monoxide (CO), and 23 separate non-methane volatile organic compounds (NMVOC). It offers monthly data globally on a 0.5°×0.5° grid for 1750-2014 (Hoesly et al., 2018), with updates for 1970-2017 (McDuffie et al., 2020) that divide each of 11 sectors into 4 fuel categories (**Table 11**). Compared to subsequent versions with fewer sectors and no fuel separation, we use the version in McDuffie et al. (2020) because it combines fuel-specific granularity with emissions totals that largely match the latest updates in https://github.com/JGCRI/CEDS (such as lower BC and OC totals). We use 2014 emissions to match the economic base-year of the GTAP10 database (Aguiar et al., 2019) used in EPPA7 (as described in Sect. 2.2.2).

We also include emissions of agricultural waste burning, the only type of open burning represented in EPPA's economic activities (Chepeliev, 2020). We follow the SSPs (van Marle et al., 2017) and GEOS-Chem (2021) by using emissions from the Global Fire Emissions Database (GFED) version 4.1s at a 0.25°×0.25° grid (van der Werf et al., 2017). Although GFED gives emissions estimates in terms of dry matter rather than specific pollutants, we use emission factors based on Akagi et al. (2011) to convert these estimates to pollutant-specific emissions, as recommended by GFED and done for the SSPs (see van Marle et al. (2017), Table C1). We use 2014 values to match the base-year inventory of EPPA7, having checked for general consistency with emissions quantities from neighboring years. We do not include emissions from wildfires, non-anthropogenic sources, or other burning sources in GFED (given their lack of representation in EPPA and GAINS). In addition, we do not currently include aviation emissions, given their exclusion from both $CEDS_{GBD\text{-}MAPS}$ and GAINS.

2.2.2 Projecting emitting activities

This paper uses full-century activity outputs from several of EPPA's global climate policy scenarios. The latest version of the EPPA model (EPPA7) has 18 regions of the world and 14 economic sectors, as summarized in Appendix B (Paltsev et al., 2021). To scale the base-year emissions inventories by future trends in EPPA, we perform sectoral mapping from each of the 12 inventory sectors (11 from $CEDS_{GBD\text{-}MAPS}$ plus agricultural waste burning from GFED) to one or more of the EPPA7 sectors (**Table 1**). The process is based on comparisons of CEDS sectors with GTAP10 (Chepeliev, 2020) and its transferal to EPPA sectors, using standard Intergovernmental Panel on Climate Change (IPCC) definitions as a common reference point (**Table 17**). Since EPPA lacks direct matches for "Waste", "Solvents", or the "Residential" emissions that are often from solid biofuels in CEDS, we use population to scale these sectors. Despite its approximations, this sectoral mapping is useful to keep emissions projections in terms of CEDS and GFED sectors, facilitating SSP comparisons and future atmospheric modeling applications.

Next, we select fuel-specific parameters to scale each emitting activity based on the approach used in the similar U.S. Regional Energy Policy (USREP) model (Yuan et al., 2019). In USREP, emissions from fuel consumption are mostly scaled by future sectoral energy consumption, while non-combustion sources are scaled by that sector's economic output (Dimanchev et al., 2019; Thompson et al., 2014). Here, we apply a similar method to EPPA as described in **Table 1**, using the four fuel categories (three for combustion, one for "process") in $CEDS_{GBD\text{-}MAPS}$. Each source's scaling is based on the proportion of its base-year emissions (**Table 11**) as follows:

$$A_{f,i,j,r,t} = \frac{E_{f,i,j,r,0}}{E_{i,j,r,0}} * \sum_{Ei} A_{f,Ei,r,t} \quad , \qquad (2)$$

where the EPPA activities $A_{f,Ei,r,t}$ are aggregated via summation across the EPPA sectors Ei that are mapped to each inventory sector (see **Table 1**). For fuel combustion, coal fuels are scaled by EPPA coal energy use trends (in joules), "liquid-fuel-plus-natural-gas" activities are scaled by aggregate oil and gas use trends, and solid biofuel sources are scaled by total sectoral energy use trends. For process-related emissions, some sources like manure management are clearly outside of the energy realm, while others (such as natural gas flaring) may reflect energy activities as well (McDuffie et al., 2020). Accordingly, we scale agricultural waste burning by crop land use trends, and energy or industry “process” sources by their sectors’ total energy trends. For agriculture, we use a “per tonne” basis for consistency with GAINS’ emissions intensity units – multiplying EPPA’s sectoral land use trends (in hectares) by linearly extended production-per-area total crop trends (in tonnes per hectare) from the Food and Agriculture Organization (FAO, 2018). The overall scaling procedure is done for each scenario, pollutant, CEDS or GFED sector, and EPPA region, having linked each CEDS or GFED sector to EPPA sectoral drivers (**Table 1**) and mapped the CEDS and GFED grids to EPPA regions.

2.2.3 Projecting emissions intensities

Finally, we scale each activity’s emissions intensity with region- and sector-specific trends from the GAINS 4.01 scenarios (GAINS Developer Team, 2021; Klimont et al., 2017). Global data and projections from 2000-2050 are available for non-agricultural sectors and air pollutant species through the Energy Modeling Forum (EMF) study scenario data sets (Smith et al., 2020) that have been updated to GAINS 4.01. However, the EMF study does not include NH_3, agriculture, or agricultural waste burning. GAINS estimates for these sectors have been provided separately and only for G20 regions. We map both data sets to the CEDS sector-fuel combinations and EPPA regions analyzed here, as described in **Table 1**, **Table 13-Table 16,** and our online repository (Atkinson et al., 2022a).

Table 1. Sectoral mapping and choice of scaling method for each inventory sector.

CEDS/GFED sector	EPPA sector(s)	CEDS fuel	EPPA activity	GAINS EMF sector classes
Agriculture	CROP, FORS, LIVE	Process	Land production	See **Table 14**
Agricultural waste	CROP	Process	Land use	See **Table 14**
Energy	COAL, ELEC, GAS, ROIL	Biofuel	Total energy	Power_Gen_Bio
		Coal	Coal energy	Power_Gen_Coal
		Oil & gas	Oil & gas energy	Power_Gen_(HLF, LLF, NatGas)
		Process	Total energy	Losses, Transformations
Industry	EINT, FOOD, OTHR	Biofuel	Total energy	End_Use_Industry_Bio
		Coal	Coal energy	End_Use_Industry_Coal
		Oil & gas	Oil & gas energy	End_use_Industry_(HLF, LLF, NatGas)

		Process	Total energy	AACID, CEMENT, CHEMBULK, CHEM, CUSM, NACID, PAPER, STEEL
Commercial	SERV	Biofuel	Total energy	End_Use_Services_Bio
		Coal	Coal energy	End_Use_Services_Coal
Residential	Population	Biofuel	Population	End_Use_Residential_Bio
		Coal	Population	"_Coal
		Oil & gas	Population	"_(HLF, LLF, NatGas)
Other (combustion)	CROP, FORS, LIVE	Oil & gas	Oil & gas energy	End_Use_Transport_(AGR, OFF)_(LLF, HLF)
Shipping	TRAN	Oil & gas	Oil & gas energy	"_OFF_(LLF, HLF)
Solvents	Population	Process	Population	CHEM, CHEMBULK
Transport	TRAN	Oil & gas	Oil & gas energy	End_Use_Transport_(NatGas, HDT_HLF, HDT_LLF, LDT_HLF, LDT_LLF, MC_LLF)
Non-road transport	TRAN	Coal	Coal energy	End_Use_Transport_Coal
		Oil & gas	Oil & gas energy	"_(NatGas, OFF_LLF, OFF_HLF)
Waste	Population	Process	Population	Waste

See online repository for full GAINS sector and fuel linkages. CEDS fuel definitions are given in Table S1 of McDuffie et al. (2020) – with bioenergy separated between solid ("Biofuel") and liquid fuels ("Oil & gas"). CEDS-GAINS fuel type discrepancies were recalibrated based on the percent of CEDS fuel emissions covered by GAINS. Residential, Solvents, and Waste sectors were scaled by EPPA population projections, given the lack of sufficient corollary sectors in EPPA. Land production combines land use from EPPA (in area units) with production per area trends from corollary FAO (2018) scenarios. GAINS EMF sectors are given in Table S3 of Rafaj et al. (2021) and https://gains.iiasa.ac.at/models/index.html.

First, we calculate emissions intensity trends for each GAINS sector by dividing the emissions time series by activity time series. Historical data are available for 2000, 2005, 2010, and 2015 – with projections for the CLE (2020, 2030, 2050) and MFR scenarios (2030, 2050). For missing activity data points, we conduct annual linear interpolation (and/or extension) for sectors with at least two values, or leave emissions intensities constant for sectors with one or no values. For trend extensions that reach zero before 2050, we assume values of zero thereafter. For the GAINS waste sectors – where only emissions (not activities) were given – we assume constant emissions intensities for CLE, versus region-specific trends to zero by 2050 for MFR (based on MFR/CLE emissions ratios) in accordance with a recent GAINS paper (Gomez Sanabria et al., 2021). NH_3 waste trends are matched to NO_x due to large data gaps.

For other NH_3 sectors, we employ a conservative approach towards estimating intensity reductions outside of the GAINS G20 regions. For MFR, we assume that the non-G20 regions follow the MFR intensity trend of their corollary G20 regions (**Table 16**) – but with constant intensities in CLE (only following the corollary if its intensity is constant or increasing). For agriculture sectors (where intensity could rise or fall due to shifting land use or dietary patterns), we also incorporate more granular sector trends from the Food and Agriculture Organization's 2050 scenarios of "Business as Usual" (CLE-like) and "Toward Sustainability" (MFR-like), which directly inform the GAINS database as well (FAO, 2018). The resulting intensity trend I combines the GAINS trend (GI) with FAO's trend for sector i relative to total production ($F_{r,t}$):

$$I_{f,i,j,r,t} = GI_{f,i,j,r,t} * \frac{F_{i,r,t}}{F_{r,t}} \quad (3)$$

This adjustment allows for the potential of a region's overall agricultural intensity to change based on shifts in the relative share of the emitting sectors within agriculture (such as livestock categories, milk production, or fertilizer tonnage). Associated FAO sectoral and regional mappings are provided in **Table 15** and **Table 16**.

Next, we prepare the GAINS sectors' emissions intensity trends for integration with EPPA activity trends. First, we scale the trends to a relative value of 1 in EPPA's base-year of 2014, using linear interpolation for the five-year GAINS values. To determine emissions intensity trends by CEDS sector-fuel combination (e.g., Industrial emissions from the "total-coal" fuel), we aggregate the more granular GAINS trends based on the proportion of the sector-fuel's emissions from that GAINS sector – adjusting to the proportion of emissions covered by GAINS in cases where not all the CEDS sector-fuel combinations had a GAINS equivalent. We repeat the process to aggregate from GAINS to EPPA regions.

2.2.4 Implemented scenarios

To illustrate an application of TAPS, we first select three scenarios from EPPA7 to represent variations in climate policy ambition (**Table 2**), based on Paltsev et al. (2021). The "Paris Forever" scenario assumes the completion of nationally determined contributions (NDCs) from the Paris Agreement (as of March 2021 with more recent adjustments for COVID-19), but no future climate policies beyond those near-term targets. The other two scenarios extend this NDC baseline to the Paris Agreement's long-term temperature goals, using a global emissions cap and price starting in 2030 to provide a 50% chance of limiting warming to 2°C or 1.5°C above pre-industrial levels. (Temperature estimates come from ensemble linkages of the MIT Earth System Model (Sokolov et al., 2018), or MESM, to EPPA's economic results). The 1.5°C scenario features an almost 50% reduction in global greenhouse gas emissions from

2025 to 2030, a highly ambitious projection. As such, these scenarios span a range from current pledges to a much more stringent set of future climate policies.

Table 2. EPPA7 scenarios analyzed, with selected SSP comparisons.

EPPA7 Scenario	Description
Paris Forever	Paris Nationally Determined Contribution (NDC) targets (as of March 2021) are met by all countries by 2030 and retained thereafter (Paltsev et al., 2021).
Paris 2°C	Same to 2030, with a post-2030 emissions cap, implemented with a global emissions price, to ensure that the 2100 global surface mean temperature does not exceed 2°C above pre-industrial levels with a 50% probability (Paltsev et al., 2021).
Paris 1.5°C	Same to 2030, with a post-2030 emissions cap, implemented with a global emissions price, to ensure that the 2100 global surface mean temperature does not exceed 1.5°C above pre-industrial levels with a 50% probability (Morris, Libardoni, et al., 2021).

EPPA7 Scenario	RF ($W\ m^{-2}$)	SSP IAMs compared	RF ($W\ m^{-2}$)	ΔTemp (°C)	CMIP6 analog
Paris Forever	5.95	RF6.0, Baseline [a] (19)	5.48-6.43	3.23-3.76	SSP4_60
Paris 2°C	3.82	RF3.4 (25)	3.33-3.57	2.13-2.28	SSP4_34
Paris 1.5°C	2.87	RF2.6 (19)	2.53-2.72	1.72-1.82	SSP1_26

Radiative forcing (RF) and IAM-based temperature change are global mean values for 2100, relative to pre-industrial levels of 1861-1880 in EPPA (Morris, Sokolov, et al., 2021) and 1850-1900 for the SSPs (IIASA, 2018). CMIP6 analog shows the SSP and RF combination that is most similar to each EPPA scenario. [a] IAM scenarios were not included if the radiative forcing (RF) difference from EPPA was greater than 0.5 $W\ m^{-2}$.

This range is reflected in the corresponding FAO (2018) scenarios used for agricultural production scaling: "Business As Usual" for "Paris Forever" and "Towards Sustainability" for the 2°C and 1.5°C scenarios. In **Table 2,** we also compare results from each EPPA scenario to CMIP6 scenarios and additional IAM runs from SSPs that have similar radiative forcing and other assumptions (Feng et al., 2020). While the "SSP5-3.4-Overshoot" scenario does fall in the EPPA forcing ranges, it assumes business-as-usual emissions in the near-term and plentiful negative emissions technologies in the long-term, in contrast to the EPPA scenarios' near-term NDCs and lack of negative emissions.

Turning to pollution control, we use this initial implementation to show the range of outcomes between GAINS CLE and MFR scenarios, based on version 6b of project ECLIPSE (Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants) as presented by Stohl (2015) and online (IIASA, 2019). After aggregating the GAINS emissions intensity trends to inventory sectors and EPPA regions (Sect. 2.2.3), we perform exponential fits for all non-constant intensity pathways to enable simpler scenario tuning and harmonization with EPPA's trends out to 2100. This approach also allows for the potential of future innovation beyond today's MFR levels, in contrast to the SSPs' treatment of the current MFR as a “floor” for intensities. (Pathways could differ based on the research question; we describe examples in the discussion and **Table 3**). Exponentials are designed to pass through base-year values of 1 and MFR waste values of zero for 2050 onward (using uncertainty weightings of 0.01 via the Python scipy curve fitting’s sigma parameter). Given the MFR scenario’s definition as the maximum feasible pollution reduction, anomalous cases with higher intensities than the corresponding CLE pathway are fixed to CLE levels.

The resulting trends in emissions intensity are reported in our online repository (before and after exponential fits), with ~5500 trajectories from the 2 GAINS scenarios, 7 pollutants, 18 EPPA regions, and ~20 CEDS sector-fuel combinations. The fit data includes reported r^2 values that range from strong (particularly for areas with full data sets such as Western Europe) to weaker in cases with incomplete data or abrupt changes in emissions intensities. The trends are highly sector- and region-specific, ranging from sharp decreases (such as 10-100x drops in some transportation cases) to occasional increases (sometimes due to projected fuel switching within the GAINS activities that had been aggregated to the 56 EMF sectors). Increased intensities include CO emissions from steel in Brazil, Africa, and Eastern Europe, as well as SO_2 coal emissions from residential (Eastern Europe) and end use industry (Western Europe). Finally, we combine the intensity trends with the linked base-year inventories and revised activity scaling (Eq. 1). Results are presented below and in the online repository, including outputs of all individual emissions trends as well as summary sheets of inventory value, activity scaling, and intensity scaling at notable timepoints (2030, 2050, 2100) for quicker comparisons.

Table 3. Example emissions intensity trends based on GAINS CLE and MFR scenarios.

Scenario	Description
No Improvements	Assume constant emission factors from base year.
CLE Forever	Follow CLE emission factors until 2050, and hold them constant afterwards.
CLE Trend Continues	Fit an exponential function to CLE 2000-2050, and extend that trend to 2100.
Granular Policy Choices	Adjust CLE trends with regional, sectoral, or fuel-specific policy scenarios.
SSP-like Improvements	SSP-specific improvements between CLE and MFR, depending on regional income level and reduction stringency of SSP.
MFR Trend Continues	Fit an exponential function to the historical GAINS data (2000-2015) + MFR scenario (2030-2050), and extend that trend to 2100.

CLE = Current Legislation; MFR = Maximum Feasible Reduction. For more detailed information on SSP scenarios, see Table 1-2 of the Supporting Information in Rao et al. (2017).

2.3 Results

2.3.1 Example scenario and SSP comparison

We illustrate an application of TAPS by providing the results for total air pollutant emission trends (**Figure 2**), sectoral breakdowns (**Figure 3**) and regional breakdowns (**Figure 4**). We also compare this implementation to corollary SSP IAM and CMIP6 scenarios (summarized in **Table 4**). For **Figure 2**, we show the full range of SSP-IAM combinations that have a similar radiative forcing to each of the three EPPA-MESM climate scenarios in **Table 2**. Though the SSPs and EPPA-MESM have slightly different temperature change estimates for a given forcing level, this process represents the closest comparison available between the two data sets. We facilitate this comparison by removing the SSP sectors that are not part of our scaling (aviation and open burning beyond agricultural waste), based on their emissions proportion in the best-fitting CMIP6 scenario (since sectoral non-CMIP6 IAM emissions are not available). This estimate may lead to slight visual differences in SSP data between **Figure 2** (IAM) and **Figure 3** (CMIP6), but acts as a reasonable first-order comparison with the TAPS scaling.

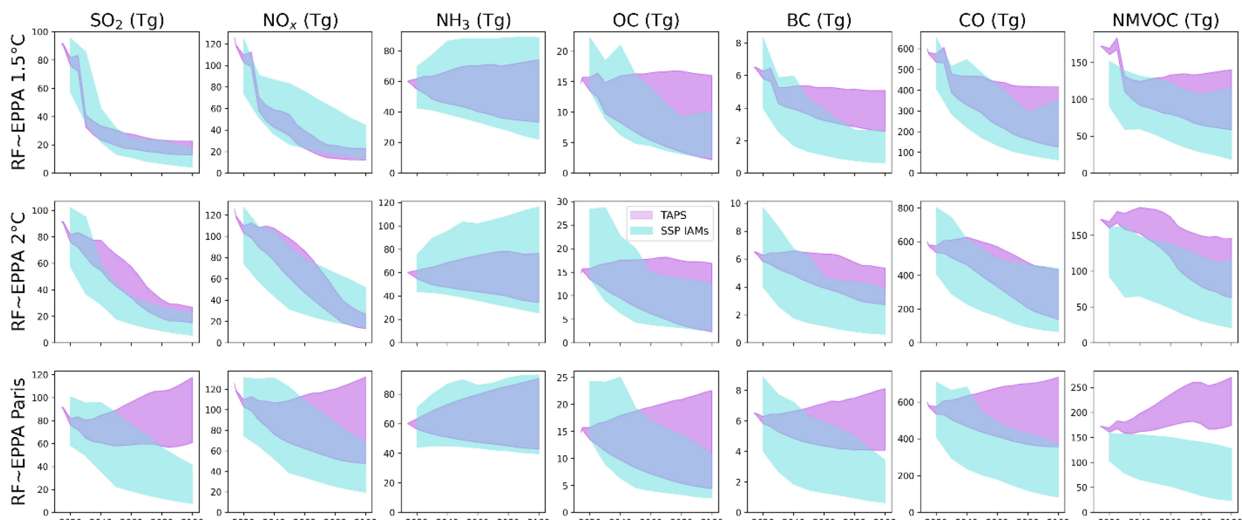

Figure 2. Global air pollutant emissions trends in TAPS example scenarios and SSP IAM corollaries. The TAPS range spans the GAINS-based scenarios of current legislation (CLE) and maximum feasible reduction (MFR) in **Table 3** (purple), as compared to the range of SSP IAM corollaries in **Table 2** (blue). IAM estimates are subtracted by sectors not scaled by TAPS (aviation and open burning beyond agricultural waste), based on their emissions proportion in the best-fitting CMIP6 scenario (since sectoral IAM emissions are not available). Quantities of NO_x are in Tg NO_2; quantities of BC, OC, and NMVOC are in Tg C.

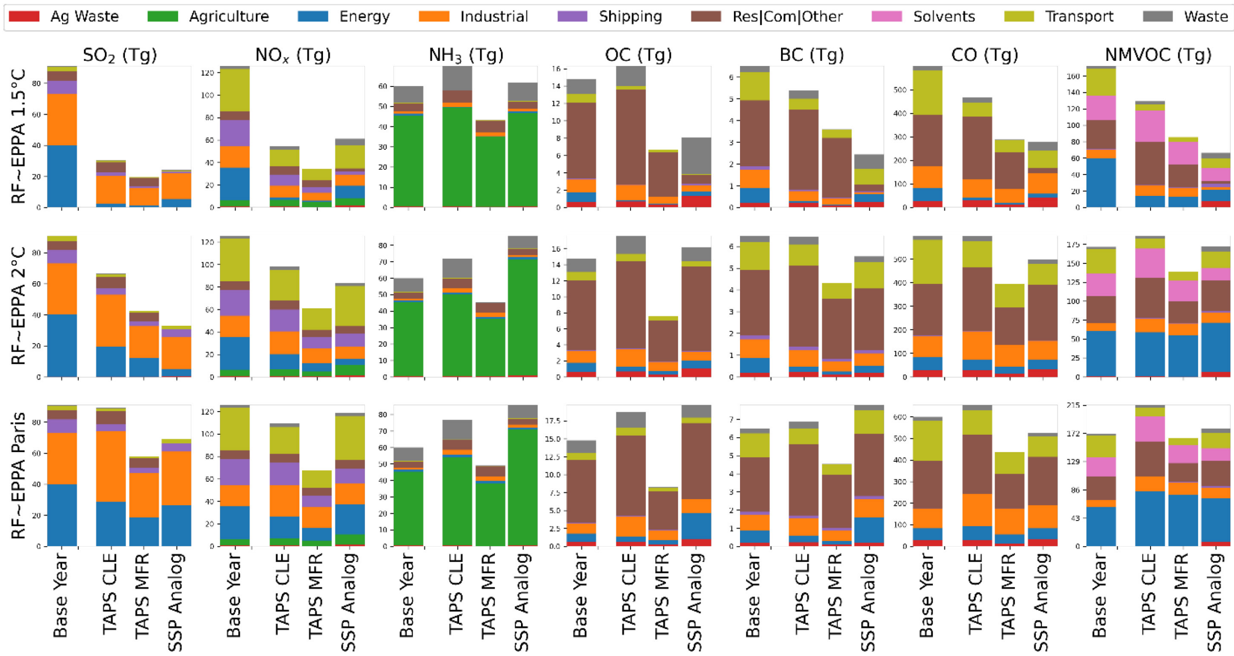

Figure 3. Sectoral emissions of air pollutants in 2050 in TAPS scenarios and SSP CMIP6 corollaries. GAINS-based TAPS scenarios include current legislation (CLE) and maximum feasible reduction (MFR) – as compared to the 2014 emissions inventories and corresponding CMIP6 scenarios of SSP1-2.6, SSP4-3.4, and SSP4-6.0 (respectively) for EPPA's 1.5°C, 2°C and Paris Forever scenarios (see **Table 2**). The 11 $\mathrm{CEDS}_{\mathrm{GBD\text{-}MAPS}}$ sectors (McDuffie et al., 2020) are condensed to the eight used by the SSPs (Hoesly et al., 2018), including the aggregation of residential, commercial, and other combustion ("Res|Com|Other"), plus agricultural waste burning ("Ag Waste") from GFED. Quantities of NO_x are in Tg NO_2; BC, OC, and NMVOC are in Tg C.

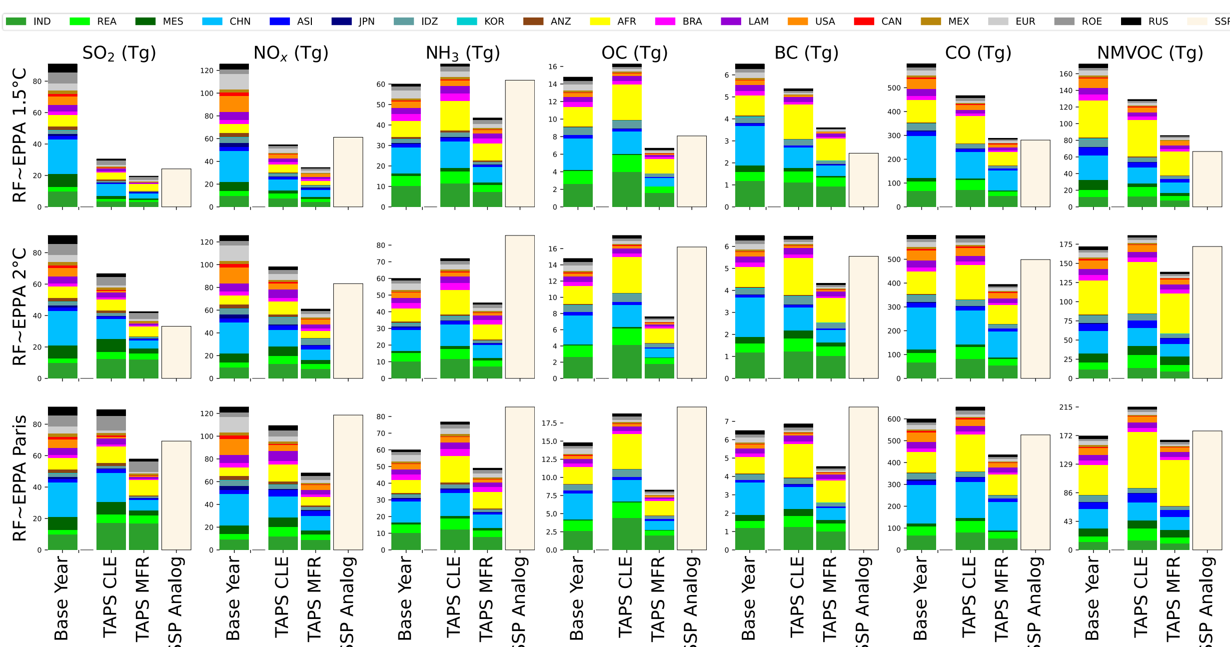

Figure 4. Regional emissions of air pollutants in 2050 in TAPS scenarios and SSP CMIP6 corollaries. See **Table 12** for EPPA region names. SSP global totals are shown due to different region boundaries.

Table 4. Summary of pathways presented.

Pathway	Base-Year Emissions	Emitting Activity Scaling	Emissions Intensity Scaling
TAPS CLE	2014; GEOS-Chem 13.0.0 defaults (CEDS, GFED) for anthropogenic emissions	EPPA7 Paris Forever, Paris 2°C, Paris 1.5°C scenarios	Fitted exponential trends from GAINS 4.01 2000-2050 CLE
TAPS MFR	2014; GEOS-Chem 13.0.0 defaults (CEDS, GFED) for anthropogenic emissions	EPPA7 Paris Forever, Paris 2°C, Paris 1.5°C scenarios	Fitted exponential trends from GAINS 4.01 2000-2050 MFR
SSP IAMs	2005; IAM-specific (Rao et al., 2017)	IAM-specific (Rao et al., 2017)	SSP-based trends via GAINS 3 (Rao et al., 2017)
SSP CMIP6	2015; past CEDS (Hoesly et al., 2018) and GFED (van Marle et al., 2017)	IAM-specific (Rao et al., 2017)	SSP-based trends via GAINS 3 (Rao et al., 2017)

SSP corollaries from the full range of IAMs are shown in **Figure 2**, while sectoral data (**Figure 3**) are only available from the CMIP6 subset. For more detailed information on IAM model inputs, see Section 2.2 of the Supporting Information in Rao et al. (2017).

When comparing initial emissions, IAM inventories differ both in base year (2005 vs. EPPA7's 2014) and emissions values (**Figure 2**) – given their variety of sources from the Emissions Database for Global Atmospheric Research (EDGAR) to GAINS to the RCP or even older IPCC inventories (Rao et al., 2017). Even after the inventories have been harmonized in the CMIP6 scenarios (Gidden et al., 2019), their use of an earlier CEDS version (Hoesly et al., 2018) leads to differences such as a base-year OC value that is 30% higher than the updated CEDS value (McDuffie et al., 2020). NMVOC inventories of emissions inside the scope of CEDS are also much lower in the IAMs, especially from the IMAGE and REMIND-MAgPIE models (IIASA, 2018).

In the TAPS example policy scenarios, trajectories do not decrease as often as in the SSPs – showing that emissions could be much higher if emissions intensity improvements are limited to current legislation. While recent studies support these cases of increased emissions (Rafaj et al., 2021), they focus on trends to mid-century. Here, many of the increases are strongest in the late century – implying that any continued improvements in the GAINS-based intensity trends are offset by further increases in activity. This contrast is strongest in industrial "process" emissions sources, where EPPA's sharp increases in activity overpower the slight decreases in emissions intensity. While the full century's trends are shown for context (**Figure 2**), the sectoral and regional plots focus on 2050 as the last year with official GAINS scenario data. We next summarize projections for each pollutant category in turn.

2.3.2 Example scenario results by pollutant

In the case of increasing SO_2 under EPPA's "Paris Forever" and GAINS' CLE scenarios, continued coal use without desulfurization and/or carbon capture is the primary factor – especially in regions with fewer current pollution controls such as Africa, South Asia, and Eastern Europe. By 2100, the doubling of industrial and residential sector emissions outpaces the decreases in energy and transport sectors. Industrial increases are driven by increased activities (4- to 10-fold by 2100 in those regions) with few intensity improvements, while residential increases are driven by a sharp increase in GAINS-based emissions intensity from Eastern Europe coal use. The GAINS MFR intensities are much lower given the additional pollution controls, halving the industrial emissions compared to CLE and leading to a 3-fold drop in energy sector emissions by 2100. Still, the increased coal activities of "Paris Forever" (especially in developing areas' non-energy sectors) prevent emissions from decreasing globally, as in Rafaj et al. (2021) but unlike the SSPs. More ambitious climate policy scenarios include rapid declines in coal energy use – leading to declining SO_2 emissions even if the intensities of remaining emissions sources (mostly industrial and residential) are nonzero.

CO and NMVOC emissions show similar trends. In the case of CO under CLE and "Paris Forever", industrial processes increase in activity (up to 10-fold in India by 2100) as well as intensity for certain regions (4-fold in Africa and 5-fold in Eastern Europe). Pollution controls in MFR reduce these increases, while causing major declines in most other sectors (including residential, unlike with SO_2). NMVOC emissions follow these general patterns, with greater influence from energy process sources that have fewer control options in GAINS and more temporal variation from EPPA trends. CLE emissions intensities are relatively flat for energy, industrial, and solvent process sources (with some increases in Brazil and much of Asia), leading to greater emissions under the "Paris Forever" scenario. Further climate policy leads to further declines in energy, transport, and industrial coal, while further pollution policy (in MFR) is more impactful for solvents, residential, and industrial process sources.

Long-term NO_x emissions also increase under less ambitious policies, given the limits of projected intensity improvements in GAINS CLE. In this pathway, increased activities in EPPA lead to increased agriculture and a doubling of industry emissions by 2100 (including a 10-fold increase in India's oil and gas fuel), offsetting initial declines from GAINS intensities and overall reductions in other sectors like energy and transport. The GAINS MFR case gives further intensity reductions, flattening industrial emissions and transitioning energy and transport to near-zero. With further climate policy in the 2°C and 1.5°C scenarios, oil and gas use in EPPA is projected to reach near-zero by late-century as well, leading to lower emissions than most of the IAMs (which may assume less steep energy declines due to their greater reliance on negative emissions).

BC and OC are driven more by residential emissions, which have limited intensity improvements in CLE but much stronger pollution controls in MFR. BC emissions are generally higher than their SSP counterparts, as increased activities overpower intensity improvements for residential, commercial, industrial, and waste sectors. Moving to MFR leads to decreases in all sectors except for commercial, while moving to a 2°C climate scenario reduces energy and industry but not the others. Pollution control actions have an even greater effect for OC. In MFR under "Paris Forever", OC residential and industrial emissions drop 8-fold and 7-fold (respectively) from 2014 to 2100, compared to increases in both sectors under CLE. Across the OC scenarios, adding pollution control ambition leads to more emissions reductions than increasing the climate policy ambition.

NH_3 also shows the pronounced effect of pollution control outside of climate policy. In CLE cases, increased agricultural production globally combines with a near-doubled intensity in Africa (by 2100) to offset slight efficiencies elsewhere. When the FAO scenario is changed from "Business as Usual" (CLE-like) to "Toward Sustainability" (MFR-like), the spread of activities is much less emissions-intensive (near-constant in Africa, Eastern Europe, and the Middle East; substantially decreasing elsewhere), and relatively flat land use trends allow for declines in overall emissions. Non-agricultural NH_3 emissions play a smaller role but follow similar patterns, with increased emissions under the limited existing policies and further reductions (such as in waste) under more ambitious policies.

2.4 Discussion

Several factors can help explain the different projection scenarios of TAPS and the SSPs. First, sectoral scaling choices differ between IAMs, as described in Section 2.2 of the Supporting Information in Rao et al. (2017). One example is the much higher value for OC waste emissions in SSP1-2.6 versus this study (**Figure 3**), which comes from a constant-emissions extension of the higher inventory value from the associated IMAGE model (IIASA, 2018). Another difference is the climate policy landscape that has changed between the SSP modeling process (mid-2010s) and the 2021 EPPA scenarios. While the latter may incorporate newer NDC pledges, the SSP IAMs sometimes assumed greater clean energy access and therefore lower biofuel-related BC emissions, for example (IIASA, 2018).

There are also differences between emissions intensity projections in GAINS 3 / ECLIPSE v5a (used by SSPs) and GAINS 4 / ECLIPSE v6b (used here), as the latter includes newer regulatory or technological levers. This is certainly the case for the waste sector, with intensity trends changing from near-constant in GAINS 3 to a net-zero MFR endpoint (elimination of open burning of municipal waste) in GAINS 4 (Gomez Sanabria et al., 2021). More granular regions and sectors, such as the refinement of residential cooking and heating (GAINS Developer Team, 2021), could also affect the pathways where those sectors play major roles (like for black and organic carbon). In addition, the updates reflect the effects of some recent policies, such as the sharp declines of SO_2 in China (Zheng et al., 2018).

It is also worth noting the differing structures of each integrated data set in TAPS, particularly with respect to the sectors and regions of CEDS, GFED, EPPA, GAINS, and FAO. The lack of direct EPPA matches for the CEDS sectors of "Residential", "Solvents", and "Waste" necessitates a scaling by population that limits the sectors' range of outcomes. We also make approximations for CEDS' solid biofuel categories, scaling by EPPA's total sectoral energy given the lack of a closer fit. Finally, the regional estimates of NH_3 trends beyond the available G20 data (chosen as constant or G20-like intensity paths for each GAINS sector) could be low or high depending on the realities in those areas. Future work could refine these assumptions as improvements become available.

Further application of TAPS could explore other emissions intensity scenarios to inform different research questions (**Table 3**). This example application demonstrates the range of outcomes between the bounds of a "continued CLE trend" and "continued MFR trend," embodied by the fitted exponentials described above. For other applications, a scenario of constant emission factors could follow other "co-benefits" studies to illuminate air quality benefits from greenhouse gas reductions alone. In addition, a "CLE Forever" case (with emission factors held at the final projected data point) could resemble the "Paris Forever" focus on short-term greenhouse gas policy, while the SSP-like scenarios could be used for more direct comparisons with their income-based pathways. Finally, additional scenario elements such as land use, diet, and active mobility could be incorporated as in recent works – given that improving such elements may lead to comparable or even greater health benefits than the pollution-specific levers explored here (Amann et al., 2020; I. Hamilton et al., 2021).

Such scenarios need not be limited to emissions intensity. With the regional, sectoral, and fuel-based EPPA outputs given in the online repository, users can readily explore the effects of more granular climate policies applied at those levels. Activity trends could be adjusted to study the effects of sector-specific policies on agricultural land use, fuel-specific policies on coal combustion levels, or region-specific policies that capture individual NDC updates (for example). Given the tool's relatively quick runtime, uncertainty analyses could explore larger ensembles of policy or other inputs to efficiently explore first-order outcome ranges, following the approach of recent EPPA studies on socioeconomic (Morris, Reilly, et al., 2021) and climate forcing trends (Morris, Libardoni, et al., 2021).

2.5 Conclusions

TAPS provides a flexible and comprehensive model for assessing climate and pollution pathways, integrating recent standard emissions inventories, long-term activity scaling, and scenario-specific emissions intensities. Results from its application to selected scenarios show lower near-term emissions than the SSPs in many cases, both from NDCs' greater climate policy ambition as well as recent pollution reduction actions now captured in GAINS. Less ambitious pathways show increased emissions in the long-term – particularly for the industrial and agricultural processes that have fewer existing controls. These increases are especially pronounced in developing regions where sharply growing activities are combined with fewer planned pollution policies. However, more ambitious climate and pollution policies can curb those increases substantially – from the SO_2 and NO_x reductions driven by fuel switching to the NH_3 reductions from land use decisions and OC reductions from pollution controls.

Future applications could explore other scenarios by adjusting a range of climate or pollution policy inputs. Assessing other climate or activity scenarios could compare the health impacts of near-term fuel switching versus long-term negative emissions. Additional emissions intensity trends could add the aforementioned elements of land use, diet, or specific innovations beyond today's technological control options. All these scenarios can be applied to specific regions, sectors, or fuels in the framework to explore more granular policies or target short-term actions with high-impact benefits.

Future tool development and linkages could consider other emissions sources – such as aviation, open burning, or wildfires – to explore the futures of additional activities that may be underestimated (Pan et al., 2020) or not fully covered by the default inventories used here. Integration with other modeling tools could examine key inter-pollutant or pollutant-climate feedbacks, such as the increased NH_3 emissions rates in a warming world (Yang et al., 2021). External coupling to other ensemble results could address important but out-of-scope elements such as meteorological uncertainty, given its importance in past studies that compared natural variability with other sources of uncertainty in health impacts analysis of air pollution (Pienkosz et al., 2019; Saari et al., 2019).

Finally, additional research with air quality and impact models could assess the health effects of TAPS emissions scenarios as well as their implications for decision-making. Quantified impacts should include a range of mortality and morbidity endpoints to capture recent epidemiological research (Danesh Yazdi et al., 2019), as well as aspects of equity, uncertainty, and sensitivity for key parameters (Hess et al., 2020). Using a combined assessment of climate and pollution policies could help reduce the siloes that have traditionally hindered the consideration of climate-health linkages in decision-making (Workman et al., 2018). Integrated impact metrics (whether through the weighting of multi-criteria decision analysis or the monetization of benefit-cost analysis) could also inform policy conversations. Ultimately, the TAPS framework could enable more flexible, efficient, and extensive scenario study of policies that affect climate change and health futures.

3. The impacts of air pollution on inclusive wealth-based sustainability: evaluating alternative metrics under an example change in future global pollution control

3.1 Introduction

The health effects of air pollution play a critical role in sustainability. Total air pollution has likely caused more annual deaths in recent years than COVID-19 (Vos et al., 2020) – with millions of premature mortalities from ambient fossil fuel particulate matter alone (McDuffie et al., 2021; Lelieveld et al., 2019). As a result, air quality is frequently emphasized in global sustainability indices, such as the health-related Sustainable Development Goal (SDG) of the United Nations (UN). However, it remains challenging to integrate these indices' many metrics (such as the dozens of health measures within the SDGs' 231 socioeconomic indicators) into a harmonized framework for sustainability decisions. Approaches include the equal weighting of the SDG Index (Sachs, 2020) as well as stakeholder-based weights in OECD's Better Life Index (2020), principal component analysis in the Social Progress Index (Nagel, 2020), or the Multidimensional Synthesis of Indicators Approach (Biggeri et al., 2019).

The Inclusive Wealth (IW) framework has gained traction as a way of evaluating progress to sustainability – particularly in its emphasis on long-term sustainability for future generations. According to Clark and Harley (2020), IW is "one of the strongest contributions of science to sustainable development over the past two decades." The framework uses a proof-based economic framework to construct a rigorous definition of sustainability as non-declining stocks of human wellbeing over time (Arrow et al., 2012) – as opposed to traditional growth metrics that simply focus on resource flows without consideration of long-term sustainability (Dasgupta, 2014). The IW framework has been applied to more than 100 countries in several retrospective UN reports (Managi et al., 2018; UNEP & UNU-IHDP, 2012; UNEP, 2014). As summarized in **Table 5**, researchers have also used IW to evaluate the sustainability of specific actions related to energy infrastructure in China (Mulvaney, 2017), Belgium (Aly and Managi, 2018), and the Middle East (Collins et al., 2017) – as well as urban planning in Japan (Ikeda and Managi, 2019) and Indonesia (Shimamura and Mizunoya, 2020). In this way, the stock-based IW approach could offer a future-oriented perspective for two purposes, helping track an entity's overall sustainability objectives as well as specific policy decisions.

However, IW studies' inclusion of health has generally been less consistent and comprehensive than other metrics. According to Arrow et al. (2012) and subsequent UN reports, health influences sustainability in at least three ways: direct effects on wellbeing; productivity; and longevity as measured by life years. Arrow et al. (2012) focus on the third component due to quantification challenges – finding that health capital exceeds all other IW components by an order of magnitude when monetized by the value of a statistical life year (VSLY). While other commenting authors questioned this use of the VSLY (K. Hamilton, 2012; Solow, 2012), Arrow et al. (2013) defended the VSLY valuation of health in a follow-up piece (Arrow et al., 2013). Nevertheless, the latest UN report excludes health capital in its "standard" approach (Managi et al., 2018) – despite a conclusion by related authors that "health stock is a vital component of global sustainable development that should be consistently included as a stock-based sustainability index" (Jumbri et al., 2018).

The inclusion of health impacts from air pollution could take several forms. Key choices include the exposure-response function(s), scope of impacts, and question of monetization. For response functions, one issue is the scarcity of cohort studies at high, globally-representative pollutant concentrations; common approaches may incorporate studies of high-concentration indoor air pollution in an Integrated Exposure Response (IER), and/or use a more flexible functional form (like the Global Exposure Mortality Model, or GEMM) to capture the studies that do exist (R. Burnett and Cohen, 2020). These functions can cover a range of impacts, including premature mortality as well as morbidities that are either acute (such as hospital admissions) or chronic (such as asthma rates). Monetized methods can include the VSL or VSLY (based on willingness to pay for the reduced risk of death), as well as direct medical costs or the wage-related cost of lost labor quantity (e.g., work days lost), quality (i.e., restricted activity days), or leisure (Matus et al., 2012). Since VSL-based methods are often much higher than wage-based costs, some authors have compared the two as upper and lower bounds (Meisner et al., 2015). For international studies where willingness to pay or other costs are not available for all countries, a common approach of "benefits transfer" uses a research-based reference value in one country to estimate the value in other countries, depending on national income and a chosen elasticity (Robinson et al., 2019).

Of the individual IW studies that do include health (**Table 5**), most use a VSLY approach (Ikeda et al., 2017; Jumbri et al., 2019). Other IW studies focus on air pollution impacts as lost labor or productivity, either as an ex-post adjustment in an inventory for India (Agarwal and Sawhney, 2021) or through interactive effects in computable general equilibrium (CGE) modelling (Collins et al., 2014). Other applications use a combination of approaches. In analyzing the relocation of Indonesia's capital city, Shimamura and Mizunoya (2020) use both VSLY and lost labor approaches to incorporate mortality, productivity, and medical cost estimates from Resosudarmo and Napitupulu (2004). For an assessment of energy infrastructure options in Egypt and Belgium, Aly and Managi (2018) evaluate VSLY-based mortalities and labor-based restricted activity days via the ExternE model (Bickel and Europäische Kommission, 2005). However, both studies use linear dose-response functions with PM_{10} – differing from the recent response function literature that emphasizes $PM_{2.5}$ and non-linearity (Ru et al., 2020; Vodonos et al., 2018).

Table 5. Review of health capital methods in Inclusive Wealth-related studies.

Year	Author	Area	Type	Time	Health Capital	Method	Scope
(2012)	Arrow et al.	5 nations	Inventory	1995-2000	Life exp.	VSL	General
(2012)	UNEP & UNU-IHDP	20 nations	Inventory	1990-2008	Life exp.	VSL	General
(2014)	UNEP	140 nations	Inventory	1990-2010			
(2018)	Managi et al.	140 nations	Inventory	1990-2014	Life exp.	VSL	General
(2012)	Mumford	USA: 48 states	Inventory	1990-2000			
(2013)	Pearson et al.	Australia basin	Inventory	1991-2001			
(2015)	Ghadimi et al.	WV USA counties	Inventory	2005-2012			
(2017)	Ikeda et al.	Japan prefectures	Inventory	1991-2010	Life exp.	VSL	General
(2018)	Yoshida et al.	Sado Island, Japan	Inventory	1990-2014			
(2018)	Lange et al.	141 nations	Inventory	1995-2014	Mortality	Labor	$PM_{2.5}$
(2020)	Jingyu et al.	China	Inventory	2000-2015			
(2021)	Zhang et al.	China, Japan	Inventory	2000-2015			
(2021)	Agarwal & Sawhney	India	Inventory	1975-2013	Mortality & morbidity	Labor	$PM_{2.5}$
(2018)	Kurniawan & Managi	140 nations	Scenarios	2014-2100			
(2018)	Jumbri et al.	140 nations	Scenarios	1990-2100	Life exp.	VSL	General
(2019)	Sugiawan et al.	104 nations	Scenarios	1993-2050			
(2019)	Ikeda & Managi	Japan	Scenarios	2014-2100	Life exp.	VSL	General
(2014)	Collins et al.	China coal use	Policy	1975-2005	Mortality & morbidity	Labor	$PM_{2.5}$
(2017)	Collins et al.	Middle East nations	Policy	2015-2050			
(2017)	Mulvaney	China coal use	Policy	2007-2030	Mortality	VSL	$PM_{2.5}$
(2017)	Ikeda et al.	Japan seawalls	Policy	2010-2030	Life exp.	VSL	General
(2018)	Aly & Managi	Egypt & Belgium power plants	Policy	2015-2050	Mortality & reduced activity days	VSL & labor	PM_{10}
(2020)	Shimamura & Mizunoya	Indonesia cities	Policy	2020-2029	Mortality, morbidity, medical cost	VSL, labor, cost	PM_{10}

Life exp. = Life expectancy; VSL = Value of a Statistical Life; UNEP = United Nations Environment Programme; UNU-IDHP = International Human Dimensions Programme hosted by the United Nations University; WV USA = West Virginia, United States of America; PM = particulate matter.

Compared to cost-based estimates of individual air pollution health impacts, an alternative approach to IW analysis could center the overall impacts on healthy life years, using combined mortality-morbidity metrics like the Disability-Adjusted or Quality-Adjusted Life Year (DALY or QALY). QALYs are often used to evaluate place-specific healthcare interventions, combining the estimated quality-of-life improvement of an intervention with its average expected duration. In contrast, DALYs focus on health threats as studied by the Global Burden of Disease (GBD) reports (Vos et al., 2020), integrating Years of Life Lost (YLL) from mortalities and Years Lived with Disability (YLD) from pre-death morbidities. Converting deaths to YLL via age-specific life expectancy has been questioned statistically (Hammitt et al., 2020) but affirmed via the age- and cause-specific baseline data of GBD (Lelieveld et al., 2020). YLD are estimated from a disease's prevalence and its disability weight from comprehensive multi-national surveys – replacing age-weighted estimates that had drawn ethics-based critiques for placing a different value on different stages of life (Arnesen and Kapiriri, 2004). This international scope marks a key difference from QALYs, which use survey-based utility weights and are more nation-specific (WHO, 2013). As a result, a recent panel of health impacts experts (Hess et al., 2020) has supported the use of QALYs for a single country (to make use of nation-specific utility weights) and DALYs internationally (given the global disability weights provided in GBD reports).

However, challenges arise when QALYs and DALYs are combined with air pollution response functions typically used in related literature (Hubbell, 2006). Beyond their additional data requirements, QALYs and DALYs do not incorporate acute effects (Bala and Zarkin, 2000) unless the year-based metric (e.g., loss of 0.3 healthy life years from a disease's poorer quality of life) is assumed to scale linearly to a symptom-day (e.g., loss of $0.3/365 = 0.0008$ healthy life years), for instance (Bell et al., 2011). Another concern for QALYs and DALYs is the issue of "double-jeopardy" (Singer et al., 1995), in which the overlap of mortalities and morbidities could skew results if they are treated separately. Schmitt et al. (2016) seek to resolve the "double-jeopardy" issue by designing a Markov model to simulate individuals' annual health state transitions between health, sickness, and death from key diseases. Others have studied the effect of national air pollution policy on both mortalities and non-acute morbidities with the metric of QALYs (Kriit et al., 2021; Lomas et al., 2016) or DALYs (Bachmann and van der Kamp, 2017; Maizlish et al., 2022).

This chapter conducts a similar investigation for global policy – focusing on the range of air quality outcomes under a climate policy scenario that meets the Paris Agreement's goals of limiting global temperature rise to 2°C above pre-industrial levels. Recent studies have increasingly pointed to a large range of air quality futures, even under this ambitious climate policy scenario. While the Representative Concentration Pathways showed a small multi-model range due to a constant assumption of pollution control (Silva et al., 2016), the Shared Socioeconomic Pathways found an exposure difference of up to 30% (within the same climate forcing) after varying the pollution control level between select economic scenarios (Rao et al., 2017). More disparate pollution control scenarios have shown larger health impact ranges, including a factor of two between a case of “fixed legislation” versus “best available technology” under a 2°C climate scenario (Vandyck et al., 2018) or a similar comparison for 1.5°C (Rafaj et al., 2021). Others have shown even greater differences if air pollution benefits are optimized, either through integrated assessment modeling (Reis et al., 2022) or from the analysis of early power plant retirements (Tong et al., 2021).

Here, we develop a theoretically-consistent approach to conduct similar health impacts assessments in the context of Inclusive Wealth theory – evaluating the difference in ambient particulate matter pollution impacts between two bounding scenarios of global pollution control. We compare these scenarios by the metric of cumulative difference in healthy life years (measured as pollution’s effect on DALYs), avoiding issues of international monetization that would skew the global distribution of benefits toward high-income areas (OECD, 2016; Reis et al., 2022). We focus on premature mortalities as well as dementia case morbidities, which are uniquely projected from a combined mortality-morbidity modeling framework (Nichols et al., 2022) and have existing global response functions for $PM_{2.5}$ (Ru et al., 2021) that have been used for similar health impacts analysis (Shindell et al., 2021). After quantifying both health endpoints, we compare traditional metrics with ours and interpret their differences.

3.2 Methodology

The following sections discuss each step of the analysis, from the policy scenarios’ precursor emissions to $PM_{2.5}$ concentrations to the studied health impacts and calculation of chosen metrics (including the cumulative difference in healthy life years for inclusive wealth).

3.2.1 Scenarios to emissions (TAPS)

We estimate global emissions of anthropogenic air pollutant precursors via the Tool for Air Pollution Scenarios (TAPS). As described in Chapter 2, TAPS combines base-year emissions inventories, projected trends in emitting activities (based on climate policy scenarios), and projected trends in their emissions intensity (based on pollution policy scenarios). We use its default data sources for each component. Inventories include the Community Emissions Data System’s Global Burden of Disease Major Air Pollution Sources project ($\mathrm{CEDS}_{\mathrm{GBD\text{-}MAPS}}$) from McDuffie et al. (2020), as well the Global Fire Emissions Database (GFED4.1s) from Van Marle et al. (2017). Scenarios of emitting activities are drawn from a recent version of MIT’s Economic Projection and Policy Analysis (EPPA7) model (Y.-H. H. Chen et al., 2015, 2017; Paltsev et al., 2005). Scenarios of emissions intensities come from version 4.01 of the Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) model (Amann et al., 2011; GAINS Developer Team, 2021; Klimont et al., 2017), using version 6b of project ECLIPSE (Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants).

The specific study scenarios are summarized in **Table 6**, using base-year emissions from 2014 to match with the EPPA7 base year. We then scale the spatial and seasonal distribution of base-year emissions by the regional year-based projections from the climate and air pollution policy pathways, as done in Feng et al. (2020) for the sixth Coupled Model Intercomparison Project (CMIP6). With climate policy, we focus on EPPA7's "Paris 2°C" scenario, which assumes completion of the Paris Agreement's 2030 Nationally Determined Contributions (as of March 2021, with more recent adjustments for COVID-19), as well as a global emissions cap and price starting in 2030 to provide a 50% chance of limiting warming to 2°C above pre-industrial levels. (Temperature estimates come from ensemble linkages of the MIT Earth System Model (Sokolov et al., 2018), or MESM, to EPPA's economic results). For pollution policy, we study two scenarios from GAINS: current legislation (CLE), which assumes compliance with existing source- and region-specific emission limits, and the maximum feasible reduction (MFR) case, which assumes gradually increasing application of the lowest-emitting currently available technologies (Amann et al., 2011; Klimont et al., 2017).

Table 6. Summary of emissions scenarios analyzed.

Pathway	Base-Year Emissions	Activity Scaling	Intensity Scaling
2050CLE	$CEDS_{GBD-MAPS}$, GFED4.1s (2014)	EPPA7 Paris 2°C scenario	GAINS 4.01 CLE to 2050
2050MFR	$CEDS_{GBD-MAPS}$, GFED4.1s (2014)	EPPA7 Paris 2°C scenario	GAINS 4.01 MFR to 2050

3.2.2 Emissions to concentrations (GCHP)

We translate precursor emissions to particulate matter concentrations via the GEOS-Chem High Performance (GCHP v13.0) model. GEOS-Chem is a global 3D model of atmospheric chemistry and transport driven by assimilated meteorological observations from the Goddard Earth Observing System (GEOS) of the NASA Global Modelling Assimilation Office (https://geos-chem.seas.harvard.edu/). GCHP is a multi-node variation that uses the native GEOS cubed-sphere grid for greater accuracy and computational efficiency (Eastham et al., 2018). GEOS-Chem simulations use a 10 minute time step for transport calculations, and a 20 minute time step for chemistry and emissions. Emissions are kept at GEOS-Chem defaults except for the scaled $CEDS_{GBD-MAPS}$ emissions, as well as GFED agricultural waste burning emissions, from TAPS. The annual scaling is applied to the monthly inventory values of emissions fluxes per second, which are used for the emissions time step of GEOS-Chem. $PM_{2.5}$ concentrations are calculated for standard conditions of 35% relative humidity (RH). The calculation is performed using the dry (0% RH) concentrations of all aerosol species, in μg m^{-3}, as follows:

$$PM_{2.5} = (NH_4^+ + NIT + SO_4^{2-}) * 1.10 + BCPI + BCPO + \{OCPO + (OCPI * 1.05)\} * (OM/OC\ ratio) + DST1 + (DST2 * 0.38) + (SALA * 1.86) + (SOA * 1.05) \quad (4)$$

where SO_4^{2-}, NIT, and NH_4^+ represent sulfate, nitrate, and ammonium mass in aerosols, respectively; BCPI and BCPO represent hydrophilic and hydrophobic BC; OCPI and OCPO represent hydrophilic and hydrophobic OC; SALA represents accumulation mode sea salt; and SOA refers to secondary organic aerosol. DST1 and DST2 represent dust with size bins of 0.2–2.0 and 2.0–3.6 µm in diameter, respectively, and 38% of the mass in the DST2 bin is assigned to $PM_{2.5}$ (as of version 13.0). The default OM/OC ratio of 2.1 is used, and the other factors represent hydroscopic growth factors for 35% RH (as described at http://wiki.seas.harvard.edu/geos-chem/index.php/Particulate_matter_in_GEOS-Chem).

For this case study, we perform two GCHP runs representing the CLE and MFR scenarios in 2050. Each case uses projected climate and meteorological outputs from the linkage of MIT's Integrated Global System Model with the National Center for Atmospheric Research Community Atmospheric Model (IGSM-CAM), as described in Monier et al. (2015). We focus on the POL3.7 scenario, which reflects the Paris 2°C policy scenario given its total radiative forcing of 3.7 W m^{-2}. These outputs are integrated with the scaled air pollutant emissions from TAPS for the 2050 scenarios, which are run for the full year (plus six months of spin-up starting in July 2049) at C48 (~2°x2.5°) resolution. We focus on the surface-level, daily average concentration of $PM_{2.5}$ for estimation of health impacts.

3.2.3 Concentrations to health impacts

This case study focuses on two major health impacts from particulate matter: premature mortality and dementia morbidity. Both allow for the inclusion of recent non-linear response functions, as well as globally projected baselines that are less widely available with other health impacts. After converting GCHP's daily average $PM_{2.5}$ concentration to an annual average, we regrid to 0.5°x0.5° for integration with demographic and health baselines.

For gridded population by five-year age group, we use the Gridded Population of the World's UN World Population Prospects (WPP)-Adjusted Population Count, version 4.11 at 30 arc-minute resolution, for 2010 as the most recent year with age groups (CIESIN, 2018). For baseline population in 2050, we scale the 2010 grid by the national 2050-to-2010 ratios from the UN WPP source used by EPPA (UN, 2019). Projections of baseline mortality rates use country-specific all-cause reference cases from Vollset et al. (2020), multiplied by the GBD 2019 country-specific fraction of mortalities from the causes covered by our chosen response function (since no age- and cause-specific projections were available from GBD). Baseline dementia rates use country-specific 2050 projections in Nichols et al. (2022), multiplied by the GBD 2019 country-specific fraction of dementia cases (GBD cause ID 543: "Alzheimer's and other dementias") from the 65-and-older age groups covered by our chosen response function. For countries without available baseline rates, the global baseline rates are applied. The age group of 65-and-older accounts for roughly 89% of global dementia cases in 2019 GBD data.

We estimate premature deaths attributable to ambient $PM_{2.5}$ by using the Global Exposure Mortality Model, or GEMM (R. Burnett et al., 2018). GEMM extends a log-linear approach by allowing for the option of other non-linear functional forms, as defined by transformations of concentration. It is based on cohort studies of ambient $PM_{2.5}$ that aim to cover the full global exposure range (including high-exposure areas). We use the response function that includes noncommunicable diseases (NCDs) and lower respiratory infections (LRIs), represented as GEMM NCD + LRI. Premature deaths in each grid cell are estimated as:

$$Mort = P_i * y_i * \left(1 - \frac{1}{R_i}\right) \tag{5}$$

where i represents each age group, P_i and y_i are the population and baseline mortality rate of the specified age group, $(1 - 1/R_i)$ is the fraction of deaths attributed to ambient $PM_{2.5}$ exposure, and R_i is the hazard ratio between incidence rates in exposed and unexposed populations. Hazard ratios in each grid cell are estimated as:

$$R(z) = \exp\{\theta \log(1 + \frac{z}{\alpha}) * \{1/(1 + \exp[- \frac{(z-\mu)}{v}]) \} \} \tag{6}$$

where z = max (0, C_{cf}), based on the grid cell's annual average $PM_{2.5}$ concentration as well as C_{cf}, the counterfactual concentration (2.4 μg m^{-3}) below which there is no additional risk. θ and its standard error are estimated by fitting the data to the Cox proportional hazard model (Cox, 1972) using standard computer software. α and μ control the function's curvature and shape (respectively), and $v = \tau * r$ (in which r reflects the range of pollutant concentrations in the GEMM cohort and τ controls the curvature). We use the age-specific set of parameters (θ, α, μ, v) estimated for NCD + LRI, including the Chinese Male Cohort, from Burnett et al. (2018) for each five-year group (ages 25-29 to ages 80-and-older). We sum the results for each age group to give the national and global impacts presented. Uncertainties for health impacts analysis are reported as a 95% confidence interval (CI) using the θ standard error.

The effect of $PM_{2.5}$ on dementia cases is explored in Ru et al. (2021), who develop GEMM-like response functions based on the "newer, convincing evidence" noted in a recent *Lancet Commission* report (Livingston et al., 2020). Given a lack of studies in high-concentration areas, Ru et al. (2021) estimate those conditions by combining ambient air pollution (AAP) and second-hand smoking studies (SHS) in an integrated response function. While assuming equitoxicity, the authors recommend this approach for global studies with a wide range of $PM_{2.5}$ concentrations, and it has been used in subsequent health impacts analyses of climate policies (Shindell et al., 2021). We select the GEMM-like non-linear functional form due to its better performance on goodness-of-fit tests when compared to a log-linear function (Ru et al., 2021). We also focus on dementia cases (rather than deaths) to avoid double-counting with the GEMM mortality function. The parameters are available in Ru et al. (2021) Table S4 (AAP+SHS) for their age group of focus (65-and-older), using their concentration range of 2.7 μg m^{-3} to 146 μg m^{-3} to calculate v and the θ standard error to estimate the 95% CI.

3.2.4 Health impacts to inclusive wealth framework

We apply health impacts to the inclusive wealth framework by measuring the cumulative difference in healthy life years (via DALYs) between policy scenarios. Our DALY calculation combines Years of Life Lost (YLL) from premature mortalities and years of life with disability (YLD) from dementia cases. For YLL, we follow GBD methods (Vos et al., 2020) by multiplying the estimated premature deaths for each country and age group by the standard life expectancy at age of death. Standard life expectancies are calculated from 2050 global population and mortality rates by age group in Vollset et al. (2020), interpolating annually from the five-year estimates. For the "95-and-older" age group in Vollset et al. (2020), we estimate annual mortality rates by fitting the pre-95 annual mortality rates to a quadratic curve ($r^2 = 0.92$) and extending the curve to age 115. With a mortality rate for each year, we take the cumulative products of the probabilities of avoiding death for each year above a certain age, and find the median age of death as the first year in which that age group's cumulative probability drops below 0.5. Finally, we find the standard life expectancy for the midpoint of each five-year age group (e.g., 27.5, 32.5…), following Ru et al. (2021) by using a weighted average to represent the midpoint of the 95-and-older group (0.4 * 97.5 + 0.3 * 102.5 + 0.2 * 107.5 + 0.1 * 112.5). We then apply these life expectancies to the GEMM age groups. These are identical except for GEMM's 80-and-older group, which we calculate as a weighted average based on the global proportion of population in each GBD age group.

For YLD, we take the product of attributable dementia cases, standard life expectancy for 65-and-older (using the same weighted average approach), and GBD disability weights –using the dementia severity splits in Appendix 1 (p. 967) of the GBD study (Vos et al., 2020). These values by severity (s) are given globally for each gender (g) and five-year age group (a); we calculate a weighted average by country (c):

$$DW_c = \sum_s (DW_s * \sum_{a,g} (f\_s_{a,g,c} * f\_p_{a,g,c})) \quad , \qquad (7)$$

where *f_s* represents the fraction of cases from a certain severity and *f_p* represents the fraction of a country's population that comes from a certain gender and age group. We present the YLL, YLD, and sum (as DALYs) to compare between scenarios – treating this difference as the effect of a policy change in each nation's stock of healthy life years.

To compare this metric with others, we also convert deaths and dementia cases to monetary terms using typical valuation methods. For dementia, we use a cost-of-illness approach (Wimo et al., 2017) that estimates cost per case in year 2015 USD for GBD regions, as well as a global trend increase from 2010 to 2015 that we use to project costs to 2050 as a first-order estimate. For mortality, we use the value of a statistical life (VSL) from a recent set of benefit-cost analysis guidelines (Robinson et al., 2019) that has been cited in recent air pollution literature (Reis et al., 2022). The VSL method of benefits transfer works as follows:

$$VSL_{target} = VSL_{reference} * (Income_{target} / Income_{reference})^{elasticity} \tag{8}$$

We follow all central estimate guidelines (Robinson et al., 2019), including a reference United States VSL of $9.4 million (in 2015 USD), an elasticity of 1.5, and a VSL lower bound of 20 times the country's income based on the assumption that VSL will likely remain higher than annual income, and that adult life expectancy should exceed 20 years on average (Robinson et al., 2019). For national income, we incorporate World Bank data for Gross National Income per capita using purchasing power parity in 2015 (World Bank, 2022) – having mapped World Bank to GBD countries and used a global average for countries with no available data. We project these VSL estimates based on regional per capita 2015-to-2050 GDP growth from the EPPA "Paris 2°C" scenario used in the TAPS emissions scenarios – having mapped countries to EPPA regions in Atkinson et al. (2022a). All costs are reported in 2015USD. While the monetized amounts are not the focus of this case study, further work could conduct sensitivity analyses with different VSL or dementia valuation assumptions.

3.3 Results

The following sections describe and interpret the scenario results for precursor emissions, pollutant concentrations, cumulative difference in healthy life years, and other health metrics.

3.3.1 Emissions

Emissions of precursor species show large, species-specific differences between scenarios (**Figure 5**). In this analysis, climate policy levels reflect EPPA7's "Paris 2°C" scenario – leading to reduced fossil fuel emissions across the two pollution control scenarios. In accordance with guidance from a recent panel of health impacts researchers (Hess et al., 2020), we also compare our scenarios with SSP4-3.4, the Shared Socioeconomic Pathway

(SSP) scenario with sectoral emissions data that has the most similar climate forcing to our scenarios (Calvin et al., 2017; Gidden et al., 2019).

In our results, energy-related emissions of sulfur dioxide (SO_2) and nitrogen oxide (NO_x) drop by more than half under the Current Legislation (CLE) pollution control scenario, and nearly disappear under Maximum Feasible Reductions (MFR). While some sectors show slight increases over time in CLE (such as industrial emissions, where increased activities overpower decreased intensities), most drop to near-zero in MFR. SSP4-3.4 is closer to MFR for SO_2, and closer to CLE for NO_x emissions.

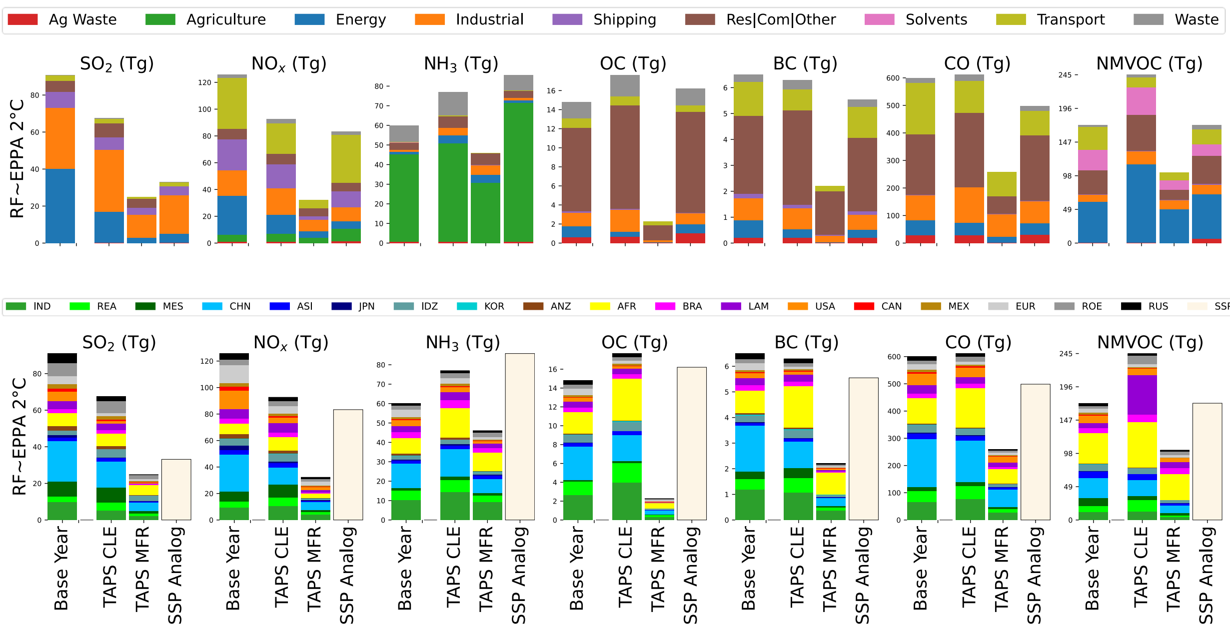

Figure 5. 2050 emissions by inventory sector and EPPA region, compared to 2014 inventory values. Quantities of NO_x are in Tg NO_2; quantities of BC, OC, and NMVOC are in Tg C. The 11 $CEDS_{GBD\text{-}MAPS}$ sectors (McDuffie et al., 2020) are condensed to the eight in the earlier version used by the SSPs (Hoesly et al., 2018), including the aggregation of residential, commercial, and other combustion ("Res|Com|Other"), plus agricultural waste burning ("Ag Waste") from GFED.

Compared to SO_2 and NO_x, primary particulate emissions show an even greater difference between scenarios – highlighting a large potential range of outcomes even under the same ambitious climate policy scenario. For example, organic carbon (OC) shows a slight increase in CLE (due to increased residential emissions with limited intensity improvements) versus a drop to near-zero in MFR. The trend is similar for black carbon (BC) and carbon monoxide (CO), with near-constant emissions trends in CLE versus less than half of the base year values by 2050 in MFR. Most remaining BC emissions are residential, while CO also includes industrial and transport sources. SSP4-3.4 results are generally close to CLE, assuming little uptake of additional policy.

Emissions of ammonia (NH_3) and non-methane volatile organic compounds (NMVOC) both increase if the extent of pollution control is left at Current Legislation – even under the 2°C climate policy scenario. For NH_3, this increase comes from agriculture and industry in regions such as India and Africa. For NMVOC, the primary driver is the energy sector in Africa and Latin America. In contrast, emissions decline under MFR for both NH_3 and NMVOC. SSP4-3.4 results are between our scenarios for NMVOC but higher than CLE for ammonia, based on an assumption of less agricultural pollution control in developing countries.

3.3.2 Concentrations

For annual average $PM_{2.5}$ concentrations, we focus on the difference between 2050 CLE and 2050 MFR scenarios to highlight the effect of the anthropogenic emissions changes. $PM_{2.5}$ concentrations in GEOS-Chem have been validated by several studies around the world (Vohra et al., 2021) and have shown high consistency with recent trends in observations (C. Li et al., 2017), though we do note the potential for underestimates in urban areas due to coarse model resolutions (Y. Li et al., 2016). Compared with $PM_{2.5}$ concentrations under Current Legislation, the concentrations under Maximum Feasible Reduction are substantially lower – including by more than 50 µg m^{-3} in parts of South Asia. MFR's lower concentrations are also notable in East and Southeast Asia as well as West Africa, the Middle East, and South American population centers in Peru and Brazil. Differences of >1 µg m^{-3} are evident in most land areas, as well as some ocean areas due decreased emissions from international shipping in addition to the prevailing meteorology.

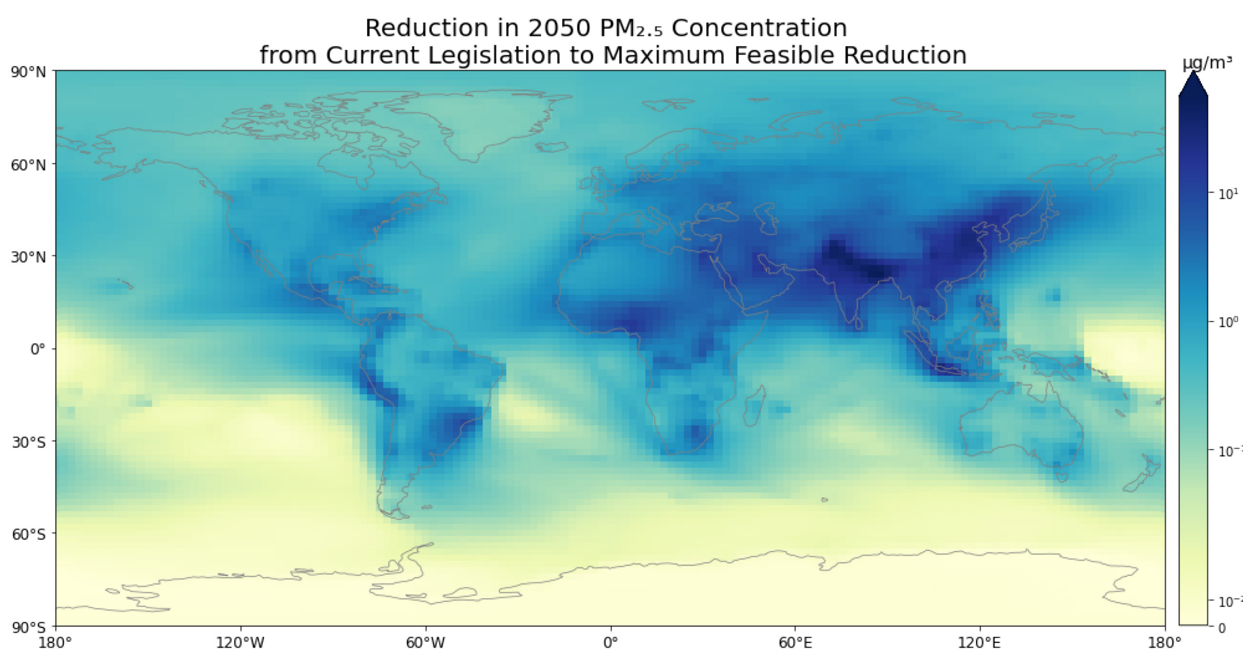

Figure 6. Difference map for mean surface-level $PM_{2.5}$ concentration in 2050 between policy scenarios.

3.3.3 Cumulative difference in healthy life years

We use the healthy life years metric (via DALYs) to estimate the inclusive wealth-based health effects of a policy change from current legislation to maximum feasible reduction. While other metrics (such as percent change from base year) have been used for other IW studies (Collins et al., 2014), we focus on the cumulative difference to emphasize the total stock-based change between the two future policy scenarios. So far, we have presented results for 2050 as the year modeled in GEOS-Chem. However, the difference between current legislation and maximum feasible reduction does not begin in 2050, but grows over time according to the GAINS scenario inputs. As an initial thought experiment, we consider a linear change in time from identical emissions in the base year of 2014 to the calculated difference between policy scenarios in 2050. Without discounting, the cumulative effects of the policy change would translate to ½ * (2050-2014) * the difference between scenarios in 2050. Under this thought experiment, the cumulative global benefits of changing pollution control levels from CLE to MFR would be a total of 1.48 (1.30-1.63) billion healthy life years (i.e., reduced DALYs) between 2014 and 2050.

Figure 7 shows the heterogenous distribution of those benefits in the modeled year of 2050. Parts of northern India and eastern China show a difference of more than 10 DALYs per square kilometer, due to substantial pollution reductions in areas of high population density. China and India combine for 56% of the benefits in 2050 from CLE-to-MFR policy change, despite accounting for less than a third of the global projected population in 2050. Other high-benefit areas include urban parts of South and Southeast Asia as well as Indonesia, Brazil, Japan, Egypt, Mexico, Northwest Europe, Central Africa, and the Northeast United States.

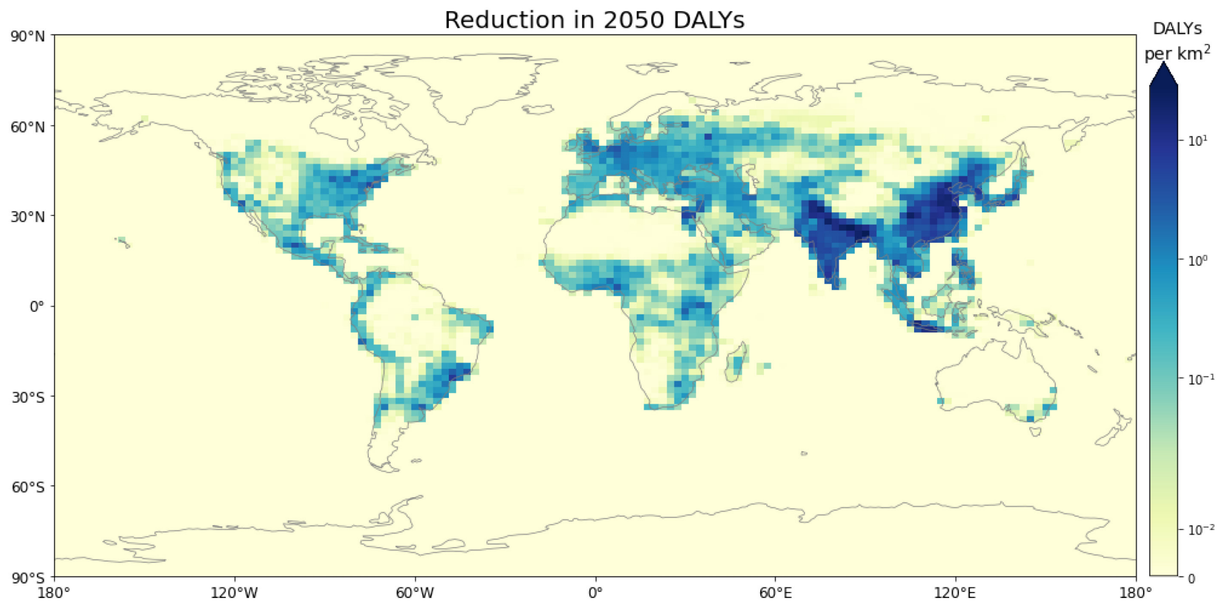

Figure 7. Difference in 2050 $PM_{2.5}$ impacts on Disability-Adjusted Life Years (DALYs) between policies. (Current Legislation vs. Maximum Feasible Reduction).

Table 7 quantifies the countries that have the highest estimated cumulative benefits for healthy life years. The top five countries are all in Asia, followed by high-population countries elsewhere such as the United States and Brazil. Different countries have different distributions of benefits between Years of Life Lost (YLL) from mortalities versus Years Lived with Disability (YLD) from morbidities (which are focused on dementia incidence for this case study). Countries with younger populations (such as India and Pakistan) have much larger proportions of benefits from mortalities, which are analyzed for ages 25-and-older via the GEMM response function. On the other hand, countries with older populations (such as the United States and Japan) have a greater fraction of benefits from avoided YLD, due to major increases in baseline dementia rates (Nichols et al., 2022) and population totals under the 65-and-older group of the Ru et al. (2021) response fraction. These results highlight the substantial influence of both mortality and morbidity impacts, depending on pollution levels as well as country-specific age structure.

Table 7. Ten countries with the greatest cumulative difference in healthy life years from CLE to MFR. We represent the difference in healthy life years as DALYs for the years 2014-2050.

Country	DALYs (millions)	YLL (millions)	YLD (millions)
Global Total	1477 (1305 - 1633)	1001 (925 – 1074)	476 (380 – 560)
China	461 (404 - 510)	265 (245 - 284)	196 (159 - 226)
India	370 (337 - 400)	313 (291 - 335)	56 (46 - 65)
Pakistan	66 (61 - 71)	60 (56 - 64)	6 (5 - 6)
Indonesia	64 (57 - 70)	50 (46 - 54)	14 (11 - 16)
Bangladesh	47 (42 - 51)	35 (33 - 38)	11 (9 - 13)
United States	44 (37 - 51)	21 (19 - 23)	23 (17 - 28)
Brazil	34 (28 - 39)	18 (16 - 19)	16 (12 - 19)
Vietnam	22 (19 - 25)	15 (13 - 16)	8 (6 - 9)
Russia	19 (17 - 22)	11 (10 - 12)	8 (6 - 10)
Japan	19 (16 - 22)	7 (6 - 7)	13 (10 - 15)

DALY = Disability-Adjusted Life Year; YLL = Years of Life Lost; YLD = Years Lived with Disability. 95% confidence intervals reflect the standard error of the health response functions. Cross-column comparisons may differ slightly due to rounding.

3.3.4 Comparison of health impact metrics

Next, we compare the healthy life years metric with other impact metrics. Health impacts have different regional distributions depending on the impact metric. **Figure 8** compares these distributions for mortality (a-c) and dementia (d-f) when looking at the original endpoint, its valuation in monetary terms, or its effect on inclusive wealth in the form of healthy life years. From Current Legislation to Maximum Feasible Reduction, the difference in deaths and dementia cases are also greatest in China and India (**Table 8** and **Table 9**), which would each avoid more than 1 million deaths and dementia cases due to the reduced air pollution in 2050. Mortality-related benefits are next-highest in parts of Asia with high pollution reductions (Indonesia, Pakistan, Bangladesh), while dementia-related benefits are more weighted towards countries with older populations (United States, Brazil, Japan).

In both cases, monetizing the benefits skews them towards high-income countries – and away from regions such as Africa and the global south (**Figure 8**b,e). Under a VSL-based approach for mortality (Robinson et al., 2019), countries such as the United States, South Korea, and Germany rank much higher when comparing benefits (**Table 8**). Similarly, valuing dementia costs under a cost-of-illness approach (Wimo et al., 2017) shows the greatest benefits in the United States, while India has been replaced in **Table 9** by countries such as Canada, Italy, and France. Total benefits range in the trillions (for deaths) and high billions (for dementia) of USD (using standard 2015 dollars), reflecting the high value of reduced pollution as well as its increased valuation over time due to projected increases in income and medical costs.

Compared to monetized measures, the healthy life years approach is distributed more like the original health endpoints, particularly with dementia (**Figure 8**c,f). However, when measuring mortality-related benefits as the reduction in Years of Life Lost (YLL), countries with younger age structures are emphasized – due to the greater number of healthy life years lost with each mortality. These countries with younger age distributions average around 15 or even 20 YLL per mortality, compared to 10 or fewer YLL per mortality for countries with older age distributions. As a result, **Table 8** shows greater YLL benefits in India than in China, and also for the Philippines and Egypt versus Japan and Russia.

The influence of national age structure is also visible for dementia YLD (**Table 9**), though less dramatic since the dementia response function in Ru et al. (2021) is focused on the over-65 population. While the years of life expectancy for 65-and-older populations can vary somewhat between countries (10.1-14.7 min-max; 11.7-13.2 IQR), the average dementia severities (based on the age- and sex-specific but globally defined GBD disability weights) vary only slightly (0.227-0.249 min-max; 0.237-0.243 IQR). When these values are multiplied with case counts to find YLD, countries with younger populations (such as Indonesia and Vietnam) occasionally show more YLD than countries that ranked higher in case counts (such as Japan and South Korea, respectively).

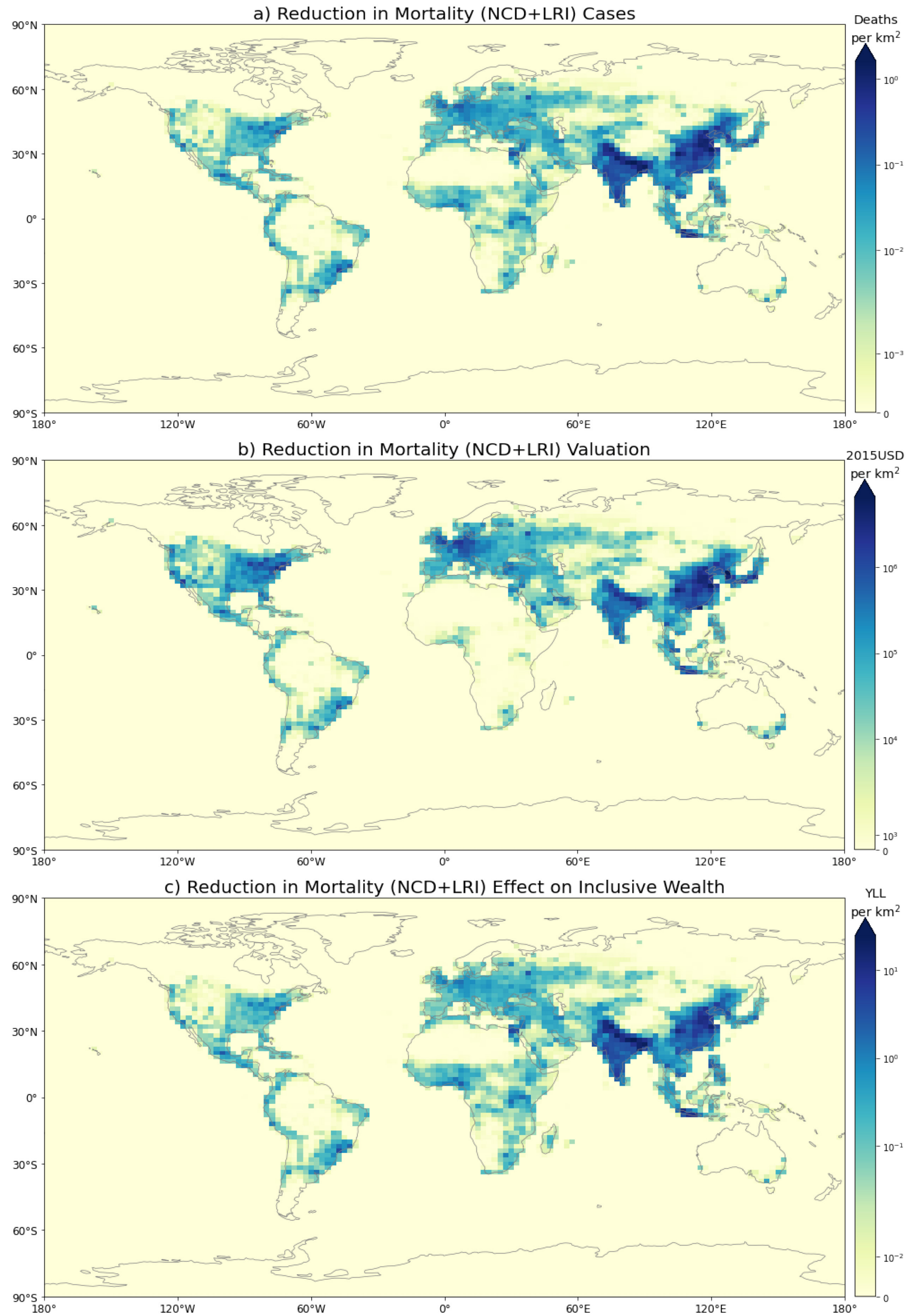

Figure 8. Difference in 2050 $PM_{2.5}$ health effects (Current Legislation vs. Maximum Feasible Reduction). Plots (a-c) map the mortalities from non-communicable diseases (NCD) and lower respiratory infections (LRI), their valuation, and their effect on inclusive wealth as healthy life years (via Years of Life Lost, or YLL).

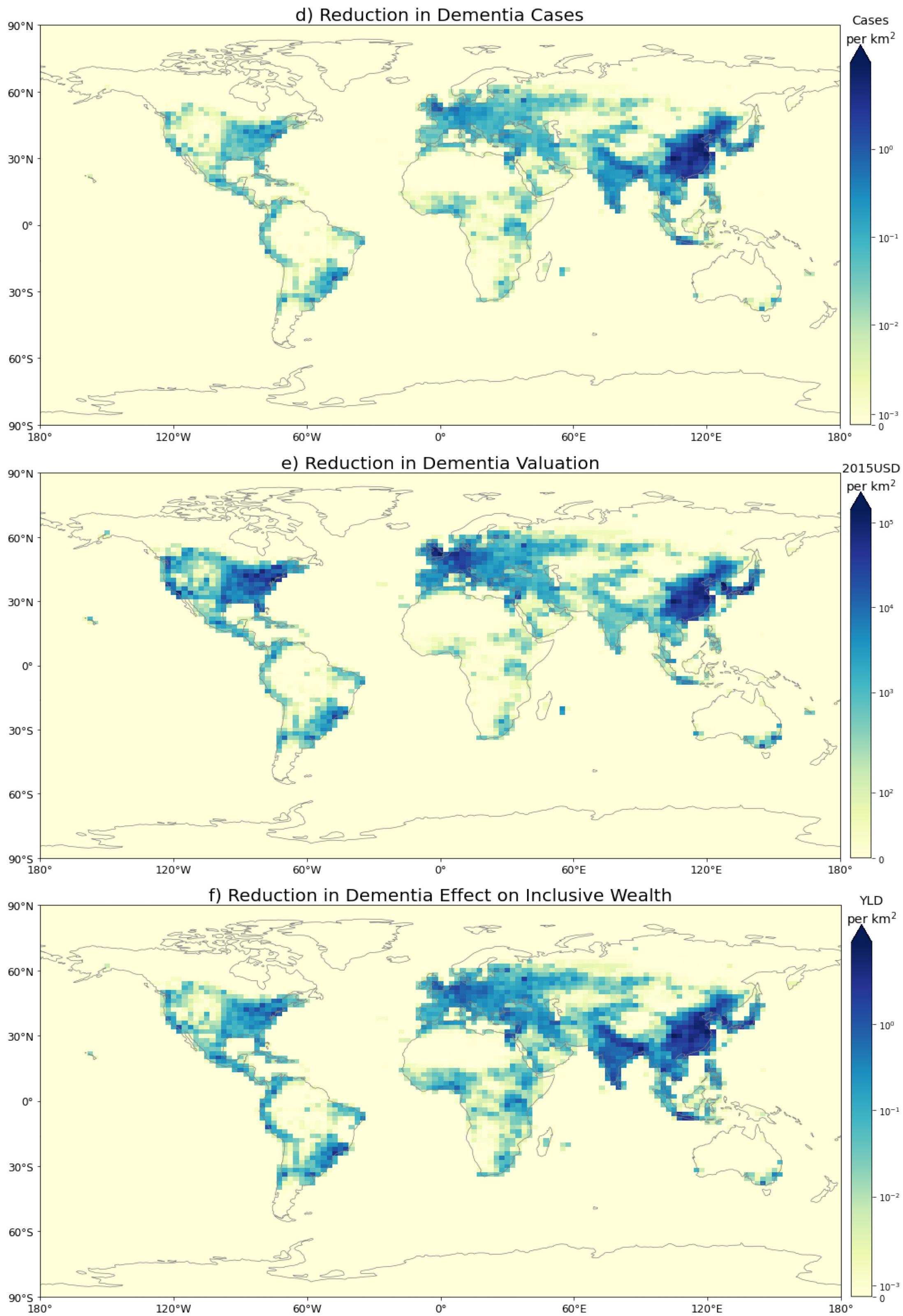

Figure 8(d-f). Difference in 2050 $PM_{2.5}$ dementia impacts (from Current Legislation to Maximum Feasible Reduction) for cases, valuation, and inclusive wealth effect (as healthy life years via Years Lived with Disability, or YLD).

Table 8. Ten countries with the greatest difference in 2050 mortality impact from CLE to MFR.

Country	Deaths	Country	Valuation	Country	YLL
China	1,425,380	China	5.2 trillion USD	India	17,410,712
India	1,129,179	India	2.2 trillion USD	China	14,716,217
Indonesia	189,967	United States	1.6 trillion USD	Pakistan	3,353,382
Pakistan	175,738	South Korea	0.6 trillion USD	Indonesia	2,772,159
Bangladesh	134,452	Japan	0.5 trillion USD	Bangladesh	1,963,789
United States	110,032	Indonesia	0.4 trillion USD	United States	1,176,719
Brazil	81,870	Germany	0.4 trillion USD	Brazil	991,890
Vietnam	64,760	China	0.2 trillion USD	Vietnam	815,313
Japan	48,261	Brazil	0.2 trillion USD	Philippines	706,726
Russia	45,839	Russia	0.2 trillion USD	Egypt	634,939

Table 9. Ten countries with the greatest difference in 2050 dementia impact from CLE to MFR.

Country	Cases	Country	Valuation (USD)	Country	YLD
China	3,853,035	United States	75,772,195,919	China	10,872,754
India	1,000,372	China	49,318,819,401	India	3,135,260
United States	463,000	Japan	23,660,186,223	United States	1,272,359
Brazil	300,144	South Korea	13,284,974,078	Brazil	871,144
Japan	269,074	Germany	12,393,464,850	Indonesia	784,820
Indonesia	252,571	Canada	11,299,018,526	Japan	695,338
Bangladesh	211,749	Brazil	8,235,898,526	Bangladesh	638,880
Thailand	163,939	Italy	7,037,343,959	Russia	457,542
Russia	157,842	France	6,114,203,691	Thailand	434,213
South Korea	151,083	Russia	5,561,661,613	Vietnam	417,824

YLL = Years of Life Lost, YLD = Years Lived with Disability, CLE = Current Legislation, MFR = Maximum Feasible Reduction. YLL and YLD sum to DALYs for the healthy life years approach.

3.4 Discussion

3.4.1 Comparison of health impact totals

Table 10 shows the global estimates by scenario for each health endpoint and metric, as well as their uncertainties based on the standard errors in the response functions. All metrics show a reduction of ~30-40% from Current Legislation (CLE) to Maximum Feasible Reduction (MFR). Such a difference is roughly similar to results in Rafaj et al. (2021) using the GAINS CLE and MFR scenarios under a 1.5°C climate policy scenario, though their focus on Asia for health impacts prevents a full comparison. While the anthropogenic emissions reductions may be greater than 30-40% (see **Figure 5**), several out-of-scope pollution sources (such as dust and open burning) were left unchanged between scenarios, leading to unchanged health impacts from those sources.

In the case of premature mortalities attributable to $PM_{2.5}$, our estimates for 2050 are higher than most present-day estimates – due to several factors such as population growth, population ageing, and choice of response function. Rafaj et al. (2021) also point to demographic factors to explain the increased health impacts even under decreased emissions – particularly with scenarios similar to the "Paris 2°C-CLE" combination used here. Compared to estimates of 8.9 million deaths in 2015 from Burnett et al. (2018), the central estimate of 11.7 million for 2050 CLE is consistent with this rationale – as substantial population growth and aging outweigh the effects of lower air pollutant emissions from climate policy. Pollution control from the MFR scenario yields a reduction from those 2015 estimates, in a similar manner to the "2°C—Best Available Technology" scenario in Vandyck et al. (2018).

In general, we note that the GEMM response function's mortality estimates are sometimes higher than other methods by a factor of two of more (Lelieveld et al., 2019; McDuffie et al., 2021). While GEMM does have a more flexible functional form (compared to log-linear functions elsewhere), the main difference is the inclusion of studies (such as the Chinese Male Cohort) that show high health impacts under high background pollution levels. Further discussion is available in R. T. Burnett et al. (2022), including an alternate "Fusion" response function that may be fruitful for comparison in future studies. Total deaths from the "Fusion" function are within 4% of the GEMM function under a consistent cohort (R. T. Burnett et al., 2022), highlighting the influence of cohort choice on the magnitude of results.

Our estimates of dementia cases attributable to $PM_{2.5}$ are also much larger than the 2015 estimates from the same response function in Ru et al. (2021), due to projected population aging in high-pollution areas (such as a tripling of the over-65 population in East and South Asia by 2050). Other sources of difference could include the population data source (UN WPP here versus SSP-specific elsewhere, for instance), baseline health projections (GBD here versus International Futures (Hughes et al., 2011) in some other studies), monetization across countries (varying by national income as shown here, versus a constant global value in Vandyck et al. (2018) or other options), chemical transport model (GEOS-Chem here versus reduced form approaches), and parameterization of the CLE and MFR scenarios within TAPS (compared to other models).

Table 10. Global health impact estimates in 2050 by metric and scenario.

Impact Metric	Current Legislation (CLE)	Maximum Feasible Reduction (MFR)	Difference from CLE to MFR
Mortalities	11.7 (10.7-12.7) million	7.5 (6.8-8.1) million	4.2 (3.9-4.6) million
Valuation	39 (36-42) trillion USD	25 (22-27) trillion USD	14 (13-16) trillion USD
YLL	156 (143-168) million	100 (91-109) million	56 (51-60) million
Dementia cases	28.8 (22.4-34.6) million	19.6 (15.1-23.4) million	9.2 (7.3-10.8) million
Valuation	713 (551-873) billion USD	444 (340-545) billion USD	272 (212-328) billion USD
YLD	83 (65-100) million	57 (44-69) million	27 (21-31) million
DALYs	239 (208-268 million)	157 (135-178) million	82 (72-91) million

YLL = Years of Life Lost; YLD = Years Lived with Disability; DALYs = Disability-Adjusted Life Years. All USD values are standardized to 2015 USD. 95% confidence intervals reflect the standard error of the health response functions. Cross-cell comparisons may differ slightly due to rounding.

3.4.2 Considerations for inclusive wealth

We now discuss broader implications for incorporating health effects in the inclusive wealth (IW) framework. As shown in **Table 5**, prior health analyses in IW studies have generally monetized the health impacts to compare them with other forms of inclusive wealth capital. However, when comparing between countries (or between localities in the case of subnational IW accounts), such monetized metrics are highly sensitive to the income levels of each area (as seen in **Table 8**). Though health impacts researchers have supported the inclusion of monetization methods in certain settings – particularly for economic modeling or policy decision-making (Hess et al., 2020; Vandyck et al., 2018) – studies that use the income-based benefit transfer method have suggested the exploration of a more egalitarian approach (Reis et al., 2022). Otherwise, monetized metrics may be best suited for single-jurisdiction analyses that do not compare areas with different incomes.

Our alternative approach avoids this sensitivity to income by focusing on the cumulative change in healthy life years (as measured by DALYs). While this method differentiates health from the other types of monetized capital in inclusive wealth, it is theoretically consistent with the IW framework. If sustainability in IW is achieved by having non-declining stocks of wellbeing, the stock of healthy life years would seem to be a logical component. Moreover, the healthy life years metric emphasizes younger populations (when compared to the original health endpoints in **Table 8** and **Table 9**) – reflecting IW's emphasis on long-term stocks (versus the short-term "flow" of a single death or disease case). Life years also translate more simply to future estimates than is true for monetary measures, which must consider the uncertainty of income projections in the "benefits transfer" approach.

However, the question of discounting may require further consideration. Prior IW studies that use VSLY assume a discount rate of 5% for the value of a life year (with sensitivities of 3% and 7%) – meaning that a life year 10 years into the future is worth 0.60 (0.48-0.74) times the value of a life year in the present (Agarwal and Sawhney, 2021; Arrow et al., 2012; Jumbri et al., 2018). While such discounting might seem at odds with the IW focus on inter-generational stocks, Dasgupta et al. (2021) argue that a discount rate of zero could overly skew priorities away from the current time. A recent panel of health impacts researchers has recommended a compromise approach in the form of "sensitivity analyses, including at least rates of 0% (with a 100-y time horizon) and 3%" (Hess et al., 2020). While we focus on undiscounted values given our short time horizons (with average life expectancies at death generally below 20 years), additional sensitivities could be considered in future work.

Future work could also apply the healthy life years metric to other policy cases or geographies, whether using the global GBD data (for DALY components of overall disease burdens, as incorporated by Sampedro et al. (2022) for the rfasst tool) or local QALY metrics (for analyzing healthcare interventions). DALY and QALYs do have certain limitations. As discussed in the introduction, there is the issue of "double-jeopardy" when mortality and morbidity are treated as separate endpoints (Hubbell, 2006). One solution is to model mortalities and morbidities together, as GBD does for the dementia cause that we focused on, and Schmitt (2016) does for a case study of cardiovascular and respiratory diseases in London. However, future studies are necessary to build out such models to more applications.

Another limitation is the issue of acute effects (such as hospital admissions), which are a major part of many morbidity impact studies (Ru, 2020) but do not translate well to year-based DALY/QALY methods except under extreme assumptions of linearity (Bell et al., 2011). In addition, these short-term flows are less commonly incorporated into the long-term stocks of inclusive wealth, unless they are assumed to follow the same depreciation rate over time as produced capital (Shimamura and Mizunoya, 2020). Because of these theoretical limitations, we currently follow Hubbell (2006) in leaving the inclusion of acute impacts to complementary analyses, such as a cost-of-illness approach. For integration of other morbidity endpoints in a "healthy life years" framework, future studies could explore response functions for other non-acute effects, such as the development of asthma (Achakulwisut et al., 2019; Tiotiu et al., 2020). And while the response functions used here were limited to the 25-and-older population, incorporating long-term effects of neonatal issues (such as low birth weight and pre-term birth) could reflect the substantial fraction of total pollution-related deaths that come from this age group (Health Effects Institute, 2020).

Analyses could also consider labor impacts as a complementary metric, as prior IW studies have done (Aly and Managi, 2018; Shimamura and Mizunoya, 2020), while being careful to avoid double-counting with the metric of healthy life years. We did not include labor (either in the form of work loss days or restricted activity days) because prior studies have found it challenging to develop response functions that hold globally in the face of diverse work customs (Ru, 2020). Moreover, labor impacts are typically focused on the working population (Lange et al., 2018), despite the concentration of air pollution mortality impacts on the oldest and youngest age groups (Health Effects Institute, 2020). However, more localized studies could incorporate these effects if there was enough place-specific epidemiological evidence and stakeholder interest.

Finally, we note the many additional impacts of air pollution that could be considered in future work. According to Wei et al. (2019), $PM_{2.5}$ has been associated with an increased risk of hospital admissions for many diseases beyond the traditional focus on cardiovascular and respiratory issues – such as renal failure, several types of infections, and fluid-based or gastrointestinal issues. Other authors have explored connections to depression (X. Zhang et al., 2017), crime (Burkhardt et al., 2020), and dozens of other issues in broader reviews (Lu, 2020). In addition, local studies have identified air pollution's intergenerational effects from impacts during one's education – whether measured by IQ score (Wang et al., 2017) or effect on future earnings (Lavy et al., 2014). Even parental exposure can affect child IQ and subsequent wage loss, as studied by Wolfe et al. (2016) for the case of lead. While such impacts are less established within global response functions, these intergenerational impacts would merit consideration in a stock-based approach like IW.

Overall, several aspects of this case study could be broadened for greater comprehensiveness. Additional sensitivities in projected population, urbanization, or baseline health data could supplement the existing confidence intervals of each response function. Analyses could be extended to ground-level ozone or other pollutants that have been linked to hundreds of thousands of annual deaths (Health Effects Institute, 2020) as well as other impacts such as asthma prevalence (Takenoue et al., 2012). Future efforts could also consider varying the response functions by demographic group if sufficient data is available (C. Chen et al., 2021). In addition, new functional forms could be tested as they become available (R. T. Burnett et al., 2022), given the reliance of GEMM on limited cohort studies in high-pollution areas (Hystad et al., 2020). High-pollution areas may exhibit different toxicities between fossil fuel and crop burning sources of $PM_{2.5}$ (Rahman, 2020) – highlighting the importance of future research into equitoxicity assumptions when possible. This topic would be especially crucial for studies involving wildfires, which have shown toxicities up to several times greater than that of non-wildfire $PM_{2.5}$ (Aguilera et al., 2021). Finally, future studies could consider including household air pollution, given its linkage to millions of annual deaths (Health Effects Institute, 2020). Since many of these choices are context-dependent, decisions should be transparent and be tailored to the target audience (Hess et al., 2020).

3.5 Conclusions

Overall, this chapter offers takeaways in two forms – showing the major influence of pollution control policy as well as the choice of metric to measure the policy's impact. Even under a 2°C climate scenario, we find a wide range of outcomes between current and maximum feasible pollution controls through 2050. While some precursor species (such as SO_2 and NO_x) decrease over time due to fossil fuel reductions from climate policy, others show constant or increasing trends under current pollution control, compared to dramatic decreases in the maximum feasible case. The result is a substantial difference in ambient $PM_{2.5}$ concentrations by 2050 – particularly in Asian countries, which show the five highest differences (among all nations) between the policies' impact on healthy life years (via DALYs). This result highlights the major health benefits of pollution control ambition in Asia, compared to other parts of the world where air pollution is either lower or predominantly from non-anthropogenic sources.

The results also highlight the distributional discrepancies of different health impacts metrics. Depending on whether one measures the original health endpoint, its monetization, or its effect on healthy life years, national benefit comparisons may differ substantially – often due to non-environmental factors such as a country's income or age structure. We apply these metric choices to discussions of the inclusive wealth framework, demonstrating an alternative option as the cumulative difference in healthy life years from a policy change. The metric of healthy life years avoids international monetization challenges, while integrating mortality and morbidity under the common measure of DALYs. Our case study shows that mortalities and morbidities are both important to different degrees in different countries, depending on the central role of population demographics (and extent of ageing).

Future studies could analyze other scenarios, years, and quantified health impacts – especially once cause-specific projections become more widely available through the GBD Future Health Scenarios project. Incorporating other morbidities or emissions sources (such as wildfires) would advance a more complete picture of air pollution impacts under the ethos of inclusive wealth. While specific methods may vary by geography and research question, we hope to advance the inclusion of air pollution's health impacts as a critical sustainability challenge within the framework of inclusive wealth.

4. Thesis conclusion

4.1 Policy implications

By demonstrating new tools and methods to analyze the effects of climate and air quality policy, this thesis shows that both climate and air quality policy are crucial for reducing the adverse health and sustainability impacts of air pollution. Under the Chapter 2 scenario of current air quality legislation and only near-term climate pledges to 2030, emissions of most pollutants increase over time – especially for sectors that are projected to grow rapidly with fewer current pollution controls. More ambitious climate policies can lead to substantial benefits (such as reduced SO_2 and NO_x emissions from fossil fuels), but more ambitious air quality policies are needed to reduce other pollutants, such as ammonia from agriculture and organic carbon from residential sources.

Beyond these overall findings, our Tool for Air Pollution Scenarios highlights the sector- and region-specific nature of emissions trends – implying an opportunity to target emissions hotspots for high-impact policy. For example, some sectors are projected to have increased emissions-intensity for certain pollutants under current legislation – such as the carbon monoxide from steel in Asia, SO_2 from coal in Eastern Europe, and NMVOC from some solvent and industrial processes in parts of Asia and Brazil. Focusing pollution controls on these activities would substantially reduce their health impacts – especially for the activities (like industrial processes in developing regions) that are projected to increase in magnitude. Actions could also target high-emitting locations within these sectors, which have been shown to have outsized health effects in a recent study at the power-plant scale (Tong et al., 2021).

Other sectors show relatively flat emissions intensities under current legislation, but opportunities for dramatic emissions reductions (or even eliminations) under the maximum feasible current policies. This difference holds even under an ambitious climate policy scenario that would meet the Paris Agreement's temperature targets (**Figure 5**) – underscoring the influence of pollution controls beyond climate policy. For instance, municipal waste burning is projected to largely maintain its emissions intensity under current legislation, but could be emissions-free by 2050 with feasible control actions (Gomez Sanabria et al., 2021). That difference is similar for agricultural waste burning, and large opportunities are available for cost-effective reduction of agricultural ammonia emissions from fertilizer and crop production (Gu, Zhang, Dingenen, et al., 2021; Gu, Zhang, Lam, et al., 2021). Finally, residential biomass burning is a critical hotspot for health impacts – given the millions of annual premature deaths from household air pollution (Health Effects Institute, 2020) on top of the outdoor air quality impacts considered here. Available technologies could reduce the vast majority of primary particulate emissions from these activities (**Figure 5**).

However, some emissions remain even under the maximum feasible application of current control technologies – implying the need for technological innovation to reduce emissions further. Examples include SO_2 emissions from industrial processes, as well as NMVOC emissions from the energy sector. Aviation may be another case (though it was not included in our data sources) – with promise for improvement since proposed technologies could reduce aviation pollution's health impacts by >90% (Prashanth et al., 2021). Even if solutions are not available right away, near-term research and development has been shown to carry important benefits for technological learning (Chantret et al., 2020). Improved technologies could also be translated across regions where feasible – in contrast to region-specific policy levers that may face different challenges in different areas. Further research could incorporate technical learning into new scenarios of emissions intensity, using the deep socio-technical transition literature (Geels, 2019; Köhler et al., 2019) to build on the scenarios in Chapter 2.

In other cases, behavioral or systemic changes beyond technology may be necessary. According to other recent studies, changes in land use, diet, and active mobility could lead to comparable or even greater health benefits than the pollution control options included in our input sources (Amann et al., 2020; I. Hamilton et al., 2021). These actions are especially important for agriculture, which remains with substantial emissions even under our maximum feasible pollution control scenario. Land conservation could also affect the emissions sources of open burning and wildfires, which were outside the scope of our data sources but are key to consider in future work. These actions may have especially strong benefits for other aspects of sustainability; according to a recent IPCC report, "pathways with emphasis on demand reductions and policies that incentivize behavioural change, sustainable consumption patterns, healthy diets and relatively low use of [carbon dioxide removal] (or only afforestation) show relatively more synergies with individual SDGs than other pathways" (Rogelj et al., 2018).

These sustainability synergies include the human health benefits of reduced air pollution – as shown by Chapter 3 through the lens of inclusive wealth. By focusing on the cumulative health effects of a policy change, we highlight the importance of near-term actions for maximum benefits. Moreover, our metric of healthy life years increases the focus on future life years for future generations, as emphasized by the definition of sustainable development in the 1987 Brundtland Report. Health effects are far from equally distributed – with the vast majority in Asia where population and pollution are both high. Demographic changes can increase these areas' vulnerability, leading to the potential for increased health impacts over time even if air pollutant emissions are reduced (K. Chen et al., 2020). These national health impact comparisons could help global efforts prioritize actions in the most vulnerable areas – in concert with other studies that identify more localized disparities by race and other factors (Tessum et al., 2021). Pollution-specific policies could greatly benefit these groups, helping to achieve pollution-related sustainability goals more readily than climate actions would alone.

4.2 Future directions for research and engagement

Beyond the case study results, this thesis lays the groundwork for a wide range of analyses to evaluate the effects of climate and air quality actions like the examples described above. Using the new Tool for Air Pollution Scenarios (TAPS), researchers could explore numerous scenarios that cover the region-, sector-, or fuel-specific interests of stakeholders – from new national climate pledges to the current questions of changing oil and gas use in Europe. Studies could also analyze an ensemble of many scenarios to identify key short-term actions with high-impact benefits – or avoid policies that might mitigate climate change but worsen air quality, such as certain forms of biomass use or bioenergy with carbon capture and storage (BECCS) for negative emissions (Vandyck et al., 2021).

Then, actions' effects on emissions could be integrated with other aspects of sustainability for more holistic decision-making – using global chemical transport models to estimate pollutant concentrations and cumulative health impacts that follow the framework of inclusive wealth. Calculations of such metrics are globally feasible using standard demographic and health projections, and avoid the income-based uncertainties of monetized approaches by focusing on the stock change of healthy life years. The focus on cumulative life years also centers the benefits of avoiding health harms in younger age groups – in line with inclusive wealth's focus on sustainability for future generations. Future work could incorporate other health effects as well as advances in the underlying methodology – particularly for the ongoing work to develop new health response functions and improve our understanding of differential toxicity for emissions sources such as wildfires.

The methodological choices may also depend on stakeholder interests – as emphasized by a recent panel of health impacts researchers (Hess et al., 2020) as well as a broad review of sustainability science (Clark and Harley, 2020). According to Cash et al. (2003), such choices should ideally combine credibility of methods, salience with values, and legitimacy of the process in the eyes of specific stakeholders. Given the variance of such elements between different stakeholders – from (inter)national policymakers to business leaders to local sustainability authorities – the development of flexible, open-source scenario tools like TAPS should be an important endeavor. Moreover, applying the credibility of recent global epidemiology to the inclusive wealth framework could help to integrate the health impacts of air pollution into broader sustainability assessments.

While the inclusive wealth (IW) framework has been developed in the academic community rather than among other sustainability decision-makers, its reach has been extending both globally and locally. Globally, the UN Environment Programme's nation-by-nation inventories have been spotlighted in blog posts and media outlets such as ARY News in Pakistan (UNEP, 2021), though the effect on decision-makers is less clear. At the same time, municipalities such as Hisayama, Japan have already begun using IW to inform their fiscal budgets, according to local researchers who also lead the UN inventories (Matsunaga and Managi, 2019). In addition, an earlier IW study in Australia organized stakeholder workshops and consulted with policy experts to inform the scope of analysis (Pearson et al., 2013). Such applications could serve as early test beds for IW policy analyses.

Others have raised questions about some of the IW framework details – including "questionable theoretical assumptions, gaps in data availability, unrealistic assumptions about the future and inability to account for distributional issues" (Roman and Thiry, 2016). A key example is the treatment of environmental tipping points. Using a framing of "weak sustainability", IW implies that certain types of capital can be substituted for others without adverse consequences (Randall, 2020). To better account for tipping points such as a loss of biodiversity or atmospheric stability, elements of "strong sustainability" could be added to emphasize the importance of protecting these stocks (Thiry and Roman, 2014). Our metric of healthy life years could be emphasized in this manner as well, given the importance of protecting human health for long-term sustainability.

Even if the formal IW framework does not fit stakeholder needs, many decision-makers are becoming increasingly interested in the intersection between climate, health, and other goals of societal sustainability. For example, decision-makers in the United States have pledged to review regulations from the lens of "public health and safety, economic growth, social welfare, racial justice, environmental stewardship, human dignity, equity, and the interests of future generations" (Biden, 2021). Other efforts are developing more formalized methods of multi-criteria decision analysis, integrating different sustainability goals through economic or stakeholder weighting (Kandakoglu et al., 2019). Examples include a benefits maximization approach to integrate equity into energy planning decisions (Nock et al., 2020), or the preference-based WELFARES framework for life cycle assessment (Grubert, 2017).

Regardless of approach, it will be crucial to continue integrating the major health impacts of air pollution into climate change and sustainability decisions. As health impacts researchers have noted, air pollution's effects are closer than climate change in both time and space (Shindell, 2020). Emphasizing near-term, localized health benefits (especially for vulnerable populations) could spur action that reduces both climate and air quality issues – as China has recently shown with its dramatic drop in SO_2 and black carbon emissions (Kanaya et al., 2020; Zheng et al., 2018). Cumulative impacts assessments can also help emphasize the benefits of rapid action – a crucial mindset to mitigate climate change as well as the health effects of air pollution. The thesis seeks to enable such work by providing more flexible capacities to analyze the effects of climate and air pollution policies on pollutant emissions, health impacts, and metrics of sustainability.

Appendix A: CEDS reference data

Table 11. Percentage of base-year (2014) CEDS emissions in each fuel consumption or process category. Values are broken down by sector and aggregated globally.

Sector	Fuel	SO_2	CO	NH_3	BC	OC	NO^{a}	$C_2H_4{}^{b}$
Agriculture	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0
	liquid-fuel-plus-natural-gas	0	0	0	0	0	0	0
	process	0	100	100	0	0	0	0
Commercial	total-coal	72	0	25	44	49	52	24
	solid-biofuel	1	0	27	49	25	11	27
	liquid-fuel-plus-natural-gas	27	100	48	7	26	38	50
	process	0	0	0	0	0	0	0
Energy	total-coal	64	51	5	7	3	10	0
	solid-biofuel	0	3	2	37	9	1	0
	liquid-fuel-plus-natural-gas	19	32	7	1	2	8	0
	process	17	14	87	55	86	81	100
Industry	total-coal	45	55	5	21	54	43	28
	solid-biofuel	0	9	38	74	20	8	26
	liquid-fuel-plus-natural-gas	20	32	10	6	26	5	8
	process	35	5	47	0	0	44	38
Non-road transport	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0
	liquid-fuel-plus-natural-gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Other	total-coal	38	1	12	23	13	10	6
	solid-biofuel	0	2	9	43	8	20	16
	liquid-fuel-plus-natural-gas	62	97	79	34	79	70	78
	process	0	0	0	0	0	0	0
Residential	total-coal	70	8	0	8	13	13	3
	solid-biofuel	20	58	97	92	70	87	96
	liquid-fuel-plus-natural-gas	10	33	3	0	17	1	1
	process	0	0	0	0	0	0	0
Shipping	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0
	liquid-fuel-plus-natural-gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Solvents	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0

	liquid-fuel-plus-natural-gas	0	0	0	0	0	0	0
	process	0	0	100	0	0	0	0
Transport	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0
	liquid-fuel-plus-natural-gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Waste	total-coal	0	0	0	0	0	0	0
	solid-biofuel	0	0	0	0	0	0	0
	liquid-fuel-plus-natural-gas	0	0	0	0	0	0	0
	process	100	100	100	100	100	100	100

[a] CEDS reports NO_x as NO and NMVOC as speciated compounds; [b] C_2H_4 is shown as an example NMVOC species. Other NMVOC species may show differences, such as more "process" emissions from solvents. Global aggregate proportions are shown here for context; full regional and speciated values are available at our online repository. CEDS fuel definitions are given in Table S1 of McDuffie et al. (2020), with bioenergy separated between solid and liquid fuels.

Appendix B: EPPA7 reference definitions

Table 12. EPPA7 regions and sectors, as described in Paltsev (2021).

Region code	Region name	Sector code	Sector name
AFR	Africa	COAL	Coal
ANZ	Australia, New Zealand & Oceania	CROP	Agriculture - Crops
ASI	East Asia	DWE	Ownership of Dwellings
BRA	Brazil	EINT	Energy-Intensive Industries
CAN	Canada	ELEC	Electricity
CHN	China	FOOD	Food
EUR	European Union+	FORS	Agriculture - Forestry
IDZ	Indonesia	GAS	Gas
IND	India	LIVE	Agriculture - Livestock
JPN	Japan	OIL	Crude Oil
KOR	South Korea	OTHR	Other
LAM	Latin America	ROIL	Refined Oil
MES	Middle East	SERV	Services
MEX	Mexico	TRAN	Transport
REA	Rest of Asia		
ROE	Eastern Europe and Central Asia		
RUS	Russia		
USA	USA		

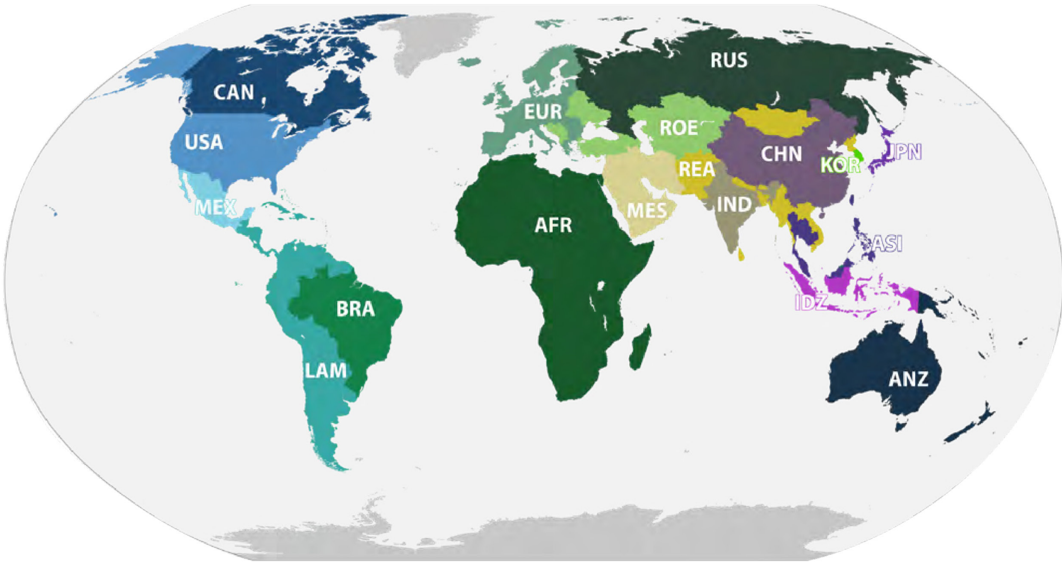

Figure 9. Map of EPPA7 regions of the world, from Paltsev (2021) with reproduction rights granted.

Appendix C: Mapping from GAINS model

Table 13. Mapping from GAINS EMF (based on IMAGE) to EPPA7 regions.

EPPA7	GAINS EMF	EPPA7	GAINS EMF	EPPA7	GAINS EMF
CAN	1 Canada	AFR	10 South Africa	IND	18 India
USA	2 USA	EUR	11 Western Europe	KOR	19 Korea
MEX	3 Mexico	EUR	12 Central Europe	CHN	20 China+
LAM	4 Rest Central America	ROE	13 Turkey	ASI	21 Southeastern Asia
BRA	5 Brazil	ROE	14 Ukraine+	IDZ	22 Indonesia+
LAM	6 Rest South America	ROE	15 Asia-Stan	JPN	23 Japan
AFR	7 Northern Africa	RUS	16 Russia+	ANZ	24 Oceania
AFR	8 Western Africa	MES	17 Middle East	REA	25 Rest South Asia

IMAGE regions are given in Figure S7.1 of Klimont et al. (2017) and compared to **Figure 2**. Regions in blue differ slightly from EPPA definitions.

Table 14. Mapping from GAINS NH_3 to CEDS/GFED inventory sectors and fuels.

Inventory sector	CEDS fuel	GAINS NH_3 sector classes	GAINS NH_3 sector class names
Ag. waste burning	Process	WASTE_AGR	Agricultural waste burning
Agriculture	Process	AGR, COWS, FCON, FERTPRO	Livestock and fertilizer (**Table 15**)
Energy	Coal	PP - BC1, BC2, DC, HC1, HC2, HC3	Power plants (brown, derived, and hard coal)
	Biofuel	PP - OS1, OS2	" (biomass and waste fuels)
	Oil & gas	PP - GAS, GSL, HF, LPG, MD	" (natural gas, gasoline, heavy fuel oil, liquified petrol gas, diesel)
	Process	CON, PROD_AGAS, WASTE_FLR	Conversion, flaring and venting
Industry	Coal	IN_OC - BC1, BC2, DC, HC1, HC2, HC3	Industrial (brown, derived, hard coal)
	Biofuel	IN_OC - OS1, OS2	" (biomass and waste fuels)
	Oil & gas	IN_OC - GAS, GSL, HF, LPG, MD	" (natural gas, gasoline, heavy fuel oil, liquified petrol gas, diesel)
	Process	IN_BO, IO_NH3_EMISS	Boiler and other emissions
Residential, Commercial	Coal	(DOM) - BC1, BC2, DC, HC1, HC2, HC3	Residential-commercial (brown/derived/hard coal)
	Biofuel	(DOM) - OS1	" (biomass)
	Oil & gas	(DOM) - GAS, GSL, HF, LPG, MD	" (natural gas, gasoline, heavy fuel oil, liquified petrol gas, diesel)
Other (combustion)	Oil & gas	TRA_OT_(AGR, CNS, LB, LD2)	Off-road engines, mopeds, construction & agriculture vehicles
Shipping	Oil & gas	TRA_OTS	Maritime
Solvents	Process	IO_NH3_EMISS	Other industrial NH_3 emissions
Transport	Oil & gas	TRA_RD	All road transportation
Non-road transport	Oil & gas	TRA_OT_INW, TRA_OT_RAI	Inland waterways, railways
Waste	Process	WT_NH3_EMISS[a]	Trash burning

See full table (with a row for each of the 198 GAINS NH_3 sectors) in Supplementary Data. CEDS fuel definitions are given in Table S1 of McDuffie et al. (2020) − with bioenergy separated between solid ("Biofuel") and liquid fuels ("Oil & gas"). Comparisons are based on Table S3 in Rafaj et al. (2021), with sectoral abbreviations described further in GAINS Online. [a]Since NH_3 "Waste" data were only available for two countries, emissions intensity trends follow NO_x "Waste" trends based on Gomez Sanabria et al. (2021).

Table 15. Mapping from GAINS agricultural sectors to FAO activities.

GAINS	FAO
AGR_BEEF	Beef and veal
AGR_COWS	Raising of cattle
AGR_OTANI-BS	Raising of buffaloes

AGR_OTANI-CM, -FU, -HO	Raising of livestock (total)
AGR_OTANI-SH	Raising of sheep
AGR_PIG	Raising of pigs
AGR_POULT	Raising of poultry
COWS_3000_MILK	Raw milk
FCON, FERTPRO	NPK_consumption

Based on GAINS sector abbreviations at https://gains.iiasa.ac.at/models/index.html and FAO sectors in regional aggregate data.

Table 16. Mapping from NH_3 data sources to EPPA7 regions.

EPPA7	G20 Corollary	FAO Corollary
CAN	USA	High-income
USA	USA	High-income
MEX	Mexico	Latin America/Caribbean
LAM[b]	Argentina	Latin America/Caribbean
BRA	Brazil	Latin America/Caribbean
AFR[b]	South Africa	Sub-Saharan Africa
EUR	United Kingdom; France; Germany	High-income
ROE[b]	Turkey	Europe/Central Asia
RUS	Russia[a]	Europe/Central Asia
MES[b]	Turkey	Near East/North Africa
IND	India[a]	South Asia
KOR	South Korea[a]	EAP excluding China
CHN	China[a]	China
ASI[b]	China[a]	EAP excluding China
IDZ[b]	China[a]	EAP excluding China
JPN	Japan[a]	EAP excluding China
ANZ	Australia	High-income
REA[b]	India[a]	South Asia

Full GAINS data were only provided for G20 regions. Countries that approximate other regions are shown in blue, while corollaries that represent a part of their EPPA regions (or vice versa) are in purple. FAO regions are shown in Figure 1.2 of FAO (2018). [a] Countries with subnational regions in GAINS were aggregated based on their proportional emissions. [b] Scaling for EPPA regions not well-captured by the GAINS G20 coverage is described in Sect. 2.2.3.

Appendix D: IPCC sectoral references

Table 17. IPCC sectoral definitions for EPPA scaling of sectors from the chosen emissions inventories.

IPCC code	Activity	CEDS sector	EPPA sectoral scaling
3	Agriculture process emissions	Agriculture	CROP, FORS, LIVE
4F	Agricultural waste burning	N/A; from GFED	CROP
1A1	Electricity/fuel production	Energy	COAL, ELEC, GAS, ROIL
1B	Fugitive fuel emissions	Energy	COAL, ELEC, GAS, ROIL
7A	Fossil fuel fires	Energy	COAL, ELEC, GAS, ROIL
1A2	Industrial combustion	Industry	EINT, FOOD, OTHR
1A5	Other industrial (combustion)	Industry	EINT, FOOD, OTHR
2A-2C, H, L	Industrial process emissions	Industry	EINT, FOOD, OTHR
6A	Other industrial (process)	Industry	EINT, FOOD, OTHR
1A4a	Commercial/institutional	Commercial	SERV
1A4b	Residential	Residential	Population
1A4c	Other combustion	Other (combustion)	CROP, FORS, LIVE
1A3d(i)	International shipping, oil tankers	Shipping	TRAN
2D	Solvents	Solvents	Population
1A3,1C	Aviation	N/A	
1A3b	Road transportation	Transport	TRAN
1A3c	Rail transportation	Non-road transport	TRAN
1A3d(ii)-e(ii)	Domestic navigation, other transport	Non-road transport	TRAN
5	Waste/wastewater emissions	Waste	Population

Inventory versions include $\text{CEDS}_{\text{GBD-MAPS}}$ (McDuffie et al., 2020) for most anthropogenic emissions, as well as GFED4.1s (van der Werf et al., 2017) for biomass burning. Since only agricultural waste burning is included in EPPA through GTAP/EDGAR, other sources of burning emissions are not scaled by EPPA outputs. Aviation was not scaled in this work due to its exclusion from both $\text{CEDS}_{\text{GBD-MAPS}}$ and GAINS. "Other combustion" includes sources from agriculture, forestry, and fishing. Sectoral scaling from EPPA largely reflects the distribution of activities in GTAP10 / EDGAR5.0 sectors (Chepeliev, 2020), which are then mapped to representative EPPA7 sectors.

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