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A Tool for Air Pollution Scenarios (TAPS v1.0) to Facilitate Global, Long-term, and Flexible Study of Climate and Air Quality Policies

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This report is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—Ronald G. Prinn,
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A Tool for Air Pollution Scenarios (TAPS v1.0) to Facilitate Global, Long-term, and Flexible Study of Climate and Air Quality Policies

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Abstract: Air pollution is a major sustainability challenge – and future anthropogenic precursor and greenhouse gas emissions will greatly affect human well-being. While mitigating climate change can reduce air pollution both directly and indirectly, distinct policy levers can affect these two interconnected sustainability issues across a wide range of scenarios. We help to assess such issues by presenting a public Tool for Air Pollution Scenarios (TAPS) that can flexibly construct and assess a variety of climate and air quality emissions pathways through its coupling with socioeconomic modeling of climate change mitigation. In this study, we develop and implement TAPS with three components: recent global and fuel-specific anthropogenic emissions inventories, scenarios of emitting activities to 2100 from the MIT Economic Projection and Policy Analysis model (EPPA), and emissions intensity trends based on the latest Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) scenario data. An initial application shows that in scenarios with less climate and pollution policy ambition, near-term air quality improvements from existing policies are eclipsed by long-term emissions increases – particularly from industrial processes that combine sharp production growth with fewer pollution control levers in developing regions. Additional climate actions would substantially reduce energy-related air pollutant emissions (such as sulfur and nitrogen oxides), while further pollution controls are especially impactful for ammonia and organic carbon. Future TAPS applications could efficiently explore diverse regional and global policies that affect these emissions, using pollutant emissions results to drive global atmospheric chemical transport models to study the scenarios' health impacts.

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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 may have led to as many as ten million mortalities in 2012 (Vohra *et al.*, 2021) – while pollutants like 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 GHG emissions for reduced air pollution (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). Yet some climate policies may actually increase air pollutant sources, such as biomass-heavy energy pathways that enable the continued use of fossil fuels (Sampedro *et al.*, 2020). 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). Each SSP defines a specific pollution control ambition, with emissions intensity trends that depend on current national income (Rao *et al.*, 2017). These trends are developed from two scenarios in the widely used Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) database: current legislation (CLE) versus maximum feasible reductions (MFR) from current technology (Amann *et al.*, 2011; Klimont *et al.*, 2017). The results are incorporated into outputs of the sixth Coupled Model Intercomparison Project (CMIP6) and presented online (IIASA, 2018; Rogelj *et al.*, 2018).

Other approaches have a narrower 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 specific policies (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 decreases in China (Zheng *et al.*, 2018) and the potential for waste burning emissions to decline to zero by 2050 under an MFR scenario (Gomez Sanabria *et al.*, 2021).

Some recent studies have used this GAINS update 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. 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 select countries. Both these latter papers focus on aggregate effects (comparing base cases to scenarios of those policy levers combined together), and are limited geographically (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 studied a variety of climate and economic policy impacts (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 (**Fig. 1**).

First, we utilize emissions inventories that are well-positioned 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. Methodology

Our estimates of air pollutant emissions involve three main inputs: a base-year emissions inventory (**Sect. 2.1**), a projected trend in energy use and other polluting activities (**Sect. 2.2**), and a projected trend in emissions intensity (**Sect. 2.3**). The following equation (based on **Fig. 1**) summarizes these components (**Eq. 1**):

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

In this way, the emissions $E_{i,j,r,t}$ 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 $f(\gamma_{f,i,j,r}t)$ in 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. 2.4**).

Public versions of the tool, outputs and underlying data are described in the code and data availability section (including processes for figure reproduction). To facilitate coupling with global atmospheric CTMs for health impact analysis, we also include 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. 2.4**), future TAPS applications could theoretically be extended to other inventories or policy model outputs if the database integration steps were completed (adjusting from **Sect. 2.1-2.3**).

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 ($\mathrm{CEDS_{GBD\text{-}MAPS}}$), 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), carbon monoxide (CO), ammonia (NH_3), black carbon (BC), organic carbon (OC), nitrogen oxides (NO_x), 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 A1**). Compared to 2021's CEDS 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 trends 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**).

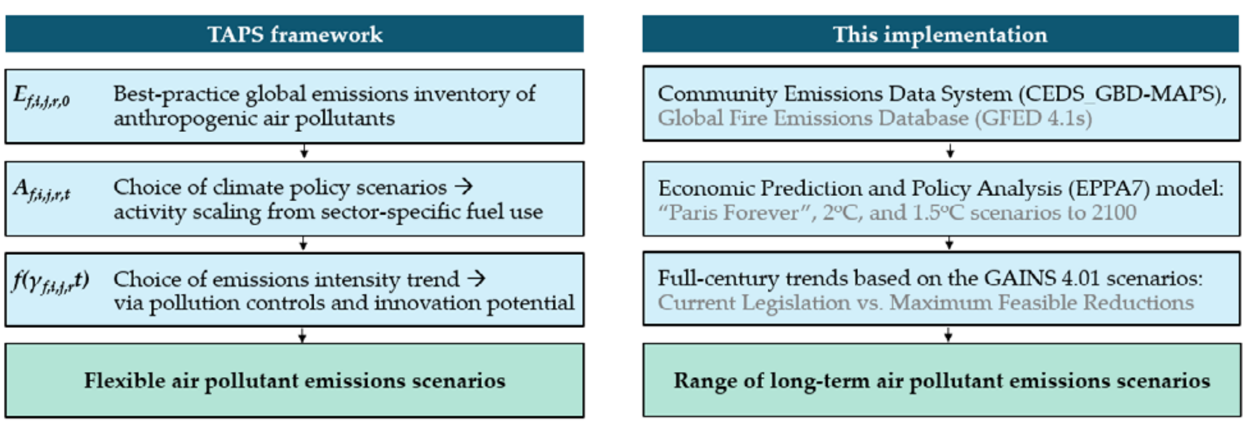


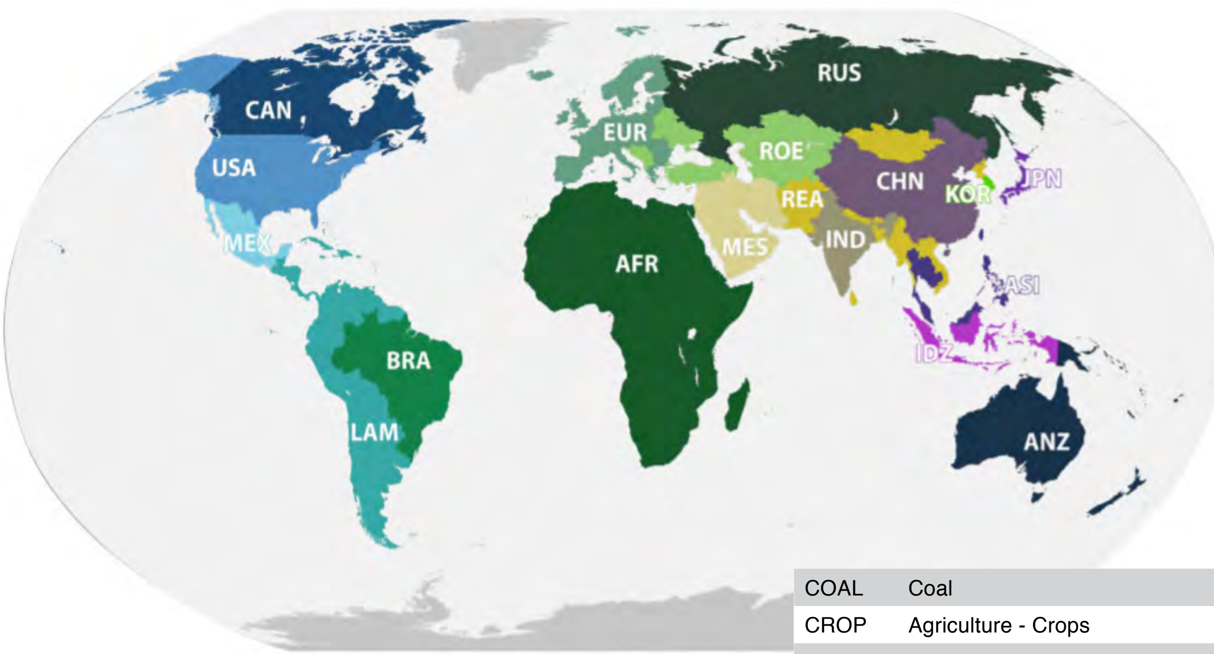
Figure 1. Summary of the Tool for Air Pollution Scenarios (TAPS) framework and implementation here, based on climate policy scenarios in EPPA7 and pollution control scenarios from the Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) database. Emissions trends are specific to each fuel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

We also include emissions of agricultural waste burning, the only type of open burning represented in EPPA's activities (Chepeliev, 2020). We follow the SSPs (van Marle *et al.*, 2017) 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 from 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 SI3). 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 $CEDS_{GBD-MAPS}$ and GAINS.

2.2 Projecting Emitting Activities

2.2.1 Choice of Economic Data Source

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 represented in **Fig. 2** (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 plus agricultural waste burning from GFED) to one or more of the EPPA7 sectors (**Table 1**). The process is based on comparisons of CEDS activities with sectoral coverage in GTAP10 (Chepeliev, 2020) and its transferal to EPPA sectors using standard Intergovernmental Panel



AFR	Africa	JPN	Japan
ANZ	Australia & New Zealand	KOR	South Korea
ASI	Dynamic Asia	LAM	Other Latin America
BRA	Brazil	MES	Middle East
CAN	Canada	MEX	Mexico
CHN	China	REA	Other East Asia
EUR	Europe (EU+)	ROE	Other Eurasia
IDZ	Indonesia	RUS	Russia
IND	India	USA	United States

COAL	Coal
CROP	Agriculture - Crops
DWE	Ownership of Dwellings
EINT	Energy-Intensive Industries
ELEC	Electricity
fd	Final Demand
FOOD	Food
FORS	Agriculture - Forestry
GAS	Gas
LIVE	Agriculture - Livestock
OIL	Crude Oil
OTHR	Other
ROIL	Refined Oil
SERV	Services
TRAN	Transport

Figure 2. EPPA7 regions and sectors, as described in Paltsev (2021).

Table 1. 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	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.

on Climate Change (IPCC) definitions as a common reference point. Since EPPA lacks sectors that match “Waste”, “Solvents”, or the “Residential” emissions that are largely 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.

2.2.2 Choice of Activity Parameters

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 2**, using the four fuel categories (three for combustion, one for “process”) in $\text{CEDS}_{\text{GBD-MAPS}}$. Each source's scaling is based on the proportion of its base-year emissions (**Table A1**) as follows:

$$A_{f,i,j,r,t} = \frac{E_{f,i,j,r,0}}{E_{i,j,r,0}} * \sum_{Ei} A_{f,Ei,r,t} \tag{2}$$

The EPPA activities $A_{\text{f,Ei,r,t}}$ are aggregated via summation across the EPPA sectors Ei that are mapped to each inventory sector (see Table 2). 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

Table 2. 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 B2-B3
Agricultural waste	CROP	Process	Land use	See Table B2-B3
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, CHEM, CHEMBULK, 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

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 sector abbreviations are described here.

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.

2.3 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 since 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 2 and Tables B1-B4.

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 B4) – 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 Tables B3-B4.

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.

2.4 Implemented Scenarios

To illustrate an application of TAPS, we first select three scenarios from EPPA7 to represent variations in climate policy ambition (**Table 3**), 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

Table 3. EPPA7 scenarios analyzed, with selected SSP comparisons.

EPPA 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, Sokolov, *et al.*, 2021).

EPPA 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 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.

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.

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 3**,** 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 pathways, we use this initial implementation to show the range of outcomes between GAINS CLE and MFR scenarios. After aggregating the GAINS emissions intensity trends to inventory sectors and EPPA regions (**Sect. 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. (Other pathways might be chosen for different research questions; we describe examples in the discussion and **Table 4**). Exponentials are designed to pass through base-year values of 1 for consistency (using a base-year uncertainty weighting of 0.01 via Python's 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 the model outputs (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 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) activities. Finally, we combine the intensity trends with the linked base-year inventories and revised activity scaling (as in **Eq. 1**). Results are presented below and in the model output files, including tables 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.

3. Results

3.1 Example Scenario and SSP Comparison

We illustrate an application of the TAPS tool by providing the results for total air pollutant emission trends (**Fig. 3**), sectoral breakdowns (**Fig. 4**) and regional breakdowns (**Fig. 5**). We also compare this implementation to corollary SSP IAM and CMIP6 scenarios (summarized in Table 5). For Fig. 3, 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 3. 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

Table 4: Example emissions intensity trends, based on GAINS scenarios of current legislation (CLE) and maximum feasible reduction (MFR).

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 national income level and reduction stringency of SSP (1 and 5 > 2 > 3 and 4).
MFR Trend Continues	Fit an exponential function to the historical GAINS data (2000-2015) + MFR scenario (2030-2050), and extend that trend to 2100.

This work shows the range between bolded scenarios as an example. For more detailed information on SSP scenarios, see Table 1-2 of the Supporting Information in Rao *et al.* (2017).

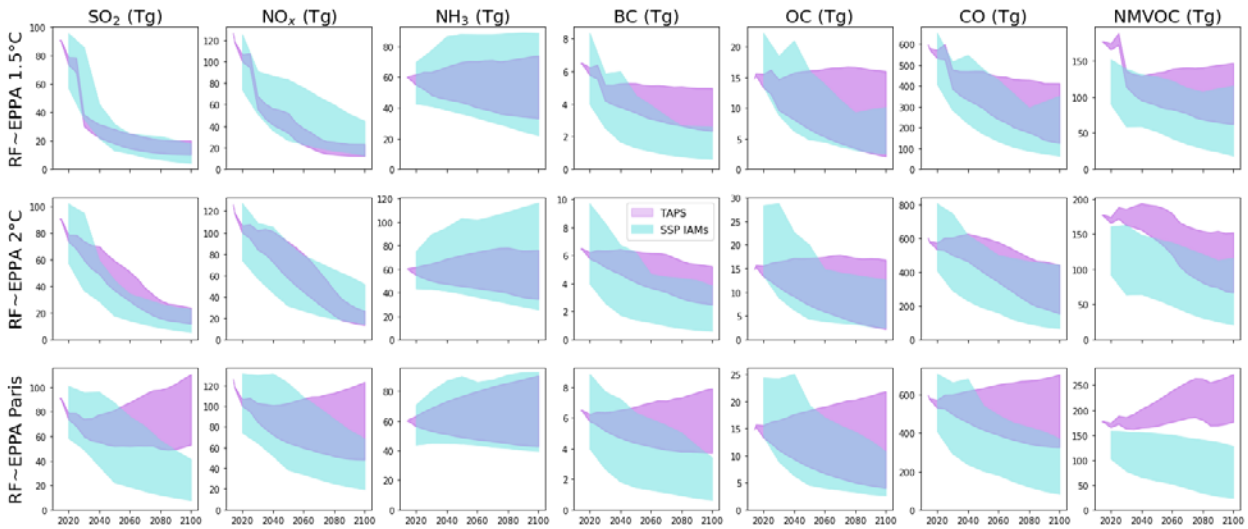


Figure 3. Global air pollutant emissions trends within the range of GAINS-based scenarios of current legislation (CLE) and maximum feasible reduction (MFR) in Table 4, as compared to the range of SSP IAM corollaries in Table 3. IAM estimates are subtracted by sectors not scaled by TAPS (aviation and open burning beyond agricultural waste), based on their emissions proportion in the best-fitting CMIP6 scenario (since sectoral IAM emissions are not available). NO_x and NMVOC quantities reflect the molecular weights of NO_2 and C, respectively.

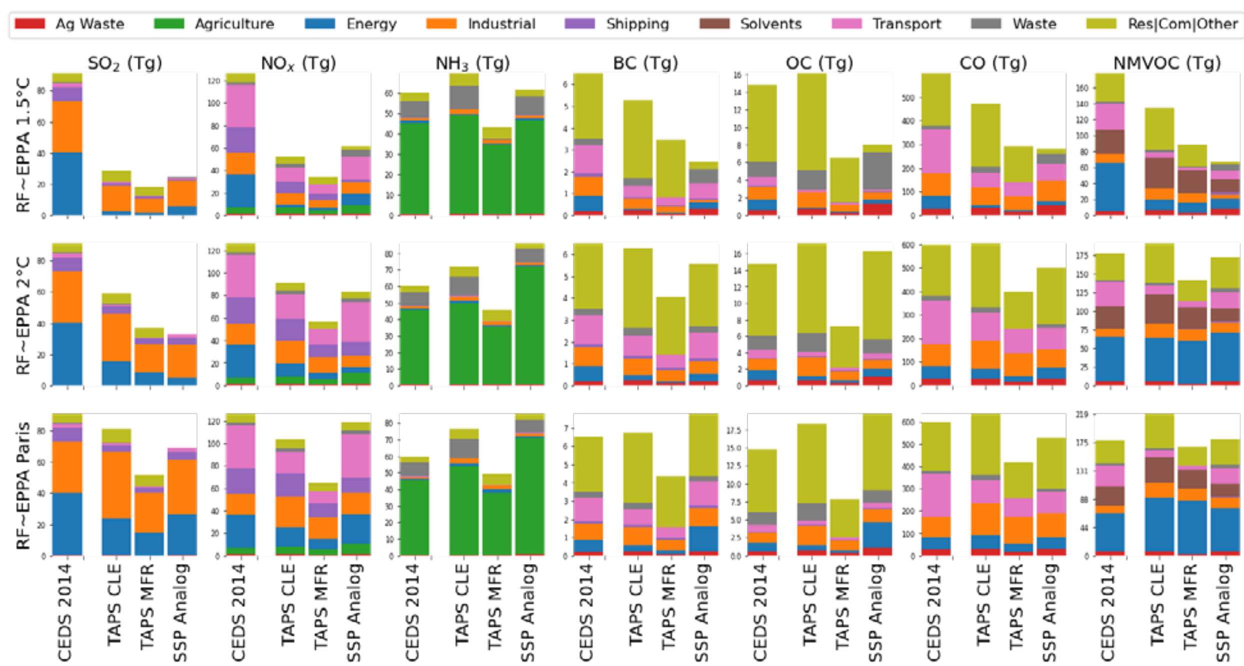


Figure 4. Sectoral emissions of air pollutants in 2050 under the GAINS-based scenarios of current legislation (CLE) and maximum technically feasible reduction (MFR) – as compared to the 2014 emissions inventories and corresponding CMIP6 scenarios of SSP1-2.6, SSP4-3.4, and SSP4-6.0 (respectively) for EPPA's 1.5°C, 2°C and Paris Forever scenarios (see Table 3). The 11 CEDS sectors (McDuffie *et al.*, 2020) are condensed to the eight in the earlier version that the SSPs employ (Hoesly *et al.*, 2018), including the aggregation of residential, commercial, and other combustion sectors ("Res|Com|Other"), plus agricultural waste burning ("Ag Waste") from GFED.

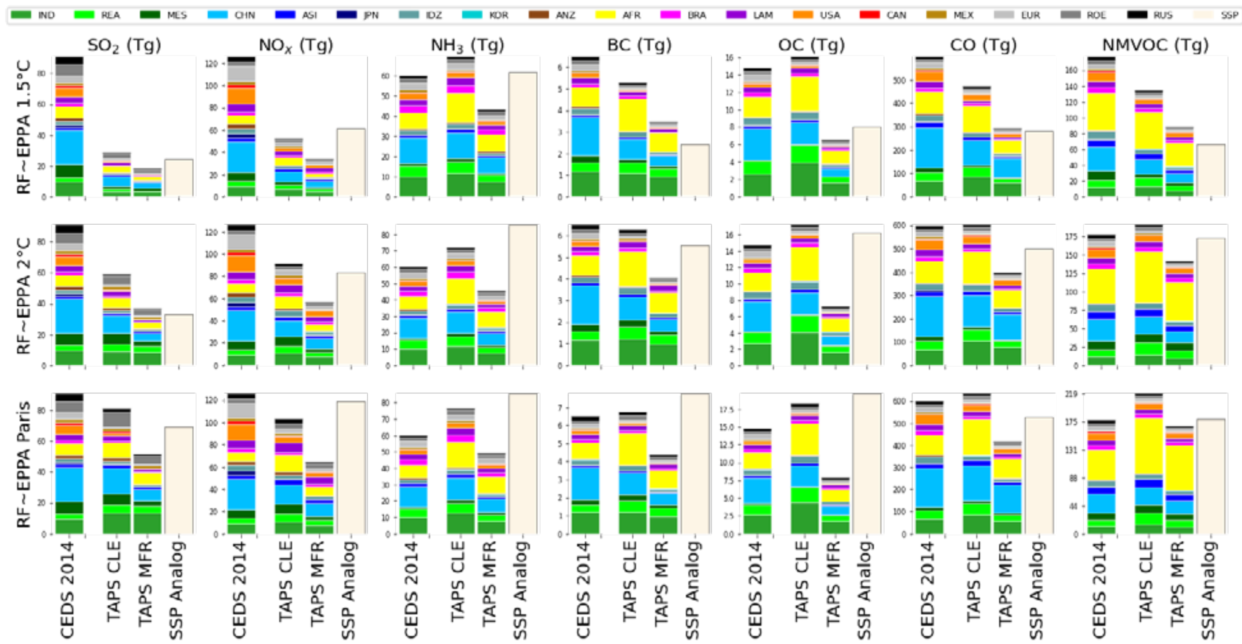


Figure 5. Regional emissions of air pollutants in 2050 under the GAINS-based scenarios of current legislation (CLE) and maximum technically feasible reduction (MFR) – as compared to the 2014 emissions inventories and corresponding CMIP6 scenarios of SSP1-2.6, SSP4-3.4, and SSP4-6.0 (respectively) for EPPA's 1.5C, 2C and Paris Forever scenarios (see Table 3). SSP values are shown as global totals due to their regional definition discrepancies.

Table 5: Summary of pathways presented.

Pathway	Base-Year Emissions	Activity Scaling	Intensity Trend
TAPS CLE	2014; GEOS-Chem 13.0.0 defaults (CEDS, GFED) for anthropogenic emissions	EPPA7 fuel-based energy (coal, oil/gas fuels), total energy (solid biofuel, most "process" fuels), land use (agriculture)	Fuel and sector-specific exponential trends from GAINS 4.01 2000-2050 CLE
TAPS MFR	2014; GEOS-Chem 13.0.0 defaults (CEDS, GFED) for anthropogenic emissions	EPPA7 fuel-based energy (coal, oil/gas fuels), total energy (solid biofuel, most "process" fuels), land use (agriculture)	Fuel and sector-specific 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)
CMIP6 Subset	*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 analogs from the full range of IAMs are shown in Fig. 3, while sectoral data (Fig. 4) 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).

(since sectoral non-CMIP6 IAM emissions are not available). This estimate may lead to slight visual differences in SSP data (e.g., NMVOC "Paris Forever" emissions totals in Fig. 3 versus Fig. 4), but acts as a reasonable first-order comparison with the TAPS scaling.

When comparing initial emissions, IAM inventories differ both in base year (2005 vs. EPPA7's 2014) and emissions values (Fig. 3) – 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 (Fig. 3), 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, before discussing SSP comparisons and further directions.

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 near-doubling of industrial and residential sector emissions outpaces the decreases in energy and transport sectors. Industrial increases are driven by increased activities (four to nine-fold by 2100 in those regions) with few intensity improvements, while residential increases are due to growth in China as well as 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 five-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 the few 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 nine-fold in Indonesia by 2100) as well as intensity for certain regions (3.5x in Africa and 5x 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 ten-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 India's industrial trend 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, energy, and waste sectors. Moving to MFR leads to decreases in all sectors except for energy and 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. From CLE to MFR under "Paris Forever", OC residential emissions drop six-fold and industry emissions are two-thirds lower (after tripling by 2100 in CLE due to major increases in South Asia's solid biofuels). In this case, 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, South Asia, 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.

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 vs. this study (Fig. 4), which comes from a constant-emissions extension of the higher inventory value from the associated IMAGE model (IIASA, 2018). Another is the near-term climate policy landscape that has changed between the SSP modeling process (mid-2010s) and the 2021 EPPA scenarios. 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 in GAINS 4 (Gomez Sanabria *et al.*, 2021). More granular regions and sectors, such as the further 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 4). 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-dependent pathways. Finally, additional scenario elements such as land use, diet, and active mobility could be incorporated as in recent works – particularly since improving such elements may lead to comparable or even greater health benefits than the pollution-specific policy levers explored here (Amann *et al.*, 2020; 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 data and code availability, 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, Sokolov, *et al.*, 2021).

5. Conclusions

TAPS provides a flexible and comprehensive model for assessing climate and pollution pathways, integrating updated standards for 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 control options. 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 have profound health effects. 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 can 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 analyses 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 hampered 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.

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6. References

Aguiar, A., M. Chepeliev, E.L. Corong, R. McDougall, and D. van der Mensbrugghe. (2019). The GTAP Data Base: Version 10. *Journal of Global Economic Analysis*, 4(1), 1–27. https://doi.org/10.21642/JGEA.040101AF

Akagi, S.K., R.J. Yokelson, C. Wiedinmyer, M.J. Alvarado, J.S. Reid, T. Karl, J.D. Crounse, and P.O. Wennberg (2011). Emission factors for open and domestic biomass burning for use in atmospheric models. *Atmospheric Chemistry and Physics*, 11(9), 4039–4072. https://doi.org/10.5194/acp-11-4039-2011

Amann, M., I. Bertok, J. Borken-Kleefeld, J. Cofala, C. Heyes, L. Höglund-Isaksson, Z. Klimont, B. Nguyen, M. Posch, P. Rafaj, R. Sandler, W. Schöpp, F. Wagner, and W. Winiwarter (2011). Cost-effective control of air quality and greenhouse gases in Europe: Modeling and policy applications. *Environmental Modelling & Software*, 26(12), 1489–1501. https://doi.org/10.1016/j.envsoft.2011.07.012

Amann, M., G. Kiesewetter, W. Schoepp, Z. Klimont, W. Winiwarter, J. Cofala, P. Rafaj, L. Hoeglund-Isaksson, A. Gomez-Sabriana, C. Heyes, P. Purohit, J. Borken-Kleefeld, F. Wagner, R. Sander, H. Fagerli, A. Nyiri, L. Cozzi, and C. Pavarini (2020). Reducing global air pollution: The scope for further policy interventions. *Philosophical Transactions of the Royal Society A-Mathematical Physical and Engineering Sciences*, 378(2183), 1–27. https://doi.org/10.1098/rsta.2019.0331

Center For International Earth Science Information Network-CIESIN-Columbia University. (2018). *Gridded Population of the World, Version 4 (GPWv4): Population Count Adjusted to Match 2015 Revision of UN WPP Country Totals, Revision 11* [Data set]. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4PN93PB

Chen, Y.-H.H., S. Paltsev, J. Reilly, J. Morris, and M.H. Babiker (2015). The MIT EPPA6 Model: Economic Growth, Energy Use, and Food Consumption. MIT Joint Program on the Science and Policy of Global Change Report 278, *Joint Program Report Series*, March, 46 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt278.pdf

Chen, Y.-H.H., S. Paltsev, J. Reilly, J. Morris, V.J. Karplus, A. Gurgel, N. Winchester, P. Kishimoto, E. Blanc, and M.H. Babiker (2017). The MIT Economic Projection and Policy Analysis (EPPA) Model: Version 5. MIT Joint Program on the Science and Policy of Global Change Technical Note 16, *Joint Program Report Series*, March, 34 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_TechNote16.pdf

Chepeliev, M. (2020). Development of the Air Pollution Database for the GTAP 10A Data Base. *GTAP Research Memorandum No. 33*. http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=6163

Danesh Yazdi, M., Y. Wang, Q. Di, Y. Wei, W.J. Requia, L. Shi, M.B. Sabath, F. Dominici, B.A. Coull, J.S. Evans, P. Koutrakis, and J.D. Schwartz (2019). Long-Term Association of Air Pollution and Hospital Admissions Among Medicare Participants Using a Doubly Robust Additive Model. *American Heart Association*, 0(0). https://doi.org/10.1161/CIRCULATIONAHA.120.050252

Dimanchev, E.G., S. Paltsev, M. Yuan, D. Rothenberg, C.W. Tessum, J.D. Marshall, and N.E. Selin (2019). Health co-benefits of sub-national renewable energy policy in the US. *Environmental Research Letters*, 14(8), 085012. https://doi.org/10.1088/1748-9326/ab31d9

FAO. (2018). *The future of food and agriculture – Alternative pathways to 2050 | Global Perspectives Studies | Food and Agriculture Organization of the United Nations*. https://www.fao.org/global-perspectives-studies/resources/detail/en/c/1157074/

Feng, L., S.J. Smith, C. Braun, M. Crippa, M.J. Gidden, R. Hoesly, Z. Klimont, M. van Marle, M. van den Berg, and G.R. van der Werf (2020). The generation of gridded emissions data for CMIP6. *Geoscientific Model Development*, 13(2), 461–482. https://doi.org/10.5194/gmd-13-461-2020

GAINS Developer Team. (2021, September). *GAINS 4.01 release notes*. https://gains.iiasa.ac.at/gains/download/release_notes.pdf?version=4.01

Gallagher, C.L., and T. Holloway (2020). Integrating Air Quality and Public Health Benefits in U.S. Decarbonization Strategies. *Frontiers in Public Health*, 8. https://doi.org/10.3389/fpubh.2020.563358

GEOS-Chem. (2021). *Emissions and Deposition Working Group—Geos-chem*. http://wiki.seas.harvard.edu/geos-chem/index.php/Emissions_and_Deposition_Working_Group#Recommended_Default_Emission_Inventories

Gidden, M.J., K. Riahi, S.J. Smith, S. Fujimori, G. Luderer, E. Kriegler, D.P. van Vuuren, M. van den Berg, L. Feng, D. Klein, K. Calvin, J.C. Doelman, S. Frank, O. Fricko, M. Harmsen, T. Hasegawa, P. Havlik, J. Hilaire, R. Hoesly, … K. Takahashi (2019). Global emissions pathways under different socioeconomic scenarios for use in CMIP6: A dataset of harmonized emissions trajectories through the end of the century. *Geoscientific Model Development*, 12(4), 1443–1475. https://doi.org/10.5194/gmd-12-1443-2019

Gomez Sanabria, A., G. Kiesewetter, Z. Klimont, W. Schöpp, and H. Haberl (2021). Potentials for future reductions of global GHG and air pollutant emissions from circular municipal waste management systems. *Nature Portfolio*. https://doi.org/10.21203/rs.3.rs-512870/v1

Hamilton, I., H. Kennard, A. McGushin, L. Höglund-Isaksson, G. Kiesewetter, M. Lott, J. Milner, P. Purohit, P. Rafaj, R. Sharma, M. Springmann, J. Woodcock, and N. Watts (2021). The public health implications of the Paris Agreement: A modelling study. *The Lancet Planetary Health*, 5(2), e74–e83. https://doi.org/10.1016/S2542-5196(20)30249-7

Hoesly, R.M., S.J. Smith, L. Feng, Z. Klimont, G. Janssens-Maenhout, T. Pitkanen, J.J. Seibert, L. Vu, R.J. Andres, R.M. Bolt, T.C. Bond, L. Dawidowski, N. Kholod, J. Kurokawa, M. Li, L. Liu, Z. Lu, M.C.P. Moura, P.R. O'Rourke and Q. Zhang (2018). Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS). *Geoscientific Model Development*, 11(1), 369–408. https://doi.org/10.5194/gmd-11-369-2018

IIASA. (2018). *SSP Database*. https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

Karlsson, M., E. Alfredsson, and N. Westling (2020). Climate policy co-benefits: A review. *Climate Policy*, 20(3), 292–316. https://doi.org/10.1080/14693062.2020.1724070

Klimont, Z., K. Kupiainen, C. Heyes, P. Purohit, J. Cofala, P. Rafaj, J. Borken-Kleefeld, and W. Schöpp (2017). Global anthropogenic emissions of particulate matter including black carbon. *Atmospheric Chemistry and Physics*, 17(14), 8681–8723. https://doi.org/10.5194/acp-17-8681-2017

Markandya, A., J. Sampedro, S.J. Smith, R. Van Dingenen, C. Pizarro-Irizar, I. Arto, and M. González-Eguino (2018). Health co-benefits from air pollution and mitigation costs of the Paris Agreement: A modelling study. *The Lancet Planetary Health*, 2(3), e126–e133. https://doi.org/10.1016/S2542-5196(18)30029-9

McDuffie, E.E., S.J. Smith, P. O'Rourke, K. Tibrewal, C. Venkataraman, E.A. Marais, B. Zheng, M. Crippa, M. Brauer, and R.V. Martin (2020). A global anthropogenic emission inventory of atmospheric pollutants from sector- and fuel-specific sources (1970–2017): An application of the Community Emissions Data System (CEDS). *Earth System Science Data*, 12(4), 3413–3442. https://doi.org/10.5194/essd-12-3413-2020

Morris, J., J. Reilly, S. Paltsev, and A. Sokolov (2021). Representing Socio-Economic Uncertainty in Human System Models. MIT Joint Program on the Science and Policy of Global Change Report 347, *Joint Program Report Series*, March, 25 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt347.pdf

Morris, J., A. Sokolov, A. Libardoni, C. Forest, S. Paltsev, J. Reilly, C.A. Schlosser, R. Prinn, and H. Jacoby (2021). A consistent framework for uncertainty in coupled human-Earth system models | MIT Global Change. MIT Joint Program on the Science and Policy of Global Change Report 349, *Joint Program Report Series*, February, 33 p. https://globalchange.mit.edu/publication/17574

Nam, K.-M., C.J. Waugh, S. Paltsev, J.M. Reilly, and V.J. Karplus (2013). Carbon co-benefits of tighter SO2 and NOx regulations in China. *Global Environmental Change*, 23(6), 1648–1661. https://doi.org/10.1016/j.gloenvcha.2013.09.003

O'Neill, B.C., E. Kriegler, K.L. Ebi, E. Kemp-Benedict, K. Riahi, D.S. Rothman, B.J. van Ruijven, D.P. van Vuuren, J. Birkmann, K. Kok, M. Levy, and W. Solecki (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change-Human and Policy Dimensions*, 42, 169–180. https://doi.org/10.1016/j.gloenvcha.2015.01.004

Paltsev, S., J. McFarland, J.M. Reilly, H.D. Jacoby, R.S. Eckaus, M. Sarofim, M. Asadoorian, and M. Babiker (2005). The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. MIT Joint Program on the Science and Policy of Global Change Report 125, *Joint Program Report Series*, August, 78 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt125.pdf

Paltsev, S., C.A. Schlosser, H. Chen, X. Gao, A. Gurgel, H. Jacoby, J. Morris, R. Prinn, A. Sokolov, and K. Strzepek (2021). 2021 Global Change Outlook. MIT Joint Program on the Science and Policy of Global Change, *Joint Program Report Series*, May, 52 p. https://globalchange.mit.edu/publications/signature/2021-global-change-outlook

Pienkosz, B.D., R.K. Saari, E. Monier, and F. Garcia-Menendez (2019). Natural Variability in Projections of Climate Change Impacts on Fine Particulate Matter Pollution. *Earths Future*, 7(7), 762–770. https://doi.org/10.1029/2019EF001195

Polonik, P., K. Ricke, and J. Burney (2021). Paris Agreement's Ambiguity About Aerosols Drives Uncertain Health and Climate Outcomes. *Earth's Future*, 9(5), e2020EF001787. https://doi.org/10.1029/2020EF001787

Radu, O.B., M. van den Berg, Z. Klimont, S. Deetman, G. Janssens-Maenhout, M. Muntean, C. Heyes, F. Dentener, and D.P. van Vuuren (2016). Exploring synergies between climate and air quality policies using long-term global and regional emission scenarios. *Atmospheric Environment*, 140, 577–591. https://doi.org/10.1016/j.atmosenv.2016.05.021

Rafaj, P., G. Kiesewetter, V. Krey, W. Schoepp, C. Bertram, L. Drouet, O. Fricko, S. Fujimori, M. Harmsen, J. Hilaire, D. Huppmann, Z. Klimont, P. Kolp, L.A. Reis, and D. van Vuuren (2021). Air quality and health implications of 1.5 °C–2 °C climate pathways under considerations of ageing population: A multi-model scenario analysis. *Environmental Research Letters*, 16(4), 045005. https://doi.org/10.1088/1748-9326/abdf0b

Rao, S., Z. Klimont, S.J. Smith, R. Van Dingenen, F. Dentener, L. Bouwman, K. Riahi, M. Amann, B.L. Bodirsky, D.P. van Vuuren, L. Aleluia Reis, K. Calvin, L. Drouet, O. Fricko, S. Fujimori, D. Gernaat, P. Havlik, M. Harmsen, T. Hasegawa, … M. Tavoni (2017). Future air pollution in the Shared Socio-economic Pathways. *Global Environmental Change*, 42, 346–358. https://doi.org/10.1016/j.gloenvcha.2016.05.012

Reis, L.A., L. Drouet, and M. Tavoni (2022). Internalising health-economic impacts of air pollution into climate policy: A global modelling study. *The Lancet Planetary Health*, 6(1), e40–e48. https://doi.org/10.1016/S2542-5196(21)00259-X

Riahi, K., D.P. van Vuuren, E. Kriegler, J. Edmonds, B.C. O'Neill, S. Fujimori, N. Bauer, K. Calvin, R. Dellink, O. Fricko, W. Lutz, A. Popp, J.C. Cuaresma, S. Kc, M. Leimbach, L. Jiang, T. Kram, S. Rao, J. Emmerling, … M. Tavoni (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, M.V. Vilariño, K. Calvin, J. Emmerling, S. Fuss, N. Gillett, C. He, E. Hertwich, L. Höglund-Isaksson, … R. Schaeffer (2018). *Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development*. 82.

Saari, R.K., Y. Mei, E. Monier, and F. Garcia-Menendez (2019). Effect of Health-Related Uncertainty and Natural Variability on Health Impacts and Cobenefits of Climate Policy. *Environmental Science & Technology*, 53(3), 1098–1108. https://doi.org/10.1021/acs.est.8b05094

Saari, R.K., T.M. Thompson, and N.E. Selin (2017). Human Health and Economic Impacts of Ozone Reductions by Income Group. *Environmental Science & Technology*, 51(4), 1953–1961. https://doi.org/10.1021/acs.est.6b04708

Sampedro, J., S.J. Smith, I. Arto, M. Gonzalez-Eguino, A. Markandya, K.M. Mulvaney, C. Pizarro-Irizar, and R. Van Dingenen (2020). Health co-benefits and mitigation costs as per the Paris Agreement under different technological pathways for energy supply. *Environment International*, 136, 105513. https://doi.org/10.1016/j.envint.2020.105513

Sarofim, M. (2007). *Climate Policy Design: Interactions among Carbon Dioxide, Methane, and Urban Air Pollution Constraints*. PhD Thesis, Engineering Systems, Massachusetts Institute of Technology, Cambridge, MA. https://globalchange.mit.edu/sites/default/files/Sarofim_PhD_07.pdf

Scovronick, N., M. Budolfson, F. Dennig, F. Errickson, M. Fleurbaey, W. Peng, R.H. Socolow, D. Spears, and F. Wagner (2019). The impact of human health co-benefits on evaluations of global climate policy. *Nature Communications*, 10, 2095. https://doi.org/10.1038/s41467-019-09499-x

Selin, N. (2021). Beyond "Co-Benefits": A New Framework for Assessing Sustainability. In *2021 Global Change Outlook* (p. 52). MIT Joint Program on the Science and Policy of Global Change. https://globalchange.mit.edu/publications/signature/2021-global-change-outlook

Shindell, D., M. Ru, Y. Zhang, K. Seltzer, G. Faluvegi, L. Nazarenko, G.A. Schmidt, L. Parsons, A. Challapalli, L. Yang, and A. Glick (2021). Temporal and spatial distribution of health, labor, and crop benefits of climate change mitigation in the United States. *Proceedings of the National Academy of Sciences*, 118(46). https://doi.org/10.1073/pnas.2104061118

Smith, S.J., Z. Klimont, L. Drouet, M. Harmsen, G. Luderer, K. Riahi, D.P. van Vuuren, and J.P. Weyant (2020). The Energy Modeling Forum (EMF)-30 study on short-lived climate forcers: Introduction and overview. *Climatic Change*, 163(3), 1399–1408. https://doi.org/10.1007/s10584-020-02938-5

Sokolov, A., D. Kicklighter, A. Schlosser, C. Wang, E. Monier, B. Brown-Steiner, R. Prinn, C. Forest, X. Gao, A. Libardoni, and S. Eastham (2018). Description and Evaluation of the MIT Earth System Model (MESM). *Journal of Advances in Modeling Earth Systems*, 10(8), 1759–1789. https://doi.org/10.1029/2018MS001277

Thompson, T.M., S. Rausch, R.K. Saari, and N.E. Selin (2014). A systems approach to evaluating the air quality co-benefits of US carbon policies. *Nature Climate Change*, 4(10), 917–923. https://doi.org/10.1038/nclimate2342

Tong, D., G. Geng, Q. Zhang, J. Cheng, X. Qin, C. Hong, K. He, and S.J. Davis (2021). Health co-benefits of climate change mitigation depend on strategic power plant retirements and pollution controls. *Nature Climate Change*, 11(12), 1077–1083. https://doi.org/10.1038/s41558-021-01216-1

Valpergue De Masin, A. (2003). *Economic Modeling of Urban Pollution and Climate Policy Interactions* [Master of Science Thesis, MIT Technology and Policy Program, and Department of Civil and Environmental Engineering]. https://globalchange.mit.edu/publication/13900

van der Werf, G.R., J.T. Randerson, L. Giglio, T.T. van Leeuwen, Y. Chen, B.M. Rogers, M. Mu, M.J.E. van Marle, D.C. Morton, G.J. Collatz, R.J. Yokelson, and P.S. Kasibhatla (2017). Global fire emissions estimates during 1997–2016. *Earth System Science Data*, 9(2), 697–720. https://doi.org/10.5194/essd-9-697-2017

van Marle, M.J.E., S. Kloster, B.I. Magi, J.R. Marlon, A.-L. Daniau, R.D. Field, A. Arneth, M. Forrest, S. Hantson, N.M. Kehrwald, W. Knorr, G. Lasslop, F. Li, S. Mangeon, C. Yue, J.W. Kaiser, and G.R. van der Werf (2017). Historic global biomass burning emissions for CMIP6 (BB4CMIP) based on merging satellite observations with proxies and fire models (1750–2015). *Geoscientific Model Development*, 10(9), 3329–3357. https://doi.org/10.5194/gmd-10-3329-2017

Vandyck, T., K. Keramidas, A. Kitous, J.V. Spadaro, R. Van Dingenen, M. Holland, and B. Saveyn (2018). Air quality co-benefits for human health and agriculture counterbalance costs to meet Paris Agreement pledges. *Nature Communications*, 9, 4939. https://doi.org/10.1038/s41467-018-06885-9

Vandyck, T., K. Keramidas, S. Tchung-Ming, M. Weitzel, and R. Van Dingenen (2020). Quantifying air quality co-benefits of climate policy across sectors and regions. *Climatic Change*. https://doi.org/10.1007/s10584-020-02685-7

Vandyck, T., S. Rauner, J. Sampedro, E. Lanzi, L.A. Reis, M. Springmann, and R. Van Dingenen (2021). Integrate health into decision-making to foster climate action. *Environmental Research Letters*, 16(4), 041005. https://doi.org/10.1088/1748-9326/abef8d

Vohra, K., A. Vodonos, J. Schwartz, E.A. Marais, M.P. Sulprizio, and L.J. Mickley (2021). Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem. *Environmental Research*, 110754. https://doi.org/10.1016/j.envres.2021.110754

Waugh, C.J. (2012). *An Integrated Assessment of Air Pollutant Abatement Opportunities in a Computable General Equilibrium Framework*. 150. S.M. Thesis, Technology and Policy Program, Massachusetts Institute of Technology, Cambridge, MA.

Webster, M., S. Paltsev, J. Parsons, J. Reilly, and H. Jacoby (2008). Uncertainty in Greenhouse Gas Emissions and Costs of Atmospheric Stabilization. MIT Joint Program on the Science and Policy of Global Change Report 165, *Joint Program Report Series*, November, 87 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt165.pdf

Workman, A., G. Blashki, K.J. Bowen, D.J. Karoly, and J. Wiseman (2018). The Political Economy of Health Co-Benefits: Embedding Health in the Climate Change Agenda. *International Journal of Environmental Research and Public Health*, 15(4), 674. https://doi.org/10.3390/ijerph15040674

Yang, Y., L. Liu, Z. Bai, W. Xu, F. Zhang, X. Zhang, X. Liu, and Y. Xie (2021). Comprehensive quantification of global cropland ammonia emissions and potential abatement. *Science of The Total Environment*, 151450. https://doi.org/10.1016/j.scitotenv.2021.151450

Yuan, M., S. Rausch, J. Caron, S. Paltsev, and J. Reilly (2019). The MIT U.S. Regional Energy Policy (USREP) Model: The Base Model and Revisions. MIT Joint Program on the Science and Policy of Global Change Technical Note 18, *Joint Program Report Series*, August, 26 p. https://globalchange.mit.edu/sites/default/files/MITJPSPGC_TechNote18.pdf

Zheng, B., D. Tong, M. Li, F. Liu, C. Hong, G. Geng, H. Li, X. Li, L. Peng, J. Qi, L. Yan, Y. Zhang, H. Zhao, Y. Zheng, K. He, and Q. Zhang (2018). Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmospheric Chemistry and Physics*, 18(19), 14095–14111. https://doi.org/10.5194/acp-18-14095-2018

Appendix A: CEDS Reference Data

Table A1. Percentage of base-year (2014) CEDS emissions from different fuel consumption vs. process sources (broken down by sector, aggregated globally).

Sector	Fuel	SO_2	CO	NH_3	BC	OC	NO[a]	C_2H_4[b]
Agriculture	coal			0			0	
	biofuels			0			0	
	oil/gas			0			0	
	process			100			100	
Energy	coal	65	11	5	2	7	50	0
	biofuels	0	1	2	8	39	3	0
	oil/gas	18	9	7	2	0	33	0
	process	17	79	85	88	54	14	100
Industrial	coal	43	42	5	53	22	54	28
	biofuels	0	8	35	19	72	8	24
	oil/gas	18	5	9	27	6	33	9
	process	38	46	51	0	0	5	40
Non-road transport	coal	0	0	0	0	0	0	0
	biofuels	0	0	0	0	0	0	0
	oil/gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Commercial	coal	71	51	25	49	44	0	24
	biofuels	1	10	25	23	48	0	24
	oil/gas	28	39	50	28	8	100	52
	process	0	0	0	0	0	0	0
Other	coal	37	10	12	13	23	1	6
	biofuels	0	21	9	8	42	2	17
	oil/gas	63	70	79	80	34	97	77
	process	0	0	0	0	0	0	0
Residential	coal	72	14	0	14	8	9	3
	biofuels	18	86	96	69	91	56	96
	oil/gas	10	1	4	17	0	35	1
	process	0	0	0	0	0	0	0
Transport	coal	0	0	0	0	0	0	0
	biofuels	0	0	0	0	0	0	0
	oil/gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Shipping	coal	0	0	0	0	0	0	0
	biofuels	0	0	0	0	0	0	0
	oil/gas	100	100	100	100	100	100	100
	process	0	0	0	0	0	0	0
Solvents	coal			0				
	biofuels			0				
	oil/gas			0				
	process			100				
Waste	coal	0	0	0	0	0	0	0
	biofuels	0	0	0	0	0	0	0
	oil/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. Global aggregate proportions are shown here for context; full regional and speciated values are used in TAPS.

Appendix B: Mapping from GAINS Database

Table B1. 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 Fig. 2. Regions in italics differ slightly from EPPA definitions.

Table B2. Mapping from GAINS NH_3 to CEDS/GFED sectors and fuels.

Inventory sector	CEDS fuel	GAINS NH3 sector classes	GAINS NH3 sector class names
Agricultural waste	Process	WASTE_AGR	Agricultural waste burning
Agriculture	Process	AGR, COWS, FCON, FERTPRO	Livestock and fertilizer (Table B3)
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, and 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

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 GAINS abbreviations described here. [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 B3. 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 and FAO sectors in regional aggregate data.

Table B4. 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 italics, while corollaries that represent a part of their EPPA regions (or vice versa) are underlined. 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. 2.3.

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