**U.S. Environmental Protection Agency**

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**Research Effort Title:**

Developing air quality and health benefit-per-ton impact factors from COBRA for

GCAM-USA

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# Introduction

Tropospheric ozone (O3) and fine particulate matter of diameter less than 2.5 microns (PM2.5) are regulated air pollutants in the United States. O3 is a secondary pollutant, formed through atmospheric reactions among nitrogen oxides (NOx) and volatile organic compounds (VOCs). Ambient PM2.5 is comprised of primary and secondary PM. Primary PM2.5 is directly emitted, while secondary PM2.5 is produced in reactions that involve precursor species such as NOx, sulfur dioxide (SO2), and ammonia (NH3).

To reduce O3 and PM2.5 concentrations, anthropogenic emissions of NOx, SO2, and primary PM2.5 traditionally have been reduced by applying pollutant-specific "end-of-pipe" controls (e.g., particulate filters) or process changes (e.g., low-NOx burners). While these controls are applied upwind and within areas with poor air quality, cost-effective control options may not exist for some source categories. As a result, ambient O3 and PM2.5 concentrations exceed National Ambient Air Quality Standards (NAAQS) in many locations (EPA 2025).

Fuel combustion is a major source of NOx, SO2, and direct PM2.5, and measures that reduce combustion (e.g., renewable energy, energy efficiency, and fuel switching, aka RE/EE/FS) can also reduce the precursors to O3 and PM2.5. RE/EE/FS tend to be more costly on a dollar-per-ton-of-emissions-reduced basis than traditional controls when reductions target only a single pollutant or precursor species; however, RE/EE/FS have the potential to reduce emissions of multiple pollutants simultaneously, potentially changing this calculus.

The benefits of RE/EE/FS in air quality management have been broadly recognized, including through guidance provided to states by the EPA (EPA 2011, 2012). Efforts to quantify the role of RE/EE/FS often target a specific sector (EPA 2025a, NREL 2025), Models and tools for evaluating RE/EE/FS across the economy are emerging as well. For example, energy and integrated assessment models have been used to develop marginal abatement cost curves that incorporate both traditional controls and RE/EE/FS (Loughlin et al., 2015; Loughlin et al., 2017). Also, benefit-per-ton values have been integrated into energy and integrated assessment models, allowing the benefits of technology and policy scenarios to be quantified (Ou et al., 2019; Roth et al., 2022; Ou et al., 2023), considered in planning decisions (Brown et al., 2013; Brown et al., 2017), and used to optimize control strategies to achieve specific health benefits cost-effectively (Ou et al., 2020).

Quantification of the benefits of scenarios involving RE/EE/FS can also be accomplished by linking energy and human-Earth system models to more comprehensive air quality modeling and health benefit tools. Recent examples for the U.S. include Wang et al. (2024) and Shankar et al. (2025), both of which used chemical transport models (CTMs) to evaluate air quality impacts of decarbonization scenarios. Full-scale CTMs are computationally intensive, potentially limiting the number of scenarios that can be examined. An alternative is to use reduced-form models (RFM), which are often statistical models built to capture the primary source-receptor relationships between emissions and air quality (citations for EASIUR, APEEP, InMAP, COBRA, Loughlin et al., 2024.

This work builds upon that of Ou et al. (2020), which integrated state-, source category-, and pollutant-specific PM-related benefit-per-ton values derived from the EASIUR RFM into a variant of the Global Change Analysis Model with state-level resolution (GCAM-USA). In that effort, a national PM health benefit improvement target was then imposed, and GCAM-USA was used to identify a mix of traditional controls and RE/EE/FS across the U.S. that cost-effectively achieved the national benefit target. While the approach provided strategies for achieving national PM-based health benefits, it was less able to provide state-specific insights. Furthermore, the analysis focused on PM and did not consider other air pollutants such as O3.

In this work, a similar approach is applied, with several important updates. First, we developed benefit-per-ton values for both PM and O3 precursors. These were developed using a more recent source-receptor (S-R) matrix than used by Ou et al. (Baker et al., 2023). We then demonstrated the use of these impact factors to evaluate the benefits of state-level health benefits, allowing a fuller comparison of air quality management strategies from one state to another. In a later phase of this work, we also added the ability to generate impacts of emissions on population-weighted state-level PM and O3 concentrations.

# Approach

Two models were used in this activity, the Global Change Analysis Model (GCAM-USA) and the CO-Benefits Risk Assessment (COBRA) model. First, GCAM-USA was used to simulate technology adoptions, fuel use, and emissions for a reference case. Reference case emissions were then fed to COBRA to develop baseline air pollution levels and health damage estimates. We then performed several thousand parametric sensitivity runs around the reference case using COBRA, incrementally modifying emissions of NOx, SO2, and PM2.5 by state and source category. The emission changes and air quality and health impacts were assessed to estimate $/ton and pollutant-concentration/ton impact factors.

These factors were integrated into GCAM-USA such that any scenario that is evaluated produces estimates of damages and air pollutant levels. Comparing the results of a reference case and policy case thus provided an estimate of the benefits of the policy. To demonstrate this approach, we compared the GLIMPSE 1.2 Reference Case with a scenario in which the sum of O3 and PM damages were reduced by a percentage increasing linearly from 0% in 2025 to 15% in 2050, applied to all states.

**2.1 Models**

Global Change Analysis Model (GCAM): GCAM is a human-Earth systems model, developed by PNNL, that simulates the co-evolution of the economy, energy system, land use, and earth systems, including how this co-evolution is shaped by policy and other external factors. GCAM is an open-source model, with code and documentation that can be found on GitHub (<https://github.com/JGCRI/gcam-core>). We used a version of GCAM 7.1 (released 2024), called GCAM-USA 7.1, in which the representation of the United States is disaggregated to the state level. GCAM-USA simulations were conducted using EPA’s GCAM Long-term Interactive Multi-Pollutant Scenario Evaluator (GLIMPSE), version 1.2.

Co-Benefits Risk Assessment Model (COBRA): COBRA is an EPA tool that is available as a desktop or web-based tool (<https://epa.gov/cobra>). We used the desktop version of the tool, which allows the development of more complex scenarios and includes a batch-mode feature that is critical for executing the thousands of GCAM runs made in this project. Desktop COBRA includes a county-level version of the 2016 EPA National Emissions Inventory (NEI) (citation), including projections to 2023, 2026, and 2028.

**2.2 Scenarios**

While the scenarios used in this project may change in the future, the following scenarios were used in demonstrating the approach.

Reference (*Ref*): *Ref* is the GLIMPSEv1.2-Ref scenario that is distributed along with EPA’s GCAM Long-term Interactive Multi-Pollutant Scenario Evaluator (GLIMPSE). It is based upon the GCAM-USA 7.1 reference scenario, but includes the following additional components, which are intended to represent current regulations and policies that would impact the evolution of the energy system:

* the Regional Greenhouse Gas Initiative (RGGI), a cap on power-sector CO2 emissions in participating states,
* state-specific renewable portfolio standards (RPS) and clean energy standards (CES),
* technology subsidies associated with the Inflation Reduction Act (IRA); and,
* ZEV market share estimates for light, medium, and heavy-duty vehicles, estimated in the EPA’s regulatory analyses of recent transportation greenhouse gas emissions rules.

DmgRdx25: DmgRdx25 reduces the health damages from each state’s emissions by a fraction increasing linearly from 0 in 2025 to 25% in 2050, relative to *Ref* levels in the same year. These targets are implemented through imposing state-specific constraints.

* 1. **Methods**

*2.3.1 Developing Benefit-Per-Ton Impact Factors*

GCAM-USA is used to estimate air pollutant emissions for the Reference scenario by sector, state, and pollutant from 2020 to 2050 in 5-year increments. State-level emissions are then mapped to the source types listed and described in Table 2. These source types were selected to represent major categories represented in the EPA’s National Emissions Inventory (NEI), but also to differentiate by emissions intensity (e.g., coal vs. non-coal in the power sector) and by impact on exposure (e.g., ground-level vs. dispersed).

Table 2. Source types used in developing and applying impact factors

|  |  |
| --- | --- |
| **Source type** | **Description** |
| EGU Coal | Coal-fired power plants |
| EGU Other | All other power plants |
| Petroleum & Related Industries | Oil and gas production, refining, and bio-refining |
| Fuel Combustion: Industry | All other industrial combustion sources |
| Fuel Combustion: Other | Residential, commercial, and institutional buildings |
| Highway Vehicles | Onroad cars, trucks, and buses |
| Off-Highway Vehicles | Airplanes, ships, rail, construction, and agricultural vehicles |
| Other Area | Smaller, distributed sources that did not fit into other categories |
| Other Point | Large stationary sources that did not fit in any other categories |

For each of these categories, state-level emissions of NOx, SO2, and primary PM2.5 were summed by source type. For 2030, 2035, 2040, 2045, and 2050, these sums were divided by the corresponding values in the 2023 NEI projection of COBRA, producing state-, source category-, and pollutant-specific factors. By multiplying these factors and the 2023 county-level NEI values, we developed *Ref* input files for COBRA that can be used to simulate any of the modeled years between 2030 and 2050. These *Ref* files served as the baseline for comparison.

Next, we conducted a parametric sensitivity analysis in which we generate alternative scenarios by reducing emissions in one state, source type, and pollutant by 10%, leaving all other values unchanged. With 49 states (conterminous U.S. plus the District of Columbia), 9 source types, 3 pollutants, and 5 simulation years, this is expected to result in as many as 6,615 unique combinations. However, since not every state has emissions from each source type in each year, the overall number of COBRA simulations is expected to be 6,435.

The COBRA tool produces 5 estimates of the monetized benefits due to decreased air pollution mortality associated with each emission reduction scenario relative to a baseline, which is *Ref* in this instance. These estimates are:

* the benefits due to decreased O3 (Turner et al., 2016),
* two estimates of the benefits due to decreased PM2.5, calculated using high (Pope et al., 2019) and low (Wu et al., 2020) estimates for the concentration-response factor linking PM2.5 concentrations to air pollution mortality; and,
* two estimates of the combined benefits due to decreased O3 and PM2.5 (one using the low PM values and the other the high values).

The COBRA outputs were used to estimate benefit-per-ton (BPT) factors, i.e., the monetized benefit, ***B***, of decreased air pollution mortality per ton of emissions reductions, ***E***. BPT factors were computed for each pollutant*,* state*,* source type*,* and year using the following equation*:*

Where:

***s****:* state

***y****:* year

***t****:* source type

***p****:* pollutant (PM2.5 or O3)

These scenarios were run through COBRA to get monetized health benefit values for each reduction scenario, comparing each reduction scenario to *Ref* for that year using a 2% discount rate. For each of the unique 6,435 COBRA runs, data was generated for each county in each state with estimates for changes in PM2.5 and O3 concentrations, total benefits ($), and PM2.5 and O3 related benefits ($).

Note that while each reduction scenario occurs in only one state, the air pollutant benefits may occur in that state and in other states. Thus, benefits were calculated by summing county-level values across the entire country.

*2.3.2 Developing Concentration Impact Factors*

In the second phase of this work, developed impact factors that translate changes in NOx, PM2.5, and SO2 emissions into changes in state-level PM2.5 and O3 concentrations. Since COBRA outputs pollutant concentrations at the county level, these factors need to be aggregated up to the state level. We plan to explore two aggregation approaches.

*2.3.3 Population-weighted aggregation*

In the first aggregation approach, we plan to use county-level populations to develop a population-weighted state-level impact factor. The output from COBRA runs gives concentration changes for PM2.5 and O3 by county for each scenario, which are matched with county population projections for each year. Our first step in generating these impact factors was to obtain a population-weighted average of the concentration changes in each state for a given scenario. These weighted averages can be expressed as:

Where:

***s****:* state

***y****:* year

***t****:* source type

***c***: county

***r***: reduction scenario

***p****:* pollutant (PM2.5 or O3)

For each county, the change in O3 and PM2.5 concentrations were multiplied by the population estimate for that county and then summed for each county within each state. Then, dividing by the total population in each state, left us with the average PM2.5 and O3 concentration changes for each state, for each reduction scenario, giving more weight to the concentration changes in more populous areas.

To get impact factors, i.e., the effect of NOx, PM2.5, and SO2 emissions reductions on the weighted averages, the weighted average for each state in each scenario was divided by the emissions reduction of that scenario. Each scenario’s population-weighted impact factor (PWIF) can be expressed as:

Where:

***s****:* state

***y****:* year

***t****:* source type

***c***: county

***r***: reduction scenario

***p****:* pollutant (PM2.5 or O3)

This gives the effect of a one-unit reduction of pollutant ***n*** (NOx, PM2.5, or SO2) on the concentration of pollutant ***p*** (PM2.5 or O3), weighted by population. This impact factor varies across states within scenarios, indicating where emissions reductions have greater impacts on PM2.5 and O3 concentrations.

*2.3.4 Selection of county with highest Ref concentration*

In addition to population-weighted impact factors, impact factors are calculated using only the change in O3 or PM2.5 concentrations in the counties with the highest base concentration levels in *Ref*. For each scenario the state-level change in concentrations is set equal to the value from the county with the highest base concentration level, for both PM2.5 and O3. We then divide the change in PM2.5 and O3 concentrations by the amount of NOx, PM2.5, or SO2 reduced in that scenario. This highest base impact factor (HBIF) can be expressed as:

Where:

***s****:* state

***r****:* reduction scenario

***c****:* county

***y****:* year

***p****:* pollutant (PM2.5 or O3)

For each scenario, these impact factors represent how a one-unit reduction in NOx, PM2.5, or SO2 affects PM2.5 and O3 concentrations in the counties with the worst initial air quality.

*2.3.5 Endogenizing Benefit-Per-Ton values in GCAM*

Once the impact-per-ton values have been developed, we integrated them into GCAM-USA as if they were emission factors. This required converting the factors from impact-per-ton-of-emissions to impact-per-unit-of-activity. In principle, this conversion is straightforward. For example, to convert a power plant NOx rate into a damage rate, the following equation was used:

1 NOx/EJout \* 1 Impact/NOx = 1 Impact/EJout

This new impact factor could then be added as an emission factor to that type of power plant.

While conceptually straightforward, we expect there to be some complications in practice. Complications include the following:

* in GCAM inputs, there is no single table of air pollutant emission factors – instead, they are distributed through many input files
* some air pollutant emission factors are defined as input-based, while others are defined as output-based
* emission factors may differ by the vintage of a technology, potentially through time, and by state or region

To address these issues, we first needed to develop a consistent set of air pollutant emission factors for all model technologies and vintages in the U.S.

To accomplish this, first, we used GLIMPSE to simulate a scenario based on *Ref* but that includes a small carbon price. The carbon price ensured that technologies that incorporate carbon capture and sequestration were not left out of the solution.

Next, the GLIMPSE-ModelInterface was used to query the model’s results using the following queries:

* Output by all technologies and vintages
* Emissions by technology and vintage

Using the results of these queries, we divided emissions by outputs to develop state-, technology-, vintage- and pollutant-specific output-based emission factors. These emission factors were then multiplied by the matching source type impact factor to produce impact-per-unit-output impact factors. These impact factors were then organized and formatted such that they can be added to technologies using the GLIMPSE-ModelInterface’s CSV-to-XML conversion utility.

We expect to use this approach to develop and integrate the following impact factors into GCAM:

* O3-related benefit per ton
* PM-related benefit per ton (using the average of the high and low PM damage estimates)
* Total benefit per ton (using the sum of the O3-related and PM-related benefit-per-ton values)

In the second phase of this work, we plan to develop O3 concentration and PM concentration impact factors by state. Thus, each pollutant source would have 51 impact factors, reflecting its impacts on downwind air pollutant concentrations within all US states and DC.

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