

EQUIVALENCY ANALYSIS OF STATE-LEVEL AIR POLLUTION
EMISSIONS ESTIMATES FROM AN INTEGRATED ASSESSMENT
MODEL: GCAM-USA

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Abstract

The use of Integrated Assessment Models (IAMs) has expanded from their primary application, global climate assessment, to examine broader environmental trends such as air pollution emissions, including those at sub-national levels. While most IAMs are evaluated for internal validity, little literature evaluates IAM performance against real-world data. In this paper, 2015 estimates from the Global Climate Assessment Model (GCAM), an IAM, of state-level air pollution from five macro-economic sectors and six air pollutants, are tested against EPA data using two equivalency analysis tests. One-sided t-tests and regression analysis determine if modeled emissions fall within 20% of U.S. Environmental Protection Agency data. The results are mixed, showing that GCAM emissions estimates from only one sector and one pollutant pass both tests, and two sectors and two pollutants pass neither test. This indicates that GCAM-USA is more appropriate for examining national trends than specific sectors or pollutants at the sub-national level.

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1. Introduction

Integrated Assessment Models (IAMs) are incredibly powerful tools used to evaluate complex global environmental phenomena. They are global, quantitative models that analyze the interactions between population, available resources, energy technologies and demand, the labor force, labor productivity, agricultural technologies, and land characteristics, and others over decades-long time horizons to study system-wide effects.¹ They have been most widely applied to climate science, examining mitigation options, climate impacts, emissions trajectories, and carbon pricing as well as future energy and land use at global or regional scales.^{2,3} IAMs can inform policymakers about the potential impacts of different climate policy options. As IAMs become more powerful and sophisticated, they are being applied to a broader range of environmental indicators beyond climate, such as air pollution, and used to examine trends at regional and even state levels. IAMs are essential tools that inform our understanding of some of the most pressing issues of our time: the impacts of climate change, the cost of resource degradation, and the health impacts of pollution, to name a few.

As the application of IAMs expands, researchers must understand, test, and communicate IAMs' strengths and limitations to a wide array of users. These models are often so large and complex that few beyond those who work on them fully understand their internal structures and embedded assumptions. Even so, now a much broader audience including academics, business leaders, and policymakers use their findings to inform decision-making. In many cases, model developers evaluate model assumptions

¹ JGCRI GCAM Team, "Overview of the Global Change Assessment Model (GCAM)" (November 8, 2017), http://www.globalchange.umd.edu/data/annual-meetings/2017/GCAM_overview_2017.pdf.

² John Weyant, "Some Contributions of Integrated Assessment Models of Global Climate Change," *Review of Environmental Economics and Policy* 11, no. 1 (January 1, 2017): 115–37, <https://doi.org/10.1093/reep/rew018>.

³ Wenjing Shi et al., "Projecting State-Level Air Pollutant Emissions Using an Integrated Assessment Model: GCAM-USA," *Applied Energy* 208 (December 15, 2017): 511–21, <https://doi.org/10.1016/j.apenergy.2017.09.122>.

for internal consistency and researchers run multiple, sometimes thousands, of scenarios defining outcome ranges rather than values. Comparing IAM estimates to existing data is a well-established and clear way to evaluate the models. Comparing modeled data to historic data is not always an option to examine model validity, as many models incorporate the most recent data available and are forward-looking. However, when data are available, comparing model outputs to historic data can be an effective method to evaluate an IAM, especially when applying the IAM to new applications or scales.

This paper uses quantitative equivalency analysis to analyze how accurately the Global Climate Assessment Model USA (GCAM-USA), an IAM, estimates air pollution emissions aggregated from fifty U.S. states. This paper attempts to answer the question “do GCAM-USA’s estimates for 2015 emissions for five macro-economic sectors and six criteria air pollutants fall within 20% of Environmental Protection Agency (EPA) emissions data?” This question is answered using two tests of equivalence: one-sided t-tests and regression analyses. In Test 1, GCAM-USA’s average pollution emissions estimates for each sector and pollutant are tested using one-sided t-tests, to see if they fall within 20% of EPA data at 90% confidence. In Test 2, GCAM-USA estimated data is plotted against EPA’s data and is used for a regression analysis to determine if the slope of the trend line falls within 20% of real-world data.

The results show that when data is aggregated from all fifty states and averaged across all sectors or all pollutants, GCAM-USA estimates closely match EPA’s data, but this average masks significant discrepancies at the sector and pollutant level. Only GCAM-USA estimates for the commercial/residential sector and NO_x pollutant fall within 20% of EPA data, passing both Test 1 and Test 2. The on-road transportation

sector and CO and NH₃ pollutants come close to passing both tests and the industrial sector and PM₁₀ pollutant pass one of the two tests. Finally, the GCAM-USA estimates for the electric sector, industrial fuels sector, PM_{2.5} pollutant, and SO₂ pollutant fail both Test 1 and Test 2, indicating that GCAM-USA does not estimate emissions from these sectors well. GCAM-USA is a useful tool, but users must understand the model's limitations and exercise discretion when using data aggregated from all fifty states and/or applying it to individual sectors or pollutants.

Section Two provides an overview of existing literature on IAM assessments and evaluation methods. Section Three describes the data and methods used for this analysis. Section Four presents the results of the comparison between GCAM-USA and EPA data and Section Five provides a discussion of these results, the study's limitations, and areas for future research.

2. Literature Review and Theoretical Framework

2.1 The Emergence of IAM Evaluation

Meadows et al. were the first to use a global model of earth systems with over a 100-year time horizon, a precursor to the IAM, and in 1972, they published their model results in the seminal work, *Limits to Growth*.⁴ In *Limits to Growth*, they predicted that exponential population growth and increased economic output would surpass global carrying capacity within one hundred years, likely resulting in “a rather sudden and uncontrollable decline in both population and industrial capacity.”⁵ Despite the dire outlook, the authors posited that it was possible to alter these trends to achieve a

⁴ Donella H. Meadows et al., *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind* (New York: Universe Books, 1972), <http://www.clubofrome.org/report/the-limits-to-growth/>.

⁵ Meadows et al., 23.

sustainable future. Meadows et al. were explicit about the limitations of their model, and models generally, which they called “imperfect, oversimplified, and unfinished.”⁶

Despite these limitations, the authors published their results believing the conclusions were relevant to policymakers and for decisions about natural resources. In doing so they sparked an important public dialogue on what constitutes sustainable global growth.⁷

Meadows et al. work mirrors modern-day challenges on how to use IAM data in a way that captures its limitations, but still serves the needs of policymakers and the public.

By the 1990s, IAMs were widely adopted as a climate change analysis tool but there were still validity concerns. In 1991, economist William Nordhaus created a mathematical model that estimated a doubling of global CO₂ concentrations would cause a 1-2% decline of global gross domestic product (GDP).⁸ Though he qualified his conclusion as “no more than an informed hunch,” by the mid-90s Nordhaus’ model was used as the basis for several IAMs.⁹ The widespread use of IAM’s that academics, including Nordhaus, freely admitted were not validated caused significant concern.¹⁰

In 1996, *Climate Change*, the preeminent journal on the subject, published a series of articles and letters documenting interdisciplinary arguments for and against the use of IAMs for climate research. Dr. Ronald Brunner, a policy scientist from the University of Colorado Boulder challenged the U.S. Global Change Research Program’s (USGCRP) use of IAMs to inform U.S. and global policy making. Brunner argued that long-term models

⁶ Meadows et al., 21.

⁷ Meadows et al., 22.

⁸ William D. Nordhaus, “To Slow or Not to Slow: The Economics of The Greenhouse Effect,” *The Economic Journal* 101, no. 407 (1991): 936, <https://doi.org/10.2307/2233864>.

⁹ James Risbey, Milind Kandlikar, and Anand Patwardhan, “Assessing Integrated Assessments,” *Climatic Change* 34, no. 3 (November 1996): 377, <https://doi.org/10.1007/BF00139298>.

¹⁰ Hadi Dowlatabadi, “Integrated Assessment Models of Climate Change: An Incomplete Overview,” *Energy Policy*, Integrated assessments of mitigation, impacts and adaptation to climate change, 23, no. 4 (April 1, 1995): 289–96, [https://doi.org/10.1016/0301-4215\(95\)90155-Z](https://doi.org/10.1016/0301-4215(95)90155-Z).

are at best “little more than educated guesses,” and that further research should focus on limited, local models for smaller-scale policymaking.¹¹ In response, Dr. Paul Edwards, a computer scientist at Stanford University, argued that even though their results can be highly uncertain IAMs are a major reason climate change became part of the global political agenda.¹² Simon Shackley, who studied climate policy and sociology at Lancaster University, responded that the true issue is communicating model uncertainties and limitations effectively to policymakers and the public.¹³ All three have been proven correct, in part. IAM results are now a standard tool used to inform global and national climate policies, and an emerging tool to examine climate and other environmental challenges at national and sub-national scales. Even so, there are still significant challenges communicating IAM results and, in particular, model limitations to the public and decision makers.

2.2 The Modern Era of IAM Evaluation

Despite their widespread adoption for climate science, IAMs have significant limitations that are not always fully addressed. Ackerman et al. found that many IAMs use over-inflated discount rates that cause the models to underutilize short-term action as a mitigation strategy.¹⁴ They argued that these models do not use the most up-to-date economic theories on uncertainty analysis and that economic data alone are insufficient to

¹¹ Ronald D. Brunner, “Policy and Global Change Research,” *Climatic Change* 32, no. 2 (February 1, 1996): 121–47, <https://doi.org/10.1007/BF00143705>.

¹² Paul N. Edwards, “Global Comprehensive Models in Politics and Policymaking,” *Climatic Change* 32, no. 2 (February 1, 1996): 149–61, <https://doi.org/10.1007/BF00143706>.

¹³ Simon Shackley, “Comments on R. D. Brunner (Climatic Change 32, 121–147) and P. N. Edwards (Climatic Change 32, 149–161),” *Climatic Change* 34, no. 3 (November 1, 1996): 547–50, <https://doi.org/10.1007/BF00139305>.

¹⁴ Frank Ackerman et al., “Limitations of Integrated Assessment Models of Climate Change,” *Climatic Change* 95, no. 3 (August 1, 2009): 297–98, <https://doi.org/10.1007/s10584-009-9570-x>.

inform climate policy.¹⁵ Wilson et al. find that IAMs tend to underestimate the emergence of new energy technologies compared to historical rate of energy technology growth and dissemination.¹⁶ Stern describes how many IAM grossly underestimate the risks of climate change, in particular catastrophic outcomes.¹⁷ These critiques serve as both a warning to IAM data users and a challenge for future model-designers.

Several academics have directly addressed model validity concerns. Risbey et al. identified quality controls as vital to IAM's long-term credibility as a policymaking tool.¹⁸ They outlined an early set of basic IAM quality control recommendations for researchers including: clearly articulate the goals of IAM research, identify the limitations of the models, and apply greater scrutiny to foundational model assumptions. Risbey et al. also cautioned against applying IAMs developed for one discipline and scale to other research areas and scales without full understanding of the underlying model mechanics, called for more evaluations of IAMs, and encouraged greater IAM funding and application diversity.¹⁹

Oreskes argued that IAMs attempt to predict the future and we cannot prove their validity *a priori*; therefore, IAM results should not be validated, but evaluated: assessed for both positive and negative results and modified, or even rejected, if necessary.²⁰

Oreskes proposed creating tests that could be passed or failed – such as comparing

¹⁵ Ackerman et al., 314.

¹⁶ C. Wilson et al., “Future Capacity Growth of Energy Technologies: Are Scenarios Consistent with Historical Evidence?,” *Climatic Change* 118, no. 2 (May 1, 2013): 393–94, <https://doi.org/10.1007/s10584-012-0618-y>.

¹⁷ Nicholas Stern, “The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models,” *Journal of Economic Literature* 51, no. 3 (2013): 838–59.

¹⁸ Risbey, Kandlikar, and Patwardhan, “Assessing Integrated Assessments.”

¹⁹ Risbey, Kandlikar, and Patwardhan, 392–93.

²⁰ Oreskes N, “Evaluation (Not Validation) of Quantitative Models.,” *Environmental Health Perspectives* 106, no. suppl 6 (December 1, 1998): 1457, <https://doi.org/10.1289/ehp.98106s61453>.

modeled data to real world data – to evaluate models.²¹ In Oreske’s conception, without a robust evaluation process, IAM results are not scientifically sound and, accordingly, are of limited utility to policymakers. While not all of Risbey et al. and Oreske’s recommendations have been consistently adopted across disciplines, they form the basis of IAM evaluation today.

As IAMs become more sophisticated and interdisciplinary, traditional evaluation methods, including those outlined by Oreske and Risbey et al., have been considered inadequate and the modeling community has responded by developing best practices to supplement IAM evaluation. Jakeman, Letcher, and Norton outlined ten steps to develop and evaluate environmental IAMs, placing emphasis on the investigator clearly defining the purposes and scope of the model and being transparent about the model’s underlying assumptions when presenting results.²² Schwantiz developed an evaluation framework specifically for climate change IAMs, which includes testing whether the model can fulfill its stated purpose, maintaining a standard of thorough documentation, exposing model limitations, evaluating the model structure, and performing behavioral tests.²³ Anderson et al. discuss how sensitivity analysis can help quell uncertainty concerns in climate change IAMs.²⁴ Despite this growing field of model evaluation theory, there are still not well-established, interdisciplinary best practices for IAM evaluation.²⁵ While

²¹ Oreskes N, 1457.

²² A. J. Jakeman, R. A. Letcher, and J. P. Norton, “Ten Iterative Steps in Development and Evaluation of Environmental Models,” *Environmental Modelling & Software* 21, no. 5 (May 1, 2006): 602–14, <https://doi.org/10.1016/j.envsoft.2006.01.004>.

²³ Valeria Jana Schwantiz, “Evaluating Integrated Assessment Models of Global Climate Change,” *Environmental Modelling & Software* 50 (December 1, 2013): 125, <https://doi.org/10.1016/j.envsoft.2013.09.005>.

²⁴ Barry Anderson et al., “Uncertainty in Climate Change Modeling: Can Global Sensitivity Analysis Be of Help?,” *Risk Analysis: An International Journal* 34, no. 2 (February 2014): 271–93.

²⁵ S. Eker et al., “Model Validation: A Bibliometric Analysis of the Literature,” *Environmental Modeling and Software*, 2019, 43–54: 49 <https://doi.org/10.1016/j.envsoft.2019.03.009>.

these more recent evaluations methods are commonly applied, fewer IAM evaluations compare model results to real world data.

2.3 Modern Methods for Evaluating IAMs

As IAM's complexity and sensitivity increases, so do the possibilities for their applications for sub-national analysis and evaluation of environmental benefits beyond climate; however, these new applications also pose challenges for IAMs built to examine global climate benefits.²⁶ IAMs should be evaluated thoroughly before their application at scales or in disciplines that they were not originally intended for, including for state-level environmental policymaking.²⁷ Sub-national and regional-scale IAMs are often limited by a lack of data availability, fractured demand, and tepid acceptance.²⁸ However, precaution is not a sufficient reason to preclude IAM use for these purposes.²⁹ Robust model evaluation that compares IAM estimates to real-world data can facilitate the use of IAM for this new array of applications.

Several state-level studies have effectively use IAMs to analyze the effects of climate change scenarios and other environmental impacts and these studies shed light on some of the challenges of IAM use at sub-national scale.^{30,31, 32} IAMs have been used to

²⁶ Shi et al., "Projecting State-Level Air Pollutant Emissions Using an Integrated Assessment Model."

²⁷ Shi et al., 2.

²⁸ Ian Kraucunas et al., "Investigating the Nexus of Climate, Energy, Water, and Land at Decision-Relevant Scales: The Platform for Regional Integrated Modeling and Analysis (PRIMA)," *Climatic Change* 129, no. 3 (April 1, 2015): 573–88, <https://doi.org/10.1007/s10584-014-1064-9>.

²⁹ The Global Change Assessment Model, "GCAM v5.1 Documentation: GCAM-USA," accessed March 31, 2019, <http://jgcri.github.io/gcam-doc/gcam-usa.html>.

³⁰ Yuyu Zhou et al., "Modeling the Effect of Climate Change on U.S. State-Level Buildings Energy Demands in an Integrated Assessment Framework," *Applied Energy* 113 (January 1, 2014): 1077–88, <https://doi.org/10.1016/j.apenergy.2013.08.034>.

³¹ Yang Ou et al., "Estimating Environmental Co-Benefits of U.S. Low-Carbon Pathways Using an Integrated Assessment Model with State-Level Resolution," *Applied Energy* 216 (April 15, 2018): 482–93, <https://doi.org/10.1016/j.apenergy.2018.02.122>.

³² Patrick Campbell et al., "Impacts of Transportation Sector Emissions on Future U.S. Air Quality in a Changing Climate. Part I: Projected Emissions, Simulation Design, and Model Evaluation," *Environmental Pollution* 238 (July 1, 2018): 903–17, <https://doi.org/10.1016/j.envpol.2018.04.020>.

compare low-carbon pathways and greenhouse gas emissions reduction policies for California.^{33,34} Markoff et al. calculate the absolute differences between their estimated city per-capita greenhouse gas (GHG) emissions and self-reported per-capita emission levels, with their estimates off by 0.3 to 24 mt CO₂ per capita, with an average discrepancy of 5.6mt CO₂.³⁵ They conclude that many of these discrepancies are due to differences in what sources are included in their modeled data as compared to cities' emissions inventories, and that defining the scope of emissions categories is vital to compare modeled emissions data to real-world estimates.³⁶ Shi et al. compare GCAM-USA estimates of state-level air pollution emissions to EPA data, analyzing both absolute differences in pollutant emissions and differences in the rate of change of pollutant emissions over time.

Few researchers have used equivalency analysis to evaluate IAMs. Equivalency analysis flips the traditional statistical analysis model on its head; instead of examining whether things (groups, means, sets of results, etc.) are different, it attempts to prove two things are the same.³⁷ The medical field uses equivalency analysis to test, for example, if a group of patients who are given a new treatment have the same outcomes as do patients given a traditional one. Rusticus and Lovato demonstrate how the use of one-sided t-

³³ Christopher Yang et al., "Achieving California's 80% Greenhouse Gas Reduction Target in 2050: Technology, Policy and Scenario Analysis Using CA-TIMES Energy Economic Systems Model," *Energy Policy* 77 (February 1, 2015): 118–30, <https://doi.org/10.1016/j.enpol.2014.12.006>.

³⁴ Geoffrey M. Morrison et al., "Comparison of Low-Carbon Pathways for California," *Climatic Change* 131, no. 4 (August 1, 2015): 545–57, <https://doi.org/10.1007/s10584-015-1403-5>.

³⁵ Samuel A. Markolf et al., "An Integrated Approach for Estimating Greenhouse Gas Emissions from 100 U.S. Metropolitan Areas," *Environmental Research Letters* 12, no. 2 (January 2017): 024003, <https://doi.org/10.1088/1748-9326/aa5731>.

³⁶ Markolf et al.

³⁷ Stefan Wellek, *Testing Statistical Hypotheses of Equivalence and Noninferiority*, 2nd ed. (New York: Chapman and Hall/CRC Press, 2010).

tests/confidence intervals can demonstrate comparability between different groups or different results, and their method can also be applied to IAM estimates.³⁸

There are significant concerns about IAM's validity, particularly when applying IAMs to new scales and applications beyond global climate science, but these concerns should not preclude their use for decision- or policy-making. When model limitations are clearly articulated, even results that lack a high degree of accuracy or precision can be incredibly informative.³⁹ Comparison of IAM results to real-world data is a proven method of model evaluation.

This study bridges gaps in the existing literature by using equivalency analysis to evaluate GCAM-USA's use for estimating air pollution emissions, a relatively new application of this IAM, when aggregating data up from the state scale. Equivalency analysis provides a framework to evaluate GCAM-USA as an air pollution modeling tool through clearly defined tests, as recommended by Oreskes and Schwantiz.⁴⁰ This research build's on Shi et al's work by using equivalency analysis to compare GCAM-USA estimates of states air pollutant emissions to EPA's state emission inventories.⁴¹

3. Data and Methods

3.1 Data Collection and Descriptive Statistics

There are two primary data sources used for this analysis: the Environmental Protection Agency (EPA)'s "[Air Pollutant Emissions Trends Data: State Average Annual](#)

³⁸ Shayna A. Rusticus and Chris Y. Lovato, "Applying Tests of Equivalence for Multiple Group Comparisons: Demonstration of the Confidence Interval Approach," *Practical Assessment, Research & Evaluation* 16, no. 7 (November 7, 2011), <http://pareonline.net/getvn.asp?v=16&n=7>.

³⁹ Weyant, "Some Contributions of Integrated Assessment Models of Global Climate Change," 130.

⁴⁰ Oreskes N, "Evaluation (Not Validation) of Quantitative Models."; Schwantiz, "Evaluating Integrated Assessment Models of Global Climate Change."

⁴¹ Shi et al., "Projecting State-Level Air Pollutant Emissions Using an Integrated Assessment Model."

[Emission Trends](#)⁴² and Global Climate Assessment Model USA (GCAM-USA) air pollution emissions estimates,⁴³ both for the year 2015. EPA’s Office of Research and Developed created a “Base Model” for GCAM-USA that was used for this analysis with data generated from the query “GHG emissions by sector_ORD_Total.”⁴⁴ GCAM-USA can generate outputs for sixteen greenhouse gases, aerosols, and short-lived climate pollutants,⁴⁵ and was calibrated using data from 2010. Estimates from its first-run year, 2015, for each state can be directly compared to 2015 state-level data from the EPA. This analysis compares the 50 state aggregate GCAM-USA and EPA data on six air pollutants: carbon monoxide (CO), ammonia (NH₃), nitrogen oxide (NO_x), particle pollution (PM10), fine particle pollution (PM2.5), and sulfur dioxide (SO₂). GCAM-USA cannot produce pollution estimates of pollution emissions for all of the economic sectors EPA measures in its emissions inventories. GCAM-USA and EPA data on five macro-economic sectors (residential/commercial, electric generation, industrial, industrial-fuels, and on-road transportation) can be directly compared to each other, as shown in Table 1.⁴⁶ Data from the off-road transportation sector were also analyzed, but ultimately excluded from this analysis due to large discrepancies between GCAM-USA and EPA data. These discrepancies may be the result of differences in assumptions on what emission sources fall into the off-road transportation category.

⁴² OAR US EPA, “Air Pollutant Emissions Trends Data,” Policies and Guidance, US EPA, July 27, 2015, <https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data>.

⁴³ The Global Change Assessment Model, “GCAM v5.1 Documentation: GCAM-USA.”

⁴⁴ Dan Loughlin, Interview with Brianna Besch., Personal Interview, May 3, 2019.

⁴⁵ “Global Change Assessment Model,” Joint Global Change Research Institute, accessed March 24, 2019, <http://www.globalchange.umd.edu/gcam/>.

⁴⁶ Loughlin, Interview with Brianna Besch.

Table 1: Sectors included in the analysis from GCAM-USA and EPA

Analysis Sector	GCAM-USA Sector	EPA Sector	EPA Tier Code
Residential/ Commercial	Residential/ Commercial	Fuel Combustion Other	3
Electric	Electric	Fuel Combustion Electric Utility	1
	Industrial	Fuel Combustion Industrial	2
	Industrial	Chemical and Allied Product Manufacturing	4
	Industrial	Metals Processing	5
Industrial Fuels	Industrial Fuel	Petroleum and Related Industries	6
On Road Transportation	On Road	Highway Vehicles	11
Off Road Transportation	Off Road	Off-Highway	12
	NA	Other Industrial Processes	7
	NA	Solvent Utilization	8
	NA	Storage and Transport	9
	NA	Waste Disposal and Recycling	10

All emissions data were converted to units of 1000 of metric tons and all measurements of less than 0.5T were rounded to zero. Data cleaning and analysis was conducted using R. Descriptive statistics are provided by sector and pollutant in Tables 2 and 3, respectively, and means for each category are presented in Table 4. Not all states had emissions estimates for every sector/pollutant, (*e.g.*, there were no estimates of NH₃ emissions from the Industrial Fuels sector) and only data points with both EPA and GCAM-USA data were included in the analysis. A total of 1,429 observations were considered, with emissions ranging from zero to 2115.710 thousand metric tons. The largest on-road transportation and CO₂ emissions data points are an order of magnitude larger than emissions from the next-highest sector and pollutant respectively, and generally comparing averages across sectors and pollutants is problematic.

Table 2: Descriptive Statistics by Sector

All data are measured in 1000 metric tons

Sector	EPA Minimum	GCAM-USA Minimum	EPA Maximum	GCAM-USA Maximum	Number of Observations
Commercial/Residential	0.025	0.042	317.657	231.826	300
Electric	0.002	0.000	260.126	131.000	299
Industry	0.009	0.003	142.008	174.142	300
Industrial Fuels	0.000	0.000	260.747	196.311	230
On-Road Transportation	0.050	0.071	1761.174	2115.710	300

Table 3: Descriptive Statistics by Pollutant

All data are measured in 1000 metric tons

Pollutant	EPA Minimum	GCAM-USA Minimum	EPA Maximum	GCAM-USA Maximum	Number of Observations
CO	0.002	0.000	1761.174	2115.710	246
NH ₃	0.006	0.003	13.667	25.852	199
NO _x	0.001	0.000	392.112	441.420	246
PM10	0.000	0.000	49.828	35.617	246
PM2.5	0.000	0.000	49.738	35.416	246
SO ₂	0.000	0.000	260.126	157.442	246

3.2 Description of Methods

Equivalency analysis tests if two groups are the same. In doing so, equivalency analysis' *null* and *alternative hypotheses* are reversed from standard statistical analysis, as shown for general cases in Equation 1 and for this analysis in Equation 2.

Equation 1

$$H_0 = \theta \leq \theta_0 - \epsilon_1 \text{ or } H_0 = \theta \geq \theta_0 + \epsilon_2$$

$$H_1 = \theta_0 - \epsilon_1 < \theta < \theta_0 + \epsilon_2$$

Where θ is the sample mean, θ_0 is a reference mean, and ϵ_1 and ϵ_2 are a pre-determined range within which the sample mean would be considered equivalent to the reference mean.

Equation 2

H_0 = the mean of the GCAM-USA estimates is less than the (EPA mean-20%) or greater than the (EPA mean+20%)

H_1 = the mean of the modeled GCAM-USA data is within $\pm 20\%$ of the EPA mean

As suggested by Oreskes, GCAM-USA data are compared to EPA data using two “Tests.” In Test 1, each pollutant and sector is subject to two, one-sided t-tests, a method described by Rusticus and Lovato, and performed using the *t.test* command in R.⁴⁷ These one-sided t-tests determined if the GCAM-USA estimated means were more than 20% below the EPA means or more than 20% above the 2015 EPA means, with 90% confidence (p-values of 0.1 or less). 20% was chosen as the standard for equivalency to be consistent with analysis by Shi et al.⁴⁸ Discussions with the EPA GCAM-USA model developers confirmed 20% as an attainable but still informative level of accuracy.⁴⁹

In Test 2, a regression analysis is used to examine the equivalency of GCAM-USA and EPA data. Plotting the GCAM-USA results against the EPA values provides additional insight into how close GCAM-USA estimates are to EPA data: if the data were a perfect match they would fall along a line with a slope of one, as shown in Figures 3 and 4. A regression analysis, performed using the *lin* and *summary* commands in R, identifies how closely each sector and pollutant fell to this ideal slope. The same 20% threshold is applied by identifying which sectors and pollutants have slopes that fall between 0.8 and 1.2. Adjusted R² values were used to provide further insight into how well the GCAM-USA modeled data compares to the EPA data.

⁴⁷ Rusticus and Lovato, “Applying Tests of Equivalence for Multiple Group Comparisons: Demonstration of the Confidence Interval Approach.”

⁴⁸ Shi et al., “Projecting State-Level Air Pollutant Emissions Using an Integrated Assessment Model”; Loughlin, Interview with Brianna Besch.

⁴⁹ Loughlin, Interview with Brianna Besch.

4. Results

4.1 Test 1: One-sided t-tests

The model estimates for some sectors and some pollutants are better than others. Figures 1 and 2 show GCAM-USA estimates and EPA's data, broken down by sector and pollutant, respectively. As described in Section 3, GCAM-USA results are considered equivalent to the EPA results if the GCAM-USA estimated means fall within $\pm 20\%$ of the EPA mean, with 90% confidence. Tables 4 and 5 show the results of Test 1, one-sided t-tests by sector and pollutant, respectively. The first row of Table 4 illustrates that across pollutants and sectors, GCAM-USA does estimate air pollution emissions within 20% of EPA data; however, it is imprudent to examine the entire dataset at once because some of the pollutants and sectors have much larger values than do others, which skews mean results. On-road transportation emissions comprise 66% of all emissions examined, and the closeness of this sector's GCAM-USA estimated mean and EPA data mean boosts the aggregated model accuracy. GCAM-USA underestimates emissions from the electric sector by nearly 25%, but the absolute value of this sector is relatively small compared to the on-road transportation sector, and therefore this discrepancy does not significantly impact the aggregated results.

Table 4 shows that only the commercial/residential sector GCAM-USA estimates fall within $\pm 20\%$ of the EPA data. GCAM-USA's on-road transportation sector estimated mean, 93.012 1000mt, is quite close to EPA's emission inventory mean of 93.968 1000mt, but this sector fails to pass the lower t-test due to the data's large standard deviation. Table 5 highlights that the GCAM-USA estimated means of both NO_x, and PM₁₀, pass Test 1. For both CO and NH₃ the means of the GCAM-USA estimates are

quite close to EPA emissions inventory means, but the GCAM-USA data's large standard deviation causes it to fail Test 1.

Figure 1: Comparison of EPA and GCAM-USA 2015 Modeled Emissions by Sector

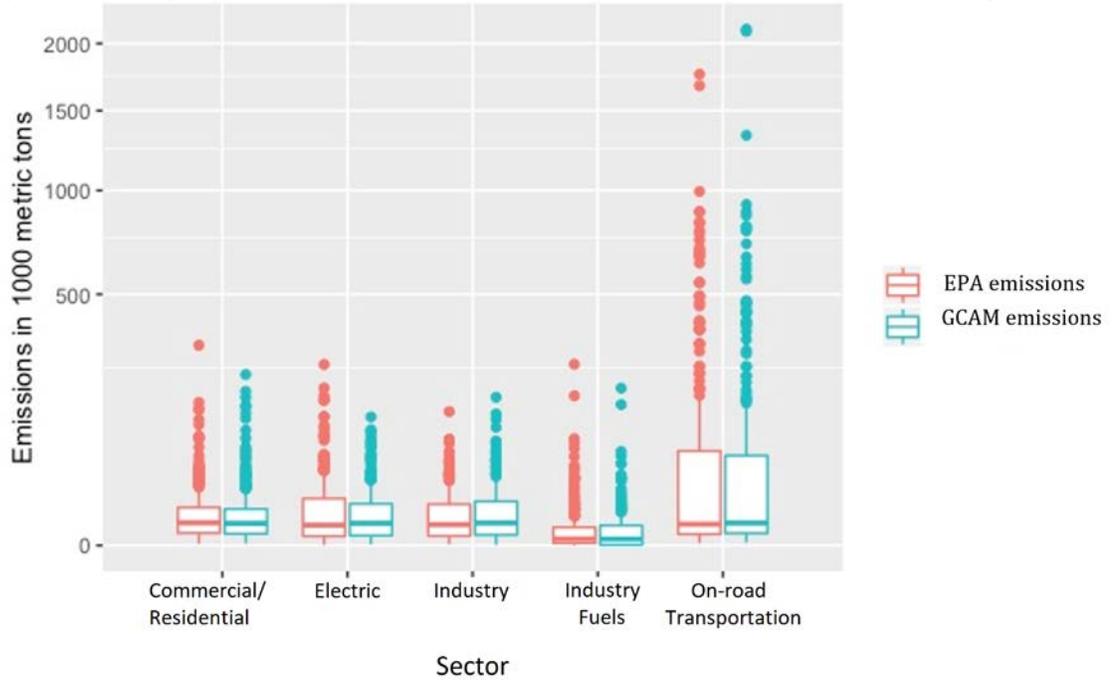


Figure 2: Comparison of EPA and GCAM-USA 2015 Modeled Emissions by Pollutant

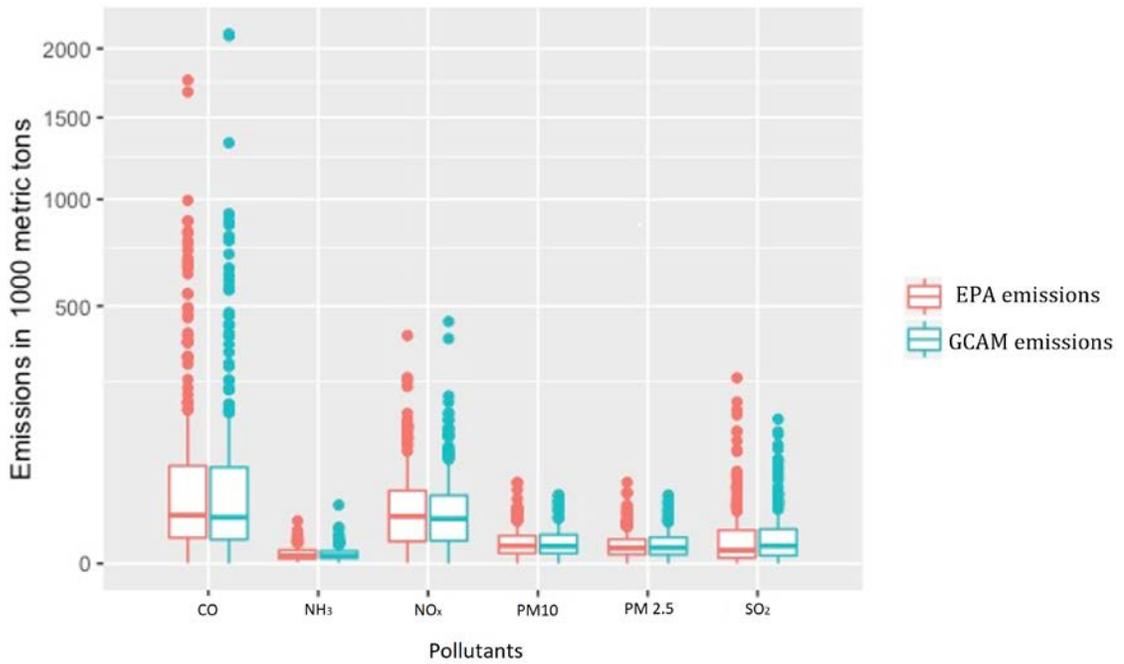


Table 4: Test 1 Results by Sector - EPA and GCAM-USA Means and One-sided t-test Results

Green-shaded cells show sectors/pollutants that have means that fall within 20% of EPA data means, with 95% confidence, passing the equivalency test. Yellow-shaded cells show sectors/pollutants that are close but do not pass the equivalency test.

Sector	EPA Mean	GCAM-USA Mean	GCAM-USA standard deviation	EPA Mean -20%	Lower GCAM-USA 95% confidence	Lower GCAM-USA t-test P value	EPA Mean +20%	Upper GCAM-USA 95% confidence	Upper GCAM-USA t-test P value
All data	33.343	28.339	119.597	23.213	23.132	0.053	34.820	33.547	0.020
Commercial/Residential	12.729	13.132	28.568	10.183	10.410	0.037	15.274	15.853	0.097
Electric	15.902	11.987	20.122	12.722	10.067	0.736	19.082	13.907	0.000
Industry	10.398	12.639	21.855	8.319	10.558	0.001	12.478	14.721	0.551
Industry Fuels	6.875	5.556	19.005	5.1	3.487	0.482	8.250	7.626	0.016
On-road Transportation	93.968	93.012	246.974	75.175	69.485	0.106	112.762	116.539	0.082

Table 5: Test 1 Results by Pollutant - EPA and GCAM-USA Means and One-sided t-test Results

Green-shaded cells show sectors/pollutants that have means that fall within 20% of EPA data means, with 95% confidence, passing the equivalency test. Yellow-shaded cells show sectors/pollutants that are close but do not pass the equivalency test.

Pollutant	EPA Mean	GCAM-USA Mean	GCAM-USA standard deviation	EPA Mean -20%	Lower GCAM-USA 95% confidence	Lower GCAM-USA t-test P value	EPA Mean +20%	Upper GCAM-USA 95% confidence	Upper GCAM-USA t-test P value
CO	113.600	111.844	266.531	90.910	83.786	0.110	136.365	139.902	0.075
NH ₃	1.069	1.124	2.252	0.855	0.860	0.047	1.282	1.388	0.161
NO _x	33.368	32.210	51.668	26.695	26.770	0.048	40.042	37.649	0.009
PM10	3.683	4.739	6.463	3.826	4.058	0.014	5.739	5.419	0.008
PM2.5	3.727	4.259	6.236	2.981	3.603	0.001	4.472	4.916	0.297
SO ₂	12.176	10.661	22.418	9.741	8.300	0.260	14.612	13.020	0.003

4.2 Test 2: Regression Analysis

Figures 3-6 show the entire dataset with GCAM-USA estimated pollution emissions plotted against the EPA 2015 emissions inventory data. Each dot represents one state's emissions of one pollutant from a single sector (*e.g.*, Alabama's commercial/residential CO emissions). Each dot's color corresponds to a different sector in Figures 3 and 4 and a different pollutant in Figures 5 and 6. If the data matched perfectly – all GCAM-USA estimates exactly matched the EPA data – the data points would fall along a line with a slope of one, as represented by the black line in each graph. Data points that fall above the black line are emissions that GCAM-USA overestimated compared to the EPA data. Alternatively, data points below the black lines are emissions that GCAM-USA underestimated compared to the EPA data.

In Figures 3 and 5, the blue line shows the regression trend of the entire dataset. In Figures 4 and 6, the colored lines show the regression trend of each respective sector and pollutant. Figures 3 and 5 show that, over the entire dataset, the regression trend falls quite close to the ideal: aggregated from all states and averaged across all sectors or pollutants, GCAM-USA national air pollution emissions estimates are slightly under the EPA emissions inventory data. Similar to the results from Test 1, results depicted in Figures 4 and 6 show that GCAM-USA has better estimates of emissions for some pollutants and sectors than it does others. Figure 4 shows that GCAM-USA's industry and on-road transportation estimates are quite close to the ideal, while fossil industry and the electric sector estimates are low. Figure 6 shows that GCAM-USA's NO_x estimates are quite close to the ideal, while PM₁₀ and SO₂ are underestimated. These results are generally consistent with the results of Test 1, shown in Tables 4 and 5.

Figure 3: 2015 EPA Emissions and GCAM-USA Estimated Emissions by Sector
 The black line, with a slope of 1, shows the ideal case if EPA=GCAM-USA. The blue line shows the regression over the entire dataset.

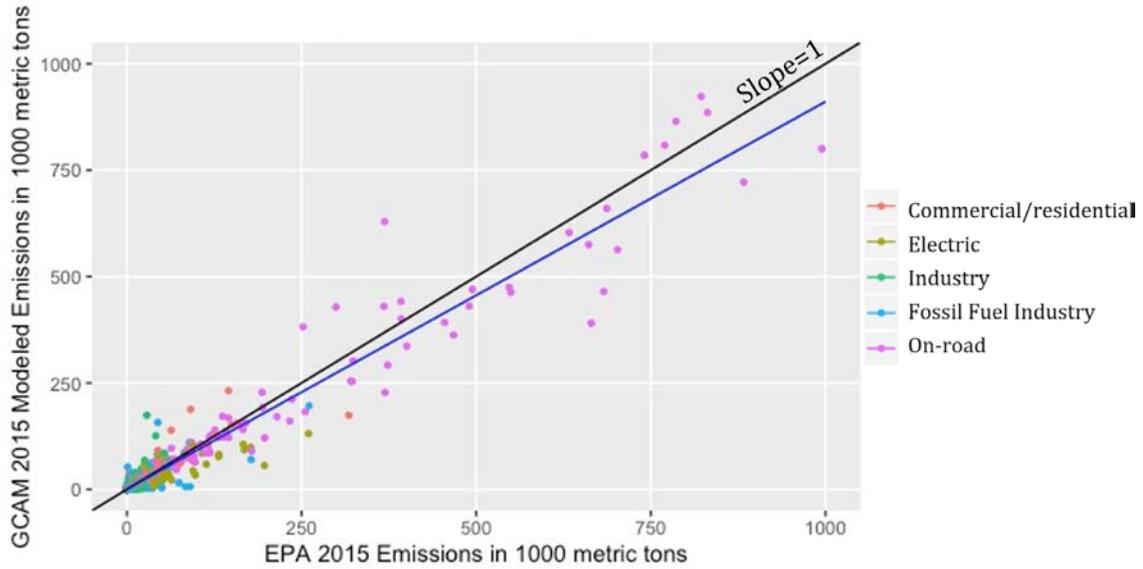


Figure 4: 2015 EPA Emissions and GCAM-USA 2015 Estimated Emissions Regressions by Sector
 The black line, with a slope of 1, shows the ideal case if EPA=GCAM-USA. The colored lines show regressions by sector.

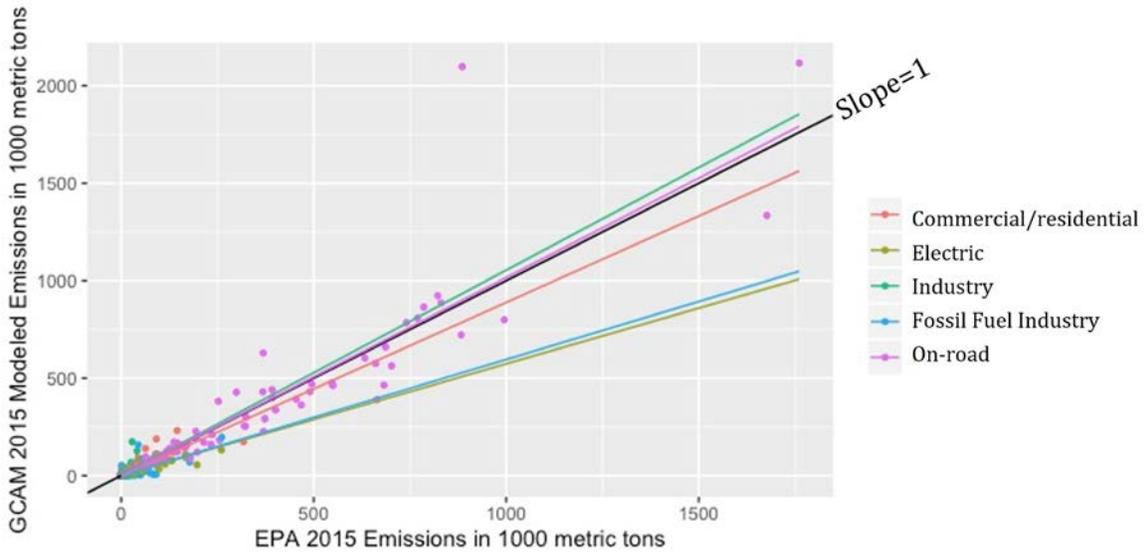


Figure 5: 2015 EPA Emissions and GCAM-USA Estimated Emissions by Pollutant
 The black line, with a slope of 1, shows the ideal case if EPA=GCAM-USA. The blue line shows the regression over the entire dataset.

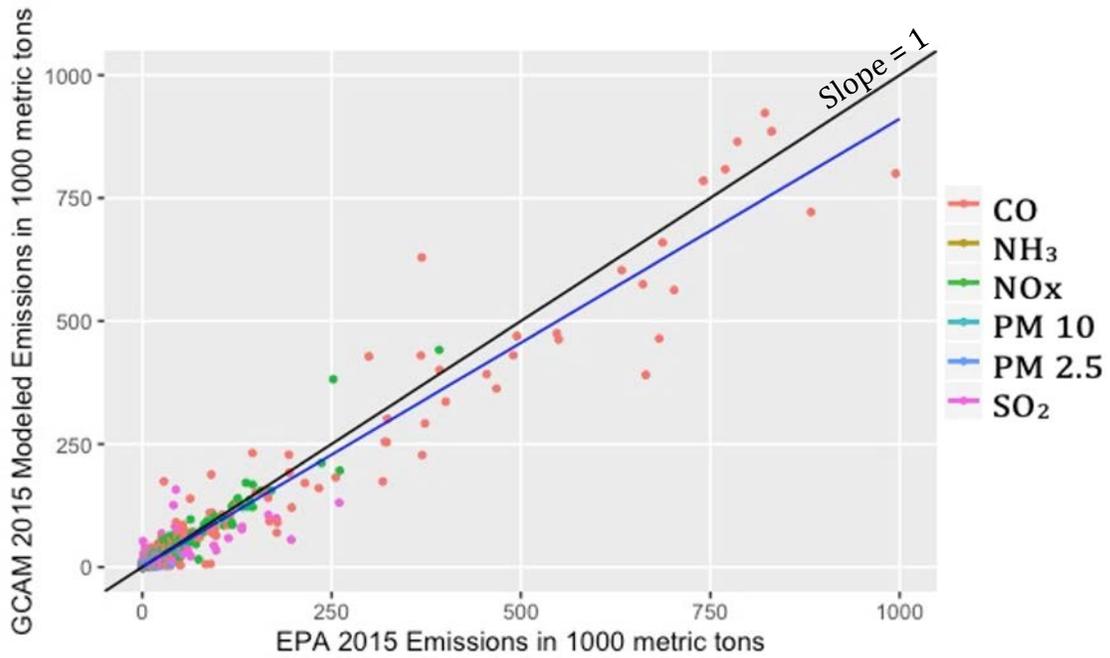


Figure 6: 2015 EPA Emission and GCAM-USA Estimated Emissions Regressions by Pollutant

The black line, with a slope of 1, show the ideal case if EPA=GCAM-USA. Colored lines show regressions by sector, the CO line is hidden behind the NO_x line.

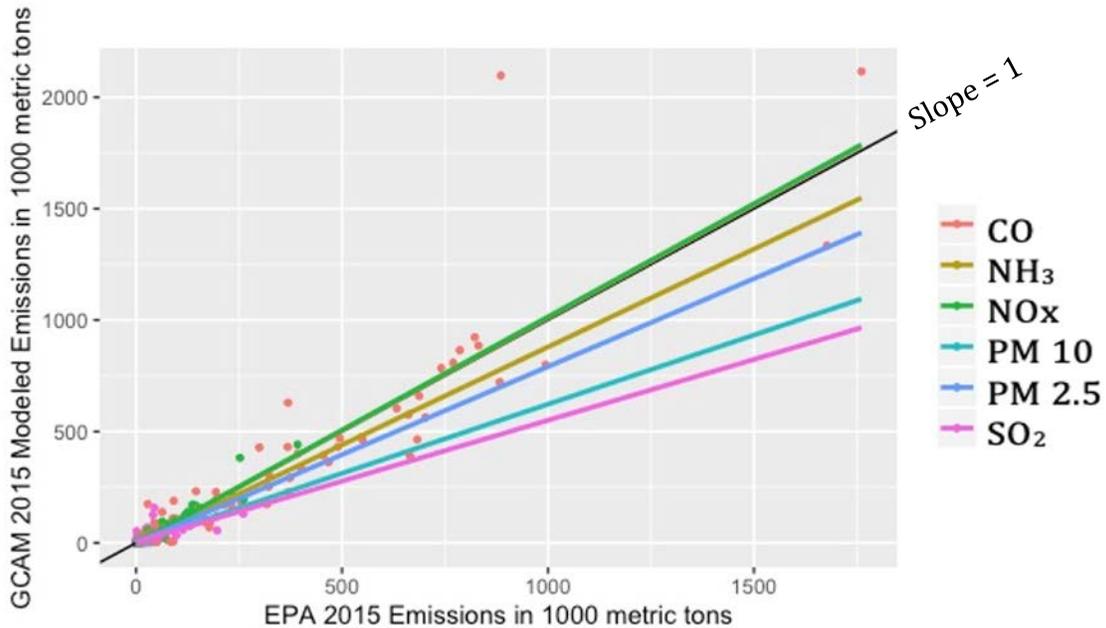


Table 6 shows the results of Test 2, listing the regression slope coefficients for the overall data, for each sector, and for each pollutant. In conducting these regressions, the EPA data is the independent variable and the GCAM-USA modeled data is the dependent variable. If GCAM-USA estimated emissions matched the EPA inventory emissions, the slope would be one; the closer the slope coefficients are to one the better the GCAM-USA estimates. All of the regression slope coefficients are statistically significant at the 99% level. Table 6 also reports the adjusted R squared value for each regression; values closer to one indicate a better fit of the regression line to the data. The green-shaded cells have slope coefficients within 20% of a slope of one and pass Test 2.

More sectors and pollutants pass Test 2, the regression analysis, than pass Test 1, the one-sided t-tests. The aggregate data regression line, with a slope of 1.003, is extremely close to the ideal slope of one and passes Test 2, but again this masks larger discrepancies seen in the sector and pollutant breakdowns. The regression lines for the commercial/residential, electric, industrial, and on-road transportation sectors also fall within 20% of a slope of one. The commercial/residential sector, on-road transportation sector, and NH_x pollutant all have slopes within 20% of one. Both CO₂ and the on-road transportation sector, which by volume comprise about 60% of all emissions included in the dataset, have slopes quite close to one, with GCAM-USA slightly overestimating emissions as compared to the EPA data. These categories also nearly passed Test 1. While the industrial sector did not come close to passing Test 1, it has a regression coefficient of 1.052, which falls within 20% of the ideal slope of one, passing Test 2. The pollutant PM₁₀ passed Test 1, but does not have a slope within 20% of one, indicating

that while GCAM-USA's mean estimate for this pollutant is close to that found in the EPA data, the distribution of data is not consistent with EPA's data.

Table 6: Test 2 Results - Regression for Overall Emissions, by Sector, and by Pollutant

Green-shaded cells have regression coefficients within 20% of a slope of one, passing the second equivalency test. Yellow-shaded cells come close to having a regression coefficient 20% of one but do not pass the equivalency test.

	Slope	Intercept	Adjusted R-Squared
EPA Emissions	1.004* (0.010)	-0.790 (1.126)	0.881
Commercial/ Residential	0.886* (0.026)	1.851* (0.831)	0.788
Electric	0.571* (0.015)	2.912* (0.537)	0.829
Industry	1.052* (0.047)	1.698 (0.920)	0.621
Industry Fuels	0.594* (0.034)	1.470 (0.857)	0.568
On-road	1.018* (0.022)	-2.718 (5.326)	0.881
CO	1.014* (0.025)	-3.441 (6.760)	0.870
NH ₃	0.879* (0.079)	0.184 (0.151)	0.385
NO _x	1.016* (0.018)	-1.683 (1.081)	0.927
PM10	0.621* (0.043)	1.770* (0.366)	0.443
PM2.5	0.790 * (0.042)	1.316 (0.301)	0.585
SO ₂	0.546* (0.029)	4.009 * (0.980)	0.591

* Indicates significance at the 0.99% level

Most of the sectors and pollutants with regression coefficients that pass Test 1 also have high adjusted R squared values, the best being for NO_x with a value of 0.927. However, NH₃ has a surprisingly low adjusted R squared value of 0.385, indicating that the regression line does not fit the data well, despite passing Test 2.

Table 7 shows the results of both Test 1 and Test 2. GCAM-USA estimates are most accurate for the commercial/residential sector and NO_x pollution, which pass both tests. GCAM-USA models the on-road transportation sector and CO and NH₃ pollutants reasonably well, as they pass Test 2 and come close to passing Test 1. The industrial sector passes Test 2 but not Test 1, while PM10 passes Test 1 but not Test 2.

GCAM-USA does not model the electric or industrial fuels sector and PM2.5 or SO₂ pollutants well: these two sectors and two pollutants failed both Test 1 and 2. It is possible that GCAM-USA does not include the same emissions sources for these sectors and pollutants that are included in the EPA inventory, causing discrepancies.

Table 7: Overall Results of Test 1 and Test 2

Sector/Pollutant	Test 1	Test 2
Entire Dataset	Yes	Yes
Commercial/ Residential	Yes	Yes
Electric	X	X
Industry	X	Yes
Industry Fuels	X	X
On-road	~	Yes
CO	~	Yes
NH ₃	~	Yes
NO _x	Yes	Yes
PM10	Yes	X
PM2.5	X	~
SO ₂	X	X

Yes = Passes test ~ = Nearly passes test X = Does not pass test

 = Passes both tests  = Nearly passes both tests  = Passes one test
 = Passes neither test

5. Conclusion

This analysis compares GCAM-USA air pollution estimates with EPA data using two equivalency tests. Test 1 compares GCAM-USA and EPA's estimated mean emissions of each sector and pollutant using one-sided t-tests. Test 2 compares GCAM-USA estimates to EPA data using a regression analysis.

GCAM-USA emissions estimates from some sectors and pollutants are better than others: only the commercial/residential sector and NO_x pass both Test 1 and 2. On-road transportation, CO, and NH₃ pass Test 2 and nearly pass Test 1, while the industrial sector and PM₁₀ pollutant pass only one test. GCAM-USA estimates from the electric and industrial fuels sectors, and from PM_{2.5} and of SO₂ pollutants do not fall within 20% of EPA data.

The discrepancy between GCAM-USA estimates and EPA data may be due to which emissions sources are included in GCAM-USA versus those in the EPA pollution inventory. Markoff et al. found significant discrepancies between modeled and reported city CO₂ emissions and attributed these differences to how cities account for imported electricity and life-cycle embodied emissions. It is likely that similar discrepancies cause GCAM-USA estimates to differ from EPA pollution inventories. IAM studies should harmonize sector emission definitions to ensure accurate emission modeling.

Future researchers looking to use GCAM-USA to estimate air pollution emissions at the state level should be aware of the model's strengths and weakness when modeling different sectors and pollutants. WHO estimates that about seven million people die from exposure to fine particle pollution (PM_{2.5}) annually⁵⁰ and there has been an emerging

⁵⁰ WHO, "Air Pollution," WHO, 2018, <http://www.who.int/airpollution/en/>.

international focus on reducing air pollution levels from particulate matter.⁵¹ GCAM-USA's estimates of PM_{2.5} are not accurate within 20% of EPA data for 2015, which suggests policymakers should exercise caution when using this data; PM_{2.5} estimates are an area for future model improvement. GCAM-USA emissions estimates from the commercial/residential, industrial, and on-road transportation sectors fall within 20% of EPA data. These sectors are significant contributors to air pollution, and estimates of their emissions can be incredibly useful for policy and decision makers looking to reduce air pollution exposure.

This study has several limitations that could be improved upon to better understand GCAM-USA emissions estimates. Emissions from the on-road transportation sector and of CO were far larger than those of the other sectors and pollutants, which skewed the data means and one-sided t-tests. Analyzing data by sector-pollutant categories (*e.g.*, CO emissions from the commercial/residential sector,) would render a more appropriate and informative analysis. Including data from future years by comparing GCAM-USA estimates for future pollution levels with EPA projected emissions, would create a larger dataset and therefore produce more accurate and robust results. Using equivalency analysis to examine which U.S. states GCAM-USA modeled well versus those modeled poorly could provide greater insight into future sub-national applications of GCAM-USA. While this paper looks specifically at air pollution, a similar analysis could be conducted for greenhouse gas emissions. Equivalency analysis could also test other GCAM-USA estimates, including other forms of pollution, biodiversity

⁵¹ "BreatheLife – A Global Campaign for Clean Air," BreatheLife 2030, accessed August 18, 2019, <https://breathelife2030.org/>; "WHO | First WHO Global Conference on Air Pollution and Health, 30 October – 1 November 2018," WHO, accessed August 18, 2019, <http://www.who.int/airpollution/events/conference/en/>; United Nations, "The Sustainable Development Goals Report 2018" (New York, 2018), 11, 27, <https://unstats.un.org/sdgs/files/report/2018/TheSustainableDevelopmentGoalsReport2018-EN.pdf>.

impacts, and land use changes. While this analysis examines if GCAM-USA air pollution estimates fall within 20% of EPA data, future research could narrow, or expand, the definition of “equivalency” at levels useful to different applications.

As use of IAMs extend to more applications and to different scales, it is important to evaluate these models’ strengths and limitations. Equivalency analysis can be used to evaluate IAM estimates, especially when the models are applied to disciplines or scales beyond their original intended uses. Evaluations, like this one, can inform future analyses of model outputs and can help developers improve IAMs. The results of equivalency tests can more clearly communicate IAM strengths and limitations to a wide range of users, particularly those who are not familiar with the technical aspects of IAMs and how the models work. IAMs do not have to be perfect to be informative. Equivalency analysis is a helpful tool to understand and communicate model strengths and limitations to policymakers, decision makers, and the public.

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7. Curriculum Vitae

Brianna Besch was born on July 26, 1991, in Atlanta Georgia. At the age of ten she moved with her family to Almaty, Kazakhstan, where she attended middle school and ninth grade before finishing high school in Cairo, Egypt. Ms. Besch graduated *summa cum laude* from Macalester College in St. Paul, Minnesota, with a Bachelor of Arts in Geography and Environmental Studies and a minor in Physics. At Macalester, she completed an undergraduate honors thesis, titled “From Local Actions to Global Solutions: Community-Based Climate Adaptation in Bangladesh.”

Ms. Besch began her career in the Education Foundation at the National Geographic Society. She then joined the Peace Corps and served for two years as an agriculture and environment volunteer in Ethiopia. While there, she worked at the Atsbi Womberta Natural Resource Department where she co-created watershed land use maps and intervention plans using GIS. She also led a team of volunteers who created a curriculum for open source geographic information systems (QGIS) and led trainings on the software for Peace Corps volunteers and staff. After Peace Corps, Ms. Besch joined the Environmental Protection Agency Office of International and Tribal Affairs, where she works on multilateral environmental policy.

In 2017, Ms. Besch began her Master’s of Science degree in Government Analytics at Johns Hopkins University. She hopes to use her degree to pursue her academic and career interests in data-driven decision making to improve international environmental policy.