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Abstract

Energy system projections from quantitative models inform actions including nearer-term and local decisions (e.g., technology adoption, infrastructure investment) as well as global and longer-term actions (e.g., international negotiations, global targets). Computational limits require model designers to balance coverage and resolution (i.e., breadth versus depth). Some models, such as the Global Change Analysis Model (GCAM), represent all energy sources and uses with less resolution than models that focus on a single sector's energy use. GCAM balances global supply and demand of all energy carriers projecting prices using internal calculations for energy sources and costs of greenhouse gas mitigation while capturing interlinkages between the energy system, water, agriculture and land use, the economy, and the climate. This globally comprehensive model was used to frame the *Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050*, which the White House released in 2021 and has been used to inform national and global economy-wide climate change mitigation discussions and strategy development for decades.

Unlike GCAM, sectoral models focus on a portion of the energy sector and with greater detail and resolution. The Regional Energy Deployment System (ReEDS) electricity-sector model, for example, projects *electricity* system capacity expansion and operation with high-fidelity representation of emerging technologies for deep decarbonization, such as variable renewable energy and energy storage, and integration of these technologies into the electric grid. The Transportation Energy and Mobility Pathway Options (TEMPO) *transportation*-sector model enables analysis of household choices, with a focus on adoption, charging, and use of electric vehicles. The Scout buildings-sector model supports detailed consideration of the policies and markets that can accelerate the adoption of electrification and energy conservation measures in *buildings*. Such sector-specific models are instrumental in informing technology research, sectoral planning strategies, and sector-specific aspects of greenhouse gas mitigation strategies in the United States.

The integrated multisector and sector-specific modeling approaches represented by GCAM and these sectoral models are complementary. The integrated multisector approach calculates energy pricing and resource allocation within the model, which is important for consistency when future conditions substantially diverge from current conditions in transformative scenarios. The sector-specific approach facilitates representation of granular details across spatial, temporal, technological, and market dimensions that enable exploration of particular interactions and trade-offs. This report presents the results of recent work to explore the differences and trade-offs between these approaches by comparing GCAM with the sector-specific ReEDS, TEMPO, and Scout models. The report compares both model structures and results, and it addresses their potential relevance and applications.

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List of Acronyms and Abbreviations

AEO	Annual Energy Outlook (U.S. Energy Information Administration)
ASHP	air source heat pump
BEV	battery-electric vehicle
CAFE	Corporate Average Fuel Economy
CAV	constant air volume
CCS	carbon capture and storage
CDD	cooling degree days
CFL	compact fluorescent lamp
CO_2	carbon dioxide
CSP	concentrating solar power
DAC	direct air capture
DOE	U.S. Department of Energy
ECM	energy conservation measure
EDITS	Energy Demand Changes Induced by Technological and Social Innovations
EEE	Energy Efficiency and Electrification
EIA	U.S. Energy Information Administration
EV	electric vehicle
ESTAR	ENERGY STAR
FCEV	(hydrogen) fuel cell electric vehicle
GCAM	Global Change Analysis Model
GDP	gross domestic product
GHG	greenhouse gas
HDD	heating degree days
HPWH	heat pump water heater
IAM	integrated assessment model
ICEV	internal combustion engine vehicle
IGCC	integrated gasification combined cycle
lbs	pounds
LCOE	levelized cost of energy
LDV	light-duty vehicle
LED	light-emitting diode
LFL	linear fluorescent lamp
LVOE	levelized value of electricity
LWR	light-water reactor
MaaS	mobility as a service
MHDV	(commercial) medium- and heavy-duty vehicles
MMT	million metric tons (usual measurement unit for CO_2 emissions)
NEMS	National Energy Modeling System
NERC	North American Electric Reliability Corporation
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory
PHEV	plug-in hybrid electric vehicle
PLCOE	profitability-adjusted levelized cost of energy
PMT	passenger miles traveled
PNNL	Pacific Northwest National Laboratory

PV	photovoltaics
ReEDS	Regional Energy Deployment System
SSP2	Shared Socioeconomic Pathway 2
tCO_2	metric tons carbon dioxide
TWh	terawatt-hours
TEDB	Transportation Energy Data Book
TEMPO	Transportation Energy & Mobility Pathway Options
VAV	variable air volume
VIUS	Vehicle Inventory and Use Survey
VMT	vehicle miles traveled
VRE	variable renewable energy
W/m^2	watts per square meter

Executive Summary

Transforming energy systems to achieve a sustainable, resilient, and equitable future is a complex, difficult, and uncertain process. The transformation must consider numerous actors, technologies, infrastructures, and physical processes across multiple, interconnected systems as they develop over decades. Quantitative models can help improve the understanding of these transformations by producing results that quantify technology deployment, performance, and utilization in scenarios that explore a range of potential futures. Analytic approaches can represent the energy system from multiple vantage points, each with distinctive geospatial, temporal, and techno-economic system scope. Energy system projections inform various stakeholders on myriad topics, from short-term and local decisions, such as technology and infrastructure deployment, to global and long-term negotiations and policy targets, such as those of the United Nations Framework Convention on Climate Change. Model designers trade off coverage and resolution within computational limits; for example, some models represent all energy sources and uses with less resolution, while others focus on a portion of the energy sector with greater detail and resolution.

The Global Change Analysis Model (GCAM) has been used for decades to inform national and global economy-wide climate change mitigation discussions and strategy development, and more recently was used to frame the *Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050*, which the White House released in 2021. To better understand the differences and trade-offs between GCAM and sector-specific models for the United States, we compared GCAM with the Regional Energy Deployment System (ReEDS) for the electricity sector, the Transportation Energy and Mobility Pathway Options (TEMPO) model for transportation, and the Scout model for buildings. Examples of the major questions that the models address are:

- **GCAM**
  - How might socioeconomic, energy, land, and water systems coevolve in the coming decades?
  - How do sectoral and regional choices interact?
  - What are the emission and climate implications of these pathways?
- **ReEDS**
  - Which electricity generation and transmission gets built?
- **TEMPO**
  - How are trips taken (using which mode and technology)?
  - How much energy is consumed and what emissions are produced?
- **Scout**
  - Which buildings technologies are adopted?
  - How much energy is consumed and what emissions are produced?

GCAM balances global supply and demand of all energy carriers by endogenously projecting prices for energy sources and costs of greenhouse gas (GHG) mitigation while capturing interlinkages between the energy system; water, agriculture, and land use; the economy; and the climate. Sector-specific models inform technology research, sectoral planning strategies, and sector-specific aspects of GHG mitigation strategies in the United States. ReEDS projects capacity expansion with high-fidelity representation of emerging technologies for deep decarbonization, such as variable renewable energy and energy storage, and their integration into the electric grid. TEMPO enables analysis of household vehicle choices, with detailed consideration of factors that influence adoption, charging, and use of electric vehicles. Scout supports detailed consideration of the policies and markets that can accelerate the adoption of electrification and energy conservation measures in buildings.

This work highlights the complementarity of these two approaches: integrated multisector and sector-specific. The integrated multisector approach ensures consistent, endogenous energy pricing and resource allocation, which can substantially diverge from current conditions in transformative scenarios, while the sector-specific approach facilitates representation of granular details across spatial, temporal, technological, and market dimensions that enable exploration of particular interactions and trade-offs.

Sector-specific comparisons show the potential complementarity of the two types of models. We aligned the categorization of technologies and selectively harmonized input assumptions because differing results primarily attributable to input assumptions would not highlight the model differences of interest. Results for electricity illustrate the challenge of representing the value of electricity generation technologies, especially variable renewable energy, as their deployment shares increase. We consider two methods to address this challenge: (1) a version of GCAM that models power sector operations with subannual detail and (2) a novel metric and method developed to enable aggregate ReEDS results to inform less detailed models as described in Mowers et al. (2023).

Results for transportation indicate GCAM and TEMPO show similar responsiveness of passenger transportation system change to carbon price. Freight results may differ due to model resolution, infrastructure representation, and discount rates. Results also differ for a scenario of 100% electric vehicle sales mandate for passenger vehicles due to longer vehicle survival assumptions in TEMPO and its modeling of household-level vehicle use resulting in greater vehicle miles traveled for older internal combustion engine vehicles in some scenarios.

The buildings sector models required the most effort to harmonize because of the greater number of equipment types and energy services represented in buildings (e.g., heating, cooling, water heating, lighting, refrigeration, and multiple appliances categories) and the greater difference in the granularity of technological detail between GCAM and Scout. Initial results for buildings show greater responsiveness in scenarios with energy efficiency and electrification measures in Scout, with GCAM being more responsive in scenarios with carbon pricing alone.

This report presents the results of model comparisons explored in this project, including comparisons of both model structure and results. Table ES-1 summarizes comparisons to GCAM for elements of model structure that are similar among all the sector-specific models. Other structural elements—from Hiremath et al. (2007), such as assumptions, top-down versus bottom-up, methodology, and choice functions—appear in the sector-specific comparisons.

Table ES-1. Comparison of Elements of Model Structure for GCAM-Integrated Modeling Framework and Sector-Specific Models

Category	GCAM v6.0	Sector-Specific Models
Purpose	• Economy-wide transitions • Cross-sectoral interactions	• Sector-specific energy technology transition options
Granularity	• Physical-based economic model • Limited technology and process detail	• Greater technological, temporal, and spatial granularity
Extent	• Global coverage (32 energy-economy regions) • Economy-wide coverage of energy sources and uses, including representation of individual sectors • 5-year time-steps through 2100	• U.S. geographical scope, often with high regional detail • Representation of individual sectors • 1-year to 2-year time-steps through 2050
Input data	• 2015 base year • Need for comprehensive, global data	• Many sector-specific inputs updated annually

Categories adapted from Hiremath et al. (2007).

This report is intended to support planning and interpretation of analytic studies and identify opportunities for model improvement. An integrated, multisector model such as GCAM is best used to understand overall global, economy-wide system change and feedbacks in response to a major shift, such as GHG mitigation. GCAM and other integrated assessment models can be used to develop consistent conditions that quantify each scenario, even for scenarios that diverge from historical precedents with respect to global economic, technological, and environmental conditions. These consistent conditions—for factors such as fuel prices, resource demands, and costs of GHG mitigation—can then serve as inputs to sector-specific models. The sectoral models can then focus on questions where greater technology and market resolution are likely to be useful.

Limitations of our model comparisons in this report arise from the imperfections of models as predictive tools and the exploratory scope of this project. Model validation is challenging at best for technological changes that lack historical precedent. Due to the exploratory scope, this study only accomplished selective harmonization and initial sensitivity analysis. Although this study presents reference and GHG mitigation scenarios, the GHG mitigation scenarios were constructed in different ways the sectors considered: electricity, transportation, and buildings. Future analysis would be required to apply consistent approaches across all sectors in a detailed multimodel climate change mitigation analysis.

Even if many of these limitations were overcome, there would still be no single answer to the question of which model should be used when, because they serve different purposes. For global, economy-wide analysis, GCAM is more appropriate than any single U.S. sector-specific model, and sector models can offer complementary U.S. detail. For sector-specific U.S. analysis, a sector model may be more appropriate, and a set of economy-wide boundary conditions must be assumed, which could be informed by a model such as GCAM for scenarios that differ from baseline conditions. For analyses targeting detail in multiple sectors, combinations of multiple models may be most useful.

Future work could improve both types of models. Streamlining processes for integrated multisector models such as GCAM to provide boundary conditions could improve sector-specific analyses. Improvements that could be made in integrated multisector models, include methods to improve representation of the value of each technology in the electric-sector, household-level transportation decisions, and the value of greater segmentation of buildings markets. Future work could apply the scenario concepts developed for in this report across all sectors (e.g., carbon price responsiveness, emissions targets, technology availability, and technology standards). We suggest future work to facilitate input harmonization and output comparison, and to test key findings in multiple models. Overall, this work shows the value of complementary modeling approaches in developing robust conclusions to inform energy technology innovation and deployment to meet GHG mitigation goals.

Table of Contents

List of Figures

List of Tables

1 Rationale for Comparison of Models

Obtaining and using energy to power the economy requires planning and investment decisions over years and decades. Quantitative models of future energy systems are useful in this context to quantify various scenarios of technology innovation, deployment, performance, and utilization to meet various scenarios of energy market demand. Numerous models depict the energy system from multiple vantage points, each with distinctive geospatial, temporal, socioeconomic, and techno-economic system[1] scope, and developed for various purposes. This report presents the results of a comparison of a model of the global integrated multisector energy-economic system with sector-specific models of three sectors in the United States—the electricity, transportation, and buildings sectors. The integrated multisector model, GCAM, produces results that inform national and global economy-wide decarbonization[2] decisions. For example, the *Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050*, which the White House released in 2021, used GCAM analysis. GCAM calculates internally consistent supply, demand, and prices for energy sources and costs of GHG[3] abatement. The results of sector-specific models inform technology research, sectoral planning strategies, and sector-specific aspects of national decarbonization strategies. In general, they offer greater granularity than a global, economy-wide model in spatial, temporal, technological, and market dimensions. In this report, we consider models for electricity, buildings, and transportation sectors—the Regional Energy Deployment System (ReEDS) model, the Transportation Energy and Mobility Pathway Options (TEMPO) model, and Scout.

Previous work has reported on multimodel comparison studies through efforts such as those of the Stanford Energy Modeling Forum (Huntington et al. 2020) and integrated assessment model comparisons (Prina et al. 2022). This report compares two very different classes of models, and it includes several models that have not previously been compared. These models were also selected for comparison because they are used within the U.S. Department of Energy and national laboratory system to consider energy technology strategies. Related work has compared global integrated assessment models with global sectoral models (Yeh et al. 2017), but has not explained how and why this particular set of detailed U.S. sector-specific models differ from the corresponding representation of the United States in GCAM. Complementarity among models is being pursued internationally as well through an ongoing project,[4] and this report contributes to understanding how each type of model might be used to complement or improve the other. This report will summarize initial comparisons of the models, explain some of the reasons for similarities and differences, identify complementary roles for each type of model, and suggest ideas for future work.

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[1] Techno-economic system refers to technologies and their market and economic context. For example, an electric sector capacity expansion model would likely represent the performance of renewable generation technologies that are most salient for capacity expansion decisions.

[2] Throughout this report, decarbonization is used as a shorthand for energy sector measures for climate change mitigation and GHG mitigation, many but not all of which emphasize on reducing emissions of carbon-based greenhouse gases. Specific metrics (e.g., metric tons CO_2) are indicated as appropriate.

[3] This refers to the overall goal of mitigating greenhouse gases even though the quantitative results are only for CO_2.

[4] "Energy Demand changes Induced by Technological and Social innovations (EDITS)," https://iiasa.ac.at/projects/energy-demand-changes-induced-by-technological-and-social-innovations-edits.

This report first describes the models and the framework that we used to compare them. It then summarizes results by sector. Finally, it offers a discussion of potential applications, conclusions, and future work.

2 Introduction to the Models and the Framework for Comparison

In this section, we first briefly describe each of the four models that were used in this work: GCAM, ReEDS, TEMPO, and Scout. We then define and summarize the model attributes that are used to structure our model comparisons. Last, we explain the metrics that are compared in the sector-specific results sections.

2.1 Overview of Models

2.1.1 Economy-Wide: GCAM

The Global Change Analysis Model (GCAM) is an integrated, multisector model developed and maintained by the Pacific Northwest National Laboratory. GCAM simulates the future evolution of, and interaction between, global energy, water, land, economic and climate systems. GCAM[5] divides the world into 32 energy-economy regions, of which the United States is one; these regions are linked through global markets for primary energy resources (e.g., oil, gas, and coal) and agricultural commodities. The model operates recursively in 5-year time-steps from 2015 to 2100, and it solves by finding the equilibrium prices and quantities of energy, agricultural, water, and emissions markets in each region and time period.

Key model inputs include socioeconomic drivers (population and gross domestic product [GDP]) for each model region and characterizations of resources (potentials, extraction costs), technologies (costs, efficiencies), and policies. Key model outputs include:

- Prices and quantities produced, and consumed for primary energy resources, intermediate energy carriers, agricultural commodities, and water
- Technology deployment and turnover in energy transformation (e.g., electricity generation, refining, gas processing, hydrogen production) and end-use sectors (including residential and commercial buildings, passenger and freight transportation, and industry)
- GHG and traditional air pollutant emissions
- Key climate outcomes.

GCAM allocates shares among competing technologies using a logit-based formulation that assumes a distribution of realized costs due to heterogeneous real-world conditions (Clarke and Edmonds 1993). Calvin et al. (2019) describe GCAM's logit choice formulation and calibration process in detail. In short, GCAM's logit exponents inform how directly the model's choice indicator (cost or profit) dictates technology shares, with lower absolute magnitude exponents broadening the logit distribution and higher absolute magnitude exponent concentrating shares in least-cost technologies. GCAM's logit exponents are exogenously specified, although some

[5] A version of GCAM similar to GCAM v6.0 (https://github.com/JGCRI/gcam-core/releases) was used for this analysis.

recent studies have used backcasting to estimate parameters for GCAM's land (K. V. Calvin et al. 2022) and agricultural trade (Zhao et al. 2021) modules. Logit share weights are calculated in the historical period (based on historical costs and technology shares) to capture non-modeled factors that influence technology choice (e.g., consumer preferences or the availability of supporting infrastructure) and ensure GCAM replicates its historical energy balance, land allocation, and trade data. By default, these share weights are fixed at historical values into the future, although they are sometimes adjusted in future periods, in cases when historical precedent might not accurately represent future behavior (e.g., for emerging technologies where factors that impeded a technology's deployment historically, such as availability of supporting infrastructure, are expected to diminish over time).

Parts of this study also use GCAM-USA, a version of GCAM with subnational detail in the United States. GCAM-USA subdivides the U.S. economy, energy, and water systems into 50 U.S. states and Washington D.C. (Binsted et al. 2022; 2020). Markets in these 51 subnational regions are solved concurrently with the other 31 non-U.S. regions in GCAM-USA; outcomes in the United States are connected to and consistent with international conditions. The subnational regions in GCAM-USA contain more detailed and more heterogeneous representations of socioeconomic drivers, renewable resource characteristics, energy transformation sectors, and end-use energy demands than the core GCAM (single U.S. region) model.

GCAM and GCAM-USA are open-source, community models, and they are available for download on GitHub.[6] A thorough description of GCAM is available in Calvin et al. (2019).[7]

2.1.2 Electricity Sector: ReEDS

The Regional Energy Deployment System Model (ReEDS)[8] is a model of electricity, generation, storage, and transmissions capacity expansion and operation in the contiguous United States. It solves via dynamic-recursive system cost minimization with 2-year time-steps (typically) for 2010–2050. The model structure includes 134 balancing areas, 17 seasonal-diurnal time-slices, and an hourly submodule that operates between every 2-year model solve to enable consideration of effects more-detailed than those of the major time-slices, such as variable renewable energy (VRE) curtailment fraction and capacity credit, and storage curtailment recovery, capacity credit, and arbitrage value.

Key inputs to ReEDS include:

- Electricity demand profiles by region and future demand growth projections
- Technology and fuel cost projections
- Detailed wind and solar resource supply curves by region
- State-level and national policies, including existing and potential future policies.

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[6] "Global Change Analysis Model (GCAM)," https://github.com/JGCRI/gcam-core, including precompiled release packages ("GCAM 6.0," https://github.com/JGCRI/gcam-core/releases).
[7] Online model documentation is available at "GCAM v6 Documentation: Table of Contents," http://jgcri.github.io/gcam-doc/toc.html.
[8] For more information, see "About the Regional Energy Deployment System Model," NREL, https://www.nrel.gov/analysis/reeds/about-reeds.html.

Key outputs of ReEDS include:

- Electricity generation and capacity by technology
- Transmission capacity and flows
- Emissions of GHG and air pollutants
- System costs.

ReEDS has been used in scenario analysis of electric-sector futures for the United States that include the Electrification Futures Study,[9] Standard Scenarios[10] studies (Cole et al. 2021; Denholm et al. 2022), and a study exploring a 100% renewable energy power system for the United States (Cole et al. 2021; Denholm et al. 2022). A public version of the model is available.[11]

2.1.3 Transportation Sector: TEMPO

The Transportation Energy & Mobility Pathway Options model (TEMPO) (Muratori et al. 2021) is a transportation energy system model encompassing the entire U.S. transportation sector. TEMPO develops projections of transportation demand, mode choice, technology choice, vehicle stock, energy consumption, and emissions for both the passenger sector and the freight sector at an annual resolution. It uses a logit formulation to estimate mode and technology shares for passenger and freight demand based on the cost and time intensity of alternative modes and technologies. TEMPO has the capability to be run at the national level (passenger and freight) or the county level (passenger only). In the passenger sector, TEMPO considers travel demand at the household level, estimating household-level mode choice, technology choice, and demand for personal vehicles. It considers household-level charging infrastructure constraints when estimating demand for and use of personal electric vehicles. In the freight sector, TEMPO models movement of freight goods in eight shipment distance bins. A medium- and heavy-duty truck technology choice incorporates differences in vehicle use across shipment distances and for vehicle classes, including infrastructure considerations.

Key inputs to TEMPO include:

- Vehicle technology attributes (including capital cost and fuel economy for on-road vehicles and operating cost for non-road modes)
- Fuel prices
- Population
- Carbon intensity of fuels.

Key model outputs of TEMPO include:

- Vehicle stock
- Energy consumption
- Service demand
- Emissions by mode, technology, and fuel.

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[9] "Electrification Futures Study," NREL, https://www.nrel.gov/analysis/electrification-futures.html.
[10] "Standard Scenarios," NREL, https://www.nrel.gov/analysis/standard-scenarios.html.
[11] "Request Access to Download Model," NREL, https://www.nrel.gov/analysis/reeds/request-access.html.

2.1.4 Buildings Sector: Scout

Scout is a stock-and-flow model of U.S. residential and commercial buildings and building components (Langevin, Harris, and Reyna 2019; Langevin et al. 2021). It is used to estimate the energy and CO_2 impacts of energy conservation measures (ECMs), and it facilitates the comparison of ECM impacts across end uses (e.g., heating, lighting, and envelope). Scout results are informed by building and equipment stock turnover and the particular ECMs included that may displace adoption of business-as-usual technologies in an analysis. Scout has flexible geographic resolution—U.S. states, the National Energy Modeling System (NEMS) Electricity Market Module regions (25), and American Institute of Architects' climate zones (5)—and it estimates ECM impacts annually from the present year through 2050.

Scout can evaluate a portfolio of ECMs in competition with each other, ensuring ECM savings impacts are not double-counted. Multiple ECMs that apply to the same market segment compete for shares of the segment based on user specified cost-effectiveness metrics, which include simple payback, internal rate of return, cost of conserved energy, or cost of conserved carbon (cost per metric ton CO_2).

Key inputs for Scout include:

- From Energy Information Administration's (EIA) Annual Energy Outlook (AEO)
  - Baseline building and technology stock turnover; technology cost, performance, and lifetime
  - Energy prices and electricity carbon intensity (can also be drawn from alternative sources)
- From the user
  - ECMs available in the current year and/or the future

Key outputs of Scout include:

- Energy savings
- CO_2 emission reductions
- Energy cost (utility bills) savings
- Economic (cost-effectiveness) metrics
- Public health costs by ECM.

2.2 Framework for Comparison

Key differences between energy system models may be described in terms of their attributes, including model extent, granularity and resolution, input data and parameters, decision approach, and time-step dynamics, as they are applied to spatiotemporal dynamics, technologies, energy resources, and energy demands. Table 1 compares GCAM with the sector-specific models as a group with respect to these attributes. In this report, we examine how some of these differences contribute to differences in model results. The list of model attributes considered here extends to two aspects of sector-specific model structure beyond those covered in the executive summary: choice functions and the methodology for handling time-steps. The electricity, transportation, and buildings sections of this report address in detail how model attributes contribute to differences in model results.

Table 1. Comparison of Elements of Model Structure for GCAM and Sector-Specific Models

Category	GCAM	Sector-Specific Models
Purpose	• Economy-wide transitions • Cross-sectoral interactions	• Sector-specific energy technology transition options
Granularity	• Economic model with physical energy and material flows • Limited technology and process detail	• Greater technological, temporal, and spatial granularity
Extent	• Global coverage (32 energy-economy regions) • Economy-wide coverage of energy sources and uses, including representation of individual sectors • 5-year time-steps through 2100	• U.S. geographical scope, often with high regional detail • Represent individual sectors • 1-year to 2-year time-steps through 2050
Input Data	• 2015 base year • Need for comprehensive, global data	• Many sector-specific inputs updated annually
Decisions	• Logit choice function • Single choice indicator (cost or profit) • Historical preferences captured in calibration (share weight) parameters	• Varies by sector ReEDS: cost minimization TEMPO: logit choice function Scout: stock and flow with choice functions
Time Step Dynamics	• Myopic (no foresight) • No explicit constraints on rates of change between time-steps	• Varies by sector ReEDS: myopic, nonlinear adjustments between time steps TEMPO: myopic; no explicit constraints on rates of change between timesteps Scout: myopic, stock turnover defines changes between time steps

Categories adapted from Hiremath et al. (2007).

2.2.1 Granularity and Resolution

One type of simplifying assumption used in models is made when phenomena are organized into discrete groups and an average or representative value is used to describe all members of that group. Depending on the application of the model, these groups may represent numerous, fine distinctions, or broader aggregations. Geospatial, temporal, technological, energy resource, and energy demand features may all be grouped into more or fewer categories depending on the need for resolution of these attributes. In this report, we identify and explain certain differences in results that are attributable to models' different levels of granularity or resolution. In considering these results, it may be useful to think about granularity in terms of a supply or demand curve: everything in a single category becomes competitive when its average value is competitive, so a lower resolution will result in "lumpier" behavior that can be either an underestimate or an overestimate relative to a more continuous depiction.

2.2.2 Extent

Models make simplifying assumptions to select a scope for geographic, temporal, technological, and energy system (resource, demand, infrastructure, dynamics) extent. For this project, we compare the U.S. region of a global model to U.S. models over 2020–2050, a period covered in both of the models. Differences in technology coverage explain some of the differences in model results, and they have been harmonized or noted. Energy resource coverage and energy demands are not comprehensive of every possibility, and areas of alignment and difference are noted.

2.2.3 Input Data and Parameters

Modeling requires input data to characterize initial conditions based on historical calibration and often future technology costs, as well as other parameters. The base year is the temporal starting point, and characterizing key attributes in the base year entails acquiring data and making assumptions to fill gaps in information. Most models (including all those in this study) uses future technology cost and performance projections from external sources. Models may use different sources of base and future year data, interpret the same sources differently, or make different assumptions to fill gaps. In this report, we harmonize certain key inputs, including to some extent both base year energy sector demand and supply as well as future technology cost and performance, but other inputs may remain as a reason for differences in results.

GCAM's historical (1975–2015) calibration data for energy production, transformation, and consumption are based on global energy balance data from the International Energy Agency (International Energy Agency 2019). These inputs are typically updated every 5 years, because the model operates in 5-year time-steps, and because updating GCAM to a new historical base year entails updating data on land allocation, agricultural production and trade, water consumption, and other parameters, in addition to energy balances. This update rate presents a particular challenge for aligning historical energy use between GCAM and sector models, which more frequently update their historical data based on yearly updates to the AEO. In this report, historical energy data are not fully harmonized between GCAM and the sector models because of the challenges of updating GCAM's historical energy balances. If future research attempted to further harmonize these historical energy data, analysts would need to decide whether to use GCAM values because of the complexity of updating its global energy balances or use the more recent AEO historical data used by the sector models and then adjust global energy balances in GCAM.

Backcasting or other benchmarking to empirical data can inform the selection of model parameters and ideally result in a model that matches behaviors in response to key drivers rather than only matching historical year values. Though each model's parameters have been carefully selected, systematic backcasting studies are only available for GCAM's land and agricultural models, as described in Section 2.1.1. The individual sector sections detail the historical calibration for each sector.

2.2.4 Decisions

Regarding choice functions, the evolution of the energy system depends on decisions, including decisions about individuals' purchases, business investments, and government investment and policies. Models represent such decisions by determining which factors are considered (e.g., cost, time, constraints such as environmental regulations, and future outcomes) and how each factor is weighted. Models may identify a single winner-take-all outcome or spread outcomes over a range of choices as a proxy for uncertainty in the factors and weighting. In this report, we identify examples where differences in the models' decision algorithms lead to different outcomes.

2.2.5 Time Step Dynamics

Another key modeling structural issue is what happens between one time-step and the next. Changes in technology, demands, and prices may be exogenous inputs to a model or may be endogenously determined. Constraints may be imposed on rates of change between time-steps. System dynamics models (e.g., Scout) simulate each time-step from the previous one based on these rates of change, in contrast to equilibrium or optimization models (e.g., GCAM and ReEDS) do not necessarily constrain rates of change between time-steps.

Input parameters, decisions, and time-step dynamics combine to determine a modeled rate of technological change in each sector, including the extent to which a model allows rates of change that have not been observed historically. In this study, we compare rates of change and reasons for differences, but we do not examine feasibility concerns.

2.3 Metrics

Despite their varying extent, granularity and resolution, parameters, decision approaches, and time-step dynamics, the models included in this study use similar types of input data—some of which are harmonized to facilitate a more direct comparison of differences in model behavior due to model structure. The models also produce similar types of outputs, which we compare to explore similarities and differences in model behaviors. We briefly describe each in this section.

Key model inputs that can be readily harmonized (across sectors) for GCAM/GCAM-USA and National Renewable Energy Laboratory (NREL) models to facilitate model comparison include:

- Technology
  - Cost
    - Overnight capital cost/purchase cost
    - Operation and maintenance costs
  - Efficiency
  - Technology lifetime
- Fuel prices
- Carbon emission prices

Generally, our approach in this study is to harmonize selected technology-specific input assumptions from the sector-specific models, which tend to be updated more frequently (e.g., annually), by changing inputs in GCAM. After running GCAM with these updated inputs, some of the resulting metrics such as fuel prices and carbon prices, which are calculated endogenously in GCAM are entered into the sector-specific models, for which these parameters are typically exogenous input assumptions. Results from the sector models for other output metrics are then compared for GCAM and the sector models. Figure 1 shows a summary of energy service demands in GCAM with input price connections from GCAM to TEMPO and Scout, as well as the comparison of results between GCAM and each sector-specific model.

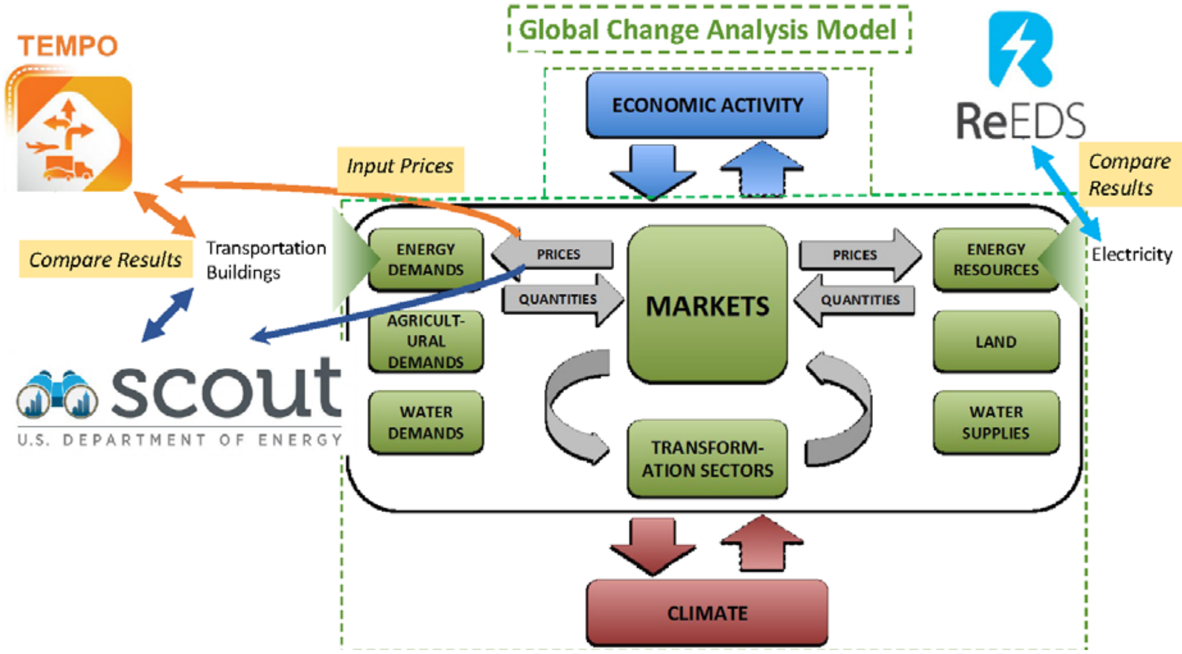

Figure 1. GCAM and three sector models—ReEDS (electricity), TEMPO (transportation), and Scout (buildings)—were used in this study.

Fuel prices from GCAM that included carbon price were passed to TEMPO and Scout for new modeling. We compared GCAM results with results from each sector model (ReEDS, TEMPO, and Scout). The GCAM portion of this figure, which is distributed under the Creative Commons Attribution 4.0 License, is based on Calvin et al. (2019) in *Geoscientific Model Development*

Key model outputs that can be compared (across sectors) to evaluate model behavior and understand key similarities and differences and their drivers include:

- Technology product: electricity generation, transportation service, building services
- Technology stock: power sector capacity, vehicle stock, building equipment stock
- Energy consumption by technology
- Emissions.

For each GCAM-sectoral model pair, we compare model outputs across these metrics categories to explore similarity and differences in model behavior. To explain the key sources of differences in model results, we compare the metrics at different levels of resolution:

- National versus subnational, where applicable
- Sector-wide versus subsector (e.g., passenger versus freight transportation, and residential versus commercial buildings).

2.4 Scenario Design for Model Comparison

We used different scenario design approaches for each of the sectors—electricity, transportation, and buildings—as shown in Table 2 (page 12), because the limited scope of the study prompted us to leverage existing work. As a result, the following sector-specific sections share common objectives but differ in specific structure and content. Our power sector work focused on an emissions reduction target; for the buildings sector, we explored responses to a carbon price under different scenarios of efficiency technology availability; and for the transportation sector, we considered variation in carbon price and response to a technology standard for zero-emission vehicles by 2035. Because the limited scope of the project did not allow fully comparable analysis in each sector, one possible future step could be to apply scenario concepts across all sectors (e.g., carbon price responsiveness, emissions targets, technology availability, and technology standards). Although this model comparison effort proceeds sector-by-sector (and scenario design differs by sector), we apply harmonized inputs from each sector to all GCAM scenarios. Additionally, while scenarios are tailored to explore sector-specific policy issues—for example, 95% power sector emissions reduction by 2035 and 100% electric vehicle (EV) passenger vehicle sales by 2035—we use a common carbon price to help facilitate comparison across sectors. The carbon price (Figure 2) is an economy-wide carbon tax consistent with 2.6 W/m2 radiative forcing. This level of greenhouse gas (GHG) effect is often used to approximate 2°C of global warming by 2100.

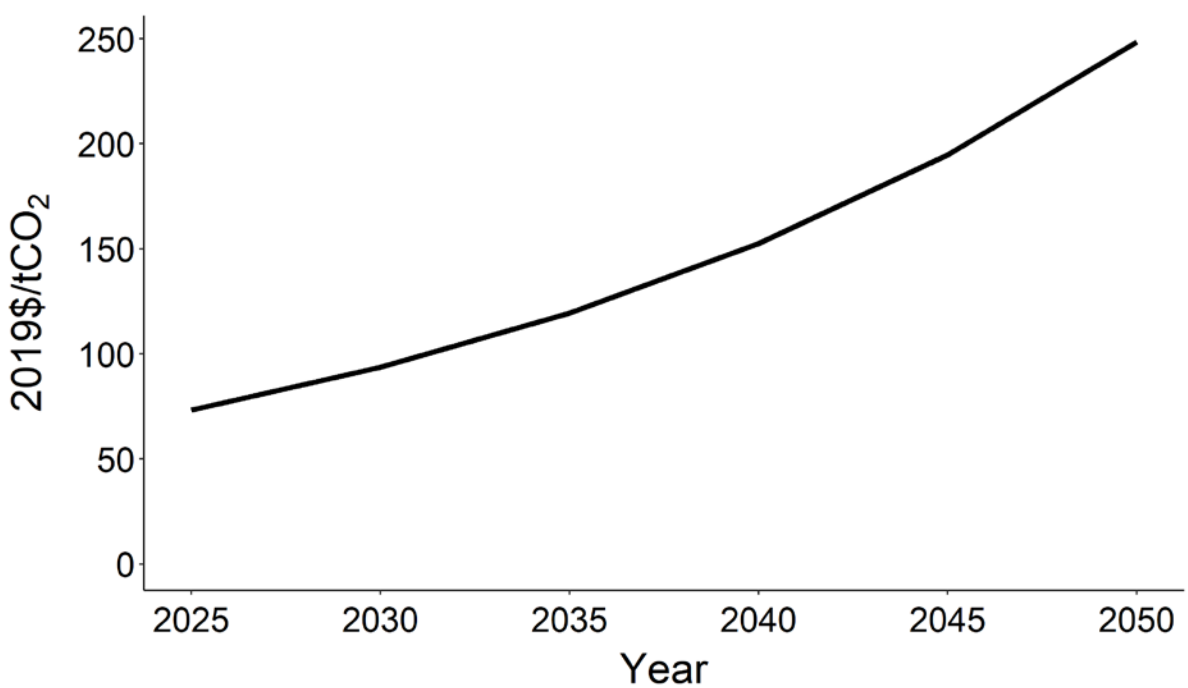

Figure 2. Economy-wide carbon price consistent with constraining end-of-century radiative forcing to 2.6 W/m^2

Price escalates at an annual hoteling rate of 5%/year.

The models' reference scenario assumptions (beyond assumptions about technology characteristics) were not explicitly harmonized for this analysis, but they are qualitatively similar. GCAM and GCAM-USA use population and GDP growth assumptions consistent with Shared Socioeconomic Pathways 2, or SSP2, scenarios (O'Neill et al. 2017; KC and Lutz 2017; Leimbach et al. 2017); however, ReEDS, TEMPO, and Scout service demands are driven (directly or indirectly) by various versions of the AEO and other sector-specific sources.[12] The models assume comparable levels of population and GDP growth to 2050; for example, GCAM-USA assumes a 19% increase in population and an 87% increase in GDP from 2020 to 2050, and AEO2021 assumes 17% and 89% increases, respectively, for population and GDP.

From a policy perspective, GCAM and GCAM-USA have limited representation of existing policies, but the models' calibration routine captures the impact of some existing policies in the near term. Broadly, the GCAM and GCAM-USA reference scenarios reflect an underlying storyline that historical trends continue in the near term due to inertia in the energy system and continuation of current policies, while longer-term outcomes are driven mostly by economic competition.

ReEDS also represents a larger suite of power-sector relevant state, regional, and federal policies in effect as of June 2021, including state renewable portfolio standards policies, California's power sector carbon cap, the Regional Greenhouse Gas Initiative, and the Cross-State Air Pollution Rule (Cole et al. 2021).

TEMPO is similar to GCAM and GCAM-USA in its policy and reference scenario perspective: its initial calibration (i.e., mode-level energy consumption) and sector-wide demand drivers (i.e., population and freight demand growth projections) are informed by AEO and may implicitly capture near-term policies, but its future projections are driven primarily by competition between modes and technologies based on economic criteria. TEMPO's Reference scenario does not include any explicit representations of future policies such as CAFE (Corporate Average Fuel Economy) standards or tax credits; future shifts in energy consumption are primarily driven by changes in exogenous technology projections.

Scout is also similar to GCAM and GCAM-USA in its underlying policy assumptions and reference scenario. Baseline building and equipment stock turnover, electricity system CO_2 intensity, and energy prices are derived from AEO. If desired for a given scenario, Scout can reflect a wide range of policy conditions more aggressive than those included in the AEO, for example, accelerated equipment stock turnover or restrictions on the adoption of certain equipment types or fuels. AEO side cases (e.g., Low Renewables Cost) can be used in Scout to define alternative baseline energy system conditions.

The models have some differences in the availability of specific technologies. For example, ReEDS has a more detailed representation of electricity storage than GCAM. GCAM includes electric and hydrogen options for short-haul aviation, while TEMPO does not. However, technology characteristics (cost and performance) were largely harmonized for this analysis.

[12] For the model versions used in this study, ReEDS and Scout use demand drivers from AEO2021, and TEMPO uses population growth from AEO2019.

Table 2. Scenario Design by Sector

Sector	Scenario Name	Policy	Other Attributes
Electricity	Ref	Reference	ReEDS Only Demand Scenarios: • HighDemand • Electrification GCAM demand is an output.
	95by2035	95% CO_2 Mitigation by 2035 in the electricity sector GCAM applies *background carbon price consistent with constraining end-of-century radiative forcing to 2.6 W/m²*	ReEDS Only Demand Scenarios: • HighDemand • Electrification GCAM demand is an output.
Transportation	Reference	Reference	—
	Carbon Price $10/t$CO_2$ $20/t$CO_2$ $30/t$CO_2$ $40/t$CO_2$ 2.6 W/m^2	Carbon price trajectory beginning at $10–$40 $/t$CO_2$ and increasing at an annual hoteling rate of 5% *Carbon price trajectory consistent with 2.6* W/m^2	—
	100% EV	100% LDV EV Sales by 2035	—
Buildings	Reference-noEEE	Reference	Reference ECMs
	Ctax-noEEE	*Carbon price trajectory consistent with 2.6* W/m^2	Reference ECMs
	Reference-Market_EEE	Reference	Market_EEE ECMs
	Ctax-Market_EEE	*Carbon price trajectory consistent with 2.6* W/m^2	Market_EEE ECMs

ECM = energy conservation measures; EEE = electrification and energy efficiency; ctax = carbon price in dollars per metric ton of CO_2 consistent with 2.6 W/m^2 radiative forcing in the year 2100

3 Electricity Sector

Electric power is often thought likely to be the first and least costly of the energy sectors for achieving substantial emissions reduction, in part because of the availability of established technologies that do not directly emit GHG ("GHG-free"). However, modeling of this sector must address several complexities. Although the electrical supply includes GHG-free technologies today (e.g., nuclear, wind, and solar), considerable uncertainty remains about the timing and ultimate potential of commercial deployment of carbon capture and storage (CCS), which could allow biomass and fossil fuel-fired powerplants to operate with greatly reduced GHG emissions.

Each technology option has strengths and weaknesses related to its specific operating characteristics in the context of the electric system. Electricity supply and demand must continually balance to ensure stability of the grid. Both electricity demand and VRE output fluctuate throughout the day and seasonally throughout the year. Also, the resource bases of VRE are spatially heterogenous and their potential to contribute to the generation mix is stronger in some regions than others. Decarbonization of the broader energy system is also expected to introduce new electricity loads as end-use sectors decarbonize (e.g., via electrification); the electric power sector must grow to accommodate these new demands (and possibly a shifting profile of demand timing and flexibility) while also reducing emissions and ensuring adequate supply continuously throughout the year.

Models that simulate the future evolution of the electric power system must balance trade-offs among scope (e.g., dynamic interaction of power supply and end-use sectors demanding electricity), geographic resolution, and temporal resolution, among other factors. In this section, we summarize the modeling approaches for three versions of GCAM with different levels of spatial and temporal detail, as well as NREL's ReEDS power sector model. We describe our efforts to harmonize key model inputs to facilitate comparison, and we introduce our scenarios that explore deep decarbonization of the power sector by 2035. We then explore and compare model results for electricity generation, power sector capacity, fuel consumption, and CO_2 emissions. We conclude this section with a discussion of key observations, including the opportunity for more-robust representation of VRE's value to the power system in GCAM by leveraging information from ReEDS.

3.1 Model Scope and Structures

Similarities and differences in model behavior can be driven by many structural factors across the categories described in Table 1 (page 6, Section 2.2). This section provides a brief description of the power sector representation for the models in this comparison. The model structure in this section will help illuminate the reasons for the different results explored in Section 3.3.

3.1.1 GCAM

GCAM's electricity sector resolves electricity demand on an annual basis, solving for the price where electricity supply equals dynamically evolving annual demands across building, industry, and transportation end-use sectors. GCAM represents conversion of nine primary energy carriers (coal, gas, liquid fuel, biomass, nuclear, hydropower, wind, solar, geothermal) into electricity, with multiple power plant technologies being represented for most fuels. CCS technologies are available for coal, gas, liquid fuel, and biomass power plant types. A full list of power plant types in GCAM are provided in Table A-1 in the appendix (page 105) . Power sector technologies are vintaged, with technical lifetimes of 30–60 years. Investment in new capacity is determined based on relative levelized costs of electricity (inclusive of capital costs, fixed operation and maintenance costs, variable operation and maintenance costs, fuel costs, cooling water costs, and policy costs or subsidies) using GCAM's imperfect, probabilistic (logit-based) choice function. Once invested, a technology continues to operate until the end of its technical lifetime unless it becomes sufficiently unprofitable (i.e., variable costs such as fuel, water, and emissions penalties exceed revenues) to merit premature retirement.

Exogenous socioeconomic drivers (population and GDP) set the initial trajectory for energy service demands in building, industry, and transportation end-use sectors. The demands vary endogenously in scenarios according to price and income elasticities. Within each end-use sector, technologies that use different energy carriers—for example gasoline internal combustion vehicles versus battery electric vehicles (BEVs) in transport, and gas furnaces versus electric heat pumps in buildings—compete on a levelized service cost basis (equipment and fuel costs) for shares of the ultimate service demand.

For this study, we made two modifications to GCAM's default power sector to better align it with assumptions used in GCAM-USA and ReEDS. First, new coal-fired generation without CCS was removed from the choice set for the United States. This was done to reflect the impact of Clean Air Act Section 111 (b) New Source Performance Standards for CO_2 emissions from new steam-generating electricity generation. Second, nuclear power plant installations were postponed until after 2025 because of the recent decrease in U.S. nuclear power plant construction, and because building a nuclear power plant requires significant lead time.

3.1.2 GCAM-USA

In GCAM-USA, electricity generation, renewable energy resources (including solar photovoltaics [PV], solar concentrating solar power [CSP], onshore wind, offshore wind, and geothermal), and all end-use demands (which consume electricity) are represented at the state level. Like GCAM, GCAM-USA represents supply and demand for electricity in terms of annual energy. However, GCAM-USA divides the competition for investments in new generating technologies into a four-segment load duration curve (base load, intermediate, subpeak, and peak), reflecting the ways different types of power plants are expected to operate; for example, base load nuclear and gas combined cycle technologies compete against each other but not against gas combustion turbines, which compete against other peaking technologies for shares of new investment. Electricity investment decisions are made at the state level, but electricity supply and demand are balanced among 15 "grid regions," or groups of states reflecting electricity market and planning areas that are consistent with the North American Electric Reliability Corporation, or NERC, regions (see Table A-2 in the appendix, page 106, for GCAM-USA grid region specification). States within these grid regions trade electricity freely among each other, and trade among these grid regions is small both historically and into the future.

GCAM-USA is included in public release versions of GCAM.[13] Detailed documentation of GCAM-USA is available as part of the GCAM Model Documentation on GitHub (http://jgcri.github.io/gcam-doc/gcam-usa.html).[14] Binsted et al. (2020) provide a detailed description of GCAM-USA's electric power sector.

3.1.3 GCAM-USA Dispatch

We also used a third version of GCAM for our electricity sector comparison. GCAM-USA Dispatch is a version of GCAM-USA with a more detailed representation of the U.S. electric power sector (M. Binsted et al. 2022; Khan et al. 2021; Ou et al. 2021; Wise et al. 2019). GCAM-USA Dispatch separates decisions about investment in new capacity that lasts for decades from decisions about how to operate that capacity to meet demand in 25 subannual electricity demand segments (day and night for every month of the year, plus an annual peak equal to the 10 highest load hours of the year). This approach combines GCAM's traditional probabilistic (logit-based) investment choice function with a linear optimal dispatch where generators are operated based on least variable cost. As with GCAM-USA, GCAM-USA Dispatch separates investment in new capacity into four segments (based on an annual load duration curve). Once capacity is invested, it can operate in any of the subannual demand segments, subject to constraints on annual availability (maintenance time) and resource availability for VRE generators like wind and solar. Electric capacity is operated to meet electricity demand in the 15 grid regions described above (Section 3.1.2); the shape of the 25 subannual demand segments vary by grid region.

The GCAM-USA Dispatch model is described extensively by M. Binsted et al. (2022). GCAM-USA Dispatch is not currently included in public model releases, but the version described by Binsted et al. (2022) is available in that paper's code repository.

3.1.4 ReEDS

The Regional Energy Deployment System (ReEDS) is a model of electricity generation, storage, and transmission capacity expansion and operation for the contiguous United States. ReEDS is a dynamic-recursive system cost minimization that typically operates in 2-year time-steps from 2010 to 2050. ReEDS divides the contiguous U.S. electricity demand into 134 balancing areas and 17 seasonal-diurnal time-slices; it also includes an hourly submodule for capturing sub-time-slice effects (e.g., VRE curtailment fraction, capacity credit, storage curtailment reduction and sub-time-slice arbitrage value).

Key inputs to ReEDS include hourly electricity demand profiles by balancing area and future demand growth projections, technology and fuel cost projections, and detailed wind and solar resource supply curves by region. ReEDS also represents several types of state-level and national policies, including existing state renewable portfolio standards and regional CO_2 emissions constraints. Key model outputs for each model year include electricity capacity by technology and region; electricity generation by technology, region, and time-slice; transmission capacity

[13] "Global Change Analysis Model (GCAM)," https://github.com/JGCRI/gcam-core; "GCAM 6.0," https://github.com/JGCRI/gcam-core/releases.
[14] "The Global Change Analysis Model (GCAM) and GCAM-USA," http://jgcri.github.io/gcam-doc/gcam-usa.html.

and flows (including transmission capacity expansion); GHG and air pollutant emissions; and electric power system costs.

3.1.5 Comparison of Model Approaches

Table 3 compares key model structures for ReEDS, GCAM, GCAM-USA, and GCAM-USA Dispatch. In terms of overall solution approach, ReEDS' objective is system cost minimization, while GCAM is a market equilibrium model with a nonlinear logit technology choice function that avoids winner-take-all outcomes. This is also true for GCAM-USA Dispatch, with the caveat that power sector capacity is optimally operated based on least variable cost, as discussed in Section 3.1.3.

Table 3. Comparison of Key Electric Power Sector Model Features of ReEDS and GCAM Versions Included in this Analysis

Feature	ReEDS	GCAM	GCAM-USA	GCAM-USA Dispatch
Solution concept	• System cost (e.g., investment, operations, fuel, and transmission) minimization	• Market equilibrium • Technology choice based on nonlinear logit formulation		• Market equilibrium • Logit investment and optimal operation in power sector
Sectoral scope	• Power sector	• Energy, water, land, and emissions		
Electricity demand	• Exogenously specified projection	• Represented endogenously in buildings (further disaggregated into residential and commercial), industry, and transportation sectors		
Spatial scope and detail	• Contiguous United States • 134 U.S. balancing areas for demand and most technologies • 356 wind and CSP resource regions	• Global coverage with the world divided into 32 energy-economy regions • United States a single region	• Global coverage with the world divided into 32 energy-economy regions • United States further disaggregated to 50 states and Washington D.C.	
Subannual dynamics related to electricity demand	• 17 time-slices per solve year (four seasons with four diurnal periods, plus peak load) • Hourly submodule for evaluating peak time periods as well as times of system curtailment	• Annual electricity demand	• Four-segment load duration curve (base load, intermediate, subpeak, peak)	• 25 time-slices (day and night for each month of the year, plus annual super-peak)

Feature	ReEDS	GCAM	GCAM-USA	GCAM-USA Dispatch
Transmission	• Balancing areas connected by an aggregated transmission system • Able to build new transmission capacity between balancing areas • System cost optimization includes transmission.	• Implicit unlimited intranational electricity trade	• States grouped into 15 grid regions • Constrained trading between regions • States within a region able to freely trade with each other	
Storage	• Includes pumped storage hydropower, compressed air energy storage, and battery technologies • Hourly submodule for hourly arbitrage and curtailment reduction	• For PV and onshore wind, both a purely variable technology and a technology paired with dedicated storage are included in the choice set.	• Same as GCAM, plus a grid-scale battery storage technology which consumes baseload electricity and supplies peak electricity.	• Under development • Not currently included in model
Renewable variability	• Hourly submodule for fractional curtailment, capacity credit, and induced operating reserve from forecast error	• As the share of variable renewable technologies on the grid increases, cost is applied to reflect diminishing contributions to electric capacity reserve and the need for additional capacity to supply reserve.		• Variable renewables receive diminishing capacity credit with increasing share of installed capacity.

All three versions of GCAM have global scope and cover economy, energy, agriculture/land, and water systems, and as a sector-specific model, ReEDS covers only the electric power sector in the contiguous United States. Electricity demands within GCAM are endogenously calculated over time to reflect changes in buildings (which are further disaggregated into residential and commercial buildings), industry, and transportation sectors. ReEDS does not include any sectors outside the power sector, so electricity demands must be exogenously defined. While GCAM has global coverage (and state-level detail for GCAM-USA and GCAM-USA Dispatch), ReEDS has greater geographic resolution for the United States, dividing the contiguous United States into 134 U.S. balancing areas for demand and representing renewable resource potentials for 356 distinct regions. ReEDS also offers greater detail related to electricity transmission, with an aggregate transmission system connecting balancing areas and the potential for explicit build-out of new transmission capacity. GCAM, operating at the national level, implicitly assumes unlimited intranational electricity trade, while GCAM-USA and GCAM-USA Dispatch allows unlimited trade within the electric grid regions (as discussed in Section 3.1.2) and some constrained inter-grid electricity trade.

In terms of temporal detail, GCAM and GCAM-USA represent annual electricity demands only (with a four-segment load duration curve capturing some dynamics related to variations in electricity load throughout the day in GCAM-USA). In contrast, ReEDS represents 17 time-slices per year (four seasons with four diurnal periods, plus peak load), and GCAM-USA Dispatch divides annual demands into 25 time-slices (day and night for each month of the year, and an annual super-peak). Thus, ReEDS and GCAM-USA Dispatch provide more detail about how capacity is operated to meet demand at various points throughout the year, as well as how VRE availability aligns with electricity demand at different points throughout the year.

ReEDS also provides significant detail about renewable energy variability and electricity storage. ReEDS includes an hourly submodule to capture key issues surrounding VRE and storage, such as renewable curtailment and arbitrage opportunities; it also includes several types of electricity storage technologies, including pumped storage hydropower and multiple battery technologies. GCAM and GCAM-USA use a simple logistic function to represent diminishing contributions of variable renewable technologies to electric capacity reserve as the share of VRE on the grid increases. GCAM-USA Dispatch uses a similar function, where VRE technologies receive diminishing capacity credits as their share of installed capacity increases, but the lost capacity credit revenue is less penalizing than the cost added by the backup function in GCAM and GCAM-USA. From a storage perspective, GCAM and GCAM-USA include technology options for PV and onshore wind paired with dedicated storage. These technologies have greater capital costs and are more expensive with low shares of VRE generation, but they become more competitive as VRE shares increase and backup costs are applied to the PV and onshore wind technologies that are not paired with dedicated storage. Electricity storage is an active area of development in GCAM-USA Dispatch, but it is not included in the model as of this analysis.

Given their different solution approaches, scopes, regional and temporal resolution, and detail related to key power sector dynamics, divergence in model results is to be expected. Each model has unique strengths (e.g., cross-sectoral interactions for GCAM and regional, temporal, and transmission/storage detail for ReEDS) and limitations, so comparing results across models and exploring synergies and differences can be highly valuable. To understand how differences in results emerge from differences in model structure, it is important to align key input assumptions for both models.

3.2 Input Assumptions, Model Alignment, and Scenarios

3.2.1 Previous GCAM-ReEDS Model Comparison Efforts

The GCAM and ReEDS teams have a fruitful history of collaboration and model comparison. Prior GCAM-USA and ReEDS harmonization efforts helped identify the most important drivers to align to promote consistency between the models' reference scenarios (Iyer et al. 2019). In that study, consistency was improved the most when fuel price drivers were passed from GCAM-USA to ReEDS and when data on renewable resource potential and quality was synchronized between ReEDS and GCAM-USA. Harmonizing electricity demand levels

(GCAM-USA to ReEDS) and information about retirement of existing generation capacity (ReEDS to GCAM-USA) had little impact on model results consistency. Updating GCAM-USA's time segments to better match those in ReEDS was detrimental to consistency. Overall, the most consistent scenario resulted from harmonizing:

- Electricity demand and fuel prices, where results from GCAM-USA were used as inputs to ReEDS
- Renewable resource data and fossil-fueled power plant retirement, where detailed input data from ReEDS was used as inputs to GCAM-USA.

A follow-on study showed that harmonization of key model inputs did not always increase consistency across a broader set of scenarios (Cohen et al. 2021). Consistency was found to vary across scenarios for a given set of harmonized inputs, with structural differences leading to persistent inconsistency. Such structural differences may be reduced by either adding more operational detail in GCAM (e.g., GCAM-USA Dispatch; results presented here) or developing simplified methods of parameterizing GCAM to reflect key dynamics from more detailed sectoral models. We discuss the potential for such an approach to reflecting technology value in GCAM in Section .

3.2.2 Harmonization in Current Model Comparison

Drawing on insights from previous GCAM-USA ReEDS model comparison exercises, this study includes harmonization of only a few key parameters. Because this study uses preexisting scenarios from NREL's 2021 Standard Scenarios (Cole et al. 2021), all the parameters were updated in the GCAM models only, although in previous studies parameter harmonization flowed in both directions. Key parameters updated for this study include:

- Power sector capital, fixed operation and maintenance costs, and variable operation and maintenance costs from NREL's 2021 Annual Technology Baseline Mid-case
- Fuel prices from the AEO2021 Reference case.

Additionally, prior harmonization efforts provided parameterizations of wind and solar resource supply curves based on ReEDS 2017, which are still used in GCAM-USA and GCAM-USA Dispatch. GCAM also uses onshore and offshore wind power resource curves developed by NREL (Eurek et al. 2017).

3.2.3 Scenarios

As mentioned above, our model comparison effort for this study leveraged preexisting ReEDS scenarios from NREL's Standard Scenarios 2021 (Cole et al. 2021), from which specific scenarios were selected to explore two key dimensions: CO_2 emissions policy and electricity demand levels. For the policy dimension, two cases were considered: a reference case (Ref) with no new CO_2 emissions mitigation policy and a case in which power sector CO_2 emissions are reduced 95% by 2035 (100% reduction by 2050) relative to 2005 levels (95by2035). In the GCAM models, an economy-wide carbon price consistent with a global radiative forcing target of 2.6 W/m^2 in 2100 is applied to all sectors in the United States, and all regions globally, to avoid market distortions that may arise from penalizing emissions from one region and sector (U.S. electric power) but not others.

Cases with varying levels of electricity demand were also drawn from the 2021 Standard Scenarios. In GCAM, electricity demand is endogenous and varies with policy case. GCAM's reference cases have higher electricity demand than the 2021 Standard Scenarios Reference demand level, which is taken from AEO2021. GCAM's reference scenario has greater electrification across all end-use sectors than AEO2021, with the biggest difference coming from transportation; GCAM's Reference case entails significant EV deployment for passenger vehicles. For these reasons, the High Demand and Electrification cases were selected from the 2021 Standard Scenarios to roughly approximate the range in electricity demand across GCAM's Ref and 95by2035 scenarios.

3.3 Results

In this section, we present the results of our model comparison for the electric sector. Other sectors' results sections have different structure and content due to differences in scenario construction for electricity, transportation, and buildings. The figures include two scenarios (Ref and 95by2035) for three GCAM models (GCAM, GCAM-USA, and GCAM-USA Dispatch) and four ReEDS scenarios (Ref and 95by2035 policy in combination with High Demand and Electrification demand levels). The key metrics compared across models include electricity generation, electricity generation shares, power sector fuel consumption (specifically natural gas), CO_2 emissions, electricity prices, and power sector generation capacity (for ReEDS and GCAM-USA-dispatch only).

These metrics are reported by scenario, year (common model years are 2020, 2030, 2040, and 2050), and technology. Some analysis was also conducted at the subnational (state or grid region level); subnational analysis is described in the appendix. One important note is that ReEDS' geographic scope is the contiguous U.S., while all GCAM versions include Alaska and Hawaii. (GCAM includes Alaska and Hawaii energy and emissions in aggregate, while GCAM-USA and GCAM-USA Dispatch include those states explicitly.) Though results for all GCAM versions include Alaska and Hawaii in the figures presented, these states represent ~0.5% of total U.S. electricity generation in 2021 and do not appreciably impact results.

3.3.1 Electricity Generation by Technology

Figure 3 presents total electricity generation by scenario. Overall, total electricity in 2050 generation ranges from roughly 5,800 TWh (ReEDS Ref-HighDemand scenario) to roughly 7,800 TWh (GCAM-USA Dispatch 95by2035 scenario). In 2050, GCAM-USA Dispatch's Ref scenario has approximately 6,300 TWh of generation, GCAM-USA has roughly 6,400 TWh, and GCAM has about 6,700 TWh. For each GCAM model, 95by2035 generation exceeds Ref generation, although the magnitude of the increased electrification in response to emissions policy varies.

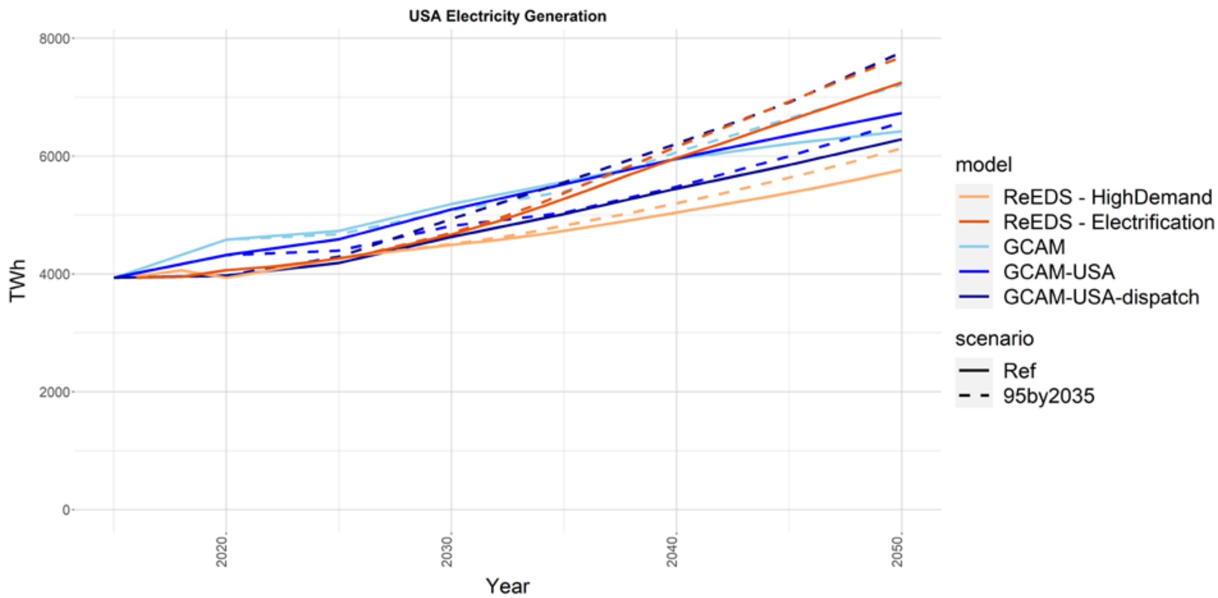

Figure 3. U.S. electricity generation by scenario

Electricity demand in ReEDS is exogenous, but some differences do emerge between the Ref and 95by2035 cases for a given demand level. This is because ReEDS includes an option for direct air capture (DAC) as a negative emissions technology in the power sector in emissions policy scenarios. DAC removes CO_2 from the atmosphere, creating negative emissions that offset remaining positive emissions from the power sector in order to help achieve the ambitious deep decarbonization targets in the 95by2035 scenario. DAC also consumes electricity to power its processes, creating additional electricity demand which causes total generation to diverge between the Ref and 95by2035 cases for a given demand level.

Figure 4 and Figure 5 present electricity generation by technology for each scenario, as well as the difference between each model and the ReEDS-HighDemand case. Results for the GCAM models and ReEDS are similar in 2020, although some differences are present because ReEDS generation and transmission capacity is calibrated to 2020 historical data while GCAM's final historical year is 2015. As the models simulate into the future, larger differences begin to emerge. Across both Ref and 95by2035 cases, GCAM and GCAM-USA have greater fossil fuel (especially natural gas) generation than ReEDS. This leads to higher emissions in the Ref case, as well as greater CCS deployment in the 95by2035 case.

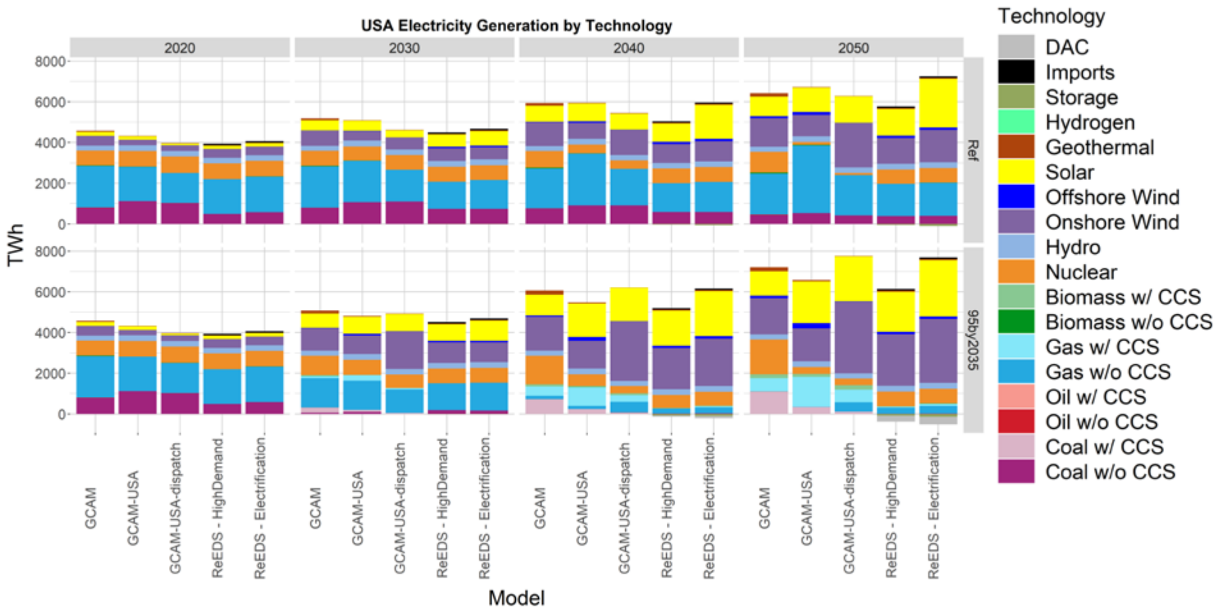

Figure 4. U.S. electricity generation by aggregate technology and scenario

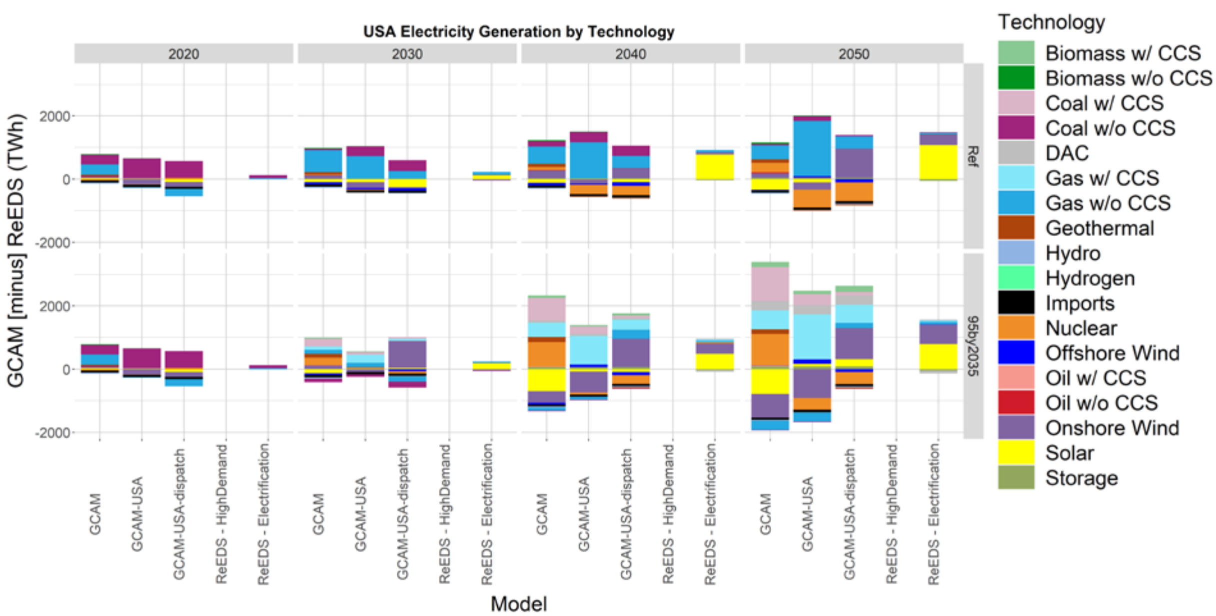

Figure 5. U.S. electricity generation by aggregate technology and scenario: Difference from ReEDS-HighDemand scenario

Nuclear generation differs across models because of differences in both input assumptions and model structure. GCAM-USA and GCAM-USA-dispatch have less nuclear generation than ReEDS because the state-level models include constraints on operating lifetime (no extension of existing nuclear operating licenses) and where new nuclear can deploy (new nuclear investment is only allowed in states which have built nuclear previously). ReEDS assumes nuclear operating licenses for all plants without currently announced retirement plans can be extended to 80-years from the original operation date. Future extensions of nuclear operating licenses and political acceptance of nuclear power are uncertain, and the models make different assumptions about these factors. GCAM simulates more nuclear generation than the other models; GCAM's lack of geographic detail makes it unable to capture these regional differences in preference for nuclear power.

With respect to VRE generation, GCAM and GCAM-USA have lower VRE (wind and solar) generation shares than ReEDS in the Ref case, with 36% and 38% of total technologies coming from VRE technologies in GCAM and GCAM-USA respectively (Figure 6 and Figure 7). GCAM-USA Dispatch has significantly higher VRE generation (56%) because it better represents operational decisions in the power sector, and because its subannual detail eliminates the need for the VRE integration cost representation used in GCAM and GCAM-USA (both dynamics are discussed in detail in subsequent paragraphs). ReEDS' HighDemand-Ref case has 47% VRE generation, while ReEDS Electrification-Ref case has 57% VRE generation, suggesting that at the margins, VRE technologies represent most additional generation in the Electrification case. Specifically, the ReEDS Electrification-Ref case has about 1,500 TWh more generation than the ReEDS HighDemand case and about 1,300 TWh more VRE generation (about 85% of the total generation difference between the scenarios).

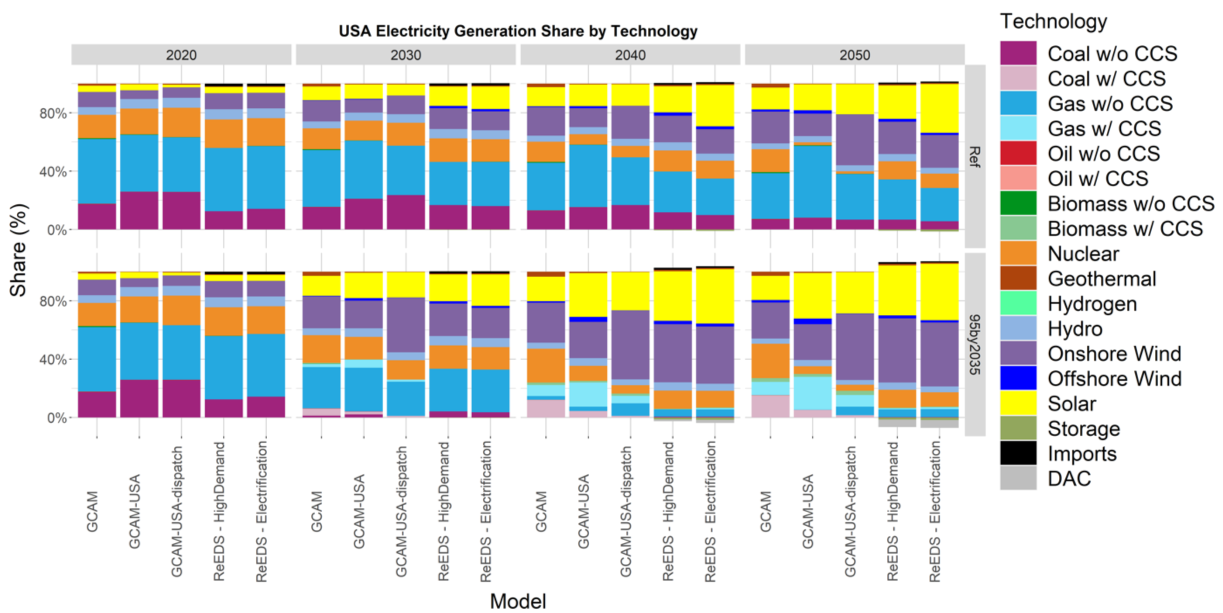

Figure 6. U.S. electricity generation shares by aggregate technology and scenario

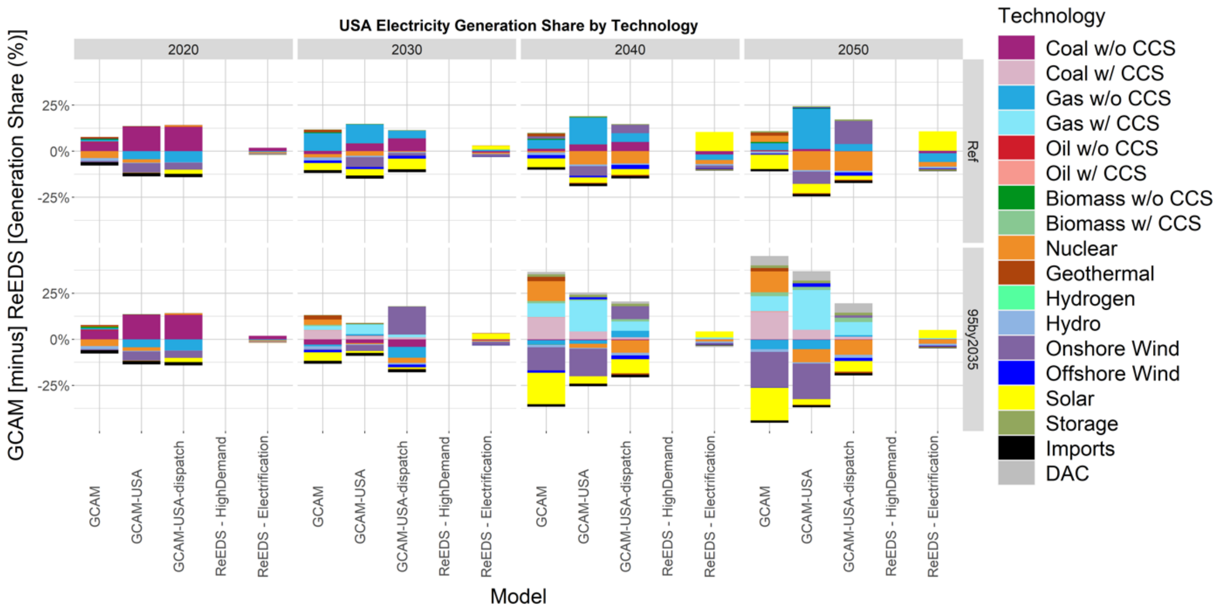

Figure 7. U.S. electricity generation shares by aggregate technology and scenario: Difference from ReEDS-HighDemand scenario

All models have higher VRE shares in the 95by2035 case than in the Ref case. GCAM has the lowest VRE generation shares (and the lowest increase relative to Ref) at 43% VRE generation in 2050; GCAM-USA simulates 60% VRE generation in the 95by2035 case in 2050, with GCAM-USA Dispatch at 74%, ReEDS-HighDemand at 80%, and ReEDS-Electrification at 84%.

For specific VRE technologies, all GCAM versions have lower solar generation shares than ReEDS. Solar generation ranges from 15% (GCAM) to 20% (GCAM-USA Dispatch) by 2050 in the Ref case, and in ReEDS it ranges from 23% (HighDemand) to 33% (Electrification) by 2050. For the 95by2035 case, solar generation ranges from 17% (GCAM) to 31% (GCAM-USA Dispatch) solar generation in 2050, and 34% (ReEDS HighDemand) to 39% (ReEDS Electrification) in 2050. With respect to wind generation, GCAM (22%) and GCAM-USA (15%) have similar onshore wind generation shares as ReEDS (22% for both demand levels) in the Ref case (2050), while GCAM-USA-dispatch is more bullish about onshore wind in the Ref case with 35% generation shares in 2050. In the 95by2035 case, GCAM (25%) and GCAM-USA (25%) simulate lower onshore wind generation than GCAM-USA Dispatch (45%) and ReEDS (43% for HighDemand and 44% for Electrification). Offshore wind does not contribute more than 4% to national electricity generation by 2050 across any model or scenario.

These differences in VRE generation are partially driven by the model's differing solution approaches: GCAM's logit choice function tends to distribute shares more broadly across technology options, while ReEDS' cost minimization objective is more likely to concentrate shares to least-cost technologies. GCAM-USA Dispatch blends the two approaches: investments are distributed using GCAM's standard logit choice function, but once invested, technologies are operated based on least variable cost, which can result in lower utilization of technologies with higher variable costs and therefore higher generation from VRE technologies.

The way GCAM and GCAM-USA represent integration costs for VRE technologies also contributes to their having lower VRE generation shares than ReEDS and GCAM-USA Dispatch. GCAM and GCAM-USA apply an integration cost to variable renewable technologies as their share of total generation increases. This cost adjustment reflects the challenges associated with the variability of VRE technologies and their reduced contributions to planning reserve as VRE generation shares increase.[15] The approach is a stylized and coarse but computationally tractable way to reflect these dynamics in GCAM's integrated, multisector modeling context. ReEDS and GCAM-USA Dispatch capture these higher-resolution impacts explicitly and thus do not employ a VRE cost adder.[16] This difference is quantified and detailed in Section 3.4.2 (page 31).

Finally, the GCAM models' representation of wind and solar supply curves may also contribute to VRE generation being different than that of ReEDS. GCAM-USA and GCAM-USA Dispatch use wind and solar resource curves based on data from ReEDS 2017,[17] and GCAM uses wind (onshore and offshore) resource curves from NREL. Updating these in GCAM to use resource curves from a newer ReEDS version may increase consistency.

3.3.2 Capacity by Technology

Figure 8 and Figure 9 present power sector capacity by technology and scenario for GCAM-USA Dispatch and ReEDS. GCAM and GCAM-USA are excluded from this comparison because they do not explicitly track capacity (although it can be estimated from annual generation using exogenous capacity factors). As shown in Figure 3 (page 21), GCAM-USA Dispatch's Ref case has somewhat higher total electricity generation than the ReEDS-HighDemand case, while the GCAM-USA Dispatch 95by2035 case has similar generation to the ReEDS-Electrification case. (Total electricity generation is obviously correlated with capacity requirements.) Overall, GCAM-USA Dispatch and ReEDS have similar levels of non-VRE (fossil, nuclear, geothermal, biomass) capacity across both the Ref and 95by2035 cases.

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[15] The maximum cost adjustment is based on the levelized capital cost of a gas combustion turbine (as the least-capital cost option for firm capacity), with the logistic function nearing maximum backup costs at about 25% generation share for solar PV and 45% for onshore wind. These parameterizations are informed by literature on integration costs of VRE, for example Ueckerdt et al. (2013).

[16] Note that ReEDS considers these operational impacts while making investment decisions. In GCAM-USA dispatch, operational outcomes inform the need for capacity investment, but technology utilization in the system operation phase does not impact expectations about technology capacity factors in the investment phase.

[17] A comparison of GCAM-USA's solar and wind resource curves before and after updating to ReEDS data is available in the supplementary data for Iyer et al. (2019).

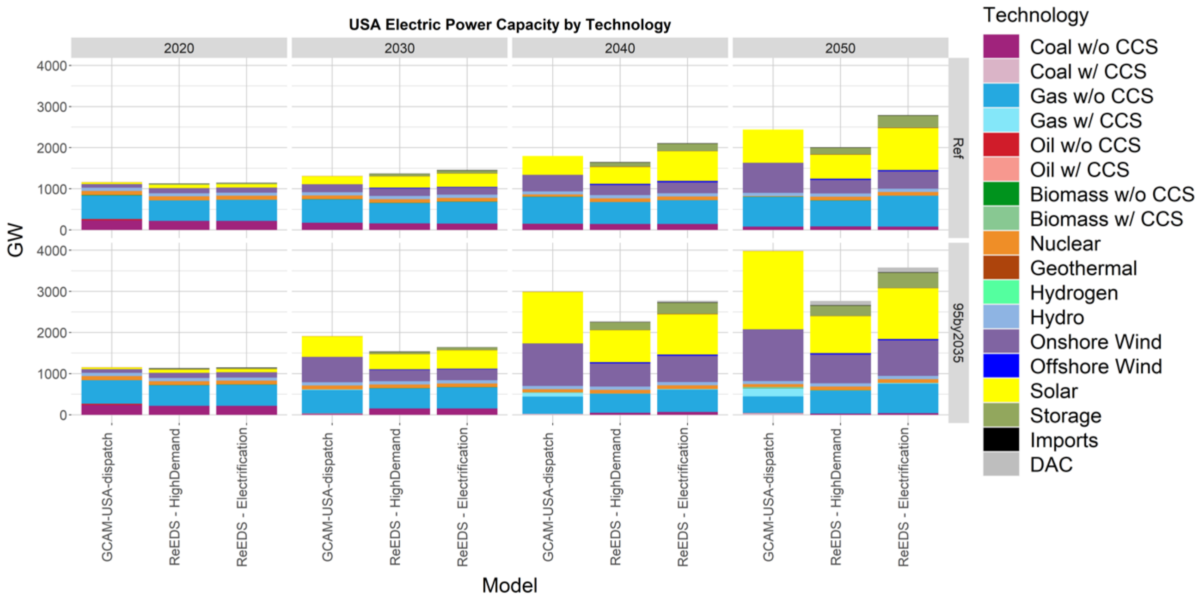

Figure 8. U.S. power sector capacity by aggregate technology and scenario

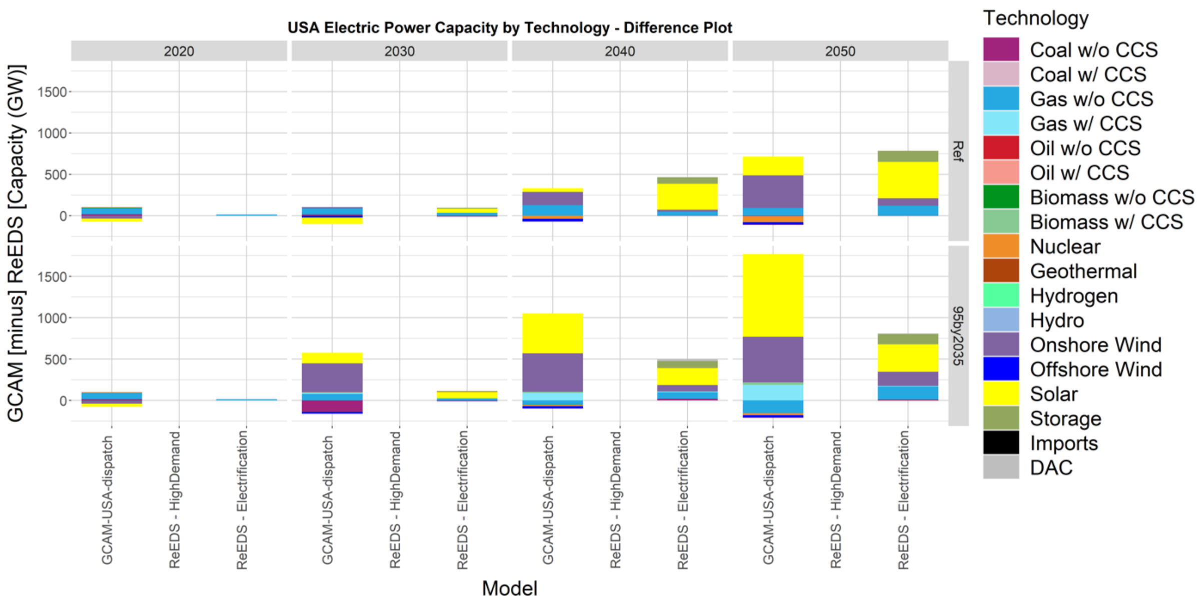

Figure 9. U.S. power sector capacity by aggregate technology and scenario: Difference from ReEDS-HighDemand scenario

GCAM-USA Dispatch tends to have greater VRE capacity than the ReEDS cases with similar electricity demand levels. Per Section 3.3.1 (page 20), GCAM-USA Dispatch and ReEDS have fairly similar VRE generation shares. This suggests a lower capacity factor (utilization rate) for VRE technologies in GCAM-USA Dispatch; these capacity factors are presented in Figure 10. Indeed, solar power and onshore wind have consistently lower utilization rates in GCAM-USA Dispatch than in ReEDS. One explanation for this dynamic is that ReEDS represents electricity storage, while GCAM-USA Dispatch does not (this is an active area of development for GCAM-USA Dispatch). ReEDS' scenarios entail 160–370 GW of electricity storage by 2050, which could help maximize the utilization and avoid curtailment of VRE technologies.

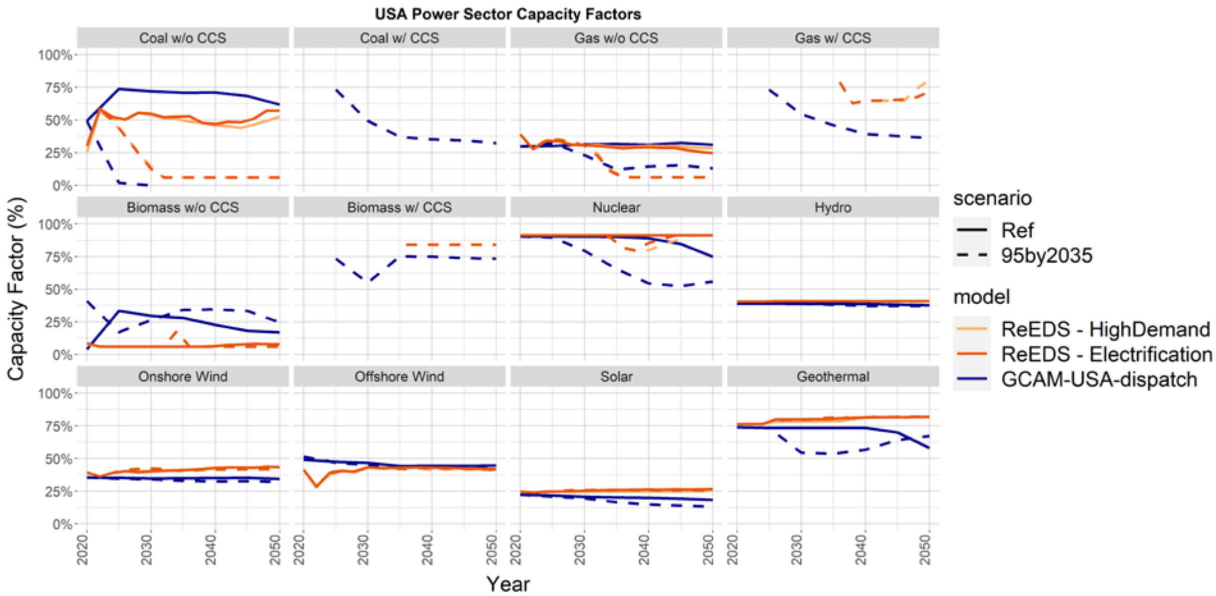

Figure 10. U.S. (national average) modeled capacity utilization factors by electricity technology and scenario

GCAM-USA Dispatch and ReEDS display similar capacity utilization for certain non-VRE technologies but not others. GCAM-USA Dispatch tends to operate coal without CCS somewhat more in the Ref case, although utilization by 2050 is similar in the models. In the 95by2035 case, GCAM-USA Dispatch retires all coal without CCS by 2035, while ReEDS keeps available some capacity around with a low (~6%) utilization rate. GCAM-USA Dispatch assumes a minimum capacity factor of 20% is required for coal capacity to remain operational; if utilization falls below this level, it is assumed revenues will be insufficient to cover fixed operation and maintenance costs and capacity will retire ahead of its technical lifetime as a result. ReEDS reflects more value streams (including dynamic capacity prices), which makes it economical for a small amount of coal to remain operational, even at very low utilization rates.

GCAM-USA Dispatch and ReEDS have very similar capacity factors for gas without CCS in both the Ref and the 95by2035 scenarios. For nuclear power, ReEDS consistently uses nuclear capacity at about 91%, while GCAM-USA Dispatch has lower utilization rates toward mid-century in the Ref case and earlier in the 95by2035 case. In GCAM-USA Dispatch, this result indicates some subannual time segments have sufficient capacity with lower generation costs than nuclear (e.g., solar, wind, hydropower, and geothermal) that nuclear power does not need to be fully utilized. GCAM-USA Dispatch does not capture operational constraints related to nuclear power (e.g., start-up times), which reflects that assumptions about nuclear power's future flexible operations may be different than those in ReEDS. To the extent that these operational constraints may lead nuclear plants to continue operating to avoid shutdowns and restarts, GCAM-USA Dispatch's representation may underestimate nuclear power's utilization rate. Additionally, the representation of electricity storage and direct air capture (DAC) in ReEDS (neither of which are included in the GCAM-USA Dispatch model used in this comparison) help shift the load profile in ways to utilize excess generation from low variable cost technologies (including VRE and nuclear), allowing nuclear capacity factors to remain high in ReEDS.

3.3.3 Fuel Consumption and CO_2 Emissions

Figure 11 presents power sector natural gas consumption by scenario. As observed in the electricity generation results in Section 3.3.1 (page 20), the GCAM models tend to have higher gas generation (and thus consumption) across scenarios in 2050 than in ReEDS. Significant differences in gas generation across models are present in 2020, which is simulated in all GCAM models but constrained to historical data in ReEDS. GCAM-USA Dispatch has the lowest gas consumption of all GCAM models in the Ref case, largely due to its explicit representation of power sector operation, where gas is often at or above the marginal generation cost for some subannual time-slices. All models display a reduction of power sector natural gas consumption in the 95by2035 case; GCAM has the lowest gas consumption of the GCAM models, largely due to its greater deployment of coal with CCS and nuclear.

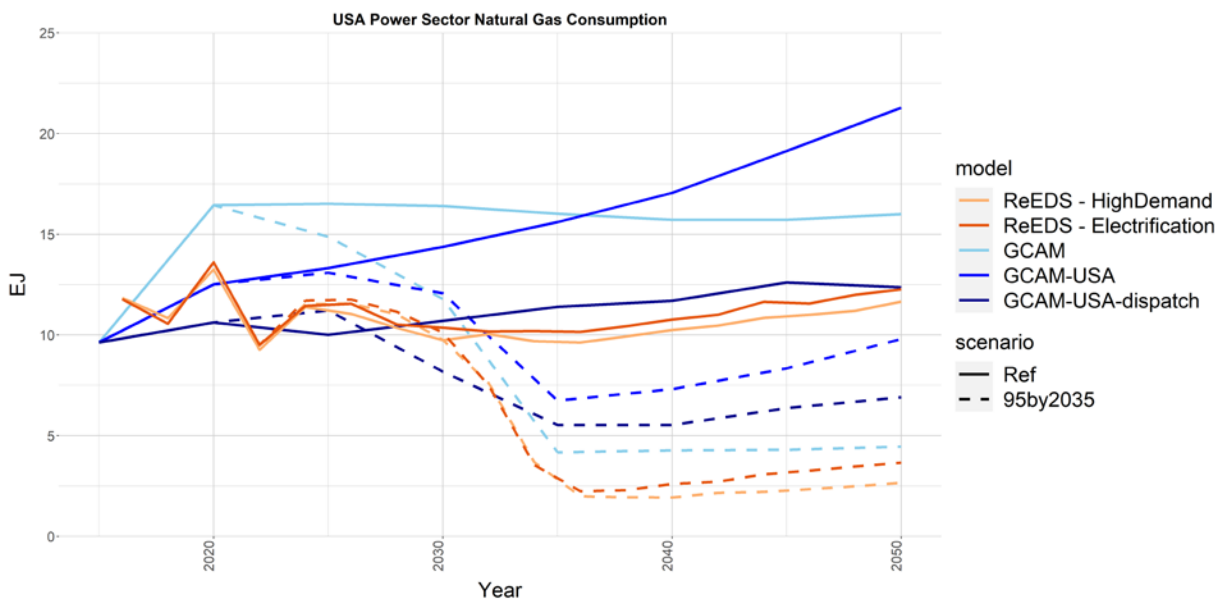

Figure 11. U.S. power sector natural gas consumption by scenario

These gas consumption results are generally correlated with CO_2 emissions (Figure 12). Each GCAM model has higher gas generation and CO_2 emissions in the Ref case relative to ReEDS. Figure 13 presents U.S. power sector CO_2 emissions by technology and scenario. The GCAM models tend to have greater emissions from coal than ReEDS in the near-to-medium term, but coal fired CO_2 emissions in 2050 are comparable across models. In the 95by2035 case, emissions are exogenously prescribed as part of the scenario design and thus are identical or nearly identical from 2035 onward. The clear exception is GCAM-USA Dispatch, which has lower emissions than the other models (and the exogenously prescribed emissions constraint) in 2025 and 2030 (both models constrain emissions to linearly decrease from current levels to the 95% reduction target in 2035). For each GCAM model, the 95by2035 case includes an economy-wide carbon price to ensure emissions across all sectors and regions are priced to avoid market distortions from inconsistent emissions pricing. In GCAM-USA Dispatch, which has greater power plant operation flexibility than GCAM and GCAM-USA, the economy-wide carbon price alone is sufficient to drive emission reductions below the power-sector emissions target in 2025 and 2030. Beyond 2030, the power sector emissions reduction target (95%+ emission reduction) is stringent enough that the sectoral emissions constraint becomes binding.

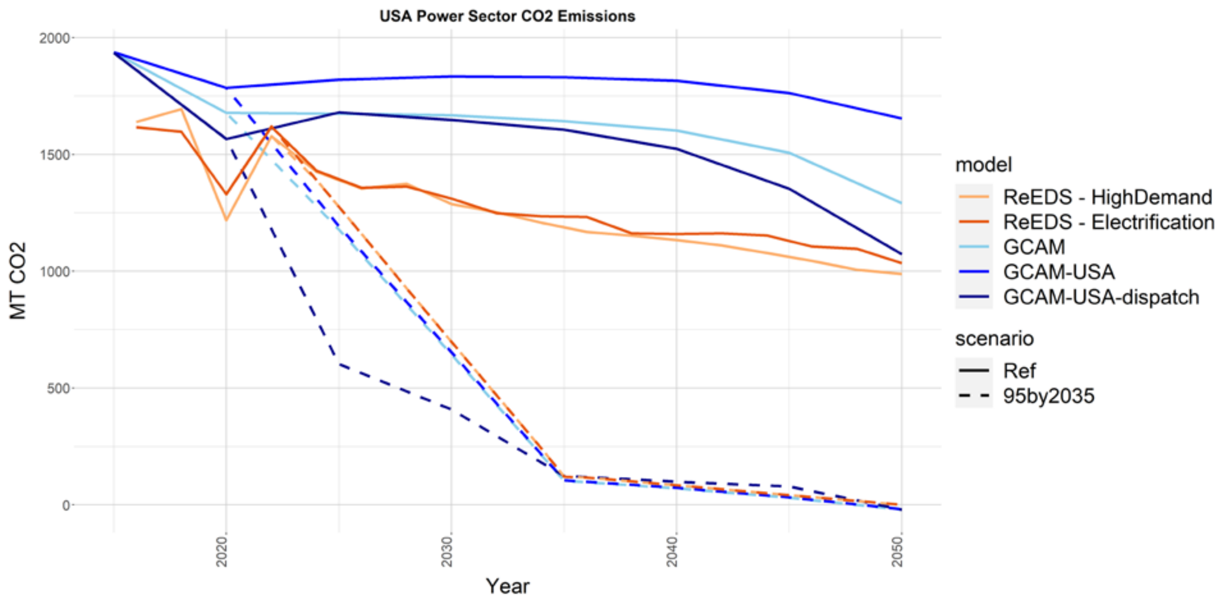

Figure 12. U.S. power CO_2 emissions by scenario

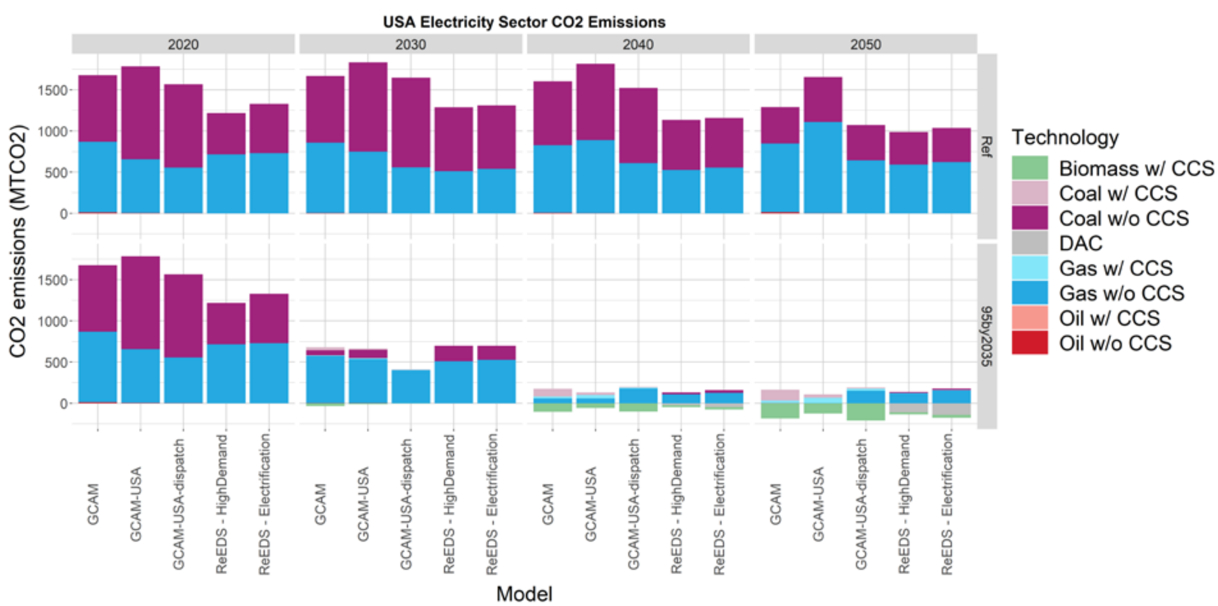

Figure 13. U.S. power sector CO_2 emissions by technology and scenario

The final emissions dynamic to point out is related to negative emissions. In the 95by2035 case, each model requires some negative emissions in the power sector to offset the remaining positive emissions from uncaptured fossil fuel generators or residual emissions from fossil fuel plants with CCS (which have capture rates less than 100%). Overall, the models require levels of negative emissions that range from 140 to 210 MT CO_2 in 2050 to meet the net-zero power sector CO_2 emissions target. The source of residual (positive) and negative emissions varies by model. Most remaining emissions from GCAM and GCAM-USA are residual emissions from fossil fuels with CCS, while GCAM-USA Dispatch and ReEDS have less CCS and more emissions from gas without CCS. This is because GCAM-USA Dispatch and ReEDS reflect the fact that fossil fuel capacity may be operated at a low capacity factor, in which case paying the emissions penalty is more cost-effective than investing additional capital in CCS when the plant will often stand idle.

For CO_2 removal, the GCAM models rely on bioenergy with CCS to offset remaining emissions. In contrast, in ReEDS, DAC produces most of the negative emissions. This is due to a combination of model structure and input assumptions. All GCAM models include a DAC capability, although it is not included in the default GCAM configuration. Additionally, DAC is not directly tied to the power sector in GCAM; DAC can be powered primarily by natural gas or electricity, and it provides a general emissions removal service that is not explicitly tied to the power sector (whereas bioenergy with CCS is a technology that both generates electricity and has negative emissions). Consistent with GCAM's default configuration, and because DAC in GCAM is not structured to provide emissions offsets for the power sector alone, DAC is not included in the GCAM scenarios in this study.

3.4 Conclusions, Key Takeaways, and Recommendations for Future Research

This section summarizes the core insights from our power sector model comparison and highlights opportunities for future research and joint model improvement.

3.4.1 Key Model Differences

GCAM and ReEDS are very different types of models. GCAM is a global, integrated multisector model while ReEDS represents the power sector in the contiguous United States. Despite fundamental differences in geographic scope, sectoral scope, temporal and geographic resolution, power sector process detail, and solution approach, the models' results are similar in several ways. In the Ref case, all three GCAM models and ReEDS simulate diminishing coal generation, increasing renewable generation, and decreasing power sector CO_2 emissions over the next three decades. In the 95by2035 case, all models increase their renewable energy generation relative to Ref, decrease use of fossil fuel power without CCS, and deploy a negative emissions technology to offset residual emissions from the power sector.

Despite similarities between ReEDS and GCAM, there are also important differences in the behavior of the models that are driven by their differing structure, resolution, and input assumptions. Because they do not capture operational dynamics in the power sector, GCAM and GCAM-USA both have greater fossil fuel generation than ReEDS, which leads to higher emissions in the Ref case and greater CCS deployment in the 95by2035 case. GCAM-USA and GCAM-USA Dispatch have less nuclear than ReEDS due to assumptions related to operating lifetime and where new nuclear can deploy. GCAM has the highest nuclear deployment; the model's coarser spatial scale fails to capture regional preferences or moratoria against nuclear power, as well as regional differences in renewable resource quality and potential, and in fuel prices that can diminish nuclear power's economic competitiveness in regions where other fuels are abundant and cheap. ReEDS has greater VRE generation shares than GCAM and GCAM-USA, due in large part to their different representations of VRE value or integration costs (described in the following section) and the more detailed representation of electricity storage in ReEDS; GCAM-USA Dispatch has somewhat lower VRE generation than ReEDS but the models are more similar in this regard.

A few key differences in model structure drive these differences in behavior. One important difference is solution approach. GCAM's logit choice function tends to distribute shares more broadly across technology options, while ReEDS' cost minimization objective is more likely to concentrate investments in least-cost technologies. The broader technology distribution leads to more diverse generation mixes in GCAM and GCAM-USA, including more natural gas generation and slower deployment of low cost VRE technologies. However, solar and onshore wind still experience the greatest increases in market share from 2020 to 2050 of all technologies across all the GCAM models. GCAM-USA Dispatch blends the logit investment and cost minimization approaches: investments are distributed using GCAM's standard logit choice function, but once invested, technologies are operated based on least variable cost. This approach results in lower utilization of technologies with higher variable costs (e.g., fossil-fueled generators), and therefore higher generation from VRE technologies relative to GCAM and GCAM-USA.

Solution approach also helps explain the greater nuclear generation in GCAM, which is less spatially resolved and thus does not reflect the geographic constraints on new nuclear installations employed in GCAM-USA and GCAM-USA Dispatch (where new nuclear is only permitted in states that have built nuclear previously). Some of the differences in nuclear generation across models are attributable to scenario assumptions; for example, GCAM-USA and GCAM-USA-dispatch assume no extension of existing nuclear operating licenses (in addition to the aforementioned geographic constraints on new nuclear installations), while ReEDS assumes existing nuclear plants extend their licenses for 80 years from their original operating date. Future extensions of nuclear power plant operating licenses are uncertain, but assumptions about these extensions could be aligned in future studies to reduce differences in nuclear generation.

The way GCAM and GCAM-USA represent integration costs for VRE technologies also contributes to their lower VRE generation shares, as discussed in Section 3.3.1 (page 20). In short, the integration cost added to VRE technologies in GCAM and GCAM-USA is a stylized and coarse but computationally tractable way to reflect the challenges associated with the variability of VRE technologies in GCAM's integrated, multisector modeling context. Conversely, ReEDS and GCAM-USA Dispatch include greater subannual temporal detail, which captures operational performance of VRE technologies and thus does not employ such a VRE integration cost adder. The next section describes this difference in detail.

3.4.2 Variable Renewable Energy Integration

It can be challenging for more aggregate models to capture the impact of increasing VRE shares on the grid, because these impacts are driven by dynamics that play out at finer temporal scales, such as how the availability of wind and solar power corresponds to demand for electricity from end-use sectors seasonally and diurnally. This challenge can be met in different ways. One approach is to incorporate greater temporal and operational detail in integrated assessment modes' power sector modules; this is the approach taken in GCAM-USA Dispatch, which contains subannual detail on power sector operations. This model comparison study showed that GCAM-USA Dispatch behaves more similarly to ReEDS with respect to key metrics like VRE generation share, compared to GCAM versions with less-detailed power sector modules. However, this approach requires significant model development and increases model complexity, data and memory requirements, and computational time. This additional detail provides value for some multisector modeling studies, such as those focused on the evolution of the power sector, low cost/high deployment of VRE technologies, or deep electrification of end-use sectors. This additional complexity may prove to be a barrier for studies focused on other sectors, energy-land-water dynamics, global interactions, or other situations where the power sector and VRE are lower priority than other topics.

An alternative approach is to derive relationships between technology value and market share from the outputs of more detailed power sector models (e.g., ReEDS) and incorporate them into more aggregate models as a cost adjustment. ReEDS developers have conceived a new metric called PLCOE (profitability-adjusted levelized cost of energy) that can be used as a single metric of competitiveness in simple models of the power sector. PLCOE scales a traditional levelized cost of energy (LCOE) metric by a "value factor" derived from ReEDS (although in theory this value factor could also be derived from other detailed power sector models). Value factor is defined as the levelized value of electricity (LVOE) of the technology (value per unit energy, where value is equal to revenue in a perfect market) divided by a benchmark value of the system (e.g., average electricity price). As a first approximation, the value factor of a technology can be assumed to be a linear function of its market share, and all technologies (not just wind and solar) require consideration of these value factor versus market share relationships. The value factor reflects the spatiotemporal and technology dynamics (including storage and transmission) of the detailed model. Details on PLCOE and value factor is available in Mowers et al. (2023) and Mowers and Mai (2021).

Figure 14 presents two different approaches to representing VRE value: the cost-adjustment currently used in GCAM and GCAM-USA (but not GCAM-USA Dispatch) and a cost-adjustment derived from the ReEDS value factor versus market share relationships as described in Mowers et al. (2023). Though the two approaches yield similar cost-adjustments for onshore wind, GCAM's cost adjustment for solar PV is significantly higher than the ReEDS-derived value for generation shares between 10% and 50%. This suggests GCAM's simplified VRE integration cost adjustment may be overly-penalizing for solar PV and depressing PV deployment, and that incorporating ReEDS-derived cost-adjustments could better reflect VRE value in GCAM and increase consistency with more detailed power sector models.

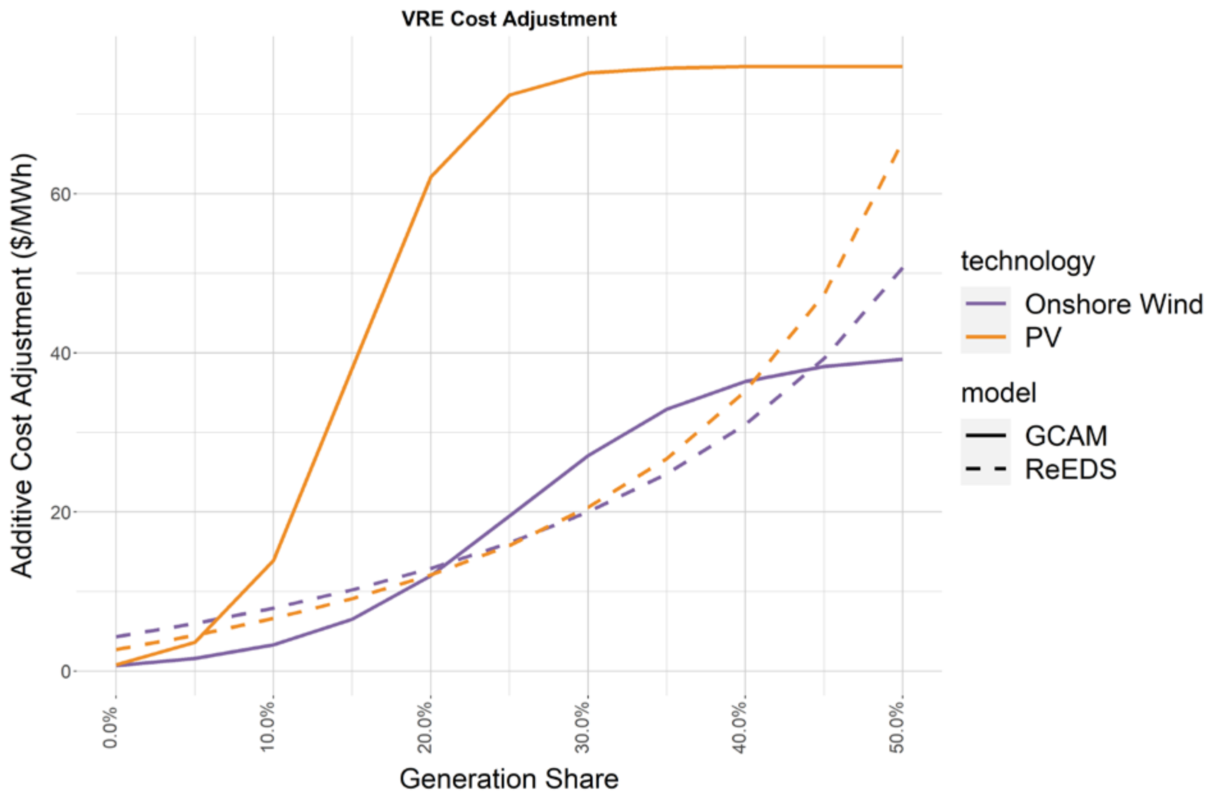

Figure 14. Comparison of VRE cost adjustment approaches

The solid lines represent the approach used in GCAM and GCAM-USA, and the dotted lines represent a cost adjustment consistent with the PLCOE metric derived from ReEDS, assuming 2030 technology costs.

3.4.3 Other Opportunities for Future Research

In addition to implementing simplified value-based (PLCOE) approaches to VRE integration costs in GCAM and GCAM-USA, a few other opportunities for additional alignment and integration of GCAM and ReEDS have emerged from this model comparison effort. One opportunity is to develop a more formalized set of boundary conditions that could be passed from GCAM to ReEDS. This could possibly include a standard set of GCAM scenarios regularly developed to provide these boundary conditions. The ReEDS' Standard Scenarios currently take boundary conditions from the AEO, which is produced using NEMS. However, while a publicly available archive version of NEMS can be used to replicate the AEO results, NEMS relies on several pay-for-license software components. Having a robust pipeline for translating GCAM scenarios to ReEDS boundary conditions could provide a valuable option for crafting additional scenarios with ReEDS using a fully open-source model to explore varying boundary conditions.

Finally, there is a need for continued dialogue among technology experts and model developers to improve the representation of key emerging technologies in the power sector, including electricity storage, negative emissions technologies, and hydrogen. As VRE gains increasing market share, electricity storage becomes increasingly important. Electricity storage has important implications for VRE (and other) technologies, and it provides important services such as frequency regulation, energy arbitrage, curtailment mitigation, and grid reliability; representing key dynamics related to energy storage is a complex challenge that merits continued model improvement. Negative emissions technologies such as bioenergy with CCS and DAC are increasingly important in the context of long-term deep decarbonization and ambitious power sector decarbonization targets. Opportunities and challenges for wide-scale deployment of these technologies (e.g., availability of bioenergy feedstock, geographic distribution of carbon storage sites, and economy-wide demands for CO_2 removal services) should continue to be explored. Hydrogen has the potential to help decarbonize sectors that are hard to electrify while also providing peaking and electricity storage services in the power sector. Multisector demands for hydrogen, energy arbitrage opportunities and economics for hydrogen production technologies, and other key dynamics related to hydrogen could be fruitful areas for future work.

4 Transportation Sector

Decarbonization of the transportation sector may require shifts in transportation demand, mode choice, and technology adoption within modes. We summarize differences in modeling approach for each of these aspects for GCAM and an NREL transportation model, the Transportation Energy & Mobility Pathway Options model (Muratori et al. 2021), and we consider their potential implications for sector-wide decarbonization results. Moreover, we consider two sets of scenarios: one exploring model response to varying levels of carbon prices and another exploring light-duty vehicle (LDV) stock turnover and its implications for sector-wide decarbonization. Other sectors' sections have different structure and content due to differences in scenario construction for electricity, transportation, and buildings.

4.1 Model Structure and Exogenous Drivers

4.1.1 The TEMPO Model

The Transportation Energy & Mobility Pathway Options (TEMPO) model (Muratori et al. 2021) is a transportation energy system model developed by NREL. Like GCAM, TEMPO's scope includes the entire transportation sector, including both passenger and freight modes, but it excludes upstream energy supply sectors such as electricity generation and refining. TEMPO computes mode and technology choice, sales of personal LDVs and commercial medium- and heavy-duty vehicles (MHDVs), vehicle stock, energy consumption, and emissions on an annual time-step. Determinants of mode and technology choice include cost (capital and operating costs), time, and infrastructure characteristics. TEMPO has been used in mode-specific and sector-wide studies, including an analysis of the decarbonization potential of MHDVs (Ledna et al. 2022) and an analysis of influential factors impacting decarbonization on a sector-wide scale (Hoehne et al. Forthcoming).

4.1.2 Model Structure and Comparison

GCAM and TEMPO's transportation sectors are organized similarly. Table 4 summarizes the models' scope and key exogenous drivers. Both models make mode and technology choice decisions using a logit formulation, which selects the market share of each mode and the share of individual technologies within modes based on the cost and time intensity of different options. The largest structural difference between models is their scope: GCAM is an economy-wide model, integrating with other sectors including electricity, buildings, and refining while TEMPO considers only the transportation sector. Cross-sectoral interactions, such as feedbacks between electricity prices and demand for electrified transportation, can be represented in GCAM but not in TEMPO, which requires exogenous assumptions or integration with other sector-specific models to represent the same dynamics. GCAM computes fuel prices and fuel carbon intensity (including carbon intensity of electricity and biomass share of liquid fuels) endogenously based on cumulative sector-wide demand, whereas TEMPO takes these factors as exogenous inputs.

Table 4. GCAM and TEMPO Scope and Key Drivers

Feature	GCAM	TEMPO
Solution concept	• Fuel prices determined via market equilibrium • Mode and technology choice based on nested logit formulation	• Mode and technology choice based on logit formulation
Model scope	• Economy-wide (all energy supply, transformation, and end-use sectors, as well as land and water systems)	• Transportation only
Spatial scope and detail	• Global coverage with the world divided into 32 energy-economy regions • United States as a single region (Only the United States was considered in this analysis.)	• United States-national or county-level (National scope was used in this analysis.)
Temporal resolution	• 5-year time-step	• Annual time-step
Exogenous drivers	• Population and GDP	• Population (passenger) • Exogenous demand trajectories (freight)
Cross-sectoral feedbacks	• Fuel prices endogenously determined based on energy supply characteristics and total demand from final energy sectors • Biofuel share of liquid fuels determined based on technology competition within refining and demand for liquid fuels and biomass across all sectors	• N/A
Passenger sector unit of resolution	• National	• Household (sampled based on National Household Travel Survey [NHTS])
Freight sector unit of resolution	• National	• Shipment distance bin

Both models are exogenously driven by population growth (Figure A-2 in the appendix, page 108), which drives demand for passenger travel. Population in GCAM's U.S. region increases from 337 million people in 2020 to 403 million people in 2050, while in TEMPO the number of households grows from 122 million to 149 million (corresponding to total populations of 333 million and 389 million people). GCAM also considers regional GDP per capita (Figure A-3 in the appendix, page 109), which is used to compute both passenger and freight demand. In both models, total passenger demand endogenously responds to changes in the cost of transportation using cost elasticities. In GCAM, freight demand is represented as a function of economy-wide GDP and an index of the aggregate price of freight service using GDP and price elasticities, similar to passenger demand. In TEMPO, total freight demand is determined exogenously based on the Freight Analysis Framework (Federal Highway Administration 2019).

Mode-and technology-level divisions are fairly similar in the passenger sector (Table 5, page 8). Differences between the models include the representation of LDV size classes (four in and two in GCAM), the inclusion of battery-electric and hydrogen fuel cell technology options in GCAM's aviation mode, and the inclusion of the passenger marine ship mode in TEMPO. The models differ more substantially in their market segmentation. GCAM computes regional passenger demand as a function of regional GDP per capita, an index representing the aggregated price of transportation, regional population, and income and price elasticities (Mishra et al. 2013). In TEMPO, passenger demand at the national level in the United States is aggregated from sampled households drawn from 60 distinct bins, which divide the consumer market based on composition (size and number of drivers), income, and urbanity (Muratori et al. 2021). Household travel demand is estimated from distributions drawn from the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration 2018), which describe trip distance and trip count distributions by household bin. TEMPO's household-level resolution allows for representation of intrahousehold dynamics, such as vehicle use among the household vehicle fleet, and for enhanced market segmentation (e.g., exploring distinctions in residential charging availability and mode availability among different household bins).

In the freight sector (Table 6, page 39), there are additional differences in resolution. While mode and technology-level resolution are fairly similar across the models, TEMPO adds resolution by shipment distance bin within each mode. Eight shipment distance bins, derived from the Freight Analysis Framework, are used to divide each freight mode, and there are differing levels of freight activity in each bin. This allows the model to represent varying use cases for freight modes, such as short-distance and long-distance applications for on-road MHDVs, and there are implications for technology choice across distance bins. It is implicitly assumed in TEMPO that freight vehicles will operate within their assigned distance bins rather than across multiple bins.

Neither model endogenously represents non-income or non-cost-based determinants of total transportation demand, including drivers such as new business models, telework, urbanization, or convenience/time intensity (though time intensity is an important determinant of allocation of demand across modes). These scenarios can be represented as exogenous inputs in both models.

A final distinction worth noting is the models' calibration years and temporal resolution. GCAM is calibrated to 2015 and models the energy system in 5-year time-steps, while TEMPO is calibrated to 2017 and uses a 1-year time-step. Differences in calibration years may result in somewhat different modeling of recent history (e.g., 2015 or 2017–2021) due to differing data sources and calibration assumptions.

Table 5. TEMPO and GCAM Passenger Mode and Technology Representation

Mode	GCAM	TEMPO
Personal LDV and mobility as a service (MaaS)	• Two size classes: car and large car, and truck • Four technologies: conventional liquids, hybrid liquids, BEV, and hydrogen fuel cell electric vehicle (FCEV)	• Four size classes: compact, midsize, sport utility vehicle, and pickup • Six technologies: conventional gasoline, hybrid, natural gas, BEV, FCEV, plug-in hybrid electric vehicle (PHEV) • Long and short electric range options for BEVs and PHEVs • MaaS contains midsize vehicles only and excludes PHEV and short-range BEV
Motorcycle/two-wheeler	• BEV and conventional liquid fuel technologies	• Conventional gasoline only
Bus	• Conventional liquid, hybrid liquids, natural gas, BEV, and FCEV technologies	• Conventional and hybrid diesel, natural gas, BEV, and FCEV technologies
Passenger rail	• High speed rail (all electric) • Passenger rail (electric and liquid fuel technologies)	• Metropolitan rail and regional rail options (electric, conventional liquid and hybrid liquid technologies)
Passenger aviation	• Separation of international and domestic aviation • Conventional liquid, electric and hydrogen technologies	• Conventional liquid technology only • Only domestic aviation represented
Passenger ship (marine)	• No passenger ship	• Conventional liquid and natural gas technologies
Non-energy	• Separate walking and cycling modes	• One mode, implicitly encompasses walking and biking

Table 6. TEMPO and GCAM Freight Mode and Technology Representation

Mode	GCAM	TEMPO
MHDV	• Three truck classes: light (under 6,000 lbs; assumed to be 15% of Class 1 trucks), medium (Class 2–6) and heavy (Class 7–8) • Four technologies: conventional liquids, hybrid liquids, BEV, and FCEV	• Three truck classes: light-medium (Class 3), medium (Class 4–6), and heavy (Class 7–8) • Technologies: conventional diesel, hybrid, natural gas, BEV, and FCEV. Short, medium- and long-range options for BEVs. • 8 shipment distance bins within each class, dividing activity based on Freight Analysis Framework shipment distance (0–99 miles to 2000+ miles)
Freight aviation	• No freight aviation	• Conventional liquids only (jet fuel) • 8 shipment distance bins, dividing activity based on Freight Analysis Framework shipment distance (0–99 miles to 2000+ miles)
Freight rail	• Electric, hydrogen, hybrid liquids and conventional liquids technologies	• Conventional and hybrid liquids technologies • 8 shipment distance bins, dividing activity based on Freight Analysis Framework shipment distance (0–99 miles to 2000+ miles)
Freight shipping (marine)	• Electric, hydrogen, hybrid liquids and conventional liquids technologies • Domestic and international shipping represented (but only domestic considered for this study)	• Conventional liquid and natural gas technology options available • Only domestic shipping is represented • 8 shipment distance bins, dividing activity based on Freight Analysis Framework shipment distance (0–99 miles to 2000+ miles)

4.2 Input Assumptions, Model Alignment, and Scenarios

We selectively aligned GCAM and TEMPO for this study to improve comparability across scenarios and better identify the importance of structural differences between the models. Figure 15 summarizes this process.

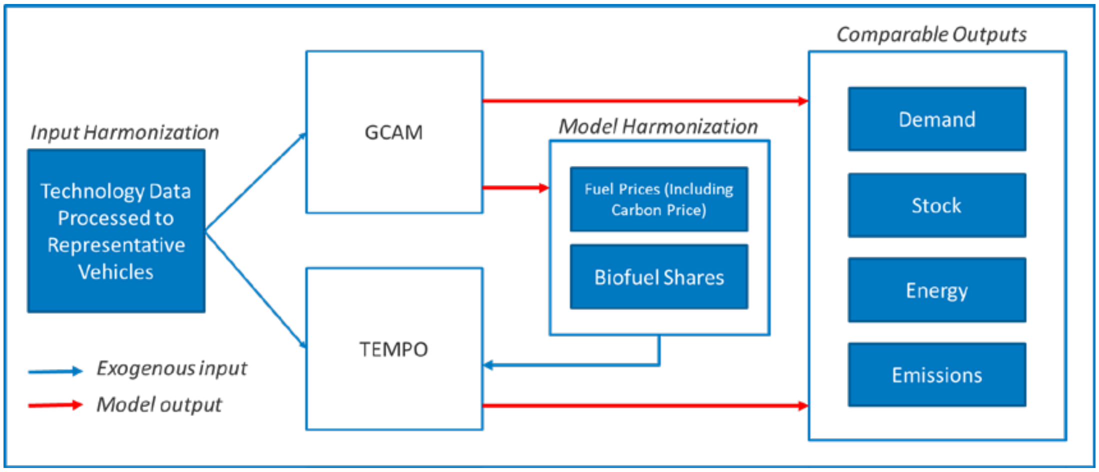

Figure 15. Overview of GCAM and TEMPO model alignment

Vehicle cost and fuel economy assumptions for on-road vehicles (passenger LDVs and freight MHDVs) were processed from vehicle simulations developed by Argonne National Laboratory to the relevant vehicle classes for each model (Islam et al. Forthcoming). For all scenarios, GCAM was run first to provide fuel price (inclusive any carbon price) and the biofuel share of liquid fuels as exogenous inputs to TEMPO. Fuel prices included electricity and hydrogen prices, which impact the estimation of technology shares for the respective technologies. TEMPO's fuel resolution was simplified for this study to align with GCAM's simpler representation of liquid fuels; for example, the gasoline, diesel, and jet fuel fuels in TEMPO were all given the same liquid fuel price from GCAM. Biofuel share was assumed to be constant across all modes as a result of GCAM's modeling of refined liquids, which assumes liquid fuels are composed of the same mix of biofuels and fossil fuels in all transportation modes. Figure A-4 through Figure A-9 (pages 114-115) plot the aligned fuel costs, biofuel shares, and vehicle cost and fuel economy assumptions used for this study. The models were then compared on the metrics of transportation demand, on-road vehicle stock, energy consumption and emissions. Seven scenarios were run: a reference scenario assuming no sector or economy-wide policies (including a carbon price), five carbon price scenarios exploring carbon prices of varying stringencies, and an LDV policy scenario simulating the impact achieving a 100% EV sales target for passenger LDVs. These scenarios are further described in Figure 16 and Table 7.

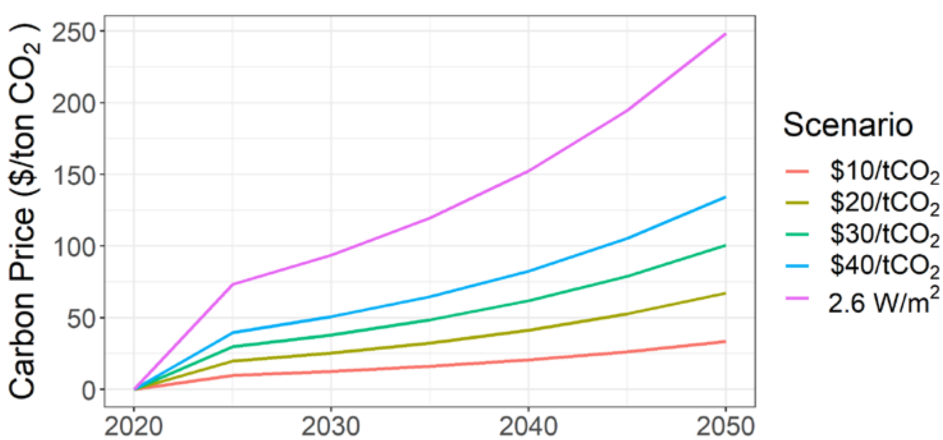

Figure 16. Carbon price trajectories (dollars per metric ton of CO_2)

Table 7. Overview of Scenarios and Key Assumptions

Scenario	Carbon Price	Sector Policies
Reference	None	None
$10/t$CO_2$	Begins at $10/t$CO_2$ in 2025	None
$20/t$CO_2$	Begins at $20/t$CO_2$ in 2025	None
$30/t$CO_2$	Begins at $30/t$CO_2$ in 2025	None
$40/t$CO_2$	Begins at $40/t$CO_2$ in 2025	None
2.6 W/m^2	Consistent with 2.6 W/m^2; begins at $70/t$CO_2$ in 2025	None
100% EV	None	100% EV sales by 2035

Carbon prices are measured in dollars per metric ton of CO_2.

Table 8 and Table 9 describe calibration sources in the passenger and freight sectors for both GCAM and TEMPO. Differences in base year calibration and assumptions about future growth may in part drive differences between models. GCAM is calibrated to a 2015 base year, with overall transportation energy demand (road, rail, air, ship) based on International Energy Agency energy balance data (International Energy Agency 2019). These data are then downscaled to more specific modes and vehicle size classes (e.g., from rail to passenger rail and freight rail, and from road to freight truck, LDV, and bus) using the variety of data sets listed in Table 8 and Table 9, principally Mishra et al. (2013).[18] Future years' transportation demands are modeled based on assumed population and GDP growth as a function of demand elasticities. TEMPO is calibrated to 2017 and relies on various sources, including the AEO2019 (EIA 2019), the NHTS (Federal Highway Administration 2018), and the Freight Analysis Framework (Federal Highway Administration 2019) to estimate current mode shares and future demand growth. The key sources used in both models are described below.

[18] The data sets used to disaggregate overall transportation energy demand to finer modes and vehicle size classes in GCAM are from data compiled in 2013, for a 2005 model base year. In part, this data selection reflects the challenges of gathering and maintaining data for a global model; detailed, globally comprehensive data on transportation energy use by sector, mode, vehicle class, and fuel are difficult to find, and the global transportation data set put together by Mishra et al. (2013) is still considered the standard in the field of global integrated assessment modeling. While GCAM's overall energy balances are calibrated to 2015 (the same base year as all other sectors and systems in the model), to the extent that mode or vehicle size class choices have shifted substantially since publication of Mishra et al. (2013) , this could lead to distortions in mode or vehicle class energy allocation (relative to newer data). Updating these data (for the regions like the United States where data are available) is an opportunity for future model improvement.

Table 8. Passenger Sector Data Sources

Mode	GCAM	TEMPO
Passenger aviation	• Bureau of Transportation Statistics (2012) • U.S. Department of Transportation (2012) • Other sources summarized by Mishra et al. (2013)	• Mode choice calibrated based on NHTS (Federal Highway Administration 2018) • Future demand based on population projections from the AEO2019 (U.S. Energy Information Administration 2019) • Occupancy assumptions from NHTS and the National Transit Database (U.S. DOT 2019)
Bus	• U.S. Department of Transportation (2012) • APTA (2011)	
Personal LDV and MaaS	• Transportation Energy Data Book (Davis, Diegel, and Boundy 2011) • U.S. Department of Transportation (2012)	
Passenger rail	• International Energy Agency energy statistics • Region-specific literature (Mishra et al. 2013)	
Non-energy	• Regional transportation survey listed in Mishra et al. (2013)	
Passenger ship (marine)	• N/A	

Table 9. Freight Sector Data Sources

Mode	GCAM	TEMPO
MHDV	• Transportation Energy Data Book (Davis, Diegel, and Boundy 2011) • VIUS (U.S. Census Bureau 2004)	• Ton-miles: Freight Analysis Framework (Federal Highway Administration 2019) • Truck vehicle miles traveled (VMT) and load factors: AEO (U.S. Energy Information Administration 2019) and VIUS (U.S. Census Bureau 2004) • Growth projections: AEO2019 (U.S. Energy Information Administration 2019)
Freight shipping (marine and domestic)	• International Energy Agency energy statistics • Region-specific literature (Mishra et al. 2013)	
Freight rail		
Freight aviation	• N/A	

4.2.1 The Reference Scenario

We first evaluated the Reference scenario to identify differences in model calibration and growth assumptions and to establish a baseline for model behavior against which subsequent scenarios could be compared. In both models, the Reference scenario assumes no supportive policies, such as a carbon price. All emissions reductions come from changes in technology cost and efficiency within and between modes. As in all scenarios, the models were aligned for on-road technology attributes, fuel prices, and biofuel shares.

Figure 17–Figure 19 (pages 44–45) compare the passenger sector between 2020 and 2050 across the metrics of transportation demand growth, energy consumption, and vehicle stock. The passenger sector is generally well-aligned between TEMPO and GCAM. Some differences are observed in demand growth; passenger miles traveled (PMT) are 9% lower in 2020 in TEMPO than in GCAM, and grow by 30% in 2050 (versus 36% in GCAM). LDV vehicle miles traveled (VMT) is closely aligned (Figure 17), suggesting that differences are driven in part by occupancy assumptions (Table A-3, page 107, in the appendix). Historical data show that PMT grew by 61% between 1990 and 2019, and VMT grew by 47% over the same period (BTS 2021). Both models project lower passenger travel growth than the historical record, potentially due to more conservative population growth forecasts.

We compared energy consumption is between GCAM and TEMPO, and to historical data from the Transportation Energy Data Book in 2019 (Davis and Boundy 2022) (Figure 18, page 44). We present results for tank-to-wheels energy consumption, excluding energy consumed during upstream processes. Compared to 2019 historical data (used as a comparison because the impacts of COVID-19 are not considered in this study), modeled 2020 energy consumption is similar in the two models. GCAM has lower LDV energy consumption than TEMPO or the Transportation Energy Data Book by about 2 EJ, likely because of differences in initial fuel economy, which is higher on average in GCAM. Aviation energy consumption is higher in GCAM than in the Transportation Energy Data Book or TEMPO by about 0.5 EJ, likely as a result of mode choice calibration. Total energy consumption is well-aligned between models from 2020 to 2050. GCAM has higher LDV hybrid adoption in all years, which lowers the average carbon intensity of the LDV mode relative to TEMPO. Tailpipe CO_2 emissions in 2020 are 1,134 MMT in GCAM and 1,181 MMT in TEMPO. Emissions reductions in 2050 are 608 MMT in GCAM (54% of 2020) and 597 MMT in TEMPO (51% of 2020), showing close alignment in model response to technology progress trajectories.

A key difference of the models is total LDV stock growth (Figure 19). In TEMPO, total vehicle stock is calibrated to AEO2019 (U.S. Energy Information Administration 2019) and grows at the rate of vehicle-owning households. Increases in demand for LDV passenger travel do not result in increases in household vehicle ownership rates, only the miles driven in each vehicle. In GCAM, total vehicle stock is not explicitly tracked but is post-calculated from total PMT demanded for LDVs using LDV occupancy factors. Demand for LDVs is a function of the cost of LDV service relative to other passenger modes. These differences imply GCAM may use more vehicles to represent the same amount of passenger travel as TEMPO.

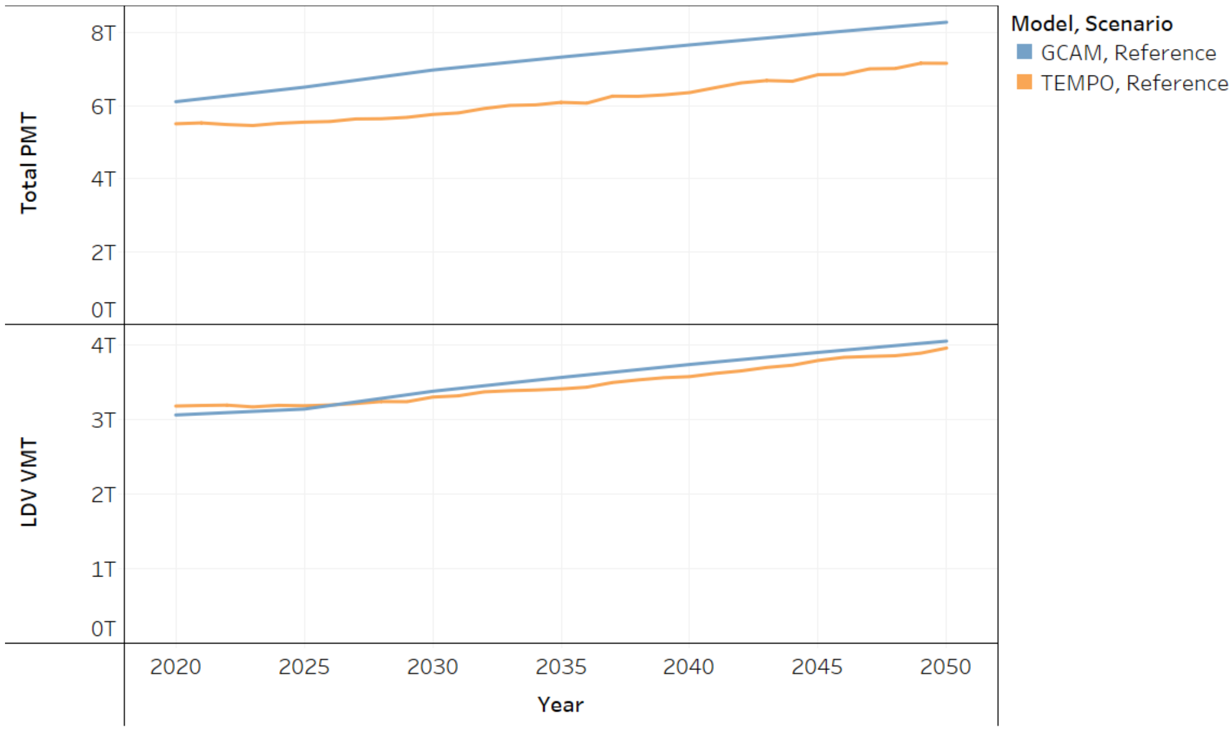

Figure 17. Reference scenario demand growth, passenger sector, 2020–2050 (GCAM and TEMPO)

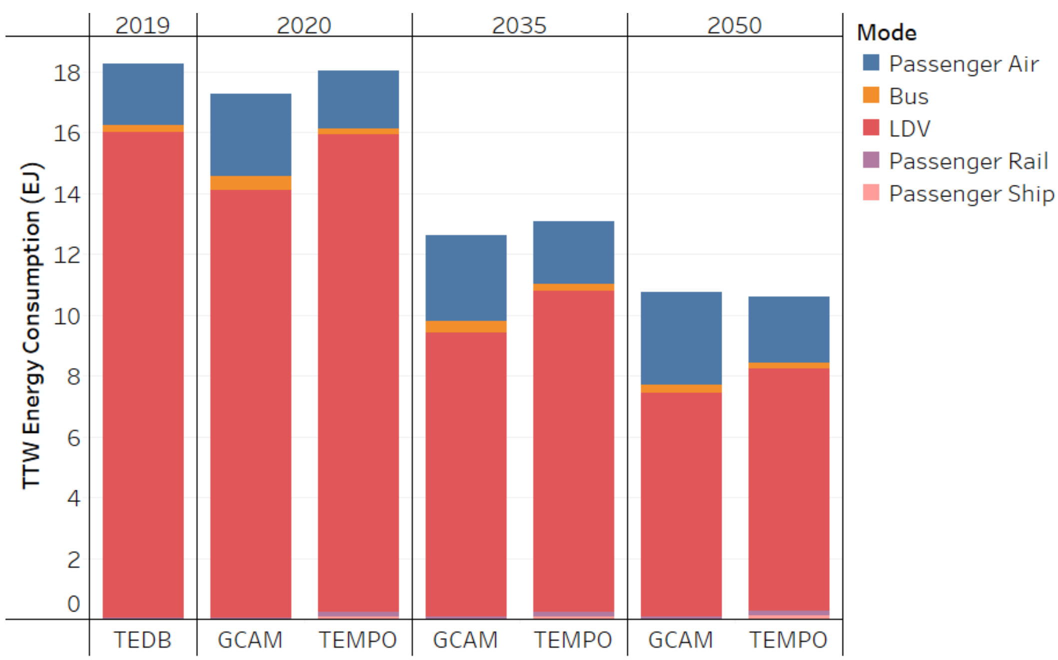

Figure 18. Reference scenario energy consumption by mode, passenger sector (GCAM and TEMPO) compared to historical data from the Transportation Energy Data Book (Davis and Boundy 2022)

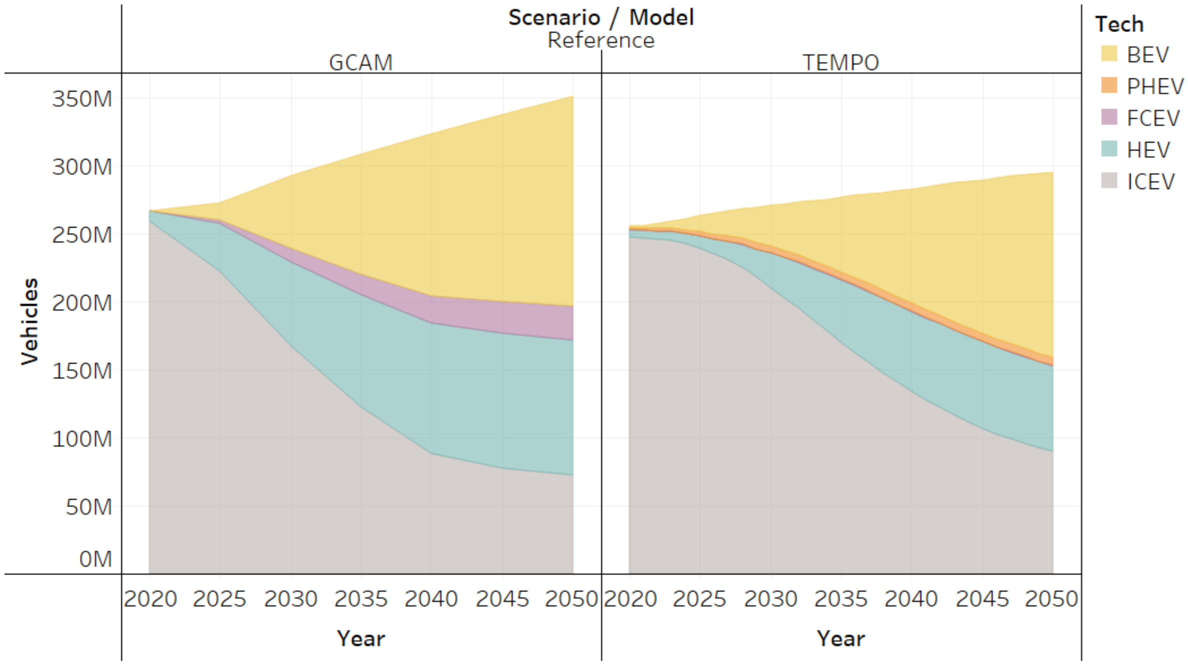

Figure 19. LDV stock in the Reference scenario, 2020–2050 (GCAM and TEMPO)

Vehicle stock in GCAM is not modeled explicitly; it is computed using a constant PMT/vehicle ratio. Vehicle stock is modeled explicitly in TEMPO, and PMT/vehicle is modeled dynamically.

Figure 20–Figure 22 (pages 46–47) present the same analysis for the freight sector. Unlike the passenger sector, the freight sector has substantially different calibration and demand growth assumptions. Initial and projected demand for ship and rail modes is substantially different, due to differences in calibration assumptions and data sources (Table 9, page 42). GCAM assumes greater initial and projected demand for freight marine shipping (domestic only) than TEMPO, while TEMPO has greater initial and projected demand for freight rail than GCAM. Also, GCAM models the deployment of zero-emission rail technologies, and TEMPO does not include these technologies as available options. Freight aviation (also referred to as freight air) is present in TEMPO but not in GCAM, but it is not a substantial source of variation.

More differences are found in MHDVs (Figure 21, page 47). Though initial and projected total VMT are similar for models for heavy trucks, GCAM projects substantially different VMT for medium and light-medium trucks. Differences in light-medium and medium truck VMT are primarily due to definitional differences between TEMPO and GCAM. GCAM defines light-medium trucks as Class 1 vehicles used for commercial purposes (assumed to be 15% of Class 1 trucks, based on data from the 2002 Vehicle Inventory and Use Survey [VIUS]). TEMPO includes only Class 3 vehicles in its definition of light-medium trucks. Class 1 vehicles are modeled with other LDVs in the passenger sector. Medium trucks in GCAM encompass Classes 2–6, whereas TEMPO includes only Class 4–6, with Class 2b vehicles (commercial light trucks) not represented. Additional differences may stem from calibration assumptions. Mode-level freight demand in TEMPO is calibrated to the AEO using a base year of 2017, while freight demand in GCAM is modeled using a base year of 2015 based on population and GDP growth. GCAM also models higher adoption of hybrid electric vehicles than TEMPO in initial and future years, while adoption of BEVs (as a share of total VMT) is similar in TEMPO and GCAM.

Figure 22 shows overall energy consumption and comparisons to historical data from the Transportation Energy Data Book (Davis and Boundy 2022). Due to differences in demand and technology choice, total energy and energy share by mode differs substantially across models in both the base year (2020) and future years. We also find some differences between modeled 2020 energy consumption and 2019 historical data. The Transportation Energy Data Book has higher heavy truck energy consumption than either GCAM or TEMPO (by 0.6–0.9 EJ). The Transportation Energy Data Book also has substantially higher freight marine shipping energy consumption than either model, possibly due to differences in distinctions between domestic and international shipping. Combined light-medium and medium truck energy consumption is similar in the Transportation Energy Data Book and in TEMPO, while GCAM's estimates are substantially higher (as they correspond to higher VMT estimates for this sector). Finally, freight rail energy consumption is aligned in the models. Freight sector CO_2 emissions in 2020 are 611 MMT in GCAM and 471 MMT in TEMPO, falling to 446 MMT in 2050 in GCAM (a decrease of 27%) and 366 MMT in 2050 in TEMPO (a decrease of 22%). This suggests the freight sector is more responsive to technology improvement assumptions in GCAM than in TEMPO in the Reference scenario.

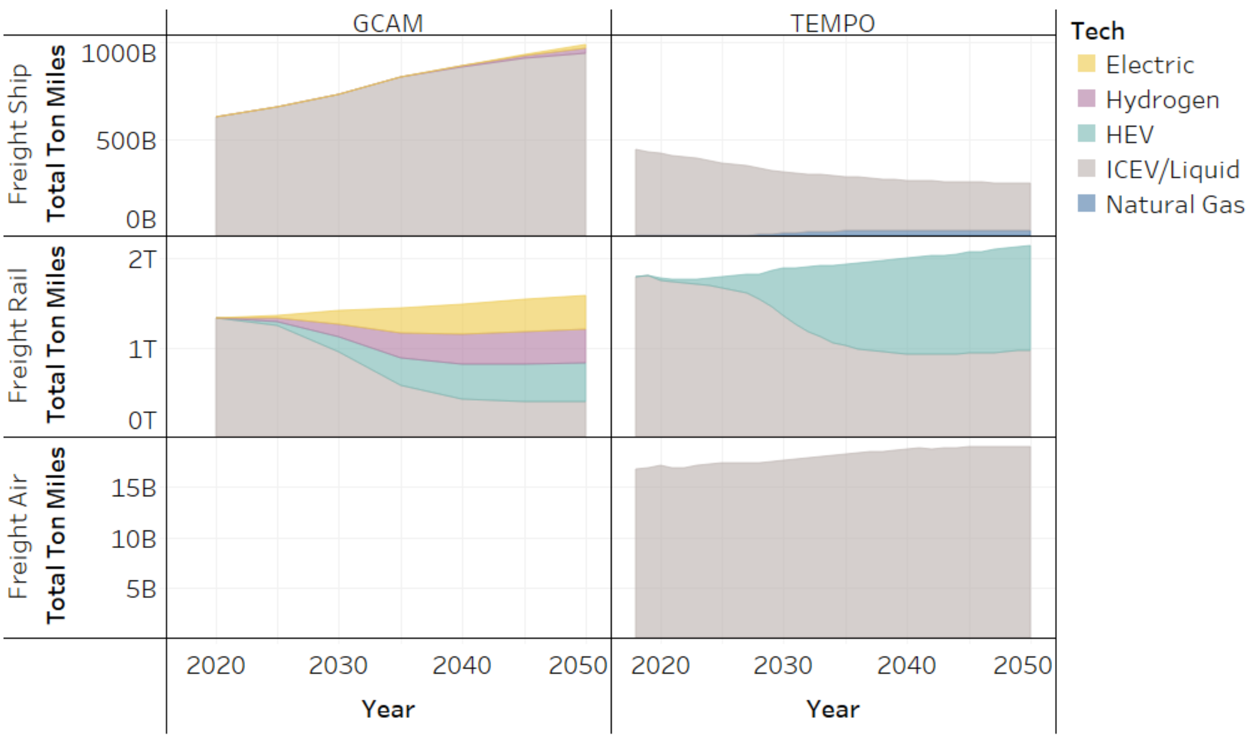

Figure 20. Freight sector Reference scenario growth trajectories, non-road modes (GCAM and TEMPO)

Axes scales are different for different modes. GCAM does not model the freight air mode. TEMPO does not model electric or hydrogen options for freight rail and ship modes.

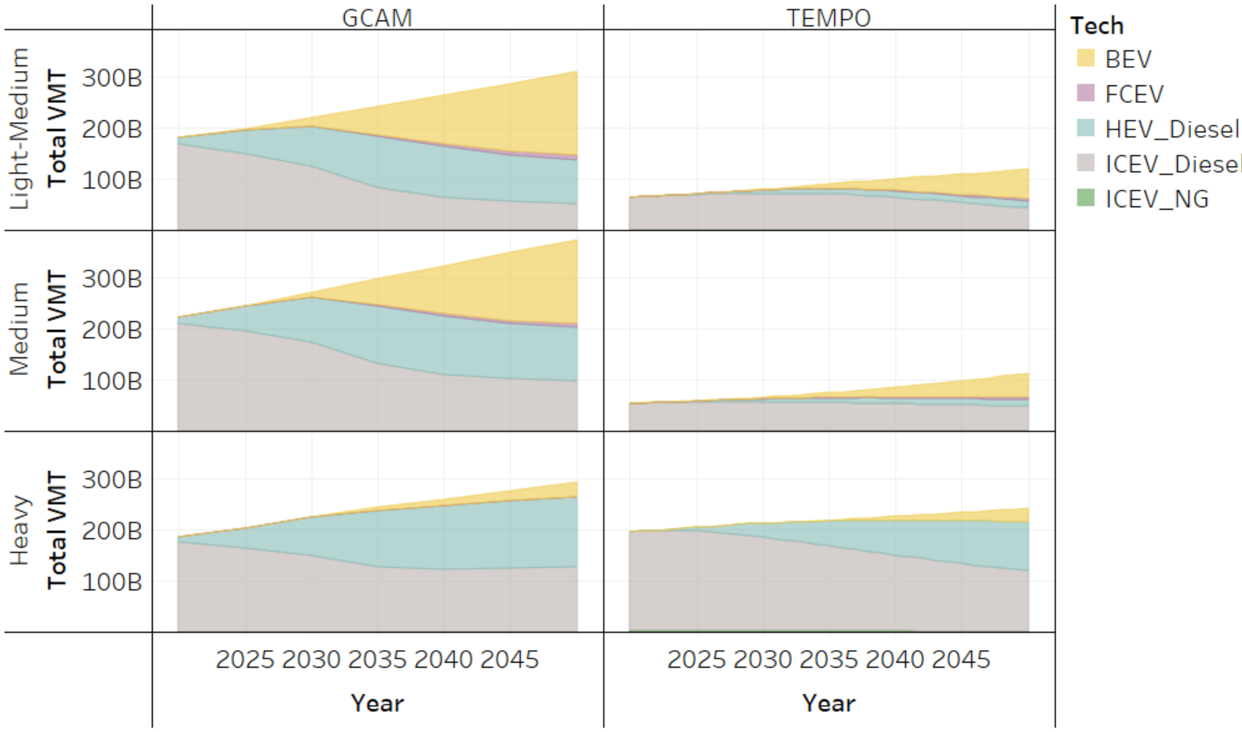

Figure 21. MHDV technology choice as a share of VMT in the Reference scenario (GCAM and TEMPO)

GCAM's light-medium and medium truck definitions differ from those for TEMPO, which accounts for differences in VMT.

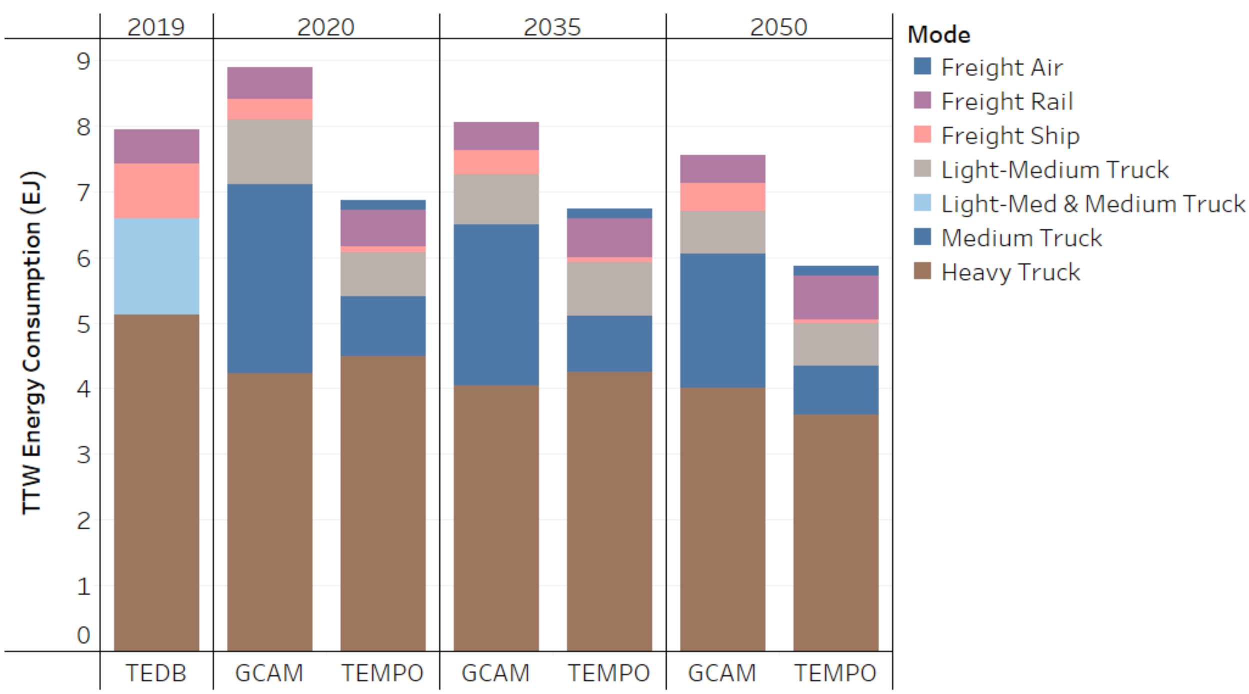

Figure 22. Freight sector Reference scenario energy consumption (GCAM and TEMPO) compared to historical data from the Transportation Energy Data Book (Davis and Boundy 2022)

TEDB = Transportation Energy Data Book

4.2.2 Carbon Price Scenarios

We next considered model responses to a carbon price compared to the Reference scenario. Model responsiveness to changes in fuel prices has substantial implications for policy analysis, including analyses of economy-wide carbon prices and sector-specific policies (e.g., road taxes or gasoline taxes). We evaluated GCAM and TEMPO's response to a set of carbon price scenarios across models to understand the following questions:

- How similarly do models respond to changes in fuel price?
- Which sectors are most responsive to a carbon price? Which sectors are less sensitive?
- Which pathways are used to achieve decarbonization goals in each model?
- How do insights differ across models, and why?

Unless otherwise stated, the CO_2 emissions presented in our main findings are for tailpipe emissions (from tank to wheels). Indirect emissions from electricity and hydrogen production and emissions from other upstream processes are not presented in the main transportation sector findings, as they are accounted for in other sectors. Figure A-1 (appendix, page 107) shows direct and indirect emissions in the transportation sector.

Figure 23–Figure 25 (pages 50–51) summarize our findings. Figure 23 plots sensitivity to increases in the price of liquid fuels in the passenger and freight sectors. TEMPO and GCAM behave similarly in the passenger sector, with a 10% increase in the cost of liquid fuels producing a 2.7% decrease in CO_2 emissions in GCAM (a fuel price elasticity of -0.27) and a 2.8% decrease in emissions in TEMPO (a fuel price elasticity of -0.28) (computed using the 2.6 W/m^2 scenario). Historical data suggest the long-run price elasticity of gasoline demand for passenger LDVs ranges between -0.3 and -0.1 (Winebrake et al. 2015b), which suggests GCAM and TEMPO's model behavior is within historical ranges, as passenger tailpipe emissions reductions generally come from the reduction of gasoline consumption.

In the freight sector, GCAM is somewhat more responsive than TEMPO to fuel price increases. A 10% increase in the cost of liquid fuels produces a 4.6% decrease in CO_2 emissions on average in GCAM and a 3.2% decrease on average in TEMPO. Compared to the historical record, the response to fuel price changes in the freight sector is greater in both models. Winebrake et al. (2015b; 2015a) find little to no decrease in energy consumption in response to fuel price increases in the U.S. single-unit and combination trucking sectors. The increased sensitivity of both models may be due to the inclusion of advanced vehicle powertrains (including BEVs and FCEVs), which allow for more substitution of non-diesel fuels than has been historically available. Both models are roughly linear in their response to price changes in both the passenger and freight sectors, with TEMPO displaying more nonlinearity in passenger sector reductions. TEMPO's nonlinearity stems from its sampling feature, which introduces some stochasticity in total passenger demand from scenario to scenario.

We evaluated the role of different decarbonization pathways, including demand and mode shifting, biofuel substitution in liquid fuels, and technology shifting, in achieving emissions reductions in each model. These factors were decomposed successively, and we evaluated the role of each changed factor while holding other factors constant. Emissions reductions from demand reduction were identified by holding mode share and emissions intensity constant at Reference scenario shares and computing emissions using total demand from the relevant carbon price scenario. Emissions reductions from mode shifting were identified by holding emissions intensity constant across modes and computing emissions using mode shares and demand from the carbon price scenario. Emissions reductions from biofuels were computed by holding technology shares constant at the Reference scenario and computing emissions from an increased share of liquid fuels. Finally, remaining emissions reductions were attributed to changes in technology shares. Because technology improvement assumptions are identical across scenarios, there are no emissions reductions from endogenous technology improvement without technology switching. In some cases, emissions attributed to mode shifting resulted in emissions increases rather than reductions, as they were considered independently of simultaneous technology shifts within modes. In these cases, mode shifting was aggregated with technology shifting, as it did not contribute an independent role to emissions reductions.

Figure 24 (page 50) and Figure 25 (page 51) show the results of this analysis, and in subsequent sections, we evaluate the role of each factor in detail. In the passenger sector, TEMPO has greater emissions reductions from demand reduction and technology shifting than GCAM, while mode shifting plays no role independent of technology shifting. TEMPO is more responsive than GCAM at lower carbon prices, although this sensitivity diminishes as carbon prices increase. In the freight sector (Figure 25), demand reductions and mode shifting mechanisms are present only in GCAM. In GCAM, technology shifting and demand reduction contribute the most to emissions reductions, and technology shifting plays a greater role at higher carbon prices. Mode shifting alone without simultaneous changes in technology choice within modes does not produce emissions reductions. In TEMPO, technology shifting is the primary mechanism by which emissions reduction are achieved. The lack of a demand reduction mechanism is a key reason for lower freight responsiveness to carbon prices in TEMPO compared to GCAM. In all scenarios and in both the passenger and freight sectors, biofuel substitution is intentionally constrained to improve model alignment. Emissions reductions from biofuel substitution decrease between the \$40/tCO_2 and 2.6 W/m^2 scenarios because biofuels in GCAM are allocated to other energy sectors (i.e., for use in electricity generation rather than in transportation) at higher carbon prices.

In the most aggressive carbon price scenario (the 2.6 W/m^2 scenario), 2050 passenger-sector tailpipe CO_2 emissions are reduced by 88 MMT in GCAM and 103 MMT in TEMPO relative to the Reference scenario. In the freight sector, CO_2 emissions are reduced by 129 MMT in GCAM and 74 MMT in TEMPO. Subsequent sections detail differences between models and the role of each decarbonization pathway in each sector, with a focus on the 2.6 W/m^2 scenario.

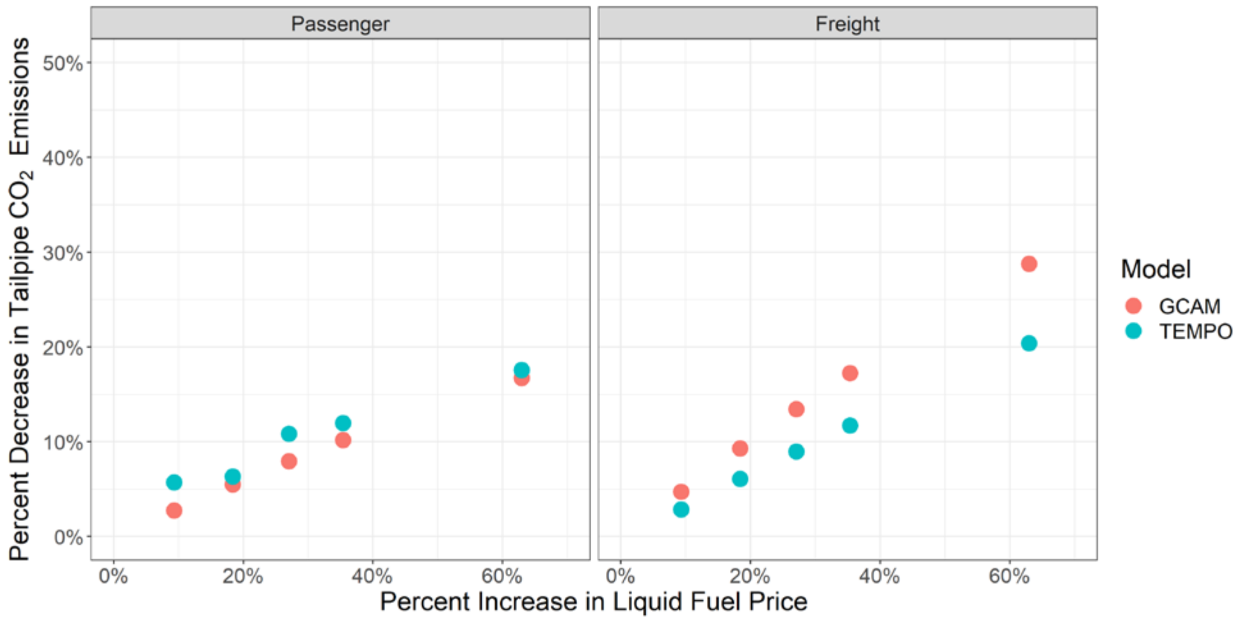

Figure 23. Decrease in tailpipe CO_2 emissions by sector for an increase in liquid fuel price (GCAM and TEMPO)

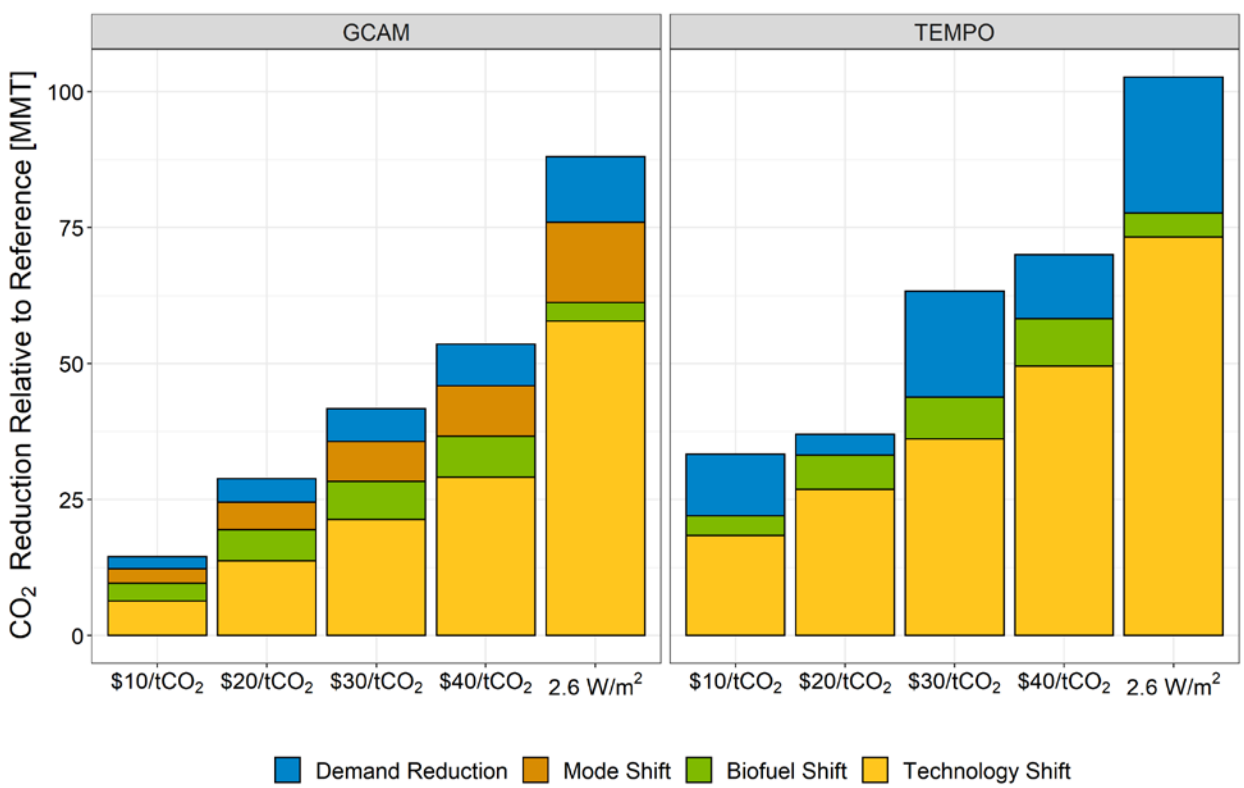

Figure 24. Decarbonization pathways for the passenger sector, 2050 (GCAM and TEMPO)

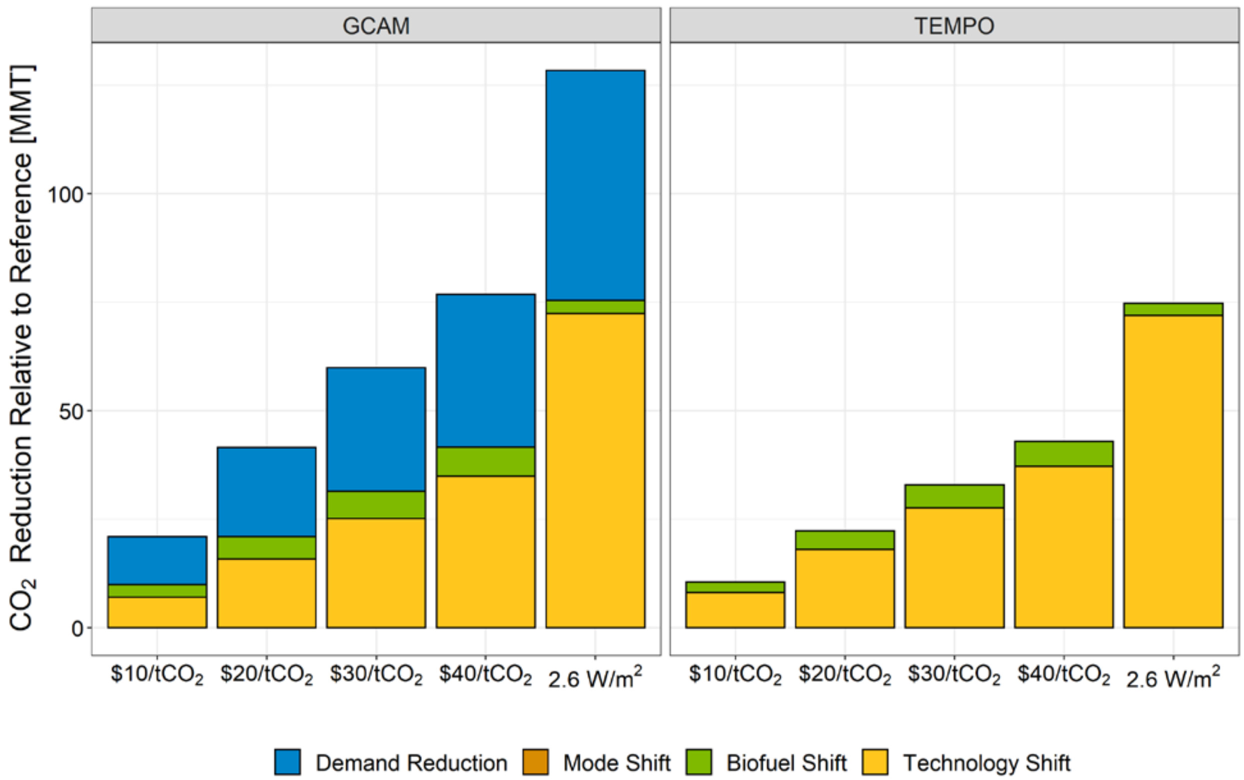

Figure 25. Decarbonization pathways for the freight sector, 2050 (GCAM and TEMPO)

TEMPO does not include demand reduction and mode shifting mechanisms in the freight sector.

Demand Reduction and Mode Shifting

Demand reduction and mode shifting play different roles in TEMPO and GCAM due to differences in model design. In GCAM under the 2.6 W/m^2 scenario in 2050, demand is reduced by 0.2 trillion PMT (2.4%) in the passenger sector and 0.6 trillion ton-miles (12%) in the freight sector. This accounts for 12 MMT (14%) of passenger-sector emissions reductions and 53 MMT (41%) of freight-sector emissions reductions. Mode shifting reduces emissions by an additional 15 MMT (17%) in the passenger sector, but by itself does not reduce emissions in the freight sector (reductions are achieved only when technology shifts are simultaneously considered). In TEMPO, only passenger sector demand reduction plays a role in decarbonization. Demand in 2050 is reduced by 0.3 trillion PMT (4.3%) and accounts for 25 MMT (24%) of emissions reductions. Differences in demand reduction stem from differences in model design. GCAM uses both price elasticities and income elasticities to compute the change in total passenger transportation demand based on the change in the cost of transportation service. TEMPO uses only price elasticities to compute the change in passenger transportation demand and translates these elasticities into changes in average trip distance and the number of trips. These differences, as well as potential differences in the fuel price share of total transportation price, produce different sensitivities to an identical carbon price.

TEMPO's demand reduction ranges between 1%–3% at lower carbon prices, with some nonlinear fluctuations occurring as a result of model stochasticity. Mode shifting does not reduce emissions in the absence of technology substitution. In GCAM, model behavior is more linear, with demand reduction and mode shifting playing a role in decarbonization across all carbon price scenarios.

Figure 26 (page 53) plots mode shifting and demand reduction by mode in GCAM and TEMPO. Mode shifting differs across models due to differences in model design. In TEMPO, mode choice is determined primarily by the time intensity of each mode rather than the cost intensity and produces no emissions reductions. Mode shifting observed in TEMPO is likely a result of stochastic model behavior. Overall, some demand shifts away from air travel, buses, and rail and toward LDV and passenger shipping due to stochastic sampling of passenger demand and system constraints. In GCAM, mode choice is more strongly influenced by cost (although mode speed and time value are considered), resulting in substantial shifts away from carbon-intensive air travel and toward less carbon-intensive modes such as bus and LDV travel.

Historical data on aviation demand suggest aviation is responsive to price, with studies on the impact of airfare taxes finding that short-distance and nonbusiness travel are more elastic than long-distance and business travel (Fukui and Miyoshi 2017; Larsson et al. 2019). Fuel price elasticities of energy consumption range from -0.17 to -0.35 (Fukui and Miyoshi 2017), implying that a 60% increase in fuel prices (as in the 2.6 W/m^2 scenario) might decrease jet fuel consumption and CO_2 emissions by 10%–21%. In GCAM under the 2.6 W/m^2 scenario, we find aviation emissions decline by 24 MMT due to demand reduction and mode switching, which represents a reduction of 14% relative to the Reference scenario, which is in line with these estimates. Studies on passenger mode substitution suggest aviation demand might substitute with high-speed rail in countries where it is present, particularly for short-haul domestic flights (Clewlow, Sussman, and Balakrishnan 2014; Wang, O'Sullivan, and Schafer 2019). However, there is little data exploring substitution between aviation and personal LDV travel in the United States. In GCAM, demand reduction from aviation occurs only for short-haul flights and is transferred to buses and LDVs. We exclude international aviation modeled in GCAM from aviation totals to ensure comparability of models. Additional research is needed to explore the empirical basis for passenger aviation substitution in the U.S. context.

Figure 26. Passenger demand and mode shifting in 2.6 W/m^2 scenario relative to the Reference scenario, 2050 (GCAM and TEMPO)

In the freight sector, endogenous demand reduction and mode shifting are present in GCAM but not in TEMPO. In TEMPO, this feature was excluded due to inadequate data. Demand reduction is a substantial driver of freight emissions reductions in GCAM, and the lack of an endogenous freight demand reduction mechanism in TEMPO accounts for nearly all the difference in freight sector emissions reductions between GCAM and TEMPO in the 2.6 W/m^2 scenario. Historical data suggest freight demand is fairly inelastic to fuel price increases and is strongly correlated to changes in GDP (Kaack et al. 2018; Winebrake et al. 2015a; 2015b; Muratori et al. 2017).

GCAM's results suggest freight demand may be more elastic to fuel price changes than has historically occurred; a 63% increase in the price of liquid fuels results in a 12% decrease in total freight demand, or a fuel price elasticity of demand of -0.19. Historical data on freight mode choice suggest mode choice decisions consider shipment rates (costs), reliability, distance, and size among other factors (Holguin-Veras et al. 2021; ITF 2022). Substitution of rail for modes such as road transport faces issues relating to reliability and flexibility. In GCAM, freight mode choice occurs primarily from shipping to the rail and light and medium road sectors (Figure 27). Future investigation could improve the empirical basis for assumptions about mode shifting in freight and could focus on the extent to which specific modes such as shipping are substitutable with other modes.

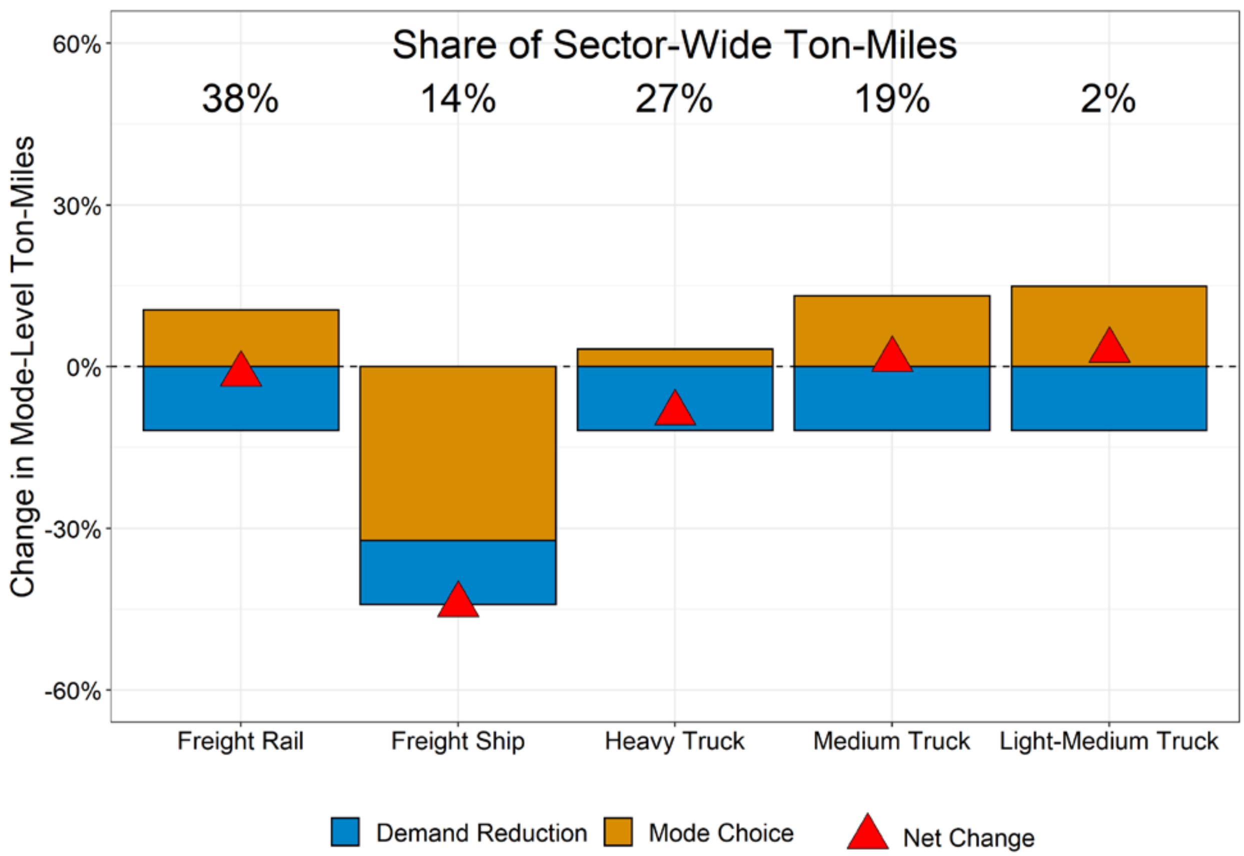

Figure 27. Freight demand and mode shifting in the 2.6 W/m^2 scenario relative to the Reference scenario, 2050 (GCAM)

Biofuels

The role of biofuels was harmonized for this assessment, resulting in similar shares across models. In GCAM, the biofuel share of liquid fuels was computed endogenously, with total biomass use constrained. Biofuels (input as the share of liquid fuel by energy) were set exogenously in TEMPO using the resulting values from GCAM. Increases in biofuel shares result in emissions reductions of 3–4 MMT in the passenger sector and 3 MMT in the freight sector in the 2.6 W/m^2 scenario in both models, comprising 2%–4% of sectoral emissions reductions relative to the Reference scenario in GCAM and 4% in TEMPO. Reductions are proportional to the share of liquid fuels within each mode, as it is assumed biofuels will be distributed evenly across all liquid fuels.

Technology Choice and Electrification

In the passenger sector, greater emissions reductions are induced by changes in technology choice in TEMPO than in GCAM. In the 2.6 W/m^2 scenario, the share of zero-emission (electricity and hydrogen) miles increases from 46% in GCAM (3.9 trillion PMT) to 53% (4.3 trillion PMT), and it increases from 34% (2.5 trillion PMT) to 44% (3 trillion PMT) in TEMPO. These increases result in 58 MMT of CO_2 reductions in GCAM and 73 MMT in TEMPO. TEMPO's emissions reductions from technology shifting are net of emissions increases from mode shifting, as noted in previous sections.

Mode-level zero-emission technology choice differs somewhat by model (Figure 28). For non-LDV modes (passenger air, bus, ship, and rail), we did not harmonize technology options or cost trajectories in TEMPO or GCAM. This results in differences in initial mode-level technology shares in the Reference scenario. In addition, GCAM includes BEV and FCEV technologies for domestic air travel, which are not present in TEMPO. These technologies increase from 16% of air PMT in the Reference scenario to 26% in the 2.6 W/m^2 scenario, and they decarbonized 69 billion PMT and reduce emissions by 19 MMT in 2050 relative to the Reference scenario. The remaining 39 MMT of reductions in GCAM come primarily from LDV emissions reductions, as the share of zero-emission PMT increases from 51% to 57% (3.3 trillion PMT to 3.7 trillion PMT). Meanwhile in TEMPO, the share of zero-emission LDV PMT increases from 42% to 53% (2.4 trillion to 2.9 trillion PMT), accounting for nearly all the reduction in emissions. (Note that GCAM electrifies a higher share of hybrid gasoline vehicles, thus producing lower emissions reductions per electrified passenger-mile). Differences in representation of LDVs, including representation of household-level travel patterns and infrastructure availability in TEMPO, may account for these differences in technology choice sensitivity. TEMPO also differs from GCAM in FCEV technology choice. FCEVs do not play a role in TEMPO due to assumed inadequacy of infrastructure , which prevent them from achieving widespread adoption in LDV and bus modes, where these technologies are represented.

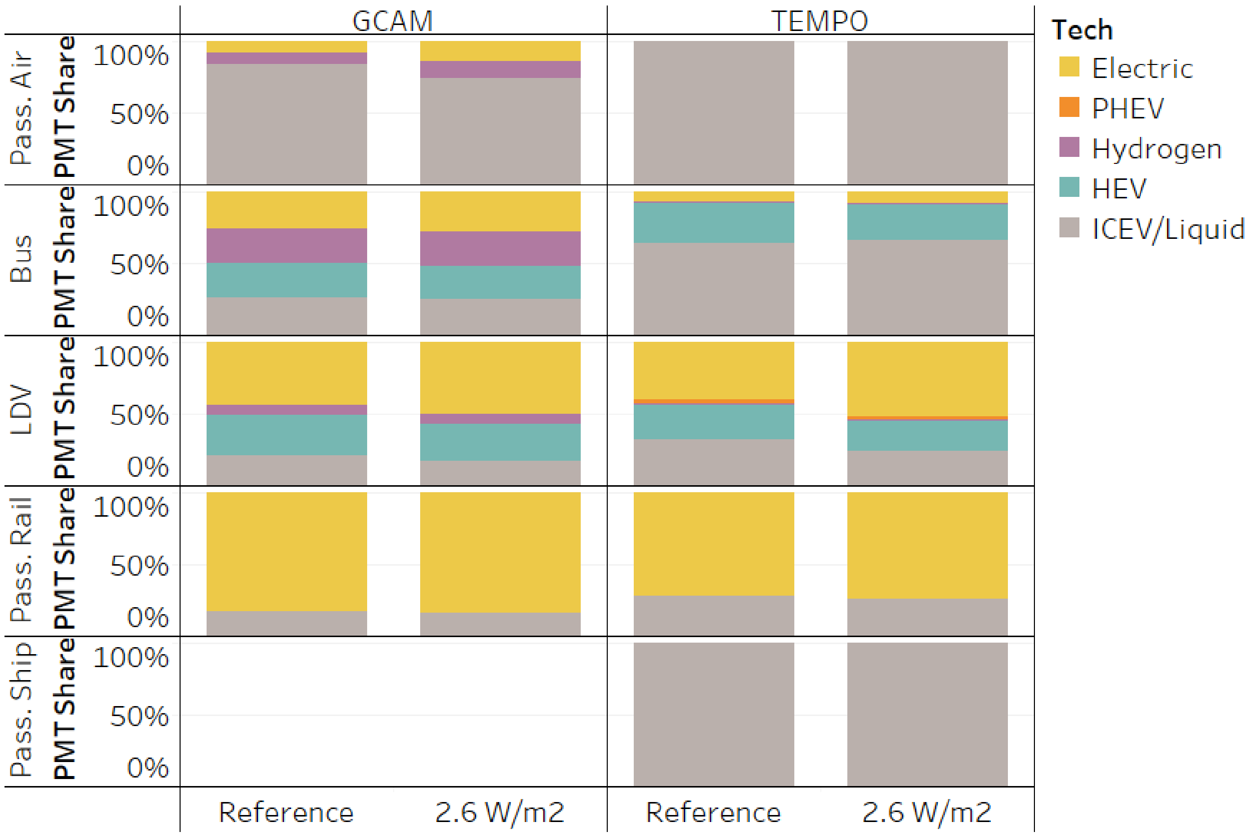

Figure 28. Passenger travel electrification (share of PMT) by scenario and mode, 2050 (GCAM and TEMPO)

In the freight sector, we observe some differences in the sensitivity of technology choice to changes in fuel prices, and these impact the sector's decarbonization potential. Overall, the share of zero-emission freight service increases from 29% to 43% (1.3 trillion ton-miles to 1.7 trillion ton-miles) in GCAM, and from 9% to 21% (0.5 trillion ton-miles to 1.1 trillion ton-miles) in TEMPO, resulting in 93 MMT of CO_2 emissions reductions in GCAM (73 MMT net of emissions changes from mode shifting) and 72 MMT in TEMPO in the 2.6 W/m^2 scenario. Because the models have different load factors and VMT assumptions across freight modes, total ton-miles are different across models.

Table 10 shows changes in the share of zero-emission miles and emissions reductions from technology switching by mode in the 2.6 W/m^2 scenario relative to the Reference scenario. Differences in emissions reductions are primarily concentrated in on-road trucking modes (light-medium, medium, and heavy trucks). The inclusion of additional zero-emission technologies in GCAM's rail and shipping sectors play a relatively small role (17% of the difference in emissions reductions versus 83% due to differences in the on-road trucking sectors). Light-medium and medium trucks are more responsive to a carbon price in GCAM than in TEMPO, while heavy trucks are more responsive in TEMPO (Figure 29, page 59). In GCAM, medium trucks are a larger share of the total freight mode than in TEMPO, resulting in greater emissions reductions when combined with greater carbon price sensitivity. The increased carbon price responsiveness of heavy trucks in TEMPO somewhat counterbalances these emissions reductions.

Table 10. Freight Sector Technology Switching by Mode, 2.6 W/m^2 Scenario Relative to the Reference Scenario, 2050

Mode	GCAM		TEMPO	
	Change in Zero-Emission Vehicle Ton-Miles as a Share of Mode (Percentage Points)	Emissions Reductions from Technology Switching (MMT CO_2)	Change in Zero-Emission Vehicle Ton-Miles as a Share of Mode (Percentage Points)	Emissions Reductions from Technology Switching (MMT CO_2)
Air	N/A	N/A	0.0	0.0
Rail	**2.0**	0.9	0.0	0.0
Ship	**16.0**	2.7	0.0	0.0
Light-Medium Truck	**14.0**	10.0	9.0	5.7
Medium Truck	**23.0**	47.0	14.0	9.6
Heavy Truck	12.0	32.1	**24.0**	56.6
Total (All Freight Sector)	**14.0**	92.7	12	71.9

The larger change (GCAM or TEMPO) appears in bold. GCAM results do not include emissions increases from mode shifting, which reduce net emissions reductions by 20 MMT.

Differences in truck mode carbon price responsiveness are potentially due to differences in model design and resolution. More investigation is needed to identify the exact drivers of these differences. Key differences between models include:

- **Discount Rate, Financial Horizon, and Vehicle Use:** TEMPO considers a time horizon of 3–5 years when balancing upfront capital cost and fuel cost savings for new vehicle purchases, using a discount rate of 7%. Meanwhile, GCAM uses a discount rate of 10% and a 15-year financial horizon. As a point of comparison, a previous NREL TCO analysis for MHDVs considers discount rates of 3 and 7% and use financial horizons that span the lifetime of the vehicle (Hunter et al. 2021). Both models multiply upfront capital costs by a capital recovery factor computed from these parameters to levelized capital costs over the lifetime of the vehicle. In general, these differences imply that GCAM's model resolution places lower weight on upfront capital cost and greater weight on future operational costs, all else equal. Differences in vehicle use assumptions (i.e., annual VMT) can also drive differences in outcomes. Even when identical technology assumptions are used, differences in VMT and financial criteria can produce substantially different cost calculations and change the trade-offs between fuel cost savings and upfront capital costs when comparing vehicle technologies. Table 11 summarizes these parameters.

Table 11. Financial and Vehicle Use Assumptions, GCAM and TEMPO MHDVs

Metric	Light-Medium		Medium		Heavy	
	GCAM	TEMPO	GCAM	TEMPO	GCAM	TEMPO
Discount Rate (%)	10	7	10	7	10	7
Financial Horizon (years)	15	3	15	4	15	5
VMT/year	25,000	12,000	45,000	11,000	45,000	10,000–200,000

- **Model Resolution and Charging Infrastructure Representation:** TEMPO models MHDVs at a higher resolution than GCAM, dividing vehicle classes into up to eight distance bins. Each distance bin has different amounts of annual and daily VMT. To the extent that BEV range exceeds daily VMT (primarily in longer distance bins), a charging time penalty is applied at a rate of $75/hour, representing an additional cost for BEV trucks in those operating ranges. Distance bins also differ in their representation of infrastructure, with shorter distance bins having greater access to overnight charging.

For light-medium and medium trucks, GCAM's increased carbon price responsiveness is likely due to its higher VMT assumptions. Light-medium and medium trucks are assumed to be driven less in TEMPO, which produces lower fuel cost savings for zero-emission powertrains. TEMPO also has more conservative financial criteria that place a greater emphasis on upfront cost and more heavily penalize vehicles with a greater capital cost.

For heavy trucks, TEMPO's increased carbon price sensitivity may be due to its increased market segmentation. Market segments with greater fuel cost savings from electrification (due to greater annual VMT) or lower charging barriers (due to lower daily driving distance) may produce more opportunities for electrification than implied by an aggregated approach. TEMPO implicitly assumes fleet management evolves such that vehicles do not operate in multiple market segments. We observe that TEMPO's heavy truck emissions reductions occur due to electrification in both short and long-distance bins (Figure 30). 38 MMT is reduced from trucks operating at longer distances, while 19 MMT is reduced from trucks operating at shorter distances. In both models, the share of FCEVs remains smaller than other powertrains due to the high price of hydrogen.

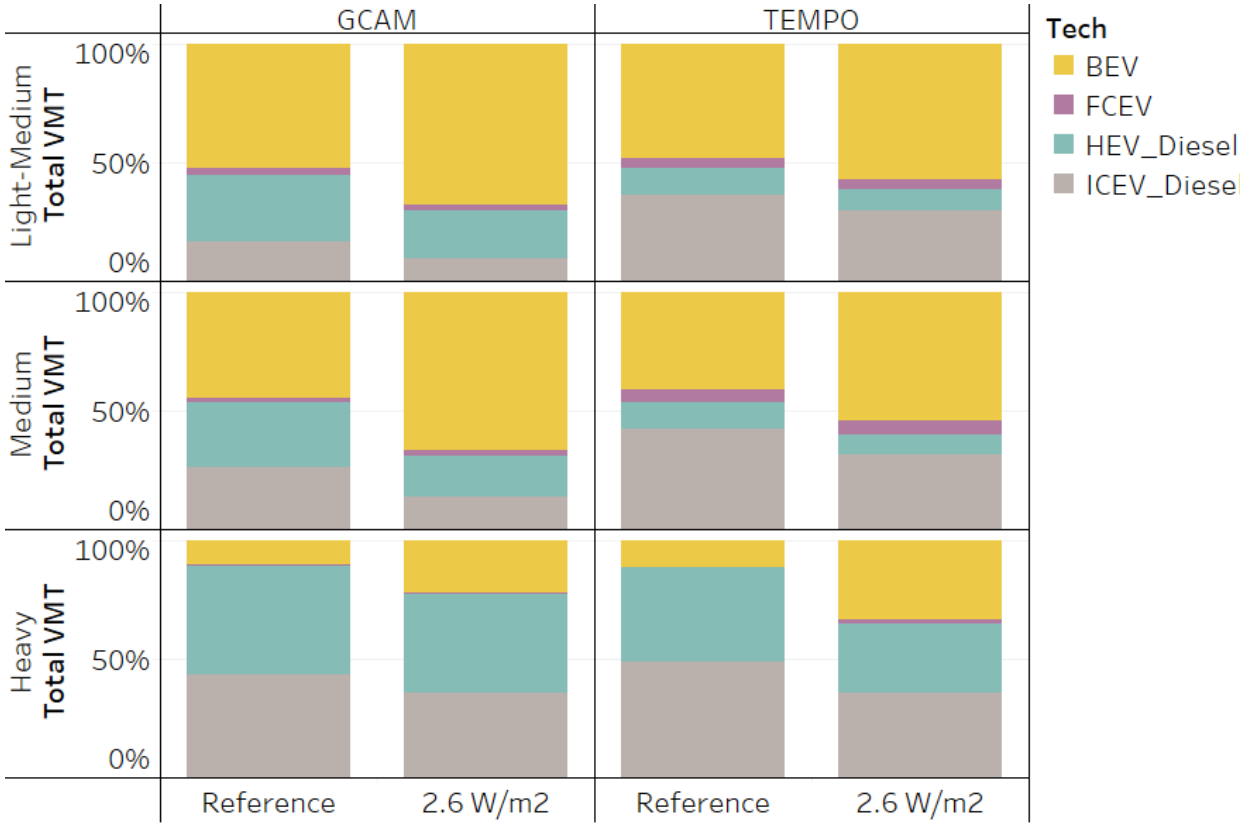

Figure 29. VMT share by technology, light-medium, medium and heavy trucks in the Reference and 2.6 W/m² scenarios, 2050

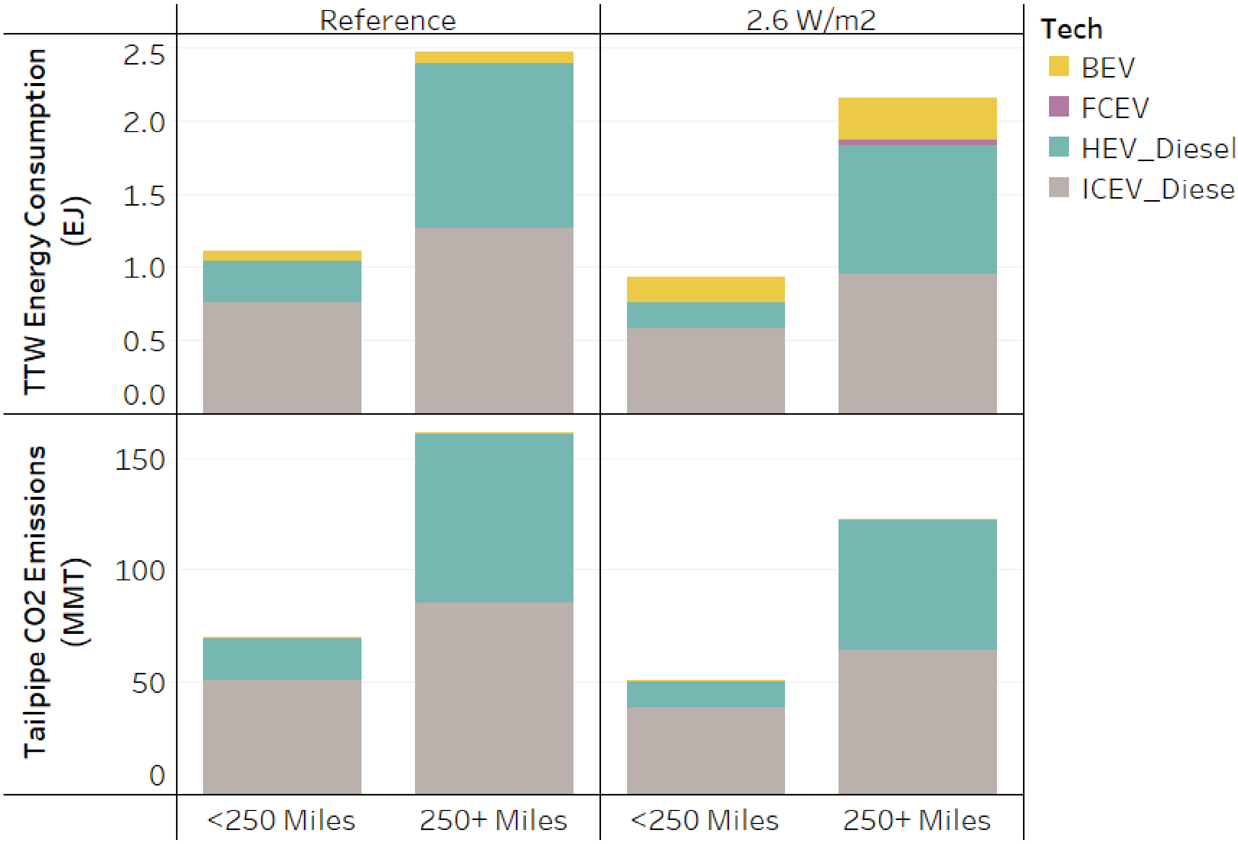

Figure 30. TEMPO heavy truck energy consumption and emissions by distance bin in the Reference and 2.6 W/m^2 scenarios, 2050

4.2.3 LDV Stock Turnover and Rapid Electrification

We also investigated the implications of a rapid LDV electrification scenario for vehicle stock, emissions, and electricity consumption outcomes. The models were run with an identical exogenous sales trajectory in which passenger LDV sales (personal LDV, fleet vehicles, and MaaS) reached 50% EV by 2030 and 100% EV by 2035. In TEMPO, EVs were defined as BEV-300s and PHEV-50s. In GCAM, EVs included only BEVs. We ran one scenario in GCAM and two scenarios in TEMPO (the 100% EV scenario). In TEMPO, scenarios explored variations in the availability of home recharging infrastructure and its implications for energy consumption and emissions outcomes (the Central scenario and the High Resid. Sensitivity). We observed substantial differences between models due to the following factors:

- **Input Assumptions:** TEMPO and GCAM differ on future vehicle stock growth assumptions (calibrated to AEO in TEMPO and determined endogenously from LDV service demand in GCAM) and vehicle retirement assumptions. Differences in vehicle retirement substantially determine residual emissions from ICEVs.
- **Model Design:** TEMPO's household-level modeling of vehicle usage allows VMT to vary with vehicle age and marginal cost of driving relative to other household vehicles. As a result, TEMPO's energy consumption results respond to factors that affect marginal cost of driving, including the availability of home and workplace recharging infrastructure.

Figure 31 presents vehicle stock results from TEMPO and GCAM for the 100% EV scenario (using TEMPO's Central scenario). In TEMPO, vehicle stock grows from 255 million vehicles in 2020 to 294 million vehicles in 2050, 250 million (85%) of which are BEVs, 12 million (4%) of which are PHEVs, and 32 million (11%) of which are ICEVs. In GCAM, differences in future vehicle stock growth assumptions result in growth from 266 million vehicles in 2020 to 361 million vehicles in 2050, 344 million (95%) of which are BEVs and 17 million (5%) of which are ICEVs. Differences in total stock stem differences in the way the models estimate vehicle stock, which is further described in Section 4.2.1 of this report (page 45).

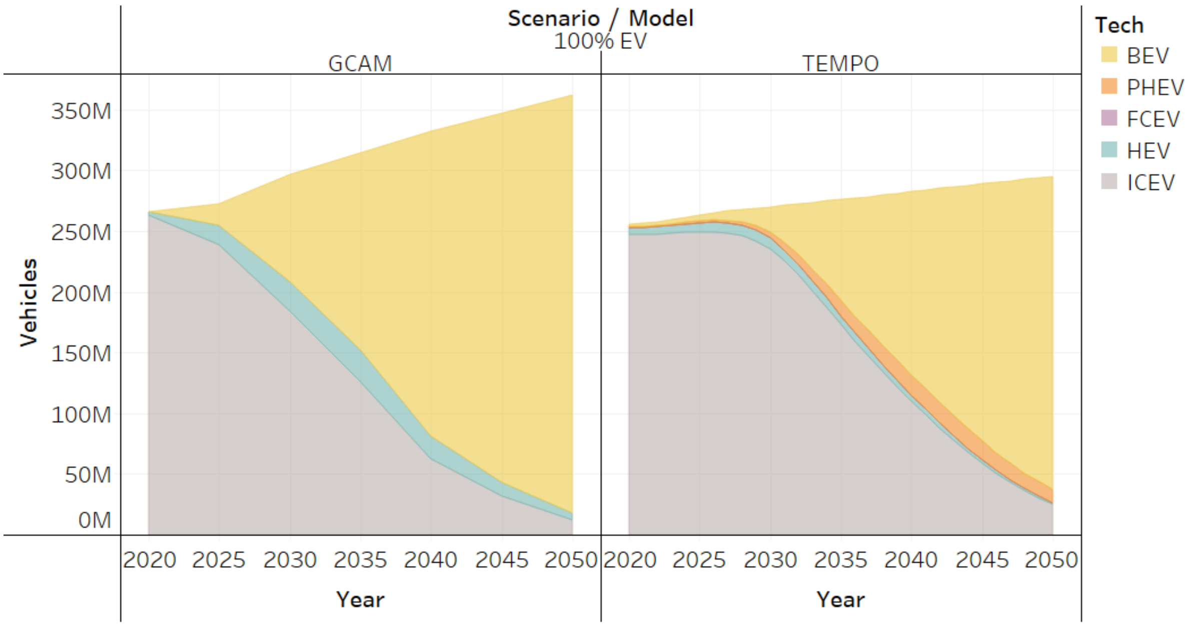

Figure 31. LDV vehicle stock (TEMPO and GCAM)

A second key difference is in vehicle retirement assumptions. TEMPO uses annual vehicle survival rates from Jacobsen and Van Benthem (2015) for vehicles aged 0–19 years. Annual survival rates for older vehicles are compiled from VISION and MOVES (ANL 2021; EPA 2021). As a result, roughly 10% of vehicles in the stock are greater than 20 years old, a figure that matches sources such as NHTS (Federal Highway Administration 2018) (Figure A-10 in the appendix, page 112). Meanwhile, GCAM assumes vehicles completely exit the stock by age 20 (for light trucks) or 25 (for cars).

Vehicle activity in TEMPO is determined at the household level, as households are allowed to select the vehicles they own for each trip. Households balance vehicle age (proxying for factors such as maintenance costs and reliability) and fuel cost (including the monetized value of time spent charging) when making vehicle use decisions. Households with access to residential charging infrastructure have a lower marginal cost of driving for their BEVs, as they do not have to rely on more expensive public infrastructure, resulting in BEVs being driven more. Vehicle activity in GCAM is not modeled in this way. In GCAM, vehicles are not explicitly modeled, but are converted from PMT using a PMT per vehicle factor. Attrition curves dictate PMT by age and vehicle retirement. It is therefore implicitly assumed each vehicle is driven equally independent of age or cost.

Figure 32 (page 62) plots the share of VMT by age in TEMPO and GCAM in 2050, showing the combined effects of vehicle survival and use assumptions, compared to VMT by age from the 2017 NHTS. Two scenarios are considered in TEMPO. The Central scenario uses moderate assumptions about residential charging, while the High Resid scenario assumes all households have access to residential charging (and thus a lower marginal cost of driving BEVs). The TEMPO Central scenario has higher rates of usage for older ICEVs than both the TEMPO High Resid scenario and the GCAM scenarios, resulting in higher emissions (Figure 33, page 63). Table 12 presents GCAM and TEMPO's ICEV VMT and total emissions in 2050, and emissions reductions relative to 2019. GCAM and TEMPO's High Resid scenario have similar mileage for ICEVs aged 16–25 years (0.2 trillion miles). However, the inclusion of vehicles over 25 years in TEMPO adds an additional 0.1 trillion miles and disproportionately more emissions, as these older vehicles have lower fuel economy.

Table 12. VMT and CO_2 Emissions by Technology, 100% EV Scenario

Emissions totals may not match breakdown due to rounding.

Metric	GCAM	TEMPO-Central	TEMPO-High Resid
Total CO_2 emissions, 2050 (MMT)	41	93	70
Percentage reduction in CO_2 emissions in 2050 relative to 2019	96	91	93
CO_2 emissions from ICEVs, 2050 (MMT)	41	87	65
VMT from ICEVs, 2050 (trillion miles)	0.2	0.4	0.3
CO_2 emissions from PHEVs, 2050 (MMT)	N/A	7	5

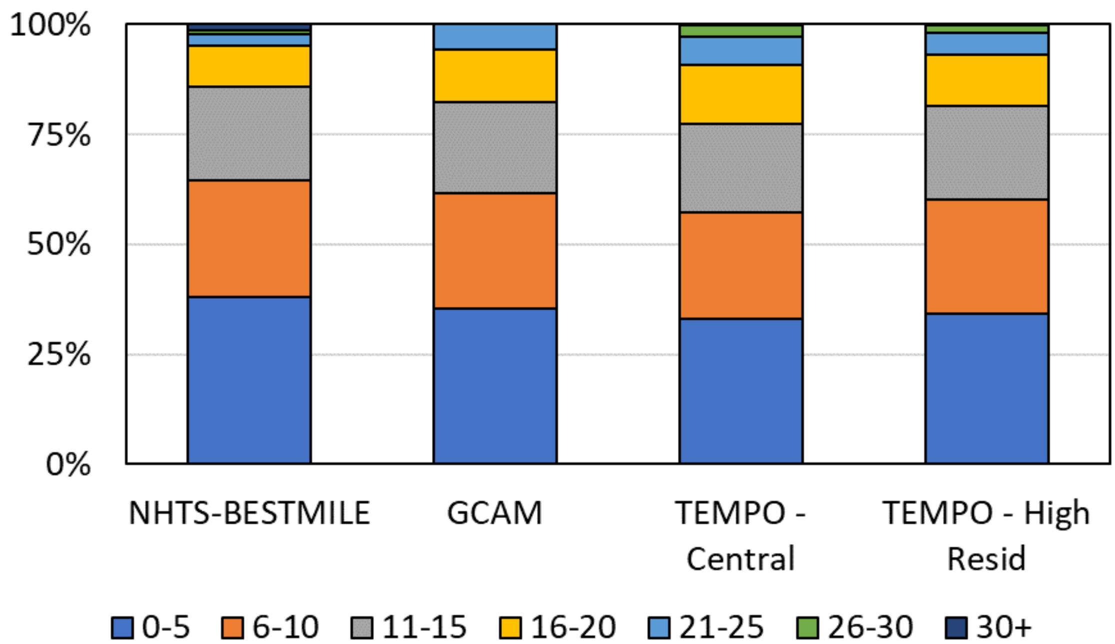

Figure 32. LDV share of VMT by vehicle age, 2050

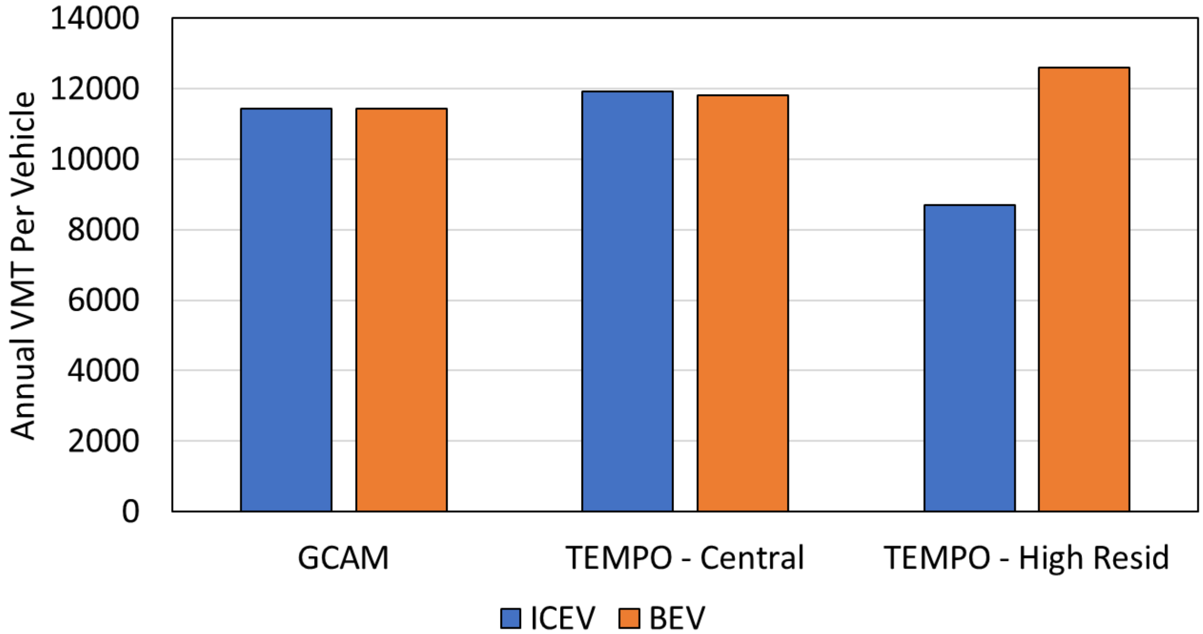

Figure 33. LDV VMT per vehicle by powertrain, model, and scenario, 2050

4.3 Conclusions, Key Takeaways, and Recommendations for Future Research

Based on the scenarios evaluated, we identified several insights regarding key sources of differences between models. We summarize the greatest differences in this section.

4.3.1 Input Assumptions, Demand Drivers, and Calibration

Differences in input assumptions, exogenous demand trajectories, and model calibration sources explain Reference scenario differences, including differences in activity levels across sectors, total sectoral growth, and projected changes in technology share from 2020 to 2050. These differences are most substantial in the freight sector, which has substantially different initial demand assumptions across modes (due to calibration differences) and substantially different growth trajectories (due to differences in exogenous and endogenous growth drivers), particularly for trucks. The passenger sector is more similar in initial calibration, projected growth, and mode share, making insights more comparable across models. However, models differ substantially on future LDV stock estimates due to differences in how vehicle stock is modeled.

In general, differences in input assumptions and calibration are most relevant when looking at *absolute* estimates given by each model (i.e., total energy consumption, demand, and stock), as opposed to differences in model response to a given scenario. Differences in model response are more strongly dictated by factors such as model structure (i.e., cost elasticities) and mode-level resolution. However, two key input assumptions may also influence relative scenario responses:

1. **Infrastructure Representation:** Differences in infrastructure representation affect technology choice and cost. In TEMPO, the assumption that hydrogen infrastructure does not rapidly grow results in no FCEV adoption for LDVs, with decarbonization occurring

through BEV adoption instead. GCAM includes FCEVs as part of the LDV and bus technology mix, although no substantial changes in shares are observed in response to a carbon price. TEMPO's EV infrastructure assumptions also affect vehicle use and energy consumption by altering the marginal cost of driving, producing up to a 25% difference in emissions between central and high infrastructure availability in the 100% EV scenario.

2. **Stock Turnover:** Alignment of stock turnover assumptions, which was not in-scope for this study, is relevant for analyses of LDV electrification. GCAM has fewer older vehicles (over 20 years) than TEMPO, resulting in TEMPO having almost twice as much ICEV stock in a scenario with 100% EV sales by 2035 (17 million vehicles in GCAM versus 32 million in TEMPO).

Alignment and sensitivity analysis on these factors should be considered in future inter-comparison exercises, and assumptions should be identified when comparing results across studies.

4.3.2 Model Structure and Resolution

Model structure and resolution are primarily responsible for the differences observed in fuel price responsiveness across models. We identified three primary structural differences with key impacts on model results:

1. Mode choice within the passenger sector can lead to differences in carbon price response across models. GCAM's greater cost responsiveness to mode choice resulted in substantially greater reductions in passenger air travel than TEMPO: 24 MMT of emissions reductions in the highest carbon price scenario. TEMPO's mode choice algorithm is more sensitive to changes in time intensity than cost intensity, resulting no emissions reductions from mode shifting. Historical data supports the greater price sensitivity of passenger aviation modeled in GCAM (Fukui and Miyoshi 2017), offering opportunities to improve model sensitivity in TEMPO.
2. Demand reduction in the freight sector produces 41% of the emissions reductions observed in GCAM, but it is absent in TEMPO due to inadequate data. This mechanism can produce substantial differences in model responsiveness in scenarios that explore increases in costs of transportation service, such as carbon prices. Historical data on freight demand reduction suggest GCAM may be somewhat more sensitive to fuel price increases than has been observed in U.S. contexts. The degree of mode shifting feasible between freight modes is also highly uncertain and has historically been influenced by several factors, including price, time, and infrastructure constraints. Further research could inform future estimates of the potential for demand reduction and mode shifting to reduce emissions within the freight sector.
3. Technology adoption algorithms differ for TEMPO and GCAM in the on-road freight sector (light-medium, medium, and heavy-duty trucks) and influence technology choice sensitivity to a carbon price, particularly for medium- and heavy-duty trucks. TEMPO uses different financial criteria and vehicle operation assumptions (VMT driven by different vehicle segments) than GCAM, resulting in differences in responsiveness to carbon prices for LDVs and medium and heavy trucks. In addition, TEMPO's enhanced sectoral resolution (variation in VMT assumptions considered for different applications

within the heavy-duty truck sector) interacts with its representation of monetized charging time to impact electrification opportunities for medium- and heavy-duty trucks. These mechanisms are not represented in GCAM. As the market for alternative-fuel vehicle evolves, TEMPO's market segmentation may be further refined to more precisely model electrification opportunities for MHDVs. This enhanced resolution might also be used to inform GCAM's representation of the sector.

On the other hand, some structural differences are less relevant to scenarios. Differences in mode availability (i.e., ship passenger travel and air freight travel in TEMPO) have little impact on scenarios. Additional zero-emission technology resolution in the freight rail and shipping sectors in GCAM has only a small impact on overall results. Overall, despite some differences in decarbonization pathways, the passenger sector is similar in its responsiveness to a change in carbon price across a range of carbon prices—this a key insight of this study.

4.3.3 Model Strengths and Areas for Future Research

Over the course of this study, we identified multiple areas for future research and model development. First, biofuels quantities were approximately harmonized for this study, but they could be modeled at a greater resolution in both models. In GCAM, biofuels are shared across all passenger and freight modes in proportion to their share of liquid fuel consumption, with no differences in the biofuel share of liquid fuel between modes. This assumption could be refined to consider factors such as the role of sustainable aviation fuel in aviation and identify mode-specific biofuel potential. Doing so may affect the relative decarbonization potential across modes. In TEMPO, further enhancements could allow competition between biofuel and liquid fuel technologies within modes, thus allowing for endogenous determination of adoption based on price.

Second, the Reference scenario could be enhanced in both models to add detail to what a business-as-usual scenario implies for emissions reductions. Both models could be enhanced by representing state-level policies (e.g., California's zero emission vehicle sales mandate), federal fuel economy standards, and other federal and regional policies. This enhancement would improve understandings of which emissions reductions are achievable absent additional interventions, and where gaps may remain.

Mode shifting and substitutability of modes could be further explored in both models, particularly in the freight sector. Identification of the degree of realistic mode shifting across freight modes (e.g., trucks versus rail, or the elasticity of shipping demand) and the capacity of each mode to accommodate additional demand without infrastructure expansion should be considered to improve the realism of scenarios in GCAM, and to implement mode shifting as a feature in TEMPO.

Finally, future research might examine long-term shifts in transportation behavior due to the impacts of the COVID-19 pandemic. Neither model includes short-term changes induced by the pandemic; however, the implications of potential long-term trends, such as increases in remote work, may be relevant to future decarbonization policies.

We also identified relative model strengths for different types of research. GCAM's strengths lie in its integration with other sectors, including electricity and refining, which allows the model to capture multisectoral feedback loops, including dynamics such as the interplay of transportation sector electrification and electricity generation, or between a carbon price and demand for biofuels. TEMPO lacks these mechanisms, thus requiring assumptions from other models regarding behavior in other sectors (e.g., the biofuel harmonization that occurred for this study). Meanwhile, TEMPO has more detailed representation of some passenger and freight sector market segments, particularly with respect to EV infrastructure, passenger travel demand, and heterogeneity in on-road medium- and heavy-duty activity. This level of detail is useful for focused, sector-specific studies, and it provides enhanced resolution that can distinguish the difficulty of decarbonizing specific subsectors and explain where and why zero emission vehicle adoption is most likely.

5 Buildings Sector

The buildings sector is a large and heterogenous energy consumer, encompassing a wide variety of building types and technologies that provide a diverse set of energy services. Broadly, buildings are categorized as either residential or commercial. Residential buildings encompass single and multifamily homes, and the technologies within providing services such as space heating and cooling, lighting, water heating, cooking, and a wide array of appliances and electronics. A wider range of buildings falls under the commercial category, from office buildings and schools to grocery stores and hospitals. Commercial buildings require many of the same energy services as residential buildings, yet the technologies that provide them can be very different to meet demands for these varied (and often large) buildings.

In this section, we compare the modeling approaches for GCAM-USA and the Scout building model to highlight their similarities and differences in modeling approaches, input assumptions, and outcomes across several scenarios.

5.1 Model Scope and Structures

5.1.1 GCAM-USA

GCAM-USA models energy consumption in the building sector for the 50 U.S. states and Washington D.C. across two aggregated building types: residential and commercial. Energy use in these buildings is further disaggregated into the 14 energy services listed in Table 13, including heating, cooling, water heating, and lighting. Within each building service category, multiple fuel types (e.g., electricity, natural gas, liquid fuels, and solid biomass) compete to supply these services; fuel types also entail a competition between different conversion technologies (typically a standard-efficiency and high-efficiency technology option). Technologies are vintaged and, once they are installed, they continue operating through the end of their technical lifetimes. Demand for building floorspace is driven by exogenously defined population and economic growth by state, but it can also vary with the average price of building energy services; exogenously specifying building floorspace is also possible. Building floorspace in turn sets the scale for demand of corresponding building services, which also varies in response to the (endogenous) price of the service, which varies in response to technology prices, fuel costs, and policy measures.

Table 13. GCAM-USA building types and energy services

Building Type	Building Service
Residential	heating, cooling, lighting, hot water, cooking, refrigerators, freezers, clothes washers, clothes dryers, dishwashers, furnace fans, televisions, computers, other
Commercial	heating, cooling, lighting, hot water, cooking, refrigeration, ventilation, office, other, non-building (e.g., streetlights)

We chose GCAM-USA for the building sector component of this model comparison study because it has a significantly more detailed building sector than GCAM. GCAM also divides the building sector into residential and commercial buildings, but it distinguishes building services into only space heating, space cooling, and other energy use. Also, GCAM does not include competition between multiple technology types within each service category and fuel type. For this study, we ran GCAM-USA from 2015 (final historical year) to 2050 to explore the future evolution of building energy use in residential and commercial buildings across multiple energy services, including energy consumption by fuel type and associated emissions.

5.1.2 Scout

Scout is a stock-and-flow model of the U.S. building sector that simulates the impacts of energy conservation measures (ECMs) on building energy use in the United States annually from the present year through 2050 (Langevin, Harris, and Reyna 2019; Langevin et al. 2021). Scout is used to estimate the energy use and CO_2 emissions impacts[19] of ECMs, and it facilitates the comparison of ECM impacts across end uses (e.g., heating, lighting, and envelope). Scout has flexible geographic resolution and can operate at the level of U.S. states (50), NEMS Electricity Market Module regions (25),[20] or American Institute of Architects' climate zones (5).[21]

Scout can evaluate a portfolio of ECMs competitively, ensuring that ECM savings impacts are not double-counted. Multiple ECMs that apply to the same market segment compete for shares of the segment based on models that represent consumer acceptance of capital costs versus operating costs. For residential buildings, a logit model is used; commercial buildings use a discrete choice model using time preference premiums. These models and their parameters are derived from the technology choice models used in NEMS (NREL 2022).

Scout includes substantial building type and technology detail (Table 14). The baseline technology options in Scout are mostly consistent with those used in NEMS, as users can introduce alternative technology options as ECMs, ranging in efficiency and availability from currently available ENERGY STAR-qualified technologies to advanced energy efficiency technologies (hereafter referred to as prospective technologies) that represent possible future improvements in technology performance that are well beyond the current state of the art.

As a forward projection model, Scout has not been formally calibrated using traditional methods. The baseline Scout obtains from AEO-NEMS is calibrated to other EIA data, such as the Residential Energy Consumption Survey and Commercial Buildings Energy Consumption Survey; these calibrations primarily ensure present and prior year data in NEMS are consistent with applicable historical EIA data. When conducting specific analyses with Scout, the model results are compared against other models configured with similar targets, as in this study, to assess whether Scout's estimates of future energy use and CO_2 emissions impacts in various scenarios are broadly consistent with models that include a representation of the buildings sector. For example, Langevin, Harris, and Reyna (2019) include comparisons to the U.S. Mid-Century Strategy, which was developed using GCAM and NEMS, among other models, and Langevin et al. (2021) include a discussion of results compared to a range of similar efforts in the literature. Of note, the primary application of Scout results is to illuminate one or more possible future scenarios and how changes in technology development, energy and technology prices, grid

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[19] Scout results include other variables outside the scope of this study, including utility bill savings and public health impacts.
[20] A map of Electricity Market Module 2020 geographic boundaries is available at "Electricity Market Module Regions," EIA, https://www.eia.gov/outlooks/aeo/pdf/nerc_map.pdf.
[21] A map of AIA climate zones is available at "Residential Energy Consumption Survey (RECS): Maps," https://www.eia.gov/consumption/residential/maps.php.

conditions, and other factors might change long-term energy use and CO_2 emissions—the absolute projected values are not intended to be predictions of future conditions.

5.1.3 Comparison of Modeling Approach

GCAM-USA and Scout employ vastly different approaches to representing the evolution of the U.S. building sector. Key elements of the models' respective approaches are summarized in Table 14. In terms of overall solution approach, Scout is a stock-and-flow model of buildings and equipment while GCAM-USA is a market equilibrium model in which supply and demand are balanced by endogenously solving for market clearing prices in each region, market, and model period. Both models use a logit model for technology choice within the buildings sector, although the logit models differ in important ways. For example, GCAM-USA uses a nested logit structure where fuels compete to meet demand within a given energy service and technologies compete within each fuel type. This structure allows endogenous fuel switching across scenarios. In contrast, Scout's technology choice model competes a much broader set of technologies; users must specify which technology or technologies an ECM is eligible to replace, as well as which fuel switching options are enabled (assuming fuel switching is rarely done in the absence of mandates or incentives).

Table 14. Comparison of Key Building Sector Model Features for Scout and GCAM-USA

Feature	Scout	GCAM-USA
Solution concept	• Stock-and-flow • Technology choice based on logit model (residential), time preference premiums (commercial)	• Market equilibrium • Technology choice based on nonlinear logit formulation
Sectoral scope	• Building sector	• Energy-water-land-emissions
Spatial scope and resolution	• United States with flexible subnational region specification (U.S. states, NEMS Electricity Market Module regions, or American Institute of Architects' climate zones	• Global coverage with the world divided into 32 energy-economy regions • U.S. disaggregated to 50 states and Washington D.C.
Demand driver	• Building and technology stock driven	• Service demand driven (in turn, driven by population and economic growth)
Demand growth	• Exogenously specified projection (AEO)	• Building floorspace and service demands represented endogenously
Building types	• **Residential:** single-family home, multifamily home, mobile home • **Commercial:** assembly, education, food sales, food service, health care, lodging,	• Residential, commercial

Feature	Scout	GCAM-USA
	• Large office, small office, mercantile/service, warehouse, other	
Discrete end uses	• **Residential:** heating and secondary heating, cooling, furnace fans and boiler pumps, lighting, water heating, cooking, refrigerators, freezers, appliances (e.g., dishwashers, clothes washers, and clothes dryers), televisions and related electronics, computers and related electronics, and other • **Commercial:** heating, cooling, ventilation, lighting, water heating, cooking, refrigeration, office computers, office electronics, other	• **Residential:** heating, cooling, furnace fans, lighting, water heating, cooking, refrigerators, freezers, dishwashers, clothes washers, clothes dryers, televisions, computers, other • **Commercial:** heating, cooling, ventilation, lighting, water heating, cooking, refrigeration, office, other, non-building (e.g., streetlights)
Technology representation	• Varies • One or more within each end use and fuel type (if applicable) combination	• Fuel-level competition, typically one standard and one high-efficiency technology option for each building service or fuel

In terms of model scope, GCAM-USA is a global model with state-level detail in the United States, and it covers all energy sectors as well as land and water. Scout represents only the U.S. building sector, but it can be flexibly configured with different subnational and regional definitions. Demand for building floorspace, equipment, and services are exogenously specified in Scout and endogenously calculated in GCAM-USA. Scout represents significantly greater building type detail (multiple residential and commercial building types) than GCAM-USA. Scout also represents more end-use categories than GCAM-USA, although the additional categories represented in Scout account for a small fraction of total building energy use. Finally, while GCAM-USA tends to include two technology options per building type, end use, and fuel type—representative standard-efficiency and high-efficiency technologies that capture the trade-off of higher upfront equipment costs and lower recurring fuel costs—Scout can model many competing technology options within each building type, end use, and fuel type.

5.2 Input Assumptions, Model Alignment, and Scenarios

5.2.1 Harmonization in Model Comparison

Both GCAM-USA and Scout require input assumptions about future technology costs, efficiencies, and lifetimes. Both models generally derive these inputs from the AEO for default or baseline technologies. However, Scout updates its input assumptions more frequently than GCAM-USA and thus Scout uses more recent AEO data.

To harmonize the two models, we updated GCAM-USA's historical building technology stock shares to be consistent with Scout, which affects GCAM-USA's share weight calibration and thus the future evolution of the building energy consumption. Additionally, we updated GCAM-USA's building technology cost, efficiency, and lifetime assumptions to match Scout's inputs. Because the two models employ different technology options, we mapped each technology in GCAM-USA to a single Scout's technology deemed to be representative of a standard, high efficiency option for that building type, end use, and scenario (Table A-3 in the appendix, page 107). GCAM-USA was also updated to use the same residential and commercial floorspace growth trajectories as Scout.

We also modified Scout in a several ways to facilitate a more direct comparison with GCAM. Scout energy prices and fuel carbon intensities were updated to match GCAM-USA's endogenously solved fuel prices and carbon intensities. By default, Scout takes these inputs from the AEO. In addition, fuel switching options must be explicitly defined in Scout; fuel switching is only available to the extent that corresponding ECMs are included in a given scenario and end use. Because GCAM's logit choice model allows for fuel switching across all end uses as the economics dictate, fuel switching ECMs were included in all Scout scenarios to be consistent with GCAM-USA. However, Scout's fuel switching measures were configured to allow electrification only—no pathway was offered for switching from electricity to fossil fuels. For the scenarios considered in this study, switching from electricity to fossil fuels was not generally favorable; thus, the exclusion of these options in Scout does not affect comparisons of results for Scout and GCAM in these scenarios. Finally, as a first-order attempt at aligning envelope efficiency of the models, envelope ECMs in Scout were mostly removed from the choice set. GCAM-USA includes an aggregate measure of stock-average building envelope efficiency, with minimal default efficiency improvements. (Future opportunities for improving GCAM-USA's representation of building envelope efficiency are discussed in Section 5.4.)

5.2.2 Scenarios

To explore the evolution of building sector under various technology and policy futures, we compared four scenarios (Table 15) that combine alternative emissions policy and ECM cases. With respect to emissions policy, the Reference case includes no policy while the Decarbonization case includes a carbon price pathway consistent with a 2.6 W/m^2 trajectory (the same carbon price pathway used in the electricity and transportation sector comparisons; see Section 4.2, page 39).

Table 15. Scenario Matrix for Building Sector

Scenario	Policy	ECMs
Ref	Reference (no explicit emissions policy)	Reference (mostly default technology options)
Decarb	Decarbonization (economy-wide carbon price consistent with 2.6 W/m^2 forcing in 2100)	Reference
Ref_EEE	Reference	Market_EEE (advanced energy efficient technologies)
Decarb_EEE	Decarb	Market_EEE

Reference and electrification and energy efficiency ECMs are defined in Table A-6, page 115, in the appendix.

From an ECM perspective, the Reference case entails current minimum efficiency and ENERGY STAR efficiency equipment with no future efficiency or cost improvements. (In Scout, a scenario with no ECMs will simply replicate the AEO scenario to which it is initialized.) The Market-EEE case explores a market-driven electrification and energy efficiency (EEE) scenario that is characterized by the introduction of advanced energy efficient technologies from 2030 onward. The Market-EEE scenario does not make other adjustments (besides technology cost and performance) to incentivize or reduce barriers to adoption for electric or energy efficient technologies. Our four building sector scenarios explore each combination of these two policy and ECM cases.

5.3 Results

In this section, we present the results of our building sector model comparison. Other sectors' results sections have different structure and content due to differences in scenario construction for electricity, transportation, and buildings. The figures present results for each of the four scenarios; we also present difference plots that show the change from each models' Ref scenario for each of the other three scenarios (Decarb, Ref_EEE, and Decarb_EEE). These difference plots help illuminate the response of each model to the same policy and technology drivers; this is helpful because there are in some cases significant baseline differences between the models (discussed in detail below).

The key metrics compared across models include final energy consumption, stock shares, and CO_2 emissions. The stock share variable is a combination of technology output (GCAM) and technology capacity (Scout). GCAM-USA does not explicitly track building equipment (technologies are tracked in terms of the service output they provide), while Scout tracks equipment stock but not necessarily service output. To bridge this gap, fuel-level shares are calculated for service output in GCAM-USA and units of equipment in Scout, providing a more apples-to-apples comparison of technology stock composition between models. Emissions figures include indirect emissions from electricity generation, which is an important contribution to the emissions footprint of the buildings sector. Because Scout was updated to use fuel carbon intensities from GCAM-USA, emissions differences are solely the result of differences in energy consumption.

We begin by comparing aggregate building sector results from GCAM-USA and Scout (across building types and end uses) under the four scenarios. We then explore results for residential and commercial buildings across end uses. Finally, we compare model results for selected end uses (e.g., heating, cooling, and water heating) in both residential and commercial buildings in further depth. Though GCAM-USA and Scout contain more than a dozen detailed end-use categories, it is not practical to present results for every category in the main text of this report. To keep the results discussion manageable, end uses are aggregated into the categories listed below, and results for some of the aggregate categories are presented only in the appendix.

- Cooling
- Heating
- Water Heating
- Lighting
- Kitchen: cooking, refrigeration, freezers, dishwashers

- Laundry: clothes washers, clothes dryers (residential only)
- Miscellaneous:
    - Residential: fans and pumps, ceiling fan, TVs, computers, and other
    - Commercial: ventilation, PCs, non-PC office equipment, and miscellaneous electric loads

An important caveat is that GCAM-USA includes a commercial "other" category that contains energy demand beyond the categories aggregated in the miscellaneous category above (ventilation, office). This commercial buildings "other" category was significantly different for GCAM-USA and Scout. In short, according to AEO2020 (EIA 2020), about 9.1 EJ of energy were delivered to commercial buildings in 2020. Because Scout did not include much of the ancillary commercial building energy consumption, it reflects only 7.0 EJ of commercial building energy in 2020.[22] GCAM-USA simulates 9.2 EJ of commercial building energy in 2020 when its commercial buildings "other" category is included; when this category is excluded, GCAM-USA simulates 7.0 EJ of commercial building energy in 2020. The scenarios considered in this study do not include equipment upgrades in the "other" category; however, to facilitate a more apples-to-apples comparison of the baselines of GCAM-USA and Scout, GCAM-USA's commercial buildings "other" category is excluded from the results and figures presented below.

5.3.1 Aggregated Building Sector Trends

Figure 34 (page 74) and Figure 35 (page 75) show total building sector final energy by fuel in 2020, 2030, 2040, and 2050 for each model and scenario, as well as the change from Ref for each model. In aggregate, 2020 building sector energy consumption is generally well-aligned between the models, with GCAM-USA simulating about 2% lower energy consumption than Scout. The models also have similar fuel mixes, although GCAM-USA has slightly higher electricity consumption than Scout in 2020 (55% of building final energy in GCAM-USA and 49% in Scout) and lower natural gas consumption (39% of building final energy in GCAM-USA and 43% in Scout). These differences exist because 2020 is a simulated period for GCAM-USA while Scout is calibrated to historical data for 2020.

As the models simulate farther into the future, greater differences in results emerge. In the Ref case, GCAM-USA simulates 11% higher total energy consumption than Scout by 2050 (23.1 EJ versus 20.7 EJ), with the largest differences coming from natural gas (3.3 EJ higher in GCAM-USA) and electricity (0.5 EJ higher in Scout). Both models simulate an increase in electricity consumption from 2020 to 2050; GCAM-USA also simulates growing natural gas consumption to 2050, while gas use decreases over time in Scout.

In the Decarb scenario, both models simulate a reduction in building final energy relative to Ref (21.5 EJ in GCAM-USA and 20.5 EJ in Scout in 2050), with GCAM-USA still simulating higher overall energy consumption and gas and making up most of the difference between models. In the Ref_EEE scenario, Scout's total building energy consumption in 2050 falls below 2020 levels (to 18.9 EJ), with most of the reduction coming from electricity. GCAM-USA has a larger reduction in total building energy consumption (3.3 versus 1.9 EJ in Scout), with the gas

[22] Beginning with v0.7.3, Scout includes commercial building "other" energy use consistent with the AEO.

accounting for about two-thirds of the difference (and electricity most of the remainder). However, GCAM-USA's total building energy consumption in 2050 still exceeds that of Scout by about 1 EJ. Finally, in the Decarb_EEE scenario, both models produce significant reductions in both gas and electricity consumption by 2050 relative to their respective Ref cases. The scenario's policy and technology efficiency measures lead total building energy consumption to fall below 2020 levels in 2050 in both models. Overall, Scout and GCAM-USA both show less response to changes in fuel prices in the Decarb policy case than in the EEE scenarios, in which changes in technology cost and performance in are found to drive much larger changes in the building sector.

Overall, for the building sector in aggregate, GCAM-USA simulates larger building energy growth to 2050 in the Ref scenario compared to Scout, but it also tends to be more responsive to the policies and ECMs in our alternative scenarios.

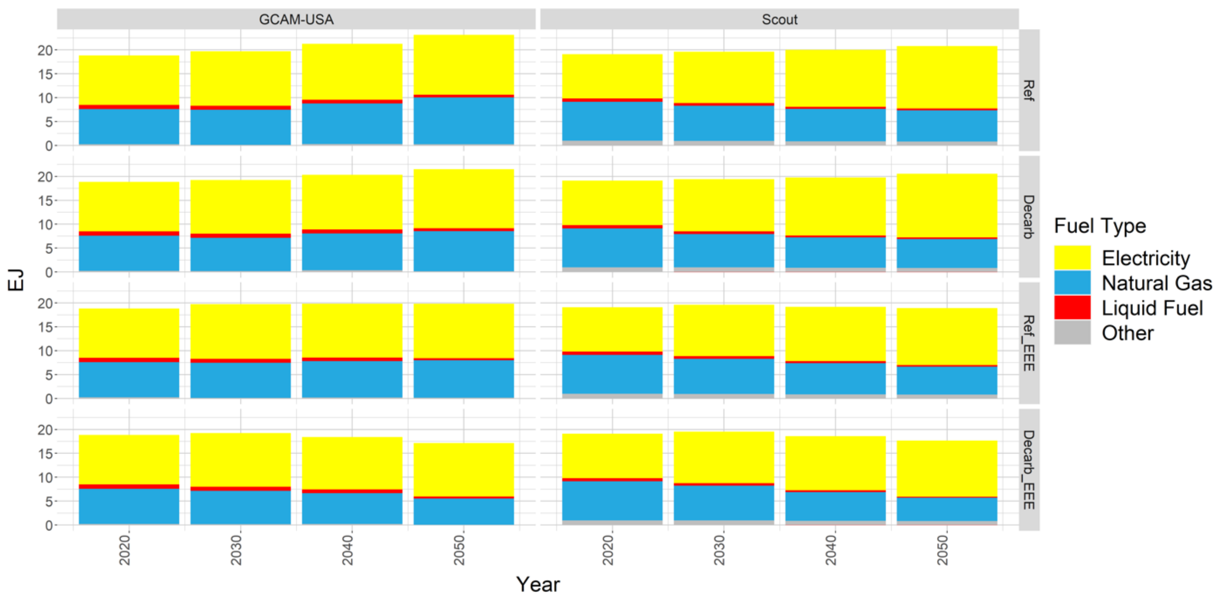

Figure 34. Total building energy consumption by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

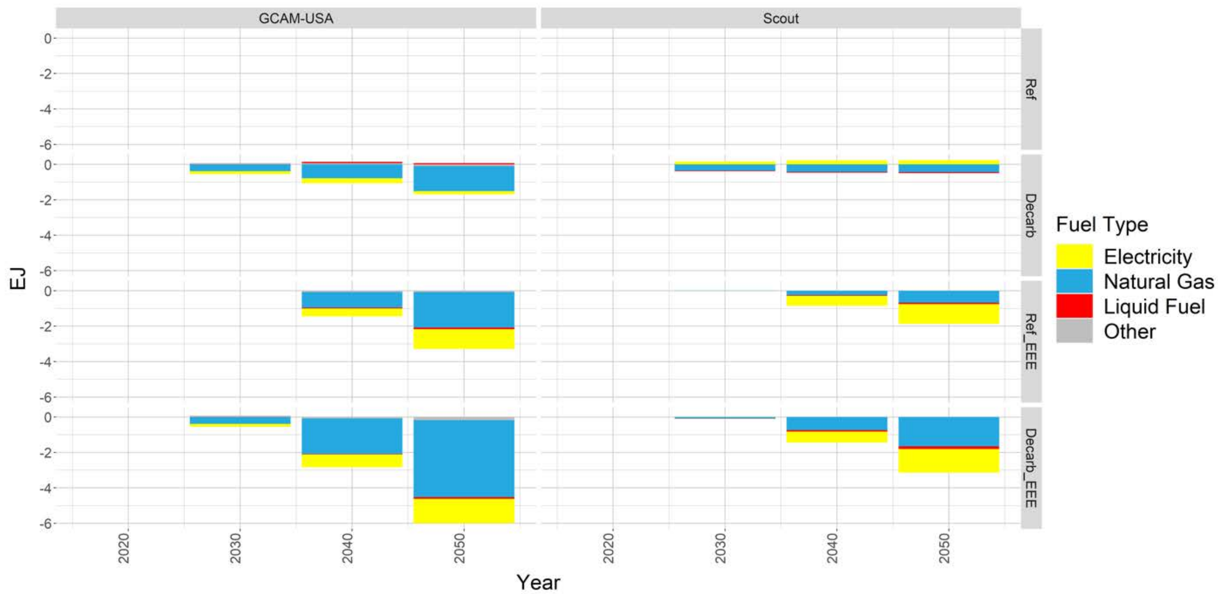

Figure 35. Change in total building energy consumption by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

Figure 36 (page 76) and Figure 37 (page 76) present building sector emissions for GCAM-USA and Scout across all four scenarios, including both direct emissions and indirect emissions associated with electricity consumed in the building sector. Note that the inclusion of indirect emissions differs from the presentation of emissions in the transportation sector (Section 4), where only direct emissions were presented, as indirect emissions represent a significant part of the historical emissions picture for buildings. (Figure A-13 and Figure A-14 in the appendix, page 119, present only direct building sector emissions.) In terms of total building sector emissions, GCAM-USA has roughly 9% higher emissions than Scout in 2020, due to its roughly 11% higher electricity consumption in 2020. Both models show small increases in emissions between 2020 and 2025 in the Ref and Ref_EEE cases, with emissions then modestly declining from 2025 to 2050. In the Decarb and Decarb_EEE scenarios, emissions reductions begin declining immediately, with the fastest rate of reductions occurring over the next decade. These near-term reductions are driven largely by decreases in electricity emissions intensity rather than changes in the building sector. Electricity emissions intensity is endogenous in GCAM-USA; these GCAM-USA emissions intensities are then passed to Scout. For both the Ref and Decarb policy cases, introduction of the EEE technologies produces noticeable but smaller emission reductions than the Decarb policy. This is consistent with results from Langevin, Harris, and Reyna (2019), who compared more and less energy efficiency and electrification of the building sector with and without grid decarbonization.

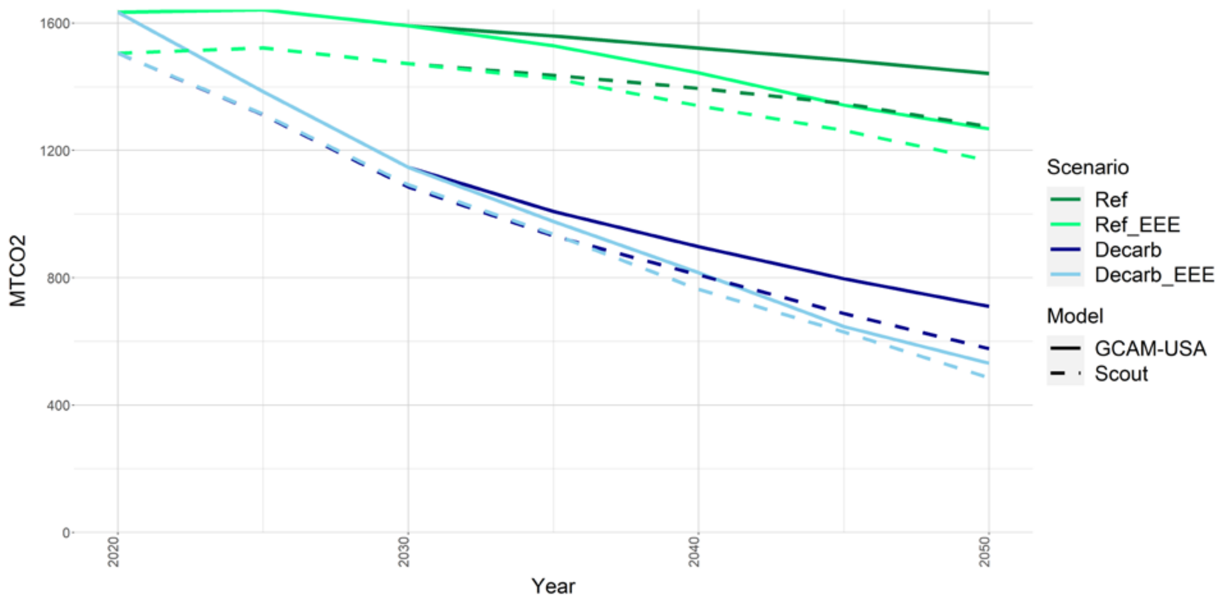

Figure 36. Total building CO_2 emissions by model and scenario, 2020–2050 (GCAM-USA and Scout)

Emissions include both direct emissions and indirect emissions from electricity generation

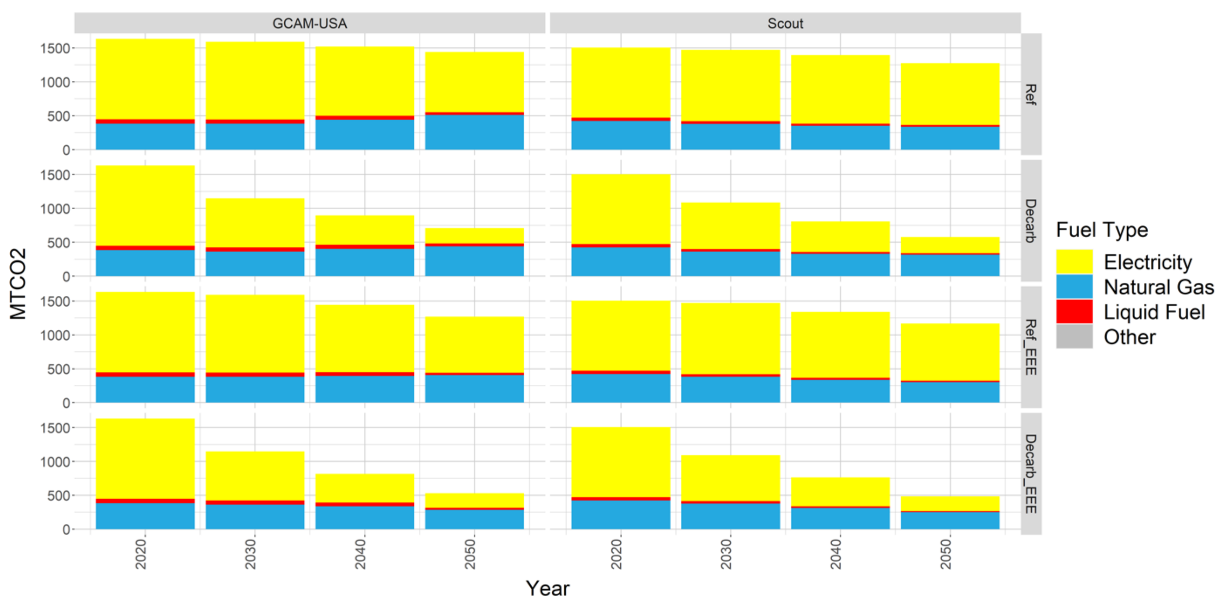

Figure 37. Total building CO_2 emissions by fuel, model, and scenario, including direct emissions and indirect emissions from electricity generation, 2020–2050 (GCAM-USA and Scout)

5.3.2 Residential and Commercial Building Sector Trends

Residential building energy results demonstrate similar trends to total building energy. Figure 38 and Figure 39 show residential building energy consumption. In 2020, total residential building energy in GCAM-USA and Scout are nearly identical, although GCAM-USA has 18% more electricity consumption and 12% less natural gas consumption. As the models simulate into the future, GCAM-USA's total residential energy consumption grows faster than Scout's. In the Ref case, GCAM-USA simulates 13% higher residential energy consumption than Scout in 2050; this difference is 6% in the Decarb scenario, 13% in the Ref_EEE scenario, and 7% in the Decarb_EEE scenario. In terms of fuel mix, GCAM-USA and Scout are very similar in 2050: in GCAM-USA, electricity meets 58% of residential building energy consumption in 2050 in the Ref scenario (59% for Scout), 61% in the Decarb scenario (62% for Scout), 59% in the Ref_EEE scenario (57% for Scout), and 64% in the Decarb_EEE scenario (62% for Scout).

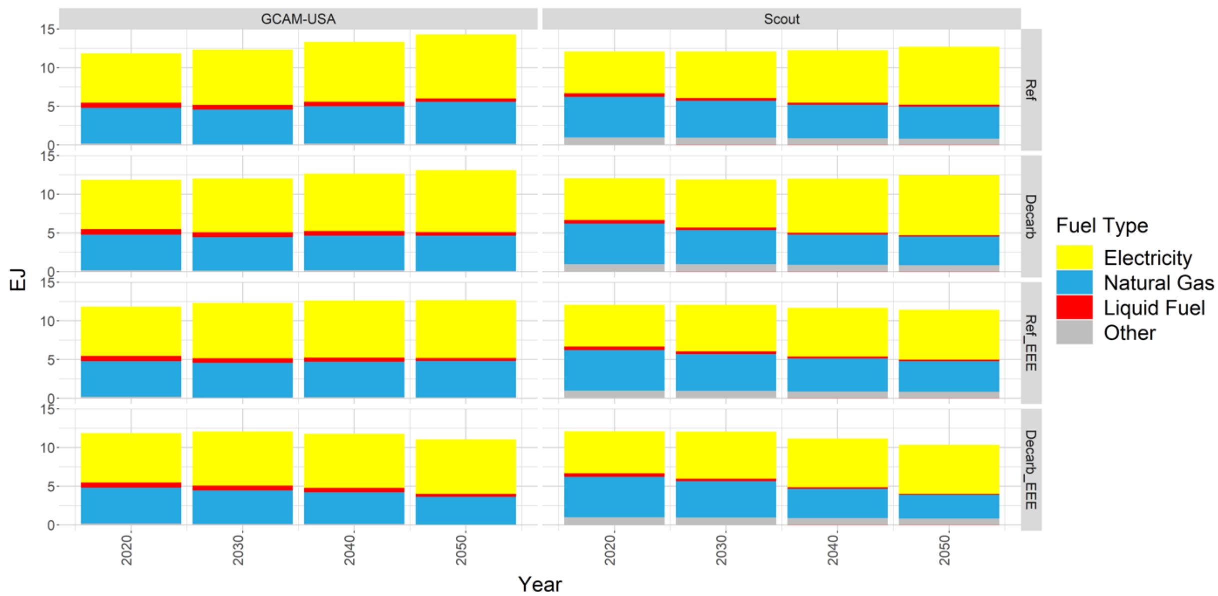

Figure 38. Residential building energy consumption by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

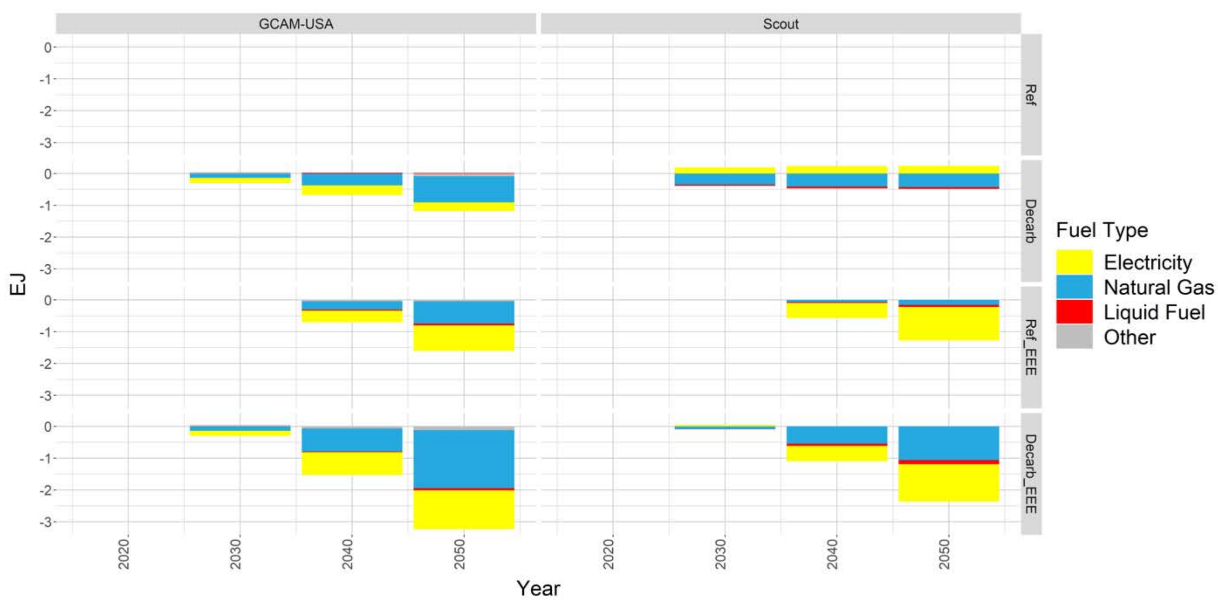

Figure 39. Change in residential building energy consumption by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

In terms of change from Ref, the models are again quite similar. In the Ref_EEE and Decarb_EEE scenarios, the models simulate similar changes from the Ref scenario, resulting in reduced consumption of all fuels. GCAM-USA simulates 11% and 23% reductions relative to its Ref scenario in the Ref_EEE and Decarb_EEE scenarios respectively; for Scout, these reductions are 10% and 19% respectively. In Scout, the greatest reductions come from electricity (first) and gas (second); GCAM-USA has similar reductions for electricity and gas in the Ref_EEE scenario (relative to Ref) and greater reductions from gas in Decarb_EEE. The Decarb scenario behaves slightly differently, with GCAM-USA simulating reductions in gas and electricity (mainly driven by residential space heating; see Section 5.3.3) while Scout simulates a reduction in gas consumption and a slight increase in electricity consumption.

Though commercial building energy consumption is similar in GCAM-USA and Scout in 2020, the models diverge significantly in future periods (Figure 40 and Figure 41). GCAM-USA simulates more growth in commercial building energy consumption in the Ref case (8.8 EJ in GCAM-USA and 8.1 EJ in Scout in 2050). In terms of fuel mix, GCAM-USA and Scout are very similar in 2020: GCAM-USA simulates that electricity meets 57% of commercial building energy consumption in 2020 (compared to 55% for Scout) and gas serves 39% of commercial building energy demand (versus 41% in Scout). In the Ref scenario in 2050, GCAM-USA's commercial building fuel mix tilts slightly more toward gas (48% electricity versus 50% gas), while Scout's commercial buildings electrify significantly (69% electricity and 29% gas). As discussed in Section 5.3.4, commercial space heating is the main driver of this difference, with commercial space heating energy increasing in significantly in GCAM's Ref scenario but modestly decreasing in Scout (by 2050 relative to 2020) due to differences in assumptions about heating degree days (HDD) and cooling degree days (CDD).

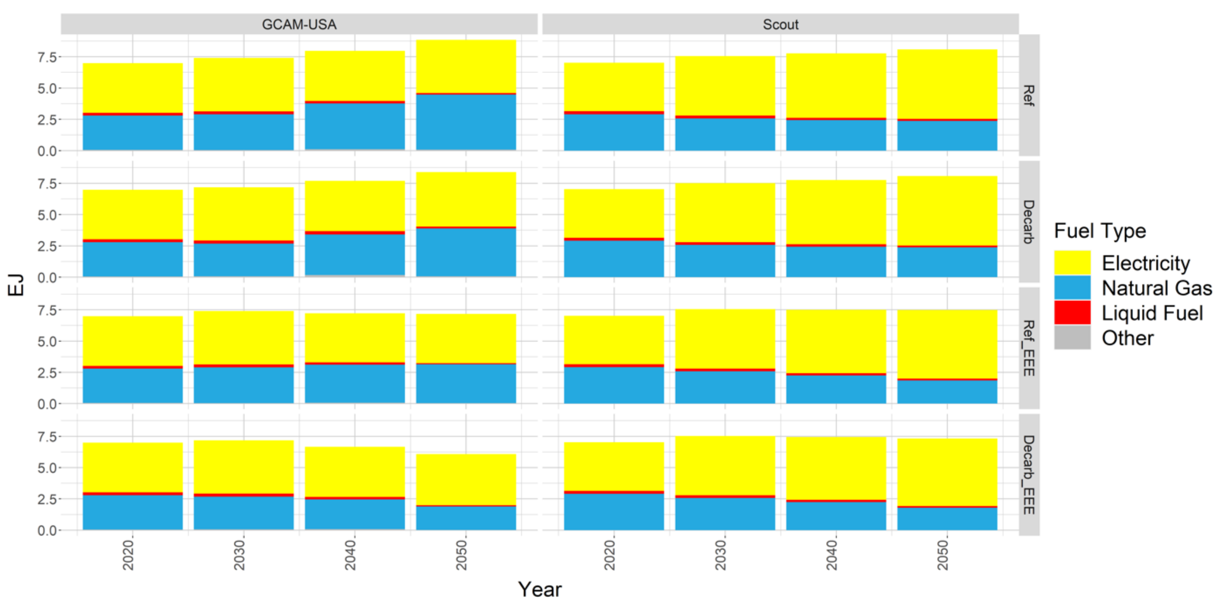

Figure 40. Commercial building energy consumption by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

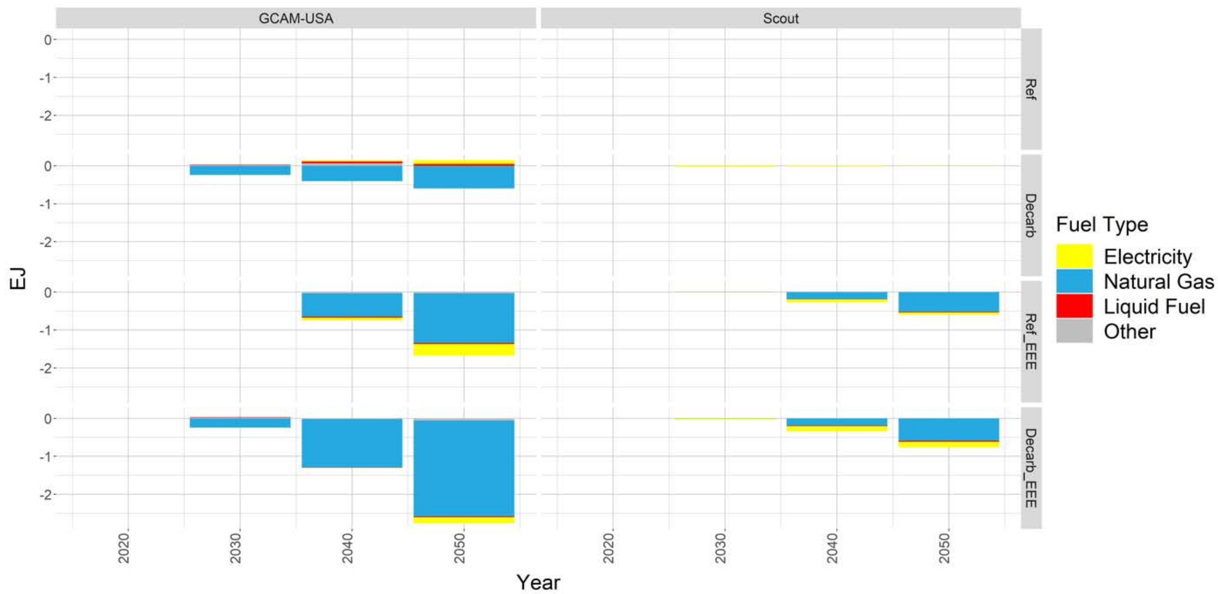

Figure 41. Change in commercial building energy consumption by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

GCAM-USA and Scout also behave differently in response to the policy and technology drivers in our scenario set. In the Decarb scenario, GCAM-USA simulates a 10% decrease in natural gas by 2050 relative to Ref, and Scout produces no meaningful change compared to Ref in response to the carbon price in Decarb alone, likely due primarily to the commercial building technology choice parameters heavily favoring low capital costs, which reduces the adoption of more efficient technologies that have even modestly higher capital costs. In the Ref_EEE scenario, both models simulate reductions in natural gas and electricity consumption, with the magnitude of the reductions in GCAM-USA values being larger than those in Scout. However, the more pronounced response in GCAM-USA than in Scout is in part a function of the greater increase in commercial building energy in the Ref case. In terms of percentage changes in natural gas consumption in the Ref_EEE scenario, GCAM-USA and Scout are more similar, with GCAM simulating a 33% reduction and Scout a 22% reduction. GCAM-USA simulates greater reductions in electricity in the Ref_EEE scenario with 7% reductions relative to Ref in 2050, while Scout's electricity reductions amount to only 1% reduction relative to Ref.

For the Decarb_EEE scenario, the changes observed in Scout (relative to Ref) are very similar to those observed in the Ref_EEE case. This is consistent with results in the Decarb scenario, in which Scout displays no meaningful response to the price of CO_2 emissions; the emissions price in the Decarb_EEE scenario entail little to no additional changes in commercial energy consumption relative to the Ref_EEE case. GCAM-USA simulates roughly 1.1 EJ additional energy savings in the Decarb_EEE scenario relative to Ref_EEE in 2050, with most of the additional reductions coming from natural gas and slightly less reductions from electricity.

As mentioned above, emissions trends for the models are consistent with the energy consumption results, because Scout was updated to use fuel carbon intensities from GCAM-USA. Emissions by scenario, fuel, and year for residential and commercial buildings are available in Figure 15 and Figure 16, respectively, in the appendix (page 120).

5.3.3 Residential Building Sector Trends for Selected End Uses

In this section, we examine two key end uses that account for more than half of residential energy use in 2020: space heating and space cooling.

Figure 42–Figure 44 (pages 81–82) present residential building energy consumption for space heating. GCAM-USA and Scout have similar levels of total energy for residential space heating in 2020, with Scout allocating about 9% more energy to residential heating in 2020. GCAM-USA allocates significantly more electricity and less gas and other fuels (mostly biomass) to residential space heating in 2020 than Scout. Over time, the models display different trends, with GCAM-USA simulating increasing energy for space heating in the Ref and Decarb scenarios, while Scout projects decreasing residential space heating energy in all scenarios. One important reason for this difference is differing assumptions about HDD and CDD, which, along with floorspace, drive demand for thermal building services. HDD/CDD drivers were not harmonized for this comparison. By default, GCAM does not include climate impacts in any sector, including future changes in HDD and CDD due to changing climate. Scout is driven by demand levels from AEO's Reference case, which includes some future climate change-driven increase in CDD and decrease in HDD. AEO2021 includes a national average 25% increase in CDD between 2020 and 2050, while HDD decrease by 6% over the same period.

In terms of change from the Ref case, there are some similarities and some differences between GCAM-USA and Scout. Both models show the smallest response relative to Ref in the Decarb case, with GCAM-USA having a larger response (13% reduction in GCAM-USA and 1% in Scout). Nearly all the residential space heating energy savings in GCAM-USA's Decarb scenario come from reduced gas consumption. In the Ref_EEE scenario, Scout's response is again small while GCAM-USA's response is larger than in the Decarb scenario: 38% and 17% reductions in electricity and gas consumption respectively.

Figure 44 shows the aggregated technology shares for GCAM-USA and Scout. For GCAM-USA, these shares represent the fraction of service output provided (e.g., heat produced); for Scout, these shares represent the fraction of units installed for that end use (e.g., space heating units). The figure shows that the changes observed in the GCAM-USA Ref_EEE scenario are largely driven by an expansion in the prevalence of electric heat pumps for residential space heating. Electric heat pumps account for 18% of residential heating service in the GCAM-USA Ref scenario in 2050, but this increases to 32% in Decarb, 38% in Ref_EEE, and 58% in Decarb_EEE. Particularly in the EEE cases, where electric heat pumps for residential space heating become 10% less expensive and more than twice as efficient (Table A-6, page 115, in the appendix), electric technologies come to comprise over 50% of residential space heating service in GCAM-USA in 2050. However, electricity consumption for residential space heating declines in these cases, due to the massive efficiency benefit of electric heat pumps[23] relative to gas or electric resistance heat.

[23] Throughout this report, the terms electric heat pumps and heat pumps refer to air source heat pumps (ASHP). The heat pumps represented in GCAM-USA and Scout are based on ASHP technologies; though Scout can model ground source heat pumps, the pricing and efficiency of the heat pumps modeled correspond to ASHPs.

Scout has near-constant shares (23%) of electric heat pumps in residential heating across scenarios and slightly greater deployment in the Decarb_EEE scenario (28%). There are a few reasons for this. Scout includes an additional cost for heat pumps installed in cold climates, making them about 15% more expensive in terms of installed costs than heat pumps installed in warmer climates; this cold climate distinction is not reflected in GCAM-USA. Additionally, Scout's choice model for residential space heating is parameterized to favor low equipment capital cost. While air source heat pumps (ASHPs) are competitive on a total lifetime cost of service basis because of their tremendous efficiency, their initial cost is still about three times that of a standard natural gas furnace, even in the Market_EEE cases. GCAM-USA's choice model, which considers LCOE service, finds electric heat pumps more appealing than Scout, which treats the high installed costs as a greater barrier to adoption.

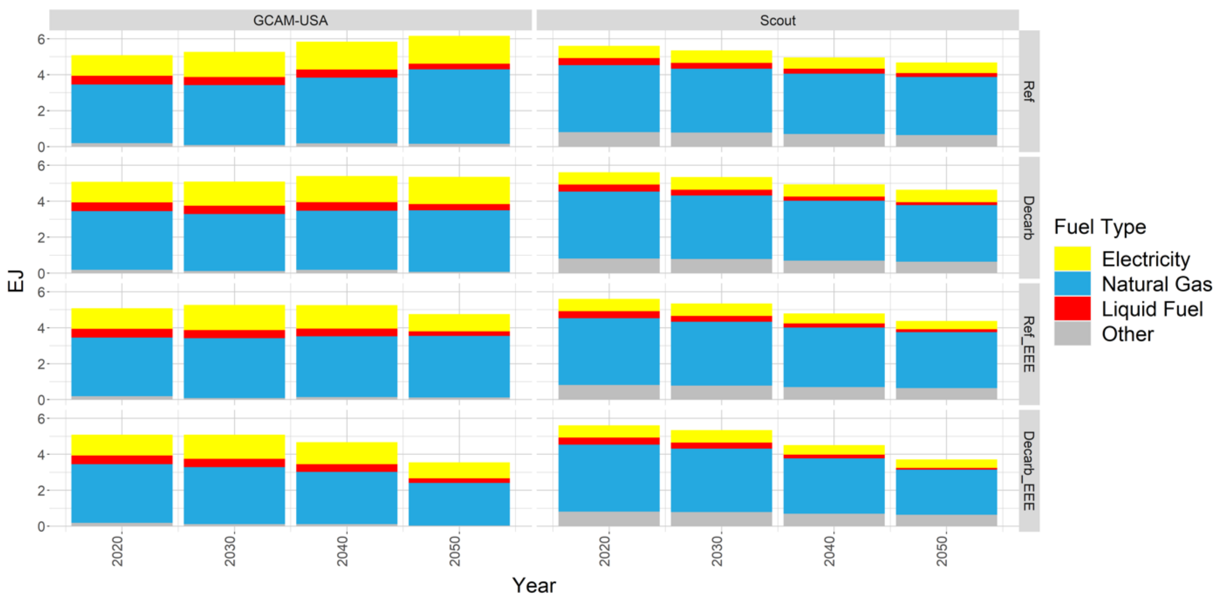

Figure 42. Residential building energy consumption for space heating by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

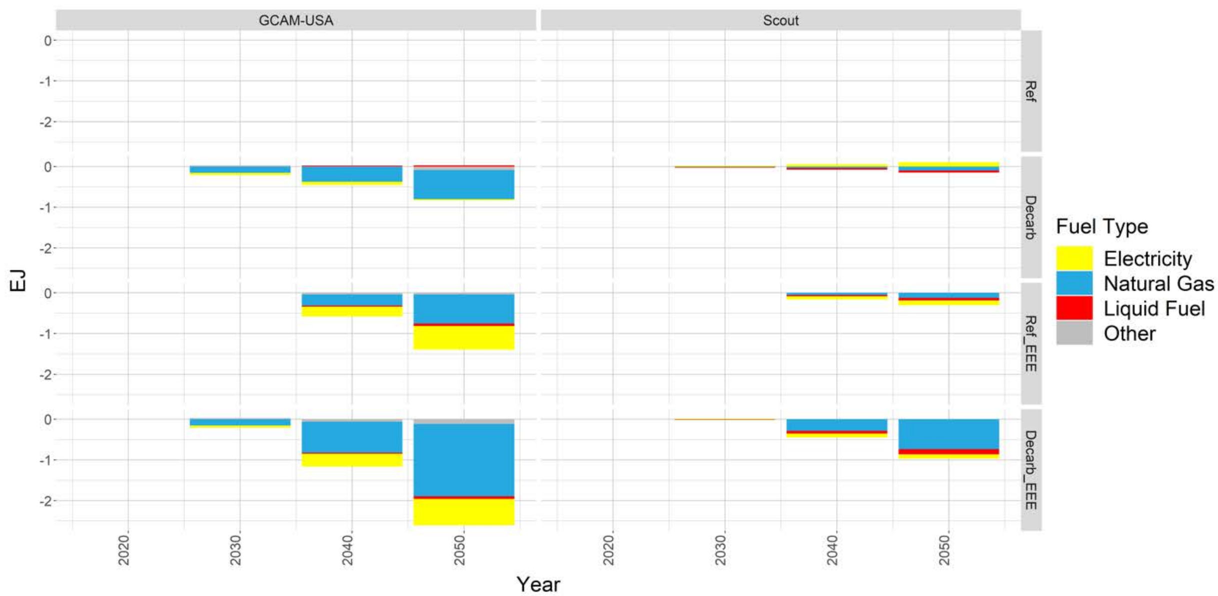

Figure 43. Change in residential building energy consumption for space heating by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

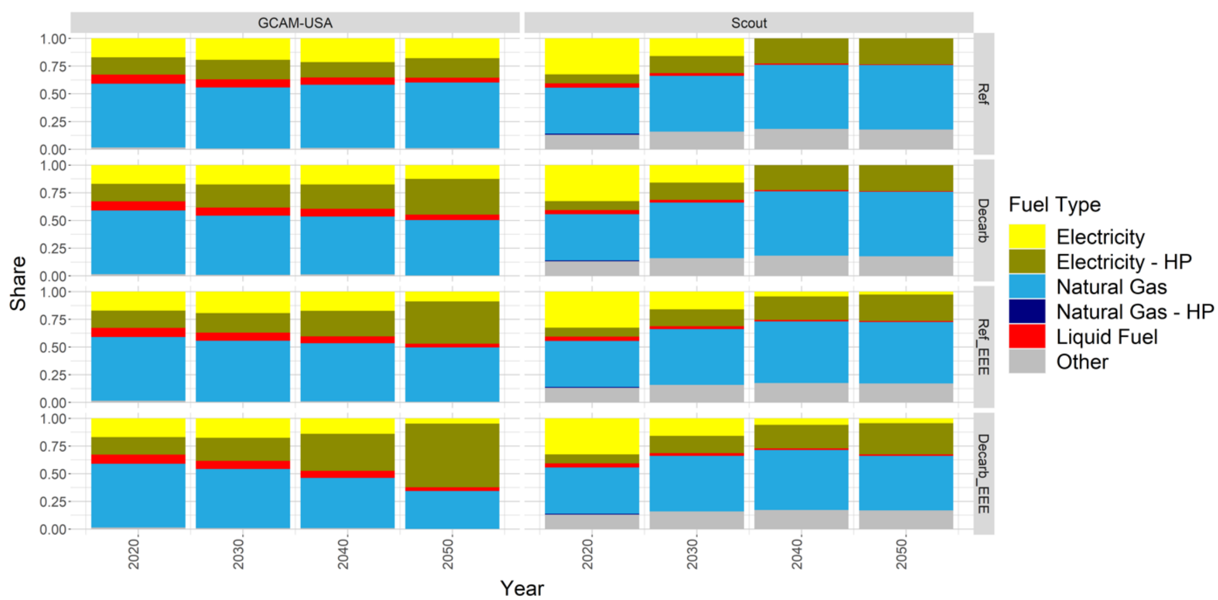

Figure 44. Residential building space heating technology shares by fuel, 2020–2050 (GCAM-USA and Scout)

Figure 45 and Figure 46 (page 83) present residential building energy consumption for space cooling. As with space heating, GCAM-USA and Scout have similar levels of total energy for residential cooling in 2020, with GCAM-USA allocating about 17% more energy to residential cooling in 2020. GCAM-USA has 100% of residential cooling energy supplied by electricity, while gas powers 7% of residential cooling in Scout.

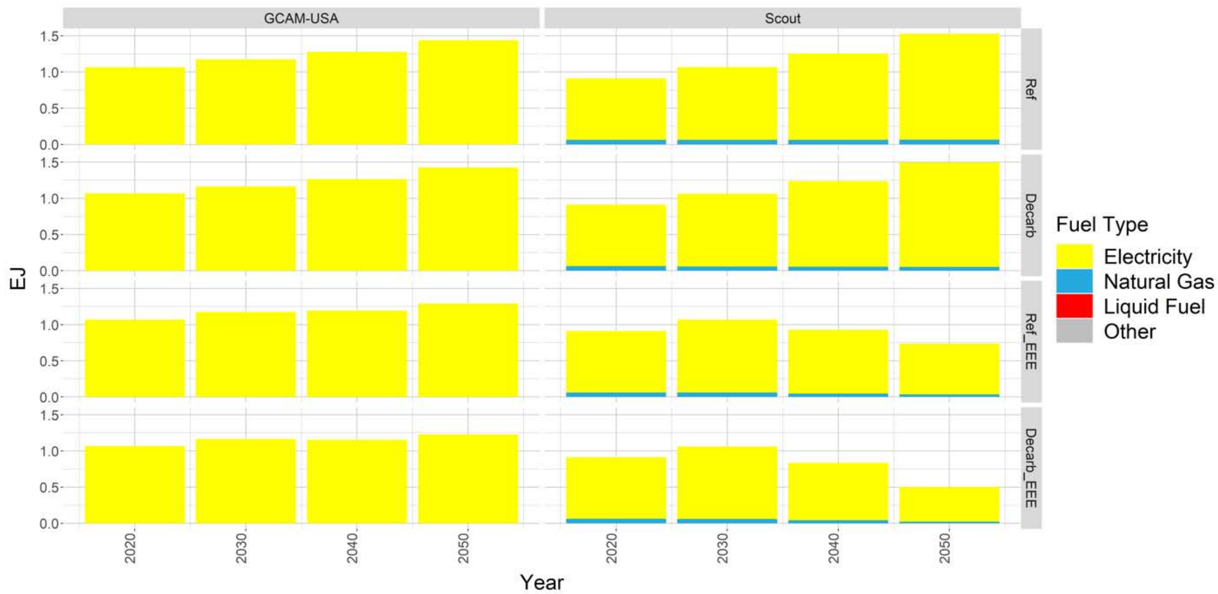

Figure 45. Residential building energy consumption for cooling by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

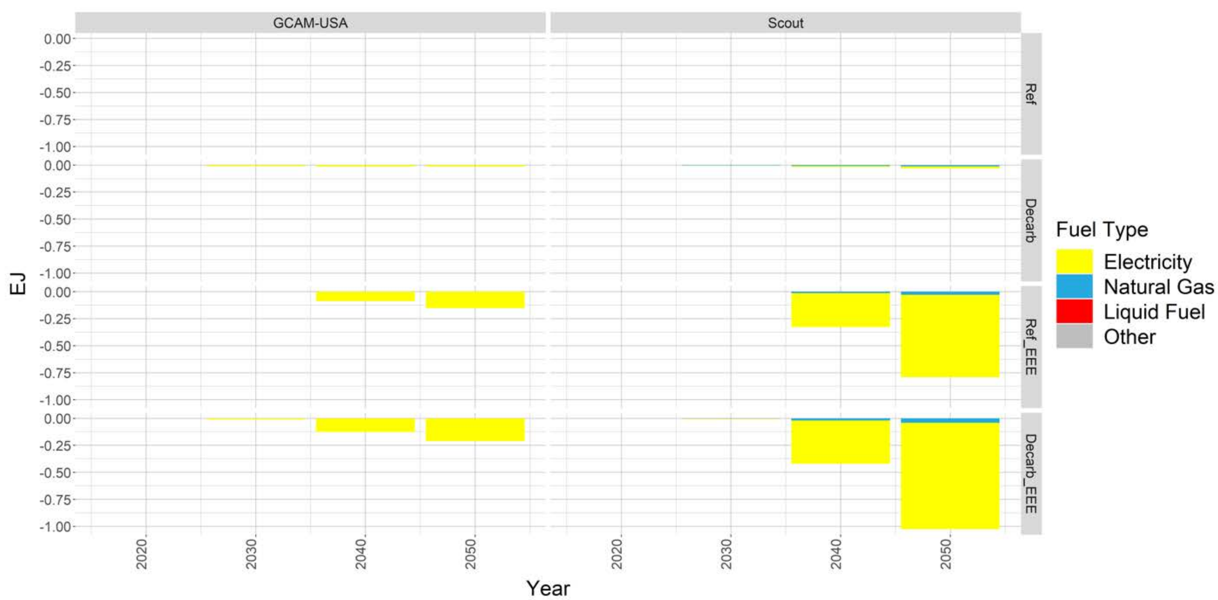

Figure 46. Change in residential building energy consumption for cooling by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

Both models simulate increasing cooling energy demand in the Ref scenario, with Scout simulating greater growth than GCAM-USA (68% versus 35% growth from 2020 to 2050) due to the inclusion of increasing CDD in the AEO baseline. The models have nearly identical residential cooling energy consumption in the Decarb scenario in 2050 and the Ref scenario. However, the models diverge significantly in the Ref_EEE and Decarb_EEE scenarios. GCAM-USA simulates 10% and 15% reductions in cooling energy consumption in those scenarios, respectively relative to Ref. In GCAM-USA, the higher-efficiency air conditioning technology option (ASHP) is more expensive than the lower efficiency central AC option on a levelized cost of service basis across all scenarios, even considering the lower equipment cost and higher efficiency of this technology in the EEE case (relative to Ref). Thus, ASHPs for air conditioning gain only 4% and 5% shares in the Ref and Decarb scenarios respectively (relative to 2020); with the improved EEE technology performance, this jumps to 17% and 22% in the Ref_EEE and Decarb_EEE scenarios respectively.

Scout simulates significantly greater residential cooling energy savings than GCAM-USA in the Market_EEE cases, with 52% and 67% reductions in the Ref_EEE and Decarb_EEE scenarios relative to Ref. This is driven by greater deployment of the ASHP technology in Scout, which occurs for a few reasons. As a stock-and-flow model, Scout tracks specific units of equipment within buildings. With respect to residential cooling, Scout's choice function for ASHP deployment considers not only the technology's competitiveness in terms of providing cooling services (as in GCAM) but also the combined value of the heating and cooling services that ASHPs provide, compared to separate heating and cooling units. Thus, when ASHPs are deployed for residential space heating, these more efficient units also provide residential space cooling services. In GCAM-USA, ASHP technologies within the heating and cooling end uses are distinct, and their deployment is a function of their cost competitiveness for providing a single service without considering their ability to provide both heating and cooling. As mentioned above, ASHPs are not very attractive for residential cooling in GCAM, and their significant deployment for residential space heating does not impact the technology's share in residential cooling.

5.3.4 Commercial Building Sector Trends for Selected End Uses

As with residential buildings, in this section, we explore two end uses within commercial buildings—space heating and space cooling—that account for roughly 40% of commercial building energy use.

Figure 47–Figure 49 (pages 85–86) present commercial space heating energy consumption. GCAM-USA allocates 18% more energy to commercial space heating in 2020 than Scout, with most of the difference coming from gas and electricity. By 2050, the models diverge significantly: GCAM-USA simulates a nearly 40% increase in commercial building space heating energy consumption in the Ref scenario, and Scout simulates an 18% reduction in energy for commercial space heating in the Ref scenario (with greater reductions in alternate scenarios). The models have similar technology shares in 2050, with gas accounting for 89% of commercial space heating in both models (Figure 49) (and technology efficiency assumptions aligned for this comparison). Thus, the differences in commercial space heating energy in the Ref case are driven mainly by differences in demand growth.

The difference in commercial space heating demand growth is not attributable to building floorspace, which is aligned for the models; commercial building space grows by roughly one-third between 2020 and 2050 (Figures A-11 and A-12 in the appendix, page 118). Assumptions related to future climate are certainly a factor, with HDD being flat in GCAM-USA between 2020 and 2050 and decreasing in Scout over the same period. However, GCAM-USA's commercial space heating demand grows by 44% from 2020 to 2050 in the Ref scenario (faster than the 33% expansion in commercial building floorspace), which implies an increase in heating demand per unit floorspace. GCAM's thermal service demands are a function of floorspace, climate (HDD and CDD), building shell characteristics, per capita income, and the price of the energy service, subject to satiation levels that capture the disutility of overheating or overcooling a space. Thus, GCAM-USA's Ref case (and alternate scenarios) entail a small positive increase in commercial space heating demand per unit of floorspace driven by future economic growth and lower heating service costs. The parameterization of thermal services in GCAM-USA reflects that heating (and cooling) demands are not completely met at present; some building owners would heat (or cool) their buildings a bit more if they had more income or if the services were less costly. This is in contrast to Scout, which takes end-use service demands as exogenous inputs (from AEO) that are fixed across scenarios.

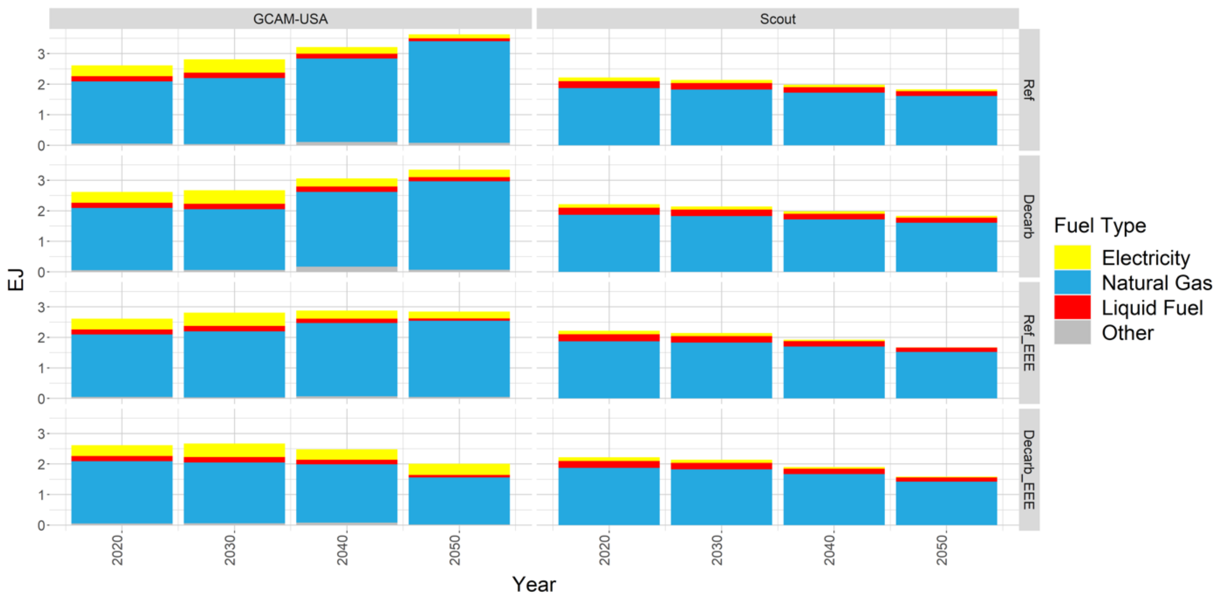

Figure 47. Commercial building energy consumption for space heating by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

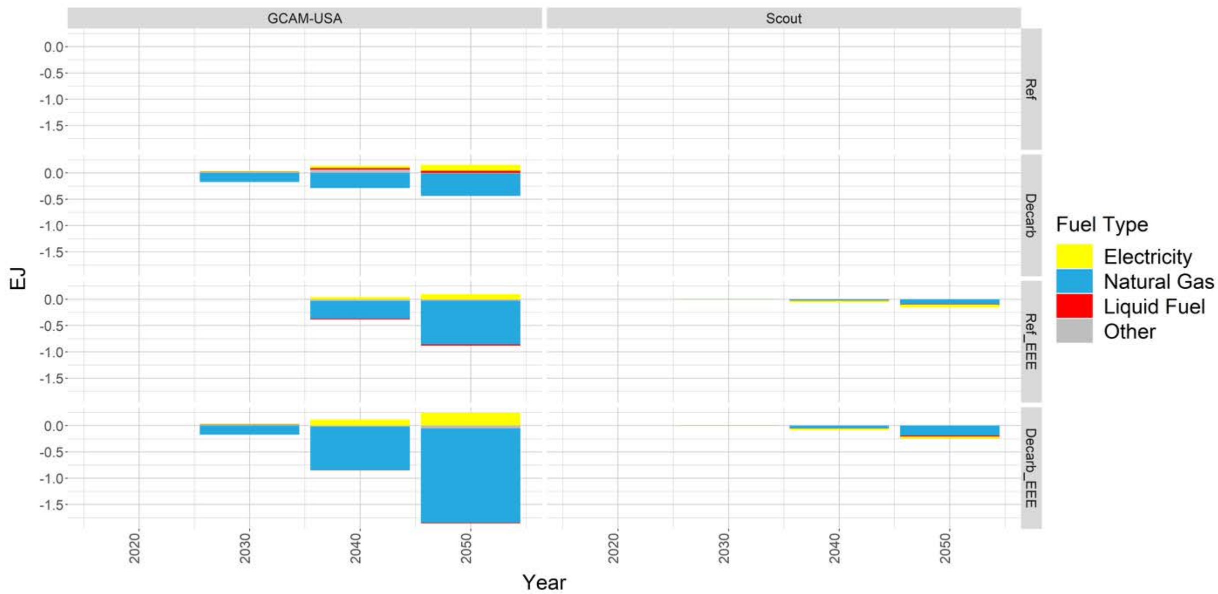

Figure 48. Change in commercial building energy consumption for space heating by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

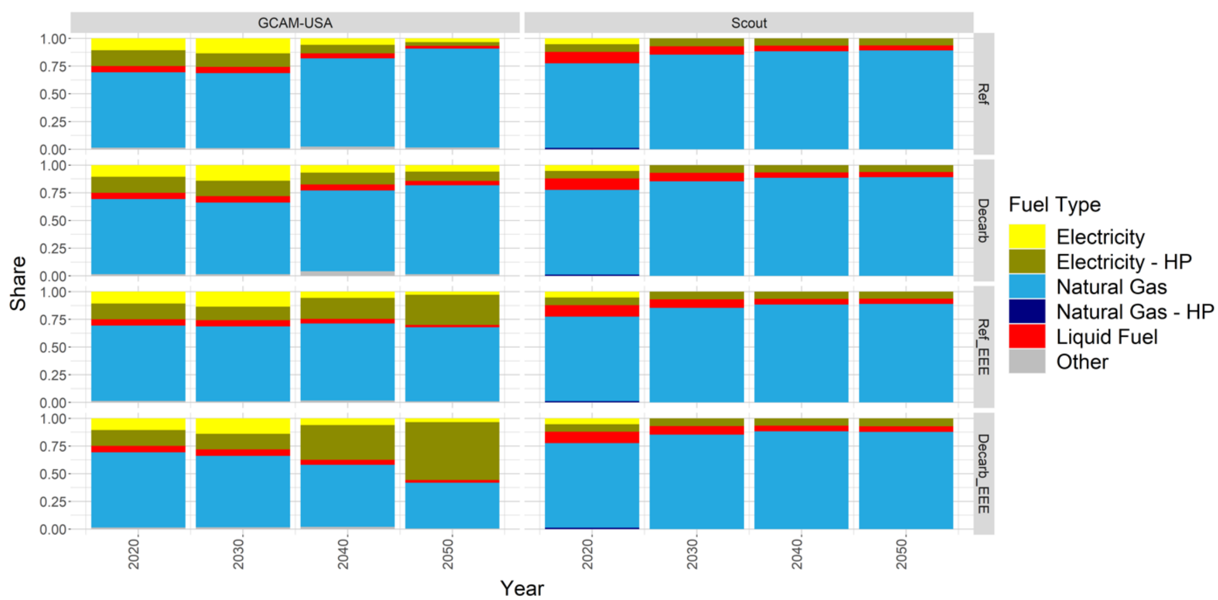

Figure 49. Commercial building space heating equipment stock by fuel, 2020–2050 (GCAM-USA and Scout)

The models also differ in their response to the technology and policy drivers in our alternate scenarios. Across the board, commercial building space heating GCAM-USA is more responsive than Scout to these policy and technology drivers. This is in part because the heating service demand growth embedded in GCAM-USA's Ref scenario creates more opportunity for new equipment to be installed in alternative scenarios, allowing them more opportunity to diverge from the Ref scenario. GCAM-USA simulates an 8% reduction in heating energy demand in the Decarb scenario in 2050 (relative to Ref), while Scout's space heating energy does not change in response to the carbon price in the Decarb scenario. Bigger differences emerge in the EEE cases, where GCAM-USA simulates an expansion of heat pump space heating for commercial buildings, leading to decreasing gas use for commercial space heating and increased electricity consumption.

As observed with residential space heating, the advanced heat pump technologies in the EEE case are less expensive (nearly two-thirds cheaper) and more efficient (75% more efficient) than those available in the Reference ECM case. In GCAM-USA, this makes electric heat pumps very economically appealing, and their deployment grows from 3% in the Ref scenario in 2050 (6% for Scout) to 9% in the Decarb scenario (6% for Scout), 27% in the Ref_EEE scenario (6% for Scout), and 52% in the Decarb_EEE scenario (7% for Scout). Because heat pumps are so efficient, electricity consumption for commercial space heating expands only modestly in the EEE cases in GCAM-USA, but gas consumption (and total energy consumption) declines significantly: gas energy consumption for commercial space heating is 25% lower in Ref_EEE and 60% lower in Decarb_EEE in 2050 than in GCAM-USA's Ref scenario.

As with residential space heating, a few factors contribute to these differences. As mentioned above, Scout distinguishes buildings in cold climates from those in non-cold climates, and it reflects higher costs for electric heat pumps suitable for cold climates. (GCAM-USA does not reflect this distinction in the scenarios in this study.) The commercial space heating technology choice parameters in Scout also favor low capital cost equipment. Finally, Scout represents several types of commercial buildings, which are all lumped into a single category in GCAM-USA. Because of this aggregation, GCAM-USA implicitly assumes electric heat pumps can replace heating systems in all commercial building types; in reality, electric heat pumps may not be a suitable replacement for some types of commercial boiler systems.

Figure 50 and Figure 51 (page 88) present energy consumption for commercial space cooling. The models differ somewhat in terms of total energy for space cooling in 2020, with GCAM-USA allocating 24% more energy to this end use in 2020 than Scout. In terms of energy mix, the models are nearly identical, with 95% of commercial space cooling powered by electricity and the remainder by natural gas. As the models simulate into the future, both models project increasing energy consumption for space cooling in the Ref case, with 21% growth occurring in GCAM-USA and 27% growth in Scout. In the Decarb scenario, both models demonstrate essentially no change from their respective Reference scenarios.

In the EEE cases, where higher efficiency commercial ASHP cooling units see installed cost decreases of 60% relative to the Reference technology case, both models simulate a contraction in commercial cooling energy use in 2050 relative to 2020. This contraction is more pronounced in GCAM-USA, which sees a 59% decrease in commercial cooling energy consumption in 2050 in both the Ref_EEE and Decarb_EEE scenarios relative to Ref. As with the residential sector, heat pump technologies in the heating and cooling end uses are disconnected in GCAM-USA; their deployment for one end use is not impacted by (and does not impact) their deployment for the other. However, in commercial buildings, the advanced ASHP technologies in the Market_EEE cases are highly competitive at providing cooling services (more so than for residential cooling). Scout's energy reductions are smaller in both absolute and relative terms, with energy savings of 24% and 31% in the Ref_EEE and Decarb_EEE scenarios, respectively, relative to Ref. As with space heating, Scout's more detailed representation of commercial building types may temper the deployment of low-cost ASHP units relative to the aggregate commercial building representation in GCAM-USA.

Figure 50. Commercial building energy consumption for cooling by fuel, year, model, and scenario, 2020–2050 (GCAM-USA and Scout)

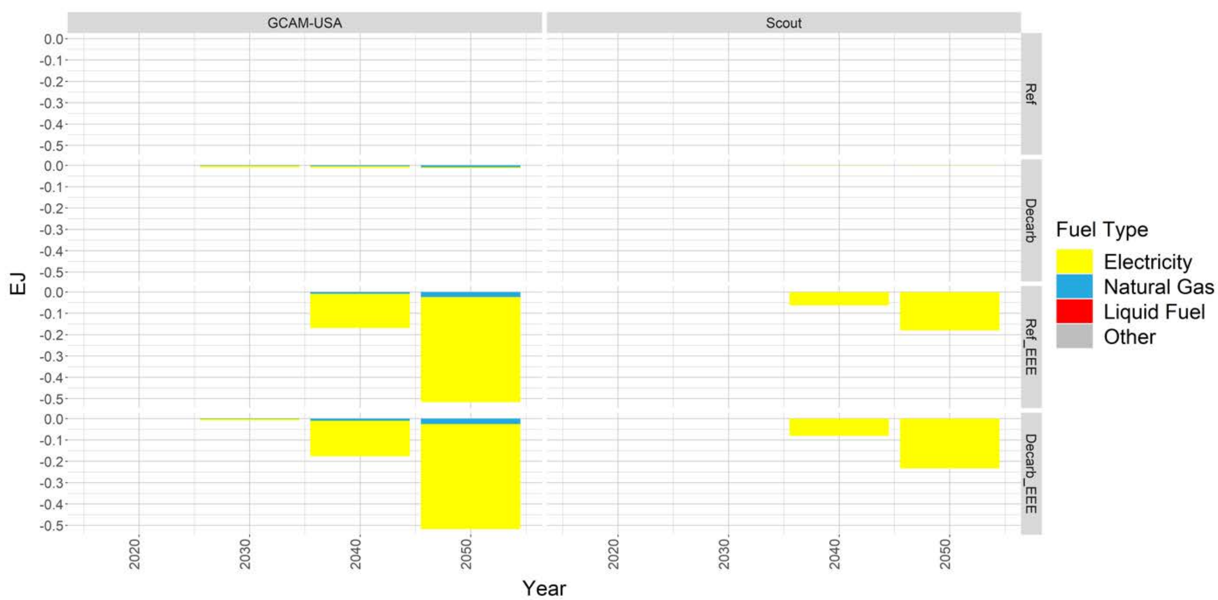

Figure 51. Change in commercial building energy consumption for cooling by fuel compared to each model's reference scenario, 2020–2050 (GCAM-USA and Scout)

5.4 Conclusions, Key Takeaways, and Recommendations for Future Research

This section summarizes the key insights related to model alignment and results comparisons from our building sector model comparison and articulates possible future research, including further alignment and other opportunities for joint model improvement.

5.4.1 Harmonization Challenges

In aggregate, building energy consumption in GCAM-USA and Scout are similar in 2020. However, as aggregate building results are disaggregated by building type and end use, larger differences between the models emerge. Scout is readily updated to data from the latest AEO, keeping its historical baseline up to date with recent historical data. GCAM-USA, on the other hand, currently uses 2015 as the final historical year to which the model is calibrated; 2020 is a simulated model period. Updating technology parameters (e.g., costs and efficiencies) is straightforward in GCAM; however, as a global, equilibrium model, advancing historical energy data to more recent years requires systematic updating across regions and sectors (as well as updates to agriculture, land, and water data). Consistent with its earlier base year, GCAM-USA uses older versions of the EIA's Residential Energy Consumption Survey, Commercial Building Energy Consumption Survey, and AEO to disaggregate building energy use to the more detailed end-use categories represented in GCAM-USA (relative to the more aggregate representation in GCAM).

In some cases, these historical (2020) differences contribute to significant differences in baseline (Reference) scenarios. Updating GCAM-USA's historical energy calibration was beyond the scope of this comparison project, but future efforts to update these data could benefit from the sector and technology mapping work from this comparison and could help improve alignment of 2020 results and Reference scenarios. Despite these challenges, this comparison made significant progress in aligning model baselines, including harmonization of floorspace growth; historical building technology stock shares; technology costs, performance, and lifetimes; fuel prices; and fuel emissions intensities. Technology harmonization was most challenging in the building sector for a couple of reasons:

- The building sector comprises a much greater number and variety of end uses than electric power (which can be characterized by a single, homogenous sector output) and transportation (which has two services: passenger and freight). Although there are several modes within passenger and freight transportation (e.g., road, rail, ship, and aviation), all technologies move either people or things, while building technologies provide a wider variety of services (e.g., cooling, heating, hot water, cooking, lighting, and numerous appliances). Ensuring consistency between per-unit costs in Scout and levelized costs per unit of service in GCAM-USA required careful consideration.
- Scout represents many technology options for each end use, while GCAM-USA tends to use representative standard efficiency and high-efficiency technologies to represent the trade-off between technologies with lower installation costs and higher fuel costs versus those with higher installation costs and lower energy costs. Selecting appropriate matches of Scout's many ECMs and GCAM-USA's representative technologies, for both a Reference and Market-EEE technology case, required careful consideration and iteration.

Important drivers that were not aligned as part of this comparison project are HDD and CDD. By default, GCAM does not include climate impacts in any sector, including future changes in HDD or CDD due to changing climate. Scout is driven by demand levels from AEO's Reference case, which includes some future climate change-driven increase in CDD and decrease in HDD. These differences lead to differing trajectories for heating and cooling energy demands for the models.

Building envelope efficiency was another area not harmonized in this study. Scout has detailed representation of building stock characteristics, including building stock demolition and new construction and many ECMs related to envelope efficiency (e.g., windows and insulation); GCAM-USA represents building envelope efficiency at an aggregate level for commercial and residential buildings. Future work could be undertaken to align GCAM-USA's aggregate envelope efficiency with the impact of the ECMs implemented in Scout.

5.4.2 Key Takeaways

Because GCAM-USA and Scout's baselines differ in some important ways, changes relative to each model's Reference scenario often provided the cleanest comparison of model behavior in response to our policy and technology drivers. In terms of change relative to Ref, GCAM-USA and Scout behave quite similarly in aggregate. The absolute magnitude of changes in GCAM-USA tends to be larger than those in Scout because of the greater growth in energy use in GCAM-USA's Reference scenario (and thus more opportunity for changes in how the system evolves).

Scout and GCAM-USA display similar responses to our alternate scenarios in residential buildings, while GCAM-USA is significantly more responsive in commercial buildings. As discussed previously, the building sector is highly heterogeneous; this is especially true for commercial buildings, which includes buildings used for assembly, education, health care, retail, lodging, offices, warehouses, and many other purposes. Scout represents a much greater level of detail with respect to these various commercial building types, their stock characteristics, and the technology options suitable for use in each. GCAM-USA consistently simulates greater deployment of electric heat pumps for heating and cooling in commercial buildings (relative to Scout). This is especially true in the Market-EEE technology case, in which electric heat pumps see significant cost reductions and efficiency improvements (relative to the corresponding technologies in the Reference case). Despite concerted efforts to map appropriate representative ECMs from Scout to GCAM-USA, the economics of electric heat pumps in commercial buildings are very compelling in GCAM; Scout's more detailed representation of heterogenous commercial building types better reflects challenges to deployment of certain technologies (e.g., electric heat pumps) for some applications. Additionally, Scout's detailed characterization of existing equipment stock within buildings allows it to consider additional costs of technology switching, such as electric panel upgrades or ductwork installation.

5.4.3 Other Opportunities for Future Research

In addition to the additional model harmonization opportunities discussed above—HDD/CDD and building envelope efficiency alignment—a few other opportunities for comparison and model improvement exist. As discussed above, Scout includes a detailed representation of the building stock and stock-related ECMs, while GCAM represents envelope efficiency in a very aggregate way. Similar to the VRE integration cost parameterization discussed in the electricity sector, it may be possible to create a response function in GCAM (parameterized using outputs from Scout) to represent envelope efficiency potential in a simplified manner. Doing so could allow building envelope efficiency to evolve dynamically in GCAM—currently, any envelope efficiency improvements must be exogenously specified by the user—in a manner consistent with or informed by the detailed envelope ECMs represented in Scout.

Additionally, future work could explore elasticities for technology or fuel switching for Scout and GCAM-USA, similar to the analysis in the transportation sector. One important observation from this comparison is that Scout and GCAM-USA both show less response to changes in fuel prices in the Decarb policy case than the EEE case; however, changes in technology cost and performance were found to drive much larger changes in the building sector. Historical data for an elasticity comparison may be more difficult to find for technology-driven response elasticity, as compared to fuel price changes in the transportation sector, which are more readily compared to historical fluctuations in oil prices.

6 Discussion and Conclusions

In this project, we developed comparisons of a global, integrated multisector model (GCAM) and U.S., sector-specific models (ReEDS, TEMPO, and Scout). We harmonized selected inputs and structural elements, and we examined results and sought to explain remaining differences. Such comparisons can inform global climate change mitigation and energy transition scenarios with detailed perspectives on granular technology development and deployment issues while showing when and how cross-sectoral interactions and GHG mitigation substantially affect technology deployment. The project identifies circumstances where value can be derived through these complementary approaches.

GCAM calculates fuel prices and carbon prices (for meeting emissions targets) that are internally consistent across global conditions for all sectors. This allows depiction of future economic conditions that are fundamentally different from the past because of GHG mitigation and other societal transitions. Integrated assessment models such as GCAM have been used for policy and strategy development because their comprehensive scope helps highlight key priorities and opportunities for meeting emission reduction goals. For example, the *Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050* (Long-Term Strategy)[24]—for which GCAM was used—shows combinations of energy efficiency, decarbonized electricity, transitions in energy carriers, non-CO_2 GHG reduction, land sinks, and CO_2 removal to reach net-zero GHG emissions, with substantial ranges across scenarios in GHG reductions by sector. The contribution of each mitigation measure was a model result consistent with scenario conditions, taking into account feedbacks, for example, between electricity demand and supply. This breadth of scope entails trade-offs with the depth of temporal, spatial, technological, and market granularity that is feasible to model.

For the major sources of GHG mitigation that GCAM identifies, sector-specific modeling with greater detail may reveal dynamics that could alter or add nuance to aspects of the strategic response. The categories of mitigation from the Long-Term Strategy that are addressed in more detailed modeling in this study are GHG-free generation, electrification, efficiency in transportation, and efficiency in buildings. Within each of these three categories, comparisons of detailed GCAM results and results of sector-specific models help elucidate the techno-economic conditions and decisions that would contribute to the level of transformational change envisioned in the Long-Term Strategy, while the global, economy-wide context from GCAM sets consistent prices for key shared resources and GHG mitigation, illustrating the complementary role of these two categories of models.

[24] *Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050*. Washington D.C.: U.S. Department of State and U.S. Executive Office of the President. November 2021. https://www.whitehouse.gov/wp-content/uploads/2021/10/US-Long-Term-Strategy.pdf.

6.1 Results: Reasons for Model Differences

This project explored the similarities and differences between GCAM and sector-specific models in the mechanisms of sectoral decarbonization. In general, many of the results from the models were broadly consistent between GCAM and sector-specific models, such that results do not indicate dramatically diverging perspectives on energy transformation opportunities. Despite overall similarities at an aggregate sectoral level, results showed differences at the subsectoral level in magnitude and types of response to changes in carbon price. For example, results in the transportation sector indicated model differences in where the mitigation effects occurred, including different levels of demand reduction, mode shifting, biofuel substitution, and technological change. Similarly, buildings subsector results showed different responsiveness of each model to the availability of ECMs. Additional work to understand and potentially resolve subsectoral differences in results might improve both GCAM and sector-specific models.

Across all sectors, the three primary reasons for differences in results are differences in:

- Model algorithms
- Spatial, temporal, technological, and market resolution
- Adjustments to technology value (beyond cost and performance inputs).

In an example of the first reason, GCAM's algorithms seek a market equilibrium and select technologies based on a nonlinear logit formulation. In contrast, ReEDS selects electricity technologies based on cost minimization for investment and operation of the electricity system. The logit formulation spreads adoption among multiple technologies and includes parameters that can be tuned to allow greater or lesser technology adoption diversity. In this study, GCAM's logit formulation tended to allow greater spread in adoption of technologies than ReEDS. In another example, Scout tracks system dynamics that approach equilibrium within stock and flow constraints. Although GCAM used equipment lifetimes from Scout for this project, the market equilibrium approach of GCAM may allow more rapid changes than the stock and flow approach of Scout because Scout represents more detailed building types and associated characteristics that may reduce the deployment of certain technologies (e.g., heat pumps) compared to the more aggregate representation in GCAM-USA. In general, if models constrain rates of change to historical levels, they may underestimate the potential for transformative changes, and if they do not, they may project rates of change that are unprecedented and potentially infeasible. Comparing results to historical changes and other feasibility metrics may inform assessment of the potential for change within the systems they represent.

The second reason for differences across the models—differences in resolution or granularity—includes differences both in the size of the categories and in content. Granularity relates to algorithm in that greater granularity means considering more specific characteristics of each category, whereas a logit-based algorithm seeks to reflect the distribution of these characteristics by spreading adoption across categories. The appropriateness and parametrization of logit choice models varies by application. For example, the commercial buildings or freight vehicles are generally characterized by least-cost competition, so other choice models, or parameters that narrow the logit distribution to reflect this least-cost competition, are appropriate. In contrast, residential buildings and passenger vehicles are subject to a wider variety of factors (e.g., consumer preferences), which makes the logit distribution a valuable tool. Similarly, large geographical areas represented as a single region (e.g., the whole United States) can be characterized by significant variation in fuel prices and non-modeled factors impacting technology choice (e.g., climate, preferences, and infrastructure), making a broader logit distribution more appropriate; however, as geographic resolution increases, variation in many of these factors decreases substantially, making tighter cost-based competition models desirable. If categories are broader, in the absence of logits, the adoption of technologies would be lumpier, and a small change in scenario assumptions can cause a larger, more sudden change in results. This can make the direction of a difference between two models suddenly flip. In general, but not always, GCAM categories (of energy services, technologies, and markets) are broader than those of the sector-specific models. Differences due to misaligned categories occur when a category in one model straddles those in another such that it must either be split or assigned to one or the other category, where such assignment puts more energy service demands in one category and fewer in another. In this study, most such alignment issues have been resolved.

For the third reason for differences—adjustments to technology value—several examples illustrate how these model differences lead to differences in results. Valuation relates to granularity in the sense that greater resolution can allow more precise valuation. One example is the difference between GCAM and TEMPO regarding the discount rate applied to calculate the present value of future fuel cost savings. Infrastructure cost and availability differences also explain different model results. For example, in the versions of the models used in this study, TEMPO generally assumes greater lag times in the development of hydrogen infrastructure than GCAM.

Given the relationships among the reasons that explain model differences, some examples feature more than one of these reasons. For commercial water heating, granularity differs between models, with GCAM assuming electrification is similar financially in all situations, whereas Scout assumes a range of deployment costs in this subsector, leading to less deployment in some circumstances (such as heat pumps in cold climates). This could also be an example of an algorithm-based difference because the logit parameters in this version of GCAM-USA may spread technology adoption more broadly, resulting in more electrification than expected based on a least-cost formulation. These logit parameters could be tuned so that GCAM results would match more closely the results of sector-specific models or empirical data when it becomes available. In other examples of multiple reasons for differences between models, the contrast of GCAM and ReEDS in determining the value of VRE to the grid represents both a difference in valuation and a difference in granularity. ReEDS explicitly tracks the ability of technologies to meet load and reserve requirements at highly resolved spatial and temporal granularity, while GCAM and GCAM-USA include additional backup costs for VRE technologies to account for these issues within their less granular frameworks. Representation of VRE—including constraints in GCAM and GCAM-USA's and temporally resolved load matching in GCAM-dispatch—leads to differences across the models. The direction and magnitude of these differences varies depending on the scenario.

As cities and states begin taking concrete steps to achieve their GHG emissions reduction goals, there is increased interest in electrification of buildings and transportation. Electrification in buildings might incur additional costs (beyond new equipment costs) to add new high current circuits, and in some buildings, upgrade electrical service and electrical panels. These costs could be a significant share of overall installation costs, particularly in residential buildings. Electrification could also introduce permitting requirements that further increase project costs. For this study, we harmonized GCAM and Scout to exclude additional costs associated with fuel switching; in practice, however, these costs will likely present a barrier to electrification (in the absence of policy interventions). Moreover, as vehicles are electrified, at least some share of privately owned LDVs will charge principally at home. When home charging is added to the set of new high current electric loads that must be accommodated in homes, the combined effects of EV charging and building electrification together should be considered in our models. Electrifying multiple end uses (including LDVs and building heating via ASHPs) may also impact the temporal profile of electricity demand and have implications for power sector capacity needs; this possibility merits future research. GCAM is well positioned, in principle, to capture these interdependencies of home charging and building electrification, but the absence of a building-level load model impedes its ability to represent the threshold costs of electrification. Precise estimation of additional costs to include in any model faces the challenge of a dearth of empirical data on fuel switching project costs. In addition, the absence of data on the present-day electrical service for buildings makes model implementation of those costs difficult, even at the aggregated stock level.

Although differences call for an explanation, similarities also need to be examined. Similar results can occur due to similar modeling approaches that may need improvement or may mask underlying differences that balance each other by differing in opposite directions.

6.2 Applications

Model selection and study design depends on the question being addressed; the metrics, level of detail, and other features of the results that are needed; and the availability of relevant data. Furthermore, advances in analysis are likely to occur iteratively, with successive approximations improving on previous work. Generally, models with less energy sector detail may be most useful to explore optimal future states with few constraints from historical precedents. If greater detail based on current and known future potential energy systems is desired, the models considered in this study become relevant. Broad, global integrated multisector models like GCAM are best used to understand overall global, economy-wide system change and feedbacks in response to a major shift, such as GHG mitigation. If an analysis needs to compare very different states of the global economy, such as with and without GHG mitigation, an integrated assessment model is likely to be useful to develop consistent conditions that quantify each scenario. Similarly, if an analysis addresses major interactions among sectors, such as allocation of scarce multisector resources, an economy-wide framework can contribute. Once global, economy-wide conditions are established, sector-specific models are best used to understand particular changes. If an analysis is exploring technology characteristics that are different from historical circumstances, or dynamics where small changes can make a big difference, sector-specific models with greater technology resolution are likely to be useful. Sector-specific models may provide granular detail on questions such as:

- Where and when would technologies be used?
- What would it take to scale up their use as rapidly as needed?
- Which specific technologies appear most competitive, and in which specific market segments?
- What types of investments or interventions might be most effective in advancing technology deployment?

6.3 Limitations

Limitations of the comparison reported here arise from the imperfections of models as predictive tools as well as the exploratory scope of this project. Model validation is challenging at best for technological changes without much historical precedent. Model validation (as possible), full harmonization (including base year alignment), and comprehensive sensitivity analysis were beyond the scope of this project, but they have been addressed in other publications about each model: GCAM (JGCRI 2022), ReEDS (NREL n.d.), TEMPO (Muratori et al. 2021), and Scout (Langevin, Harris, and Reyna 2019; Langevin et al. 2021). In particular, when harmonizing historical energy use between GCAM and sector models, a key question must be answered: should GCAM values be used because of the complexity of the global energy balances, or should sector models be used, forcing adjustments to global energy balances in GCAM? This study accomplished selective harmonization and initial explorations of sensitivities across these models.

Future work would benefit from first more fully harmonizing the models and performing extensive sensitivity analyses to understand which input factors and parameters are most influential. Although this study presents reference and GHG mitigation scenarios, the GHG mitigation scenarios were constructed in different ways for each sector: the ReEDS scenario used targets 95% CO_2 reduction in the electricity by 2035; a set of new TEMPO scenarios constructed for this study explore multiple carbon price trajectories, while another scenario explores a 100% EV mandate; and the Scout scenarios use a carbon price trajectory consistent with 2.6 W/m^2 radiative forcing, with two different sets of ECMs. The power sector focused on an emissions reduction target; the buildings sector explored response to a carbon price under different scenarios of efficiency technology availability; the transportation sector considered variation in carbon price and response to a technology standard for zero-emission vehicles by 2035. Future analysis would be required to apply each of these approaches across all sectors in a detailed multimodel decarbonization analysis. Even if many of these limitations were overcome, there is no single answer to the question of which model should be used when, because they serve different purposes. For global, economy-wide analysis, GCAM is more appropriate than any single U.S. sector-specific model, and sector models can offer complementary U.S. detail. For sector-specific U.S. analysis, a sector model may be more appropriate, and a set of economy-wide boundary conditions must be assumed, which could be informed by a model such as GCAM for scenarios that differ from baseline conditions. For analyses targeting detail in multiple sectors, combinations of multiple models may be most useful.

Interpretation of our results and conclusions should consider the following limitations of this work:

- Many of the technologies, demographics, and environmental conditions envisioned in future scenarios have no historical precedent, which poses fundamental challenges to analysis. Models cannot predict the future, and opportunities to validate their behavior and performance may face challenges—but still need to be pursued.
- Model validation, full harmonization (including base year alignment), and comprehensive sensitivity analysis are key analytic steps that were beyond the scope of this study. Using multiple models, as we have done, can contribute to addressing uncertainty, but is not a substitute for these steps.

- This study accomplished selective harmonization and initial explorations. This was not a multimodel decarbonization analysis. It explored a small set of scenarios with a focus on comparing behavior of the models.
- There is not a one-size-fits-all prescription of which model is better or which model should be used when.
- Models are best used for what-if explorations and quantification of the consequences of scenarios. (What would need to happen, and when, for certain goals to be reached?) Sensitivity analysis, multimodel studies, and direct inclusion of uncertainty in modeling can improve the assessment of uncertainty and increase the robustness of insights that inform decision makers.
- Global, integrated multisector models such as GCAM have broad geographic and sectoral scope, which necessarily entails trade-offs with the level of detail that can be represented for specific sectors and technologies.
- Sector-specific models such as ReEDS, TEMPO, and Scout generally use scenarios to set input conditions of factors such as fuel prices, other sectors' resource demands and costs of GHG mitigation, and technologies' cost and performance. These model are not designed to capture interactions of sectors, but they can provide greater regional, temporal, technological, and process detail about dynamics within a sector that impact technology deployment.
- Both types of models must continuously improve with regard to key technological, market, and policy assumptions and uncertainties.
- Reasons for differences and similarities in model results were not fully resolved in this study.

6.4 Outcomes and Recommendations

This report shows the potential value of GCAM in establishing scenario conditions for sector-specific models and the potential value of sector-specific models in exploring scenario specifics in greater detail. We used fuel prices from GCAM in sector-specific models in their reference scenarios and their GHG mitigation scenarios and compared differences in GCAM versus sectoral models' responses. These comparisons may help identify priority topics for further analysis. In addition, sectoral explorations show opportunities for model improvement. Because clean electricity generation has long been identified as a major GHG reduction strategy, past work has compared estimates of renewable electricity capacity expansion for GCAM and ReEDS. The two modeling approaches that emerged from that work—adding detail to GCAM and using results from one model to inform another—could be considered for other mitigation categories as well. In transportation, many decisions are made at the household level. TEMPO seeks to represent such decisions, for example allowing modeling of changes in usage of different vehicles depending on factors important to households, such as convenience of recharging. Findings about households as agents, once validated, could be used to develop simplified representations for use in integrated assessment models such as GCAM. In buildings, greater segmentation of buildings markets in Scout could pinpoint technology opportunities and challenges. This greater level of detail could similarly support refined adoption functions in integrated assessment models.

We recommend future steps to facilitate input harmonization and output comparison, validate the models relative to empirical data for key parameters and results, and test key findings in multiple models. Overall, this work shows the value of complementary modeling approaches in developing robust conclusions to inform energy technology innovation and deployment to meet GHG mitigation goals. Productive future steps could include further harmonization across models, especially to address the challenge of discrepancies in historical energy use and increase consistency of scenario concepts (e.g., carbon price responsiveness, emissions targets, technology availability, technology standards) across all sectors.

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Appendix. Supplementary Data and Information

This appendix provides supplementary data and information for each of the three sectors—electricity, transportation, and buildings.

Electricity Sector

Table A-1. GCAM Power Sector Technologies

Fuel	Technology
coal	coal (conv pul)
coal	coal (conv pul CCS)
coal	coal (IGCC)
coal	coal (IGCC CCS)
gas	gas (steam/CT)
gas	gas (combined cycle)
gas	gas (combined cycle CCS)
refined liquids	refined liquids (steam/CT)
refined liquids	refined liquids (CC)
refined liquids	refined liquids (combined cycle CCS)
biomass	biomass (conv)
biomass	biomass (conv CCS)
biomass	biomass (IGCC)
biomass	biomass (IGCC CCS)
nuclear	Gen_II_LWR
nuclear	Gen_III
hydro	hydro
wind	wind
wind	wind_storage
solar	PV
solar	PV_storage
solar	CSP
solar	CSP_storage
geothermal	geothermal
rooftop_pv	rooftop_pv
wind	wind_offshore

Table A-2. GCAM-USA Grid Regions

Grid Region	States
Alaska grid	Alaska
California grid	California
Central East grid	Indiana, Kentucky, Michigan, Ohio, West Virginia
Central Northeast grid	Illinois, Missouri, Wisconsin
Central Northwest grid	Iowa, Minnesota, North Dakota, Nebraska, South Dakota
Central Southwest grid	Kansas, Oklahoma
Florida grid	Florida
Hawaii grid	Hawaii
Mid-Atlantic grid	District of Columbia, Delaware, Maryland, New Jersey, Pennsylvania
New England grid	Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont
New York grid	New York
Northwest grid	Idaho, Montana, Nevada, Oregon, Utah, Washington
Southeast grid	Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Caroline, Tennessee, Virginia
Southwest grid	Arizona, Colorado, New Mexico, Wyoming
Texas grid	Texas

Transportation Sector

Direct and Indirect Transportation Sector Emissions

In the main body of this report, we show only direct (tailpipe) transportation sector CO_2 emissions, omitting indirect emissions produced from electricity generation and hydrogen production. Here, we plot both direct and indirect transportation sector emissions for the Reference and 2.6 W/m^2 scenarios.

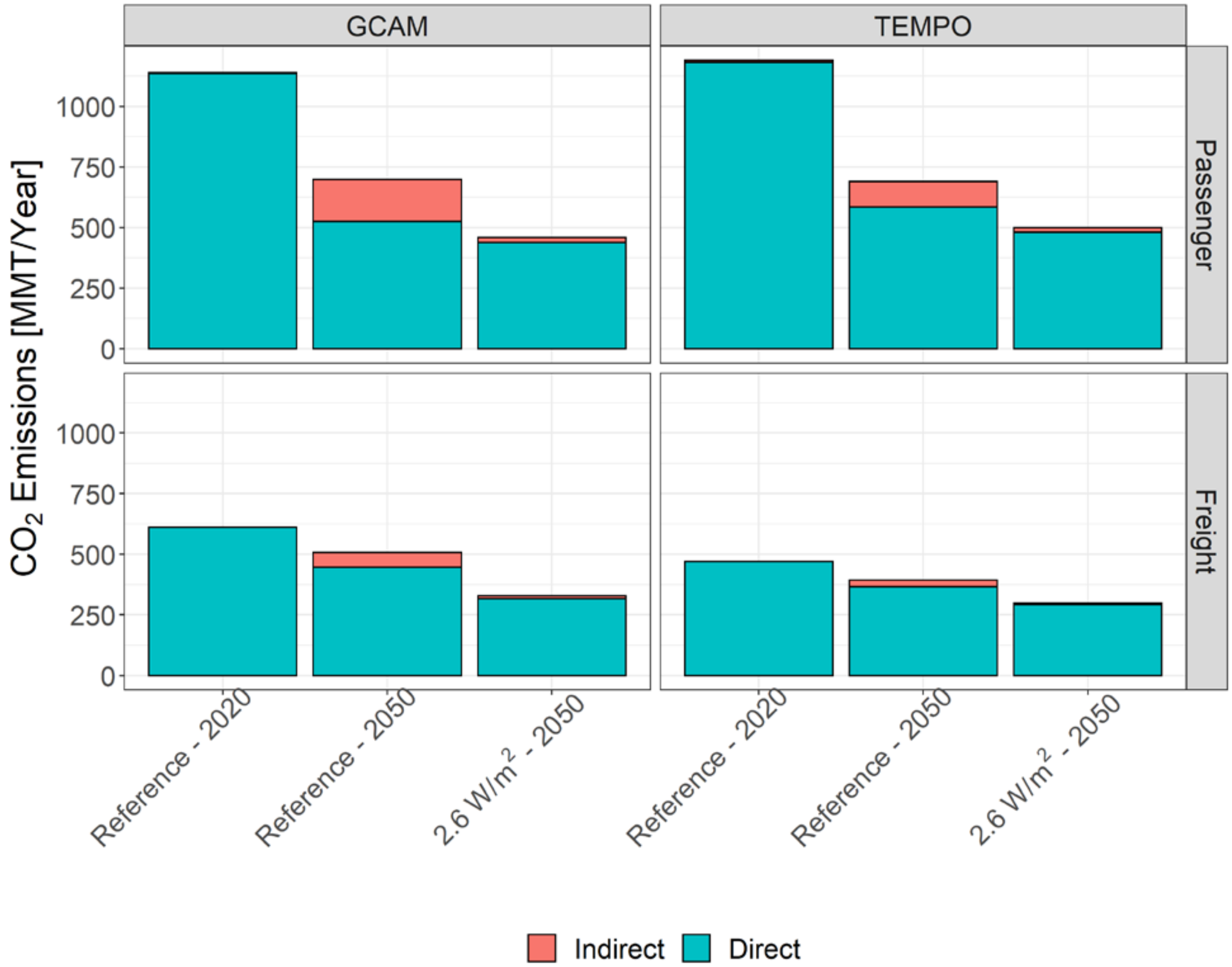

Figure A-1. Direct and indirect transportation sector CO_2 emissions in the Reference and 2.6 W/m^2 scenarios (TEMPO and GCAM)

Other Assumptions

Table A-3. Passenger Occupancy Assumptions (Passengers/Vehicle)

Subsector	TEMPO[1]	GCAM[4]
Passenger Air	109.2	135.2
Bus	23.3	18.4
Passenger Rail	25–35	30–149
LDV	1.2[2]–1.6[3]	1.58–1.65
Motorcycle	1.05	1.1
Passenger Ship	130	N/A

[1]Non-LDV occupancy factors are from the National Transit Database (U.S. Department of Transportation 2019)

[2]Applies to MaaS and LDV fleets

[3]Computed endogenously based on NHTS (FHWA 2018)

[4]Computed from Bureau of Transportation Statistics tables 1-40 and 1-35.

Table A-4. Freight Load Factor Assumptions (Tons/Vehicle)

Subsector	TEMPO[a]	GCAM
Freight Air	37	N/A
Freight Rail	6,996	3,217
Freight Ship	1,437	1,000
Light-Medium Truck	1.2	0.3
Medium Truck	2.4	2.1
Heavy Truck	10.4	4.2

[a] Truck load factors are computed from VIUS (U.S. Census Bureau 2004) and account for deadheading.

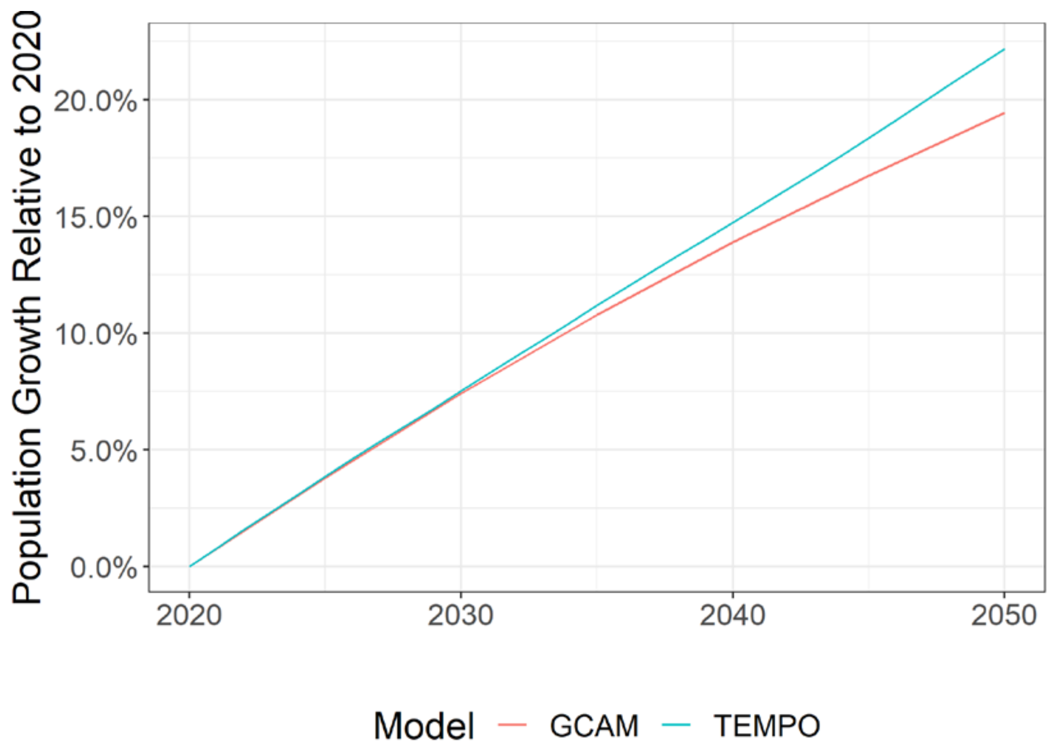

Figure A-2. Exogenous population assumptions (TEMPO and GCAM)

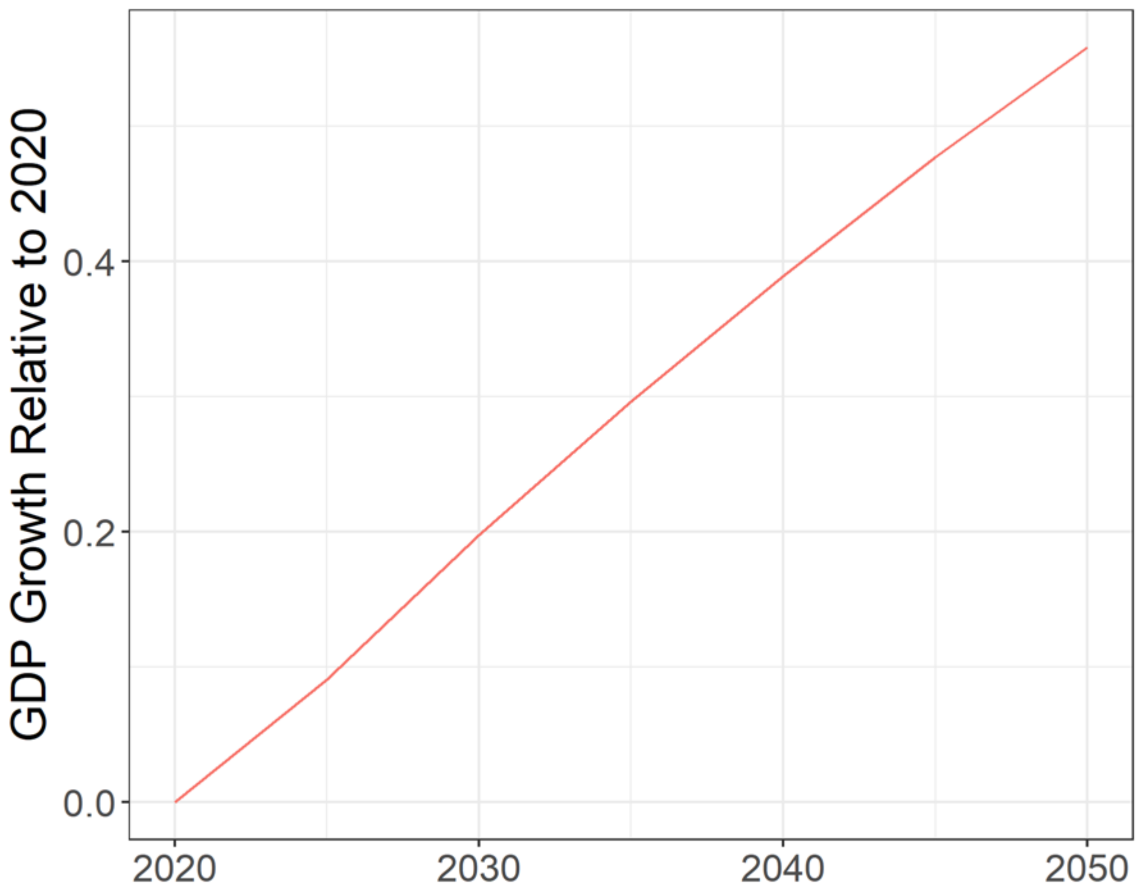

Figure A-3. Exogenous GDP assumptions (GCAM)

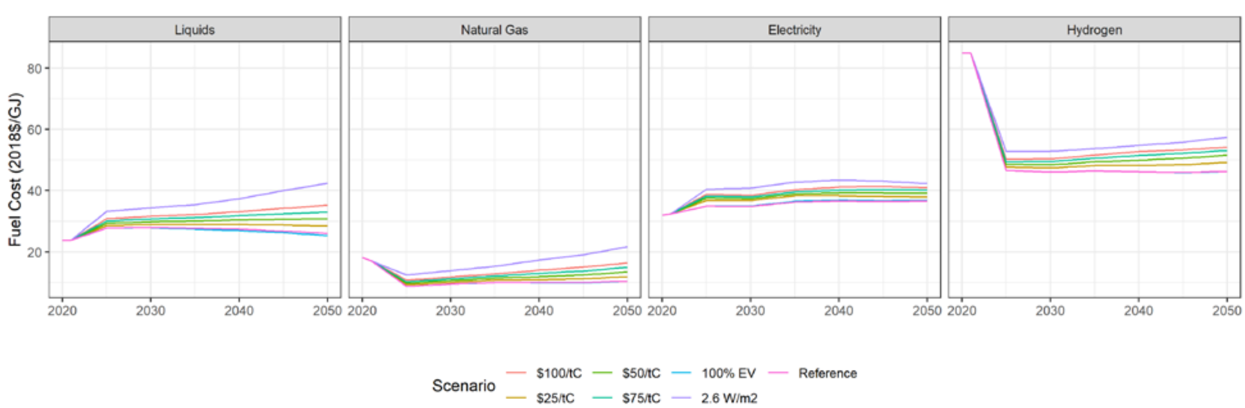

Figure A-4. Fuel cost assumptions

Fuel costs in TEMPO are interpolated from default 2020 values to GCAM values in 2025.

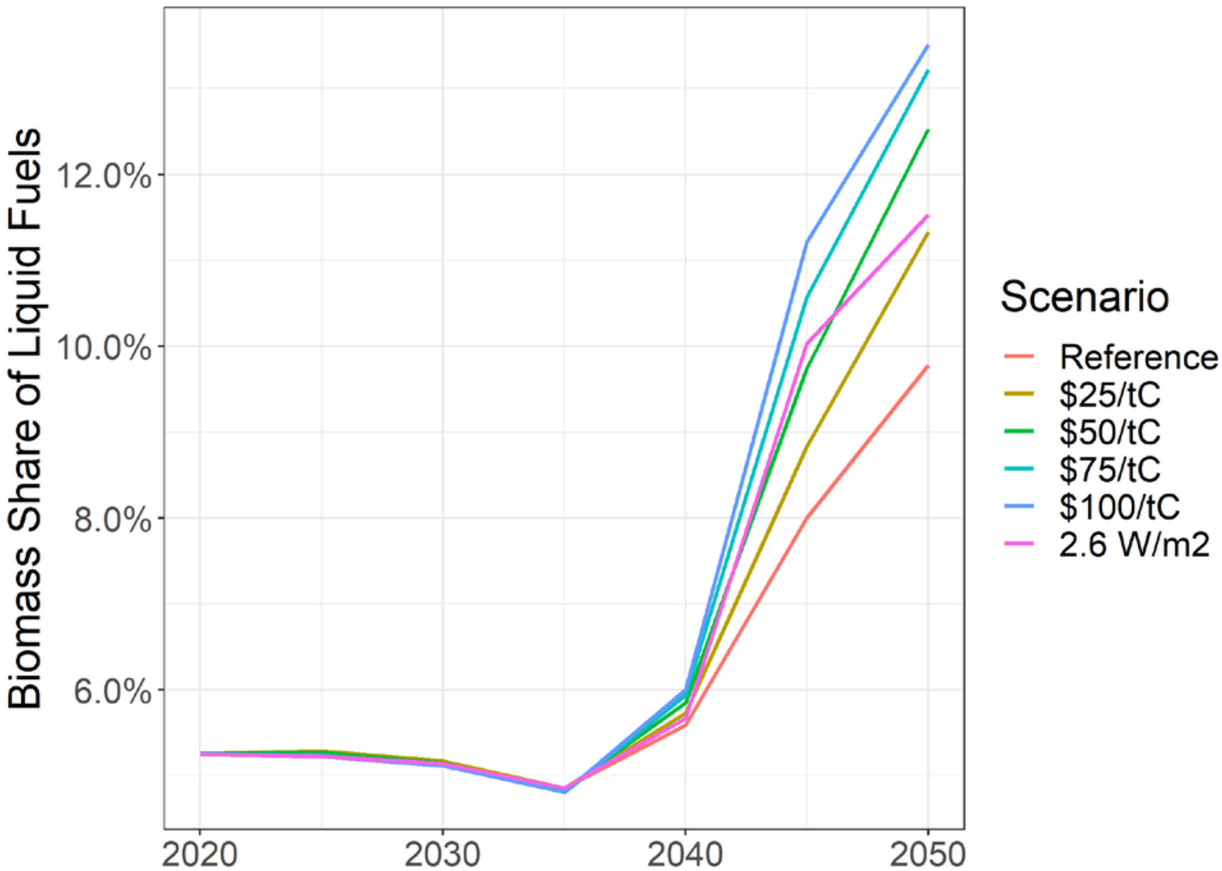

Figure A-5. Biofuel shares by scenario (TEMPO and GCAM)

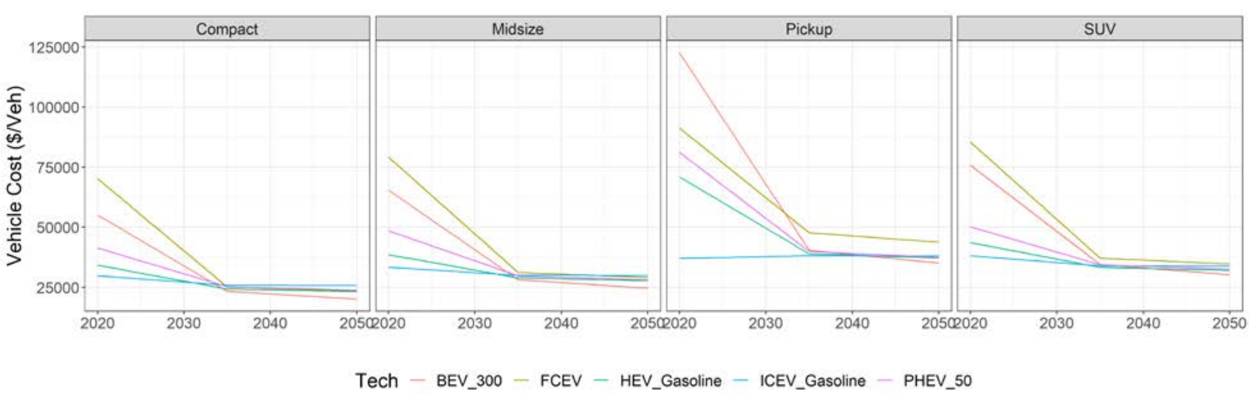

Figure A-6. Technology costs, LDV, processed from vehicle simulations developed by Argonne National Laboratory (Islam et al. Forthcoming)

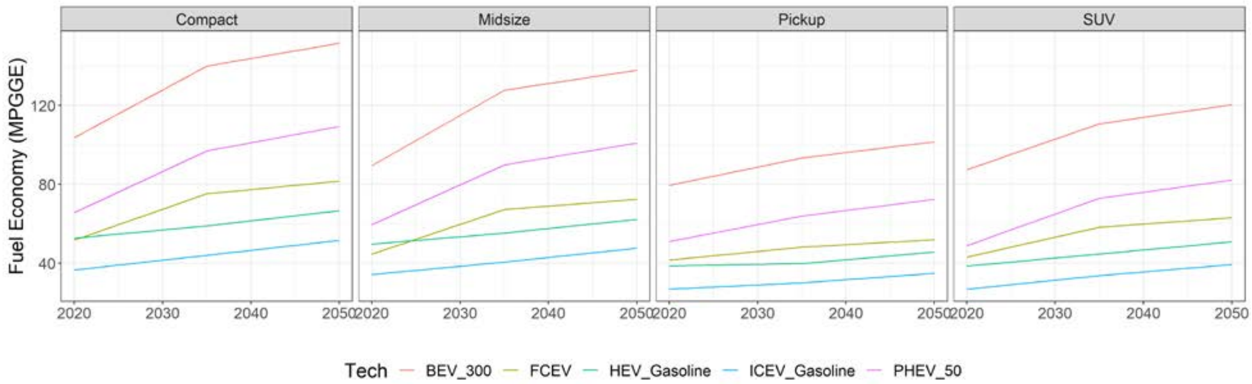

Figure A-7. Fuel economy, LDV, processed from vehicle simulations developed by Argonne National Laboratory (Islam et al. Forthcoming)

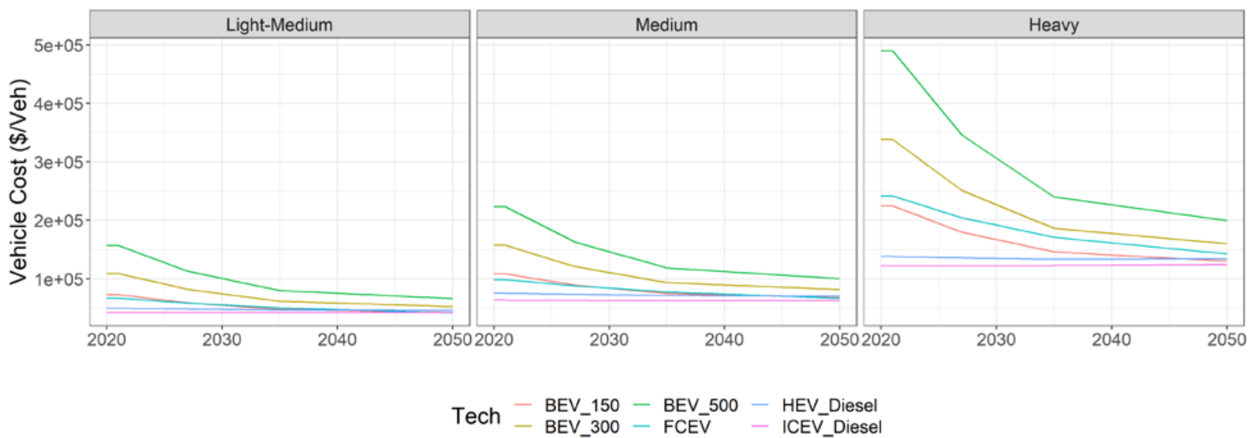

Figure A-8. Technology capital costs, MHDV trucks, processed from vehicle simulations developed by Argonne National Laboratory (Islam et al. Forthcoming)

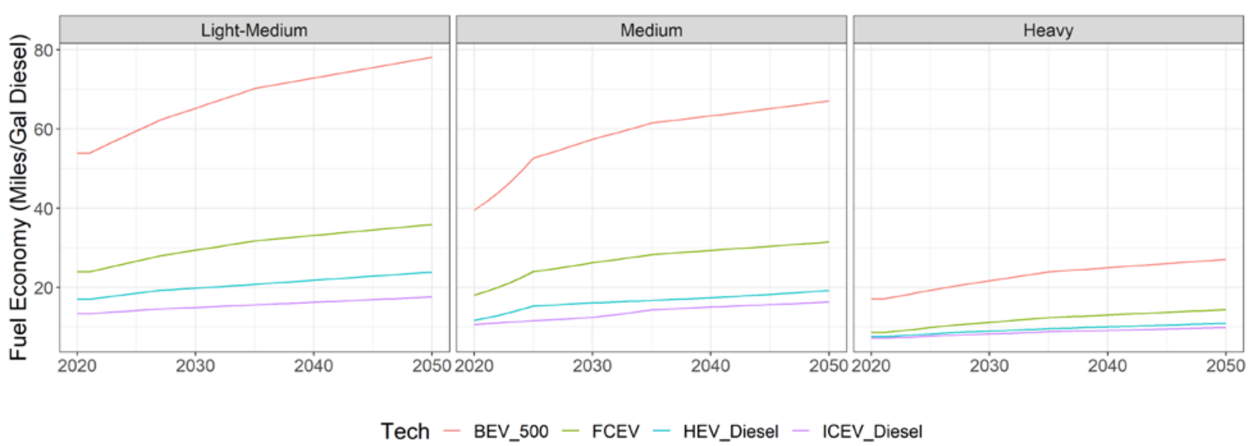

Figure A-9. Fuel economy, MHDV trucks, processed from vehicle simulations developed by Argonne National Laboratory (Islam et al. Forthcoming)

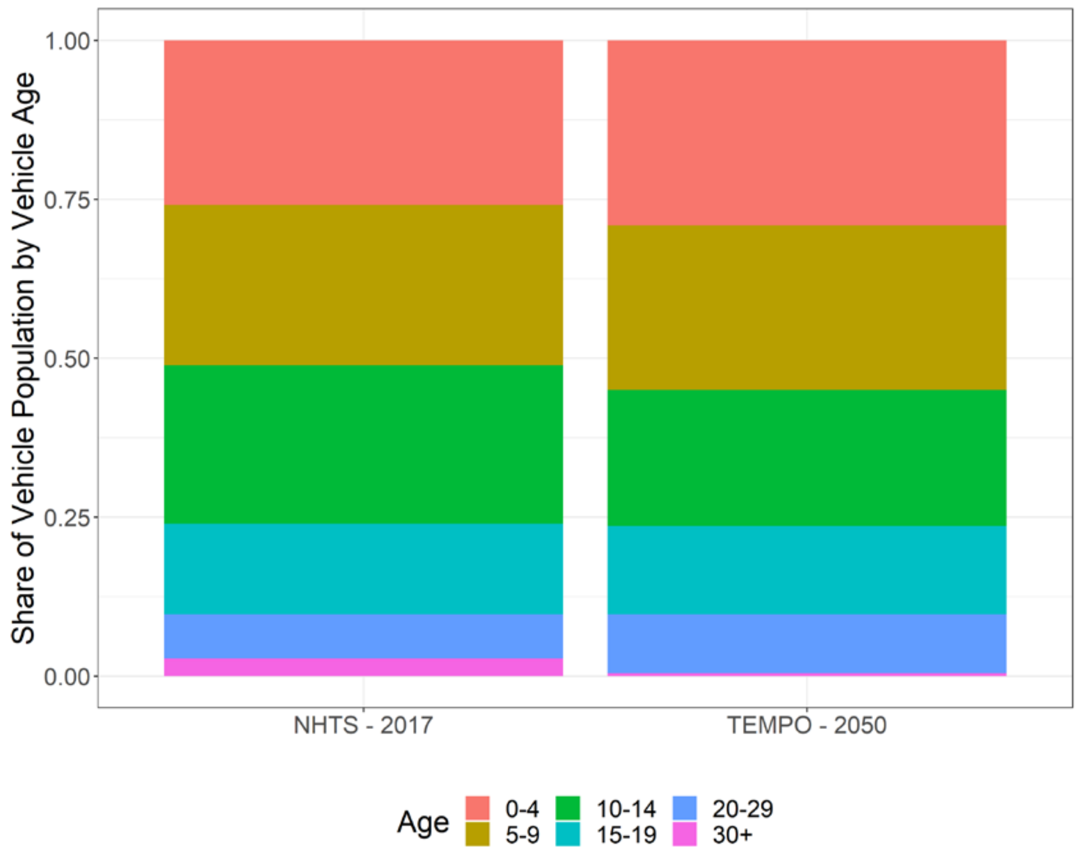

Figure A-10. Vehicle population by age, TEMPO and NHTS (Federal Highway Administration 2018)

Buildings Sector

Table A-5. Mapping of GCAM-USA and Scout Technologies

Building Type	End Use	Fuel	GCAM-USA Technology	Mapped Scout Technology—noEEE	Mapped Scout Technology–MarketEEE
commercial	cooking	electricity	electric range	electric_range_oven_24x24_griddle	electric_range_oven_24x24_griddle
commercial	cooking	electricity	electric range hi-eff	electric_range_oven_24x24_griddle	electric_range_oven_24x24_griddle
commercial	cooking	gas	gas range	gas_range_oven_24x24_griddle	gas_range_oven_24x24_griddle
commercial	cooking	gas	gas range hi-eff	gas_range_oven_24x24_griddle	gas_range_oven_24x24_griddle
commercial	cooling	electricity	air conditioning	rooftop_AC	rooftop_AC
commercial	cooling	electricity	air conditioning hi-eff	ENERGY STAR Com. ASHP (LFL)	Prospective Commercial ASHP (LFL)_cooling
commercial	cooling	gas	gas cooling	gas_chiller	gas_chiller
commercial	heating	electricity	electric furnace	electric_res-heat	electric_res-heat
commercial	heating	electricity	electric heat pump	ENERGY STAR Com. ASHP (LFL)	Prospective Commercial ASHP (LFL)_heating
commercial	heating	gas	gas furnace	gas_furnace	gas_furnace
commercial	heating	gas	gas furnace hi-eff	gas_furnace	gas_furnace
commercial	heating	refined liquids	fuel furnace	oil_furnace	oil_furnace
commercial	water heating	electricity	electric heat pump water heater	HP water heater	Prospective Commercial HPWH
commercial	water heating	electricity	electric resistance water heater	elec_water_heater	elec_water_heater
commercial	water heating	gas	gas water heater	gas_water_heater	gas_water_heater
commercial	water heating	gas	gas water heater hi-eff	ENERGY STAR Commercial Gas WH v. 2.0	ENERGY STAR Commercial Gas WH v. 2.0
commercial	water heating	refined liquids	fuel water heater	oil_water_heater	oil_water_heater
commercial	lighting	electricity	fluorescent	T8 F28	T8 F28
commercial	lighting	electricity	incandescent	100 W equivalent CFL Bare Spiral	100 W Equivalent CFL Bare Spiral
commercial	lighting	electricity	solid state	LED Integrated Luminaire	LED Integrated Luminaire
commercial	office	electricity	office equipment	PCs	PCs

Building Type	End Use	Fuel	GCAM-USA Technology	Mapped Scout Technology—noEEE	Mapped Scout Technology–MarketEEE
commercial	refrigeration	electricity	refrigeration	Commercial Supermarket Display Cases	Commercial Supermarket Display Cases
commercial	refrigeration	electricity	refrigeration hi-eff	Commercial Supermarket Display Cases	Prospective Commercial Refrigeration
commercial	ventilation	electricity	ventilation	CAV_Vent	CAV_Vent
commercial	ventilation	electricity	ventilation hi-eff	VAV_Vent	VAV_Vent
residential	clothes dryers	electricity	clothes dryer	drying	drying
residential	clothes dryers	electricity	clothes dryer hi-eff	ENERGY STAR Electric Dryers	Prospective Residential Dryer
residential	clothes dryers	gas	clothes dryer	drying	drying
residential	clothes washers	electricity	clothes washer	clothes washing	clothes washing
residential	clothes washers	electricity	clothes washer hi-eff	clothes washing	clothes washing
residential	computers	electricity	electricity	desktop PC	desktop PC
residential	cooking	electricity	electric oven	cooking	cooking
residential	cooking	gas	gas oven	cooking	cooking
residential	cooking	gas	gas oven hi-eff	cooking	cooking
residential	cooling	electricity	air conditioning	central AC	central AC
residential	cooling	electricity	air conditioning hi-eff	ENERGY STAR Res. ASHP (LFL)_cooling	Prospective Residential ASHP (LFL)_cooling
residential	dishwashers	electricity	dishwasher	dishwasher	dishwasher
residential	dishwashers	electricity	dishwasher hi-eff	dishwasher	dishwasher
residential	freezers	electricity	freezer	freezers	freezers
residential	freezers	electricity	freezer hi-eff	freezers	freezers
residential	furnace fans	electricity	electricity	fans and pumps	fans and pumps
residential	heating	biomass	wood furnace	stove (wood)	stove (wood)
residential	heating	electricity	electric furnace	resistance heat	resistance heat
residential	heating	electricity	electric heat pump	ENERGY STAR Res. ASHP (LFL)_heating	Prospective Residential ASHP (LFL)_heating
residential	heating	gas	gas furnace	furnace (NG)	furnace (NG)

Building Type	End Use	Fuel	GCAM-USA Technology	Mapped Scout Technology—noEEE	Mapped Scout Technology–MarketEEE
residential	heating	gas	gas furnace hi-eff	Res. Fossil Heating, ESTAR_furnace (NG)	Res. Fossil Heating, ESTAR_furnace (NG)
residential	heating	refined liquids	fuel furnace	furnace (distillate)	furnace (distillate)
residential	heating	refined liquids	fuel furnace hi-eff	Res. Fossil Heating, ESTAR_furnace (distillate)	Res. Fossil Heating, ESTAR_furnace (distillate)
residential	water heating	electricity	electric heat pump water heater	ENERGY STAR Res. HPWH	Prospective Residential HPWH
residential	water heating	electricity	electric resistance water heater	electric WH	electric WH
residential	water heating	electricity	electric resistance water heater hi-eff	ENERGY STAR Res. HPWH	Prospective Residential HPWH
residential	water heating	gas	gas water heater	water heating	water heating
residential	water heating	gas	gas water heater hi-eff	ENERGY STAR Gas Storage WH v. 4.0	ENERGY STAR Gas Storage WH v. 4.0
residential	water heating	refined liquids	fuel water heater	water heating	water heating
residential	water heating	refined liquids	fuel water heater hi-eff	water heating	water heating
residential	lighting	electricity	fluorescent	general service (CFL)	general service (CFL)
residential	lighting	electricity	incandescent	general service (incandescent)	general service (incandescent)
residential	lighting	electricity	solid state	general service (LED)	general service (LED)
residential	other	electricity	electricity	ceiling fan	ceiling fan
residential	refrigerators	electricity	refrigerator	refrigeration	refrigeration
residential	refrigerators	electricity	refrigerator hi-eff	ENERGY STAR Refrigerator	Prospective Residential Refrigeration
residential	televisions	electricity	electricity	TV	TV

Table A-6. Costs and Efficiencies for Select Heating and Hot Water Technologies

Building Type	End Use	Fuel	Technology	Year	Cost - Ref	Cost - EEE	Efficiency - Ref	Efficiency - EEE
Commercial	heating	electricity	electric furnace	2020	2.589	2.589	1	1
Commercial	heating	electricity	electric furnace	2035	2.589	2.589	1	1

Building Type	End Use	Fuel	Technology	Year	Cost - Ref	Cost - EEE	Efficiency - Ref	Efficiency - EEE
Commercial	heating	electricity	electric furnace	2050	2.589	2.589	1	1
Commercial	heating	electricity	electric heat pump	2020	10.354	10.354	3.4	3.4
Commercial	heating	electricity	electric heat pump	2035	10.354	3.958	3.4	6
Commercial	heating	electricity	electric heat pump	2050	10.354	3.958	3.4	6
Commercial	heating	gas	gas furnace hi-eff	2020	1.235	1.235	0.794	0.794
Commercial	heating	gas	gas furnace hi-eff	2035	1.244	1.244	0.803	0.803
Commercial	heating	gas	gas furnace hi-eff	2050	1.247	1.247	0.805	0.805
Commercial	hot water	electricity	electric heat pump water heater	2020	12.163	12.163	3.9	3.9
Commercial	hot water	electricity	electric heat pump water heater	2035	12.163	1.653	3.9	3.9
Commercial	hot water	electricity	electric heat pump water heater	2050	12.163	1.653	3.9	3.9
Commercial	hot water	electricity	electric resistance water heater	2020	2.695	2.695	0.97	0.97
Commercial	hot water	electricity	electric resistance water heater	2035	2.695	2.695	0.97	0.97
Commercial	hot water	electricity	electric resistance water heater	2050	2.695	2.695	0.97	0.97
Commercial	hot water	gas	gas water heater hi-eff	2020	1.272	1.272	0.94	0.94
Commercial	hot water	gas	gas water heater hi-eff	2035	1.296	1.276	0.992	0.949
Commercial	hot water	gas	gas water heater hi-eff	2050	1.301	1.281	1.003	0.96
Residential	heating	electricity	electric furnace	2020	1.176	1.176	0.98	0.98
Residential	heating	electricity	electric furnace	2035	1.176	1.176	0.98	0.98
Residential	heating	electricity	electric furnace	2050	1.176	1.176	0.98	0.98
Residential	heating	electricity	electric heat pump	2020	6.524	6.524	2.7	2.7
Residential	heating	electricity	electric heat pump	2035	6.524	5.904	2.7	6
Residential	heating	electricity	electric heat pump	2050	6.524	5.904	2.7	6
Residential	heating	gas	gas furnace hi-eff	2020	2.853	2.853	0.93	0.93
Residential	heating	gas	gas furnace hi-eff	2035	2.853	2.853	0.93	0.93
Residential	heating	gas	gas furnace hi-eff	2050	2.853	2.853	0.93	0.93
Residential	hot water	electricity	electric heat pump water heater	2020	16.675	16.675	3.3	3.3
Residential	hot water	electricity	electric heat pump water heater	2035	16.675	18.212	3.3	3.55
Residential	hot water	electricity	electric heat pump water heater	2050	16.675	18.212	3.3	3.55

Building Type	End Use	Fuel	Technology	Year	Cost - Ref	Cost - EEE	Efficiency - Ref	Efficiency - EEE
Residential	hot water	electricity	electric resistance water heater	2020	6.831	6.831	0.93	0.93
Residential	hot water	electricity	electric resistance water heater	2035	6.831	6.831	0.93	0.93
Residential	hot water	electricity	electric resistance water heater	2050	6.831	6.831	0.93	0.93
Residential	hot water	electricity	electric resistance water heater hi-eff	2020	16.675	16.675	3.3	3.3
Residential	hot water	electricity	electric resistance water heater hi-eff	2035	16.675	18.212	3.3	3.55
Residential	hot water	electricity	electric resistance water heater hi-eff	2050	16.675	18.212	3.3	3.55
Residential	hot water	gas	gas water heater hi-eff	2020	17.969	17.969	0.68	0.68
Residential	hot water	gas	gas water heater hi-eff	2035	17.969	17.969	0.68	0.68
Residential	hot water	gas	gas water heater hi-eff	2050	17.969	17.969	0.68	0.68

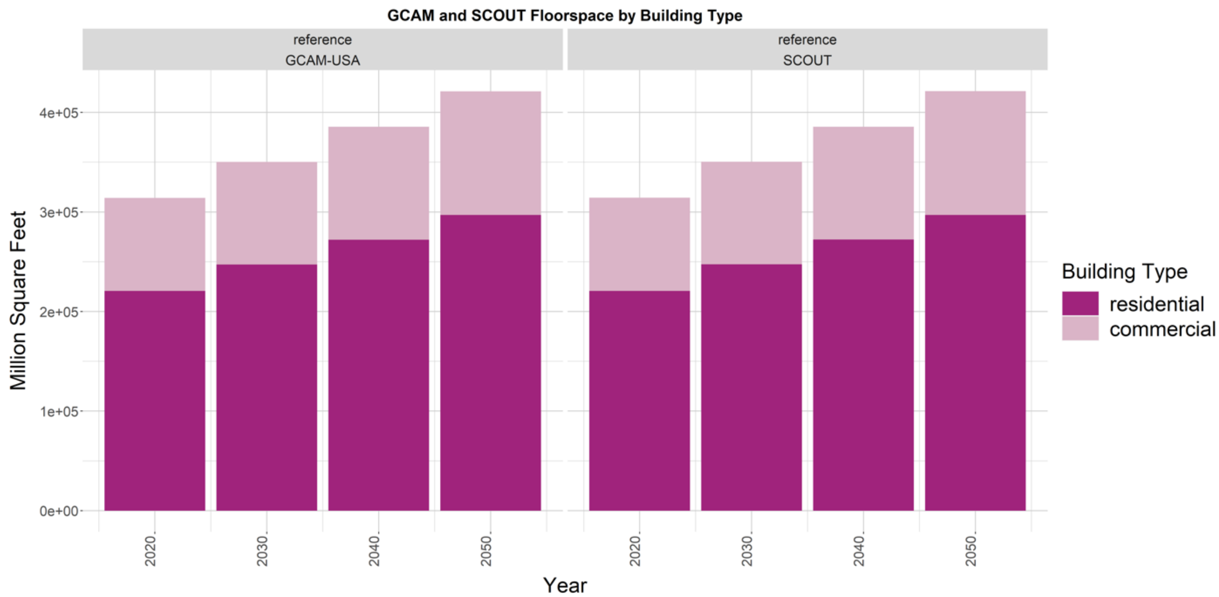

Figure A-11. Building floorspace by model and building type

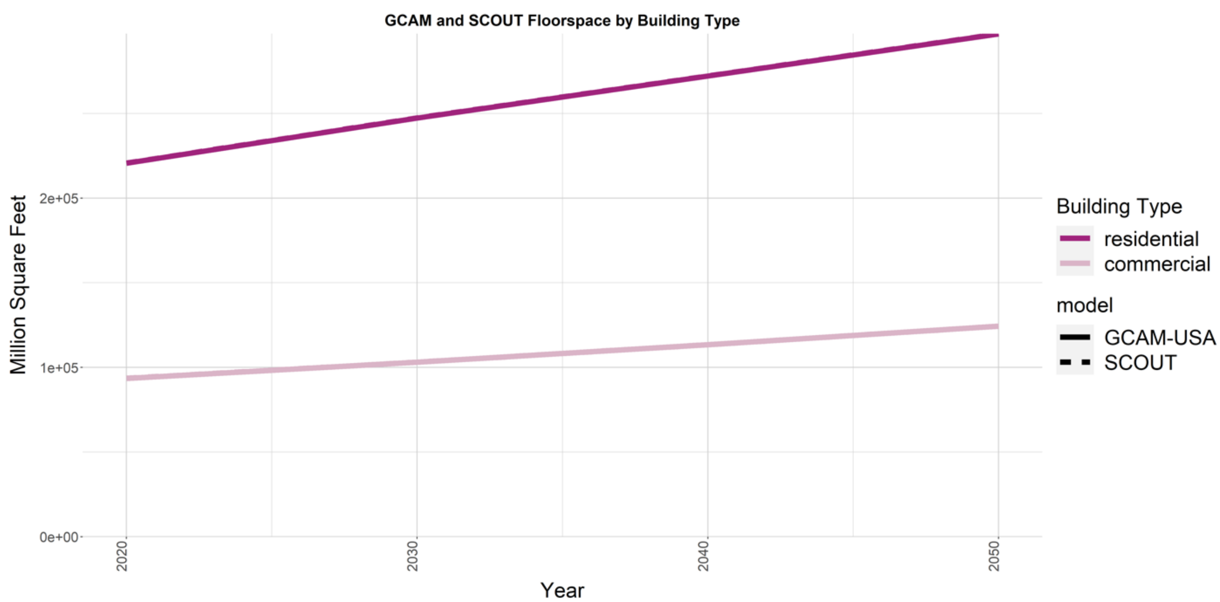

Figure A-12. Building floorspace by model and building type

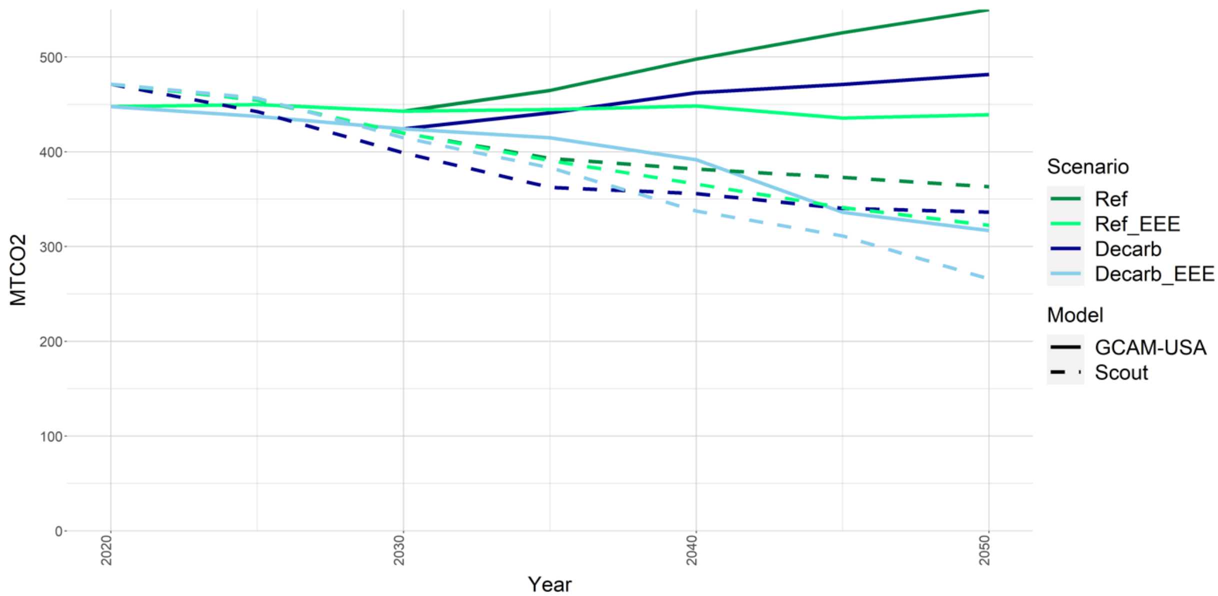

Figure A-13. Building sector CO_2 emissions by model and scenario, including only direct emissions from fuel combustion in buildings.

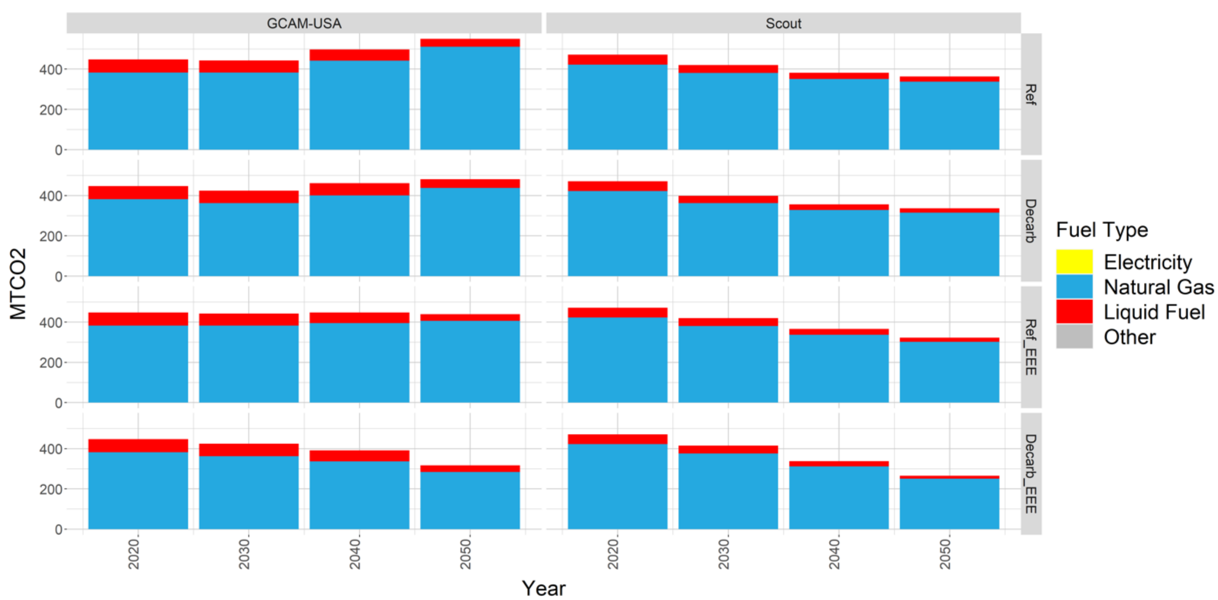

Figure A-14. Building sector CO_2 emissions by fuel, model, and scenario, including only direct emissions from fuel combustion in buildings

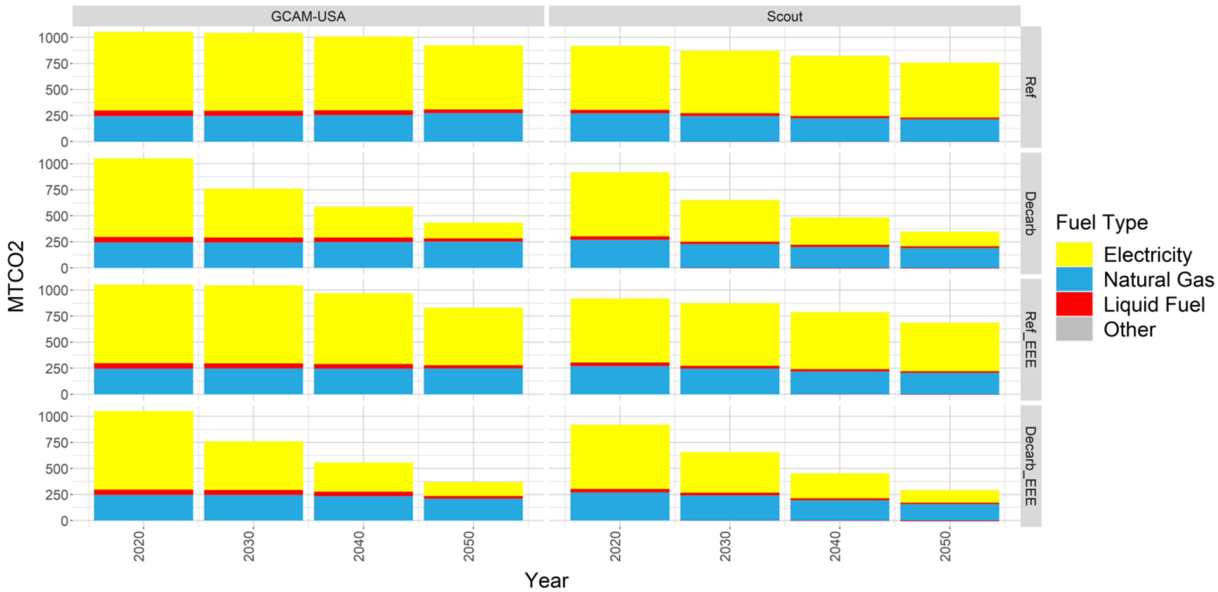

Figure A-15. Residential building CO_2 emissions by fuel, model, and scenario

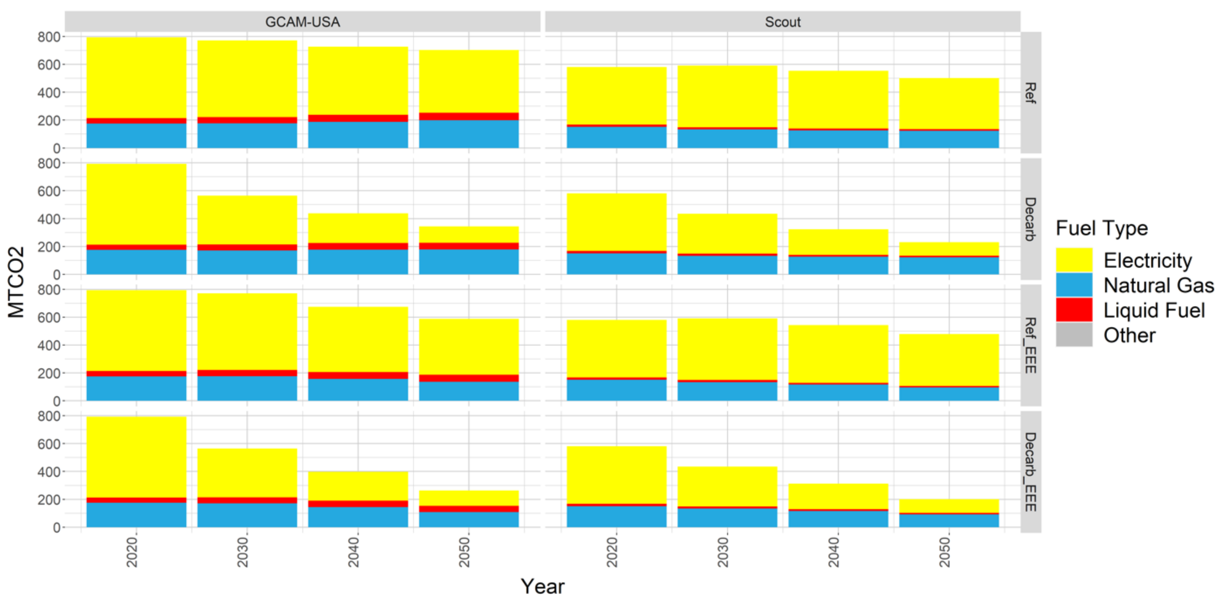

Figure A-16. Commercial building CO_2 emissions by fuel, model, and scenario