Large ensemble exploration of global energy transitions under national emissions pledges

Jacob Wessel[a,*], Gokul Iyer[b,d], Jonathan Lamontagne[a], Thomas Wild[b,c,d], Yang Ou[e,f], and Haewon McJeon[g]

[a] Department of Civil and Environmental Engineering, Tufts University, Medford, MA 02155, United States
[b] Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, MD 20740, United States
[c] Department of Civil and Environmental Engineering, University of Maryland, College Park, MD 20740, United States
[d] Center for Global Sustainability, School of Public Policy, University of Maryland, College Park, MD 20740, United States
[e] College of Environmental Sciences and Engineering, Peking University, Beijing 100871, China
[f] Institute of Carbon Neutrality, Peking University, Beijing 100871, China
[g] Graduate School of Green Growth & Sustainability, Korea Advanced Institute of Science and Technology, Daejeon 34141, Korea

Key Points:

- Energy transition costs, as measured by multiple metrics, can be unevenly distributed across a wide range of future states of the world
- Regional investment risk has global implications for mitigation pathways
- The relative role of different carbon dioxide removal options in meeting decarbonization goals varies across regions

Abstract: Global climate goals require a transition to a deeply decarbonized energy system. Meeting the objectives of the Paris Agreement through countries' Nationally Determined Contributions and Long-Term Strategies represents a complex problem with consequences across multiple systems shrouded by deep uncertainty. Robust, large-ensemble methods and analyses mapping a wide range of possible future states of the world are needed to help policymakers design effective strategies to meet emissions reduction goals. This study contributes a scenario discovery analysis applied to a large ensemble of 5,760 model realizations generated using the Global Change Analysis Model. Eleven energy-related uncertainties are systematically varied, representing national mitigation pledges, institutional factors, and techno-economic parameters, among others. The resulting ensemble maps how uncertainties impact common energy system metrics used to characterize national and global pathways toward deep decarbonization. Results show globally consistent but regionally variable energy transitions as measured by multiple metrics, including electricity costs and stranded assets. Larger economies and developing regions experience more severe economic outcomes across a broad sampling of uncertainty. The scale of CO_2 removal globally determines how much the energy system can continue to emit, but the relative role of different CO_2 removal options in meeting decarbonization goals varies across regions. Previous studies characterizing uncertainty have typically focused on a few scenarios, and other large-ensemble work has not (to our knowledge) combined this framework with national emissions pledges or institutional factors. Our results underscore the value of large-ensemble scenario discovery for decision support as countries begin to design strategies to meet their goals.

Keywords: multi-sector modeling, energy transition, scenario discovery, Nationally Determined Contributions, Paris Agreement, uncertainty analysis

1. Introduction

Global climate policy is taking shape across multiple scales and using a variety of strategies to address diverse sets of objectives. Most notably, the Paris Agreement has been at the forefront of international cooperation and accountability in limiting global warming from anthropogenic climate change (United Nations, 2015). Under this multilateral agreement, countries periodically submit and update Nationally Determined Contributions (NDCs) to articulate intended action plans. Though unique to each country, NDCs typically lay out shorter-term emissions reduction goals (e.g., by 2030) (UNFCCC, 2022a). In addition to NDCs, countries have also communicated long-term strategies (LTS), many of which contain net-zero targets (usually for 2050), to help inform and align near-term activities (UNFCCC, 2022b). In order to meet the goals set forth by the Paris Agreement, a major global transition to a deeply decarbonized energy system is underway (UNFCCC, 2023).

The global energy system is the largest contributor to CO_2 emissions (>90%), through sectors including electricity generation, transportation, industry, and buildings (IEA, 2021). Therefore, decarbonization pathways must consider abatement strategies across the full landscape of energy-related emissions. However, there are many technological, financial, and policy tools available to help shape future pathways, as well as exogenous forces driving potential outcomes (Riahi, 2022). There is significant future uncertainty associated with the evolution of energy systems coming from many sources, such as socioeconomics, technology, institutions, demand patterns, and climate feedbacks, to name a few (Fodstad et al., 2022; Yue et al., 2018). These issues represent deep uncertainties with unknown functional forms which cannot be well-characterized by a probability distribution, and dynamically evolve across sectors with complex and potentially wide-reaching consequences (Srikrishnan et al., 2022; Workman et al., 2021).

As countries begin to implement emissions reduction pledges outlined in their NDCs, deep uncertainties (Walker et al., 2013) associated with the energy transition will emerge and impose challenges on decisionmakers in designing strategies to meet emissions goals (Paredes-Vergara et al., 2024). For decision makers, it is important to gain an understanding of a very wide range of plausible outcomes and characterize their associated pathways, in order to provide informed guidance on the most critical drivers as well as potential tradeoffs and synergies arising from different combinations of uncertain factors. In the context of a global energy transition driven by national decarbonization commitments, mapping and exploring a broad outcome space can help identify key challenges and opportunities, and how they may be distributed across regions, under a robust set of circumstances.

Previous research in this space has typically focused on a select few plausible futures to explore, which limits the range and diversity of outcomes (Fawcett et al., 2015; Iyer et al., 2015b; Kriegler et al., 2018; Ou et al., 2021). Other work has examined structural differences across multiple models, but with limited sampling of uncertainty (Arango-Aramburo et al., 2019; Browning et al., 2023; Burleyson et al., 2020; Kober et al., 2016; Lucena et al., 2016; McFarland et al., 2015; Pietzcker et al., 2017; van de Ven et al., 2023; Van Der Zwaan et al., 2016; Wilkerson et al., 2015). While there are existing large ensemble studies to draw from (Groves et al., 2020; Huppmann et al., 2018; McJeon et al., 2011), there remains a dearth of research contributing a systematic exploration of a wide range of uncertainties using large-ensemble simulations to characterize NDC- and LTS-consistent energy transitions. Refer to the supplementary information for further discussion on current literature. The present study addresses this gap by applying scenario discovery to the Global Change Analysis Model (GCAM) (Bond-Lamberty et al., 2022) to explore how future uncertainties in the energy system drive global and national pathways toward deep decarbonization under Paris Agreement emissions pledges. In doing so, our study characterizes global and regional outcomes across a broad uncertainty space and identifies decision-relevant drivers and tradeoffs to assist planners in designing robust strategies to meet their long-term decarbonization goals.

Our large ensemble of model realizations is generated using GCAM (Calvin et al., 2019), described briefly in Section 3.1. Eleven categories of energy-related sensitivities and a suite of output metrics, illustrated in Figure 1, are systematically varied within the model configuration. These scenario factors represent national mitigation pledges, institutional factors, and techno-economic parameters, and are described in more detail in Section 3.2, followed by a description of the scenario discovery framework. Results are presented for ten aggregated global regions, constructed from GCAM's 32 geopolitical regions. Section 4 characterizes the impacts of the uncertainty space on outcomes of interest such as electricity price, stranded assets, and negative emissions, to identify drivers of global and regional pathways toward deep decarbonization under national emissions pledges. The paper concludes with a discussion of results and implications for robust mitigation policy, highlighting the value of large-ensemble scenario discovery frameworks for countries beginning to design strategies to meet their goals.

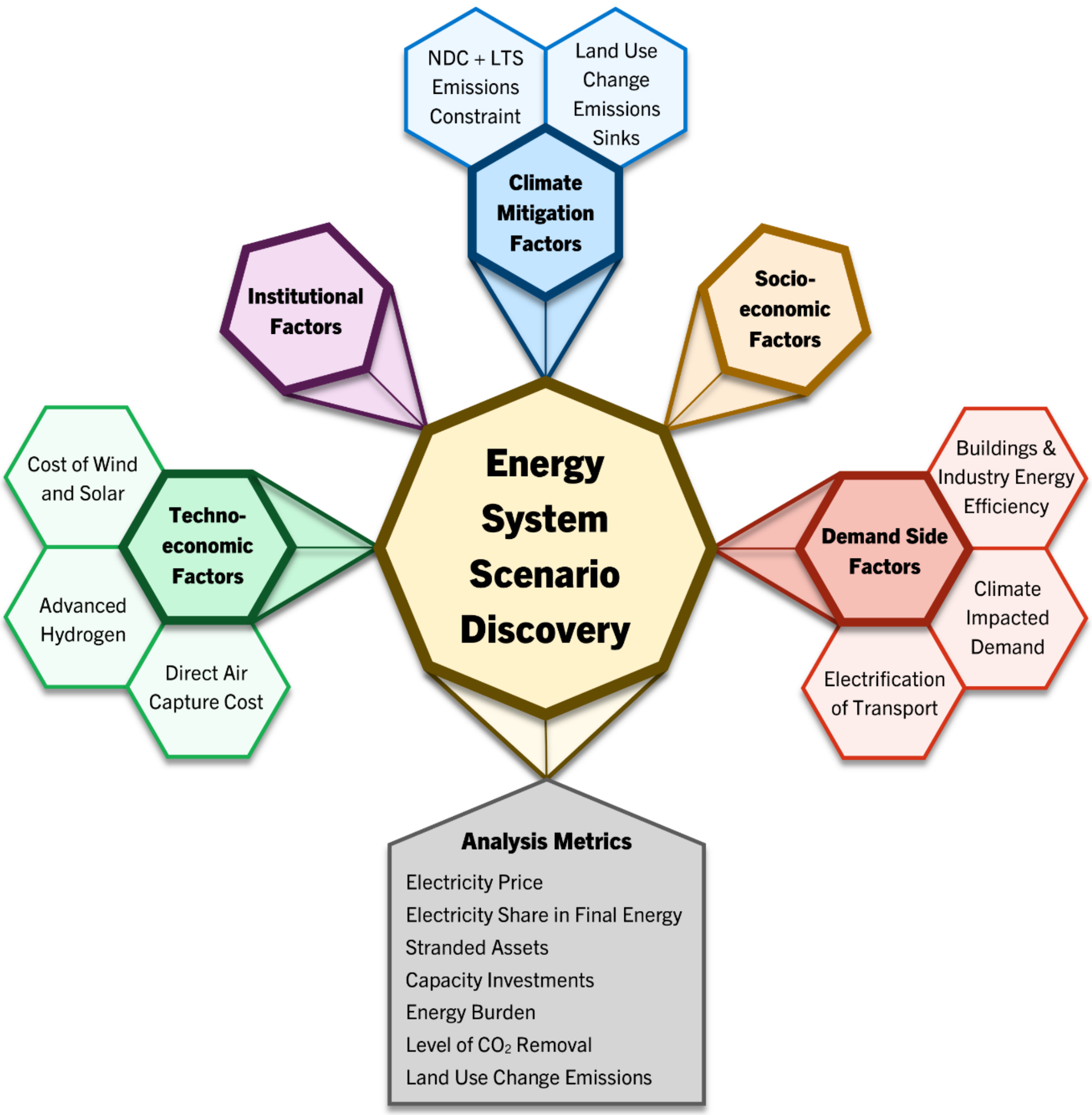

Figure 1: Categories of sensitivities varied in the ensemble and analysis metrics used.

2. Background

Some level of uncertainty will generally accompany any model used to aid planning decisions, inform policy, or otherwise convey insight about the systems and processes it represents (Beven, 2018). Over the last century, uncertainty has been described by several hierarchies and classifications using a variety of methods (Walker et al., 2003). A common dichotomy applied to uncertainty is to categorize it as epistemic (reducible through, e.g., more data or improved knowledge of the truth) or aleatory (irreducible due to inherent randomness) (Kiureghian and Ditlevsen, 2009). In simulation and optimization modeling, uncertainty can also be categorized as parametric (uncertainty in model parameters' true values), structural (uncertainty in the mathematical abstractions of real-world processes), and sampling (coverage from sampling a random variable, i.e., aleatory uncertainty) (Srikrishnan et al., 2022).

The severity of a given uncertainty can range from well-characterized (a single probability distribution and a single objective) to a state of deep uncertainty, in which the likelihood of different scenarios is completely unknown or cannot be agreed upon (Lempert et al., 2003). The concept of deep uncertainty can be traced through the 20th century from Knightian uncertainty (Knight, 1921) and the inability to quantify outcomes or human decisions using probability distributions, through "wicked problems" (Rittel and Webber, 1973) and the possibility of fundamental disagreements on objectives, problem formulations, and model functional forms. Well-characterized uncertainty can be mitigated in modeling through a variety of methods, such as sensitivity analysis for parametric uncertainty (Pianosi et al., 2016), comparing across multiple models to address structural uncertainty (Marangoni et al., 2017; van de Ven et al., 2023), and Monte Carlo analysis for sampling uncertainty of a stochastic process (New and Hulme, 2000). However, deep uncertainty in inherently interconnected and complex systems may be more difficult or even impossible to assess using these standard methods. Further, the lack of probabilistic data and tools available to deeply uncertain systems can shift the research goals from predicting system behavior to analyzing sets of "what-if" scenarios. This philosophy is central to exploratory modeling (Bankes, 1993).

Exploratory modeling is a generalized approach developed to study systems dealing with deep uncertainty (Bankes, 1993; Lempert, 2002). Whereas the traditional view of a model as a probabilistic predictive tool may be concerned with uncertainty *quantification*, an exploratory modeling framework primarily involves uncertainty *characterization*, which instead aims to describe and characterize the influential factors driving a model's outcome space through systematic computational experimentation (Kwakkel and Pruyt, 2013). By assessing many plausible alternatives with the goal of decision support, exploratory modeling can help identify vulnerabilities as well as robust solutions when significant deep uncertainty prevents probabilistic analysis (Kasprzyk et al., 2013; Lempert, 2019).

Communicating insights from large ensembles of model realizations is often done using scenarios which, in this context, refer to small numbers of narrative storylines describing sets of conditions, trends, pathways, and vulnerabilities packaged in interpretable and decision-relevant clusters (Garb et al., 2008). Scenarios enable discussion about future states of the world without relying on probabilistic forecasts (Lempert, 2013). Scenario analysis exists broadly across domains, but is particularly useful in climate and human-earth systems modeling (for a review, see EEA, 2009). Distilling information from many (dozens to millions) modeled futures into a handful of digestible scenarios can be done with techniques such as scenario discovery, a model-agnostic approach to developing scenario narratives in complex systems (Lempert et al., 2006; Groves and Lempert, 2007). Scenario discovery can refer to any methodology aimed at identifying areas of interest within the outcome space of a model via a systematic exploration of deep uncertainties, with the ultimate goal of connecting critical drivers (model parameters and structural forms, exogenous uncertainties, policy levers) to outcome metrics and narrative storylines to inform decision-making (Lempert et al., 2008; Bryant and Lempert, 2010; Lempert et al., 2003). This approach is used widely in human-earth systems modeling (McJeon et al., 2011; Kwakkel et al., 2013; Shortridge and Guikema, 2016; Lamontagne et al., 2018; Moksnes et al., 2019; Dolan et al., 2022; Birnbaum et al., 2022; Morris et al., 2022; Guivarch et al., 2022; Woodard et al., 2023) using a variety of statistical, machine learning, and data mining techniques (Lempert et al., 2008; Kwakkel and Jaxa-Rozen, 2016; Kwakkel and Cunningham, 2016; Jafino and Kwakkel, 2021; Steinmann et al., 2020). In this study, we apply scenario discovery to

GCAM, an actively developed and widely used multisector model for large ensemble analyses; refer to Section 3.1 for more details.

3. Methods

3.1. Global Change Analysis Model (GCAM)

GCAM is a global model with detailed process representations of and interactions across five systems: energy, water, agricultural and land use, water, and economy. The model runs in five-year time steps starting from 2015 (the calibration year) out to 2100. This study adapts GCAM v6 (Bond-Lamberty et al., 2022) with assumptions used in the creation of GCAM-LAC (Khan et al., 2020), which breaks out Uruguay as a standalone region. While a detailed description of the GCAM model is available [here], the description below provides a summary of the energy system which is most relevant to this study.

GCAM solves each modeling period through market equilibrium, linking the five integrated systems across 33 geopolitical regions (32 in the core model, plus Uruguay) which are further divided into 235 water basins and 384 land use regions. These solutions determine market-clearing prices and quantities of energy, water, agriculture, land use, and emissions markets in each region and time step, informed only by the conditions in the previous period and driven by exogenous socioeconomic assumptions as well as representations of policies, resources, and technologies. Greenhouse gas (GHG) emissions are tracked endogenously for 24 gases.

Flows of energy in GCAM can be described by renewable and nonrenewable primary energy resources being collected and transformed through various processes into final energy carriers (e.g., electricity, hydrogen, fossil fuels) in order to meet the demands of the buildings, industry, and transportation end use sectors. Individual technologies and processes compete for market share on a levelized cost basis, which is comprised of exogenous non-energy capital costs and endogenous fuel costs, subject to any technology or emissions policies implemented. Fossil fuel resources, uranium, wind, and rooftop PV utilize exogenous supply curves to determine resource costs, which increase with higher cumulative extraction/deployment levels. A logit choice model controls market competition, which protects against a single technology dominating the market share.

The energy system in GCAM is coupled with the agriculture and land use system mainly through commercial biomass (supplied by the agriculture and land use system and demanded by the energy system) and fertilizer (supplied by the energy system and demanded by the agriculture and land use system). Additionally, cooling water is demanded by many technologies within the energy system, linking it with GCAM's water system. CO_2 emissions are tracked when fossil fuels are combusted or converted to other forms, while agriculture and land use change (LUC) emissions are tracked via the amount of land use change within a region.

3.2. Uncertain factors varied in this analysis

Figure 1 gives an overview of the large ensemble of GCAM realizations developed in this work, and individual sensitivities are also summarized in Table 1. Broadly, the sensitivities we draw from represent a wide range of energy system and economic uncertainties, which are arranged into five categories. Sensitivities were developed from a review of the broad energy transition literature, identifying commonly varied as well as potentially underexplored uncertainties. When applicable, implementation of these sensitivities is based on previous studies using GCAM and referenced in Table 1. The sensitivities are varied discretely rather than sampled across a continuous range, and are combined in a full factorial ensemble. This resulted in a total of 5,760 unique model realizations.

Table 1: Description of sensitivities varied in the ensemble.

Type	Name	Sensitivities	Short Description / Representation in GCAM	Key Global Dynamics	Adapted From
Climate Mitigation	NDC + LTS Emissions Constraint	*Reference*: no constraint *Climate Pledges*: goals achieved as stated	Countries achieve long-term strategies, shorter-term pledges, and net-zero targets as stated, followed by a minimum decarbonization rate thereafter. Implemented as a regional constraint on CO_2 emissions consistent with stated short-term (2030) goals and long-term (2050-2060) strategies.	Lower emissions, introduces CDR, reduces fossil fuel reliance	Iyer et al., 2022; Ou et al., 2021
	Land Use Change Emissions Sinks	*Reference*: 10% scaling up over time *High*: 100% (only used with climate pledges)	For NDC + LTS runs, adjusts the fraction of the carbon price passed to the land use system Varies land use emissions sinks and alters the economic balance struck with net emissions from the energy system.	Allows the energy system to emit more to reach the same mitigation goals	This study
Socio-economic	Population and GDP	*Reference*: SSP2 *Sensitivities*: SSP1, SSP3, SSP4, SSP5	Five paired socioeconomic pathways are used, consistent with the five SSP representations in GCAM. Note that only population and GDP are varied here; these parameters are decoupled from the full SSP scenarios.	Varies the magnitude of economic activity which affects nearly all sectors	Calvin et al., 2017
Institutional	Institutional Factors	*Reference*: equal investment risk *Risk*: differences across regions & technologies	Modeling differences in regional and technological investment risk by affecting the cost of financing clean energy projects	Reduced investment in renewables	Iyer et al., 2015a
Techno-economic	Wind and Solar Capital Costs	*Reference*: ATB moderate *High cost*: ATB conservative *Low cost*: ATB advanced	Forecast of overnight capital costs for wind and solar technologies, varied together and consistent with core sensitivities available in GCAM.	Influences adoption of wind and solar, cost of electricity, and mitigation costs	NREL, 2019
	Direct Air Capture Cost	*Reference*: SSP2 consistent *High cost*: SSP3 consistent	Varying cost of Direct Air Capture, a key negative emissions technology. Attempting to completely remove CCS and DAC from the model caused a majority of NDC + LTS scenarios to become infeasible.	Reduced CDR, higher carbon price, increased hydrogen and electricity from biomass	Fuhrman et al., 2021
	Advanced Hydrogen	*Reference*: GCAM core assumptions *Advanced hydrogen*: see Ref.	Modeling advanced scaling of hydrogen in the energy system through centralized hydrogen transport and distribution infrastructure, represented by pipeline.	Increased hydrogen production and use	Wolfram et al., 2022
Demand Side	Industry Energy Efficiency	*Reference*: GCAM core assumptions *High efficiency gains*: see Ref.	Energy efficiency improvements over time across industries including cement, iron and steel, chemicals, fertilizer, aluminum, and other aggregate end uses of industry. Modeled as reduced input energy, reduced feedstock use, reduced carbon intensity of cement, and adjustments to income elasticity.	Reduced energy and electricity consumption in industry, lower CO_2 emissions, lower cement production	Gambhir et al., 2022
	Buildings Energy Efficiency	*Reference*: GCAM core assumptions *High efficiency gains*: see Ref.	Energy efficiency improvements over time in the buildings sector. Modeled as higher heating and cooling efficiency improvements, reduced plug load in households, reduced floor space.	Reduced final energy in buildings, lower CO_2 emissions and electricity use	Gambhir et al., 2022
	Transport Electrification	*Reference*: GCAM core assumptions *High electrification*: see Ref.	Advanced electrification of transport sector. Modeled as increased share of electric vehicles over time, phaseout of liquid fuel vehicles, increasingly electrified freight transport by truck and rail, demand shifts towards transit, ride-sharing, and less aviation and shipping.	Reduced final energy in transport, lower CO_2 emissions, increased hydrogen	Gambhir et al., 2022

	Climate Impacts on Demand	*Reference*: no impacts *Impacted demand (no climate pledges)*: RCP6.0 *Impacted demand (climate pledges)*: RCP2.6	Varying heating and cooling degree days in each region according to global climate model (GCM) outputs. Sensitivity case is consistent with RCP6.0 for runs with no emissions policy, and with RCP2.6 for runs with emissions policy. HadGEM2-ES was chosen as roughly a median case from among a set of GCMs.	Marginal increases in building electricity consumption and total climate forcing	Hartin et al., 2021

3.2.1. Climate mitigation

As part of the climate mitigation sensitivity, we consider countries' emission mitigation pledges. Specifically, we use assumptions from the "Updated pledges - Continued ambition" scenario in (Iyer et al., 2022; Ou et al., 2021). This constraint assumes that countries achieve stated long-term strategies, shorter-term pledges, and net-zero targets, followed by a minimum decarbonization rate thereafter.

Another sensitivity we include only for simulations with climate pledges implemented is the *Level of Land Use Sinks*, implemented through policy action by adjusting the rate at which land use change emissions are priced. Increasing this rate incentivizes afforestation, allowing the energy system to emit more CO_2 (Calvin et al., 2014; Wise et al., 2009).

3.2.2. Socioeconomic factors

Here, we implement changes in population and GDP consistent with assumptions in the five Shared Socioeconomic Pathways (SSPs) (Calvin et al., 2017; O'Neill et al., 2017, 2014; Riahi et al., 2017). The SSP scenarios include numerous components in addition to these socioeconomic markers, driven by narrative descriptions of diverging development strategies across sectors. Note that the resulting model sensitivities applied in this study are not full representations of the SSPs, but rather the socioeconomic components of population and GDP are disaggregated and used as a separate uncertainty.

3.2.3. Institutional factors

We consider the quality of institutions as well as technology-specific risks in providing comparative advantage for securing mitigation investment and development across regions. Following the methodology in Iyer et al. (Iyer et al., 2015a), we apply 1) regional variations in investment risks to the energy sector via the cost of capital based on a GDP-weighted model of institutional quality, here constructed with data from the World Bank (World Bank, 2020); and 2) premiums on "high-risk" clean energy technologies to represent, e.g., regulatory challenges and market uncertainty.

3.2.4. Techno-economic sensitivities

Cost of Wind and Solar is varied between low, medium, and high levels, consistent with the core forecast assumptions present in GCAM created from the National Renewable Energy Laboratory's Annual Technology Baseline (ATB) report (NREL, 2019). *Advanced Hydrogen* assumes an advanced scaling of hydrogen in the energy system through centralized transport and distribution infrastructure (pipeline) and increases the share of hydrogen vehicles adopted; it is adapted from the advanced hydrogen GCAM assumptions in (Wolfram et al., 2022). *Direct Air Capture Cost* increases the costs of Direct Air Capture (DAC) from the reference level to a "high" level consistent with the SSP3 formulation parameterized in (Fuhrman et al., 2021). Carbon dioxide removal (CDR) technologies such as DAC and bioenergy with carbon capture and storage (BECCS) have been previously identified as a significant factor in affecting net-zero pathways (Iyer et al., 2021).

3.2.5. Demand-side sensitivities

Industry Energy Efficiency and *Buildings Energy Efficiency* are separate sensitivities which reduce energy in industrial and buildings end-use sectors by adjusting coefficients related to energy efficiency and use. These two sensitivities are implemented based on assumptions in (Gambhir et al., 2022). *Electrification of Transport* models an increased share of electric vehicles and freight transport over time as well as shifts towards transit, ridesharing, and lower aviation and shipping demand, also using assumptions from (Gambhir et al., 2022). *Climate Impacts on Demand* updates the number of heating and cooling degree days (and thus building energy demands) in each region using output from the HadGEM2-ES climate model. These impacts are calibrated to RCP6.0 (a pathway with significant 3-4°C warming) for simulations with no mitigation policy, and to RCP2.6 (a sub-2°C warming pathway) for emissions-constrained runs. Refer to (Hartin et al., 2021) for details on the methodology. Climate-impacted electricity supply generated from wind and solar PV was also considered but ultimately excluded from this study, as previous work found potential climate impacts and their associated uncertainty to have only a modest impact on future generation compared to other uncertainties considered (Santos Da Silva et al., 2021; Zapata et al., 2022).

3.3. Output metrics

The bottom panel of Figure 1 lists energy-economic metrics used in the analysis, which represent commonly reported benchmarks, performance metrics, and quantitative descriptors of the bulk electric power system and broader energy system. We compute these metrics at the regional level, though in some cases present them as global aggregations. *Electricity Price* is given as the marginal cost of generation (analogous to a wholesale price exclusive of regional tariffs or subsidies), an important benchmark for estimating energy costs over time, and is weighted by total electricity generation when aggregated across regions. *Electricity Share* gives the rate of electrification in a region as a percentage of total final energy. Increased electrification is necessary for incorporating more renewables in the energy mix, while sectors which cannot easily be electrified are considered “hard-to-abate” (Paltsev et al., 2021). *Energy Burden* is calculated in each region as per capita spending on residential energy use divided by per capita GDP, and is a widely used metric for energy equity and energy justice considerations (Baker et al., 2023). *Capacity Investments* and *Stranded Assets* are economic metrics reporting the costs of new capacity additions and premature capacity retirements in the power sector, respectively, due to implementing climate pledges (Binsted et al., 2020; Iyer et al., 2015b; Zhao et al., 2021). Finally, *Level of CO_2 Removal* and *LUC Emissions* quantify the global CO_2 budget pathway for mitigation in each realization. *Level of CO_2 Removal* includes the negative emissions technologies BECCS and DAC, while *LUC Emissions* reports negative emissions from land use carbon sinks. In order to meet emissions pledges, CO2 from the energy system must be reduced through a combination of clean generation (e.g., wind and solar), carbon capture (of thermal generation point sources), negative emissions technologies (BECCS and DAC), and natural carbon sinks (e.g., forest cover). Increased removal of CO_2 from the atmosphere would allow the energy system to emit more to reach the same goal; conversely, decarbonization efforts in the energy sector can reduce the need for CO_2 removal technologies. Further detail on how each metric is computed from GCAM outputs is given in the Supplemental Information.

3.4. Scenario discovery

We perform scenario discovery to identify combinations of features which drive relevant outcomes in our ensemble. Quantifying the influence of individually varied uncertain factors can be generally referred to as a feature importance analysis, another model-agnostic collection of techniques that compute the relative strength of the effect a feature has on the ability to predict a specific variable or metric (Saarela and Jauhiainen, 2021). This is often done through fitting a machine learning model using, e.g., classification and regression trees (CART), logistic regression, or the patient rule induction method (PRIM) (Breiman et al., 1984; Lempert et al., 2008; Kwakkel and Cunningham, 2016; Friedman and Fisher, 1999), and evaluating that model by computing scores or ranks for feature importance using indicators such as squared error reduction, Shapley values, classification rate, permutation importance, or Gini index (Chen et al., 2023; Parr et al., 2024). In this study, we train a random forest model (Breiman, 2001) to quantify the relative importance of each uncertain factor in determining energy system outcomes, both globally and for aggregated regions. Feature importance for this model is computed using the mean reduction in squared prediction error achieved by including a given feature. Rather than fit a binary classification model to assess only the most extreme outcomes, we use regression to characterize the full distribution of futures supplied by our ensemble.

3.5. Outcome space under mitigation pledges

The modeled climate pledges result in a fundamental transformation of the global economy and accelerate a low-carbon energy transition. Model realizations with mitigation pledges show consistent emissions reductions over time, while unconstrained scenarios exhibit wide variability in their peak emissions and associated climate forcing, highlighting the deep uncertainty in the future energy system in the absence of policy (Supplementary Figure S1). Similarly, land use emissions generally plummet under the climate pledges during the short- (2030) to medium-term (2050) transition to offset energy system emissions (Supplementary Figure S2). The global electricity generation mix reveals that climate pledges cause wind and solar to be the primary generation sources to replace fossil fuels as the leading source of electricity (Supplementary Figure S3 and Figure S4). Fossil fuels remain relevant, however, due to countries without stringent emissions reductions as well as maturation of technologies to remove CO_2 from the atmosphere or capture it from point sources. Supplementary Figure S5 and Figure S6 illustrate the adoption of two negative emissions technologies for emissions-constrained simulations, along with scenarios from IPCC AR6 shown in black (Riahi, 2022). The rise in these technologies after mid-century coincides with the relaxation of land use sinks seen in Supplementary Figure S2.

4. Results

Our study highlights three key findings as discussed in the following sections:

- Costs of the energy transition, as measured by multiple metrics, can be unevenly distributed across a wide range of future states of the world.
- Regional investment risk has global implications for mitigation pathways.
- The scale of CDR determines how much the energy system can continue to emit, but the relative role of different CDR options in meeting decarbonization goals varies across regions.

4.1. Costs of the energy transition, as measured by multiple metrics, can be unevenly distributed across a wide range of future states of the world

4.1.1. Electricity price

The top panel of Figure 2 shows distributions of electricity price in 2050 across all model realizations both with and without climate pledges for each aggregated region in GCAM, as well as weighted (by total generation) averages globally. Globally, future electricity prices tend to decrease from the 2015 (calibration year) average in the absence of policy, while usually increasing when mitigation pledges are met. There is some overlap between the two boxplots, meaning that the lowest-price NDC + LTS cases can experience lower costs than the most expensive *No Policy* cases. The increase in electricity price due to mitigation policy as well as the deviation from historical prices varies considerably across regions. Russia and the Middle East (regions without stringent emissions reductions by 2050 at the time of writing) have a significant proportion (92% and 76%, respectively) of NDC + LTS simulations with prices below historical levels due to relatively low carbon prices and no economic incentive to adopt potentially more costly clean technologies. China and India, two highly populated and rapidly developing regions with ambitious decarbonization pledges, experience the greatest cost increases. Notably, while the price variability in the *No Policy* cases is large, the introduction of climate pledges greatly increases the variance of electricity price outcomes in all regions. This suggests the need for more adaptive policy planning or better regional coordination to manage this uncertainty.

In addition to the impacts on the electric power system imposed by emissions pledges, electricity price is also driven by many assumptions related to technology costs and performance, demand levels, and the enabling environment for new solutions. The bottom panel in Figure 2 illustrates the results of a random forest analysis quantifying the impact of the scenario factors on global weighted average electricity prices in 2050. Resembling a decision tree, this alluvial diagram divides the full 5,760-member ensemble into subsets based on the four most influential drivers of electricity price, in order of importance. The vertical axis is scaled and color-coded to show average prices for different scenario combinations, with the global average for the full ensemble marked with a dashed line. Factor branches for each split are reported at the bottom of the figure. Thus, the national emissions pledges (NDCs + LTS) rank as the most critical driver of electricity prices in 2050, followed by the *Institutional Factors* sensitivity, *Cost of Wind and Solar* (high vs. medium or low), and *Socioeconomic Factors* (SSP1/5 vs. SSP2/3/4). The range of average prices is quite wide, showing that different combinations of inputs can have significant effects on global price outcomes. Electricity prices are highest when investment costs (*Institutional Factors*) are regionally and technologically differentiated and the *Cost of Wind and Solar* is high, in combination with either low population (SSP1) or high GDP (SSP5). Additionally, this plot reveals the subset of realizations which implement emissions pledges and still result in a lower global average electricity price in 2050 (uniform institutions and low or medium VRE cost). A more complete picture of feature importance across sensitivities, metrics, time periods, and regions is shown in Supplementary Figure S7 and Figure S8.

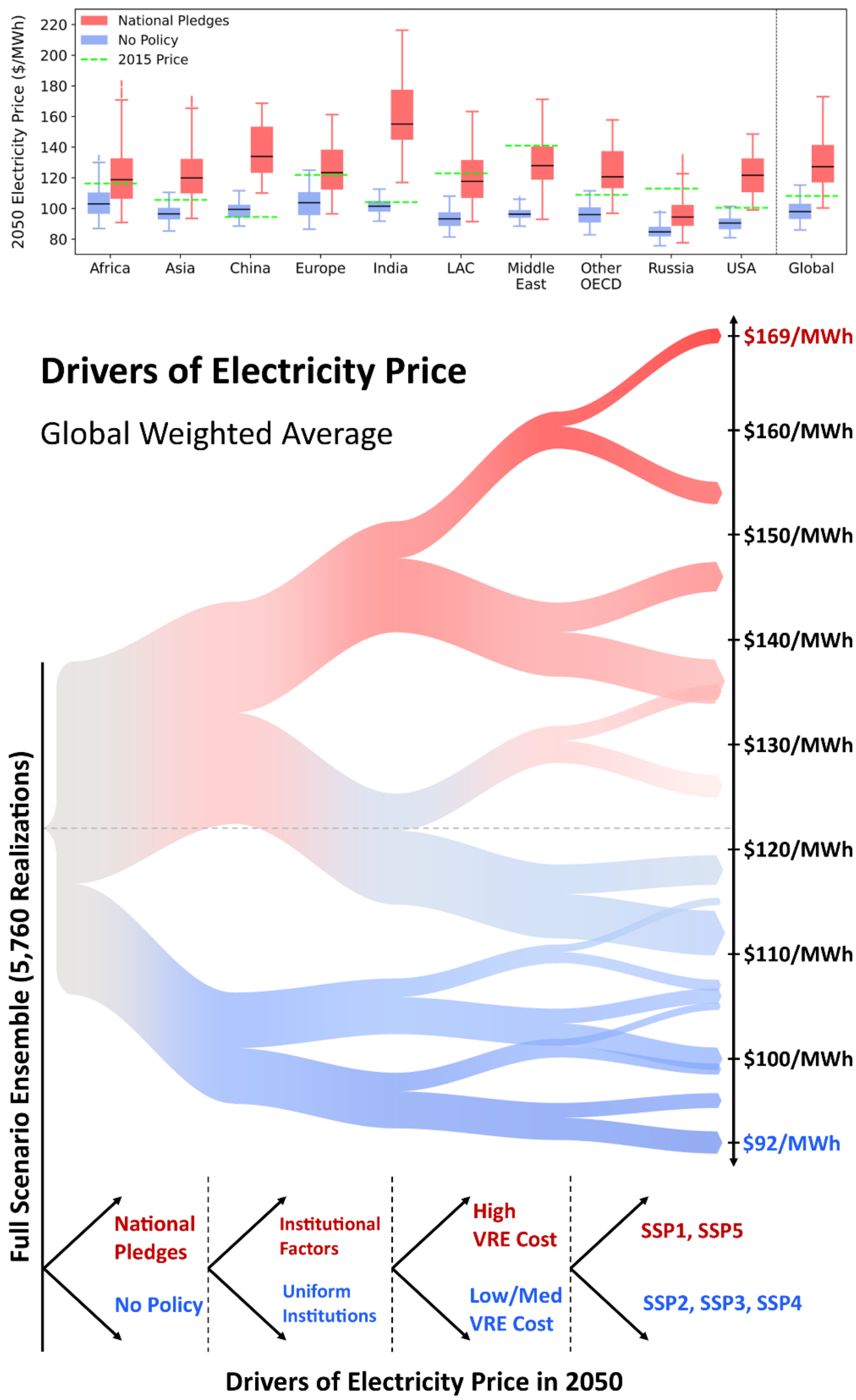

Figure 2: (top) Regional and global weighted electricity price for model regions, split between scenarios with and without climate pledges implemented. Model calibration year 2015 prices are shown for comparison; **(bottom)** most influential drivers of global weighted average electricity price ($/MWh) in 2050, defined as marginal cost of generation. Similar to a decision tree, the full scenario ensemble is divided into subsets based on the scenario features shown below each split, with earlier splits corresponding to higher influence. The width of each path segment is scaled according to the number of model realizations traveling through it, while the vertical midpoint of each splitting node corresponds to the average price on the right. The global average price for the full scenario ensemble is marked with a dashed gray line; prices

above this level are shaded red, while lower prices are shaded blue. Splits are determined using a random forest implementation in R. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. “Asia” includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. “LAC” refers to Latin America and the Caribbean.

4.1.2. Stranded assets

Stranded assets in the form of premature retirements of electric generating capacity are shown in Figure 3. The left panel shows a global time series through 2100, while the right panel gives a snapshot of 2050 across regions. Climate mitigation pledges increase stranded assets in all cases, consistent with previous work (Binsted et al., 2020), but significant variability is observed throughout the wide range of transition pathways sampled. Globally, most premature retirements happen in the shorter-term period of rapid transition from the present until around 2050. Regionally, larger economies and developed regions with net-zero pledges show the greatest stranded assets, while regions with less strict climate goals suffer fewer stranded assets. Interestingly, these results were found to change very little when scaled by regional GDP, rather than reporting total value of the stranded assets. Thus, this metric suggests that regional variability in climate pledge ambition can also manifest as disproportionate differences in stranded assets, independent of other factors and across a broad uncertainty space. Several of these regions, especially India and China, also experience the highest increase in electricity prices as shown in Figure 2.

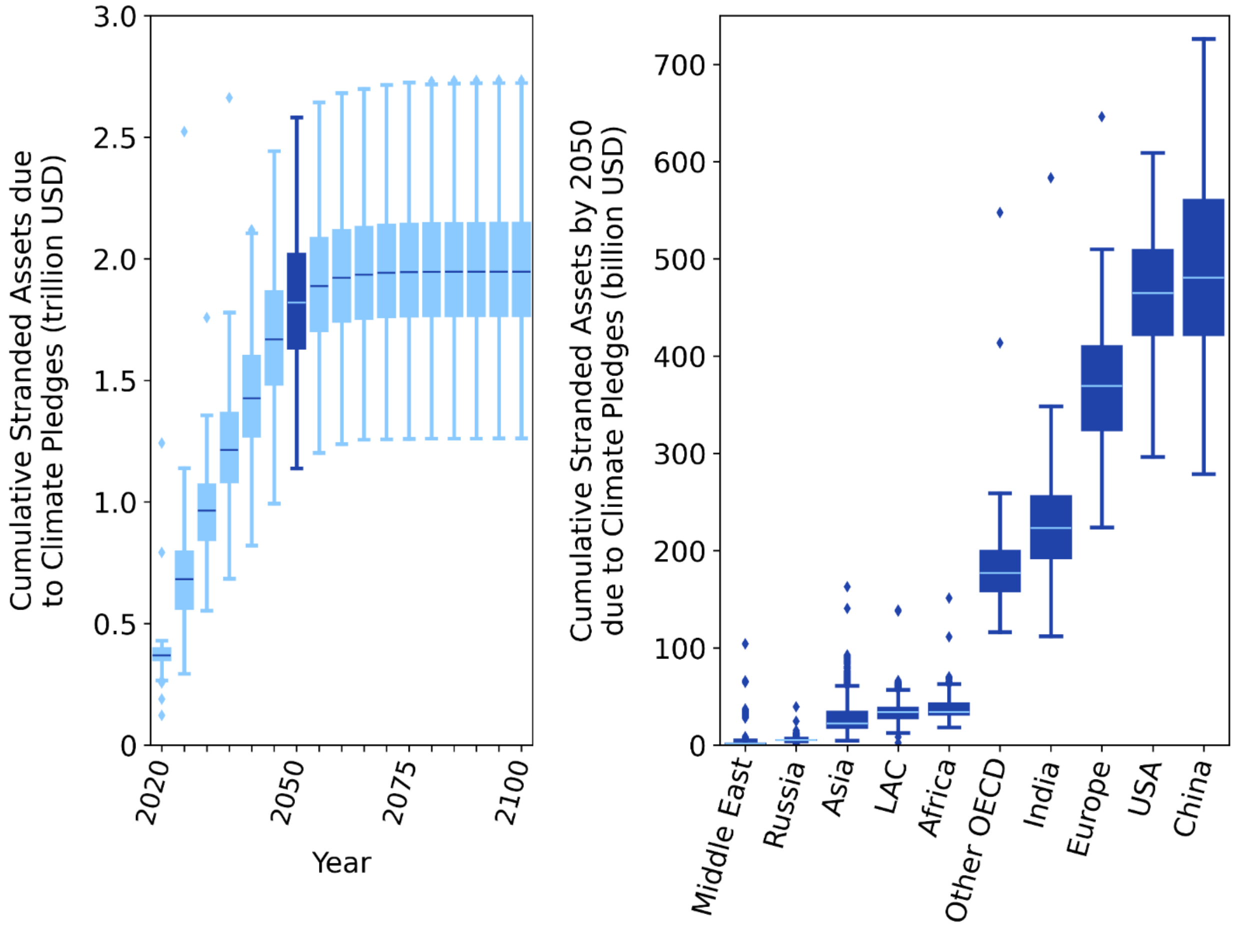

Figure 3: (left) Cumulative stranded assets (costs associated with premature retirements of generating capacity) globally over time due to implementing climate pledges, with the year 2050 highlighted; (right) cumulative stranded assets in 2050 for aggregated global regions due to implementing climate pledges. Values are computed as the difference between pairs of scenarios which differ only by the inclusion of national emissions pledges. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. “Asia” includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. “LAC” refers to Latin America and the Caribbean.

4.1.3. Energy burden

Distributions of average household energy burden in NDC + LTS scenarios are plotted over time in the left panel of Figure 4. Though this metric represents an oversimplification of energy equity measures, these long-term aggregate trends reveal temporal patterns as well as systemic differences across regions. Energy burden is decreasing over time, robust to our ensemble of uncertainties, even though electricity costs tend to rise as a result of mitigation efforts. The clear outlier is Africa (especially in the near-term), due in part to a high usage of traditional biomass, which is tracked in GCAM as a separate commodity in certain regions. Additionally, as for many developing regions, lower rates of access to energy and financial markets obscure this already aggregated measure when viewed per capita. However, despite the regional differences seen early on, energy burden in 2100 becomes more homogeneous across regions (in terms of both the mean and the spread of the outcomes), due to the minimum continued mitigation ambition built into the NDC + LTS policy scenario (Ou et al., 2021). The right panel of Figure 4 gives the difference in energy burden in 2050 due to climate pledges (darker boxes, mostly increases) as well as *Buildings Energy Efficiency* (pale boxes, exclusively decreases). Although mitigation policy tends to increase energy burden, increased energy efficiency in buildings is seen to offset these increases. Regions with the highest energy burden in the left panel tend to also experience the greatest benefits from increasing energy efficiency.

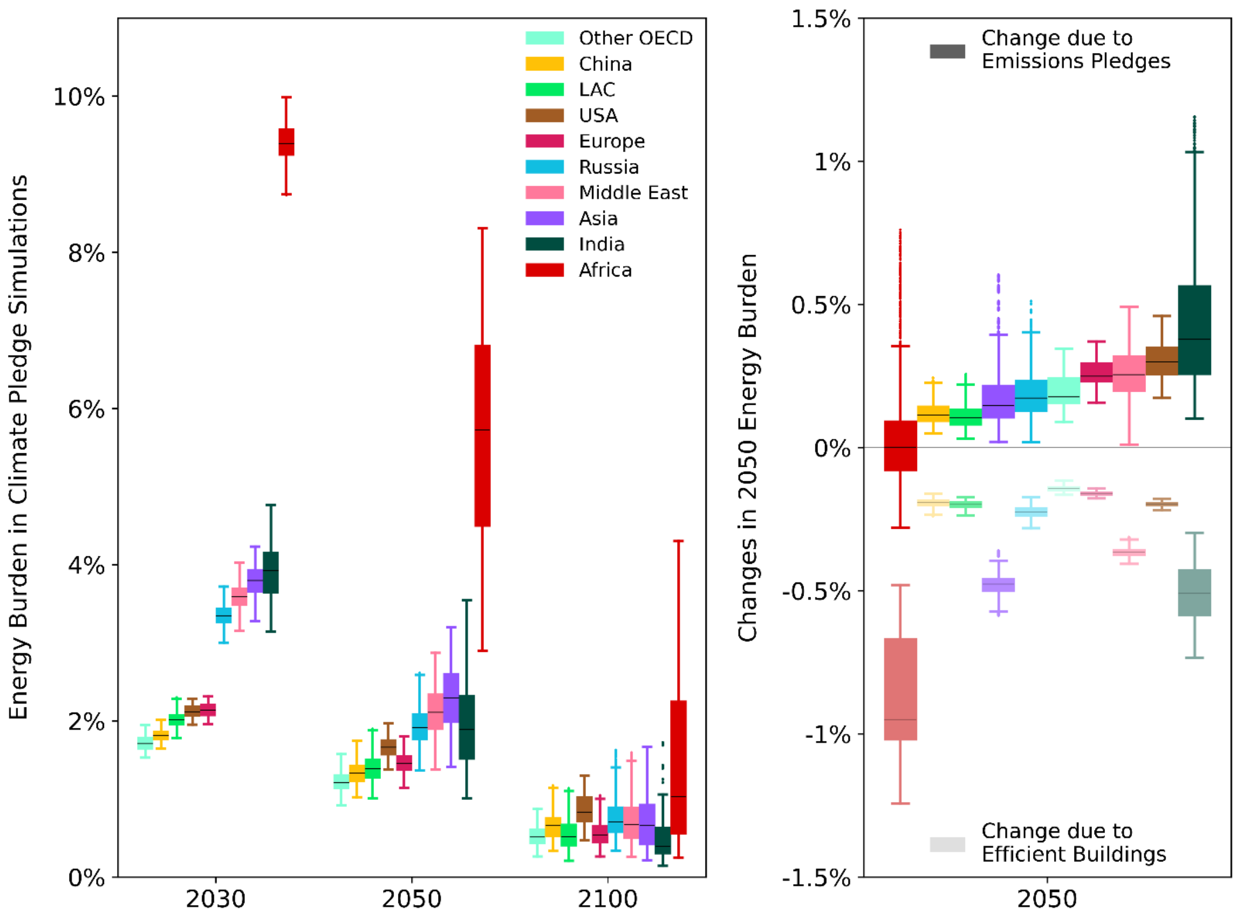

Figure 4: (left) Residential energy burden, computed as a ratio of residential energy spending to GDP per capita, for aggregated global regions for three model periods, showing the 3,840 simulations with climate pledges; **(right)** Change in energy burden caused by two scenario sensitivities (climate pledges and *Buildings Energy Efficiency*) for each model configuration, computed as the difference between pairs of realizations which differ only by inclusion/exclusion of these two scenario levers. Note that the changes shown are absolute changes in the energy burden, which carries units of percent, rather than percent changes in energy burden. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. "Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. "LAC" refers to Latin America and the Caribbean.

The feature importance heatmap for energy burden in Figure S7 identifies a similar list of critical drivers as seen for electricity price. In this case, however, the influence of *Socioeconomic Factors* outweighs both *Institutional Factors* and *Cost of Wind and Solar*, and is roughly equal in importance to *Buildings Energy Efficiency.* The emergence of this sensitivity in driving energy burden is a result of energy burden being tied to residential energy use. Although *Buildings Energy Efficiency* does not show up as a top driver of electricity prices, its uncertainty can still have hidden implications for the average household, and could help alleviate economic strain caused by rising costs of energy. Passenger transport service costs, another potential measure of energy burden, are shown in Figure S9.

4.2. Regional investment risk has global implications for mitigation pathways

Figure 5 maps cumulative distribution functions (CDFs) of the standardized difference in global 2050 model outcomes resulting from regionally and technologically differentiated investment costs. These observed differences are specifically a result of the *Institutional Factors* sensitivity, which represents one manifestation of the variability in accessing capital for low-carbon development due to investment risk. This metric is highlighted for its prominence in driving economic outcomes, as shown through feature importance in Figure S7. For most metrics, the curve lies to one side of zero; these cases show a consistent impact of *Institutional Factors* across the ensemble (e.g., electricity price always increases, consistent with Figure 2). Across a broad range of uncertainties, a higher energy burden is seen as well, along with lower electrification rate and stranded assets; these results follow intuitively considering the higher costs of capital experienced in these scenarios. Because less investment is garnered for low-carbon energy and negative emissions technologies, the resulting carbon price increases to offset the emissions, and thus more land use emissions sinks are utilized. If clean energy investments are stifled through disparities in institutional quality in a region, attempts to offset the continuing emissions can result in further cost increases under mitigation policy. Supplementary Figure S10 shows CDFs for individual regions.

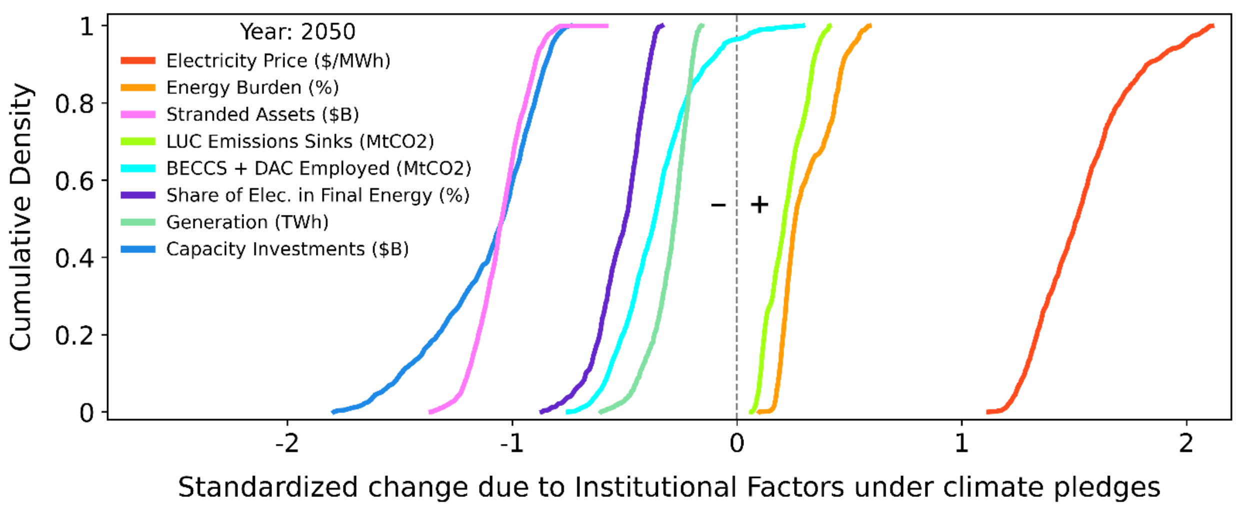

Figure 5: CDF plot showing standardized changes in the values of select metrics when institutional factors are switched on in each scenario configuration (only showing scenarios with NDCs + LTS implemented). Values on the horizontal axis represent the number of standard deviations from the mean for each metric. A curve lying entirely to the right (left) of zero implies that institutional factors always increase (decrease) that metric. These curves are not intended to represent probabilities of exceedance, but rather are empirical distributions of model output constructed from differences between pairs of model realizations. Note that a steep CDF curve suggests that varying this sensitivity results in a very consistent change in the outcome; it does not represent underlying variability of the outcome itself.

4.3. CDR deployment determines allowable energy system emissions, but the relative role of different CDR options in meeting decarbonization goals varies across regions

Figure 6 shows emissions and sinks over time and the distribution of the timing of net-zero CO_2 across our scenario ensemble under national climate pledges. CO_2 from the energy system is reduced through a combination of clean generation, carbon capture, CDR, and natural carbon sinks; allowable energy system emissions are therefore determined by net CO_2 removal. On average, global net-zero CO_2 is achieved around 2060 under the modeled emissions trajectories. Figure S11 and Figure S12 show the variability in the timing of net-zero CO_2 across each sensitivity and across regions, respectively; the most critical drivers globally are *Socioeconomic Factors* and *Direct Air Capture Cost*.

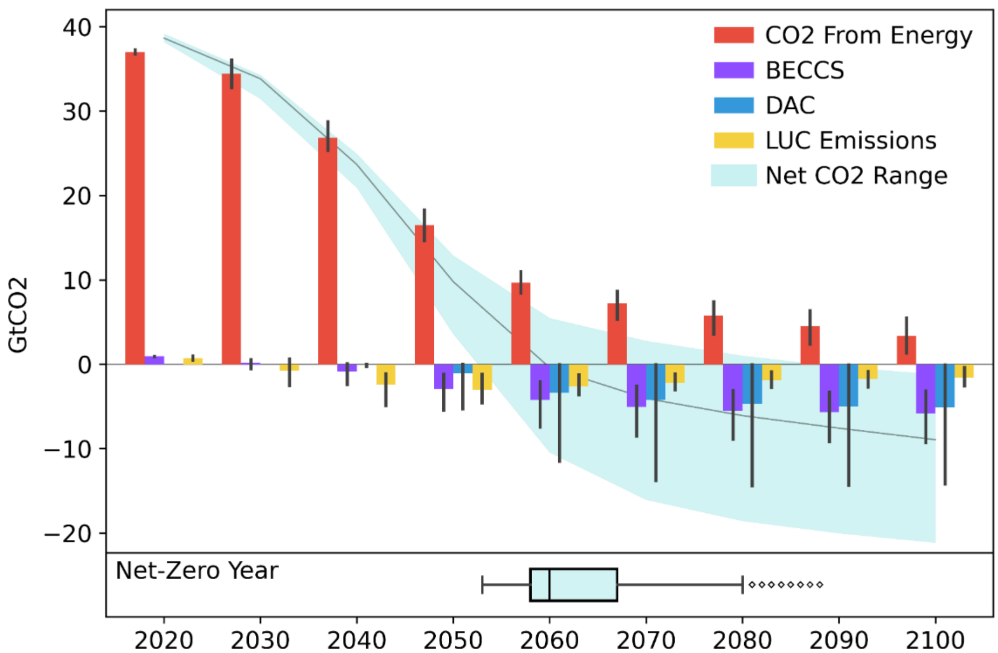

Figure 6: The use of negative emissions technologies and terrestrial carbon sinks to offset energy system emissions. Error bars show the full range of outcomes across the scenario ensemble for the 3,840 realizations that implement climate pledges. The pale shaded region in the background gives the range for net CO_2 emissions by summing the individual components. The boxplot at the bottom of the figure shows the distribution of years in which global net-zero CO_2 is achieved.

Tradeoffs affecting energy system CO_2 emissions are further illustrated in Figure 7 through a parallel axis plot, which shows the cumulative net sum by 2050 of each emissions component from Figure 6 across the NDC + LTS simulations in our ensemble. Each line represents a single realization and is grouped by color based on the *Direct Air Capture Cost* and *Level of Land Use Sinks* sensitivities. Thicker lines depict a "representative" scenario from each group following a mean pathway. By 2050, the amount of CO_2 sequestered by terrestrial carbon sinks shows the strongest tradeoff with energy system CO_2 emissions (first two columns of Figure 7). This illustrates the flexibility afforded to the energy system by the land use system in the form of land use sinks. Additionally, a tradeoff emerges between these land use sinks and deployment of CDR technologies, confirming the complementary roles of these decarbonization solutions (i.e., deploying more BECCS or DAC requires fewer land use sinks to meet the same goal, and vice-versa). Finally, high-cost DAC scenarios are shown to deploy very little of this technology by 2050, leading to a system favoring other CDR options and reduced emissions from energy.

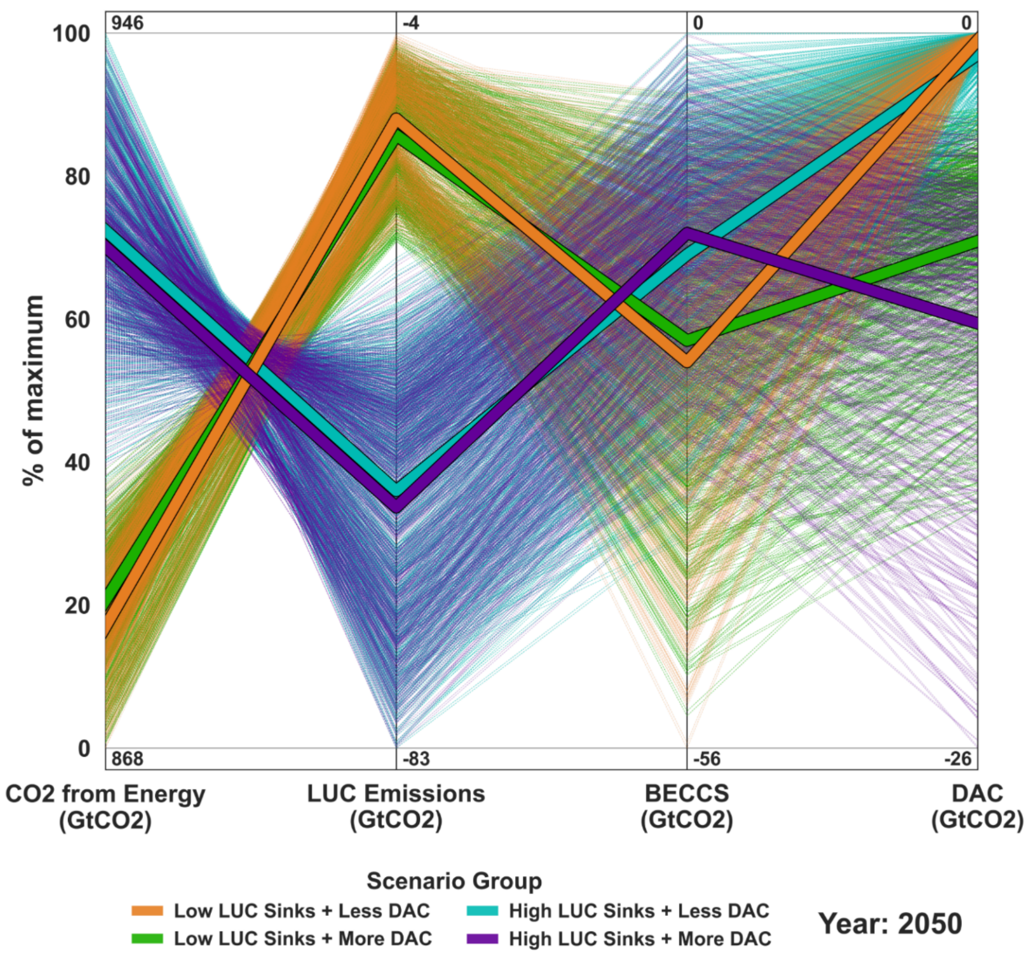

Figure 7: Parallel axis plot showing cumulative CO_2 emissions budget contributions under climate pledges in 2050. Scenarios are grouped according to the *Direct Air Capture Cost* and *Level of Land Use Sinks* sensitivities, and each column is scaled independently according to each metric's minimum and maximum values. Thicker lines depict a "representative" scenario from each group following a mean pathway. Each column is oriented according to its net contribution to CO_2 emissions, such that the bottom of the plot is the direction of net negative emissions.

Quantifying the direct effect of the *Level of Land Use Sinks* in each region across our ensemble is one way to examine the robustness of the results. Figure 8 plots CDFs for the difference in two outcomes between pairs of NDC + LTS realizations which differ only by this sensitivity, which updates the carbon pricing scheme to place a higher value on reducing emissions in the land use system. These curves are constructed for the year 2050, before *Direct Air Capture Cost* becomes the dominant driver of CDR investment. Differences are standardized rather than showing a percent change, due to the values for CDR adoption and LUC emissions sinks approaching zero in many scenarios.

Figure 8 shows the complementarity of CDR technologies and terrestrial carbon sinks, confirming broadly that increased land use sinks is tied to reduced deployment of BECCS and DAC regionally, consistent with the global finding. However, this is not a universal result, as some scenarios show these metrics increasing or decreasing together in certain regions, such as in Africa or the Other OECD countries. The horizontal range of these curves shows regional variability as well as wide-ranging effects of the sensitivity on these outcomes, suggesting that the role of different CDR options in meeting decarbonization goals varies across regions, considerable uncertainty remains in how a policy targeting land use emissions sinks would affect a region's mitigation pathway.

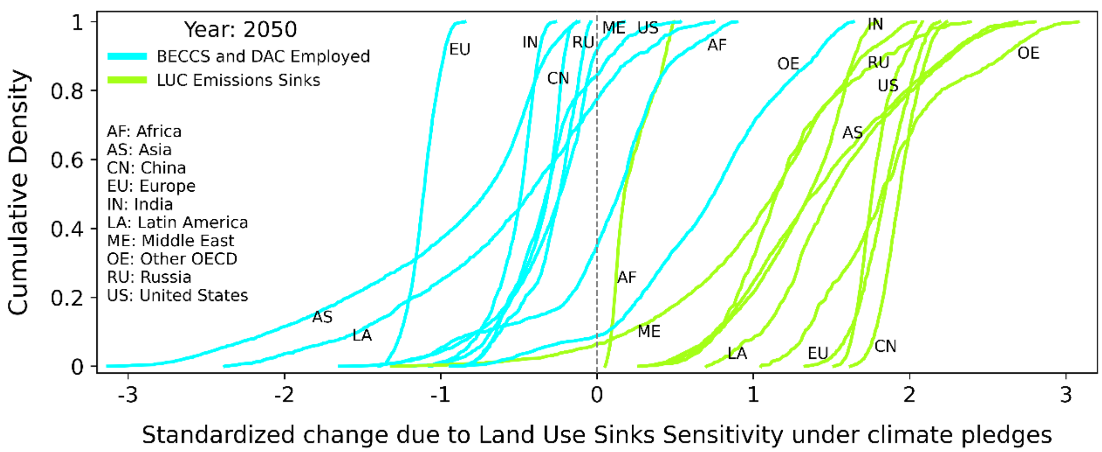

Figure 8: CDF plot showing standardized regional changes in the values of CDR adoption ("BECCS and DAC Employed") and land use sinks ("LUC Emissions Sinks") when the *Level of Land Use Sinks* sensitivity is implemented (only for scenarios with climate pledges). A curve lying entirely to the right (left) of zero implies that this LUC emissions sensitivity always increases (decreases) that metric's value. Positive values correspond to greater emissions reduction via that method. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. "Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia.

5. Conclusion

5.1. Discussion of results

Curbing anthropogenic carbon emissions to limit temperature increase is a global objective, requiring sustained effort from all nations. However, international commitments and pledges can unevenly distribute responsibility and/or the financial burden of decarbonization among countries and regions due to comparative advantages in renewable resources, favorable institutions, and how ambitious each country's mitigation pledges are (Marino and Ribot, 2012; Markkanen and Anger-Kraavi, 2019; Sovacool, 2021). This work establishes a new large ensemble of model realizations which vary a broad suite of energy-related sensitivities with countries' NDC + LTS pledges in order to gather robust insights into energy transition pathways as governments begin to implement climate mitigation measures to meet Paris Agreement temperature goals. Our results suggest that the costs of the energy transition, as measured by multiple metrics, can be unevenly distributed across regions and scenario-dependent in both magnitude and relative impact throughout a wide range of future states of the world. The variable increase in electricity prices and stranded assets across regions due to the implementation of national emissions pledges exemplifies this result, as shown in Figure 2 and Figure 3, respectively.

Stranded assets in particular represent an economic risk associated with transitioning away from a fossil-fuel based energy system. Strategic long-term planning of energy infrastructure is a significant challenge given the relatively long economic lifetimes of projects compared to the agreed upon time frames in which CO_2 emissions reductions are necessary. Forced or premature retirements of generating capacity due to policy drivers (e.g., enforcing emissions reductions) can have implications for energy prices, as levelized costs are generally computed over full economic lifetimes. We find that larger economies and developed regions with net-zero pledges (e.g., USA, Europe, India, and China) show the greatest losses here, while regions with less ambitious climate goals suffer fewer stranded assets. In addition to high electricity costs and stranded assets, some developing countries (e.g., Africa and India) also consistently experience greater increases in energy burden to meet their decarbonization goals.

In determining the most critical drivers for our outcomes of interest across the NDC + LTS simulations, we find regionally and technologically differentiated investment costs (*Institutional Factors*) to carry a high importance for several metrics, as seen in Supplementary Figure S7 and Figure S8. Our results indicate that negative outcomes emerge (higher electricity costs and energy burden, lower electrification, more land use sinks needed to meet emissions goals) when the cost of capital for clean energy projects is adjusted to reflect regional variations in institutional quality and investment risk, especially for developing countries and regions which carry generally higher risks. Additionally, such regions could be less resilient to such economic strain, especially under emissions constraints. These findings are consistent with work from which our *Institutional Factors* sensitivity was adapted (Iyer et al., 2015a) across a broad uncertainty space. These findings also underscore the role of lowering investment risks (especially in developing regions) through public institutions to encourage private investment or otherwise incentivize development.

The wide variety of investment pathways to meet national emissions pledges is closely tied to the scale and type of CDR. The speed at which technologies like DAC mature can be a limiting factor in their use over relevant near- to medium-term mitigation timeframes. Across our ensemble, the strongest tradeoff controlling energy system emissions through 2050 is the global stock of land use sinks. Given the complementarity of these natural carbon sinks with engineered CDR technologies, the adoption and diffusion of BECCS and DAC can help alleviate the burden on the land use system, while a larger global stock of terrestrial carbon sinks can dampen the need for these technologies.

5.2. Future work

Our new ensemble can be used as a novel dataset to inform international climate strategies and research for decision support, and can be expanded or narrowed in focus to other individual regions or additional sensitivities. The broad global and regional dynamics characterized in this work can benchmark further analyses and provide insight on the impact of various uncertainties on the robustness of a given pathway, while model outputs can be used for multi-model comparisons. Further, this ensemble can be used to provide boundary conditions to inform finer-scale decarbonization modeling exercises with, e.g., more detailed power system models.

Some of the limitations of this study lend themselves to future work. First, we made several simplifying assumptions to assemble a wide range of uncertainties and maintain computational tractability while leveraging the strengths of our chosen modeling platform. We limited the number of unique cases for each sensitivity to allow for higher dimensionality. Some sensitivities (e.g., *Cost of Wind and Solar*) represent specific forecasted predictions, while others (e.g., *Level of Land Use Sinks*) are modeled to capture an upper bound. A more thorough continuous sampling of sensitivities could yield a more detailed ensemble, but would prohibitively increase the size of the ensemble without necessarily adding additional insight. Future work could further examine the cross-sectoral consequences of this uncertainty space across the food-energy water nexus using additional parametric sensitivities. Although the sensitivities considered in our ensemble generally focus on the energy system, the coupled feedbacks observed in our simulations reveal noteworthy implications across sectors (e.g., water availability, food prices) that were not explored here.

Second, we quantified metrics at aggregated scales. For example, electricity price impacts and considerations of energy inequities such as energy burden can become hidden when spatial scales are aggregated, and populations are homogenized. While research in this space generally resolves to much finer spatial scales from neighborhood- to household-level (Ross et al., 2018), aggregate analyses such as the present study can still illuminate systemic differences across regions, especially as they relate to national energy pathways and decarbonization strategies. These insights still hold relevance on an intergovernmental policy scale. Future work could apply downscaling techniques on the model outputs or soft-coupling to a higher-resolution model to explore distributional outcomes and compare metrics across scales.

Finally, our study does not attempt to capture emergent behaviors, disruptive innovations, or other potential system shocks due to e.g., climate change, which could add additional deep uncertainty and complexity to the system. Other frameworks such as agent-based modeling could be integrated or coupled with GCAM to capture such dynamics, but would add significant complexity and computational burden. Nonetheless, this work provides a rich dataset for the advancement of scenario research, to which other machine learning methodologies could be applied.

Data and Code Availability Statement

GCAM is an open-source model available at https://github.com/JGCRI/gcam-core.

Plutus is an open-source model available at https://github.com/JGCRI/plutus.

All post-processed model output data used in this analysis and code to run the ensemble, query output databases, process query data, and generate all figures is published on Zenodo at https://doi.org/10.5281/zenodo.10895134 and will be made open upon publication.

Acknowledgements

This material is based upon work supported by the National Science Foundation under Grant No. 1855982. H.M. was supported by the National Research Foundation of Korea under BP Grant: RS-2023-00219466. The authors acknowledge the Tufts University High Performance Compute Cluster (https://it.tufts.edu/high-performance-computing) which was utilized for the research reported in this paper.

Author Contributions

Conceptualization, J.A.W., J.R.L., and G.I.; Methodology, J.A.W., J.R.L., and G.I.; Formal Analysis, J.A.W.; Resources, J.R.L., G.I., Y.O., and H.M.; Data Curation, J.A.W.; Writing – Original Draft, J.A.W.; Writing – Review & Editing, J.A.W., G.I., J.R.L., T.B.W., Y.O., and H.M.; Visualization, J.A.W.; Supervision, J.R.L. and G.I.; Funding Acquisition, T.B.W. and J.R.L.

References

Arango-Aramburo, S., Turner, S.W.D., Daenzer, K., Ríos-Ocampo, J.P., Hejazi, M.I., Kober, T., Álvarez-Espinosa, A.C., Romero-Otalora, G.D., Van Der Zwaan, B., 2019. Climate impacts on hydropower in Colombia: A multi-model assessment of power sector adaptation pathways. Energy Policy 128, 179–188. https://doi.org/10.1016/j.enpol.2018.12.057

Baker, E., Carley, S., Castellanos, S., Nock, D., Bozeman, J.F., Konisky, D., Monyei, C.G., Shah, M., Sovacool, B., 2023. Metrics for Decision-Making in Energy Justice. Annu. Rev. Environ. Resour. 48, 737–760. https://doi.org/10.1146/annurev-environ-112621-063400

Bankes, S., 1993. Exploratory Modeling for Policy Analysis. Oper. Res. 41, 435–449. https://doi.org/10.1287/opre.41.3.435

Beven, K., 2018. Environmental Modelling: An Uncertain Future? CRC Press, London. https://doi.org/10.1201/9781482288575

Binsted, M., Iyer, G., Edmonds, J., Vogt-Schilb, A., Arguello, R., Cadena, A., Delgado, R., Feijoo, F., Lucena, A.F.P., McJeon, H., Miralles-Wilhelm, F., Sharma, A., 2020. Stranded asset implications of the Paris Agreement in Latin America and the Caribbean. Environ. Res. Lett. 15, 044026. https://doi.org/10.1088/1748-9326/ab506d

Birnbaum, A., Lamontagne, J., Wild, T., Dolan, F., Yarlagadda, B., 2022. Drivers of Future Physical Water Scarcity and Its Economic Impacts in Latin America and the Caribbean. Earths Future 10, e2022EF002764. https://doi.org/10.1029/2022EF002764

Bond-Lamberty, B., Patel, P., Lurz, J., Kyle, P., Calvin, K., Smith, S., Snyder, A., Dorheim, K.R., Horowitz, R., Binsted, M., Link, R., Kim, S., Graham, N., Narayan, K., Turner, S.W.D., S, A., Feng, L., Lochner, E., Roney, C., Lynch, C., Horing, J., Khan, Z., Durga, S., O'Rourke, P., Huster, J., McJeon, H., Ou, Y., Iyer, G., Wise, M., Weber, M., 2022. JGCRI/gcam-core: GCAM 6.0. https://doi.org/10.5281/zenodo.6619287

Breiman, L., 2001. Random Forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324

Breiman, L., Friedman, J., Stone, C.J., Olshen, R.A., 1984. Classification and Regression Trees. Taylor & Francis.

Browning, M., McFarland, J., Bistline, J., Boyd, G., Muratori, M., Binsted, M., Harris, C., Mai, T., Blanford, G., Edmonds, J., Fawcett, A.A., Kaplan, O., Weyant, J., 2023. Net-zero CO2 by 2050 scenarios for the United States in the Energy Modeling Forum 37 study. Energy Clim. Change 4, 100104. https://doi.org/10.1016/j.egycc.2023.100104

Bryant, B.P., Lempert, R.J., 2010. Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. Technol. Forecast. Soc. Change 77, 34–49. https://doi.org/10.1016/j.techfore.2009.08.002

Burleyson, C.D., Iyer, G., Hejazi, M., Kim, S., Kyle, P., Rice, J.S., Smith, A.D., Taylor, Z.T., Voisin, N., Xie, Y., 2020. Future western U.S. building electricity consumption in response to climate and population drivers: A comparative study of the impact of model structure. Energy 208, 118312. https://doi.org/10.1016/j.energy.2020.118312

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., Wise, M., 2017. The SSP4: A world of deepening inequality. Glob. Environ. Change 42, 284–296. https://doi.org/10.1016/j.gloenvcha.2016.06.010

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R.Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S.J., Snyder, A., Waldhoff, S., Wise, M., 2019. GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. Geosci. Model Dev. 12, 677–698. https://doi.org/10.5194/gmd-12-677-2019

Calvin, K., Wise, M., Kyle, P., Patel, P., Clarke, L., Edmonds, J., 2014. Trade-offs of different land and bioenergy policies on the path to achieving climate targets. Clim. Change 123, 691–704. https://doi.org/10.1007/s10584-013-0897-y

Chen, H., Covert, I.C., Lundberg, S.M., Lee, S.-I., 2023. Algorithms to estimate Shapley value feature attributions. Nat. Mach. Intell. 5, 590–601. https://doi.org/10.1038/s42256-023-00657-x

Dolan, F., Lamontagne, J., Calvin, K., Snyder, A., Narayan, K.B., Di Vittorio, A.V., Vernon, C.R., 2022. Modeling the Economic and Environmental Impacts of Land Scarcity Under Deep Uncertainty. Earths Future 10, e2021EF002466. https://doi.org/10.1029/2021EF002466

EEA, 2009. Looking back on looking forward: a review of evaluative scenario literature — European Environment Agency (EEA Technical Report No. ISSN 1725-2237). European Environment Agency.

Fawcett, A.A., Iyer, G.C., Clarke, L.E., Edmonds, J.A., Hultman, N.E., McJeon, H.C., Rogelj, J., Schuler, R., Alsalam, J., Asrar, G.R., Creason, J., Jeong, M., McFarland, J., Mundra, A., Shi, W., 2015. Can Paris pledges avert severe climate change? Science 350, 1168–1169. https://doi.org/10.1126/science.aad5761

Fodstad, M., Crespo del Granado, P., Hellemo, L., Knudsen, B.R., Pisciella, P., Silvast, A., Bordin, C., Schmidt, S., Straus, J., 2022. Next frontiers in energy system modelling: A review on challenges and the state of the art. Renew. Sustain. Energy Rev. 160, 112246. https://doi.org/10.1016/j.rser.2022.112246

Friedman, J.H., Fisher, N.I., 1999. Bump hunting in high-dimensional data. Stat. Comput. 9, 123–143. https://doi.org/10.1023/A:1008894516817

Fuhrman, J., Clarens, A., Calvin, K., Doney, S.C., Edmonds, J.A., O'Rourke, P., Patel, P., Pradhan, S., Shobe, W., McJeon, H., 2021. The role of direct air capture and negative emissions technologies in the shared socioeconomic pathways towards +1.5 °C and +2 °C futures. Environ. Res. Lett. 16, 114012. https://doi.org/10.1088/1748-9326/ac2db0

Gambhir, A., George, M., McJeon, H., Arnell, N.W., Bernie, D., Mittal, S., Köberle, A.C., Lowe, J., Rogelj, J., Monteith, S., 2022. Near-term transition and longer-term physical climate risks of greenhouse gas emissions pathways. Nat. Clim. Change 12, 88–96. https://doi.org/10.1038/s41558-021-01236-x

Garb, Y., Pulver, S., VanDeveer, S.D., 2008. Scenarios in society, society in scenarios: toward a social scientific analysis of storyline-driven environmental modeling. Environ. Res. Lett. 3, 045015. https://doi.org/10.1088/1748-9326/3/4/045015

Groves, D.G., Lempert, R.J., 2007. A new analytic method for finding policy-relevant scenarios. Glob. Environ. Change, Uncertainty and Climate Change Adaptation and Mitigation 17, 73–85. https://doi.org/10.1016/j.gloenvcha.2006.11.006

Groves, D.G., Syme, J., Molina-Perez, E., Calvo Hernandez, C., Víctor-Gallardo, L.F., Godinez-Zamora, G., Quirós-Tortós, J., Denegri, F.D.L., Murillo, A.M., Gómez, V.S., Vogt-Schilb, A.,

2020. The Benefits and Costs of Decarbonizing Costa Rica's Economy: Informing the Implementation of Costa Rica's National Decarbonization Plan Under Uncertainty. RAND Corporation.

Guivarch, C., Le Gallic, T., Bauer, N., Fragkos, P., Huppmann, D., Jaxa-Rozen, M., Keppo, I., Kriegler, E., Krisztin, T., Marangoni, G., Pye, S., Riahi, K., Schaeffer, R., Tavoni, M., Trutnevyte, E., van Vuuren, D., Wagner, F., 2022. Using large ensembles of climate change mitigation scenarios for robust insights. Nat. Clim. Change 12, 428–435. https://doi.org/10.1038/s41558-022-01349-x

Hartin, C., Link, R., Patel, P., Mundra, A., Horowitz, R., Dorheim, K., Clarke, L., 2021. Integrated modeling of human-earth system interactions: An application of GCAM-fusion. Energy Econ. 103, 105566. https://doi.org/10.1016/j.eneco.2021.105566

Huppmann, D., Rogelj, J., Kriegler, E., Krey, V., Riahi, K., 2018. A new scenario resource for integrated 1.5 °C research. Nat. Clim. Change 8, 1027–1030. https://doi.org/10.1038/s41558-018-0317-4

IEA, 2021. Net Zero by 2050 - A Roadmap for the Global Energy Sector, Net Zero Emissions. IEA.

Iyer, G., Clarke, L., Edmonds, J., Fawcett, A., Fuhrman, J., McJeon, H., Waldhoff, S., 2021. The role of carbon dioxide removal in net-zero emissions pledges. Energy Clim. Change 2, 100043. https://doi.org/10.1016/j.egycc.2021.100043

Iyer, G., Ou, Y., Edmonds, J., Fawcett, A.A., Hultman, N., McFarland, J., Fuhrman, J., Waldhoff, S., McJeon, H., 2022. Ratcheting of climate pledges needed to limit peak global warming. Nat. Clim. Change 12, 1129–1135. https://doi.org/10.1038/s41558-022-01508-0

Iyer, G.C., Clarke, L.E., Edmonds, J.A., Flannery, B.P., Hultman, N.E., McJeon, H.C., Victor, D.G., 2015a. Improved representation of investment decisions in assessments of CO2 mitigation. Nat. Clim. Change 5, 436–440. https://doi.org/10.1038/nclimate2553

Iyer, G.C., Edmonds, J.A., Fawcett, A.A., Hultman, N.E., Alsalam, J., Asrar, G.R., Calvin, K.V., Clarke, L.E., Creason, J., Jeong, M., Kyle, P., McFarland, J., Mundra, A., Patel, P., Shi, W., McJeon, H.C., 2015b. The contribution of Paris to limit global warming to 2 °C. Environ. Res. Lett. 10, 125002. https://doi.org/10.1088/1748-9326/10/12/125002

Jafino, B.A., Kwakkel, J.H., 2021. A novel concurrent approach for multiclass scenario discovery using Multivariate Regression Trees: Exploring spatial inequality patterns in the Vietnam Mekong Delta under uncertainty. Environ. Model. Softw. 145, 105177. https://doi.org/10.1016/j.envsoft.2021.105177

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environ. Model. Softw. 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Khan, Z., Wild, T.B., Carrazzone, M.E.S., Gaudioso, R., Mascari, M.P., Bianchi, F., Weinstein, F., Pérez, F., Pérez, W., Miralles-Wilhelm, F., Clarke, L., Hejazi, M., Vernon, C.R., Kyle, P., Edmonds, J., Castillo, R.M., 2020. Integrated energy-water-land nexus planning to guide national policy: an example from Uruguay. Environ. Res. Lett. 15, 094014. https://doi.org/10.1088/1748-9326/ab9389

Kiureghian, A.D., Ditlevsen, O., 2009. Aleatory or epistemic? Does it matter? Struct. Saf., Risk Acceptance and Risk Communication 31, 105–112. https://doi.org/10.1016/j.strusafe.2008.06.020

Knight, F.H., 1921. Risk, Uncertainty and Profit. Houghton Mifflin.

Kober, T., Falzon, J., Van Der Zwaan, B., Calvin, K., Kanudia, A., Kitous, A., Labriet, M., 2016. A multi-model study of energy supply investments in Latin America under climate control policy. Energy Econ. 56, 543–551. https://doi.org/10.1016/j.eneco.2016.01.005

Kriegler, E., Bertram, C., Kuramochi, T., Jakob, M., Pehl, M., Stevanović, M., Höhne, N., Luderer, G., Minx, J.C., Fekete, H., Hilaire, J., Luna, L., Popp, A., Steckel, J.C., Sterl, S., Yalew, A.W., Dietrich, J.P., Edenhofer, O., 2018. Short term policies to keep the door open for Paris climate goals. Environ. Res. Lett. 13, 074022. https://doi.org/10.1088/1748-9326/aac4f1

Kwakkel, J.H., Auping, W.L., Pruyt, E., 2013. Dynamic scenario discovery under deep uncertainty: The future of copper. Technol. Forecast. Soc. Change, Scenario Method: Current developments in theory and practice 80, 789–800. https://doi.org/10.1016/j.techfore.2012.09.012

Kwakkel, J.H., Cunningham, S.C., 2016. Improving scenario discovery by bagging random boxes. Technol. Forecast. Soc. Change 111, 124–134. https://doi.org/10.1016/j.techfore.2016.06.014

Kwakkel, J.H., Jaxa-Rozen, M., 2016. Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. Environ. Model. Softw. 79, 311–321. https://doi.org/10.1016/j.envsoft.2015.11.020

Kwakkel, J.H., Pruyt, E., 2013. Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. Technol. Forecast. Soc. Change, Future-Oriented Technology Analysis 80, 419–431. https://doi.org/10.1016/j.techfore.2012.10.005

Lamontagne, J.R., Reed, P.M., Link, R., Calvin, K.V., Clarke, L.E., Edmonds, J.A., 2018. Large Ensemble Analytic Framework for Consequence-Driven Discovery of Climate Change Scenarios. Earths Future 6, 488–504. https://doi.org/10.1002/2017EF000701

Lempert, R., 2013. Scenarios that illuminate vulnerabilities and robust responses. Clim. Change 117, 627–646. https://doi.org/10.1007/s10584-012-0574-6

Lempert, R.J., 2019. Robust Decision Making (RDM), in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty: From Theory to Practice. Springer International Publishing, Cham, pp. 23–51. https://doi.org/10.1007/978-3-030-05252-2_2

Lempert, R.J., 2002. A new decision sciences for complex systems. Proc. Natl. Acad. Sci. 99, 7309–7313. https://doi.org/10.1073/pnas.082081699

Lempert, R.J., Bryant, B.P., Bankes, S.C., 2008. Comparing Algorithms for Scenario Discovery. RAND Corporation.

Lempert, R.J., Groves, D.G., Popper, S.W., Bankes, S.C., 2006. A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. Manag. Sci. 52, 514–528. https://doi.org/10.1287/mnsc.1050.0472

Lempert, R.J., Popper, S.W., Bankes, S.C., 2003. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation.

Lucena, A.F.P., Clarke, L., Schaeffer, R., Szklo, A., Rochedo, P.R.R., Nogueira, L.P.P., Daenzer, K., Gurgel, A., Kitous, A., Kober, T., 2016. Climate policy scenarios in Brazil: A multi-model comparison for energy. Energy Econ. 56, 564–574. https://doi.org/10.1016/j.eneco.2015.02.005

Marangoni, G., Tavoni, M., Bosetti, V., Borgonovo, E., Capros, P., Fricko, O., Gernaat, D.E.H.J., Guivarch, C., Havlik, P., Huppmann, D., Johnson, N., Karkatsoulis, P., Keppo, I., Krey, V., Ó Broin, E., Price, J., van Vuuren, D.P., 2017. Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways. Nat. Clim. Change 7, 113–117. https://doi.org/10.1038/nclimate3199

Marino, E., Ribot, J., 2012. Special Issue Introduction: Adding insult to injury: Climate change and the inequities of climate intervention. Glob. Environ. Change, Adding Insult to Injury: Climate Change, Social Stratification, and the Inequities of Intervention 22, 323–328. https://doi.org/10.1016/j.gloenvcha.2012.03.001

Markkanen, S., Anger-Kraavi, A., 2019. Social impacts of climate change mitigation policies and their implications for inequality. Clim. Policy 19, 827–844. https://doi.org/10.1080/14693062.2019.1596873

McFarland, J., Zhou, Y., Clarke, L., Sullivan, P., Colman, J., Jaglom, W.S., Colley, M., Patel, P., Eom, J., Kim, S.H., Kyle, G.P., Schultz, P., Venkatesh, B., Haydel, J., Mack, C., Creason, J., 2015. Impacts of rising air temperatures and emissions mitigation on electricity demand and supply in the United States: a multi-model comparison. Clim. Change 131, 111–125. https://doi.org/10.1007/s10584-015-1380-8

McJeon, H.C., Clarke, L., Kyle, P., Wise, M., Hackbarth, A., Bryant, B.P., Lempert, R.J., 2011. Technology interactions among low-carbon energy technologies: What can we learn from a large number of scenarios? Energy Econ., Special Issue on The Economics of Technologies to Combat Global Warming 33, 619–631. https://doi.org/10.1016/j.eneco.2010.10.007

Moksnes, N., Rozenberg, J., Broad, O., Taliotis, C., Howells, M., Rogner, H., 2019. Determinants of energy futures—a scenario discovery method applied to cost and carbon emission futures for South American electricity infrastructure. Environ. Res. Commun. 1, 025001. https://doi.org/10.1088/2515-7620/ab06de

Morris, J., Reilly, J., Paltsev, S., Sokolov, A., Cox, K., 2022. Representing Socio-Economic Uncertainty in Human System Models. Earths Future 10, e2021EF002239. https://doi.org/10.1029/2021EF002239

New, M., Hulme, M., 2000. Representing uncertainty in climate change scenarios: a Monte-Carlo approach. Integr. Assess. 1, 203–213. https://doi.org/10.1023/A:1019144202120

NREL, 2019. 2019 Annual Technology Baseline. NREL (National Renewable Energy Laboratory), Golden, CO.

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

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Change 122, 387–400. https://doi.org/10.1007/s10584-013-0905-2

Ou, Y., Iyer, G., Clarke, L., Edmonds, J., Fawcett, A.A., Hultman, N., McFarland, J.R., Binsted, M., Cui, R., Fyson, C., Geiges, A., Gonzales-Zuñiga, S., Gidden, M.J., Höhne, N., Jeffery, L., Kuramochi, T., Lewis, J., Meinshausen, M., Nicholls, Z., Patel, P., Ragnauth, S., Rogelj, J., Waldhoff, S., Yu, S., McJeon, H., 2021. Can updated climate pledges limit warming well below 2°C? Science 374, 693–695. https://doi.org/10.1126/science.abl8976

Paltsev, S., Morris, J., Kheshgi, H., Herzog, H., 2021. Hard-to-Abate Sectors: The role of industrial carbon capture and storage (CCS) in emission mitigation. Appl. Energy 300, 117322. https://doi.org/10.1016/j.apenergy.2021.117322

Paredes-Vergara, M., Palma-Behnke, R., Haas, J., 2024. Characterizing decision making under deep uncertainty for model-based energy transitions. Renew. Sustain. Energy Rev. 192, 114233. https://doi.org/10.1016/j.rser.2023.114233

Parr, T., Hamrick, J., Wilson, J.D., 2024. Nonparametric feature impact and importance. Inf. Sci. 653, 119563. https://doi.org/10.1016/j.ins.2023.119563

Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., Wagener, T., 2016. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environ. Model. Softw. 79, 214–232. https://doi.org/10.1016/j.envsoft.2016.02.008

Pietzcker, R.C., Ueckerdt, F., Carrara, S., De Boer, H.S., Després, J., Fujimori, S., Johnson, N., Kitous, A., Scholz, Y., Sullivan, P., Luderer, G., 2017. System integration of wind and solar power in integrated assessment models: A cross-model evaluation of new approaches. Energy Econ. 64, 583–599. https://doi.org/10.1016/j.eneco.2016.11.018

Riahi, K. (Ed.), 2022. Mitigation Pathways Compatible with Long-term Goals, in: Climate Change 2022 - Mitigation of Climate Change. Cambridge University Press, pp. 295–408. https://doi.org/10.1017/9781009157926.005

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Change 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Policy Sci. 4, 155–169. https://doi.org/10.1007/BF01405730

Ross, L., Drehobl, A., Stickles, B., 2018. The High Cost of Energy in Rural America: Household Energy Burdens and Opportunities for Energy Efficiency. ACEEE.

Saarela, M., Jauhiainen, S., 2021. Comparison of feature importance measures as explanations for classification models. SN Appl. Sci. 3, 272. https://doi.org/10.1007/s42452-021-04148-9

Santos Da Silva, S.R., Iyer, G., Wild, T.B., Hejazi, M.I., Vernon, C.R., Binsted, M., Miralles-Wilhelm, F., 2021. The implications of uncertain renewable resource potentials for global wind and solar electricity projections. Environ. Res. Lett. 16, 124060. https://doi.org/10.1088/1748-9326/ac3c6b

Shortridge, J.E., Guikema, S.D., 2016. Scenario Discovery with Multiple Criteria: An Evaluation of the Robust Decision-Making Framework for Climate Change Adaptation. Risk Anal. 36, 2298–2312. https://doi.org/10.1111/risa.12582

Sovacool, B.K., 2021. Who are the victims of low-carbon transitions? Towards a political ecology of climate change mitigation. Energy Res. Soc. Sci. 73, 101916. https://doi.org/10.1016/j.erss.2021.101916

Srikrishnan, V., Lafferty, D.C., Wong, T.E., Lamontagne, J.R., Quinn, J.D., Sharma, S., Molla, N.J., Herman, J.D., Sriver, R.L., Morris, J.F., Lee, B.S., 2022. Uncertainty Analysis in Multi-Sector Systems: Considerations for Risk Analysis, Projection, and Planning for Complex Systems. Earths Future 10, e2021EF002644. https://doi.org/10.1029/2021EF002644

Steinmann, P., Auping, W.L., Kwakkel, J.H., 2020. Behavior-based scenario discovery using time series clustering. Technol. Forecast. Soc. Change 156, 120052. https://doi.org/10.1016/j.techfore.2020.120052

UNFCCC, 2023. Outcome of the first global stocktake (Draft decision No. FCCC/PA/CMA/2023/L.17), Conference of the Parties serving as the meeting of the Parties to the Paris Agreement, Fifth session. United Nations, United Arab Emirates.

UNFCCC, 2022a. Nationally determined contributions under the Paris Agreement (Synthesis Report No. GE.22-17490(E)), Conference of the Parties serving as the meeting of the Parties to the Paris Agreement. United Nations, Sharm el-Sheikh.

UNFCCC, 2022b. Long-term low-emission development strategies (Synthesis Report No. GE.22-17493(E)), Conference of the Parties serving as the meeting of the Parties to the Paris Agreement. United Nations, Sharm el-Sheikh.

United Nations, 2015. United Nations Treaty Collection, C.N.92.2016.TREATIES-XXVII.7.d.

van de Ven, D.-J., Mittal, S., Gambhir, A., Lamboll, R.D., Doukas, H., Giarola, S., Hawkes, A., Koasidis, K., Köberle, A.C., McJeon, H., Perdana, S., Peters, G.P., Rogelj, J., Sognnaes, I., Vielle, M., Nikas, A., 2023. A multimodel analysis of post-Glasgow climate targets and feasibility challenges. Nat. Clim. Change 13, 570–578. https://doi.org/10.1038/s41558-023-01661-0

Van Der Zwaan, B., Kober, T., Calderon, S., Clarke, L., Daenzer, K., Kitous, A., Labriet, M., Lucena, A.F.P., Octaviano, C., Di Sbroiavacca, N., 2016. Energy technology roll-out for climate change mitigation: A multi-model study for Latin America. Energy Econ. 56, 526–542. https://doi.org/10.1016/j.eneco.2015.11.019

Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., Krayer von Krauss, M.P., 2003. Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. Integr. Assess. 4, 5–17. https://doi.org/10.1076/iaij.4.1.5.16466

Walker, W.E., Lempert, R.J., Kwakkel, J.H., 2013. Deep Uncertainty, in: Gass, S.I., Fu, M.C. (Eds.), Encyclopedia of Operations Research and Management Science. Springer US, Boston, MA, pp. 395–402. https://doi.org/10.1007/978-1-4419-1153-7_1140

Wilkerson, J.T., Leibowicz, B.D., Turner, D.D., Weyant, J.P., 2015. Comparison of integrated assessment models: Carbon price impacts on U.S. energy. Energy Policy 76, 18–31. https://doi.org/10.1016/j.enpol.2014.10.011

Wise, M., Calvin, K., Thomson, A., Clarke, L., Bond-Lamberty, B., Sands, R., Smith, S.J., Janetos, A., Edmonds, J., 2009. Implications of Limiting CO2 Concentrations for Land Use and Energy. Science 324, 1183–1186. https://doi.org/10.1126/science.1168475

Wolfram, P., Kyle, P., Fuhrman, J., O'Rourke, P., McJeon, H., 2022. The value of hydrogen for global climate change mitigation. https://doi.org/10.21203/rs.3.rs-2074134/v1

Woodard, D.L., Snyder, A., Lamontagne, J.R., Tebaldi, C., Morris, J., Calvin, K.V., Binsted, M., Patel, P., 2023. Scenario Discovery Analysis of Drivers of Solar and Wind Energy Transitions Through 2050. Earths Future 11, e2022EF003442. https://doi.org/10.1029/2022EF003442

Workman, M., Darch, G., Dooley, K., Lomax, G., Maltby, J., Pollitt, H., 2021. Climate policy decision making in contexts of deep uncertainty - from optimisation to robustness. Environ. Sci. Policy 120, 127–137. https://doi.org/10.1016/j.envsci.2021.03.002

World Bank, 2020. Doing Business 2020: Comparing Business Regulation in 190 Economies. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1440-2

Yue, X., Pye, S., DeCarolis, J., Li, F.G.N., Rogan, F., Gallachóir, B.Ó., 2018. A review of approaches to uncertainty assessment in energy system optimization models. Energy Strategy Rev. 21, 204–217. https://doi.org/10.1016/j.esr.2018.06.003

Zapata, V., Gernaat, D.E.H.J., Yalew, S.G., Silva, S.R.S. da, Iyer, G., Hejazi, M., Vuuren, D.P. van, 2022. Climate change impacts on the energy system: a model comparison. Environ. Res. Lett. 17, 034036. https://doi.org/10.1088/1748-9326/ac5141

Zhao, M., Binsted, M., Wild, T., Khan, Z., Yarlagadda, B., Iyer, G., Vernon, C.R., Patel, P., Silva, S.R.S. da, Calvin, K.V., 2021. plutus: An R package to calculate electricity investments and stranded assets from the Global Change Analysis Model (GCAM). J. Open Source Softw. 6, 3212. https://doi.org/10.21105/joss.03212

Appendix A. Supplemental Information

A.1. Literature Review

Since the adoption of the Paris Agreement and the emergence of Nationally Determined Contributions (NDCs) and Long-term Strategies (LTS), model-based research has actively explored the feasibility, implications, and opportunities surrounding these policies and other emissions reduction pathways. Many of these studies focus on the policy implementation while relying on business-as-usual assumptions in other areas of the modeling framework. (Iyer et al., 2015b) examine the NDCs in 2015 and the energy-economic implications across policy scenarios which vary the timing of mitigation actions. (Fawcett et al., 2015) also assess these NDC pledges by computing probabilistic temperature outcomes with a global climate model based on several scenarios constructed with an integrated assessment model. (Ou et al., 2021) then evaluate the updated 2020 NDC pledges using additional simulations, emphasizing that additional ambition is needed to achieve long-term goals. These studies use a limited number of scenarios in determining emissions trajectories, trading off the evaluation of uncertainty with finely-tuned scenario pathways. (Gambhir et al., 2022) approach emissions mitigation using several temperature target scenarios as well as an NDC scenario to identify transition risk metrics within an integrated assessment framework. The authors find that different types of risks emerge as being most sensitive to the future temperature pathway on different timescales. (Binsted et al., 2020) used NDC scenarios to quantify the economic implications of stranded assets under the Paris Agreement, finding significant cost burdens associated with the policies. (Santos Da Silva et al., 2019) model two NDC scenarios using an integrated assessment framework in which one scenario does not have access to CCS technologies, and evaluates resulting food-energy-water nexus outcomes.

There exists also a broad literature of uncertainty and sensitivity analysis centered around climate mitigation modeling research. However, many of these studies evaluate only a few deeply uncertain factors in their simulations, often only implemented individually rather than through a factorial ensemble. (Iyer et al., 2015a) explore varying the cost of financing clean energy projects in the electric power sector across regions due to investment risk and variations in institutional quality under a generic 50% emissions reduction policy. This study found that these disparities in investment risks significantly affected the total costs of mitigation, and that more industrialized regions take on a greater share of the mitigation requirements. (Kanyako and Baker, 2021) perform an uncertainty analysis on wind energy costs for a carbon tax and a 1.5° scenario, exploring impacts on wind generation share across a distribution of cost forecasts. (Ou et al., 2018) compare two low-carbon pathways (each comprised of several technology assumptions) in the US under two different mid-century emissions reductions targets, evaluated with water consumption and air pollution metrics. (Moksnes et al., 2019) prepare an ensemble of 324 scenarios varying six uncertain factors related to energy systems (including a simple CO_2 target) and perform scenario discovery on the resulting cost and capacity mix outcomes.

Several studies use an ensemble of model realizations in climate mitigation contexts. McJeon et al., 2011 uses a large, 768-member ensemble and scenario discovery to explore the impacts of technology assumptions on stabilization costs under two temperature stabilization scenarios. Groves et al., 2020 develops 3,003 realizations of Costa Rica's decarbonization plan to assess the economic value of the plan independent of international pledges. Although many previous modeling efforts have examined impacts of climate mitigation measures and parametric uncertainties on energy-economic outcomes, there remains a gap in evaluating countries' NDC + LTS pledges across a wide range of deeply uncertain factors in a large ensemble framework. This study seeks to confirm the results of prior research in a robust NDC- + LTS-consistent mitigation context, as well as examine interactive effects of previously independent sensitivity factors in a large ensemble of model realizations.

Table S1: Non-exhaustive list of existing work.

Authors	Short Description	Approach to Uncertainty
McJeon et al., 2011	768-member large ensemble of GCAM runs exploring impacts of technology assumptions on stabilization costs	Scenario discovery, reporting density and coverage statistics on extreme outcomes
Fawcett et al., 2015	600-member temperature projection ensemble applied to several GCAM Paris Agreement scenarios	Temperature outcomes presented probabilistically
Isley et al., 2015	XLRM framework generating 6,000 combinations of uncertain parameters and 6 policies in agent-based model	Exploratory modeling to explore decarbonization rates and policy choices
Iyer et al., 2015b	Four GCAM scenarios varying model assumptions to explore Paris Agreement implications on 2°C	Using a small number of detailed representative scenarios to assess implications of INDCs
McFarland et al., 2015	Set of temperature projections applied to GCAM-USA, ReEDS, IPM to look at electricity supply/demand	Multi-model comparison
Wilkerson et al., 2015	Carbon price scenarios applied to GCAM, MERGE, and EPPA	Multi-model comparison
Kober et al., 2016	Climate policies centered on Latin America, using GCAM, POLES, TIAM-ECN, and TIAM-WORLD	Multi-model comparison
Lucena et al., 2016	Five scenarios of Brazil's energy mix using EPPA, GCAM, MESSAGE-Brazil, Phoenix, POLES, and TIAM-ECN	Multi-model comparison
Van Der Zwaan et al., 2016	Five scenarios of energy technology deployment in Latin America using EPPA, GCAM, Phoenix, POLES, TIAM-ECN, and TIAM-WORLD	Multi-model comparison
Pietzcker et al., 2017	Integration of wind and solar in IAMs using AIM/CGE, IMAGE, MESSAGE, POLES, REMIND, and WITCH	Multi-model comparison
Kriegler et al., 2018	Strengthening short-term goals to meet Paris Agreement with 13 scenarios across three policy dimensions using REMIND-MAgPIE	Constructing representative scenarios with detailed sectoral assumptions to assess policy impacts
Lamontagne et al., 2018	33,750-member ensemble of GCAM runs splitting SSP assumptions into individually sampled elements	Scenario discovery using CART
Arango-Aramburo et al., 2019	Climate-impacted hydropower in Colombia using two GCMs, two RCPs, and 4 IAMs: GCAM, TIAM-ECN, MEG4C, Phoenix	Multi-model comparison
Lamontagne et al., 2019	5,200,000-member ensemble using DICE, sampling 24 uncertain factors and growth rate of global abatement	Time-varying sensitivity analysis
Moksnes et al., 2019	324-member ensemble using OSeMOSYS-SAMBA to explore South American electricity infrastructure	Scenario discovery using a Gaussian mixture model and PRIM
Binsted et al., 2020	Four global GHG mitigation scenarios using GCAM to explore stranded assets in Latin America	Used 36 sensitivity scenarios to perform sensitivity analysis

Burleyson et al., 2020	Four scenarios each run using GCAM-USA and BEND to explore US buildings electricity consumption	Two-model comparison
Groves et al., 2020	3,003-member ensemble varying over 300 uncertainties to explore Costa Rica's national decarbonization plan	Scenario discovery using PRIM to identify vulnerabilities
Dolan et al., 2021	3,000-member ensemble of GCAM runs varying seven dimensions of uncertainties to explore impacts of water scarcity	Scenario discovery using CART
Kanyako and Baker, 2021	1,000-member ensemble of GCAM runs with technology costs sampled from expert elicitation data	Uncertainty propagation from expert elicitation data
Ou et al., 2021	Five emissions scenarios using GCAM coupled with simple climate model MAGICC	Probabilistic temperature outcomes using detailed emissions scenarios
Solano-Rodríguez et al., 2021	XLRM framework generating 480 alternatives for oil production in Latin America using BUEGO	Latin hypercube sampling to generate ensemble of alternatives
Birnbaum et al., 2022	3,000-member ensemble of GCAM runs exploring water scarcity in Latin America	Scenario discovery using CART
Gambhir et al., 2022	11 scenarios of temperature outcomes and socioeconomic/technological choices for 2°C pathways using GCAM	Comparison of risk metrics across detailed representative scenarios
Browning et al., 2023	Using three scenarios to analyze net-zero by 2050 in the US across 16 models	Multi-model (and multi-modeling team) comparison of detailed representative scenarios
Huang et al., 2023	28,706-member ensemble of GCAM runs coupled with TM5-FASST to explore air quality implications from climate mitigation under uncertainty	Large ensemble scenario analysis and model coupling
van de Ven et al., 2023	Three scenarios of climate action applied to GCAM-PR, GEMINI-E3, MUSE, and TIAM-Grantham	Multi-model comparison to explore feasibility of climate ambition
Woodard et al., 2023	3,989-member ensemble of GCAM runs varying 12 uncertainties chosen from expert elicitation	Scenario discovery using CART

A.2. Computing Metrics from GCAM Ensemble

Table S2: Descriptions of each metric and how each is calculated from GCAM outputs.

Metric	Short Description
Electricity Price	Marginal levelized cost of new generation (analogous to wholesale electricity costs). When aggregated from several regions, a weighted average based on total regional electricity generation is applied. Queried directly from GCAM outputs.
Electricity Share in Final Energy	Also termed "Electrification Rate", the proportion of total final energy delivered to end use sectors as electricity in each region. When aggregated from several regions, a weighted average based on total regional final energy is applied. Total final energy is queried directly from GCAM outputs, from which the proportion of electricity can be computed.
Stranded Assets	The cumulative costs of premature retirement of electric generating capacity over time in each region. Can be split by technology. Premature retirement refers to a generating unit being forced offline before the end of its economic life (e.g., due to mitigation policy constraining emissions or increasing costs to inefficient levels). Results from individual regions can be summed. Stranded assets are computed from GCAM outputs using the "plutus" R package (Zhao et al., 2021).
Capacity Investments	The cumulative capital costs of new electric generating capacity over time in each region. This metric gives one angle of a policy's economic impacts, and can be split by technology. Capacity investments are computed from GCAM outputs using the "plutus" R package (Zhao et al., 2021).
Energy Burden	An aggregated metric of distributional energy justice, computed as a residential energy burden by dividing per capita residential energy expenditures by per capita GDP. From GCAM outputs, residential energy expenditures are computed using residential building service costs (which includes levelized installed costs of service equipment in addition to fuel costs) and final energy consumption in residential sectors. Population and GDP are exogenous inputs to GCAM. This metric does not include transport service costs.
Level of CO_2 Removal	The quantity (mass of CO_2) removed from the atmosphere via Bioenergy with CCS (BECCS) and Direct Air Capture (DAC). Results from individual regions can be summed. Queried directly from GCAM outputs.
Land Use Change Emissions	The net quantity (mass of CO_2) of land use change emissions, representing regional and global carbon stocks. Results from individual regions can be summed. Queried directly from GCAM outputs.

A.3. Supplemental Figures

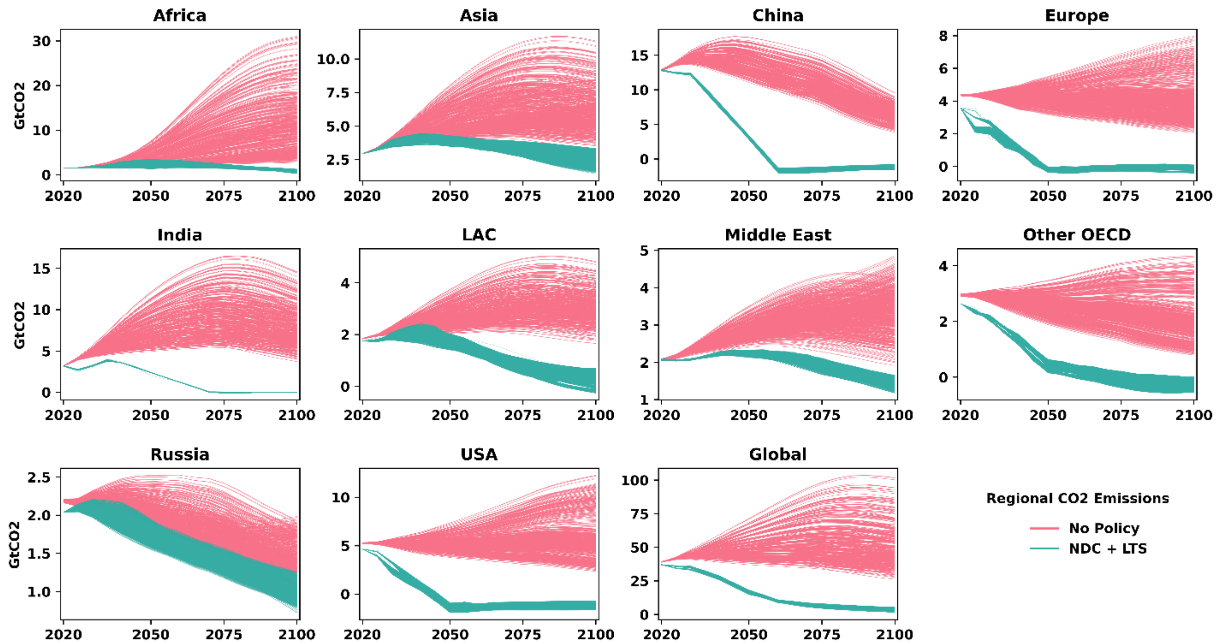

Figure S1: CO_2 emissions trajectories across regions and globally, split by climate pledge policy sensitivity. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. “Asia” includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. “LAC” refers to Latin America and the Caribbean.

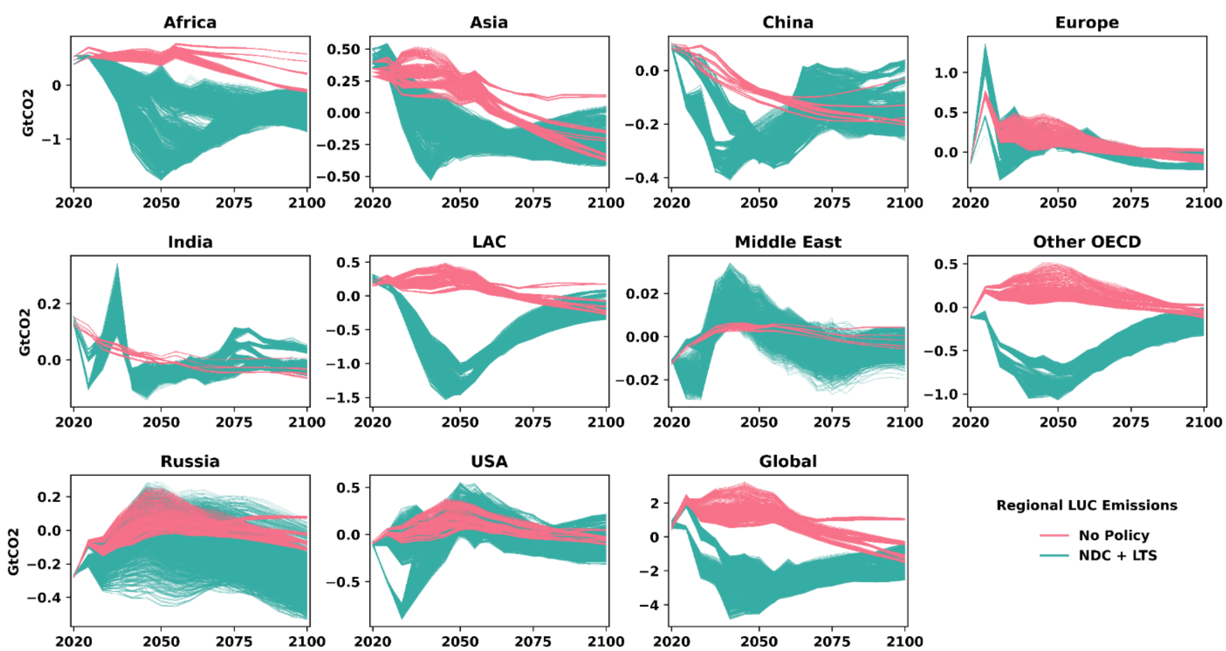

Figure S2: Land use change emissions trajectories across regions and globally, split by climate pledge policy sensitivity. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. “Asia” includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. “LAC” refers to Latin America and the Caribbean.

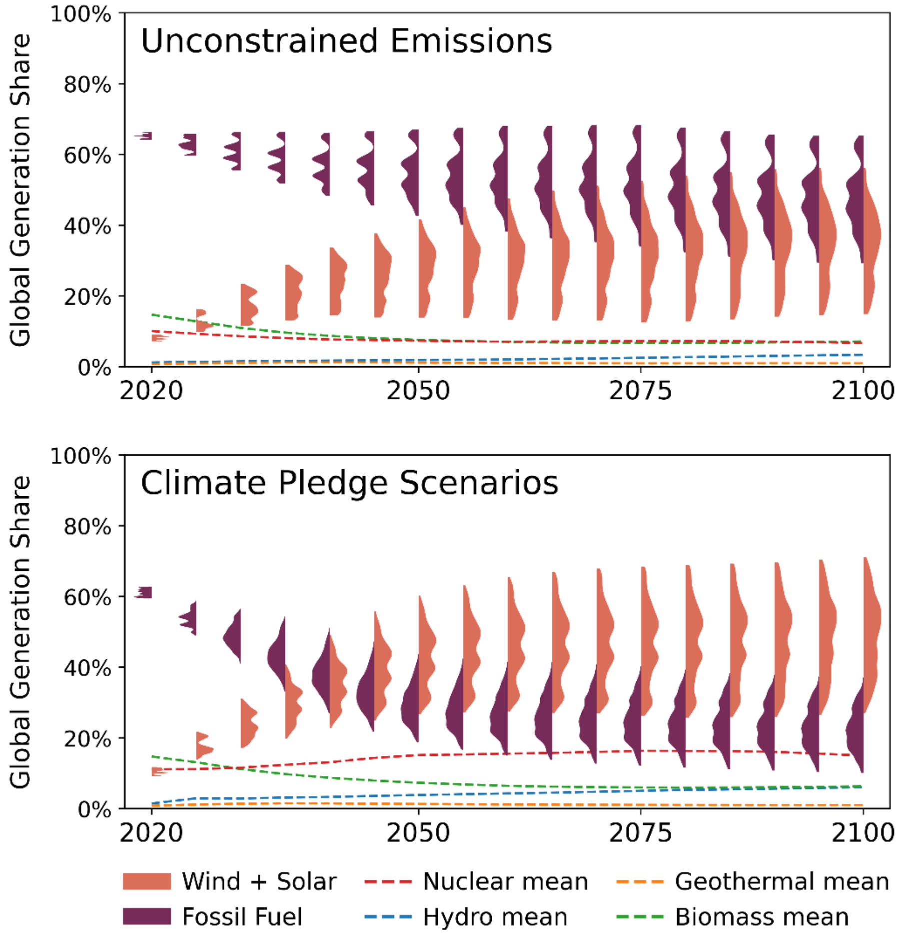

Figure S3: Evolution of the electricity generation mix as a split violin plot for No Policy cases (top) and climate pledge scenarios (bottom). Fossil fuels remain dominant in the No Policy case, although renewables still increase over time. In the NDC + LTS case, wind and solar trade places with fossil generation to become the leading producer of electricity. Fossil generation does not go to zero, partially because not every country has committed to NDC/LTS pledges, but also because of the significant amount of CO_2 removal technologies employed in the model. Variability for other generation types is relatively small; these are shown instead as dotted lines representing the mean.

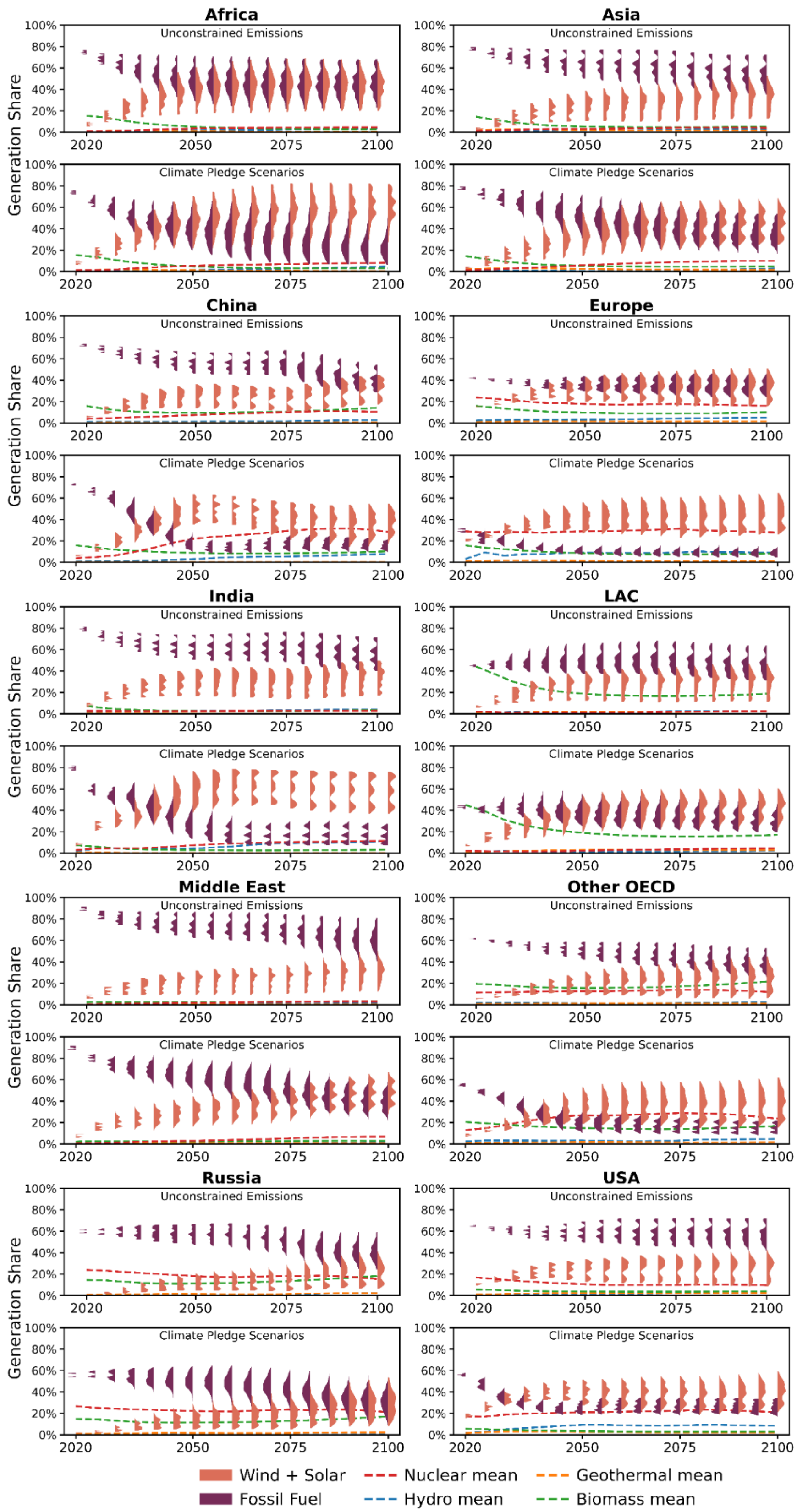

Figure S4: Generation share violin plots similar to Figure S3, split out into ten aggregated global regions.

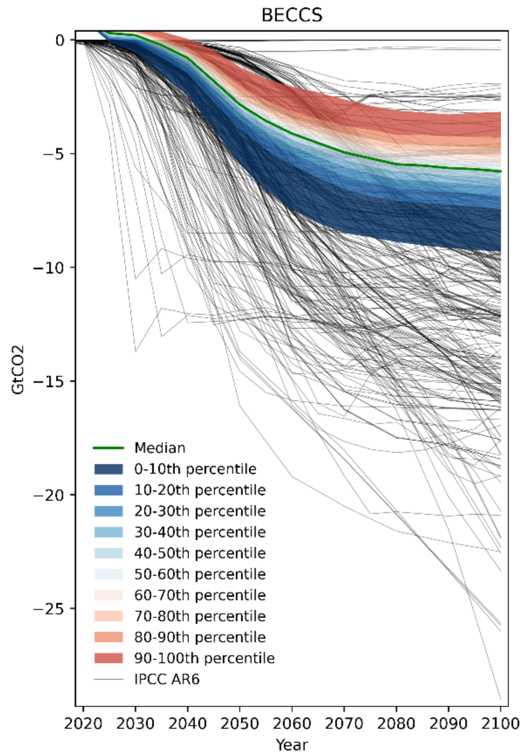

Figure S5: Bioenergy with CCS (BECCS) for climate pledge scenarios as percentiles. Negative values represent CO_2 being removed. Black lines show scenarios from IPCC AR6 (Riahi, 2022).

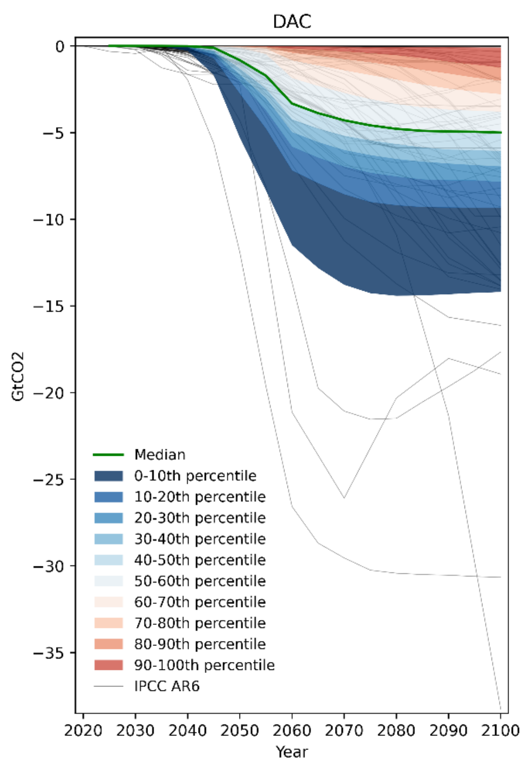

Figure S6: Direct Air Capture (DAC) for climate pledge scenarios as percentiles. Negative values represent CO_2 being removed. Black lines show scenarios from IPCC AR6 (Riahi, 2022).

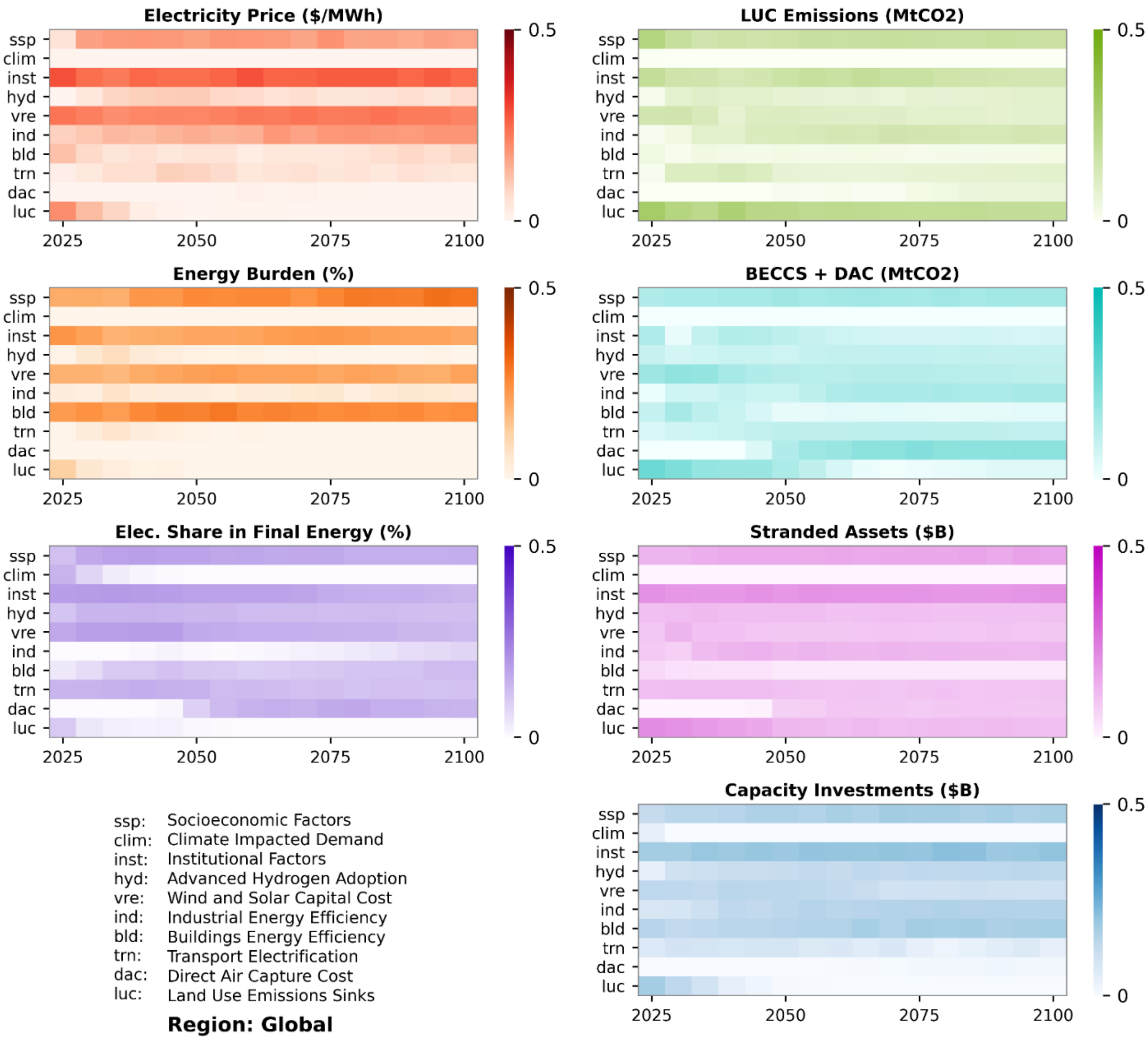

Figure S7: Feature importance analysis for seven representative metrics across the 3,840 simulations implementing national climate pledges. Each panel is presented as a heatmap quantifying relative influence by the scenario sensitivities in each row on each output metric over time. A higher score (darker color) indicates higher influence in the random forest model from the inclusion of each feature (listed in bottom left of figure). Because only NDC + LTS scenarios are examined here, this sensitivity is not listed. In general, *Socioeconomic Factors* is a relevant driver in nearly all outcome metrics, as it controls the scale of economic activity as well as resource demand. The electricity price panel confirms the critical drivers seen in Figure 2, while also notable is the increasing potential role of *Industry Energy Efficiency*, which affects industrial sectors including iron & steel, cement, aluminum, chemicals, and fertilizer production. This sensitivity also has an increasing importance in several other economic metrics as well as negative emissions. Feature importance is quantified by the average improvement in mean squared error (MSE) achieved in the random forest model from permuting each feature in out-of-bag samples, scaled to sum to one in each timestep. Feature importance here does not in itself indicate the direction of influence.

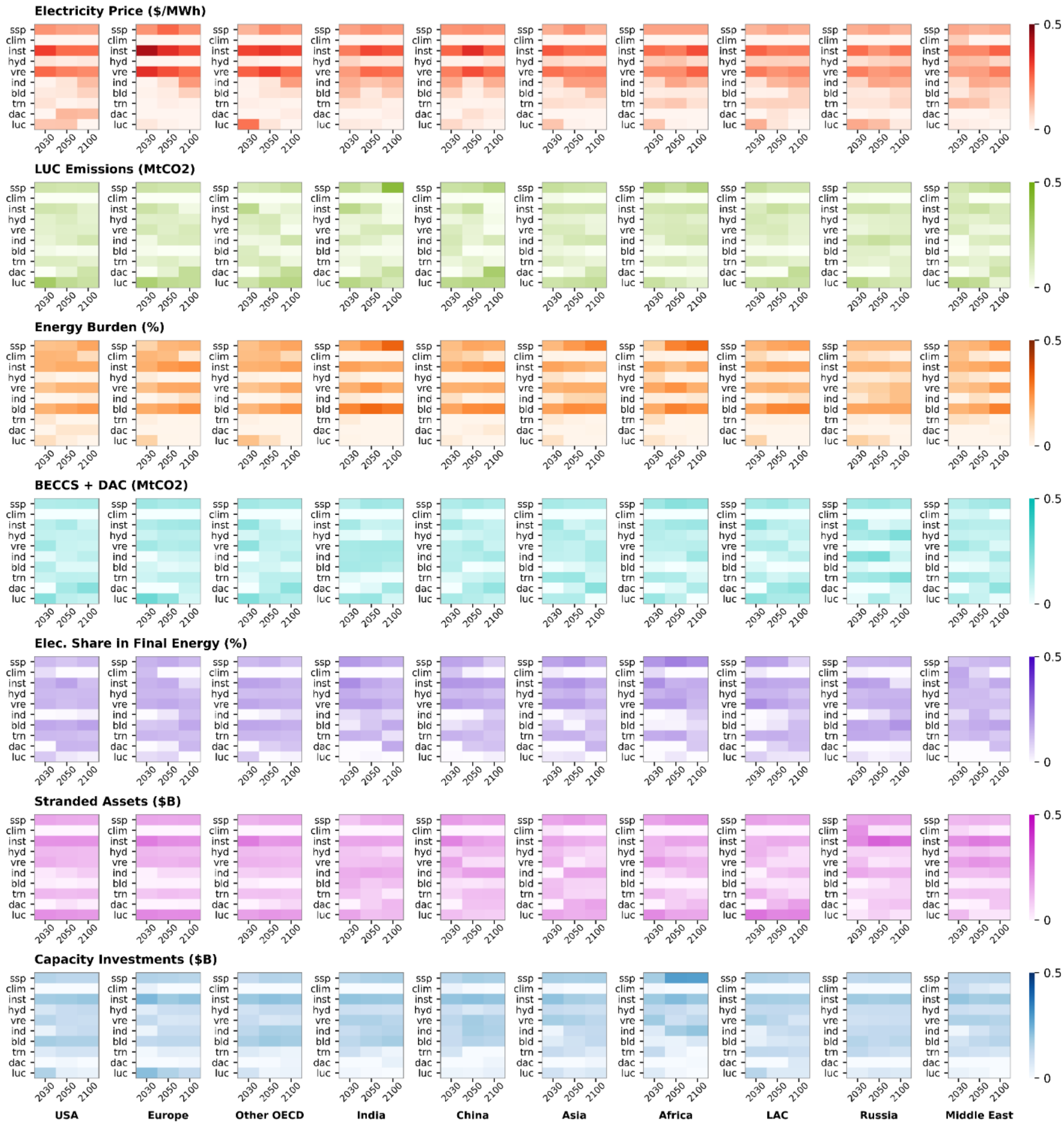

Figure S8: Feature importance analysis for seven representative metrics across the 3,840 simulations implementing national climate pledges, split by region (column) and only showing values for 2030, 2050, and 2100. Each panel is presented as a heatmap quantifying relative influence by the scenario sensitivities in each row on each output metric. A higher score (darker color) indicates higher influence in the random forest model from the inclusion of each feature. Because only NDC + LTS scenarios are examined here, this sensitivity is not listed.

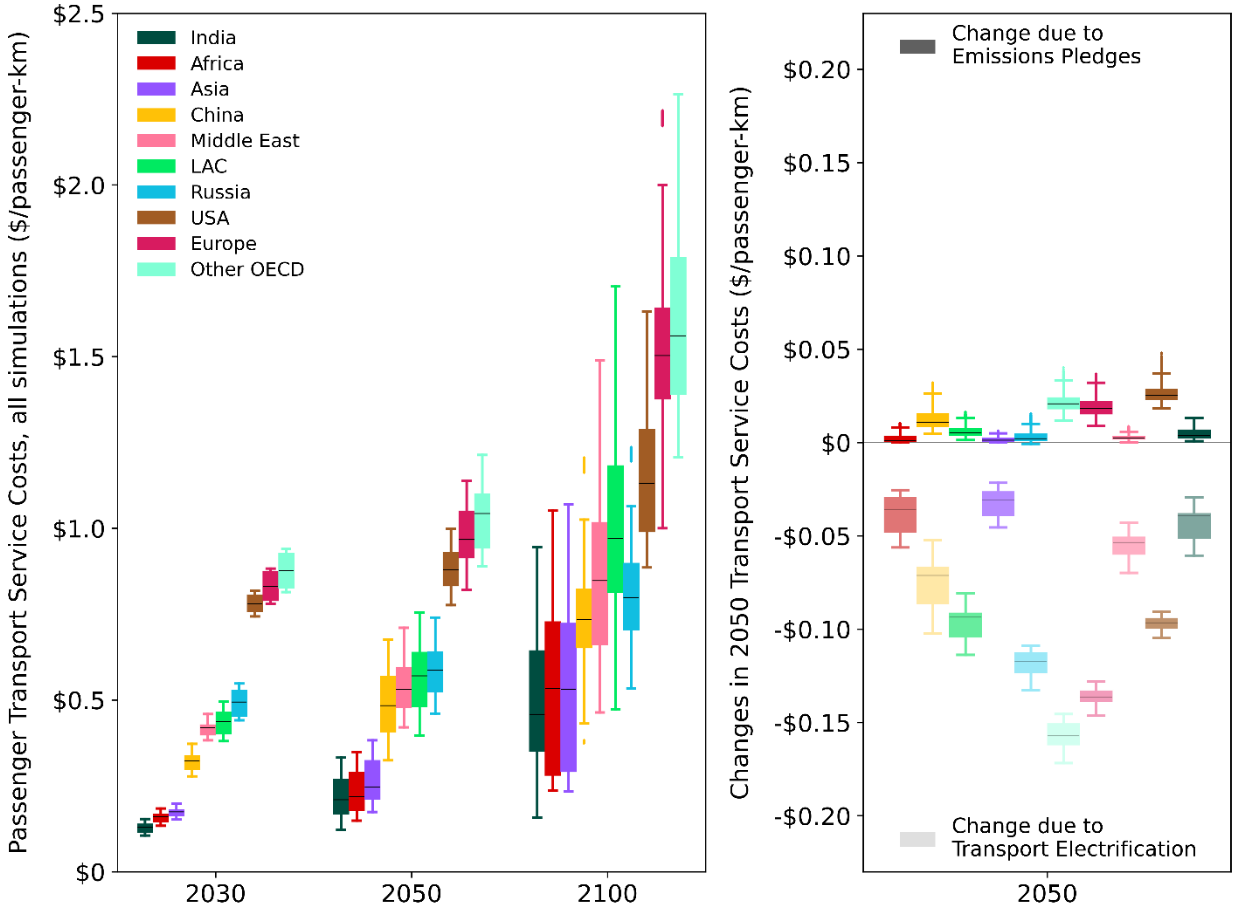

Figure S9: (left) Cost of transport services in the passenger transport sector for aggregated global regions in three model periods, showing all 5,760 simulations; **(right)** Change in passenger transport service costs caused by two scenario sensitivities (climate pledges and *Electrification of Transport*) for each model configuration, computed as the difference between pairs of realizations which differ only by inclusion/exclusion of these two scenario levers. Developed regions tend to experience the highest costs, a trend which does not change over time. Passenger transport service costs increase over time across regions, but total expenditures remain relatively stable when scaled by GDP. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. “Asia” includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. “LAC” refers to Latin America and the Caribbean.

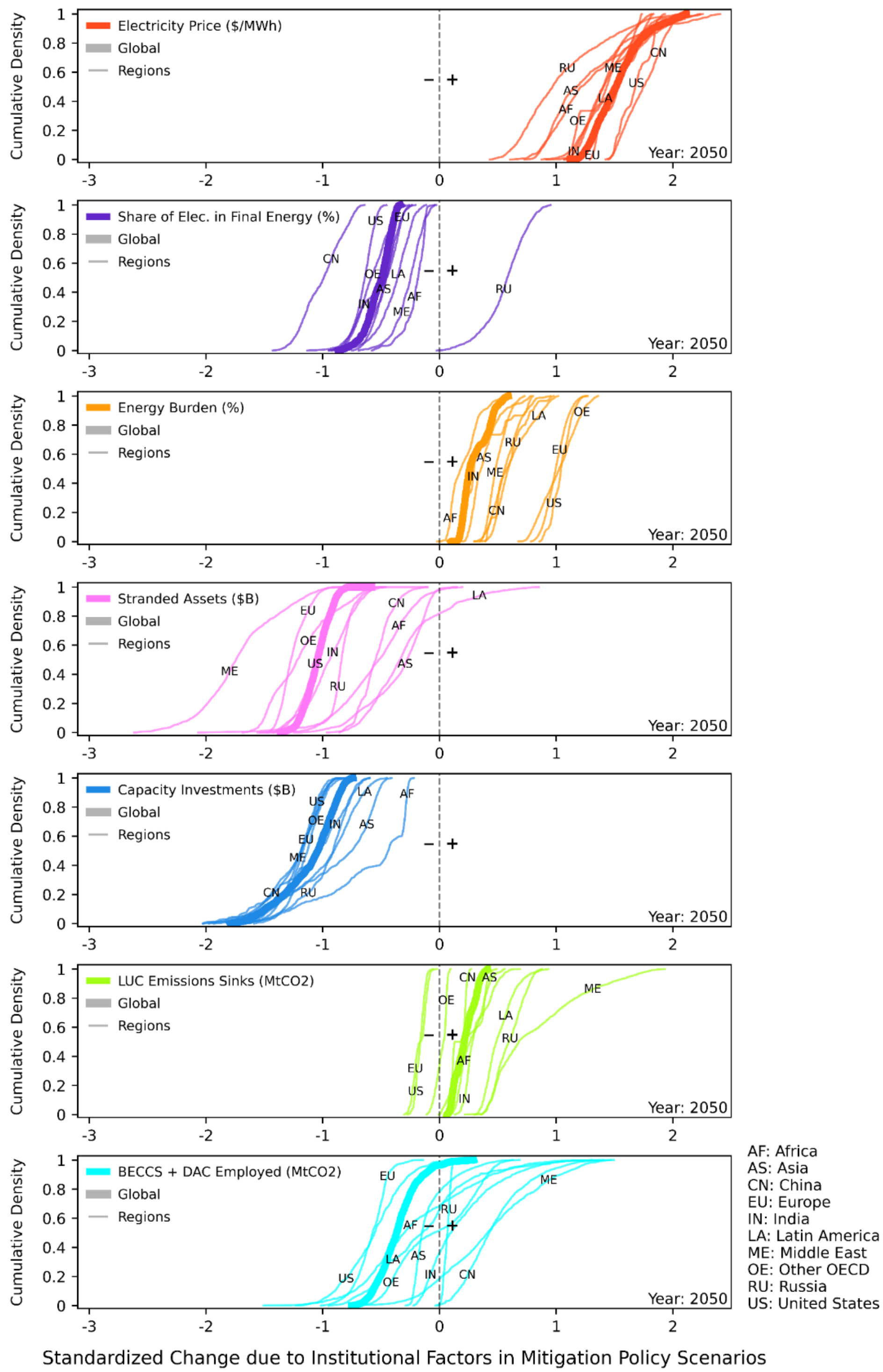

Figure S10: CDF plot showing standardized changes in the values of select metrics when investment costs are regionally and technologically differentiated in each scenario configuration (only showing scenarios with NDCs + LTS implemented). A curve lying entirely to the right (left) of zero implies that institutional factors always increase (decrease) that metric. Thicker lines refer to global weighted means, while thinner lines refer to ten aggregated global regions (legend at bottom right). Note that a steep CDF curve here suggests that varying this sensitivity results in a very consistent change in the outcome; it does not represent the underlying variability of the outcome itself.

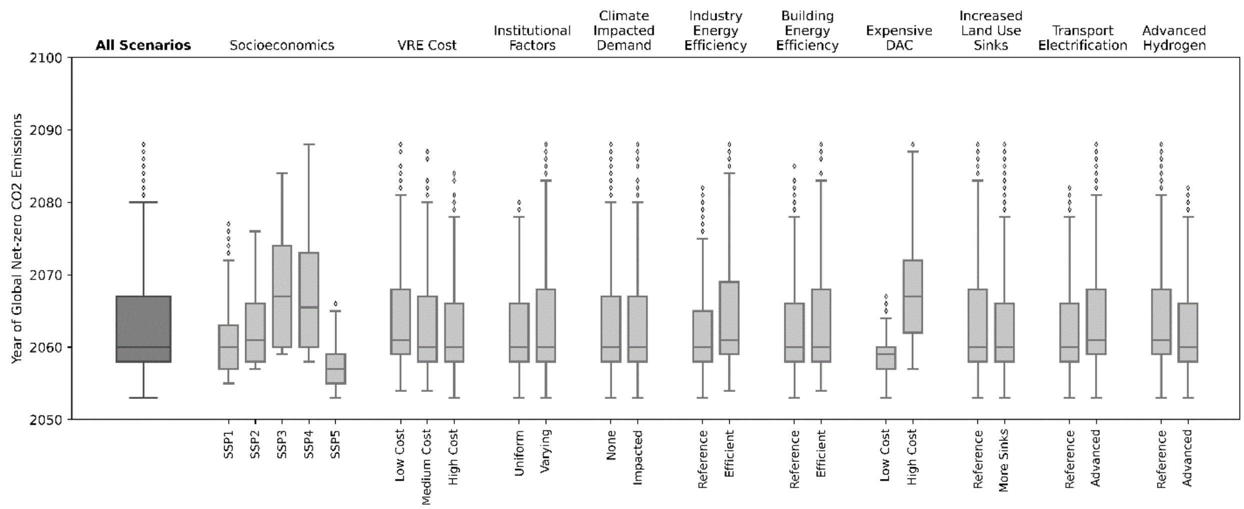

Figure S11: Year in which global net-zero CO_2 emissions is achieved across all realizations with national emissions pledges, split by scenario sensitivity. Visually, *Socioeconomic Factors* and *Direct Air Capture Cost* show the greatest variability, followed by *Industry Energy Efficiency* and *Cost of Wind and Solar* (VRE Cost). Net-zero year is determined by linear interpolation between GCAM's five-year timesteps.

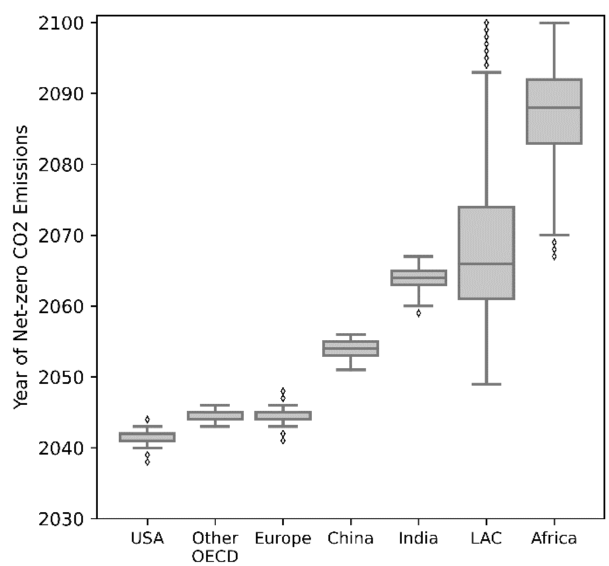

Figure S12: Year in which net-zero CO_2 emissions is achieved across aggregate regions, for all realizations with national emissions pledges. Russia, Asia, and Middle East do not reach net-zero in any simulation due to one or more countries within each region not reaching net-zero. For LAC, 93 realizations out of 3,840 do not reach net-zero by 2100. For Africa, 103 realizations out of 3,840 do not reach net-zero by 2100.