Large ensemble exploration of global energy transitions under national emissions pledges

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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.

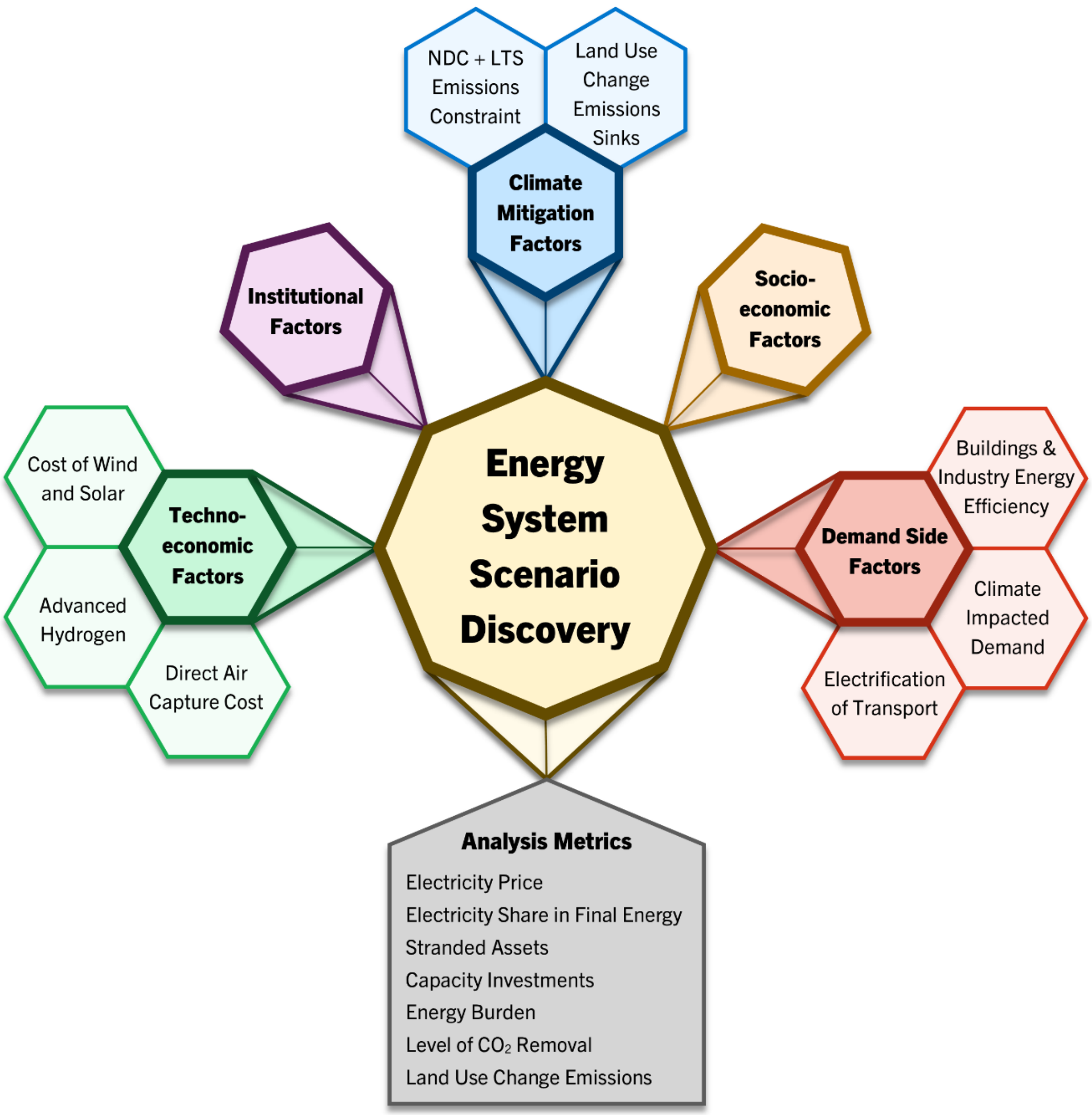

Figure 1: Categories of sensitivities varied in the ensemble and analysis metrics used.

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.

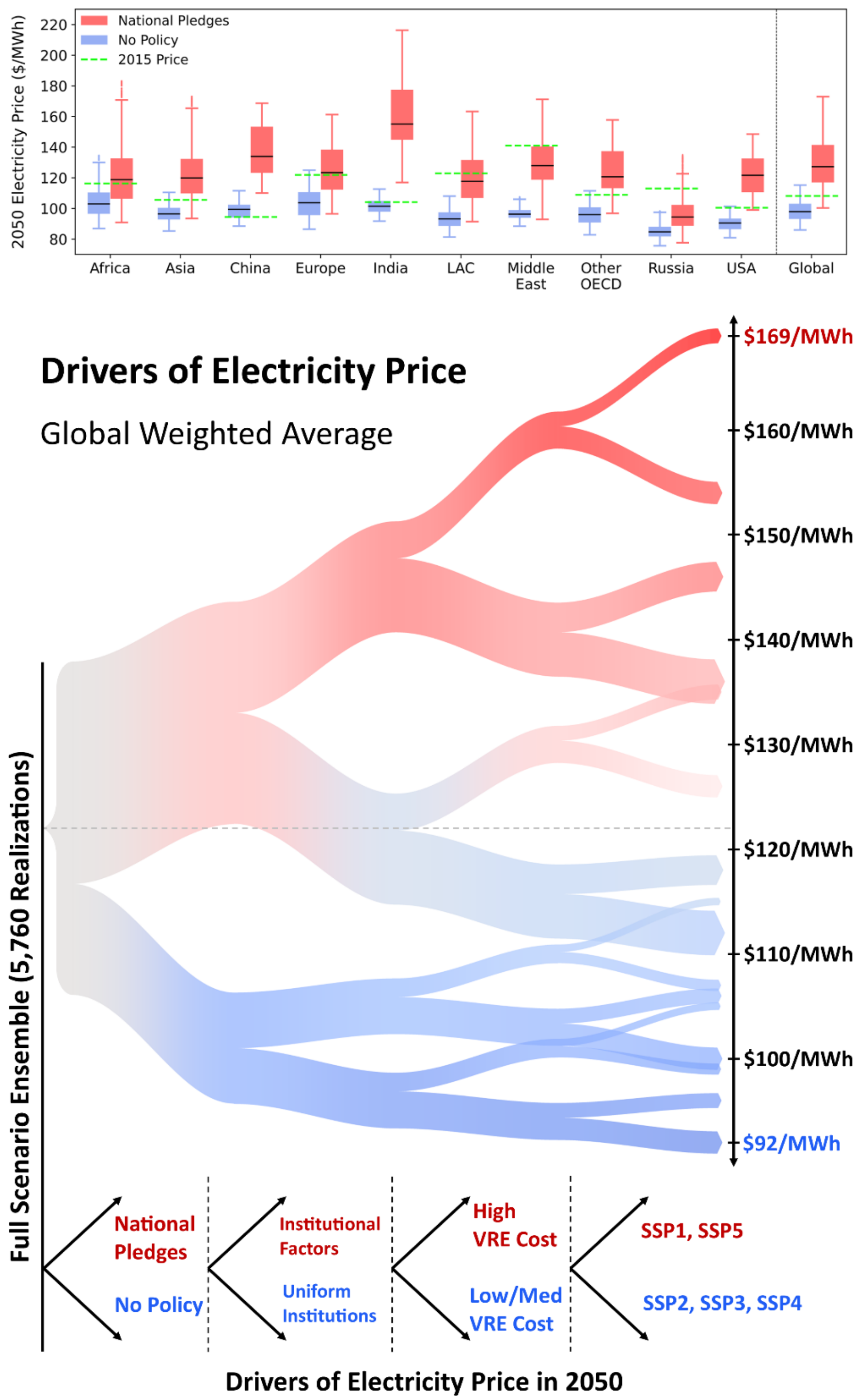

Figure 2: (top) Regional and global weighted electricity price for model regions, split between scenarios with and without climate pledges implemented. Model calibration year 2015 prices are shown for comparison; **(bottom)** most influential drivers of global weighted average electricity price ($/MWh) 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.

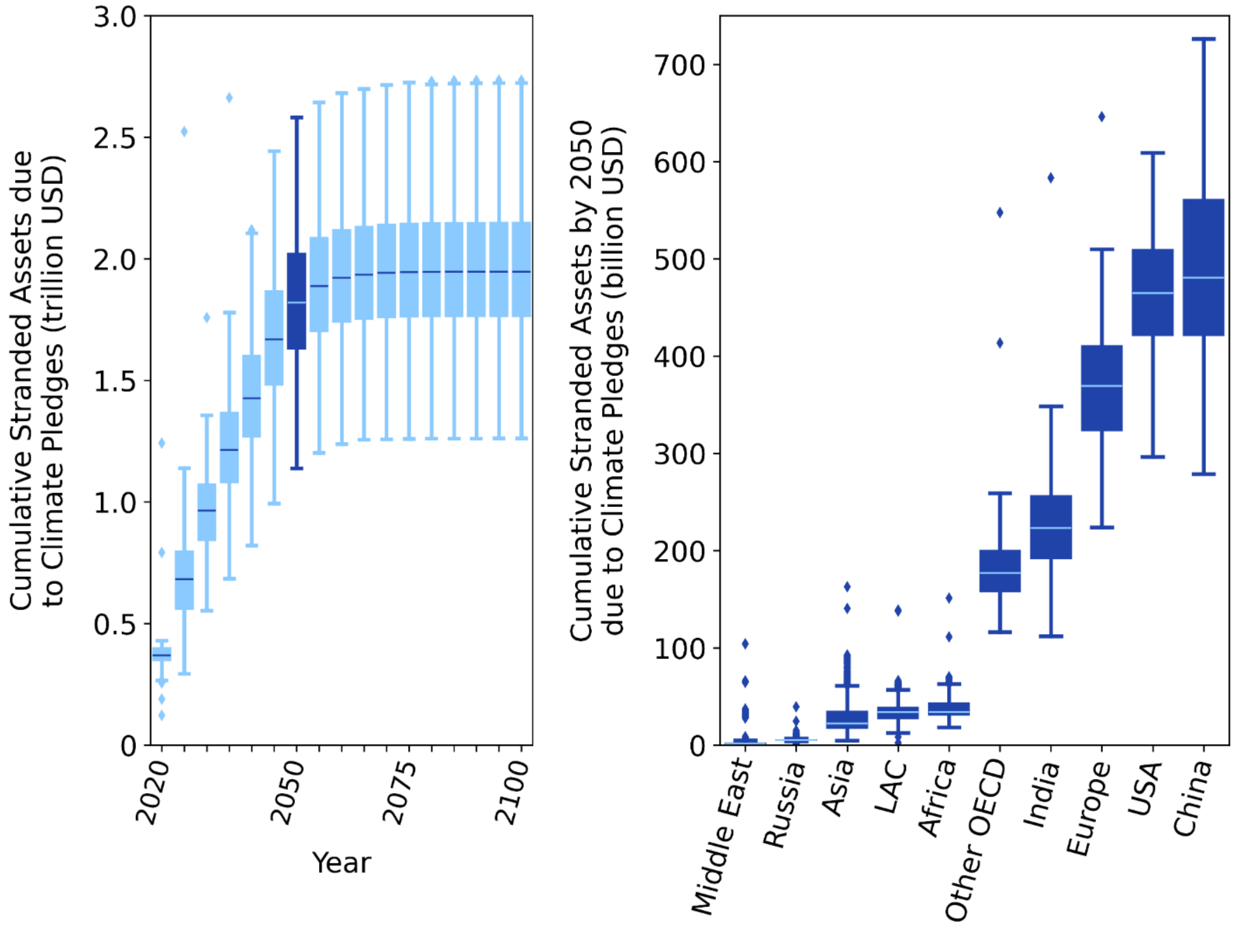

Figure 3: (left) Cumulative stranded assets (costs associated with premature retirements of generating capacity) globally over time due to implementing climate pledges, with the year 2050 highlighted; (right) cumulative stranded assets in 2050 for aggregated global regions due to implementing climate 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.

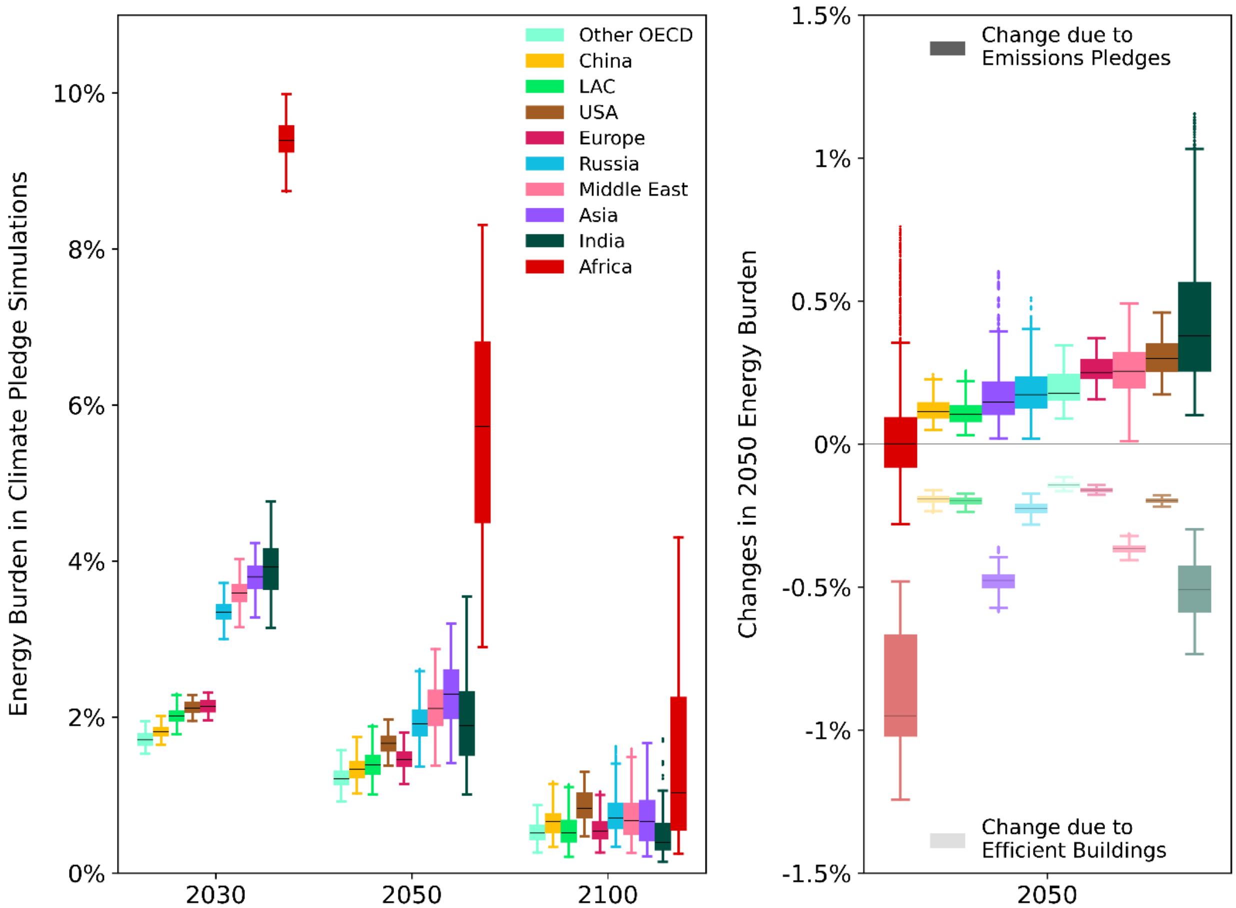

Figure 4: (left) Residential energy burden, computed as a ratio of residential energy spending to GDP per capita, for aggregated global regions for three model periods, showing the 3,840 simulations with climate pledges; **(right)** Change in energy burden caused by two scenario sensitivities (climate 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.

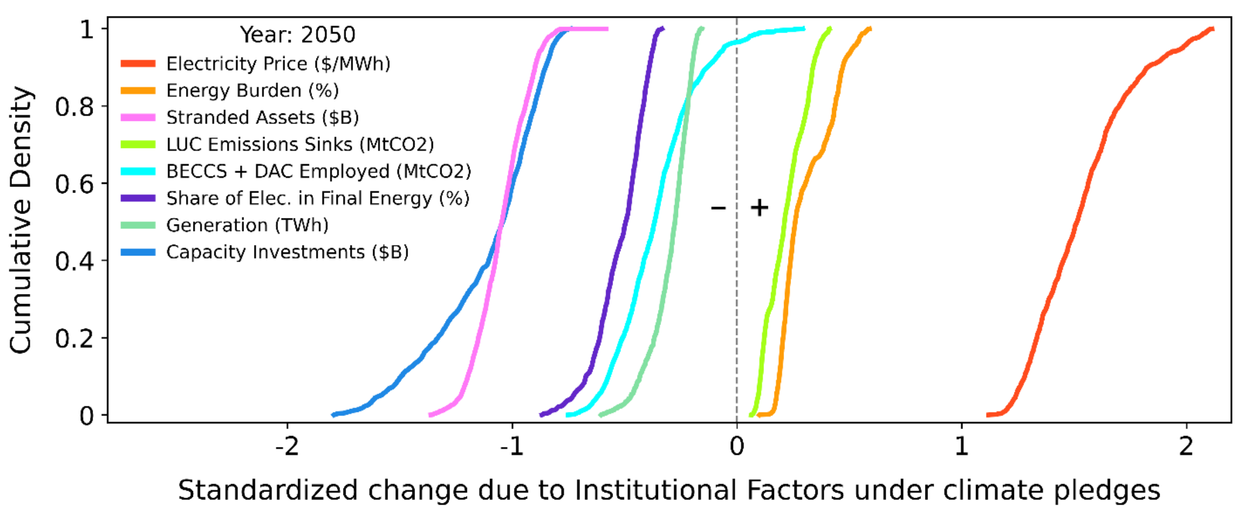

Figure 5: CDF plot showing standardized changes in the values of select metrics when institutional factors are switched on in each scenario configuration (only showing scenarios with NDCs + LTS implemented). Values on the horizontal axis represent the number of standard deviations from the mean for each 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*.

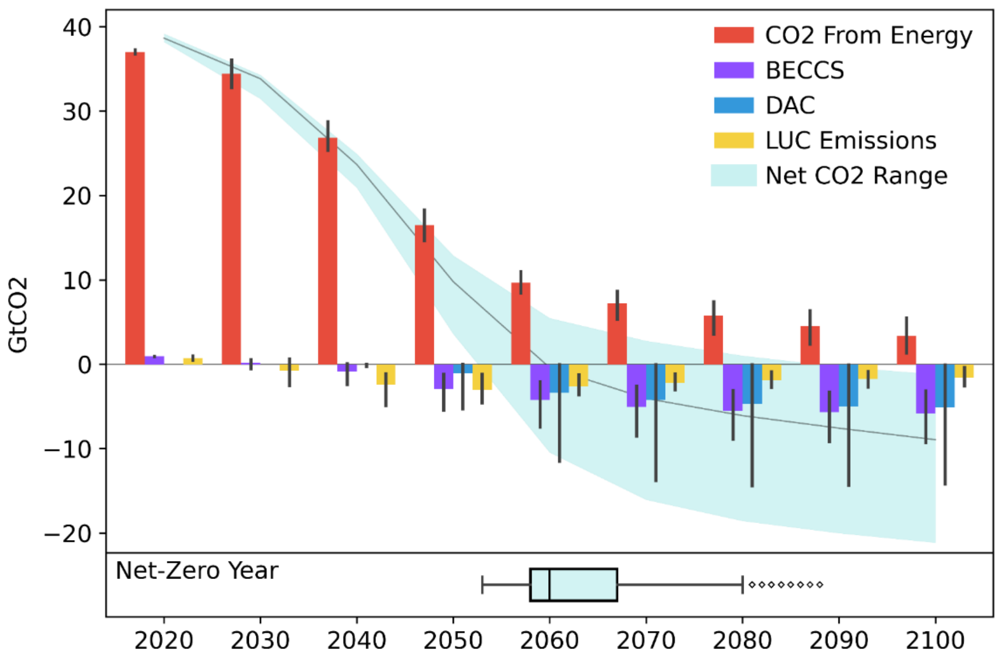

Figure 6: The use of negative emissions technologies and terrestrial carbon sinks to offset energy system emissions. Error bars show the full range of outcomes across the scenario ensemble for the 3,840 realizations that implement climate pledges. The pale shaded region in the background gives the range 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.

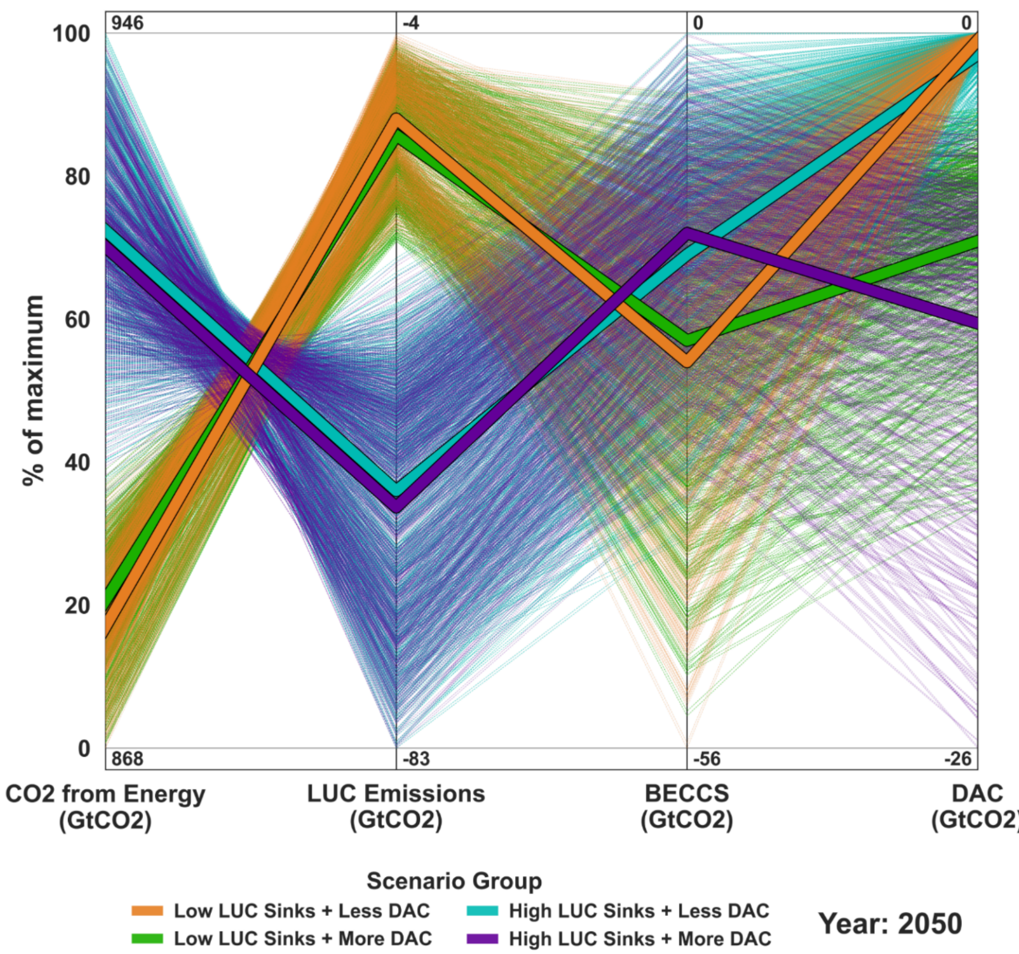

Figure 7: Parallel axis plot showing cumulative CO_2 emissions budget contributions under climate pledges in 2050. Scenarios are grouped according to the *Direct Air Capture Cost* and *Level of Land Use Sinks* sensitivities, and each column is scaled independently according to each metric's minimum and 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.

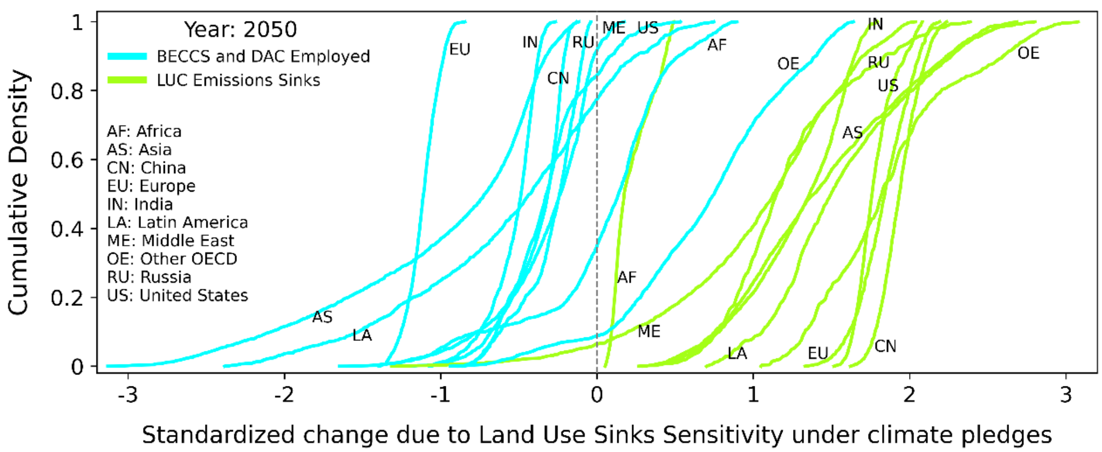

Figure 8: CDF plot showing standardized regional changes in the values of CDR adoption ("BECCS and DAC Employed") and land use sinks ("LUC Emissions Sinks") when the *Level of Land Use Sinks* sensitivity is implemented (only for scenarios with climate pledges). A curve lying entirely to the right (left) 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.

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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.

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