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Special Collection:
Multi-Sector Dynamics: Advancing Complex Adaptive Human-Earth Systems Science in a World of Interconnected Risks

Key Points:

- Energy transition costs can, by multiple metrics, unevenly impact larger economies, and developing regions under a wide range of futures
- Regional investment risk has global implications for mitigation pathways, robust to broad uncertainties and with strong relative impacts
- The relative role of different carbon dioxide removal options in meeting decarbonization goals varies across regions and scenario pathways

Supporting Information:

Supporting Information may be found in the online version of this article.

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Large Ensemble Exploration of Global Energy Transitions Under National Emissions Pledges

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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.

Plain Language Summary Most countries have pledged to significantly reduce greenhouse gas emissions over the next few decades. These emissions primarily come from burning fossil fuels for electricity, heat, energy for industrial processes, and transportation fuel. Converting to cleaner forms of energy requires transforming the energy system. However, decision makers must consider the countless, unpredictable ways the future could unfold. Modelers address this "deep uncertainty" by running computer simulations many times and computing how impactful various inputs are on the outcome. We explore different ways countries may meet emissions reduction goals and how impacts vary regionally, considering 11 sources of uncertainty with 5,760 simulations. We find larger economies and developing regions experience the most severe economic outcomes consistently across our wide range of inputs. Further, removing carbon dioxide from the air through engineered and natural solutions allows some flexibility to continue emitting during the transition, but the role of different options varies regionally, and is subject to future costs and the way emissions are priced. Previous work has typically focused on representative scenarios, rather than a "large ensemble," and has not combined this framework with modeling national emissions pledges. These findings are helpful for decisionmakers as countries design strategies to meet their goals.

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

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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, 2022b). 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, 2022a). 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 greenhouse gas emissions (34% in 2019), of which over two-thirds comes from electricity and heat (IPCC, 2022). Other energy-intensive sectors including transportation (15%), industry (24%), and buildings (6%) bring this global contribution to roughly 80%. 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; G. C. Iyer, Edmonds, et al., 2015; 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 Supporting Information S1 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; Calvin et al., 2019) 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, described briefly in Section 3.1. Eleven energy-related uncertain factors 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 10 aggregated global regions, constructed from GCAM's 32 geopolitical regions. Section 4 characterizes uncertainty in outcomes of interest such as electricity price, stranded assets, and carbon dioxide removal (CDR), 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.

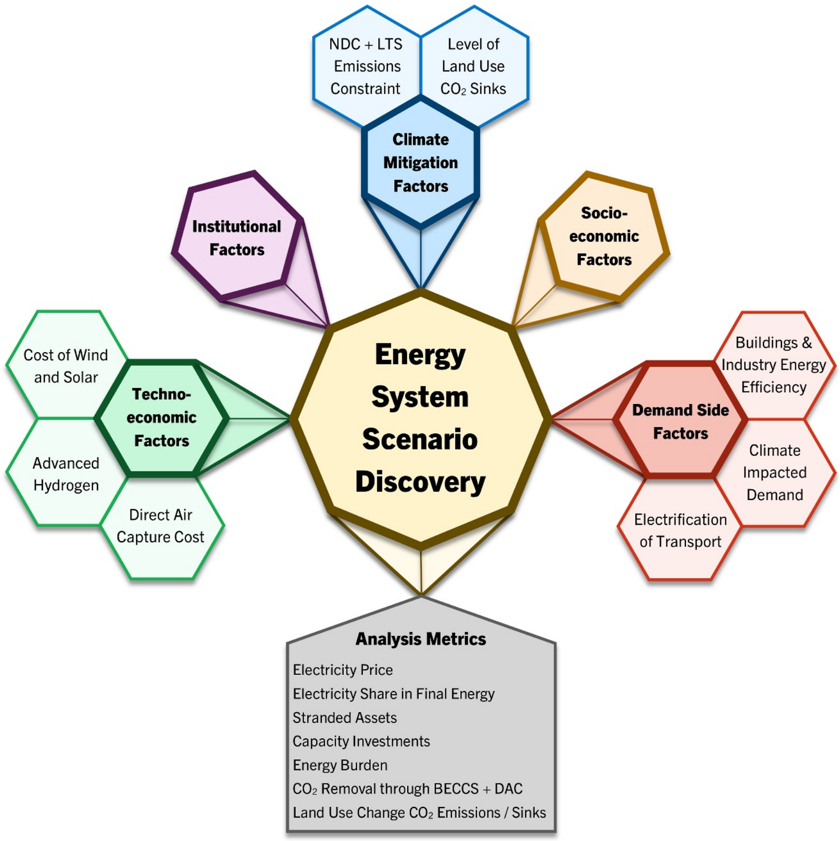

Figure 1. Uncertain factors varied in the ensemble and analysis metrics used.

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 & 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 & 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 & 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).

10.1029/2024EF004754

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 & 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 (Groves & Lempert, 2007; Lempert et al., 2006). 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 (Bryant & Lempert, 2010; Lempert et al., 2003, 2008). This approach is used widely in human-earth systems modeling (Birnbaum et al., 2022; Dolan et al., 2022; Guivarch et al., 2022; Kwakkel et al., 2013; Lamontagne et al., 2018; McJeon et al., 2011; Moksnes et al., 2019; Morris et al., 2022; Shortridge & Guikema, 2016; Woodard et al., 2023) using a variety of statistical, machine learning, and data mining techniques (Jafino & Kwakkel, 2021; Kwakkel & Cunningham, 2016; Kwakkel & Jaxa-Rozen, 2016; Lempert et al., 2008; 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, climate, and economy. The model runs in 5-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 (https://github.com/JGCRI/gcam-doc), 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) CO_2 emissions are tracked via the amount of LUC 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 the individual uncertain factors are also summarized in Table 1. Broadly, the uncertain factors we draw from represent a wide range of energy system and economic uncertainty, and are arranged into five groups. Sensitivity cases for each uncertain factor (variations away from each factor's reference case) 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 uncertain factors 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.

3.2.1. Climate Mitigation

To introduce climate mitigation, we consider countries' GHG emission mitigation pledges. Specifically, we use assumptions from the "Updated pledges-Continued ambition" scenario in (G. Iyer et al., 2022; Ou et al., 2021). This regional constraint assumes that countries achieve stated LTS, shorter-term pledges, and net-zero emissions targets, followed by a minimum decarbonization rate thereafter.

Another uncertain factor we include only for simulations with climate pledges implemented is the *Level of Land Use CO_2 Sinks*, implemented through policy action by adjusting the rate at which LUC CO_2 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., 2014, 2017; 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 inputs 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 uncertain factor.

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. In the "Reference" case, all regions are modeled with uniform institutions and investment costs. Following the methodology in G. C. Iyer, Clarke, et al. (2015), we then apply for the "Risk" sensitivity case (a) 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 (b) premiums on "high-risk" clean energy technologies to represent, for example, regulatory challenges and market uncertainty. Regionally heterogeneous cost of capital has also been demonstrated to reduce potential bias in energy modeling (Egli et al., 2019).

3.2.4. Techno-Economic Factors

Cost of Wind and Solar is varied between low, medium, and high levels, consistent with the core capital cost forecast assumptions present in GCAM created from the National Renewable Energy Laboratory's Annual Technology Baseline report (NREL, 2019). These two technologies (wind and solar PV) comprise the primary intermittent or variable renewable energy technologies. *Advanced Hydrogen* assumes an advanced scaling of hydrogen in the energy system through centralized transport and distribution infrastructure (pipeline) and

10.1029/2024EF004754

Table 1
Description of Uncertain Factors Varied in the Ensemble

Type	Name	Number of discrete cases	Discrete cases modeled	Short description/representation in GCAM	Key global dynamics	Adapted from
Climate mitigation	NDC + LTS emissions constraint	2	*Reference*: no constraint *Climate Pledges*: goals achieved as stated	Countries achieve long-term strategies, shorter-term pledges, and net-zero targets as stated in target years, followed by a minimum continued rate of decarbonization thereafter (See Ref.). Implemented as a regional constraint on GHG emissions consistent with stated short-term (2030) goals and long-term (2050–2060) strategies. Note that the carbon pricing scheme is applied only to fossil fuel and industrial CO_2 emissions and land use change CO_2 emissions, though all modeled GHGs are included in the emissions constraints	Lower emissions, introduces engineered CDR technologies (BECCS + DAC), reduces fossil fuel reliance	G. Iyer et al. (2022), Ou et al. (2021)
	Level of and use CO_2 sinks	2 (*High* sensitivity only applied to climate pledge realizations)	*Reference*: 10% of carbon price in 2020, scaling linearly to 100% by 2100 *High*: 100% in all periods (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 carbon sinks and alters the economic balance struck with net emissions from the energy system	Allows the energy system to emit more CO_2 to reach the same mitigation goals	This study
Socio-economic	Population and GDP	5	*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	2	*Reference*: equal investment risk *Risk*: differences across regions and technologies	Modeling differences in regional and technological investment risk by affecting the cost of financing clean energy projects	Reduced investment in renewables	G. C. Iyer, Clarke, et al. (2015)
Techno-economic	Wind and solar capital costs	3	*Reference*: ATB moderate *High cost*: ATB conservative *Low cost*: ATB advanced	Forecast of overnight capital costs for variable renewable energy (VRE) technologies (i.e., wind and solar PV), 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	2	*Reference*: SSP2 consistent *High cost*: SSP3 consistent	Varying cost of direct air capture, a key engineered CDR technology. Attempting to completely remove CCS and DAC from the model caused a majority of NDC + LTS scenarios to become infeasible	Reduced DAC, higher carbon price, increased hydrogen and electricity from biomass	Fuhrman et al. (2021)
	Advanced hydrogen	2	*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	2	*Reference*: GCAM core assumptions	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 energy and electricity consumption in industry, lower	Gambhir et al. (2022)

Table 1
Continued

Type	Name	Number of discrete cases	Discrete cases modeled	Short description/representation in GCAM	Key global dynamics	Adapted from
			High efficiency gains: see Ref.	reduced input energy, reduced feedstock use, reduced carbon intensity of cement, and adjustments to income elasticity	CO_2 emissions, lower cement production	
	Buildings energy efficiency	2	*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	2	*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 toward 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	2 (forcing for *Impacted demand* case depends on mitigation scenario)	*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)

increases the share of hydrogen vehicles adopted; it is adapted from the advanced hydrogen GCAM assumptions in (Wolfram et al., 2022). *Direct Air Capture (DAC) Cost* increases the costs of DAC from the reference level to a "high" level consistent with the SSP3 formulation parameterized in Fuhrman et al. (2021). Engineered 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 (G. Iyer et al., 2021).

3.2.5. Demand-Side Factors

Industry Energy Efficiency and *Buildings Energy Efficiency* are separate uncertain factors which reduce energy in industrial and buildings end-use sectors by adjusting coefficients related to energy efficiency and use. These two factors 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 toward 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 uncertain factors 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 (Akpan & Olanrewaju, 2023; Blair et al., 2015; DeCarolis et al., 2017; Dodds et al., 2015; Ibrahim et al., 2023). 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; G. C. Iyer, Edmonds, et al., 2015; Zhao et al., 2021). Finally, *CO_2 Removal through BECCS and DAC* and *LUC CO_2 Emissions* quantify the global CO_2 budget pathway for mitigation in each realization. *CO_2 Removal through BECCS and DAC* includes the two engineered CDR technologies, while *LUC CO_2 Emissions* reports the net carbon flows between the land system and the atmosphere (the *Level of Land Use CO_2 Sinks*, therefore, is an equivalent magnitude of carbon flows but with an opposite sign). In order to meet emissions pledges, CO_2 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), CDR 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 Supporting Information S1.

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 & Jauhiainen, 2021). This is often done through fitting a machine learning model using, for example, classification and regression trees, logistic regression, or the patient rule induction method (Breiman et al., 1984; Friedman & Fisher, 1999; Kwakkel & Cunningham, 2016; Lempert et al., 2008), 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 (Figure S1 in Supporting Information S1). Similarly, LUC emissions generally plummet under the climate pledges during the short- (2030) to medium-term (2050) transition to offset energy system emissions (Figure S2 in Supporting Information S1). 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 (Figures S3 and S4 in Supporting Information S1). 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. Figures S5 and S6 in Supporting Information S1 illustrate the adoption of BECCS and DAC 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 Figure S2 in Supporting Information S1. Though our modeling of emissions reduction pathways includes all GHGs, the analysis presented focuses on CO_2 emissions.

4. Results

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

- Costs of the energy transition, as measured by multiple metrics, are unevenly distributed across regions under a wide range of future states of the world.
- Regional investment risk has global implications for mitigation pathways, robust to broad uncertainties and with strong relative impacts, underscoring the need for de-risking investments.
- The scale of CDR determines how much the energy system can continue to emit, but the relative role of different CDR options (namely BECCS, DAC, and land use sinks) in meeting decarbonization goals varies across regions and scenario pathways.

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

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. 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. 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 reduction goals 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

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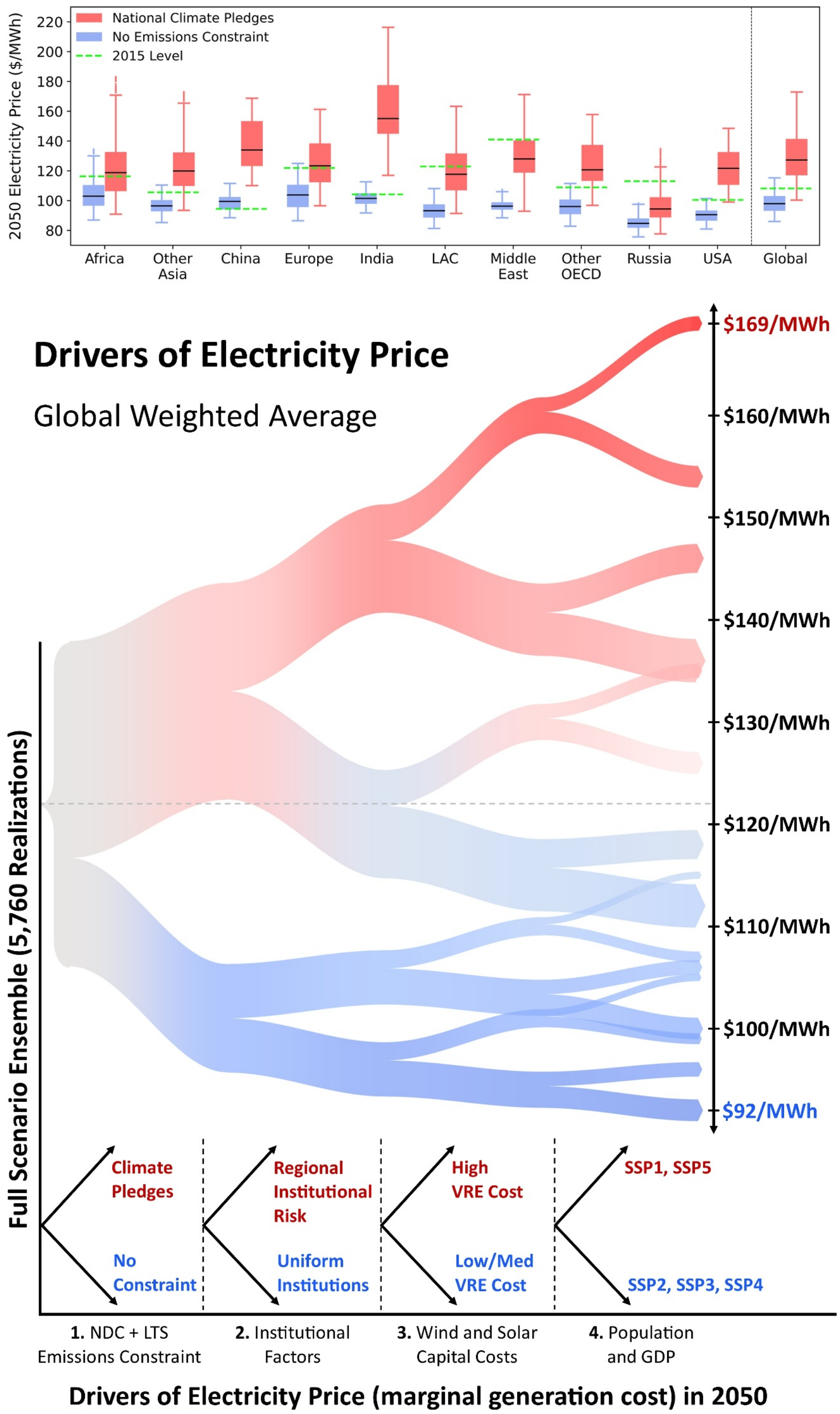

Figure 2. (top) Regional and global weighted electricity price for model regions, split between scenarios with and without climate pledges implemented. Model calibration year 2015 prices are shown for comparison; (bottom) most influential drivers of global weighted average electricity price ($/MWh) in 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. "Other Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. "LAC" refers to Latin America and the Caribbean.

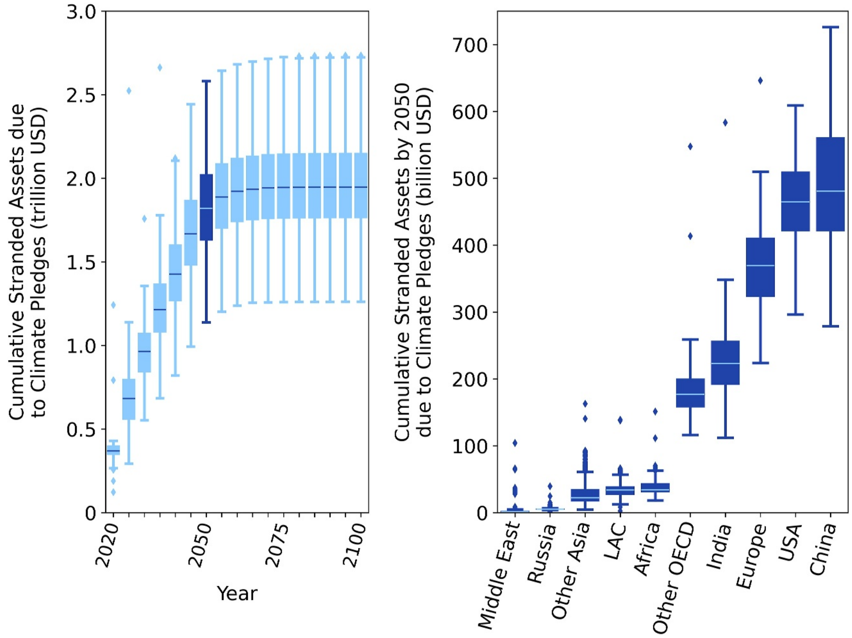

Figure 3. (left) Cumulative stranded assets (costs associated with premature retirements of generating capacity) globally over time due to implementing climate pledges, with the year 2050 highlighted; (right) cumulative stranded assets in 2050 for aggregated global regions due to implementing climate 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. "Other Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. "LAC" refers to Latin America and the Caribbean.

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 weighted prices for different scenario combinations, with the mean 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 *Institutional Factors*, *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 SSP1 (lowest population, high GDP) or SSP5 (low population, highest GDP). 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 wind and solar cost). A more complete picture of feature importance across uncertain factors, metrics, time periods, and regions is shown in Figures S7 and S8 in Supporting Information S1.

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.

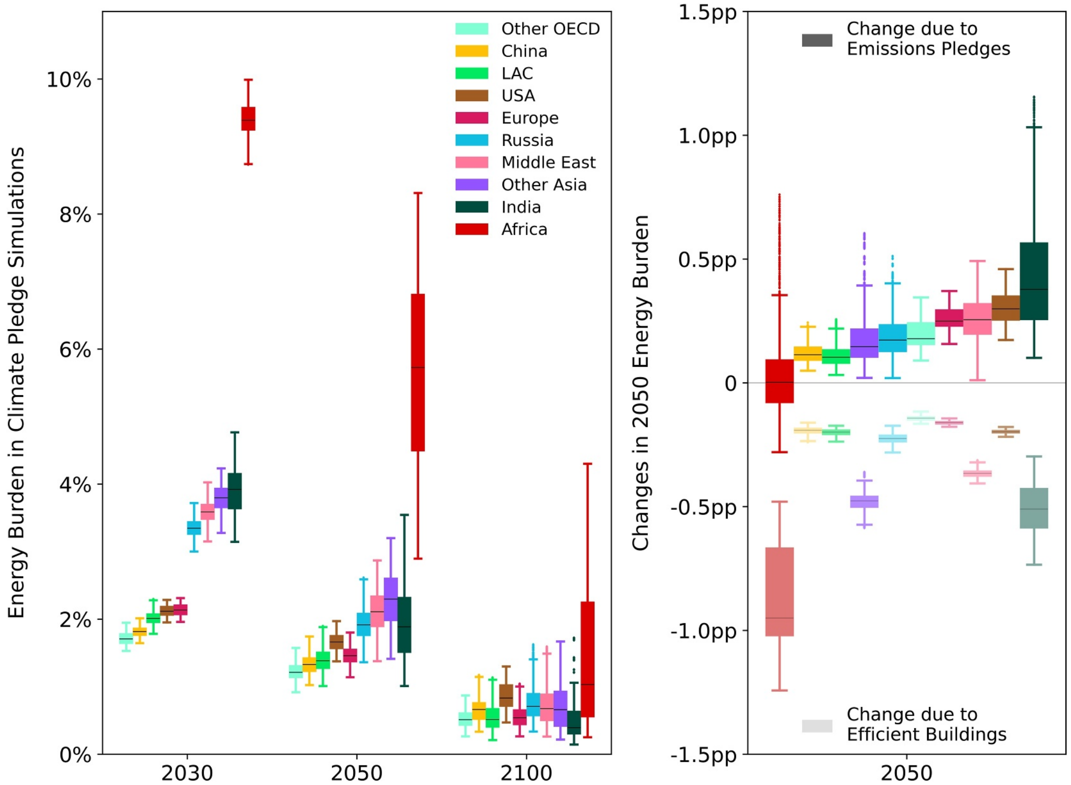

Figure 4. (left) Residential energy burden, computed as a ratio of residential energy spending to GDP per capita, for aggregated global regions for three model periods, showing the 3,840 simulations with climate pledges; (right) Change in energy burden caused by sensitivities in two uncertain factors (climate pledges and *Buildings Energy Efficiency*) for each model configuration, computed as the percentage point (pp) difference between pairs of realizations which differ only by inclusion/exclusion of these two scenario factors. 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. "Other Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia. "LAC" refers to Latin America and the Caribbean.

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; that is, accounting for regional differences in the scale of economic activity did not appreciably alter the relative outcomes. 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.

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. This is generally due to increases in per capita GDP over time, as well as baseline efficiency improvements in buildings energy use. 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,

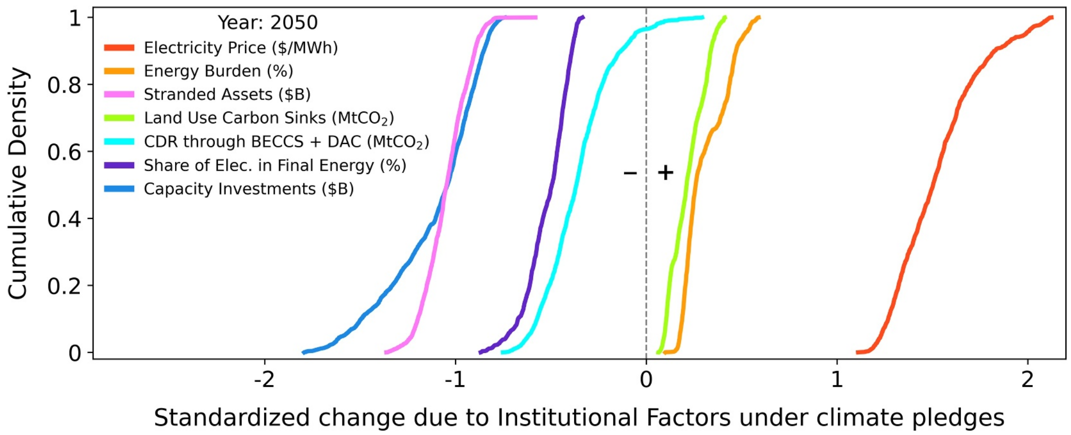

Figure 5. Cumulative distribution function (CDF) plot showing standardized changes in the values of select metrics when institutional factors are switched on in each scenario configuration (only showing scenarios with nationally determined contributions + long-term strategies implemented). The horizontal axis represents the number of standard deviations separating the two values used to compute each change. 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 factor results in a very consistent change in the outcome; it does not represent underlying variability of the outcome itself.

energy burden in 2100 becomes more homogeneous across regions (in terms of both the mean and the spread of the outcomes), due to the NDC + LTS policy scenario construction in Ou et al., 2021, in which countries without net-zero pledges continue decarbonizing beyond 2030 at the same rate required to achieve their shorter-term NDC goals, or at a minimum rate of 2% (whichever is greater). 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), which represent two influential drivers of energy burden in our ensemble. 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.

The feature importance heatmap for energy burden in Figure S7 in Supporting Information S1 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 factor 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 in Supporting Information S1.

4.2. Regional Investment Risk Has Global Implications for Mitigation Pathways

Figure 5 maps empirical cumulative distribution functions (CDFs) of the difference in standardized global 2050 model outcomes resulting from regionally and technologically differentiated investment costs. These observed pairwise differences are computed to isolate the effect of *Institutional Factors*, 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 in Supporting Information S1. The curves are composed by rank-ordering the resulting distributions of computed values, creating monotonically increasing empirical CDFs. Metrics are standardized in order to compare different scales on the same plot; thus, the difference between standardized values represents the number of standard deviations (computed from the full ensemble) separating the two values. 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). Further, a steep CDF curve suggests little variability in the magnitude of the change, suggesting that in those cases, *Institutional Factors* may be highly influential but

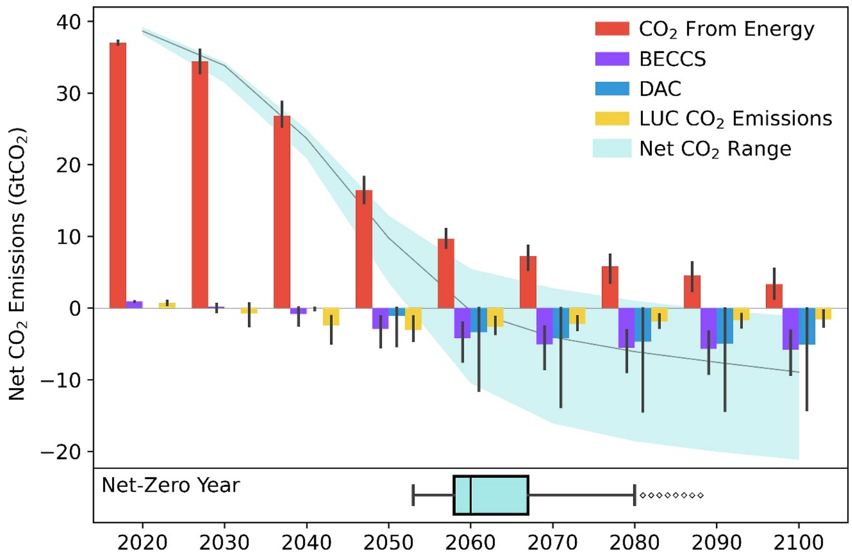

Figure 6. The use of engineered carbon dioxide removal technologies and natural land use sinks (negative land use change emissions) to offset energy system CO_2 emissions. Error bars show the full range of outcomes across the scenario ensemble for the 3,840 realizations that implement climate pledges. 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.

interacting little with other uncertain factors in the ensemble. In contrast, curves with a more gradual slope correspond to higher variability in the distribution of pairwise responses, such as the electricity price curve (and especially the upper tail). Here, the horizontal range of the curve is wider, and approximately the highest 10% of increases due to *Institutional Factors* (cumulative density >0.9) show significantly higher variability still, which are realizations consistent with the findings in Figure 2. Across a broad range of uncertainties, a higher energy burden is seen, 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 CDR technologies, the resulting carbon price increases to offset the emissions, and thus more land use 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. Figure S10 in Supporting Information S1 shows CDFs for individual regions.

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 CO_2 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 from BECCS and DAC, and natural land use 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. For regions in which every country has a net-zero pledge in place, the timing of net-zero has low variability. It is the regions without such mitigation goals that primarily drive the variability seen in the boxplot in Figure 6, pushing global net-zero past 2080 in some cases. Figures S11 and S12 in Supporting Information S1 show the variability in the timing of net-zero CO_2 across each uncertain factor and across regions, respectively; the most critical drivers globally are *Socioeconomic Factors* and *DAC Cost*.

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 *DAC Cost* and *Level of Land Use CO_2 Sinks* factors. Thicker lines depict a "representative" scenario from each group following a mean pathway. Here, a tradeoff can be defined as any instance in which two lines cross paths between

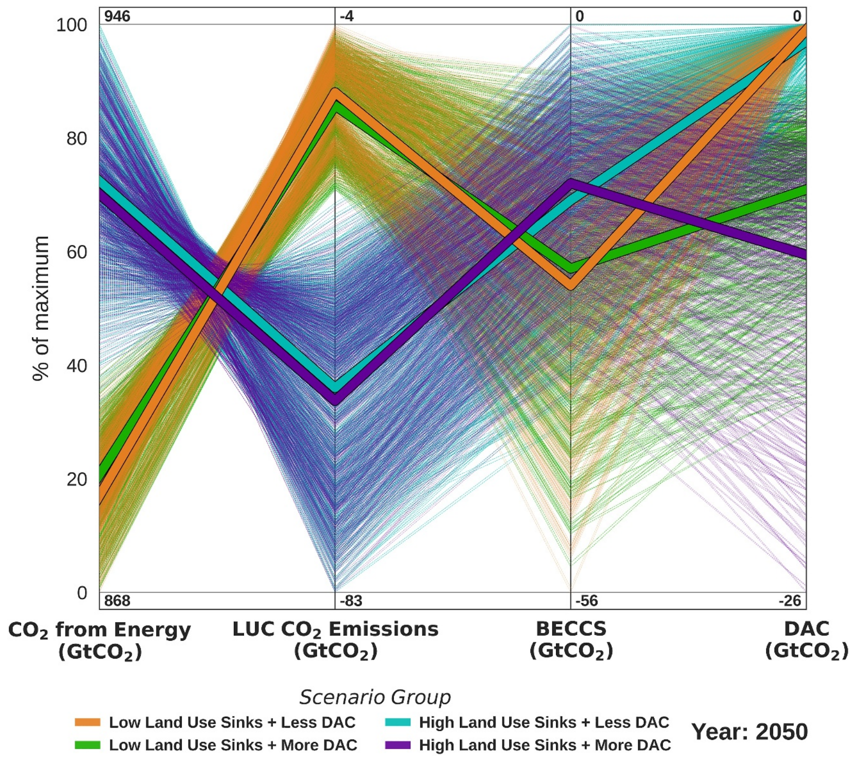

Figure 7. Parallel axis plot showing cumulative CO_2 emissions budget contributions under climate pledges in 2050. Scenarios are grouped according to the *Direct Air Capture Cost* and *Level of Land Use CO_2 Sinks* factors, and each column is scaled independently according to each metric's minimum and maximum values. Thicker lines depict a "representative" scenario from each group following a mean pathway. A tradeoff occurs when two lines cross paths in between columns. 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.

columns, while the slopes and proximity of the lines indicate the strength and consistency of the tradeoff or relationship across the ensemble.

By 2050, the amount of CO_2 sequestered by carbon sinks in the land system 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 carbon sinks. Additionally, a tradeoff emerges between these carbon sinks and deployment of engineered CDR technologies (BECCS and DAC), confirming the complementary roles of these decarbonization solutions (i.e., deploying more BECCS and 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.

To examine the robustness of the outcomes stemming from the *Level of Land Use CO_2 Sinks* on a regional scale, we quantify the direct effect of varying this uncertain factor in each region across our ensemble. Figure 8 plots CDFs for the difference in two outcomes between pairs of NDC + LTS realizations which differ only by this uncertain factor, 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 *DAC Cost* becomes the dominant driver of engineered CDR investment. Differences are standardized rather than showing a percent change, due to the reference case values for CDR adoption approaching zero in many realizations.

Figure 8 shows the complementarity of BECCS and DAC with land use 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. As in Figure 5, a steep CDF curve suggests a lack of compound interactive or synergistic effects between the *Level of Land Use CO_2 Sinks* sensitivity and other uncertain factors in determining the plotted metrics, as seen in several of the larger economies

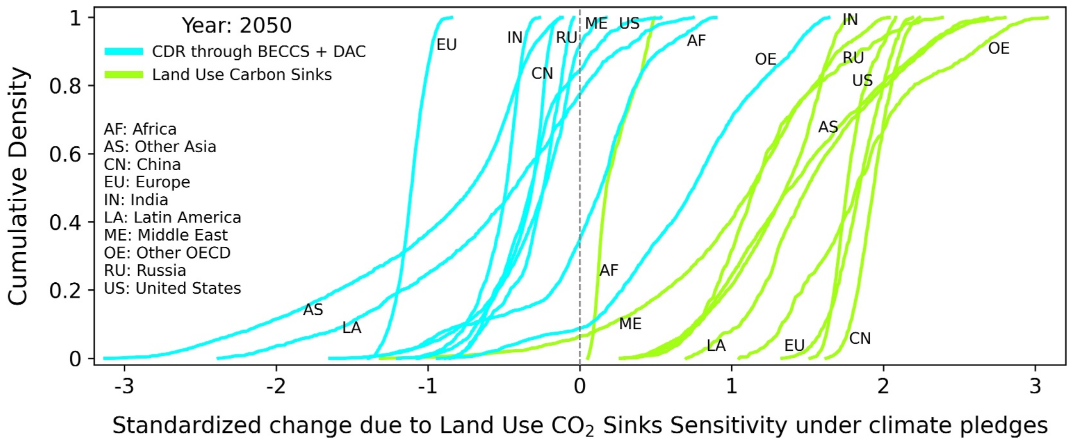

Figure 8. Cumulative distribution function plot showing regional changes in the standardized values of engineered carbon dioxide removal adoption ("CDR through BECCS + DAC") and land use sinks ("Land Use Carbon Sinks") when the *Level of Land Use CO_2 Sinks* sensitivity case is implemented (only for scenarios with climate pledges). The horizontal axis represents the number of standard deviations separating the two values used to compute each change. A curve lying entirely to the right (left) of zero implies that this increase in the *Level of Land Use CO_2 Sinks* always increases (decreases) that metric's value. Positive values for each metric correspond to more net carbon pulled *out of* the atmosphere via that method. "Other OECD" includes Canada, Japan, South Korea, Australia, and New Zealand. "Other Asia" includes Pakistan, Indonesia, Central Asia, South Asia, and Southeast Asia.

with net-zero targets, such as Europe and China. Alternatively, regions such as Other Asia and Latin America, show a wider range of outcomes, due to less stringent CO_2 reduction pledges and therefore lower deployment of negative emissions strategies. The horizontal range of these curves shows the regional variability and wide-ranging effects of the *Level of Land Use CO_2 Sinks* sensitivity on these outcomes, suggesting that the role of different CDR options in meeting decarbonization goals varies across regions, and that considerable uncertainty remains in how a policy targeting land use carbon sinks would affect a region's mitigation pathway.

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 & Ribot, 2012; Markkanen & Anger-Kraavi, 2019; Sovacool, 2021). This work establishes a new large ensemble of model realizations which vary a broad suite of energy-related uncertain factors 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 Figures 2 and 3, respectively. Our 5,760-member ensemble provides valuable insight regarding the robustness and nuance of these results under a broad sampling of uncertainty.

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 the presence of net-zero emissions pledges in large, developed regions (e.g., USA, Europe) as well as other large economies (e.g., India, China) correspond to 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 Figures S7 and S8 in Supporting Information S1. 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. 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 case was adapted (G. C. Iyer, Clarke, et al., 2015) across a broad uncertainty space. Modeled representations of institutional differences remain somewhat under-explored (especially under an expanded sampling of uncertain factors), and our results speak to the importance of including such regional differences with regard to institutions and interest rates in multi-region studies.

The investment pathways to meet national emissions pledges explored in this ensemble are also closely tied to the scale and types of CDR utilized. 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 land use sinks can dampen the need for these technologies. Still, additional considerations would ultimately influence the decision making in navigating these tradeoffs, such as impacts on air quality and ecosystem services under different land use regimes.

5.2. Future Work

Our new ensemble can be used as a novel data set 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 and uncertain factors. 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, for example, 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 uncertain factor to allow for higher dimensionality. Some factors (e.g., *Cost of Wind and Solar*) represent specific forecasted predictions, while others (e.g., *Level of Land Use CO_2 Sinks*) are modeled to capture an upper bound. The cost sensitivity of engineered CDR technologies includes DAC but does not vary the cost of BECCS, as BECCS can be applied in a variety of sectors while cost ranges for each of these applications are not readily available. A more thorough continuous sampling of uncertain factors 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 uncertain factors 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 higher-resolution models or data sets, such as regional population income distributions (Narayan et al., 2024), 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 for example, 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. However, the modeling framework employed aids in laying a foundation for multi-sector ensembles of increasingly large sample sizes and structural complexity, to meet the growing demand for training data for next-generation deep learning models. Nonetheless, this work provides a rich data set for the advancement of scenario research, to which other machine learning methodologies could be applied.

Data 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 (Wessel et al., 2024).

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