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Representing Socio-Economic Uncertainty in Human System Models

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Abstract: Future global socio-economic development pathways and their implications for the environment are highly uncertain as are the technology mixes associated with different global environmental targets. To develop a range of possible future outcomes, we develop probability distribution estimates for key input parameters of a model of global human activity. Latin Hypercube Sampling is applied to draw 400 samples from the probability distributions for each uncertain input variable, including costs of advanced energy technologies, energy efficiency trends, fossil fuel resource availability, elasticities of substitution, population, and labor and capital productivity. The sampled values are simulated through a multi-sector, multi-region, recursively dynamic model of the world economy. The results are 400-member ensemble simulations describing future energy and technology mixes as well as GDP and emissions. We find that many patterns of energy and technology development are consistent with various long-term environmental pathways and that sectoral output for most sectors is little affected through 2050 by the long-term temperature target, but with tight constraints on emissions, emission intensities must fall much more rapidly. We also combine uncertainty quantification and scenario discovery to investigate scenarios with similar values for one outcome and the range of other outcomes in those scenarios. This analysis illustrates how many combinations of outcomes can be consistent with an outcome of interest. For example, many different technology outcomes can be consistent with high or low economic growth.

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1. Introduction

There are major uncertainties in human systems that affect how they will evolve over time. Past work to quantify these uncertainties has shown them to be of importance similar to those in the Earth system itself in determining likely future environmental outcomes (Sokolov *et al.*, 2009; Webster *et al.*, 2012). There have been a number of uncertainty studies of future global economic development and emissions dating back to the 1980's (e.g. Reilly, *et al.* 1987; Peck and Teisberg, 1993; Nordhaus and Popp, 1997; Pizer, 1999; Webster, *et al.*, 2002; Baker, 2005; Hope, 2006; Nordhaus, 2008; Webster *et al,* 2012, Anthoff and Tol, 2013; Lemoin and McJeon, 2013). However, the global economic outlook, technology costs, and other factors have changed considerably over the past decade, making it useful to revisit these uncertainties. For example, there has been slower economic growth than previously assumed, falling costs of low-carbon energy options and government interventions worldwide directed at expanding the role of renewables. Gillingham, *et al.* (2018) is a more recent multi-model uncertainty study, but it focused on only two uncertain socio-economic variables—population and economic growth.

A contribution of our study is to undertake an extensive assessment of uncertain socio-economic variables. This includes uncertainty in the nature of technology development and available physical resources to determine what patterns of technology and resource use are consistent with various environmental outcomes. It also includes uncertainty related to the ease of substitution between inputs to production.

We undertake formal uncertainty quantification of future global socio-economic outcomes—developing probability distributions of key model parameters, sampling from the distributions, and exploring the range and likelihoods of model outcomes. This approach is complementary to other approaches for understanding the range of possible future outcomes. These include: sensitivity analysis (varying one parameter at a time), scenario analysis (creating multiple storylines and varying many parameters simultaneously to match the story), and comparisons of results from different models. An advantage of formal uncertainty quantification is that it more completely explores the range of values of inputs, and reveals how uncertainties in different variables interact. Formal uncertainty quantification is also a way to put error bars on projections, increasingly seen as a necessary component of research (CBO, 2005; InterAcademy Council, 2010; Gillingham, *et al,* 2018; Hausfather and Peters, 2020).

In our paper, we focus on sectoral outcomes and the technology mix consistent with different 21st century global temperature pathways. Section 2 outlines the overall methodology. Section 3 briefly describes features of the global economic-emissions model used in the uncertainty analysis. In Section 4, we discuss the parameters modeled as uncertain and the development of probability density functions for each. Section 5 provides results. Section 6 offers concluding remarks.

2. Methodology

To quantify socio-economic uncertainties, we employ Monte Carlo analysis. In this approach, we choose probability-weighted values of all uncertain parameters, and then simulate the model hundreds or thousands of times to generate probability distributions of outcomes of interest. There are several important steps, including: (1) choosing a model appropriate to the task, (2) identifying the most important uncertain variables and obtaining probability distributions for each, (3) sampling from the distributions, (4) simulating an ensemble of model runs, and (5) analyzing the results.

Given our focus on the range of sectoral outcomes and technology pathways consistent with different global mean surface temperature outcomes, an appropriate model must simulate emissions of radiatively active pollutants over the longer horizon to capture the long-lasting effects of those emissions, include multiple economic sectors, and include detail on energy technologies. The Economic Projection and Policy Analysis (EPPA) was designed to be linked with an earth system model and, as described in the next section, covers multiple sectors of the economy and includes technology and resource detail so that the cost of technologies and availability of different resources can be easily varied.

This study builds on earlier work (Webster *et al.* 2012; 2008) where extensive sensitivity analysis was conducted to identify the most important model parameters for consideration. A similar set of parameters, with a few additions, is included as uncertain here. Distributions of parameter values were developed using statistical analysis of historical data, review of the scientific literature and, expert elicitation as appropriate (described in Section 3). For example, there is substantial econometric work that estimates elasticities of substitution among inputs, and standard errors estimated in that work is used to estimate uncertainty around the elasticity values. For advanced technologies that remain immature and without widespread commercialization, there is little historical data that could be the basis of statistical analysis. Moreover, as the technology matures, historical costs are likely not going to be indicative of future costs. Fortunately, interest in the potential future cost of these technologies has led to studies that attempt to quantify future cost ranges, relying on explicit expert elicitation methods, or one way or another relying on the judgement of experts.

We employ Monte Carlo simulation, using Latin Hypercube Sampling (LHS) to draw samples from each input probability distribution (Iman and Helton, 1988; McKay *et al.*, 1979). LHS simply divides the distribution for each variable into equal probability segments. The mid-point values for each segment of each variable are chosen randomly, without replacement. Each random selection across all variables creates one ensemble member. The process generates an ensemble size equal to the number of probability segments. We used 400-member ensembles, shown to be adequate when using LHS, whereas simple random sampling often requires thousands or tens of thousands of samples (Webster *et al*, 2008). This improvement in sampling efficiency is important when simulating more computationally-intensive models. This sampling strategy assures that every segment of the distribution, including segments in the distribution tails, is sampled exactly once.

An important contribution to uncertainty is how governments around the world might intervene to limit emissions or advance or limit different technologies. Our simulation strategy is to develop different ensembles that represent different levels of intervention in markets rather than representing the government interventions as explicitly uncertain. In particular, we introduce constraints on emissions consistent with different global mean temperature outcomes. This allows us to investigate our primary question: What sectoral outcomes and technology mixes are consistent with different temperature outcomes?

3. An Economic-Emissions Model of the Global Economy

The Economic Projection and Policy Analysis (EPPA) model is a recursive-dynamic, multi-region, multi-sector general equilibrium model of the world economy (Chen *et al.*, 2016; Paltsev *et al.*, 2005). The version applied here includes an updated and expanded number of technology options as described below. It was designed to develop projections of economic growth, energy transitions and anthropogenic emissions of greenhouse gases and air pollutants. The model projects economic variables (GDP, energy use, sectoral output, consumption, prices, etc.) and emissions of greenhouse gases (CO_2, CH4, N2O, HFCs, PFCs and SF6) and other air pollutants (CO, VOC, NOx, SO2, NH3, black carbon, and organic carbon) from combustion of carbon-based fuels, industrial processes, waste handling, agricultural activities and land use change. The MIT Integrated Global Systems Model (IGSM) (Sokolov *et al.*, 2017) combines the EPPA model of human activity and the MIT Earth System Model (MESM) (Sokolov, *et al.*, 2018) of the Earth's physical and biological systems. It projects environmental conditions that result from human activity, including concentrations, temperature, precipitation, ice and snow extent, sea level, ocean acidity and temperature, and vegetation among other outcomes. The IGSM allows the development of emissions pathways consistent with different 21st century temperature outcomes.

The economic model used in this paper is built on the Global Trade Analysis Project Version 8 (GTAP 8) economic dataset (Narayanan *et al.*, 2012) which provides a consistent representation of regional production, bilateral trade flows, and markets. Energy and land markets are supplemented with accounting in physical units. This economic data is augmented with additional information on advanced technologies, greenhouse gases and air pollutants emissions, taxes and details of selected economic sectors. The data are aggregated to 18 regions (**Figure 1**) and 18 sectors (**Table 1**). Additional detail in the energy sector is added in the form of advanced technology alternatives that are incorporated using bottom-up engineering detail (**Table 2**). The approaches for defining the costs and penetration of these advanced technologies are described in Morris *et al.* (2019a,b).

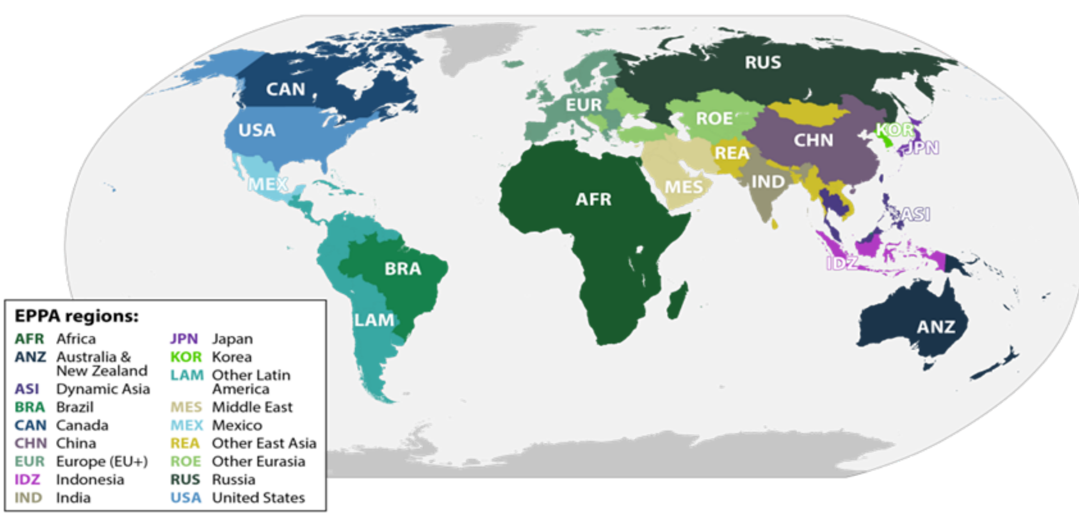

Figure 1. Regional representation in the global economic model.

Table 1. Sectors and abbreviations.

Abbr.	Sector	Abbr.	Sector	Abbr.	Sector
CROP	Agriculture - Crops	ROIL	Refined Oil	ELEC: hydro	Hydro Electricity
LIVE	Agriculture - Livestock	GAS	Gas	EINT	Energy-Intensive Industries
FORS	Agriculture - Forestry	ELEC: coal	Coal Electricity	OTHR	Other Industries
FOOD	Food Products	ELEC: gas	Gas Electricity	DWE	Dwellings
COAL	Coal	ELEC: petro	Petroleum Electricity	SERV	Services
OIL	Crude Oil	ELEC: nucl	Nuclear Electricity	TRAN	Commercial Transport

Table 2. Advanced technologies in the energy sector.

First generation biofuels	Hydrogen	Advanced gas (NGCC)	Bio-electricity w/ CCS
Second generation biofuels	Advanced nuclear	Advanced gas w/ CCS	Wind power combined with bio-electricity
Oil shale	Advanced coal	Wind	Wind power combined with gas-fired power
Synthetic gas from coal	Advanced coal w/ CCS	Bio-electricity	Solar generation

*CCS = carbon capture and storage.

The model's production and consumption sectors are represented by nested Constant Elasticity of Substitution (CES) production functions (or the Cobb-Douglas and Leontief special cases of the CES) shown in **Figure 2** (also see Chen *et al.*, 2016; Paltsev *et al.*, 2005 for deviations from this structure for specialized sectors such as oil refining and agriculture). The base year of the model is 2007. It is calibrated to economic and energy data from the IMF (2018) and IEA (2017) for 2010 and 2015 and then it is solved recursively in 5-year time steps from 2020 to 2100. The model is designed for projecting long-term trends, so it does not capture business cycles or short-term shocks such as those that often occur in, for example, commodity markets that play out over periods of less than the 5-year time step of the model.

A model solution must meet three conditions: market clearance conditions (supply must equal demand), zero profits (the cost of inputs should not exceed the price of the output), and income balance (expenditures must equal income, accounting for savings, subsidies and taxes). Production technologies are chosen based on their relative competitiveness given the characterization of input requirements for the technology, which, in turn, determine the cost of the technology given prices for the inputs. Base year prices for all inputs are in the base economic data of the model, and future technology costs depend on how prices change for inputs used by the technology. Input prices change over time depending on the dynamics of the model, including changes in the labor force, investment and capital availability, resource availability/depletion and

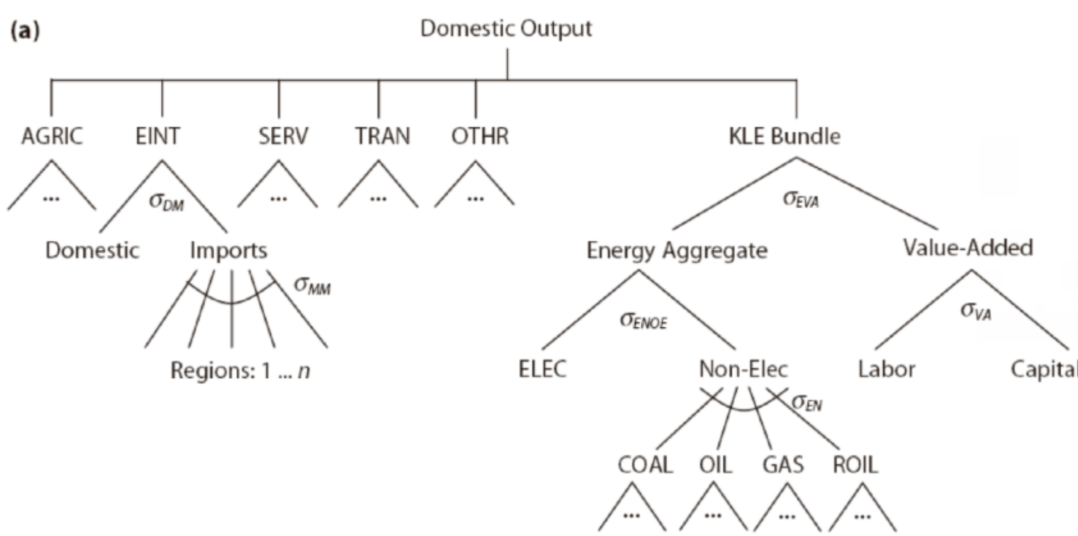

Figure 2. Example of the CES nest structure for production sectors in EPPA. Parameters that govern energy demand (and abatement costs) are substitution elasticities for energy-non-energy (σ_{EVA}), labor-capital (σ_{VA}), electricity-fuels (σ_{ENOE}) and that among fuels (σ_{EN}).

existing or new policies or constraints. All technologies require capital and labor inputs, and so capital and labor productivity improvement (a major component of the dynamics of the model) drives down technology costs over time. The model also traces inter-industry and inter-regional demands. These influences combine to determine the resulting technology mix. As applied here, there are no environmental feedbacks on the economy.

4. Development of Distributions for Uncertain Model Parameters

An uncertainty assessment of a previous version of the economic model (Webster *et al.*, 2008) serves as a point of departure. That effort included extensive sensitivity testing to identity the most important uncertain parameters. New distributions were created for those parameters where a review of data and information indicated revisions were needed. These include new distributions for population growth, GDP growth (determined by labor and capital productivity), energy technology costs, energy productivity (i.e., autonomous energy efficiency improvement (AEEI)), fossil fuel resource availability and the rate of technology penetration. Distributions for all uncertain parameters are presented in **Table 3**, followed by a discussion of how these were developed. Distributions are normalized to have a median of 1 so that when applied the median is the reference level for the parameter in the model. Accounting for region- and sector-specific distributions, a total of over 150 distributions are developed. For technology-related variables that are sampled separately for regions or sectors (e.g., AEEI coefficients and elasticities of substitution), as well as other parameters, we specify a correlation structure (**Table 4**), following Webster *et al.* (2008). Other variables such as GDP and population growth among regions also are correlated as described in the following sections.

Table 3. Distributions for Uncertain Socio-Economic Model Parameters. * Table continued on next page

Parameter Category	Parameter	Specific Region/Sector	Distribution
Population		By Region	See **Figure 3**
GDP (Capital & Labor Productivity)		By Region	See **Table 5**
AEEI		Each region w/ separate distribution	Normal(1,0.55)
Advanced Technology Costs *(Uniform distributions of cost scalars with 50% probability between minimum and median, and 50% between median and maximum. Median = 1. [MIN, MAX] is given here for each technology.)*		NGCC	[0.798, 1.148]
		New Coal	[0.643, 1.410]
		Nuclear	[0.590, 1.558]
		Solar	[0.542, 2.083]
		Wind	[0.489, 2.035]
		Bioelec	[0.504, 1.659]
		Gas CCS	[0.816, 1.335]
		Coal CCS	[0.840, 1.536]
		BioCCS	[0.553, 1.767]
		WindGas	[0.544, 1.767]
		WindBio	[0.378, 2.282]
		Bio-Oil	Pearson5(14.8, 40.6, Shift(1))
Fossil Fuel Resource Stocks		Oil	Beta(1.537,3.5787,0.3405,2.7563)
		Gas, Coal	Beta(1.1127,2.213,0.2552.7501)
Technology Penetration Rates		All advanced technologies	Uniform(1.014, 1.589)
Urban Pollutant Initial Inventories	SO_2	Each region w/ separate distribution	Normal(1,0.3)
	CO	ALL	Normal(1, 0.25)
	BC, OC, VOC, NOx, NH_3	ALL	Lognormal(1.0439, 0.3132)
	CH_4	AGRI	Beta(1.8, 1.8, 0.4, 1.6)
		COAL, OTHR, FOOD	Beta(2, 2, 0.89, 1.11)
		GAS, OIL, EINT	Beta(2, 2, 0.86, 1.14)
		FD	Beta(1.8, 1.8, 0.96, 1.04)
		ROIL	Beta(2, 2, 0.86, 1.14)

Note: All distributions are normalized to have a median of 1. * Table continued on next page

Table 3 (continued). Distributions for Uncertain Socio-Economic Model Parameters.

Parameter Category	Parameter	Specific Region/Sector	Distribution
Urban Emission Trends		SO_2, BC, OC	Beta(7, 7, 0.155, 3.107)
		NOx, VOC, CO, NH_3	Beta(3, 7, 0.4114, 2.467)
Elasticities of Substitution	Energy vs. Capital/Labor	ALL	Normal(1, 0.3)
	Electric vs. Non-Electric	ALL	Normal(1, 0.15)
	Interfuel Substitution	Electricity, Energy Int.	Normal(1, 0.25)
		All Others	Normal(1, 0.15)
	Labor vs. Capital	Agriculture	Gamma(1.2564, 1.0666)
		Oil, Coal, Natural Gas	Normal(1, 0.087229)
		Electricity	Gamma(1.2564, 1.0666)
		Energy Intensive	Normal(1, 0.2158)
		Services	Gamma(25.82, 0.03923)
		Other	Beta(4.9776, 5.1354, 0, 2.0338)
		Transportation	Gamma(42.252, 0.02119)
		Dwellings	Beta(4.9776, 5.1354 ,0, 2.0338)
		Food	Beta(4.9776 ,5.1354, 0, 2.0338)
	Energy vs. Non-Energy	Final Demand	Loglogistic(0, 1, 3.9743)
	Resource Supply	Coal, Oil, Natural Gas	Beta(1.5, 2.8 ,0.507, 2.03)
Abatement Cost Elasticities	CH_4 Elas. In Agriculture	USA, CAN	Pearson5(4.8285, 4.044)
		MEX, IDZ, BRA, AFR, LAM	Beta(3.2254, 3.1, 0, 1.957)
		JPN	Beta(3.207, 4.709, 0.143, 2.303)
		ANZ	Beta(7.8, 7.8, 0, 2.0)
		EUR	Beta(2.8, 5.6, 0.042, 2.23)
		ROE	Beta(5.6, 6.8, 0.024, 0.193)
		RUS	Beta(3.7, 5.6, 0, 2.56)
		ASI, KOR	Beta(2.1, 4.1, 0, 3.121)
		CHN	Loglogistic(-0.053, 1.053, 3.657)
		IND	Beta(7.57, 11.355, 0.0017, 2.53)
		MES	Beta(3.2284, 3.46, 0, 2.079)
		REA	Beta(3.229, 3.4608, 0, 2.0795)
	N_2O Elas. in Agriculture	USA, CAN, JPN, EUR, ANZ, KOR	Beta(8.7, 7.8, 0, 1.89)
		MEX, ROE, RUS, ASI, CHN, IND, BRA, AFR, MES, LAM, REA, IDZ	Beta(5.094, 5.294, 0, 2.042)
		RUS	Beta(7.795, 5.5, 0.2532, 1.517)
		ROE	Beta(4.2, 4.3, 0, 2.026)
Vintaging		ALL	Gamma(10.428, 0.09904)

Note: All distributions are normalized to have a median of 1.

Table 4. Correlated subsets of uncertainty parameters.

Parameter	Correlated Across (dimensions of matrix)	Correlation Coefficient
AEEI	Regions (16x16)	0.9
Elasticity of Substitution (L,K)	Sectors (8x8)	0.8
Methane Elasticities (cost)	Regions (16x16)	0.8
N_2O Elasticities (cost)	OECD, LCD, FSU, EET (4x4)	0.8
Fossil Resources	Oil, Natural Gas (2x2)	0.9
Urban Pollutant Time Trends	Urban Pollutants (7x7)	0.9

4.1 Population

An advance from the earlier uncertainty analysis using the EPPA model is the availability of revised population projections that are now explicitly probabilistic (UN, 2015 Revision). The UN Population Division provides 1,000 country-level samples of population projections from 2015 to 2100 in five-year time steps. We aggregated the country-level projections to the regions in our model, and to world population projections. From the 1,000 world projections, we draw 400 Latin hypercube samples for 2100. We then identify the UN projections associated with the 400 sampled 2100 world populations, and use the corresponding projections for EPPA regions from 2020-2100 as our 400 samples. These samples reflect the correlation of population growth between countries assumed by the UN. **Figure 3** shows the 5th, 50th and 95th percentiles based on the 400 samples, the 1,000 samples from the UN and the 10,000 samples from the UN 2015 report. The 400 samples approximate well the distributions for the larger sample sizes.

4.2 GDP and Labor and Capital Productivity

Under the main formulation of the economic model, GDP is endogenous, determined by assumptions about labor and capital productivity trends, labor growth, savings and investment, and other features of the model's dynamics. The model also has an option to target specific GDP levels through a multiplier instrument on capital and labor productivity. Because data on GDP growth and its variability are more readily available than data on labor and capital productivity, we estimate uncertainty in future GDP. We follow the approach of Webster *et al.* (2008) using econometric forecasting techniques to specify long-run GDP growth in each region as a random walk with drift. Parameterization of the stochastic growth model is based on analysis of country-level GDP data (Conference Board, 2015) for the period 1950-2015 for each region, extending the data series by 15 years from that available in Webster *et al.* (2008). We aggregate the historical data to the regional aggregations in our model so that we directly estimate uncertainty in regions relevant to our simulations. We calculate the volatility (standard deviation) from the growth rate time

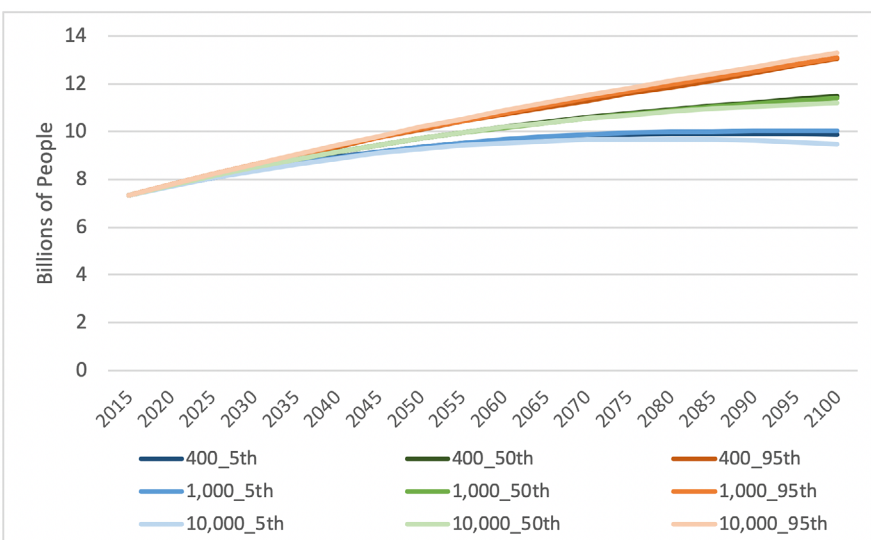

Figure 3. World population for the 5th, 50th and 95th percentiles based on 400 samples, 1,000 samples and 10,000 samples from the UN.

series and use that result to develop normal probability distributions of shocks to GDP growth in each region. We also estimate the correlation of shocks (excursions from the mean) across regions. The drift term (mean) in the random walk procedure is based on reference growth rates in the model for each region, which reflect current judgements of long-term growth for regions as well as factors such as slowing population and labor force growth. The random walk uses the drift term plus randomly sampled stochastic shocks to generate 400 sample GDP paths for each region in one-year steps from 2015 to 2100. GDP growth rates in 5-year steps are then calculated for each of the 400 sampled GDP paths.

For each region and the world aggregate, **Table 5** shows the average annual GDP growth rates and standard deviations for the historic period of 1950-2015, as well as the 5th, 50th and 95th percentiles of the projected average annual growth rates from 2015-2100. The random walk with drift approach to specifying uncertainty means that growth over the long term for any region exhibits less variability than for any 5-year time period. Also, global growth is less variable (90% probability bounds of 2.1% to 2.5%) than any individual region because regional growth rates are not perfectly correlated, so that it is unlikely that a sample with high (or low) growth in all regions will be drawn.

Each GDP path is consistent with a set of capital and labor productivity values. We run an initial ensemble targeting the 400 sample GDP paths by using the multiplier instrument on labor and capital productivity, holding all other variables at their reference levels. From this initial ensemble, we obtain a set of 400 trajectories of labor and capital productivities over time by region consistent with the variability of historical GDP in each region. This set of labor and capital productivities is then used in all final ensembles, using the endogenous GDP model setting, allowing other uncertain factors such as the population and labor force growth, resource availability, energy productivity, technology costs, and ease of substitution among inputs to affect simulated GDP growth in the final ensembles.

4.3 Advanced Energy Technology Costs

A principle contribution of this study is to investigate patterns of technology deployment that are consistent with different global mean surface temperature targets. Specification of the cost of advanced energy technologies will directly affect those patterns as the lowest cost technology options are chosen in model solutions. Each advanced tech-

Table 5. Mean and standard deviation of historical annual growth rates, and 5th, 50th and 95th percentiles of projected average annual growth rates for 2015-2100.

Region	Historical 1950-2015		Projected Average Annual Growth Rate 2015-2100		
	Av Annual	Std Dev	5th	50th	95th
AFR	3.9%	1.7%	3.1%	3.4%	3.7%
ANZ	3.5%	1.7%	1.7%	2.1%	2.5%
ASI	5.8%	2.5%	1.8%	2.3%	2.8%
BRA	4.4%	3.7%	2.1%	3.0%	3.8%
CAN	3.5%	2.4%	1.3%	1.8%	2.3%
CHN	6.9%	5.1%	2.0%	2.9%	3.9%
EUR	2.9%	2.0%	1.1%	1.5%	1.9%
KOR	6.8%	5.1%	1.4%	2.3%	3.3%
IDZ	4.9%	4.2%	1.8%	2.7%	3.5%
IND	5.0%	3.1%	2.7%	3.4%	4.0%
JPN	4.5%	4.2%	0.7%	1.5%	2.2%
LAM	3.4%	2.7%	2.3%	2.7%	3.3%
MES	4.9%	4.0%	2.0%	2.7%	3.3%
MEX	4.2%	3.5%	2.1%	2.7%	3.4%
REA	4.6%	1.9%	3.0%	3.4%	3.7%
ROE	2.7%	5.3%	1.6%	2.6%	3.7%
RUS	2.7%	6.0%	0.9%	1.9%	3.0%
USA	3.1%	2.3%	1.3%	1.7%	2.2%
WORLD	3.9%	1.4%	2.1%	2.3%	2.5%

nology shown in Table 3 is represented with a nested CES production structure. We define the relative costs of each in the base year of the model using a "markup" approach as described in Morris *et al.* (2019a). The markup represents the cost of an advanced technology relative to the cost of the conventional technology against which it competes. For electricity generation technologies, the markup is relative to the price received for electricity generation. A markup of 1.5 therefore means that the technology is 50% more expensive in the base year than the price of electricity in that year. The multiplier can be less than 1.0. The base year markups are determined based on a levelized cost of electricity (LCOE) approach, and are region-specific. Over time, the relative costs of technologies change endogenously as the costs of inputs change and substitution of inputs occurs. Advanced technologies endogenously enter if and when they become economically competitive with existing technologies, or disappear if they are no longer competitive.

There has been great interest in the costs of advanced technologies, which has lead to a variety of attempts to describe uncertainty around these costs. Because historical data is limited, does not exist at all, or is not relevant to future costs of the technologies, a common approach for developing estimates of uncertainty has been expert elicitation (e.g. Baker *et al.*, 2009; Bosetti *et al.*, 2012; Anadon *et al,* 2012) and further attempts to aggregate various expert elicitation studies (e.g. Baker *et al.*, 2015). These approaches are an option for assigning probability distributions to technology costs. However, there are well-known issues with overconfidence by experts in their assessments (e.g. Lin and Bier, 2008), and aggregating distributions across experts and across studies tends to lead to multi-modal probability distributions. Another source of estimates of uncertainty are cost ranges developed by the IEA (IEA, 2015a). This source provides minimum, median and maximum estimates for energy technology cost components of different technologies (e.g., overnight capital cost, fixed operation and maintenance (O&M) costs, variable O&M costs, efficiency, capacity factor). While these IEA estimares do not provide a full quantification of the distribution of costs, there appears to be more consistency across technologies than in other expert elicitation studies. We use the IEA ranges for each cost component to calculate minimum, median and maximum LCOE values for each advanced electricity generation technology.

We convert the cost ranges to a unitless scalar by dividing by the median cost. We construct probability distributions of the cost scalars, making use of the limited information we have for them, by assuming half of the probability weight is uniformly distributed between the minimum and median cost scalars, and half is uniformly distributed between the median and maximum cost scalars. For most technologies the minimum cost is more tightly constrained—there is a clear lower bound because costs cannot fall below zero. An exception is natural gas combined cycle (NGCC) where the maximum cost is more tightly constrained, because this technology is relatively well-known so the high end is well-constrained but there is still uncertainty about how much costs may fall. Note that mark-up multipliers are not applied to fuel inputs, as the significant effect of fuel cost uncertainty is simulated in the ensemble.

We take 400 samples from the cost scalar distributions and multiply each sample by the base region-specific markup costs that account for regionally varying cost factors such as different fuel and capital costs. Technology costs vary across regions, but the sampled cost scalar is applied in all regions, and is intended to represent uncertainty in the basic technology costs, as opposed to the variation that exists across regions due to variation in regional input costs.

While costs are a key driver, there are other factors that affect the penetration of advanced technologies, including model assumptions about the pace of deployment (see Section 3.6), technology-specific policies (e.g., renewable portfolio standards), political constraints and public acceptance. Political and social acceptance is particularly important for advanced nuclear and CCS technologies, especially bioelectricity with CCS (BECCS). Whether these technologies will be pursued/allowed/publically accepted or not, and to what extent, is extremely uncertain, and varies by region. In this study, we assume that coal and gas CCS are not limited by acceptance, but advanced nuclear faces additional costs to overcome social, political and regulatory barriers. We have chosen to specify BECCS as unavailable because the costs remain too uncertain, land use implications are a major concern, and the potential constraints and concerns around storage are issues. BECCS, if available, and not exceptionally costly, can become the dominating low-carbon solution, allowing emissions from other sectors to continue (Fajardy *et al.*, 2020).

4.4 Energy Productivity Growth (Autonomous Energy Efficiency Improvement (AEEI))

The economic model assumes an exogenous rate of energy productivity growth (often referred to as autonomous energy efficiency improvement, AEEI). We estimate uncertainty in the rate of AEEI, using historical data and a simple aggregate model following those widely used in demand studies (*e.g.,* Bohi, 1981; Yatchew and No, 2001; Li and Maddala, 1999). In these, the good's own-price and GDP are the main explanatory factors, allowing for an additional time trend effect—the residual AEEI. We use GDP data from the Penn World Tables (PWT) (Feenstra, 2015), energy consumption data from IEA (2015b), and energy price data from IEA (2015c). We limit our investigation to the period 1970 to 2007 given data availability and to avoid complications introduced by the global recession of 2008-2009. We combine coal, oil, gas, and electricity prices using a divisia price index by weighting each fuel by its value share of total energy.

The estimated model is:

$$\ln E_t = \alpha + \beta \ln P_{t-1} + \theta \ln GDP_{t-1} + \gamma t + \varepsilon \quad (1)$$

where E_t is aggregate energy use in year t, P_{t-1} is the aggregate energy price, GDP_{t-1} is the Gross

Domestic Product, α, β, θ, and γ are estimated parameters, ε is the error term, and "ln" is the natural logarithm. In this logged form, parameters are directly interpretable as elasticities.

To estimate the long-term effect, we then introduce a lagged dependent variable, the Koyck lag transformation (Kmenta, 1971):

$$\ln E_t = \alpha(1-\lambda) + \lambda \ln E_{t-1} + \beta(1-\lambda)\ln P_{t-1} + \theta(1-\lambda)\ln GDP_{t-1} + \gamma(1-\lambda)t + \eta_t \quad (2)$$

where $\boldsymbol{\eta}_t = \boldsymbol{\varepsilon}_t - \boldsymbol{\lambda\varepsilon}_{t-1}$, and λ is the strength of the lag effect. The directly estimated parameters include the $(1-\lambda)$ factor and are the short-run response, as shown in Kmenta (1971). The long-run response is derived by dividing the estimated parameter by $(1-\lambda)$. We estimate equations (1) and (2) with different variation (e.g., omissions and restrictions on the estimated parameters) (**Table 6**). We ultimately use the lagged effects model (specification 4 in Table 6), for which standard errors of estimates of γ (the coefficient on the time trend term reflecting AEEI) are about 55% relative to the best estimate.

For AEEI, we assume a normal distribution, with a standard deviation of 0.55, and apply sampled values as a multiplicative factor for AEEI as specified in the default settings, which vary by region and sector. We assume the AEEI is driven in part by technology, which would be to some extent commonly available across the world, so impose a correlation of 0.9 among all regions. Uncertainty, sampled for each region with correlation among other regions, is applied to scale the time path of energy efficiency up or down relative to the median EPPA path.

4.5 Fossil Fuel Resource Availability

The model includes a specification of the total stock of remaining fossil resources, depleting them over time. The total physical amount of the resource and the elasticity of substitution between the resource and other inputs in the production function are important assumptions. Together, they determine the cost increase as depletion occurs. We use the distribution from Webster *et al.* (2008) for the fossil resource supply elasticity. For uncertainty in the available fossil resources, we use the global resource assessment by the U.S. Geological Survey (USGS, 2013). This report gives a detailed assessment of fossil resources in terms of undiscovered, reserve growth, remaining reserves, and cumulative production for geologic formations in all regions.

Table 6. Energy consumption as function of price, GDP, and time with and without lagged effects.

			Estimated Parameters						Calculated Values			
Equation Specification			α	β	θ	γ		λ	R^2			
			Constant	Short-Term Price Elasticity	Income Elasticity	Residual Time Trend	Short-Run AEEI% per year	Dependent Variable Lag	% Variance Explained	Long-Run AEEI% per year	Long-Run Price Elasticity	Long-Run GDP Elasticity
(1)	1	All	5.384 (6.924)	-0.120*** (0.0371)	0.269 (0.208)	0.00268 (0.0066)	-0.268359 (0.6650)		0.954			
(1)	2	Const, Price, GDP	8.185*** (0.391)	-0.112*** (0.0314)	0.353*** (0.0136)				0.954			
(1)	3	θ=1	29.55*** (0.974)	-0.0543 (0.0372)	1 (0)	-0.0205*** (0.0005)	2.0291304 (0.0498)					
(2)	4	Koyck LAG, Pr, GDP, t	-7.30 (5.787)	-0.0686*** (0.0297)	-0.196 (0.182)	0.00934* (0.0051)		0.716*** (0.142)	0.975	-3.3434 (1.8911)	-0.24155	-0.6901
(2)	5	Koyck LAG, PR, GDP	2.992*** (1.176)	-0.0480 (0.0284)	0.121** (0.0518)			0.650*** (0.142)	0.972		-0.1371	0.3457
(2)	6	Koyck θ=1	30.45*** (1.187)	-0.023 (0.0440)	1 (0)	-0.0232*** (0.0022)		0.242 (0.186)		3.0143 (0.2768)	-0.0303	1.3193

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We use the 5th and 95th percentiles relative to the median for the world resource estimates, which gives a range of 46% to 190% of the median value for oil and 33% to 215% of the median value for natural gas. These standard errors are then applied to a normal distribution. We assume the same distribution for coal and natural gas. The samples are then multiplied by the default regional resource estimate in the model. For sampling, correlation of 0.9 is assumed between oil and gas resources.

4.6 Rate of Technology Penetration

As described in Morris *et al.* (2019b), the model includes an adjustment cost formulation to represent the scaling up of advanced technologies. The representative agent in each region is endowed with small amounts of specialized resources—technology-specific factors (TSF)—that are an input in each advanced technology. The endowment of this resource (investment in TSF, INVTSF) grows as a function of output of the technology (OUT) in the previous period, accounting for depreciation (δ):

$$INVTSF_{s,r,t+1} = \theta_{TSF} * \boldsymbol{ba}[OUT_{s,r,t} - (OUT_{s,r,t-1}(1-\delta_O)]$$

Capacity expansion is thus constrained in any period by the amount of the TSF resource and the ability to substitute other inputs for it. As output expands over time, the endowment of TSF increases, and it eventually becomes a non-binding factor on capacity expansion. Morris *et al.* (2019b) estimated the rate of penetration (the *ba* coefficient) for several historical examples of new technologies (**Table 7**). Here, we represent uncertainty in the rate of technology penetration by assuming a uniform distribution for *ba* spanning the range of *ba* estimates for different technologies in Table 5 (e.g., 1.014 to 1.589).

4.7 Additional Uncertain Parameters

The elasticities of substitution at each level of the nested CES functions determine the relative ease of substituting one input for another—the flexibility of the technology. Critical elasticities of substitution in the production structures in the model (Figure 2) to which results are sensitive include those between labor and capital, electricity and fuels, energy and value-added (labor and capital), and different fuels. Econometric estimates of these parameters include standard errors. Based on a review of the literature, we did not find significant reason to update the distributions used in Webster *et al.* (2008) that were based on econometric estimates in the literature. Similarly, the evidence on the probability distribution for the resource supply elasticities for fossil fuels did not provide a reason to update the estimates in Webster *et al.* (2008). Each fuel is sampled independently from this distribution (*i.e.* no correlation).

Conventional pollutants such as particulates and ozone precursors are associated with fossil fuel combustion and other activities. They are modeled by specifying an initial inventory for each substance and activity-specific emissions factors for each sectors. A combination of technology advances and regulation has generally led to a decline in emissions per unit of activity, similar to the decline in energy use explained by the AEEI. We model the evolution of the activity-specific emissions factors over time, according to:

$$F_{i,j,t} = F_{i,j,0}\exp(\gamma_j t)$$

where $F_{i,j,t}$ is the emissions factor for economic sector *i*, pollutant *j*, and time *t*, $F_{i,j,0}$ is the emissions factor in the initial year, and γ_j is the uncertain trend parameter for pollutant *j*. Webster *et al.* (2008) based the uncertainty in the time trend γ on data and analysis by Stern (2006, 2005; Stern and Common, 2001), which used observed emissions to estimate a stochastic emissions frontier for 15 different countries. While we have updated the initial inventories for pollutants for the current version of the model (EC, 2013), we continue to use the distributions from Webster *et al.* (2008) for uncertainty around the initial inventories and uncertainty in the pollutant trends as we did not find compelling evidence to update them.

The ability to reduce methane (CH_4) and nitrous oxide (N_2O) emissions is implemented by using a nested CES

Table 7. Range of estimates for technology penetration rate parameter.

	Regression Information					
	Start Year	End Year	% in Start	$\beta1$	Intercept	Standard Error
Nuclear US	1970	1987	1.40%	1.014*	21685*	0.042
Nuclear France	1966	1982	1.45%	1.199*	1942	0.097
Solar Germany	2009	2014	1.18%	1.014*	4891	0.093
Wind US	2008	2013	1.18%	1.053*	17788*	0.027
Wind China	2010	2013	1.13%	1.315*	9495	0.157
Shale Gas US	1999	2011	1.42%	1.589*	-169*	0.035
Hybrid Vehicles US	2005	2014	1.15%	1.098*	201702*	0.025

*Statistically significant with a P-value < 0.05

production function where conventional inputs can be substituted for CH_4 or N_2O emissions (Reilly *et al.*, 2006; Hyman *et al.*, 2003). The value of the elasticity of substitution between emissions and conventional inputs can be estimated from marginal abatement curves developed from bottom-up studies of abatement potential in various sectors that emit these gases. We have not found reason to update the uncertainty ranges used in Webster *et al.* (2008) as applied to these elasticities.

Another factor shown to be important is the rate of capital turnover**.** The capital stock is dynamically updated in the model for each region and sector, as determined by the capital vintaging procedure (Chen *et al,* 2016). In each period, a fraction of the malleable capital becomes non-malleable for future periods. Letting K_m represent the malleable portion of capital and K_r the rigid portion, the procedure can be described as follows. New capital installed at the beginning of each period starts out in a malleable form. At the end of the period a fraction φ of this capital becomes non-malleable (vintaged) and frozen into the prevailing techniques of production. The fraction (1 – φ) is that proportion of previously installed capital that is able to have its input proportions adjust to new input prices to take advantage of intervening improvements in energy efficiency or changing prices—essentially allowing the possibility of retrofitting previously installed capital. We treat the share of vintaged (non-malleable) capital as uncertain. There was no compelling evidence to support an update of the uncertainty estimates in Webster *et al.* (2008).

5. Monte Carlo Simulation Results

We develop four ensemble simulations differing in the assumed degree of government intervention in markets to limit emissions. The first ensemble ensemble reflects a "business-as-usual" scenario including existing interventions in energy markets, including renewable energy targets that many countries have, nuclear and hydro power development plans, and the like, as reflected in the IEA world energy outlook (IEA, 2018). A second ensemble includes, in addition, the assumption that countries will meet their Nationally Determined Contribution pledges and maintain those commitments through the end of the simulation period, modeled as a constraint on covered emissions (Reilly et. al., 2018). A third ensemble assumes a constraint on emissions such that the global mean temperature stabilizes at less than 2°C above preindustrial levels with a 66% likelihood given uncertainty in the Earth system response to radiative forcing. A fourth ensemble assumes a constraint on emissions that limits the global mean temperature increase to less than 1.5°C with a 50% likelihood. We determined the emissions constraint needed to meet the temperature goals for the third and fourth ensemble using the MIT Earth System Model (MESM). With these constraints determined, we use the same samples of uncertain parameters in each ensemble to ensure comparability.

Once the ensembles are completed, we use the emissions results to simulate 400-member ensembles of earth system outcomes that include uncertainty in the earth system response to determine the temperature outcome in all four ensembles. By design, the 3rd and 4th ensembles produce the 2°C and 1.5°C warming results with a 66% and 50% likelihood, respectively. The focus in this paper is on the technology mix and sectoral emissions consistent with these various environmental goals and interventions. The outcomes of the climate ensembles are described in detail in Morris *et al.* (2020). Briefly, the median and standard deviation of 2091-2100 temperature increases above preindustrial in these four ensembles are 3.5°C (+/- 0.45), 3.1°C (+/-0.39), 1.9 C (+/- 0.23) and 1.5°C (+/- 0.18).

As a shorthand, in the figures below we refer to ensembles by the median temperature outcome at the end of the century.

5.1 Sectoral Output and Emissions

As various sectors and industries consider their relationship to environmental outcomes, there has been increasing interest in what level of emissions from different industries are consistent with various global temperature levels. One might expect there to be considerable uncertainty given that overall economic growth, and hence the level of output from each industry, is uncertain, as is the size of and emissions from other sectors and industries. We use box and whisker plots to summarize output (in trillions of 2019 U.S. dollars) from our ensembles for six aggregated sectors that together cover all of industry—agriculture, commercial services, electricity, energy intensive industry & mining (which includes the supply of fossil fuels), other manufacturing, and commercial transportation. The low end of the whisker for global output in nearly all sectors (reported in trillion 2019 US dollars) is above the 2020 level in all reported years (2030, 2040, 2050, and 2100) and growing over time (**Figure 4**). Our primary focus is the next few decades, but we include a boxplot for 2100 as well. By that time, the median output of most sectors is generally more than 4 times larger than the level in 2020. The interquartile range (the boxes) are quite tightly constrained through 2050 for most sectors. Even the whiskers (1.5 times the interquartile range) are fairly narrow, although graphically this is somewhat distorted by the year 2100 results being much higher. Also, through 2050, there is not much difference among the various temperature ensembles. The exceptions are that the 1.5C ensemble distributions, especially by 2050, drop somewhat compared with the other three ensembles. Thus, except in those cases, the constraints on emissions and other interventions do not have a significant effect on sector output through 2050.

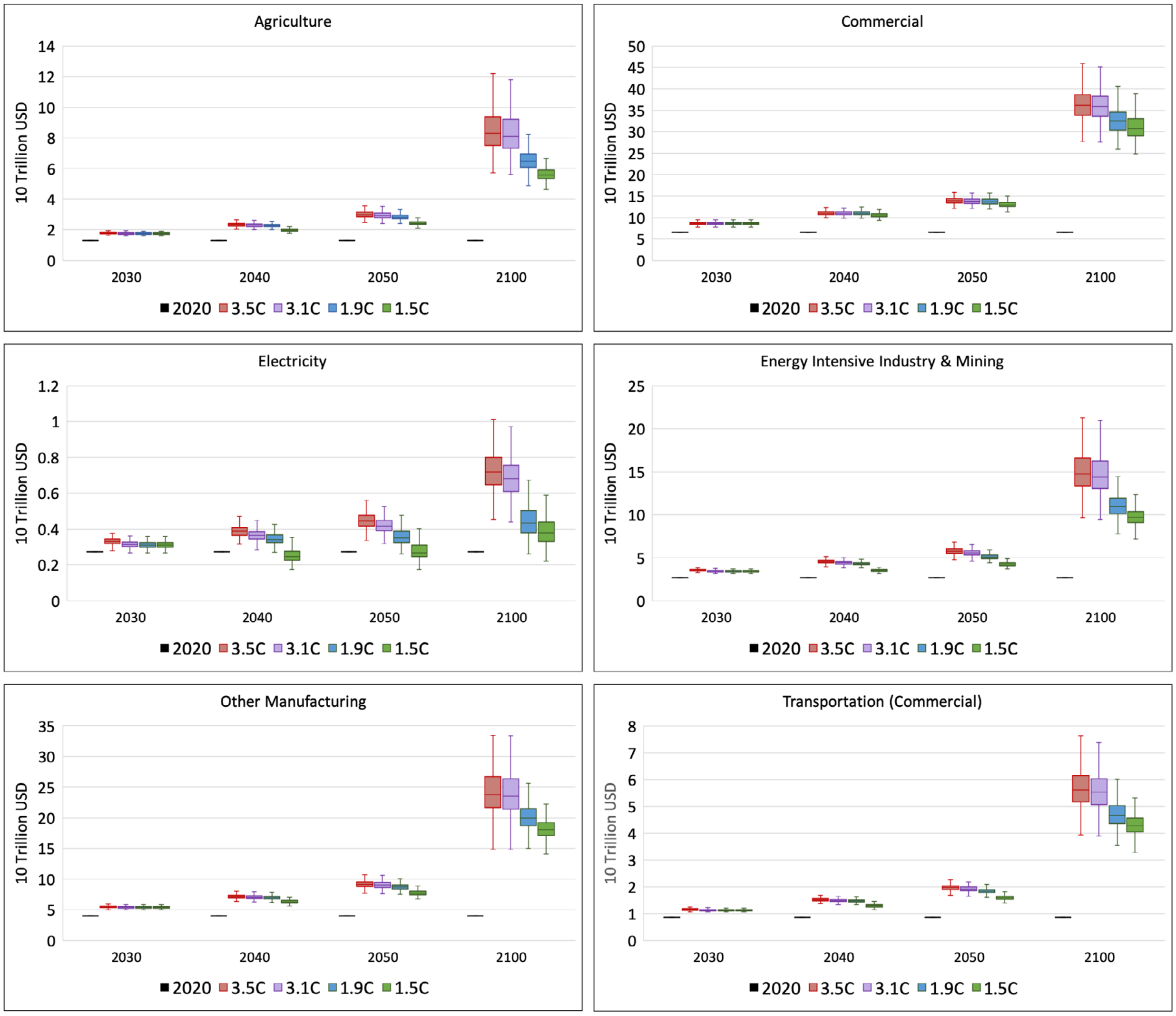

Figure 4. Box and whisker plots for global sectoral output (trillions of 2019 US Dollars). The 2020 output level is shown as a black line in front of the scenario results in each time period to easily compare future output to current levels.

The primary exceptions to the observations above are the electricity sector and the 2100 results for all sectors where there is a greater difference in sector output among the four ensembles. The median electricity output is about flat at or slightly decreasing from the 2020 level through 2050 for the 1.5C ensemble, indicating electricity output consistent with that temperature level has a significant chance of being lower than 2020 output by 2040 and 2050. While there is difference among ensembles, the lower end of the whiskers in 2050 remains at or above 2020 electricity output for all other ensembles, including the 1.9C ensemble. By 2100, it is likely that electricity sector output will be above 2020 output, although at the extreme it could be at or slightly below the 2020 level. These trajectories are affected by demand response and energy efficiency improvements. It is important to note that because output reflects price times quantity, it could be the case in some ensemble members that very low electricity prices (e.g. due to penetration of cheap renewables) drive lower sector output.

The year 2100 results show more effect on output of all sectors from the constraints on emissions. The results for 2100 should be interpreted with care as the ongoing need to reduce emissions could well lead to innovations that would allow sector output to remain higher. While innovation is implicitly captured in our representation of uncertainty in sector response via the range of substitution elasticities, as well as energy efficiency improvements, the central tendency of those distributions are around the current estimated response and the elasticity formulation does not allow for radical transformation of production processes.

It is also of note is that, embedded in results for Energy Intensive Industry & Mining, we find that output from the fossil fuel supply sectors (coal, oil and gas) falls to near zero by 2100 under the 1.9C and 1.5C scenarios. This is consistent with the dramatic decline in fossil fuel use in primary energy under those scenarios (see Figure 8).

For specific companies in various sectors seeking to be on a path consistent with given temperature targets, a useful metric is emissions intensity per unit of output. This can be evaluated within a company without consideration of the company's size relative to the overall sector. Note that many current environmental standards focus not only on direct emissions coming from a company's operations, but also emissions attributed to electricity they use, and emissions related to the production of inputs used in the sector. Since this analysis comprehensively treats all emissions in all sectors simultaneously, however, the focus here is on the direct emissions from the sector. The current (year 2020) global emissions intensities of output vary considerably by sector, with electricity by far the most intensive (45 tonnes of CO_2 equivalent per unit of output measured in thousands of 2019 dollars, $tCO_2eq/\$1000$) and the commercial sector the least intensive (0.12 $tCO_2eq/\$1000$) (**Figure 5**). Commercial Transportation is the second highest, after electricity, at just under 9 $tCO_2eq/\$1000$. Agriculture and Energy Industry & Mining come in at just over 6 $tCO_2eq/\$1000$. Other Manufacturing is quite low at just under 0.4 $tCO_2eq/\$1000$.

The emissions intensities drop in all sectors over time in all four ensembles. Even in the least constrained 3.5C ensemble, intensities drop by around 40% by 2050 from their 2020 levels. There is a fairly wide range of sectoral emissions intensities potentially consistent with each temperature target at least through 2050, but by 2100 all sectors need to have emissions intensities near zero in the 1.9C and 1.5C ensembles. As constructed, global emissions over

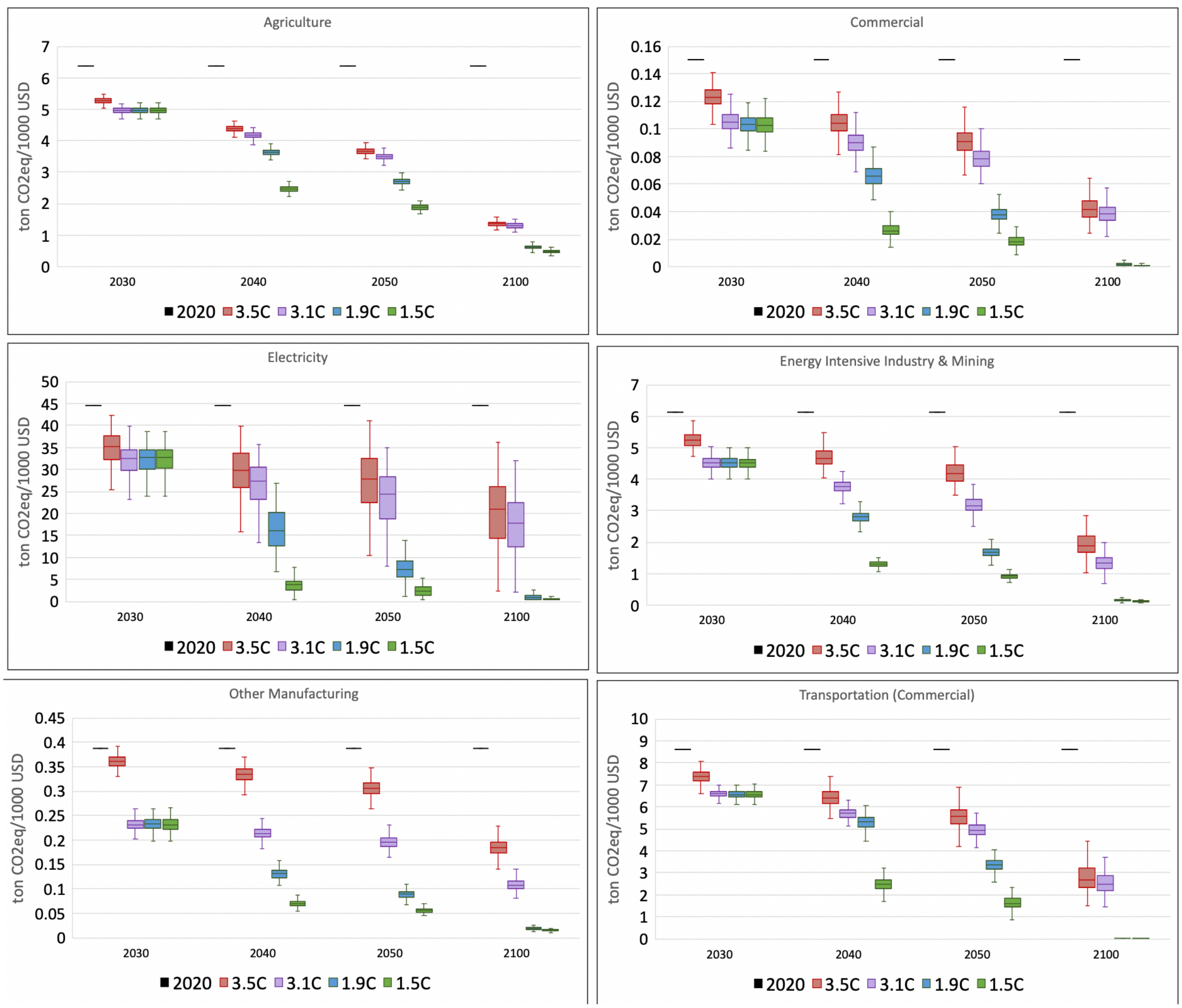

Figure 5. Box and whisker plots for global sectoral emissions intensity (tons of CO_2 eq/\$1000 of output in 2019 US dollars). The 2020 emissions intensity is shown as a black line in front of the scenario results in each time period to easily compare future emissions intensity to current levels.

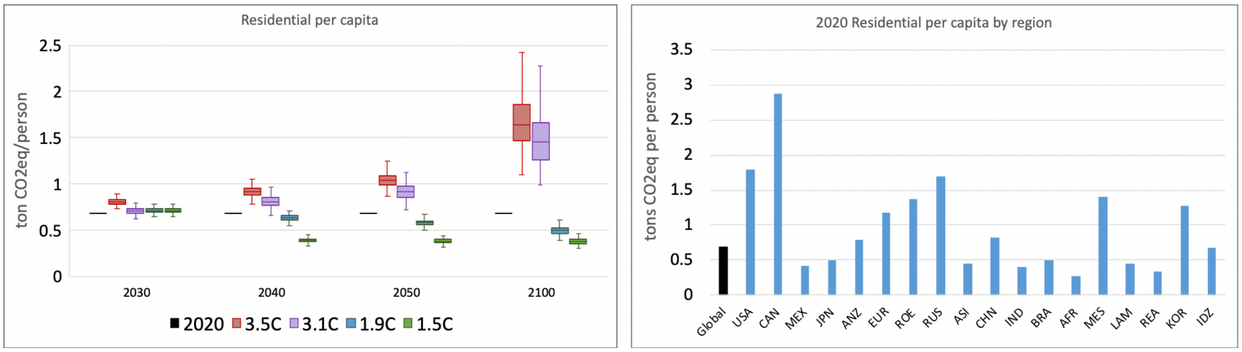

Figure 6. Box and whisker plots for residential (including private vehicles) emissions (tons CO_2 eq) per capita and 2020 emissions per capita by region.

time in the 1.9C and 1.5C cases are constrained to meet an identical global path in all ensemble members. Thus, if emissions in one sector are relatively higher, emissions in other sectors must be commensurately lower to meet the global emissions target for that year. Emissions from agriculture drop the least among the sector because of the difficulty of reducing methane from rice paddies and livestock, and nitrous oxide from soils. Emissions or sinks for CO_2 from land use change are not included in the agriculture total, and are accounted as a separate land use source or sink. Representation of additional abatement opportunities in the model could also affect how quickly emissions and emissions intensities fall in the sectors.

For households and private vehicles, a more common measure of intensity is emissions per capita. Here we also include only direct emissions from households and private vehicles, and not emissions attributable to vehicle production, electricity consumption or other consumption goods. In this case, the emissions paths among the ensembles diverge over time with average global per capita emissions growing considerably in the 3.5C and 3.1C ensembles, but falling in the 1.9C and 1.5C ensembles (**Figure 6**). In the 3.5C and 3.1C ensembles, the median average global per capita emissions by 2100 is near the level of emissions per capita in the US in 2020. The range of emissions intensities in the 3.5 C and 3.1C ensembles are also fairly wide. In these ensembles, the modeled interventions in the market are not targeted to meet a specific emissions or temperature goal, and so higher emissions contribute to higher temperatures, other things equal.

Current emissions per capita vary substantially among countries. Our model is resolved for 18 countries/regions. Emissions per capita in several regions are currently near or somewhat below the levels we estimate as consistent with the 1.9C and 1.5C ensembles. There is room for modest growth in emissions per person in Africa, on average, and to remain about where they currently are in Mexico, India, Latin America and other similar regions, if Canada, the US, and other more developed regions reduce their emissions to the global average that is associated with these ensembles. In general, all of regional economies are growing over time, and so if we measured emissions intensity for households as emissions per \$1000 dollars of final consumption, that would tend to show a pattern similar to industry sectors (emissions per \$1000 dollars declining in all scenarios).

Total global emissions across all sectors also diverge in the ensembles. As indicated above, the 3.5C and 3.1C ensembles are not targeted to meet a specific global emissions or temperature goal, and global emissions are therefore uncertain, but growing, in these ensembles. The 1.9C and 1.5C ensembles, however, are constrained to meet a specific global emissions path in all ensemble members which requires emissions to decrease over time. **Figure 7** compares total global GHG emissions results from our four ensembles with those from the IPCC 5th Assessment Report (AR5) (IPCC, 2014). Our ensembles span much of the AR5 range of emissions. Our high end of emissions is lower than that in the AR5. Updated model assumptions based on slower economic growth, falling costs of low-carbon energy options and government interventions worldwide directed at expanding the role of renewables result in our lower high end of emissions.

5.2 Primary Energy and Electricity Generation Technologies

Investment plans in the energy sector will depend on how demand for and use of energy sources change over time. The pattern over time for use of a specific fuel or technology depends on both how demand changes (due to population, economic growth, and elasticities of substitution, among other variables) and how resource availabilities and the costs of competing technologies change in the future. These uncertainties are captured in each ensemble. Patterns of use also depend on the nature of interventions in the market, captured by the different ensembles. We show results for global primary energy sources including primary electricity (**Figure 8**).

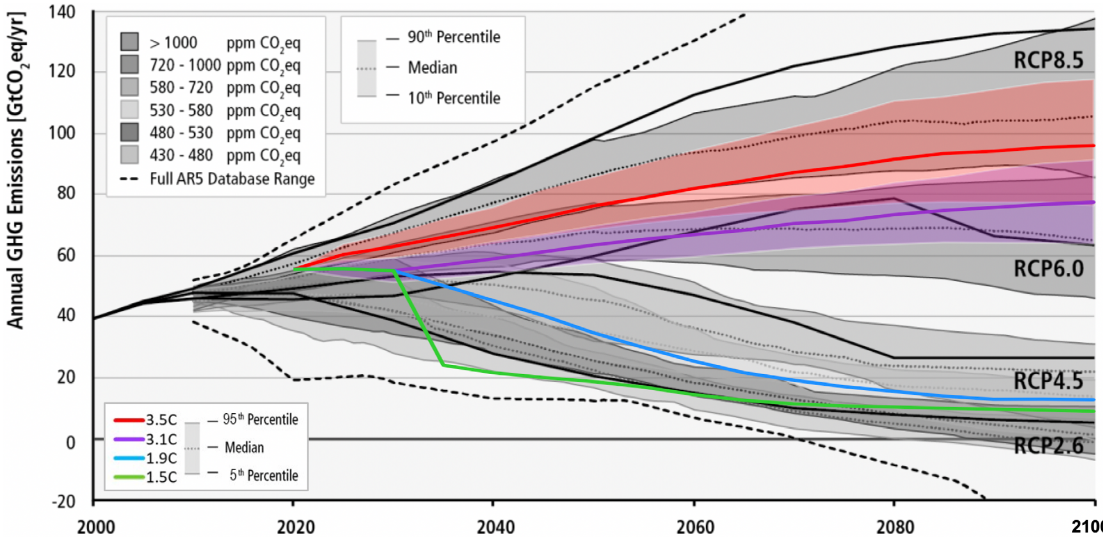

Figure 7. Total global GHG emissions range (for the 3.5C and 3.1C ensembles) and emissions constraint (for the 1.9C and 1.5C ensembles) in Gt CO_2eq compared with scenarios in the IPCC Fifth Assessment Report (AR5) (IPCC, 2014)..

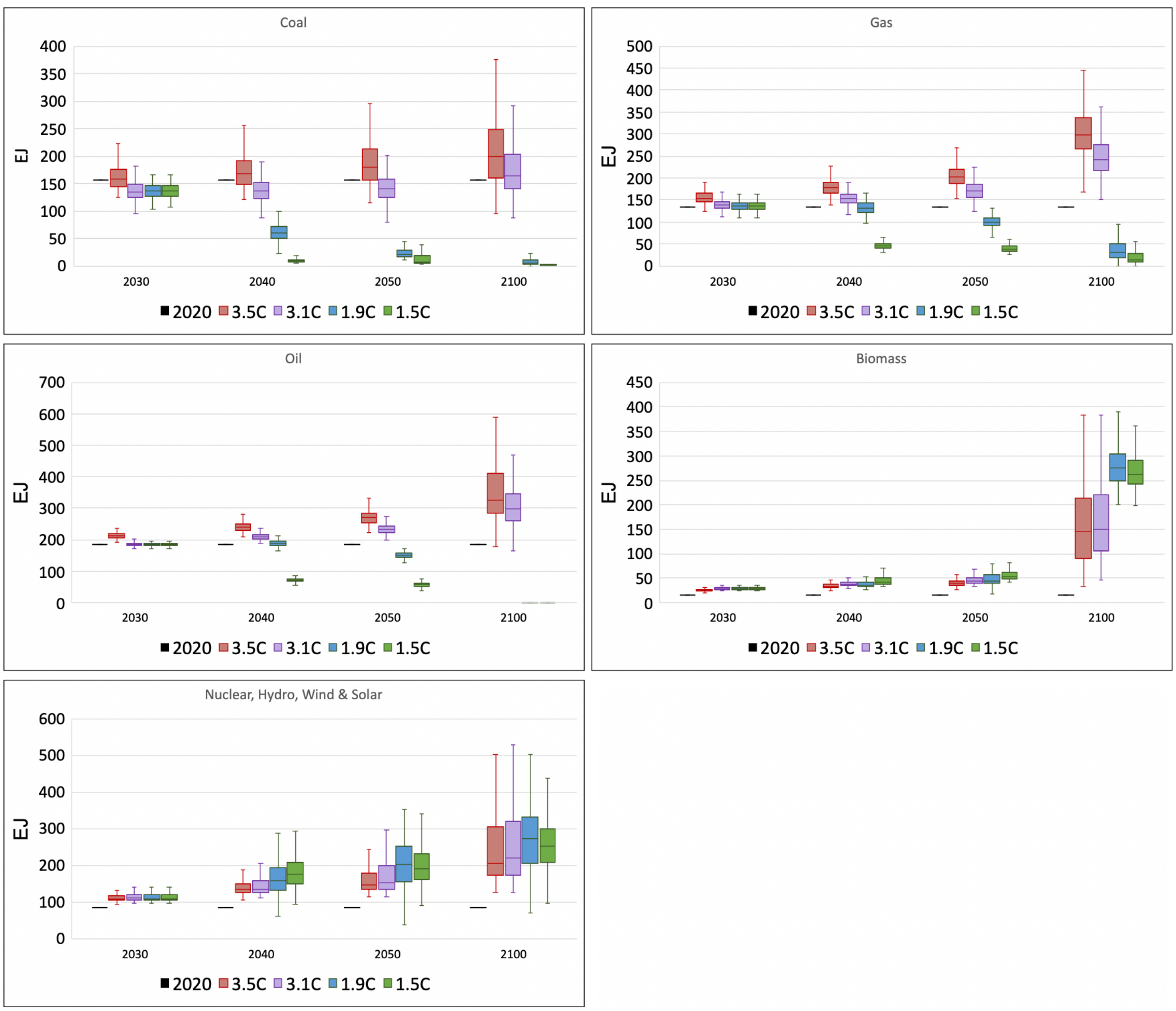

Figure 8. Box and whisker plots for global primary energy production (EJ) including coal, oil, gas, biomass, and primary electricity (nuclear, hydro, wind & solar). The 2020 primary energy level is shown as a black line in front of the scenario results in each time period to easily compare future primary energy production to current levels. Oil in 2100 for 1.9C and 1.5C is not visible in the figure as it is zero.

The median use of primary electricity (the sum of nuclear, hydro, wind & solar electricity converted to primary energy equivalance) grows robustly in all four ensembles. By 2050, median primary electricity has increased by 50 to 100 percent compared with its production in 2020, and by 2100 median production has doubled to nearly tripled. The range of use in the future widens considerably by 2040, especially in the 1.9C and 1.5C ensembles. On the low extreme of the boxplot, global production for 2040, 2050 and 2100 is roughly equal to production in 2020 in the 1.5C ensemble, but lower than 2020 in the 1.9C ensemble. On the high-end, production is around 5 times the 2020 level by 2100 in all four ensembles. Median production of biomass energy also grows considerably in all ensembles by 2100, expanding 7.5 to 12.5 times. Through 2050, expansion of median biomass production is similar to primary electricity, increasing around 2 to 2.5 times. There is greater uncertainty in the role of biomass production in the 3.5C and 3.1C ensembles in 2100.

Natural gas and oil use share a similar general pattern, expanding substantially in the 3.5C and 3.1C ensembles and contracting to near zero (for gas) and zero (for oil) by 2100 in the 1.9C and 1.5C ensembles. Of greater interest from an investment perspective, in all but the 1.5C ensemble, median gas and oil use does not decline through 2040 and remains substantial in 2050. This reflects the fact that the emissions constraint needed to remain consistent with the 1.5C temperature outcome is quite tight even in the near term. In contrast, median coal use declines in 2030 from 2020, and continues to decline further in all but the 3.5C ensemble.

Some of the results for fossil fuel use can be explained by results for the fossil technologies used globally for electricity production (**Figure 9**). Specifically, coal and gas generation disappear by 2050 in the 1.9C and 1.5C ensembles, coal

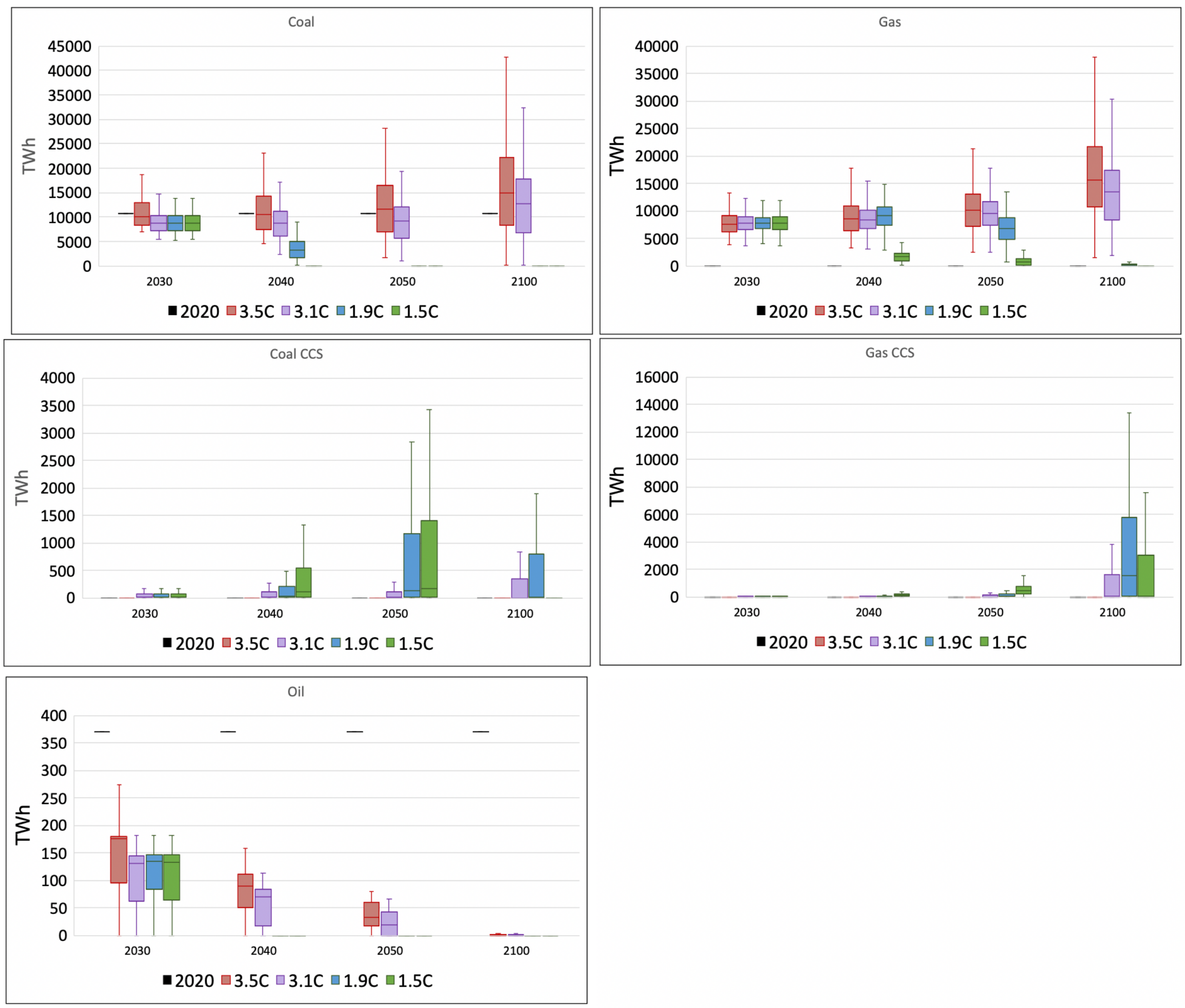

Figure 9. Box and whisker plots for fossil fuel-based electricity generation technologies. The 2020 generation level is shown as a black line in front of the scenario results in each time period to easily compare future generation to current levels. Boxplots that do not appear in future years indicate that the generation technology in question is no longer part of the electricity mix under that scenario.

as early as 2040 in the 1.5C ensemble. However, the range for use of coal and gas generation with carbon capture and storage (CCS) is wide, although the median amount of generation with these CCS technologies tends to be at zero or quite low relative to current generation levels for coal and gas without CCS. The sizable chance that coal or gas CCS or both may be used in the 1.9C and 1.5C ensembles explains why some of these fuels remain in primary energy, whereas oil disappears completely. Oil-based electricity generation is only about 3.5% of current coal or gas generation largely because it is generally not cost competitive given oil prices. Given the limited role of oil-based generation, and the fact that a CCS version of oil-based generation is not an option in the model, it is not surprising that oil generation disappears completely from the generation and primary energy mix. In a situation of tight constraints on carbon emissions, which greatly lowers demands of oil products elsewhere in the economy, oil prices fall, and so in reality oil-based generation with CCS could be competitive in some situations. However, there is no reason to expect oil to be more competitive than gas or coal generation with CCS because the steam-based generation is similar to coal, and any of the approaches for carbon capture that would be used with coal or gas could be used with oil as well.

The non-fossil fuel-based electric generation technologies generally all show significant growth in all ensembles at median results, even at the low end of the interquartile range (**Figure 10**). Wind & solar show the most potential, producing in the range of 10,000 to 15,000 TWh annually by 2100 at median levels across the ensembles. In 2100, wind & solar production is actually somewhat higher in the 3.5C and 3.1C ensembles. This result is driven by the fact that there is less overall demand for electricity under the 1.9C and 1.5C (which may not be the case with additional electrification options represented in the model), as well as the potential for nuclear to outcompete renewables in the future (particularly given integration costs associated with higher renewable penetration levels). Wind & solar also show more potential in the next few decades. Nuclear and biomass-based generation show more moderate potential through 2050, but greater potential in 2100. Nuclear in particular shows the possibility of production in 2100 as large or larger than wind & solar. As one might expect, there is generally a larger range for these individual technologies than for the primary electricity combined—if one of the non-fossil technologies is particularly low cost, the others are squeezed out, and there is a good chance that at least one of them will be lower cost. Hydro generation is tightly constrained at the high end given the specification of resource availability and assumptions about the time path over which these resources could be developed. Much of the potentially available hydro power is in Africa, and so its development depends on growth in electricity demand in the region.

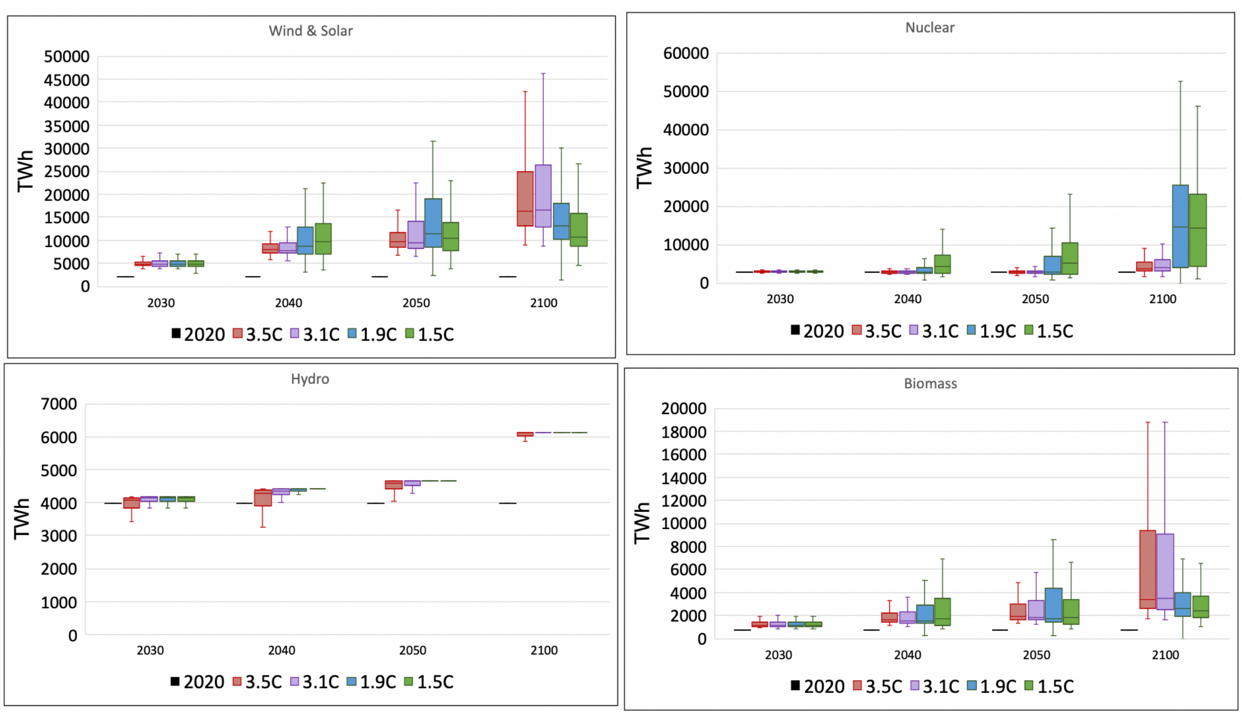

Figure 10. Box and whisker plots for non-fossil fuel-based electricity generation technologies. The 2020 generation level is shown as a black line in front of the scenario results in each time period to easily compare future generation to current levels.

5.3 Scenario Discovery

A limitation of results of a formal uncertainty analysis as presented above is that they do not maintain the relationship of a particular outcome (e.g. nuclear power production) as part of a scenario where all other outcomes have specific values. For example, a scenario with a lot of nuclear generation would likely mean lower levels of production from other generation sources, other things equal. Of course, other things may not be equal: for example, a scenario may have rapid economic growth with overall high electricity demand and similar costs for all technologies so that they all operate at a relatively high level. The uncertainty analysis above does not focus on individual internally consistent scenarios. However, combining uncertainty quantification with scenario discovery approaches can identify individual scenarios of interest from the ensembles.

Scenario discovery is a model-based approach for scenario development aimed at finding areas of interest within large, multi-dimensional databases of simulation model results. It involves screening databases of model simulations (often through statistical/machine learning/data-mining algorithms) to identify outcomes of interest and their conditions for occurring. It can then inform the development of specific individual scenarios to explore in depth. Another common mode of scenario development is to create one or more "consistent" stories that hang together. However, a danger with the storyline approach is that one may be over confident that only one narrow set of outcomes can be part of a consistent story. Scenario discovery approaches can avoid this error and can identify variables associated with given outcomes of interest without defining *a priori* which variables are likely to be most important. Scenario discovery is a particularly useful tool in multisector dynamics research where the complexity of interacting systems, multiple uncertainties and emergent behavior make it difficult to know a priori what factors are most important. Several recent studies have employed the approach (e.g. Lamontagne *et al.*, 2018; Quinn *et al.*, 2018; Herman *et al.*, 2015).

Here we employ a scenario discovery approach designed to make use of the large ensembles we developed in the previous sections of the paper in order to investigate scenarios with similar values for one outcome and evaluate the range of other outcomes in those scenarios. Our hypothesis is that there are wide ranging values of other outcomes consistent with a given outcome of interest. Combinations of values of other outcomes are "consistent" in that they were produced with a model that connects them all together.

To explore this scenario discovery approach, we focus on the 1.9C ensemble, and choose scenarios where this target is met under high, median, and low US economic growth. We focus on the 95th, 50th, and 5th percentile values of economic growth. We include the +/- 1 scenario (the scenarios directly below or above the 95th, 50th, and 5th), so that we have 3 separate scenarios for each of the 3 economic growth levels. We then plot the percentiles for the values of other outcomes in 2050 in each of the scenarios as radar plots (**Figure 11**). The percentiles reflect where the value of an outcome falls for the given scenario compared to its value in all of the 400 ensemble members.

The top panel in Figure 11 is the radar plot for high US economic growth. The dark green line is the 95th percentile economic growth scenario. It has very high biomass electricity ("Biomass") in 2050—near the 95th percentile of biomass electricity production, but wind & solar production ("Wind&Solar") are only at about the 50th percentile, gas with CCS ("Gas CCS") is near the 5th percentile, and gas generation ("Gas") is at the 50th percentile level. GDP in the rest of the world ("ROW USA") in this case is relatively low (20th percentile), suggesting relatively low non-US emissions, which allows for higher US emissions – non-electricity US emissions ("USA Non-Elec Emi") are at their 90th percentile level, while emissions from the US electric sector ("USA Elec Emi") are near their 60th percentile level.

In contrast, the 95th-1 scenario of US economic growth (light green) has gas generation near the 90th percentile, more gas with CCS, more wind and solar, and again high levels of biomass-based generation. US electric sector and non-electric sector emissions are near their extreme high outcome. GDP in the rest of the world is very low (10th percentile), suggesting less emissions in other parts of the world allow for more emissions in the US. The 95th+1 scenario (dashed green) has moderate levels for all the plotted outcomes except biomass generation is again at a relatively high level. While not plotted, coal, coal with CCS, oil, and nuclear generation in the US are all non-existent in 2050 in all of these scenarios.

At median economic growth (middle panel, dark blue), gas with CCS is the major electricity supply source (near the 90th percentile), gas is near the 30th percentile, and wind and solar are near their lowest level, as is biomass generation. GDP in the rest of the world is relatively high, uggesting higher non-US emissions, which means US emissions must be relatively low. In the 50th+1 scenario (dashed blue), electricity production is mainly wind & solar with some biomass, but very little gas or gas with CCS. US emissions are very low, with non-electric emissions at about the 30th percentile level and electric sector emissions near their extreme low. GDP in the rest of the world is high, at about their 90th percentile level. The 50th-1 scenario (light blue) is one with a lot of generation from gas with CCS, and wind & solar, but little from biomass.

The low US economic growth outcomes (bottom panel), again shows three fairly different patterns of electric generation technology use.

An important note to these results: because we are plotting the percentile outcome for each technology, the same percentile values do not mean the same levels of generation for each technology. In the earlier boxplots, the median case for gas with CCS in 2050 was for no production, while even the lowest outcome for wind and solar was a slight increase from present, at least for the world total. So even a relatively low percentile for wind & solar may mean these technologies are generating more electricity than gas with CCS. The percentiles do, however, tell us how the

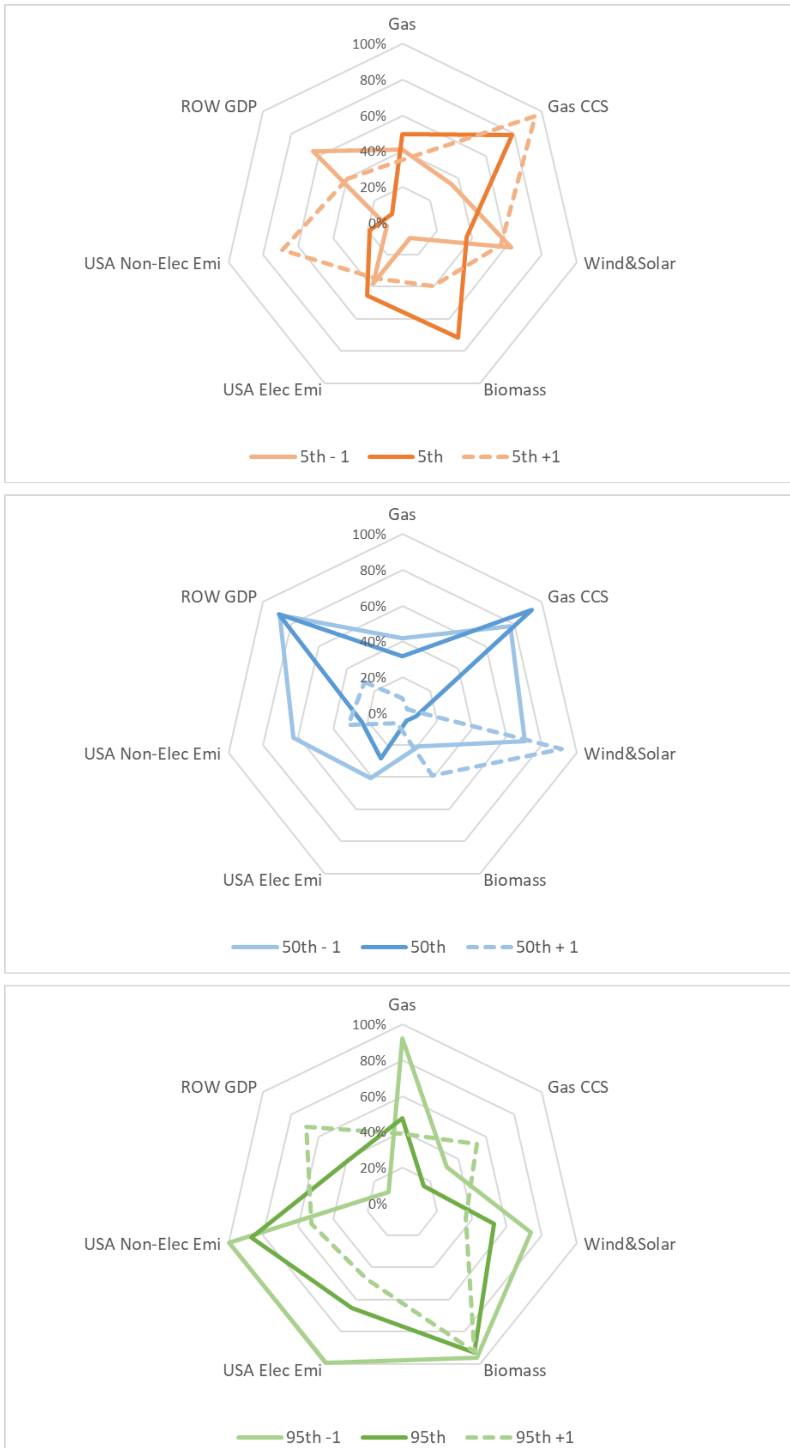

Figure 11. Radar plots for scenarios with high (95th percentile), median (50th percentile), and low (5th percentile) US economic growth through 2100, showing the 2050 values of other outcomes in those scenarios.

technology's generation in a specific scenario compares to that technology's generation in all 400 ensemble members and whether it is above or below average for the ensemble.

Comparing among the three growth outcomes (high, low and median), it appears there is some tendency for high growth to be associated with high emissions in the US, though not necessarily. We might expect this tendency given that high economic growth would tend to create greater US demand for all energy types and higher emissions such that it is more likely that more abatement will occur outside the US where economic growth is unlikely to be as high as in the US. However, given all the other uncertainties that can counter the tendency for higher emissions, it appears only weakly present. There is very high biomass electricity in all three high scenarios, but that is more coincidental. To test that further, we extended the exploration to more high growth scenarios (95^{th} +/-10) and found that while biomass electricity tends to be above average in the high US economic growth cases, it is not always at very high percentiles.

This approach demonstrates that there are many different pathways for technology development that are consistent with the 1.9C long-term temperature goal. There are also many different pathways that are consistent with a particular US GDP outcome under the 1.9C target.

6. Concluding Remarks

This paper demonstrates how available information (historical data, scientific literature, expert judgment, etc.) can be used to develop probability distributions for important socio-economic uncertainties in economic-emissions models. We can then sample from those distributions, employing Monte Carlo simulation, in order to quantify the uncertainty in key human system model outcomes. Here we focus on sectoral and technology outcomes, exploring results consistent with different 21^{st} century global temperature pathways. We find that for most sectors, overall output is little affected by the long-term environmental pathway through mid-century. The electricity sector is an exception, with the level of government intervention leading to differences in output as early as 2040.

While sectoral output is little affected by the level of government intervention, emissions intensities for industries must fall more with tighter constraints. Although emissions intensities fall for all sectors in all ensembles, they fall more rapidly under the 1.9C and 1.5C ensembles, reaching near zero for all sectors. We find a divergence in ensembles for residential emissions per capita, with the 3.5C and 3.1C ensembles leading to growing emissions per capita over time and the 1.9C and 1.5C leading to falling emissions per capita over time. In terms of total global GHG emissions, our ensembles span much of the AR5 range provided by IPCC (2014).

We also find that there are many patterns of energy and technology development consistent with long-term environmental pathways. The distributions of energy and technology developments we estimate provide information for assessing risks of investing in different technologies.

We also combine our ensembles with scenario discovery, providing the ability to explore a full range of outcomes while also maintaining intact individual scenarios. We are able to identify scenarios that have similar outcomes in one dimension and explore the range of outcomes along other dimensions in those scenarios. This approach provides a foundation to identify individual scenarios of interest and further explore tipping points in scenarios (e.g. what might lead one scenario toward a lot of wind & solar vs. other technologies).

In addition to providing information about risks that can aide decision-making and identifying scenarios of interest, our uncertainty quantification approach can also provide a better understanding of model responses and offer insight into areas for further research and model development. For example, under tight emissions constraints, there is a question as to whether the model has sufficient abatement opportunities represented (e.g., for agriculture, energy intensive industry and residential sectors) after mid-century when emissions need to trend toward zero.

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