

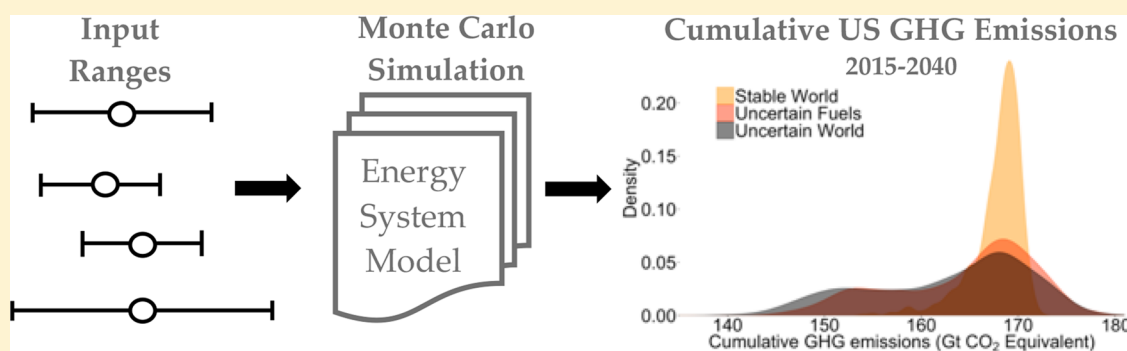
US Energy-Related Greenhouse Gas Emissions in the Absence of Federal Climate Policy

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S Supporting Information



ABSTRACT: The planned US withdrawal from the Paris Agreement as well as uncertainty about federal climate policy has raised questions about the country’s future emissions trajectory. Our model-based analysis accounts for uncertainty in fuel prices and energy technology capital costs and suggests that market forces are likely to keep US energy-related greenhouse gas emissions relatively flat or produce modest reductions: in the absence of new federal policy, 2040 greenhouse gas emissions range from +10% to –23% of the baseline estimate. Natural gas versus coal utilization in the electric sector represents a key trade-off, particularly under conservative assumptions about future technology innovation. The lowest emissions scenarios are produced when the cost of natural gas and electric vehicles declines, while coal and oil prices increase relative to the baseline.

INTRODUCTION

The US is the second largest energy-related greenhouse gas emitter¹ and therefore critical to global efforts to mitigate climate change. The US intends to formally withdraw from the Paris Agreement, and key policies aimed at curbing greenhouse gas emissions—in particular the Clean Power Plan and revised CAFE standards—face a highly uncertain fate. Inaction on the federal level is tempered by state-level action, including California’s SB32,² the Regional Greenhouse Gas Initiative (RGGI) covering 9 northeastern states,³ and renewable portfolio standards active in over 35 states.⁴ In addition to federal and state policy, market forces will play a critical role in shaping the future US energy system over the next several decades. Reasons for optimism include low natural gas prices⁵ as well as dramatic drops in the cost of solar photovoltaics⁶ and lithium ion batteries used for grid storage and electric vehicles.⁷ While prevailing market forces are likely to temper unconstrained greenhouse gas emissions at the national level, the US will eventually need to produce deep emissions reductions in order to avoid the worst effects of climate change. The US had previously acknowledged the need for such reductions. For example, the US nationally determined contribution (NDC) under the Paris Agreement is 26–28% below 2005 levels by

2025, and the Mid-Century Strategy suggests an 80% reduction below 2005 levels by 2050.⁸

Given the anticipated lack of near-term federal action to address climate change, it is critical to evaluate potential baseline emissions scenarios in the absence of federal climate policy. In addition, careful model-based analysis of baseline scenarios can help inform discussions regarding the timing and structure of future climate and energy policy. The US Energy Information Administration (EIA) utilizes the National Energy Modeling System (NEMS) to produce the Annual Energy Outlook (AEO).⁹ The AEO includes a Base Case as well as several side cases that typically focus on variations in economic growth, fuel resource cost and availability, and rates of technology innovation. For example, AEO 2017 includes a total of seven cases that are repeated with and without implementation of the EPA Clean Power Plan.⁹ While these internally consistent scenarios provide a sketch of potential midterm energy futures, they belie the underlying market uncertainty that could push the US energy system in different directions in the absence of new

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Table 1. Sectoral-Level Detail in the Temoa Input Database

sector	description
fuel supply	Fuel prices are specified exogenously. Baseline projections are drawn from the 2017 Annual Energy Outlook. ⁹ There is no limit on fuel availability except for biofuel use in the transportation sector. ³⁵
electric	The electric sector includes 34 generating technologies. Air pollution control retrofits for coal include low NO _x burners, selective catalytic reduction, selective noncatalytic reduction, and flue gas desulfurization. Costs and performance characteristics are largely drawn from the EPA U.S. nine-region MARKAL database, ²⁸ and existing capacity estimates are drawn from the US EIA. ⁹
transportation	The transportation sector is divided into four modes: road, rail, air, and water. Road transport is modeled with greater detail by dividing it into three subsectors: light duty transportation, heavy duty transportation, and off-highway transportation. The light duty sector includes 6 size classes and 9 different vehicle technologies. Data is largely drawn from the EPA U.S. nine-region MARKAL database. ²⁸
industrial	Given the high degree of heterogeneity in the industrial sector, it is modeled simplistically as a set of fuel share constraints that are calibrated to the 2017 Annual Energy Outlook. ⁹
commercial	The commercial sector includes the following end-use demands: space heating, space cooling, water heating, refrigeration, lighting, cooking, and ventilation. A total of 83 demand technologies are included to meet these end-use demands. Data is largely drawn from the EPA U.S. nine-region MARKAL database. ²⁸
residential	The residential sector includes the following end-use demands: space heating, space cooling, water heating, freezing, refrigeration, lighting, cooking, and appliances. A total of 69 demand technologies are included to meet these end-use demands. Data is largely drawn from the EPA U.S. nine-region MARKAL database. ²⁸

policy. Several other recent modeling efforts have projected US energy technology deployment and greenhouse gas emissions but generally focus on scenarios under proposed or hypothetical federal policy and use a limited number of scenarios to address parametric uncertainty.^{10–18}

In this analysis, we utilize Tools for Energy Model Optimization and Analysis (Temoa),¹⁹ an open source, publicly available energy system optimization model (ESOM), to examine a large set of baseline US energy futures through 2040. Our objective is to rigorously explore the future decision landscape and quantify greenhouse gas (GHG) emissions in a future where energy system changes are driven by market forces rather than top-down federal policy. We employ a sensitivity technique called the Method of Morris^{20,21} to rank order the input parameters that produce the largest effect on emissions. We then incorporate the ten most sensitive parameters into a suite of Monte Carlo simulations that indicate how US energy-related GHG emissions may change under different future assumptions. The full set of results is used to identify plausible combinations of assumptions that can lead to either very high or low emissions, which can inform our understanding of future baseline emissions and suggest pathways to lower emissions in the absence of new federal policy.

MODEL AND DATA

The analysis is performed with an open source energy system optimization model (ESOM) called Temoa, which operates on a single region input database representing the continental United States. The model source code and data are publicly available through GitHub,²² and an exact copy of the files used to produce this analysis is archived through Zenodo.²³ Key features of the model and input data set are described here, with additional information provided in [Section 1 of the Supporting Information](#).

Tools for Energy Model Optimization and Analysis (Temoa). Temoa¹⁹ is an open source, bottom-up ESOM, similar to MARKAL/TIMES,²⁴ OSeMOSYS,²⁵ and MESSAGE.²⁶ Temoa employs linear optimization to generate the least-cost pathway for energy system development. The model objective function minimizes the system-wide present cost of energy provision over a user-specified time horizon by optimizing the installation and utilization of energy technologies across the system. Technologies in Temoa are explicitly defined by a set of engineering-economic parameters (e.g., capital costs, operations and maintenance costs, conversion efficiencies) and are linked together in an energy system network through a flow

of energy commodities. Model constraints enforce rules governing energy system performance, and user-defined constraints can be added to represent limits on technology expansion, fuel availability, and system-wide emissions. The model formulation is detailed in Hunter et al.,¹⁹ and the Temoa source code is publicly available on Github.²² Since the model formulation evolves over time, revised model documentation can be found on the project Web site.²⁷

Input Data. The input database used in this analysis is largely drawn from the EPA MARKAL database²⁸ and represents the US as a single region. The time horizon extends from 2015 to 2040, with 5-year time periods. For example, the 2015 period covers the years 2015 to 2019. The results for each year within a given time period are assumed to be identical. Temporal variation in renewable resource supply and end-use demands is captured through representation of three seasons (summer, winter, intermediate) and four times of day (a.m., p.m., peak, night). Fuel price trajectories are drawn from the Annual Energy Outlook (AEO)⁹ and specified exogenously. While assuming a fixed fuel price trajectory does not capture demand-price feedbacks, it simplifies the execution and interpretation of the sensitivity analysis. The model tracks emissions of CO₂, NO_x, and SO₂ as well as CH₄ leakage rates from natural gas systems. We assume a methane leakage rate equivalent to 1.4% of total natural gas delivered,²⁹ which is lower than both NETL³⁰ and EDF³¹ estimates of 1.6 and 1.65%, respectively. Given the ability to mitigate methane leakage and the multidecadal time scale of our analysis, use of the EPA estimate was deemed appropriate. Methane emissions are transformed into CO₂-equivalents using a global warming potential (GWP) of 25.²⁹ This GWP value complies with the international inventory reporting guideline under the United Nations Framework Convention on Climate Change.²⁹ The input database and baseline assumptions are detailed in the [Supporting Information](#), and a brief sectoral description of the input data set is provided in [Table 1](#).

The Temoa baseline scenario is designed to be conservative. The baseline assumes that the Clean Power Plan is not implemented and does not include California's cap-and-trade system or RGGI. The baseline includes the aggregate effect of state-level renewable portfolio standards as well as prevailing tax incentives, including the production tax credit for wind³² and a 10% tax credit on utility scale solar PV throughout the time horizon.³³ To orient our baseline to a familiar projection, our input assumptions draw heavily on the AEO⁹ and Assumptions to the AEO.³⁴ The Temoa baseline results are compared with AEO in [Supporting Information Figures S2–S7](#).

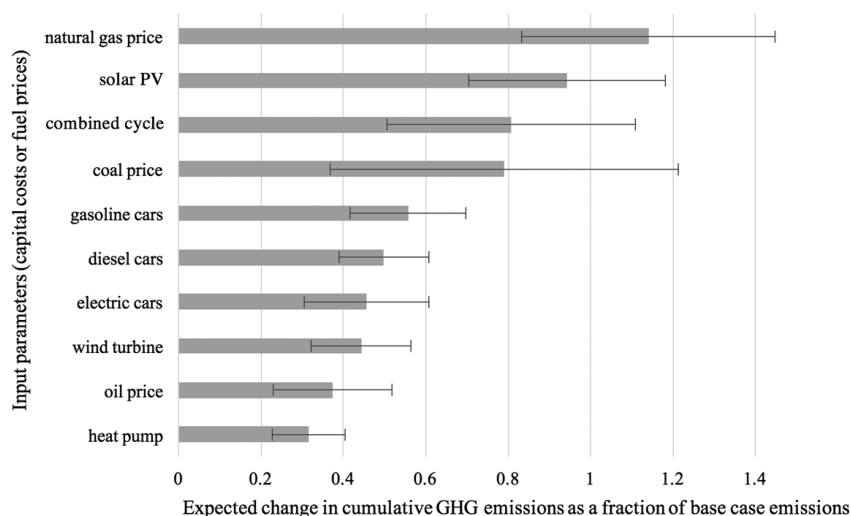


Figure 1. Method of Morris results indicating the ten input parameters that produce the largest effect on cumulative GHG emissions (2015–2040), ranked from largest to smallest effect. Parameters labeled “price” represent fuel prices, while all others represent capital costs. The horizontal axis indicates the magnitude of the expected change in cumulative GHG emissions relative to the baseline value. Each input parameter is tested at 25 distinct values over a range representing $\pm 20\%$ of its baseline value. The length of the bar indicates the average effect, while the error bars indicate the 95% confidence intervals.

ANALYSIS FRAMEWORK

Our methodological approach shares common elements with previous work. For example, we utilize large scale scenario generation and cluster analysis similar to the Robust Decision Making (RDM) approach;^{36,37} however, we are not attempting to identify a policy strategy. In addition, recent studies have used ESOMs to generate a large ensemble of near optimal scenarios to derive policy relevant insights, but such work has focused on European applications.^{38–40} Below we describe each element of our framework in turn.

Method of Morris. Following work by Usher,⁴¹ we utilize a global sensitivity method called Method of Morris^{20,21} to identify the model inputs that produce the largest effect on cumulative GHG emissions over the model time horizon. The method produces a reliable sensitivity measure with a minimum number of runs and can handle a large number of uncertain parameters, making it suitable for use with data-intensive ESOMs.⁴¹ We consider price variation in 6 different fuels and 35 technology-specific capital costs. (See the [Supporting Information](#) for additional details on the Method of Morris formulation and problem setup used in this analysis.) For simplicity, each parameter is varied within a range representing $\pm 20\%$ of its baseline value rather than trying to identify specific ranges for each parameter separately, which are subject to considerable future uncertainty.

Monte Carlo Simulation. Next, we perform a Monte Carlo simulation where we consider variation in the ten most sensitive parameters selected from the Method of Morris analysis. Our objective is to quantify how variation in the ten most sensitive technoeconomic parameters can affect the resultant range in GHG emissions. Given the high uncertainty associated with these future parameter values, we do not attempt to quantify different ranges, probability distributions, or correlations between parameters. Rather, a uniform distribution and range is assumed for each parameter, similar to other studies.^{40,42–44}

As a result, the full set of model results indicates the range of future emissions pathways and suggests possible outcomes but should not be interpreted probabilistically. When investigating low emissions outcomes relying on specific combinations of

realized parameter values, we consider the plausibility of those parameter combinations ex post. The required number of model runs for the Monte Carlo simulation is assumed independent of the number of uncertain inputs;⁴⁵ 1000 runs are conducted within the simulation. To minimize the computational time, we create an embarrassingly parallel⁴⁶ implementation of the framework. The model runs are parallelized using the “joblib” Python library.⁴⁷ We run the model using a workstation containing two Multi-Core Intel Xeon E5-2600 series processors, representing a total of 12 compute cores.

k-Means Clustering. Rather than examine the raw set of 1000 model runs, we employ *k*-means clustering to examine a limited number of representative points. The *k*-means algorithm partitions the data set by creating groups or clusters with similar features. The algorithm minimizes the Euclidean distance between the centroids of each cluster, where each cluster consists of centroid values representing the 10 uncertain input parameters plus cumulative emissions (see the [Supporting Information](#) for more details). We separate the data into ten clusters, which provide enough points to identify relationships between input values and the resultant level of cumulative CO₂ emissions. Larger numbers of clusters were tested, but the configuration of centroids did not yield additional insights.

The *k*-means clustering algorithm is a well-established methodology applied to separate data sets into homogeneous groups of observations. The method was first developed by Lloyd⁴⁸ and has been widely used as a nonhierarchical clustering approach. Other methods such as principal component analysis,⁴⁹ hierarchical and other nonhierarchical clustering methods,^{50,51} and supervised and unsupervised learning algorithms⁵¹ could also be used for our purpose. However, in this work we make use of the *k*-means method for clustering due to its simplicity, efficiency, and successful application in several areas of the literature.⁵²

Uncertainty Cases. We develop three different cases to represent different levels of future uncertainty and repeat the Monte Carlo simulation, consisting of 1000 model runs, for each case. We refer to the first case as ‘Stable World’, which denotes a relatively stable future in which the ten most sensitive

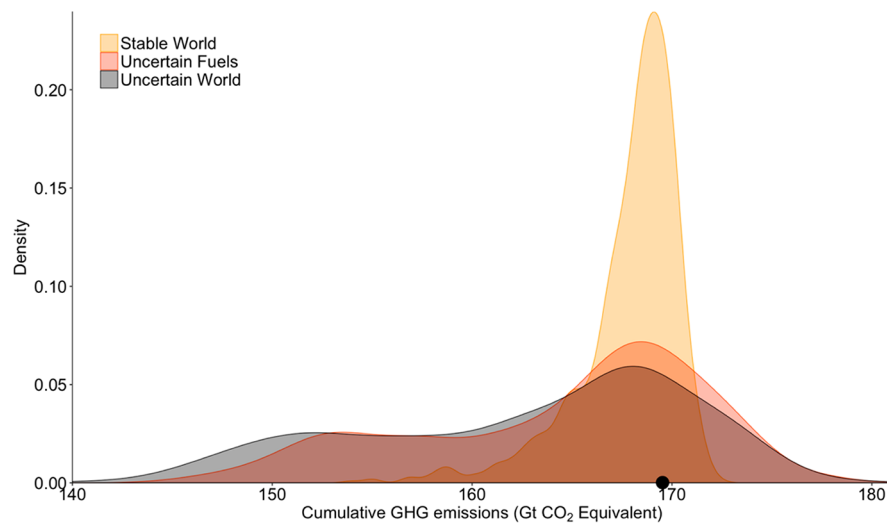


Figure 2. Kernel density estimates of cumulative GHG emissions from 2015 to 2040 for three cases: Stable World, Uncertain Fuels, Uncertain World. The modeled baseline GHG emissions are estimated to be 169 Gtonnes of CO₂ equivalent, represented by the black dot on the horizontal axis. Larger ranges in input parameters produce large ranges in cumulative GHG emissions, with results skewed toward cumulative emissions below the baseline value.

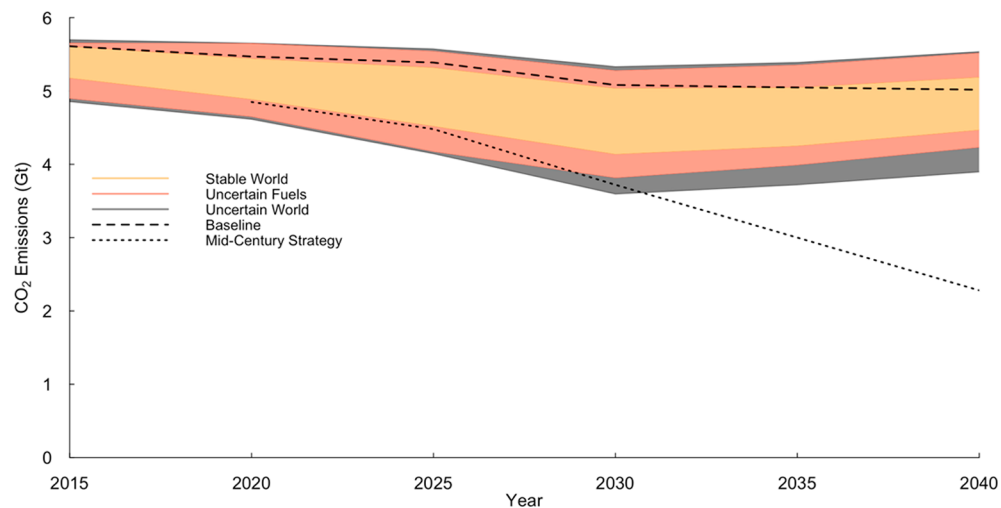


Figure 3. Ranges of projected CO₂ emission pathways in the three modeled cases, with the baseline emissions scenario and the Mid-Century Strategy (MCS) included for reference. All three cases could result in emission pathways significantly lower than the base case. In the first model time period (2015–2019), technology capacity remains fixed except for new wind and solar, which have been experiencing rapid year-over-year growth. Thus, emissions variations in the first time period are due to differences in the utilization of existing capacity as well as new installed renewable capacity. See the [Supporting Information](#) for further discussion of the baseline scenario results.

parameters selected from Method of Morris vary within $\pm 20\%$ of their baseline values. The second case, ‘Uncertain Fuels’, allows natural gas and oil prices to vary within $\pm 80\%$ of their baseline values, consistent with their longer-term historical range over the last 50 years.^{53,54} The remaining eight parameters in the Uncertain Fuels case vary within $\pm 20\%$ of their baseline values, as in the Stable World case. The third case, ‘Uncertain World’, allows natural gas and oil prices to vary within $\pm 80\%$ of their base value, while the other eight uncertain input factors vary within $\pm 40\%$ of their baseline values.

RESULTS AND DISCUSSION

The presentation of results follows the order described in the [Analysis Framework](#) section. We begin by presenting results from the Method of Morris sensitivity analysis, followed by the Monte Carlo simulations associated with each of the three

uncertainty cases. The raw Monte Carlo results are used to examine the range of future cumulative emissions and the role that natural gas prices play in determining emissions. Finally, we present results from *k*-means clustering to assess how variations in technology cost and fuel prices lead to different emissions outcomes.

Identifying Key Sensitivities. The Method of Morris results ([Figure 1](#)) indicate that natural gas prices have the largest overall effect on cumulative GHG emissions. In the electric sector, coal prices and capital costs for solar photovoltaics, wind, and combined-cycle gas turbines also have a measurable effect on total emissions. The inclusion of capital costs associated with battery electric vehicles, conventional gasoline vehicles, and diesel vehicles indicates that the light duty vehicle sector can also have an effect on emissions. Below the tenth most sensitive parameter (heat pump capital cost), the average effect on

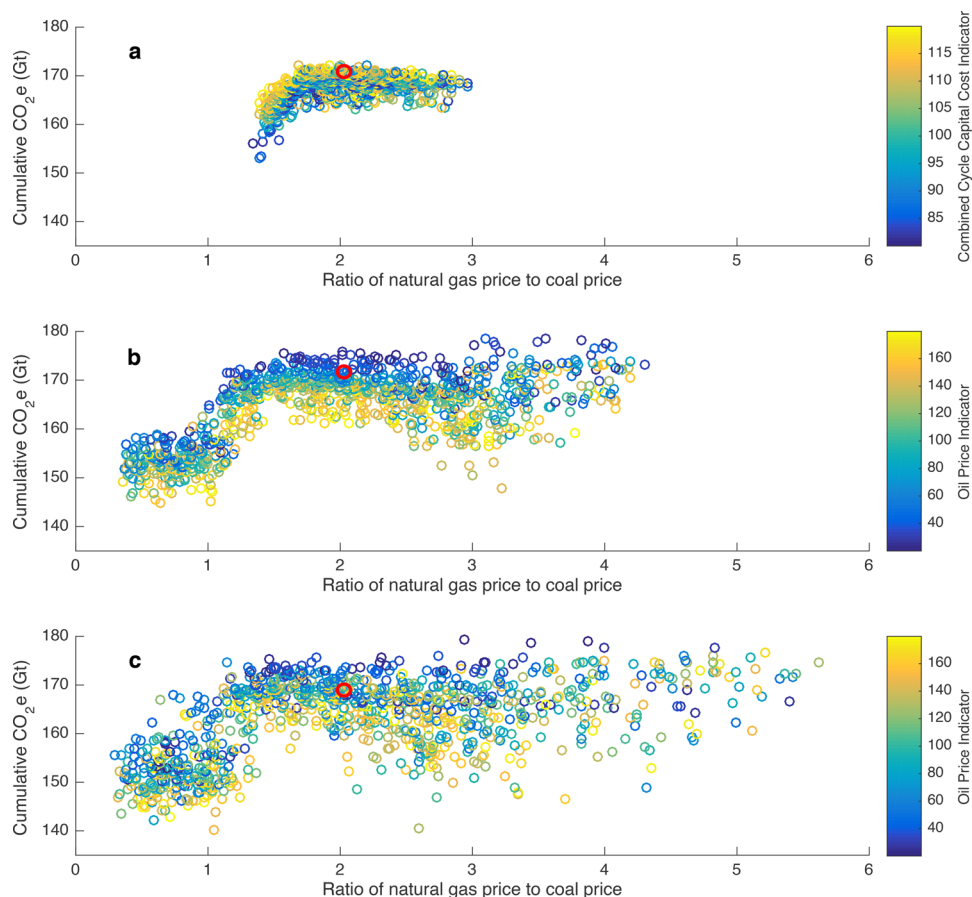


Figure 4. Cumulative GHG emissions versus the ratio of natural gas to coal prices. Each subplot represents the full set of 1000 runs associated with each case: (a) Stable World, (b) Uncertain Fuels, and (c) Uncertain World. In each case, the red circle represents the baseline projection. Each point in the Stable World case is colored by the capital cost of combined-cycle natural gas turbines, while points in the other two cases are colored by the oil price. These factors help explain the variability in cumulative GHG emissions at a given fuel price ratio. The color bar indicates the scalar value used to adjust the input parameter value in the Monte Carlo simulation.

cumulative GHG emissions is less than 0.25% of the base case cumulative emissions. In general, the small relative changes in cumulative emissions reflect inertia in the energy system: a change in any single parameter takes time to reach its full effect on technology deployment and has a limited effect across the system.

We repeated the Method of Morris analysis with a $\pm 40\%$ input parameter range and found that it generates the same top ten parameters as shown in Figure 1; however, oil price rises to the second rank, while the relative order of the other inputs stays the same.

Baseline GHG Emissions under Future Uncertainty.

The ten parameters with highest sensitivity (Figure 1) are selected for inclusion in a suite of Monte Carlo simulations that indicate how US energy-related GHG emissions may change under different future assumptions. The distribution of cumulative GHG emissions from the three cases is shown in Figure 2 where kernel density estimation⁵⁰ is employed to smooth out the raw histogram results.

In the Stable World case, the distribution of cumulative GHG emissions is clustered around the baseline scenario (169 GtCO₂e), with a range extending to a minimum emissions level of 153 GtCO₂e. By comparison, both the Uncertain Fuels and Uncertain World cases exhibit a wider range in cumulative GHG emissions than Stable World, but both are skewed toward lower emissions. Thus, allowing a wider range in fuel prices

($\pm 80\%$) flattens the distribution of cumulative emissions and increases the proportion of scenarios with emissions lower than the baseline. Moving from Uncertain Fuels to Uncertain World increases the highest emissions scenario by 1% and decreases the lowest emissions scenario by 3.2% relative to the cumulative emissions level in the baseline scenario. Overall, Figure 2 indicates that wider input ranges related to fuel costs and technology investment costs increase the proportion of emissions scenarios below the baseline. For reference, our baseline cumulative GHG emissions are 6.2% higher than the AEO reference case without the Clean Power Plan.⁹ Part of this discrepancy is due to our consideration of CO₂-equivalent emissions from methane leakage during natural gas production, processing, and transport, which AEO does not report. If only CO₂ emissions are compared, the difference is 3.2%. Across all modeled scenarios, methane leakage ranges from 1.6% to 4.1% of total CO₂e emissions.

The CO₂ emissions trajectories associated with the three cases are presented in Figure 3 and compared with the energy-related CO₂ emissions from the Mid-Century Strategy (MCS) for deep decarbonization.⁸ The MCS outlines a path for the US to meet its commitments under the Paris Accord and ultimately achieve an 80% reduction below 2005 emissions levels by 2050.

Figure 3 indicates that it may be possible to meet the US 2025 commitments in the absence of federal policy; however, market

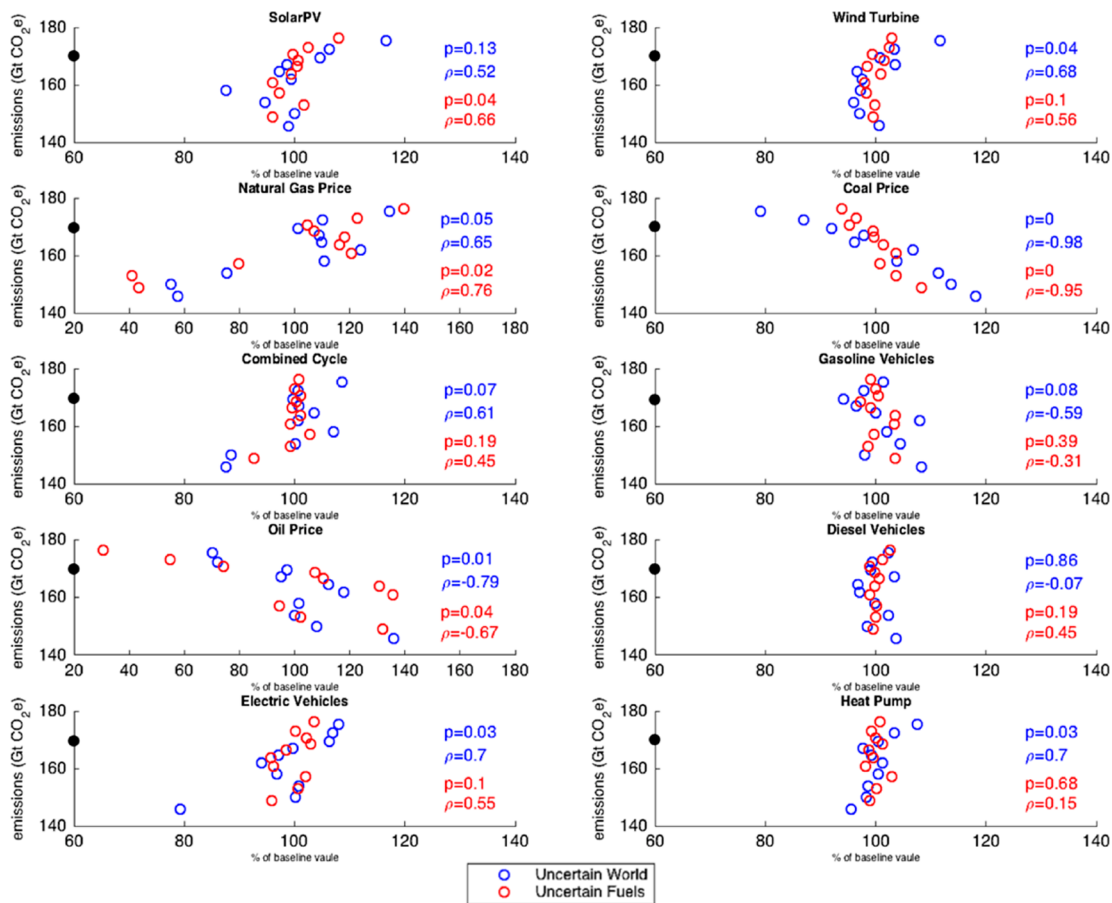


Figure 5. Centroid values associated with uncertain inputs (*x*-axis) versus cumulative GHG emissions (*y*-axis). The centroid values represent scaling values, which are expressed as a fraction of the assumed baseline value. *X*-axis ranges correspond to the allowable ranges in the Uncertain Fuels and Uncertain World cases. The Spearman rank correlation coefficients (ρ) and *p*-values help to identify the degree of monotonicity between each input and emissions. Cumulative baseline emissions are shown by the black dot on the *y*-axis.

forces alone are not enough to sustain the emissions reductions prescribed by the MCS post-2025.

The Effect of Fuel Prices in the Power Sector on GHG Emissions. In addition to total GHG emissions, we examine the underlying trends in technology deployment that drive the emissions shown in Figures 2 and 3. Since the Method of Morris results indicated that emissions are highly sensitive to natural gas and coal prices, we plot cumulative GHG emissions versus the average ratio of natural gas to coal prices across all model time periods (Figure 4). In the Stable World case (Figure 4a), there is a linear increase in emissions as the natural gas price increases relative to coal, which is due to the direct substitution of natural gas with coal to produce baseload electricity. Around a price ratio of approximately 1.8, however, the cumulative GHG emissions reach a plateau because baseload electricity production from coal reaches a maximum. At low price ratios, the variation in emissions at a given fixed price ratio is largely explained by variation in the capital cost of advanced natural gas combined cycle capacity. However, at higher price ratios above 1.8, the variability in cumulative emissions increases as variations in other input parameter values begin to exert their influence under high natural gas prices.

In the Uncertain Fuels case (Figure 4b), coal and natural gas prices still largely explain cumulative emissions when the price ratio is below 1.8, as in the Stable World case. However, the wider range associated with input natural gas and oil prices in the Uncertain Fuels case leads to a wider range in cumulative GHG

emissions. The maximum variation in GHG emissions at a given fuel price ratio is approximately 33 GtCO₂e in the Uncertain Fuels case and 18.4 GtCO₂e in the Stable World case. While the spread in cumulative emissions increases in the Uncertain Fuels case, it is largely skewed toward lower emissions. At a given natural gas to coal price ratio, oil prices help explain the variation in cumulative emissions, particularly at price ratios less than two.

In the Uncertain World case (Figure 4c), the variability in cumulative emissions as a function of fuel price ratio further increases because other input parameters play a larger role in determining emissions. Compared with the Uncertain Fuels case, oil prices are not as clearly correlated with cumulative emissions at a given price ratio. Emissions in all three cases are skewed toward lower values. In addition, there is a fairly consistent emissions ceiling; cumulative emissions do not exceed 180 GtCO₂e in any of the three cases.

The Effect of All Uncertain Inputs on GHG Emissions. Figure 4 indicates that the cumulative GHG emissions are strongly influenced by input parameters other than natural gas and coal prices in the Uncertain Fuels and Uncertain World cases. *k*-Means clustering is applied to Monte Carlo results to condense the full set of 1000 runs from each case into a more manageable 10 clusters, which can be used to identify other key input parameters influencing cumulative emissions. Each of the ten clusters is defined by ten centroids representing the input parameter scaling factors used in the Monte Carlo simulation and another centroid representing cumulative GHG emissions.

The centroids are extracted from their clusters, grouped by input parameter, and plotted versus the associated cumulative emissions in Figure 5. Parameters that demonstrate a monotonic relationship with cumulative emissions and a wider spread in centroid values suggest a stronger effect on the emissions outcome.

Spearman rank correlation coefficients are used to quantify the relationship between the centroid values and associated cumulative emissions. Spearman coefficients quantify the correlation between parameter value ranks and are thus an appropriate choice because they measure the degree of monotonicity between variables and do not require a linear relationship. High Spearman coefficients with low p-values (<0.05) indicate that changing a given input parameter produces a consistent directional change in emissions. The capital costs of solar PV, wind, electric vehicles, and heat pumps as well as natural gas, coal, and oil prices have high Spearman coefficients (>0.6) and low p-values (<0.05) in at least one of the Uncertain Fuels and Uncertain World cases. Coal and oil prices exhibit negative correlation, while renewable and heat pump capital costs as well as natural gas prices show positive correlation with emissions. Although heat pump capital cost exhibited a low coefficient of variation (3%) in the Uncertain World case, we investigated the raw scenario results further and found that it had little effect on cumulative emissions.

Assessment of the Highest and Lowest Emissions Outcomes. The cluster results can also be used to identify the parameter combinations that produce the highest and lowest emissions outcomes, which can inform future policy discussions. Clustering analysis is applied separately to the 50 model runs in both the Uncertain Fuels and Uncertain World cases that produce the highest and lowest 5% cumulative GHG emissions (Figure 6). In Figure 6, centroids are grouped by cluster to demonstrate how a particular set of centroids comprising a cluster produces a given emissions outcome. We consider the six

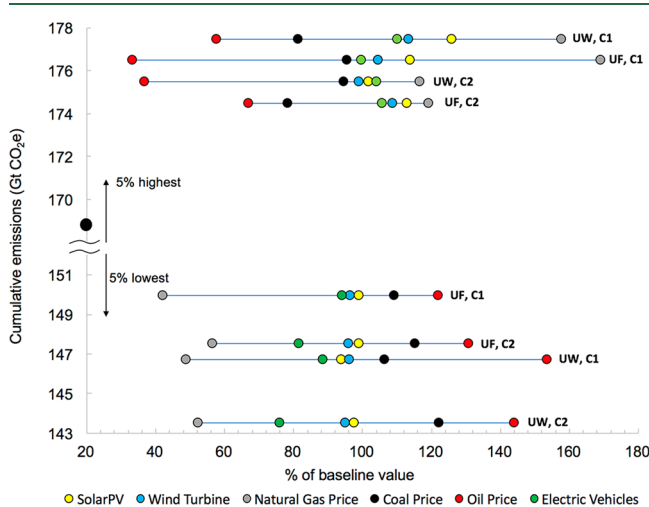


Figure 6. Application of k -means clustering to the 5% highest and lowest emission runs from the Monte Carlo simulation for both the Uncertain Fuels (“UF”) and Uncertain World (“UW”) cases. Each horizontally aligned row represents a single cluster (“C1” or “C2”), and each colored dot represents the centroid value associated with a specific parameter within the given cluster. The centroid values on the x -axis represent the scaling factors applied to baseline estimates and used in the Monte Carlo simulation; cumulative GHG emissions associated with each cluster are plotted on the y -axis. Cumulative baseline emissions are shown by the black dot on the y -axis.

input parameters with high Spearman correlation coefficients (>0.6) that are statistically significant at the 5% level in either the Uncertain Fuels and Uncertain World cases and whose centroids have a coefficient of variation greater than 10%. Two clusters per case and emissions level (high or low) are generated; more clusters tended to produce redundant results.

In the Uncertain Fuels case, both the highest and lowest emissions regimes are characterized by opposing oil and natural gas prices. The centroid values reflect the wider allowable range in natural gas and oil prices ($\pm 80\%$) compared to coal prices and capital costs for alternative technologies ($\pm 20\%$). Because baseline natural gas prices are currently near the lower end of their historical price range, the price reductions required to produce the lowest emissions clusters would be difficult to achieve. Furthermore, since this analysis does not account for correlation between input parameters, we need to consider ex post whether a future with low natural gas prices and high oil prices is plausible. With the advent of shale gas in North American markets, the historically strong correlation between oil and natural gas prices has been weaker since 2007.^{53,54} While there are studies indicating that this decoupling was a temporary phenomenon,⁵⁵ others show that Henry Hub prices are decoupled from WTI prices.^{56,57} Thus, the degree of decoupling between oil and natural gas prices is uncertain, and the assumption here of decoupled prices in the future is at least plausible.

In the Uncertain World case, the centroids associated with the highest emissions clusters include low oil prices and high natural gas prices, with a discernible shift toward lower coal prices and higher capital costs for alternative technologies compared to the base case. We investigated the individual scenarios that comprise the two high emissions clusters, and all are consistent with the centroid values. The centroids associated with the lowest emissions clusters in the Uncertain World case merit careful examination, as they suggest ways in which the lowest emissions pathways can be achieved. In the Uncertain World low emissions clusters, capital cost reductions in electric vehicles coupled with low natural gas prices and high coal prices lead to low electric sector emissions, relatively cheap electricity, and therefore a cost-effective deployment of electric vehicles to supplant gasoline vehicles. The comparison between C1 and C2 in Uncertain World is instructive: relative to C1, the C2 cluster achieves lower emissions with higher coal prices and lower electric vehicle costs. Cluster 2 of Uncertain World achieves the lowest observed emissions with low natural gas prices (52% of baseline), low electric vehicle prices (76% of baseline) coupled with high oil (144% of baseline) and coal prices (122% of baseline). Note that these centroid values do not indicate the relative contribution that each parameter makes to emissions reductions. However, inspection of Figure 6 indicates that the drop in electric vehicle capital cost from Uncertain Fuels Cluster 1 to Uncertain World Cluster 2 is a significant contributor to the 4% drop in cumulative emissions relative the baseline. By contrast, the total drop in cumulative emissions from the baseline to the lowest emissions scenario is approximately 17%. Thus, electric vehicle deployment is not the dominant factor behind lower emissions, consistent with Babae et al.³⁵

While the k -means clustering results strongly suggest the need for low natural gas prices coupled with high oil and coal prices, they obscure some of the underlying variation in the individual scenarios produced by the Monte Carlo simulation. For example, Figure 7 shows the variation in electric sector installed

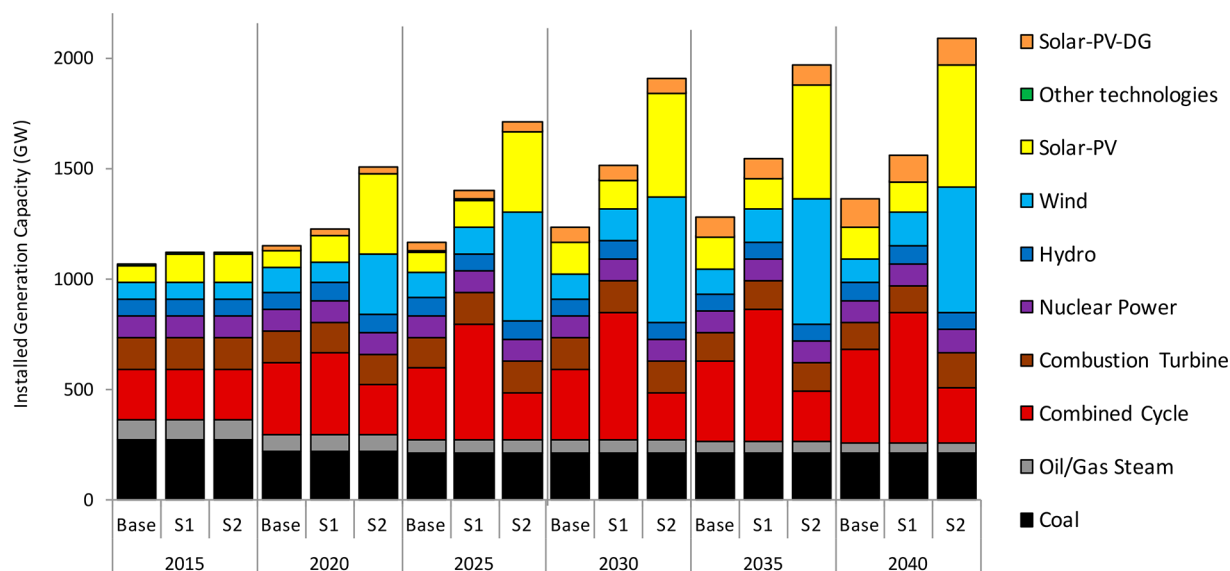


Figure 7. Comparison of electric sector capacities in three scenarios: the baseline scenario and two scenarios drawn from the set of 50 lowest emissions scenarios. “S1” represents a low emissions scenario drawn from Uncertain World Cluster 2 that is consistent with the centroid values shown in Figure 6. “S2” represents a low emissions scenario drawn from Uncertain World Cluster 1 that shows a result significantly different from the associated centroid values.

capacity between the baseline and two scenarios drawn from the set of 50 lowest emissions scenarios.

The electricity capacity results shown in Figure 7 illustrate the potential diversity in individual scenario results. “S2” shows a much higher penetration of wind and solar PV compared to either the baseline or “S1”. The “S2” scenario achieves among the lowest cumulative greenhouse gas emissions (140 GtCO_{2e}) with high fossil fuel prices and high combined-cycle turbine cost coupled with capital costs for wind, solar PV, and electric vehicles that are more than 30% below their baseline value.

Policy Insights and Caveats. Energy system models are often used to examine a limited number of scenarios that reflect carefully considered states of the world; however, the results often ignore high levels of future uncertainty and can thus be misleading. There is a critical need to introspect energy models to quantify key assumptions, sensitivities, and uncertainties. Real world uncertainty includes a broader array of considerations, such as the prevailing political climate, public acceptance of alternative energy technology, and potential policy actions at the state or regional level that are not captured here. Nonetheless, a careful examination focused on technology cost and performance in a systems context can yield useful insight for policy makers.

Our analysis focuses on technoeconomic uncertainty related to fuel prices and technology-specific capital costs, thus providing an indication of how changes in costs can produce different base case outcomes. We do not attempt to model different ranges or correlations among uncertain inputs, which could affect the shape of the emissions distributions shown in Figure 2. Even with a more sophisticated representation of input data, we would not expect a change in the basic insight that technoeconomic uncertainty skews cumulative emissions toward values below the baseline. Our approach here is to conduct the sensitivity analysis with a simplified representation of input data and then examine key relationships *ex post* for plausibility. This approach leaves open the possibility for new insights. For example, the lowest emissions scenarios rely on low natural gas prices and high oil and coal prices, which led us to

consider the degree of price decoupling between these resources. While our assumption of decoupled prices is plausible, future work could test price correlations and their effect on emissions.

Overall, the model results indicate that market forces operating in the absence of new federal climate or energy policy will tend to produce emissions trajectories that remain relatively flat or produce modest reductions: the 2040 emissions range from -23% to $+10\%$ of the baseline estimate. By comparison, the 2040 emissions across the AEO 2017 scenarios (without the Clean Power Plan) range from $+4\%$ to -5% of the AEO reference scenario.⁹ Thus, the broader consideration of input uncertainty in this analysis produces a wider range in future emissions, but the range skews toward lower emissions. Our results show consistency with results from Barron et al.,⁵⁸ where most of the scenarios show relatively flat emissions trajectories in comparison with historical levels. By contrast, Clark et al.¹⁴ and Zhu et al.⁵⁹ project higher emissions over the next several decades due to greater reliance on fossil fuels. In our analysis, there are more parameter value combinations that decrease emissions through the deployment of natural gas and renewables than increase emissions through the increased deployment of coal. For perspective, the cumulative difference between the highest and lowest emissions scenario from 2020 to 2025 is approximately 1.8 times the 2015 emissions level,²⁹ and the same cumulative difference from 2020 to 2040 grows to nearly 6.6 times the 2015 emissions level.²⁹ These variations in emissions are significant and illustrate the importance of considering technoeconomic uncertainty in future no-policy scenarios. Applying sensitivity techniques that extend beyond conventional scenario analysis can broaden future energy and emissions pathways, and could help inform subsequent policy efforts.

If technology innovation remains low and technology costs track close to their baseline values, then the key trade-off will be natural gas versus coal utilization in the electric sector. The model results suggest that the continuation of low natural gas prices will lead to additional coal plant retirements, similar to

other studies.^{9,60} Market forces, policies, and regulations that promote natural gas over coal in the electric sector will lead to lower emissions, though concerted effort is required to minimize upstream methane leakage from natural gas systems.⁶¹ The cluster results (Figure 5) indicate that coal, oil, and natural gas prices as well as capital costs for wind, solar PV, and electric vehicles produce a statistically significant effect on cumulative emissions. The lowest emissions scenarios generally rely on lower natural gas prices and electric vehicle costs in addition to higher oil and coal prices relative to the baseline. The full set of centroids associated with renewable capital costs suggests that they are playing a meaningful role in lowering emissions. For example, Figure 5 indicates that lower solar PV costs (12% below the baseline) play a role in achieving cumulative emissions of 160 GtCO₂e, which is 5% below the baseline level. Our choice of the 50 scenarios with lowest emissions was illustrative; changing the size of the lowest emissions set could also affect centroid values.

We devised our base case to be conservative. More optimistic assumptions about renewables in the baseline could shift the cost threshold at which renewables are deployed at large scale. In addition, our model does not include the EPA Clean Power Plan.⁶² While the collective requirement under state-level renewable portfolio standards is included, we did not explicitly model emissions caps in California or the Northeastern states under RGGI. These existing policies, combined with additional state-level efforts to reduce emissions and increase the deployment of renewables, could produce significant GHG reductions beyond those estimated here. Our analysis indicates that energy market forces, operating in the absence of significant new policy, will hold emissions close to current levels or produce modest reductions. While it is heartening that a hiatus in federal energy and climate policy will not produce a dramatic rise in emissions, aggressive policy action will be required to produce the level of GHG reductions required to avoid the worst effects of climate change.

■ ASSOCIATED CONTENT

🔗 Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.8b01586.

Description of model input data, baseline scenario results, and mathematical formulation of Method of Morris and *k*-means clustering algorithm (PDF)

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Notes

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